Machine Translation of Morphologically Rich Languages Using Deep Neural Networks

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Abbreviations

Abbreviation	Full Term
Ar	Arabic
BLEU	Bilingual Evaluation Understudy
Ch	Chinese
CNN	Convolutional Neural Network
CRF	Conditional Random Field
Cz	Czech
De	German
DNN	Deep Neural Network
EM	Expectation-Maximization
En	English
Es	Estonian
Fa	Farsi
Fi	Finnish
Fr	French
FTM	Factored Translation Model
Gr	Greek
He	Hebrew
HSMX	Hierarchical Softmax
Hu	Hungarian
LM	Language Model
LSTM	Long Short-Term Memory
MCW	Morphologically Complex Word
MRL	Morphologically Rich Language
MT	Machine Translation
NLM	Neural Language Model
NLP	Natural Language Processing
NMT	Neural Machine Translation
NN	Neural Network
OOV	Out Of Vocabulary
PBSMT	Phrase-based Statistical Machine Translation
POS	Part Of Speech
ReLU	Rectified Linear Unit
Ru	Russian
SGD	Stochastic Gradient Descent
SMT	Statistical Machine Translation
Tr	Turkish
TTR	Type Token Ratio

Machine Translation of Morphologically Rich Languages Using Deep Neural Networks

Peyman Passban

Abstract

This thesis addresses some of the challenges of translating morphologically rich languages (MRLs). Words in MRLs have more complex structures than those in other languages, so that a word can be viewed as a hierarchical structure with several internal subunits. Accordingly, word-based models in which words are treated as atomic units are not suitable for this set of languages. As a commonly used and effective solution, morphological decomposition is applied to segment words into atomic and meaning-preserving units, but this raises other types of problems some of which we study here. We mainly use neural networks (NNs) to perform machine translation (MT) in our research and study their different properties. However, our research is not limited to neural models alone as we also consider some of the difficulties of conventional MT methods.

First we try to model morphologically complex words (MCWs) and provide better word-level representations. Words are symbolic concepts which are represented numerically in order to be used in NNs. Our first goal is to tackle this problem and find the best representation for MCWs. In the next step we focus on language modeling (LM) and work at the sentence level. We propose new morpheme-segmentation models by which we fine-tune existing LMs for MRLs. In this part of our research we try to find the most efficient neural language model for MRLs. After providing word- and sentence-level neural information in the first two steps, we try to use such information to enhance the translation quality in the statistical machine translation (SMT) pipeline using several different models. Accordingly, the main goal in this part is to find methods by which deep neural networks (DNNs) can improve SMT.

One of the main interests of the thesis is to study neural machine translation (NMT) engines from different perspectives, and fine-tune them to work with MRLs. In the last step we target this problem and perform end-to-end sequence modeling via NN-based models. NMT engines have recently improved significantly and perform as well as state-of-the-art systems, but still have serious problems with morphologically complex constituents. This shortcoming of NMT is studied in two separate chapters in the thesis, where in one chapter we investigate the impact of different non-linguistic morpheme-segmentation models on the NMT pipeline, and in the other one we benefit from a linguistically motivated morphological analyzer and propose a novel neural architecture particularly for translating from MRLs. Our overall goal for this part of the research is to find the most suitable neural architecture to translate MRLs.

We evaluated our models on different MRLs such as Czech, Farsi, German, Russian, and Turkish, and observed significant improvements. The main goal targeted in this research was to incorporate morphological information into MT and define architectures which are able to model the complex nature of MRLs. The results obtained from our experimental studies confirm that we were able to achieve our goal.

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Chapter 1

Introduction

The main goal of this thesis is to explore neural architectures which can be used independently for machine translation (MT) purposes, as end-to-end purely neural translation engines, or can be embedded as complementary modules into existing translation models in order to boost their performance. Therefore, the thesis is mainly about the application of neural networks (NNs) in MT. Along with the main direction of the thesis we also focus on issues related to the translation of morphologically rich languages (MRLs). We are interested in investigating the impact of morphological information on neural MT models.

Without considering the translation approach (neural or statistical), MT can be viewed as a loop consisting of three steps in which *i*) a source constituent is detected, *ii*) required information including syntactic, semantic, and other types of information related to the constituent is collected and *iii*) finally, it is transfered to a target form which is the end of the translation process for that constituent. By "constituent" we mean a translation unit which can vary from a single character to a chunk of text (phrase), i.e. in IBM models (Brown et al., 1993) the translation unit is the word, whereas existing phrase-based statistical machine translation (PBSMT) models (Koehn et al., 2003) consider the phrase as the translation unit. There are also models (Luong et al., 2010; Eyigöz et al., 2013) in which the translation units are defined based on subword units (characters or morphemes). The last approach is more common in neural systems rather than non-neural counterparts. Both conventional and neural approaches are extensively discussed in the next chapters.

The selection of the translation unit directly affects the whole pipeline as all steps have to be customized accordingly. In word- or phrase-based models the first step segments a source sequence into words, and if required, phrases are extracted. At the second step, statistical information (word co-occurrences etc.) is retrieved from a pre-trained model. For syntax-based models the procedure is almost the same with a single difference where the constituent is a syntax rule (instead of a word or phrase). In these paradigms word-level information is further targeted. The last step generates word- or phrase-level translations. In subword-based models these steps are quite different where in the first step we separate morphemes (subunits) instead of words. The second step relies more on subword-level information rather than statistical and syntactic information, and the third step requires a post-translation phase to merge subword-level translations.

Words in MRLs have more complex structures compared to those in non-MRLs, so that a word can be viewed as a hierarchical structure with several internal subunits. The Farsi[1] word ‘$\textit{ānqlāb}_1.\textit{y}_2.\textit{tryn}_3.\textit{hā}_4.\textit{yšān}_5.\textit{nd}_6$’ meaning ‘$\textit{they}_4$ $\textit{are}_6$ $\textit{the}_3$ $\textit{most}_3$ $\textit{revolutionary}_{1,2}$ $\textit{group}_{4,5}$’ is a good example of such structures (see Table 2.1 for more details). Each subunit can carry a meaning and/or have a syntactic role. Therefore, it intuitively seems that word-based models in which words are treated as atomic units are not suitable for this set of languages, and intra-word dependencies within morphologically complex words (MCWs) should be extracted. As a commonly used and effective solution, morphological decomposition is applied to break up words into atomic and meaning-preserving units to reveal such dependencies, but this raises other types of problems. Our goal in this thesis is to investigate these problems.

According to the aforementioned issues discussed so far, the thesis tries to address

[1] We use the DIN transliteration standard to show the Farsi alphabets; `https://en.wikipedia.org/wiki/Persian_alphabet`.

problems such as: why and where morphological segmentation is required in MT, the optimal representation for MCWs, which of the character-level or morpheme-level segmentation yields a better performance in translating MRLs, what happens if a linguistically-precise morphological analyzer is not available, how morphological information can be used in SMT and neural MT (NMT), and what is the impact of such information.

1.1 Research Questions

In this research we follow specific goals which define our research questions. As previously mentioned, we work with NNs in which both the input and output should be numerical vectors. Accordingly, before designing any MT model, characters, morphemes, and words, as inputs and outputs in our case should be efficiently encoded into a numerical vector space. This process is called *'embedding learning'* (Mikolov et al., 2013a). Word embeddings preserve syntactic and semantic relations as well as contextual information. In addition to these types of information we wish to highlight morphological dependencies in our embeddings, which is the focus of our first research question (**RQ1**). Clearly, in **RQ1** we try to answer this question: *What is the best representation for MCWs?* The model proposed for this research question is expected to provide a flexible framework to take morphologically complex structures with several subunits as its input and provide the surface-form embedding as well as subunit embeddings for the input and its internal constituents.

At the next step, we look beyond word-level modeling and focus on sequence modeling. The main challenge here is to model morphologically complex constituents at the sequence level. Language modeling by nature is a hard problem. It becomes more severe when the vocabulary is diverse and the out-of-vocabulary (OOV) word rate is high, a phenomenon frequently encountered in MRLs. We specifically try to solve problems related to rare and unknown words in language modeling, which are covered by the second research question (**RQ2**). In **RQ2**, our goal is to answer this question: *What is the most effective neural language model (NLM) for MRLs?* The model proposed for this research question is expected to receive a sequence of subword units as its input and model the sequence better than other word-, morpheme-, and character-level counterparts. Segmenting words into subunits is also another responsibility defined in this part of the research.

To answer the third research question (**RQ3**), we study methods by which we could incorporate NN-generated information into the conventional SMT pipeline. In **RQ3** we try to enhance the quality of SMT models using results from the previous research questions. Similarly, in this part we focus on MRLs. However, our models are not only limited to this set of languages. **RQ3** mainly answers this question: *How do/can deep neural networks (DNNs) improve SMT?* The framework proposed in this research question is expected to take an existing SMT engine as the input and enrich its different modules with neural features.

The fourth and last research question (**RQ4**) targets NMT models for MRLs. We try to perform an end-to-end translation in purely neural settings. Existing neural architectures are not suitable for MRLs, as they do not consider morphological units as separate units. Accordingly, we propose several compatible neural architectures, and the main goal is to answer this question: *How can we (fine-)tune NMT models for translating MRLs?* Neural architectures proposed for this part of the research should be able to accept different types of inputs, provide high-quality representations for them, and generate the final translation better than other models. They should also be able to embed morphological information into different modules of the neural architecture.

1.2 Thesis Structure

The thesis is organized in three main parts. The first part, including Chapter 1 and Chapter 2, explains the structure of the thesis along with fundamental concepts which we require to explain and expand our ideas. The second part covers the core research and answers our research questions in Chapters 3 to 7. The last part explains how this research contributes to our field and concludes the thesis with some avenues for future work in Chapter 8. More detailed information about each chapter is as follows:

- Chapter 1 explains the skeleton of the thesis along with the achievements and contributions.

- Chapter 2 provides basic concepts which we need to express the core ideas of the thesis. Since the thesis is about MRLs, DNNs, and their application in MT, first we have an introduction to problems related to morphology. Afterwards, we explain the fundamentals of SMT. We also discuss different neural architectures. Apart from these introductory topics, Chapter 2 reviews the related literature. For the purpose of clarity, modularity, and consistency, we only review SMT models in this chapter. All other chapters start with an introductory section followed by a background section including the literature review and continue with other subjects.

- Chapter 3 explains the problem of embedding learning and reviews related models. It proposes a new embedding model for MCWs and discusses an attempt to incorporate morphological information into word embeddings.

- Chapter 4 is about neural language modeling for MRLs. It discusses different models for decomposing MCWs and proposes count-based and statistical models in this regard. In this chapter, we not only propose a novel NLM but also using our models, we manipulate n-gram-based language models (LMs) to provide better translations.

- Chapter 5 studies the use of NN-generated features in SMT. We use the findings of the previous research questions to improve SMT quality. We boost factored translation models and enrich the phrase table using word and phrase embeddings. Methods in Chapter 5 are language-independent, so while we focus on MRLs in our experiments they can be applied to any language.

- Chapter 6 discusses end-to-end neural architectures for sequence modeling and translation. In our models we try to capture morphological complexities both on source and target sides, where we use better morpheme segmentation models and design neural models particularly for MRLs.
- Chapter 7 manipulates the neural architecture and proposes an NMT engine which is designed particularly for translating from MRLs. This chapter introduces our new NMT engine with a double-channel encoder and double-attentive decoder.
- Chapter 8 concludes the thesis and explains our plans for future work. We summarize the thesis in this chapter and provide a roadmap which declares the goals achieved so far and including some questions which should be solved in the future.

1.3 Contributions

The summary of the main contributions of the thesis is as follows:

- Developing a bilingual corpus of ∼600K English–Farsi sentences.
- Developing a state-of-the-art neural part-of-speech (POS) tagger for Farsi.
- Incorporating morphological information into word embeddings (**RQ1**).
- Mitigating the OOV word problem in embedding learning and language modeling (**RQ1** and **RQ2**).
- Proposing an unsupervised segmentation model for MCWs (**RQ2**).
- Developing a state-of-the-art NLM for MRLs (**RQ2**).

- Learning bilingual and mixed embeddings (**RQ3**).

- Enriching SMT phrase tables using word and phrase embeddings (**RQ3**).

- Proposing compatible NMT models for MRLs (**RQ4**).

- Discovering an optimal morpheme segmentation scheme for NMT (**RQ4**).

1.4 Publication

Publications which are directly related to the research conducted in this thesis include:

- **Passban, P.**, Hokamp, C., and Liu, Q. (2015a). Bilingual distributed phrase representations for statistical machine translation. In *Proceedings of MT Summit XV*, pages 310–318, Miami, Florida, USA.

- **Passban, P.**, Way, A., and Liu, Q. (2015b). Benchmarking SMT performance for Farsi using the TEP++ corpus. In *Proceedings of The 18th Annual Conference of the European Association for Machine Translation (EAMT)*, pages 82–89, Antalya, Turkey.

- **Passban, P.**, Hokamp, C., Way, A., and Liu, Q. (2016a). Improving phrase-based SMT using cross-granularity embedding similarity. *Baltic Journal of Modern Computing*, 4(2):129–140.

- **Passban, P.**, Liu, Q., and Way, A. (2016b). Boosting neural POS tagger for Farsi using morphological information. *ACM Transactions on Asian and Low-Resource Language Information Processing (TALLIP)*, 16(1):4:1–4:15.

- **Passban, P.**, Liu, Q., and Way, A. (2016c). Enriching phrase tables for statistical machine translation using mixed embeddings. In *Proceedings of The 26th International Conference on Computational Linguistics (COLING)*, pages 2582–2591, Osaka, Japan.

- **Passban, P.**, Liu, Q., and Way, A. (2017a). Providing morphological information for SMT using neural networks. *The Prague Bulletin of Mathematical Linguistics*, 108:271–282, Prague, Czech Republic.

- **Passban, P.**, Liu, Q., and Way, A. (2017b). Translating low-resource languages by vocabulary adaptation from close counterparts. *ACM Transactions on Asian and Low-Resource Language Information Processing (TALLIP)*, *In press.*

Chapter 2

Fundamental Concepts

Since our research questions are deeply related to MRLs and morphological information, we begin with an introduction to morphology. We review morphology-related problems along with different morphological operations (see Section 2.1). We discuss why a language is labeled as *“morphologically complex”* or *“isolating”* (Pirkola, 2001) (see Section 2.1.1). In this thesis morphological and NN-generated information is intended to serve SMT models, so first we need to understand the framework itself. Accordingly, we explain the SMT framework. After providing this prerequisite knowledge we review SMT models which have been proposed particularly for MRLs. Apart from SMT, another key concept of the thesis is (D)NNs, so the last part of this chapter (see Section 2.4) reviews the fundamentals of NNs including different architectures.

2.1 An Introduction to Morphology

Morphology is the field of studying ways by which words are built up from smaller fundamental units, morphemes (Jurafsky and Martin, 2009). Morphology lies between phonology and syntax in linguistics. Figure 2.1 illustrates the relation of morphology with other linguistic fields (Uí Dhonnchadha, 2002). Morphemes are fundamental units in morphology which are categorized into five main classes of *stems*, *prefixes*, *suffixes*, *infixes*, and *circumfixes*. Each morpheme is a meaning-bearing unit which is not further decomposable (they are atomic units). They may have syntactic roles as well as semantic roles.

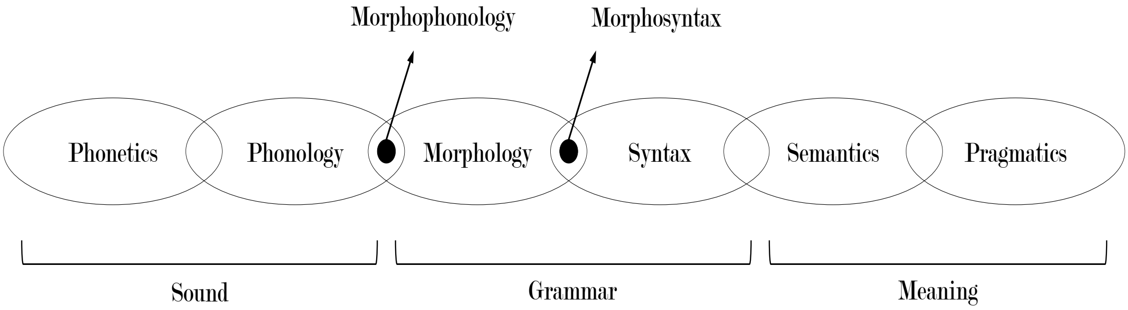


Figure 2.1: Where morphology lies in linguistics (Uí Dhonnchadha, 2002).

A prefix precedes a stem, e.g. *pre* in *preprocess* is a prefix. A suffix appears after a stem, e.g. *dom* is a suffix in *freedom*. An infix is an affix inserted inside a word stem. This affix type is not very common in English but in languages such as Arabic, most morphological (and even semantic and syntactic) transformations are carried out via infixes, e.g. the Arabic[1] verb اِجْتَهَدَ (ijtahada) meaning *'he worked hard'* is a transformation derived from جَهَدَ (jahada) meaning *'he strove'*. The infix تَ (t) in the middle of the verb acts as a comparative and also slightly changes the meaning. A circumfix is a more complicated constituent which occurs in languages such as Czech, Dutch, and German. It has two parts, one residing at the beginning of words and the other at the end. For example in German, the past participle of some verbs is formed by adding '*ge*' to the beginning of the stem and '*t*' to the end; so the past participle of the verb '*sagen*' meaning '*say*' is *gesagt* (Jurafsky and Martin, 2009).

As previously mentioned, a morpheme is the smallest unit of words, and each word can be viewed as a morpheme or a combination of different morphemes. The stem can exist independently and it is hence called a *free morpheme*, but other

[1] We provide the transliterated form of Arabic words within parenthesis along with the original form. To encode Arabic words we use the standard Buckwalter transliteration; `https://en.wikipedia.org/wiki/Buckwalter_transliteration`.

affixes are always attached to stems, so they are referred to as *bounded morphemes*. Morphologically simple languages like English does not tend to combine more than four or five morphemes, whereas morphologically complex languages can easily have nine or ten morphemes in a word. This phenomenon is very common in agglutinative languages such as Farsi or Turkish. Table 2.1 shows examples for this case.

Word	**Translation**
Turkish:	
terbiye	good manners
terbiye+siz	rude
terbiye+siz+lik	rudeness
terbiye+siz+lik+leri	their rudeness
terbiye+siz+lik+leri+nden	from their rudeness
terbiye+siz+lik+leri+nden+mis	it was because of their rudeness
Farsi:	
drāmd	income
pr+**drāmd**	wealthy
pr+**drāmd**+tar	more wealthy
pr+**drāmd**+tar+in	the most wealthy
pr+**drāmd**+tar+in+hā	the most wealthy people
pr+**drāmd**+tar+in+hā+yshān	the most wealthy group of them
pr+**drāmd**+tar+in+hā+yshān+nd	they are the most wealthy group of them

Table 2.1: Examples of MCWs in agglutinative languages. Morphemes are sequentially added to change the form, meaning, and syntactic role of the word. The bold-faced morpheme is the stem.

Table 2.1 shows that in agglutinative languages, as a subset of MRLs, morphemes can be easily stacked to construct complex structures. This feature is a simple indication that MCWs are multi-layer and hierarchical structures and cannot be treated as atomic units.

Word formation or affixation is a process whereby different morphemes and affixes are combined together. There are four general ways of *inflection*, *derivation*, *compounding*, and *cliticization* to combine different morphemes (morphological operations). In *inflection* the word's appearance is changed depending on the context. Usually the new inflected word stays in the same grammatical class to which the original word belongs, i.e. both '*work*' and its inflected form *work*$\boxed{\textit{ed}}$ are English verbs. In *derivation* a new word is formed on the basis of an existing word, e.g. *happy* and *happiness*. It can be said that the idea behind both *inflection* and *derivation* is similar in a way that they produce a new constituent with a distinctive difference where the constituent produced by *inflection* is a new word form whereas *derivation* produces a grammatical variant of the base word.

Compounding is the process of combining multiple word stems to yield a new structure with a new meaning, e.g *with+out* → *without.* This phenomenon is very common in Farsi. *Cliticization* is less common than other types in which a stem is combined with a clitic to form a new word. A clitic is a syntactic morpheme which acts like a word but is reduced in form and attached to another word, such as *ve* in *I've*.

The affixation operations reviewed so far are known as *concatenative.* There is another group of morphological operations called *non-concatenative*, which has a more complex affixation system. One of the well-known members of this group is the *templatic* or *root-and-pattern* morphology (Beesley, 1998; Soudi et al., 2007), which is commonly used in Semitic languages such as Arabic. There are different patterns or templates acting as placeholders in Arabic. Root letters reside in specific positions within patterns and new words are derived from pattern-specific combinations which fuse root letters with other morphemes. Fusions are not simple and linear. Root and affix characters are combined in interleaved forms.

A pattern can be viewed as a morphological system which takes root and morpheme letters as its inputs and combines them in an exclusive way so that the position of each character, their relation with each other, agreements and all deformations are controlled by the pattern. It generates a new syntactically correct and meaningful word. For example, let us suppose the root letters are ك (k), ت (t) and ب (b). If these letters occur in the فـاَعـل[2] (faa-il) template, the new word would be كـاَتـب (kaatib) meaning *'writer'*, but if they are processed by the فـعـل (fa-ala) template the result would be كـتـب (kataba) meaning *'he wrote'.* As can

[2] The original form without boxes is فاَعل.

be seen, templates influence a word's semantic and syntactic roles. In this system, the first letter of the root always resides in the ﻓ (f) position, the second letter in the ﻋـ (no equivalent in English)[3] position and the last letter in the ل (l) position. Our examples also obey this substitution rule where ﻓ$_1$, ﻋـ$_2$ and ل$_3$ are substituted by ك$_1$, ت$_2$ and ب$_3$, respectively. Figure 2.2 shows this procedure. These two instances illustrate only a simple transformation model, but there are more complex forms in other Arabic templates.

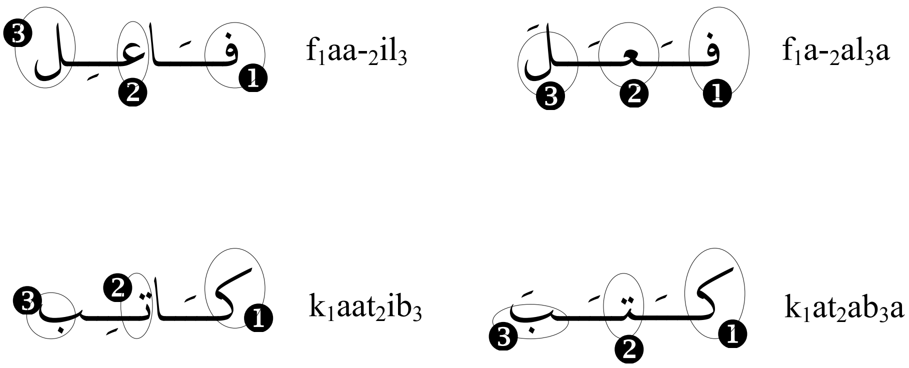


Figure 2.2: Arabic patterns and the letter substitution system. The first line shows two Arabic patterns and the second line, words in those patterns. As the figure depicts, in this case ﻓ (1), ﻋـ or ع (2) and ل (3) which are the reserved letters of the pattern (act as placeholders) are substituted by ك (1), ت (2) and ب (3), respectively.

2.1.1 Morphological Complexity

In this section we explain several qualitative and quantitative criteria which enable us to measure the morphological complexity of languages. All natural languages have their own morphological system. Some languages have complex word-formation rules and some others are more straightforward. In this section we try to define a border to separate languages which are referred to as MRLs from other simpler languages. First we explain two quantitative criteria to this end.

The first criterion is based on *Kolmogorov* complexity (Vitányi and Li, 2000; McWhorter, 2001). The *Kolmogorov* complexity of a string is the length of the

[3] It is a consonantal sound which is pronounced similar to the æ sound but they are not really the same.

shortest computer program (or any computational system) which can generate the string as its output. The idea that an object with a more complex structure than others takes longer to be described is what *Kolmogorov* complexity aims to formalize. The example below from Bane (2008) clarifies the problem:

$$a = 10101010101010101010$$

$$b = 11010001101101011001$$

The string a can be described in English as *10 ten times* whereas b has no structure and needs a longer and more complex statement to be explained. Therefore, according to *Kolmogorov* complexity, a language with a complex morphology needs more bits to be explained.

Bane (2008) designed an experiment to compare different languages in terms of *Kolmogorov* complexity. In the experiment, upper bound of the *Kolmogorov* complexity of the Bible was measured for thirteen languages. Languages such as Dutch, French, German, and Hungarian consume much more bits than morphologically simpler languages such as English and Spanish to describe the same text (the Bible). Similar to *Kolmogorov* complexity there are other criteria which explicitly measure the morphological complexity using mathematical models. For more information see Bane (2008), which defines a metric based on the minimum description length.

The second quantitative criterion frequently used in the literature is the type-token ratio (TTR), which is a simple standard to show the morphological complexity of languages. The TTR measures the ratio of *types* (unique words) in a given corpus against the number of *tokens* (all words), for which the number of *types* is divided by the number of *tokens*. Clearly, the ratio varies in the range $[0, 1]$ where MRLs have higher TTRs (closer to 1) than non-MRLs. In our experiments we report the number of words (tokens) and unique words (types) by which we can compute the TTR for our corpora.

There is another qualitative categorization for measuring the morphological complexity, which labels natural languages as *analytic* or *synthetic* (Pirkola, 2001). An *analytic* language is a type of language with a very low morpheme-per-word ratio. Bulgarian is a good example for this category (Rehm and Uszkoreit, 2012). There is also a specific subtype of this category called *isolating*, which has similar properties but simpler morphological structures. This category could be considered as an extreme case of *analytic* languages, where each word contains a single morpheme. Mandarin Chinese is a good example for this category.

A *synthetic* language is a language with a high morpheme-per-word ratio. The morphological richness in this category is more than the *analytic* category. Most Indo-European languages are from this family. *Synthetic* languages can be divided into two groups of *agglutinative* and *fusional* (or *inflectional*).

An *agglutinative* language is a type of synthetic language with a morphology system that primarily uses agglutination. In the *agglutinative* combination, atomic morphemes are sequentially added to the stem and the forms of the morphemes do not change after the combination. They collocate with each other to construct the final word, where each unit has its own syntactic role. Turkish is a good example for this category (Kuribayashi, 2013).

A *fusional* language is a language in which one form of a morpheme can simultaneously encode several meanings. These languages may have a large number of morphemes in each word, but morpheme boundaries are difficult to identify as they are fused together. Germanic and Romance languages are in this category. The opposite of a highly *fusional* language is a highly *agglutinative* language.[4] Figure 2.3 shows the relations between these different groups. This classification also gives us clues about the complexity of languages. In our experiments we select languages which do not belong to the *isolating* group.

In this section (Section 2.1) we tried to briefly review the problem of morphology. For more linguistic details see De Groot (2008), Delahunty and Garvey (2010), and

[4] We introduced a hierarchy for different groups but it should be noted that there are no clear-cut boundaries among these categories.

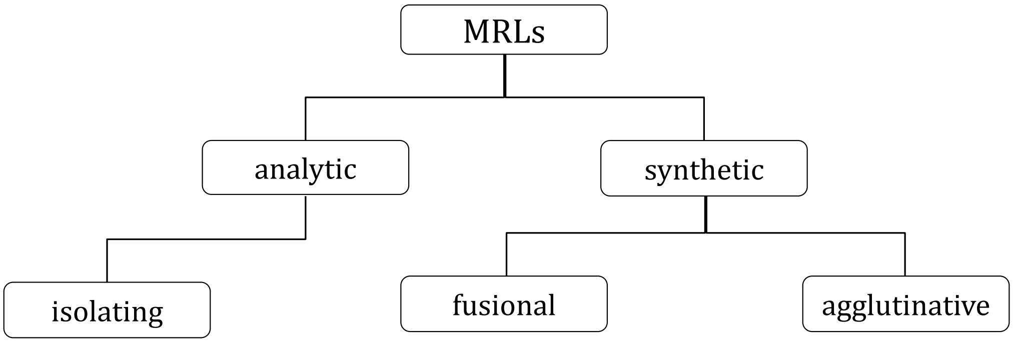


Figure 2.3: Qualitative categorization of morphologically complex languages.

Lieber (2015). We briefly reviewed two criteria to distinguish MRLs from non-MRLs. We also defined a qualitative criterion. Morphological problems are very important in the field of MT as they directly affect the complexity and performance of an MT system. They also have a tight relation with the data sparsity problem and OOV rate. Figure 2.4 from Koehn (2005) summarizes these morphology-related problems.

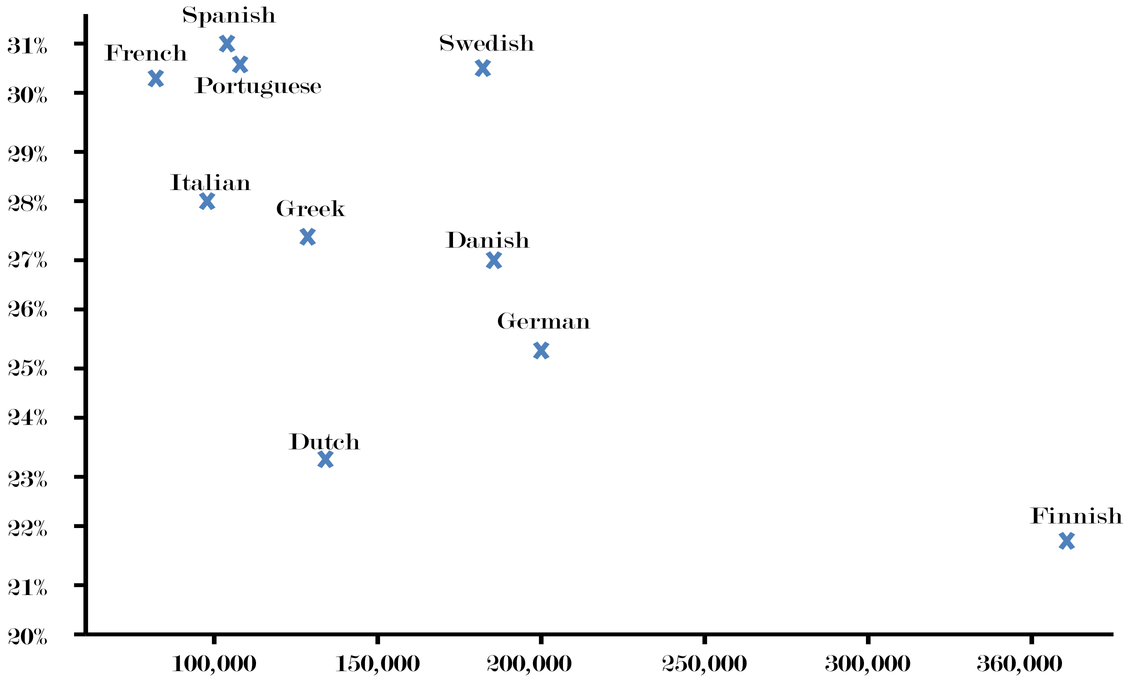


Figure 2.4: Vocabulary size vs. MT performance. The figure shows how morphological complexity can affect the final performance. The x axis shows the vocabulary size and the y axis is the BLEU score.

Figure 2.4 shows the relation between the vocabulary size and BLEU (see Papineni et al. (2002) for more information), when translating into English. As the figure shows, the vocabulary diversity which is a direct consequence of the rich morphology affects MT performance. Motivated by such issues and based on our investigations, we recognized that to address the problem of morphology, language such as Farsi (Fa), German (De), and Turkish (Tr) are suitable for our experimental studies (see Chapter 6 for the reason), so we evaluate our models and report their results on these languages. We also have some experiments on other languages such as Czech (Cz) and Russian (Ru). In the next chapters we give more detailed information on statistics of our corpora and their morphological specifications.

2.2 Statistical Machine Translation

We are interested in SMT (Och and Ney, 2000; Lopez, 2008; Koehn, 2009) and specifically PBSMT (Zens et al., 2002; Koehn et al., 2003) in this thesis. PBSMT is an extension to previously-proposed word-based models (Brown et al., 1993), in which translation is performed at the phrase level. The whole PBSMT pipeline can be summarized in three general steps of word alignment, phrase extraction and decoding.

In the first step of the PBSMT pipeline,[5] alignments between source and target words are identified. Each word is mapped to its counterpart(s) on the opposite (target) side. This process is performed by the well-known Expectation-Maximization (EM) algorithm (Dempster et al., 1977). EM is an unsupervised algorithm which starts from random estimations for word alignments (the expectation or E step) and tries to rectify and improve approximations (the maximization or M step) over iterations. For more detailed information and examples on word alignment see Brown et al. (1993) and Koehn (2009). The EM algorithm for word alignment was implemented in the `GIZA++` toolkit (Och and Ney, 2003) [6] which is frequently used by different models.

A word may not be the best candidate as the smallest unit of translation. Some-

[5] Data preprocessing is not considered as a PBSMT submodule.

[6] `http://www.fjoch.com/giza-training-of-statistical-translation-models.html`.

times one word on the source side is translated into more than one word on the target side, or vice versa (Koehn, 2009), so word-based models do not perform well in such cases. Figure 2.5 illustrates this problem where an English sentence is translated into Farsi. As the figure shows, any word-level model would have serious problems with this example. Blocks of consecutive words are translated altogether, not word by word. Motivated by such difficulties, the phrase-based (phrase-level) translation model was proposed (Zens et al., 2002; Koehn et al., 2003). In this type of translation the goal is to segment sentences into phrases[7] and find a set of target phrases which maximizes the translation probability of a target translation given a source sentence. This problem is formulated as in (2.1):

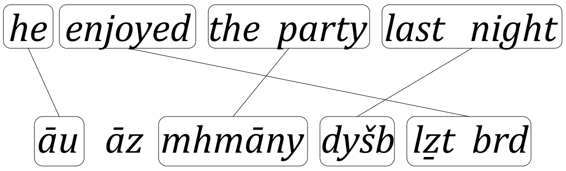


Figure 2.5: Phrase-level translation. The figure tries to illustrate complex word alignments. The Farsi word *āz* is aligned to (nothing) the *Null* token.

$$\mathbf{e}_{best} = \arg\max_{\mathbf{e}} p(\mathbf{e}|\mathbf{f}) \tag{2.1}$$

where **e** and **f** are the target and source sentences, respectively. Applying the Bayes' rule, the translation direction can be inverted, as in (2.2):

$$\mathbf{e}_{best} = \arg\max_{\mathbf{e}} p(\mathbf{f}|\mathbf{e}) p_{LM}(\mathbf{e}) \tag{2.2}$$

where $p_{LM}(\mathbf{e})$ incorporates the impact of a language model. As a very basic description, a language model measures how fluent the generated translation is. Chapter 4 extensively discusses language modeling. The PBSMT model works at the phrase level so in order to generate the translation sentences are decomposed into phrases,

[7] Phrases are not necessarily linguistic phrases in this approach, which means any set of consecutive words can be considered as a phrase.

as in (2.3):

$$p(\bar{f}_1^I|\bar{e}_1^I) = \prod_{i=1}^{I} \phi(\bar{f}_i|\bar{e}_i) d(start_i - end_i - 1) \tag{2.3}$$

where the foreign sentence $\mathbf{f}$ is broken up into I phrases $\bar{f}_i$, ϕ is the phrase-translation probability function which is based on word alignments. For more information on the phrase-translation probability and the relation of source and target phrases see Figure 5.1 and Koehn (2009). $d(.)$ indicates the reordering function. In translation results some phrases may occur in wrong positions, which the reordering function penalizes wrong word orders.

In PBSMT, a source sentence is segmented into many phrases and each source phrase can have several target translations, which the best one should be selected according to the source sentence and context. Clearly, this is a search problem where we should find the best source phrase (segmentation) at each step, find the best counterpart on the target side, and generate the final sentence-level translation. The decoder is responsible for this process in which many syntactic, semantic, and reordering features are involved to show how phrases are tightly related to each other. These features help the decoder search and find the best match. In SMT, the decoding process is modeled via the log-linear framework (Och, 2003), where we can define unlimited number of features for each phrase pair. In Chapter 5, we define 6 new features in order to generate better translations. The decoder is implemented via well-known search models such as *beam search* (Koehn, 2004a) by which the best match is searched for a given source phrase.

In Section 2.2, we briefly reviewed the SMT pipeline in which (given a parallel corpus) translationally equivalent words are aligned to each other and phrases are extracted based on word alignments. Then the decoder takes a source sentence as the input, considers all possible phrases in the sentence and finds the best match for each source phrase. Matches are connected to each other in a way that generates a fluent target sentence. In the next section we review models which fine-tune this pipeline in order to make it more compatible for MRLs.

2.3 SMT for MRLs

In the previous sections we studied the problem of morphology and its relevance to our research. Similarly, we explained SMT and related topics which can help us elaborate our research. In this section we try to review various SMT approaches that are suitable for translating MRLs. All techniques proposed to tackle the problem of morphology are extensions to existing SMT models. However, there are a few instances which tried to address the same problem in the NMT framework, which we postpone their investigation to Chapter 6, where a basic knowledge of NMT is provided, and then we study the incorporation of morphological information.

There are three general approaches to translating MRLs. The first approach manipulates the decoding process and directly incorporates morphological information for translation (Type 1). The second approach does not change the decoder but performs translation in multiple steps (Type 2). For translating from MRLs, first a MCW is transformed into a simpler form and then translation is performed using these basic forms. In such models MT engines do not have to deal with complex structures. In translating into MRLs the direction is reversed, so that a simple word is enriched step-by-step to reach the final complex form. In this approach additional complementary tools such as classifiers and stemmers are used. The third approach can be viewed as a subclass of the second approach, in which neither the decoding nor the translation process is manipulated, but the source-side data is preprocessed to change MCWs into more suitable forms for MT engines (Type 3). Similarly, post-translation processing is also carried out to transform translations into more accurate forms. All pre/post-processing steps are performed outside the decoding phase. The third approach is the easiest solution compared to the others. We review different examples for all of these approaches in the following section.

2.3.1 Incorporating Morphological Information at Decoding Time (Type 1)

A factored translation model (Koehn and Hoang, 2007), which is an extension to PBSMT, is the most suitable example for incorporating any additional annotation, including morphological information, at decoding time. The main problem with PBSMT is that it translates text phrases without any explicit use of linguistic information, which seems beneficial for a fluent translation. In factored models each word is extended by a set of annotations, so a word in this framework is not only a token, but a vector of factors. For example a simple word in PBSMT can be represented by a vector of {word (surface form), lemma, POS tag, word class, morphological information}. Clearly, the new representation is richer than that of the word's surface form. As the main focus in factored models is on word-level enrichments, clearly it addresses the problem of morphology which fits our case.

Let us have a closer look at the model. In word-based or phrase-based approaches each word is treated independently, i.e. *'studies'* has no relation to *'studied'*. If only one of them was seen during training, translation of the other one would be hard (or even impossible) for any MT engine, even though they come from the same root. Translation knowledge of their shared stem, along with extra morphological information, could help us translate both of them (and even all derivative forms of the stem). This property not only provides solutions for this sort of morphological issues but also addresses the data sparsity problem at the same time. A factored translation model follows a similar approach and performs better than other word-based models for MRLs (see Section 5.2.3).

Translation in factored models is generally broken up into two translation and one generation steps. A source lemma is translated into a target lemma. Morphological and POS factors are translated into target forms and the final form is generated based on the lemma and other factors. Factored models follow the same implementation framework as the phrase-based model. In these models the translation step operates at the phrase level whereas generation steps are word-level operators. The pipeline is illustrated step-by-step to translate the German word *Häuser* into English. We use the same example reported in Koehn and Hoang (2007):

- Factored representation: (**surface form**: Häuser), (**lemma**: Haus), (**POS**: NN), (**count**: plural), (**case**: nominative)
- Translation (mapping lemmas): Haus → house|home|building|shell
- Translation (mapping morphology): NN|plural-nominative-neutral → NN|plural, NN|singular
- Generation (generating surface forms):
  - house|NN|plural → houses
  - house|NN|singular → house
  - home|NN|plural → homes

Multiple choices can generate multiple surface forms which result in phrase expansions. Training is performed similar to the basic phrase-based model. Word phrases are extracted with standard models. Factors are also treated as words whose phrases are extracted in the same way as surface forms. Generation distributions are estimated on the output side only, i.e. word alignments play no role here. The generation model is learned on a word-for-word basis. Obviously, a factored model is a combination of several components which can be easily integrated into the log-linear translation model. A simple form of the entire pipeline is illustrated in Figure 2.6

The factored translation model is the most well-known model which explicitly addresses the morphology problem in SMT. We are able to boost this approach by our morphology-aware word embeddings. We provide more detailed information on our model in Chapter 5. Apart from the factored model we wish to review two other models which study the same problem with different approaches.

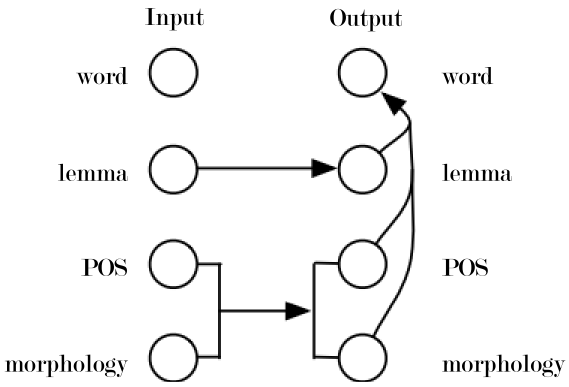


Figure 2.6: The high-level architecture of the factored translation model (Koehn and Hoang, 2007).

Dyer (2007) proposed a model for translating from MRLs. The goal is to capture source-side complexities. The system is based on a hierarchical phrase-based model (Chiang, 2007) and evaluated on Czech→English. The main intuition behind the model is to extend the noisy channel metaphor, where the new model is referred to as the *noisier* channel. It suggests that an English source signal is a distorted variant of a morphologically neutral French signal. In the noisy channel model, the French signal is known as a noise-free signal whereas the noisier channel assumes the French signal is noisy, as it is a result of another distortion applied by a morphological process to the original source signal. This part of the distortion can be modeled separately apart from the main noisy channel.

In order to implement the noisier channel, first lemma forms of Czech words are extracted. Corpora consisting of truncated forms are also generated, using a length limit of 6. This means that for all words, the first 6 characters only are taken into account and the rest is discarded. Hierarchical grammar rules are induced based on surface, lemmatized, and truncated forms. These three grammars are combined together for use by a hierarchical phrase-based decoder, such that the model's performance was improved by 10%.

Williams and Koehn (2011) proposed another model to manipulate the decoder in order to translate into MRLs. The model is an extension to a string-to-tree model by which unification-based constraints were added to the target side of the model.

The main idea is to penalize implausible hypotheses during search. They applied the model to English→German and were able to improve performance over the baseline model. The aforementioned three models are examples for incorporating morphological information into the decoding phase; see Table 2.2 on page 44 for the summary of similar models

2.3.2 Multi-Step Translation (Type 2)

A dominant amount of research in SMT for MRLs belongs to models which we call *multi-step translation models*. In these models, additional tools such as morphological analyzers are usually deployed to decompose complex words. Such models are designed based on decomposed constituents to translate from/into those units, not complex surface forms. Therefore, there is at least one additional mid-translation phase to balance the morphological symmetry between source and target sides. Classifiers are also commonly used in these models whereby complex surface forms are induced using simpler forms (such as lemmas) together with contextual information provided for the classifier.

The models of Lee (2004) and Goldwater and McClosky (2005) are well-known instances of multi-step models. Lee (2004) proposed a technique to balance the morphological and syntactic symmetry between source and target languages. The model was evaluated on Arabic as the rich side. First, words are segmented into prefix(es)-stem-suffix(es) sequences. Both sides of the training corpora are also annotated with POS tags. Because of the segmentation phase, each word is unpacked to multiple morphemes, some of which contribute to translation but others playing no role. Lee (2004) proposed a technique to identify which morphemes should be deleted (as they have no role), which ones should be merged and which ones should be treated as independent constituents, during translation. This issue is illustrated in Figure 2.7, which depicts the process of translating part of an English sentence "*Sudan: alert in the red sea to face build-up of the oppositions in Eritrea*" into an Arabic sentence "*AlswdAn: AstnfAr fy AlbHr AlAHmr lmwAjhp H$wd llmEArDp*

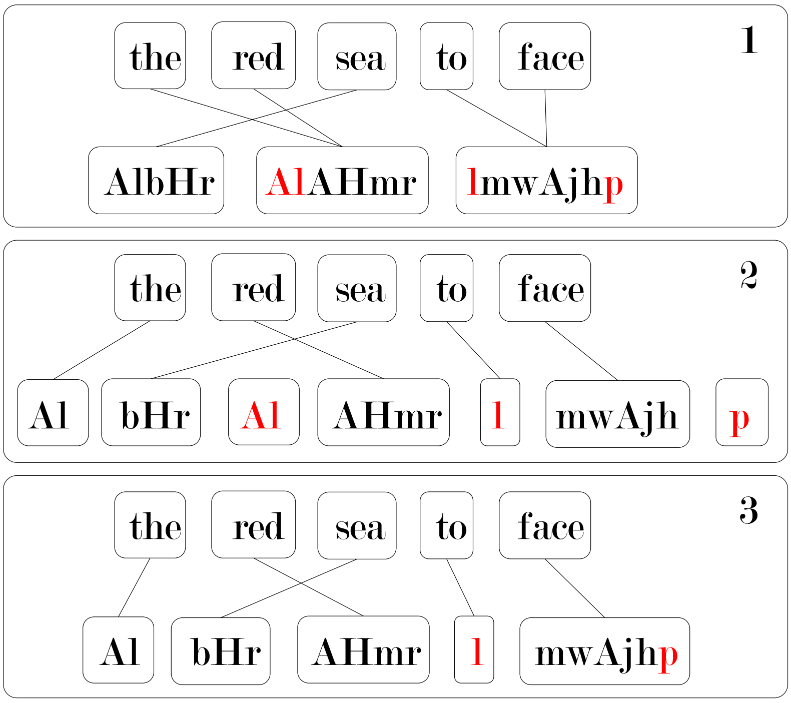


Figure 2.7: The model proposed by Lee (2004) for translating complex Arabic words. The model decides to either keep segmented morphemes or delete them.

dAxl ArytryA".

After segmenting Arabic words (Block 2), *'AlAHmr'* is changed to *'Al'* + *'AHmr'* and *'lmwAjhp'* to *'l'* + *'mwAjh'* + *'p'*. The algorithm proposed in this work identifies that *'Al'* from *'AlAHmr'* is redundant and has no role in translation, so it is deleted. *'l'* from *'lmwAjhp'* carries a meaning so it should be treated as an independent unit in this context, and *'p'* from *'lmwAjhp'* should be merged with *'mwAjh'*, as it can only contribute to the translation phases in that form. The algorithm of Lee (2004) calculates some probabilities based on POS tags and the co-occurrence of words and morphemes, and decides to keep, merge or delete morphemes.

Goldwater and McClosky (2005) proposed another model but the main intuition is the same as Lee (2004). For sparse datasets and MRLs, estimating word-to-word alignment probabilities is hard, as in such cases most words occur at most a handful of times. This problem becomes more severe as the morphological richness increases. Motivated by this problem, Goldwater and McClosky (2005) proposed a new model and applied it to Czech. They decompose words into morphemes to reduce the data sparseness. In Czech, a lot of information resides in bounded morphemes (see Section 2.1), which is encoded as function words in English. To model this phenomenon, they enriched decomposed morphemes by adding extra annotations. This is performed to mitigate the information loss during lemmatization. By this technique they changed complex Czech words to simple units with some extra guiding information. These units are easy to handle, and were able to considerably improve their SMT engine.

Another model was proposed by El Kholy and Habash (2012) to address morphological problems in Arabic. They focused on the three most common morphological problems in Arabic MT, which according to automatic and human evaluations on MT outputs are gender, number, and the determiner clitic. Similar to all other methods they also proposed word segmentation, but this raised other serious problems. Tokenized words should be de-tokenized on the target side, but because of the fusional and non-concatenative morphology of Arabic, the de-tokenization process could be just as challenging as translation itself. It also requires much orthographic and morphological processing (El Kholy and Habash, 2010). To cope with the problem they carried out translation in multiple steps and used classifiers. First an SMT engine is trained to translate from English words and POS tags into tokenized Arabic lemmas plus zero or more morphological features. Figure 2.8 illustrates the data format for this module. They used lemmas (not stems), as this makes translation models tighter. This is a notable simplification because a lemma in Arabic can have two stems on average.

EngWord#POS

Saddam#NN hussein#NN ’s#POS half-brother#NN refuses#VBZ to#TO return#VB to#TO iraq#NN

ArabLem#Det

Âax#det γayor#0 šaqiyq#det li+#na Sad˜Am#0 Husayon#0 rafaD#0 ςawodah#det Ăilaý#na ςirAq#det

Figure 2.8: Data preparation for Arabic MT proposed in El Kholy and Habash (2012)

They did not use factored models nor was the decoding procedure changed, but they only changed the data format. English words and Arabic lemmas were enriched by POS and morphological tags, respectively. They trained a PBSMT model on this data format. For the next step they predicted the morphological class of translated words, using the conditional random field (CRF) toolkit (Lafferty et al., 2001). They trained a CRF model using Arabic information (Figure 2.8), word alignments, and English words. After predicting the morphological tag of all the words, the next step is morphology generation. Another SMT engine either a factored or phrase-based mode is trained which takes lemmas and morphology tags and translates them into inflected word forms.

Minkov et al. (2007) and Toutanova et al. (2008) proposed models for translating into Arabic and Russian. The goal is to predict inflected word forms. They collect a rich set of syntactic and morphological information from source and target sentences. First an MT engine is run to generate translations. Each word is converted into its stem form, then a correct inflected form of the word is predicted based on context and stem information. A maximum entropy Markov model was used in their research which is trained using Equation (2.4):

$$P(\bar{y}|\bar{x}) = \prod_{t=1}^{n} p(y_t|y_{t-1}, y_{t-2}, x_t) \tag{2.4}$$

As can be seen, the model is a second-order Markov model, where y_{t-1} and y_{t-2} are previously-generated outputs and x_t denotes the context at position t.

Chahuneau et al. (2013) used the same mechanism to translate into Russian, Hebrew and Swahili. First, a discriminative model is trained to predict inflections of target words from rich source-side annotations. They also used their model to generate artificial word- and phrase-level translations, which are referred to as *synthetic* phrases. In their model, the input is an English sentence **e** together with any available linguistic analysis of the sentence. The output **f** is composed of a sequence of stems and a morphological inflection pattern for each stem. The whole process is modeled by Equation (2.5):

$$p(f|e,i) = \sum_{\sigma\star\mu=f} \underbrace{p(\sigma|e_i)}_{st.g.} \times \underbrace{p(\mu|\sigma,\mathbf{e},i)}_{inf.g.} \tag{2.5}$$

The *st.g.* part models generating a stem σ and the *inf.g.* part models its inflected form μ in the position i. The model assumes that there is a deterministic function that maps stems and morphological inflections to target surface forms. This function is denoted by the $\sigma \star \mu = f$ notation. $p(.)$ values are collected from training corpora based on source context and morphological feature vectors. For more detailed information see Chahuneau et al. (2013).

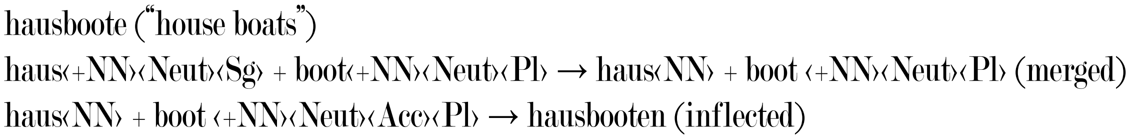
The baseline system in their model is a hierarchical phrase-based model which by default generates grammars for a training data. They have a mechanism to extend this grammar. First, they train a PBSMT model on a parallel corpus and perform translation. Afterwards, surface forms are replaced with their stems. By use of the probabilistic model explained in Equation (2.5), new inflected forms are generated for stems. This step generates synthetic phrases whose quality is evaluated with the log-probability of the main translation model. High-quality phrases are added to the main model to extend the grammar and provide better translations.[8]

German is another MRL for which a considerable amount of MT research work is available. Koehn and Knight (2003) proposed a way for compound splitting. Compounds are created by joining existing words together. Modeling the compounding operation has a significant impact on MT quality as it reduces the amount of OOVs. First, they split a compound word into all possible subunits. A valid subunit is a constituent which exists as a free morpheme (see Section 2.1) in training corpora. There could be several segmentations for each word, so the most frequent candidate is selected based on a specific count function.

Cap et al. (2014) also focused on compounding for German. The approach has two steps. First to balance the degree of morphological complexity between source

[8] The source code for this project is available at: `https://github.com/eschling/morphogen`.

and target languages, compounds are split and words are lemmatized. To make the splitting phase more accurate, parsing and POS tagging information is also explored. Translation is performed where separated units should be merged thereafter, to make correct compounds. This process is illustrated in Figure 2.9.



hausboote (“house boats”)
haus‹+NN›‹Neut›‹Sg› + boot‹+NN›‹Neut›‹Pl› → haus‹NN› + boot ‹+NN›‹Neut›‹Pl› (merged)
haus‹NN› + boot ‹+NN›‹Neut›‹Acc›‹Pl› → hausbooten (inflected)

Figure 2.9: Compound merging in German, based on the model proposed in Cap et al. (2014).

Figure 2.9 shows a data structure generated by the first phase. Compounds are merged together. Merged forms are not necessarily correct so another process is applied to make the final inflected forms. For merging and inflection-generation, a CRF model and SMOR (Schmid et al., 2004), a rule-based word formation model, is used.

SMT solutions for handling the rich morphology problem in German are not limited to these models alone. For example, Fraser (2009) and Fritzinger and Fraser (2010) addressed compounding. Fraser et al. (2012) performed translation in two steps: English word → German stems and additional markups → German words.

Along with Arabic, Czech and German, some other morphology-aware SMT models have been proposed which study Turkish. In this language, syntax and morphology has a tight relation. Yeniterzi and Oflazer (2010) trained a factored model to enhance Turkish MT quality. The model relies on syntactic analysis of English. Source words are enriched with dependency and POS annotations. Then morphological tags for the Turkish side are produced. Unlike other models, complex Turkish words are not decomposed in this approach. Because of the nature of Turkish, word alignments between English and Turkish words are sparse, as many English words have no counterparts (i.e. they are mapped to nothing) on the Turkish side. By use of dependency links, unaligned words are attached to words with alignments. For example, in translating *‘On their economic relations’* into Turkish, there is no alignment for *'On'* and *'their'*, so *'On'* and *'their'* are attached to *'relations'*, as there are dependency links from these words to *'relations'*, and *'relations'* has an alignment link to a Turkish word. Some new rules were defined for the dependency parser to generate such merged links.

El-Kahlout and Oflazer (2010) proposed another model for Turkish which segments MCWs and benefits from English POS tags. They also used a morpheme-aware language model to re-rank n-best lists generated by the decoder.

Research for MT of MRLs is not limited to the languages reviewed so far. Similar to El-Kahlout and Oflazer (2010), Virpioja et al. (2007) used a morpheme-aware language model for translating Nordic languages. Clifton and Sarkar (2011) proposed a model for Finnish. Words are segmented using Morfessor (Creutz and Lagus, 2002) and Paramor (Monson et al., 2008), and then a post-processing morpheme prediction system is set up to generate the final translation. This approach uses a CRF model similar to that of Toutanova et al. (2008). Fishel and Kirik (2010) trained a factored model for Estonian. Avramidis and Koehn (2008) extended a PBSMT model by syntactic and semantic annotations for the English-to-Greek and -Czech directions. For a summary of these models, see Section 2.5.

2.3.3 Morphological Processing for Translation (Type 3)

The task of preprocessing (and normalization) is very language-dependent and is usually defined based on morphological and syntactic properties of languages. Habash and Sadat (2006) proposed a preprocessing scheme for Arabic. Singh and Habash (2012) performed the same for Hebrew. They compared two rule-based and unsupervised models and were able to improve over the baseline model by +3.5 BLEU points. Rasooli et al. (2013) defined orthographic and morphological processing rules for a Farsi-to-English model. We also addressed the same problem in our research (Passban et al., 2015).

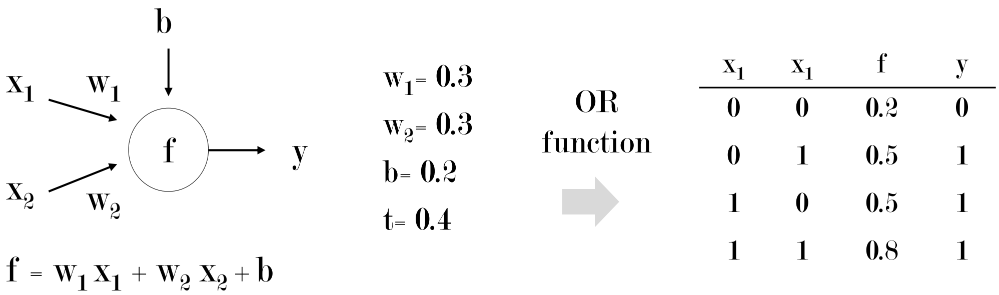
Mehdizadeh Seraj et al. (2015) did not change the decoding process, nor did they perform any preprocessing. They used a multilingual paraphrase database and translated OOVs. They applied their model to Arabic→English and achieved an improvement of +1.3 BLEU score over the baseline model. There are many other models which fall into this group. For a summary of such models, see Section 2.5.

2.4 Deep Neural Networks

Theoretical results demonstrate that we require deep architectures in order to learn complicated functions (Bengio, 2009). A deep architecture is a composition of many simple computational units, such as in NNs with many hidden layers and neurons. In this section we discuss the fundamentals of DNNs and explain the necessity of transforming NNs to DNNs. A large set of parameters are involved in DNNs that should be optimized to produce desirable outputs. Clearly, this is a challenging optimization task which makes the training of DNNs more complicated. In this section we review issues regarding such problems and study potential solutions.

Any machine-learning technique scaled for big data and complex problems can be claimed as *deep*. The common feature of all these models is that they consist of a massive number of computational units, which makes them suitable for large-scale settings. Although deep learning is not limited to a specific group of models, almost all successful solutions have been implemented by NNs. NNs are distributed computational models inspired by the human brain. They are distributed because an input signal is processed by many interconnected computational processing units (neurons). Neurons are located in layers and sequentially connected to each other via weights. Weights show the connection strength between nodes. Each node is a simple mathematical function. There should be a cost function for each NN in order to compute errors. An input is passed through various layers and produces an output. The prediction error is computed with respect to the output and back-propagated to the network to update weights (network parameters). The final goal is to find an optimal configuration of weights. After reaching the optimal configuration, the network is ready to process any random input in order to map it to the output form.

McCulloch and Pitts (1943) proposed a simple neural model for the first time. Figure 2.10 illustrates a single neuron, where it takes two input signals x_1 and x_2 and implements the simple summation function. Input signals are connected to the neuron through weights which show the significance of each signal. An optional bias signal b can also be added. If the summation result f exceeds a predefined threshold t, the neuron's output y would be 1, otherwise it is set to 0. Using such a simple mechanism, basic functions like the logical *OR* can be modeled. For such a function we can set $w_1 = 0.3$, $w_2 = 0.3$, $b = 0.2$ and $t = 0.4$.



x1	x1	f	y
0	0	0.2	0
0	1	0.5	1
1	0	0.5	1
1	1	0.8	1

Figure 2.10: Architecture of a simple neuron to model the logical *OR* function.

A single neuron can model simple functions but for more complicated functions we need more complex structures. As a classic example in machine learning, there is no single-neuron NN which is able to model the logical *XOR* function. However, we can learn it easily through a combination of two neurons. As another example, it is impossible to learn $f(x) = x * \sin(a * x + b)$ with a simple NN (Bengio, 2009), but if we make a network as in Figure 2.11, we can force each unit to model a specific part of $f(x)$. The network on the left-hand side distributes the estimation of the final output over different nodes, and asks each of them to approximate a computation associated to a specific part of f, whereas the network on the right-hand side tries to compute the output via a single unit which is impossible.

Figure 2.11 shows the main idea behind DNNs. Simple units and architectures are not able to provide precise approximations for complex functions. Different nodes and units are stacked on top of each other to enable NNs to learn functions through

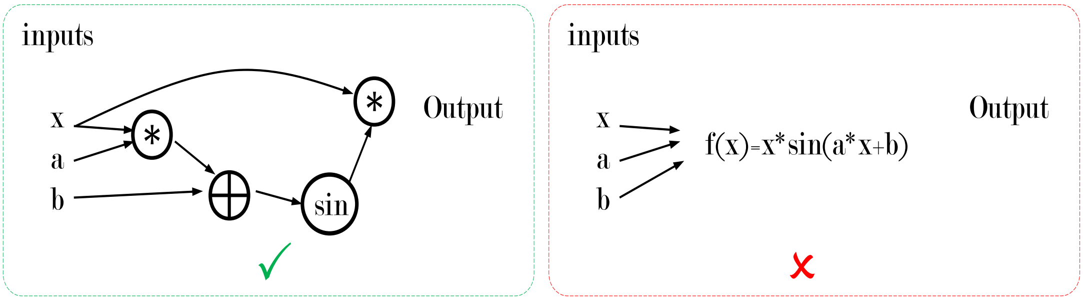


Figure 2.11: Distributed function approximation using DNNs (Bengio, 2009).

a multi-step and distributional procedure. To learn a complex data distribution, the network's architecture and a training algorithm manage the learning procedure, and distribute the function approximation over different nodes. Figure 2.12 visualizes[9] an NN which tries to learn a real-world classification problem over a complex data distribution.

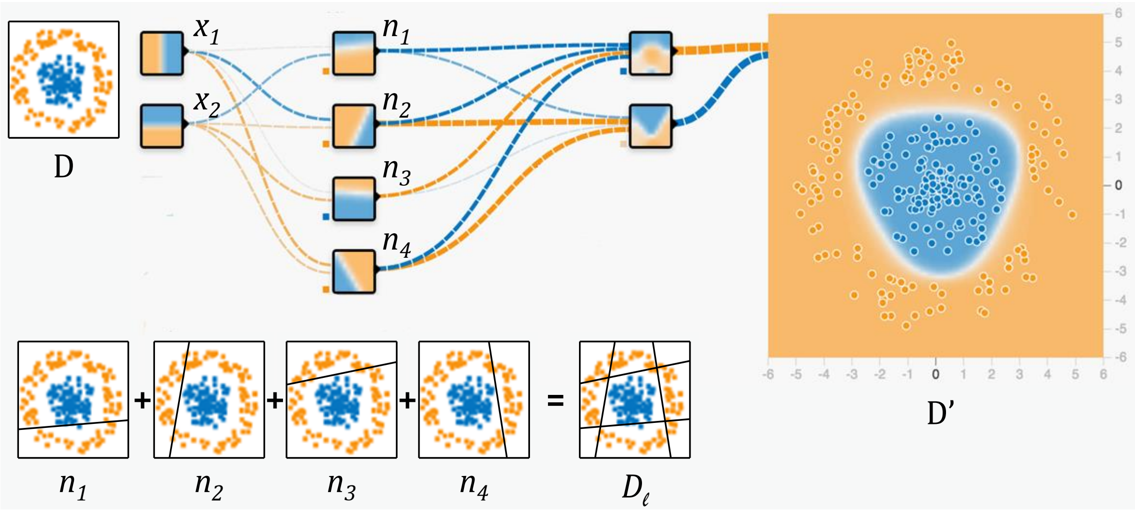


Figure 2.12: Visualizing the process of data-distribution learning via NNs. The figure shows which node learns which part of the distribution.

The NN in Figure 2.12 tries to learn the distribution D. D' is an approximation learned by the NN for the real distribution. The figure also illustrates the nodes (magnified) in the first layer to show which node learns which part of the distribution. A single node in the first layer is not solely able to learn D, but a combination of nodes can provide an acceptable approximation. D_l is a distribution learned by the

[9] We use the tool developed by Daniel Smilkov and Shan Carter; `http://playground.tensorflow.org/`.

nodes n_1 to n_4.

We now understand the necessity of designing DNNs. In order to have precise approximations, we need to stack several layers one on top of another. In the next section we discuss how to connect layers together and explain different neural architectures. For more information on the fundamentals of deep learning, see Arel et al. (2010), Bengio et al. (2013) and Schmidhuber (2015).

2.4.1 Feed Forward Neural Models

Multi-layer feed-forward (MLF) models are the most popular NN types applied to a wide range of problems. An MLF consists of multiple neurons which reside within layers. The first layer is known as the "input layer" and the last layer is the "output layer". There could be one to many internal layers between the input and output layers which are called "hidden layers". A single-layer network (one hidden layer) can only solve linearly-separable problems, so multiple layers are connected to each other to empower the network. Each computational neuron in layers is a non-linear mathematical function. *Tanh*, *Sigmoid* (Karlik and Olgac, 2011), *Rectified Linear Unit* (*ReLU*) (Nair and Hinton, 2010), *Leaky ReLU* (He et al., 2015) and Maxout (Goodfellow et al., 2013) are some commonly used functions.

Neurons are connected through weights. There may or may not be a connection between a random pair of neurons. Weights are multiplied by input signals and linearly summed together. An optional bias value could also be added to summation results. This computation is formulated as in (2.6):

$$\begin{aligned} y &= f(Wx + b) \\ y_i &= \sum_j f(w_j x_j + b_i) \end{aligned} \tag{2.6}$$

where y represents the h-th layer, a vector with n neurons. Each of those neurons are referred to by y_i; $i \in [1, n]$. x is the (h-1)-th layer with m neurons. m is not necessarily equal to n. $W \in \mathbb{R}^{m \times n}$ is a weight matrix which maps x to y and

$b \in \mathbb{R}^n$ is a bias vector. An MLF is an NN which sequentially connects layers to each other. In theory, a two-layer MLF is mathematically able to approximate any function (Hornik et al., 1989), but it rarely appears in practice.[10] For more detailed information on MLFs, see Bebis and Georgiopoulos (1994).

2.4.2 Recurrent Neural Models

In some cases the input has a constant form which can be modeled using predefined structures. For example, the character recognition task falls in this group, as inputs are images with constant dimensions. If we represent each character with a 28 × 28 matrix of black and white pixels, there is always a structure with $28 \times 28 = 784$ elements at the input layer. For such cases MLFs are the best alternatives, but all problems cannot be straightforwardly modeled in this way. In most cases the input has a temporal, dynamic or sequential structure, e.g time series, words or sentences are sequential structures, which means the length of the inputs varies from one instance to another. Accordingly, we do not have a constant structure for the whole data set and MLFs are not able to model these phenomena.

To tackle this problem, recurrent neural networks (RNNs) have been proposed. An RNN is an MLF with at least one feed-back connection, which means there is a loop or recurrency connection over one (or more than one) hidden layer. The loop adds the last state or the output of the hidden layer to its input. This is simply formulated as in (2.7):

$$\begin{aligned} h_t =& f_h(W_{i:h}x_t + W_{h:h}h_{t-1}) \\ y_t =& f_o(W_{h:o}h_t) \end{aligned} \tag{2.7}$$

where $x \in \mathbb{R}^n$ is an input vector and $W_{i:h} \in \mathbb{R}^{n \times d}$ is a weight matrix which connects the input layer to the hidden layer. Recurrency is applied through the $W_{h:h} \in \mathbb{R}^{d \times d}$ matrix. $h_t \in \mathbb{R}^d$ and h_{t-1} indicate the hidden states at the time steps t and $t-1$, respectively. The hidden layer is connected to the next layer $y \in \mathbb{R}^m$ through

[10] `http://neuralnetworksanddeeplearning.com/chap4.html`.

$W_{h:o} \in \mathbb{R}^{d \times m}$. f_h and f_o are non-linear functions which are applied to the input and output of the hidden layer. This architecture is not exactly different from MLFs, but rather a simple extension. Any recurrent network can be converted into an MLF by unfolding over time, so RNNs by nature inherit all mathematical properties of MLFs. An example of an unrolled version of an RNN and the recurrency mechanism is illustrated in Figure 2.13.

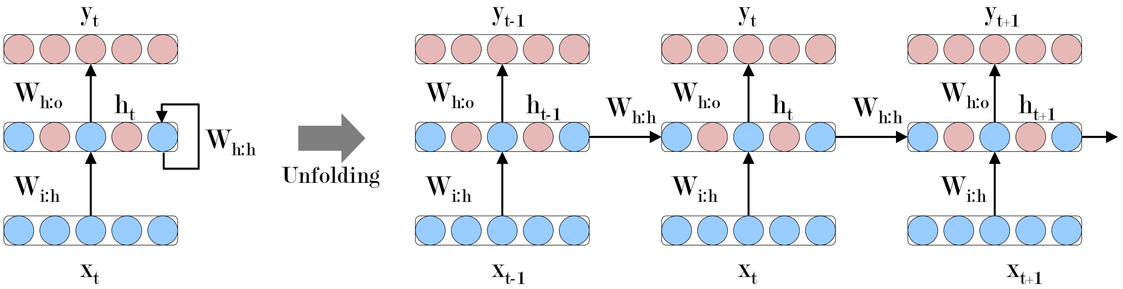


Figure 2.13: Unrolling an RNN over time.

The loop mechanism enables RNNs to accept variable-length sequences as their inputs. Furthermore, at each time step t a summary of all preceding elements before x_t resides in hidden states. Clearly, this mechanism is very useful for NLP tasks, which we will discuss in the next chapters. Simple RNNs are not powerful enough to summarize complex structures and capture their properties. They also have problems in remembering long-distance dependencies. To mitigate these shortcomings, extended RNNs with memory units (Hochreiter and Schmidhuber, 1997; Sukhbaatar et al., 2015) have been proposed which we also use in our research (see Chapter 4).

2.4.3 Convolutional Neural Models

Convolutional models implement the mathematical convolution operation. Convolution is a process on two signals, the input and filter (or kernel), produces an output. The output is typically viewed as a modified version of the input, or a non-linear combination of the input and filter. The convolution function is formulated as in (2.8):

$$y_n = \vec{x} \otimes \vec{f} = \sum_{i=-\infty}^{+\infty} x_i f_{n-i} \tag{2.8}$$

where all x, f and y are one-dimensional signals and y has m elements ($1 \leqslant n \leqslant m$). The model assumes that the output signal is a deformed version of the input in the presence of a filter. The filter is applied to highlight and extract specific features of the input. This is the main intuition behind the convolution operation.

Convolutional neural networks (CNNs) are usually explored for complex data structures such as RGB images or natural language sentences. An RGB image is a result of a non-linear (fusional) integration of different complex pixels. A natural language sentence has a similar structure as it combines words and characters in a way that is dictated by syntactic and morphological rules. These fundamental units (pixels, words etc.) are complex because they carry and combine information from different sources. In RGB images all red, green and blue sources are involved in a pixel, or in sentences, words are affected by different morphological, syntactic, semantic and contextual restrictions (different sources of information).

In order to extract information existing in such complex structures, a hierarchical and fusional architecture is required. The architecture should be able to take simple elements (RGB signals or characters) and fuse them to construct basic units (colourful pixels or words). Then it should have a hierarchical mechanism to integrate such basic units to construct the final output (images or sentences). The forward or generation pass is a bottom-up procedure going from very basic elements toward a complex result, and the backward or decomposition path is a top-down procedure which crunches a complex constituent into subunits, and reveals information concealed at each hierarchy. CNNs by their very nature provide such a mechanism.

The computation explained in Equation (2.8) can be extended for 2D or 3D settings, and applied to different tasks such as image processing (Krizhevsky et al., 2012) or sentence modeling (Kalchbrenner et al., 2014). In such CNNs, it is assumed that the state h_t is a complex version of the state h_{t-1}. Accordingly, elements in h_t have more complex structures than those of h_{t-1}. This can be viewed as a procedure in which several elements in a layer contribute to make a high(er)-level element in the following layer(s). The procedure is gradually and continuously applied layer-by-layer to reach the final output. The convolution operation is usually followed by a pooling operation, so that the main transformation is applied to an input signal, and then a pooling operation is used to select average, minimum, or maximum values from the convolution's output. Pooling is carried out to attenuate the impact of noise and select high-grade signals.

The process of gradually reaching a high-level description of an RGB image by use of a CNN is illustrated in Figure 2.14. The input data is a set of 2D matrices (an input with several channels). A 2D convolution function is applied to different regions (red and green windows) of the input to make new forms (red and green cells). Applying the convolution function and the filter to all regions generates a convolved signal which encodes information with a more dense structure. Based on the type of the filter some important properties of the input are also highlighted in the convolved signal. Finally, a pooling operation is applied (e.g. a 2-by-2 max-pooling function).

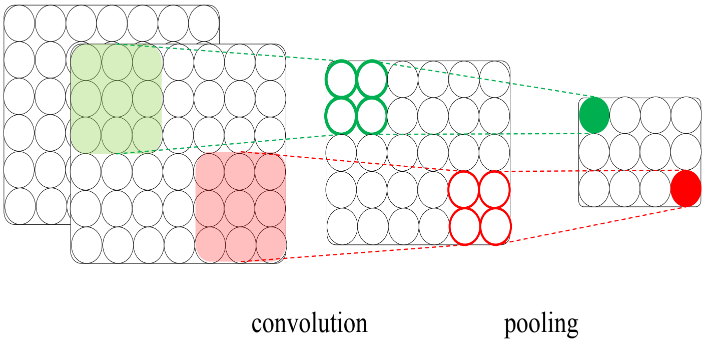


Figure 2.14: The convolution operation in CNNs.

These operations are successively applied to extract high(er)-level representations and reach the final output in the end. The final output could be a word which describes the class of the input image, or any description about it. This pipeline is not exclusive for RGB images, i.e. a natural language sentence can be represented by a cube or a matrix at the input layer (see Chapter 3). Then a convolution operation is applied. At each layer a new representation of the sentence is generated, and based on the task for which the NN is trained, some features of the sentence are highlighted. For example in the sentence compression task, redundant words are truncated as the sentence is passed through layers. In Chapter 3, CNNs are used for similar (NLP) tasks.

2.4.4 Training Neural Networks

This section explains how to train an NN and find optimal values for network parameters (weights, biases etc.) with respect to a given task (Li Deng, 2014; Goodfellow et al., 2016). To train NNs, we use a well-known principle in machine learning known as *empirical risk minimization* (Vapnik, 1991), whereby we convert the problem of training NNs into an optimization problem, as shown in (2.9):

$$\arg\min_{\theta} \frac{1}{T} \sum_{t} \ell(f(x^{(t)}; \theta), y^{(t)}) + \lambda\Omega(\theta) \tag{2.9}$$

The parameter set θ should be optimized in a way which the NN approximates the function $f(.)$ with the minimum cost according to the loss function ℓ. $x^{(t)}$ is the t-th training example whose class label is $y^{(t)}$. The term added to the end of the equation is a regularizer to penalize certain values of θ.

To optimize Equation (2.9), gradient-based methods such as the *stochastic gradient descent* (SGD) algorithm are used (Bottou, 2010). Algorithm 1 shows how SGD functions. In this algorithm values are updated after processing each example. Training happens through Steps 5 and 6. In NN training, the number of iterations is controlled by the epoch size which one epoch is the same to one iteration over all training examples. To apply the SGD algorithm we need to define the loss function ℓ, a procedure to compute gradients of network parameters and a regularizer. It is also important to correctly initialize parameters, as it directly affects the NN's performance.

Suppose an NN is trained for a classification task, so we expect the NN to give an estimation of the class c to which a given input x belongs: $f(x)_c = p(y = c|x)$.

Algorithm 1 Stochastic Gradient Descent (SGD)

```
procedure SGD
    initialize $\theta$;                                  ▷ $\theta \equiv \{W^{(1)}, b^{(1)}, ..., W^{(L+1)}, b^{(L+1)}\}$
                                                           ▷ L: the number of hidden layers
    for N iterations:
        for each training example $(x^{(t)}, y^{(t)})$:
            $\Delta$ = -$\nabla_\theta \ell(f(x^{(t)}; \theta), y^{(t)}) - \lambda \nabla_\theta \Omega(\theta)$
            $\theta \leftarrow \theta + \alpha \nabla$
```

The goal is to maximize the probability of finding the correct class label $y^{(t)}$ given $x^{(t)}$. Using the negative log-likelihood criterion the maximization problem can be converted to a problem for minimizing the negative of the function, which gives us (2.10):

$$\ell(f(x), y) = -\log f(x)_y \tag{2.10}$$

where y is the true class and $f(x)_y$ is the y-th element of the output layer which indicates an estimation of x belonging to that class. Optimizing (maximizing or minimizing) a mathematical function is equal to optimizing the logarithm of the same function as the logarithm is a monotonically increasing function. It also simplifies the computation drastically, as the logarithm function is an easily-derivable function. The loss function defined in this way is referred to as *cross entropy*, which is commonly used in many neural models such as our embedding learning models in Chapter 3.

2.4.5 Sequence Modeling with DNNs

Sequences are the key concepts of this thesis. A word/sentence could be seen as a variable-length sequence of characters/words for which we require specific architectures. The training procedure explained so far is suitable for MLFs and shallow NNs which consist of a limited number of layers. However, there is a serious difficulty with all gradient-based models when they are used to train deep networks for variable-length inputs. In deep architectures, each parameter receives an update proportional to the NN error with respect to its current value. Gradient values usually vary in the range $(-1, 1)$ or $[0, 1)$, and the back-propagation step computes gradients by the chain rule. This means that for nodes which reside in front layers, these small values are multiplied n times to compute gradients. Clearly, after several steps the gradient (error signal) decreases exponentially by the order of n, and the front layers are trained very slowly. Accordingly, the gradient cannot affect such layers as much as we expect. This shortcoming causes an incomplete training and is known as the "*vanishing gradient*" problem.

This phenomenon is very common in RNNs, because each RNN can be viewed as a very deep NN when it is unfolded. To cope with this problem, long short-term memory (LSTM) networks (Hochreiter and Schmidhuber, 1997) were proposed. In LSTMs, layers are equipped with memory units which mitigate the gradient vanishing problem. Chapter 4 discusses LSTMs in more detail.

Similar to the vanishing problem, the "*gradient explosion*" is another issue in training DNNs. If the gradient value is a big number, after n times multiplication it grows exponentially which makes the NN unstable. The gradient explosion problem is the opposite point of the vanishing problem. To control the explosion, gradient values which exceed a predefined threshold are clipped. This simple solution was proposed by Mikolov (2010) for the first time. To understand the difficulties of training DNNs and RNNs, see Pascanu et al. (2013).

Although (efficient) training of RNNs is quite challenging, they are still the best candidates for NLP tasks. The loop-form architecture of RNNs enables us to handle variable-length sequences, and techniques proposed for dealing the vanishing and explosion problems help us train high-quality networks, therefore, it is possible to model sequences via RNNs. Sequences could be modeled in either monolingual or multilingual settings, and we have both in this thesis. In the monolingual setting we train the NN using sentences for language-modeling purposes. In this setting the NN is fed by a sequence and the output of the network is *i*) the best word from the same language (the language of the sequence) which can appear as the next word, and *ii*) the probability of such a sequence occurring in the language. Basically, a language model scores the fluency of the input sequence and in some cases tries to complete it by predicting subsequent words.

In the multilingual setting we have a similar architecture where the input sequence is from a source language and output words (to be predicted) from a target language. Words from the other language are interpreted as translations of source words, and the model which follows this architecture is known as the *neural translation engine*. To implement such models (language modeling and translation) we could have a very similar neural architecture, in which words (or any other unit such as characters, morphemes etc.) are consumed sequentially, one after another. At each time step the hidden state of the network is updated by an input word and includes a summary of the entire input sequence. After consuming the last word, the hidden state is an internal representation for the whole sequence. This mechanism could be easily implemented by an RNN which is referred to as the encoder RNN. We need a mechanism to decompose the encoded sequence and decode it into our desired output. In language modeling the output should be the next word and in translation the translation of an input word. We place a classifier on top of the encoder to sample from a vocabulary to predict the best output. The classifier could also be an RNN. This architecture is applied to almost all sequence-modeling problems including language modeling and translation. These topics are extensively discussed in Chapters 4, 6, and 7.

2.5 Summary

In this chapter we explained the fundamental concepts of our research as essential prerequisites of the thesis. First we addressed the problem of morphology. We described the problem itself and defined some criteria to distinguish MRLs from non-MRLs. Then we explained the SMT pipeline. In Section 2.3, we summarized some of the most important models which addressed the problem of morphology in SMT. We categorized these models into three classes. The first group incorporates morphological information at decoding time and manipulates the decoding process. The second class performs multi-step translation, using external tools such as morphological analyzers and classifiers. Models in this group try to balance the morphological complexity between source and target languages. The main idea behind these models is to gradually translate words from a simple source form into a complex target form or vice versa. The third group provides an easier solution compared to the others, which proposes text-processing models to change MCWs to simpler forms. A summary of all models reviewed in this chapter is shown in Table 2.2. Finally, we studied DNNs. We explained what a DNN is, what types of architectures it might have and how it is trained. Chapter 2 provided prerequisites for our research questions. In the next chapter we study our first research question and explain how we can train morphology-aware word embeddings.

#	System	Lang.	Summary
1	Koehn and Knight (2003)	De–En	Models word compounding in German.
2	Lee (2004)	En–Ar	Proposes an algorithm which decides to keep, merge or delete morphemes after segmentation, before aligning to English words.
3	Goldwater and McClosky (2005)	Cz–En	Enriches morphemes with additional information and applies word truncating.
4	Habash and Sadat (2006)	Ar–En	Preprocessing.
5	Dyer (2007)	Cz–En	The noisier channel: an extension to the hierarchical PB-SMT model. Combines different grammars to decode complex source languages.
6	Koehn and Hoang (2007)	En–De En–Cz En–Es En–Ch De–En Ch–En	Factored translation models.
7-8	Minkov et al. (2007) and Toutanova et al. (2008)	En–Ar En–Ru	a) An SMT model translates English. b) MT outputs are stemmed. c) Inflected forms are generated by use of a 2^{nd}-order Markov model.
9	Virpioja et al. (2007)	Nordic	SMT with morpheme-aware language models.
10	Avramidis and Koehn (2008)	En–Gr En–Cz	A phrase based model extended by syntactic and semantic tags.
11	El-Kahlout and Oflazer (2010)	En–Tr	Word segmentation for Turkish along with a morpheme-aware language model to re-rank translation results.
12	Fishel and Kirik (2010)	Es–En	A Factored translation model. Word segmentation with Morfessor.
13	Fritzinger and Fraser (2010)	En–De	Models word compounding in German.
14	Yeniterzi and Oflazer (2010)	En–Tr	Uses dependency annotations to enhance a factored translation model.
15	Clifton and Sarkar (2011)	En–Fi	A two-step model which segments words using Morfessor and Paramor and generates morphological information by a CRF model.
16	Williams and Koehn (2011)	En–De	An extension to the string-to-tree model by applying unification-based constrains on the target side.
17	El Kholy and Habash (2012)	En–Ar	Multi-step translation: a) Translates English words into Arabic lemmas. b) Predicts morphology tags of Arabic words with a CRF classifier. c) Translates tags and lemmas into inflected Arabic forms.
18	Fraser et al. (2012)	En–De	Translates English words to German stems, enriches data with additional morphology markups and translates stems into German words.

19	Singh and Habash (2012)	En–He	Preprocessing.
20	Chahuneau et al. (2013)	En–Ar En–Ru En–Sw	A probabilistic model which generates inflected forms from stems and source-side information. The model also generates artificial or synthetic phrases to be included in the main translation model.
21	Rasooli et al. (2013)	Fa–En	Orthographic and morphological preprocessing.
22	Cap et al. (2014)	En–De	Models word compounding in German. A CRF model and SMOR (a rule based word formation model) was used in this work.
23	Aranberi and Labaka (2015)	En–Hu En–Fi	A factored translation model (`https://www.taus.net/think-tank/reports/translate-reports/fighting-morphology-in-smt`).
24	Mehdizadeh Seraj et al. (2015)	Ar–En	Uses a multilingual paraphrase database to translated OOVs.

Table 2.2: Summary of SMT models for MRLs. Models are sorted in chronological order.

Chapter 3

Learning Compositional Embeddings for MRLs

In the last chapter we studied the importance of morphology, provided prerequisite knowledge to explore our research questions, and reviewed SMT models for MRLs. In this chapter we focus on our first research question and introduce models by which we can incorporate morphological information into word embeddings.

Word embeddings are real-valued word representations in an n-dimensional feature space. Recent work has shown that these distributed representations can preserve meanings, as well as semantic and syntactic dependencies. However, existing word-embedding models have some deficiencies, especially with regard to MRLs. In most popular models, each word is treated as an atomic unit which is not suitable for complex words. In MRLs words can be viewed as hierarchical structures which contain meaning-preserving internal subunits (morphemes). In this chapter, we propose a novel architecture designed to model intra-word relations. Through various experiments we show that the proposed model performs better than other existing models for complex structures.

Word embeddings have recently become ubiquitous in NLP tasks (Collobert et al., 2011). They are an efficient means of transferring knowledge from large datasets into task-specific models which may have very limited training data (Mikolov et al., 2013b). Historically, the concept of distributed representations for symbolic linguistic units was introduced by the vector space model of Salton et al. (1975), and expanded by techniques such as latent semantic analysis (Deerwester et al., 1990), latent Dirichlet allocation (Blei et al., 2003), and random indexing (Sahlgren, 2005).

Recently, NNs have become the established state-of-the-art for creating distributed representations of characters, words, sentences, and documents. Hinton (1984) proposed an NN-based embedding model for the first time. This work introduced the idea of a "shared learning space", where embeddings themselves are also trainable parameters of the model. In this chapter, we discuss a CNN designed to generate better representations of MCWs. Complex words are decomposable structures which are particularly common in languages that rely heavily upon agglutination (see Table 2.1). According to previous findings, not only the inter-word dependencies and contextual information (Huang et al., 2012; Mikolov et al., 2013a) but also the intra-word dependencies (Luong et al., 2013) affect word embeddings, so our proposed model takes both types of information into account.

The main problem with existing word-based models (Mikolov et al., 2013a; Pennington et al., 2014) is their deficiency in modeling rare words. Our CNN composes word embeddings from subunit embeddings and tries to solve this problem. For example, '*distinctness*' and '*unconcerned*' are very rare, occurring only 141 and 340 times in Wikipedia documents (Luong et al., 2013), even though their corresponding stems '*distinct*' and '*concern*' are very frequent (35323 and 26080, respectively). In such cases word-based models generate poor word representations, whereas better surface-form embeddings can be generated by combining subunit (stem and affixes) embeddings. The problem becomes more serious for words which were never observed during training. Our model is able to produce embeddings for unseen words by composing the representations of their morphological subunits.

Motivated by the aforementioned challenges, we develop a new CNN which explicitly targets some of the problems of morphology and learns more representative embeddings. The way we fuse together different types of information to make embeddings is quite novel. We also apply a 3D convolution function and propose a new cubic data structure as the CNN input. The input cube encompasses information for internal subunits of context words. By proposing our architecture we try to address shortcomings of existing embedding-learning models. The way our architecture differs from others, along with our motivations and contributions, can be summarizes as follows:

- Usually, RNNs are the most preferred neural models when working with textual data, but we propose a CNN-based solution. The baseline model (Luong et al., 2013) in our experiments benefits from a very powerful RNN-based design and introduces the *recursive* architecture to train word embeddings (see Section 3.1 for more details). Experimental results show that our model is able to surpass their RNN-based architecture with better results.

- In existing models, the word's embedding is generated using information from its adjacent words. In our architecture, we use a cubic data structure which provides information about adjacent words, their stems, prefixes, and suffixes. The architecture assumes that any subword unit of a word can be affected by any other subword unit of other neighbouring words, e.g. in other existing models we cannot provide the stem of a word with information about the stem, prefixes, or suffixes of other words, whereas in our model the stem, prefixes, and suffixes of each word are affected by stems, prefixes, and suffixes of other words.

- Although including subword (morpheme) information is very important to have high-quality and morphology-aware embeddings, the way such information is used (and combined) is crucial. Information carried by such units can be less useful (or even useless) when they are processed by a weak combination model. Existing models simply sum or concatenate subword embeddings to construct the surface-from embedding, which is not the best way. Here in this chapter, we discuss different methods by which subword embeddings can be combined, and argue that the proposed convolutional method is a better way to combine subword embeddings.

In the next sections we will review the fundamentals of the embedding-learning task, together with our proposed architecture and experimental studies.

3.1 Embedding Learning

Several early models such as Bengio et al. (2003) utilized word embeddings but did not address the embedding-learning task itself (as an independent problem). They also did not directly use morphological information in embeddings. In Bengio et al. (2003); Botha and Blunsom (2014); Dos Santos and Zadrozny (2014); Kim et al. (2016), embeddings are trained with respect to a specific task. Therefore, trained embeddings are only useful for the specific experimental settings and training contexts. There is only a limited amount of work which has addressed embedding training as an independent problem. A very successful example is *Word2Vec*[1] (Mikolov et al., 2013a) which almost all other work has followed this unsupervised approach. The main intuition behind our model is also the same, but the internal operation of the model enables representations to directly benefit from morphological information.

Word2Vec is a simple feed-forward model in which a target random word of an input sequence is selected to be predicted by use of its surrounding context. Embeddings are updated with respect to error values of the prediction phase. More formally, the network tries to compute $P(w_i|C)$ where w_i is the target word and C indicates its context. In the simplest scenario the context C is a preceding word just before the target word and the network includes one hidden layer h with the weight matrices $W_{i:h} \in \mathbb{R}^{|input| \times d}$ and $W_{h:o} \in \mathbb{R}^{d \times |\mathcal{V}|}$, where $\mathcal{V}$ is the vocabulary set and d is the size of h (hidden layer). The probability of each word given its context is estimated via *Softmax*, which is a scalar function which maps values of its input

[1] `https://code.google.com/p/word2vec/`.

vector into the range $[0, 1]$, so that new values could be interpreted as probabilities. *Softmax* is formulated as in (3.1):

$$P(w_t = j|C) = \frac{\exp(h_t.w^j + b^j)}{\sum_{j' \in \mathcal{V}} \exp(h_t.w^{j'} + b^{j'})} \tag{3.1}$$

where w^j is the j-th column of $W_{h:o}$ and b^j is a bias term. The input of *Softmax* is $h_t \in \mathbb{R}^d$ and its output is $v \in \mathbb{R}^{|\mathcal{V}|}$. The j-th cell of v is interpreted as the probability of selecting the j-th word from $\mathcal{V}$ as the target word. Based on *Softmax* values the word with the highest probability is selected and the error is computed accordingly. Error values are back-propagated to the NN in order to update network parameters. Word embeddings are part of those parameters which are updated too.

3.1.1 Subword-level Information for Embeddings

As previously mentioned, MCWs are structures with internal dependencies. Current models treat words as atomic units, and are thus unable to benefit from the compositional nature of MCWs. An MCW can be viewed as an ordered sequence of morphemes, so methods developed for sequences of words are a promising avenue of investigation. Luong et al. (2013) used a recursive sentence-modeling network (Socher et al., 2011) to model MCWs. While the original model works over words they adapted the model to work at the morpheme level in order to generate word embeddings.

Based on their definition, embeddings of MCWs are gradually built up from their morphemic representations (Luong et al., 2013). First, they segment words where each word is changed to a prefix(es)-stem-suffix(es) sequence. There is a specific embedding for each subunit. Then they sequentially combine the embedding of each subunit with that of the following one, and continue this process until reaching the final embedding, which is the surface form. We use the example studied in their paper to clarify the procedure. In order to build the embedding for the word '*unfortunately*', the embeddings of '*un*' and '*fortunate*' are combined. The new internal embedding generated by this combination is supposed to represent '*unfortunate*'. At the next step, the internal embedding is combined with the embedding of '*ly*' to generate the surface-form embedding.

The combination to generate an internal embedding based on two subword units is carried out through a transformation (weight) matrix, where the concatenated embedding of subwords is multiplied by the matrix, i.e. the combination is based on a dot product. The model of Luong et al. (2013) seems to be appropriate for processing variable-length words and sentences, as it relies on a recurrent/recursive architecture. The model is able to generate better results compared to other existing models, which is our baseline for all experiments.

Another idea to extract subword information is to work at the character level. In the models of Dos Santos and Zadrozny (2014) or Kim et al. (2016), words are broken up into characters. A convolutional layer is established over character embeddings to create word-level embeddings. They applied this method to POS-tagging and language-modeling tasks, respectively. According to their results, working at the character level is a better alternative to model MCWs.

Approaches based on morpheme-level representations find a middle-ground solution between word- and character-level modelings. According to experimental results from Cotterell and Schütze (2015), words with close embeddings in the feature space share morphological subunits. Botha and Blunsom (2014) incorporated morphology embeddings in the language-modeling task and studied the impact of subword embeddings. In our research, unlike previous models (Qiu et al., 2014) we explicitly use morphological information within the embedding task rather than within other downstream tasks. Therefore, our setting is different from language-modeling (and other similar) settings. However, the problem of incorporating subword information is also investigated in the fields of language modeling and machine translation in Chapters 5 and 6.

3.2 Learning Morphology-Aware Embeddings

Our model uses CNNs to produce compositional embeddings. CNNs are suitable models when the input data has a complex structure (such as 3-channel RGB images or natural language sentences). Convolution is a mathematical operation on an input (variable, vector, multi-dimensional tensor etc.) and a filter[2] (with the same shape of the input but not necessarily the same size), producing an output that is typically viewed as a modified version of the input or a non-linear combination of the input and filter. We believe that the combinatorial pipeline enabled by CNNs is well suited to model MCWs.

An MCW can be viewed as a convolutional result of its subunits. In the existing convolutional embedding models (Kalchbrenner et al., 2014; Dos Santos and Zadrozny, 2014), an input sentence/word with n words/characters is represented by a 2D tensor $I \in \mathbb{R}^{d \times n}$ in which the i-th column indicates the embedding ($\mathcal{E}$) of the corresponding word/character s_i: $\mathcal{E}(s_i) = I[:, i] \in \mathbb{R}^d$, where d is the embedding size, and $[:, i]$ indicates all possible rows and the i-th column in the matrix I. A convolutional function over I fuses all columns together. A limitation of these models is that using a matrix-form input captures only contextual information, losing information conveyed by the subword units.

In our model we wish to capture subword, word-level, and context-level information in a single representation. We thus extend the 2D input to a 3D representation, which also includes subword representations. We propose a cubic data structure (3D tensor). The cubic input I_c is made up of lemma ($\mathcal{L}$), prefix ($\mathcal{P}$) and suffix ($\mathcal{S}$) planes: $I_c \in \mathbb{R}^{3 \times (n+m) \times d}$. Each plane is a 2D tensor with the shape $d \times (n+m)$. In the lemma plane $\mathcal{L}$ the i-th column represents the embedding of the i-th word's lemma which is surrounded by the lemma embeddings of other words. With the same structure, $\mathcal{P}$ and $\mathcal{S}$ planes include $n + m$ embeddings belonging to the affixes of (context) words. In the embedding task, the target word is not included in the (matrix-form) input.

[2] The *filter* is sometimes referred to as the *kernel* in the literature.

Accordingly, we do not have lemma, suffix and prefix embeddings of the target word in the input cube. In our setting n and m indicate the number of preceding and following words before and after the target word, respectively. Figure 3.1 illustrates an example of an input cube.

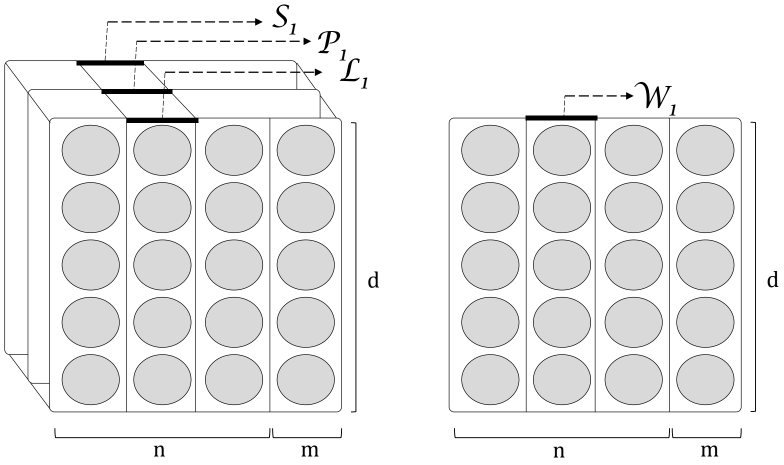


Figure 3.1: The cubic and matrix data structures for the input string [w_0 w_1 w_2 w_3 w_4]. Lemma, prefix and suffix embeddings for each word is referred to by $\mathcal{L}_i$, $\mathcal{P}_i$ and $\mathcal{S}_i$, respectively, and $\mathcal{W}_i$ indicates the surface-form embedding. $n = 3$, $m = 1$ and the target word is w_3. The first 3 columns include the related embeddings for w_0 to w_2 and the fourth column includes the embedding for w_4. We emphasize that the data structure on the right-hand side is used by previous embedding models and our model benefits from the cube on the left-hand side.

The network takes the cube as its input and convolves the planes with a specific multi-plane convolution function. In our case we incorporate contextual as well as intra-word information. Similar to the matrix-form input we have information about the target word's context. Moreover, by use of the lemma and affix planes we have access to subword-level information. Our cubic/multi-plane convolution module applies a series of convolution operations where each operation is a 3D extension of the standard 2D convolution function. The entire process can be formulated as in Equation (3.2). The convolution module takes a multi-plane data structure (in our case 3-plane) and generates another data structure with one or more planes, as in (3.2):

$$O_c^{p,i,j} = \sum_{l=1}^{|P|} \sum_{s=1}^{w_F} \sum_{t=1}^{h_F} F_c^{p,l,s,t} \times I_c^{l,(i-1)+s,(j-1)+t} \tag{3.2}$$

where I_c, O_c and F_c are the input, output and filter, respectively. Since in our setting the input, output and filter are all cubic data structures, they are shown with the 'c' subscript. O_c could have one to many planes which are referred to by the 'p' superscript. Each plane within O_c is a 2D tensor whose values are accessible through the (i, j) coordinates, i.e. $O_c^{p,i,j}$ shows the value of the i-th row and the j-th column in the p-th plane of the multi-plane output O_c. l is the plane index and $|P|$ shows the number of input planes. In our setting both I_c and F_c are 3-plane structures so $|P| = 3$. w_F and h_F are the width and height of each plane in the filter. Finally, the (s, t) tuple shows the coordinates of each plane in the filter F_c. The first superscript of filter (p) says to which plane in O_c the filter belongs. In our setting $I_c \in \mathbb{R}^{(m+n) \times d}$ (see Figure 3.1).

3.2.1 Network Architecture

Our network is proposed in order to learn embeddings for MCWs. To this end: *i*) first we take a cubic data structure as the input which includes embeddings for lemmas and affixes of n preceding and m following words around the target word; *ii*) we apply the 3D convolution function over the cube to combine its elements; *iii*) then apply other mathematical functions and transformations (such as non-linearity) to the convolution result and reshape it into a vector; and *iv*) at the end, the final vector is passed to a *Softmax* layer in order to predict the target word. To implement such a pipeline we propose the following architecture.

The first layer of our architecture is a lookup table which includes embeddings for lemmas, suffixes, and prefixes. The lookup table is treated as a matrix of network parameters whose values are updated during training. From each sentence in the training set, one word is randomly selected as the target word. During training, we process sentences multiple times and different words are selected as the target word. All words from the training sentence are decomposed into subunits (each word is decomposed into 1 lemma, 1 prefix and 1 suffix). Based on the selected target word, corresponding lemma and affix embeddings for context words are retrieved from the lookup table and placed in the cube. In our implementation, we use a window of

10 words around the target word, namely n=m=5. This means that if the target word is the fifth word in a sentence, the first plane of the input cube includes prefix embeddings for $word_i$ where $0 \leqslant i \leqslant 10$ & $i \neq 5$. Similarly, the second and the third planes include suffix and lemma embeddings for the same set of context words. n and m are hyperparameters of the model, both of which we set both m and n to 5 to make our work comparable to others (see Section 3.3 for more details). The look-up table is a matrix with $|\mathcal{V}|$ rows and d columns, where $\mathcal{V}$ is the vocabulary set and d is the embedding size (see Section 3.3 for more details).

In the second layer the multi-plane convolution function is applied. The input data is a 3-plane cube which the convolution module changes to a more dense structure with 6 planes, i.e. the input instance at each step with the shape $3 \times (n+m) \times d$ is transformed to a data structure with $6 \times w_{out} \times d_{out}$ dimensions, where $w_{out} = \lfloor \frac{(m+n)-w_F}{2} \rfloor$ and $d_{out} = \lfloor \frac{(d)-h_F}{2} \rfloor$. In our setting $w_F = h_F = 5$. We empirically recognized these numbers to be the best trade-off between the training time and the network accuracy. We also apply max-pooling to the 6-plane convolution result, where each plane is segmented into 2×2 windows whose maximum values are selected (one maximum value from each of those 4-cell windows).

The next layer applies non-linearity, where we transform each cell of the 6-plane data structure with *rectifier* units. For the purpose of generalization and preventing over-fitting, we also placed a *dropout* layer with $p = 0.3$ after the non-linear layer. Srivastava et al. (2014) extensively discussed the advantages of using *rectifier+dropout* layers. Up to this layer we have a data structure with several planes. We unfold the planes and reshape them all into a single vector. The vector is passed through another *rectifier+dropout* layer and is mapped to a 200-dimensional vector.

All cells of the final vector are processed by a hierarchical Softmax (*HSMX*) function to produce the probability distribution over classes (words). *Softmax* is a very expensive function in terms of time and space complexities. To deal with this problem, we used *HSMX* (Morin and Bengio, 2005) which first finds the correct word cluster and then looks for the correct word within the cluster. Similar to Kim et al. (2016), we pick the number of clusters $K = \lceil\sqrt{\mathcal{V}}\rceil$ and randomly split $\mathcal{V}$ into mutually exclusive and collectively exhaustive subsets $\mathcal{V}_1, ..., \mathcal{V}_K$ of (approximately) equal size. *HSMX* in our setting is formulated as in (3.3):

$$P(w_t = j|C) = \frac{\exp(h_t.w^k + b^k)}{\sum_{k'=1}^{K} \exp(h_t.w^{k'} + b^{k'})} \times \frac{\exp(h_t.w_k^j + a_k^j)}{\sum_{j' \in \mathcal{V}_k} \exp(h_t.w_k^{j'} + a_k^{j'})} \tag{3.3}$$

where similar to the regular *Softmax* function (Equation (3.1)), w_t is the target word, C is the context (in our case the cube) and h_t is the output of the last layer just before *HSMX*. The first term is the probability of picking the cluster k and the second is the probability of selecting the word j given the cluster k. With the regular *Softmax* layer the network processes $2,500,000$ tokens in ~9 hours whereas with *HSMX* it is reduced to ~1.5 hours (both on GPUs).

The network is trained using SGD and back-propagation (Rumelhart et al., 1988). All parameters of the model are randomly initialized over a uniform distribution in the range $[-0.1, 0.1]$. Filters, weights, bias values and embeddings are all network parameters which are tuned during training. The lemma/affix embedding size for the English experiment is 50 (see Section 3.3) and 200 for the other experiments. We use the negative log likelihood criterion to compute the cost. More formally, we wish to maximize the average log-probability in our network, as in (3.4):

$$\frac{1}{J}\sum_{j=1}^{J} \log p(w_j|C_j^i) \tag{3.4}$$

where J shows the number of all words in a training corpus, and w_j is the target word whose context information is represented by the cube C_j^i. One w_j can have different context cubes which is shown with the i superscripts. Figure 3.2 shows the network architecture.

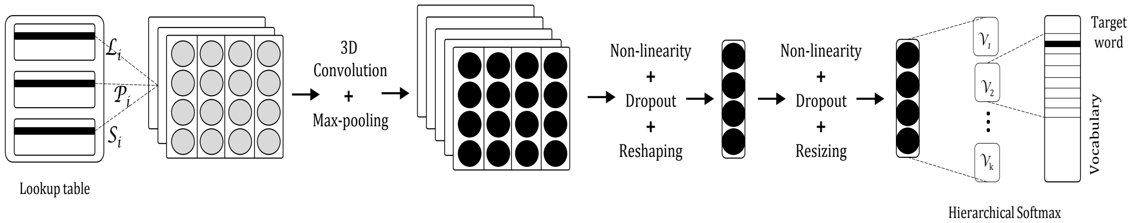


Figure 3.2: Network Architecture.

3.2.2 Word Embeddings

In our pipeline each word is decomposed into 3 subunits whose embeddings are trained via the CNN proposed in the last section. Since subunit embeddings are part of the neural architecture and involved in the prediction phase (forward pass), they are directly updated through the error back-propagation pass. After training we have high-quality lemma and affix embeddings which preserve information about themselves and lemmas and affixes of other context words. However, our final goal is to have high-quality embeddings for surface forms, not subunits. In order to generate surface-form embeddings we propose four simple models:

- **Model A**: in this model the word's surface-form embedding is generated through the concatenation of its subunit embeddings, namely $\mathcal{W}_i = \mathcal{P}_i.\mathcal{L}_i.\mathcal{S}_i$, where $\mathcal{W}_i$ indicates the surface-form embedding for w_i and $\mathcal{P}_i$, $\mathcal{L}_i$ and $\mathcal{S}_i$ are prefix, lemma, and suffix embeddings available through the lookup table.

- **Model B**: in this model we add another plane to the input cube. In the new data structure the fourth plane includes surface-form embeddings, e.g. the i-th column of the first, second, third, and fourth planes includes $\mathcal{P}_i$, $\mathcal{S}_i$, $\mathcal{L}_i$ and $\mathcal{W}_i$, respectively. With this technique we directly train surface-form embeddings using the proposed architecture.

- **Model C**: in this model we sum subunit embeddings to generate the word embedding, which means $\mathcal{W}_i = \mathcal{P}_i + \mathcal{L}_i + \mathcal{S}_i$.

- **Model D**: this model is an extension to the previous model, in which we use a weighted summation of subunit embeddings to generate the surface-form embedding, namely $\mathcal{W}_i = \alpha \times \mathcal{P}_i + \beta \times \mathcal{L}_i + \gamma \times \mathcal{S}_i$, where α, β and γ are weights and show the contribution/impact of each subunit. Weight values can be estimated as in (3.5):

$$\alpha = \frac{c(pre_{w_i})}{c(all)}; \beta = \frac{c(lem_{w_i})}{c(all)}; \gamma = \frac{c(suf_{w_i})}{c(all)} \tag{3.5}$$

where $c(.)$ counts the number of the occurrence of each subunits, i.e. $c(lem_{w_i})$ is the number of words whose lemma is lem_{w_i}. $c(all)$ is equal to $c(pre_{w_i}) + c(lem_{w_i}) + c(suf_{w_i})$. With this type of modeling, word embeddings are generated based on their subunits where the impact of each subunit is taken into account, so that if a word has a rare prefix its impact is attenuated in the surface-form embedding and the surface-form embedding relies more on its lemma or suffix. For example, in the surface-form embedding of *'infra+structure+s'*, it is better to focus more on *'structure'* and *'s'* which frequently occur in English words (as a lemma and suffix), rather than *'infra'* which is not a very frequent prefix.

3.3 Experimental Results

Although some prior work addressed the morphological representations in various language-processing tasks (Botha and Blunsom, 2014; Dos Santos and Zadrozny, 2014; Cotterell and Schütze, 2015; Kim et al., 2016), only Luong et al. (2013) studied this problem for the word-embedding task and is the work most related to ours. We compare our work to that of Luong et al. (2013) (see Table 3.1) to evaluate the quality of our embeddings, and to make the work comparable we use the same training set, embedding size, context-window size, test sets, and evaluation methods.

The most common way of intrinsically evaluating the quality of word-embedding models is to estimate the correlation between their scores and human judgments on similar word pairs. For this purposes one of the most frequently used datasets is *Wordsim*353 (Finkelstein et al., 2001).[3] The collection includes 353 word pairs accompanied with human-assigned similarity judgments. We evaluate our model on *Wordsim*353. Luong et al. (2013) developed a new dataset of rare words (*RareWord*).[4] The set includes 2034 word pairs with a similar structure to *Wordsim*353 (both are English datasets). The surface-form of rare words is not frequently seen in training corpora, but other forms (in a different tense or lemma form etc.) might occur frequently. If an embedding model could capture subword-level information, it should have better performance on such a dataset. We evaluated our model on this dataset too.

As a training set we use the April 2010 snapshot of the Wikipedia[5] corpus (Shaoul and Westbury, 2010), which was tokenized and lowercased in a pre-processing step. The baseline model also uses the same training set. In Luong et al. (2013), word embeddings were initialized by the *HSMN* embeddings (Huang et al., 2012). *HSMN* includes embeddings for $138,218$ unique words, covering all words from *RareWord* and 419 words from *Wordsim*353 (419 out of 439 unique words). In our experiment we use the same vocabulary set along with those uncovered words from *Wordsim*353, which are not included in *HSMN*.

In the training corpus we keep all those paragraphs which include at least one of the vocabulary words and exclude other paragraphs. We replace all numbers with “NUM” and words not in the vocabulary with “UNK”. After preprocessing, the final training corpus includes $15,469,077$ paragraphs and $919,646,155$ words. Using the training corpus, lemma and affix embeddings of the vocabulary set are trained. Afterwards, we explore the techniques discussed in Section 3.2.2 to generate surface-form embeddings.

As previously mentioned, *Wordsim*353 and *RareWord* include word pairs where their semantic similarity is indicated with a human-assigned number. For each pair, we retrieve the embeddings of the words (of the pair) and estimate their distance

[3] `http://www.cs.technion.ac.il/~gabr/resources/data/wordsim353/`

[4] `http://stanford.edu/~lmthang/morphoNLM/`

[5] `http://www.psych.ualberta.ca/~westburylab`

using the *Cosine* similarity, which is a number in the range $[-1, 1]$. First we map the number to the range $[0, 1]$ and then using Spearman's rank correlation, we compare the generated number with the human judgment. The model whose results have a better correlations with human-assigned numbers is a better model. Table 3.1 summarizes the results obtained by Luong et al. (2013) and our embeddings.

Embeddings	*Wordsim*353	*RareWord*
HSMN (Huang et al., 2012)	62.58	1.97
+stem (Luong et al., 2013)	62.58	3.40
+cimRNN (Luong et al., 2013)	62.81	14.85
+csmRNN (Luong et al., 2013)	64.58	22.31
Model A	62.22	17.93
Model B	**66.16**	24.01
Model C	64.93	23.93
Model D	65.43	**26.92**

Table 3.1: Results for the word-similarity task. Numbers indicate Spearman's rank correlation coefficient ($\rho \times 100$) between similarity scores assigned by different neural networks and human annotators.

The first pair of numbers in Table 3.1 shows the correlation of the *HSMN* embeddings with human judgments. *+stem* is the case when unknown words are represented by their stem embeddings. Luong et al. (2013) proposed two models of *cimRNN* and *csmRNN*. The first model tries to optimize embeddings using a recursive neural network. By use of the recursive model they tried to capture intra-word (morpheme-level) information. In the second model, *cimRNN* was used within a language model. The motivation behind the second model (*csmRNN*) is to capture contextual information along with intra-word information. The last four rows show our models which yield better results than the recursive model.

Our results consistently improve on previously reported numbers, especially for *RareWord*. There could be two possible reasons: *i*) in the model of Luong et al. (2013), the network has a reference embedding table. Embeddings for each word are generated and the error is computed based on the distance between reference and generated embeddings. The network tries to make new embeddings as close as possible to the reference embeddings. This form of learning degrades the impact of morpheme-level information, as reference embeddings are provided by word-based methods such as Collobert et al. (2011) or Huang et al. (2012). Although *cim-RNN* tries to learn morpheme-level information, by comparing its results to reference embeddings it (implicitly) forces the network to learn word-level embeddings; and *ii*) to the best of our knowledge, for the first time Botha and Blunsom (2014) combined subword-level information by linearly summing the corresponding embeddings. However, other models such as Luong et al. (2013) and Kim et al. (2016) have argued that a simple linear combination might not be ideal, and they instead proposed convolutional and recursive approaches. The recursive model is also a variation of summation over morpheme embeddings but not as simple as the model of Botha and Blunsom (2014). In our proposed model we have different types of subword-level information. They are all combined together through a convolutional process, which enables the network to have multi-granular information about its input. Perhaps this type of fusion works better than other models (linear, recursive, etc.). These discrepancies (*i* and *ii*) between the models could be the source of the different results achieved. In the next section we describe more experiments to investigate the proposed model from other perspectives.

3.4 Further Investigation of Experimental Results

In this section we try to address some issues regarding the network architecture and embeddings in order to extensively analyze the proposed pipeline.

3.4.1 POS and Morphology Tagging Experiments

Since English is not considered as an MRL, in addition to the English experiment we designed another experiment on Farsi and German. We evaluate our embeddings in the POS-tagging task. For this experiment we use a simplified version of our neural POS tagger (Passban et al., 2016a), which is a multi-layer perceptron with 4 layers. The first layer is the input layer and includes word embeddings. The second and third layers are *tanh* layers with 300 and 200 units, respectively. The fourth layer is a *Softmax* layer to compute class probabilities over POS tags. For this experiment, the embedding size is 200 and word embeddings are produced by Model D.

We run the neural POS tagger with two different settings. In one setting the network input is the word embedding ($[\mathcal{W}_i]$), and in the other one we enrich the input by adding the embedding of one preceding word ($[\mathcal{W}_{i-1}, \mathcal{W}_i]$). We estimate the accuracy of the neural POS tagger when it is initialized by our own, *Word2Vec* and *GloVe*[6] (Pennington et al., 2014) embeddings. To train embeddings and the POS tagger for Farsi we used the `UPC`[7] corpus (Seraji, 2015), which is a collection of $2,704,028$ words, with $66,629$ unique words, $59,865$ unique lemmas, 368 unique prefixes, and 1096 unique suffixes. To segment Farsi words we used our in-house morphological analyzer which is a rule-based model. We used the first 2 million words for training, the next $200,000$ words for tuning and the next $200,000$ words for testing. The tagset size for `UPC` is 31.

For German we used the first part of the `DEWAC 1.3` corpus from the `WaCKy`[8] collection (Baroni et al., 2009). To segment German words we used the NLTK lemmatizer.[9] We selected the same number of words for the training, tuning and test sets. The German corpus includes 53 POS tags, $2,232,913$ words, $185,895$ unique words, $136,876$ unique lemmas, 11 prefixes, and 153 unique suffixes. The results for the POS-tagging task are reported in Table 3.2.

According to the results from Table 3.2, *GloVe*'s performance is well below that of the other models. Our model works better than *Word2Vec* for both languages.[10] We believe that this is because our embeddings preserve subword-level (morphological) information and boost tagging performance. We train morphology-aware embeddings which were able to enhance the performance of the neural POS tagger.

[6] `http://nlp.stanford.edu/projects/glove/`.

[7] UPC is a commonly used dataset in this field which is available at: `http://stp.lingfil.uu.se/~mojgan/UPC.html`.

[8] `http://wacky.sslmit.unibo.it/doku.php?id=start`.

[9] `http://www.nltk.org/api/nltk.stem.html?highlight=lemmatizer`

[10] We do not have access to the source of other embedding models to train on Farsi and German.

	Input	GloVe	Word2Vec	Model D
Farsi	$[\mathcal{W}_i]$	90.09	93.28	**96.11**
	$[\mathcal{W}_{i-1}, \mathcal{W}_i]$	92.65	93.65	**96.64**
German	$[\mathcal{W}_i]$	81.20	86.22	**87.74**
	$[\mathcal{W}_{i-1}, \mathcal{W}_i]$	81.84	87.20	**88.64**

Table 3.2: Results for the POS-tagging experiment. Numbers indicate the accuracy of the neural POS tagger. According to word-level paired t-test with $p < 0.05$, our results are significantly better than other models.

Clearly, the main reason behind proposing our new architecture is to obtain high-quality word embeddings, and both the word-similarity and POS-tagging experiments confirm that our model could be an appropriate alternative in this regard. We report some additional results from the model to further support this claim. Figure 3.3 illustrates the behaviour of our tagger during the training phase. The x axis shows the first 200 training iterations, and the y axis is the error rate (100 - *accuracy*). We see that when the tagger is internalized with our embeddings (blue), it quickly converges to the final result (after almost 220 iterations), whereas almost 600 iterations are required to reach the same point with *Word2Vec* embeddings (red). This indicates that our embeddings provide richer information for the tagger. Furthermore, for the first iteration the initial error rate is about 45 for *Word2Vec* while this number is 33 for ours. The initial error rate also confirms that our embeddings (by nature) are more representative than those of *Word2Vec*, as even without fine-tuning the embeddings with respect to the POS-tagging task, they are able to provide acceptable representations.

Since we learn morphological information about words, we are interested in estimating the impact of embeddings on the morphology-tagging task too. We used the same setting, embeddings and network as in the POS-tagging task. Given the input data, we try to tag its morphology class. The tag for each word is defined as the combination of its affixes, *"prefix+suffix"*. The Farsi and German corpora have 1818 and 154 morphology tags, respectively. Results for the morphology-tagging task are reported in Table 3.3.

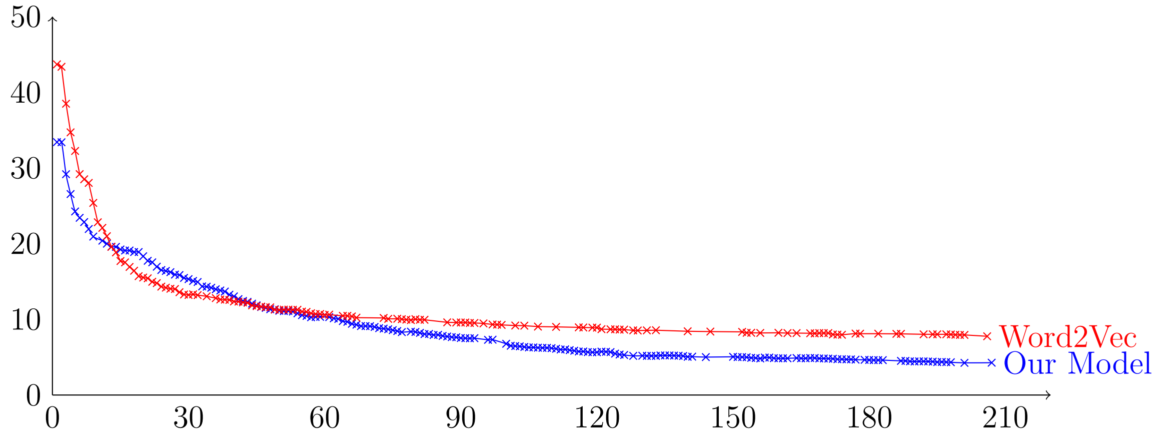


Figure 3.3: Comparison of the convergence speed between *Word2Vec* and our model for the POS-tagging task. The x axis shows the iteration number and the y axis is the error rate.

The trend in Table 3.3 is similar to the results of the POS-tagging task where we significantly outperform other models. As expected, our embeddings were able to predict the morphological tags more precisely because of their awareness of morphological information. The large number of classes in Farsi makes the classification process much harder but our model still provides acceptable performance. According to word-level paired t-test with $p < 0.05$, when the both POS and morphology taggers are initialized using our embeddings, results are significantly better than when embeddings are initialized by *Word2Vec*.

	Input	GloVe	Word2Vec	Model D
Farsi	$[\mathcal{W}_i]$	72.53	74.01	**74.76**
	$[\mathcal{W}_{i-1}, \mathcal{W}_i]$	72.82	74.08	**75.00**
German	$[\mathcal{W}_i]$	79.00	83.38	**85.29**
	$[\mathcal{W}_{i-1}, \mathcal{W}_i]$	79.48	83.75	**86.01**

Table 3.3: Results for the morphology-tagging experiment. Numbers indicate the accuracy of the neural tagger. According to word-level paired t-test with $p < 0.05$, our results are significantly better than other models.

3.4.2 Impact of Using Different Architectures

The proposed network has a complex architecture whose parameters can directly affect its final performance. There are also other alternatives such as the segmentation scheme which play the same role. In this section we try to show the impact of each module. We have a cubic data structure and a convolution function in our network. The idea behind proposing such a model is to provide a richer representation of words. We believe that the convolutional module preserves and combines subword-level information better than other models, so we compared it to other simpler combination models. Table 3.4 summarizes the results of this comparison. Numbers in the table indicate Spearman's rank correlation coefficient between similarity scores assigned by different neural architectures and human annotators. We evaluated the models on the *RareWord* dataset.

Embeddings	Concat	Sum	W-sum	Model D
RareWord	15.11	18.31	19.44	**26.92**

Table 3.4: Impact of different subword-combination models on the word-similarity task.

The first column (*Concat*) belongs to a simple feed-forward architecture in which words are segmented into affixes and lemmas. In the forward pass, context words are represented by a concatenation of their subunit embeddings. Accordingly, this model can be viewed as an extension to the *CBOW* setting of *Word2Vec*, where for each context word the concatenation of subunit embeddings is used instead of the surface-form embedding. *Concat* does not include any convolutional module, so it is quite different from Model A. In Model A, subunit embeddings are trained through a convolutional process and concatenated outside of the NN, after the completion of training, whereas in *Concat* subunit embeddings are directly retrieved from the lookup table, concatenated and consumed in the forward pass.

Sum has the same architecture as *Concat* with only one difference. In order to make the surface-form embedding in *Sum*, word and subunit embeddings are linearly combined together, i.e. for each context word the surface-form embedding is equal to $\mathcal{P}_i + \mathcal{L}_i + \mathcal{S}_i + \mathcal{W}_i$. A variation of this architecture was used in Botha and Blunsom (2014) for modeling which has a different setting with embedding learning but the main idea is the same.

W-sum is an extension to *Sum* where each component has a dedicated weight. The weight values are learnable network parameters and set during training, so the surface-form embedding in this model is generated by $w_i^1\mathcal{P}_i + w_i^2\mathcal{L}_i + w_i^3\mathcal{S}_i + w_i^4\mathcal{W}_i$. Results obtained by different architectures demonstrate that involving the convolutional process in the learning pipeline boosts the final performance.

In the proposed architecture we use a 3-plane cube which is mapped to a 6-plane structure. This number is a trade-off between complexity and accuracy. Mapping the 3-plane cube to more dense structures provides better correlations but (almost) doubles the training time. The correlation obtained with our model for the word-similarity task on *RareWord* is 26.92 (Table 3.1) whereas if we map the same cube to a 7-plane structure, the final correlation will be 27.04. The improvement from 26.92 to 27.04 is negligible but the difference in the training time is significant.

In our model words are segmented into three different subunits of prefix, lemma and suffix. We use the NLTK toolkit to lemmatize English words.[11] What remains before the lemma is considered as a prefix and what comes after the lemma is considered as a suffix. With this type of segmentation we always have 3 planes in the input cube which provides the best performance. We studied another alternative architecture, where we decomposed words using *Morfessor*[12] (Smit et al., 2014). Each word may have one to many (more than 3) subunits. Accordingly, we enlarged the cube to a multi-plane structure. Since different words could be segmented into different number of subunits and it is not possible to have a dynamic number of planes in the neural architecture, the number of the input planes should be controlled, so we used a 6-plane structure instead of the cubic input. Words which have fewer than 6 subunits are padded with "*Null*" and for those which consist of more than 6 subunits we consider the first 5 subunits as separate subunits and the rest of them as a single unit. Therefore, for all cases we have 6 units (which means 6 planes). However, using more than 3 subunits did not help at all and only delayed the training phase.

[11] We emphasize that we lemmatize words instead of stemming.

[12] `http://morfessor.readthedocs.io/en/latest/`

It also decreased the performance for some experiments. With a 6-plane input the final correlation on *RareWord* is 21.73 which is considerably worse than that of the 3-plane structure.

3.4.3 Analytical Study

To complete our experimental study, apart from all quantitative analysis we designed another experiment which qualitatively studies our embeddings. For this experiment we analyzed some random examples from our embeddings to see if the model is able to capture morpheme-level similarities. To this end we selected Farsi verbs and retrieved the top-10 most similar embeddings for each word. We investigated whether the retrieved samples are related to the verb. Table 3.5 illustrates one example from this experiment. The table shows results for the Farsi verb *'krdn'* meaning *'doing'*. Vectors retrieved for the verb are semantically related to each other. Furthermore, they have similar forms and syntactic structures which confirms that our model can preserve/learn semantic, syntactic and morphological similarities altogether.

#	**Verb**	**Similarity**	**Translation**
1	knd	0.801	if he does
2	myknnd	0.757	he is doing
3	krdnd	0.719	they did
4	knnd	0.684	they do
5	knym	0.670	we do
6	krdH	0.625	done
7	nmyknd	0.624	they do not do
8	nmyad	0.6146	does not come
9	myknym	0.6141	we are doing
10	krd	0.606	did

Table 3.5: The top-10 most similar embeddings to the Farsi verb *'krdn'* meaning *'doing'*. **Similarity** is the Cosine distance between *'krdn'* and the retrieved verb.

3.5 Summary

In this chapter we discussed a new word-embedding model which is able to explicitly capture morphological information. Our approach decomposes surface forms into smaller units and trains embeddings for them; then a word-level embedding is generated by combination of such subunit embeddings. Results reported from the proposed model confirm that it outperforms systems which do not take morphological information into account. On the word-similarity task, for both common and rare words, we perform better than the state-of-the-art recursive model. Moreover, we applied the proposed model to Farsi and German POS tagging, to further evaluate our morphology-aware embeddings. For the tagging tasks our model clearly outperforms word-level models. Via the architecture discussed in this chapter we are able to efficiently model MCWs. Our morphology-aware embeddings are also used in the next chapter to improve translation quality.

Chapter 4

Morpheme Segmentation for Neural Language Modeling

In the last chapter we introduced our models to learn morphology-ware word embeddings. In this chapter we look beyond word-level modeling and work at the sentence level, which is referred to as *language modeling* in the field of NLP. Recently, neural language models (NLMs) have appeared as powerful alternatives to conventional n-gram models. They perform efficiently in most cases but still have serious problems with MRLs. Words are treated as atomic units in existing word-level NLMs, which is not suitable for MRLs as words are complex structures in this set of languages and should be processed at the subword level. Morpheme-level and character-level NLMs have been proposed to address this issue. In this chapter, we further explore this problem by tuning the state-of-the-art character-level model (Kim et al., 2016) in order to propose better language-modeling alternatives. We also propose data-driven and count-based morpheme segmentation[1] models to process MCWs, prior to being used by NLMs. Through the segmentation process, MCWs are decomposed into different sets of consecutive characters. Our proposed models benefit from the

[1] In NLP, *word segmentation* is usually known as a process in which words are separated from each other but here we tend to segment words into their subunits, so we use the term *morpheme segmentation*. In our models, morphemes are not necessarily linguistic morphemes and could be any set of consecutive characters.

advantages of both character-level and morpheme-level decompositions. We evaluated our models on English and four MRLs, namely Czech, Farsi, German, and Russian, and observed significant improvements for all experiments.

In this chapter the main goal is to propose data-driven techniques to extract *basic* units of languages. A set of basic units is a set by which all constituents of the language can be modeled (represented). A particular language could have several basic sets with different levels of granularities. Using this definition, a set of unique words (vocabulary) can be considered as the set of basic units, because each word is a basic element in itself. With the same logic, a set of stems and all possible affixes plays the same role, as stems and affixes are basic units and can be combined to generate new linguistically correct constituents. However, there is a key difference between these two sets. The first set includes thousands (or even millions) of surface forms and all new constituents generated via the set are only limited to that. Therefore, it is not possible to model unseen forms (which do not exist in the set or include unseen subunits), whereas the second set is able to partially mitigate this problem as the chance of modeling an unseen constituent via a combination of stems and affixes is very high. Another advantage of the second set compared to the first one is its size. The size of a set including all stems and affixes is considerably smaller than the size of the vocabulary set, which enables us to model much more constituents via a much smaller set.

The alphabet is the third alternative which can be considered as the set of basic units for any language. All possible constituents in a language can be generated via a combination of letters. This third set has the smallest size and the finest granularity, that is able to thoroughly solve the problem of generating unseen words. Modeling constituents via the alphabet set looks a promising avenue of investigation, and thus recent models have been designed based on characters. Character-level models receive a sequence of characters as the input and try to extract meaningful relations between characters. Models proposed based on this idea are successful and have shown impressive results. However, there are still unanswered questions related to these models, some of which we address in the next sections.

Morpheme-level NLMs (see Section 4.1) feed the neural architecture with subword units instead of words. In contrast, character-level models are designed based on the assumption that the subword-level representation may not be the best (machine-understandable) input form, so they prefer to receive a sequence of characters as the input and extract the relation between subunits by themselves. In this approach characters are supposed to be basic units of the language, which is a correct assumption but it complicates the problem. Characters are neutral units, namely any character can collocate with any other character with no constraint. This much flexibility can entail serious problems for neural models. Moreover, treating words and sentences as sequences of characters drastically increases the computational complexity. One sentence includes a limited number of words and neural models are able to handle this much complexity without difficulty, but when the same sentence is decomposed into characters it is changed to a very long sequence with hundreds of units, so modeling such a long sequence and remembering the relation between units is quite challenging or even impossible.

Considering these issues, we propose segmentation models which are able to control the level of granularity of the segmentation scheme. The granularity provided by word-level (and sometimes morpheme-level) models is too coarse for MCWs, and the granularity of the character-level model could be too fine. We are not sure as to which yields the best performance, because there are different results based on different architectures. We believe that to answer this question we should have different segmentation models with tunable granularity levels, where we can search for and decide what the best granularity level is. In this research, we tried to design such models, where the granularity level is tunable and lies in between the word-level and character-level segmentations. Detailed information of the models and their justification are discussed in the next sections.

Since our approach changes words into more understandable forms for NLMs, it outperforms word- and morpheme-level models. It is also able to partially address the shortcomings of character-level NLMs, as it decomposes words into blocks blocks (sets of consecutive characters) which are bigger than characters, which means that the final generated sequence is not very long. Shorter sequences are easier to process for neural models. Furthermore, in our case the search space becomes smaller and more tractable. In the character-level model the history is based on a chain of characters and the next character could be any other character, but in our model the history is constructed based on a sequence of morphemes which conveys a specific meaning with a specific structure and expects a particular token in the following step(s). To benefit from the advantages of our approach we should find the best level of granularity for representing words in the context of language modeling which is the main contribution of this research.

4.1 Background

Language modeling is the process of assigning a probability to a given sequence of words. An LM measures how likely a sequence of words is to occur in a text. It addresses the fluency feature of the given sequence, so that a sequence with a good word order has a higher probability. The most popular types of LMs are count-based or n-gram models which function based on the Markov chain assumption. In such models the probability of a sequence is computed by the conditional probabilities of words given their history, as in (4.1):

$$P(S) = P(w_1, ..., w_m) = \prod_{i=1}^{m} P(w_i|w_1^{i-1}) \tag{4.1}$$

where S is the given sequence of length m. The model conditions the probability of each word over a chain of preceding words. Since computing the probability over the entire chain is not computationally feasible, it is usually limited to a bounded set of n most recent words, as in (4.2):

$$P(w_i|w_1^{i-1}) \simeq P(w_i|w_{i-n+1}^{i-1}) \tag{4.2}$$

The assumption states that the probability of a word is affected by its n preceding words. Obviously, a long history is preferable but such an assumption is made in practice because of computational restrictions and limited data resources. These models are known as n-gram models and the limited-history problem is the main disadvantage of these models.

NLMs (Alexandrescu and Kirchhoff, 2006; Mikolov et al., 2011; Botha and Blunsom, 2014; Kim et al., 2016) have been proposed to solve the limited-history problem. Generally in NLMs, embeddings of input words (words of an input sequence) are combined to make an internal representation of the whole sequence. At the output layer the next word (in the chain) is predicted given the input/internal representation and the conditional word probabilities, and the probability of the sequence is computed accordingly. The work by Bengio et al. (2003) is the main basis for all other NLMs and follows this architecture. Although this model performs better than analogous n-gram models, it also suffers from the limited history as it considers only the last n words in the prediction phase. To extend the history from n words to the entire sequence Mikolov et al. (2010) proposed a recurrent architecture.

NLMs are able to solve the limited-history problem (through the recurrency feature) but both neural and n-gram models have fundamental problems with large vocabularies and out-of-vocabularies (OOVs) phenomena which are commonly encountered in MRLs. To address this issue, subword-level models have been proposed (Sutskever et al., 2011). The most impactful NLMs which explicitly address the rich morphology problem are the *morpheme-level log-bilinear* (MLBL) and *character-level* (CLM) models, proposed by Botha and Blunsom (2014) and Kim et al. (2016), respectively. Our NLM relies extensively on these models with a similar architecture to CLM. Botha and Blunsom (2014) extended the well-known log-bilinear LM (Mnih and Hinton, 2007) for MRLs. It benefits from morpheme-level and word-level information as the surface-form and subunit embeddings are linearly combined to build the word representation. The model is able to achieve better performance compared to existing word-level NLMs. CLM uses character-level information. Each word is decomposed into characters and they are combined via a convolutional process. Results reported from CLM indicate that such an architecture could be an appropriate model for MRLs (see Section 4.4 for more details). In this chapter we also address the same problem and try to find an optimal segmentation for MCWs. Experimental results demonstrate that the proposed segmentation model enables our NLM to perform better than the state-of-the-art morpheme-level (Botha and Blunsom, 2014) and character-level (Kim et al., 2016) NLMs. The impact of the proposed model is more tangible for languages with rich morphology.

4.1.1 Related Work

Language modeling is a well-studied problem with broad applications in different fields such as speech processing, machine translation and information retrieval, and covers numerous languages and architectures. In this section we review conventional and neural LMs which either have the same concerns as we do or which efficiently utilize neural architectures for language-modeling purposes.

To address the rich-morphology problem, the class-based approach (Brown et al., 1992) was proposed. Bisazza and Monz (2014) reviewed the application of this approach for language modelling. The main idea behind class-based models is to group words with the same distribution into equivalent classes and estimate class probabilities instead of word probabilities. Since LMs work with word classes, they are no longer sensitive to morphological variations and surface forms, which might allow the rich-morphology problem to be mitigated. Factored (Bilmes and Kirchhoff, 2003) and maximum entropy models (Shin et al., 2013) are other approaches which are suitable for MRLs. Instead of working with surface forms, each word is represented by a set of factors over which the word conditional probabilities are computed. A factor can be any function or annotation which provides extra information about the word itself, and its behaviour, semantic, grammatical role and context.

A group of NLMs achieved state-of-the-art results because of their optimal neural architecture. Pascanu et al. (2014) studied the behaviour of deep recurrent neural networks (RNNs) in language modeling. RNNs are the best alternatives in this regard, since their recurrent (iterative) nature allows them to read the entire sequence and preserve its features within hidden layers. Pascanu et al. (2014) tried several deep and complex architectures to obtain the best result (see Table 4.1). Zaremba et al. (2014) proposed a deep long short-term memory (LSTM) RNN. Simple RNNs usually perform better than feed-forward models for sequences but they still have problems to model long-distance dependencies. The vanishing gradient problem is another common issue of simple RNNs (Pascanu et al., 2013). LSTM units were proposed to solve these problems (Hochreiter and Schmidhuber, 1997). LSTMs work as memory units which are able to memorize longer dependencies (see Section 4.4 for more details). Wang et al. (2015) designed a convolutional architecture for their LM. Our model is also a convolution network combined with an LSTM RNN. Zhang et al. (2015) proposed an encoding model to encode the input sequence into a fixed-length vector and developed a feed-forward architecture to work over the vector. These models and their performance on the English Penn Treebank (PTB) (Marcus et al., 1993) are summarized in Table 4.1. PTB is a standard dataset on which all LMs are evaluated in order to make them comparable.

Model	**PTB PPL**
DeepRNN (Pascanu et al., 2014)	107.5
DeepLSTM (Zaremba et al., 2014)	**78.4**
*gen*CNN (Wang et al., 2015)	116.4
FOFE (Zhang et al., 2015)	108.0
CLM (Kim et al., 2016)	78.9

Table 4.1: Results reported from state-of-the-art NLMs on PTB. PPL refers to perplexity which is a standard to evaluate LMs (lower is better). The table only reports the best performance achieved by the models.

There are NLMs that were proposed particularly for MRLs such as factored NLMs. Factored models have neural versions where the intuition behind them is the same as non-neural models. Each word is represented by embeddings of its factors instead of the surface-form embedding (Alexandrescu and Kirchhoff, 2006). There are two main models, namely MLBL (Botha and Blunsom, 2014) and CLM

(Kim et al., 2016), which are known to be the most impactful NLMs for MRLs and explicitly address the problem of rich-morphology problem. Figure 4.1 illustrates their architecture.

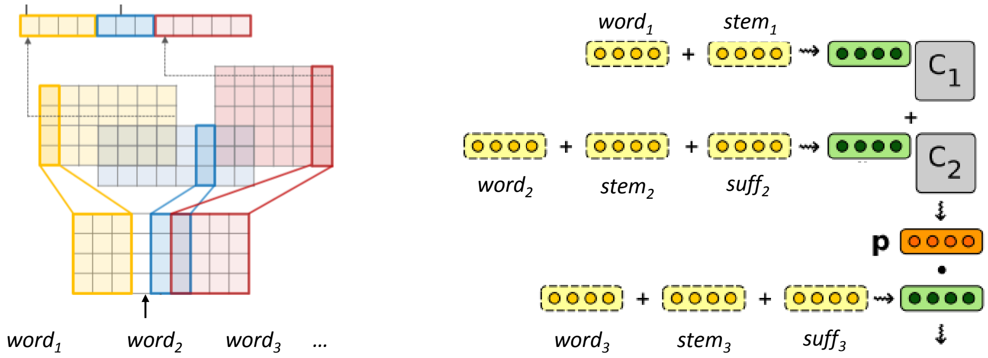


Figure 4.1: The network on the left-hand side is the character-level architecture (Kim et al., 2016). *word*$_2$ is segmented into characters and different filters with different widths are applied to construct the word-level representation. The network on the right-hand side is the morpheme-level architecture (Botha and Blunsom, 2014). Subunit embeddings are linearly summed with the surface-form embedding to build the final representation for each word (C_i).

Our NLM relies extensively on these models with a similar architecture to CLM. As previously mentioned, Botha and Blunsom (2014) extended the well-known log-bilinear LM (Mnih and Hinton, 2007). The original log-bilinear model is perhaps the simplest neural language model. The model is a feed-forward network where the probability of predicting the next word w_i in the chain is estimated by linearly combining the representations of the context words w_0 to w_{i-1}. In the model extended by Botha and Blunsom (2014), each word is represented by the combination of its surface-form and subword embeddings. The combination was quite successful and surpassed all word-based models. Unlike MLBL, CLM works at the character-level where character embeddings are learnable network parameters which are updated during training. They are combined via a convolutional layer and passed through a *highway* layer to make the word representation. CLM showed promising results for MRLs. Its performance on PTB[2] is also reported in Table 4.1.

[2] PTB results are not available for Botha and Blunsom (2014).

4.2 Morpheme Segmentation

Sequence segmentation has recently become very important for many NLP tasks such as POS tagging, language modeling and translation (Botha and Blunsom, 2014; Dos Santos and Zadrozny, 2014; Chung et al., 2016; Costa-jussà and Fonollosa, 2016; Kim et al., 2016; Luong and Manning, 2016). One of the main problems with neural models is their inability to handle large vocabularies and complex words. Moreover, their performance drops considerably in the presence of OOVs. Morpheme segmentation is usually applied as a solution but it raises other types of problems. For morpheme-level segmentation, a precise morphological analyzer have to be provided as segmentation errors can directly affect the final performance. However, it is not always possible to have such a high-quality analyzer. *Morfessor* (Smit et al., 2014), an unsupervised model, is commonly used for this purpose, e.g. MLBL uses *Morfessor* to decompose MCWs.

Recently, character-level segmentation has been proposed which usually provides better results than morpheme-level methods. However, it is debatable as to which of them (morpheme-level or character-level) provides the optimal segmentation. According to discussions (Botha and Blunsom, 2014; Sennrich et al., 2016b), the gain achieved by morpheme-level neural models is mainly because of the segmentation scheme rather than the neural architecture. However, this is not very clear as far as character-level models are concerned, as they usually explore quite complex and deep networks, and different alternatives might affect the performance. For example, Ling et al. (2015) applied character-level segmentation, developed a quite complex architecture and used pre-trained models but could not achieve comparable results to state-of-the-art models, whereas Chung et al. (2016) applied the same segmentation model with better performance than previously reported work. Accordingly, it is still questionable which model mainly affects the final performance: the segmentation model or the neural architecture. It should also be mentioned that the model of Chung et al. (2016) benefits from a mixed segmentation scheme. Chung et al.

(2016) have morpheme-level segmentations in the encoder of their neural translation engine and a character-level segmentation in the decoder.

We believe that character-level segmentation does not provide an optimal representation. CLM reported state-of-the-art results but for Russian which has a very rich morphology, Kim et al. (2016) (Table 5) shows that the morpheme-level model still works better. A similar situation was also reported in Vylomova et al. (2016) where morpheme-level segmentations outperform character-level models for some MRLs. Characters are not meaning-bearing units. They can appear in every word regardless of its semantics, structure and context. There are many words which share the exact or similar set of characters but have quite different meanings, e.g. *'salt'* and *'last'* or *'except'* and *'expect'*. Character subunits do not preserve any specific information. Furthermore, the surface form is completely destroyed when a word is decomposed into characters. The surface form preserves a significant amount of important information. Therefore, we believe that words should not be completely decomposed into characters. However, we do not want to imply that character-level information is not useful at all.

Results reported from different experimental studies related to morpheme segmentation issues demonstrate that:

- Morpheme segmentation is not always required. It is only applied to languages that have limited resources and a high OOV rate, in order to mitigate the data sparsity problem. If enough data is available a model based on surface forms (words without any segmentation) could be the best solution. Dos Santos and Zadrozny (2014) report POS-tagging results where a word-level model works better than a character-level counterpart. Note also that the word-based model of Zaremba et al. (2014) has the best perplexity score on the PTB dataset among all other morpheme- and character-level models.

- From a linguistic perspective, a precise morphological analyzer can provide the best segmentation. However, finding such a tool can be impossible for some languages.

- For situations where we do not have access to such a precise analyzer, character-level models are the best and even the only solution.

- According to experimental results, for a particular set of languages, morpheme-level models work better and for some of them character-level models provide better performance, so it is not very clear which one is a good solution to deal with MRLs.

Motivated by the aforementioned issues, in our research we try to find a middle-ground solution that benefits from the advantages of all existing approaches. If we capture the strengths of both paradigms we may obtain better results. To this end we propose novel count-based segmentation models which combine both character-level and morpheme-level models.

4.3 Count-based Segmentation for MCWs

Experimental results demonstrate that models which rely on word- and morpheme-level segmentations perform well in the presence of enough data and preprocessing tools, but it is not always feasible to guarantee this. Character-level models could be considered as backup solutions for such situations, as they are not dependent on tools and data as much as other models. However, character-level models require powerful neural architectures. In such models the main goal is to connect related characters to each other via a neural computation (not through segmentation), which is carried out through convolutional modules. Usually, such convolutional computations are quite costly, e.g. in the model of Kim et al. (2016) about 500 convolution operations are applied to each word in the first layer, and then the result is sent to other following layers. Such a convolutional process is a complementary process to prepare the input for neural language modeling which imposes significant overheads, i.e. for the same task (in the best case) the character-level model should have at least one layer more than other counterparts.

Regarding the aforementioned issues we can conclude that the granularity level of the input dictates the network architecture and affects the computational complexity. Accordingly, we can debate important questions that: *"Do we really need a complex model to work at the character level?"* or *"Is the granularity provided by the character-level segmentation optimal?"* Although the set of characters of a language is the minimal set and is able to model all possible constituents, we believe that it is not the optimal set. Existing state-of-the-art NLMs are designed to work with character inputs, but it seems there is an easier way to solve the problem with simpler models and different levels of granularity. Instead of asking the neural architecture to decipher the relation among characters via complex convolutional structures, we can explicitly solve the segmentation problem via a non-neural model prior to performing language modeling, and feed the network with better segmented units. We hope that by making the input data slightly more complex than that of the character-level input, we will be able to mitigate the complexity of the neural computation/architecture.

To study our hypothesis we compare and evaluate different segmentation schemes. Existing segmentation models such as *Morfessor* (Smit et al., 2014) or the *Byte-pair* model (Sennrich et al., 2016b) do not provide different/tunable granularity levels. *Morfessor* is an unsupervised segmentation model which tries to extract linguistically correct morphemes. The level of granularity provided by this model is in between the word level and the character level, but it is not tunable. *Byte-pair* is a similar model which processes words to extract frequent subunits. It relies on statistical information and does not pay attention to linguistic rules. It takes a training corpus and merges the most frequent character n-grams together. Through merging, it generates a number of new tokens/blocks, the number of which should not exceed a user-defined upper bound. The level of granularity of this model is almost the same as *Morfessor*. These two models do not completely satisfy our needs to study the hypothesis, so we propose new segmentation models with tunable granularity levels. However, together with our models we also study *Byte-pair* and *Morfessor*. The next sections explain our models.

4.3.1 Model A: Greedy Selection

In the first proposed model we use bigger subunits (blocks) than characters. The proposed segmentation model takes a string (word) as its input and finds the longest and frequent substring within its input. A frequent substring is a substring which occurs at least θ times in a training corpus, where θ is a parameter of the model. We refer to the longest and frequent substring as *main*. If there is any other substring before and after *main*, the segmentation function is applied to them too. Clearly this is a recursive pipeline to find the longest and frequent substring at each step. At the end, if there exists some remainder that are not frequent, they are all decomposed into characters. The pseudo-code of the model is illustrated in Algorithm 2.

Algorithm 2 CountSegmentation (InputS, Start, End, θ)

```
procedure CountSegmentation
                                  ▷ Start: index of the first character of InputS.
                                  ▷ End: index of the last character of InputS
    (main,index) = find(InputS)
                                  ▷ main: the longest & frequent substring within InputS.
                                  ▷ index: index of the main's first character.
    if main != null then
        Store main
        L = length(main)
        CountSegmentation(InputS,Start,index-1,$\theta$)
        CountSegmentation(InputS,index+L,End,$\theta$)
    else
        decompose all reminders into characters
```

The process is an optimization problem to find segmentation boundaries which try to jointly maximize the length and frequency criteria. For a given input string with a length L, there can be $\frac{L\times(L+1)}{2}$ character n-grams, e.g. for the sequence S=*abcd* with $L = 4$, the list of character n-grams is equal to {a, b, c, d, ab, bc, cd, abc, bcd, abcd}. Among character n-grams some of them are frequent based on statistics of the training corpus. At each step of the segmentation process, we select an n-gram which is frequent and has the longest length compared to other frequent alternatives.

In the character-level decomposition, the idea is to segment strings into their basic subunits which are characters (the alphabet set of the corpus). Then by using of different neural architectures, an attempt is made to reveal the relation between related characters (Kim et al., 2016). This is a bottom-up approach, going from a character-level representation to a morpheme- and word-level representation. The intuition behind our model is partly the same with some distinctive differences. We believe that the set of basic elements of each corpus is not only limited to its characters. If a set of consecutive characters occurs frequently, then it could be considered as a basic element. Accordingly, we introduce new atomic blocks (instead of just characters) which include one or more characters, and all words can be transformed/decomposed through these blocks.

To clarify the process we use a dummy example. For a given sequence s=*'aabcxy'* with two frequent substrings *'ab'* and *'xy'*, the word-level segmentation keeps s as it is and the character-level model blindly maps s to *'a.a.b.c.x.y'* regardless of any other criterion. In contrast, according to the count-based segmentation model, if there are frequent substrings in s, they could be substantial units for other strings and should be treated as atomic units, similar to characters, in which case the final segmentation should be *'a.ab.c.xy'*. Clearly, in *'ab'* all of *'a'*, *'b'* and *'ab'* substrings are frequent but as *'ab'* has the longest length, it is selected from that part of s.

We also have a real-world example for this procedure. Figure 4.2 shows the count-based segmentation process for a complex Farsi word which was taken from our training corpus. The input word is *'prdrãmdtrynhã'* meaning *'the people with the highest salary'*. Based on statistics of the Farsi training corpus (see Section 4.5), the longest and most frequent substring is *'ãmd'* which is a 3-gram constituent. This means that there is no frequent n-gram with $n > 3$ and *'ãmd'* has the highest frequency among all other 3-grams. *'ãmd'* is separated and the segmentation model is applied to its preceding (*L-string*) and following substrings (*R-string*). Each substring is considered as a new input for the model which has a dedicated *main*, *L-string* and *R-string*. The model is recursively applied until all frequent substrings –*'ãmd'*, *'dr'*, *'tr'* and *'hã'*– are separated. There are still two substrings remaining, namely *'pr'* and *'yn'*. These two substrings are not considered as frequent in our setting, so they are decomposed into characters. The final decomposition result by the proposed model is: *'prdrãmdtrynhã'* ⇒ *'p.r.dr.ãmd.tr.y.n.hã'*.

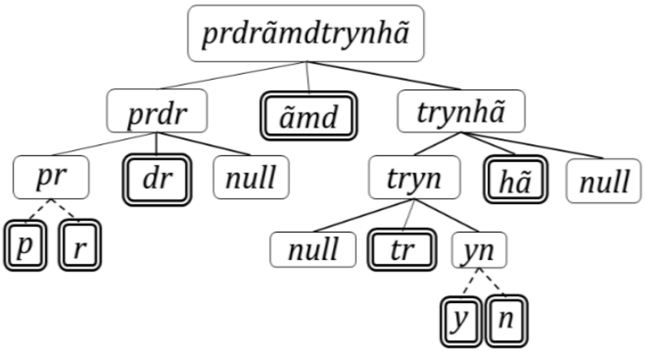


Figure 4.2: The process of segmenting *'prdrãmdtrynhã'*. *main* for each node is its offspring in the middle. The nodes before and after *main* are *L-string* and *R-string*, respectively. Dotted and solid lines indicate the character-level and morpheme-level decompositions. Final states are illustrated with double lines.

The segmentation model benefits from the advantages of the word-level, morpheme-level and character-level models. If the input string's surface-form is frequent, the model does not decompose it and uses the original form. If it is considered as a rare sequence, it is decomposed into characters, and if the string is neither frequent nor rare it is segmented into sets of characters. There might be one or more characters in each set which means that the model uses a hybrid segmentation (as in the aforementioned Farsi example).

In Model A and all other models the frequency of a subunit is computed using the training corpus (not the lexicon/vocabulary), in which we consider all occurrences of the subunit. We do not cross word boundaries for collecting frequency information, i.e. words are separated from each other (space-to-space), segmented into all possible character *n*-grams and the number of occurrences is counted for each *n*-gram.

4.3.2 Model B: Adaptive Thresholding

Model B is a simple extension to Model A. In the previous model, at each step we select a subunit which is the longest and frequent, i.e. the subunit has to occur at least θ times in the training corpus. This frequency criterion treats all subunits (character n-grams) equally, which means it expects, for example, a 2-gram to be as frequent as a 4-gram. We know this assumption is not correct and fair, and may lead to a wrong segmentation, especially for high(er)-level character n-grams (longer blocks). To address this problem we propose an adaptive thresholding mechanism which tries to make a connection between the frequency threshold and the length of the subunit. To this end, instead of the longest frequent subunit, we select a subunit which is the longest and occurs Freq_d^n times, where Freq_d^n is defined as in (4.3):

$$Freq_d^n = \frac{Freq}{l(n)} \tag{4.3}$$

In (4.3) *Freq* is the user-defined (external parameter) frequency and $l(n)$ is the length of the subunit. The intuition behind our model is that, if for example a unigram should occur more than $Freq$ times to be considered as frequent, a bigram has to occur (approximately) two times fewer to be frequent as the probability of appearing a bigram is almost half of the probability of appearing a unigram. In other words, a bigram with the frequency *Freq* can be as important as a unigram with the frequency $2 \times Freq$. By proposing this technique we try to define different thresholds for different character n-grams, and inform the segmentation model as to how important the n-gram category (to which the subunit belongs) is. Similar to (4.3) we can define another criterion as in (4.4):

$$Freq_d^n = \sqrt[l(n)]{Freq} \tag{4.4}$$

The intuition behind this criterion is the same as the previous one, but it uses a different mechanism. In our experiments, these two variations of Model B are referred to as Model B$_{div}$ and Model B$_{root}$, respectively.

4.3.3 Model C: Mutual Information-based Selection

In Model C, instead of taking the length and frequency constraints into account, we rely on a mutual-information-based score. The model processes the input string character by character. It estimates how strong the relation between a pair of consecutive characters is, and computes a score based on mutual information. There is also a user-defined threshold for the model. If for a given pair of characters the score is higher than the threshold the model keeps two characters together, otherwise those characters should be separated as they are weakly related to each other. Such mutual information-based models are very common for Chinese word segmentation (Xue et al., 2003; Zeng et al., 2011) and we adapted the technique to our purposes.

In this model we try to compute $BP(L|R)$ at each step, which shows how strongly the character set L is related to R. The model defines a break point between L and R if the relation is not strong. To compute $BP(L|R)$ we follow the model proposed in Tang et al. (2010), in which a window of two characters is considered for both L and R. In our model we can define three types of character groups. A group of characters appear at the beginning of strings (words) for which $BP(L|R)$ is computed as in (4.5):

$$BP(L|R) = BP(c_1|c_2c_3) = \min\Big(MI(c_1, c_2), MI(c_1, c_2c_3)\Big) \tag{4.5}$$

where c_1 is the first character of the string and would be separated from the string if the connection between c_1 and c_2c_3 is weak.

A group of characters appearing at the end of input strings for which $BP(L|R)$ is computed as in (4.6):

$$BP(L|R) = BP(c_{n-2}c_{n-1}|c_n) = \min\Big(MI(c_{n-1}, c_n), MI(c_{n-2}c_{n-1}, c_n)\Big) \tag{4.6}$$

where c_n is the last character and the segmentation model puts a break point before n_c if $BP(c_{n-2}c_{n-1}|c_n)$ is lower than the threshold.

For those characters which neither appear at the beginning nor the end of strings (middle characters), $BP(L|R)$ is computed as in (4.7):

$$\begin{aligned} BP(L|R) = BP(c_{i-2}c_{i-1}|c_ic_{i+1}) = \min\Big(&MI(c_{i-1}, c_i), \\ &MI(c_{i-2}c_{i-1}, c_i), \\ &MI(c_{i-1}, c_ic_{i+1}) \\ &MI(c_{i-2}c_{i-1}, c_ic_{i+1})\Big) \end{aligned} \tag{4.7}$$

If the connection between $c_{i-2}c_{i-1}$ and c_ic_{i+1} is weak, the model puts a break point between c_{i-1} and c_i. MI is a score defined based on mutual information and is computed as in (4.8):

$$MI(x, y) = \log \frac{\frac{frq(xy)}{N_g}}{\frac{frq(x)}{N_g}\frac{frq(y)}{N_g}} \tag{4.8}$$

where x and y can be any random character n-gram. $frq(x)$ is a function which counts how many times x appears in the training corpus. N_g shows the number of all character n-grams which has an equal length to the parameter of frq, e.g. in $frq(c_ic_{i+1})$, N_g is the total number of bigrams or for $frq(c_{i-2}c_{i-1}c_ic_{i+1})$, N_g shows the number of all 4-grams.

4.3.4 Model D: Dynamic Programming-based Segmentation

Models A to C introduce morpheme segmentation models with tunable levels of granularity. They help us feed neural models (NLMs or NMT engines) with multi-granular subword units, but they have a serious problem, namely their dependency on the external parameter (θ or m). Other similar models such as *Byte-pair* or *Morfessor* also suffer from the same shortcoming. Their performance is highly influenced by the external parameter and they can only help us provide our desirable result when the external parameter is set to an optimal value. Finding such a value is usually performed in an empirical manner which can be quite costly (or even impossible) for (very) deep neural models. Therefore, apart from these parameter-dependent techniques, we need to have a model which has no external parameter. Model D employs principles of *dynamic programming* and provides such a solution.

The morpheme segmentation problem is an optimization problem, where a sequence can be viewed as a container of character n-grams and the task of segmentation is to find the best boundaries between such n-grams. There could be several segmentation patterns for a single sequence, where the best segmentation is defined based on the evaluation metric we consider for the task. For example, to provide a linguistically correct segmentation we expect the model to separate stems from syntactic affixes (valid affixes which exist in the language), or in *Byte-pair* we try to set boundaries in a way which generates up to S unique symbols for the entire corpus (S is a predefine vocabulary size). Figure 4.3 illustrates an example of a Turkish sequence (word) with different segmentation boundaries to elaborate this issue.

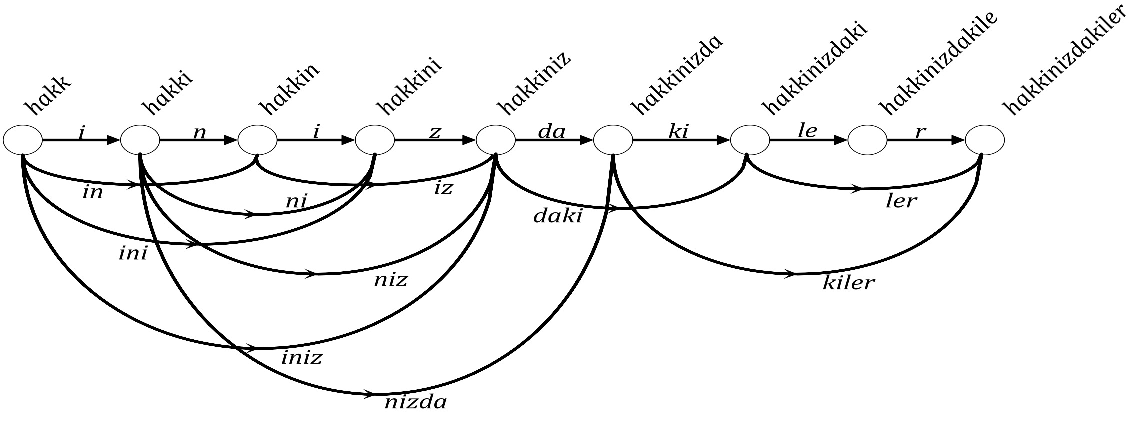


Figure 4.3: Different segmentation boundaries for the Turkish word *'hakkinizdakiler'* meaning *'things about you'*. Different paths yield different segmentations for this word.

As Figure 4.3 shows, we can have several segmentation patterns for the Turkish word *'hakkinizdakiler'* meaning *'things about you'* such as *'hakk.in.i.z.da.ki.ler'*, *'hakk.i.niz.da.ki.ler'*, *'hakk.i.nizda.ki.ler'* etc., as *'i'*, *'in'*, *'ini'*, *'niz'*, *'nizda'*, *'da'*, *'daki'*, *'ki'*, *'kiler'*, *'le'*, and *'ler'* are all valid suffixes in Turkish (*hakk* is the stem). Different segmentation models provide different patterns based on different criteria. If the model prioritizes linguistic aspects, probably the best segmentation would be *‘hakk.in.iz.daki.ler’*, but if it considers the frequency feature together with linguistic constraints the final segmentation would be *‘hakk.i.n.i.z.da.ki.le.r’*. Therefore, the problem is an optimization problem and different results can be obtained based on different constraints.

As we do not have access to a precise morphological analyzer for all languages, we try to benefit from statistical techniques to find a suboptimal segmentation. It should also be noted that nothing forces us to find linguistically correct segmentations. Existing (NLP) models are flexible/powerful enough to work with different segmentation schemes and the only prerequisite is that they work with a limited set of *basic* units. With this assumption, we try to discover such a set of *basic* units. In our model we consider two constraints, namely length and frequency. We wish to find (disjunctive) boundaries between sets of characters which maximize both constraints at the same time. If we only consider the length constraint then all words (or sequences in general) would stay in their original form and the model would give the surface form as its output. Similarly, if we only take the frequency constraint into account we would not obtain the best result as the model will decompose words purely into characters. We try to make a balance between these two paradigms and obtain a better segmentation scheme. We mentioned that it could be challenging to assign an optimal value to these parameters, so we propose a model to set them automatically.

If a unit frequently occurs in a corpus, there is a chance for the unit to be a *basic* element of the language. However, we should define a prescriptive criterion for this situation. We know that all frequent units are not *basic* or they could be *basic* (such as characters) but not useful for our purposes. Since a frequency threshold labels a unit as frequent or infrequent, finding an appropriate threshold is a critical issue. A mechanism should be defined to recognize the threshold value but it can make the segmentation model fragile, as its performance would totally rely on a single parameter which is very context-dependent. A wrong threshold could lead to wrong segmentations. Another important issue about the threshold is that when it is set to a particular value such as θ all units with frequencies higher than θ are considered as frequent and, all other units with lower frequencies even with very close values to θ (such as *θ-1*) are neglected. Accordingly, even in the presence of an optimal threshold it is a very strict constraint to treat units based on a single value.

As far as problems caused by frequency-based models are concerned, it is not an appropriate idea to set a global threshold value and we can decide to select (or skip) a unit based on its *context* and *adjacent* units. Furthermore, it seems that another complementary constraint should be included too, namely the length of units. Similar to the frequency threshold we cannot have a global value for this criterion. We do not know how many characters are enough to make an atomic block and we cannot set a predefined value. Any set of characters with any random length could be a *basic* block. So, apart from finding a dynamic and context-dependent frequency value for each subunit, the segmentation algorithm should also be able to find dynamic boundaries.

According to the discussion so far, it is not possible to separate subunits based on predefined global length and frequency constraints and the model should set dynamic values at each step. We propose a model in this regard. More formally, given two m-tuples of positive numbers $< v_1, v_2, ..., v_m >$ and $< l_1, l_2, ..., l_m >$, and $L > 0$, we wish to determine the subset $A \subseteq \{1, 2, ..., m\}$ that maximizes (4.9a), subject to (4.9b):

$$\sum_{a \in A} v_a \tag{4.9a}$$

$$\sum_{a \in A} l_a = L \tag{4.9b}$$

An input sequence (word) with the length L can include up to M sub n-grams where $M = \frac{L \times (L+1)}{2}$ and $1 \leqslant n \leqslant L$. The a subscript in Equation (4.9) indicates the index for each of these sub n-grams. The final goal is to select a subset of such n-grams (finding A) which satisfies all constraints. l_a indicates the length of the a-th n-gram and v_a is its value in the training corpus. A simple example can hopefully clarify the problem. The set of all possible sub n-grams extracted from the word *'the'* is $\{t_1,\ h_2,\ e_3,\ th_4,\ he_5,\ the_6\}$ ($L = 3$ so there are $\frac{3\times4}{2}$ sub n-grams). Our model tries to find a subset of these n-grams which maximizes the optimization constraints so that their combination gives us the original word *'the'*. Patterns such as *'t.he'* ($A = \{1, 4\}$) or *'the'* ($A = \{6\}$) could be possible alternatives as results of the segmentation process, but a pattern such as *'t.th.e'* ($A = \{1, 4, 3\}$) is wrong, as this violates the length constraint and does not generate the original surface form.

In order to solve the problem formulated by equation (4.9), we need to define l_a and v_a. It is clear that what the length value l_a is for each n-gram. For v_a, a simple estimation could be the frequency of each n-gram, as because it shows the importance (value) of the n-gram. However, with this simple estimation characters would have much higher values than others, which means the final result would be the same as (or very similar to) the character-level segmentation. This is not our desirable result so we approximate the value of each character n-gram v_a with (4.10):

$$imp(n) \times freq(n_a) \tag{4.10}$$

where $freq(n_a)$ shows the frequency of the a-th n-gram in the entire training corpus and $imp(n)$ indicates the impact/importance of that n-gram category (to which n_a belongs), i.e. $imp(n)$ tries to make a balance between length and frequency. Clearly the frequency of a single character (unigram) is much higher than other n-grams, but we know that there is only a limited number of unigrams in the corpus. There could be up to 500 unique unigrams in a corpus but each of them could occur millions of times. Accordingly, unigrams are important in terms of frequency but the category to which they belong is not very popular/important in the corpus. Similarly the number of bigrams is considerably fewer than trigrams but the frequency of each bi-gram is much higher than trigrams. There should be a mechanism that shows how frequently a character n-gram occurs and how important the n-gram category is among others. To this end we define $imp(n)$ which shows the portion of a specific

n-gram category among all other n-grams which might be estimated as in (4.11):

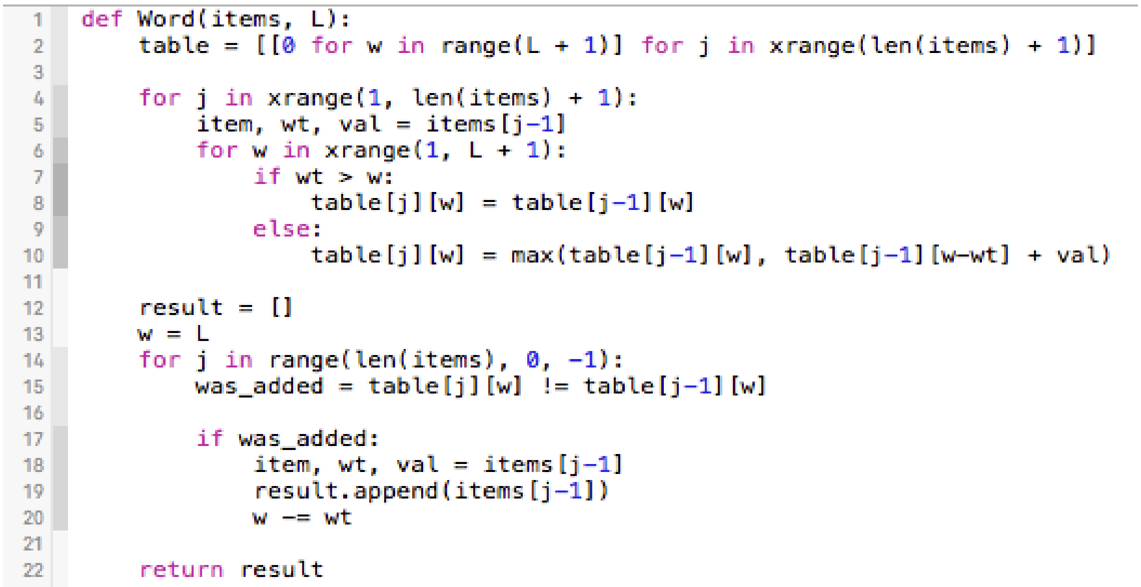
$$imp(n) = \frac{count(n)}{\sum_{n'=1}^{N} count(n')} \tag{4.11}$$

where *count(n)* enumerates how many n-grams exist in the corpus and N indicates the length of the longest n-gram possible in the corpus.

Our segmentation model is defined based on these criteria. In order to implement our model we propose a dynamic programming-based solution. To select the best subset of all items (character n-grams) for the input sequence, at each step we iteratively add a new item to an existing subset which is the optimal set up to that step. The new item is selected in a way where the combination of a new item and the existing set is another *optimal* set with one more member. We can compute the value of the obtained segmentation at the i-th step (the total value of the items selected up to the i-th step) with $V(i, L)$ as in (4.12):

$$V(i, L) = \begin{cases} 0 & \text{if } i = 1 \\ V(i-1, L) & \text{if } l_i > L \\ \max\Big(V(i-1, L), v_i + V(i-1, L-l_i)\Big) & \text{otherwise} \end{cases} \tag{4.12}$$

The model starts with an empty set and by the model explained in (4.12) adds a single item to the set. This procedure continues until the optimal set of subunits (A) is reached. We select items which satisfy our constraints and make a segmentation pattern for a given word. Figure 4.4 illustrates the python code for Equation (4.12). `Word()` is a function which takes two inputs and segments the word. The first input is a set of tuples which provides all possible character n-grams of the word (to be segmented) and their values, and the second one is the length of the word. For example, when we segment the word '*the*', the set of all character n-grams and their values would be similar to *items*=$\{$('*t*',v_t),('*h*',v_h),('*e*',v_e),('*th*',v_{th}),('*he*',v_{he}),('*the*',v_{the})$\}$ and the length L is 3.



```python
def Word(items, L):
    table = [[0 for w in range(L + 1)] for j in xrange(len(items) + 1)]

    for j in xrange(1, len(items) + 1):
        item, wt, val = items[j-1]
        for w in xrange(1, L + 1):
            if wt > w:
                table[j][w] = table[j-1][w]
            else:
                table[j][w] = max(table[j-1][w], table[j-1][w-wt] + val)

    result = []
    w = L
    for j in range(len(items), 0, -1):
        was_added = table[j][w] != table[j-1][w]

        if was_added:
            item, wt, val = items[j-1]
            result.append(items[j-1])
            w -= wt

    return result
```

Figure 4.4: Morpheme segmentation with Model D.

4.3.5 Segmentation Quality

There are user-defined external parameters –the frequency threshold or θ in Model A and Model B, and the BP threshold or m in Model C– which define the granularity level of segmentations and directly affect the final output. Table 4.2 illustrates the impact of these parameters.

As the table shows, the external parameters define segmentation boundaries. In the given example the input is a long sequence of characters, including several words joined to one another, and the model is expected to find the correct boundaries between words. However, in our experiments we never have such an input as the input is always a word. We use this (artificial) example to show that the granularity level of our models could vary from a sentence to a character. It should also be noted that if the results provided in the table are not precise enough, the reason is because *i*) our models are designed to segment words (in order to extract basic subunits) not sentences, and also *ii*) the given input is quite complex as it is a long sequence with meaningful subunits. The collocation of characters from different words can mislead the segmentation model.

Our segmentation models are proposed in order to find the optimal *basic* set that maximizes the performance of our neural language model, but it is also inter-

Model	**Parameter**	**Output**
Model A	$\theta = 10,000$	th.is.is.as.i.m.p.le.pr.e.pr.o.ce.ss.ing.st.e.p
	$\theta = 5,000$	th.is.is.as.im.pl.ep.re.pro.c.ess.ing.st.ep
	$\theta = 1,000$	this.is.as.imp.le.pre.pro.ces.sing.ste.p
	$\theta = 500$	this.is.asi.mple.pre.pro.cess.ings.te.p
	$\theta = 100$	this.isa.simpl.epre.process.ings.tep
Model B$_{div}$	$\theta = 10,000$	thi.si.sa.si.mp.le.pre.pro.c.ess.ing.ste.p
	$\theta = 5,000$	this.is.as.im.ple.pre.pro.ces.sing.ste.p
	$\theta = 1,000$	this.is.asi.mple.pre.process.ings.te.p
	$\theta = 500$	this.isa.simpl.epre.process.ings.tep
	$\theta = 100$	this.isa.simple.pre.processing.step
Model C	$m = -1$	this.is.a.s.i.mple.p.rep.r.ocessings.t.ep
	$m = -2$	this.is.a.s.i.mple.p.reprocessings.tep
	$m = -3$	this.is.as.i.mple.p.reprocessings.tep
	$m = -10$	this.is.as.i.mple.p.reprocessingstep
	$m = -20$	thisisasimplepreprocessingstep

Table 4.2: Different segmentations with different levels of granularity for the input sequence *'thisisasimplepreprocessingstep'*. We emphasize that this is a quite complex example which is never faced in the training phase. We used this example to show that the granularity level in our models can vary from the sentence level (to separate words) to the character level (to extract characters). **Model B**$_{root}$ generates the same results as **Model B**$_{div}$.

esting to see how precisely they can perform when they are studied as independent modules. However, we emphasize that our goal is not to find linguistically correct morpheme segmentations, and the main goal targeted here is being able to control the level of granularity of intra-word segmentations, which is not provided by existing morpheme- and character-level models. In order to evaluate our models we use the dataset provided by `Morpho Challenge 2010`,[3] a shared task on morpheme segmentation. We use the English and Turkish datasets in our evaluation. Our models are trained on the training set to learn the statistics of words and character n-grams. Then we fine-tune them using the development set to find the best values of the external parameters. Finally, we apply them to the test set to see how they segment unseen words. For both English and Turkish we combined the original

[3] `http://morpho.aalto.fi/events/morphochallenge2010/datasets.shtml`.

training and development sets which gives us more than 1500 manually annotated samples. We select the first 900 instances for training, the next 300 instances as the development set and the remaining 300 instances as the test set.[4] The results for this experiment are reported in Table 4.3.

Language	Model	Correct	Incorrect
English	Morfessor	**47%**	53%
	Model A	26%	74%
	Model B	33%	67%
	Model C	39%	61%
Turkish	Morfessor	29%	71%
	Model A	20%	80%
	Model B	27%	73%
	Model C	**34%**	66%

Table 4.3: Results for the morpheme segmentation task. **Model B**$_{div}$ and **Model B**$_{root}$ performed equally in this task so we showed both of them with Model B.

As the table shows, despite not being proposed for the morpheme segmentation task, our models are able to produce comparable results to *Morfessor* which is a powerful and well-known model in the field. As all models including *Morfessor* (the version we use) are unsupervised models and the annotated dataset provided by the shared task is quite small, we use additional corpora to enrich our training sets. For the English set we used PTB and for the Turkish dataset we used the Turkish part of the corpus of news articles in the Balkan languages (Tiedemann, 2009).[5]

Apart from Models A to C, we also studied Model D and *Byte-pair*. These models are not supposed to extract syntactically correct morphemes. They are count-based models which try to find the optimal set of *basic* units with statistical rules, so it is not a meaningful comparison to evaluate these models in the previous morpheme segmentation scenario. Moreover, there is no intrinsic evaluation for these models as they are only evaluated extrinsically in neural language modeling or translation tasks. However, we can provide some examples from these segmentation models and

[4] The test set is not available through the link of the shared task and we had to combine and separate the dataset in this way to produce a test set for our experiment.

[5] `http://opus.lingfil.uu.se/SETIMES2.php`

qualitatively evaluate their performance.

Figure 4.5 illustrates examples of these models when Turkish sequences are segmented. Turkish is a highly agglutinative language so we can easily show segmentation boundaries for Turkish words.

Scheme	**Segmented Sequence**
Turkish Seq.	[görünüşe]$_{1}$ [göre]$_{2}$ [söylemeyeceğinden]$_{3}$ [çok]$_{4}$ [eminsin]$_{5}$
bpe-5K	[görünüş•e]$_{1}$ [göre]$_{2}$ [söylemey•eceğ•inden]$_{3}$ [çok]$_{4}$ [emin•sin]$_{5}$
bpe-30K	[görünüşe]$_{1}$ [göre]$_{2}$ [söylemey•eceğinden]$_{3}$ [çok]$_{4}$ [eminsin]$_{5}$
bpe-50K	[görünüşe]$_{2}$ [göre]$_{2}$ [söylemey•eceğinden]$_{3}$ [çokeminsin]$_{4,5}$
Our model	[görü•nüş•e]$_{1}$ [gör•e]$_{2}$ [söyle•mey•eceği•nden]$_{3}$ [çok]$_{4}$ [e•m•in•sin]$_{5}$
Translation	[seems like]$_{1,2}$ [you've made sure]$_{4,5}$ [to not tell]$_{3}$
Turkish Seq.	[fırtınayi]$_{1}$ [buraya]$_{2}$ [getirecek]$_{3}$
bpe-5K	[fırt•ın•ayı]$_{1}$ [buraya]$_{2}$ [getir•ecek]$_{3}$
bpe-30K	[fırtın•ayı]$_{1}$ [buraya]$_{2}$ [getirecek]$_{3}$
bpe-50K	[fırtın•ayı]$_{1}$ [buraya]$_{2}$ [getirecek]$_{3}$
Our model	[fırt•ın•ayı]$_{1}$ [bura•y•a]$_{2}$ [get•ir•ecek]$_{3}$
Translation	[it's gonna bring]$_{3}$ [that storm]$_{1}$ [here]$_{2}$

Figure 4.5: Different segmentations provided by *Byte-pair* and Model D. We use superscripts to make a connection among words, their translation and segmented forms. • shows the segmentation boundary. *bpe*-**x***K* means the *Byte-pair* model trained to extract **x** thousands different symbols. *Turkish Seq.* is the given Turkish sentence and *Translation* is the English counterpart of the Turkish sentence.

As the figure shows our model provides a considerably better segmentation. In the first example *e* is separated from the first and second words, which shows two important properties of our model: *i*) first, the model provides a hybrid character-level and morpheme-level segmentation; *ii*) second, it tries to learn meaningful relations among subunits through the training phase and separate based on the context and adjacent subunits. There are several *e* characters in the sequence but the model separates only those of the first and second words. The reason for this is because those specific characters play the role of a suffix in those words and they are not simple characters. Although the model does not benefit from linguistic knowledge, through the dynamic segmentation process it learns the constructive role of subunits. Selecting the *e* characters from the first and second words and not separating those of the other words could confirm this issue. Similar properties can be seen for other words, e.g. the segmented form of the fifth word in the first example is very close to segmentations generated by models which rely on linguistic databases.

The segmentation scheme provided by *bpe*-$5K$ is closer to ours but such a segmentation is generated when all words of our training corpus are mapped to only 5K unique symbols. Such a drastic simplification never happens in practice, as in neural models we usually map the input vocabulary to (about) 30K (or 35, 40, 50) *Byte-pair* tokens. This means that to achieve an acceptable segmentation (similar to ours) the *Byte-pair* model should be run with a very specific setting (which is then not fair to compare with other models). For normal settings reported in the table such as 30K or 50K, the *Byte-pair* model does not perform well. For these cases it does not change surface forms, which means *Byte-pair* manipulates only a limited number of words and does not efficiently change the corpus. In some cases it has even negative affects over words, e.g. in the first example for *bpe*-$50K$ the fourth and fifth words are combined together, which not only does not solve the problem but also makes the corpus harder to translate (it destroyed the original corpus).

4.4 Network Architecture

We segment input words to convert them into sequences of basic units, then they are sent to our NLM. The proposed network architecture is slightly different from CLM in the input layer, but other basic parts are almost the same. The network includes 5 main modules. The input sequence $S = w_1, ..., w_m$ is processed word by word. Each word is decomposed into different character blocks. For a given word w_i the segmentation result is $B_i = \{b_i^1, ..., b_i^l\}$ where b_i^j indicates the j-th block of w_i which can be a single character or a set of consecutive characters. From a lookup table, embeddings for blocks ($b_i^j; 1 \leqslant j \leqslant l$) are retrieved. The lookup table is basically a weight matrix which contains embeddings. It is part of the neural architecture whose values are updated during training. Clearly in our case the lookup table includes block embeddings (which is different from that of CLM). Embeddings retrieved from the table are combined together which yields a matrix-form data structure. For w_i, the matrix-form data structure is $C_i \in \mathbb{R}^{e \times l}$, where the j-th column $c_i^j \in \mathbb{R}^e$ indicates the embedding of b_i^j and e is the morpheme embedding size. C_i is padded with 'Null' columns to handle the variable length of different words.

C_i is a numerical representation for w_i which preserves different types of information including n-gram information. To extract such information, several convolution functions are applied with different filters. This model was explored for the first time for language modeling by Kim et al. (2016). In our convolution module we follow the same model. For each C_i the convolution module provides a vector f_{C_i}, as in (4.13):

$$f_{C_i}[k] = \sigma((C_i[:][k : k + w - 1] \circledast F) + a) \tag{4.13}$$

where $F \in \mathbb{R}^{e \times w}$ is a filter of width w_F, a is a bias value, σ is a non-linear function, $C_i[:][k : k + w - 1]$ indicates the k-to-$(k + w - 1)$-th columns of C_i, and $\circledast$ is the 2D convolution operation. After applying the convolution function the maximum value of f_{C_i} is selected, as in (4.14):

$$y_i = \max_k f_{C_i}[k] \tag{4.14}$$

The idea behind these computations is to capture the most important and strongest (the maximum value) feature for a given filter. Each filter provides specific n-gram information where the size of n-gram corresponds to the filter width. In CLM, different filters are scrolled over characters to capture different types of information and connect related characters to each other. In the proposed segmentation model, since we have a hybrid segmentation scheme, we already connected related characters to each other (they appear as sets of consecutive characters in blocks). Frequent character sequences are not decomposed and stay together. This means that instead of finding relations through convolutional computations, we explicitly provide this type of information via our segmentations. The convolutional computation can be interpreted as a complementary process in our case.

As previously mentioned, different filters with different sizes are applied, so with

m filters $F_1, ..., F_m$ the convolution module's output is $y^i = [y_1^i, ..., y_m^i]$ which is a new representation for the word w_i. Word representations (vectors) are passed to a *highway* layer (Srivastava et al., 2015). In the *highway* network one additional affine transformation is applied to obtain a better set of features. Equation (4.15) shows the difference between the simple (4.15a) and *highway* (4.15b) connections:

$$y = g(Wx + b) \tag{4.15a}$$

$$y = t \odot g(W_H x + b_H) + (1 - t) \odot x \tag{4.15b}$$

where $g()$ is a nonlinearity, $t = \sigma(W_t x + b_t)$ is called the *transform* gate, and $(1 - t)$ is called the *carry* gate. The depth of neural networks has a direct impact on their performance but as the depth grows training becomes more difficult. *Highway* networks are effective models which provide deep but easily-trainable networks.

The fourth and main module of the NLM is an LSTM module which is fed by the output of the *highway* module at each time step. LSTM units are the best alternatives for sequence modeling as they are able to model long-distance dependencies and mitigate the vanishing gradient problem. In our setting, an LSTM unit takes y_t (LSTM input), h_{t-1} (previous hidden state) and m_{t-1} (previous memory vector) as its input and produces h_t and m_t via the calculations in (4.16):

$$\begin{aligned}
i_t &= \sigma(W_i y_t + U_i h_{t-1} + b_i) \\
f_t &= \sigma(W_f y_t + U_f h_{t-1} + b_f) \\
o_t &= \sigma(W_o y_t + U_o h_{t-1} + b_o) \\
g_t &= \tanh(W_g y_t + U_g h_{t-1} + b_g) \\
m_t &= f_t \odot m_{t-1} + i_t \odot g_t \\
h_t &= o_t \odot \tanh(m_t)
\end{aligned} \tag{4.16}$$

where i_t, f_t and o_t indicate the input, forget and output gates, respectively. $\sigma(.)$ is an element-wise sigmoid function and W_ρ, U_ρ and b_ρ, $\rho \in \{i, f, o, g\}$, are all network parameters. For more information about the application of LSTMs in sequence modeling, see Sutskever et al. (2014), Zaremba et al. (2014) and Kim et al. (2016). At the end, we have a selection module which is implemented by a *softmax* function. The output generated by the LSTM module is a representation of the input sequence which is considered as *history* (see Equation 4.1). The goal in the prediction module is to predict the most likely word from a target vocabulary with respect to *history*.

We follow the same training procedure as CLM to train our network (training algorithm, parameter initialization etc). The learning criterion for the network is the negative log-likelihood (NLL) of the input sequence S, as in 4.17:

$$NLL = -\sum_{t=1}^{m} \log P(w_t|w_1^{t-1}) \tag{4.17}$$

where the conditional word probability is a value generated by a *softmax* module. The whole architecture of our NLM is illustrated in Figure 4.6.

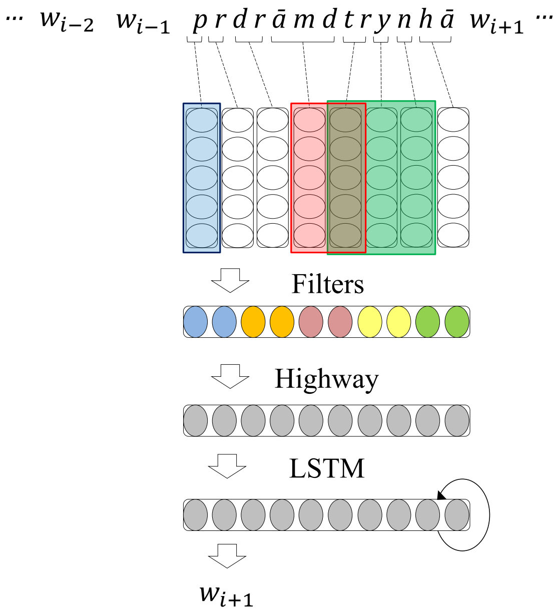

··· w_{i-2} w_{i-1} p r d r ā m d t r y n h ā w_{i+1} ···
Filters
Highway
LSTM
w_{i+1}

Figure 4.6: The figure depicts the third time step when processing the input string s=[... w_{i-2} w_{i-1} w_i w_{i+1} ...]. The complex Farsi word is decomposed into blocks. Different filters (shown by different colors) are applied over blocks to extract different (n-gram) features. The vector generated by the filters is processed by a highway and an LSTM module to make the prediction, which is the next word w_{i+1}. At each time step, the filters are only applied to the current word.

In our setting the batch size is 25 (25 sentences in each batch), the sequence length is 30 and we train the network for 22 epochs. In the input module we set the morpheme-embedding size e to 30 and word embedding-size to 200. As our filters, we used 6 sets of filters with width $[1, 2, 3, 4, 5, 6]$ of size $[25, 50, 75, 100, 125, 150]$. All these values are determined based on our empirical studies and the information provided in Kim et al. (2016). We use $ReLU$ to apply non-linearity within the *highway* module which is a one-layer network. For regularization we placed two *dropout* layers (Hinton et al., 2012) before and after the LSTM module with $p = 0.4$ for each. The LSTM module includes two hidden layers of size 300. We refer to this configuration as the *default* configuration in Section 4.5.

4.5 Experimental Results

We compare our models to other four different models of MLBL, CharCLM, WordCLM, and MorphCLM. MLBL is the model proposed by Botha and Blunsom (2014). CharCLM is the character-level neural language model (CLM) with the *default* configuration. WordCLM and MorphCLM are variations of CLM where the first one takes surface-form embeddings as the input without any prepossessing and segmentation, and the second one linearly combines the word's surface-form embedding with morpheme embeddings. Morphemes for MorphCLM are provided by *Morfessor*.

We evaluate the model on Czech (Cz), English (En), Farsi (Fa), German (De) and Russian (Ru). Since our model is an extension to CLM, in order to make our work comparable, we use the same datasets (test, validation and training sets) as CLM and MLBL. We add Farsi as a new dataset to our experiments. To the best of our knowledge, this is the first time that an NLM has been evaluated on this language. We use the Farsi side of the `TEP++` corpus (Passban et al., 2015) which is a collection of ∼600K parallel English–Farsi sentences, to train the Farsi model. Table 4.4 provides some statistics about our training corpora, and the optimal value for the external parameter. Model D has no external parameter and learns to extract subunits automatically.

Lang.	$\mathcal{T}$	$\mathcal{V}$	$\mathcal{C}$	$\mathcal{M}_A$	θ_A	$\mathcal{M}_{B_{div}}$	$\theta_{B_{div}}$	$\mathcal{M}_{B_{root}}$	$\theta_{B_{root}}$	$\mathcal{M}_C$	m_C	$\mathcal{M}_D$
Czech (Cz)	1m	46k	101	3,481	500	1,528	5k	1,284	10	670	1	1,636
German (De)	1m	37k	74	2,522	700	1,701	5k	1,143	10	914	1	2,949
English (En)	1m	10k	51	1,655	700	1,569	3k	1,066	10	582	1	1,070
Farsi (Fa)	1m	37k	55	1,460	500	889	3k	945	10	543	1.5	1,431
Russian (Ru)	1m	63k	62	1,079	2k	756	10k	1,505	10	829	1	2,987

Table 4.4: Statistics of datasets. $\mathcal{T}$, $\mathcal{V}$, $\mathcal{C}$ and $\mathcal{M}$ indicate the number of tokens, word vocabulary size, character vocabulary size, and the number of different blocks for each language, respectively. θ is the frequency threshold and m is the break-point threshold. The subscript indicates to which model the parameter belongs.

As is standard, we use perplexity (PPL) to measure the quality of NLMs. The perplexity of a given sequence S with n words is computed by $\exp(\frac{NLL}{n})$ (NLL was defined in Section 4.4). According to our experiments, the perplexity of the proposed model (Model C as the best model) on PTB is 91 whereas CharCLM obtained 103. We emphasize that these numbers are based on the *default* configuration. Our model's performance is comparable (slightly better) to that of CharCLM on PTB, but as English is not usually considered to be an MRL, it is not the main interest of this research. We perform other experiments on some MRLs, the results of which are reported in Table 4.5.

System	**Language**			
	Czech (Cz)	German (De)	Farsi (Fa)	Russian (Ru)
WordCLM	503	305	-	352
WordCLM$_{bp}$	341	239	113	230
WordCLM$_{dp}$	**330**	231	107	**215**
MLBL	465	296	-	304
MorphCLM	414	278	-	290
MorphCLM$_{bp}$	500	291	175	330
MorphCLM$_{dp}$	460	264	175	330
CharCLM	385	239	128	259
CLM$_A$	365	230	110	243
CLM$_{B_{div}}$	365	230	**105**	220
CLM$_{B_{root}}$	362	230	110	230
CLM$_C$	340	**223**	**105**	233

Table 4.5: Perplexity scores for different MRLs (lower is better).

In Table 4.5, **WordCLM** is the CLM of Kim et al. (2016) where each word is represented by the surface-form embedding, which is directly sent to the *highway* module (no convolutional process). This model is a surface-form-based model which works with thousands of tokens (e.g. 63K for Russian, as in Table 4.4). Clearly, this large number of tokens makes the modeling process challenging. **WordCLM**$_{bp}$ and **WordCLM**$_{dp}$ have the same architecture as **WordCLM** where instead of words they work with *Byte-pair* (*bp*) and Model D (*dp*) tokens, respectively. The perplexity scores for these two models are significantly better than the word-based model, and compete with those of character-based models. We were expecting such good results as the number of unique tokens is significantly decreases in these models (e.g. from 36K to 2,987 for Russian). The neural model used for this task is quite powerful which is able to provide precise predictions when it works with a limited set of tokens.

MLBL is the model of Botha and Blunsom (2014). In **MorphCLM**, each word is represented by the summation of surface-form and subword embeddings, and the neural architecture is the same as the previous one, which means there is no convolutional module. Subword embeddings are linearly combined and the final embedding is sent to the *highway* module. In this model subword units are separated by *Morfessor*. We also introduce two extensions for this architecture, namely **MorphCLM**$_{bp}$ and **MorphCLM**$_{dp}$. In the first and second extensions subwords are segmented via *Byte-pair* and Model D, respectively. Results for these extensions are not as well as other results, and this did not surprise us as *Byte-pair* and Model D are not supposed to generate linguistically correct morphemes and we do not expect to obtain a high-quality embedding for a word when we combine the embeddings of its *bp* or *dp* subunits. In our experiments, to make our results comparable we extract the same number of tokens for both Model D and *Byte-pair*.

Finally, the last 5 rows show CLM and our models with the *default* configuration where input sequences are processed by the character-level and our segmentation models, respectively. As the table shows, because the set of *basic* units extracted via Models A to C is (supposed to be) better than the set of characters our NLMs perform better than **CharCLM**.

In Section 4.3, we debated two important questions: *"Do we really need a complex model to work at the character level?"* and *"Is the granularity provided by the character-level segmentation optimal?"* Table 4.5 fully addressed these two questions. For Czech and Russian which are morphologically complex languages, a simple NLM working with *dp* tokens is able to generate better results than more complicated subword-based models. This shows that in the presence of high-quality segmentations we do not need to explore complicated neural models (we will further discuss the impact of effective segmentations in Section 6.3.1.1). Moreover, the character-based model performs better when it is fed with our *basic* units (not characters). This confirms that the simple character-based segmentation scheme does not provide the optimal granularity.

4.5.1 Discussion

In this section we try to address two different properties to analyze the model from different perspectives. The first issue that we wish to discuss is the size of training corpora. Recently, Józefowicz et al. (2016) trained huge neural networks with different architectures for language modeling. They trained deep models on very large corpora (on the one billion word benchmark[6] (Chelba et al., 2013)) using massive hardware resources (the best performance was reported from a model trained over 32 Tesla K40 GPUs for 3 weeks). According to their comparisons, the architecture proposed by Kim et al. (2016) provides state-of-the-art results. As our model is an extension to that architecture, it is supposed to perform better, but it cannot be claimed without evaluating the model in practice. In large-scale experimental settings the model might behave differently. We cannot afford the setting and resources described in Józefowicz et al. (2016) but we are able to design a comparable experiment. To evaluate the performance of our (best) models in the presence of large vocabularies, we use two large Farsi and German corpora. Information about

[6] `http://www.statmt.org/lm-benchmark/`.

the corpora and experimental results are reported in Tables 4.6.

	Data					PPL		
Language	$\mathcal{V}$	$\mathcal{C}$	$\mathcal{M}_C$	m_c	$\mathcal{M}_{dp}$	**CLM**	**CLM**$_C$	**WordCLM**$_{dp}$
German	637k	319	9122	1	71k	342	**340**	387
Farsi	336k	132	6513	1.5	38k	290	**280**	305

Table 4.6: Experimental results for large datasets. m_c is the extrenal parameter of Model C. *dp* stands for dynamic programming and indicates the tokens extracted via Model D.

The German corpus was built using the `Europarl-v7`[7] collection (Koehn, 2005). We selected 1.9 million sentences from the German side of the English–German corpus and for Farsi, we selected the same number of sentences from the Hamshahri[8] collection (AleAhmad et al., 2009), which is a standard dataset of monolingual sentences and frequently used in Farsi language processing research.

Table 4.6 summarizes the advantages and disadvantages of different approaches. The main advantage of the character-based model is its ability to handle very large datasets. It transforms everything into a limited set of characters which facilitates the language-modeling task. However, the level of granularity provided by the character-based model is not optimal, so we use our tunable models. When words are segmented with Model C the neural language model is able to perform better, but we know that it could be hard to set the best value for the external parameter of Model C. There is also another model, namely **WordCLM**$_{dp}$, for which we do not need to set the external parameter. The training procedure for this model is 15 hours faster than **CLM**$_C$, but its performance is slightly worse. We can summaries different properties of these approaches in this way: *i*) **CLM** performs well for large datasets but the character-level segmentation is not the best segmentation scheme; *ii*) **CLM**$_C$ is more precise compared to **CLM**, but it requires a complicated training procedure; *iii*) finally, **WordCLM**$_{dp}$ is fast and has no external parameter but it may fail to perform equally for large datasets. However, its performance is not far

[7] `http://www.statmt.org/wmt16/translation-task.html`

[8] `http://ece.ut.ac.ir/dbrg/hamshahri/`

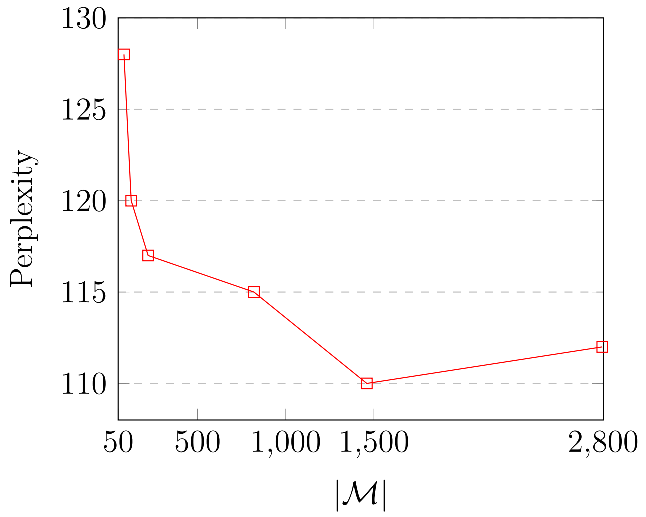


Figure 4.7: Impact of different θ values on PPL and $|\mathcal{M}|$.

from that of $\mathbf{CLM}_C$.

The second issue which can be discussed is the segmentation scheme itself. As previously mentioned, we think that the improvement gained by character-level models is not only because of the segmentation model. As an example in CLM, the *highway* module directly affects word representations. Kim et al. (2016) extensively discussed this matter and provided several examples. We believe that the strength of our model relies heavily on the chosen segmentation technique, rather than the neural architecture. Our performance does not rely on *highway* layers as much as CLM, as if we add/remove a layer to/from the *highway* module in the *default* configuration (in Model C), the final perplexity would stay almost unchanged, whereas if we do the same with CharCLM (add one extra layer or remove a layer from the *highway* module), its performance fluctuates (perplexity changes) by 10 to 20 points. Therefore, our segmentation scheme by its very nature is able to provide richer and more representative information.

In our models the final output is highly influenced by the external parameters (θ and m), so that it is necessary to find their best value to obtain the optimal output. However, with some random values such as $m = 1$ or $\theta = 500$, our models can provide comparable results to state-of-the-art models. We designed an experiment to show how these parameters affect the number of blocks and the model's performance. In our experiment we studied Model A (on Farsi) with different θ values. As Figure 4.7 shows, the best perplexity score achieved by the model is 110 where $\theta = 500$, which generates a basic set of 1460 blocks. This means that by the given frequency threshold, all existing words in the corpus can be encoded by 1460 atomic units. When the threshold is increased the model starts to react similarly to CLM, because the basic units become smaller so that the basic set becomes closer to the alphabet set. For example with $\theta = 10,000$, the basic set includes 124 blocks and the perplexity is 120. We can see the opposite trend when the θ value is decreased. When the threshold is set to a value smaller than 500 the basic set is not optimal any more and it downgrades the performance of the NLM, because with smaller θ values the chance of selecting longer blocks is higher and the basic set becomes too sparse., e.g. with $\theta = 200$ the size of the basic set is 2795 which results in a perplexity score of 112, which is worse than 110. As the value of θ decreases this negative trend continues up to $\theta = 100$, and after this threshold the quality of the model drops drastically.

4.5.2 Neural Language Modeling for SMT

All issues discussed so far are purely related to language modeling. Language models are frequently used in different fields such as MT. In this section we show the application of language modeling in SMT and explain how the proposed NLM enables us to provide better translations. To this end we designed a simple experiment, where we manipulate the n-gram language model with our NLM which means we do not change anything but the n-gram scores. The n-gram-based language model includes n-grams and their associated scores. We recompute those scores with our NLM models. Results for this experiment are shown in Table 4.7.

In this experiment we trained different SMT engines to translate from English (En) into German (De) and vice versa. To train the En–De engines we used the `WMT-15` datasets.[9] For the training set we randomly selected 2M sentences. Our

[9] `http://www.statmt.org/wmt15/translation-task.html`.

NLM	En→De	**Imp.**	De→En	**Imp.**
Baseline	15.25	0	20.13	0
WordCLM	15.78	+0.53	20.44	+0.31
WordCLM$_{dp}$	**16.27**	**+1.02**	20.72	+0.59
WordCLM$_{bp}$	16.24	+0.99	20.72	+0.59
MorphCLM	15.85	+0.60	20.83	+0.70
CharCLM	15.89	+0.64	20.85	+0.72
CLM$_A$	16.18	+0.93	**20.96**	**+0.83**
CLM$_{B_{div}}$	16.15	+0.90	20.84	+0.71
CLM$_{B_{root}}$	16.11	+0.86	20.92	+0.79
CLM$_C$	16.20	+0.95	20.90	+0.77

Table 4.7: Boosting n-gram-based LMs with NLMs. Improvements (**Imp.**) are statistically significant according to the results of paired bootstrap re-sampling with $p = 0.05$ for 1000 samples (Koehn, 2004b)

models were evaluated on `newstest-2015` and tuned using `newstest-2013`. We trained them using Moses (Koehn et al., 2007) with the default configuration, tuned via MERT (Och, 2003) and evaluated using BLEU (Papineni et al., 2002).

In Table 4.7, **Baseline** shows the baseline systems which are phrase-based SMT models. For our baseline models we trained 5-gram language models on the monolingual parts of the bilingual corpora using SRILM (Stolcke, 2002). Other settings indicate enhanced models for the baseline systems where n-gram counts are recomputed using different NLMs. **Imp** is the difference between the baseline score and the score obtained after embedding the NLM, which shows the impact of the NLM. As the table shows using the NLM instead of/along with the n-gram-based LM considerably improves the quality of both the directions.

4.6 Summary

In this chapter we proposed an extension to the state-of-the-art character-level NLM. We did not drastically change the neural architecture but developed new segmentation models to decompose morphologically complex words. Our proposed models are simple and unsupervised models. The models learn the segmentation scheme from a training corpus. The granularity provided by the models falls in between character-level and morpheme-level models. They define a new set of basic units (alphabet) for the given corpus. Through the training phase, they learn to connect a set of related and consecutive characters to one another to construct new blocks. The proposed neural language-modeling pipeline outperforms existing models for all of our experiments. We studied our models from different perspectives and discussed the impact of the external parameters. Following this, we used our NLM in the SMT pipeline. In our future work we plan to focus more on the generation aspect of our neural language model.

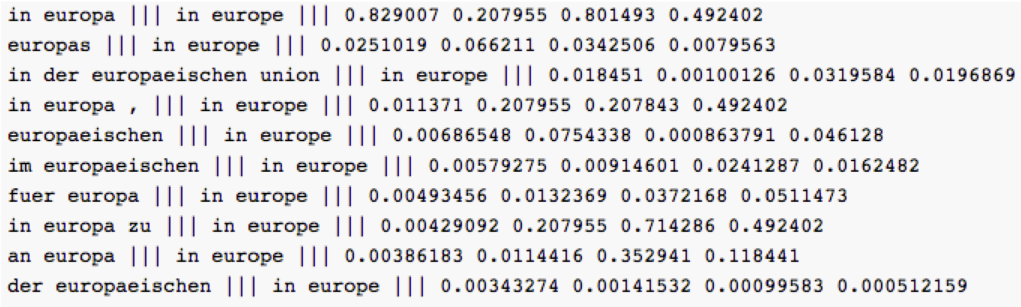
Chapter 5

Boosting SMT via NN-Generated Features

In this chapter we benefit from neural features generated by our NNs (reported in Chapters 3 and 4) to boost SMT models. First we introduce a general pipeline to incorporate word and phrase embeddings into SMT. By use of embeddings, not only is the SMT model informed with syntactic and semantic (similarity) information, but also we define different word-, phrase-, and sentence-level features to provide better translations. We show how to use monolingual and bilingual embeddings. Accordingly, training embeddings in the SMT context, especially bilingual embeddings, is one of the key contributions of the chapter. Our pipeline is investigated from different perspectives through different experiments. We evaluated our models by translating between English (En) and Czech (Cz), Farsi (Fa), French (Fr), and German (De) and observed significant improvements for all language pairs. The main goal targeted in this chapter is to introduce a pipeline by which neural features can be incorporated into the SMT pipeline, so models in this chapter are not only limited to MRLs and can be applied to any language. However, as we are interested in this set of languages, we designed our experiments based on MRLs and improved our models via morphological information, which were reported in Section 5.2.3.

5.1 Incorporating Embeddings into Phrase Tables

The process of PBSMT can be interpreted as a search problem for the best target-side match for a given input sentence where the score at each step of exploration is formulated as a log-linear model (Koehn, 2009). For each candidate phrase, the set of features is combined with a set of learned weights to find the best target counterpart of the provided source sentence. Because an exhaustive search of the entire candidate space is not computationally feasible, the space is typically pruned via some heuristics, such as using beam search (see Chapter 2). The discriminative log-linear model allows the incorporation of arbitrary context-dependent and context-independent features. Thus, features such as those in Och and Ney (2002) or Chiang et al. (2009) can be combined to improve translation performance. The standard baseline bilingual features (in the phrase table) included in Moses (Koehn et al., 2007) by default are: the *phrase translation probability* $\phi(e|f)$, *inverse phrase translation probability* $\phi(f|e)$, *direct lexical weighting* $lex(e|f)$, and *inverse lexical weighting* $lex(f|e)$.[1] The structure of the phrase table is illustrated in Figure 5.1.



```
in europa ||| in europe ||| 0.829007 0.207955 0.801493 0.492402
europas ||| in europe ||| 0.0251019 0.066211 0.0342506 0.0079563
in der europaeischen union ||| in europe ||| 0.018451 0.00100126 0.0319584 0.0196869
in europa , ||| in europe ||| 0.011371 0.207955 0.207843 0.492402
europaeischen ||| in europe ||| 0.00686548 0.0754338 0.000863791 0.046128
im europaeischen ||| in europe ||| 0.00579275 0.00914601 0.0241287 0.0162482
fuer europa ||| in europe ||| 0.00493456 0.0132369 0.0372168 0.0511473
in europa zu ||| in europe ||| 0.00429092 0.207955 0.714286 0.492402
an europa ||| in europe ||| 0.00386183 0.0114416 0.352941 0.118441
der europaeischen ||| in europe ||| 0.00343274 0.00141532 0.00099583 0.000512159
```

Figure 5.1: The figure shows the structure of a German-to-English phrase table where the first constituent at each line is a German phrase which is separated by ||| from its English translation. The following 4 scores after the English phrase are default bilingual scores extracted from training corpora. These scores show how phrases are semantically related to each other. The decoder selects the best phrase pair at each step based on these scores.

[1] Although the features contributed by the language model component are as important as the bilingual features, we do not address them in Chapter 5, since they traditionally only make use of the monolingual target language context, and we are concerned with incorporating bilingual semantic knowledge.

The scores in the phrase table (see Figure 5.1) are computed directly from the co-occurrence of aligned phrases in the training corpora. A large body of recent work evaluates the hypothesis that co-occurrence information alone cannot capture contextual information as well as the semantic relations among phrases (see Section 5.1.1). Therefore, many techniques have been proposed to enrich the feature list with semantic information. In our model, we define six new features for this purpose. All of our features indicate the semantic relatedness (similarity) of source and target phrases. Our features leverage contextual information which is lost by the traditional phrase extraction operations. Specifically, on both sides (source and target) we look for any type of constituents including phrases, sentences, or even words which can fortify the semantic information about phrase pairs.

Our main contributions in this model are threefold: *i*) we define new similarity features and embed them into PBSMT to enhance the translation quality; *ii*) in order to define the new features we train bilingual phrase and sentence embeddings using an NN. Embeddings are trained in a joint distributed feature space which not only preserves monolingual similarity and syntactic information but also represents cross-lingual relations; and *iii*) we indirectly incorporate external contextual information using the neural features. We search in the source and target spaces and retrieve the closest constituent to the phrase pair in our bilingual embedding space.

5.1.1 Background

Several models such as He et al. (2008); Liu et al. (2008); Shen et al. (2009) studied the use of contextual information in SMT. The idea is to go beyond the phrase level and enhance the phrase representation by taking surrounding phrases into account. This line of research is referred as discourse SMT (Hardmeier, 2014; Meyer, 2014). Because NNs can provide distributed representations for words and phrases, they are ideally suited to the task of comparing semantic similarity. Unsupervised models such as *Word2Vec* or *Paragraph Vectors* (Le and Mikolov, 2014) have shown that distributional information is often enough to learn high-quality word and sentence embeddings.

A large body of recent work has evaluated the use of embeddings in MT. A successful use-case was reported in Mikolov et al. (2013b), where they separately project words of source and target languages into embeddings, then try to find a transformation function to map the source embedding space into the target space. The transformation function was approximated using a small set of word pairs extracted using an unsupervised alignment model trained with a parallel corpus. This approach allows the construction of a word-level translation engine via a very large amount of monolingual data and only a small number of bilingual word pairs. The cross-lingual transformation mechanism allows the engine to search for translations of OOVs by consulting a monolingual index which contains words that were not observed in the parallel training data. The work by Martinez Garcia et al. (2014) is another model that follows the same paradigm. However, MT is more than word-level translation.

In Martínez et al. (2015), word embeddings were used in document-level MT to disambiguate the word selection. Tran et al. (2014) used bilingual word embeddings to compute the semantic similarity of phrases. To extend the application of text embedding beyond single words, Gao et al. (2013) proposed learning embeddings for source and target phrases by training a network to maximize the sentence-level BLEU score. Costa-jussa et al. (2014) worked at the sentence-level and incorporated the source-side information into the decoding phase by finding the similarities between phrases and source embeddings. Some other models re-scored the phrase table (Alkhouli et al., 2014) or generated new phrase pairs in order to address the OOV word problem (Zhao et al., 2015).

Our network makes use of some ideas from existing models, but also extends the information available to the embedding model. We train embeddings in the joint space using both source- and target-side information simultaneously, using a model which is similar to that of Devlin et al. (2014). Similar to Gao et al. (2013), we make embeddings for phrases and sentences and add their similarity as feature functions to the SMT model.

5.1.2 Proposed Model

Our proposed model is explained in two main parts. Section 5.1.2.1 shows what the data format is for our model, as we need to generate a special training corpus to train our model. This section also studies our similarity features. Section 5.1.2.2 explains the neural architecture and how the architecture enables us to train document-level[2] and bilingual embeddings. Our training model provides unique embeddings for all words, phrases, and sentences in the training corpus. In our case, embeddings are distributed structures which are supposed to provide bilingual and contextual information. Such information is quite useful for any SMT engine whereby we enrich the phrase table. The extended phrase table in our model includes 6 scores (features) additional to those 4 default scores, which convey similarity and contextual information.

5.1.2.1 Training Bilingual Embeddings

In order to train our bilingual embeddings, we start by creating a large bilingual corpus. Each line of the corpus may include:

- a source or target sentence,
- a source or target phrase,
- a concatenation of a phrase pair (source and target phrases which are each other's translation),
- a tuple of source and target words (each other's translation).

Sentences of the bilingual corpus are taken from our SMT training corpora. Accordingly, phrases and words are from the phrase tables and lexicons, generated by

[2] In the literature *document* is a term which is used for any chunk of a text such as characters, words, phrases, sentences, and paragraphs.

the alignment model and phrase extraction heuristic used by the SMT model. This means that the bilingual corpus is a very large corpus with $2 * |c| + 3 * |pt| + |bl|$ lines where $|c|$ indicates the number of source/target sentences, $|pt|$ is the size of the phrase table and $|bl|$ is the size of the bilingual lexicon. $|c|$ is multiplied by 2 because we have $|c|$ source sentences (one sentence per line) and $|c|$ target sentences. Similarly, $|pt|$ is multiplied by 3 as there are $|pt|$ source phrases, $|pt|$ target phrases and $|pt|$ concatenated phrases (paired). The structure of the bilingual training corpus is illustrated in Figure 5.2.

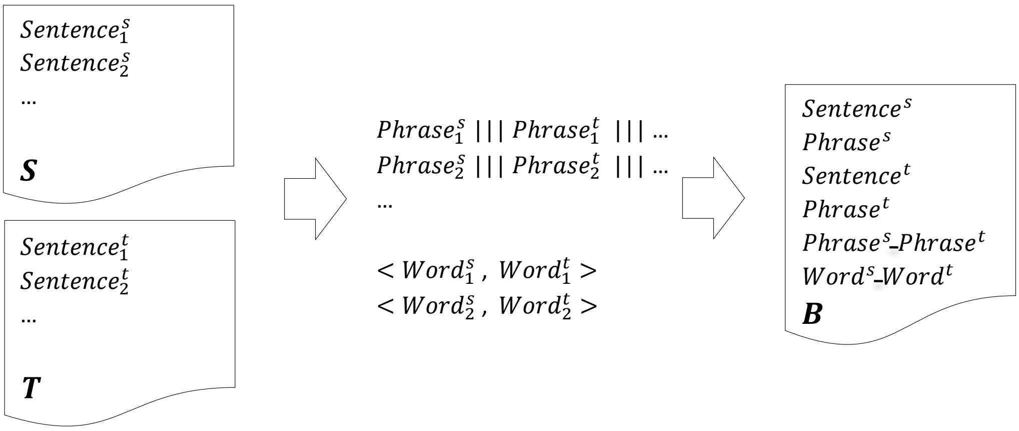


Figure 5.2: S, T, and B indicate the source, target, and bilingual corpora, respectively. The SMT model generates the phrase table and bilingual lexicon using S and T (shown in the middle). The bilingual corpus consists of 6 different sections of 1) all source sentences (*Sentence*^{s}), 2) all source phrases (*Phrase*^{s}), 3) all target sentences (*Sentence*^{t}), 4) all target phrases (*Phrase*^{t}), 5) all phrase pairs (*Phrase*^{s}-*Phrase*^{t}) and 6) all bilingual lexicons (*Word*^{s}-*Word*^{t}).

By use of the concatenated phrases and bilingual tuples we try to score the quality of both sides of the phrase pair, by connecting phrases with other phrases in the same language, and with their counterparts in the other language. The next section discusses how the network benefits from this bilingual property.

In our model we have an embedding matrix whose rows represent the bilingual corpus, namely each line of the bilingual training corpus has a dedicated vector (row) in the embedding matrix. During training these vectors are updated to obtain high-quality embeddings. After training, we would have a unique embedding for each word, phrase, and sentence in each language (source and target). We use such embeddings (Section 5.1.2.2 explains how we train embeddings) to extract phrase-level and contextual information to enrich the phrase table.

As mentioned, the model trains a dedicated embedding for each phrase in the phrase table. Such an embedding is used in the phrase table with the hope that it will provide semantic information about the phrase itself. Since our embeddings are bilingual, the phrase embedding is also able to provide semantic information about the target side and the target phrase. This property is definitely useful to guide the decoder. Apart from phrase-level embeddings we can use other word and sentence embeddings to fortify existing phrase-level information and provide contextual information.

In order to enrich the phrase table with our bilingual embeddings, first we compute the semantic similarity between source and target phrases in phrase pairs. The similarity shows how phrases are semantically related to each other. The *Cosine* measure is used to compute the similarity, as in (5.1):

$$similarity(\mathcal{E}_s, \mathcal{E}_t) = \frac{\mathcal{E}_s.\mathcal{E}_t}{||\mathcal{E}_s|| \times ||\mathcal{E}_t||} \tag{5.1}$$

where $\mathcal{E}_s$ and $\mathcal{E}_t$ indicate embeddings for the given source and target phrases, respectively. We map *Cosine* scores into the range $[0, 1]$. This can be interpreted as a probability indicating the semantic relatedness of the source and target phrases. The similarity between the source phrase and target phrase is the first feature and is referred as *sp2tp*. Apart from this score, we compute five more scores for each phrase pair.

Among source-side embeddings (word, phrase, or sentence embeddings) we search for the closest match to the source phrase. The closest match has the minimum distance to the source phrase. There might be a word, phrase, or sentence on the source side which can enhance the source phrase representation and facilitate its translation. We use the source-phrase embedding as it is supposed to enrich the phrase table by proving semantic information about the source phrase, but nothing limits us to work at the phrase level so we can provide further information by using embeddings of other source-side documents. Although other source-side embeddings might not be directly related to the source phrase, as they are distributed representations they can carry relevant information to the source phrase and/or provide contextual information. If the closest match retrieved for the source phrase belongs to a sentence, that might be the sentence from which the source phrase was extracted. Clearly taking that sentence into account would provide contextual information for the given phrase. If the closest match belongs to a phrase, that is probably a paraphrased form of the original phrase (or a translationaly equivalent phrase), and if the closest match belongs to a word, that is probably a keyword which conveys the main meaning of the phrase (see Figure 5.3 and Table 5.1 for more clarification). We compute the similarity of the closest source match to the source phrase which is referred to as *sp2sm* in our setting. This is another feature that we extract for our model.

We also look for the closest match of the source phrase on the target side. As we jointly learn embeddings, structures that are each other's translation should have close embeddings. We find the closest match to the source phrase among target-side embeddings as there might be some target-side contextual information which can be useful for the decoder. We compute the similarity of the closest target match to the source phrase, which is labeled as *sp2tm*. We compute the same similarities for the target phrase, namely the similarity of the target phrase with the closest target match (*tp2tm*) and the closest source match (*tp2sm*). The source and target matches may preserve other types of semantic similarity as they are the most representative constituents for the given phrase pair on the source and target sides. Therefore we compute the similarity between the source match and target match (the *sm2tm* feature). All new features are added to the phrase table and used in the tuning phase to optimize the translation model. Figure 5.3 tries to clarify the relationship between different matches and phrases.

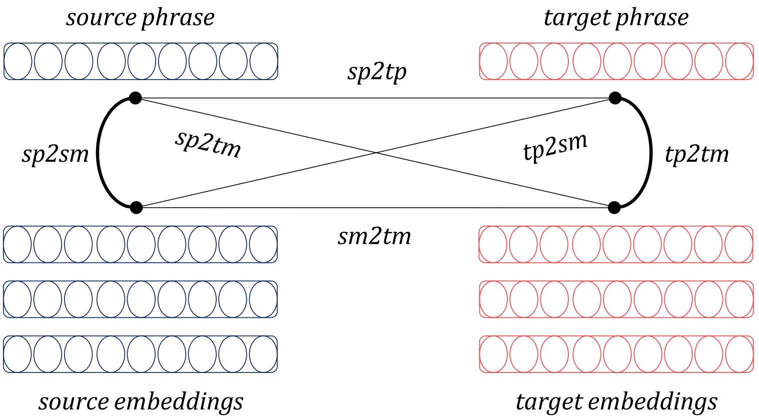


Figure 5.3: *sp, tp, sm* and *tm* stand for *source phrase, target phrase, source match* and *target match*, respectively. The embedding size for all types of embedding is the same. The source/target-side embedding could belong to a source/target word, phrase, or sentence. The labels on the links indicate the Cosine similarity between two embeddings which is mapped to the range [0,1].

5.1.2.2 Training Document Embeddings

We have explained how to build the bilingual corpus and compute semantic features. Now we discuss the network architecture to train bilingual embeddings. Our network is an extension of Devlin et al. (2014) and Le and Mikolov (2014). In those methods, documents (words, phrases, sentences and any other chunks of text) are treated as atomic units in order to learn embeddings in the same semantic space as that used for the individual words in the model. The model includes an embedding for each document which in our case may be a monolingual sentence, a monolingual phrase, a bilingual phrase pair, or a bilingual word pair. During training, at each iteration a random target word (w^t) is selected from the input document to be predicted at the output layer by using the context and document embeddings (typical *Word2Vec* approach). The context embedding is made by averaging embeddings of adjacent words around the target word. Word and document embeddings are updated during training until the cost is minimized. The model learns an embedding space in which constituents with similar distributional tendencies are close to each other. More formally, given a sequence of $S_i = w_1, w_2, ..., w_n$ the objective is to maximize the log probability of the target word given the context and document vector, as in (5.2):

$$\frac{1}{n}\sum_{j=1}^{n}\log p(w_j^t|C_i^{w^t}, D_i) \tag{5.2}$$

where $w_j^t \in S_i$ is randomly selected at each iteration. D_i is the document embedding for S_i and C^{w^t} indicates the context embedding which is the mean of embeddings for m preceding and m following words around the target word w^t.

As previously mentioned, S_i could be a monolingual sentence (one line from *Sentence*^{s} or *Sentence*^{t} in Figure 5.2) or phrase (one line from *Phrase*^{s} or *Phrase*^{t} in Figure 5.2), in which w^t and adjacent words are from the same language. In other words, the context includes m words before and m words after the target word. S_i also could be a concatenation of source and target phrases (one line from *Phrase*^{s}-*Phrase*^{t} in Figure 5.2). In that case context words are selected from both languages, i.e. m words from the source (the side from which w^t is selected) and m words from the target side. Finally, S_i could be a pair of source and target words (one line from *Word*^{s}-*Word*^{t} in Figure 5.2) where C^{w^t} is made using the target word's translation. The word on one side is used to predict the word on the opposite side. In the proposed model, m is the upper bound.

Table 5.1 illustrates some examples of the context window. The examples are selected from the English–Farsi bilingual corpus (see Section 5.1.3). In C_1 the context window includes 2 words before **better** and 2 words after. In this case the target word and all other context words are from the same language (indicated by the 's' subscript). In the second example the input document is a concatenation of English and Farsi phrases, so C_2 includes m (or fewer) words from each side (indicated with different subscripts). In the final example the input document is a word tuple where the target word's translation is considered as its context.

As shown in Huang et al. (2012), word vectors can be affected by the word's surrounding as well as by the global structure of a text. Each unique word has a specific vector representation and clearly similar words in the same language should

D_1	know him **better** than anyone
C_1^{better}	[know, him, than, anyone]$_s$
D_2	know him **better** than anyone . *āv rā bhtr āz hrks myšnāsy*
C_2^{better}	[know, him, than, anyone]$_s$ + [*āv*, *rā*, *bhtr*, *āz*, *hrks*]$_t$
D_3	**better** . *bhtr*
C_3^{better}	[*bhtr*]$_t$

Table 5.1: Context vectors for different input documents. w^t (the word to be predicted) is **better** and $m = 5$ (context). Italics are in Farsi (transliterated forms).

have similar vectors (Mikolov et al., 2013a). By means of the bilingual training corpus and our proposed architecture, we tried to expand the monolingual similarities to the bilingual setting, resulting in an embedding space which contains both languages. Words that are direct translations of each other should have similar/close embeddings in our model. As the corpus contains tuples of $< word_{L_1}, word_{L_2} >$, embeddings for words which tend to be translations of one another are trained jointly. Phrasal units are also connected together by the same process. Since the bigger blocks encompass embeddings for words and phrasal units, they should also have representations which are similar to representations of their constituents.

In our neural architecture we have a multi-layer feed-forward network. In the input layer we have an embedding matrix. Each row in the matrix is dedicated to one specific line in the bilingual corpus. During training embeddings are tuned and updated. The network has only one hidden layer. The input for the *Softmax* layer is $h = W(C_i^{w^t} \bullet D_i) + b$, where W is a weight matrix between the input layer and the hidden layer, b is a bias vector and $\bullet$ indicates the concatenation function. The output of *Softmax*, $V \in \mathbb{R}^{|\mathcal{V}|}$, is the distribution probability over classes which are words in our setting. The j-th cell in V is interpreted as the probability of selecting the j-th word from the target vocabulary $\mathcal{V}$ as the target word. Based on *Softmax* values the word with the highest probability is selected and the error is computed accordingly. The network parameters are optimized using stochastic gradient descent and back-propagation (Rumelhart et al., 1988). All parameters of the model are randomly initialized over a uniform distribution in the range [-0.1,0.1].

Weight matrices, bias values and word embeddings are all network parameters which are tuned during training. Figure 5.4 illustrates the whole pipeline.

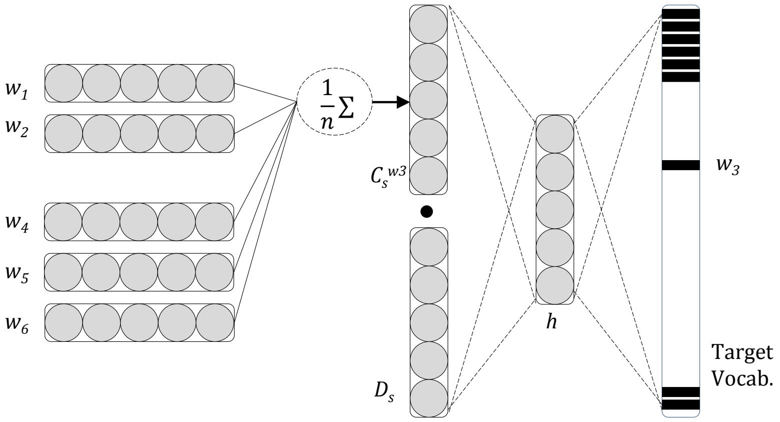


Figure 5.4: Network architecture. The input document is $S = w_1\ w_2\ w_3\ w_4\ w_5\ w_6$ and the target word is w_3. In the backward pass document embeddings for w_1, w_2, w_4 to w_6, and D_s are updated.

To enrich the phrase table properly, we need to have high-quality embeddings which preserve contextual information. The neural architecture proposed here is one of the well-known models which has been evaluated for many tasks (Devlin et al., 2014; Le and Mikolov, 2014), so it can guaranty that we would have high-quality embeddings. Moreover, our bilingual corpus also helps us train high-quality embeddings. It is large enough to cover almost all words and all co-occurrences. There are millions of words in the bilingual corpus which is sufficient to reach an acceptable quality for word embeddings. Accordingly, sentences and phrase embeddings would also have the same quality as they are based on those (millions of) words. It should be also noted that we do not only rely on words to train phrase and sentence embeddings, as we have a sufficient number of training instances for them too. We usually have millions of parallel sentences in MT corpora which are included in the bilingual corpus. Phrase tables generated using such parallel corpora are also quite large, e.g. there are more than 30 million phrase pairs in one of our German–English phrase tables. All these numbers ensure us that we can rely on our model and corpus for training high-quality embeddings. The next section explains our experimental study and shows the impact of our embeddings.

5.1.3 Experimental Results

We evaluated our new features on two language pairs: English–Czech and English–Farsi. Both Czech and Farsi are morphologically rich languages; therefore, translation to/from these languages can be more difficult than it is for languages where words tend to be discrete semantic units. Farsi is also a low-resource language, so we are interested in working with these pairs. For the En–Cz and En–Fa pairs we used the `Europarl` (Koehn, 2005) corpus and `TEP++` corpus (Passban et al., 2015), respectively. We randomly selected 1K sentences for testing and 2K for tuning, and the rest of the corpus for training. The baseline system is a PBSMT engine built using Moses (Koehn et al., 2007). We used MERT (Och, 2003) for tuning. In the experiments we trained 5-gram language models on the monolingual parts of the bilingual corpora using SRILM (Stolcke, 2002). We used BLEU (Papineni et al., 2002) as the evaluation metric.

We added our features to the phrase table and tuned the translation models. Tables 5.2 and 5.3 show the impact of each feature. The embedding size for these experiments is 200. We also estimated the translation quality in the presence of the all features (we run MERT for each row of the tables). Bold numbers are statistically significant according to the results of paired bootstrap re-sampling with $p = 0.05$ for 1000 samples (Koehn, 2004b). Arrows indicate whether the new features increased or decreased the quality over the baseline.

Feature	**En–Cz**	↑↓	**Cz–En**	↑↓
Baseline	28.35	0.00	39.63	0.00
sp2tp	28.72	**0.37** ↑	40.34	**0.71** ↑
sp2sm	28.30	0.05 ↓	39.76	0.13 ↑
sp2tm	28.52	0.17 ↑	39.79	0.16 ↑
tp2tm	28.00	0.35 ↓	39.68	0.05 ↑
tp2sm	28.94	**0.59**↑	39.81	0.18 ↑
sm2tm	28.36	0.01 ↑	39.99	**0.36** ↑
All	29.01	**0.66** ↑	40.24	**0.61** ↑

Table 5.2: Impact of the proposed features over the En–Cz engine.

Results reported in Tables 5.2 and 5.3 show that the new features are useful and

Feature	**En–Fa**	↑↓	**Fa–En**	↑↓
Baseline	21.03	0.00	29.21	0.00
sp2tp	21.46	**0.43** ↑	29.71	**0.50** ↑
sp2sm	21.32	0.29 ↑	29.74	**0.53** ↑
sp2tm	21.40	**0.37** ↑	29.56	**0.35** ↑
tp2tm	20.40	0.63 ↓	29.56	0.35 ↑
tp2sm	21.93	**0.90** ↑	29.26	0.05 ↑
sm2tm	21.18	0.15 ↑	30.08	**0.87** ↑
All	21.84	**0.81** ↑	30.26	**1.05** ↑

Table 5.3: Impact of the proposed features over the En–Fa engine.

positively affect the translation quality. Some of the features such as *sp2tp* are always helpful regardless of the translation direction and language pair, so this feature is the most important of our feature. The *sm2tm* feature always works effectively in translating into English and the *tp2sm* feature is effective when translating from English. In the presence of all features results are significantly better than the baseline system in all cases. Some of the features are not as strong as the others (*tp2tm*) and some of them behave differently based on the language (*sp2tm*). With these feature we (partly) incorporate contextual information by use of multi-granular similarities among embeddings.

5.2 Further Investigation of Neural Features

We introduced a framework to leverage word embedding in the SMT pipeline. In this section we study the framework from different perspectives. First we study how powerful the proposed model is to capture semantic relations. We provide examples from embeddings to highlight this property. Afterwards we study whether the model is applicable to other languages. We do not necessarily need to train bilingual embeddings, so this implies we explain a model to use monolingual embeddings as well as morphology-aware embeddings to boost (phrase-based and factored) SMT models. In a separate section we discuss the neural architecture and show that the proposed feed-forward architecture can be substituted with a better convolutional model. Finally, we take a look at the performance and quality issues. Our enhanced SMT model improves the quality in terms of the automatic evaluation metric, BLEU, but we wish to determine that the model actually changes translations, so we perform human evaluations to verify this.

5.2.1 Capturing Semantic Relations

Numbers reported in Section 5.1.3 indicate that the proposed method and features result in a significant enhancement of translation quality, but it cannot be decisively claimed that they are always helpful for all languages and settings. Accordingly, we tried to study the impact of features not only quantitatively but also qualitatively.

Based on our investigation, the new features seem to help the model determine the quality of a phrase pair. As an example for the English phrase *"but I'm your teammate"* in the phrase table, the corresponding Farsi target phrase is *"āmā mn hm tymyt hstm"* which is the exact translation of the source phrase. The closest match in the source side is *"we played together"* and in the target side is *"Ben mn ānjā bāzy krdm"* (meaning *"I played in that team"*). These retrieved matches indicate that we retrive something related and useful in our model which can help the decoder generate better translations.

Note also that by comparing the outputs we noticed that before adding our features, the word *"your"* in the English phrase was not translated. In translation into Farsi, possessives are sometimes not translated as the verb implicitly shows them, but the best translation is a translation including possessives. After adding our features, the translation of *"your"* did appear in the output. In terms of linguistic issues this is an important achievement in Farsi translation as it is very hard to solve this problem by automatic translation models alone, and the fact that our solution (at least) addressed and slightly mitigated the problem is encouraging.

The proposed model is expected to learn cross-lingual similarities along with monolingual relations. To study this feature Table 5.4 illustrates how the proposed model can capture cross-lingual relations. It can also model similarities in different

Query	***sadness***
1	<*apprehension*, nervous>
2	*emotion*
3	<*ill*,sick>
4	pain
5	<*money*,money>
6	*benignity*
7	<*may he was punished*,punished harshly>
8	is really gonna hurt
9	i know tom ' s dying
10	<*bitter*,angry>

Table 5.4: The top-10 most similar vectors for the given English query. Recall that the retrieved vectors could belong to words, phrases or sentences in either English or Farsi as well as word or phrase pairs. The items that were originally in Farsi have been translated into English, and are indicated with *italics*.

granularities. It has word-level, phrase-level and sentence-level similarities. Retrieved instances are semantically related to the given queries.

5.2.2 Using Semantic Features for Other Languages

We reported our results on the Cz–En and Fa–En pairs. As we wanted to focus on a language that has been not studied extensively, we chose Farsi. As Farsi is a low-resource and complex language, improving its quality is an important achievement. There exist many parallel corpora, systems, techniques and tools for well-studied languages, so (small) enhancements such as the proposed model in this chapter might not be so useful and interesting, as words, phrase tables or other components such as language models etc. for such languages are already rich enough to provide high-quality translations and do not necessarily need additional features. Along with Farsi we also tried to study the impact of our model on Czech as another morphologically complex language. Results were quite successful for both languages but to give a better understanding of the model and provide more experimental studies, we also applied our model to two well-studied languages, French and German.

For French and German we used the same experimental setting as that of Farsi and Czech (Europral Corpus, Moses, SRILM, MERT etc.). Since the most important

System	En–Fr	Fr–En	En–De	De–En
Baseline	29.21	27.31	15.25	20.13
Extended	29.92	27.95	15.56	20.64
Improvement	+0.71	+0.64	+0.31	+0.51

Table 5.5: For training the French and German engines we randomly selected 2M sentences from the Europral collection. The phrase table for the extended system is enriched with our novel *sp2tp* feature. Improvements in the last row are statistically significant according to the results of paired bootstrap re-sampling with $p = 0.05$ for 1000 samples (Koehn, 2004b).

feature is *sp2tp*, we report our experiments only on this feature. Table 5.5 shows the results. Similar to the previous experiments, our model is also able to improve the En–De and En–Fr engines. Improvements for French are more tangible than those of German which could be because of the closer similarity of French and English. It is usually claimed that these two languages are close to each other and, as *sp2tp* tries to extract semantic relations, it performs well on this pair.

5.2.3 Using Morphology-Aware Embeddings in SMT

We use word embeddings to improve the translation quality. In our experiments we applied our techniques to complex languages such as Farsi and German. We also have a model to train high-quality embeddings for such languages (see Chapter 3). It intuitively seems that if we use our morphology-aware embeddings we might obtain better results. To this end we designed two experiments. In the first experiment we use monolingual embeddings (as they are) in factored translation models, and in the second experiment we turn our embeddings to bilingual forms.

We discussed the factored translation model (see Section 2.3.1) and explained that they use a set of factors to represent words. In our experiments designed for Farsi and German, we use embeddings to define new factors. We have three factors of lemma, POS tag and morphology tag for each word. To lemmatize words we used our in-house morphological analyzer for Farsi and NLTK for English and German. We used our neural model (Passban et al., 2016a) for tagging. Using morphology-aware embeddings we cluster word vectors. We defined 1000 clusters for Farsi and German (due to their rich morphology) and 200 clusters for English. The morphology tag is the cluster label for each word. In this experiment everything is the same as in previous experiments. Table 5.6 shows the results for using morphology-aware embedding in the factored translation model to translate Farsi and German.

System	**En–Fa**	**Fa–En**	**En–De**	**De–En**
Baseline	21.03	29.21	15.25	20.13
Factored	22.61	30.91	16.07	21.15
Improvement	+1.58	+1.70	+0.82	+1.02

Table 5.6: Results for factored translation models enhanced with morphology-aware embeddings. Improvements in the last row are statistically significant according to the results of paired bootstrap re-sampling with $p = 0.05$ for 1000 samples.

In the second experiment we change monolingual morphology-aware embeddings to bilingual forms. In our Farsi and German experiments, instead of starting from random values and training bilingual embeddings, we initialize them with our morphology-aware embeddings. That is, we have the same feed-forward architecture discussed in the last section to train bilingual embeddings initialized using morphology-aware embeddings from Chapter 3. Table 5.7 reports related results to this experiment. In this experiment we basically repeat the same experimnet reported in Table 5.5 but in the previous experiment we had simple bilingual embeddings while in this one we enhanced our embeddings with morphological information. The embeddings are initialized via morphology-aware embeddings and then manipulated by our feed-forward model to learn cross-lingual dependencies. As the table shows when our embeddings are informed with morphological information through initializing with high-quality embeddings, they perform better.

System	**En–Fa**	**Fa–En**	**En–De**	**De–En**
Baseline	21.03	29.21	15.25	20.13
Extended	21.46	29.71	15.56	20.64
Extended$^+$	21.73	29.80	15.76	20.81
Imp.	+0.70	+0.59	+0.51	+0.68

Table 5.7: *Baseline* is a PBSMT model. *Extended* is a system enriched with the *sp2tp* feature where the neural model is initialized with random values. *Extended*$^+$ is a type of *Extended* where the neural model is initialized with morphology-aware embeddings. *Imp* shows the difference between *Baseline* and *Extended*$^+$ and indicates the impact of using morphology-aware embeddings. Improvements in the last row are statistically significant according to the results of paired bootstrap re-sampling with $p = 0.05$ for 1000 samples.

5.2.4 Training Bilingual Embeddings Using Convolutional Neural Networks

We designed a feed-forward architecture to learn bilingual embeddings. We also enhanced the model by use of morphology-aware embeddings. In this section, we propose a novel convolutional architecture which provides better bilingual embeddings.

In existing models (Mikolov et al., 2013a), the input data structure is a matrix and the setting is monolingual. Each column in the matrix includes an embedding (a vector) for one of context words. In our convolution model we expand the input matrix to a 2-plane tensor i.e. each plane is a matrix, in order to change the monolingual setting into a bilingual version. Training instances in our setting are pairs of translationally equivalent source and target sentences. The first and second planes include embeddings for source and target words, respectively. In embedding models, the target word (the word to be predicted) is not included in the input matrix. Similarly we do not have that in our input tensor. We randomly select a word either from the source or target side of (s, t) (a bilingual sentence pair) as the target word and remove all information about it and its translation(s)[3] from the input tensor. What remains after removing the target word and its translation(s) are

[3] Sometimes the alignment function assigns more than one target word to a given source word.

‘context words’. Embeddings for source context words are placed in the first plane by the order of their appearance in s. Then the counterpart/translation of each column in the first plane is retrieved (among the target-side embeddings) according to the alignment function (in Moses), and placed in the same column in the second plane.

The example below clarifies the structure of the input tensor. For s=*“I will ask him to come immediately .”* with a Farsi translation t=*“mn âz âû xvâhm xvâst ke fûrn byâyd .”*, the word alignment provided by a PBSMT engine is $a(s, t)$ = [0-0, 1-3, 2-4, 3-1, 3-2, 4-7, 5-6, 6-7, 7-6, 8-8] which is illustrated in Figure 5.5.

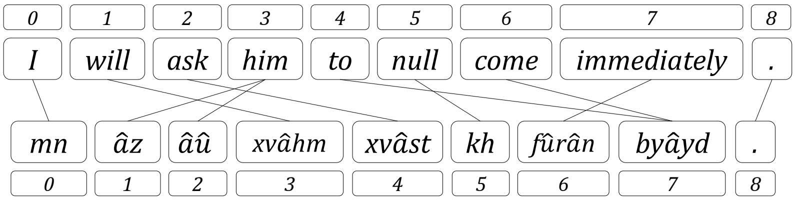


Figure 5.5: Word alignments provided by a PBSMT engine for a given (s, t) example. *‘him’* is selected as the target word so *‘him’* and its translations are excluded from the input tensor.

$a(.)$ is an alignment function which generates a list of i-j tuples. i indicates the position of a source word w_i^s within s and j is the position of the translation of w_i^s within t (namely w_j^t). If *‘him’* is randomly selected as the target word, *‘him’* and its translations (*‘âz’* and *‘âû’*) are all removed from the input tensor, and embeddings for the rest of the words are loaded into the input tensor according to i-j tuples. Embeddings for source words except *‘him’* are sequentially placed in the first plane. For the second plane, each column c includes the embedding for the translation of a source word located in the c-th column of the first plane. If the embedding of each word is referred to by $\mathcal{E}$, the order of source and target embeddings in the first and second planes is as follows:

$$p_1 = [\mathcal{E}(w_0^s), \mathcal{E}(w_1^s), \mathcal{E}(w_2^s), \mathcal{E}(w_4^s), \mathcal{E}(w_5^s), \mathcal{E}(w_6^s), \mathcal{E}(w_7^s), \mathcal{E}(w_8^s)]$$
$$p_2 = [\mathcal{E}(w_0^t), \mathcal{E}(w_3^t), \mathcal{E}(w_4^t), \mathcal{E}(w_7^t), \mathcal{E}(w_5^t), \mathcal{E}(w_7^t), \mathcal{E}(w_6^t), \mathcal{E}(w_8^t)]$$

Our CNN takes the 2-plane tensor as its input and combines its planes through a convolution function explained in Chapter 3. The first layer of our architecture is a lookup table which includes word embeddings. For each training sample (s, t), w_p is selected. Embeddings for context words are retrieved from the lookup table and placed within the input tensor based on the alignment function. Through the multi-plane convolution, planes are convolved together. The output of convolution is a matrix in our setting. Based on the structure of our multi-plane convolution, it is possible to map the 2-plane input to a new structure with one-to-many planes, but we generate a structure with only one plane (a matrix) in order to speed up the training phase. The new generated matrix contains information about source and target words, their order and relation. We reshape the matrix to a vector and apply non-linearity by a *Rectifier* function. To prevent over-fitting, we place a *Dropout* layer with $p = 0.4$ after *Rectifier*. The output of the *Dropout* layer is a vector which is passed to a *Softmax* layer. The network was trained using stochastic gradient descent and back-propagation (Rumelhart et al., 1988). All parameters of the model are randomly initialized over a uniform distribution in the range $[-0.1, 0.1]$. Filter, weights, bias values and embeddings are all network parameters which are tuned during training.

Using convolutional embeddings (instead of feed-forward embeddings) enables us to obtain better results. For example results of an experiment on the En–Fa pair are illustrated in Table 5.8 which is a confirmation to this claim.

System	**En–Fa**	**Fa–En**
Baseline	21.03	29.21
Feed-forward	21.46 (+0.43)	29.71 (+0.50)
Convolutional	21.58 (**+0.55**)	29.93 (**+0.72**)

Table 5.8: Experimental results on the En–Fa pair. The feed-forward model shows an SMT engine enriched with the *sp2tp* feature. The convolutional model is the same engine where embeddings were generated with the convolutional network. Improvements are statistically significant according to the results of paired bootstrap re-sampling with $p = 0.05$ for 1000 samples.

5.2.5 Human Evaluation

After training our SMT models, we encountered instances which show that our new features drastically change translations, so in addition to quantitative evaluations, we looked at the output of our engines to confirm that the proposed pipeline affects the translation process in a particular way. Table 5.9 compares translations between the baseline SMT system and the enriched model via the *sp2tp* feature. Based on our analysis, the new feature positively affects word selection. Extended translations include better words than baseline translations. Furthermore, translations provided by the extended models have better grammatical structures. They are also semantically close(r) to the reference translations. The second and third examples are a clear indication of these issues. For the third example, in spite of a very low BLEU score the translation provided by the extended engine is a perfect translation.

If we compare the baseline and reference translations in the Farsi example, there is almost nothing shared between these two translations, whereas in the extended translation we see that almost all words are identical to those of the reference. In the extended translation, مجموعه meaning *'collection'* is redundant based on the reference sentence while this is a perfect word should exist in the translation but the reference does not include it. The other differences with the reference are تو meaning *'you'* and میاید meaning *'will come back'*. The Farsi word برمیگرده meaning *'will be back'* in the reference translation is substituted by میاید in the extended translation which is not wrong, as these two words can be used interchangeably in Farsi, but BLEU is not able to recognize these linguistic similarities and the human evaluation is the best way to capture and study such phenomena. Similarly, the missing word تو in the extended translation is not problematic at all as the verb in Farsi by its very nature provides the pronoun information. Accordingly, تو is ineducable from the verb itself and its absence does not make the translation wrong or even less fluent.

In order to complete the evaluation process, we asked a native Farsi speaker to evaluate our results from the perspectives of fluency and adequacy. We prepared a list of 100 sentences, randomly selected from translations of the extended model.

System	Translation	sBLEU
	Example 1 (En)	
Reference	i would like to return to the matter of the embargo to conclude .	100
Baseline	i would like to revisit (to) the issue of the embargo in conclusion .	27.58
Extended	i would like to return to the issue of the embargo to conclude .	78.25
	Example 2 (En)	
Reference	subject to these remarks , we will support the main thrust of the fourçans report . however , we have to criticise the commission ’ s economic report for lacking vision .	100
Baseline	it is on these observations that we shall broadly the (main thrust) fourçans report (. however) we must also consider the economic report from the commission (’ s) a certain lack(ing) of breath	7.39
Extended	it is under these comments that we will approve in its broad outlines the fourçans report by UNK however , (we) the commission ’ s economic report a certain lack(ing) of breath .	22.37
	Example 3 (Fa)	
Translation	anyway your collection will have its emerald star back in .	-
Reference	به هر حال آن ستاره سبز به کلکسیون آکواریوم تو برمیگرده .	100
Baseline	به هر حال (آن) مجموعه جا دوستان آنها زمردین میارم .	13.74
Extended	به هر حال آن مجموعه سبز به کلکسیون آکواریوم (تو) میاید .	26.48

Table 5.9: Translation results from different models. Differences between reference and candidate translations are underlined and missing translations are shown within parenthesis. sBLEU indicates the sentence-level BLEU score.

The evaluator marked each translation’s fluency and adequacy with scores in the range of 1 to 5 which for the fluency feature 1 means *incomprehensible* and 5 means *flawless* and for the adequacy feature, 1 means *none* and 5 indicates *all meaning*. Results obtained from this experiment are reported in Table 5.10.

	Fluency		**Adequacy**	
	Base	Extended	Base	Extended
En→Fa	2.43	**2.63**	3.10	**3.43**

Table 5.10: Average fluency and adequacy scores for 100 translations. *Base* and *Ext* show the baseline and extended systems, respectively.

As Table 5.10 shows, the proposed model positively affects both the fluency and adequacy of translations. To discuss this experiment with more details, we report exact numbers in Figure 5.6. Each translation is marked with two scores.

Clearly, there are 100 fluency and 100 adequacy scores for the evaluation set. Results can be interpreted from different perspectives, some of which we briefly mention below. For the baseline model, the fluency rate of 38% of translations is 3, but this percentage is raised to 45% in the extended model. 27% of the baseline translations are disfluent (scale 2) but in the extended model this is reduced to 19%. For the adequacy feature the condition is even better. Translations which could not properly convey the meaning are changed to translations which are more acceptable for our evaluators. The number of bad translations is reduced in the extended model and correspondingly, the number of high-quality translations is increased.

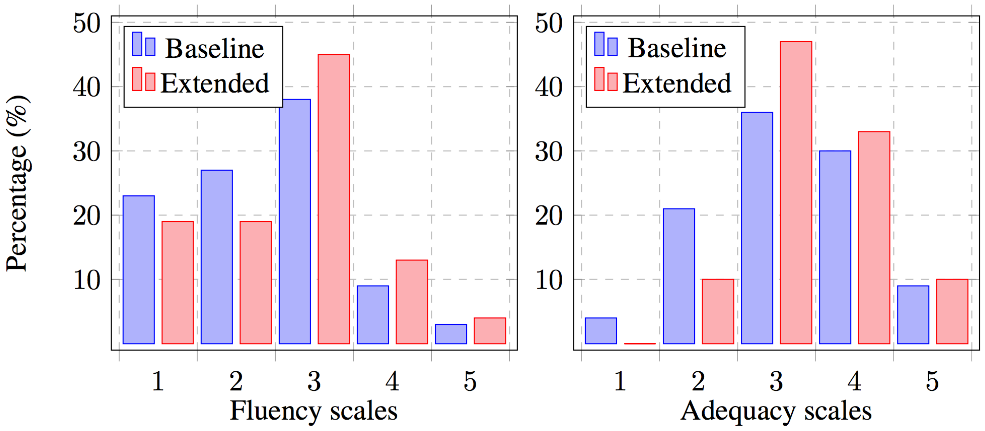


Figure 5.6: Human evaluation results on En→Fa translation.

5.3 Summary

In this chapter we introduced a framework to train bilingual embeddings and proposed techniques to incorporate such features into the SMT model. Our bilingual embeddings preserve semantic and syntactic information as well as cross-lingual similarities. Using bilingual embeddings we extract different word-, phrase- and sentence-level features for the SMT model which yield significant improvements. We also noted that it is not necessary to have bilingual embeddings. We boosted factored translation model through monolingual but morphology-aware embeddings. In another experiment we tried to enrich embeddings with morphological information which was also a successful model. The architecture of the embedding-learning network is the key concept in training. We tuned the convolutional function explored in Chapter 3 for the task of embedding training and generated better results than the feed-forward model. Finally, to conform that our techniques effectively help the SMT model and not only improve the BLEU score, we performed human evaluation and analyzed our results.

In the next chapter we will introduce a completely different paradigm for MT which is known as neural machine translation (NMT). NMT models are end-to-end purely neural models which do not follow the statistical pipeline but have their own architecture. We explain the framework and introduce our models which propose more compatible architectures for translating MRLs.

Chapter 6

Morpheme Segmentation for Neural Machine Translation

In the last chapter we studied SMT and methods by which we can incorporate morphological and neural information into SMT. In this chapter[1] we try to address the same problem with neural models. Recently, NN-based models have become increasingly popular in different NLP fields including MT. NMT models have been proposed as successful alternatives for conventional statistical models, which not only boost existing systems and enhance their quality but also introduce new research lines to further enrich the field. NMT provides a framework that enables us to incorporate different types of annotations and external knowledge much better than the existing log-linear model. The whole translation process is based on millions of different features that are learned in supervised and unsupervised manners. Accordingly, there is no need for *feature engineering* and everything is performed (semi-)automatically, which is the main difference between neural and log-linear approaches. In the log-linear model (see Chapter 2), different features are defined *a prior* for the system, whereas the neural engine starts from a random setting for features and gradually optimizes to reach the optimal configuration.

[1] In this chapter we frequently refer to Models A to D which we mean the segmentation models proposed in Chapter 4.

In this chapter we attempt to provide a comprehensive analysis of NMT models. We introduce the framework and review the literature to summarize existing models in this area. Then, we propose methods which are particularly designed for translating MRLs. We perform our experiments on German, Russian, and Turkish. We select these languages for specific reasons. German has a complex morphology which includes almost all morphological behaviour (fusional structures, agglutinative structures, compounds etc.). Furthermore, all well-known models have an experimental analysis on German which makes it an important language for our comparative experiments. Russian has a fusional morphology which is suitable to study the strength of character-based models. Finally, Turkish is a highly agglutinative language by which we can study the impact of our morpheme-segmentation models.

6.1 Neural Machine Translation (NMT)

NMT is not a new research field as its history goes back to almost twenty years ago when Forcada and Ñeco (1997) proposed the encoder-decoder framework for the first time. In that work a simple neural framework was proposed for basic translation using finite state automata. In the proposed architecture the source side is encoded into a numerical representation and outputs are sampled from the encoded source input. The model was very basic with a limited number of neurons. Forcada and Ñeco (1997) posited that the encoder-decoder framework is potentially a very powerful alternative for sequence-modeling tasks but the strength of the model could not be investigated at the time because of the lack of computational resources. Recently, several models (Schwenk et al., 2006; Kalchbrenner and Blunsom, 2013; Cho et al., 2014b; Sutskever et al., 2014) were proposed based on the same framework that could efficiently benefit from that architecture to perform MT and language modeling.

The intuition behind all these models is the same with slight differences that we discuss here. As the model in Cho et al. (2014b) directly addresses the encoder-decoder framework, we discuss the model in detail. The model consists of two RNNs. One RNN encodes the source side into a fixed-length representation. By the encoding, an internal representation of the sequence (sequence-level embedding) is produced. The other RNN is fed with source-side information to decode a sequence of target symbols. Both the encoder and decoder modules are trained jointly to maximize the conditional probability of the target sequence given a source sequence. This framework has the potential of being used as an independent end-to-end translation engine as well as being embedded into conventional MT pipelines. Furthermore, it is able to perform any sequence-to-sequence mappings such as parsing (Luong et al., 2015a; Konstas et al., 2017), POS tagging (Ma and Hovy, 2016), caption generation (Laokulrat et al., 2016) etc.

More formally, the model can be described as follows. For a given input sequence $\mathbf{x} = x_1, ..., x_n$, at each time step t, the encoder's hidden state is updated as in (6.1):

$$s_t = f(s_{t-1}, x_t) \tag{6.1}$$

where $f(.)$ applies non-linearity and s_{t-1} is the previous state. The encoder consumes all input symbols until the end of the sequence is arrived at. The last hidden state h_n is a summary of all previous states and represents $\mathbf{x}$. Then the model freezes the encoder and switches to decoding mode. The hidden state of the decoder is initialized with the input representation, i.e. the decoder is informed about the source sequence. In NMT, this information is referred to as *context* ($\mathbf{c}$). At each time step t, the decoder's hidden state h_t is updated conditioned on the previous state h_{t-1}, the last generated target symbol y_{t-1} and $\mathbf{c}$, as formulated in (6.2):

$$h_t = f(h_{t-1}, y_{t-1}, \mathbf{c}) \tag{6.2}$$

To sample the next target symbol both h_t and $\mathbf{c}$ are used. The decoder needs to compute a probabilistic value over the target vocabulary, as in (6.3):

$$P(y_t|y_{t-1}, y_{t-2}, ..., y_1, \mathbf{c}) = g(h_t, y_{t-1}, \mathbf{c}) \tag{6.3}$$

where $g(.)$ is a function like *Softmax* which generates valid values in the range [0,1]. Clearly the next target word is selected based on a history which is provided by h_t. These steps explain the most basic model for NMT, but there are more sophisticated alternatives, such as using the beam search algorithm for decoding (Sutskever et al., 2014) or more complex recurrent models (Chung et al., 2016).

Simple RNNs are not able to remember long-distance dependencies. In order to address this shortcoming, RNNs have been equipped with memory units. Hochreiter and Schmidhuber (1997) proposed *long short-term memory* (LSTM) networks to this end. Cho et al. (2014b) also proposed a variation of LSTMs called *gated recurrent unit* (GRU), which is a simplified model with an almost equivalent computational power. These models are frequently used in NMT. A high-level view of the framework is illustrated in Figure 6.1.

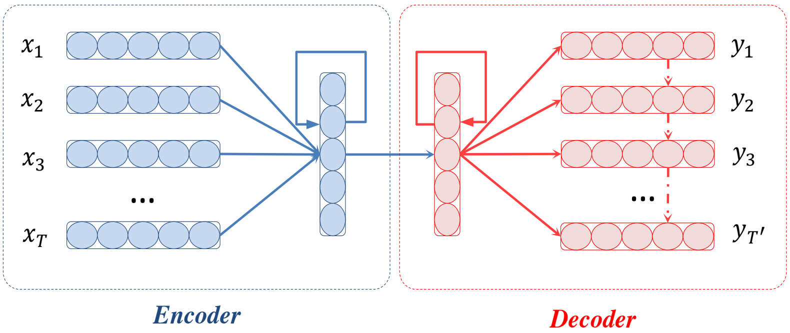


Figure 6.1: A high-level view of the encoder-decoder architecture. The direction of arrows show the impact of each unit on other units. The information flow from s_t to h_t starts when all input symbols have been processed.

The basic encoder-decoder model suffers from a serious problem, whereby an input sequence is squashed into a fixed-length representation and the decoder has to sample everything based on the representation. Bahdanau et al. (2014) demonstrated that this is a bottleneck for NMT, especially when the input sequence is long or has a complex structure. The other problem with the basic architecture is that the contribution of all source words is equal, because they (all) are summarized into one vector. However, this rarely happens in practice. In real-world scenarios, each target word is affected by a specific set of source words, not all of them at once. To cope with this problem the attention mechanism was proposed (Bahdanau et al., 2014), by which the decoder searches different parts of the input sequence to find the most relevant words for the prediction phase. The model thus establishes a soft alignment module over words. We know that **c** is computed by a nonlinear computation applied to all encoder hidden states, as in (6.4):

$$\mathbf{c} = f(\{s_1, ..., s_n\}) \tag{6.4}$$

where in the simplest scenario $\mathbf{c} = s_n$. In attention-based models **c** is dynamically defined for each state of the decoder, which gives us (6.5):

$$p(y_i|y_1, ..., y_{i-1}, \mathbf{x}) = g(h_i, y_{i-1}, \mathbf{c}_i) \tag{6.5}$$

Each state has its own context vector which is exclusively defined for y_i. $\mathbf{c}_i$ is a weighted summation over all encoder states, so that lower (or zero) weights are assigned to irrelevant words and the impact of relevant words is maximized by assigning higher weights. This mechanism can be formulated as in (6.6):

$$\mathbf{c}_i = \sum_{j=1}^{n} \alpha_{ij} s_j \tag{6.6}$$

where α denotes the weight assigned to each state, as in (6.7):

$$\begin{aligned} \alpha_{ij} &= align(s_j, h_{i-1}) = \frac{\exp{(e_{ij})}}{\sum_{k=1}^{T_x} \exp{(e_{ik})}} \\ e_{ij} &= a(s_j, h_{i-1}) \end{aligned} \tag{6.7}$$

$e(.)$ denotes an alignment model and scores the relevance of source words to the i-th target symbol. $a(.)$ is a combinatorial function that can be modeled through a simple feed-forward connection, as in (6.8):

$$a(h_{i-1}, s_j) = v_a^\intercal \tanh(W_a h_{i-1} + U_a s_j) \tag{6.8}$$

v_a (vector), W_a and U_a (matrices) are all network parameters. The difference between the basic encoder-decoder model and its extension with an attention mechanism is illustrated in Figure 6.2.

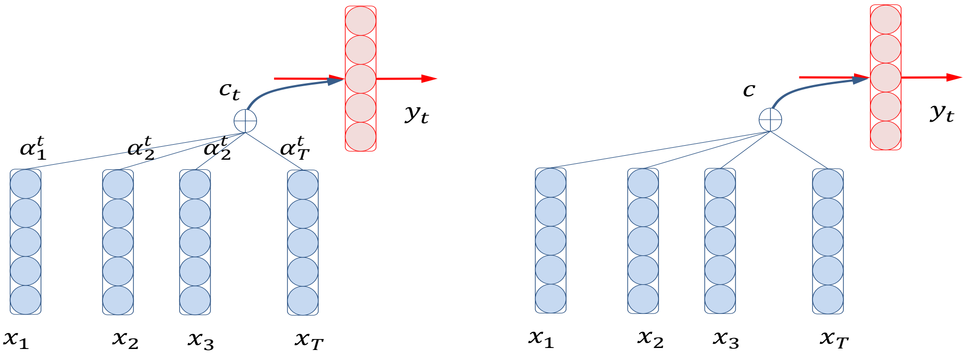


Figure 6.2: The network on the right-hand side depicts the basic encoder-decoder model which summarizes all input hidden states into a single vector. The network on the left-hand side is an encoder-decoder model with attention which defines a weight for each of the input hidden states. α_i^t indicates the weight assigned to the i-th input state to make the prediction of the t-th target symbol.

In all encoder-decoder models and their attention-based extensions, network parameters are jointly learned during training to maximize the translation probability of a target sequence given a source sequence, for all training instances, as in (6.8):

$$\max_\theta \frac{1}{M} \sum_{m=1}^{M} \log(\mathbf{y}_m | \mathbf{x}_m) \tag{6.9}$$

where θ is a set of network parameters and M indicates the size of the training set.

6.2 Literature Review

In this section we try to cover NMT models which showed promising results and introduced successful solutions/architectures. Models are discussed in four main sections. Section 6.2.1 introduces the problem, reviews the main/basic architecture, studies models and techniques which can boost the basic architecture, and explains models which addressed different aspects of the translation problem such as incorporating monolingual features into the NMT pipeline or the impact of morphological information. Section 6.2.2 explains how flexible and powerful the NMT architecture is, which can be used for other NLP tasks such as image/video caption generation or multi-modal MT. It also reviews some multi-purpose networks in order to train a single neural model to learn multiple NLP tasks. Section 6.2.3 studies potential problems we can face when training deep neural models. As we know, NMT engines are very deep models and it is quite challenging to find an optimal configuration for a deep model with millions of parameters. This section addresses this problem and introduces simple techniques to train effective and efficient NMT engines. Finally, Section 6.2.4 reviews hybrid models which benefit from neural techniques to improve existing SMT models.

6.2.1 Main Models in NMT

As previously mentioned, the main idea of using NNs for modeling sequences started with Forcada and Ñeco (1997), where a very simple network with a handful of neurons was used in this regard. The paradigm was successful in theory but it failed in practice, due mainly to the limitation of computational resources available at the time. The research in the field has not stopped as NNs are now one of the main computational models in artificial intelligence (and MT). Accordingly, other similar models such as Bengio et al. (2003) and Schwenk (2010) were proposed to address the MT problem. They were able to achieve some promising results, but neural models were never considered as serious alternatives for machine translation, language modeling, and other similar tasks at that time. With the appearance of new technologies and powerful computational tools/models, the field started to change, to a point where neural models have become the best solutions for many problems.

Kalchbrenner and Blunsom (2013) proposed a novel NN-based translation model with better perplexity than conventional and statistical models. The model used a convolutional architecture. Auli et al. (2013) proposed a similar but recurrent model for language modeling and translation. They used the same model to re-rank sequences to boost the performance of existing non-neural models. These networks are comparable to state-of-the-art statistical models. However, for the first time Cho et al. (2014b) proposed a model with a pure neural architecture that was able to outperform statistical models. The intuition behind the model is extensively explained in Cho et al. (2014a). They discussed different perspectives of the model and discussed what such a model can learn.

Although the model by Cho et al. (2014b) could outperform other models, it had some serious problems which have now been solved. One of the main problems was the attention problem (discussed in the last section). Bahdanau et al. (2014) mitigated the problem by proposing an attention mechanism. The basic attention mechanism is a simple summation over all source-side hidden states. Using such a mechanism provides a very dense and complex representation which makes the decoding of the target string very hard and inaccurate. Luong et al. (2015c) proposed a more effective attention method whereby an appropriate position (instead of considering all states) is identified within the source sequence. The intuition is that the target state h_i is mostly affected by a specific source symbol and a limited set of context words around it. Instead of assigning weights to all states, a limited subset of them are selected. The correct (most appropriate) position p_i is set according to (6.10):

$$p_i = S.\sigma\big(v_p^\intercal \tanh(W_p h_i)\big) \tag{6.10}$$

where S indicates the source-sentence length and v_p and W_p are network parameters to set up the p_i value. The sigmoid function $\sigma(.)$ fluctuates in the range $[0, 1]$ so its multiplication with S gives a position in the range [0,S]. W_p acts as a mapper which takes the current state of the decoder h_i and predicts the most relevant source position. By use of p_i, attention weights are defined as in (6.11):

$$\alpha_{ij} = align(h_i, s_j)\exp\left(-\frac{(j-p_i)^2}{2\omega^2}\right) \tag{6.11}$$

In Equation (6.11), the decoder always focuses on a fixed-dimensional window of $2\omega + 1$ states with s_{p_i} at the centre (ω states before and ω states after s_{p_i}). This effective approach to attention significantly improved the model.

The network in Cho et al. (2014b) is based on gated units. Gated recurrent units extend simple RNNs with memory units but they are not as powerful as LSTMs. Motivated by such a shortcoming, Sutskever et al. (2014) proposed another model based on LSTM units. This work is one of the most important models in the field of NMT as it inspired many other models.

The models by Bahdanau et al. (2014); Cho et al. (2014b); Sutskever et al. (2014) are known as the base models of NMT. Researchers started to propose new architectures and extensions to make these models as powerful as possible. A large body of recent work studied the *open vocabulary* problem, as NMT models have serious problems with large vocabularies and OOVs. When the size of vocabulary grows to even modest size, neural models fail to provide acceptable translations. Jean et al. (2015) changed the neural architecture for target word prediction and proposed an efficient way of computation to handle large sets of vocabularies. The technique is very similar to negative sampling (Goldberg and Levy, 2014). For the same problem, Luong et al. (2015d) proposed a post-editing phase on translation results to substitute unknown words with their translations. This is a very simple technique but showed promising improvements over the baseline model. Luong and Manning (2016) manipulated the encoder to achieve the open vocabulary setting. The model benefits from a hybrid representation. Words that are known are treated as they are, but for OOVs, a word-level representation (embedding) is changed to a character-level representation. Any unknown word is represented as a set of character embeddings. This model is not only useful for OOVs but can also be used for MCWs.

In order to handle MCWs at the encoder side, Sennrich et al. (2016b) decomposes words using the *Byte-pair* segmentation scheme. The *Byte-pair* model is a simple form of data compression in which the most frequent pair of consecutive bytes (characters) of a corpus are combined together to make a new atomic symbol. This is a simple but efficient count-based model. Sennrich et al. (2016b) does not change the neural architecture but only manipulates words through a preprocessing step. Unlike this model, Costa-jussà and Fonollosa (2016) drastically changed the neural architecture, with words decomposed into characters. Character embeddings are combined through a convolutional function to construct the word-level representation. An RNN module is placed on top of the convolutional layer to connect words to each other, in order to provide the source-side representation. Costa-jussà and Fonollosa (2016) applied the neural architecture proposed by Kim et al. (2016) to NMT.

Monolingual features are as important as bilingual features in MT. Language models are the main source of monolingual knowledge for SMT models which help provide more fluent translations, but NMT models do not directly benefit from such useful information. Vaswani et al. (2013) and Gülçehre et al. (2015) proposed models to embed language models into NMT systems. There are two main approaches in this regard. In one approach NLMs are used to re-rank MT outputs. In the other approach different techniques are proposed to add the language-modeling component as an additional source of information together with the decoder. For example, to generate a target translation, a sequence is selected which maximizes both the translation and language-modeling scores. The score from the decoder shows how good the translation result is in terms of adequacy, and the score from the language model shows how fluent it is. This architecture could be interpreted as an interpolation of a decoder and a language model which are jointly trained to make the final prediction. Sennrich et al. (2016a) proposed a slightly different pipeline to use monolingual features. They generate some artificial (synthetic) sentences to enrich the training dataset. They also back-translate target sentences to make the parallel corpus as rich as possible and train an NMT system on a very large parallel corpus.

NMT models work based on millions of parameters which are learned by the network through training. They enable the neural architecture to find the best translation but have no clue about the syntactic and/or semantic structure of languages. It could be quite useful if we feed neural models with such information. A small number of research papers have proposed models to enrich the existing set of (numerical) features by explicitly defining complementary linguistic features. Sennrich and Haddow (2016) implemented a factor-based model in the neural framework. Each word is represented by a set of factors, and a concatenation of all factors is considered as the source-sentence representation. Li et al. (2016) address another linguistic point, by incorporating a named-entity recognition module which separates name entities from other constituents. Names are translated separately (or kept unchanged) from other parts of the sentence and the new sentence is manipulated by the NMT model. Considering this linguistic feature enabled the system to provide more precise and fluent results. There are a limited number of papers which explicitly incorporate linguistic knowledge into the neural pipeline. Clearly, neural models require linguistic information but how this should be incorporated efficiently and how such information should be embedded is still an open question.

6.2.2 Multi-Task Multilingual NMT Models

NMT models have been proposed for MT purposes, but they can be considered as general-purpose models for other sequence-learning tasks. Luong et al. (2015b) use a single DNN for multi-task sequence-to-sequence learning. They have multiple inputs and multiple outputs. They designed the network for many-to-one and one-to-many settings, e.g. the network is fed with an English sentence whose POS annotations, parsing labels, and translations are generated at the output. This is a one-to-many task. In the many-to-one setting they use several encoders and one decoder. For example, on the source side a German sequence along with an image representation of the sentence is provided to the network to generate the target (English) translation. This work elaborates a very important aspect of DNNs. Since everything relies on numerical values (network parameters), there is no restriction on input/output signals and any type of data (text, image, video etc) could be manipulated using the same neural model. In one-to-many settings, different types of outputs can be generated using a single source-side representation and this is possible only in neural models. In non-neural models, each task requires a specific solution and architecture, as the data type is different. Similarly, in neural models as everything is changed into numerical forms, different inputs with different data types can be combined together.

The idea of using multiple encoders/decoders in a single network and training them jointly is an interesting idea that makes sequence-learning models very flexible to perform quite complex tasks. The auxiliary encoder/decoder channel(s) makes sequence representations richer which yields better results. Firat et al. (2016a) used the same idea for multi-way multi-lingual NMT. The model includes multiple encoders and multiple decoders which are jointly trained together. Each encoder-decoder pair is responsible for translating a particular source language into a particular target language, but the key feature of the model is the use of multilingual information. Since all encoders and decoders are trained together, the encoder for a specific language pair has information about other languages. This architecture can be considered as a multi-source translation engine which uses several languages to translate into a specific target language. The other important advantage of the model is sharing parameters among different translation paths. For example, to translate L_1 and L_2 into L_3 and L_4, we have to train four (all possibilities) different NMT models, which means four encoders, four decoders, four attention mechanisms etc. with millions of parameters. In this pipeline we only need to have two encoders and two decoders and other parameters and modules such as the attention component and most of the weight parameters could be shared across languages. This is a significant achievement in terms of time and computational complexities.

The multi-path translation framework builds the source-side representation by combining information from different source channels (languages), where one of the source languages is the main one and other additional languages are incorporated to enrich its representation as much as possible. This architecture looks suitable for translating low-resource languages. A language with a small amount of data could rely on other source languages, or –in the ideal case, as all encoders are sharing some parameters– the source-side representation could be generated completely based on other languages without using the low-resource language at all. Firat et al. (2016b) and Johnson et al. (2016) developed zero-resource and zero-shot models in this regard. These models target languages for which (no or) only a small amount of parallel sentences are available. They use NMT models in two ways. In the first setting pivoting is applied. To translate from L_1 into L_2 a pivot language L_p is used, which means L_1 is translated into L_p first, and L_2 translations are generated from L_p sentences. In the second scenario, first L_1 is mapped into a rich-resource language, for which there is a large amount of parallel sentences between that language and L_1. Afterwards, using the many-to-one architecture, a small number of L_1 sentences are added to the result of the first phase to make the final translation pass.

In sum, we have covered several aspects of NMT models. We described how recent research papers tried to address the (linguistic) complexity problem by proposing different word-segmentation schemes and attention mechanisms. They also provided solutions to incorporate linguistic information and performed other sequence-learning tasks. Some models targeted the data scarcity problem and tried to tune models for low-resource languages.

6.2.3 Effective Training Techniques for Deep Neural Models

All NMT models suffer from a serious problem. DNNs are quite expensive models which require several weeks to be trained, and compared to existing statistical models they are considerably slower at run time. Motivated by such problems Kim and Rush (2016) and See et al. (2016) have proposed more efficient models. In the first solution (Kim and Rush, 2016) a high-quality model is trained. The model is a large but precise translation model which consists of millions of parameters and takes a long time to be trained. After making the main model, a child model is trained based on it. The child model does not deal with the task itself nor the parameters. It only tries to imitate the behaviour of the main model. Accordingly, the child model is a small model which tries to learn a simple classification task, namely to make consistent predictions with those of the main model. The main model has to capture different types of morphological, syntactic, and semantic complexities of a source language and translate them into a target language. The parameter set (weights, biases etc.) in the main model preserves information about languages, but the child model has just a limited number of parameters which represent properties of the main model. The child model can be seen as a sub-model which learns only one (or some limited) aspect of the problem and all it has to do is to imitate the main model regardless of the translation task and its complexities.

The second solution (See et al., 2016) uses a simpler idea. The goal of training NNs is to find optimal weight values and connections, which means we do not necessarily need precise values so that a rough estimation might be enough to reach the network configuration. In the model of See et al. (2016), useless weights and connections are pruned using a threshold. Furthermore, weights are represented with fewer floating points, with weights rounded to the nearest value. This simple technique is able to reduce the number of parameters by up to 40%.

6.2.4 Hybrid Statistical and Neural Models

Nowadays NMT engines are state-of-the-art models but this does not mean that the SMT approach is redundant as SMT models still perform well for many settings. There is also a new research line which tries to mix the two approaches. The SMT pipeline involves different components (see Chapter 2). Some research papers have proposed models to replace or boost each of these components with neural alternatives. For example, Duh et al. (2013) use NNs to select better sentences to train high-quality SMT engines. Yang et al. (2013) and Tamura et al. (2014) used neural models instead of the EM-based model to perform word alignment. Li et al. (2014) designed a neural reordering function. Hybrid (NMT+SMT) models are not limited to these examples and we mentioned here only some of the most important instances.

6.3 Improving NMT for MRLs with Subword Units

The main interest of this section is to focus on dealing with morphologically complex structures in NMT, by segmenting them into more machine-understandable units via different morpheme-segmentation models. Complex structures could reside on both source and target sides. One way to cope with this problem is to manipulate training corpora via morpheme segmentation models (as we do in this section). In this approach we do not need to treat source and target sides differently, as source, target, or both sides can be morphologically rich and the segmentation model is able to handle these different settings. The other way to deal with this problem is to fine-tune neural architectures in order to adapt them to work with MRLs. Character-based decoding (Chung et al., 2016) is an example of this approach, in which a target word is generated character by character instead of sampling the surface form. Comparisons between character-based and other decoders demonstrate that character-based decoding performs considerably better, and it can be considered as a potential solution when we translate *into* MRLs. However, we still have problems when translating *from* MRLs. There are models (Costa-jussà and Fonollosa, 2016; Lee et al., 2016) which have been proposed particularly for translating from MRLs, but they do not explicitly address the problem. They are character-based models that only empower the encoder-decoder model with convolutional modules with the hope that the new model will be able to provide better results in the presence of complex inputs, but they do not benefit from useful morphological information. This gap persuades us to propose a better model for translating from MRLs which is the topic of Chapter 7.

In this chapter we apply our segmentation models to reduce the morphological complexity for NMT. We also compare our models to existing state-of-the-art models. Our focus in this chapter is on translating into MRLs. However, we also provide experimental results for other settings. More specifically, we want to compare complex character-based decoders to simple neural models that work with subunits, and find out whether we can surpass those complex architectures with simpler counterparts. In the next chapter we will demonstrate that segmentation alone is not enough when we translate from MRLs, so we will propose a novel NMT architecture in this regard.

Although NMT has recently achieved impressive results and become the first alternative to produce state-of-the-art MT translations, it still has serious problems with OOVs and rare words. It also fails in the presence of large vocabularies. It has been discussed earlier that these phenomena are commonly encountered in MRLs, which makes their translation so challenging. Morpheme segmentation is the most common solution proposed in this regard. When MCWs are decomposed into simple units, NMT engines no longer need to work with complicated surface forms, which boosts their functionality. However, using segmentation models also raises other types of problems.

There are different methods to extract subword units from MCWs. A group of segmentation models relies on linguistic knowledge and tends to extract linguistic morphemes, such as *Morfessor* (Smit et al., 2014). The main problem with this category is the difficulty of developing such models. A morphological analyzer for a particular language may not always be available. Moreover, existing models which work for a handful of languages do not perform very precisely, as the task of morpheme segmentation is quite challenging.

There is another group of models which performs at the character level, and breaks up words into characters. We demonstrated earlier (see Section 4.2) that for character-level segmentation we need complex neural architectures. This expensive requirement makes the translation process even more complicated. Character-level segmentation also increases the length of the sequence. We know that neural models have serious problems with long sequences, so we only prefer character-level segmentation where there is no alternative.

Finally, there is a third group of models which leverages statistical information and segments words based on frequency information. We introduced examples of these models in Section 4.3. The *Byte-pair* model (Sennrich et al., 2016b) also belongs to this category. These models do not require linguistic knowledge which reduces the cost of developing such models and makes them more popular. However, optimizing these models for the specific task at hand could be difficult. For example, the *Byte-pair* model performs differently when vocabulary size varies, or different results are obtained when the external parameter of our segmentation model is changed. In some (small) neural models it is possible to find the best value of the external parameter empirically, by setting a random value to the parameter, evaluating the network's performance, and updating the parameter with respect to the network's performance. We carried out a similar process in Section 4.5 as it takes a limited time to retrain an NLM, but it is too expensive to do the same for NMT as the same process (retraining) can take at least three weeks for any NMT engine.

As far as NMT models are concerned, we preferably need segmentation models that are fast and have no (or a minimum number of) external parameters. This was the main reason we proposed our dynamic programming-based model (Model D) in Section 4.3.4. We applied the model to the problem of neural language modeling, but because of its specific properties it can also serve the NMT field. In the next section we explore different segmentation models and compare different settings for translating into MRLs.

6.3.1 Experimental Study

In order to make our work comparable with other existing models we tried to use a similar architecture. Our NMT engine is a four-layer encoder-decoder model with attention. We trained the model using SGD and Adam (Kingma and Ba, 2015). The model is trained until the BLEU score (Papineni et al., 2002) on the validation set stops improving. The gradient norm is clipped with the threshold 1.0. All weights in our network are initialized from a uniform distribution $[-0.01, 0.01]$. The beam size is 12 and the mini-batch size is 50. We have bidirectional GRUs at the input layer followed by another unidirectional GRU layer. The encoder includes these two layers. The decoder consists of two unidirectional GRU layers. The GRU layer size is 1024 and all tokens are represented with 512-dimensional embeddings.

We use German and Russian in our experiments as all existing models proposed for this task have studied these languages. Moreover, these two languages include morphologically complex constituents which make them appropriate for our experimental study. To train our models we use the standard `WMT-15` datasets.[2] We use `newstest-2013` for the development sets and `newstest-2015` for testing our models. In addition to these languages we also provide experimental results for Turkish, which is a highly agglutinative language and can clearly reflect the impact of different segmentation models. As our English–Turkish training corpus we use the `OpenSubtitle2016` collection (Lison and Tiedemann, 2016)[3] from which we randomly select 4M sentences for the training set and 3K for each of the development and test sets. Table 6.1 reports some statistics about our corpora.

As the table shows, our segmentation model is able to map very large vocabulary sets into smaller sets with a reasonable number of tokens. The simplification provided by our segmentation model considerably mitigates the complexity of the problem and boosts NMT engines. In order to process large datasets in NMT, it is very common to keep frequent words unchanged and substitute infrequent words

[2] `http://www.statmt.org/wmt15/translation-task.html`

[3] `http://opus.lingfil.uu.se/OpenSubtitles2016.php`.

Corpus	**De–En**		**Ru–En**		**Tr–En**	
	German	English	Russian	English	Turkish	English
Sent.	4.2M		2.1M		4.0M	
Token	96,406,624	103,905,690	39,819,227	44,026,780	17,915,076	24,875,286
Type	390,726	268,133	317,859	181,600	178,672	108,699
dp	54,370	19,777	45,375	13,569	10,097	5,255
mr	36,488	27,612	27,266	21,142	13,831	18,691

Table 6.1: Sent. shows the number of parallel sentences in the corpus. Token and Type indicate the number of words and unique words, respectively. *dp* is the number of unique tokens generated by Model D and *mr* is the number of unique tokens generated by Morfessor.

with a specific token such as *UNK*. This process would change the surface form of a significant number of words, which obviously affects translation quality. Accordingly, for these situations models such as ours could be the best alternative, as it changes nothing and preserves all information.

6.3.1.1 Experimental Results

We studied all recent models that we are aware of which provide experimental results for German and Russian, and compare them to our models. We also report some experimental results on Turkish. Results obtained from our models and other state-of-the-art models are reported in Table 6.2.

There are 4 systems reported for English→German in Table 6.2. The model of Chung et al. (2016) is an encoder-decoder model with a character-level decoder. It takes sequences of *bp* tokens as its input and samples either a character or a *bp* token at each times step. The model is quite powerful and introduced the effective implementation of character-based decoding for the first time.

The other model belonging to Firat et al. (2016a) is known as the multi-way multilingual NMT model. It benefits from multilingual information for translating a language pair. In this model many languages contribute to the building of a representation of the source sentence which is then translated into a particular target sentence. The model has several encoders and several decoders.

	Model	**Source**	**Target**	**Direction**	**BLEU**
En→MRL	Chung et al. (2016)	*bp*	*bp*	En→De	20.47
	Chung et al. (2016)	*bp*	*char*		21.33
	Firat et al. (2016a)	*bp*	*bp*		20.59
	Sennrich et al. (2016b)	C2/50K	C2/50K		22.8
	Our model	*dp*	*dp*		**23.41**
	Chung et al. (2016)	*bp*	*bp*	En→Ru	25.30
	Chung et al. (2016)	*bp*	*char*		**26.00**
	Firat et al. (2016a)	*bp*	*bp*		19.39
	Sennrich et al. (2016b)	C2/50K	C2/50K		20.90
	Our model	*dp*	*dp*		24.71
	Chung et al. (2016)*	*bp*	*char*	En→Tr	18.01
	Our model	*bp*	*bp*		16.76
	Our model	*dp*	*dp*		**21.05**
MRL→En	Costa-jussà and Fonollosa (2016)	*word*	*word*	De→En	18.83
	Costa-jussà and Fonollosa (2016)	*char*	*word*		21.40
	Firat et al. (2016a)	*bp*	*bp*		24.00
	Lee et al. (2016)	*bp*	*char*		25.27
	Lee et al. (2016)	*bp*	*char*		25.83
	Our model	*dp*	*dp*		**27.13**
	Firat et al. (2016a)	*bp*	*bp*	Ru→En	22.40
	Lee et al. (2016)	*bp*	*char*		22.83
	Lee et al. (2016)	*char*	*char*		22.73
	Our model	*dp*	*dp*		**23.07**
	Chung et al. (2016)*	*bp*	*char*	Tr→En	23.11
	Our model	*bp*	*bp*		23.17
	Our model	*dp*	*dp*		**23.46**

Table 6.2: *bp*, *char*, and *dp* show the *Byte-pair*, character-level and dynamic programming-based encodings. The bold-faced number in each category is the best BLEU score. The second and third columns show the data format for the encoder and decoder. C2/50K means the model keeps the 50K most frequent words and segments the remainder into bigrams. De, En, Ru, and Tr stand for German, English, Russian, and Turkish, respectively. * indicates that the original work did not provide the result for that specific experiment and the result belongs to our implementation of that architecture.

The third system for English→German is the model of Sennrich et al. (2016a), which proposed the *Byte-pair* model. The paper reports different improvements over the baseline model using different *Byte-pair* settings but the best performance is achieved when the 50K most frequent words are selected and the reminder is segmented into bigrams (C2/50K). This shows that a simple technique can outperform *Byte-pair* and provide better results. *Byte-pair* suffers from some problems as it is an unsupervised model which only takes the frequency criterion into account. However, we do not mean that *Byte-pair* is not useful as it served has NMT models very well.

The last row in the English→German section illustrates our model which is able to outperform all other models. It shows that we do not necessarily need complicated neural architectures such as those of the multi-way multilingual or character-based models, and in the presence of a good segmentation model such as ours or *Byte-pair* we are able to provide comparable or even better results with much simpler architectures.

For the English→Russian setting there is no new model (apart from the aforementioned ones). For this setting the best performance is obtained by the model of Chung et al. (2016), which is not unsurprising. Russian is a fusional language with morphologically rich structures and it is very challenging to apply segmentation models for this language, so character-based decoding could be the best alternative when translating into Russian. However, our model also provides a close result to the best model with the basic encoder-decoder architecture.

For English→Turkish we compare four models. For the first two systems we reimplemented the character-based decoder of Chung et al. (2016). For the last two systems we used our own model with *bp* and *dp* tokens. The number of *bp* and *dp* tokens are the same. Results from this part demonstrate that our simple model outperforms the complex character-based model due to the effective segmentation technique used in our model. It also shows that for the same neural architecture, tokens generated by our segmentation model are more useful than those of *Byte-pair*.

Apart from the En→MRL(De|Ru|Tr) setting, we also report experimental results for the opposite direction, namely MRL→En. The table reports results from the model of Costa-jussà and Fonollosa (2016) for the De→En direction. The model has a complex architecture where there is deep a convolutional module at the first layer to capture source-side complexities, which makes the model suitable for translating from MRLs. This complicated architecture is also unable to compete with our simple architecture enriched with high-quality morpheme segmentations. For the other two languages (Russian and Turkish) we can see a similar trend which means that *dp* tokens are able to positively affect the translation of the MRL→En direction similar to the previous direction.

Table 6.2 shows that our simple model with the *dp*→*dp* setting provides the best (or very close to the best) BLEU score for all experiments. We believe that our segmentation model serves the NMT pipeline well, but it should also be interesting to see the impact of other models and see how different segmentation schemes work with each other. To this end, we designed another experiment whose results are summarized in Table 6.3.

		Target				
		w	*mr*	*bp*	*dp*	*char*
Source	*w*	20.60	20.79	20.77	20.75	20.77
	mr	17.93	19.12	19.01	18.94	19.03
	bp	21.00	21.45	23.19	22.91	23.33
	dp	21.13	21.47	23.01	**23.41**	23.40
	char	19.87	22.71	23.18	23.27	23.21

Table 6.3: Impact of different morpheme-segmentation schemes. *w* is the word's surface form and *char* is the character. *mr*, *bp*, and *dp* show the unique tokens generated by *Morfessor*, *Byte-pair* and *Model D*. Numbers are BLEU scores for English→German.

In Table 6.3, for *char*→*char* we use the fully character-based model of Lee et al. (2016), for →*char* we use the model of Chung et al. (2016), and for the remaining settings we use our own neural model. Results in this table belong to our own implementations of the aforementioned architectures. As the table shows, the best score is obtained for *dp*→*dp*. The table shows a similar trend to that of Table 6.2 and confirms that with a better segmentation model our simple encoder-decoder model is able to provide comparable results to those of more complex neural models. Our segmentation model not only provides high-quality results but also improves the quality of other architectures when it is used with other segmentation models.

The most important properties of the different segmentation models illustrated in Table 6.3 can be summarized as follows:

- When translating into an MRL, it is better to work with a character-based decoder or sample from *dp* tokens.
- Except for the *mr*-based decoder, all other decoders provide their best results when the encoder works with *dp* tokens.
- For the *w*-, *mr*-, and *bp*-based encoder, character-level decoding is the best alternative.
- For the *char*- and *dp*-based encoders, the *dp*-based decoder is the best alternative.

Apart from these segmentation models we also proposed three other models in Chapter 4, namely Models A to C. As previously mentioned, it is quite hard to find the optimal value for the external parameter of these models when they are used in NMT settings, and this was our main motivation to propose Model D. However, we selected the best model of Models A to C (which is Model C) and fine-tuned it for the English→German translation task. The best BLEU score obtained for this experiment was 22.17 when both sides are segmented with Model C which is 1.24 BLEU points lower than that of Model D.

6.4 Summary

This chapter provides useful information about NMT models and their behaviour with regard to MRLs. This chapter directly addresses problems that negatively influence the performance of neural models when they work with MRLs. The chapter started with the fundamentals of the NMT field. We explained that the encoder-decoder architecture dominates other models. We provided detailed information about the architecture and discussed how it maps a source language into a target language. The introductory section was followed by another section which reviewed existing NMT models. We studied models which introduced novel techniques and/or boosted other existing models. We also introduced models which are useful for translating MRLs.

Together with reviewing other models, we also studied the segmentation problem for NMT and tried to find the best segmentation scheme for this task. We compared our simple NMT model to more complex counterparts and showed that we do not necessarily need to have such complicated neural architectures, and in the presence of an effective segmentation model we are able to obtain state-of-the-art results. Our findings in the next section show that a good segmentation model alone is not enough, and in order to obtain the best performance we need to redesign the neural architecture to take the maximum advantage of morphological information.

Chapter 7

Double-Channel NMT Models for Translating from MRLs

In the last chapter we discussed neural settings which are useful for translating MRLs. In this chapter we propose an NMT architecture which is particularly designed to deal with morphological complexities on the source side. In this scenario the source language is an MRL that is translated into English, so the neural model and specifically the encoder should be able to handle morphologically complex inputs. We have already noted that treating an MCW as an atomic unit is not suitable, as it consists of several meaning-bearing subunits. It should also be noted that those units not only preserve semantic information, but they also have syntactic roles. It is very hard (or even impossible) to benefit from (all) subunit information within an MCW when it is treated as a single word. It also complicates the neural computation as it forces the network to learn all those intra-word relations by itself. To address these problems, existing NMT models explore word-segmentation techniques.

When processing an MRL via morpheme-segmentation models, we should pay attention to a very important issue. Complex constituents can be segmented based on either linguistically motivated or non-linguistic criteria. We explored non-linguistic (count-based) morpheme-segmentation models in Chapter 6, but in this chapter we use morphological analyzers which segment words into meaningful and linguistically correct units, as opposed to random subunits. The morphological analyzer used in this chapter separates the stem from other syntactic affixes, but those used in Chapter 6 segment words without linguistic knowledge and treat all subword units equally. Clearly, the stem and affixes provide us with useful information by which we can boost the NMT engine. Such a useful segmentation scheme enables us to redesign the neural architecture in order to take the maximum advantages of morphological information. Accordingly, we propose a new architecture to better understand the nature of the input MRL and explore morphological information in a better way. In our design we have two different encoders to process stems and affixes separately. This double-channel mechanism is the main contribution of this chapter.

In subword-based NMT models words are segmented into their subunits. This approach, by its very nature seems a promising solution, as it changes the sparse surface-form-based vocabulary set into a much smaller set of fundamental units, e.g. *Morfessor* employs linguistic criteria and segments words into stems and affixes. The size of a set including stems and affixes is considerably smaller than that of the vocabulary set (see Table 7.1), especially for MRLs in which several words can be derived from a single stem. This solution not only mitigates the complexity but also addresses the OOV problem, as the chance of facing an unknown surface form is much higher than the chance of facing an unknown stem and/or affix.

Together with models which rely on linguistic criteria there are other types of unsupervised, data-driven, or statistical models which do not necessarily obey linguistic rules but segment words using frequency features. The *Byte-pair* model or our models in Chapter 4 are examples of them. Both linguistically motivated and statistical approaches suffer from various problems which can be summarized as follows:

- When a sequence of words is segmented into subwords, the length of the sequence is increased which can downgrade the accuracy of the sequence-modeling process. Neural models are very sensitive to the length of the input sequence.

- At this stage the segmentation process (in NMT) is somewhat random in which we change the surface form of words, decrease the size of the vocabulary set and gain better results. However, from a linguistic point of view, it is still questionable how and why segmentation models improve the quality. We are still not sure which segmentation scheme yields the best result.

- It should also be discussed what the best or most compatible neural architecture is when words are segmented into subunits. Existing subword-level models benefit from the basic (original) encoder-decoder architecture, where an encoder reads subunits one after another and feeds the decoder, but we believe that there should be a better way to benefit from morphological or subword information, as the existing architecture is not designed to work at the subword level.

Character-level models perform differently from subword-level models and segment words into characters, not subwords (or morphemes). All the aforementioned problems discussed for subword-level models also apply to this approach. Moreover, processing the input with the basic encoder-decoder model when it is a long sequence of characters does not provide acceptable results, which means character-level models must have their own architecture. They usually use a convolutional module at the input layer to read characters, extract their relations and build the word-level representation. This convolutional computation could be quite costly, e.g. in one of their models Lee et al. (2016), use 200 convolutional filters of width 1 along with 200 filters of width 2, 250 filters of width 3, and continue up to a filter size of 300 with width 8. This much computation is carried out only in one layer, so in addition they have max-pooling layers followed by 4 highway layers and then the recurrent encoder-decoder architecture. As can be seen this is quite a complex architecture which is determined by the type of the input data (a sequence of characters). Such a network includes millions of parameters and it is challenging to reach the best configuration in training.

In the last paragraphs we reviewed existing approaches to facing the problem of rich morphology on the source side and explained their potential disadvantages. However, we do not mean that these models are not useful, as they are state-of-the-art models and produce high-quality translations. The main issue we are trying to point out here is that existing architectures either the character-based or the simple encoder-decoder one is not the best alternative to work at the subword level. It seems there are techniques to further benefit from subword units, using simpler and more compatible architectures.

Motivated by the aforementioned problems, we propose an NMT architecture with a double-source encoder and double-attentive decoder. Our model takes its inputs from two different channels: one channel which is referred to as the *main* channel sends stem information (main input), and the other one (the *auxiliary* channel) sends affix information. If the input is $w_0, w_1, ..., w_n$ for the (original) encoder-decoder model, our proposed architecture takes two sequences of $\varsigma_0, \varsigma_1, ..., \varsigma_n$ and $\tau_0, \tau_1, ..., \tau_n$ through the main and auxiliary channels, respectively, where w_i shows the surface form of a word whose stem is ς_i, and affix information associated with w_i is provided by τ_i. In our setting the affix token τ_i is the combination of a word's suffixes and prefixes (see Section 7.2 for more details).

The new neural architecture is based on a hypothesis which assumes the *core semantic unit* is the stem. The translation generated on the target side could appear in different surface forms but it should convey the core meaning dictated by source-side stems. Therefore, to generate a translation the minimum requirement is stem information. Designing/defining the translation process based on stems simplifies the problem drastically, because we no longer need to work with complex surface forms as inputs. The sentence representation generated based on stems provides the decoder with high-level source-side information. It could also steer the decoder toward potentially correct words (gisting), but the decoder needs more than this to generate precise translations. Accordingly, stem information is accompanied with auxiliary information supplied by the affix channel.

There are two main reasons why we model the problem in this way (two input channels), which are the main contributions of this work. We can have different words on the target side (morphologically naive) which are all translations of a single stem. The reason they differ from one another and appear in different forms is because the source-side stem collocates with different affixes. By having different input channels we can model these combinations to help the decoder with word formation/selection. This is the first reason behind our design. Furthermore, the neural model (embedding-learning model, NLM, NMT model etc.) is not totally able to extract all information preserved in MCWs when it works with surface forms, so we can simplify the process by explicitly showing subword units (instead of surface forms) to the network. This is the second reason we process stems and affixes separately. This double-source model requires its own specific neural architecture which is elaborated in the next section.

7.1 Proposed Architecture

In our architecture, given an input sequence $w_1, w_2, ..., w_n$, words are segmented into their stems (ς) and affix tokens (τ). Regarding the structure of the input data, our encoder should process two tokens (stem and affix) instead of one (word) at each time step. Accordingly, the neural architecture should be adapted to the new data structure. To this end, we equipped our encoder with two GRU networks (RNNs with GRUs). The stem RNN reads stems one after another to update its hidden state, and the other one (affix RNN) reads affix tokens. The process can be formulated as in (7.1):

$$\begin{aligned} s_t &= f(s_{t-1}, \varsigma_t) \\ a_t &= f(a_{t-1}, \tau_t) \end{aligned} \tag{7.1}$$

where s_t and a_t are the hidden states of the stem and affix RNNs, respectively, at time step t.

Clearly the length of the stem and affix sequences are equal (each stem has a dedicated affix token), so we have an equal number of time steps for both RNNs. When the final time step is reached, i.e. all stems and affixes have been consumed, we have s_n and a_n which represent the summary of the stem and affix sequences, respectively. The decoder should be informed about source-side information to start sampling/generation. To this end, in the original encoder-decoder model we simply initialize the first hidden state of the decoder with the last hidden state of the encoder. However, the simple initialization method is not applicable in our case as the encoder generates two representation vectors. Therefore, to feed the decoder with source-side information, we place a fully-connected layer with a transformation matrix between the encoder and decoder by which both of the source vectors are mapped to the first hidden state of the decoder, as in (7.2):

$$h_0 = tanh\big(W_{\varsigma\tau}[s_n \bullet a_n]\big) \tag{7.2}$$

where the decoder is initialized with h_0, $tanh$ applies non-linearity, $W_{\varsigma\tau} \in \mathbb{R}^{(|s_n|+|a_n|)\times|h_0|}$ is the transformation matrix and $\bullet$ indicates the concatenation operation.

At each time step the decoder samples a token from the target vocabulary. In the simple encoder-decoder model (see Equation (6.5)), the decoder makes the prediction based on its hidden state h_t, the last predicted token y_{t-1} and a dedicated context vector $\mathbf{c}_t$. The context vector is exclusively defined for each time step using all source-side hidden states and the last hidden state of the decoder (Equations (6.6) and (6.7)). In our case we have two sets of source-side hidden states and the decoder pays attention to both instead of one. Equation (7.3) shows this structure:

$$y_t = g(h_t, y_{t-1}, \mathbf{c}_t^{\varsigma}, \mathbf{c}_t^{\tau}) \tag{7.3}$$

where the next target token is predicted based on the last predicted token y_{t-1}, the decoder's hidden state h_t and two context vectors. Our decoder benefits from a double-attentive mechanism instead of the simple attention model; $\mathbf{c}_t^{\varsigma}$ is the stem-based context vector and provides information about source stems, and $\mathbf{c}_t^{\tau}$ is the affix context vector which informs the decoder about morphological properties of the input sequence.

In order to construct the stem-based context vector $\mathbf{c}_t^{\varsigma}$, the decoder pays attention to input stems to weight relevant stems with higher scores, as in (7.4):

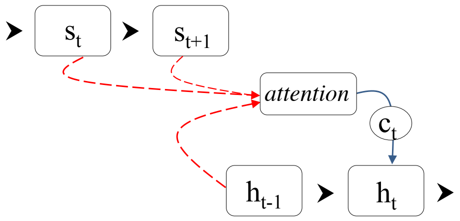
$$\begin{aligned} \mathbf{c}_t^{\varsigma} &= \sum_{t'=1}^{n} \alpha_{tt'} s_{t'} \\ \alpha_{tt'} &= \frac{\exp(e^{\varsigma}_{tt'})}{\sum_{k=1}^{n} \exp(e^{\varsigma}_{tk})} \\ e^{\varsigma}_{tt'} &= \mathbf{a}_{\varsigma}(s_{t'}, h_{t-1}) \end{aligned} \tag{7.4}$$

The equation shows that the decoder tries to select relevant stems at each time step which can help it make better predictions. $\mathbf{c}_t^{\varsigma}$ summarizes all source stems and informs the decoder about the impact of each stem.

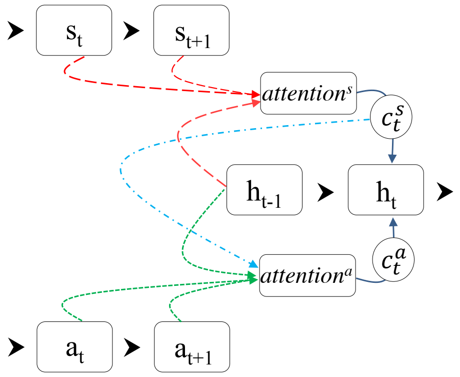
The affix context vector is constructed with a slightly different mechanism which is formulated as in (7.5):

$$\begin{aligned} \mathbf{c}_t^{\tau} &= \sum_{j=t'}^{n} \beta_{tt'} a_{t'} \\ \beta_{tt'} &= \frac{\exp(e^{\tau}_{tt'})}{\sum_{k=1}^{n} \exp(e^{\tau}_{tk})} \\ e^{\tau}_{tt'} &= \mathbf{a}_{\tau}(a_{t'}, [h_{t-1} \bullet \mathbf{c}_t^{\varsigma}]) \end{aligned} \tag{7.5}$$

The equation shows that affix tokens are weighted given the hidden state of the decoder and the stem context vector. We know that affixes associate with their stems, so to select the best affix we need to consider the impact of stems along with the decoder's information. Experimental results show that this combination obtains better performance (see Section 7.2). Figure 7.1 tries to visualize our double-attentive attention module.



(a) This figure shows the original attention mechanism where the source side encoder consumes one word at each time step and updates its hidden state s_t. The decoder constructs the context vector $\mathbf{c}_t$ based on the decoder's previous hidden state and all source-side hidden states. The context vector is used along with the (current) hidden state h_t to generate the output.



(b) This figure shows the double-source encoder, where the stem RNN takes one stem at each time step and updates s_t, and the affix RNN updates a_t after consuming the t-th affix token. The stem-based context vector is generated by *attention*$^{\varsigma}$. The affix-based context vector is constructed using information provided by all of the affix-RNN's hidden states, the decoder's previous hidden state and the stem context vector.

Figure 7.1: A comparison between the simple and double-attentive attention models. It should be noted that the figure only shows connections associated with the attention module.

7.2 Experimental Study

Our NMT model is a GRU-based encoder-decoder model. On the encoder side we have two RNNs, one for stems and the other for affix tokens. Both RNNs include two GRU layers where the first layer is a bidirectional layer and the second layer is a unidirectional layer. Stems and affix tokens are represented with 512-dimensional embeddings. The encoder is connected to the decoder through the affine connection described in Equation (7.2). On the decoder side, we have the double-attentive attention module and two GRU layers. The GRU size for both of the encoder and decoder is 1024. Since experimental studies demonstrated that character-based decoding yields better translations, our decoder works at the character level. Moreover, as the main goal in this chapter is to show the impact of our proposed encoder, we prefer to keep the target side constant for all models and compare the impact of different encoding techniques. However, we also provide a few examples from models with different decoding techniques. Similar to input tokens, target tokens are also represented with 512-dimensional embeddings. The network was trained using stochastic gradient descent with Adam (Kingma and Ba, 2015). The mini-batch size is 80, the beam search width is 20, and the norm of the gradient is clipped with the threshold 1.0.

Our models are trained to translate from German and Russian into English. We used the `WMT-15` datasets, where the German–English corpus includes 4.5M parallel sentences and the size of the Russian–English corpus is 2.1M. The `newstest-2013` and `newstest-2015` datasets are used as the development and test sets, respectively. We selected these datasets to make our work comparable with existing models. As we are interested in translating from MRLs, we pre-process the training corpora to segment words and extract stems and affixes. Table 7.1 provides related statistics for our training copora.

	English–German		**English–Russian**	
	En	**De**	**En**	**Ru**
Sentence	4.2M		2.1M	
Token	$103,692,553$	$96,235,845$	$43,944,989$	$39,694,475$
Type	$103,574$	$143,329$	$70,376$	$119,258$
Stem	$21,223$	$26,301$	$15,964$	$19,557$
Affix	$13,410$	$24,054$	$9,320$	$17,542$
Prefix	$3,104$	$5,208$	$2,959$	$3,324$
Suffix	$3,285$	$4,974$	$2,219$	$3,460$
char	355	302	360	323
dp	19,777	54,370	13,569	45,357

Table 7.1: **En**, **De** and **Ru** stand for English, German and Russian, respectively. *Sentence* is the number of parallel sentences in the corpus. *Token* is the number of words. *Type* shows the number of unique words. *Stem*, *Prefix*, *Suffix* and *Affix* show the number of unique stems, prefixes, suffixes and affix tokens in the corpus. *char* shows the number of unique letters. *dp* shows the number of tokens generated by Model D (Section 4.3.4).

The table shows different statistics about the training corpora along with the number of affixes for each corpus. We segment input words with *Morfessor*. The longest subunit is selected as the stem. What appears before the stem is the prefix and what follows the stem is considered as the suffix. A word may have none (null), one or many prefixes and suffixes, by which their combination construct the affix token in our implementation.

It is clear what the stem RNN takes as its input at each time step. The encoder has an embedding table for stems. Each row of the table is a unique vector representing a particular stem. The encoder processes the main sequence (stem sequence), retrieves the related embedding for each stem and sends that to the stem RNN. We can have the same mechanism for prefixes and suffixes, which means the encoder has separate suffix and prefix embedding tables. It retrieves associated prefix and suffix embeddings for each word, combines them (vector summation) and sends the combined vector to the affix RNN. This architecture is referred to as the *pre-suf* extension of the proposed model in our experiments. If a word has more than one prefix/suffix the encoder retrieves all of them, and if it has none the encoder uses a null embedding.

In the *pre-suf* extension, what the affix RNN receives as its input is a vector which has some information about morphological properties of the associated stem (word). We believe that the encoder and affix RNN could be provided with richer information, so we propose the *affix* extensions. In these extensions we combine all prefixes and suffixes to generate the new affix token, e.g if $word_i = prefix_i^1 + stem_i + suffix_i^1 + suffix_i^2$, the affix token τ_i would be $prefix_i^1 + suffix_i^1 + suffix_i^2$. The embedding of the new affix token is different from the summation of the embeddings of the prefix and suffix and introduces a new token. In the *affix* extensions, apart from the stem-embedding table the encoder has a dedicated embedding table for affix tokens. Therefore, the affix RNN at each time step takes an affix token instead of the summation of prefixes and suffixes. Table 7.1 shows the number of unique affix tokens for each corpus.

The embedding of the affix token defined for each word is a new unit which preserves information about: *i*) morphological properties of its related word, *ii*) morphological properties of other words appearing in the sentence, and *iii*) the collocation and order of different prefixes and suffixes, at the word and sentence level. It seems that the simple combination of prefix and suffix embeddings in the *pre-suf* extension cannot preserve this amount of information, as the role of each suffix/prefix is clear, but in this extension, we can expect the neural network to learn such useful information through the training phase (and store it in the affix-embedding table).

Model	Source	Target	De→En	Ru→En
Baseline	ς+*pre*+*suf*	*char*	22.11	22.79
Costa-jussà and Fonollosa (2016)	*word*	*word*	18.83	-
	char	*word*	21.40	-
Firat et al. (2016a)	*bp*	*bp*	24.00	22.40
Lee et al. (2016)	*bp*	*char*	25.27	22.83*
	char	*char*	25.83*	22.73
Our model				
dp-model	*dp*	*dp*	**27.13**	23.07
dp-model	*dp*	*char*	26.79	22.81
pre-suf	$[\varsigma]^1$ $[pre+suf]^2$	*char*	26.11	22.95
affix-$\mathbf{c}^{\varsigma}\mathbf{c}^{\tau}$	$[\varsigma]^1$ $[\tau]^2$	*char*	26.74	**23.44**
affix-$\mathbf{c}^{\tau}$	$[\varsigma]^1$ $[\tau]^2$	*char*	26.29	23.40

Table 7.2: Source and Target indicate the data type for the encoder and decoder, respectively. ς is the stem, *pre* is the prefix and suf is the suffix. τ is the affix token. *bp*, *dp*, and *char* show the *Byte-pair*, dynamic programming-based, and character-level encodings, respectively. The bold-faced score is the best score for the direction and the score with * shows the best performance reported by other existing models. According to paired bootstrap re-sampling (Koehn, 2004b) with $p = 0.05$, the bold-faced number is significantly better than the score with *. Brackets show different channels and the + mark indicates the summation, e.g. $[\varsigma]^1$ $[pre+suf]^2$ means the first channel takes a stem at each step and the second channel takes the summation of the prefix and suffix of the associated stem.

Results obtained from our experiments are reported in Table 7.2. The first row of the table reports results from an encoder-decoder model where the decoder works at the character level and uses the architecture proposed by Chung et al. (2016). The first row can be considered as a baseline for all other models reported in the table, as it does not use any complicated neural architecture. For each word it simply sums stem, prefix, and suffix embeddings together and sends the summed vector as the word representation to the GRU-based encoder. Although the model is quite simple, it is able to generate comparable results to other complex architectures. This fact reinforces our claim that existing neural architectures are not suitable to work at the subword level. If we find a better way to provide the neural model with subword information, we will be able to improve translation quality still further.

The second row shows the model proposed by Costa-jussà and Fonollosa (2016) in which a complicated convolutional module is used to model the relation between characters and build the word-level representation. The simple baseline model performs better than this model. The third row belongs to Firat et al. (2016a) which is a multi-way multilingual NMT model. The fourth row shows a fully character-level model (Lee et al., 2016) where both the encoder and decoder work at the character level. As previously discussed this model has quite a complicated architecture.

The last block shows 5 variations of our model. *dp-model* is an encoder-decoder NMT engine with single source channel. Both the source and target sides for this model are segmented using our dynamic programming-based model (Model D). This model is also reported with another setting where the encoder consumes *dp* tokens and the decoder samples a character at each time step.

In the *pre-suf* model the encoder has two GRU RNNs, one for stems and the other for prefixes and suffixes. At each time step, the stem RNN takes one stem embedding. On the other channel the affix RNN takes an embedding which is the summation of the prefix and suffix embeddings of the word whose stem is processed by the stem RNN at the same time step.

The *pre-suf* model has two input channels and benefits from the double-attentive attention mechanism. This new architecture enables the *pre-suf* model to perform better than the very complicated fully character-based model. This is an indication that the character-level representation does not necessarily provide the best representation, and our model is able to perform better as its architecture is more compatible with the nature of MRLs. The impact of the compatible neural architecture becomes more important when we compare the baseline and *pre-suf* models. The input format is exactly the same for both, but the baseline model simply sums stem, prefix and suffix embeddings and sends them to the original encoder, whereas our model has two different channels to process stem and prefix/suffix information. It shows that our proposed architecture is able to process morphological information better than the baseline model.

The *affix*-$\mathbf{c}^{\varsigma}\mathbf{c}^{\tau}$ variation is the best model among our double-channel models, where we have stem tokens and affix tokens. As previously discussed, assigning a unique embedding to the combination of prefixes and suffixes instead of summing their embeddings generates better results and provides richer information.

The third and last variation, *affix*-$\mathbf{c}^{\tau}$, shows the impact of our architecture on the decoder side. As we modeled in Equation (7.5), attention weights assigned to the affix-RNN's hidden states are computed based on the decoder's hidden state and the stem context vector. As affix tokens provide complementary information to stem information, the affix context vector should be aware of the content of the stem context vector, so we proposed the model explained in Equation (7.5). If we only consider the decoder's information to compute affix weights, the equation will be revised as in (7.6):

$$\begin{aligned}
\mathbf{c}_t^{\tau} =& \sum_{j=t'}^{n} \beta_{tt'} a_{t'} \\
\beta_{tt'} =& \frac{\exp(e_{tt'}^{\tau})}{\sum_{k=1}^{n} \exp(e_{tk}^{\tau})} \\
e_{tt'}^{\tau} =& \mathbf{a}_{\tau}(a_{t'}, h_{t-1})
\end{aligned} \tag{7.6}$$

In the *affix*-$\mathbf{c}^{\varsigma}\mathbf{c}^{\tau}$ version, the energy between the decoder's (t-1)-th state and the affix-RNN's t'-th state was computed by $e_{tt'}^{\tau} = \mathbf{a}_{\tau}(a_{t'}, [h_{t-1} \bullet \mathbf{c}_t^{\varsigma}])$, whereas this version simplifies the computation by estimating $e_{tt'}^{\tau}$ with $\mathbf{a}_{\tau}(a_{t'}, h_{t-1})$. The model described in Equation (7.6) is implemented in the *affix*-$\mathbf{c}^{\tau}$ extension. Results obtained from this extension show that, although the architecture is also successful compared to other exiting models, its performance is worse than the model which (additionally) involves the stem context vector to compute affix weights.

For German→English, the best BLEU score is obtained when our model has a single encoder channel and works with *dp* units. However, this does not mean that the double-source encoder is not effective; rather, that these two models study the same problem from different perspectives. One model tries to handle morphological complexity by segmenting complex structure into *basic* units, and the other approach adapts the neural architecture to benefit from morphological information. Although having a good segmentation model could be quite useful, it is not enough alone to address all problems. Results from the Russian→English supports this claim. For this direction the character-based (Costa-jussà and Fonollosa, 2016; Lee et al., 2016) or subword-based (*dp-model*, Baseline, and Firat et al. (2016a)) models should perform well, as they all benefit from segmentation techniques which can reduce the complexity of Russian, but the best score remained with double-channel model. In addition to the Russian experiment, we also have results when we translate from Turkish. We observed similar properties for this language too. Table 7.3 summarizes results from the Turkish experiment.

Model	**Source**	**Target**	**BLEU**
Baseline	ς+*pre*+*suf*	*char*	22.98
char-model	*bp*	*char*	23.11
char-model	*dp*	*char*	23.27
dp-model	*bp*	*bp*	23.17
dp-model	*dp*	*dp*	23.46
affix-$\mathbf{c}^{\varsigma}\mathbf{c}^{\tau}$	$[\varsigma]^1$ $[\tau]^2$	*char*	**23.81**

Table 7.3: Experimental results for Turkish→English. *char*, *bp*, and *dp* show the character, *Model D*, and *Byte-pair* tokens. ς, *pre*, and *suf* are the stem, prefix, and suffix, respectively.

Our Turkish models are trained using the same dataset as in Section 6.3.1, and the number of *bp* and *dp* are the same. In Table 7.3 the baseline model uses a character-based decoder. It linearly sums the stem, prefix, and suffix embeddings for each word to build its surface-form embedding on the encoder side, which could be a good alternative when translating from MRLs. *char-model* has the same neural architecture as the baseline, but it consumes *bp* or and *dp* tokens. Each token is treated as a single independent unit, which means subunit tokens of a word are not summed to build the surface-form representation. *dp-model* is our model from Chapter 6. The last row in the table is our best double-encoder model which obtained the best BLEU score. Similar to the Russian experiment, for this language the morpheme-segmentation model is also unable to help the neural architecture achieve the best BLEU score, while Turkish is a highly agglutinative language and the segmentation-based solution should have worked perfectly for it.

According to the Russian and Turkish experiments, we can conclude that the best performance is achieved when the neural architecture is able to (better) understand the nature of its inputs and outputs, which means that we may have to redesign the neural architecture accordingly. Although morpheme segmentation is quite useful for NMT, it is not the best solution to cope with difficulties of translating (from) MRLs.

7.3 Conclusion

In this chapter we focused on morphological complexities on the source side and tried to equip the encoder to handle complex inputs. The proposed model includes two separate channels to consume stems and affix tokens. In our experiments, we showed that this double-input encoder seems to be a suitable architecture when translating from MRLs. Since the encoder has two input channels it generates two source-side representations. Accordingly, the decoder had to be fine-tuned to handle the extra representation vector. To this end, we designed a double-attentive attention mechanism to control the information flow in both channels. Our model generates better results and seems able to better inform the neural model with morphological information, compared to other existing models.

Chapter 8

Conclusions and Future Study

The research conducted in this thesis addresses the problem of morphology in the context of MT. Statistical and neural approaches to MT suffer from serious shortcomings, which almost all explicitly or implicitly involve morphology. OOVs are commonly encountered in translating morphologically rich languages. Moreover, according to recent research (Bentivogli et al., 2016; Tu et al., 2016; Toral and Sánchez-Cartagena, 2017), a considerable amount of wrong translations belong to the categories of *'missing words'* and *'wrong surface forms'*, which can be related to the problem of morphology. Clearly, the second one is a direct consequence of the problem of morphology. The first one is also related as MT models do not decompose MCWs during translation, which leads to wrong results. Since an MCW preserves more information and subunits than a simple non-MCW, all subunits are not completely translated and some target words are missed in the target translation.

In order to address these problems, we decided to study the problem of morphology and its impact on MT models. First we explained what morphology is and how it helps us construct new words. Chapter 2 covers introductory and fundamental concepts. We reviewed several important models in the field of SMT, which in some way incorporate morphological information into the translation pipeline. Models are divided into three main categories. One approach does not change the translation architecture but preprocesses the training corpora, decomposing morphologically complex structures into simpler and atomic units. For this approach, it should be discussed that what happens if there is no (precise) morphological analyzer for a language.

The other approach manipulates the decoding procedure by directly exploring morphological criteria. The decoder is extended with additional morphological information and the word selection is controlled by such constrains.

The last approach tries to make a morphological symmetry between the complex and simple(er) sides. First, words are lemmatized and then translation is performed based on simplified units. Finally, translations generated by such a model are processed through an additional step, in which classifiers are used to gather contextual information in order to detect the correct surface form of each word. Classifiers essentially take the simplified form of a word and generate the correct inflected or morphologically complex form.

Along with SMT-related topics, one important part of Chapter 2 relates to DNNs. In this thesis the main platform to perform MT is NNs. We reviewed the fundamentals of deep learning. The procedure for training a neural network was explained and we introduced a number of well-known neural architectures. Both Chapter 1 and Chapter 2 provide background knowledge about the research carried out in the thesis, but the core research is explained in Chapters 3 to 6. Each chapter studies a dedicated research question which is introduced at the beginning of the chapter. The history of the research question and related models are discussed thereafter. The last part of each chapter covers the problem itself and a potential solution.

Chapter 3 introduces an embedding-learning model for MCWs. In order to translate languages via NNs, we should be able to encode characters, words, and other constituents into numerical forms. In this regard, the best solution is to use document embeddings, but existing embeddings such as those of *Word2Vec* or *GloVe* are not compatible with our datasets. Since our corpora include MCWs, such word-based models fail to provide representative embeddings, as they are not able to go deeper and extract intra-word relations. They function based on the surface form of words, which is clearly not the ideal choice for our setting. In order to mitigate this shortcoming we propose a new CNN-based model, which includes a multi-channel data structure as its input. Each channel consists of a specific type of information representing a particular aspect of the word. In experiments designed in Chapter 3, the input includes three channels of prefix, stem, and suffix, which means we try to train embeddings for subword units. The cubic data structure preserves information about words and subunits, as well as information about context words and their subunits. Feeding a network with this amount of information helps the model provide better connections among words and train better embeddings.

We designed a specific 3D convolution function to process the proposed data structure. Our model is not the first embedding-learning network which benefits from subword-level information, but because of *i*) the way we represent words and *ii*) the convolution technique, we are able to better benefit from subword information. In Chapter 3 we evaluated the impact of different techniques to combine subunit vectors. The experiment confirmed that the 3D technique outperforms other models. The only concern about the model is that it has a complex architecture, so that when it is plugged into a high(er)-level model such as an NLM or NMT engine, it could make the whole pipeline complex and delay the entire procedure. Neural models by their very nature are already complex enough, so we do not want to make them more complicated. Accordingly, in future work we plan to find a better way to combine this technique with other models. Except for this shortcoming, we believe that the model provides a very efficient framework, not only for word-embedding tasks but also for other NLP tasks, e.g. the flexibility provided by the proposed cubic data structure enabled us to use the same NN for our MT purposes. Instead of representing subunits in the cube, we stored translationally equivalent words in different channels and trained bilingual embeddings (Passban et al., 2016b).

Chapter 4 looks beyond word-level modeling. Word embeddings are generated by the technique proposed in Chapter 3, but we need more than word-level information.

In this chapter we study the language-modeling problem to work at the sequence level. Simply put, the main responsibility of a language model is to predict the best word given a history of its preceding words, which is a quite challenging task. There could be different alternatives for a given history and the model should select the best one based on the context. The problem becomes even harder in the presence of morphologically complex structures. If we decompose an MCW, we might be able to obtain a more informative history. Accordingly, state-of-the-art models work at both morpheme and character levels. First, subunit information is combined to provide the word-level representation, then words are consumed one after another to make the final history. Although morpheme-based models outperform word-level models which the reason is clear, they cannot compete with character-based counterparts. We believe that there are two main reasons for this: *i*) almost all character-level models are quite complex and utilize powerful neural modules such as CNNs with hundreds of filters, highway layers etc. Therefore, it is not very clear whether the main gain comes from the network architecture, or the representation form; and *ii*) morpheme-level models combine subword-level information with a simple linear summation or concatenation function. This type of combination may not be powerful enough to reveal the relations between morphemes. As we showed in Chapter 3, an efficient combination technique can yield quite different results.

It does not (intuitively) seem appropriate to consider a single character as the atomic unit of a language, as characters can appear in every word regardless of its syntactic and semantic role. They give no information about the word to which they belong, but morphemes can easily provide such information. Accordingly, we think that there should be a middle-ground solution which takes advantages of both approaches. One solution is to manipulate morpheme-based models with a better combination technique, e.g. replacing a simple summation function with our 3D convolution function, which we leave for future work. The other solution which was proposed in Chapter 4 is to push character-level models toward morpheme-level models. Words should not be completely decomposed into characters. Existing models separate all characters, and then combine them via a convolutional process to make a connection among them. We follow the same approach but not via neural computations. Before training an NLM, we make a hybrid segmentation of words by use of our technique. If there is a set of consecutive characters that frequently appear together, they may try to build up a bigger block and we think that they should stay together. Accordingly, we extract frequent character n-grams within words, keep them as they are, and separate the remainder into characters. Using this technique, we are able to better model languages. At the end of the segmentation procedure we have a set of atomic symbols which include characters and n-grams.

The segmentation models in Chapter 4 enable us to achieve better performance, but clearly they are sub-optimal as they rely on a threshold (or other external parameters) to extract frequent blocks. Finding an optimal value for the threshold is crucial for our models. For these versions of our models we compare different settings in our experiments and empirically set the threshold value. Motivated by these problems we also proposed another model which has no external parameter. Both paradigms have their own advantages and disadvantages, which we summarized in Chapter 4. In our future work we are interested in finding a model which benefits from the advantages of both approaches (tunable level of granularity with no external parameter). The second plan for future work is to use our NLM in SMT/NMT models. We evaluated the impact of incorporating NLM signals in the SMT pipeline and improved the translation engine, but we re-scored probabilities of the n-gram-based LM with our neural model. This is not the best way to use the NLM, so in future work we will try to find a solution to incorporate neural scores at decoding time.

Chapter 5 is complementary to the preceding, which trains word and sentence embeddings. All these neural features can be used in the SMT pipeline to boost translation engines. In Chapter 5, first we proposed a framework to train bilingual embeddings; MT is a bilingual setting so we need more than monolingual embeddings. The proposed architecture is a feed-forward neural model which is an extension to Devlin et al. (2014) and Le and Mikolov (2014). By means of such a model we train bilingual word-level, phrase-level and sentence-level embeddings, and define different feature functions to show the relatedness of bilingual words and phrases to one another. We also try to capture contextual information. Incorporating such neural features results in better BLEU scores, but we support our results with qualitative evaluations through different experiments. This chapter also shows that there could be better architectures than a feed-forward model. The architecture is substituted with a convolutional counterpart which gives even better results. One of the important achievements of the chapter is that we do not necessarily need to train bilingual embeddings in order to boost SMT models, as we introduced a way to benefit from monolingual embeddings to enrich the decoder.

Chapter 6 tries to propose neural models to translate MRLs. It complements Chapter 4, as similar to that chapter we perform sequence modeling, but the main difference is that the models in this chapter are designed for multilingual settings. It is hard to train a deep neural model to work with millions of parallel sentences, so models have to be efficient, effective, and fast enough. We also show the impact of morphological information, despite the fact that this makes the problem even harder. In this chapter we explained the established NMT framework, namely the encoder-decoder model. Then we fine-tuned the model to work for MRLs. In our models, we studied the impact of different segmentation schemes and recognized the best setting for working with MRLs. Our dynamic programming-based segmentation model performed very well for our NMT engines and obtained the best result.

In Chapter 7, we proposed a model to translate from MRLs. In this model the neural model takes two input tokens at each time step. One input represents the stem and the other one represents morphological information of the word to which the stem belongs. The main idea behind this separative design is to reduce the complexity on the source side. Since the encoder generates two different representations at each step, the decoder should be customized accordingly. The original decoder takes one input, whereas ours has two inputs. The decoder also has two attention modules to select the most relevant information from both channels. This model was proposed for translating from MRLs. Experimental results demonstrate that compared to other existing models ours has a more compatible architecture with the complex nature of MRLs.

In Chapters 6 and 7, we proposed different models to study NMT of MRLs from different perspectives and addressed different shortcomings in the field. There are different languages in terms of the morphological categorization which we provided in Chapter 2 (see Figure 2.3). We are interested in fusional and agglutinative types of languages in this thesis. In fusional languages morphemes are combined in a very complex way and there is no clear boundary between them. Moreover, the surface form of morphemes can be changed after the combination. Accordingly, preprocessing MCWs and analysing them from a morphological point of view might not be the best solution if we want to provide high-quality translations for such structures. Instead, we should find neural models which are able to take MCWs and handle their complexity themselves. Considering all word-, morpheme-, and character-level NMT models, it seems that character-based models could be better alternatives compared to others. The convolutional transformation applied to characters in character-based models can partially simulate the word formation procedure in fusional languages. We are not able to exactly model the process but we can expect the neural model to learn it automatically. The multi-filter convolutional process is the only existing model to deal with this sort of complexity in fusional languages, but it could be boosted or even replaced with other techniques which is one of our future plans.

In contrast to fusional languages, there are agglutinative types in which morphemes are clearly separable from each other. For this key reason we can easily rely on morpheme segmentation and morpheme-based neural models for this set of languages, so in our research we evaluated our segmentation model (Model D) on preprocessing the training corpus and obtained significant improvements. We also proposed the double-channel encoding model to work at the morpheme level. It seems that we do not necessarily require complex character-based models for agglutinative languages and simple techniques for manipulating and processing morphemes can lead to better results.

We believe that Chapters 6 and 7 provided useful information on NMT of MRLs and studied the problem from different perspectives. There is still room for further investigation which we leave for future work. For our future work in the field of NMT, we target four main goals: *i*) we are interested in designing a model which is able to translate from an MRL into another MRL. When both source and target sides are complex, a simple encoder-decoder model will fail to provide fluent translations, so we will try to find architectures to control complexities of both sides; *ii*) we are planning to work on the decoding side and constrain the decoder with morphological information, as we think it can boost the quality when we translate into MRLs; *iii*) we plan to apply the sequence-to-sequence model used for MT tasks in Chapters 6 and 7 to other NLP tasks such as parsing, POS tagging, morphological segmentation etc; finally *iv*) we tend to train neural models for low-resource languages. We know that deep-learning-based models are data-hungry models and need a massive amount of resources to provide acceptable results. Our plan is to train small and efficient neural models with affordable resources and datasets. We already started this research path by developing a model for translating Azeri (Passban et al., 2017), and plan to further expand our models.

In Chapter 8 we tried to summarize all other chapters. We explained the core idea of each chapter and discussed what questions the chapter tried to solve. We reviewed the proposed solutions and enumerated their shortcomings (and also their advantages). For each chapter we mentioned that what questions were solved and what questions remained unanswered. We addressed some complimentary ideas for our future work. In this thesis, we believe that we could contribute to our field as we collected data and provided a bilingual corpus, and designed and implemented different NLP tools such as a morphological analyzer and POS tagger. Our solutions introduced new models for embedding learning, language modeling, and machine translation. We also enhanced the NMT framework to work better for MRLs.

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