



# Exploring variable interactions with Restricted Boltzmann Machines

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## Introduction

The interactions between clinical predictive factors for disease are often far more complicated than a simple summation. In-MINDD aims to identify factors for dementia and examine interactions in order to construct an optimum predictive model.



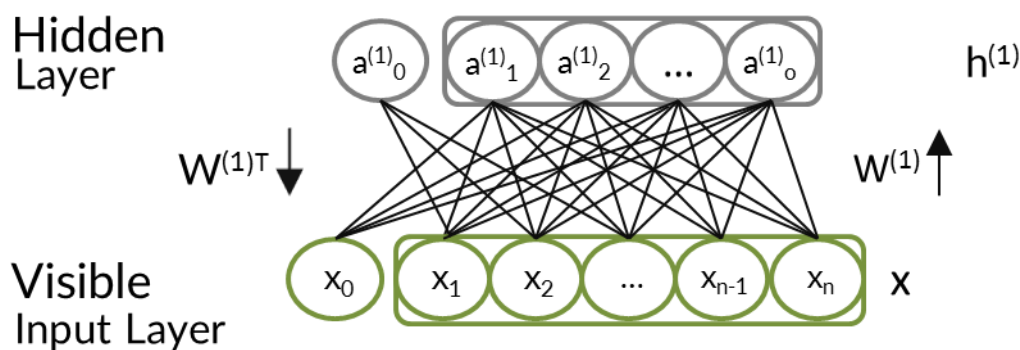
## Work to Date

To date, we have built a framework that:

- Constructs shallow and deep architectures
- Automates hyper-parameter selection
- Allows for model export and import in a standard format
- Provides for analysis of parameter updates during

In previous work this framework has been used to model high-dimensional clinical data

## The Restricted Boltzmann Machine (RBM)



- Two layer neural network
- One hidden and one visible layer
- Energy-based model
- Learns how to represent and reconstruct the data from the hidden layers

## Experiment Results and Evaluation

The dataset – from the Maastricht Ageing Study – consists of ten binary variables describing the presence or absence of each In-Mindd predictive factor. The variables are: smoking, moderate alcohol consumption, obesity, cholesterol, diabetes, renal disease, cognitive activity, depression, physical activity and hypertension.

The optimum number of hidden nodes (11) was found through 256 trials of random search for hyper-parameters.

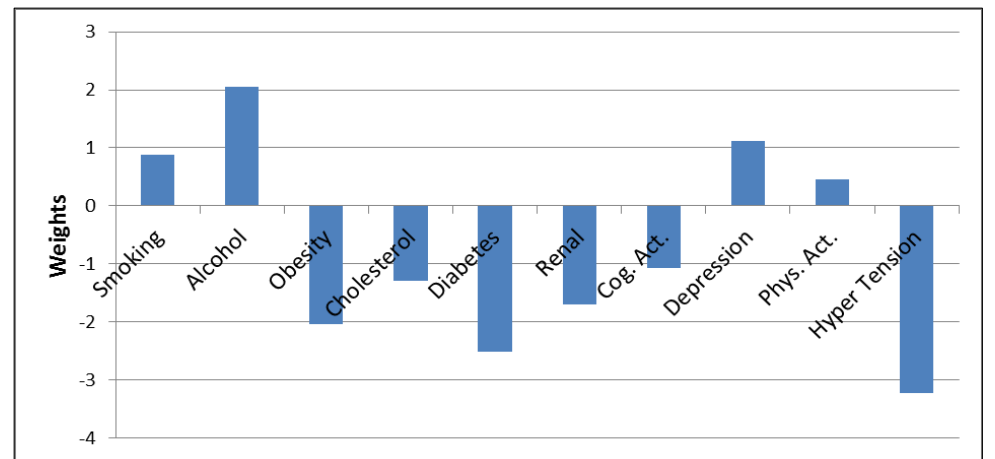


Fig. 1. Composition of first learned feature

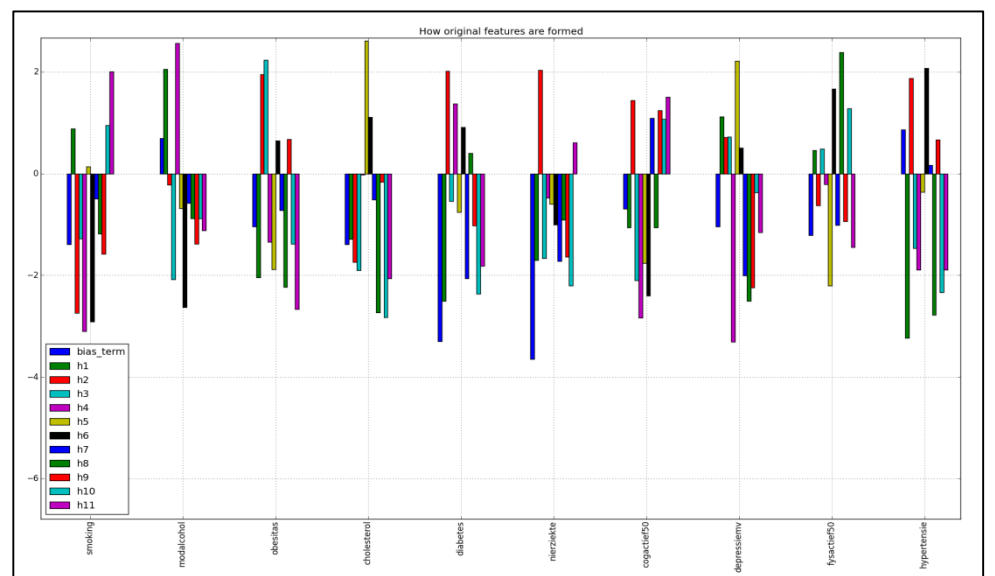


Fig. 2. Weights for each hidden node

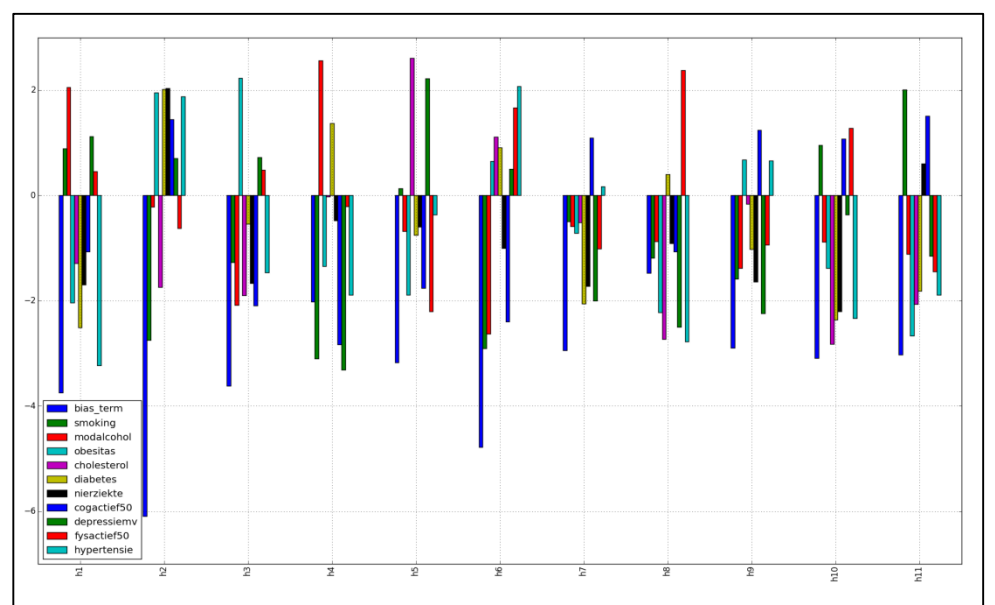


Fig. 3. Reconstruction Weights

## Conclusions and Future Work

RBM's can successfully model clinical variable interactions in an unsupervised setting, although the results require clinical validation. Our next steps are to use these variables to predict dementia and compare our results to the baseline model found by clinical partners through Cox's hazards regression.