Essay - Cognition and Computation

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1 Introduction

The EMNIST [1] Balanced dataset is derived from the NIST Special Database 19. It has 47 classes: digits (0-9), uppercase letters (A-Z), some lowercase letters (a,b,d,e,f,g,h,n,q,r,t). Consists in a total of 131600 samples, 112800 being for training and 18800 for testing. It provides a consistent and fair classification, with equal number of samples for each class, despite being sufficiently challenging.

A possible neural network used to model and classify these samples is the Deep Belief Network. It consists in a composition of Restricted Boltzmann Machines, the hidden layer of one serves as visible layer of the next.

A RBM is generative stochastic neural network used to learn the probability distribution over its inputs. This implies that the activation level of a neuron is a representation of a probability. The input is present in a set of visible neurons. It can extract statistical structure information in a set of hidden neurons. We use maximum likelihood learning to update the weights aiming for a accurate top-down reconstruction. The most probable configurations of hidden and visible neurons are specified by the energy function based on the connection weights.

These characteristics of RBMs allows us to use a stack of them, a DBN, to learn multiple levels of representation and thus better hidden representations that can serve as examples of a class. The DBN is trained with the constrastive divergence algorithm, reducing the discrepancy between the real and the learned probability distribution.

Perceptton

Feed Forward Neural Netowrks....

2 Hyper Parameters

The parameters used can be found in the following table.

Parameter	Value
Hidden Layers Sizes	1000, 1000
Gibbs Sampling Steps (k)	1
Learning Rate	0.1
Initial Momentum	0.9
Final Momentum	0.9
Weight Decay	0.00001

Table 1: Hyper Parameters of the Deep Belief Network

These parameters were isolated and tested, i.e. starting from the 1st lab parameters, I changed only one of the parameters and found the best value, did this for all parameters and use the best of each in this final combination. This, obviously does not guarantee the best results, because the parameters can be the best when isolated but not the best combination of

all of them. We can although consider these values as a good approximation to the best case. The objective was to reduce the average reconstruction error in the DBN training phase.

Enabling learning rate decay decreased the average reconstruction error but the weight representations were not as expected, due to a very small gradient, so it will be disable in this case. The Xavier weights initialization is also disabled because it did not produce any measurable performance improvement.

To serve as comparison we can use Feed Forward Neural Networks, one with 1 hidden layer and another with 2 hidden layers, all of size 1000.

The Perceptron and FFNNs were trained in the same way, using an stochastic gradient descent optimizer with learning rate of 0.05 and the cross entropy loss function, for 1000 epochs.

3 Results

DBN	474s
Perceptron	453s
FFNN with 1 layer	932s
FFNN with 2 layers	927s

Table 2: Training Time

To achieve a training time close to the sum of the DBN and Perceptron training time, the FFNN with 2 hidden layers was trained in 60 epochs and the one with 1 hidden layer was trained in 150 epochs.

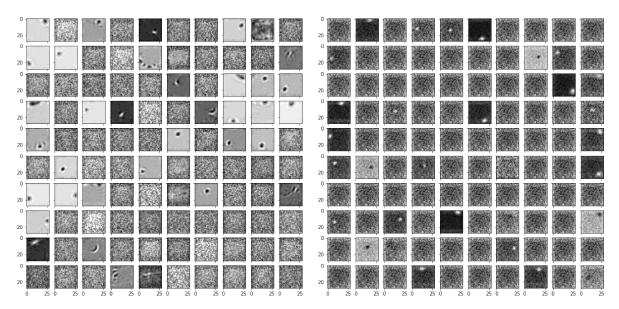
3.1 Accuracy

DBN	61.95%
FFNN with 1 layer	30.76%
FFNN with 2 layers	14.37%

Table 3: Accuracy

The DBN accuracy is a very good result, given that the EMNIST article [1] shows an 64% result for a OPIUM-based model with hidden layer size of 1000. The FFNNs produce lower accuracy as expected, the addition of a second hidden layer significantly decreased accuracy.

3.2 Representations



- (a) Representation of the 1st hidden layer
- (b) Representation of the 2nd hidden layer

Figure 1: Representations of the DBN hidden layers

These results show simple feat... The 2nd hidden layer representation is a bit more \dots

3.3 Dendrograms

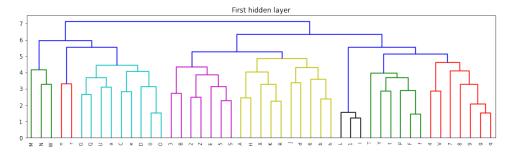


Figure 2: Dendrogram for 1st hidden layer

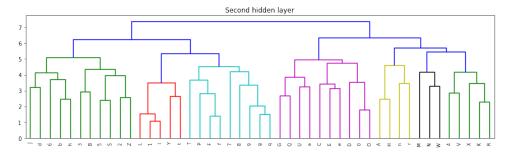


Figure 3: Dendrogram for 2nd hidden layer

These results show

3.4 Confusion Matrix

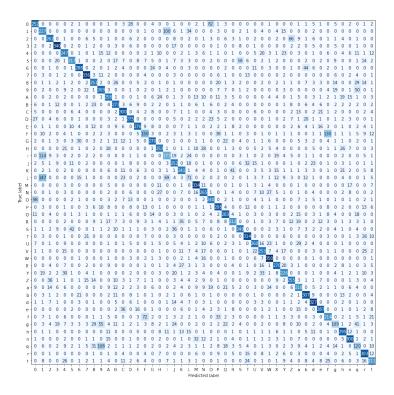


Figure 4: Confusion Matrix

We can clearly see the similarities between letters as an human expects. "q" and "9", "L" and "1" \ldots

3.5 Robustness to Noise

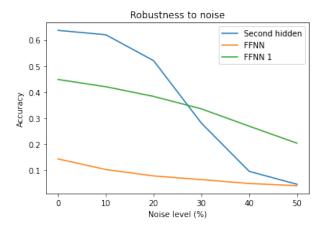


Figure 5: Robustness to noise

The FFNN with 2 hidden layers is generally worst. The DBN has the best accuracy until 30% noise level. The FFNN clearly are less affected by noise.

References

[1] G. Cohen, S. Afshar, J. Tapson, and A. van Schaik, *EMNIST: An extension of MNIST to handwritten letters*, 2017. arXiv: 1702.05373.