Some topics in Deep Learning

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November 7th, 2015

Outline

- Recap: Deep Learning, RBM and Unsupervised pre-training
- Another method: Convolutional Neural Network (CNN)
- Some simulation results
- Extensions of Deep Learning: Recommender System

Recap: Deep Learning

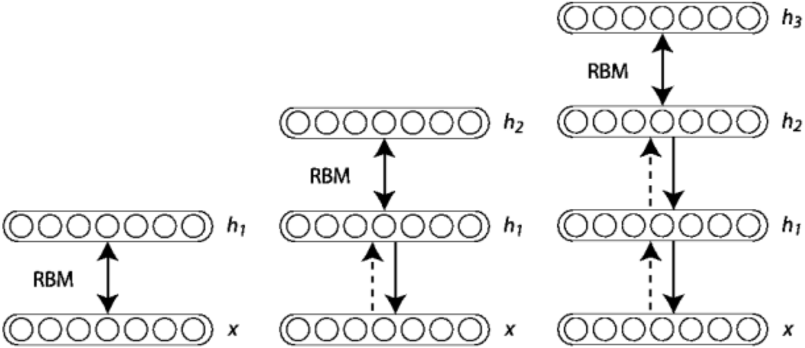


Figure 1: Deep Neural Network with RBM as the building block.

Recap: Deep Learning

Train a Deep Neural Network

- Pre-train with RBM: layer-wise training
- Train RBM: One-step Markov Chain
- Fine tuning: backpropagation

Convolutional Neural Network (CNN)

Some basics

- Before 2006, only one kind of Deep Neural Network can be trained with good performance, which is **CNN**.
- Inspired by human visual field.
- Exploits **spatially-local correlation**.
- A CNN contains three types of layers:
  - Convolutional layer
  - Pooling layer
  - Fully-connected layer

CNN: Sparse connection and Shared weights

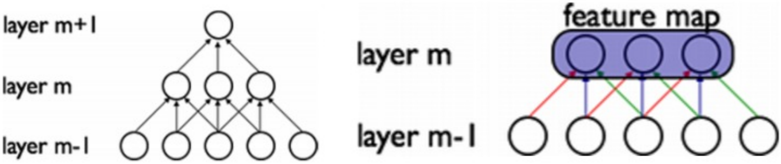


Figure 2: (**Left**) The receptive field is 3. (**Right**) Weights of the same color are shared, they are constrained to be identical.

- **Gradient Descent** can still be used, with minor changes.
- The constraints make the learning algorithm more **efficient**.

CNN: 4-dimensional weight tensor

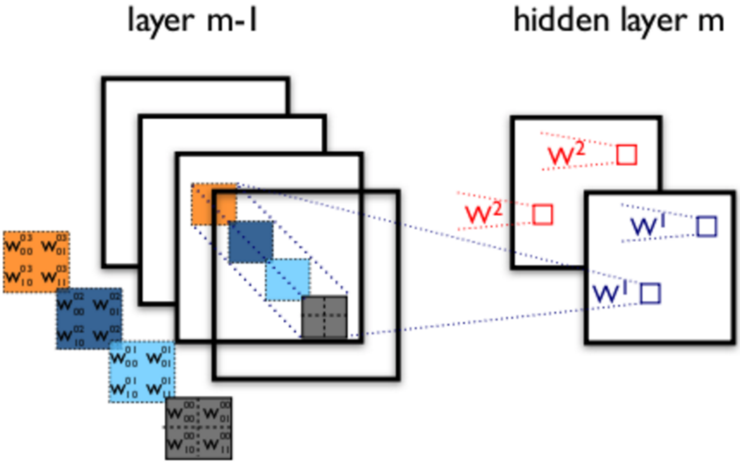

layer m-1
hidden layer m
W^2
W^2
W^1
W^1
W^{03}_{00} W^{03}_{01}
W^{03}_{10} W^{03}_{11}
W^{02}_{00} W^{02}_{01}
W^{02}_{10} W^{02}_{11}
W^{01}_{00} W^{01}_{01}
W^{01}_{10} W^{01}_{11}
W^{00}_{00} W^{00}_{01}
W^{00}_{10} W^{00}_{11}

Figure 3: The figure shows two layers of a CNN. Layer m-1 contains four feature maps. Hidden layer m contains two feature maps.

CNN: example

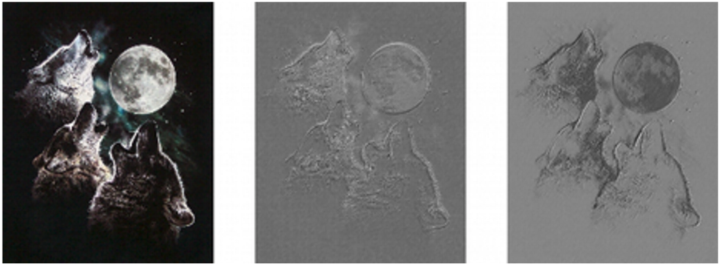


Figure 4: The output of the previous two-layer CNN, it acts as a **filter** which detects the **edge**.

CNN: Pooling and Fully-connected layers

Pooling layer

- The goal of this layer is to **reduce the dimension**.
- The pooling layer takes small **rectangular blocks** w/o overlapping.
- The layer **subsamples** from each block to produce a single output.
  - Maximum
  - Average
  - Linear combination
  - ...

Finally, after several convolutional and max pooling layers, the neural network ends with **fully connected** layers.

Simulation: Effects of depth and pre-training

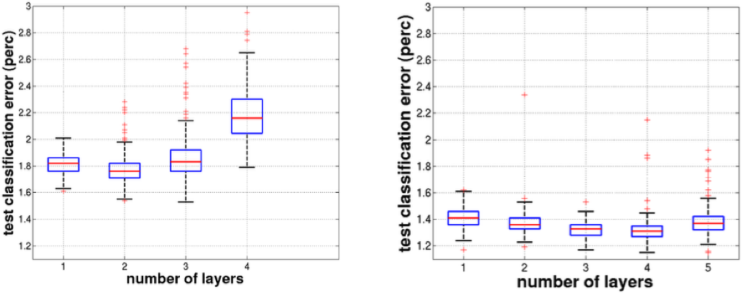


Figure 5: Effect of depth on performance for a model trained (**left**) without unsupervised pre-training and (**right**) with unsupervised pre-training

Simulation: Effect of pre-training

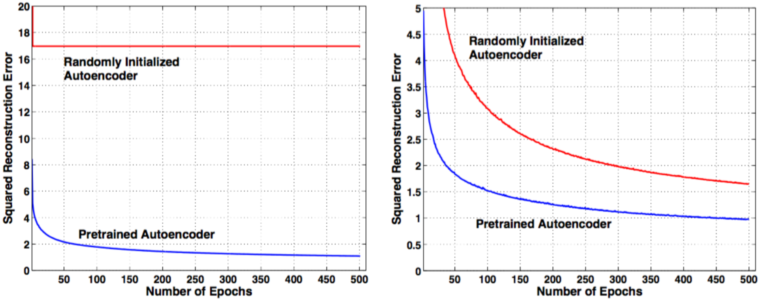


Figure 6: The average squared reconstruction error.

Left panel: The deep 784-400-200-100-50-25-6 autoencoder.
Right panel: A shallow 784-532-6 autoencoder.

Simulation: Effect of layer size

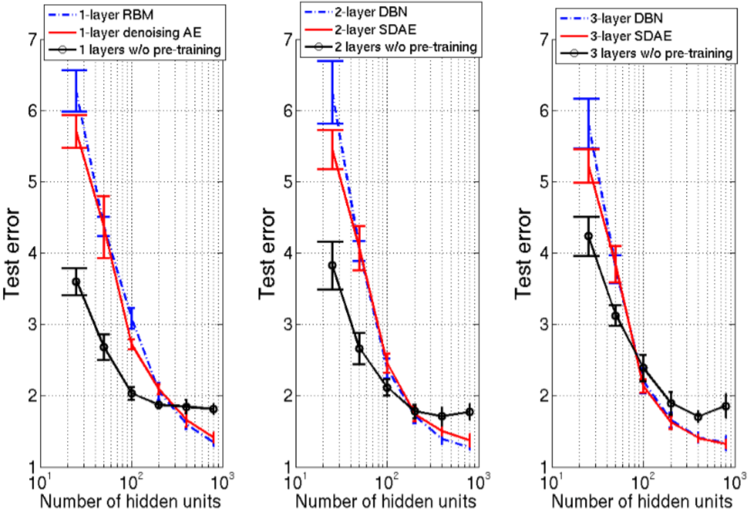
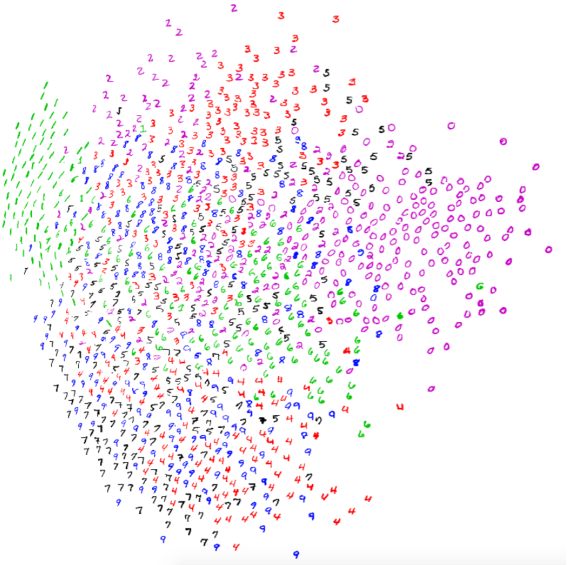
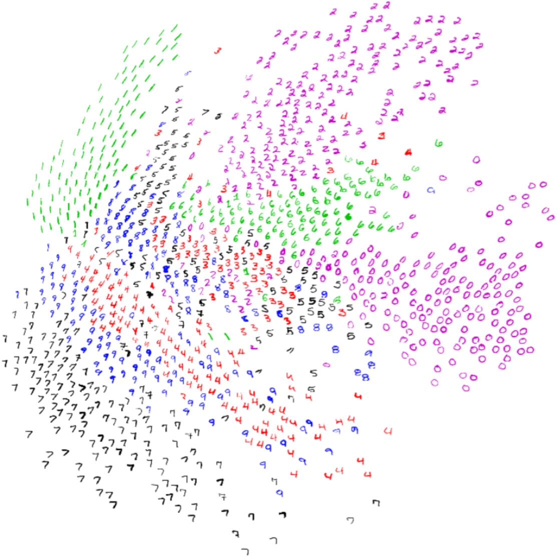


Figure 7: Pre-training hurts for **smaller layer sizes** and **shallower** networks, but it helps for all depths for **larger** networks.

Simulation: PCA visualization on `MINST` data



Simulation: Classification of MINST data by a 784-1000-500-250-2 autoencoder



Extension: Recommender System using RBM

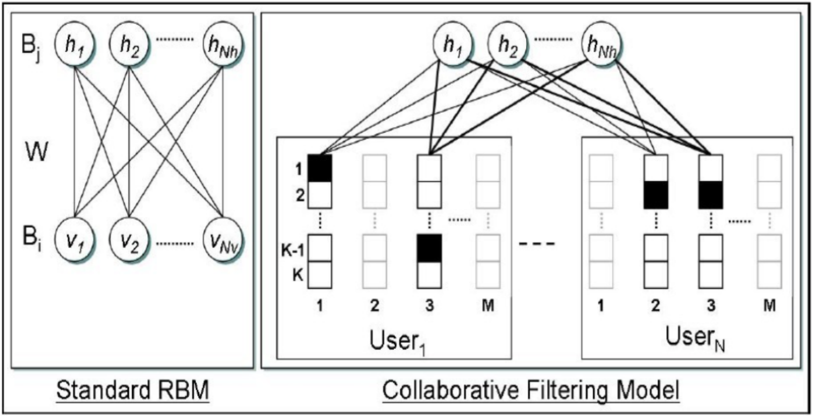


Figure 8: (**Left**) Standard RBM, (**Right**) Collaborative Filtering RBM

Conditional RBM

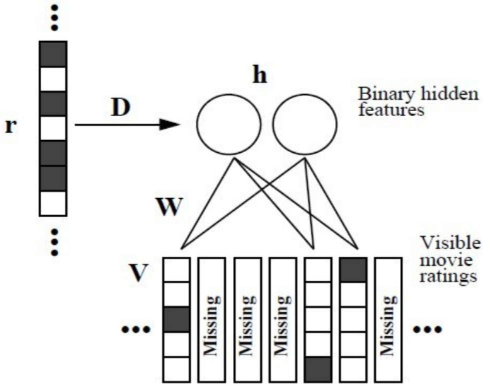


Figure 9: Conditional RBMs in Collaborative Filtering.

`r` is a binary vector indicating all the movies the user rated.

Performance

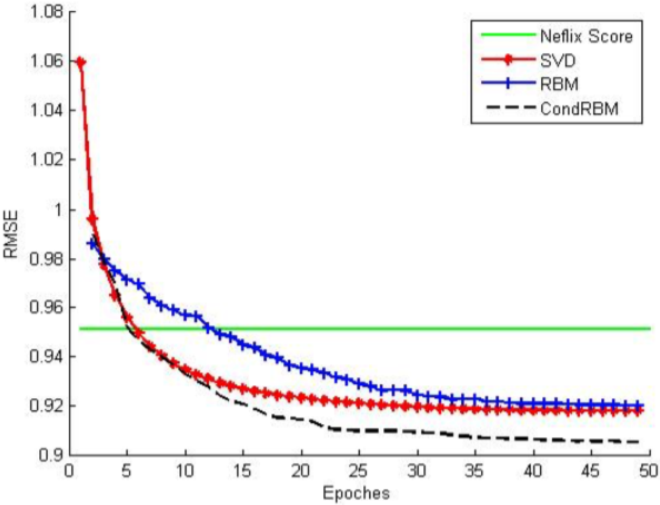


Figure 10: Performance of 5 methods on Netflix data