Project proposal - Probabilistic graphical models

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1 Motivation: subject introduction

A Restricted Boltzmann Machine (RBM) is a undirected energy-based probabilistic graphical model which can be seen as a two layer neural network (visible and hidden units). RBMs can be used to model and learn important aspects of a probability distribution of a training data. They are called restricted, because we impose restrictions on the network topology, by allowing only connections between units of different layers. RBM are energy-based, since they define probability distribution through an energy function. Learning corresponds to shaping the energy so that desirable configurations have a low energy and thus maximize probability of training data under the model. Maximum likelihood learning is challenging for undirected graphical models because MLE parameters cannot be found analytically and the log likelihood gradient based optimization is not tractable. This optimization requires obtaining samples through Markov Chain Monte Carlo, which is computationally demanding.[2],[3],[1]

2 Operational organization

2.1 Plan of work

- Theory of Restricted Boltzmann Machines, and advanced training techniques
- Implementing RBM on MNIST data in python
- Compare the performance speedup using a deeplearning library (TensorFlow)
- Experimenting how RBM training depends on different parameters (learning rate, batch size, Contrastive divergence steps, number of hidden units...)
- Experimenting on robustness of RBM learning (white or black background, image translation..)

2.2 Expected work sharing

- Xi will be focused on the work regarding the python implementation of RBM running on CPU, experimenting on different values such as learning rate, n hidden layers, batch size, n CD steps...
- Othman will focus on the comparing the performance of the python implementation with tensorflow one.
- Finally, Chaïmaa will work on assessing the robustness of RBM algorithm with respect to background change (black and white)
- Other applications of RBM will be tackled depending on advancement.

3 First results

Training the RBM model on MNIST data, with parameters (learning rate = 0.001, batch size = 100, n hidden units = 100). After 100 epoch of training we obtain the following samples fig: 1. At the first iterations, we had random black and white pixels for the generated samples. After 100 iterations, we can see that the model starts learning the distribution of the data, since it has become able to generate images looking like hand-written digits.

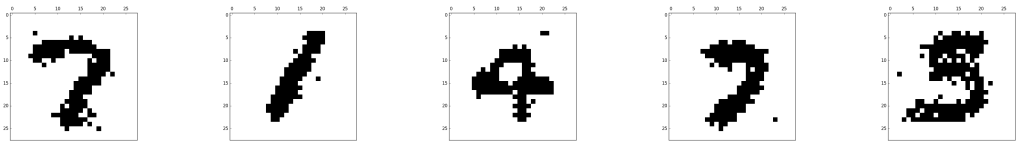

Figure 1: Generated samples After 100 epochs

References

[1] Asja Fischer and Christian Igel. Training restricted boltzmann machines: An introduction. *Pattern Recognition*, 47(1):25–39, 2014.

[2] Geoffrey Hinton. A practical guide to training restricted boltzmann machines. *Momentum*, 9(1):926, 2010.

[3] Tijmen Tieleman. Training restricted boltzmann machines using approximations to the likelihood gradient. In *Proceedings of the 25th international conference on Machine learning*, pages 1064–1071. ACM, 2008.