Nizhny Novgorod State University
Institute of Information Technologies, Mathematics and Mechanics
Department of Computer Software and Supercomputer Technologies

Educational course «Introduction to deep learning using the Intel® neon™ Framework»

Lecture №6 Unsupervised learning: autoencoders, restricted Boltzmann machines, deconvolutional networks

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Content

1 Abstract

The lecture discusses speculative approaches to reducing the amount of labeled data that are necessary for constructing effective deep neural networks [3]. The considered approaches are used for pre-training the network weights, i.e. constructing a "good" initial approximation for the subsequent training of the network based on the labeled training dataset, or for reducing the feature space dimension [5, 6]. These include autoencoders, restricted Boltzmann machines, and deconvolutional neural networks.

The autoencoder is a neural network that attempts to approximate the output signal to the input one, i.e. to construct the best approximation of the identity transform. Among the well-known varieties of autoencoder, you can distinguish ***sparse autoencoders*** [13], ***contractive autoencoders*** and ***denoising autoencoders*** [14]. Autoencoder can be considered as a feed-forward network [3], therefore for training it is permissible to use the backpropagation algorithm based on the gradient optimization methods. The lecture examines the methods of training autoencoders. In the case of multi-layered networks, it is possible to build ***a stack of autoencoders*** and train each autoencoder sequentially as a feed-forward network, which will gradually reduce the feature space dimension and adjust the parameters of the coding layers.

The restricted Boltzmann machine (RBM) [1, 7, 8] is a probabilistic analog of the autoencoder. By analogy with the stack of autoencoders it is possible to construct a stack of restricted Boltzmann machines. If the neuron states at each hidden layer depend on the previous and the next layers, then this model is called the ***deep Boltzmann machine*** (DBM) [4]. After the stack of the restricted Boltzmann machines is trained, the system can be considered as a single probabilistic model, called the ***deep belief network*** (DBN) [9]. A deep belief network fundamentally differs from the deep Boltzmann machine. During the lecture, general approaches to training these groups of models are considered.

Deconvolutional neural networks were originally proposed as a convolutional version of sparse autoencoders used to visualize feature maps of convolutional neural networks [10]. Later, the idea of deconvolutional networks was widely used in solving the problem of semantic segmentation [11, 12], since they allow you to get an output feature map comparable in size with the input image.

In the lecture we consider an example of the pre-training the weights of a multilayered fully-connected neural network using the stack of autoencoders to solve the problem of classifying a person's sex from a photo. We develop program for training and testing models using the Intel® neon™ Framework.

2 Literature

2.1 Books

1. Haykin S. Neural Networks: A Comprehensive Foundation. – Prentice Hall PTR Upper Saddle River, NJ, USA. – 1998.
2. Osovsky S. Neural networks for information processing. – 2002.
3. Goodfellow I., Bengio Y., Courville A. Deep Learning. – MIT Press. – 2016. – [http://www.deeplearningbook.org].

2.2 Further reading

4. Salakhutdinov R.R., Hinton G.E. Deep Boltzmann Machines [http://proceedings.mlr.press/v5/salakhutdinov09a/salakhutdinov09a.pdf].
5. Hinton G.E., Salakhutdinov R.R. Reducing the Dimensionality of Data with Neural Networks [http://www.cs.toronto.edu/~hinton/science.pdf].
6. Ioffe S., Szegedy C. Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift – [http://arxiv.org/abs/1502.03167].
7. Carreira-Perpinan M.A., Hinton G.E. On Contrastive Divergence Learning – [http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.443.5593&rep=rep1&type=pdf].
8. Hinton G.E. A Practical Guide to Training Restricted Boltzmann Machines [https://www.cs.toronto.edu/~hinton/absps/guideTR.pdf].

9. Hinton G.E., Dayan P., Frey B. J., Neal R.M. The wake-sleep algorithm for unsupervised neural networks // Science. – 1995. – Vol. 268, pp. 1558–1161.
10. Zeiler M.D., Krishnan D., Taylor G.W., Fergus R. Deconvolutional Networks [http://www.matthewzeiler.com/wp-content/uploads/2017/07/cvpr2010.pdf].
11. Noh H., Hong S., Han B. Learning Deconvolution Network for Semantic Segmentation [https://arxiv.org/pdf/1505.04366.pdf].
12. Fu J., Liu J., Wang Y., Lu H. Stacked Deconvolutional Network for Semantic Segmentation [https://arxiv.org/pdf/1708.04943.pdf].

2.3 References

13. Ng A. Sparse autoencoder// CS294A Lecture notes [https://web.stanford.edu/class/archive/cs/cs294a/cs294a.1104/sparseAutoencoder.pdf].
14. Vincent P., et al. Stacked Denoising Autoencoders: Learning Useful Representations in a Deep Network with a Local Denoising Criterion [http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.297.3484&rep=rep1&type=pdf].