Individual Activity 1

IA5008 Sistemas neuronales

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Abstract

Nowadays deep learning has been increasingly used. Conventional machine learning is limited by the choose of a good feature representation method. Deep learning outperforms this weaknesses by constructing its own data representation in several hidden layers, each of these may represent distinct data features. Thus, deep learning doesn't depend on human intervention for building the required representations. In this work, one of the first articles published in the Nature magazine [1] is discussed and its sections briefly reviewed.

Supervised Learning

Based on a large collection of labeled data a deep learning algorithm produces a vector of scores by category. Then it assign weights that minimizes error using the opposite direction of the gradient vector (steepest descent). Stochastic gradient descent is usually used to average the direction of steepest descent from a set of samples. Generalization ability of the model is measured by exposing it to a new test set. Shallow linear models require a good feature extractor to make them invariant to poses. Deep learning bypasses these difficulties by learning good features automatically, each layer is non-linear.

Backpropagation to train multilayer architectures

Multilayer architectures can be trained using backpropagation and gradient descent. The gradients with respect to the weights can be propagated from the output to the input. The results of one layer are weighted, summarized and passed through a non-linear function such as ReLU (rectified linear unit), tanh, logit and probit. Hidden units (neither input nor output) allow non-linearity's for the last layer to use.

Even though in the beginning it was thought that gradient descent was doomed to get stuck in local minima, in practice on large networks the system nearly always produces solutions of similar quality. Most of the saddle points have similar values of the objective function.

Interest in neural networks was revived in 2006 when researchers introduced unsupervised learning procedures to create layers of feature detectors. These layers would model the features in the layer below and reduce interconectivity.

Convolutional neural networks

Convolutional neural networks are a kind of deep learning network that is ideal for data that comes in multiple arrays. It has convolutional and pooling units at the lowest level and thus reduce the interconnection between layers exponentially. Convolutional layer extract motifs invariant of location while pooling units reduce complexity. Motifs hierarchical structures exists in many areas such as speech, sound, images or video. Conversely to the neocognitron, it also uses gradient decent on the form of back propagation.

Image understanding with deep convolutional networks

Convolutional networks have been used in detection, segmentation and recognition. For segmentation are particularly useful because images can be labeled at a pixel label. Computer vision community interest in convolutional networks was revived after the ImageNet competition in 2012 boosted by GPU hardware and new dropout technique, ReLU non-linear function and parallel algorithms.

Distributed representations and language processing

Composition structure brings about two advantages: 1. generalization to new combinations, 2. exponential reduction in connections by composing multiple layers of representations. Distributed representations feature maps are not mutually exclusive and can correspond to acceptable variations. Vector representations are a good example. There are two paradigms of representation for cognition: 1. logic-inspired and 2. neural-network-inspired. Logic-inspired paradigm ignores the internal structure of an instance of a symbol and relies on external equality and rules of inference. By contrast, neural networks performs intuitive inference from vectors, weights and scalar non-linearities. These representations were put to use in natural language processing by finding vectors close to each other in the vector space which in turn means a close semantic relationship.

Recurrent neural networks

Recurrent neural networks RNN's process an input sequence and stores in their hidden units a state vector with some kind of memory. Thus it is suitable to use it for any time related input such as speech and video. However, the gradient is very sensitive to each step. Encoders and decoders can be used to translate between languages. This method doesn't use inference rules on symbolic word representations. Beside other languages, one can also translate to images. Explicit memory can also be added to the model to store long term information using long short-term memory (LSTM). This is achieved by using a special neuron that is connected to itself.

Conclusions and the future of deep learning

Unsupervised representation contruction poises a new paradigm that had great results for supervised deep neural networks training. However, a lot of work remains undone in unsupervised learning. *Generative Adversarial Networks* are a great example in which a deep network can be used to generate new content. Combinations between RNNs, Convolutional Networks and reinforcement learning are also great oportunities of improvement in computer vision and natural language processing.

The advent of unsupervised representation construction can be regarded to exarcebate many ethical problems exposed by [2] in chapter 26 :

1. The use of AI systems might result in a loss of accountability. One way of verifiying the results of a neural network in a domain area is to expose it to distinct data representations understandable by humans. However, deep neural networks construct their own representations at each layer, so this is no longer possible.
2. The success of AI might mean the end of the human race. An AI that builds its own representations can reach the singularity faster because it doesn't have to interact with humans. Also, maximization functions for embeding Asimov (1942) laws can become convoluted and hard to code.

References

[1] Y. Lecun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, no. 7553, pp. 436–444, 2015.

[2] P. Norvig, *Artificial Intelligence: A Modern Approach*. 2012.