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Sticky Reasoning within Learning Representations

Yann LeCun
NEW YORK UNIVERSITY
70 WASHINGTON SQUARE S
NEW YORK, NY 10012-1019

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14. ABSTRACT

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While this work used generative adversarial networks (GAN), we found the concept wanting and proposed a new formulation of GANs called Energy-Based GAN. Our method was the first to allow the generation of realistic images at 128x128 resolution. Generative models, such as GANs are a key component of unsupervised procedures that can generate complex patterns from latent variables drawn from a simple distribution [Zhao ICLR 2017] (over 550 citations to date).
Next, we developed an unsupervised representation learning method based on the concept of regularized auto-encoder. An auto-encoder is a deep learning architecture that is trained to reproduce its input on its output, while funneling the representation through an information bottleneck. In previous methods, the information bottleneck is implemented by making the dimension of the representation small (e.g. PCA, hourglass auto-encoders), by making the representation sparse (e.g. sparse auto-encoder with L1 regularization of the code), or by normalizing the code vector and adding noise to it (e.g. Variational Auto-Encoders).

15. SUBJECT TERMS

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Sticky Reasoning within Learning Representations.

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Yann LeCun
New York University

In this project, we addressed two questions: (1) how to learn abstract representations of data such as text and video; (2) how design trainable architectures that have persistent memory and can perform long chains of reasoning.

1. Learning abstract representations of text and images

One goal of learning representations of data is to produce representations in which the explanatory factors of variations are disentangled. We first proposed an architecture and learning procedure that automatically learns representations of images in which the content is separated from the pose. The method is completely unsupervised, not requiring that the pose or the identity of the object in the image be provided [Mathieu NIPS 2016].

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Lastly, we proposed an architecture for unsupervised learning of dependency graphs that can be transferred from one task to another in natural language processing [Zhao NIPS 2018] (collaboration with Russ Salakhutdinov, CMU).

2. Reasoning and Memory in Deep Learning Systems

A major challenge in modern machine learning is to get learning systems to perform long chains of reasoning. Recurrent neural nets have been the topic of extensive research along those lines. But traditional recurrent nets don't seem to be able to remember a state for very long. In fact, the ability to memorize (to possess stable states) was long thought to be incompatible with gradient-based learning procedures such as back-propagation through time (BPTT), as the gradients would vanish through time steps where the state is stable. However, one can escape this conundrum by using ideas from quantum mechanics: it is possible to store memories, not in stable states, but in stable orbits. One simply needs to constrain the dynamics of the network to be reversible to solve the vanishing gradient problem. It is possible to read out a stable memory from a continuously-evolving orbit through a non-linear pooling operation on the state vector. This is somewhat similar to a quantum-mechanical system whose dynamics is unitary (and therefore invertible with no stable state), and where a "measurement" removes the information relative to the rotating phase thereby producing a stable state. The method was shown to perform tasks that require long-term storage of information with higher accuracy than previous methods [Henaff ICML 2016].

Next, we proposed a deep learning architecture that is capable of maintaining a current state of the world in its memory, and to update it in the face of new information (like an event). For example, if a system reads a sentence like "john walks to the kitchen", it should maintain a memory slot for "john" storing a vector that encodes John's attributes, such as "location=kitchen". Similarly, the system should possess a memory slot for "kitchen" whose state vector represents the fact that John is present in it. The architecture is composed of a number of recurrent sub-networks, each of which is meant to represent the attributes of an entity (such as John or the kitchen). When the system is fed a sentence describing an event, it produces a key vector that is compared each of the entities' key vectors and allows the entity's state vector to be updated of the keys match. The system is trained by being fed a sequence of events and a question about the final state of the world. It is then given the answer to the question and, through backpropagation, to update its parameters to produce the given answer. This was the first method to solve all the 20 of the so-called bAbI question-answering tasks [Henaff ICLR 2017].

This led us to pursue work on learning predictive world models. A world model is a trainable function (a neural net) that predicts the nect state of the world, given the previous state and an action taken by the agent. One of the main issues in learning such models is to deal with the intrinsic unpredictability of the real world (or of simulated stochastic environments). Once a model of the world is trained, it can be used to plan a sequence of actions so as to optimize a particular objective. For example, if a learning agent is to land a spaceship on the moon or rendez-vous with another spacechip in orbit, it must possess a model of its own dynamics. Planning a trajectory under these conditions is called Model Predictive Control (MPC). But the problem is somewhat complicated when the actions are discrete. We propose a method to learn a predictive model and to learn a policy with discrete and continuous action spaces. Planning by minimizing an objective can be seem as a special case of a general form of reasoning. Many forms of reasoning and inference can be reduced to optimization problems [Henaff 2017a] [Henaff 2017b].

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