Yann LeCun's Cake Explained

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I have been asked about the evolution of different machine learning algorithms such as supervised learning, unsupervised learning, and reinforcement learning. I realized that it was basically asking about Yann LeCun's Cake and it will be fun to discuss about it.

I believe that these are actually very powerful concepts, yet everyone can relate to, since we all do a little bit of learning ourselves everyday. Let's take playing Super Mario games as an example:

Supervized Learning (SL) indicates that human need to teach a machine what to do at every step, and the machine just mimic the detailed behavior of human--e.g., jump or move actions at specific situations in Super Mario. **Imitation Learn** [1] is a special flavor of supervized learning for which human just behave freely in an environment without any effort taylored to teaching machines. There are two drawbacks to supervized learning:

1. machine are constrained to strategies which human already know, because they are just imitating.
2. there is no guarantee of quality, even if a machine can mimic human 95% of the time, the 5% failure can still ruin the whole effort.

Reinforcement Learning (RL) is exactly that's needed to cure the above two drawbacks to supervized learning, and gives machine the potential of surpassing human. For RL a machine can freely explore all kinds of strategies without any help from human. It strengthens (reinforces) strategies which leads to reward--e.g. passing a stage in Super Mario or getting more coins. When done right, it can often go beyond what human knows--e.g., in Atari and AlphaGo. There is guarantee of quality (in a mathematical sense), since the machine is directly optimizing the quantity which we care about. However, there are two major issues with RL, which I think are not about RL itself but how people do RL:

1. there need to be a space of strategies for the machine to explore. The search is futile if the space is poorly designed--e.g. memorizing action decisions based on the exact full image of a game. I think unsupervized representation learning will be a key to this problem.

2. efficiency in model optimization is poor. E.g. the best learning algorithm learns to play “Atari games at about 18 million frames (around 90 hours) of gameplay, while most humans can pick up a game within a few minutes.” [2]. We have this problem even for problems with well defined search spaces (e.g. semantic parsing) and applying more statistical learning theory will definitely help.

Unsupervized Learning (UL) indicates that the machine is not just optimizing the quantity we care about, but also tries to explain the world itself--by predicting all the observations that it has access to. Because the world has way more information than the quantity we care about, we can afford to train very complex models which give good representations.

A good representation makes supervized learning dramatically easier. For example computer vision models often need thousands of labeled examples (e.g., ImageNet) to learn a concept (e.g. cat), while children usually only need one example to learn to classify cat from other animals. The reason is that, without given any labels, children have already learnt a representation in which cats are far away from all other animals, which was a lot of learning done. Then all the parents did was just to put a label (the word “cat”) on it. It is fair to say that children learn to distinguish cats from non-cats without any supervision.

A recent work [3] from Berkeley showed an impressive result that very competitive Super Mario agents can be trained without even specify a goal of winning the game. Their model is only trained to find observations in the Super Mario world that it cannot understand. And that goal alone is enough for the model to form complex gaming strategies.

Unsupervized learning solves a key issue in ML -- to come up with good representations. However, its development will be a long process of discovering new model structures.
For that we can get help from two areas:

1. the results from psychology and neuroscience are inspiring to new model structures, since animals are solving similar intelligence problems which are faced by the machines.
2. applications of the AI technology is a strong motivation for us to keep investing in the innovations in this area.

Now I can cite “Yann Lecun's Cake”, which he presented at NIPS 2016: “if machine learning is a cake, then unsupervized learning is the actual cake, supervized learning is the icing, and RL is the cherry on the top.” Supervized learning has been very helpful to us, and will continue to be; RL gives machine the potential to surpass human; unsupervized learning builds up the foundation to both of them, and is really the next big thing for AI research.

References

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