Can Computer Think

Mohamed El. Kuku

November 19, 2017

Abstract

Recent advances in machine learning have had a huge impact in AI. Thanks to the huge amount of data available today, and the computations resources, we are now able to obtain results that surpasses human experts in vision, language, and even in some of the very difficult tasks such as radiology. That also make ask question: have we built intelligent machines. This article discusses current success in the field of deep learning, and try to understand what makes a computer program, intelligent. To the extent that most of use cases concerns, we can conclude that we have built machines that are capable to do what it was designed for, achieving an unprecedented level of intelligence. Though, we have not yet built a general intelligent machines, and also no: Skynet is not coming any soon.

1 What is Intelligence

To answer this question, I believe, we first need to answer: what thinking really is. For decades, scientists were trying to mimic the human brain. And they failed.

What is conscious? Does it define intelligence? Is there any secret recipe that we are missing?

Deep learning is now the man of the show. It just magically works out of the box. In recent ImageNet [1] competition, CNN [2] has achieved an accuracy that surpassed human. This is very big. In Go [3], an ancient game, a machine learning algorithm was able to beat the best player in the world in this game. Notice that Go is way too harder than chess game, for start, there are 10^{170} board configurations–more than the number of atoms in the known universe [3].

The bottom line is human do not need that such huge amount of data to e.g., play well at go, or to know a cat just from one picture of it–and to generalize too.

2 To Learn is To Generalize

To learn is to generalize, is to tick into hidden layers searching for meanings. In natural language processing, using not-even-deep networks such as word2vec [4], we were able to *infer* relationship from our training, that we did not ask the network to do. The learned word representations capture meaningful semantics regularities in a very simple way. The regularities are observed as a constant vector offset between pairs of words sharing a particular relationship. If we denote the vector for word i as x_i, and focus on the singular/plural relation, we find that,

$$x_{family} - x_{families} \approx x_{car} - x_{cars}.$$

2.1 Why BigData

The brain is very efficient is using data. We are not. Our current algorithms need tons of data to perform the most basic tasks in vision or language. A toddler does not need to see thousands of pictures of a cat to recognize it.

There are two paths: the engineers, practitioners path, and the scientists or philosophical path. The former needs just immediate results, the later however, needs to dig even more, to understand how things work the way they do. Research depends on funding–which is becoming ever harder. We need to digest the basics. But not organization prefers direct applicable results. That is probably why researchers like Yoshua Bengio preferred not to work to any corporation. And that is why also, Geoffrey Hinton launched his Vector institute to do basic research in machine learning.

3 Artificial General Intelligence

This is a long term research goal. We are currently rely on supervised learning to build our models. Supervised learning needs training data–which makes its inference only local to this data, up-to some extent. To fix that, the obvious way is to use the opposite of our underlying model, to use unsupervised learning. Unfortunately, unsupervised learning is not as successful as it sibling is. Transfer learning might be our best shot so far. But it is definitely not the solution. There is some interesting phenomena in our brain that allows it to easily achieve intelligence, and understand relationship.

3.1 What are we missing

Several years ago, before 2012 Alex's [2] model, deep learning was there. The reason why deep learning was not as dominant as the case now, is basically because we had not had that much of data, nor that much of computational resources (GPUs). Alex model was indeed a breakthrough, but since then there was not as much breakthrough (maybe except for GAN [5]).

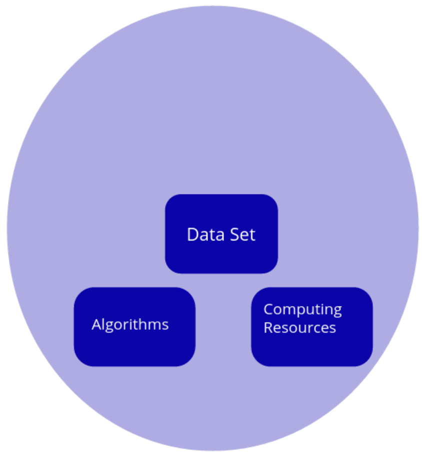

Figure 1: The current (hyper)parameters in machine learning practice. Now, we have lots of data, and access to even lots of resources computing. But we still lack in the algorithms part. Algorithms are difficult to develop, they are lifetime research, however their impact is really huge. Big players in machine learning, and hence AI, are the big tech companies. They just need direct results. They need to plug this *'AI'* in their cameras and social apps. The bright side however, is that their competition is what drives the current very fast pace of machine learning research.

Have we reached the intrinsic limitations of our current algorithms. That might be correct, which also suggest why prominent researchers like Hinton suggests to rethink about the whole back-propagation thing [6]. In Figure 3.1, shows the parameter space of current machine learning research. Ironically, lots of breakthrough in machine learning happens because of hyper-parameters tuning–we tinker them to find the best configurations. In this case, we only have three parameters to tune such that we find the best configurations. The dataset is no longer the issue, even in historically known secret field like biology research, we now have access to freely available dataset. The computing resources is also not the problem. Thanks to nVidia and AWS one can scale to whatever extent they like (assuming that the funding is available). The only left parameter is the algorithm. Well, that is both good and bad. At least we do not have scary parameters to try and tune. We only just have one. The problem is, the underlying theory behind deep learning (and machine learning) consists of statistics and probabilities, optimization, calculus, linear algebra, in addition to computer science field. That means we basically need to go through so many fields to solve this problem.

4 What Next

We have achieved huge success in many aspects of Artificial Intelligence. This should not be forgotten. It is also good and healthy that the deep learning community has variety of diversity: people are coming from all kind of fields and give their contributions and their unique perspective. Having both theory oriented, and production-ready researchers is good as well, in that we can get the benefit from the two worlds.

The answer of this question, whether we will ever have intelligent machines, will lead us to unprecedented quest. That will question our own intelligence, our feelings, and everything we once thought is human. Perhaps we are missing the *Rosetta Stone*, or perhaps intelligence is just deep layers that uses weights to make decision. We are on the edge of something very big. Something fundamental that will challenge all of our pre-knowledge–all of our believes and thoughts. It will hit very hard, but the pay-off will be huge. We will, in any case, get to know what are we better than ever before.

For me, as a machine learning researcher and practitioner, it is a lifetime research topic. I think, we should use artificial intelligence to help *us* understand how our brains work, not the other way around. This research of understanding what intelligence is will lead me to a quest To the extent that most of our AI use cases concern, we can happily rely on our current AI technology. We cannot however say that, these machines are intelligent. We need to figure out what intelligence really is, first. The current research path led us to unprecedented results, but basic research, is important.

References

[1] Olga Russakovsky, Jia Deng, Hao Su, Jonathan Krause, Sanjeev Satheesh, Sean Ma, Zhiheng Huang, Andrej Karpathy, Aditya Khosla, Michael Bernstein, Alexander C. Berg, and Li Fei-Fei. ImageNet Large Scale Visual Recognition Challenge. *International Journal of Computer Vision (IJCV)*, 115(3):211–252, 2015.

[2] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. Imagenet classification with deep convolutional neural networks. In *Advances in neural information processing systems*, pages 1097–1105, 2012.

[3] Wikipedia. Go (game) — wikipedia, the free encyclopedia, 2017. [Online; accessed 19-November-2017].

[4] Tomas Mikolov, Ilya Sutskever, Kai Chen, Greg S Corrado, and Jeff Dean. Distributed representations of words and phrases and their compositionality. In *Advances in neural information processing systems*, pages 3111–3119, 2013.

[5] Ian Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. Generative adversarial nets. In *Advances in neural information processing systems*, pages 2672–2680, 2014.

[6] AXIOS. Artificial intelligence pioneer says we need to start over, 2017. [Online; accessed 19-November-2017].