Franco Nori: Machine Learning Applied to Computationally Difficult Problems in Quantum Physics

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Machine Learning Applied to Computationally Difficult Problems in Quantum Physics

At the NTT Research Summit Upgrade 2020 this past September, Dr. Franco Nori, at the University of Michigan Physics Department, presented examples of novel uses of machine learning applied to three quantum physics problems:

1. Efficiently identifying quantum phases and phase transitions
2. Increasing the efficiency of quantum state tomography
3. Analyzing experimental data

The first problem stems from issues encountered when attempting to calculate unknown quantum phases in an efficient manner using certain types of machine learning, which come with some limitations. Dr. Nori presented cutting-edge machine learning technology that overcomes such limitations.

When training a neural network, data can either be labeled (supervised) or unlabeled (unsupervised). That is, one can nurture a network with, say, pictures of cats and dogs, and then train it to identify newly introduced images as either cats or dogs. It's much more challenging to identify a cat or a dog if the algorithm hasn't been provided labels of these objects, as is the case with a quantum system where not only are the phases unknown, but the parameters as well. To then identify a dog vs. a cat (in this case, a quantum phase transition), we must first be able to identify the features of a dog.

“This is difficult to do because there is no symmetry breaking, no local order parameters, and in complicated cases you cannot compute the topological properties analytically or numerically,” Dr. Nori said.

Dr. Nori, and his colleagues Yanming Che, Clemens Gneiting, and Tao Liu, suggest in their recently published article two aspects that can assist in these complex calculations:

- Manifold machine learning, which can successfully retrieve topological quantum phase transitions in momentum and real spaces
- Chebyshev distances, as opposed to Euclidean, which provide sharper clustering performance

Dr. Nori goes into detail about how these two methods work together to sharpen the results of identifying quantum phase transitions. He notes that once these two aspects are in place, a diffusion map can then be applied, which then allows physicists like Dr. Nori to learn about quantum phase transitions in an unsupervised (unlabeled) way.

The second example he provided involves quantum state tomography, a process in physics where quantum states are reconstructed using measurements from similar quantum states with identical density matrices. Currently, quantum tomography requires many different measurements and computations that are used to reconstruct the state of a quantum system. These methods become wildly inefficient, in terms of both cost and time, as the quantum system scales up in size. Dr. Nori proposed the use of machine learning can overcome the problem of scale.

“A very important process like tomography… cannot be done because there is a computationally hard bottleneck,” he said. “Machine learning is designed to efficiently handle big data, so the question we’re asking is: ‘Can machine learning help us to solve this bottleneck?’”

Dr. Nori discussed two potential solutions to this problem, both works in progress. The first is an iterative procedure called Eigenstate Extraction with Neural Network Tomography that Dr. Nori and his colleagues Abhijeet Melkani and Clemens Gneiting recently published. The project showed that it’s possible to use a neural network to calculate pure quantum states (those with the same patterns) to then determine mixed quantum states (those without a discernable pattern). This method is both cost-efficient and scalable, and provides a viable use case for others seeking to apply machine learning to quantum physics problems.

The second proposed solution involves a new type of machine learning, Conditional Generative Adversarial Networks.

“In this framework you have two neural networks which are essentially having a duel, they’re competing with each other,” Dr. Nori said. “They must train each other on data using standard gradient-based methods. So, we demonstrate that our quantum state tomography and the adversarial network can reconstruct the optical quantum state with very high fidelity… Perhaps within a single evolution of the generator network.” This solution speeds up the process by orders of magnitude, allows physicists to input fewer initial measurements, and provides greater accuracy overall.

The first two examples of machine learning applied to quantum physics problems give rise to the third example: managing experimental data. The solutions discussed in the presentation all rely on immense amounts of data from the frontiers of quantum physics. As Dr. Nori stated, machine learning is meant to handle big data, and that includes data from state-of-the-art experiments.

For the full transcript of Franco Nori's presentation, click here.

Watch Franco Nori's full presentation below.