A neural network as an anchor point

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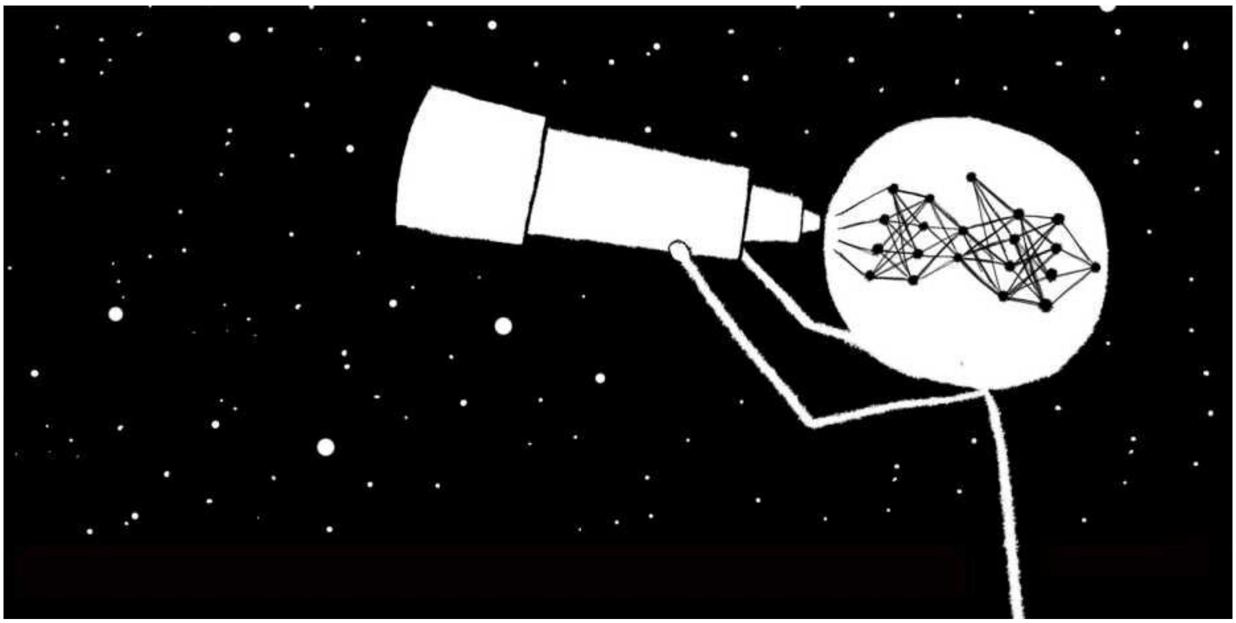

Which astronomical worldview does a neural network arrive at if it is fed nothing but observational data as measured from Earth? Credit: Tony Metger / ETH Zurich

Quantum mechanics is a well-established theory, but at a macroscopic level it leads to intractable contradictions. Now ETH physicists are proposing to resolve the problem with the aid of neural networks.

Necessity is the mother of invention. "So far, all our attempts to resolve the contradictions inherent within quantum mechanics have failed," says Renato Renner, "which is why we're now trying a different approach."

And it's a very potent approach, too—even if Renner, who is Professor for Theoretical Physics, labels it an "act of desperation": in a recent publication, written together with his doctoral student Raban Iten, his Master's student Tony Metger and other members of his group, Renner shows how using artificial intelligence can help to provide deeper insights into physical concepts.

Is a black box the way forward?

The point of departure is the statement that quantum mechanics—never mind that experiment after experiment has confirmed it—leads to contradictions. "When we pointed out a year ago that there must be a fundamental problem with quantum mechanics since you can't apply quantum mechanics to the users of quantum mechanics, we got all sorts of reactions, and lots of feedback as a result. But so far, nobody has come up with a way to resolve this elemental dilemma," Renner says.

At first, the idea that artificial intelligence might be able to help seems surprising. After all, neural networks—the key element of artificial intelligence—effectively operate like a black box. You can teach them to recognize faces on photos, but there's no way of knowing exactly how they go about performing that task. So how can a physicist hope to learn anything from them?

Condensed information

The ETH researchers' answer was to design a two-part "tandem" neural network. The first part of the network gets the ball rolling by calculating parameters that are helpful to perform physical tasks. Based on this, the second part then tackles a specific problem. Meanwhile, the first part keeps adjusting the parameters until the second part is able to master the tasks at hand.

"What we're essentially doing here is imitating the principle of physical formulae," Renner explains, "since these tell you in condensed form which parameters you need to combine, and how, in order to carry out a particular task." The first part of the neural network doesn't communicate any specific physical formulae to the second part. Rather, the physicists can extract the parameters that cross the interface between the two parts and derive physical formulae from them—again using specialized computer programs. "Once a neural network has learned how to solve quantum mechanical problems, perhaps it will find an alternative way to describe quantum systems—at least, that's what we're hoping," Renner says.

The principle works

The ETH physicists have demonstrated that the idea is fundamentally sound by way of simple physical tasks. They had the tandem neural network calculate where the planet Mars could be seen in the night sky at a given time. But all that the scientists gave the network to work with was data on the positions of the planet and the sun as observed over time from Earth.

The neural network subsequently identified the relevant parameters as the ones required to calculate the position of Mars on the basis of the heliocentric worldview. In other words, the neural network found the "right" answer, even though the initial data gave absolutely no direct indication of the fact that Earth and Mars both orbit the sun, rather than Earth being the center of our solar system.

Unencumbered by assumptions

As things stand, the ETH physicists' tandem network is not in a position to resolve complex quantum mechanical problems. "But our work shows that it could well be a promising instrument for us theoretical scientists," Renner says. The neural network's great advantage is that it is not influenced by any set of prior assumptions. "Naturally, it's also possible to explain the motion of Mars assuming Earth is at the center. But that makes the calculations much more elaborate," Renner says. "We find ourselves at a similar point in quantum physics: we have a theory that can explain a great many phenomena, but we're perhaps blind to another, much more elegant description of things."

How do we reach the right answer?

Renner is well aware that searching for a different description will be tough, since the next big question is already hanging in the air: What initial data should the neural network be fed? "The task with the planets was basically an easy one, because we knew in advance which initial data would lead to the right answer," Renner says. "But if we're looking for new insights, that's knowledge that we just don't have."

More information: Raban Iten, et al. Discovering physical concepts with neural networks. : arXiv:1807.10300v2 [quant-ph] arxiv.org/abs/1807.10300 , journals.aps.org/prl/accepted/ … 6166090ef41fa6ad4c34

Provided by ETH Zurich

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