New method for automated control leverages advances in AI

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Credit: Donald Jorgensen | PNNL

The design of real-world automated control systems that do everything from regulating the temperature of skyscrapers to running the widget-making machine in the widget factory down the street requires expertise in sophisticated physics-based modeling. The need for this modeling expertise increases operational costs and restricts the applicability of automated control to systems in which marginal operational performance improvements lead to huge economic benefits, according to data scientists.

With unlimited access to supercomputers and mountains of data, engineers can train artificial intelligence systems such as deep neural networks, a type of machine learning model, to perform automated control. But many people lack access to the necessary computational power to do so, or the ability to generate the amount of data needed to train a controller that has a deep neural network.

What's more, these types of deep neural networks are so-called black-box models, which means that the factors they use to make decisions are hidden from the end user.

In addition to the lack of interpretability, the behavior of standard deep neural networks is difficult to certify, which prevents their use in applications where the safety and performance of the controller must be guaranteed, explained Aaron Tuor, a data scientist at the Pacific Northwest National Laboratory (PNNL) in Richland, Wash.

"What we are trying to do is bring this deep-learning–based modeling into a more data efficient regime enabling its use in real-world applications, which may need interpretability and guarantees of operation that black-box deep-learning modeling can't offer," he said.

Safe and efficient automated control

Tuor and his colleagues are developing a method for designing automated controllers that leverages advances in deep learning and control theory to embed the known and learn the unknown physics of the system to be controlled.

This hybrid approach holds promise for bringing safe and efficient deep-learning automated control technology to a wider range of industrial and engineering systems, such as building energy systems optimization, solid-phase processing, and unmanned aerial and underwater vehicles.

Embedding the known physics of the system into the controller makes it suitable for applications for which having performance guarantees is critical. The approach overcomes concerns about the reliability of black-box machine learning models used to control critical systems, added Tuor.

"If you are in an operational environment where you can't just have the deep learning make any decision whatsoever, you can enforce some bounds on the decision to be taken and the expected outcome of the controlled system," he said.

Gray box modeling

Tuor and his PNNL colleagues Ján Drgo?a and Draguna Vrabie recently applied their hybrid approach to ordinary differential equations. Differential equations are essentially complex mathematical formulas that engineers frequently use to build physics-based models and controls for the operation of real-world systems.

While physics-based models are suitable for mission-critical systems, they do not easily transfer from one system to the next and require specific expertise in the underlying physics of the modeled system.

In the hybrid approach, the PNNL researchers model the differential equation as a deep neural network. Known physics are represented as distinct layers in the deep neural network, which focuses the data needs to train the model on the remaining layers.

Embedding the known physics also opens the model to analysis because the model is no longer a black box—the hybrid approach provides insight into why the model is making certain decisions.

"You can think of this as gray-box as opposed to black-box modeling," said Tuor.

The hybrid approach has the capability of capturing the complex feedback interactions of real-world systems. This allows for accurate predictions of system behavior as well as system optimization for safe performance, according to the researchers.

Proof of concept

To prove the concept, Tuor and his colleagues used the technique to model and control a building thermal system. The best-performing solutions were those that had domain knowledge embedded in the structure of the neural network.

Tuor and his colleagues recently presented the results in a paper at the 2020 International Conference on Learning Representations, a virtual gathering of experts in deep learning. Since then, the team has moved on to more complex systems and will soon apply the method to a manufacturing process at PNNL called friction stir welding, which is a process of welding without melting metal.

"We'll have the ability to take the methods we are developing and deploy them on a real physical process to really validate that this is a useful technology," said Tuor.

From there, he added, the team plans to apply the technique to everything from autonomous cars and trucks to extended autonomous missions for solar unmanned aerial vehicles and autonomous missions for unmanned underwater vehicles.

More information: Constrained Neural Ordinary Differential Equations with Stability Guarantees. openreview.net/forum?id=mTmgaxwynS

Provided by Pacific Northwest National Laboratory

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