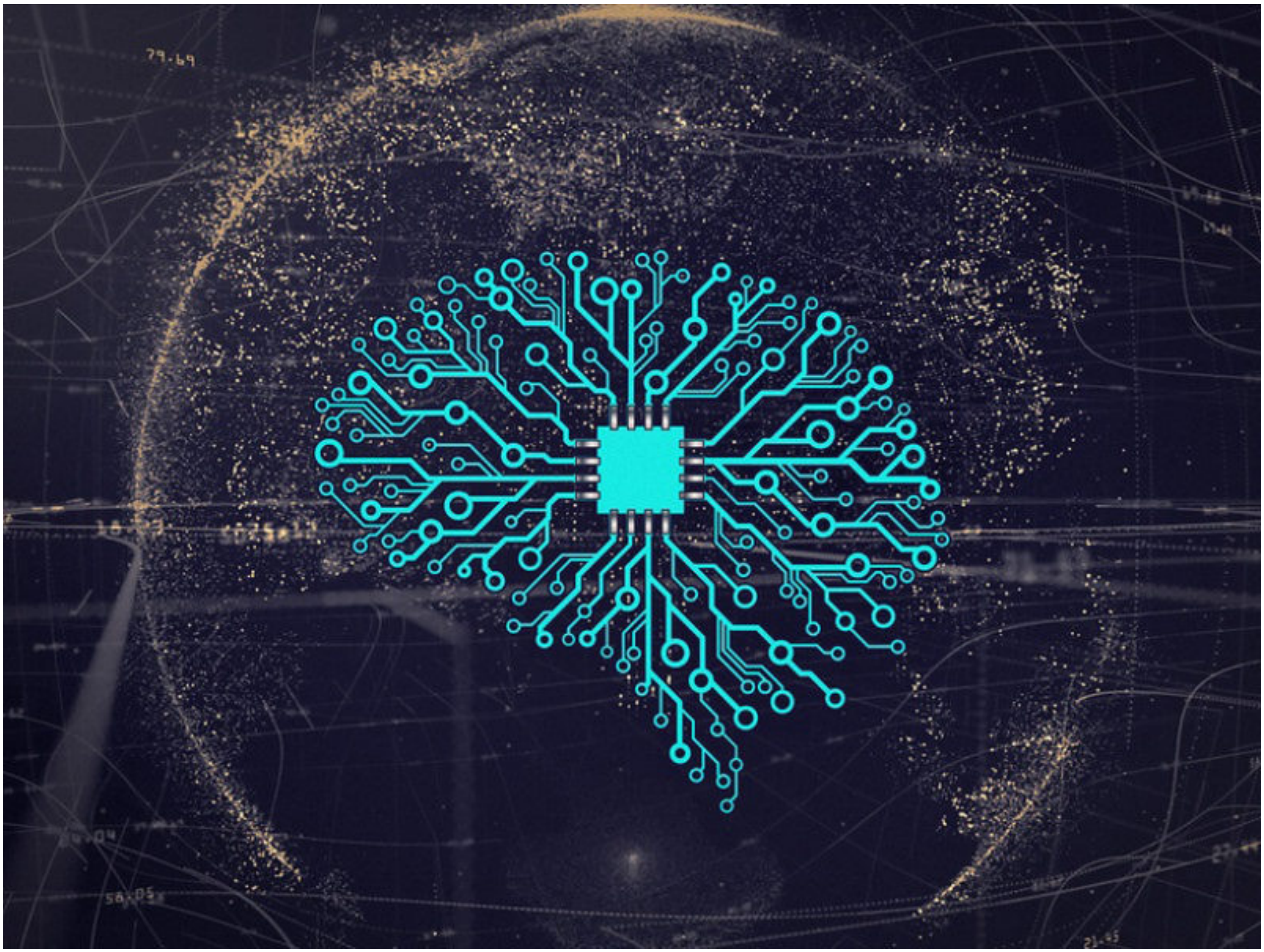
# Editors' Vox

Perspectives on Earth and space science: A blog from AGU's journal editors

## Tackling 21st Century Geoscience Problems with Machine Learning

A new cross-journal special collection invites contributions on how machine learning can be used for solid Earth observation, modeling and understanding.



Which problems of twenty-first century geoscience can machines learn to solve? A new special collection of papers across four AGU journals will explore. Credit: Mike MacKenzie/Flickr (CC BY 2.0)

By Andrew Curtis, Daniel O'Malley, Gregory C. Beroza, Paul A. Johnson, and Elita Lion 7 October 2020

*Papers for the "Machine learning for Solid Earth observation, modeling and understanding" special collection can be submitted to the* Journal of Geophysical Research: Solid Earth (https://agupubs.onlinelibrary.wiley.com/hub/jgr/journal/21699356/features/call-for-papers), Geochemistry, Geophysics, Geosystems (https://agupubs.onlinelibrary.wiley.com/hub/journal/15252027/call-for-papers.html), Tectonics (https://agupubs.onlinelibrary.wiley.com/hub/journal/19449194/features/call-for-papers), *or* Earth and Space Science (https://agupubs.onlinelibrary.wiley.com/hub/journal/23335084/call-for-papers.html).

What are the principle controls on the climate? How can we anticipate and mitigate the effects of geohazards? What is in the Earth's subsurface? When is the next large earthquake likely to occur? Such questions – which are easy to ask but more difficult to answer – are at the heart of modern geoscience.

Seeking answers to such questions depends on scientific research delving into the complex underlying relationships between measurable data and physical properties as expressed through geosystem models. A branch of science first developed in the 1980s is now contributing real answers to these and other questions using a different approach: by focusing on the questions directly.

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It has become clear that machines can learn and use complex patterns in data, or in parameter-data relationships to answer questions posed. "Machine Learning" is a generic term that encompasses the enabling techniques, with intriguing names such as neural networks, support vector machines, random forests, variational inference, and many others.

Machine learning first emerged from the field of Artificial Intelligence (AI) in which computers emulate human behavior. However, machine learning is now applied to solve a wide variety of scientific problems, driven by a broad field of scientists who study learning algorithms. For some references on current progress, see "The Data Problem", the August 2020 issue of Eos (https://eos.org/wp-content/uploads/2020/07/EOS_AUG20.pdf).

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Machine learning methods have at least two important advantages over other methods: first, they have found answers to questions that no human has been able to solve; second, they solve some problems extremely quickly.

Well-publicized examples include an algorithm, called *AlphaZero,* that learned to play chess better than grand-masters, and to beat all humans at our most complex board game 'Go' [Silver et al., 2018 (https://doi.org/10.1126/science.aar6404)]; both games were learned by the algorithm in a matter of hours – by playing against itself millions of times and learning from its mistakes.

Other machines have learnt to interpret combinations of images from multiple cameras and data from a variety of other sensors in a fraction of a second to allow self-driving cars to function in complex, real-world environments [Fridman et al., 2019 (https://doi.org/10.1109/ACCESS.2019.2926040)].

In the geosciences, amongst many other applications, machines have learnt to provide rapid early-warning locations and future forecasts of earthquakes [Kaeufl et al., 2015 (https://doi.org/10.1785/0120150010); Hulbert et al., 2020 (https://doi.org/10.1038/s41467-020-17754-9)], image the Earth's subsurface [Meier et al., 2007 (https://doi.org/10.1029/2007GL030989)], locate seamounts and characterize Earth surface dynamics [Valentine and Kalnins, 2016 (https://doi.org/10.5194/esurf-4-445-2016)] and identify geological features on Mars [Palafox et al., 2016 (https://doi.org/10.1016/j.cageo.2016.12.015)].

A characteristic of some machine learning methods is that, until recently, they have not provided any *understanding* about the relationships between data and solutions or decisions that they make. For example, a machine can learn to produce an image of the Earth's subsurface given geophysical data without providing any human intuition about how it did so. This rightly invokes a level of skepticism of machine-learned solutions, which must be overcome by rigorous testing using structured protocols. Nevertheless, for many scientists, finding an answer to a question is more important than the need for intuition of how it was found – at least in some circumstances.

For others in the field, though, this is unsatisfactory. How can an opaque method be trusted to generalize to previously unseen situations without encoding an understanding of system behavior? This distrust in 'black-box' algorithms has led to the design of new types of machine learning techniques that reveal some of the logic of their inner workings. Called *Explainable Artificial Intelligence*, such methods design rules that are understandable intuitively, and which can be combined to solve problems. The idea is that understanding will add confidence in machine-learned solutions and increase scientific understanding of the questions posed.

Importantly, this also contributes to the emerging field of *Ethical Artificial Intelligence*, the study of how AI and machine learning can be used in a manner that does not pose unreasonable moral challenges. Given the wide variety of fields in which machine learning is now used, a lack of intuition about its inner workings may allow unintentional biases to go unnoticed, which in turn can produce harmful results (e.g., Obermeyer et al., 2019 (https://doi.org/10.1126/science.aax2342)). Amongst recent examples, a gender bias in available information led to distinctly unfair algorithms for recruiting women versus men, and for interpreting medical images [Larrarazabal et al., 2020 (https://doi.org/10.1073/pnas.1919012117)]. It is safe to assume that some types of geoscientific data are equally biased, so ethical AI may provide important pointers on how to obtain more objective results.

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A new special collection on Machine learning for Solid Earth observation, modeling and understanding (https://agupubs.onlinelibrary.wiley.com/hub/jgr/journal/21699356/features/call-for-papers) addresses the many open challenges when developing and using machine learning methods in geoscience.

The collection will bring together papers that demonstrate new scientific results, as well as progress in developments or applications of machine learning or other data science techniques to a broad array of solid Earth topics.

Contributions are expected to clearly identify new knowledge and/or understanding that has arisen or that might arise through machine learning applications, as well as their evaluations/validations.

Papers can be submitted to *JGR: Solid Earth* (https://agupubs.onlinelibrary.wiley.com/hub/journal/21699356/aims-and-scope/read-full-aims-and-scope), *Geochemistry, Geophysics, Geosystems* (https://agupubs.onlinelibrary.wiley.com/hub/journal/15252027/aims-and-scope.html), *Tectonics* (https://agupubs.onlinelibrary.wiley.com/hub/journal/19449194/aims-and-scope/read-full-aims-and-scope) or *Earth and Space Science* (https://agupubs.onlinelibrary.wiley.com/hub/journal/23335084/aims-and-scope.html) as fits most appropriately with the journal's scope and requirements.

This special collection was proposed and organized by Isabelle Manighetti (Editor-in-Chief, *JGR: Solid Earth*), Claudio Faccenna (Editor-in-Chief, *Geochemistry, Geophysics, Geosystems*), Peter Fox (Editor-in-Chief, *Earth and Space Sciences*), and Taylor Schildgen (Editor-in-Chief, *Tectonics*). The Guest Editors who will be handling the submissions are listed below.

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