Testing a machine learning approach to geophysical inversion

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Ground-penetrating radar, shown being used above, is one source of observations for which geophysical inversion is used. Credit: Comprehensive Nuclear-Test-Ban Treaty, CC BY 2.0

A common problem in the geosciences is the need to deduce unseen physical structure based on limited observations. For instance, a ground-penetrating radar observation attempts to infer underground structure without any in situ measurements. This class of problems is called inversion, in which an assumed physical model is repeatedly adjusted until it is consistent with observations.

The results of inversion can be heavily affected by the choice of models, which acts as a Bayesian prior. And because models are generally less complex than the physical world is, the process can also result in an oversimplified solution. To combat these difficulties, it is common to augment a theoretical model with known real-world instances, such as evidence gathered from outcroppings or boreholes. This combination can result in a number of model permutations to provide more realistic diversity for the prior.

Recent advances in this approach have been achieved on the basis of machine learning techniques. Convolutional neural networks similar to those used in computer vision have proven successful in integrating many training samples to produce more nuanced priors with increased spatial resolution. Lopez-Alvis et al. examine one such neural network approach: the variational autoencoder (VAE).

Variational autoencoders are capable of more than just "regurgitating" past training data. They can generate new samples that are consistent with, but not identical to, the sorts of patterns observed in the input images. The authors test this capability by comparing VAEs trained using individual input images with ones trained on sets of images across synthetic and real observational data.

One key result of the study is that VAEs trained using collections of images appear to perform better than those based on only a single input. In fact, the combined VAE performs nearly as well as the single best training image for both synthetic and field data. Thus, rather than searching for the "right match" model by performing many inversions with different inputs, it is significantly more efficient to combine the training inputs into one VAE and perform only one inversion.

This study is published in the *Journal of Geophysical Research: Solid Earth*.

More information: J. Lopez-Alvis et al, Geophysical Inversion Using a Variational Autoencoder to Model an Assembled Spatial Prior Uncertainty, *Journal of Geophysical Research: Solid Earth* (2022). DOI: 10.1029/2021JB022581

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