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# Editorial: Geophysical inversion and interpretation based on new generation artificial intelligence

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artificial intelligence, geophysical inversion, geophysical interpretation, nonlinear mapping, classification problem

#### Editorial on the Research Topic

Geophysical inversion and interpretation based on new generation artificial intelligence

## 1 Research Topic goal

Geophysical inversion and interpretation are two closely related tasks at essential for realizing the value of the geophysical data obtained at a high cost. The former provides the basis for geological interpretation, while the latter is used to make the final exploration decisions based on the results of the inversion. Specifically, geophysical inversion transforms the observed data into the physical properties of the geological targets, such as velocity, density, electrical resistivity, and so on. Geophysical interpretation infers the general characteristics of the target based on the physical properties obtained from the inversion. It estimates the type of geological structure of the target, e.g., an oil and gas reservoir or a mineralized body, etc. The reliable inversion and interpretation of geophysical data is the most challenging problem in geophysics, especially considering the incompleteness and inaccuracy of the observation, the complexity and diversity of the geological targets, and the approximate nature of the physical and mathematical models.

Geophysical inversion, in a general case, is a nonlinear mapping problem, while interpretation is a classification problem guided by geological knowledge. The new generation of artificial intelligence (AI) algorithms, represented by deep learning, have powerful statistical nonlinear modeling and classification capabilities. Therefore, it is believed that deep learning could play an essential role in solving complex geophysical inversion and interpretation problems. The AI-based methods have been successfully applied to solve many geophysical inversion and interpretation problems, such as first arrival travel time detection, fault identification, earthquake event auto-detection, seismic facies identification and classification, seismic signal denoising, wave impedance inversion, electromagnetic wave inversion, seismic velocity modeling, and so on. At the same time, the powerful potential of the new generation AI methods in solving complex geophysical inversion and interpretation problems is far from being realized.

We initiated this Research Topic to promote the application of new-generation AI methods to solve the complex geophysical problems and to document the progress of geophysical inversion and interpretation techniques. It serves as a forum for researchers in related fields to contribute state-of-the-art ideas and approaches for solving complex geophysical inversion and interpretation problems using new-generation AI methods. The main topics are intelligent identification of very weak geophysical signals, intelligent target recognition with minimal physical anomalies, complex structure imaging, complex reservoir identification, simultaneous inversion of multimodal geophysical data, and comprehensive interpretation of multimodal geological and geophysical data.

## 2 Overview of published papers

There are eight papers collected for this Research Topic, involving rock property parameters prediction (three papers), specific geological target identification (two papers), geophysical inversion (one paper), random noise suppression (one paper), and Rayleigh wave dispersion (one paper).

# 2.1 Prediction of specific rock property parameters

Determining the characteristic parameters of the target by inversion is a common task in geophysical exploration (e.g., determining the porosity and oil/gas saturation of a reservoir). For some of the parameters, there are unknown quantitative relationships between the parameters that need to be determined and the observed geophysical data. These parameters can only be estimated based on the statistical relationship between the observed data and the corresponding parameters. One can significantly improve the prediction accuracy and computational efficiency of such parameters by using deep learning methods. Three papers in this Research Topic present the research progress in this development.

Su et al. propose a porosity prediction method for tight sandstone reservoirs based on a Transformer mapping transformation network. The method takes multiple seismic attributes as input data and porosity as output data. The Transformer mapping transformation network consists of an encoder, a multi-head attention layer, and a decoder. It is optimized for training with a gating mechanism and a variable selection module. In a practical case, the method achieves a 95% match rate for tight sandstone reservoir porosity. Ma et al. developed a deep neural network (DNN) embedding-based gas-bearing prediction scheme. The result predicted by the proposed method in deep carbonate reservoirs in China's Sichuan Basin is in good agreement with the actual situation. Njinju et al. present a large-volume velocity-to-density conversion factor calculation method based on mutual information coupling technology.

# 2.2 Identification of specific geological targets

Interpreting geophysical images and identifying specific objects are the most critical tasks in geophysical exploration. The solution to this problem is traditionally done manually by experts based on their experience and knowledge; therefore, the interpretation or identification results may depend on the interpreter. One can develop objective and efficient intelligent geophysical interpretation techniques by using AI. Two articles in this Research Topic show the recent research progress in this direction.

Salt structure identification is an important but difficult task in oil and gas seismic exploration, considering the complex geometry and variable shapes of the salt domes. Li et al. propose a hybrid method to identify salt structure, which combines the U-net model, multiple distillation, and self-distillation methods. The identification of karst caves in seismic images is another example of a challenging problem in seismic imaging. Huang et al. develop an end-to-end convolutional neural network to detect karst caves on 2D seismic images. They employ a class-balanced loss function to overcome the imbalance between caves and non-caves to ensure convergence.

#### 2.3 Miscellaneous topics

There are many unsolved problems in geophysical inversion and interpretation. The three articles in this Research Topic present 2D airborne electromagnetic (AEM) data inversion, noise suppression, and Rayleigh wave dispersion modeling based on deep learning, respectively.

Liu et al. adopt the U-net network for the 2D fast imaging method of the frequency-domain AEM data. The synthetic and field data tests demonstrate that the proposed method provides better resolution and efficiency than the traditional inversion algorithm. Sun et al.propose an improved cycle-consistent generative adversarial network (CycleGAN) for seismic random noise suppression method, which combines U-net and Resent structures to enrich the diversity of extracted features. To improve the network's stability, the authors replace the conventional GAN cross-entropy loss function with the least square difference loss function. Cui et al. propose a deep learning method for efficiently constructing the Rayleigh-wave phase velocity (VR) dispersion curve in a horizontally layered formation. They use a fully connected dense neural network to directly learn the relationships between shear-wave velocity (Vs) structures and dispersion curves.

## **3** Discussion and perspectives

### 3.1 Training dataset

The insufficient amount of labeled data is the main factor that restricts the application of the new generation of artificial intelligence in geophysical inversion and interpretation. Most researchers use forward modeling to generate training data for deep neural networks. The intrinsic structure of the data generated by computer simulation is subject to the petrophysical and field response models used in the forward modeling. These models include many hypothetical approximations. Therefore, the data generated using forward modeling may not always be suitable for training deep networks for high-precision rock parameter prediction. There may be an alternative way to solve this problem by using AI to learn the intrinsic structural characteristics of the geophysical response of real known geological formations and then generate the training data.

### 3.2 Deep network architecture

Many deep network architectures have been proposed over the last decade. Commonly used architectures in geophysical inversion and interpretation include Convolution Neural Networks (CNN), U-net, Long Short-Term Memory (LSTM), Transformer, etc. The problems of geophysical inversion and interpretation are quite diverse. Finding the most appropriate deep network architecture for different problems is one of the current research priorities. In perspective, it may be the best solution to study and construct a general composite deep network architecture for various geophysical inversion and interpretation problems.

### 3.3 Physics-integrated deep networks

Hybrid deep learning, jointly driven by both data and physical laws, may be the best solution for solving complex geophysical inversion and interpretation problems. The key lies in properly incorporating physical laws and geological and geophysical knowledge in the deep learning process. One way is to design a specific network architecture following the physical laws, which is called "physics-based" network. The second way uses the physical laws to constraint the networks, which is called "physics-guided" network. The third way incorporates physics into some modules during network design to force it obey the prior knowledge, and so on.

## 3.4 Geo-GPT

The success of Open AI GPT-4 has inspired us to propose the creation of a similar Geo-GPT for geophysical inversion and interpretation of multimodal geological and geophysical data. The combination of GPT (Generative Pre-trained Model) ideas and DT (digital twin) ideas could form an intelligent complex for modeling

and inversion of oil and gas reservoir and mineralization zone, which would benefit the international geophysical community.

## Author contributions

All authors listed have made a substantial, direct, and intellectual contribution to the work and approved it for publication.

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# Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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