# GeoAI and deep learning

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In recent years, the extensive growth in artificial intelligence (AI) has led to a significant growth of its applications in both the industry and academic communities. AI comprises a system's ability to "correctly interpret external data, to learn from such data, and to use those learning to achieve specific goals and tasks through flexible adaption" (Kaplan and Haenlein 2019, 15). In a technical sense, AI is a suite of algorithms that instruct machines to learn and mimic human intelligence with regard to vision, reasoning, communication, and other tasks. Andrew Ng, the former head of Google Brain, described AI as the new electricity (Ng 2016) that will transform how we think, how we work, and how we do science.

GeoAI, or geospatial artificial intelligence, represents an exciting research area that links AI with location-based analytics and big data for geospatial problem-solving. Today, geospatial data, such as remote sensing imagery, data streams from Internet of Things (IoT) devices, and Global Positioning System (GPS) records from mobile sensors, are proliferating (Li, Batty, and Goodchild 2020). The high volume, variety, and velocity of data pose significant challenges to early analytical tools designed to handle "small" and "good" data. GeoAI differs from traditional approaches in its outstanding ability to process big data. By offering a novel, data-driven, theory-free way to mine big data, GeoAI can discover new knowledge and hidden patterns from data of various sources.

As an interdisciplinary expansion of traditional AI, GeoAI develops as AI advances. In fact, the efforts to combine AI and geography can be dated back to the 1980s (Smith 1984). The authors of *Artificial Intelligence in Geography* (Openshaw and Openshaw 1997) systematically introduced AI methods which were considered cutting edge at the time, such as expert systems and neural networks (NNs), as well as their practical use in geography. This work opened a chapter for integrating the two fields. Despite the enthusiasm, GeoAI also drew questions in its early days as to an overly abstracted model due to limited computing resources and the model's questionable performance in real-world applications. The recent boom in GeoAI has brought this research area to the forefront of GIScience research. Three factors contributing to the rapid development of GeoAI are the exponential growth of data (i.e., big data); the immense availability of computing power; and more importantly, the advances in cutting-edge algorithms, such as machine learning and deep learning (Li 2020).

Machine learning refers to a set of AI algorithms designed with the aims of identifying hidden patterns and/or deriving new knowledge with little human intervention. Compared to the classic, theory-guided, model-driven approach, machine learning gains valuable information and knowledge by exploiting data. There are two categories of machine learning techniques: shallow machine learning and deep learning. Shallow machine learning, such as Naive Bayes classifier and random forest, identifies the nonlinear relationships between the input (X) and the output (Y) through an iterative learning process. Here, X denotes the known attributes

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of an entity or other kinds of independent variables that may relate to the outcome Y, which could be a category in a classification problem or a continuous value in a regression problem. The process to derive X (a set of independent variables) is called feature engineering. Shallow machine learning models often require expert knowledge and substantial manual work to define and compute the prominent features that help identify Y. However, this often leads to misinterpretation of relationships between features and outcomes in the real world. If some important features are overlooked in model training, the results could be biased or of low transferability across different study areas. The emergence of deep learning techniques as a new research paradigm helps address these issues by enabling automated feature extraction in the learning process.

Deep learning refers to computer models which learn by combining multiple processing layers to extract representations of data automatically in support of classification or other decision-making tasks. A popular deep learning architecture is the deep convolutional neural network (CNN), which evolves from a traditional fully connected neural network (NN). Figure 1 illustrates a simple, multilayer, NN and a CNN that support deep learning. Figure 1(a) shows that the mapping between the input and output is through fully connected layers containing multiple neurons in three layers: an input layer, a hidden layer, and an output layer. The network can be expanded by adding more hidden layers and more nodes in each layer, but there can only be one input layer and one output layer. There are four nodes in the input layer, representing input values for four attributes or features that could affect the output. There is one node in the output layer, meaning that this is a binary classification problem, and each input data record could belong to only one of the two values (i.e., 0/1). Similarly, there are three nodes in the hidden layer. What these hidden nodes represent, however, is difficult to interpret.

A CNN alters the computational process of a traditional NN from global operations to local operations. The global operation of traditional NNs proceeds with the dense connections between adjacent layers in which each node in the previous layer connects to every node in the immediate next layer. The local operation in a CNN applies the convolution operation, which uses a convolution filter moving across the input image to extract local signatures and assemble them to produce a feature map (Figure 1b). This local operation allows the data processing and model training to be performed in parallel, either on a graphics computing unit (GPU) or a cloud-based cluster, such that the model can achieve convergence quickly.

In a CNN, multiple convolutional layers can be stacked together (there are three in the example in Figure 1) to subsequently extract low-level features (by layers closer to the input data) to high-level semantics (further down in the pipeline) which are important to the discernment of objects and/or the type of event. After the convolution layers, the feature map is serialized into a 1-D vector for a fully connected layer to produce the final classification or prediction.

The revolutionary nature of deep learning and its outstanding capability in extracting hidden patterns from big data has quickly attracted attention in many scientific domains. The number of AI-related research publications has increased sixfold from 2000 to 2018 (Statt 2018). Material scientists have developed AI models that are capable of recreating chemistry's periodic table of elements by automatically parsing a material database, identifying elements with similar chemical properties, and then clustering them in an unsupervised manner (Zhou *et al*. 2018). Mathematicians use AI to solve

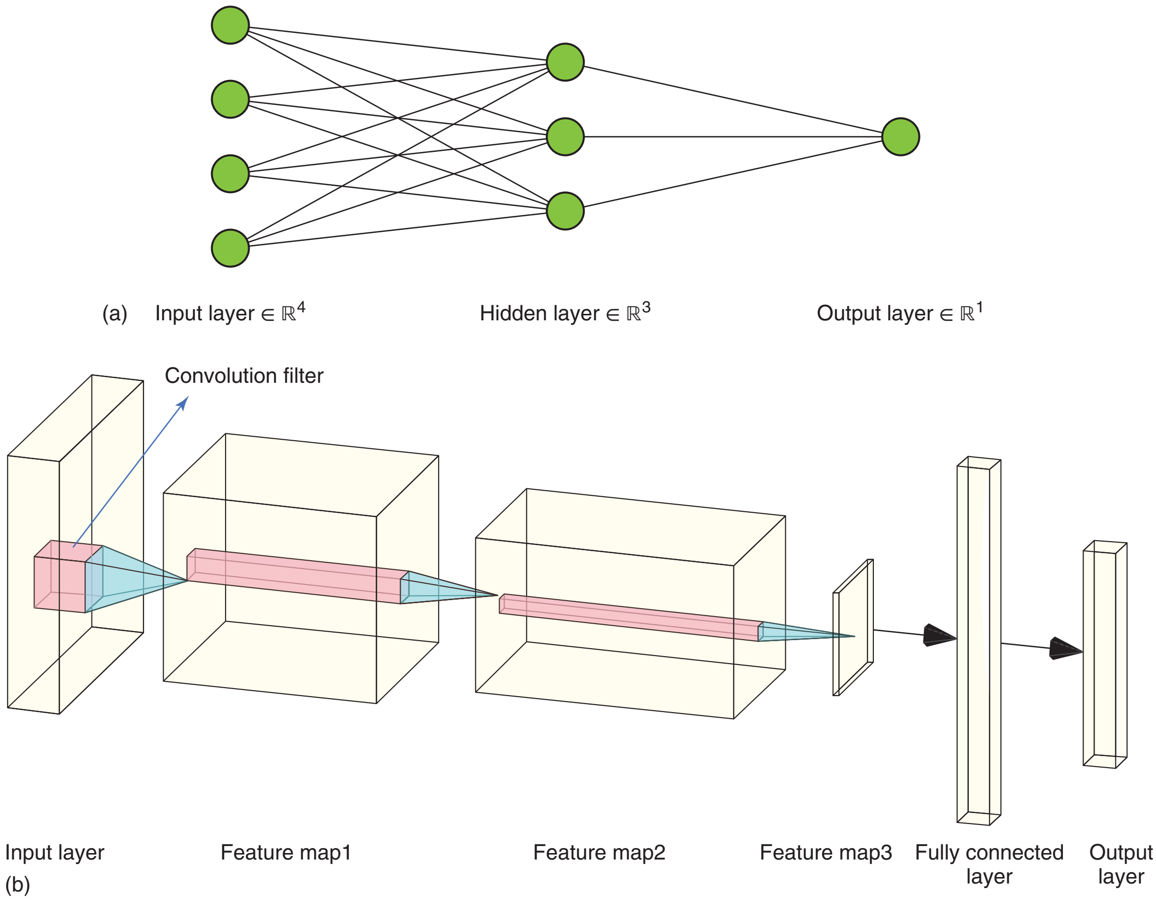


**Figure 1** Examples of (a) a fully connected neural network and (b) a convolutional neural network.

high-dimensional partial differential equations (Han, Jentzen, and Weinan 2018). Medical sciences leverage AI to detect unexpected pharmacological effects, such as adverse drug events, by exploring various drug interactions (Ryu, Kim, and Lee 2018). Applications and appealing research using AI can also be found in the fields of psychology, neuroscience, and astronomy.

The upward trend of research adopting AI in geography is also evident. Since 2015, research using GeoAI, especially deep learning, has increased dramatically in many subdisciplines of geography. In the domains of physical geography and Earth system science, scientists have explored and verified the applicability of deep learning in (i) classification and anomaly detection (e.g., when extracting extreme weather patterns); (ii) regression (e.g., when predicting river runoff in ungauged catchments); and (iii) state prediction (e.g., when developing hybrid physical–convolutional network models to make predictions on temporal changes). In human geography, researchers have tried to predict individuals' socioeconomic status and political views from scenes in neighborhoods. In the more technical fields, such as remote sensing and geographic information science, numerous studies are reported related to image recognition, including classification, object detection, and pixel-level image segmentation.

Besides deep learning, another GeoAI technique, knowledge graph, has also been the focus of recent interest by geospatial researchers. Many big-tech companies, such as Google and Facebook, have used large-scale knowledge graphs to assist smart search and automated query and answering with chatbots, for example. As its name suggests, knowledge graph is a graph that models world entities and the semantic relationships among them. An entity could be a geospatial entity, such as a city or a river, or it could be a moving object, such as a person or a vehicle. It could also be a digital object, such as a computer model. In a nutshell, any object, real or virtual, that can be abstracted as an entity characterized by different properties can be added as a node in the knowledge graph. The semantic linkage (the edge of a graph) among the entities could be a simple, superclass–subclass relationship or it could be any other association relationship, such as "resultIn" or "isSimilarTo."

If we call deep learning a type of data-driven method that makes a machine smart, the knowledge graph serves a knowledge-driven approach which helps a machine to gain implicit knowledge by modeling explicitly the entities and their interrelationships. A knowledge graph and inference rules facilitate semantic reasoning to discover missing relationships among entities and further expand the knowledge. Indeed, deep learning and knowledge graphs are not exclusive to each other. Constructing a scalable knowledge graph requires a machine to automatically process massive unstructured or semistructured text documents and to perform effective information extraction. Deep learning techniques can extensively support this task because they can analyze big data and generate semantic composition through embedding techniques and nonlinear mapping.

GeoAI techniques are widely used in industry and are considered to be key methodological innovations toward harnessing the data revolution and achieving convergence research. In 2019, the US National Science Foundation established a new program called Convergence Accelerator. The program has been actively funding diverse teams composed of researchers from academia, industry, government agencies, and nonprofit organizations to conduct novel research for building an open knowledge network (OKN). The purpose of the OKN is to foster interdisciplinary research and the fast conversion of knowledge produced in academia to commercial and other real-world scientific applications. Knowledge graph is deemed to be the backbone technology enabling the cross-domain knowledge network that is open, transparent, and scalable.

Although it is being actively developed, GeoAI research is still in its infancy. AI is often questioned as being black box and therefore less interpretable. Inheriting the AI properties, GeoAI faces challenges in theoretical justifications and methodological advances. Clearly, geography is a natural home for GeoAI technology to find its value and applications, but research on the concept should go beyond a simple import of AI technology from computer science into geography. What makes GeoAI more valuable is the exportation of domain knowledge, especially spatial principles (such as spatial autocorrelation and spatial heterogeneity), back to the computer science domain toward developing more powerful AI models for geographic inquiries. Recent studies have made notable advances. For instance, Li, Hsu, and Hu (2021) described a weakly supervised deep learning model to support high-accuracy object detection with only weak labels (i.e., a total object count vs accurate object bounding boxes). The authors achieved this by incorporating the spatial autocorrelation stated in Tobler's First Law in Geography to convert the 2-D object detection problem into a 1-D temporal classification problem. An optimization function successfully incorporates the weak labels to detect object locations even without this exact information provided in the training data. Experiments using well-known benchmark datasets in computer science have shown that the proposed model achieves state-of-the-art performance as compared to existing models. The method has also shown satisfying capability to detect Mars craters and natural features on the Earth surface.

The issue of how to make a GeoAI model more explainable by opening up the black box of its learning process is also of urgent concern. The ability to explain allows researchers to compare the similarities and differences in the human and machine reasoning processes to evaluate the trustworthiness of the machine predictions. In addition, detection of geospatial entities is quite different from AI applications in computer science, such as those involving image scene interpretation. Natural features, such as mountains and ridges, are difficult to detect because they often possess complex structures, diverse appearances, and vague boundaries (Li and Hsu 2020). Hence, the natural complexity calls for new solutions beyond those used by existing AI models to effectively resolve the quandaries for which they were designed to address. Integrating geospatial knowledge into a data-driven decision pipeline could elevate the deep learning-based solution to the next level, toward a human–machine convergent research paradigm.

Meanwhile, as GeoAI is data hungry, the development of openly shared benchmark datasets, especially under community-driven efforts, is a key to ensure the successful evaluation of GeoAI models and the advancement of the field. Finally, efforts are needed from the entire geospatial community to create and expand on education and training of the next-generation workforce so that its members will be capable of conducting cutting-edge GeoAI research. Innovative curriculum development to improve students' computing, programming, and spatial thinking skills is of great demand in higher education. All these actionable items, in both research and education, will ensure the prosperous future of GeoAI.

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**SEE ALSO:** Geographic data mining; Geographic information science; Machine learning; Parallel computing; Spatial data science

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