Artificial Intelligence

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What is AI?

The idea ‘a machine that thinks’ dates back to ancient Greece. However, machinery intelligence was not in the discussion until the famous ‘Turing Test’ proposed by Alan Turing. In that test, a human interrogator tried to distinguish between a machine and a person based on their textual responses to questions (Turing, 1950). In 1956, John McCarthy coined the term ‘artificial intelligence’ (AI) at the first-ever AI conference at Dartmouth College. From then on, a number of definitions of AI have surfaced over the past decades (Russell & Norvig, 2021). We may now regard AI as *the science and engineering of making intelligent machines, especially intelligent computer programs* (McCarthy 2004). Meanwhile, AI research is not limited to designing intelligent machines only, but also includes studies that utilize intelligent computational methods to advance knowledge in a variety of domains and to address the most challenging problems facing our society.

The evolution of AI methods

Despite the recent booming prosperity, AI has experienced rises and falls since its inception. Following its early highlights in the 1960s and 70s, AI research went through the ‘AI winter’ due to the bottleneck of addressing real-world problems. Methodologically, the past decades witnessed the three waves of neural network development: i.e., cybernetics from the 1940s to 60s, connectionism from the 1980s to 90s, and the deep learning era starting from 2006. More specifically, the first perception model was proposed in the 1950s to derive weights by learning input samples in a way of imitating nervous activities in the brain (Rosenblatt, 1958). The second wave came with connectionism in cognitive science, in which key concepts for modeling intelligent systems based on neural networks were proposed, such as distributed representations (Hinton et al., 1984), back-propagation (Rumelhart et al., 1986), long-short term memory (Hochreiter & Schmidhuber, 1997), and convolutional networks (Yann et al., 1998). The third wave started with the deep neural networks (DNN) and thereafter a series of DNN architectures (LeCun et al., 2015), such as the various forms of convolutional neural networks (CNN) and recurrent neural networks (RNN), were proposed for tasks such as image classification and natural language understanding. More recently, novel AI models, such as generative adversarial networks (GAN) (Goodfellow et al., 2014) and deep reinforcement learning (Mnih et al., 2015), have kept pushing the frontiers of solving challenging problems in more complex systems with rich sources of data observations.

The integration of AI and geographic research

The integration of AI and geographic research is not completely new. Early studies back in the 1980s have explored how AI and geographic research could be brought together regarding their theories, epistemologies, scientific methods, and applications (Couclelis, 1986; Openshaw, 1997). In 1998, Manfred M. Fischer proposed a computational neural network which was a prototype that combined spatial analysis and models with AI techniques (Fischer, 1998). These early studies found that neural networks could offer greater representational flexibility than traditional geographic models, and could provide new insights for solving some key geographic problems such as spatial pattern classification, spatial clustering or categorization, spatial function approximation, spatiotemporal prediction, and spatial optimization. In the past two decades, various types of big geo data that describe the locational nature of physical and human phenomena have become available. Geographers finally have the opportunity to scrutinize the Earth's surface system in a more systematic and data-driven manner (Reichstein et al., 2019). In this context, and along with the fast advancements of AI methods, *geospatial artificial intelligence* (GeoAI) has emerged as an interdisciplinary research area where AI techniques are developed and utilized for geographic knowledge discovery and beyond (Janowicz et al., 2019). This area is rapidly evolving and is receiving tremendous attention from academia, industry, and moreover, the general public (Hu et al., 2019; Gao, 2021).

Among the big geo data available nowadays, a large amount of them is related to human geography and captures various aspects of human activities in the geographic space. Examples include GPS-based location trajectories, geotagged social media, mobile phone location data, spatial footprints of buildings, traffic flows, road networks, points of interest (POI), street view imageries, socioeconomic data, and spatial epidemiological data. By combining these human activity related geo data and novel AI methods, we can study a wide range of human geography topics such as place perception, human mobility, traffic congestion, public health, disaster response, geodemographics, crimes, and many others. Meanwhile, due to the complex mechanisms of many geographic phenomena, their diverse representation modes, and data incompleteness issues, specialized methods, such as those based on AI models, are needed to overcome some of these challenges and better address the problems in geographic research (Zhu et al., 2020). In the following section, we discuss some of the existing studies that integrated AI and human geography research.

AI for human geography research

<u>AI for place studies.</u> *Place* is an important concept in human geography, and it has been generally considered as *space* filled with human experience (Tuan, 1977). Machine learning and deep learning models, coupled with various types of big geo data, enable us to understand place from spatial, temporal, and thematic perspectives (Janowicz et al., 2019). For example, Gao et al. (2017) synthesized multiple types of geotagged social media data and used an unsupervised clustering method to identify the spatial boundaries of vague place names such as 'NorCal' and 'SoCal' (Fig. 1a). McKenzie et al. (2015) trained a support vector machine (SVM) model based on the temporal

patterns (an example is shown in Fig. 1b) in which people interact with POIs and other information to classify the type of places. Hu et al. (2019) used an unsupervised topic model, latent Dirichlet allocation (LDA), to extract thematic topics (Fig. 1c) from online neighborhood reviews to understand the perceptions of people toward their living environments. Researchers also used AI models to examine the spatial interactions among places. For example, Zhu et al. (2020) employed a graph convolutional neural network (GCNN) to model the connections of places in order to understand and predict their characteristics. Existing research also applied deep learning models to street view images and geotagged photos to extract various types of information about places, such as demographics (Gebru et al., 2017), perceived safety (Zhang et al., 2018), place emotions (Y. Kang et al., 2019), and playability (Kruse et al., 2021).

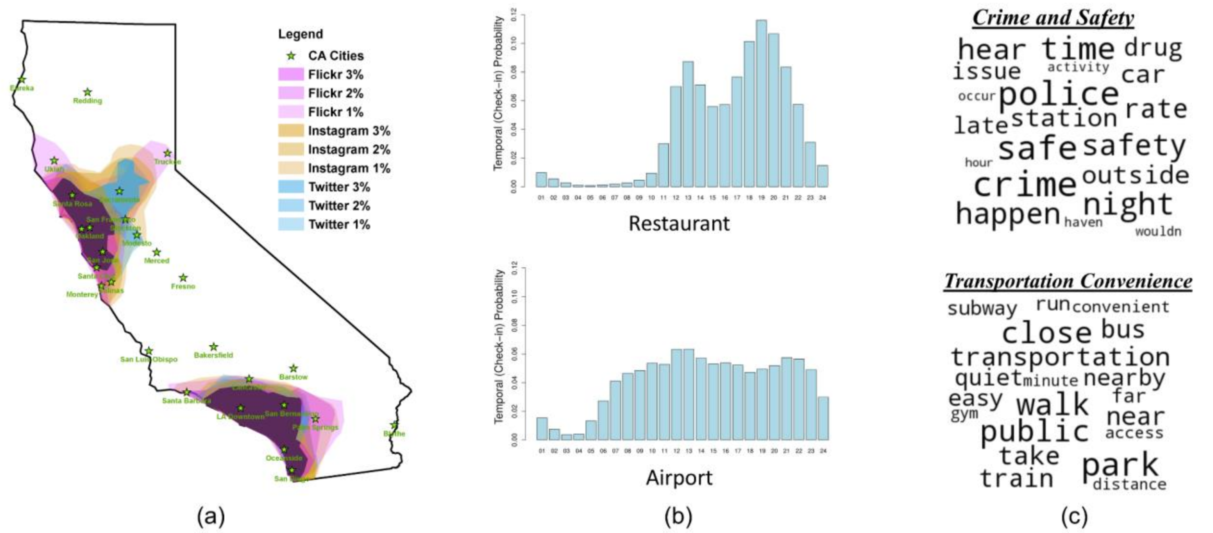

Figure 1. Examples of using AI methods for studying the spatial, temporal, and thematic dimensions of place. (a) Spatial boundaries of 'NorCal' and 'SoCal' identified from multiple geotagged social media data; (b) temporal patterns of two different types of places; (c) thematic topics extracted from online neighborhood reviews.

<u>AI for human mobility and human dynamics</u>. Human mobility and human dynamics are another important research topic in human geography (Shaw & Sui, 2020). The availability of GPS location data from vehicles and mobile phones, location-based social media check-ins, subway smart card data, and other datasets enables us to quantitatively measure and predict how people move around in geographic space (Y. Liu et al., 2015). Noticing the limitation of low-frequently sampled mobile phone location data, Li et al. (2019) proposed a machine learning based method to interpolate and reconstruct human movement trajectories. Zhao et al. (2020) proposed a temporal graph convolutional network (T-GCN) model that improves traffic forecasting by capturing spatial and temporal dependencies simultaneously. Ren et al. (2020) introduced a long short-term memory (LSTM) neural network into the ST-ResNet to form a hybrid integrated-DL model which improved the prediction of citywide spatio-temporal flow volumes. Liu et al. (2017) proposed the Road2Vec model which utilized the embedding technique to capture the implicit

spatial interactions among road segments in order to enhance short-term traffic forecasting. Given the importance of human mobility to traffic management and intelligent transportation systems, there exist many other studies that use AI methods to perform better spatiotemporal predictions of human movements (Deng et al., 2016; Zhang et al., 2019).

AI for public health, disaster response, population studies, and other areas. In addition to place studies and human mobility, AI methods and techniques have been developed and used to address problems related to many other aspects of our human society. In public health, AI methods have been employed to understand the environmental factors and social determinants that may impact the health of the general public (Boulos et al., 2019). Various machine learning and deep learning methods were utilized to tackle challenges during the COVID-19 pandemic (Hou et al., 2021; Mbunge et al., 2021). In disaster response, AI models, such as CNNs and RNNs with improved model architectures, were developed to collect real-time situation information on the ground and to locate the people who need help (Yu et al., 2019; Wang et al., 2020). In population studies, Xing et al. (2020) demonstrated how remote sensing imagery can be used for reliable estimation of human activity volumes by adding neighborhood effects into a raster-based CNN model. Huang et al. (2021) systematically compared four deep learning models in estimating population distribution from remote sensing images as well as the bias in the trained models. Studies on many other topics have also utilized AI methods, such as crime prediction (H.-W. Kang & Kang, 2017) and geoprivacy protection (Rao et al., 2021).

Summary and future directions

Artificial intelligence and big geo data enable us to study human geography from new perspectives and to discover new knowledge about our human society. While we have reviewed some of the recent advancements, various challenges exist that may need to be addressed in future research. First, AI models often need to be trained with labeled data. While many geospatial datasets exist, there is still a lack of high-quality labeled data due to the required manual effort for data annotation. Thus, one direction is to study possible approaches that can facilitate the creation of labeled datasets so that we can train and use AI models for human geography research with more data support. Second, geospatial datasets are always collected in certain geographic regions, making the trained model difficult to be generalized to other regions. Therefore, another possible direction is to study methods that allow the trained AI models to be transferred from one geographic area to another, so that we can facilitate the examination of human geography phenomena across different regions. Third, while AI models often have outstanding performance in prediction and classification, many of them function like black boxes and it is difficult to explain their internal process to researchers and decision makers (Gahegan, 2020). Enhancing the explainability of AI models is another direction that can promote their usage in human geography research.

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