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GUEST EDITORIAL

Symbolic and subsymbolic GeoAI: Geospatial knowledge graphs and spatially explicit machine learning

1 | SYMBOLIC AND SUBSYMBOLIC ARTIFICIAL INTELLIGENCE

The field of Artificial Intelligence (AI) can be roughly divided into two branches: Symbolic AI and Connectionist AI (or the so-called Subsymbolic AI). Symbolic AI focuses on research based on classical logic and higher-level symbolic (human-readable) knowledge representations. It posits the use of declarative knowledge in reasoning and learning as critical to producing intelligent behavior (Goel, 2022). Examples are logical inference, symbolic reasoning, ontology engineering (Allemang & Hendler, 2011; Battle & Kolas, 2011; Hobbs & Pan, 2006; Hu et al., 2013; Janowicz et al., 2019), and in part knowledge graphs (KGs) (Hoffart et al., 2013; Janowicz et al., 2022; Noy et al., 2019; Singhal, 2012; Zhu, Janowicz, Mai, et al., 2022). In contrast, Connectionist AI advocates the idea of explaining intelligence using artificial neural networks (van Eijck & Visser, 2012). It assumes that the learning of associations or correlations from data (with little or no prior knowledge) is crucial for understanding mental phenomena (Goel, 2022). Examples are deep learning and representation learning techniques (Goodfellow et al., 2020; Hamilton et al., 2017; LeCun et al., 2015; Mai, Janowicz, Yan, et al., 2020; Vaswani et al., 2017), which are currently the dominating techniques in AI. Current breakthroughs in narrow AI are largely due to these technological successes in designing artificial neural networks, while having access to large-scale datasets for training, and with high-performance computing being readily available (Goel, 2022; Janowicz et al., 2020).

More recently, an increasing number of studies have been trying to combine these two approaches to develop scalable and interpretable AI models, the so-called Neural-Symbolic AI. Examples include AlphaGo Zero (Dalgaard et al., 2020) and Neural Symbolic Machines (Liang et al., 2017), which made use of symbolic reasoning in conjunction with neural networks in a reinforcement learning framework for the game Go, or KG-based question answering. KG embeddings (Dong et al., 2014; Hamilton et al., 2018; Mai et al., 2019; Nickel et al., 2012, 2016; Wang et al., 2014) and relational machine learning (Battaglia et al., 2018; Nickel et al., 2015; Schlichtkrull et al., 2018) are other typical examples.

2 | SYMBOLIC AND SUBSYMBOLIC GEOAI

This special collection is the continuation of efforts that began with the GIScience'2021 workshop on "Methods, Models, and Resources for Geospatial Knowledge Graphs and GeoAI (GeoKG & GeoAI 2021)," which was followed by an open call for full-paper submissions.

From a geospatial point-of-view, Geospatial AI (GeoAI), as an interdisciplinary field combining Geography, GIScience, and AI, advocates the idea of developing and utilizing AI techniques in geography and earth science research (Janowicz et al., 2020). This, in turn, benefits downstream tasks in health (Kamel Boulos et al., 2019), urban studies (Liu & Biljecki, 2022), traffic prediction (Polson & Sokolov, 2017), earth system science (Ham et al., 2019), and so on. GeoAI can also be categorized into two branches: Symbolic GeoAI and Subsymbolic GeoAI.

2.1 | Symbolic GeoAI: Geospatial KGs

One research direction in Symbolic GeoAI are Geospatial KGs (GeoKGs) (Janowicz et al., 2022; Kuhn et al., 2014). GeoKGs, as symbolic representations of geospatial knowledge, are at the core of GeoAI and facilitate many intelligent applications such as geographical question answering (Chen et al., 2013; Kuhn et al., 2021; Mai, Janowicz, Cai, et al., 2020; Nyamsuren et al., 2021; Scheider et al., 2021), geospatial knowledge summarization (Yan et al., 2019), geospatial data integration (Bernard et al., 2022; Sun et al., 2021; Trisedya et al., 2019), or geographic knowledge discovery (Hu et al., 2015; Jiang et al., 2018; Li et al., 2012; Mai, Janowicz, Prasad, et al., 2020; Park & Lee, 2022). In fact, geospatial data play an important role in the Linked Open Data cloud (Kuhn et al., 2014), since space and time are essential for describing the relationships among events, people, and objects. However, many KGs treat geographic entities as ordinary entities in which the spatial footprints of places and the unique spatial operations (e.g., cardinal directions, topological relations, routing operations) are neglected, which leads to suboptimal and unsatisfactory results. Compared with generic KG research, there are many unique research questions to be asked for GeoKGs, such as how to model the evolution of geographic entities (e.g., administrative regions) across space and time (Bernard et al., 2018, 2022; Kauppinen et al., 2008), how to perform spatial-aware place retrieval and place similarity assessment (Chen et al., 2013; Mai, Janowicz, Cai, et al., 2020; Park & Lee, 2022; Santos et al., 2018), how to take into account uncertainty and vagueness when computing (spatial) associations among geographic entities for geographic data integration and question answering (Mai, Jiang, et al., 2022; Regalia et al., 2019; Santos et al., 2018), and so on. This special collection includes two articles that answer some of those questions.

In the first article, Bernard et al. (2022) present a framework called *Theseus* for automatic creation of GeoKGs for geographic divisions as well as their evolution over time. The article addresses three main questions: (1) how to represent geographic divisions in a GeoKG? (2) how to represent their evolution over time within a GeoKG? (3) how to detect those territorial changes and create GeoKGs automatically? The *Theseus* framework was built to answer those three questions. Given two versions of the geographic divisions at different times, represented as two Shapefiles, *Theseus* first uses a data pre-processing application named *Theseus Prep* to transform each Shapefile into a pre-formatted TSN-shapefile format, as well as a Theseus PostGIS database which are aligned with their defined territorial statistical nomenclature (TSN) ontology. Next, the geographic division data are triplified into KGs with the TSN ontology. Then, an automatic change detection algorithm is used to detect and create the KG of geographic division changes by using a TSN Change ontology. Finally, a Graphical User Interface is developed to explore and query the geographic divisions and their evolution over time. *Theseus* represents a holistic framework for geographic division evolution over time, from data collection to automatic change detection, KG construction, and KG visualization.

In the second article, Park and Lee (2022) present a Spatial-Semantic integrated Indoor KG (*SSIKG*) for place-based retrieval and route guidance in indoor environments. *SSIKG* contains two layers, namely a spatial layer and a semantic layer. The spatial layer is a symbolic representation of geographic entities in the indoor environment, as well as the navigation paths among them. The semantic layer includes the semantic information about indoor places, such as place categories, opening times, user reviews, keywords, and the similarity scores between entities. By representing both the spatial and semantic information of indoor places into a KG, the authors show that *SSIKG* can answer various questions regarding indoor place-based retrieval and route guidance, by considering both spatial proximity, connectivity, and semantic similarity.

2.2 | Subsymbolic GeoAI: Spatially explicit machine learning

In terms of the other branch, we have that the use of subsymbolic AI approaches such as deep neural networks, to solve geospatial problems, is also a common component of GeoAI research. Although some existing deep learning architectures for tasks, such as image classification, image segmentation, question answering, modeling language and vision, or entity recognition, can be readily used for GeoAI tasks such as classification and object detection in remote sensing images (Bastani et al., 2022; Camps-Valls et al., 2021), land use classification (Camps-Valls et al., 2021), geographic question answering and question answering over Earth observation products (Coelho et al., 2021; Silva et al., 2022), remote sensing image captioning (Ramos & Martins, 2022), or place name recognition and resolution (Cardoso et al., 2021; Kulkarni et al., 2021; Liu et al., 2022), some unique challenges emerge which require special model designs, training objectives, or data pre-processing techniques, for instance by incorporating spatial principles and spatial inductive biases. We call this kind of practices *spatially explicit machine learning* (Janowicz et al., 2020; Li et al., 2021; Mai, Janowicz, Yan, et al., 2020; Mai, Jiang, et al., 2022; Yan et al., 2017, 2019; Zhu, Janowicz, Cai, & Mai, 2022). Some of the unique challenges include how to represent different types of spatial data into the embedding/subsymbolic space (Mai, Janowicz, et al., 2022), how to achieve geographic generalizability for a given machine learning/deep learning model (Goodchild & Li, 2021; Li et al., 2022), how to perform transfer learning across space and tasks (Fibæk et al., 2022), how to avoid geographic biases in GeoAI models (Liu et al., 2022), and so forth. This special collection also includes two innovative articles that tackle two questions we mentioned above.

The third article in this special issue collection, by Li et al. (2022), proposes a novel few-shot transfer learning (FSTL) method to improve the geographic generalizability of deep learning models for OpenStreetMap (OSM) missing building footprint detection. After the supervised training of a building detection model on fully labeled regions, FSTL is used to transfer the learned knowledge to label-sparse regions (e.g., Cameroon and Mozambique). Previous research shows that the generalizability (including replicability) of deep learning models across geographic space is weak (Goodchild & Li, 2021). Li et al. (2022) demonstrate that, compared to the state-of-the-art approaches such as Google Open Building (Sirko et al., 2021) and Facebook's High-Resolution Settlement Layer (Tiecke et al., 2017), the proposed few-shot learning approach achieves better accuracy in new label-sparse areas with just a couple of few-shot samples.

The fourth article, from Fibæk et al. (2022), presents a deep learning model for population estimation in areas geographically distinct from Northern Europe. The two major contributions of this article are as follows: (1) the authors demonstrate how to use the same deep learning architecture and transfer learning to solve three tasks—structure area prediction, structure type classification, and population prediction for Ghana and Egypt based on Sentinel data; (2) the authors show how to use multi-sensor data to produce high-resolution population estimation for both daytime and nighttime, using deep learning.

3 | CONCLUSION AND NEXT STEPS

In this editorial, we first discussed the differences and connections between Symbolic AI and Subsymbolic AI. Next, we highlight the prominent components of Symbolic GeoAI and Subsymbolic GeoAI—Geospatial Knowledge Graphs and Spatially Explicit Machine Learning. Four articles are included in this special collection, with two articles focusing on GeoKGs, while the other two address spatially explicit machine learning. We believe that both components are indispensable for GeoAI research. Special thanks are owed to the authors, and especially to all of the reviewers for their informative and insightful peer reviews.

We believe that this special collection provides a good overview of the current state-of-the-art in GeoAI research. In addition, the contributions also raise many interesting GeoAI research questions such as: (1) How to combine deductive methods from symbolic GeoAI with the representations and induction from deep learning models used by subsymbolic GeoAI to build neuro-symbolic GeoAI models? (2) To improve model generalizability across space and time, instead of using the FSTL method as Li et al. (2022) did, can we directly learn a hypernetwork to simulate how the model's parameters change based on the location and time with meta-learning method (Tenzer et al., 2022)? (3) Given the increasing popularity of foundation models (FMs) in the natural language and vision communities, such as GPT-3 (Brown et al., 2020), CLIP (Radford et al., 2021), PaLM (Wei et al., 2022), and DALL·E2 (Ramesh et al., 2022), could we build a FM for GeoAI which, after pretraining, can be easily adapted to multiple symbolic GeoAI and subsymbolic GeoAI tasks, involving the use of different data modalities (Mai et al., 2022a)? (4) How can we address important ethical aspects, such as better accounting for and mitigating issues of bias, fairness, and transparency (Shin & Basiri, 2022; Zheng & Sieber, 2022), how to reduce the environmental footprint of model training, and how to better connect to communities studying ethics of technology (Goodchild et al., 2022).

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