A Review and Synthesis of Recent GeoAI Research for Cartography: Methods, Applications, and Ethics

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Introduction

Recent years have witnessed the development of artificial intelligence (AI) technologies that are capable of solving a wide range of practical problems. Scholars from cartography and GIScience have collaborated on several pioneer works that integrate geospatial artificial intelligence (GeoAI) into cartography. Such a topic has become a promising research area that is rapidly growing in cartography and GIS communities due to the following two reasons: First, GeoAI techniques based on machine learning and deep learning algorithms may achieve better performances in solving traditional cartographic tasks compared with classic statistics approaches. For instance, GeoAI-based approaches performed better in geographic objects (e.g., POIs, road networks, map contents) detection and identification from maps (Jiao et al., 2021; Touya et al., 2020; Usery et al., 2021), topics often considered as part of data assembly and generalization within cartography. More importantly, GeoAI could be useful in assisting cartographers to address several new cartographic tasks beyond generalization that existing GIS tools are unable to tackle. For example, the artistic part of the maps has long been believed to condense the cartographers' creativity, inventiveness, perception, and experience. Machines only can be utilized as "tools" by cartographers and cannot create "real" artwork. Recent breakthroughs in AI have achieved great success in modeling aspects of art such as the creation or analysis of artistic work including painting, style transfer, art generation, and aesthetics (Demir et al., 2021; Santos et al., 2021). There have been pioneering works that utilize such approaches for map style transfer (Christophe et al., 2022; Kang et al., 2019) and map generalization (Feng et al., 2019; Touya et al., 2019; Usery et al., 2021).
Here, we present a literature review and systhesis summarizing general workflows, approaches, techniques, as well as applications that utilize GeoAI for solving cartographic tasks to provide a comprehensive overview of the integration of GeoAI in cartography. Inspired by Janowicz et al., (2020), the bigger picture question *Q* that motivate the research community to move forward about the integration of GeoAI in cartography might be: *Can we develop an artificial cartographer assistant so that cartographers are no longer focused on the usage of cartographic tools and technical details but more on artistic map creation?* This review, we believe, will provide valuable insights into the measuring of success in this research community following this *Q*, as well as demonstrate how specific research topics contribute to this blueprint. From this review and synthesis, we also noticed that, despite the potential of GeoAI for cartography, the ethics of GeoAI in cartography remain underdeveloped (Nelson et al., 2022). Therefore, we also discussed the ethics, challenges, and opportunities of GeoAI for cartography.

To complete the review, we performed a keyword search between 2015 to April, 2022 via the Scopus database including the terms “cartography”, “GeoAI”, “deep learning”, “map”, “spatial explicit model”, etc.

A General Framework of Integrating GeoAI in Cartography

We first propose a general computational framework that abstracts the workflows of integrating GeoAI into cartography (Figure *1*). Such a framework contains four steps: (1) map data can be downloaded and generated from diverse cartographic data sources; (2) vector and raster map data can be processed, converted, and formatted, and cartographic knowledge might be encoded and extracted to suit the input requirements of machine learning and deep learning approaches; (3) diverse machine learning and deep learning models are applied for training and learning cartographic representation and knowledge; and (4) evaluation approaches to measure and judge the results to examine whether results of models are robust and solid including such as objective achine-based metrics and subjective human-centered evaluation.

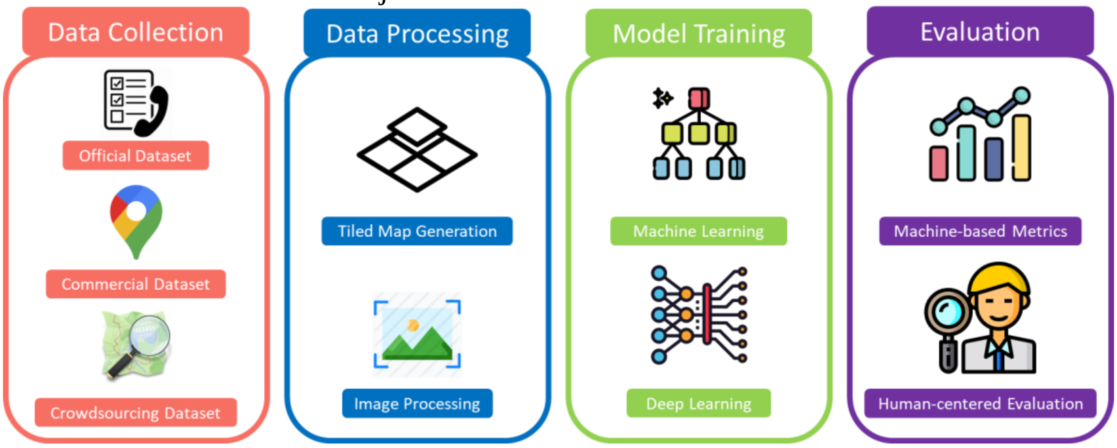

Figure 1 A computational workflow for GeoAI in cartography

Map Data Collection

There are three types of data sources that are widely used for the research of GeoAI in cartography. Authoritative geographic datasets released by governments usually have high data quality that meets cartographers' demands but might be limited and restricted to specific types and regions. For example, the TOP10NL dataset published by the *Dutch Cadastre, Land Registry and Mapping Agency* has high data quality but is limited to the Netherlands. Commercial datasets are provided by several commercial companies such as Google Maps, Bing Maps, and Baidu Maps. These datasets are relatively high-quality while may cost more, take longer downloading time, and may have copyright issues. Crowdsourced datasets collected by open-source map services such as OpenStreetMaps (OSM) provide abundant freely geographic data while the data quality may vary in different regions.

GeoAI Methods

Five categories of GeoAI approaches are frequently used in the current studies in cartography: (1) Decision trees: decision trees are tree-like models for decision-making. Existing studies have utilized multiple decision tree approaches (e.g., random forest) for cartographic tasks such as settlement selection (Lisiewicz & Karsznia, 2021); (2) Deep convolutional neural networks (DCNNs): such approaches are widely used for identifying patterns of images and thereby have been used for raster-based maps processing (Feng et al., 2019); (3) Generative adversarial networks (GANs): GANs contains a generator and a discriminator, and have been widely used for generating data such as map generation and map style transfer (Kang et al., 2019); (4) Graph neural networks (GCNs): DCNNs and GANs are widely used for images which are inappropriate for vector-based maps. While GCNs can handle vector data by constructing graphs in map data (R. Zhao et al., 2020); (5) Reinforcement learning: such methods are developed based on rewarding positive actions while punishing undesirable ones, and have been used for geographic object alignment (Duan et al., 2020).

Evaluation

The output from the GeoAI models should also be evaluated to know whether results meet cartographers' demands and whether the model deployed achieve expectations. Machine-based evaluation might be defined based on several commonly used metrics. Also, it is necessary to collect cartographers' feedback to keep human-in-the-loop in improving the results of deep learning approaches.

GeoAI Applications for Cartography

In this section, we list several applications that use GeoAI for cartography.

Map Object Identification

Map object identification refers to the detection and extraction of geographic objects from maps. Prior work includes identifying various geographic objects such as wetlands (Ståhl & Weimann, 2022), urban extents (Uhl et al., 2021), road networks (Cira et al., 2021; Touya & Lokhat, 2020; Uhl et al., 2022), and building footprints (Feng et al., 2020; Z. Li et al., 2021), from multiple data sources such as historical maps (Ståhl & Weimann, 2022; Uhl et al., 2021, 2022) and aerial images (Feng et al., 2020). Another key topic refers to the alignment of the same geographic entities from different sources of maps, which also requires map object identification. For example, existing studies have aligned road segmentation and buildings from multiple maps (Duan et al., 2020; Sun et al., 2021). In addition, it is necessary to build map ontology for connecting different map objects using knowledge graphs (Mai et al., 2022).

Map Generation

With the advancement of GeoAI, it is possible to generate maps directly from other sources of datasets such as remote sensing images. The output of such tasks is usually full map tiles rather than discrete map features and objects. For example, existing studies have adopted GANs for multiscale map generations (X. Chen et al., 2021, 2022; J. Li et al., 2020, p. 20; B. Zhao et al., 2021). In addition, prior work also have investigated approaches for other map generation with machine learning like metro map generation (Fister, 2021). Also, Hu et al., (2021) proposed a deep learning approach for augmenting GIS data for map-making.

Map Style Transfer

Map style transfer refers to the process of reproducing or mimicking artistic styles from existing maps or paintings to unstyled maps. It can be seen as an intersection between map stylization and neural style transfer from computer science. Since the pioneering work that adopted GANs for map style transfer (Kang et al., 2019), map style transfer has become a popular research field that caught on quickly throughout the cartography community (Bogucka & Meng, 2019; Christophe et al., 2022).

Cartographic Design Evaluation

GeoAI approaches also may benefit the evaluation of map designs. For example, T. Chen et al., (2021) evaluated the color quality of maps using a learning-based approach. Robinson, (2019) evaluated the design and social dissemination characteristics of maps. Kang et al., (2019) classified whether an input image is a map or not. Armstrong, (2019) proposes an architecture for a deep learning approach for dot map evaluation.

Automatic Map Labelling

Map labeling refers to the production and annotations of geographic objects and is a crucial element of maps. Existing work have investigated approaches for map labeling automation. For instance, existing studies have used AI approaches to automate the process of label placement (Y. Li et al., 2020; Pokonieczny & Borkowska, 2019) and classified annotations from maps (Ren & Hou, 2020).

Map Generalization

Map generalization is a classic cartographic task that has attracted researchers' attention for decades (A. H. Robinson et al., 1995). It refers to the process of simplifying detailed maps to smaller-scale maps with the major semantic and structural characteristics maintained. Prior work has employed machine learning approaches for point-based generalization, and deep learning approaches for cartographic generalizations based on polylines and polygons.

For point-based cartographic generalization, existing studies have employed decision tree-based approaches for human settlement selection (Izabela & Karolina, 2020; Karsznia & Weibel, 2018; Lisiewicz & Karsznia, 2021).

While for cartographic generalization based on polylines and polygons, deep learning has been utilized since 2019 for map generalization (Feng et al., 2019). After that, existing studies investigated more cartographic generalization tasks for polyline and polygon objects using deep learning and achieved decent results. For example, prior work has adopted GCNs for road network selection (Zheng et al., 2021), and utilized an artificial neural network for polyline simplification (Du et al., 2022).

Building generalization is another key topic in cartographic generalization. Existing studies have applied deep learning approaches including GCNs and DCNNs to address multiple issues in different steps of building generalization such as building simplification (Kang et al., 2021; M. Yang et al., 2022), building group pattern identification (Bei et al., 2019; Yan et al., 2020; R. Zhao et al., 2020), and building displacement (Liu et al., 2021).

Map Content Inference

Map content inference refers to finding out the location of the map, i.e., given an input map, the locations and contents should be figured out. Existing studies have proposed several approaches using deep learning to infer the content of the map from images (Dobesova, 2020; Evans et al., 2017; Hu et al., 2021; Touya et al., 2020). In addition to referencing map content, existing studies have employed machine learning approaches for labeling regions with different characteristics (Scheider & Huisjes, 2019), and classifying map themes (Z. Yang et al., 2020).

Discussion

Ethics of GeoAI in Cartography

Despite the success of studies using GeoAI in cartography, we discovered that the ethics of GeoAI for cartography remain underdeveloped. Though there are multiple ethical challenges in the field, here, we summarize discussion on two specific ethical challenges noted in the literature: commodification and bias.

The data and artistic styles of maps as commodities is one ethical challenge in this field (Crampton, 1995). Should we charge for data and artistic styles produced by machines? On the one hand, academic researchers prefer to endorse open-access datasets and models which empower the replicability and reproducibility of academic studies (Wilson et al., 2021); on the other hand, the copyright of the datasets, style schemes should be protected.

Another issue is bias such as data bias, model bias, cartographic representation bias (Jobin et al., 2019; Miller, 1995; Nelson et al., 2022). The quality of crowdsourcing datasets may vary across different regions. Also, the GeoAI approaches may also have biases that have been criticized recently (Roselli et al., 2019). The models trained in one downtown area may have limited transferability to the rural area. It is necessary to tackle biases in GeoAI approaches for cartography.

Limitations

We also acknowledge several limitations of GeoAI in cartography. First, most GeoAI approaches are "black-box" in which the explainability of models is often criticized (Jobin et al., 2019). Second, several technologies, though have produced promising results, are still far from being applied to real applications as they may also face several challenges such as requiring larger computing resources, and loss of spatial structures in maps (Kang et al., 2019).

Conclusion

In this work, we present a timely review of cartography research with GeoAI. We summarize the workflows, data sources, methods, and applications in this field. We also make discussions about the ethics and challenges of GeoAI in the scope of cartography. We hope such a review paper could measure the current progress in the community of GeoAI for cartography, and bring more insights into the future research of cartography.

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