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TECHNICAL CONTRIBUTION

# Current topics and challenges in geoAI

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**Abstract**

Taken literally, geoAI is the use of Artificial Intelligence methods and techniques in solving geo-spatial problems. Similar to AI more generally, geoAI has seen an influx of new (big) data sources and advanced machine learning techniques, but also a shift in the kind of problems under investigation. In this article, we highlight some of these changes and identify current topics and challenges in geoAI.

**Keywords** Social sensing · Explainable AI · Smart cities · Explicit models

## 1 Introduction

The term 'geoAI' is a combination of 'geo,' as in 'geographic' or 'geography,' and 'AI,' i.e., 'Artificial Intelligence.' The 'correct' definition of geoAI is debatable.[1] However, it seems safe to say that methods and techniques of Artificial Intelligence (AI) have been for a long time—and continue to be—applied to solving problems of a geographic nature. In that, the last 10–15 years have seen many changes. There is a lot more, and a lot more diverse, data available, the kinds of problems addressed have become broader, but also focus shifted, and following developments in AI more generally, methods and approaches applied in geoAI have changed. In this paper, we aim at providing an overview of some of the current developments and challenges in geoAI. We start with the (data) sources and some currently dominant areas of research. We then explain how increasing digitalization of our environments has led to more dynamic and more complex situations and requirements for geoAI, and briefly discuss some issues the new methods may bring along. We end the article with a short excursion into the 'geography of indoors.'

## 2 Spatial is Special, or is it?

"Spatial is special" is a claim often made in the geo-spatial sciences [3]. Different aspects or properties of geographic space and the phenomena playing out in these spaces have been identified that may make it special [13, 36], among them the underlying physical and geometric properties and restrictions that hold in the real world, the fact that results of spatial computations are dependent on scale and location, and an inherent uncertainty in the data. Tobler's first law of geography is often cited in this context: "everything is related to everything else, but near things are more related" [65]. Among others, an important consequence of these inherent properties of spatial data is that data points (samples) are usually not independent, as it is often assumed in various statistical and machine learning methods.

Because geographic space may have specific properties that make spatial data different from other kinds of data, some researchers call for designing spatially explicit models (see, e.g., [30, 36]). For such models, some form of spatial representation (e.g., coordinates or place names) would be an essential part of their implementation, and they would make use of fundamental spatial concepts, for example, neighborhood. Their results would also depend on the location of the phenomena under investigation [30]. An example would be to explicitly account for geographic distance and

[1] We offer one suggestion in our discussion article found in this issue.

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distance decay, i.e., Tobler's first law ("near things are more related"), in determining the similarity of different point of interest (POI) types [32, 73]. Employing (spatially or other) explicit models usually results in a more complex model architecture, which may turn out to be unnecessary given enough data to train more general models. Whether or not such explicit models are needed is a current debate in geoAI (e.g., [30, 77]; see also both interviews and the discussion article in this issue).

## 3 Crowdsourcing and Volunteered Geographic Information

As in several other domains, over the last two decades many more, and much more diverse, data sources have become available. Assessing and processing geographic data used to be expensive and left to specialists working in government agencies, industry, or academia. But developments in Web technology (Web 2.0 and beyond), social media, and open source and open data movements have changed the situation tremendously. This holds true for 'obviously' geographic data, such as freely available Landsat earth observation data[2] or topographic data in OpenStreetMap[3], which has been compiled and maintained by volunteers around the world. But it also results in data that is less obviously geographic being used to answer geographic questions.

Previous to what might be considered 'the data revolution,' geographic data in particular was usually curated by trained experts often working for some government agency (e.g., surveyors and GIS experts). These agencies guarantee certain criteria regarding data quality and correctness. With the 'new' data created by volunteer amateurs in crowdsourcing and volunteered geographic information attempts [19], these guarantees essentially vanished. Consequently, research has investigated the quality of VGI data sources, in particular OpenStreetMap, regarding, for example, their completeness (coverage), accuracy, or plausibility [18, 24]. Generally, findings show that given enough 'eyeballs,' i.e., contributors, for an area, data quality can have a high standard, but there are also large differences between different geographic areas (e.g., urban vs. rural, but also between countries) [25, 46]. Such research also includes approaches to automatically detecting potential data quality issues using geoAI methods [2, 32]. We expect that possible future methods used in a geographic context will likewise need to account for specific quality dimensions of spatial information, such as spatial resolution, completeness and accuracy.

There have also been several efforts to collect and provide spatial data for specific (research) questions, such as people's perception of place [4, 55], or data to train models for visual question answering [43] or place recognition [76].

## 4 Major Areas of Research

There are various areas of research in geoAI. Here, we name a few of the (currently) dominant ones.

### 4.1 GeoAI for Handling Geographic Information Sources

In recent years a large focus has been on extracting 'geography' from data that is not obviously geographic, at least not in the same structured way as topographic data. Such data includes (large) corpora of text (e.g., travel guides, hiking protocols), annotated photographs (possibly coming with coordinate information of where the photo was taken), recordings of movements (trajectories), or social media data, e.g., Twitter streams or Foursquare check-ins, again possibly being georeferenced. Georeferencing allows for anchoring essentially any kind of data, such as maps, photographs, or texts, in a geographic space by annotating the data with a geographic coordinate [26]. All this data contains more or less hidden geographic information that research aims to exploit for inferring all kinds of information and answering various geographic questions.

Such work can roughly be seen as data mining in that it aims at extracting information that is not immediately accessible in the underlying data. Today, most of this work applies methods and techniques from (deep) machine learning, such as clustering, decision trees, or neural networks. Research is data-driven, methods often 'black box,' and the chosen methods do not always seem to (explicitly) account for properties and principles of (geographic) space. On the other hand, results are often highly interesting and useful, and the chosen approaches in combination with the large amounts of data now available allow answering questions or solving problems that were not possible before [30, 77].

Image processing and image understanding turn out to be one of the most successful areas deep learning methods are applied to. Image processing and understanding are also crucial in environmental remote sensing. Thus, not surprisingly, machine learning, and deep learning in particular, sees prevalent use in remote sensing as well [74, 77]. Deep learning is used for various tasks in remote sensing, for example, landcover classification [10, 39], data fusion and downscaling [49], or the reconstruction of missing data [75]. Deep learning is also employed in extracting environmental parameters, which relates to the debate of whether explicit

[2] https://landsat.gsfc.nasa.gov

[3] https://www.openstreetmap.org/

models are needed for processing geospatial data [71] (see also the interview with D. Tuia; this issue).

Similar to image processing, deep learning has led to tremendous advances in natural language processing (NLP) [48]. These advances allow for extracting geographic information from (unstructured) textual descriptions in natural language [29], often for identifying locations [62] or *places* [5], or for interpreting narratives about landscapes [50]. Such work is considered part of geographic information retrieval (GIR) [31] and may also be useful for geographic question answering (geoQA) [43, 44, 56], dealing with questions of plausibility and relevance, among others.

Finally, given the ubiquity of mobile devices, which offer a plethora of sensors, and the popularity of social media, many humans nowadays leave a digital trace while going about their everyday (and not so everyday) activities. Analyzing these digital traces to better understand human dynamics is often called *social sensing* [1]. Work in social sensing includes extracting human mobility patterns [60], identifying familiarity with an environment [51], or urban planning [52]. *Place* is often a fundamental concept in social sensing, used as a reference system and to anchor human behavior in a space. Accordingly, identifying places from human digital traces is another important topic [28, 57, 58].

### 4.2 Modeling Dynamic Spatial Systems

The ever increasing digitalization of every day life and the push of AI systems out of research labs and specialist hands into our everyday environments provide a lot of challenges and opportunities, many of them (geo-)spatial in nature. Smart cities [22] and smart homes [64]—including the idea of digital twins [7, 66], self-driving vehicles [20], robots in healthcare, retail, and our homes, but also tackling global pandemics all act and happen in (geographic) space, entail the need to solve spatial problems, and require some understanding of space. They all have in common that they operate in (highly) dynamic situations with changes that are often hard to fully predict, a high degree of uncertainty [13], and that they require interacting (in a broad sense) with people who are not experts on the respective systems' inner workings [53]. One particular method useful for modeling such systems are spatial simulation methods, for example, cellular automata [8] or agent-based simulations [12], which can be used to study health interventions in a city [61], among others.

## 5 Interacting with geoAI Systems

Instead of using geoAI to interact with geographic data sources in novel ways, or to model complex spatial systems, "intelligence" is also needed on another level, namely to help users interact with geoAI systems themselves. This is required since, although geoAI systems tend to substitute human skills, removing humans (entirely) from the loop has turned out to be difficult or is unwanted. Furthermore, since geoAI models often remain opaque, it becomes difficult for humans to interact with them. Thus, human-computer interaction is becoming more and more relevant for research in geoAI (see also the discussion article in this issue).

The influx of modern machine learning methods, in particular deep learning, has also imported the well-known issues that these methods bring along, namely issues of transparency, explainability, fairness, and so on. Since many questions these methods are applied to have far-reaching implications, such as in urban planning [40], demographics [42], or environmental conservation [68], the issues become highly critical and relevant. Some authors argue that given the special nature of geo-spatial phenomena and data, explainable AI (XAI) techniques cannot be applied 'out of the box' to geoAI, but instead spatially explicit XAI is required [72].

One approach towards more explainable geoAI is to explicitly model the procedures and the kind of data they operate on in terms of geo-analytic purposes and corresponding data transformations. Currently, knowledge about the provenance and quality of data products, as well as the choice of data and workflows towards particular goals is still largely dependent on human intelligence. Yet, dealing with *purposes of geographic information* is essential for scaling up intelligent use of data across many geoinformation sources [11]. Current geoAI methods are hardly capable of incorporating purposes and procedures for automating geocomputation, which remains an important bottleneck. To tackle this challenge, geoAI may need to build on research about workflow synthesis [34], service description and composition [38], as well as cyberinfrastructures [69]. Furthermore, geoAI requires pragmatic knowledge to handle the information possibilities given in geodata, be it for the purpose of geo-information retrieval [31], automating geocomputational workflows [27], or for geo-analytic (indirect) question-answering [56] (see also the discussion article in this issue).

Another example for focusing on human-computer interaction in geoAI is the use of spatial concepts and relations in spatial representations and processing that match human concepts. Often used in applications targeted to layman users, such as navigation assistance or location-based services, work includes qualitative spatial representations and reasoning [14], the use of spatial and semantic hierarchical structures in representing environments [54, 67], identifying features of an environment that allow linking local actions or views, e.g., in wayfinding, with the overall, global structure of a space [59, 63], or the generation [45] and resolution [21] of spatial referring expressions, among others.

## 6 The Geography of Indoors

Finally, an increasing number of geoAI research and researchers turn their attention to indoor spaces. This is often motivated by similar reasons as discussed in Section 4.2. The incorporation of digital technology as being fundamental to operating indoor spaces, for example, in smart homes and digital twins, is fundamentally a spatial (or spatio-temporal) problem. Despite this, there seem to be important differences between outdoor (or proper geographic) spaces and indoor spaces that pose certain challenges [54]. For example, there appears less general agreement on how best to represent the base 'topographic' data of indoor spaces, even if there are standardization efforts and standards available, e.g., indoorGML[4], or BIM [33]. Spatial data tends to be relative to a given building (or ensemble of buildings); there is no global coordinate system employed across buildings in different cities or countries. In part, this may be due because the seamless integration of indoor and outdoor is still a largely unsolved problem [41]. And maybe also in part because global positioning, as provided, e.g., by the Global Positioning System (GPS), is not available indoors for lack of satellite visibility (the GPS signal does not penetrate walls). There is no globally available, uniform way of positioning somebody or something in an indoor space. Thus, reliably positioning people and other (mobile) items indoors is another ongoing research issue [70]. Techniques here often use some form of inference or (implicit) reasoning about likelihoods over some sensor readings (e.g., WiFi, Bluetooth, or infrared) to determine a position [23, 37, 47]. Many of the application areas mentioned in Section 4.2 then also transfer to indoors, with self-driving vehicles maybe of lesser concern, even though mobile robots may take their place in some sense. Most work in indoor geoAI seems to focus either on the (smart) management of large indoor complexes or on providing location-based services to a building's users. Just like indoor spaces appear to be more segregated than outdoor spaces, research on indoors seems to make less use of 'common solutions' than its outdoors counterpart.

## 7 Summary

In this short article, we aimed at providing an overview on current developments, topics, and challenges in geoAI. As discussed, similar to other areas of AI, the processing of geo-spatial data faces issues of transparency and explainability (among others) that come with the use of largely black box (deep) machine learning methods. On the other hand, these methods together with a large range of various data, which have become available over the last decade or two, allow tackling much more complex problems than was previously possible. At the same time we are faced with increasingly complex systems of an inherently spatial nature, e.g., smart cities and self-driving vehicles, which require advanced and fast processing of potentially large amounts of data, and potentially new forms of interaction. Finally, while it remains an open question whether 'spatial' is as 'special' as it is often claimed, i.e, whether explicit models are required to properly deal with spatial data and problems, in our opinion, repeated illustrations of general models' (seemingly) nonsensical failures, which can have drastic consequences (as in the case of self-driving vehicles), make a need for spatial model explainability and a focus on the transparency of model purposes appear rather likely. In that, current geoAI can benefit and make use of a large body of previous work addressing the formal representation of space and spatial relationships (e.g., [9, 15–17]), including 'spatial' ontologies [6, 35].

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[4] http://www.indoorgml.net

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