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EDITORIAL

GeoAI in urban analytics

Introduction

We are writing this editorial piece at the peak of the current Artificial Intelligence (AI) 'spring' as generative models quickly cross the bridge from the confines of academic and industry labs into our everyday lives. During times like this, one might be excused from forgetting how old the application of AI approaches in geography is. Geographers have been here before. About forty years ago, Smith (1984) wrote:

> AI techniques, if properly applied, should also allow researchers to spend a greater proportion of their time on creative thinking and less on technical drudgery. As with any set of tools, the techniques of AI cannot replace a hard-earned understanding of some phenomenon and will almost certainly be overvalued and misused by some practitioners. [Nevertheless], if used with care, the techniques of AI will prove of great benefit to such an applied, problem solving discipline as geography. (p. 157).

It is in the subsequent issue of the same journal that we find Nystuen's (1984) comment, suggesting that *'[b]enefit to geography from such an alliance [with AI] is questionable considering that our own directions are murky enough'* (p. 358). Smith, in Nystuen's view, should be *'a little more critical in his appraisal of the scope of possible applications'* (Nystuen 1984, p. 359).

The debate between Smith and Nystuen unfolded during the 'AI spring' of the 1980s, but the same hopes and concerns around a data-driven (rather than theory-driven) geography echo through the discipline's history. From Openshaw's (1992, 1998) work on AI tools for spatial modelling and analysis to Miller and Goodchild (2015) discussion of data-driven geography in the wake of big data, to the emergence of GeoAI (Janowicz *et al.* 2022) – primarily used as a shorthand for geospatial AI, encompassing the efforts towards creating spatially-explicit models in the era of deep learning. As detailed by Miller and Goodchild (2015), these 'waves' are evolutionary rather than revolutionary. These approaches are founded in abductive reasoning and foster the same discussions, tensions and shifts between nomothetic (law-seeking) and idiographic (description-seeking) knowledge that can be traced back to the very origins of the discipline. Traditional AI approaches have long been part of Geographical Information Science (GIScience), including research both on unsupervised learning approaches to geographical data mining (e.g. geodemographic classification and dimensionality reduction, see e.g. Miller and Han 2009) and supervised methods of inference (e.g. spatial autocorrelation and geographically weighted regression, see e.g. O'Sullivan and Unwin 2003). At the same time, each 'wave' is unique, and the current AI spring has again brought new challenges and opportunities.

This special issue stemmed from a session organised at the Annual International Conference of the Royal Geographical Society (with IBG) in August 2021, which aimed to explore those challenges and opportunities with a particular focus on deep learning and human geography. The previous decade had seen unprecedented advances in image processing following the seminal paper on Alexnet (Krizhevsky *et al.* 2012), the emergence of large language models (LLMs) based on the transformer architecture (Vaswani *et al.* 2017), as well as the development of graph neural networks (Bruna *et al.* 2013, Hamilton *et al.* 2017). While those approaches to deep learning have found wide use in many aspects of GIScience and remote sensing (e.g. computer vision in geospatial applications), their application to human geography has been slower (Harris *et al.* 2017). Complementing the special issue introduced by Janowicz *et al.* (2020) on 'Artificial intelligence techniques for geographical knowledge discovery', this special issue focuses on GeoAI as a broader geographical AI and its applications in urban analytics (Liu and Biljecki 2022). The next section introduces the articles included in this special issue, while the final section contextualises the main themes emerging from those articles in the current, fast-paced landscape shaken by the emergence of foundation models (Bommasani *et al.* 2021).

Overview of articles in this special issue

The articles included in this special issue span a broad range of topics within urban analytics (Singleton *et al.* 2018, Batty 2019), a field at the intersection between GIScience and urban studies, where traditional methods in AI and machine learning have long been used to analyse sociodemographic and mobility data. Notably, unsupervised clustering methods such as k-means have been used for creating geodemographic classification from highly multidimensional sociodemographic datasets, such as the decennial census, since the pioneering work of Webber and Craig (1976). In this special issue, De Sabbata and Liu (this issue) present a novel approach to spatial geodemographic classification that leverages deep learning through graph neural networks to account for neighbourhood effects. The authors illustrate how their framework can enable the creation of a classification with minimal attribute preprocessing but highlight how its usage currently requires specialised expertise and engagement with a wide range of possible designs (e.g. deciding on the number and types of layers, activation functions and learning rate). Moreover, while classic approaches to interpreting the classification are still applicable to the resulting classification, the inner workings of the neural networks lack direct interpretability and will require the use of emergent eXplainable AI (XAI) for graph neural networks (Liu *et al.* 2023). New forms of data have also been explored to compensate, supplement or substitute the classic approaches to collecting socioeconomic data. According to Batty (2019), this idea has been an important field of research and a key characteristic of urban analytics for more than a decade. The widespread availability of open satellite imagery and the increased digitalisation of our daily lives have led to the emergence of large 'exhaust' datasets (Kitchin 2014) that can be reused. Nilsson and Delmelle (this issue) point out how Twitter (now X) has been one of the key alternate sources of data that several authors have explored to understand our cities beyond census data. The authors explore property listings, a less commonly used source of textual geographical information. Building on a theoretical framework based on house filtering and lifecycle models, the authors used an embedding-based text classification approach to explore the micro-geographical housing dynamics.

The digital transformation has also produced large collections of human mobility data, unlocking the possibility of studying mobility patterns at a high level of detail. Yu and Wang (this issue*)* present a novel framework that enables the identification of transport modes directly from GPS data without requiring additional information such as road network or driving sensing data. The authors adopt key concepts from natural language processing to formalise and identify salient points of change in speed and direction and use a graph structure to connect those salient points into a dependency graph. A graph neural network is then used to learn an effective representation of the data from the original sequence and the dependency graph to solve downstream tasks such as transport mode identification. At the same time, researchers have also raised severe concerns about the uses and abuses of such data. New methods that could allow the publication of such data in a privacy-preserving manner become crucial, especially as open scholarship practices become widespread. Rao *et al.* (this issue) propose an approach based on conditional adversarial training that can generate high-quality synthetic trajectory data, preserving the mobility patterns of raw trajectory data while ensuring a pre-defined level of trajectory privacy protection. The architecture adopts an adversarial training approach, where a trajectory generator component is trained to create synthetic trajectories, while a trajectory critic component is trained to distinguish between real and synthetic trajectories. The two components are pitted against one another during training, as the generator component tries to fool the critic component by creating synthetic trajectories that are indistinguishable from the raw data in their overall characteristics, while an anonymity module is used to ensure privacy protection. The authors demonstrate how the model can offer better privacy for raw data compared to several baselines while preserving their spatiotemporal characteristics.

Street-view imagery has been widely used in conjunction with computer vision approaches in urban analytics to study a range of topics, for example, quantifying walkability or estimating socioeconomic variables. Law *et al.* (this issue) discuss how such models present a particular challenge when aiming to develop XAI approaches. While most computer vision tasks can rely on the presence of certain elements in a section of the image, tasks in urban analytics tend to require an understanding of the emergent properties of the entire image (e.g. estimating greenness). Instead of the commonly used heatmaps, the authors propose an approach based on counterfactual explanations, which illustrate how an input image should be changed to change the model output. For instance, an input image from an urban street can be artificially altered to shift the output of a model from low to medium to high greenness by injecting artificially generated trees into the image. Their user study indicates that this approach can provide non-expert users with a better understanding of image-based classifiers and regressors for street view analysis, despite the limited realism of the counterfactuals. Along a similar line of inquiry, Jin *et al.* (this issue) tackle the issue of black-box AI in urban analytics, proposing a spatially-explicit version of the local, interpretable, model-agnostic explanation. The approach is model-agnostic as it does not rely on an understanding of the internal workings of the model, but rather explores how the output of the model changes as small variations are applied to the input values, identifying the most prominent input factors driving the output. The authors demonstrate how the model can be used to interpret how different variables impact the prediction locally. In the presented case study, the authors are able to understand the importance of path dependency in residential mobility dynamics.

Research opportunities and challenges

From the papers in this issue, we begin to see the emergence of three themes that may be crucial for the future development of GeoAI in urban analytics. First, ethical considerations should be at the very core of GeoAI. The issue of model explainability was already among the key concerns raised by Openshaw (1992), and Jin *et al.* (this issue) and Law *et al.* (this issue) illustrate how it is even more crucial now, given the expanding complexity of current models. However, Xing and Sieber (2023) highlight how the semantic and social aspects of explainable GeoAI approaches must also be considered in addition to the technical ones. Other authors have also raised concerns about the social biases, diversity and ecological sustainability (in GIScience, see Janowicz 2023) of GeoAI models and their impacts on people's everyday lives. As foundation models (text to text, text to image) become one of the tools routinely used by geographers, our community will necessarily have to engage with the broader debates surrounding the design and uses of foundation models (Bommasani *et al.* 2021). While a detailed discussion of the ethical concerns raised by foundation models is beyond the scope of this editorial, we refer the reader to the 'stochastic parrots' paper by Bender et al. (2021), which has become foundational for a critical understanding of LLMs, and the useful taxonomy of both upstream and downstream risks posed by LLMs proposed by Weidinger *et al.* (2022). Among others, the National Institute of Standards and Technology, an agency of the U.S. Department of Commerce, has put forward an AI Risk Management Framework[1]. To embed GeoAI approaches into viable scientific and decision-making tools, researchers will also have to engage with new and emerging challenges, such as the presence of deepfakes (Seow *et al.* 2022), 'model poisoning' (Shan *et al.* 2023) and a 'delete culture' (Floridi 2023) beyond privacy – where information can be made unavailable where necessary through removing or blocking, and models can be asked to edit or delete the information encoded in their structures (Meng *et al.* 2022).

Second, AI is unlocking new ways to engage with forms of data that have become prominent over the past decade, from text (Nilsson and Delmelle this issue) to street-view imagery (Law *et al.* this issue). Foundation models are likely to play an important role in the future of urban analytics, allowing scholars and analysts to interface with and explore large textual, imagery and video datasets. However, the integration of symbolic and sub-symbolic GeoAI approaches (Mai *et al.* 2022b) is non-trivial, especially as multi-modal models become more popular and complex (Bhattacharyya *et al.* 2023). The recent advances in foundation models and generative AI are taking us one step closer to the moonshot objective suggested by Janowicz *et al.* (2020) of creating an '*artificial GIS analyst [enabling] a Siri-like interaction for the masses*' (p. 631) – today the reference point might be ChatGPT or GitHub Copilot. However, the scientific assessment of the capabilities, limitations, and risks of these models is ongoing, and the road ahead might still be long and uncertain. For instance, although LLMs do store knowledge implicitly, at the time of writing, they do not provide a reliable form of knowledge and logical reasoning (Berglund *et al.* 2023), especially about spatial information (Mai *et al.* 2022a, Cohn 2023, Ji and Gao 2023).

Third, incorporating geographical theories and concepts is the cornerstone of the development of GeoAI approaches. Advances in AI can provide new ways to tackle core geographical concerns, such as effectively encoding together location and time to enable spatiotemporal data processing (Rao *et al.* this issue) or exploring neighbourhood effects through graph neural networks (De Sabbata and Liu this issue). Crucially, geographical relationships do not necessarily need to be focused solely on location and distance. The capabilities demonstrated by deep learning approaches to handle large and diverse sets of data and relationships among data hold the promise to integrate a broader range of relationships, from commuting to social and geopolitical ones, which can be crucial in urban studies.

The key research question that emerges when combining the three themes above in the context of the widespread adoption of foundation models as the cornerstone of many future methods and studies is, not only how do we adapt foundation models for geospatial applications (Mai *et al.* 2023), but more broadly: how do we ground such models in geographical theory and ethics to unlock a broader use of AI in geography? That is, how do we make sure that such models have a broader geographical knowledge and the capability to 'reason' with core geographical concepts such as spatial heterogeneity, scale, place, emotions or the performance of everyday life? Looking ahead, the research agenda for

GeoAI should aim to accompany its focus on spatially-explicit AI models – which is how GeoAI is most commonly understood, as a shorthand for geospatial artificial intelligence – with a broader purposeful aim to do geography with AI, a geographical artificial intelligence. That will be particularly important in urban analytics, as current foundation models hold the promise to bridge the long-standing divide between quantitative and qualitative studies of our cities and our experiences of them. Such an aim will require closer collaboration with our colleagues in other branches of geography, for instance, exploring a more-than-quantitative approach to everyday geographies, as suggested by Bennett and De Sabbata (2023). Looking beyond the current hype, both geospatial and geographical AI open up a vast landscape of technical and ethical questions, which this special issue hopes to raise rather than provide answers to.

Note

1. https://www.nist.gov/itl/ai-risk-management-framework

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No potential conflict of interest was reported by the author(s).

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