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EDITORIAL

GeoAI

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Research in artificial intelligence (AI), geography, and geographic information science (GIScience) has had multiple fruitful points of contact during the past decades. More than 30 years ago, [5, 21, 26] suggested how AI methods could be used for spatial modelling and geographic problem-solving, including neural nets for regression modelling, spatial optimisation, spatial pattern recognition, and spatial simulation, but also the use of spatial knowledge bases and expert systems [20]. Thus, from the very beginning of *geoAI*[1], both data-driven (machine learning (ML), optimisation, and simulation) methods, as well as theory development was taken into focus. While some geographers at the time complained about an apparent lack of theory in AI, [5] argued that a cognitive and computational engineering approach might have the capacity to advance theory as well as method development in geography based on testing formal and computational representations of qualitative as well as quantitative concepts. And indeed, such an approach towards geography and geographic information bore fruits. For example, spatial simulation models formed the basis of urban modelling and complexity science [3], spatial pattern detection, ML classification and regression have been adopted in geographic analysis [14, 17], and natural language processing (NLP) techniques for georeferencing texts [10]. Furthermore, knowledge representation and reasoning methods in AI have inspired the development of spatial calculi for spatial reasoning [4, 6, 30], as well as geospatial knowledge models in the Semantic Web [7], ontologies of space [8], and, more recently, spatial knowledge graphs [11]. These different strands of work have resulted in new geographic information retrieval (GIR) methods [22], digital twins of cities [2], as well as progress in human-computer interaction, orientation, and wayfinding [23].

In recent times, subsymbolic AI methods, such as deep learning and representation learning, have enabled an increase in quality and scalability of data processing methods in remote sensing [29], geographic information retrieval [27] as well as geographic question-answering (GeoQA) [15, 16]. At the same time, knowledge about geographic information processes has become an indispensable resource for AI itself. Such knowledge is needed not only for modelling geographic information concepts [12, 25], and for making opaque models transparent [31], but also for understanding what kind of intelligence is needed to refer to place [9, 13, 18] and to handle geographic space [19, 24]. Among others, researchers are currently working on formal theories of space [1] and geographic quantities [28]. Understood in this broader sense, namely as the intelligence needed to handle geographic information, geoAI has the potential to fundamentally improve the way geographic information can be processed and interpreted by both humans and machines.

In this special issue, we look at research investigating the kind of knowledge needed to account for geography and space with(in) intelligent machines.

1 Content

1.1 Overview and Discussion

Our *overview article* further outlines the developments sketched above and provides a survey of current areas of research within geoAI, in particular, geoAI for handling various information sources, interaction with geoAI systems, and the question of whether explicit spatial models, i.e., models that incorporate some a-priori spatial knowledge, are needed in geoAI.

[1] We use the term loosely here, but see also the definitions in our overview and discussion paper in this issue.

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In our *discussion article* (*Pragmatic GeoAI—Geographic information as externalized practice*), we discuss important problems and blind spots of contemporary geoAI methods that prevent them from handling brittle models, uncertainty with respect to geo-data quality, and fitness for purpose. These issues seem to be caused by current structuralist approaches to geoAI missing out on the procedural knowledge needed to account for data provenance and information possibilities, the purposes and requirements of map transformations, and the conceptualisations needed to interpret maps. These shortcomings lead to 8 dilemmas that exist largely due to a lack of pragmatic knowledge. We discuss pragmatic geoAI as a way to put pragmatics at the center of modeling, and we suggest a core action model including transformations and conceptualizations of maps. Finally, we discuss to what extent such an approach might deal with these dilemmas.

1.2 Technical Contributions

In the article *Remember to correct the bias when using deep learning for regression*, Christian Igel and Stefan Oehmcke investigate what happens when we use a deep learning regression model that was trained, e.g., to predict the amount of canopy for each cell of a remote sensing image, in order to sum up predictions, e.g., over larger areas to estimate the amount of canopy. Since deep learning models usually minimize the mean squared error, not the absolute total error or the error change with respect to the bias parameter of the regression, error residuals are not guaranteed to sum up to zero on test data, which can accumulate to large errors when summing up canopy amounts. The authors propose introducing a simple bias correction step after training and validation to prevent this problem.

In search of buildings' flood risk indicators from street view imagery data—An investigation of data sources and analysis tools investigates the quality of street view imagery data sources and computer vision methods to detect building features vulnerable to flooding, such as basements. The authors Anh Vu Vo and Michaela Bertolotto discuss possible indicative features, data sources and algorithms for this purpose, and they report about a preliminary experiment performed with the (freely available) *Mapillary* data source.

Manuel Baer and Ross Purves present work on semi-automatically generating large natural language corpora of landscape descriptions using small curated corpora as seed in their article *Generating large corpora of landscape relevant natural language using actively crowdsourced landscape descriptions and sentence-transformers*. As is common practice in NLP now, source and target corpora get vectorized, and then cosine similarity is used to identify the text most likely to be relevant for the target corpora. The authors demonstrate the benefits of using sentence transformers over a purely lexical approach; TF*IDF in this case.

An important aspect of geographic information retrieval and question answering is identifying what (types of) geographic information the user is referring to. In their paper *Automated interpretation of place descriptions: determining entity types for querying OSM*, Madiha Yousaf, Tobias Schwartz, and Diedrich Wolter present an approach that given a natural language input (a query) provides a ranked list of likely OpenStreetMap (OSM) tags that represent the entities referred to in the input. Noun-to-tag and tag-to-tag similarity is used to improve existing semantic similarity measures, such as word2vec or BERT, as demonstrated in an extensive evaluation.

1.3 Project Report

In the article *UR Walking—Indoor navigation for research and daily use*, Bernd Ludwig, Gregor Donabauer, Dominik Ramsauer and Karema Al Subari report about results of the project *URWalking*, which realized a navigation aid for indoor navigation at the University of Regensburg. The tool is integrated with advanced indoor tracking strategies using inertial sensors and map information. Indoor routing uses genetically optimised edge weights reflecting cognitively simple way-finding strategies. Data collected with the tool was used to evaluate wayfinding decision models, to predict areas of interest, landmark salience scores and needs for assistance using AI methods.

1.4 Interviews

GeoAI and beyond is an interview with Krzysztof Janowicz, a professor for Geoinformatics at the University of Vienna and the University of Santa Barbara, California. Krzysztof has played an important role in linking GIScience with the Semantic Web community. More recently, he has focused on what he calls spatially explicit modeling in geoAI, which is deep representation learning enhanced by some form of a-priori spatial knowledge, such as geographic distance decay or spatial geometry, and which can be used, e.g., to improve information retrieval and question-answering. In this interview, we discuss the impact of the new developments in geoAI for data-driven machine learning, for conceptual modeling and explicit forms of spatial knowledge, whether it can really be claimed that the latter are made obsolete, what the remaining role of semantics is, which specific shortcomings these geoAI approaches bring with them, and what this all has to do with parrots, and with the recent breakthroughs in AI, such as GPT-3.

GeoAI as collaborative effort is an interview with Devis Tuia, associate professor at the Ecole Polytechnique

Fédérale de Lausanne (EPFL) in Switzerland, where he heads the Environmental Computational Science and Earth Observation (ECEO) laboratory. Devis' current work focuses on interpretable deep learning in environmental modeling, human-machine interaction in remote sensing, and digital wildlife conservation. In the interview, we discuss how the explosion in available data and the developments in machine learning have impacted remote sensing, that geoAI necessarily has to be a collaborative effort for it to have an impact, the benefits of open data, the difference between 'semantics' in remote sensing vs. the rest of the world, why you don't need to be afraid that somebody may outperform your model, and how, sometimes, an important task in research is finding a generator for a ship.

2 Service

2.1 Journals

Some of the main journals in geoAI include:

ACM Transactions on Spatial Algorithms and Systems[2]

Annals of the American Association of Geographers(AAAG)[3]

Computers, Environment and Urbvan Systems (CEUS)[4]

Geoinformatica[5]

International Journal of Applied Earth Observation and Geoinformation[6]

International Journal of Geographical Information Science (IJGIS)[7]

Journal of Spatial Information Science (JOSIS)[8]

Semantic Web - Interoperability, Usability, Applicability [9]

Spatial Cognition & Computation[10]

Transactions in GIS[11]

2.2 Workshops and Conferences

There are several (yearly or biannual) conferences and workshops that specifically address questions of geospatial processing and geoAI. These events are often decidedly multi- and interdisciplinary. We list some of the prominent ones below. But papers addressing issues of geoAI can also be found at the major AI conferences, such as AAAI, IJCAI, or ECAI.

2.2.1 Conferences

ACM International Conference on Advances in Geographic Information Systems (SIGSPATIAL)[12]

Established in 1993, yearly conference organized by the ACM Special Interest group SIGSPATIAL covering all conceptual, design, and implementation aspects of geospatial data.

Conference on Spatial Information Theory (COSIT)[13]

Established in 1993, biannual conference focusing on theoretical aspects of space and spatial information.

GIScience conference series[14]

Established in 2000, biannual conference focusing on all aspects of geographic information science.

AGILE conference series[15]

Established in 1998, annual conference of the "Association of Geographic Information Laboratories in Europe (AGILE)".

ISPRS Congress[16]

Established in 1913, 4-annual conference of the "International Society for Photogrammetry and Remote Sensing (ISPRS)".

2.2.2 Workshops

ACM SIGSPATIAL *International Workshop on AI for Geographic Knowledge Discovery*[17]

First: 2017 as "1st Workshop on Artificial Intelligence and Deep Learning for Geographic Knowledge Discovery".

Co-located: with ACM SIGSPATIAL conference.

Content: geospatial image processing and transportation modeling, digital humanities, cartography, public health, disaster response, and social media analysis

International Workshop on Spatial Cognition and Artificial Intelligence

First: 2018

Co-located: with different 'spatial' conferences, such as GIScience or COSIT

2 https://dl.acm.org/journal/tsas.

3 https://www.tandfonline.com/journals/raag21.

4 https://www.sciencedirect.com/journal/computers-environment-and-urban-systems.

5 https://www.springer.com/journal/10707.

6 https://www.sciencedirect.com/journal/international-journal-of-applied-earth-observation-and-geoinformation.

7 https://www.tandfonline.com/journals/tgis20.

8 https://josis.org.

9 https://www.semantic-web-journal.net.

10 https://www.tandfonline.com/journals/journals/hscc20.

11 https://onlinelibrary.wiley.com/journal/14679671.

12 https://www.sigspatial.org/.

13 http://geosensor.net/cositseries/.

14 https://giscience.org.

15 https://agile-online.org/.

16 https://www.isprs.org/society/congress.aspx.

17 https://geoai.ornl.gov/acmsigspatial-geoai/.

Organization: IFIP TC12 working group on Artificial Intelligence and Cognitive Science[18]

Content: inter- and cross-disciplinary exploration of current topics in geoAI, e.g., interactive location-based services, smart cities, challenges of 'black box' AI, etc.

International Workshop on Methods, Models, and Resources for Geospatial Knowledge Graphs and GeoAI[19]

First: 2021

Co-located: with GIScience 2021[20]

Content: neural symbolic reasoning based on unstructured text and automatic knowledge graph construction.

Workshop on Artificial Intelligence for National Mapping and Cadastral Agencies (NMCAs)[21]

First: 2021

Co-located: Conference on Spatial Data Infrastructures (JIIDE)[22]

Organization: EuroGeographics/EuroSDR

Content: geoAI in the context of national mapping and cadastre agencies

Workshop on Complex Data Challenges in Earth Observation[23]

First: 2021

Co-located: with IJCAI-ECAI 22[24]

Content: high-resolution remote sensing data and machine learning challenges posed by characteristic heterogeneity and correlation structures

Workshop on Practical GeoAI Ethics[25]

First: 2022

Organization: OGC/Ordnance Survey

Content: ethical principles of work at the intersection of geospatial data and AI/automated decision-making

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