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EDITORIAL

Automated Map Generalization: Emerging Techniques and New Trends (Editorial)

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Abstract
Automated map generalization has been a major area of research for decades but has still not reached maturity. Besides the needs for more adaptive algorithms, a fundamental question remains: How can we transfer human generalization knowledge into a computational system more effectively? Previous efforts do not seem capable to fully overcome the "knowledge acquisition bottleneck." As new theories and technologies emerged in artificial intelligence (particularly deep learning), computers are now able to tackle human-level tasks with superior performance, showing great potential in automated generalization. Meanwhile, crowdsourced geographic information and social sensing is growing at an increasing speed, and the needs for visualizing and analyzing massive geo-referenced data at various scales are numerous. It is therefore necessary to adapt map generalization to these fields. This highlights the potential of applying map generalization in the visual, interactive, and exploratory analysis of abstract (e.g., hierarchical relations) and physical (e.g., movement trajectories) data. This topical collection brings six contributions reporting recent progress and trends in automated generalization in various aspects mentioned above, with which we hope to trigger further discussion and research in our field with new ideas and methodologies.

Keywords Map generalization · Deep learning · Visualization

Endeavors to automated map generalization have been around for more than 30 years (McMaster and Shea 1988). As a research field relying heavily on computer science, it is not uncommon to see emerging computer science approaches introduced and adapted into the field. As spatial is special, lots of efforts have been made to design algorithms that can account for spatial and geographical peculiarities that map generalization cares about (see Burghardt et al. 2014 for a review). Indeed, the use of artificial intelligence in automated generalization dates back to the early times of the field (Weibel 1991). The bottleneck has been the gathering and formalization of the knowledge for decision in map generalization ever since (Weibel et al. 1995; Touya et al. 2019).

For decades, the mindset of the researchers has been that not only the generalization output (i.e., generalized maps) should mimic paper maps, but also the processes in which generalization is carried out should follow human reasoning (e.g., analyzing structures, enriching data, applying generalization operators, and handling inter-theme relations and conflicts). More recently however, it seems that at least the latter may be no longer a necessity. This is especially the case when deep learning researchers found that machine intelligence can acquire internal representations of "knowledge," and find its own way to problem-solving, both of which are different from human cognition (Goodfellow et al. 2016; Olah et al. 2018). Nowadays, deep learning begins to attract attention of researchers in map generalization. Convolutional neural networks, for example, seem to be able to generate simplified representations from detailed representations of geography, where simplification, enlargement, and typification can be learned with only maps before and after generalization provided (e.g., Feng et al. 2019; Kang et al. 2019;

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Courtial et al. 2021). But these are just the start of the story; a lot of issues remain to be addressed for real applications in map generalization.

On the other hand, map generalization is also witnessing wider applications in other fields, such as information visualization and data privacy preservation (or data anonymization), in which massive trajectory data need to be generalized for various reasons (Andrienko et al. 2017; Mahdavifar et al. 2022). Hence, it is timely to organize this special issue, to swiftly gather new developments in our field and to shed some light on future research.

In this topical collection, we have six contributions from five countries, with topics that roughly fall in four categories. The first category deals with non-standard data themes that are made more and more available these days (e.g., movement data). The second group discusses how cutting-edge deep learning techniques can be useful in, e.g., label placement and how to evaluate results obtained by deep learning approaches. The third category addresses the smooth generalization during interactive geovisualization. The last one presents a symbol generalization problem in a map production setting. Each of them is introduced as follows.

Due to increased use of GPS-enabled devices, movement data available to us are increasing dramatically, making them potentially useful for unraveling and predicting patterns of human or animal behavior (Long et al. 2018). However, the sheer amount of data also poses challenges to data processing and analysis. Data aggregation and generalization are usually a choice in simplifying and compressing movement trajectories. Liu et al. (2021), for instance, propose a semantic-based generalization approach to simplifying trajectory data. The problem of trajectory generalization is that existing algorithms ignore behavior characteristics of movement (e.g., standstill or drop-by point). This makes the inference of such behaviors impossible after the generalization. In this paper, the contributors try to simplify the trajectory data while preserving important behavior/semantic points in a controlled way, successfully transferring the hallmark of map generalization in the spatial domain to the spatiotemporal domain. It is also easy to envision that such a trajectory generalization is highly useful when user privacy is concerned.

The mysterious and vastly under surveyed seabed has now been scanned by more accurate and more data hungry instruments. This has been generating a huge amount of raw data every day. As discussed previously, having more data is not just about the volume, but it changes also the problem. Hence, faster and more efficient generalization algorithms are necessary to analyze such data, or simply to visualize it. Yu et al. (2022) design an algorithm that can generalize dense multi-beam echo soundings (MBES) efficiently and effectively. The authors' purpose is for nautical charting. In addition to the usual constraints of cartographic legibility and navigational safety, they also aim to integrate generalized MBES with existing chart soundings. To do so, existing soundings on the chart were used as a guidance during the generalization of MBES, and much better results were obtained.

The next two contributions focus on the potential and issues of using deep learning in automated cartography. Harrie et al. (2022) systematically analyze the label placement problem in city wayfinding maps, identify potential challenges, and propose potential solutions including both rule-based and deep learning techniques. In particular, the authors propose to use convolutional neural networks to evaluate different labeling solutions, and to identify cluttering situations, or to formulate the label placement problem as a deep reinforcement learning. Requirements for labeling city wayfinding maps are discussed in detail so as to help identify potential techniques in the future. Next, deep learning based map generalization is directly discussed. In recent use cases, generalization is often performed on raster version of vector datasets, in favor of using a bunch of deep learning models available in computer vision. To be specific, Courtial et al. (2022) showcase the generalization of mountain roads by formulating the generalization as a semantic segmentation task, and as an image generation task as well. They show the importance of evaluation which is needed in every step during the deep learning based generalization, and adapt the constraint-based evaluation for the raster images generalized by the deep models. The paper presents some first results on explicitly assessing the quality of generalization output by deep learning models.

Zooming in and out a web map is common during navigation and location-based services. However, map representations at different scales usually differ from each other and, therefore, create a discontinuous experience in spatial cognition. To improve this situation, Peng et al. (2023) present a space-scale cube (SSC) data structure and a greedy algorithm, which help to perform online generalization operations such as merging of areal objects (e.g., land-use parcels) for a more smooth experience during the zooming and navigation of web maps. Apparently, merging of areal objects is a discrete generalization operation which only happens at certain points of map scales. The proposed SSC data structure and algorithm are capable of transforming the discrete merging into a continuous transition between two discrete states (e.g., before and after the merging). The data structure is sent to the client side where the generalization (pre-computed) is retrieved from SSC using GPU, which greatly accelerates the processing and guarantee its client-side performance.

The last one is a map production-oriented research. Motivated by a topographic mapping project launched by Czech Republic authorities, Staněk et al. (2022) present fine-grained algorithms for the graphical generalization of morphological discontinuity symbols at large scales. The algorithms were implemented as ArcGIS plugins and can be used to reduce the heavy loads in the manual editing of the localized morphological discontinuities. The results show that the discontinuity symbols can be simplified and conflicts between symbols reduced, leading to a more legible appearance of the map. Remaining issues would be to further lower the percentage of the remaining conflicts.

This special issue is of course a small collection on map generalization, and the contributions in this collection only cover a small portion of the topics raised in the beginning of this editorial. We hope to see more results in the near future, especially in adapting emerging technologies in automated generalization/cartography, as well as applying generalization on different and massive datasets or in different domains.

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