Progress in Constructing an Open Map Generalization Data Set for Deep Learning

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Abstract

Recent pioneering works have shown the potential of a new deep-learning-backed paradigm for automated map generalization. However, this approach also puts a high demand on the availability of balanced and rich training sets. We present our design and progress of constructing an open training data set that can support relevant studies, collaborating with the Swiss Federal Office of Topography. The proposed data set will contain transitions of building and road generalization in Swiss maps at 1:25k, 1:50k, and 1:100k. By analyzing the generalization operators involved in these transitions, we also propose several challenges that can benefit from our proposed data set. Besides, we hope to also stimulate the production of further open data sets for deep-learning-backed map generalization.

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1 Introduction

Map generalization is a cartographic process for deriving a target map or database at a reduced scale from a source database by reducing the contents and complexity of the map while preserving necessary information of the map at the source scale [12]. Despite a long history of attempts to develop a fully automated pipeline with the assistance of machine learning [13, 9], map generalization still requires significant manual intervention by expert cartographers. The recent success of deep learning (DL, [8]) in computer vision has led researchers in cartography to adapt DL models toward an end-to-end map generalization workflow. Current studies focus on the generalization of buildings [16, 5] and roads [3, 4] in transitions between large scales, e.g. 1:5k to 1:20k, using raster- or vector-based data models.

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The success of DL models exploits the increased complexity of neural network infrastructures to increase the learning capacity, but it also needs the support of big data. In the early stage of DL in computer vision applications, big open data sets such as ImageNet [7] contributed to the development of models by serving as baselines and allowing researchers to focus on improving the methods. Similarly, applying DL in map generalization also needs the support of big data. Unlike classical computer vision tasks (e.g., semantic segmentation and instance segmentation) that solely focus on individual objects, map generalization mainly targets the global organization of geographic objects, which is comprehensively influenced by their geometric and semantic characteristics. Besides, different scales involve different generalization criteria [10]. Therefore, training sets for DL applications in map generalization need extra effort, compared to computer vision.

To promote the progress of automated map generalization models in the era of deep learning, we set out to construct an open data set for map generalization as one of the major tasks in the DeepGeneralization project with support from swisstopo, the Swiss Federal Office of Topography. This report presents the design and the most recent progress in implementing the data set.

2 Design

2.1 Raw data and scope

The raw data sets contributed by swisstopo include KRM_25 (cartographic reference model at 1:25k; KRM: *Kartografisches Referenzmodell* in German) and DKM_25/50/100 (digital cartographic model at 1:25k/50k/100k, respectively; DKM: *Digitales Kartografisches Modell* in German). KRM is directly derived from swisstopo's Topographic Landscape Model (TLM) without much geometric adjustment. DKMs are the generalized geometries of the KRM that end up in the final map products. Besides essential information such as the geometry and other necessary attributes, each entity in each raw data set has a UUID to trace the possible transformation between maps. A join table is applicable to trace the changes between two consecutive scales, such as aggregation for the generalization between two maps.

While cartographers at swisstopo have a well-documented and well-established workflow for map generalization, the matching of UUIDs between maps of two consecutive scales is not guaranteed. A missing UUID on a smaller-scale map might be the result of deletion or aggregation. It is not always a reduction in UUIDs, as a generalized map may have new geometric entities that do not exist in the source map, due to cartographic reasons. For example, a road with two segments in the 1:25k map may have three segments in the 1:50k map. In addition, there is no information regarding the generalization operators applied. Therefore, matching is still needed to link the records in different maps, especially based on the spatial relationships among the geometries.

A balanced training set is critical for machine-learning models. In the context of map generalization, the balance can regard the instances of different map generalization operators, the spatial contexts/constraints between buildings and roads, land use contexts such as urban vs. rural, etc. Following the recent rise of explainable AI (XAI, [6]), researchers may also want to evaluate if one network structure works better for one map generalization task than another or how the network performs for a specific operator. Researchers thus may want to build up their own sampling strategies to balance the instances based on specific operators or geometric metrics. Thus, to better serve the community, only clarifying the corresponding relationship between a source entity and its target entity in the generalized map is not enough. We decided to include the map operator descriptions as part of the metadata for the map generalization cases.

Based on current research priorities, the planned data set will cover the transformations of buildings and roads between the three scales with vector-based outputs, from which raster-based representations can be easily derived.

2.2 A conceptual model for map generalization transformations

The transformations between the three scales we are using mainly include the generalization operators selection (elimination), simplification, aggregation, displacement, exaggeration, typification, and smoothing. We categorize the operators into atomic operators, including all aforementioned operators except typification, which is categorized as a complex operator that consists of atomic operators. Our classification is based on cartographic knowledge and the cardinality between the source and target geometries: An atomic operator involves $1:1$ or $N:1$ relationships, while complex operators such as typification usually involve $N:M$ relationships. The complex operators are hard to characterize formally, as they involve many scenarios for which even professional cartographers may not reach a consensus.

Based on the conceptual model, we thus formalize the operators in a generalization transformation between a source geometry and a target geometry as a series of selected atomic operators using a set $T \subset \{deletion, simplification, displacement, aggregation, exaggeration, smoothing\}$. A complete transformation thus consists of the source and target entities and the operator set for each pair of source and target entities.

2.3 An automated workflow

To derive corresponding source-target pairs and the applied generalization operators from the raw data sets, an automated workflow was designed, as manual matching is impossible due to the large number of samples.

The matching workflows for buildings and roads are performed separately, though both start with the UUID-join table. For building matching and operator detection, an additional spatial join was applied to the source and target buildings to find intersecting pairs. With the intersection table, *aggregation* was determined if a target building spatially overlaps with more than one source building. *Displacement* was detected if centroids of buildings with the same UUID exceed a buffer distance. *Simplification* was identified based on the change in terms of shape complexity [2]. Only entities not being part of an aggregation were fed into the *enlargement* detection module, as we regard the aggregated buildings as new, synthetic entities. *Deletion* was determined if a UUID was removed from the target map. All modules exported the decision as a binary result, which form a 5-dimension map-operator vector.

The workflow for determining generalization operators on roads is more challenging. Currently, we are still developing the matching module. The reason is that roads involve more complex geometric changes compared to the buildings, such as Figure 1. The spatial relationships between road segments cannot be simply inferred by intersection detection. The matching also relies on proper distances to describe the similarity between two lines. We chose the number of vertices, curviness, and sinuosity as the main metrics to characterize roads. However, how to determine the map operators based on the transformation of metrics between maps with different scales still need further conceptualization and development.

2.4 Database schema

The proposed data set will be delivered as two loosely connected databases: A Postgres database will store the geometry, UUID, and other attributes from the raw swisstopo data set. A MongoDB database will be used to store the transformation information of entity pairs,

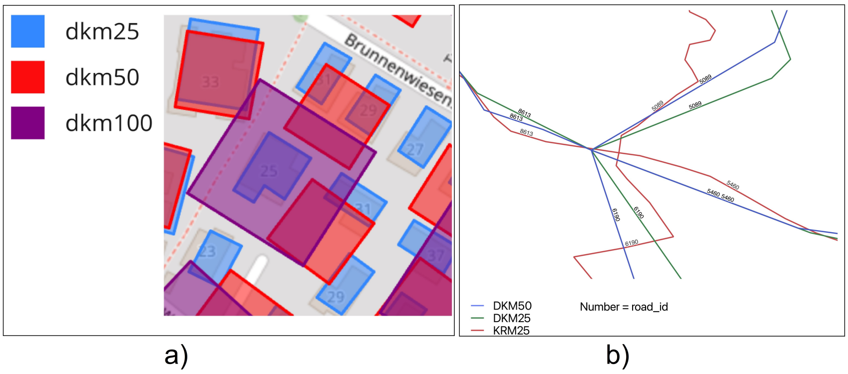

Figure 1 a. An example of buildings; b. An example of roads at an intersection.

with individual collections for buildings and roads. We chose a NoSQL solution because transformation information differs case by case, while MongoDB has minimal data structure constraints. Each collection will contain the associated UUIDs with modeled operator types and metrics to characterize the transformation between the two entities. The collection will also have metrics extracted from the geometries, such as the number of vertices and shape complexity, which can benefit the data set users to design their own sampling strategies for compiling a customized training data set.

3 Constructing progress

Our workflow for buildings is well established and was applied to transitions between 1:25k and 1:50k maps in Switzerland, in which the source and the target map are both at medium scales, for preliminary testing. It can be observed that most of the building geometries are displaced after the generalization (Figure 2.a). Cases with only a single operator are rare. The instances of different combinations of the automated map operators are also highly imbalanced (Figure 2.b), suggesting that learning the implicit map generalization rules can be challenging.

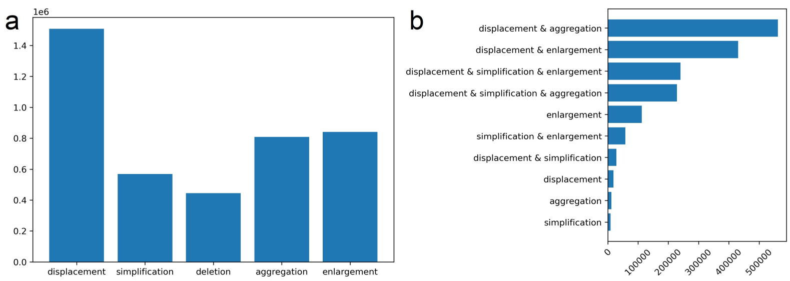

Figure 2 Map generalization operator cases of 2,078,548 building entities in 1:25k to 1:50k. a. By operator type; b. By operator combinations.

4 Research agenda

Challenge 1: Learning dominant but neglected operators

Using deep learning to explicitly learn individual generalization operators is mainly based on vector maps, which can reduce the manual intervention of expert cartographers (e.g., for setting thresholds). As illustrated in Figure 2.a, *displacement* is the predominant operator involved in map generalization within medium scales, followed by the *enlargement*, *aggregation*, *simplification*, and *deletion* operators. Unfortunately, it seems that the more dominant operators, including *displacement* and *enlargement*, are paid less attention to while some studies have attempted to learn *aggregation* [15], *simplification* [16], and *deletion* [14]. Therefore, research efforts should be particularly directed towards learning *displacement* and *enlargement* by formulating them as learnable tasks and introducing feasible models.

Challenge 2: Developing end-to-end generalization models

While the learning of individual generalization operators benefits the explicit modeling of cartographic knowledge and achieves the generalization of a part of map objects, it is still necessary to chain these intermediate outputs for more map objects to produce the final generalized map. Therefore, a second stream of raster-based deep learning models has great potential to enable end-to-end map generalization [4, 5]. The existing studies mainly work on the *aggregation*, *simplification*, and *deletion* operators and their combinations [5]. However, Figure 2.b shows that map generalization for medium scales also involves a large portion of combinations of *displacement* and other operators, as well as further, different combinations. Therefore, the raster-based deep learning models should be further developed using a more comprehensive data set that contains the dominant operator combinations (e.g., our demonstrated swisstopo data set) to improve their capacity for end-to-end solutions.

Challenge 3: Understanding learned cartographic knowledge

While Challenge 1 is result-oriented, it is also important to understand what specific cartographic knowledge a DL network learns. From the pragmatic perspective, this can contribute to better fine-tuning strategies for learning; from the theoretical perspective, it helps to gain scientific knowledge on the capacity and limitations of DL network architectures. XAI methods such as Grad-Cam [11] for raster-based data and those in GraphXAI [1] for vector-based graphs can help gaining interpretation of the knowledge a DL network learns. The result can also guide the optimization or chaining of modules in an end-to-end generalization workflow in Challenge 2, if the final generalization turns out to be a cascading multi-module workflow.

5 Future work

In future work, we would like to take a closer look at the validation of the generalization operator modeling and its effectiveness on the 1:50k to 1:100k generalization of buildings, with the help of swisstopo cartographers. The generalization operator modeling for roads will continue. Once the data set is published, a crowd-sourcing-like approach may also be applied for collecting corrections of specific transformations.

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