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Efficient operator annotation for deep learning in cartographic building generalization

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Abstract:

Map generalization is critical for geographical information presentation. There have been several paradigm shifts with many efforts to fully automate map generalization processes, from rule-based to constraint-based, agent-based, and machine learning (ML) approaches. However, in today's production systems manual intervention by professional cartographers is still needed due to the complexity of the process. Recently, deep learning (DL) has been eyed as a new paradigm for automated map generalization due to its capacity to model complex contextual relationships. However, early studies have provided evidence that the datasets used so far for training DL models are imbalanced in terms of map generalization operators. For building generalization between large-scale maps, only simplification and aggregation are involved, while for medium to small-scale maps, buildings are increasingly subject to enlargement, displacement and typification. Imbalanced data can be a severe issue in machine learning tasks, and resampling is a common solution to moderate the negative impact. However, current datasets for map generalization are randomly sampled from vector or raster map databases, without clear annotations of map generalization operators for individual samples. It thus remains unclear what generalization operators are applied to individual samples and to what degree a map dataset is imbalanced, which further makes proper resampling processes difficult. To answer these questions, labeling map generalization samples is essential.

This study presents a map generalization operator classification workflow for annotating individual building samples in generalization transitions by leveraging Snorkel, a labeling framework based on weak supervision (Ratner et al., 2020). Snorkel is able to wrap different labeling strategies, such as manual labeling, heuristic rule-based labeling, and ML-based labeling, into the same framework and provides a label estimation model to solve possible conflicts. We adopted the framework as displayed in Figure 1 for labeling vector-based building databases. The workflow was applied to a seamless building database provided by swisstopo (the Swiss national mapping agency) containing all buildings across Switzerland generalized to 1:10k, 1:25k and 1:50k.[1] The outcome of our approach are two datasets representing the transitions from 1:10k to 1:25k and 1:25k to 1:50k, respectively. To the best of our knowledge, this constitutes the first attempt at developing a semi-automated workflow for annotating massive amounts of examples for map generalization without substantial manual labeling.

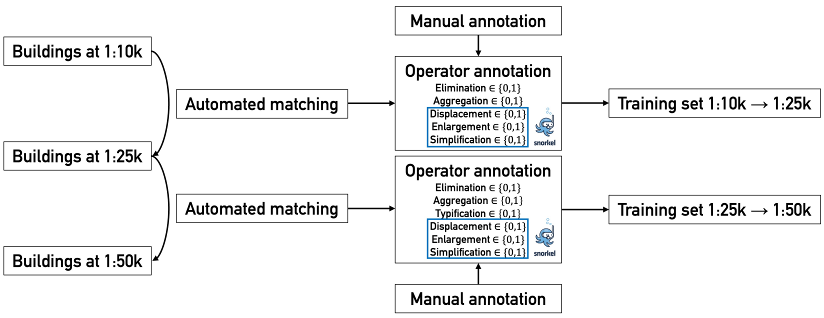

Figure 1. Workflow for deriving the training datasets.

To determine the generalization operators applied to a given building, the first step consisted of matching the buildings between the scales. In order to facilitate efficient propagation of incremental updates throughout the scales, swisstopo maintains feature links between the datasets (Duchêne et al., 2014). Since the transition between 1:10k and 1:25k is mainly characterized by the application of independent generalization operators, leveraging these links in combination

[1] These scales were all derived by swisstopo from the base topographic landscape model swissTLM3D, captured at a scale of approx. 1:5,000.

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with simple spatial criteria yielded satisfactory matching accuracy. However, in the transition from 1:25k to 1:50k, the dominant presence of the typification operator established the need for identifying many-to-many relationships. To this end, the buildings were partitioned into street blocks according to the Swiss road network generalized to the target scale of 1:50k. To match the buildings within the street blocks, the approach proposed by Zhang et al. (2014) was followed, which assigns each building at the larger scale its most likely counterpart(s) at the smaller scale based on a relaxation technique that exploits contextual information.

Based on the matched buildings, we identified the presence or absence of the following generalization operators for every individual building at the respective larger scale: *elimination*, *aggregation*, *typification*, *displacement*, *enlargement*, and *simplification*. As typification is not applied at large scales, it was only annotated for the scale transition from 1:25k to 1:50k. The presence of elimination, aggregation, and typification is determined entirely by the building matching process:

- **Elimination**: The building at the larger scale cannot be matched to any building at the smaller scale.
- **Aggregation**: For a given building at the larger scale, there are other buildings at the larger scale that are matched to the same building at the smaller scale.
- **Typification**: If a building at the larger scale is matched to multiple buildings at the smaller scale, these buildings at the smaller scale are considered the result of a typification. Consequently, any other buildings at the larger scale that are matched to them are also subject to typification.

All buildings that were not classified as eliminated were subsequently annotated with the operators *displacement*, *enlargement*, and *simplification* using the Snorkel framework. For each operator, multiple (potentially conflicting) labeling functions were determined, which may contribute to the identification of its presence or absence. Additionally, the approach involved a set of manually labeled examples, which were incorporated into the Snorkel annotation process to monitor and validate the performance of the different labeling functions, choosing the combinations and parameters that yielded the highest accuracy on the hand-labeled examples. The Snorkel framework further offers the possibility of outputting label probabilities that act as an indicator representing the confidence in the presence or absence of a given operator. Figure 2 illustrates the results of the building matching and generalization operator annotation processes for both scale transitions. To validate the results of our workflow, we plan to involve trained cartographers to perform the quality assessment.

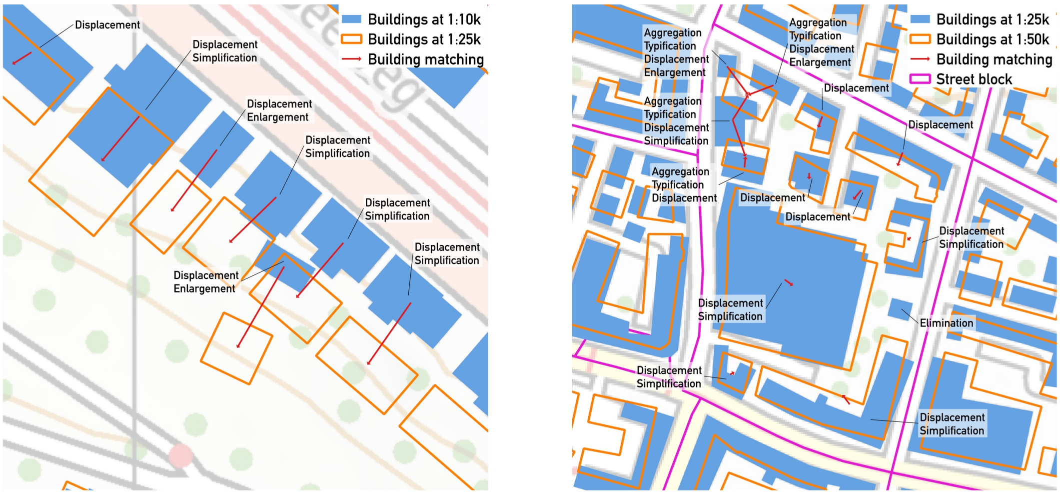

Figure 2. Building matching and annotated generalization operators for 1:10k to 1:25k (left) and 1:25k to 1:50k (right).

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