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Building simplification of vector maps using graph convolutional neural networks

Zhiyong Zhou*, Cheng Fu, Robert Weibel

Department of Geography, University of Zurich, Zurich, Switzerland, 1st Author - zhiyong.zhou@geo.uzh.ch, 2nd Author - cheng.fu@geo.uzh.ch, 3rd Author - robert.weibel@geo.uzh.ch

* Corresponding author

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Abstract:

Buildings form one of the most important object classes of topographic maps and its generalization is a very critical process to create cartographic models at multiple scales (Brassel and Weibel, 1988, Regnauld and McMaster, 2007)). In particular, the simplification operator, which reduces the number of points representing a line or polygon boundary (Stanislawski et al., 2014), serves building generalization significantly.

Building simplification has experienced decades of research. The conventional approaches to automating this problem introduce a range of criteria or constraints to detect redundant vertices or edges on boundaries of building polygons. The major criteria include edge length (Regnauld et al., 1999, Sester, 2005), edge number (Haunert and Wolff, 2010), area (Buchin et al., 2016), and so on. Recent advances in deep learning have the potential to bring map generalization research to a new era. Specific to the generalization of buildings or polygons, Cheng et al. 2013 used backpropagation neural networks to detect and simplify small corners, intrusions, and extrusions in rasterized footprints of buildings. Feng et al. (2019) applied mainstream deep learning architectures for image segmentation, including U-Net, residual U-Net, and GAN, to generalize image-based building maps. While these deep learning-based approaches, which implicitly model the simplification operator, achieve promising performance for building generalization, they are prone to cause deformed boundaries in generalized buildings, owing to the purely image-based inputs.

Therefore, it is reasonable to attempt to adopt vector maps as input to preserve the straight-line, often rectangular shapes of boundaries in building generalization. However, there are so far only few works on building generalization of vector maps using deep learning. Some studies have approached some pre-processing operations of generalization, e.g., structure recognition (Yan et al., 2019), building grouping (Yan et al., 2020), and shape coding (Yan et al., 2021), most of which are based on graph neural networks (GCNs). Recently, a classifier was trained using a backpropagation neural network to select the most appropriate conventional simplification algorithms for different shapes of buildings (Yang et al., 2022), but it still falls short of explicitly modeling the associated generalization operators, such as simplification, most importantly.

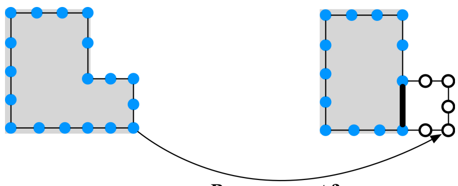

Figure 1. Graphical illustration motivating the proposed approach

Although in principle it has been shown that GCNs are capable of encoding vector map objects, it is still unclear how GCNs could work for end-to-end map generalization, that is, vector maps in and vector maps out. This study targets one of the major generalization operators involved in vector map generalization, simplification. Inspired by the excellent capability of GCNs to capture the geometric characteristics of vector map objects (Yan et al., 2019), we propose a building simplification approach using GCNs. Since the key process to simplify the polygon of a building is to decide which of its corner points should be removed, the building simplification problem is formulated as a node-level classification task on building graphs in this study (see Figure 1). Note that we assume in our solution that collinear Steiner points have been added along the segments of the building boundary to unify the input graph size (i.e., the number of points) for GCNN. In this study, the graph size is set as 64 as suggested by Yan et al. (2021) and they are interpolated equally after the regulated size (i.e., 64) subtracts the number of original corner points of a polygon.

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Figure 2 illustrates the workflow of the proposed approach. It is composed of three parts: feature engineering to construct geometric and topological features for an individual vertex in a building graph; graph convolutional neural network (GCNN) training based on the given dataset; and post-processing to reconstruct the polygon from the graph. The features are the same as used by Yan et al. (2019), including three types for local characteristics of vertices, and four types for regional characteristics. Afterwards, the features are fed to the GCNN to train and classify if each vertex in a polygon graph should be removed or not. Finally, to create a complete vector map product at the target scale, a post-processing step, which reconstructs polygons based on those vertices that are not removed, is conducted. In the experiment, the Stuttgart dataset (Feng et al., 2019), which contains a source map at the scale of 1:5,000 (accommodating 175,756 polygons) and three target maps at the scales of 1:10,000, 1:15,000, and 1:25,000, were used to train the GCNN for building simplification. We built and trained the GCNN using PyTorch and PyTorch Geometric. Since the study is still ongoing, the results are expected to become available before the conference and they will be compared with typical machine learning approaches.

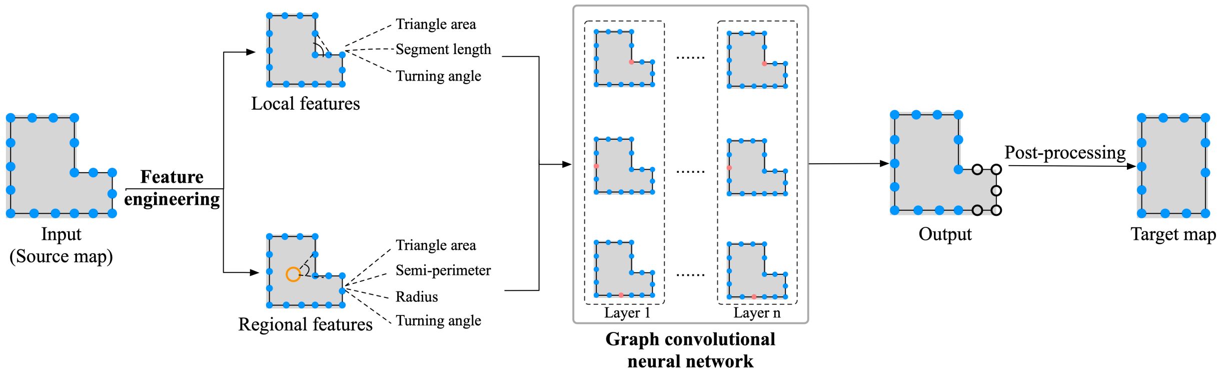

Figure 2. The workflow of the proposed approach

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References

Brassel, K. E. and Weibel, R., 1988. A review and conceptual framework of automated map generalization. *International Journal of Geographical Information System* 2(3), pp. 229–244.

Buchin, K., Meulemans, W., Renssen, A. V. and Speckmann, B., 2016. Area-preserving simplification and schematization of polygonal subdivisions. *ACM Transactions on Spatial Algorithms and Systems (TSAS)* 2(1), pp. 1–36.

Feng, Y., Thiemann, F. and Sester, M., 2019. Learning cartographic building generalization with deep convolutional neural networks. *ISPRS International Journal of Geo-Information* 8(6), pp. 258.

Haunert, J.-H. and Wolff, A., 2010. Optimal and topologically safe simplification of building footprints. In: *Proceedings of the 18th sigspatial international conference on advances in geographic information systems*, pp. 192–201.

Regnauld, N. and McMaster, R. B., 2007. A synoptic view of generalisation operators. In: *Generalisation of geographic information*, Elsevier, pp. 37–66.

Regnauld, N., Edwardes, A. and Barrault, M., 1999. Strategies in building generalisation: modelling the sequence, constraining the choice. In: *ICA Workshop on Progress in Automated Map Generalization, Ottawa, Canada*, pp. 372–378.

Sester, M., 2005. Optimization approaches for generalization and data abstraction. *International Journal of Geographical Information Science* 19(8-9), pp. 871–897.

Stanislawski, L. V., Buttenfield, B. P., Bereuter, P., Savino, S. and Brewer, C. A., 2014. Generalisation operators. In: *Abstracting geographic information in a data rich world*, Springer, pp. 157–195.

Yan, X., Ai, T., Yang, M. and Tong, X., 2021. Graph convolutional autoencoder model for the shape coding and cognition of buildings in maps. *International Journal of Geographical Information Science* 35(3), pp. 490–512.

Yan, X., Ai, T., Yang, M. and Yin, H., 2019. A graph convolutional neural network for classification of building patterns using spatial vector data. *ISPRS journal of photogrammetry and remote sensing* 150, pp. 259–273.

Yan, X., Ai, T., Yang, M., Tong, X. and Liu, Q., 2020. A graph deep learning approach for urban building grouping. *Geocarto International* pp. 1–24.

Yang, M., Yuan, T., Yan, X., Ai, T. and Jiang, C., 2022. A hybrid approach to building simplification with an evaluator from a backpropagation neural network. *International Journal of Geographical Information Science* 36(2), pp. 280–309.

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