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A Point Cluster Generalization Method based on Graph Convolutional Network

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Abstract:

Automatic map generalization has long been an important problem in the field of geographic information science. During the transformation of map scale from large to small, the conflict and congestion of map symbols are inevitable, and the selection and simplification of objectives become the basic strategy for problem solving, which contains a complex decision-making process (Ai and Zhang, 2022). Traditionally, a rule-based approach is generally used for decision making. However, due to the existence of particular conditions, often the selection rules need to be continuously patched and combine multiple judgments, which leads to an increasingly complex system of generalization rules for maps. Therefore, it is necessary to seek new ideas for map simplification in the context of the difficulty of exhausting different conditions to establish a map generalization system. Currently, since a number of established series of scale products exist in the field of cartography, it is possible to select typical areas to create samples and apply data-driven methods to establish the map generalization process. The conditions for the application of artificial intelligence methods in the field of map generalization are available.

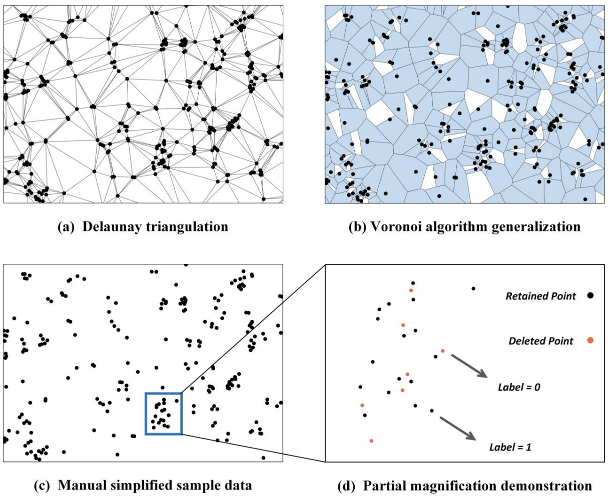

Figure 1. Sample construction process for a point cluster

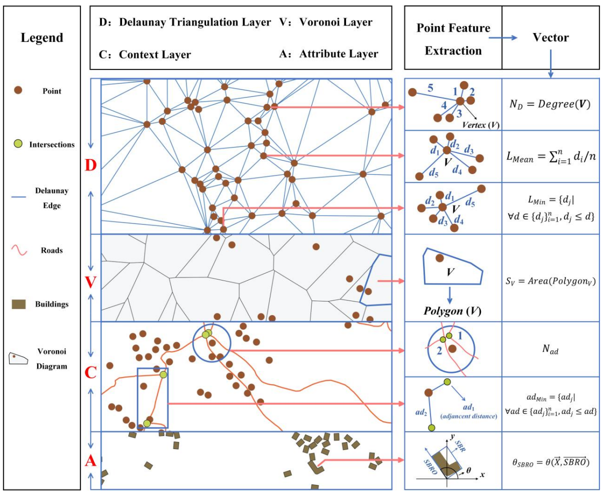

Figure 2. Feature vector extraction for point cluster

Aimed at the above problems, this study introduces graph convolutional neural network for map generalization and applies it to the point cluster selection operation. First, the original data are pre-processed and the point cluster data are organized into a graph structure connected by neighbouring points by constructing a Delaunay triangulation, and the sample data for training is constructed (Figure 1). For the label construction of the training data, a combination of spatial algorithms (Ai and Liu, 2002) and manual intervention is used to classify each point as retained or deleted. Secondly, geographic and geometric features of the points are extracted. The features for training are obtained from the graph structure of each point and its contextual proximity, such as the area of the Voronoi diagram, the number of Delaunay edges, and the shortest distance between adjacent road intersections (Figure 2). Finally, a topological adaptive graph convolutional network (TAGCN) with multiple convolutional kernels is introduced (Du et al., 2017), and an automatic generalization model based on the graph convolutional network for point clusters is constructed based on it (Figure 3). In this study, the abstracted point features of buildings in Zhongjiang County, Sichuan Province, China, were selected as the experimental data, and the training results achieved an accuracy of 87% on the test set.

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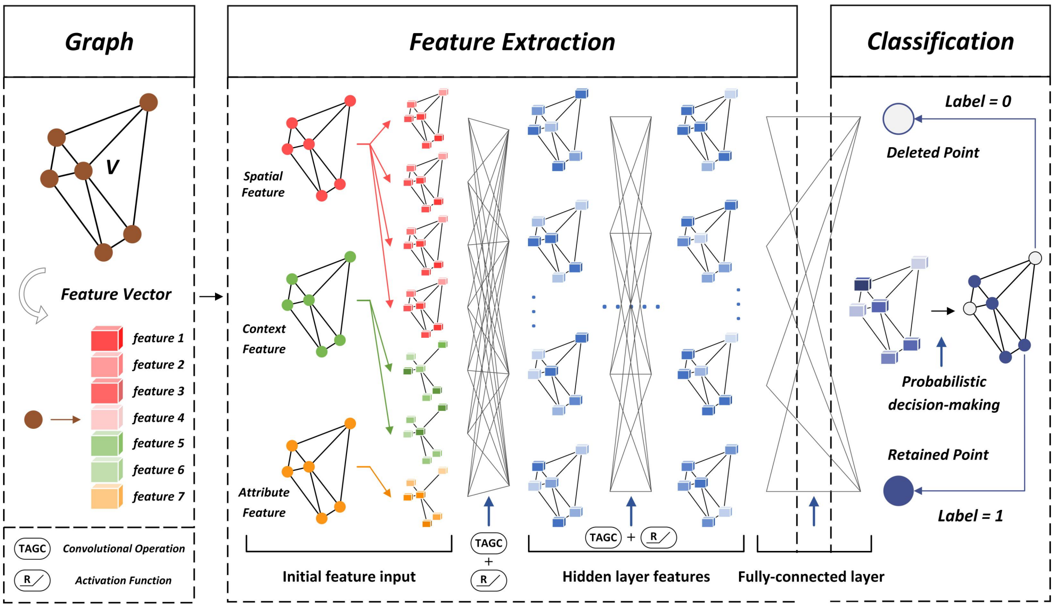
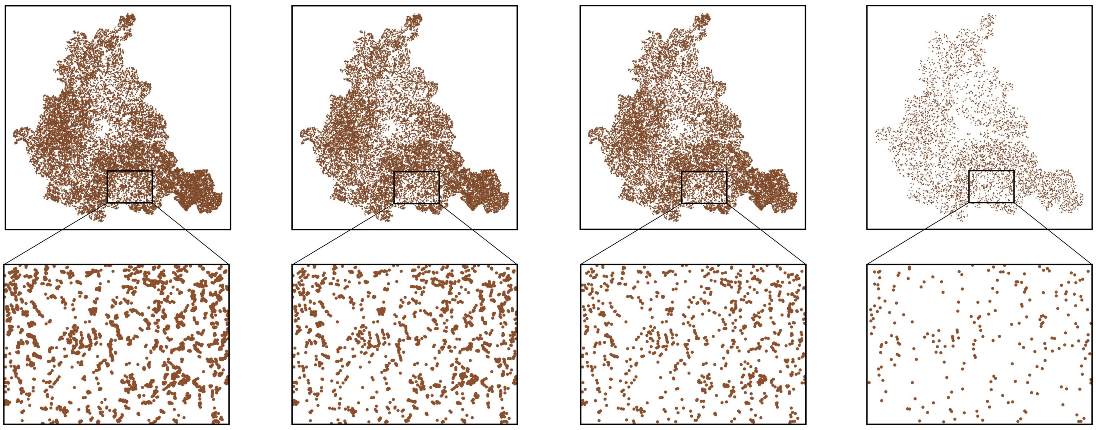


Figure 3. Architecture of the graph convolutional network model.

The results obtained by the GCN model (Figure 4) training have good performance in many aspects: in terms of quantitative relationship, the total error of the GCN selected results compared with the sample data was within 4% in the range of each township administrative region; in the aspect of overall shape preservation, structural similarity (SSIM) was introduced to evaluate the morphological similarity before and after the point cluster generalization (Wang et al., 2004), and the evaluation results show that the results of GCN selection outperform other selection algorithms in terms of overall and local morphological preservation; in terms of contextual proximity, the GCN selected results successfully learned the features of the sample data closer to the road intersections, and the algorithm tends to retain the points close to the road intersections. In summary, it is feasible to use GCN in the field of point cluster automatic generalization, which has considerable potential with a wide scope for further improvement.



(a) Original point cluster **(b) Ratio = 30%** **(c) Ratio = 60%** **(d) Ratio = 90%**

Figure 4. Generalization results of different simplification levels using GCN model.

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