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Map Generalization Method Supported by Graph Convolutional Networks

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Abstract. Map generalization has always been a key research issue in cartography. With the continuous development of the information age, massive amounts of map data are being generated, and how to effectively achieve multi-scale representation of large-volume vector data of various types has become a pressing challenge. Traditional methods of map generalization, which rely heavily on human-specified rules and set thresholds, tend to be complex and inefficient. Furthermore, they are often significantly influenced by the subjective factors of cartographers. To address these challenges, this study introduces graph-based deep learning techniques into the field of map generalization. Tailored generalization strategies were designed for point features, polyline features, and polygon features, enabling this data-driven approach to facilitate map generalization tasks from different perspectives. A comprehensive map generalization framework was developed for various feature types by integrating domain knowledge with data-driven techniques. This framework includes the construction of graph structures for different geographic objects, the extraction of feature vectors, and the design of deep learning network models. Experimental results demonstrate that the proposed method delivers good visual performance while preserving the various characteristics of the original map during the generalization process.

Submission Type. Model; Algorithm

BoK Concepts. [AM14-2] Approaches to point, line, and area generalization

Keywords. Graph convolutional network, data-driven, map generalization, deep learning model

1 Introduction

Automatic map generalization has long been a key research focus in cartography and related fields and is regarded as one of the fifteen high-frequency research topics in geographic information science (Wu et al., 2023). As a complex decision-making process during scale transformation, map generalization involves numerous influencing factors, including the recognition of geographic feature patterns, the selection of simplification operators, and the evaluation of generalization quality metrics. Traditional generalization methods have aimed to summarize as many rules as possible to achieve map simplification. However, due to the diversity and complexity of generalization tasks, it is challenging to summarize all rules into a universal algorithm. In this background, deep learning techniques have become increasingly necessary. By the assistance of sample-driven network models, these techniques can uncover and integrate the complex, implicit rules of generalization, enabling the development of map generalization algorithms that do not rely on manually defined rules or parameter settings.

Since the concept of deep learning was introduced (Hinton, 2006), it has been widely adopted across various fields due to its outstanding performance and independence from prior knowledge. In recent years, the rapid advancement of deep learning has significantly enhanced the ability to extract patterns from data, especially in the field of geographic information science. Currently, various decision-making processes powered by artificial intelligence have been increasingly applied to numerous tasks. For instance, in the field of remote sensing, convolutional neural networks (CNNs) can

automatically extract features from image data through various neurons and hierarchical layers (Wang & Tian, 2021) and have been successfully used for denoising (Zhu et al., 2022), enhancement (Lalitha & Latha, 2022), and classification (Luo & Ji, 2022). However, in the context of complex vector map data, which is not organized in grid arrays, traditional CNNs are unsuitable for processing non-Euclidean structured data. Therefore, the conventional approach relying on two-dimensional convolutional layers to extract spatial information from images cannot be directly applied.

The emergence of graph convolutional networks has made it possible to apply deep learning techniques to spatial vector data (Kipf, 2016), as most geographic vector data can be transformed into graph-structured patterns that are recognizable by GCNs. This vector graph structure can be integrated into deep learning, enabling neural networks to utilize and learn from the rich spatial and neighborhood information embedded in vector data. Therefore, graph neural networks (GCNs) are becoming popular tools for researchers addressing various vector data issues, demonstrating promising results in tasks such as pattern recognition (Yan et al., 2019; Yu et al., 2022), similarity metrics (Li et al., 2023; Yu et al., 2023), and filling gaps in polylines (Yu et al., 2022).

The development of map generalization techniques also requires the support of graph deep learning technologies. Over the decades of advancements in cartography, an extensive collection of multi-scale vector map data has been accumulated, providing a substantial sample base for learning models to uncover the hidden principles of map generalization. This facilitates better adaptation to the challenges of the big data era. In this study, graph-based deep learning techniques are introduced into the field of map generalization, and an algorithmic framework integrating domain knowledge with data-driven approaches is proposed. For point, polyline, and polygon features in geographical space, this study designs graph structure construction methods and feature vector extraction schemes according to their respective data characteristics. Furthermore, suitable graph network architectures are selected to construct simplification models for map generalization tasks. In addition, follow-up post-processing operations are designed based on the training results to ensure that the final generalized data exhibits improved visual quality and simplification performance.

2 Methods

For geospatial data, point features, polyline features, and polygon features each possess distinct dimensions and structural characteristics. For example, point features have a dimension of zero and lack internal shape, meaning that generalization of point clusters primarily focuses on selection operations (deletion or retention), making the generalization steps relatively straightforward. In contrast, polyline features and polygon features present a more complex situation. For instance, in the case of road network data, the generalization process must also consider the shape of the features themselves, as well as the topological relationships between the roads. Therefore, it is necessary to design targeted generalization methods for different types of features.

2.1 Point cluster generalization model

The primary step in inputting map vector data into a graph neural network is constructing the graph structure (Xiao et al., 2024). Unlike data such as road networks or river systems, point clusters lack inherent connections between individual points. Therefore, it is necessary to introduce Delaunay triangulation method to establish connections among the points within the point cluster (Delaunay, 1934). The most commonly used methods for generating Delaunay triangulation include incremental insertion approach (Macedonio et al, 1991), divide-and-conquer approach (Lee & Schachter, 1980), and triangulation growth approach (Mirante & Weingarten, 1982). Figure 1 illustrates the process of generating the graph structure for a sample point cluster dataset and the sample construction. First, a Delaunay triangulation is constructed for the entire point cluster, and subsequently, slender edges along the boundary are removed. The resulting pruned Delaunay triangulation constitutes the final graph structure.

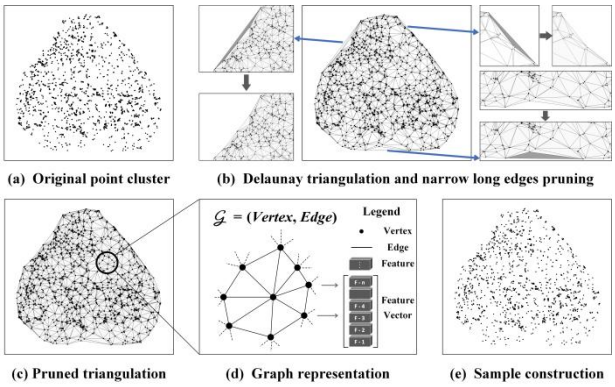


Figure 1. The process of generating graph structure and samples.

The second step before inputting the sample data into the graph neural network model for training is the design and extraction of feature vectors. For point cluster generalization tasks, it is necessary to extract several relevant parameters that can reflect the spatial

distribution of point features from aspects such as neighbor relationships, contextual characteristics, and internal attributes, to serve as input data for the learning model. During the feature extraction process, the point cluster is transformed into four layers: the Delaunay triangulation layer, the Voronoi diagram layer, the contextual layer, and the attribute layer. From these layers, a total of seven features are extracted, including the number of neighboring points, the Voronoi area, the number of adjacent road intersections, SBRO (Smallest bounding rectangle orientation), among others. The extraction methods are illustrated in Figure 2.

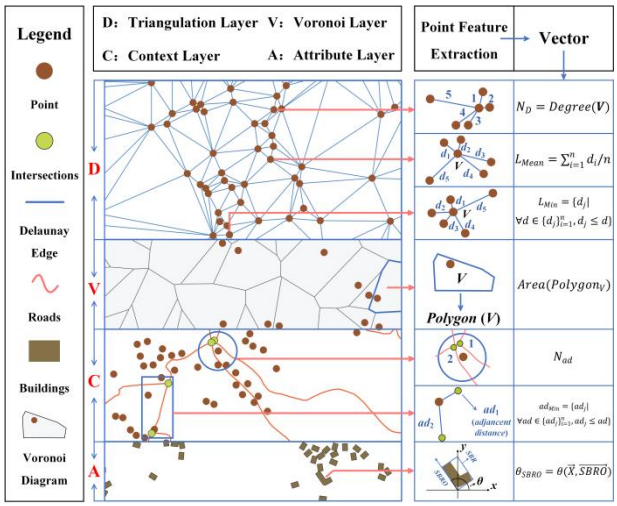


Figure 2. Feature vector extraction for point cluster.

After constructing the feature vectors for the point cluster data, a graph neural network model related to point cluster selection can be designed. In order to enable the learning model to capture and utilize information from more distant point neighbors, thus making it more suitable for the automatic generalization tasks of point clusters, this study opts for the Topology Adaptive Graph Convolutional Network (TAGCN) as the foundational network for the generalization model (Du et al., 2017). In TAGCN, the hyperparameter K is reserved as the number of filter layers and used to construct a set of size-1 up to size-K filters to avoid the linear approximation. Affected by the free hyperparameter K, the output feature map is a weighted sum of convolution results from filters with different sizes:

$$\mathbf{y}_f^{[\ell]}(i) = \sum_{k=1}^{K} \sum_{c=1}^{C_\ell} \sum_j g_{c,f,k}^{[\ell]}\, \omega\left(p_{j,i}^k\right) \mathbf{x}_c^{[\ell]}(j) + b_f \mathbf{1}_{N_\ell} \quad (1)$$

Where $\omega\left(p_{j,i}^k\right)$ is the sum of the weights of all the length-k paths from j to i, and the weight of each path is defined as the product of the edge weights along the path, denoted as $\phi\left(Path_{0,m}\right) = \prod_{k=1}^{m} A_{v_{k-1},v_k}$, m is the length of the path (v_k, v_{k+1}). Furthermore, $\mathbf{1}_{N_\ell}$ represents the N_ℓ dimension vector of all ones. Due to the characteristic in point cluster generalization, the architecture using TAGCN in this study is shown in Figure. 3.

Through this trained model, point features can be preserved or deleted based on the classification of the model's output label values of 1 and 0, thereby achieving the generalization of point cluster data.

2.2 Road network generalization model

As a representative data type of polyline features, road networks present a more complex generalization process due to the necessity of considering the influences of topological relationships. This study designs a scheme for road generalization through the merging of road mesh polygons. In this scheme, each road and its adjacent two road mesh polygons will be treated as two separate geographic objects. These new geographic objects are termed MLSU (Mesh-line Structure Unit), and the method for constructing the graph structure of these special geographic objects is illustrated in Figure 4. Since each road corresponds to two MLSU structures, the MLSU-based graph structure needs to be bilayered. This bilayer graph structure can more accurately reflect the adjacency relationships among the various MLSU structures.

For this novel type of geographic object, feature extraction primarily considers three aspects: road features, mesh features, and interaction features, resulting in a total of 30 extracted features. Specifically,

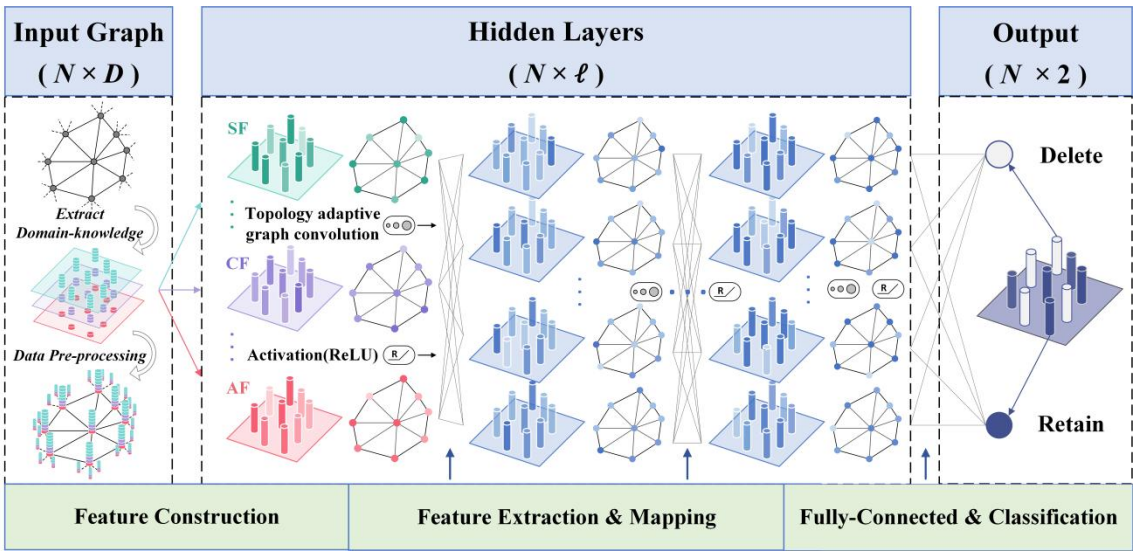


Figure 3. Architecture of the graph convolutional network model for point cluster generalization.

for road features, 22 features were extracted in this study. These road-related polyline features are derived from four dimensions: semantics, neighborhood, geometry, and complexity. Key parameters include road hierarchy, road type, stroke length, meandering index, Voronoi Area, fractal dimension, etc. The detailed feature items and extraction methods are shown in Figure 5.

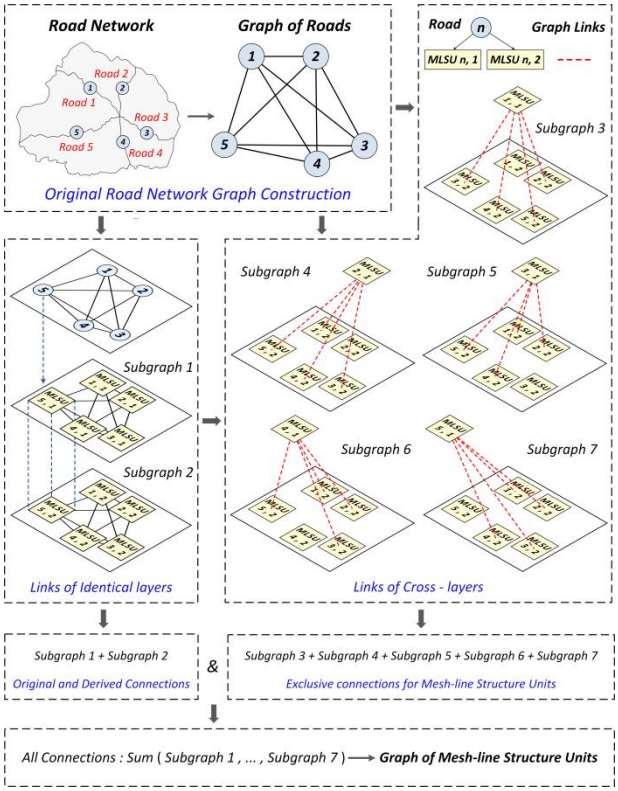


Figure 4. The graph structure construction process.

With the development of graph neural network technologies, an increasing number of network models are being employed to address issues related to geographic polyline features. Among these, GraphSAGE has been widely used and applied in studies addressing tasks such as automatic segmentation of river network patterns and road network analysis (Yu et al., 2022). As an inductive model, GraphSAGE offers strong scalability, making it commonly used in research. However, for the generalization of road networks, the challenges differ from traditional pattern classification problems, as they exhibit greater uncertainty and diversity in generalized outputs. As a result, instead of focusing solely on the scalability of GraphSAGE, the key priority in road generalization models is to extract deeper generalization rules from graph structures. Consequently, the Topology adaptive graph convolutional network, with its ability to accurately extract information from higher-order neighbors, is potentially more suitable for solving complex map generalization tasks. Therefore, for the road generalization graph network model, this study employs the same TAGCN model used for point cluster generalization and utilizes it to construct a network model for road generalization. The specific design of the model structure is illustrated in Figure 6.

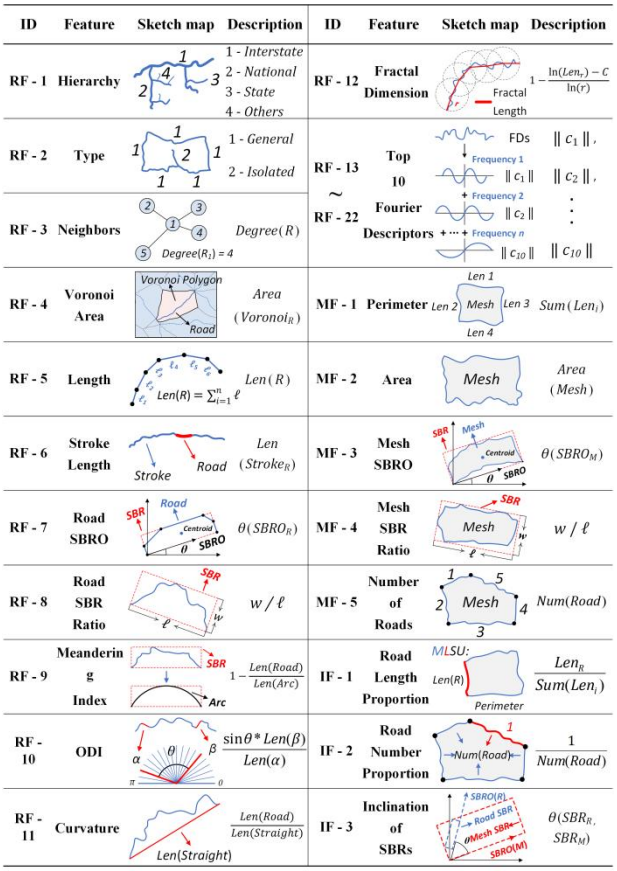


Figure 5. Diagram of the extraction method for all 30 features.

2.3 Polygon generalization model

Geographic information data for polygon features is typically stored as a series of coordinate points, with the corresponding polygons represented by connecting the first and last points to form closed shapes. Consequently, the vertices of these polygons serve as the key features for analysis and generalization. Similar to the generation of graph structures for point clusters, the graph structure for polygon features can also be constructed using Delaunay triangulation. To construct the Delaunay structure for polygon features, all vertices of the polygons must first be extracted. These vertices are then used to generate a Delaunay triangulation following the same methodology applied to point clusters. In this study, the construction of graph structures is carried out by regarding the triangular units of the Delaunay triangulation as graph vertices. Figure 7 illustrates the process of constructing a triangular unit-based graph structure using the Delaunay triangulation framework. In Figure 7 (c), triangle 10 is adjacent to triangles 9, 11, and 14. Then, in the graph structure illustrated in Figure 7

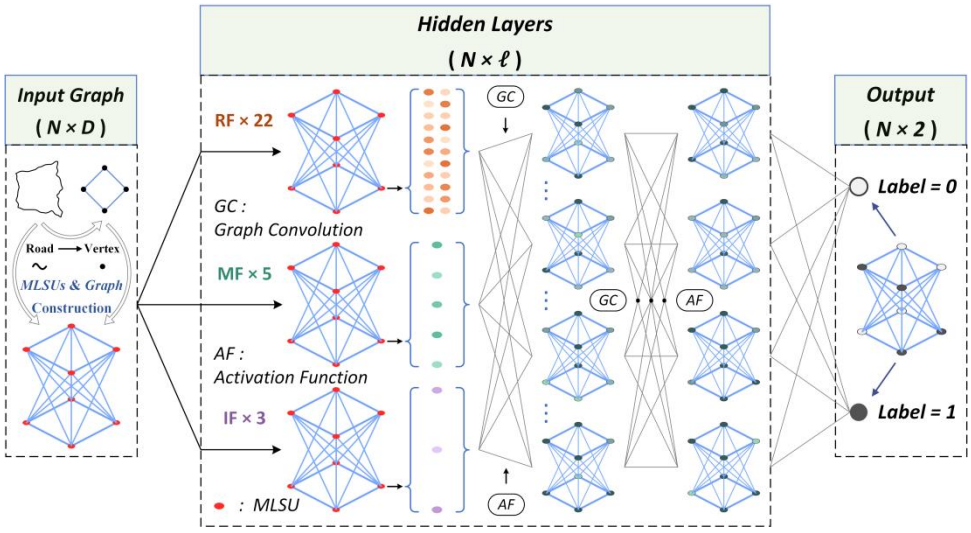
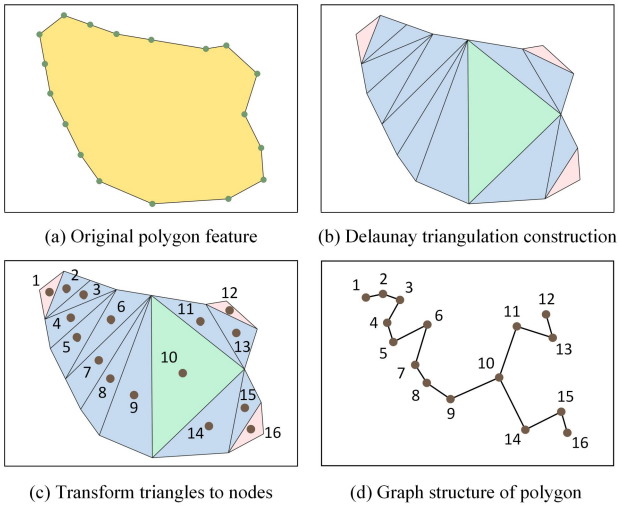


Figure 6. Architecture of the graph convolutional network model for road network generalization.

(d), node 10 is also interconnected with corresponding nodes 9, 11, and 14 .

In general studies of complex polygon or polyline feature generalization, the detailed extraction and analysis of shape characteristics is a challenging process. In current deep learning research, the feature extraction steps for these types of features also tend to be relatively complex. However, in this study, since polygon features are divided into numerous small, independent triangles using Delaunay triangulation, the feature extraction process only needs to consider the characteristics of these triangles. Consequently, the complexity of the feature vector construction process in this study is significantly reduced compared to other deep learning methods. A total of 9 triangle features were extracted, including the lengths of the three edges of each triangle, the triangle's area, the aspect ratio of the triangle's minimum bounding rectangle, and the radius of the triangle's circumcircle, etc.



(a) Original polygon feature (b) Delaunay triangulation construction

(c) Transform triangles to nodes (d) Graph structure of polygon

Figure 7. The graph structure construction process of polygon feature.

For polygon feature generalization, the GraphSAGE network was adopted to construct the map generalization model. GraphSAGE is a model that learns effective node representations through sampling and aggregation while maintaining computational efficiency. By sampling the local neighborhood of each node, it reduces computational complexity and leverages neighborhood information for node embedding learning. Traditional graph neural networks typically perform calculations over the entire graph, whereas GraphSAGE significantly reduces computational complexity through localized aggregation. For the complex polygon feature generalization tasks in this study, the constructed Delaunay triangulation often contains a large number of triangular structures. Due to its high computational efficiency, the GraphSAGE network was selected and employed to construct the map generalization model for polygonal features. The specific design of the model structure is shown in Figure 8.

2.4 Data and Software Availability

A Figureshare repository containing point cluster data, road network data, ocean polygon data, and the code for performing point generalization and road generalization can be accessed via the following link: https://doi.org/10.6084/m9.figshare.28204343. The point cluster dataset includes 92,803 points. This point cluster was abstracted from the singular dwelling buildings in Zhongjiang County, Sichuan Province, China. For road network data, the dataset selected roads at scales of 1:1,000,000 and 1:2,000,000 from the southern region of the United States. The five states of North Carolina, South Carolina, Kentucky, Tennessee, and Georgia were chosen as the training set, comprising a total of 13,715 roads, while the three states of Oklahoma, Louisiana,

and Arkansas were selected as the test set, consisting of a total of 5,930 roads. The 1: 1,000,000 scale raw data was downloaded from USGS (U.S. Geological Survey), and the 1: 2,000,000 scale generalized data were sourced from USDA (U.S. Department of Agriculture). The polygon features used for the experiment are Aegean Sea polygon data. The experimental data was divided into a total of 146,725 triangular structures through Delaunay triangulation, of which there are 50,764 triangles with a label value of 1 and 95,961 triangles with a label value of 0.

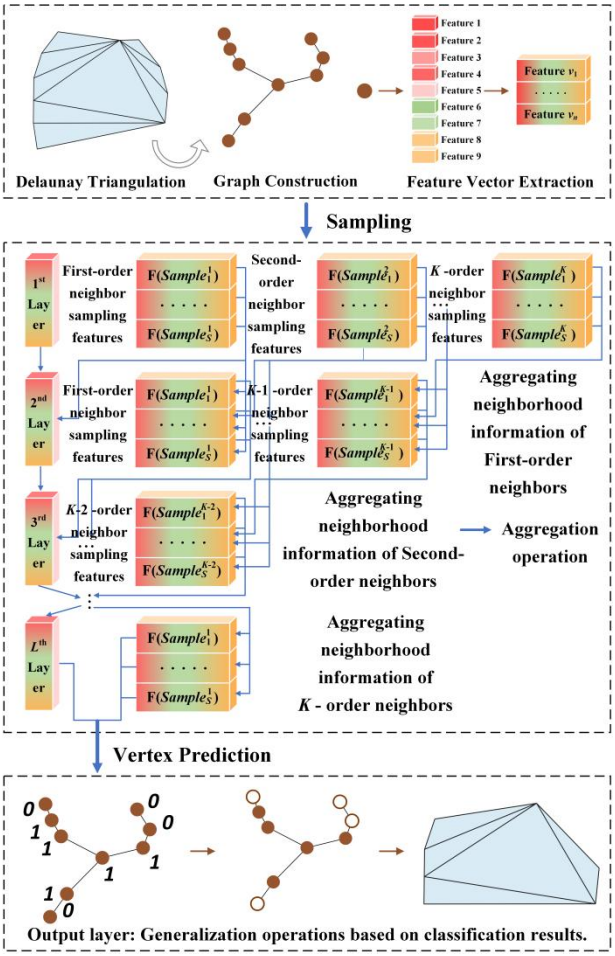


Figure 8. Architecture of the graph convolutional network model for polygon generalization.

3 Experimental Results

3.1 Point cluster generalization results

In the point generalization model presented in Section 2.1, the retention probability value for each point in the map can be obtained. This value represents the quantified likelihood of retention calculated after considering multiple factors. Points with higher probability values indicate greater importance within the point cluster, thus lower likelihood of being deleted. The probability p_i of all points is combined into a vector $V_p = (p_1, p_2, \ldots, p_n)$, where n is the number of points. The index vector $\boldsymbol{IV}$, which represents the order of importance of points, is obtained by sorting the V_p according to the rule from largest to smallest, and is expressed as:

$$\boldsymbol{IV} = (I_1, I_2, \ldots, I_i, \ldots, I_n) \quad (2)$$

Where $p_{I_i} > p_{I_{i+1}}$ and I_i is the index of the points with importance rank i. IV records the order of importance of all points and the generalization of the point cluster can be achieved by gradually deleting the points corresponding to the end elements of this vector. According to this rule, it is possible to freely set the number of points to be retained according to the simplification requirements. As shown in Figure 9, the generalization results have a good visualization performance in different simplification ratios:

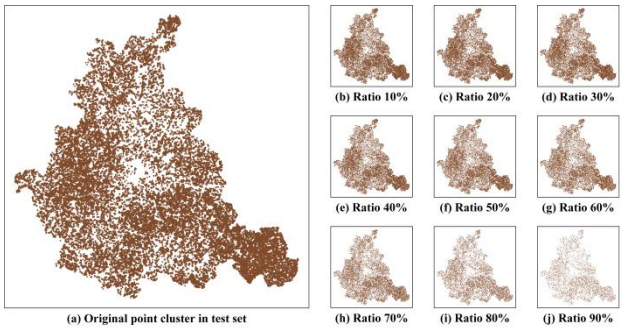


Figure 9. Generalization results of different simplification levels using proposed model.

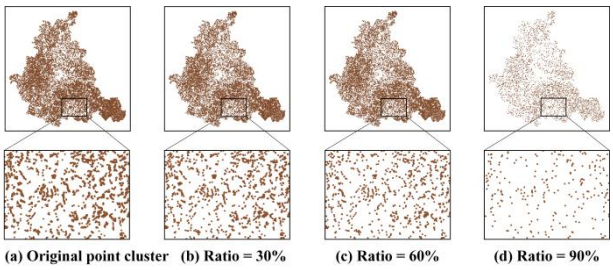


Figure 10. Zoom-in results of different simplification levels using GCN model.

It can be observed that the generalization results exhibit good visual performance at different map scales. A comparison of the ten point clusters shown in Figure 9 and 10 reveals that the visual representation of the simplification results for point clusters transitions smoothly from a generalization rate of 0% (original data) to a generalization rate of 90%, with a relatively uniform distribution and no instances of excessive generalization in any particular area. This further demonstrates the effectiveness of the point cluster generalization model proposed in this study.

3.2 Road network generalization results

In the road network generalization model presented in Section 2.2, each MLSU corresponding to a road is assigned a label of either 1 or 0 after classification by the deep learning network model. This label signifies whether the polygon feature corresponding to the mesh in that MLSU should be merged with an adjacent polygon near the road. To prevent unexpected merging operations between two meshes due to errors in the training results, this study specifically introduces an AND gate in the generalization process following model training. This means that the merging operation will only be executed if both MLSUs agree to merge the adjacent mesh polygons along the road. In the case of Road 1, the output classification results of the two MLSUs after the AND gate processing yield a value of 1, indicating that the two mesh polygons need to be merged along the edge of Road 1. The newly formed polygon is the actual combination result of the two meshes under the influence of the road. Therefore, the generalization process based on deep learning model is illustrated in Figure 11.

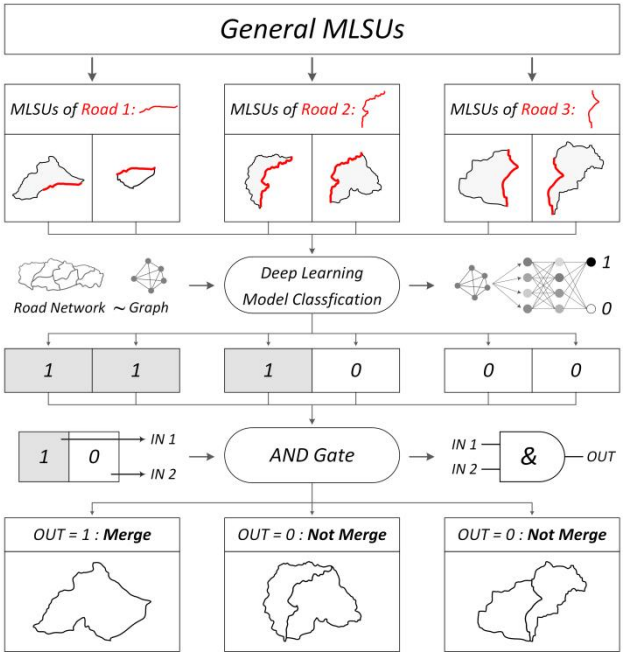


Figure 11. Generalization process for road network.

Based on the generalization process demonstrated in Figure 11, the generalized results for the road network can be further obtained, as shown in Figure 12. Initially, the original road network is transformed into a mesh polygon structure, which then undergoes a mesh merging operation before ultimately being converted into polylines. A comparative analysis between the original data and the generalized results within the experimental areas reveals that the proposed road network generalization method achieves a more appropriate simplification effect in all three test areas, without exhibiting instances of excessive generalization in localized regions. Additionally, the radial pattern of major roads in Oklahoma and Arkansas, as well as the road density distribution in the northwestern and southeastern regions of Louisiana, have been well-preserved in the simplified results obtained by the algorithm. This further reflects the effectiveness of the proposed polygon feature generalization model.

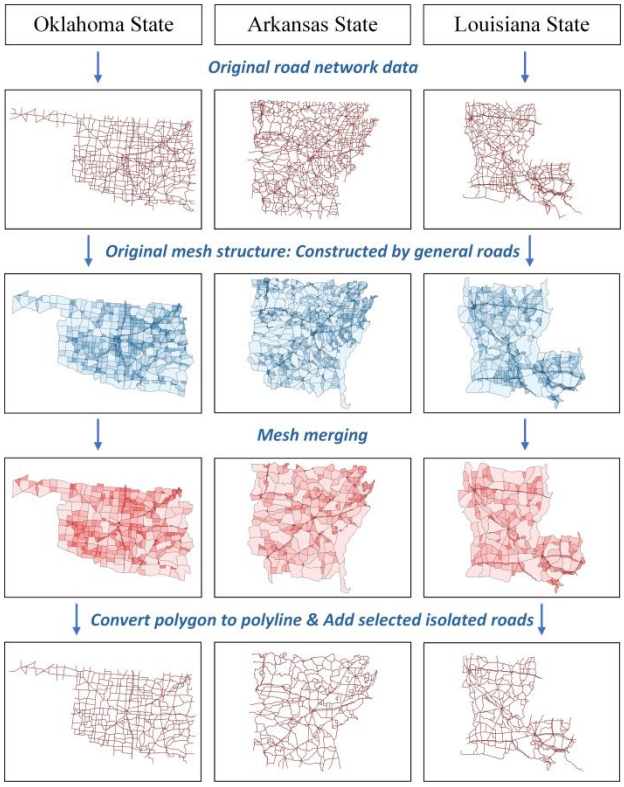


Figure 12. Road generalization results.

3.3 Polygon generalization results

In the polygon feature generalization model presented in Section 2.3, the output label values can be directly used to determine whether the target triangles should be retained during the generalization process, thereby obtaining the preliminary generalization results of the polygon features after training with the graph neural network. However, the output data derived directly from the network model cannot serve as the final results for polygon feature generalization. Unlike the study of point features, the generalization operation needs to consider the impact of the adjacency relationships between different triangles on the results. As shown in Figure 13, three demonstration areas have been selected: Santorini island, Milos island, and the Southern Euboean Gulf. The scattered and fragmented triangles appearing in the twelve sub-regions in Figure 13(g-i) represent instances of misjudgments encountered during the learning process of the graph network model. Among these, most of the fragmented triangles should have output values of 0

(delete) in the model but were mistakenly classified as 1 (retain). Such misclassifications of the label values for these triangles significantly affect the visual performance and generalization quality of the simplification results. Therefore, additional operations are necessary to further process and optimize the direct output results from the trained model, executing deletion or merging operations.

In the polygon feature generalization results illustrated in Figure 14, the initial scale of the experimental data is 1:40,000, while the target generalization scale is 1:2,500,000. By locally zooming in on and comparing the three demonstration areas, it can be observed that the generalization results effectively accomplish the simplification tasks for polygon features. Taking Milos Island as an example, the generalization result at the scale of 1:2,500,000 significantly reduces most details in terms of shape representation compared to the original data. The remaining polygon shapes adequately describe the general outline of the island, preserving the shape information of the original polygon features. Thus, this also demonstrates the effectiveness of the polygon feature generalization model proposed in this study.

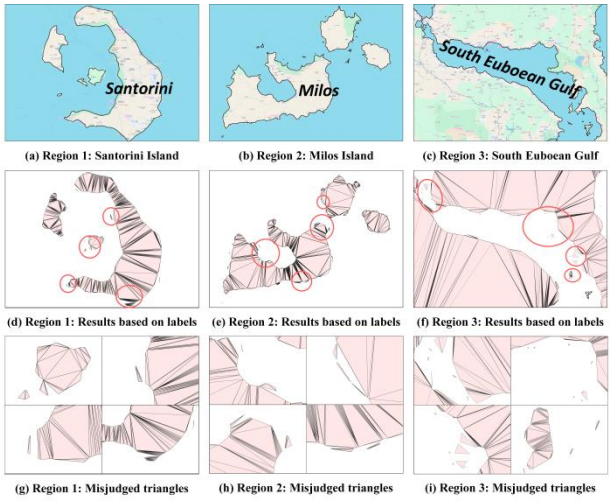


Figure 13. Fragmented triangles produced in the generalization results directly output by training.

(a) Test dataset of original map scale

(b) Generalized data of target map scale

(c) Zoom-in demonstration

Figure 14. Processed results of polygon feature generalization.

4 Conclusion

Most of the traditional spatial generalization methods are purely geospatial domain knowledge-based simplification algorithms that use a single set of control parameters and cannot take into account the performance of the generalization results from all perspectives. This research introduces GCN into map generalization and proposes a data-driven simplification scheme that combines geographic domain knowledge in map generalization. The advantages of this simplification strategy are, firstly, that the fundamental role of domain knowledge is fully exploited compared to the purely data-driven mode in the field of remote sensing. Geographic knowledge is an important achievement in the field of map generalization gained over decades of development, and although each individual aspect of it has certain limitations at some level, it still allows for the acquisition of rich neighbourhood information on geographical objects. Secondly, the graph neural network can combine the extracted features and reasonably balance the influence between the factors, allowing the trained model to not only learn the distribution pattern of the generalized geographical features, but also to avoid the influence of human factors on the simplified results. This strategy can be applied to the generalization of point features, polyline features, and polygon features, which to some extent reflects its feasibility and applicability. Experiments on three different types of data also demonstrate that the graph deep learning-based generalization approach is effective, capable of achieving generalization of map spatial data. Moreover, the results of the generalization show good performance, with a strong visual representation. In terms of algorithmic time consumption, vector data inputs typically contain only several to dozens of dimensions per node, resulting in significantly smaller input data scales compared to raster image data. This inherently reduces temporal costs during training and inference processes relative to raster-based approaches, demonstrating that the time expenditure of graph deep learning-based map generalization algorithms remains within acceptable thresholds. Consequently, this study proposes a potential solution for automated map generalization. Furthermore, emerging deep learning architectures - including encoder-decoder frameworks, Transformer models, and Generative Adversarial Networks (GANs) - provide novel methodologies for analyzing and processing graph-structured vector data. Future research could leverage encoder-decoder architectures with Transformer-enhanced attention mechanisms to achieve superior adaptability in capturing global dependencies and integrating contextual information. Such advancements may facilitate deeper exploration of cartographic generalization principles.

Meanwhile, GANs offer a generative paradigm through adversarial training, where the generator progressively learns authentic data distributions by competing with the discriminator. This adversarial mechanism shows promising potential for implementing feature simplification in map generalization tasks, potentially enabling more intelligent and data-driven cartographic transformations.

Declaration of Generative AI in writing

The authors declares that they have not used Generative AI tools in the preparation of this manuscript. Specifically, the AI tools were utilized for language editing, but not for generating scientific content, research data, or substantive conclusions. All intellectual and creative work, including the analysis and interpretation of data, is original and has been conducted by the authors without AI assistance.

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