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Identification of Generalization Rules Using a Hierarchical GNN

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Abstract:

Formulating rules is a key issue in deterministic cartographic generalization. By deterministic generalization we mean that there is an explicit rule that determines which operator should be used to process the object. The parameters of this operator are derived implicitly from the collision rate, the spatial situation of the object, and its graphical representation. The issue with this approach is the considerable variability of the situations, which complicates the acquisition of solutions through both operator queries and the comparison of the generalization design with existing solutions. Consequently, the utilization of machine learning to discern the underlying rules is warranted. The utilization of GNN is proposed for such a post, as the graph structure is well-suited for the documentation of both the spatial context and the characteristics of the objects in question. The utilization of GNN in the context of cartographic generalization is not a novel concept. Analogous notions are delineated in the extant literature, as evidenced by the seminal works cited in references [1] and [2]. Our current research builds on previous experiments with the nondeterministic generalization of historical centers using GNN convolution. However, this was a very specific problem and essentially only one key scale change. Although the goals are now more general - to identify the operators and input objects that affect the state of the target object - we decided to start again with the building map element. The problem of transforming the built-up is well described, as is the influence of other map features. Another assumption is that knowledge of object transformations over the full-scale range can help to identify the behavior of an object under individual scale changes. Hierarchical GNNs are a way to implement this assumption.

This activity focuses on automatically identifying transformation rules for buildings in cartographic generalization. A cartographic database of topographic maps at scales of 1:25,000, 1:50,000, and 1:100,000 is used to analyze built-up areas. The initial data for the analysis comes from the nationwide detailed database ZABAGED. Built-up areas occupy a significant portion of medium-scale maps, and their generalization depends on buildings, roads (primarily the street network), vegetation, and water features. The shapes of buildings and their immediate surroundings are essential for transforming built-up areas at different scales. In cartographic practice, buildings may be removed entirely, merged with neighboring buildings, simplified, displaced, or typified (either individually or in groups) when transitioning to a smaller scale. The challenge is that these mechanisms are sometimes applied to individual buildings and at other times to variously defined groups of buildings. This is the primary motivation for using a suitable machine learning method to determine the applied operator, precursor(s), and influencing objects for each building.

Input data are collected in the QGIS environment using PyQGIS-based scripts. Each building is represented as a polygon, and geometric and contextual characteristics are calculated for each one. These characteristics include area, shape index, number of edges, boundary line orientation, and contextual indicators, such as building density in the street block or proximity to vegetated areas. Reference maps at target scales are processed similarly to monitor changes to each building. The result of this preprocessing phase is a comprehensive spatial database in which every building, as well as the surrounding roads and vegetation, is precisely located and has its own set of attributes and relationships.
To determine how a building should be generalized, the data must be transformed into a graph. We experiment with different approaches to transform different aspects of building generalization into a hierarchical graph. In the proposed approach, we have hetero-GNN with nodes for buildings and contextual objects with attributes. Edges represent relationships between nodes and parent relationship between scales. The graph is then converted into a format suitable for PyTorch Geometric, a library built on the PyTorch framework that specializes in graph-based learning.

A key component of the solution is the use of hierarchical graph neural networks, which combine methods that employ an in-scale encoder shared across all scales, building pooling, cross-scale blocks to capture attention from neighboring scales, a matcher, and a sequential decoder for each scale. The objective at this stage is to identify the operator, source built-up objects, and influencing objects for each built-up object. The learned representation is progressively compared with finished maps at all three scale levels. This allows us to see how closely the neural network's output matches the approach taken by human cartographers.

We use partial supervision for learning. For selected objects, we create labels containing the operator and computed change parameters for nodes, machine buildings, and context objects for edges. Metrics include assigning sources and context objects, estimating operators and change parameters, and sequencing operators within scales.

Ultimately, this method is expected to provide consistent, interpretable rules for automating the cartographic generalization of buildings at various scales. Besides speeding up the process, this method may produce new recommendations that have not been formally defined. These rules could then be applied to map the given area and other regions with similar built-up areas. Furthermore, if this approach proves successful for buildings, it could be adapted for other geographic objects.

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