Towards Cartographic Knowledge Encoding with Deep Learning: A Case Study of Building Generalization

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Introduction

Map generalization, the process of simplifying detailed maps to smaller scale maps with the major semantic and structural characteristics maintained, plays a key role in multi-scale cartographic representation. For decades, cartographers have explored various approaches for map generalization, such as vector-based algorithms (e.g., Douglas-Peucker algorithm), raster-based algorithms (e.g., erosion and dilation (Damen, van Kreveld, & Spaan, 2008)), and traditional machine learning algorithms (e.g., decision trees, support vector machines (SVM) (Karsznia & Weibel, 2018)).

Recently, due to the rapid development of deep learning, several researchers have employed deep convolutional neural networks in solving cartographic problems. Compared with traditional approaches, deep learning methods have the following characteristics: (1) deep learning methods can learn the cartographic knowledge from the existing map products directly which means cartographic patterns such as generalization rules and map style sheets are not necessary as input; (2) deep learning methods can take the entire map as a whole for training while traditional cartographic rules focus on specific map objects; (3) deep learning methods are still black-boxes which means that it is hard to understand their underlying theories while traditional rules are easy to be understood and customed by cartographers. Indeed, there have been studies using deep learning for solving the cartographic problems which achieved great success and provide innovative paradigms. For example, Kang, Gao, & Roth, (2019)used generative adversarial nets (GANs) to transfer different cartographic styles across various map data types; Feng, Thiemann, & Sester, (2019) compared three convolutional neural networks (CNN) for building generalization and showed the potential of deep learning in map generalization; Yan, Ai, Yang, & Yin, (2019) improved the accuracy of building patterns classification significantly by employing graph convolutional networks (GCN). They also used GCN for shape coding and cognition of buildings (Yan, Ai, Yang, & Tong, 2020).

Despite their success, these studies may still face two challenges. First, current research focuses more on the usage of deep learning algorithms, while limited cartographic knowledge are encoded in these approaches. In other words, existing cartographic rules (knowledge-driven) are hardly involved in current data-driven approaches. Second, these studies are hard to reproduce as they are based on restricted data and professional software. A general computational framework is needed for customizing data production, model training, and evaluation, so that researchers can carry out their cartographic tasks fast and easily.

In this paper, we propose a novel framework for map generalization using advanced deep learning methods. We ask: (1) How to encode cartographic knowledge in deep learning algorithms? (2) What generalization patterns can be learned by the deep learning algorithms? (3) How to effectively perform the full workflow only using common GIS software and open source data?

Method

Data Preparation

The building data is downloaded from the TOP10NL digital topographic dataset from the Land Registry, Netherlands. It covers the full regions of the Netherlands, and opens to the public with unified production criteria so that the data quality can be guaranteed. Though there are various data types, we only take buildings into consideration for generalization in this paper.

The TOP10NL dataset is stored as vector data. While CNNs require images as input which are raster-based data. Therefore, it is necessary to transfer vector data to raster data. To do so, we employ GeoServer to publish map services and use GeoWebCache to render map tiles at specific scale levels and particular regions. Two datasets are generated in this paper, the original TOP10NL data, and the generalized data based on the original data. To generate the latter one, various generalization functions in the ArcGIS toolbox can be used to set different parameters and thresholds. Here, we only take *Simplify Building* as an example in this paper. The generalized map data is created with a simplification tolerance of 20 meters and a minimum area of 20 square meters. After uploading the two datasets to GeoServer and rendering them as map tiles, 1500 images are stored in black and white colours, where black refers to buildings. Figure 1 shows several examples of the original and generalized data.

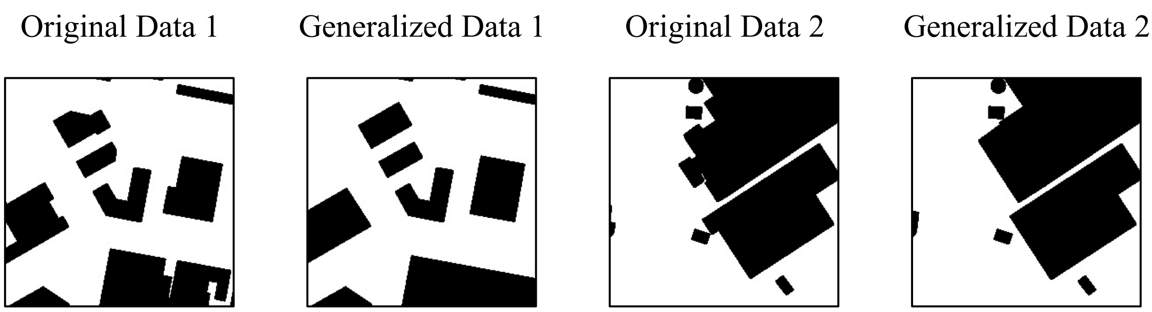

Figure 1: Examples of the original and generalized data rendered using GeoServer and TileCache. Data source: TOP10NL dataset. The ArcGIS *Simplify Building* function is used for map generalization.

Model Training

In our previous study (Kang et al., 2019), we discovered that generative adversarial nets (GANs) can learn several generalization operators (e.g., selection, enhancement, etc.) effectively. Similarly, GANs have shown potential for building generalization in existing studies (Feng et al., 2019). Though existing studies show that GCN can be used for vector data-based map generalization, while GANs might be appropriate for raster-based map generalization. Given that both vector data-based and raster data-based map generalization are two key components in map generalization, and the main focus is to encode cartographic knowledge into deep learning models, we only employed GANs here.

Inspired by the previous works, in this paper, we employ GANs for map generalization.

GANs consist of two components, namely the generator *G* and the discriminator *D*. The *G* is designed to generate images that have a realistic view based on the input images, and the *D* aims at distinguishing the real input images and the generated "fake" images. Following an adversarial training process, GANs can generate images under specific rules with auxiliary information. Specifically, we employ two types of GANs in this research, namely CycleGAN and GcGAN (geometry-consistent generative adversarial network) (Fu et al., 2018). The loss function of CycleGAN is illustrated as follows:

$$\mathcal{L}_{CycleGAN} = \mathcal{L}_{GAN}(G, D_Y, X, Y) + \mathcal{L}_{GAN}(F, D_X, X, Y) + \lambda\mathcal{L}_{Cycle}(G, F)$$

GcGAN is an extended model based on CycleGAN. Its loss function is illustrated as follows. The only difference to the CycleGAN is the $\lambda\mathcal{L}_{Geo}(G, F, X, Y)$, where it can encode various geometry transformations into the model. More specifically, it can ensure the geometry consistency of the input and output data. Therefore, the output data should follow the same geometry transformation with the input data.

$$\mathcal{L}_{GcGAN} = \mathcal{L}_{GAN}(G, D_Y, X, Y) + \mathcal{L}_{GAN}(F, D_X, X, Y) + \lambda\mathcal{L}_{Geo}(G, F, X, Y)$$

As our main focus is to encode cartographic knowledge in deep learning models, we expect to involve a set of map generalization rules in the models, such as proximity, similarity, continuity, connectedness, closure, common region, etc. Here, we only take two specific geometry transformations in GcGAN as examples: rotation and vertical flip. The hypothesis is that cartographic generalization is direction invariant, in other words, the two generalized images based on input image and rotated image/vertical flipped image should be the same. However, in CycleGAN, the model may learn that buildings with top left corners should be generalized while with bottom right corners should not be generalized. Since GcGAN can encode knowledge like this, we use it for encoding cartographic knowledge in the map generalization process.

Evaluation

Currently, the evaluation of the results is based on human observation to compare the example outputs of different algorithms. On the one hand, generalization results are subjective there are no optimal quantitative measurements from a cartographic perspective. On the other hand, pixel-based image measurements from a computer aspect may not be used to evaluate the generalization results comprehensively. For instance, the generalized data may change its original position, which will increase the error and therefore influence the evaluation results.

Results

Figure 2 shows some results. Intuitively, it can be referred that GcGAN (both with rotation transformation and vertical flip transformation) performs better than CycleGAN. For instance, in the first row, the building in the red circle is generalized to a rectangle based on the current generalization approach as ground truth. The result of CycleGAN still maintains its original shape, while GcGANs remove the corners of the building, and its shape becomes smoother. Similarly, in the second row, the building corners in the red circle are removed and the connectors between two buildings become smoother. The results not only show that GcGAN is more suitable for building generalization, but also show the importance of encoding cartographic knowledge in deep learning algorithms.

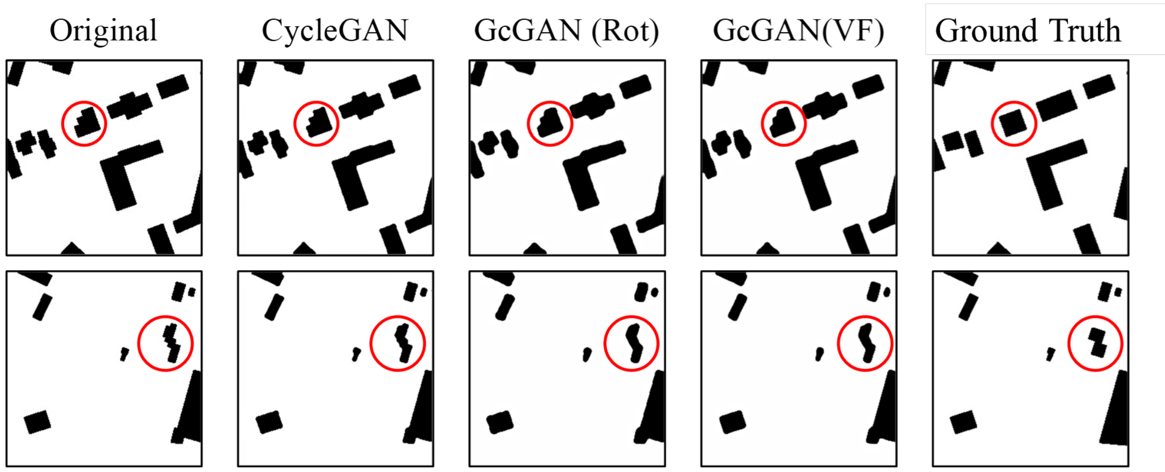

Figure 2: Results of the building generalization using CycleGAN and GcGAN. From left to right: original data, CycleGAN, GcGAN with rotation transformation, GcGAN with vertical flip transformation, and generalized data as the ground truth. Red circles show some examples for the comparison among different algorithms.

Discussion and Conclusion

In summary, our research proposes a novel framework for map generalization using deep learning approaches. By encoding several basic geometry transformations into the GANs model, the map generalization patterns can be learned more compared with the baseline algorithm. In addition, since our framework only relies on common GIS software and open source data, it is easy to reproduce, implement and customize the workflow of deep learning-based map generalization process. The results show potential in involving cartographic knowledge in deep learning for solving cartographic problems.

Also, there is still room for further improvements. First, the performances of models are still not good enough as only limited improvement has been achieved. In the next step, we will try to encode more cartographic knowledge, not only the geometry transformation, but also cartographic theories such as visual representations, proximity, similarity, continuity, etc, into the deep learning methods. Second, current generalized data are only based on several simple rules using ArcGIS, while map generalization is a complex process and more operators should be involved in the future.

Though challenges still exist, we demonstrate the pioneer works in such an emerging research direction that integrates deep learning in cartography. More fruitful discussions will be expected in the AutoCarto symposium.

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