International Cartographic Association
Association Cartographique Internationale

Line Displacement using Siamese LSTM Autoencoder

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Keywords: Line displacement, Automated generalization, Siamese LSTM Autoencoder, Deep learning

Abstract:

In the process of map creation and automated generalization, an increasing use of machine learning (ML) and deep learning models can be observed (Harrie et al. 2024, Zhang et al. 2024). Promising results have already been achieved regarding specific generalisation operations such as the simplification of lines (Yu & Chen 2022, Du, Wu, Zin, Liu & Gong 2022) or polygons, particularly in the context of building representation (Yan & Yang 2024, Feng, Thiemann & Sester 2019, Zhou, Fu & Weibel 2023). Nevertheless, the potential has not yet been fully exploited, particularly regarding the usage of deep learning approaches for displacement operations. Previous approaches to line displacement are based on geometric construction of displacement vectors, optimization techniques such as snakes, elastic beams, genetic algorithms or least squares adjustment. Touya and Lokhat (2020) provide a detailed description.

This research builds upon a previous master's thesis and aims to model the displacement of two isolated line features using a Siamese autoencoder architecture (shown in Figure 1). The development of the Siamese LSTM AE was motivated based on the results achieved by Yu and Chen (2022) using a multi-layer neural network model, which stacks multiple autoencoders for polyline simplification. Thereby, the authors highlight the role of hidden layers by obtaining multi-scale representations from them. The Siamese model architecture enables simultaneous processing of two distinct polylines, which is necessary for the additional displacement task.

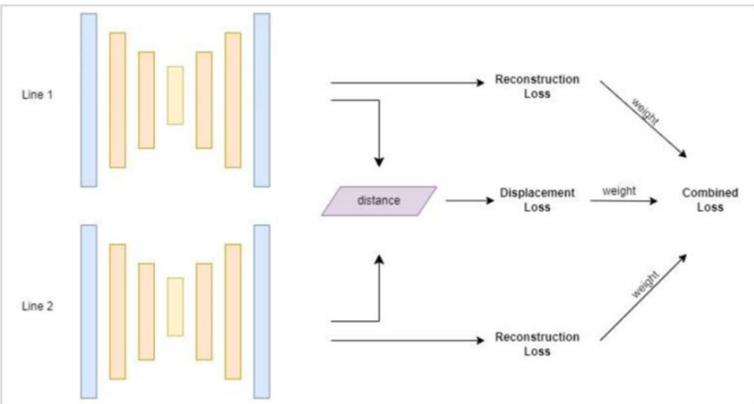

Figure 1: Architecture of the Siamese LSTM Autoencoder for Line Displacement

The displacement prediction is a semi-supervised learning problem, where the input to the model is a representation of the original line, and the target is a displaced line consisting of new coordinates. The model learns to reconstruct the inputs through the autoencoder architecture, while using a newly introduced loss function to realize the displacement. In addition to the commonly used Mean Squared Error (MSE) loss, the loss function consists of the *Displacement Loss*. This loss is based on the shortest perpendicular distances from all vertices of the reconstructed line B to the sublines of reference line A. By minimizing this loss, the model encourages a maximized distance of displacement of one or both lines with respect to each other.

Initially, the dataset was composed of synthetic lines that were parallel and randomly stretched sinusoids. Subsequently, pairs of polylines were selected from the train network in OpenStreetMap, from which a training data set in the form (50, 70, 2) was sampled. All data was normalized resulting in a Min-Max-Scaling and extrapolated embedding was added to reduce noise at the sequence endpoints.

Until now, only qualitative results have been obtained to evaluate the model's performance (shown in Figure 2). It can be noted that the lines have been displaced with the loss function, and that the degree of the displacement was determined by the weighting. However, topological errors still persist, and for more complex features, the error between the original and predicted shape appears to be less pronounced (see bottom right).

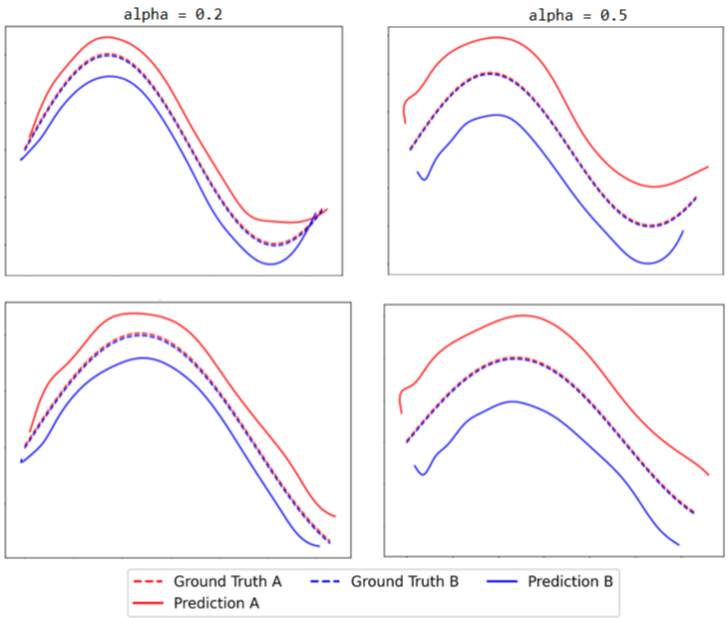

Figure 2: Displacement of both lines tested on synthetic line with displacement weight=0.2 (left) and weight=0.5 (right).

Although the initial results seem to be promising, four research questions emerged that will be investigated in the course of the study presented here:

1. How well does the model generalize to real-world data beyond very simple or synthetic examples?

Initial experiments were conducted on synthetically generated datasets as well as on very simple parallel railway tracks extracted from OpenStreetMap (OSM). In both cases, line geometries required endpoint extrapolation to enable embedding, which limits the direct applicability to real-world use cases. Therefore, further development is needed.

2. What impact do different hyperparameter configurations have on the quality of displacement?

The influence of various hyperparameter settings, particularly the weighting of the displacement loss, remains underexplored. Topological inconsistencies in output geometries indicate that the loss function may need to be extended to penalize structurally incorrect displacements more explicitly. In terms of optimization strategies, common approaches such as random or grid search should be tested; additionally, more advanced methods like Bayesian optimization might offer a more efficient exploration of the hyperparameter space by balancing exploration and exploitation.

3. How does the Siamese LSTM Autoencoder perform compared to a graph-based model such as Graph Convolutional Neural Networks (GCNN)?

As shown by Zhou, Fu, and Weibel (2023) in the context of building simplification, multi-task GCNNs effectively preserve structural relationships. A comparison would highlight the differences between sequential versus graph-based approaches for object displacement.

4. To what extent can the automated displacement process be integrated into existing map-making workflows?

Despite promising initial results, current methods are not yet ready enough for an integration into Geographic Information Systems (GIS). Significant improvements – especially regarding the output quality – are required before a broader use becomes feasible.

For this reason, the present work represents a significant step in the automation of the map production process, especially in the further development of deep learning technologies in the field of cartography.

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