diffIRM: A Diffusion-Augmented Invariant Risk Minimization Framework for Spatiotemporal Prediction over Graphs

Abstract

Spatiotemporal prediction over graphs is challenging because real-world data suffers from the Out-of-Distribution (OOD) generalization problem, where the test data comes from a different distribution with regard to the training one. To address this issue, Invariant Risk Minimization (IRM) has emerged as a promising approach for learning invariant representations across different environments. However, IRM tends to degenerate to Empirical Risk Minimization (ERM) when applied to deep learning models due to overfitting. To avoid such a degeneration, we propose diffIRM, a novel approach that integrates the diffusion model into the IRM framework. Specifically, diffIRM augments the spatiotemporal graph data (such as human mobility) using a conditional diffusion model, which takes in conditions (such as COVID-19 case rates and demographic features) and generates diverse training environments. Then the augmented spatiotemporal graph data is used to train Graph Neural Networks with the penalty of IRM. We provide theoretical proof that the training environments generated by the diffusion model can guarantee the performance of IRM. Experiments on two real-world spatiotemporal datasets on graphs demonstrate that diffIRM outperforms the baselines and shows superior generalization ability for data with significant distribution shift.

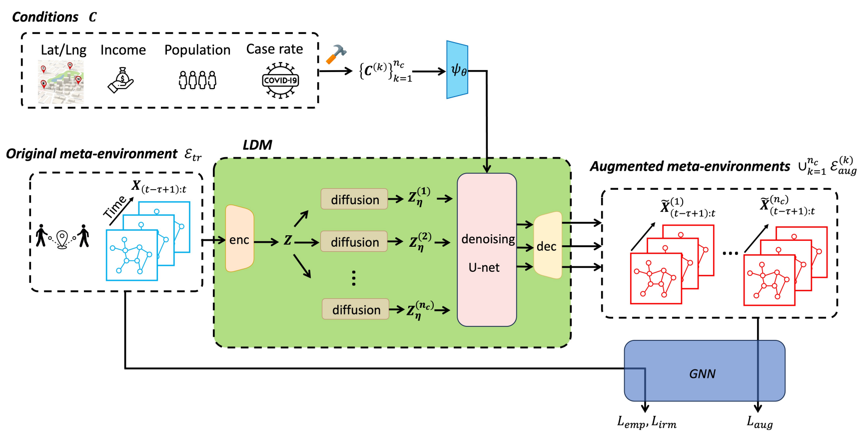
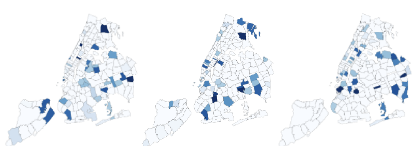
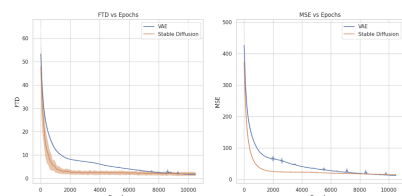


Figure 1: Model architecture of diffIRM



(a) 50% case rate, total visit $= -18.5$. (b) 100% case rate, total visit $= 0.39$ (c) 200% case rate, total visit $= 309$

(a) Generated Total Visit Corresponding with Different Case-rate with generated total



(a) FTD change in the training process. (b) MSE change in the training process

(b) Fréchet inception distance vs Epochs

Figure 2: Latent Diffusion Model Results