AUCOGNN: AUTOMATED GRAPH GENERATION FOR ROBUST AND FAIR LEARNING UNDER DISTRIBUTION SHIFTS

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Abstract

Graph Neural Networks (GNNs) have achieved remarkable success in various node classification and link prediction tasks by effectively capturing structural and feature-based dependencies in graph-structured data. However, their performance and fairness often degrade under distribution shifts**,** where the training (source) and deployment (target) graphs differ in structural properties, node features, or label distributions. Such shifts are common in real-world applications, including social networks, financial systems, and healthcare networks, where demographic bias and representation disparities can exacerbate unfair predictions across sensitive groups. Addressing both generalization and fairness under distribution shifts is therefore a critical challenge in modern graph learning.This work introduces AuCoGNN**,** a novel framework designed to enhance graph fairness learning by leveraging automated graph generation to approximate the target distribution. The proposed methodology first constructs a synthetic source graph and simulates a shifted target domain through controlled alterations in homophily, node connectivity, and feature distributions. To bridge the distribution gap, an automated graph generation module iteratively searches for graph generator parameters that replicate target statistics, including average degree, density, and sensitive-group connectivity, producing additional graphs for training augmentation.