ABSTRACT

Insurance fraud poses a significant challenge to the insurance industry, causing substantial financial losses. While traditional fraud detection methods focus on individual claims, fraudsters often collaborate in networks involving multiple parties and insurance claims. To address these complex fraud schemes, this thesis applies Graph Neural Networks (GNNs) to heterogeneous graph data. Building on vehicle claim data from R+V Insurance, a graph representation is created where claims, customers, and vehicles form distinct node types connected through various relationships. Different GNN architectures like Graph Attention Networks and GraphSAGE are applied to the dataset to capture these interconnected network patterns. Experimental results show that heterogeneous GNN models outperform both traditional machine learning approaches like LightGBM and conventional homogeneous GNNs in fraud detection.

To enhance interpretability for investigators, in this work the explainability method GNNExplainer, originally designed for homogeneous graphs, is adapted for heterogeneous GNNs. Building upon this foundation, a novel message passing GNNExplainer is proposed, reducing explanation variability by leveraging the message passing mechanism to identify relevant edges.

Based on these interpretability advances, a Network Extraction Algorithm is developed that identifies fraudulent networks within the graph structure. It produces concise networks for targeted investigations, enabling experts to analyze complex network fraud efficiently. A network report summarizes the extracted networks, while an interactive visualization presents the explanation results, providing investigators with comprehensive insights into suspicious patterns. Examples with fraudulent networks demonstrate how this integrated approach reveals real-world fraud patterns.

Keywords: Insurance Fraud Detection, Heterogeneous Graph Neural Networks, GNNExplainer, Network Visualization