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FRAUD DETECTION IN ONLINE PRODUCT REVIEW SYSTEMS VIA HETEROGENEOUS GRAPH TRANSFORMER

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Abstract- In online product review systems, users are allowed to submit reviews about their purchased items or services. However, fake reviews posted by fraudulent users often mislead consumers and bring losses to enterprises. Traditional fraud detection algorithm mainly utilizes rule-based methods, which is insufficient for the rich user interactions and graph-structured data. In recent years, graph-based methods have been proposed to handle this situation, but few prior works have noticed the camouflage fraudster's behavior and inconsistency heterogeneous nature. Existing methods have either not addressed these two problems or only partially, which results in poor performance. Alternatively, we propose a new model named Fraud Aware Heterogeneous Graph Transformer (FAHGT), to address camouflages and inconsistency problems in a unified manner. FAHGT adopts a type-aware feature mapping mechanism to handle heterogeneous graph data, then implementing various relation scoring methods to alleviate inconsistency and discover camouflage. Finally, the neighbors' features are aggregated together to build an informative representation. Experimental results on different types of real-world datasets demonstrate that FAHGT outperforms the state-of-the-art baselines.

1. INTRODUCTION

Internet services have brought human beings with ecommerce, social networking, and entertainment platforms, which not only facilitate information exchange but also provide chances to fraudsters. Fraudsters disguise themselves as ordinary users to publish spam information or collect user privacy, compromising the interest of both platforms and users. In addition, multiple entities on the Internet are connected with multiple relationships. Traditional machine learning algorithms cannot handle this complicated heterogeneous graph data well. The current approach is to model the data as a heterogeneous information network so that similarities in characteristics and structure of fraudsters can be discovered. Due to the effectiveness in learning the grap representation, graph neural networks (GNNs) have already been introduced into fraud detection areas including product review mobile application distribution cyber crime identification and financial services However, most existing GNN based solutions just directly apply homogeneous GNNs, ignoring the underlying heterogeneous graph nature and camouflage node behaviors. This problem has drawn great attention with many solutions proposed Graph Consis found that there are three inconsistency problems in fraud detection and further proposed two camouflage behaviors. These problems could be Camouflage: Previous work showed that crowd workers could adjust their behavior to alleviate their suspicion via connecting to benign entities like connecting to highly reputable users, disguise fraudulent URLs with special or generate domain-independent fake reviews via generative language model to conceal their suspicious activities.Inconsistency: Two users with distinct interests could be connected via reviewing a common product such as food or movies. Direct aggregation makes GNNs hardly distinguish the unique semantic user pattern. Also, if a Use r is suspicious, then the other one should be more likely to be distrustful if they are connected by common activity relation since fraudulent users tend to post many fraudulent reviews in the same short period. To address the above two problems, many methods have been proposed. Graph Consis addresses the inconsistency problem by computing the similarity score between node embeddings, which cannot distinguish nodes with different types. CAREGNN enhances GNN-based fraud detectors against camouflaged fraudsters by reinforcement learning based neighbor selector and relation aware aggregator. Its performance still suffers from the heterogeneous graph. In this paper, we introduce the Fraud Aware Heterogeneous Graph Transformer(FAHGT), where we propose heterogeneous mutual attention to address the inconsistency problem and design a label-aware neighbor selector to solve the camouflage problem. Both are implemented in a unified manner called the “score head mechanism”. We demonstrate the effectiveness and efficiency of FAHGT on many real world datasets. Experimental results suggest that FAHGT can significantly improve KS and AUC over state-of-the-art GNNs as well as GNN-based fraud detectors.The advantages of FAHGT can be summarized as follows: _ Heterogeneity: FAHGT is able to handle heterogeneous graphs with multi-relation and multi-node type without designing meta-path manually _ Adaptability: FAHGT attentively selects neighbors given a noise graph from real-world data. The selected neighbors are either informative for feature aggregation or risky for fraud detection. Efficiency: FAHGT admits a low computational complexity via a parallelizable multi-head mechanism in relation scoring and feature aggregation. Flexibility: FAHGT injects domain knowledge by introducing a flexible relation scoring mechanism. The score of a relation connecting two nodes not only comes from direct feature interaction but is also constrained by domain knowledge.

2. EXISTING SYSTEM

For GNNs on spatial domain, samples a tree rooted at each node and computes the root’s hidden representation by hierarchically aggregating hidden node representations from the bottom to top. further proposes to learn in the spatial domain by computing different importance of neighbor nodes via the masked selfattention mechanism. All these methods are designed for homogeneous graphs. They cannot be directly applied to a heterogeneous graph with multiple types of entities and relations.

In recent years, lots of heterogeneous GNN based methods have been developed. and Deep- transforms a heterogeneous graph into several homogeneous graphs based on handcrafted meta-paths, applies GNN separately on each graph, and aggregates the output representations by attention mechanism. constructs meta-paths between nodes with the same object type. first samples a fixed number of neighbors via random walk strategy. Then it applies a hierarchical aggregation mechanism for intra-type and intertype aggregation. extends transformer architecture to heterogeneous graphs. They directly calculate attention scores for all the neighbors of a target node and perform aggregation accordingly without considering domain knowledge. For relation-aware graph fraud detectors, their main solution is to build multiple homogeneous graphs based on edge type information of the original graph then perform type independent node level aggregation and graph level concatenationlearns weighting parameters for different homogeneous subgraph. both adopt attention mechanism in feature aggregation and SemiGNN further leverages a structure loss to guarantee the node embeddings homophily. Some works directly aggregate heterogeneous information in the graph. For instance, under a user-review-item heterogeneous graph, learns a unique set of aggregators for different node types and updates the embeddings of each node type iteratively.

Disadvantages

In the existing work, the system did not implement Fraud Aware Heterogeneous Graph Transformer(FAHGT) to measure frauds exactly.

This system is less performance due to lack of META RELATION SCORING.

3. PROPOSED SYSTEM

GraphConsis addresses the inconsistency problem by computing the similarity score between node embeddings, which cannot distinguish nodes with different types. CAREGNN enhances GNN-based fraud detectors against camouflaged fraudsters by reinforcement learning based neighbor selector and relation aware aggregator. Its performance still suffers from the heterogeneous graph. In this paper, the system introduces the Fraud Aware Heterogeneous Graph Transformer(FAHGT), where we propose heterogeneous mutual attention to address the inconsistency problem and design a label-aware neighbor selector to solve the camouflage problem. Both are implemented in a unified manner called the “score head mechanism”. We demonstrate the effectiveness and efficiency of FAHGT on many real world datasets. Experimental results suggest that FAHGT can significantly improve KS and AUC over state-of-the-art GNNs as well as GNN-based fraud detectors.

Advantages

The advantages of FAHGT can be summarized as follows.

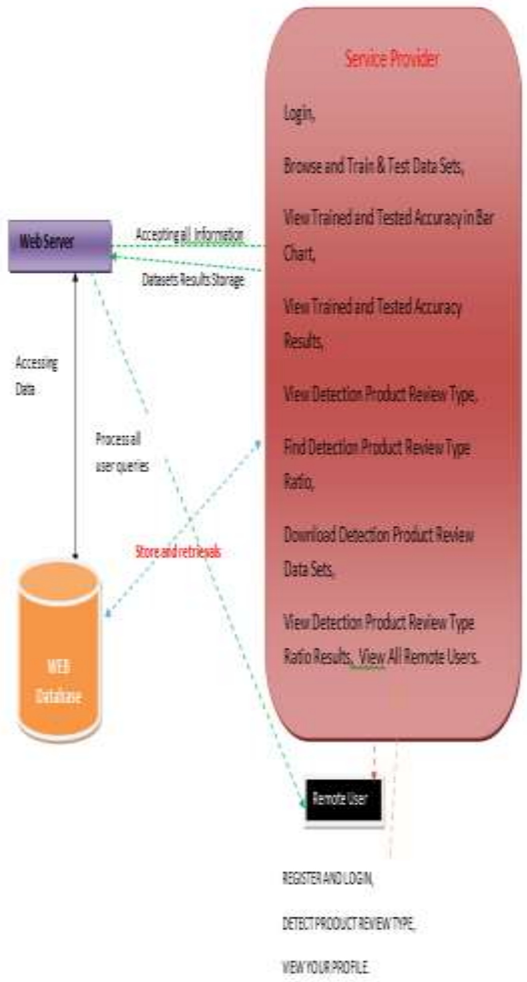
Heterogeneity: FAHGT is able to handle heterogeneous graphs with multi-relation and multi-node type without designing meta-path manually.

Adaptability: FAHGT attentively selects neighbors given a noise graph from real-world data. The selected neighbors are either informative for feature aggregation or risky for fraud detection.

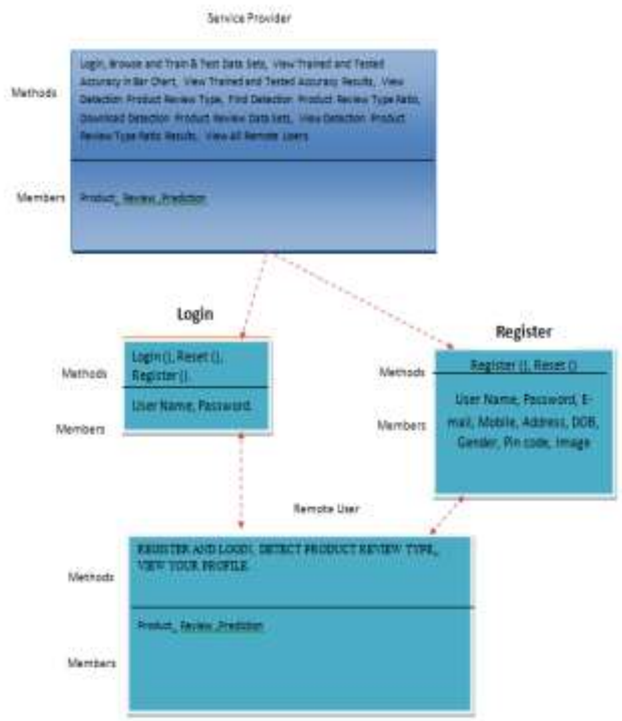
Efficiency: FAHGT admits a low computational complexity via a parallelizable multi-head mechanism in relation scoring and feature aggregation.

Flexibility: FAHGT injects domain knowledge by introducing a flexible relation scoring mechanism. The score of a relation connecting two nodes not only comes from direct feature interaction but is also constrained by domain knowledge.

Architecture Diagram


Service Provider
Login,
Browse and Train & Test Data Sets,
View Trained and Tested Accuracy in Bar Chart,
View Trained and Tested Accuracy Results,
View Detection Product Review Type,
Find Detection Product Review Type Ratio,
Download Detection Product Review Data Sets,
View Detection Product Review Type Ratio Results, View All Remote Users.
Web Server
Accepting all Information
Datasets Results Storage
Accessing Data
Process all user queries
Store and retrievals
WEB Database
Remote User
REGISTER AND LOGIN,
DETECT PRODUCT REVIEW TYPE,
VIEW YOUR PROFILE.

➢ Class Diagram :


Service Provider
Methods
Login, Browse and Train & Test Data Sets, View Trained and Tested Accuracy in Bar Chart, View Trained and Tested Accuracy Results, View Detection Product Review Type, Find Detection Product Review Type Ratio, Download Detection Product Review Data Sets, View Detection Product Review Type Ratio Results, View all Remote Users
Members
Product_, Review_Prediction
Login
Methods
Login (), Reset (), Register ()
Members
User Name, Password
Register
Methods
Register (), Reset ()
Members
User Name, Password, E-mail, Mobile, Address, DOB, Gender, Pin code, Image
Remote User
Methods
REGISTER AND LOGIN, DETECT PRODUCT REVIEW TYPE, VIEW YOUR PROFILE
Members
Product_, Review_Prediction

4. PRELIMINARY INVESTIGATION

The first and foremost strategy for development of a project starts from the thought of designing a mail enabled platform for a small firm in which it is easy and convenient of sending and receiving messages, there is a search engine ,address book and also including some entertaining games. When it is approved by the organization and our project guide the first activity, preliminary investigation begins. The activity has three parts:

Request Clarification
Feasibility Study
Request Approval

5. REQUEST CLARIFICATION

After the approval of the request to the organization and project guide, with an investigation being considered, the project request must be examined to determine precisely what the system requires. Here our project is basically meant for users within the company whose systems can be interconnected by the Local Area Network(LAN). In today's busy schedule man need everything should be provided in a readymade manner. So taking into consideration of the vastly use of the net in day to day life, the corresponding development of the portal came into existence.

6. FEASIBILITY ANALYSIS

An important outcome of preliminary investigation is the determination that the system request is feasible. This is possible only if it is feasible within limited resource and time. The different feasibilities that have to be analyzed are

Operational Feasibility
Economic Feasibility
Technical Feasibility

Operational Feasibility

Operational Feasibility deals with the study of prospects of the system to be developed. This system operationally eliminates all the tensions of the Admin and helps him in effectively tracking the project progress. This kind of automation will surely reduce the time and energy, which previously consumed in manual work. Based on the study, the system is proved to be operationally feasible.

Economic Feasibility

Economic Feasibility or Cost-benefit is an assessment of the economic justification for a computer based project. As hardware was installed from the beginning & for lots of purposes thus the cost on project of hardware is low. Since the system is a network based, any number of employees connected to the LAN within that organization can use this tool from at anytime. The Virtual Private Network is to be developed using the existing resources of the organization. So the project is economically feasible.

Technical Feasibility

According to Roger S. Pressman, Technical Feasibility is the assessment of the technical resources of the organization. The organization needs IBM compatible machines with a graphical web browser connected to the Internet and Intranet. The system is developed for platform Independent environment. Java Server Pages, JavaScript, HTML, SQL server and WebLogic Server are used to develop the system. The technical feasibility has been carried out. The system is technically feasible for development and can be developed with the existing facility.

6.1 REQUEST APPROVAL

Not all request projects are desirable or feasible. Some organization receives so many project requests from client users that only few of them are pursued. However, those projects that are both feasible and desirable should be put into schedule. After a project request is approved, it cost, priority, completion time and personnel requirement is estimated and used to determine where to add it to any project list. Truly speaking, the approval of those above factors, development works can be launched.

7. SYSTEM DESIGN AND DEVELOPMENT

7.1 INPUT DESIGN

Input Design plays a vital role in the life cycle of software development, it requires very careful attention of developers. The input design is to feed data to the application as accurate as possible. So inputs are supposed to be designed effectively so that the errors occurring while feeding are minimized. According to Software Engineering Concepts, the input forms or screens are designed to provide to have a validation control over the input limit, range and other related validations.This system has input screens in almost all the modules. Error messages are developed to alert the user whenever he commits some mistakes and guides him in the right way so that invalid entries are not made. Let us see deeply about this under module design.Input design is the process of converting the user created input into a computer-based format. The goal of the input design is to make the data entry logical and free from errors. The error is in the input are controlled by the input design. The application has been developed in user-friendly manner. The forms have been designed in such a way during the processing the cursor is placed in the position where must be entered. The user is also provided with in an option to select an appropriate input from various alternatives related to the field in certain cases.Validations are required for each data entered. Whenever a user enters an erroneous data, error message is displayed and the user can move on to the subsequent pages after completing all the entries in the current page.

8. CONCLUSIONS

In this paper, we propose FAHGT, a novel heterogeneous graph neural network for fraudulent user detection in online review systems. To handle inconsistent features, we adopt heterogeneous mutual attention for automatic meta path construction. To detect camouflage behaviors, we design the label aware scoring to filter noisy neighbors. Two neural modules are combined in a unified manner called “score head mechanism” and both contribute to edge weight computation in final feature aggregation. Experiment results on real-world business datasets validate the excellent effect on fraud detection of FAHGT. The hyper-parameter sensitivity and visual analysis further show the stability and efficiency of our model. In summary, FAHGT is capable of alleviating inconsistency and discover camouflage and thus achieves state-of-art performance in most scenarios. In the future, we plan to extend our model in handing dynamic graphs data and incorporate fraud detection into other areas, such as robust item recommendation in E-commerce or loan default prediction in financial services.

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