REPPRESENTING FINE GRAINED CO OCCURRENCES FOR BHEHAVIOR BASED FRAUD DETECTION

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ABSTRACT

With the rapid expansion of online shopping comes an increase in cybercrime. An essential part of the ever-changing e-commerce landscape is the identification of online payment fraud, a problem that online service providers encounter. Online payment fraud detection using behavior-based approaches is seen as a promising approach. Using low-quality behavioral data to generate high-resolution behavioral models is a huge difficulty, though. The focus of this effort is on resolving this issue as it pertains to improving data for behavioral modeling. Using a knowledge graph, we are able to derive association between transactional attributes that occur in a fine-grained manner. We also use heterogeneous network embedding to master the art of comprehensive relationship representation. Specifically, we investigate individualized network embedding strategies for various behavioral models, including models at the population level, models at the individual level, and generalized-agent based models. Experiments conducted on a real dataset obtained from a commercial bank have confirmed the performance improvement achieved by our strategy. It can greatly enhance the effectiveness of representative behavioral models when it comes to detecting online banking payment fraud.

This is the first study that we are aware of that uses network embedding methods on co-occurrence connections at the attribute level to improve data for diverse behavior models.

Index Terms—Online payment services, fraud detection, network embedding, user behavioral modeling

1. INTRODUCTION

There has been a pervasiveness of online payment services. However, there are security dangers associated with the improved convenience [1]. The diversity, specialization, industrialization, concealment, scenario, and cross-regional nature of cybercrime affecting online payment services makes security prevention and management of online payment incredibly tough [2]. An immediate and thorough solution is required for the identification of online payment fraud. One successful model for detecting online payment fraud is the behavior-based approach [3]. The following are some of the benefits of Gen Rally: As a first step, behavior-based solutions provide a positive user experience throughout deployment by utilizing a non-intrusion detection scheme. Second, it can validate each transaction and flip the pattern of fraud detection from one-time to continuous. Finally, for the fraudster to get their hands on the victim's money, they still need to break the rules of user behavior, even if they mimic the victim's everyday operations. Methods based on behavior can identify the outlier. Lastly, instead than replacing existing detection approaches, this behavior-based approach may be utilized collaboratively as an additional layer of security.

2. EXISTING SYSTEM

Researchers Vedran et al. showed that social behavior might be accurately predicted by delving into the intricate relationship between social and geographical behavior. To forecast user actions, Yin et al. presented a probabilistic generative model that integrates semantic knowledge with spatiotemporal data. The challenge of user identification via histogram matching between the anonymous and original datasets was investigated by Naini et al. To find compromised high-profile accounts, Egele et al. suggested a behavior-based approach. By gathering and analyzing user clickstreams of a popular OSN, Ruan et al. performed research on online user behavior.

Using suggested surveys, Rzecki et al. developed a data collecting system to examine the performance of one-finger movements on a smartphone screen and recommended the optimal classification approach for person recognition. Using seven different forms of behavioral

biometrics—hand-waving, gait, touchscreen, keyboard, voice, signature, and general profiling—Alzubaidi et al. studied representative techniques for user verification on smartphone devices in smartphone authentication.

For the purpose of identifying unusual Twitter behavior, Lee and Kim put up a suspicious URL detecting method. A malicious account detection system was developed and put into action by Cao et al. to identify both fictitious and hacked user accounts. For the purpose of user matching across several OSNs, Zhou et al. presented a FRUI method. By establishing a connection between an IP address and an online account, the EVILCOHORT system developed by Stringhini et al. may identify fraudulent accounts on any service. By framing the issue as a matching problem of utterances before and after a specific decision point, Meng et al. introduced a static sentence-level attention model for text-based speaker change detection. For the purpose of dealing with suspicious and anomalous actions, such as the ongoing production of false user accounts, account hacking, and other forms of online misconduct, Rawat et al. presented three approaches.

In order to identify hacker identities, learn about hacker content, and identify characteristics that differentiate hacked from regular tweets, VanDam et al. concentrated on researching compromised Twitter accounts. Moreover, they demonstrated that additional meta-information might enhance the identification of hacked accounts. Using a graph convolutional network, Zhao et al. presented a semi-supervised network embedding model that can capture the overall and local structure of a network of protein-protein interactions, even in the absence of information for each vertex. Solving the problem that the Dirichlet Multinomial Mixture model lacks access to background knowledge when modeling short texts, Li et al. integrated word semantic relations into latent topic learning using the word embedding approach.

To account for residents' out-of-area travel and other activities, Baqueri et al. offered a framework that incorporates external travel to fix skewed trip patterns into the overall activity-travel schedule. To improve phrase similarity modeling, Chen et al. presented a collaborative and adversarial network (CAN) that explicitly models the shared properties of two sentences. To further use developer-related parameters (such as the number of developers working on a class) as predictors of classes' change-proneness, Catolino et al. developed and tested a novel change prediction model.

3. PROPOSED SYSTEM

By depicting and mining more fine-grained attribute-level co-occurrences, the system suggests a new and successful data improvement technique for behavioral modeling. In order to represent the co-occurrences at the attribute level, we use heterogeneous relation networks. We then use heterogeneous network embedding methods to extract these associations.In order to provide a cohesive interface between behavioral models and network embedding methods, the system adjusts the maintained relationship networks based on the behavioral model categorization. A real-world scenario involving an online banking payment service is used to apply the suggested techniques by the system. On a set of typical measures for online fraud detection, our approaches are proven to be far superior to the state-of-the-art classifiers.

4. SYSTEM ARCHITECTURE

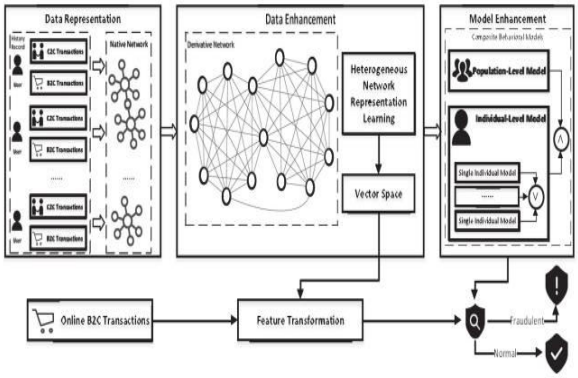


Fig 4.1 System Architecture

5. IMPLEMENTATION

5.1 User module:

Here, shoppers can peruse available servers, choose one they like, and then pay for it online using a variety of methods, including transferring funds directly to the provider's account (if they have their login credentials), all without leaving the convenience of their own home.

5.2 Service module:

Here the service provider can update the user's perspective with the new services or goods.The next step is for the user to browse the different services, choose the one they need, and finally, proceed to the payment page to activate the service.

5.3 Bank Transaction module:

After choosing an online payment service in the transaction module, the user will be sent to this page. The user will apply for a loan to pay for the service in this module. After the bank administrator verifies the user's information, the loan will be granted and the money will be credited to the user's account. After that, the consumer may pay the service provider straight into their account.

5.4 Admin module:

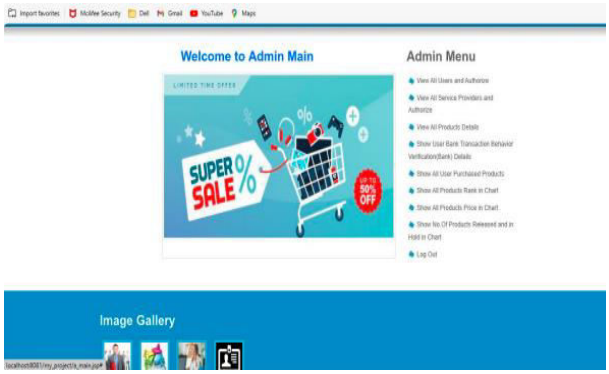
Using the admin module, the administrator may grant users access and add newly released services to the user side. The administrator's buying history and bank details are immediately accessible once he logs in. In the admin section, you will find

all of the user information, including their transaction history.

6. OUTPUT RESULTS

Home page

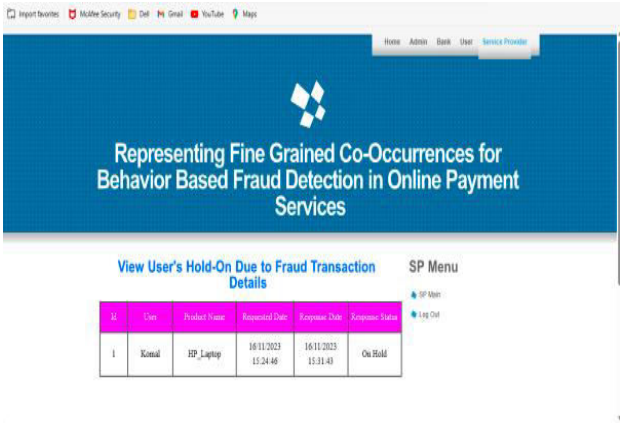
Admin Menu Page



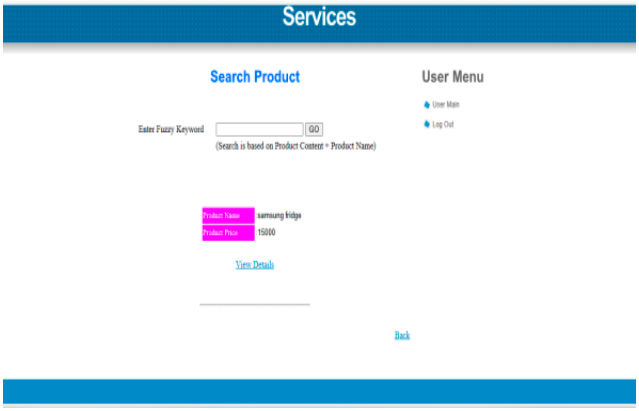
Product Purchase & Approval

5	Manjunath	Sandisk_PenDrive	26/09/2022 12:02:04	26/09/2022 12:02:10	Approved and Purchased
6	omkar	Dell_Laptop	26/09/2022 12:06:35	26/09/2022 12:06:41	Approved and Purchased
7	rakesh	Dell_Laptop	26/09/2022 12:07:37	26/09/2022 12:07:42	Approved and Purchased
8	Shoba	Dell_Laptop	17/10/2022 18:09:37	17/10/2022 18:21:49	Approved and Purchased
9	Komal	HP_Laptop	17/10/2022 19:00:01	17/10/2022 19:01:50	Approved and Purchased
10	Komal	HP_Laptop	16/11/2023 15:24:46	16/11/2023 15:31:43	On Hold
11	Komal	Samsung Fridge	16/11/2023 15:36:48	16/11/2023 15:37:51	Approved
12	snigdha	Samsung Fridge	16/11/2023 17:43:54	16/11/2023 17:55:42	Approved and Purchased
13	snigdha	Samsung Fridge	17/11/2023 14:33:56	17/11/2023 14:34:15	Approved
14	snigdha	HP_Laptop	18/11/2023 10:27:38	18/11/2023 10:28:27	Approved
15	omkar	HP_Laptop	20/11/2023 10:31:30	null	Requested

Purchase Detected As Fraud



Product Search Page



Product Purchase Rank

7. CONCLUSION

We offer a data improvement strategy that models the co-occurrence associations of transactional characteristics for behavioral models in online payment fraud detection. This approach is successful. So, for

various kinds of behavioral models, such individual-level and population-level models, we construct tailored co-occurrence relation networks and describe the method of heterogeneous network embedding to depict data from online transactions. The approaches are tested and proven on a real-world dataset throughout implementation. Using just lightweight feature engineering approaches, they achieve better results than the top classifiers. Consequently, our techniques can potentially be a practical model for automated feature engineering.

8. REFERENCES

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