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Composite Modeling for Identity Security in Social Networks

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ABSTRACT

With this effort, we want to provide a pathway from raw behavioural data to a behavioural model that can identify online identity theft effectively, quickly, and robustly. We zero in on this problem in OSNs, where users often keep composite records of their behaviours, including offline check-ins and online user-generated content (UGC), which is multimodal and of poor quality. We verify that various record dimensions have a complementing impact when modelling users' behavioural patterns, which is an informative discovery. We recommend a combined (rather than fused) model to record aspects of a user's composite behaviour that occur both online and offline in order to fully take use of this complimentary impact. Using the real-world datasets Foursquare and Yelp, we compare the suggested joint model against both standard models and their combined model. According to the testing data, our model works better than the current ones. For Foursquare, the area under the receiver operating characteristic curve (AUC) is 0.956, and for Yelp, it is 0.947. For example, with Foursquare, the recall (true positive rate) may reach up to 65.3% and Yelp, 72.2%, while the equivalent disturbance rate (false-positive rate) is below 1%. We ensure our method's short reaction latency by achieving these achievements by assessing just one composite behaviour. Cybersecurity experts would benefit from this research since it would provide light on the question of whether or not individuals' composite behavioural patterns may be used to enhance real-time online identity verification.

INTRODUCTION

Composite Behavioral Modeling for Identity Theft Detection in Online Social Networks ,Cheng Wang , *Senior* In this work, we aim at building a bridge from coarse behavioral data to an effective, quick-response, and robust behavioral model for online identity theft detection. We concentrate on this issue in online social networks (OSNs) where users

usually have composite behavioral records, consisting of multidimensional low-quality data, e.g., offline check-ins and online user-generated content (UGC). As an insightful result, we validate that there is a complementary effect among different dimensions of records for modeling users' behavioral patterns. To deeply exploit such a complementary effect, we propose a *joint* (instead of *fused*) model to capture

both online and offline features of a user's composite behavior. We evaluate the proposed joint model by comparing it with typical models and their fused model on two real-world datasets: Foursquare and Yelp. The experimental results show that our model outperforms the existing ones, with the area under the receiver operating characteristic curve (AUC) values 0.956 in Foursquare and 0.947 in Yelp, respectively. Particularly, the *recall* (true positive rate) can reach up to 65.3% in Foursquare and 72.2% in Yelp with the corresponding *disturbance rate* (false-positive rate) below 1%. It is worth mentioning that these performances can be achieved by examining only one composite behavior, which guarantees the low response latency of our method. This study would give the cybersecurity community new insights into whether and how real-time online identity authentication can be improved via modeling users' composite behavioral patterns.

II.EXISTING SYSTEM

Sitova *et al.* [53] introduced hand movement, orientation, and grasp (HMOG), a set of behavioral features to continuously authenticate smartphone users. Rajoub and Zwiggelaar [15] used

thermal imaging to monitor the periorbital region's thermal variations and test whether it can offer a discriminative signature for detecting deception. However, these biometric technologies usually require expensive hardware devices which makes it inconvenient and difficult to popularize.

Abouelenien *et al.* [30] explored a multimodal deception detection approach that relied on a novel dataset of 149 multimodal recordings, and integrated multiple physiological, linguistic, and thermal features. These works indicated that users' behavior patterns can represent their identities. Many studies turn to utilize users' behavior patterns for identifications. Behavior-based methods were born at the right

moment, which plays important roles in a wide range of tasks including preventing and detecting identity theft. Typically, behavior-based user identification includes two phases: user profiling and user identifying.

User profiling is a process to characterize a user with his/her history behavioral data. Some works focus on statistical characteristics, such as the mean, variance, median, or frequency of a variable, to establish the user profile.

Naini *et al.* [55] studied the task of identifying the users by matching the histograms of their data in the anonymous dataset with the histograms from the original dataset. But it mainly relied on experts' experience since different cases usually have different characteristics.

Egele *et al.* [7] proposed a behavior-based method to identify compromises of individual high-profile accounts. However, it required high-profile accounts which were difficult to obtain.

Other researchers discovered other features, such as tracing patterns, topic and spatial distributions, to describe user identity. Ruan *et al.* [32] conducted a study on online user behavior by collecting and analyzing user clickstreams of a well-known OSN.

Lesaege *et al.* [31] developed a topic model extending the LDA to identify the active users. Viswanath *et al.* [56] presented a technique based on principal component analysis (PCA) that accurately modeled the "like" behavior of normal users in Facebook and identified significant deviations from it as anomalous behaviors. Zaeem *et al.* [33] proposed an approach that involved the novel collection of online news stories and reports on the topic of identity theft. Lichman and Smyth [48]

proposed MKDE model to accurately characterize and predict the spatial pattern of an individual's events.

Tsikerdekis and Zeadally [57] presented a detection method based on nonverbal behavior for identity deception, which can be applied to many types of social media. These methods above mainly concentrated on a specific dimension of the composite behavior and seldom thought about utilizing multidimensional behavior data. Sekara *et al.* [58] explored the complex interaction between social and geospatial behavior and demonstrated that social behavior can be predicted with high precision. It indicated that composite behavior features can identify one's identity.

Yin *et al.* [42] proposed a probabilistic generative model combining the use of spatiotemporal data and semantic information to predict user's behavior. Nilizadeh *et al.* [49] presented POISED, a system that leverages the differences in propagation between benign and malicious messages on social networks to identify spam and other unwanted content. These studies implied that composite behavior features are possibly helpful for user identification.

Disadvantages

- 1) LDA model performs poorly in both datasets which may indicate its performance is strongly sensitive to the data quality.
- 2) CF-KDE and LDA model performs not well in Yelp dataset comparing to Foursquare dataset, but the fused model [17] observes a surprising reversion.
- 3) The joint model based on *relative anomalous score* S_r outperforms the model based on *logarithmic anomalous score* S_l .
- 4) The joint model (i.e., JOINT-SR, the joint model in the following content of the system all refer to the joint model based on S_r) is indeed superior to the fused model.

III.PROPOSED SYSTEM

In this article, we propose an approach to detect identity theft by using multidimensional behavioral records which are possibly insufficient in each dimension. According to such characteristics, we choose the online social network (OSN) as a typical scenario where most users' behaviors are coarsely recorded [39]. In the Internet era, users' behaviors are composited by offline behaviors, online behaviors, social behaviors, and perceptual/cognitive behaviors. The

behavioral data can be collected in many applications, such as offline check-ins in location-based services (LBSs), online tips-posting in instant messaging services, and social relationship-making in online social services. Accordingly, we design our method based on users' composite behaviors by these categories.

In OSNs, user behavioral data that can be used for online identity theft detection are often too low-quality or restricted to build qualified behavioral models due to the difficulty of data collection, the requirement of user privacy, and the fact that some users have a few several behavioral records. We devote ourselves to proving that a high-quality (effective, quickresponse, and robust) behavioral model can be obtained by integrally using multidimensional behavioral data, even though the data is extremely insufficient in each dimension.

Advantages

- 1) We propose a joint model, CBM, to capture both online and offline features of a user's composite behavior to fully exploit coarse behavioral data.
- 2) We devise a relative anomalous score S_r to measure the occurrence rate of each composite behavior for realizing real-time identity theft detection.

3) We perform experiments on two real-world datasets to demonstrate the effectiveness of CBM. The results show

that our model outperforms the existing models and has the low response latency.

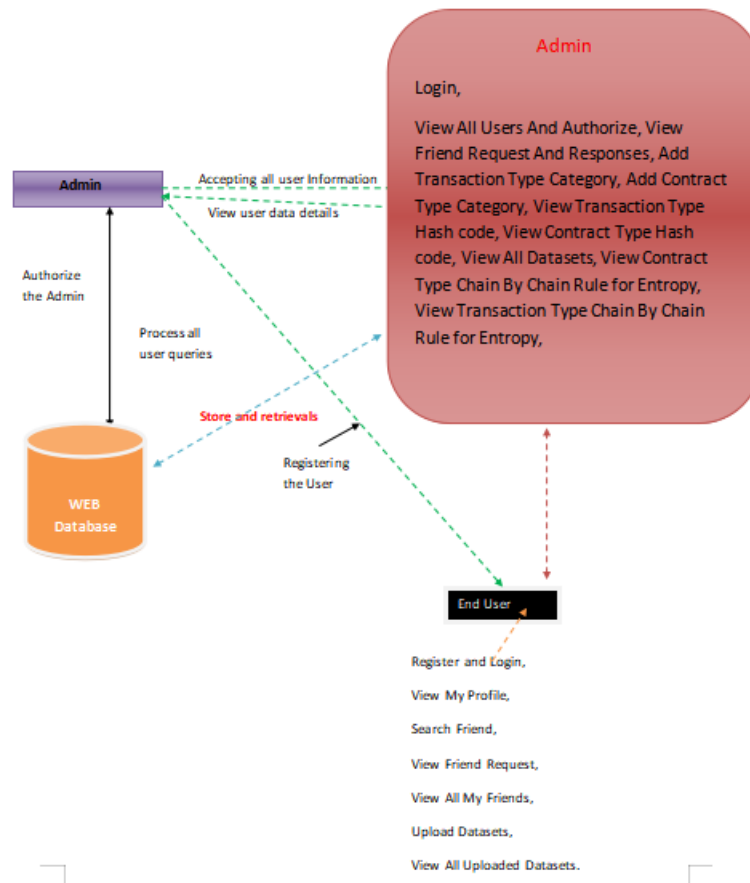


Fig:Architecture diagram

IV.MODULES

Admin

In this module, the Service Provider has to login by using valid user name and password. After login successful he can do some operations such as Login, View All Users And Authorize, View Friend Request And Responses,

Add Transaction Type Category, Add Contract Type Category, View Transaction Type Hash code, View Contract Type Hash code, View All Datasets, View Contract Type Chain By Chain Rule for Entropy, View Transaction Type Chain By Chain Rule for Entropy, View Find Transaction Type, View Transaction Type Chain

Size Results, View Contract Type Chain Size Results.

View and Authorize Users

In this module, the admin can view the list of users who all registered. In this, the admin can view the user's details such as, user name, email, address and admin authorizes the users.

End User

In this module, there are n numbers of users are present. User should register before doing any operations. Once user registers, their details will be stored to the database. After registration successful, he has to login by using authorized user name and password. Once Login is successful user will do some operations like Register and Login, View My Profile, Search Friend, View Friend Request, View All My Friends, Upload Datasets, View All Uploaded Datasets.

V.CONCLUSION

For user identification in OSNs, we explore the possibility of constructing a rung on the ladder from low-quality behavioural data to a high-performance behavioural model. A combined probabilistic generative model that integrates online and offline behaviours is proposed, taking full use of the complimentary impact among OSN users' multidimensional behaviours. Comprehensive assessments on real-life OSN datasets support the developed joint model's performance in

terms of detection effectiveness, response latency, and robustness when used to identity theft detection in OSNs. In particular, compared to the previous fused model, the joint model performs far better.

Once the account's access control is compromised, our behavior-based approach primarily seeks to identify identity thieves. After that, integrating our approach with more conventional approaches to address the issue of identity theft is both simple and encouraging.

VI.REFERENCES

- [1] J. Onaolapo, E. Mariconti, and G. Stringhini, "What happens after you are pwnd: Understanding the use of leaked Webmail credentials in the wild," in *Proc. Internet Meas. Conf.*, Nov. 2016, pp. 65–79.
- [2] A. Mohan, "A medical domain collaborative anomaly detection framework for identifying medical identity theft," in *Proc. Int. Conf. Collaboration Technol. Syst. (CTS)*, May 2014, pp. 428–435.
- [3] Y.-A. de Montjoye, L. Radaelli, V. K. Singh, and A. S. Pentland, "Unique in the shopping mall: On the reidentifiability of credit card metadata," *Science*, vol. 347, no. 6221, pp. 536–539, Jan. 2015.
- [4] P. Hyman, "Cybercrime: It's serious, but exactly how serious?" *Commun.*

- ACM*, vol. 56, no. 3, pp. 18–20, Mar. 2013.
- [5] L. Bilge, T. Strufe, D. Balzarotti, and E. Kirda, “All your contacts are belong to us: Automated identity theft attacks on social networks,” in *Proc. 18th Int. Conf. World Wide Web (WWW)*, 2009, pp. 551–560.
- [6] J. Lynch, “Identity theft in cyberspace: Crime control methods and their effectiveness in combating phishing attacks,” *Berkeley Technol. Law J.*, vol. 20, no. 1, pp. 259–300, 2005.
- [7] M. Egele, G. Stringhini, C. Kruegel, and G. Vigna, “Towards detecting compromised accounts on social networks,” *IEEE Trans. Dependable Secure Comput.*, vol. 14, no. 4, pp. 447–460, Jul. 2017.
- [8] T. C. Pratt, K. Holtfreter, and M. D. Reisig, “Routine online activity and Internet fraud targeting: Extending the generality of routine activity theory,” *J. Res. Crime Delinquency*, vol. 47, no. 3, pp. 267–296, Aug. 2010.
- [9] K. Thomas, C. Grier, J. Ma, V. Paxson, and D. Song, “Design and evaluation of a real-time URL spam filtering service,” in *Proc. IEEE Symp. Secur. Privacy*, May 2011, pp. 447–462.
- [10] H. Li *et al.*, “Bimodal distribution and co-bursting in review spam detection,” in *Proc. 26th Int. Conf. World Wide Web*, Apr. 2017, pp. 1063–1072.
- [11] A. M. Marshall and B. C. Tompsett, “Identity theft in an online world,” *Comput. Law Secur. Rev.*, vol. 21, no. 2, pp. 128–137, Jan. 2005.
- [12] B. Schneier, “Two-factor authentication: Too little, too late,” *Commun. ACM*, vol. 48, no. 4, p. 136, Apr. 2005.
- [13] M. V. Ruiz-Blondet, Z. Jin, and S. Laszlo, “CEREBRE: A novel method for very high accuracy event-related potential biometric identification,” *IEEE Trans. Inf. Forensics Security*, vol. 11, no. 7, pp. 1618–1629, Jul. 2016.
- [14] R. D. Labati, A. Genovese, E. Muñoz, V. Piuri, F. Scotti, and G. Sforza, “Biometric recognition in automated border control: A survey,” *ACM Comput. Surv.*, vol. 49, no. 2, p. 24, 2016.
- [15] B. A. Rajoub and R. Zwiggelaar, “Thermal facial analysis for deception detection,” *IEEE Trans. Inf. Forensics Security*, vol. 9, no. 6, pp. 1015–1023, Jun. 2014.
- [16] M. M. Waldrop, “How to hack the hackers: The human side of cybercrime,” *Nature*, vol. 533, no. 7602, pp. 164–167, May 2016.
- [17] C. Wang, B. Yang, J. Cui, and C. Wang, “Fusing behavioral projection models for identity theft detection in

- online social networks,” *IEEE Trans. Comput. Social Syst.*, vol. 6, no. 4, pp. 637–648, Aug. 2019.
- [18] C. Shen, Y. Li, Y. Chen, X. Guan, and R. A. Maxion, “Performance analysis of multi-motion sensor behavior for active smartphone authentication,” *IEEE Trans. Inf. Forensics Security*, vol. 13, no. 1, pp. 48–62, Jan. 2018.
- [19] C. Wang and H. Zhu, “Representing fine-grained co-occurrences for behavior-based fraud detection in online payment services,” *IEEE Trans. Dependable Secure Comput.*, early access, May 4, 2020, doi: [10.1109/TDSC.2020.2991872](https://doi.org/10.1109/TDSC.2020.2991872).
- [20] H. Zheng *et al.*, “Smoke screener or straight shooter: Detecting elite sybil attacks in user-review social networks,” in *Proc. 25th Annu. Netw. Distrib. Syst. Secur. Symp. (NDSS)*, San Diego, CA, USA, Feb. 2018, pp. 259–300.
- [21] R. T. Mercuri, “Scoping identity theft,” *Commun. ACM*, vol. 49, no. 5, pp. 17–21, May 2006.
- [22] G. Stringhini, P. Mourlanne, G. Jacob, M. Egele, C. Kruegel, and G. Vigna, “EVILCOHORT: Detecting communities of malicious accounts on online services,” in *Proc. USENIX Secur.*, 2015, pp. 563–578.
- [23] Q. Cao, X. Yang, J. Yu, and C. Palow, “Uncovering large groups of active malicious accounts in online social networks,” in *Proc. ACM SIGSAC Conf. Comput. Commun. Secur.*, Nov. 2014, pp. 477–488.
- [24] G. Stringhini, C. Kruegel, and G. Vigna, “Detecting spammers on social networks,” in *Proc. 26th Annu. Comput. Secur. Appl. Conf. (ACSAC)*, 2010, pp. 1–9.
- [25] Y. Yao, B. Viswanath, J. Cryan, H. Zheng, and B. Y. Zhao, “Automated crowdturfing attacks and defenses in online review systems,” in *Proc. ACM SIGSAC Conf. Comput. Commun. Secur.*, Dallas, TX, USA, Oct. 2017, pp. 1143–1158.