As per UGC guidelines an electronic bar code is provided to seure your paper

International Journal for Modern Trends in Science and Technology, 8(09): 146-149, 2022

ISSN: 2455-3778 online
DOI: https://doi.org/10.46501/IJMTST0809030
Available online at: http://www.ijmtst.com/vol8issue09.html

Analyzing Large-Scale Public Transit Records to Identify Pickpocket Suspects

P Naveen Kumar [1] | B. N. Srinivasa Gupta [2]

[1]PG Scholar, Department of Computer Science, SVKP &Dr K S Raju Arts & Science College(A), Penugonda, W.G.Dt., A.P, India
[2]Associate Professor in Computer science, SVKP &Dr K S Raju Arts & Science College(A), Penugonda, W.G.Dt., A.P, India

To Cite this Article
P Naveen Kumar and B. N. Srinivasa Gupta . Analyzing Large-Scale Public Transit Records to Identify Pickpocket Suspects. International Journal for Modern Trends in Science and Technology 2022, 8(09), pp. 146-149. https://doi.org/10.46501/IJMTST0809030

Article Info
Received: 22 August 2022; Accepted: 12 September 2022; Published: 17 September 2022.

ABSTRACT

Massive amounts of data amassed by automated fare collection (AFC) systems offer chances to examine both individual travel habits and societal mobility trends in metropolitan settings. Studies that have already been done using AFC data have mostly on detecting passenger movement patterns. However, we cleverly used such data to pinpoint potential pickpocket suspects. For the public transportation system to improve customer happiness and safety, pickpocketing must be stopped. But in reality, it might be difficult to tell burglars from from normal travellers.In the current study, we created a suspect identification and surveillance system that can locate potential pickpockets based on their daily transportation logs. To be more precise, we first identified a number of helpful features from each passenger's regular transportation activity. Then, using a two-step strategy, we were able to recognise thieves—who frequently engage in unusual travelling behaviors—by combining the advantages of supervised classification models with unsupervised outlier identification. Results from experiments showed how successful our approach is. A prototype device was also created for future usage by security officers.

Index Terms: Automated fare collection, mobility patterns, public safety, and anomaly detection are some of the topics covered.

1. INTRODUCTION

Public transport passengers are prone to distraction in crowded environments where they are often rushed from one place to another. When their focus strays from their possessions, they are often targeted by pickpockets [1, 2]. According to reports, in the first nine months of 2014, Beijing arrested 350 pickpockets on subways and 490 on buses.1 Others around the world, including Barcelona, Rome and Paris, Pickpocketing is also a problem in many major cities of the United States.2 Indeed, it is difficult to detect theft activity by cunning thieves who know how to escape undetected. Providing intelligent monitoring and tracking tools for transportation system security personnel is essential.Transactional records gathered by automated fare collection (AFC) systems are now available to study passengers' movement patterns and urban dynamics due to significant advancements in information technology and infrastructure [3, 4, 5, 6, 7]. The majority of current research focuses on finding recurring, group mobility patterns, such commute flows and transportation networks. The first research to concentrate on detecting thieves using AFC data is ours. Because it is feasible to distinguish between suspects and ordinary passengers using behavioural variations recorded in the mobility footprints, it is possible to identify thieves using AFC recordings.These practises include travelling regular routes with haphazard stops, making needless transfers, and travelling for a lengthy period of time. It is now possible to create an intelligent system that automatically extracts particular, defined behavioural elements and dynamically identifies and tracks pickpocket suspects.

The identification of thieves using AFC records is not a straightforward outlier detection issue. The distinction between an outlier and a known thief is depicted . Several routes between hot areas A and B are seen. Aclose look reveals that most travellers use a configuration that is close to ideal (e.g., requires the fewest transfers or travels the shortest distance or time). However, a traveller (a known suspect) who followed the route A->C->D->B appears suspicious because B may be reached without stopping at C or D. Passengers who display such odd behaviour will be chosen for further scrutiny based on the aforementioned observation.A different traveller, however, who takes the route from E to B is an outlier since so few people do. But this traveller is probably simply a typical traveller from a less populated region. It might be difficult to spot criminals since not all trips taken by frequent passengers appear to be routine. Regular commuters may occasionally go to see friends or other destinations, but these travels may raise suspicion because to how much they differ from customary passenger behaviour.

A significant number of AFC data are being gathered from millions of passengers, adding to the complexity of the situation, even though only a small percentage of them are pickpockets in reality. Finding such a tiny group of individuals inside such a huge dataset is like looking for a needle in a haystack. In the meanwhile, we must successfully construct a decision support system using our expertise based on model development. To help security professionals carry out their duties more effectively, such a technology must offer real-time decision suggestions.

2. LITERATURE SURVEY

As urban sensing data, such as GPS traces, call detail records, and smart card logs, grow ubiquitous, research efforts devoted to analyzing such data have resulted in a number of works in recent years. In the context of mining public transportation data, in this section, we provide a brief review of the related work.

The first group of existing literature focuses on finding patterns in passenger activity records. Such knowledge can be useful in a variety of applications, and plays a vital role in effectively finding and satisfying passenger needs. Examples include assessing the performance of the transit network, identifying and optimizing problematic or flawed bus routes, improving the accuracy of passenger flow forecasted between two regions, and making service adjustments that accommodate variations in ridership on different days. In particular, [4] estimated the crowdedness of various stations in the transportation network using AFC data. [9] measured the variability of transit behaviors on different days of the week. In addition, different studies have investigated unique characteristics of traveling patterns of the elderly [10], students, and adults [9], which provided interesting insights for understanding behavioral differences of sub-populations.It has been suggested that human mobility patterns follow a high degree of spatial and temporal regularity,and are thus highly predictable [11, 12]. By identifying trip patterns, these studies typically aimed to discovering movement patterns by finding frequently visited places of regular passengers, who traveled the same sequence of places at a similar time of day. For example, [13] identified spatiotemporal patterns from GPS traces of taxis for night bus route planning. [14] tried to predict the most common routing preference of past passengers by identifying the most frequented travel paths during a certain time period [3] analyzed sets of moving objects, like traffic patterns, bird migration and explain movement patterns.

3. PROBLEM STATEMENT

Finding patterns in passenger activity records is the main emphasis of the System of extant literature. Such information may be applied to many different situations and is essential for efficiently identifying and meeting passenger demands. Examples include evaluating the effectiveness of the transportation system, identifying and fixing troublesome or inefficient bus routes, increasing the precision of anticipated passenger flow between two locations, and modifying service to account for fluctuations in passengers on different days.In example, [4] used AFC data to predict how packed specific stations in the transit network were. The variability of transit behaviour over the weekdays was assessed by [9].

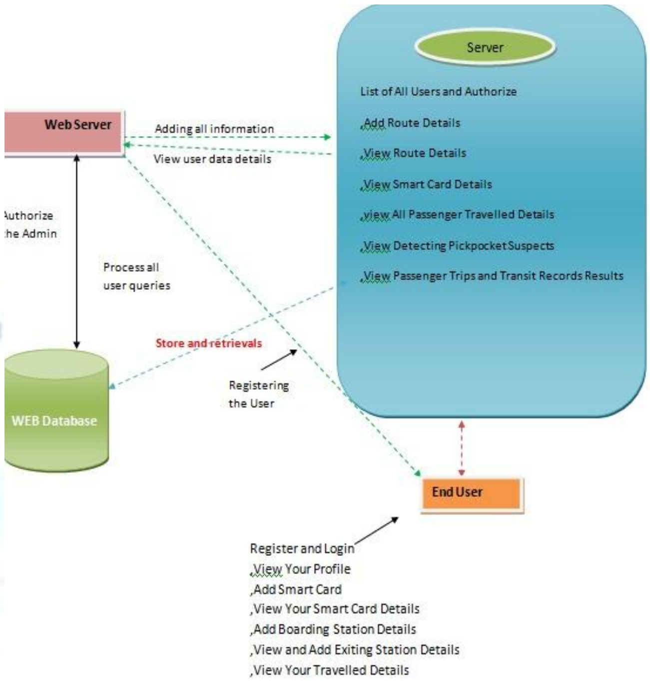
There are currently two types of research that identify abnormalities in urban sensing data: ones based on locations and ones based on trajectories. A system that learnt the context of several functional zones in a city was described by [15] along the lines of location-based anomaly detection, and this framework served as the foundation for our feature extraction method.

Additionally, [16] tried to identify ad hoc connections between spatiotemporal anomalies. [17] extracted representative phrases from social media posts when city-specific events like accidents or demonstrations occurred. [18] found black-hole or volcano patterns in metropolitan human movement data that might be used to swiftly pinpoint gathering events like concerts and football games. Such abnormalities can be found and used to provide alarms and offer information for intelligent decision support systems, such as ones that smooth traffic flow.

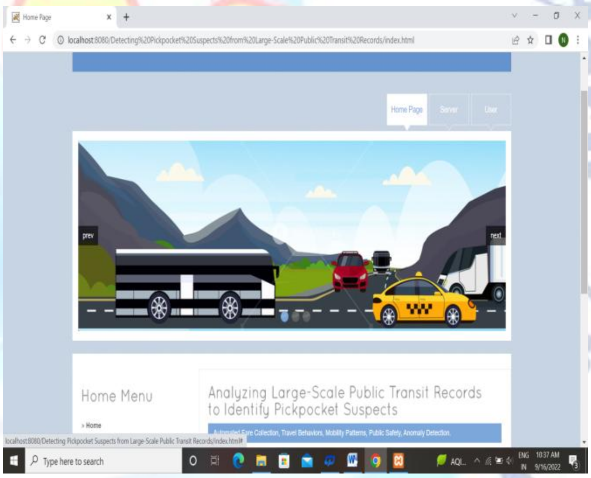
Disadvantages

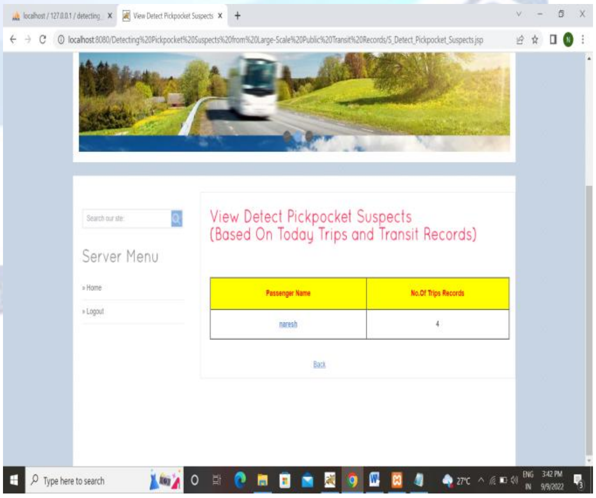
- There is no smart card-based travel since all passenger activity patterns and transit records are manually maintained.
- The system was unable to identify criminals in accordance with the no-checkout rule because thieves engaged in victim-reported incidents were not apprehended. Instead, the system classified thieves manually based on how they travelled. To be more specific, the system first recognised every person on board at the same moment, then it displayed their journey paths to see if their patterns of movement were common.

5. SYSTEM ARCHITECTURE



5. RESULTS





6. CONCLUSION

In this project, we mined extensive transportation information to create a suspect detection and tracking system. The device makes it possible to conduct active monitoring in high-risk regions and helps identify pickpocket suspects. To be more precise, we initially built a feature representationfor passenger profiling. Then, in order to discriminate between regular travellers and potentialpickpockets, we developed a revolutionary two-step framework. Finally,we created aprototype system for end usersusing real-worlddatasets from various sources for model training and validation.

The usefulness of our suggested strategy was demonstrated by experimental findings using real-world data.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

REFERENCES

[1] G. R. Newman and M. M. McNally, "Identity theft literature review," United States Department of Justice, Report 210459, July 2005.

[2] M. Felson and R. V. Clarke, "Opportunity makes the thief: Practical theory for crime prevention," Policing and Reducing Crime Unit: Police Research Series, Report 98, 1998.

[3] T. L. C. da Silva, J. A. F. de Macedo, and M. A. ˆ Casanova, "Discovering frequent mobility patterns on moving object data," in MobiGIS, 2014, pp. 60–67.

[4] I. Ceapa, C. Smith, and L. Capra, "Avoiding the crowds: understanding tube station congestion patterns from trip data," in UrbComp, 2012, pp. 134–141.

[5] X. Ma, Y.-J. Wu, Y. Wang, F. Chen, and J. Liu, "Mining smart card data for transit riders travel patterns," Transportation Research Part C, vol. 36, pp. 1–12, 2013.

[6] K. Zheng, Y. Zheng, N. J. Yuan, S. Shang, and X. Zhou, "Online discovery of gathering patterns over trajectories," IEEE Transactions on Knowledge and Data Engineering, vol. 26, no. 8, pp. 1974–1988, 2014.

[7] Y. Liu, C. Liu, J. Yuan, L. Duan, Y. Fu, H. Xiong, S. Xu, and J. Wu, "Intelligent bus routing with heterogeneous human mobility patterns," Knowledge and Information Systems, 2016, forthcoming, DOI: 10.1007/s10115-016- 0948-6.

[8] B. Du, C. Liu, W. Zhou, Z. Hou, and H. Xiong, "Catch me if you can: Detecting pickpocket suspects from large-scale transit records," in KDD, 2016, pp. 87–96.

[9] C. Morency, M. Trepanier, and B. Agard, "Analysing ´ the variability of transit users behaviour with smart card data," in ITSC, 2006, pp. 44–49.

[10] M. J. Sung, "Analysis of travel patterns of the elderly using transit smart card data," in TRB, no. 11-2357, 2011.

[11] M. C. Gonzalez, C. A. Hidalgo, and A.-L. Barabasi, ´ "Understanding individual human mobility patterns," Nature, vol. 453, no. 7196, pp. 779–782, 2008.

[12] C. Song, Z. Qu, N. Blumm, and A.-L. Barabasi, "Limits ´ of predictability in human mobility," Science, vol. 327, no. 5968, pp. 1018–1021, 2010.

[13] C. Chen, D. Zhang, Z.-H. Zhou, N. Li, T. Atmaca, and S. Li, "B-planner: Night bus route planning using largescale taxi gps traces," in PerCom, 2013, pp. 225–233.

[14] W. Luo, H. Tan, L. Chen, and L. M. Ni, "Finding time period-based most frequent path in big trajectory data," in SIGMOD, 2013, pp. 713–724.

[15] J. Yuan, Y. Zheng, and X. Xie, "Discovering regions of different functions in a city using human mobility and pois," in KDD, 2012, pp. 186–194.

[16] W. Liu, Y. Zheng, S. Chawla, J. Yuan, and X. Xing, "Discovering spatio-temporal causal interactions in traffic data streams," in KDD, 2011, pp. 1010–1018.

[17] B. Pan, Y. Zheng, D. Wilkie, and C. Shahabi, "Crowd sensing of traffic anomalies based on human mobility and social media," in GIS, 2013, pp. 344–353.

[18] L. Hong, Y. Zheng, D. Yung, J. Shang, and L. Zou, "Detecting urban black holes based on human mobility data," in GIS, 2015, pp. 35:1–35:10

Authors Biography

P.Naveen Kumar currently pursuing MCA in SVKP & Dr.K.S Raju Arts & Science College affiliated to Adikavi Nannaya University, Rajamahendravaram. His research interests include Data Structures, Web Technologies, Operating Systems, Data Science and Artificial Intelligence

B.N.Srinivasa Gupta is working as Associate Professor in SVKP &Dr K S Raju Arts & Science College, Penugonda, A.P.He received Masters Degree in Computer Applications from AndhraUniversity and Computer Science & Engineering from Jawaharlal Nehru Technological University Kakinada(JNTUK), Kakinada, India. His research interests include Data Mining, Cyber Security, Artificial Intelligence.