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Predicting the Impact of Disruptions to Urban Rail Transit Systems

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Abstract: Over the past few decades, service disruptions of rail transportation systems have increased in major cities for a number of reasons, such as power outages, signal issues, etc. The impacts of disruptions on users and transit networks are studied and projected. This makes it easier for service providers to set both short- and long-term goals to enhance their offerings. We precisely establish two metrics—stay ratio and journey delay—to assess the impact. In order to overcome the main challenge of unusual data scarcity—namely, the fact that there were only 6 documented disruptions in our one-year data sets—we propose structuring the issue as a training problem on a feature space relevant to alternate commuter route choices. We demonstrate that the new feature space correlates to more comparable data distribution across different disruptions, which is helpful for creating disruptor predictors that can be used more widely. We test and evaluate our approach using a dataset from real transit cards. The result clearly shows that our strategy performs better than a variety of benchmark techniques.

Keyword: Service disruption, impact prediction, data scarcity

I. INTRODUCTION

Rapid rail is the backbone of urban city public transport systems (PTS). Even a little rail system fault might have significant repercussions and gravely hurt the PTS. Our research shows that the Mass Rapid Transit (MRT) rail system frequently experiences major disruptions due to a range of factors, including technical difficulties, bad weather, human injuries, etc. The commute of tens of thousands or even thousands of commuters may be impacted. Numerous them are compelled to abandon the PTS and use alternative modes of transportation.

This paper aims at predicting the impact of rail system disruptions at the time of occurrence. Such knowledge not only benefits the PTS provider in understanding the degradation of service, making better emergent plans and planning appropriate new services in PTS to improve system resilience, but also benefits commuters in preparing for the hazards brought by disruptions [1] [2]. Specifically, we define the following two metrics to assess the impact of disruptions. (1) Stay ratio indicates the percentage of rail riders who choose to stay within the PTS and take alternative rail lines and/or buses to complete their trip. (2) Travel delay indicates the extra time spent on alternative routes for those who stay within the PTS. Obviously, higher stay ratio and lower travel delay indicate smaller impact by a disruption.

Although there have been efforts made to analyzing the influence of abnormal conditions of railway on commuter, most of them apply empirical knowledge or simplified human behavior models to reason human choices, and based on that analyze the impact on commuters. Some exploit real transportation data to understand human behaviors, but they are often limited to normal PTS conditions. In this paper, adopting a unique approach, we explore the transportation data during rail system disruptions and learn from the true human choices. We train a human behavior model from those abnormal data and apply the model to predict the impact of future disruptions.

II. EXISTING SYSTEM

Examples include Pan et al. who forecast future incidents using the average impact of comparable previous incidents, Fang et al. who forecast future travel delays using post incident travel delays and contextual variables, and Garib et al. who utilize statistical models based on contextual features. The majority of earlier studies did not thoroughly investigate generalization capacity and did not include the number of real-world scenarios that this work does.

Other study focuses on using the post-incident traffic flow as an input to forecast the traffic flow under abnormal conditions. However, it is impossible to accurately predict how the traffic flows will affect passengers. In summary, no study has yet evaluated the effects of actual occurrences while also examining the generalizability of a model to predict the consequences of potential future incidents.

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1) The system doesn't have a method Analyzing Under-disruption Choices.
2) There is no system to analyze accurate disruptions on large data sets.

"Huijun Sun a , Jianjun Wu a, Lijuan Wu b , Xiaoyong Yan b , Ziyou Gao b [2] propose the development of a model that estimates the effects of a disruption in an urban rail transit network taking into account the spatiotemporal factors involved. Based on the AFC data, an efficient Bayesian method was introduced to identify the disruption according to the number of tap-in passengers collected by AFC system. To estimate the effects of a disruption, passenger behaviors were divided into 3 groups: missed passengers, detoured passengers, and delayed passengers.

Then a model was developed to analyze the delay caused by the disruption, including average delay time, maximum delay time, and rate of punctual arrivals. By using that model, the affected stations could be determined. Finally, the validity of the model and method was verified by a case study involving the Beijing rail transit network. The results show that the model can be used to estimate the effects of a disruption on the urban rail transit network mathematically and quantitatively.

Lijun Sun, Der-Horng Lee, Alex Erath, Xianfeng Huang,[4] this present propose, present a methodology to analyze smart card data collected in Singapore, to describe dynamic demand characteristics of one case mass rapid transit (MRT) service. The smart card reader registers passengers when they enter and leave an MRT station. Between tapping in and out of MRT stations, passengers are either walking to and fro the platform as they alight and board on the trains or they are traveling in the train.

To reveal the effective position of the passengers, a regression model based on the observations from the fastest passengers for each origin destination pair has been developed. By applying this model to all other observations, the model allows us to divide passengers in the MRT system into two groups, passengers on the trains and passengers waiting in the stations. The estimation model provides the spatio-temporal density of passengers. From the density plots, trains' trajectories can be identified and passengers can be assigned to single trains according to the estimated location

Hugo Estrada-Esquivel, Alicia Martínez-Rebollar, Pedro Wences-Olguin, Yasmin Hernandez-Perez , Javier Ortiz-Hernandez [5] are currently exploring the possibility of improving the precision of arrival time prediction, taking into account the information of all of the monitored buses in order to determine the current traffic conditions that could affect a specific zone of the city.

To do that, the open data of mobility in cities is being captured and placed in a unified data space. One example of the open data considered in current research is the real-time loca- tion of metrobuses of Mexico City, which provides the location of 700 public buses in the city every 30 s. Furthermore, in order to consider the real-time traffic conditions in cities, the data of APIs of mobility applications is currently being used.

III PROPOSED SYSTEM

The system proposes the novel notion of domain projection to overcome the data distribution mismatch between training and testing sets, especially in the case of data scarcity. Both the training and testing sets of our data are sparse, which is comparable to but distinct from the condition of canonical transfer learning. As a result, it is impossible to profile the distribution in its entirety. We emphasise the significance of proactively locating a feature space where the extracted feature distributions for the training and testing disturbances are the same.

The proposed domain projection method unifies our understanding of disruptions by their impact on commuter route choices by specifically converting the original training problem on the feature space relevant to the disruption itself to a new training problem on a different feature space relevant to alternate commuter route choices.

A model trained from the converted feature space can be extended to all disturbances as long as commuter route choices can be inferred from the interruptions.
1) The system has developed with huge amount of data sets to measure accurate disruptions.
2) An efficient Domain projection to convert the prediction problem in the domain of disruption into that in the domain of interested alternative routes (IARs) that may be chosen by the commuters during disruptions, where we may address the challenge of data scarcity and train a generalizable

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IV SYSTEM ARCHITECTURE

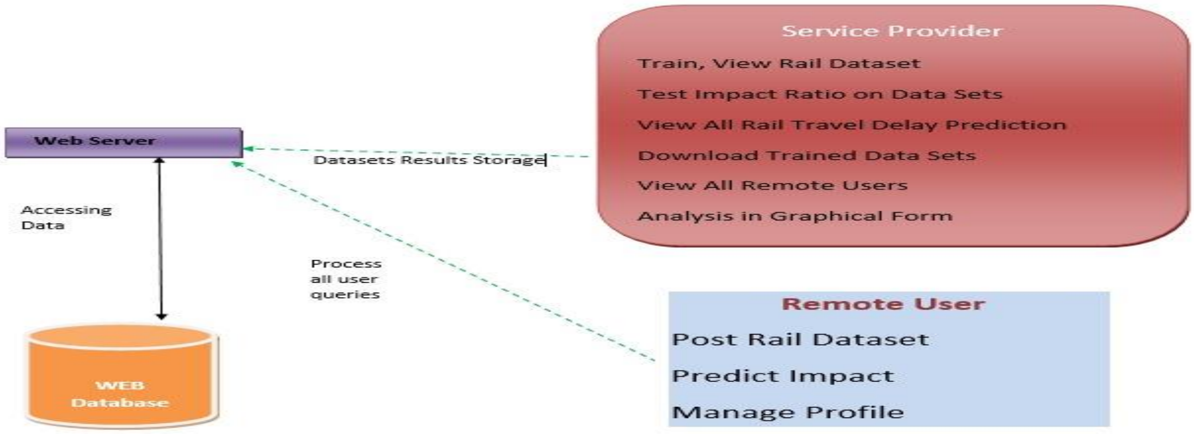

Fig 3.1 System architecture

This system consists of two modules like Remote User and Service Provider. User first upload the dataset the system to predict the delay and impact status and manage their profile. Then service provider train and view the dataset and give the information about the travel delay prediction and impact ratio with graphical form and download trained dataset. The web server processes all user queries and storage the dataset result. Then web server accessing the web database.

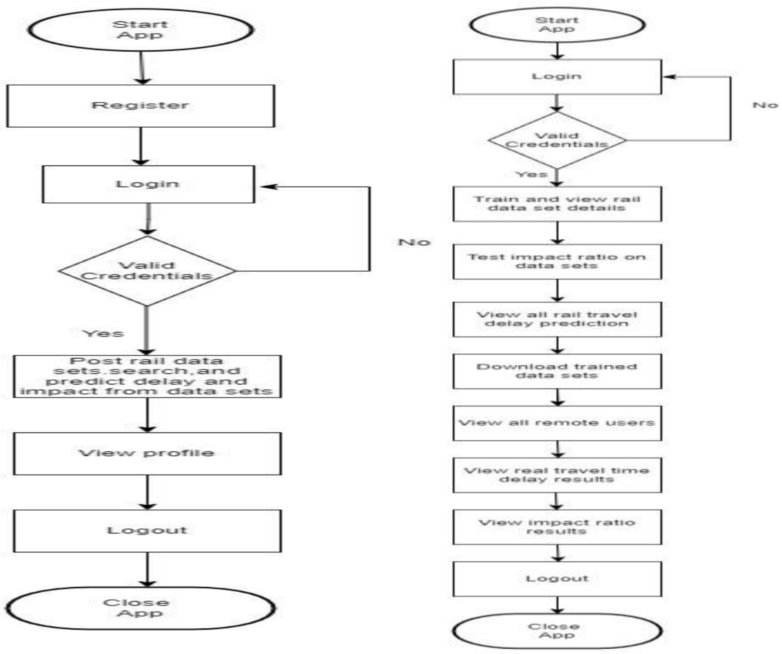

Figure 3.2 Flowchart Implementation

This system consists of two modules like Remote User and Service Provider. The flow of implementation is a picture that represents workflow or process of a system. On the startup screen when the user first register to the system providing basic details like name, email, password, city, mobile number. After the register user can login to the system then select dataset to the documents and upload to system the information of dataset will be displayed in the screen. The system predicts the delay and impact status in the dataset. And user profile can also be viewed.

After user upload the dataset, the service provider will login using valid username and password. Then view the details of training and test dataset. Find the train ratio, predict the train delay, download trained and tested dataset, view the result using graphical form.

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V. RESULT AND ANALYSIS

In this section, we introduce priors works on impact prediction of transportation incidents, as well as technologies relevant to our approach. Impact Prediction. Except for studies regarding to the detection of abnormal circumstances of transportation incidents, e.g., railway failures, tragic congestion, there have also been efforts made to predict their impact. Some works predict the impact by reasoning human reactions or the damage to network structure, most of which lack measurement study of real incidents. Most existing studies are not validated with real world incidents at the scale of this paper. Other studies focus on forecasting the tragic low under anomalous conditions taking a period of post-incident tragic low as input. The tragic lows, however, cannot be translated to in-grained impact to commuters. To sum up, so far there is no existing study which measures impact from real incidents, and meanwhile explores the reliability of models being trained on scarce data to predict the impact of a variety of future incidents.

V. CONCLUSION

We offer a comprehensive solution to forecast the effects of train system disruptions based on actual commuter behaviors during interruptions. In order to overcome the issue of insufficient training data, we suggest projecting a disruption and its impacted OD into a unique domain of properties abstracted from commuters' alternate route possibilities. Training accuracy and capacity for generalization have both greatly improved. Experimental results using real-world data show the efficacy of our proposed approach.

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