



PREDICTING THE IMPACT OF DISRUPTIONS TO URBAN RAIL TRANSIT SYSTEM

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Abstract

Service disruptions of rail transit systems become more frequent in the past decades in urban cities like Singapore, due to various reasons such as power failures, signal errors, etc. We study and predict the impact of disruptions to transit systems and commuters. This benefits service providers in making both short and long term plans to improve their services. Specifically, we define two metrics, stay ratio and travel delay, to quantify the impact. To tackle the main challenge of abnormal data scarcity, i.e., only 6 observed disruptions in our one-year data records, we propose to format the problem into a training problem on a feature space relevant to alternative route choices of the commuters. We demonstrate the new feature space corresponds to more similar data distribution among different disruptions, which is beneficial for training more generalisable predictors for future disruptions. We implement and evaluate our approach with a real-world transit card dataset. The result clearly shows that our method outperforms a range of baseline methods.

1. INTRODUCTION

The rapid rail system is the backbone of the public transit systems (PTS) in urban cities. Malfunction of the rail system even in a small region may have ripple effects and significantly impair the PTS. According to our study on Singapore Mass Rapid Transit (MRT) rail system, major disruptions take place due to many reasons including technical faults, extreme weathers, human injuries, etc. The journey of thousands or even tens of thousands of commuters may be impaired. Many of them have to quit the PTS and resort to other transportation alternatives (e.g., taxis).

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 analysing the influence of abnormal conditions of railway on



commuters [3]–[5], most of them apply empirical knowledge or simplified human behaviour models to reason human choices, and based on that analyze the impact on commuters. Some exploit real transportation data to understand human behaviours, but they are often limited to normal PTS conditions. In this paper, taking a unique approach, we explore the transportation data during rail system disruptions and learn from the true human choices. We train a human behaviour model from those abnormal data and apply the model to predict the impact of future disruptions.

Being simple in rationale, our approach is especially challenged due to the scarcity of abnormal data, i.e., those from only 6-8 major disruptions per year. A direct challenge comes from the lack of training data for us to build an accurate model using supervised learning. The limited observation of disruptions makes the trained model difficult to generalize, i.e., applicable to future disruptions unseen in the training stage. The problem becomes more challenging if we consider that only the trips of regular commuters (which is a small portion of the total affected commuters) can be utilized to analyze human behaviours, extract features and label impact metrics, because for irregular commuters there is no way to infer their original travel intention and thus no confidence with regard to their choices under disruptions.

In order to address the above challenges, we propose a novel idea of domain projection to tackle the data distribution mismatch between training and testing sets especially in the situation of data scarcity. Similar but different to the situation of

canonical transfer learning, our data in both the training and testing sets is scarce and hence no big picture of the distribution can be profiled. Therefore, we claim the importance of proactively finding a feature space where the training and testing disruptions share similar distributions of extracted features. Specifically, the proposed domain projection method converts the original training problem on the feature space relevant to disruption itself to a new training problem on a different feature space relevant to alternative route choices of the commuters,

2. EXISTING SYSTEM

- ❖ Sun et al. [5] estimates the normal spatio-temporal distribution of commuters in rail system, and try to infer the number of affected commuters when there is a disruption. Sun et al. [4] try to reason commuters' travel delay based on their choices (e.g., stay or leave PTS). Yin et al. [11] define the impact as the damage to rail network efficiency, and utilize graph theory to quantify the impact of disruption. Some works predict impact based on actual mobility data measured from real world.
- ❖ Examples include Pan et al. [12] who take the average impact of similar historical incidents to predict that of future incidents, Fang et al. [3] who leverage contextual features and post-incident travel delays to predict future travel delays, and Garib et al. [13] who use statistical models based on contextual features to predict travel delay. Most existing



studies have not thoroughly investigated the ability of generalization and are not validated with real world incidents at the scale of this paper.

- ❖ Other studies focus on forecasting the traffic flow under anomalous conditions [14]–[16] taking a period of post-incident traffic flow as input. The traffic flows, however, cannot be translated to fine-grained impact to commuters. To sum up, so far there is no existing study which measures impact from real incidents, and meanwhile explores the model generalizing ability to predict the impact of a variety of future incidents.

Disadvantage

- 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.

3.PROPOSED SYSTEM

- ❖ The system proposes a novel idea of domain projection to tackle the data distribution mismatch between training and testing sets especially in the situation of data scarcity. Similar but different to the situation of canonical transfer learning, our data in both the training and testing sets is scarce and hence no big picture of the distribution can be profiled. Therefore, we claim the importance of proactively finding a feature space where the training and

testing disruptions share similar distributions of extracted features.

- ❖ Specifically, the proposed domain projection method converts the original training problem on the feature space relevant to disruption itself to a new training problem on a different feature space relevant to alternative route choices of the commuters, which unifies our view of disruptions by their effect on commuter route choices. A model trained from the converted feature space can thus be generalized to arbitrary disruptions as long as the commuter route choices can be inferred from the disruptions.

Our contributions are summarized as follows:

- To the best of our knowledge, this is the first study of impact prediction of rail system disruptions that learns models from true human behaviors' in disruptions.
- The system proposes a novel domain projection method to address the challenges arising from data scarcity, with which we are able to build an accurate and more generalizable model for arbitrary disruptions.
- The system implements and experimentally evaluates our approach with the Singapore MRT ride records in year 2015 that involve 6 major disruptions. The results demonstrate that our method outperforms all the baseline methods.

Advantages



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 model.

3. 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, ie. preliminary investigation begins. The activity has three parts:

4. 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.

4.1 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.

5. SYSTEM DESIGN AND DEVELOPMENT

INPUT DESIGN

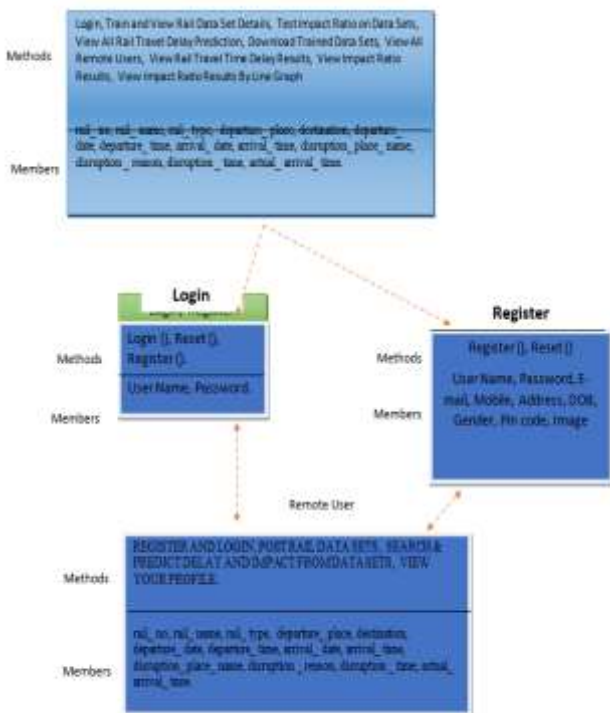
Input Design plays a vital role in the life cycle of software development, it requires very careful attention of developers. The input design is to feed data to the application as accurate as possible. So inputs are supposed to be designed effectively so that the errors occurring while feeding are minimized. 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 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.

Class Diagram :



6. CONCLUSIONS

We propose a comprehensive solution to predict the impact of rail system disruptions, based on the real behaviors of affected commuters during disruptions. To tackle the challenge of training data scarcity, We propose to project a disruption and its affected OD into a different domain of features abstracted from commuters’ alternative route choices. The training accuracy and generalizing ability are greatly improved. Experimental results using real-world data demonstrate the effectiveness of our proposed solution.

7. REFERENCES

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