Predicting the Impact of Disruptions to Urban Rail Transit Systems

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Abstract: In big areas like Singapore, service interruptions of rail transport systems have increased over the last several decades for a variety of causes, including power outages, signal problems, etc. We research and project the effects of interruptions on passengers and transportation networks. Making both short- and long-term goals to enhance their services is facilitated by this for service providers. To measure the effect, we specifically specify two metrics: stay ratio and trip delay. We suggest formatting the issue as a training problem on a feature space pertinent to commuters' alternate route preferences in order to address the primary obstacle of atypical data scarcity, which is represented by the only 6 reported interruptions in our one-year data sets. We show that the new feature space correlates to more comparable data distribution across various disruptions, which is advantageous for developing more broadly applicable disruptor predictors. With a dataset from actual transportation cards, we put our strategy into practise and assess it. The outcome unequivocally demonstrates that our strategy outperforms a number of benchmark methods.

1. INTRODUCTION

As an alternative payment mechanism, cryptocurrencies are becoming more and more popular. These currencies' foundation is blockchain, which provides security and anonymity. It guarantees the immutability of data and permits pseudonymous behaviour from the parties involved in transactions. Blockchain records are openly verifiable. To maintain a Sybil-resistant network, Bitcoin mining depends on Proof-ofWork (PoW) [1], [2], and [3].PoW reduces transaction throughput since it requires a lot of time and resources [4], [5].Protocols at layer two provide a solution to the scalability issue. It allows users to conduct transactions off-chain and significantly reduces the amount of data processing required on the blockchain.

The literature review [6] lists many solutions, including payment channels, channel factories, payment channel hubs, side chains, and commit chains. Payment Channels [7] and are often used in several applications. It is modular and does not call for significant modifications to the protocol layer. By locking their cash for a certain amount of time, two parties may mutually decide to establish a payment channel. Payments are routed via an existing network of channels by nodes that are not directly linked by a payment channel. This network of linked payment channels is known as a PCN, or payment channel network. The two most well-known networks are Raiden Network for Ethereum [8] and Lightning Network for Bitcoin . It is difficult to create payment and routing mechanisms for these networks that protect user privacy. The majority of routing algorithms concentrate on determining a single route for a transaction. Finding a single route for a high-value transaction is a difficult challenge, however. Channels along a route could not have enough balance after a number of payments have been completed in the network for them to transmit the cash. High-value payments should instead be divided along many pathways in these situations to improve the success rate of transactions. However, designing a protocol for multi-path payment is not simple, and we go over the difficulties encountered.

A Description Of The Project: We propose CryptoMaze, an efficient, privacy-preserving, atomic multi-path payment protocol. Our protocol optimizes the setup cost by avoiding the formation of multiple off-chain contracts on a channel shared by partial payments. To date, no other protocol has been able to achieve this optimization.

- Our protocol ensures balance security, i.e., honest intermediaries do not lose coins while forwarding the payment.
- Our protocol description ensures unlinkability between partial payments.
- We have modeledCryptoMaze and defined its security and privacy notions in the Universal Composability or UC framework.
- Experimental Analysis on several instances of Lightning Network and simulated networks show that our proposed payment is as fast as Atomic Multi-path Payment . The run time is around 11s for routing a payment of 0.04 BTC in a network instance of 25600 nodes.The communication overhead is within feasible bounds, being less than 1MB. The code is available in .

2. LITERATURE SURVEY

2.1 Existing System

In order to predict the number of commuters who would be impacted by a disruption, Sun et al. assess the typical spatio-temporal distribution of passengers in the train system. Based on their decisions (such as whether to remain or depart PTS), Sun et al.'s attempt to justify commuters' journey delays. Yin et al. use graph theory to measure the effect of interruption and define the impact as the harm to rail network efficiency. On the basis of mobility data collected from the real world, several studies provide effect predictions.

For instance, Pan et al. used the average impact of comparable historical incidents to forecast the impact of future incidents, Fang et al. used contextual features and post-incident travel delays to forecast future travel delays, and Garib et al. used statistical models based on contextual features to forecast travel delay. Most previous research have not examined generalisation ability in depth and have not been confirmed at the size of this article using real-world situations.

Other research focuses on predicting traffic flow in unusual circumstances. using the post-incident traffic flow period as the input. However, it is impossible to convert the traffic patterns into a precise effect on commuters. In conclusion, there has not yet been a research that assesses the effects of actual occurrences while also investigating a model's generalizability to forecast the effects of various future incidents.

2.2Proposed System

In order to address the data distribution mismatch between training and testing sets, particularly in the context of data scarcity, the system puts forward the innovative notion of domain projection. Our data is sparse in both the training and testing sets, which is similar to but distinct from the condition of canonical transfer learning. As a result, no broad picture of the distribution can be profiled. Therefore, we stress the need of proactively identifying a feature space where the distributions of extracted features for the training and testing disturbances are identical.

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, the proposed domain projection method unifies our understanding of disruptions by their impact on commuter route choices. As long as commuter route options can be inferred from the interruptions, a model trained from the converted feature space may be generalised to all disturbances.

The following is a summary of our contributions:

To the best of our knowledge, this is the first research of its kind that builds models using actual human behaviours during disruptions in order to forecast the effect of train system interruptions.

The system implements and experimentally evaluates our approach with the Singapore MRT ride records in year 2015 that involve 6 major 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 results show that our strategy performs better than any baseline method.

2.2 TLD PROJECTION

The concept of domain projection, which seeks to identify a feature domain where the trained model is more susceptible to future disturbances, is discussed in this section.

Impact indicators are connected to impacted OD and disruption characteristics. For instance, a disruption with more broken connections may result in a lower stay ratio because there is a more rapid mismatch between transit demand and capacity, and a higher travel delay since alternate routes in PTS take longer to travel. A simple fix is to use supervised learning to build a model based on interruption and OD parameters like beginning time, amount of broken connections, etc.

The functional relationship between features and impact measures that potentially apply to future disruptions may not be captured by the model being trained on limited training disturbances, which could lead to under-fitting. To demonstrate such a perspective, we designate the area of disruption and OD features as D1 = (X1, P1), where X1 is a d1-dimension feature space and each impacted OD may be represented by a point X = x1,..., xd1 X1 with the probability given by P1(X). The impacted ODs of the detected disruptions are reduced to planar points using PCA (principal component analysis) and visualised as points in X1 (features mentioned in Table II). We can observe from the outcome displayed in Figure

1(a) that distributions of points with various disruptions seldom ever coincide. The main cause of this issue is the mismatch between the data distributions of what we can see and what we wish to anticipate due to the restricted number of disruptions that we can witness.

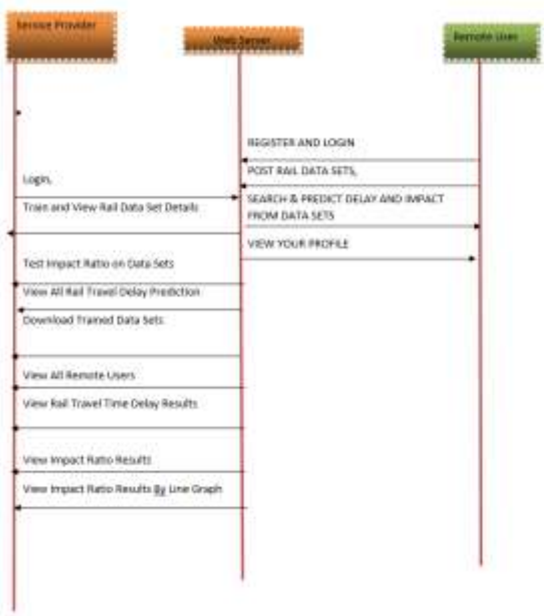


Fig 1: System Flow

3. SYSTEM ANALYSIS&DESIGN

3.1Getting Regular Commuting People

Commuters who are impacted have three options: using alternate PTS routes, using other forms of travel, or combining both. We can identify their presence in PTS during a disruption based on the transport card information. However, since commuters' travel plans may vary daily, making it challenging to determine their initial OD, it is impossible to deduce the impacted commuters' preferences. We suggest identifying habitual commuters whose travel patterns (i.e., departure time and OD) are steady enough to allow for the determination of their initial OD. Next, on behalf of all PTS users, we concentrate our analysis on those frequent commuters.

We get the list of ODs for each commuter throughout the disruptive hours of the day for a sufficiently long past period (for example, pass two months) prior to the disruption date in order to identify habitual commuters for a given disruption. The highest frequency is indicated by mh, while the frequencies of other ODs in the list are given by m1, m2,... The dominating OD is what we refer to as having frequency mh. Then, we begin to eliminate irregular commuters. To filter out sporadic users of the rail system, we delete those whose mhmax(1 2 P i mi,), which is set to 5. Then, we group commuters with the same mh value. We exclude the top 25% of commuters in each cluster who have the highest entropy, or P i qi logqi, where qi = mi/P i mi. We include only impacted regular commuters whose dominant OD is one of the affected ODs and assume dominant OD to be the regular commuter's initial travel strategy.

3.2 Examining Options with Low Disruption

We further investigate the decisions made by the group of frequent commuters who are impacted by interruptions. We discover that more than 90% of the ODs that are impacted have low stay ratios—less than 0.5—which suggests that affected commuters are more likely to depart the PTS when a disruption occurs. Over 90% of those who remain in PTS till arrival have travel delays of little more than 50 minutes.

Additionally, we examine the detours taken by commuters who remain in PTS till arrival. A list of bus and/or rail services, each identified by the bus service name or a pair of rail stations, is used to represent a route.

For an alternative route, the list of transit modals that correspond to it is recognised as the route pattern. We discover that the top four route combinations selected by impacted commuters—(bus,), (bus, bus), (bus, rail), and (rail, bus)—account for 86% of all commutes. Additionally, the walking distance between two services that follow one another is often less than 500 metres, and the detouring rate—that is, the ratio of the distance travelled by an alternate route to the amount travelled via the original route—is under 1.5. When we create IARs in Section IV-C, they will act as limitations. **Generation of Interested Alternative Routes**

We initially produce candidates for each impacted OD by utilising depth-first searching to route on the network of bus and damaged rail lines . Candidates must adhere to the Section IV-B requirements for walking distance (500 metres), diversion rate (1.5), and route design (being among the top 7 patterns). Additionally, we collect actual IARs from our transit records.

Negative candidates that are not true IARs are given the 0 label, whereas real IARs are given the 1. Since there are many more candidates than true IARs (i.e., only approximately 2.6 per impacted OD), there is a large disparity between the two groups (about 1 to 15,000). We use negative sampling on the pool of applicants to correct the imbalance. In other words, sample instances of candidates based on how similar they are to genuine IARs; the closer an instance is to a true IAR, the more likely it is to be sampled. To be more precise, we take into account a number of similarity factors, including the quantity of service transfers, the number of train and bus stations, the duration of waiting times, and walking distance. Each dimension is adjusted to lie inside the interval [0, 1].

The similarity between each pair, one from genuine IARs and the other from candidates, is then determined via cosine similarity. Each candidate is then represented by a 5D vector.

We train a binary classifier for IAR identification using the attributes in labels from genuine IARs, and sampled negative candidates so that we may use it to differentiate true IARs from others in the event of a disruption in the future.

We train the classifier using ensemble learning, a supervised learning approach that uses distinct subsets of training data to train a number of models (in our case, Decision Trees), and then aggregates the results by majority vote. Additionally, it controls the issue of class disparity. We may create candidate IARs for each OD that will be impacted by future interruptions and then use the classifier to determine the actual IARs.

3.3 System Architecture:Predictors Construction

The stay ratio and trip delay predictors are trained independently.

We use Equations (1) and (2) to get the stay ratio and travel delay (i.e., labels) for an impacted OD. Additionally, for the input, each IAR's features are concatenated to create a vector, with zeros substituted for any characteristics that are not relevant. According to the length of the route pattern, each IAR belongs to a certain group.

In order to create the aggregated vector, element-wise statistical aggregations, such as mean, max, and min, over all group members are computed for each group.

Backward elimination is then used to identify the final essential characteristics after we concatenate the aggregated vectors of all groups (in ascending order by the length of the route pattern). We use SVR to model the association between the IAR features and two impact measurements and train the two predictors using training samples of processed IAR features and labels.

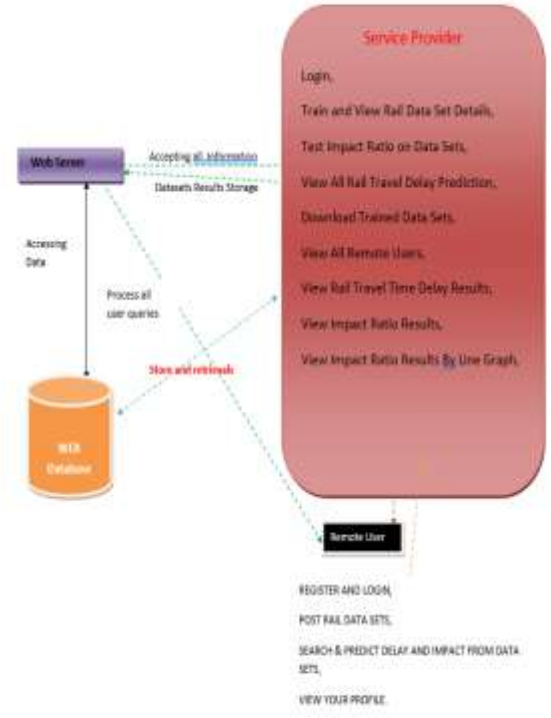


Fig 2 : System Architecture

3.4 Data Flow Diagram : Whenever a new system is developed, user training is required to educate them about the working of the system so that it can be put to efficient use by those for whom the system has been primarily designed. For this purpose the normal working of the project was demonstrated to the prospective users. Its working is easily understandable and since the expected users are people who have good knowledge of computers, the use of this system is very easy.

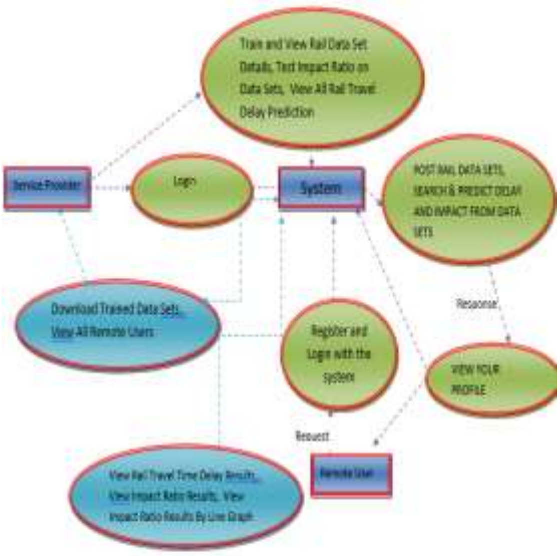
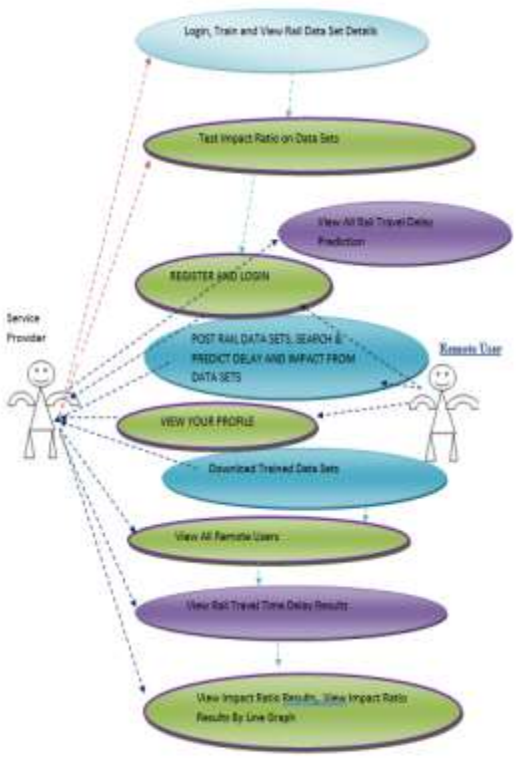


Fig 3: Data Flow Diagram

Fig 4 Use Case UML Diagrams



5. CONCLUSION

Based on the actual passenger behaviours during interruptions, we provide a complete approach to forecast the effects of train system disruptions. We propose to project a disruption and its impacted OD into a distinct domain of attributes abstracted from commuters' alternate route choices in order to address the problem of training data shortage. Both training accuracy and generalisation skills have significantly increased. The efficacy of our suggested strategy is shown by experimental findings utilising real-world data.

6. FUTURE SCOPE

This research exclusively focuses on the passengers in the interrupted part since they are affected by the interruptions most directly and to the greatest degree, whether via simulation or effect evaluation. According to the analysis in Section 2, the impacted train users might disperse around the URT network. As a result, the impacted bus riders are not only in the disrupted area. Much more bus routes and bus riders would be added to the simulation system if the study was extended to include the whole public transportation system. As the problem deteriorates, we continue to work on it. Additionally, the study's definition of a rail interruption may be expanded to include a full line or even a portion of a network.

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