CrowdAtlas: Estimating Crowd Distribution within the Urban Rail Transit System

Jinlong E†, Mo Li†, Jianqiang Huang‡
†Nanyang Technological University, Singapore ‡Alibaba Group, China
ejinlong89@gmail.com, limo@ntu.edu.sg, jianqiang.hjq@alibaba-inc.com

Abstract—While the urban rail transit systems are playing an increasingly important role in meeting the transportation demands of people, the precise awareness of how the human crowd is distributed within the urban rail transit system is highly necessary, which serves to a range of important applications including emergency response, transit recommendation, commercial valuation, etc. Most urban rail transit systems are closed systems where once entered the travelers are free to move around all stations that are connected into the system and are difficult to track. In this paper, we attempt to estimate the crowd distribution within the urban rail transit system based on the entrance and exit records of all the rail riders. Specifically, we study Singapore MRT (Mass Rapid Transit) as a vehicle and leverage the tap-in and tap-out records of the EZ-Link transit cards to estimate the crowd distribution. Guided by a key observation that the passenger inflows and arrival flows at various MRT stations are spatio-temporally correlated due to behavioral consistence of MRT riders, we design and implement a machine learning based solution, CrowdAtlas, that accurately estimates the crowd distribution within the MRT system. Our trace-driven performance evaluation demonstrates the effectiveness of CrowdAtlas.

1. INTRODUCTION

An urban rail transit system is generally an electric railway system operating on an exclusive right-of-way [1], where passengers can travel freely among stations in different lines. In virtue of fast velocity and large capacity, the rail transit systems have become the most important urban public transportation service in recent years. Especially in many metropolises, the average daily ridership has reached millions (e.g., ~5 million in London [2] and ~3.5 million in Singapore [3]).

Since travelers are free to move around all the stations once they enter the transit system, it is essential to have a fine estimation of how people are distributed within the transit system. Such information is important to providing critical resilience guarantees, e.g., emergency evacuation in response to railway disruptions or terrorist attacks. It is also useful to other value-add businesses, e.g., real-time transit recommendations based on crowdedness, or commercial valuation with crowd flows.

In this paper, we attempt to accurately estimate the crowd distribution within the urban rail transit system and take Singapore MRT (Mass Rapid Transit) system as a vehicle to study the problem. We collect one-year EZ-Link card data of Singapore MRT, involving daily rides (from both tap in and tap out) of 5 lines and 102 stations, totaling 1.2 billion records. With those records, we specifically study the two major lines (namely East-West line, or EW line, and North-South line, or NS line) that span across the country and possess the heaviest ridership (~1.5 million rides take place on those two lines everyday). Fig. 1 depicts a map of the two MRT lines and the 52 affiliated stations.

Achieving accurate estimation of crowd distribution in the MRT, however, is challenging owing to the limited information. With the EZ-Link card data we have the knowledge of the riders that enter the MRT system, but the travelers are free to move around all the stations. Fine reasoning the crowd movement needs to overcome the uncertainties that arise from the ride time and the trip destinations. Through analysis over historical MRT trip data, we have a key observation that the passenger inflows and arrival flows at various MRT stations are spatio-temporally correlated due to behavioral consistence of MRT riders.

Guided by the observation, we design and implement a machine learning based solution, CrowdAtlas, that is able to capture MRT riders’ transition probabilities and based on that perform accurate online estimation of the crowd distribution. In particular, CrowdAtlas builds a neural network model that learns the flow correlation, i.e., the riders’ transition probabilities among stations and across time from a high volume of historical MRT trips. With the model and all the tap-in records, the number of MRT riders at any MRT station can thus be estimated by aggregating the riders transitioned from all origin stations and from all past time beings. We perform comprehensive evaluations with EZ-Link data traces.
Our trace-driven evaluation results – the overall MAPE (Mean Absolute Percentage Error) is less than 15%, suggest that CrowdAtlas is able to produce accurate estimation of crowd distribution for most stations.

II. PROBLEM FORMULATION

A passenger’s rail transit ride begins from tapping in at the origin station. There are various travel and sojourn time involved during the passenger’s stay within the MRT system, which finally ends when the passenger taps out at the destination station. Additionally, if the origin and destination stations are in different lines, extra sojourn time is incurred at the interchange stations. A sequence of these ride activities is depicted in Fig. 2.

Suppose there are \( n \) stations \( S = \{s_j\} (j = 1, 2, \ldots, n) \) for the rail transit system, and a passenger’s ride start time is \( \tau \). Based on that, a station’s inflow is defined as the number of passengers tapping in the station at time \( \tau \), which is a \( \tau \)-dependent variable. We regard the inflow set of all stations \( I = \{I_j\} (j = 1, 2, \ldots, n) \) to be known, as generally these inflows could be obtained by the MRT operator in real time. Similarly, we can define a station’s outflow \( O_j^\tau \) as the number of passengers tapping out the station at time \( \tau \), which is also obtained by the MRT operator every minute.

A station’s arrival flow is defined as the number of passengers presently arriving at that station (from other stations). The present number of passengers at each station can be derived by summing inflow and arrival flow at the present time as well as the sojourn passengers’ number at that station, which can be derived from previous arrival flows minus outflows (see §III-B for details). The goal is thus to estimate a set of all stations’ arrival flows at present time \( t \), i.e., \( A = \{A_k^t\} (t > \tau; k = 1, 2, \ldots, n) \).

Special challenge comes from the nature of our problem – to instantly estimate the crowd distribution at present time. To estimate the arrival flow at time \( t \), we do not have passengers’ tap-out records that take place after time \( t \), i.e., we only have the start information (time and station) of those open trips. As a station’s arrival flow is brought by other stations’ inflows, we define transition probability \( p_{oa}^{\tau t} \) which describes the probability that a passenger arrives in station \( s_o \) at time \( t \) given the ride starts from station \( s_a \) at time \( \tau (\tau < t) \). The relation between the two flow sets \( A \) and \( I \) is

\[
A_k^t = \sum_{j=1}^{n} \int_{0}^{t} I_j^t \ p_{jk}^t \, dt, \quad \forall s_k \in S. \quad (1)
\]

The transition probability for any individual passenger is affected by his/her destination station \( s_d \) as well as ride time \( T_r \) (i.e., time spent in the rail transit system), which can be described as a function \( p_{oa}^{\tau t} = f(s_o, T_r) \). It is challenging to accurately obtain \( p_{oa}^{\tau t} \) due to the uncertainties of both destination \( s_d \) and ride time \( T_r \).

We collect a large-scale EZ-Link transit card data of all Singapore MRT trips in a whole year, involving ~2.8 million average daily ridership among 5 lines and 149 stations. We specifically study the two the major MRT lines – EW and NS lines that involve 52 stations spanning across the country with ~1.5 million rides everyday. Here we extract one month data to illustrate and quantify the two uncertainties. Fig. 1 depicts the two MRT lines, where each station is named in the format of “line name + number” (e.g., EW15, or NS14). Transfers may take place at 3 interchange stations marked in the figure (i.e., NS1/EW24, EW13/NS25, and EW14/NS26).

**Ride-Time Uncertainty.** A passenger’s ride time \( T_r \) comprises several time periods between ride activities – walking time, waiting time, travel time (as illustrated in Fig. 2). They are affected by either passenger behaviors (e.g., walking speed, shopping activities, waiting) or train scheduling (different speeds and schedules). As a result, the ride time may vary subject to an unknown distribution \( (T_r \sim F^t_r(t)) \). For the above two-line dataset, the maximum, minimum and median ride times from a terminal station EW1 to all other stations are depicted in Fig. 3 respectively (separately by EW/NS line). The ride time variance is observed at each destination station with a growing trend as the station interval increases. There exists even higher variance when transfer is involved in the trip due to the additional uncertainty of transfer time.

**Destination Uncertainty.** It is manifest that a passenger’s destination station \( s_d \) is unknown until his/her ride ends. Here we concern the destinations of a batch of passengers who depart from the same origin station, and we inspect if their distribution is analytical by studying the MRT trips. Fig. 4 depicts the destination distributions of passengers departing from two major stations of high inflows (EW15 and NS1/EW24).
might be
\( F(\text{NS1/EW24}) \) with more travel diversities further
\( \tau(\text{d}) \) NS1/EW24 12:00-13:00
\( \sim \) s(b) EW15 12:00-13:00
\( \text{(b) EW15} \) between any pair of origin-
\( = p_{\text{ROWD}} \) is determined by both ride start and
\( p_{\text{ROWD}} \) can be
\( \text{ROWD} \) is consistent across all days. In view of such an observation,

\( \text{transition probability} \)
\( \text{temporal variations.} \)
\( \text{Fig. 5} \) suggests
\( \text{similar} \)
\( \text{MRT lines} \) over 5 different weekdays, where we see similar
\( \text{proportions of passengers} \)
\( \text{stations} \) (on the x-y plane). Comparing the destination distribution
different origin stations and different start times, we clearly see that the destinations are subject to another unknown
distribution among stations \( (s_d \sim F_{\text{d}}(s)) \), which suggests both temporal and spatial variations. In addition, interchange
\( \text{stations} \) (e.g., NS1/EW24) with more travel diversities further increase such uncertainty.

**Key Observation.** Instead of looking at the individual ride behaviors with such high uncertainties, we attempt to
study the collective behaviors based on a large volume of passengers. Through quantitative analysis on a number of
origin-destination station pairs, we observe spatio-temporal correlations between their inflows and arrival flows. Fig. 5
depicts the proportions of passengers transitioned from EW15 to EW27 (within the same MRT line) and to NS14 (across two
MRT lines) over 5 different weekdays, where we see similar temporal variations. The observation from Fig. 5 suggests
that the transition probability \( p_{\text{d}}^{\tau t} \) between any pair of origin-destination stations and across any time span \( \tau \rightarrow t \) might be consistent across all days. In view of such an observation,

![Fig. 4. Destination distributions from two representative stations during peak and off-peak hours.](image)

![Fig. 5. Passenger transitions between (a) a pair of stations in the same MRT line, and (b) a pair of stations across different MRT lines.](image)

In a peak hour 7:00-8:00 and an off-peak hour 12:00-13:00 respectively. The proportions of passengers ending at various stations (on z axis) are projected to the map of the two MRT lines (on the x-y plane). Comparing the destination distribution from different origin stations and different start times, we clearly see that the destinations are subject to another unknown distribution among stations \( (s_d \sim F_{\text{d}}(s)) \), which suggests both temporal and spatial variations. In addition, interchange stations (e.g., NS1/EW24) with more travel diversities further increase such uncertainty.

**Key Observation.** Instead of looking at the individual ride behaviors with such high uncertainties, we attempt to
study the collective behaviors based on a large volume of passengers. Through quantitative analysis on a number of
origin-destination station pairs, we observe spatio-temporal correlations between their inflows and arrival flows. Fig. 5
depicts the proportions of passengers transitioned from EW15 to EW27 (within the same MRT line) and to NS14 (across two
MRT lines) over 5 different weekdays, where we see similar temporal variations. The observation from Fig. 5 suggests
that the transition probability \( p_{\text{d}}^{\tau t} \) between any pair of origin-destination stations and across any time span \( \tau \rightarrow t \) might be consistent across all days. In view of such an observation,

we attempt to build a machine learning model to learn such transition probabilities among stations and across time from the high volume of historical MRT trips.

### III. CrowdAtlas Design

Guided by the above real-world trace analysis, we design CrowdAtlas for online estimation of the crowd distribution. Fig. 6 sketches the architecture of CrowdAtlas, which comprises two major components.

**Correlation Learning:** It builds a neural network model to learn the flow correlation among all stations, and consequently derive the transition probabilities \( p_{\text{d}}^{\tau t} \) between all pairs of MRT stations from inflows to arrival flows. With a list of features (start time, origin station, etc.) encoded as input, the model is trained based on historical MRT trip data to output transition probabilities between two stations over any time period.

**Online Estimation:** It takes the transition probabilities \( p_{\text{d}}^{\tau t} \) from the neural network model as input, and thus the passenger number at any MRT station (i.e., crowd distribution) can be estimated in real time based on its present inflow and the arrival flow derived based on inflows from other stations and at previous time beings as well as the transition probabilities from those stations.

#### A. Correlation Learning with Neural Network

As mentioned above, the transition probability \( p_{\text{d}}^{\tau t} \) can be expressed as a function of two factors ride time and destination \( (p_{\text{d}}^{\tau t} = f(s_d, T_r)) \), which cannot be directly derived due to the uncertainty of both factors. Instead, we design a neural network model to learn the transition probabilities between an arbitrary pair of stations and at arbitrary time of a day from flow correlation among historical MRT trip records.

**Feature Extraction.** \( p_{\text{d}}^{\tau t} \) is determined by both ride start and present arrival information (time and station). Here we name the above four factors as start time, origin station, present time, and present station. Note that the present station refers to the station a passenger is presently arriving at or is about to arrive at (if the passenger is presently on the MRT train). We acquire training samples by transforming the MRT trip records with ride start and end time, as well as the origin and destination stations. Each MRT trip record [tap-in time, origin station, tap-out time, destination station] is transformed to a training sample of [start time, origin station, present time, present

---

**Fig. 6. Architecture of CrowdAtlas.**

<table>
<thead>
<tr>
<th>Monday</th>
<th>Tuesday</th>
<th>Wednesday</th>
<th>Thursday</th>
<th>Friday</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>12</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>16</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>20</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Table:** Proportion of passengers at various destinations from two representative stations during peak hours.

<table>
<thead>
<tr>
<th>Start time (h)</th>
<th>Monday</th>
<th>Tuesday</th>
<th>Wednesday</th>
<th>Thursday</th>
<th>Friday</th>
</tr>
</thead>
<tbody>
<tr>
<td>7:00-8:00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>12:00-13:00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

---

**Fig. 4. Destination distributions from two representative stations during peak and off-peak hours.**

**Fig. 5. Passenger transitions between (a) a pair of stations in the same MRT line, and (b) a pair of stations across different MRT lines.**

---

**Fig. 6. Architecture of CrowdAtlas.**
station] (where the difference between train arrival time and tap-out time is negligible for training with high volume of data).

On this basis, we further derive \( \Delta t = \text{present time} - \text{start time} \) for each record, and filter the records with \( \Delta t \in [RT_{\text{min}}, RT_{\text{max}}] \) as training samples (\( RT_{\text{max}} \) and \( RT_{\text{min}} \) are the reasonable maximum and minimum ride time among stations shown in Fig. 3). For each training sample, we set (\text{start time, origin station, delta time}) as input features of the neural network, and take a passenger’s present station in the record as the label. Accordingly, for a group of start time, origin station and delta time, the output of neural network is a distribution of transition probabilities to all stations that the passenger probably arrives at present. In addition, to support learning the correlation among stations in multiple lines, we re-index all stations in a sequence with all interchange stations in the front, followed by the rest of the stations by MRT lines.

**Neural Network Structure.** Fig. 7 depicts the neural network structure, which is composed of an input layer, an output layer and two hidden layers. To avoid the negative influence of feature values on training weight changes, we conduct one-hot encoding for each feature and the label. We use ReLU as the activation function of the hidden layers to relieve the gradient vanishing problem [4], and use softmax as the activation function of the output layer to generate probability distribution [5]. Finally, we adopt cross entropy as the loss function, which indicates the closeness between two distributions [6], and set Adam [7] as the optimizer.

**B. Online Estimation of Crowd Distribution**

Through learning with the neural network, transition probabilities \( p^t_{rj} \) between any two stations \( s_j, s_k \in S \) for any time \( \tau, t \) during MRT operation hours can be obtained from the neural network at real time. For passengers starting from any station \( s_j \) and time \( \tau \), we can acquire the inflow \( I^t_{jr} \) by counting the tap-in records. Accordingly, we can estimate the distribution of passenger number \( F^t_{\text{in}}(r,t) \) at an arbitrary arrival station \( s_r \) in each minute \( t \) by \( F^t_{\text{in}}(r,t) = I^t_{jr} p^t_{jr} \). On this basis, we can derive the present arrival flow of a station \( A^t_r \) by aggregating the arriving passengers from different origin stations in a given duration (the concerned start time for each origin station \( \tau_j \) depends on its travel time to the present station). This can be expressed as

\[
A^t_r = \sum_{\tau=\tau_j}^{t-1} \sum_{j} F^t_{rj}(r,t), \quad \forall s_r \in S, t > \tau. \tag{2}
\]

To acquire a station \( s_r \)’s total passenger number, its present inflow \( I^t_{jr} \) should be added. In addition, passengers who have earlier arrived but not yet tapped out are also considered. We obtain the outflow \( O^t_{rj} \) of station \( s_r \) at time \( \tau' \in [t-T_s, t-1] \) by counting the tap-out records, where \( T_s \) is the maximum sojourn time at the destination station. These passengers who have tapped out should be removed from the arrival flows \( \{A^t_r\} \) during the above period. Therefore, the overall crowd distribution among stations can be estimated by

\[
F^t_N(r,t) = I^t_r + A^t_r + \sum_{\tau=t-T_s}^{t-1} (A^\tau_r - O^\tau_r). \tag{3}
\]

**IV. EXPERIMENTS**

We conduct experimental study with EZ-link data traces to evaluate the estimation performance of CrowdAtlas.

**A. Data Preparation and Training**

We collect one-year EZ-Link data of Singapore MRT trips, and extract a dataset of ride records within the two major lines EW and NS (as depicted in Fig. 1) for all evaluations below. To reduce the data size, we only retain 6 major fields of each record – [origin station, tap-in date & time, destination station, tap-out date & time]. As the total number of stations in the two MRT lines is 52 and we conduct training in batches by the hour of start time, the unit numbers of input and output layers are 192 and 52 respectively. On this basis, we set the unit numbers of two hidden layers as 150 and 100. Each time we take records on weekdays\(^1\) of two months for training and records on the weekdays or weekends of the following week for testing. The selected data of different dates will be shuffled before they are input into the neural network. The training is conducted for 200 epochs so that the loss function converges.

**B. Trace-Driven Performance Evaluation**

We extract EZ-link data traces of the testing days and infer the passenger trajectories, through which we obtain a set of derived ground truths, i.e., the crowd distribution among the 52 stations at any time being. The historical data provides complete start and end information of all MRT trips that take place before or after any given present time \( t \). This allows us to reconstruct the ground truth of crowd distribution with no uncertainties in trip ride time and destinations.

We first study the neural network’s learning performance by comparing CrowdAtlas estimation and the ground truth of passengers from a same origin station and a given start time. Fig. 8 gives the comparison results from two different origin stations EW1 and EW15 on a typical testing weekday.

\(^1\)The passengers’ travel demand pattern on weekends might be different from that on weekdays, which could be separately trained likewise.
We quantitatively measure the estimation accuracy in a time scale,

\[ MAPE = \frac{100\%}{T} \sum_{t} |(y_t - \hat{y}_t)/y_t|, \]

where \( \hat{y}_t \) and \( y_t \) (\( t = 1, 2, \ldots, T \)) are the estimated and ground-truth passenger numbers at different time beings. Table I gives the MAPEs statistics of both CrowdAtlas and the baseline across different station region and line groups on weekdays in 30 and 60 minutes respectively. We see that the MAPEs of CrowdAtlas are much smaller compared with the baseline for all stations, and their overall MAPEs are \( \sim 14\% \) versus \( \sim 28\% \).

V. RELATED WORK

There are some studies relevant to our topic, and we summarize them as follows.

**Passenger Behavior Study of Rail Transit System.** Previous works on the rail transit system attempted to estimate passen-
ger’s travel time [11], plan their travel route [12], or analyze the mobility patterns [13] based on the transit card records. Some researchers further leverage cellular data collected from passengers’ mobile phones to capture their travel routes and transfer activities, and conduct estimation of crowd density at stations [14], [15]. All existing studies, however, are only able to extract passengers’ travel demands but not their present statuses in real time. Most studies are based on historical data only and with heuristic models. On the other hand, emergency events like railway disruptions have been studied in the transportation field, which mainly focuses on optimizing the route design of bus bridging services in presence of rail system failures [16], [17]. All existing studies assume that the crowd distributions at disrupted stations are known. Our work can produce accurate online estimation of crowd distribution within the rail transit system, which differs from existing data driven analytical studies and fills the gap of existing railway disruption studies in the transportation field.

**Machine Learning for Transport Analysis.** Machine learning techniques have been applied to transport analysis and prediction in recent years mainly due to their powerful capabilities in extracting hidden characteristics from historical mobility data. For instance, traffic speed prediction has been intensively studied by exploiting deep learning models including LSTM [18], CNN [19] and combination of them [20]. Likewise, traffic flow prediction has also been studied based on learning models like SAE [21] or CNN with grid partition [22]. In addition, reinforcement learning has been utilized to control traffic lights for improved road utilization [23] and dynamically reposition bikes for minimum customer loss [24]. Most existing studies, however, focus on road traffic learning. In contrast, our learning objective within the rail transit system is of a different purpose and more challenging, given that less knowledge on the transport operation can be extracted from the transit card data that only provides the start and end information of the trips leaving the trip details empty.

**VI. Conclusion**

In this paper, guided by a key observation that the passenger inflows and arrival flows at various MRT stations are spatio-temporally correlated due to the behavioral consistence of MRT riders, we design and implement CrowdAtlas, which builds a neural network model to learn the passenger transitions among stations within the urban rail transit system and based on that perform online estimation of the crowd distribution. Comprehensive performance evaluations are done with EZ-Link data traces that demonstrates CrowdAtlas’s high accuracy and effectiveness.

**Acknowledgment**

This research is supported, in part, by NRF Singapore under its grant SDSC-2019-001, Alibaba Group through Alibaba Innovative Research (AIR) Program and Alibaba-NTU Singapore Joint Research Institute (JRI), and Singapore MOE Tier 1 grant RG18/20. Any opinions, findings and conclusions or recommendations expressed in this material are those of the author(s) and do not reflect the views of funding agencies.

**References**