

Institute for Infocomm Research

## Identifying Tourists from Public Transport Commuters

#### Mingqiang Xue ^

- Huayu Wu ^
- Wei Chen ^
- Wee Siong Ng ^
- Gin Howe Goh #



# ^ Institute for Infocomm Research# Land Transport Authority of Singapore

Institute for Infocomm Research (I<sup>2</sup>R)

### Outline

- Introduction
- Backgroud
- Our Approach
  - Station Ranking
  - Label Inference
- Experiments
- Case Study
- Related Work
- Conclusions

- Tourism industry, a key economic driver for Singapore:
  - 15 million foreign visitors a year
  - 23 billion Singapore Dollar receipts in 2012
- Understanding tourists travelling behaviors is important:
  - Where do they go?
  - How they travel from one place to another?
  - Where do they stay?
- Useful to stake holders:
  - Government (tourism board, city planning, public transport): better planning, improve existing services
  - Private (travel agencies, taxis, hotels, restuarants, advertising etc): better or new business

- A highly efficient transport system in Singapore
  - Buses, MRTs, LRTs
  - Payment mostly with commuter card (EZ-link)
  - Trajectories (partially) recorded
- Utilized by both locals, business travellers, and tourists in Singapore

• Who Are the Tourists Among the Commuters?







### **Main focus**

### **Background – public transport**

- The public transport system
  - MRT, similar to the subway in NYC

 – LRT, short distance neighborhood railway transport

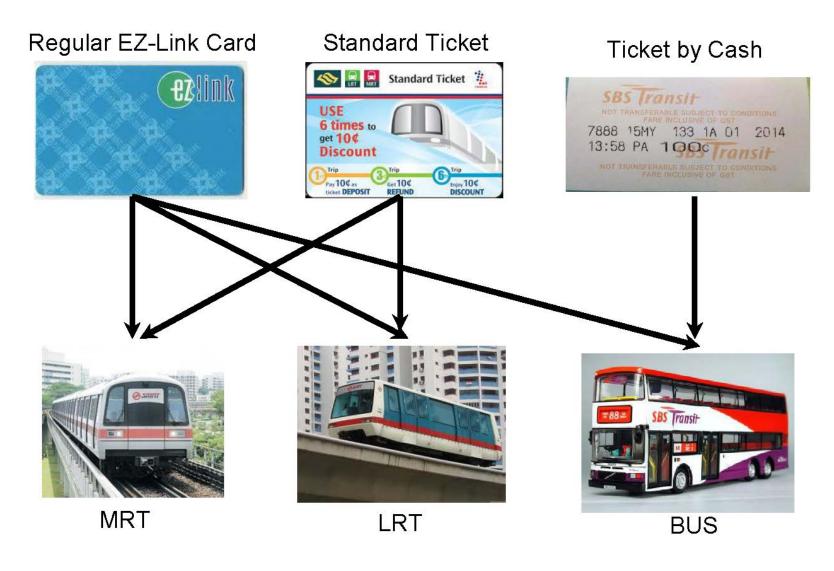






– Bus

### **Background – ticketing & Payment**



### **Background – travel record**

Field	Description
Card_Number_E	Card ID for this ride
Transport_Mode	BUS, LRT, or MRT
Entry_Date	Date when ride started
Entry_Time	Time when ride started
Exit_Date	Date when ride ended
Exit_Time	Time when ride ended
Payment_Mode	Method of payment
Origin_Location_ID	Starting location of the ride
Destination_Location_ID	Ending location of the ride

### The travel record Schema

### Background

- Many tourists use standard tickets to travel around
- Tourists travelling patterns from standard tickets records
  Problem: discontinued trajectories, no bus records, size could be small
- Our goal: identify tourists from regular EZ-link card users

### **Our Approach**

- A Two staged processs:
  - Stage 1: Initialization
    - Score each MRT/LRT station based on the attractiveness to tourists
  - Stage 2: Iterative Refinement
    - Update the scores for both MRT/LRT stations and tourists in a graph
    - Classify one as a tourist/non-tourist after the final iteration

- *t* a tourist commuter
- $m_i$  an event that a commuter has visited station *i*
- We solve for each station:

Score  $s_{m_i} \sim \Pr(t|m_i)$ 

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- $m_i$  an event that a commuter has visited station *i*
- $n_i^s$  number of trips with standard tickets at station *i*
- $n_i^r$  number of trips with regular EZ-link card at station *i*
- $n_i^t$  number of trips from tourists with standard tickets at station *i*

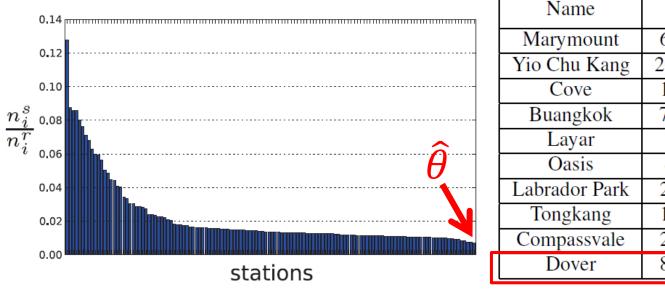
Score 
$$s_{m_i} \sim \Pr(t|m_i) = \Pr(t) \cdot \frac{\Pr(m_i|t)}{\Pr(m_i)}$$

The estimation of  $Pr(m_i|t)$ :

- Idea: standard tickets records, but isolate the effects of locals
- $\hat{\theta}$  is the probability that a local uses a standard ticket

$$\hat{\Pr}(m_i|t) = \frac{n_i^t}{\sum_i n_i^t} \text{ where } n_i^t = n_i^s - n_i^r \cdot \hat{\theta}$$

• The estimation of  $\hat{\theta}$ :



Name	$n_i^s$	$n_i^r$	$\frac{n_i^s}{n_i^r}$	
Marymount	6218	629435	0.009879	
Yio Chu Kang	20361	2067636	0.009847	
Cove	1817	189873	0.009570	
Buangkok	7454	787463	0.009466	
Layar	345	37211	0.00927	
Oasis	489	53696	0.009107	
Labrador Park	2473	292858	0.008444	
Tongkang	1295	158299	0.008181	
Compassvale	2705	358175	0.007552	
Dover	8963	1247247	0.007186	
		$\hat{\theta}$	7	



Dover surroundings: - An isolated educational institution - No closeby residences

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Score 
$$s_{m_i} \sim \Pr(t|m_i) = \Pr(t) \frac{\Pr(m_i|t)}{\Pr(m_i)}$$

The estimation of  $Pr(m_i)$ :

$$\hat{\Pr}(m_i) = \frac{n_i^s + n_i^r}{\sum_i n_i^s + n_i^r}$$

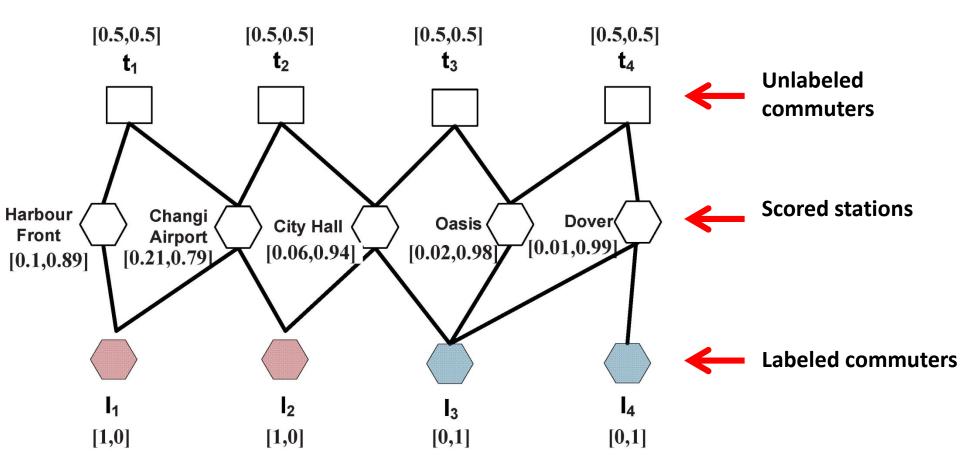
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Score 
$$s_{m_i} = \Pr(t) \cdot \frac{\Pr(m_i|t)}{\Pr(m_i)}$$

where 
$$\hat{\Pr}(t) = \frac{\sum_i 2n_i^t}{\sum_i n_i^s + n_i^r}$$

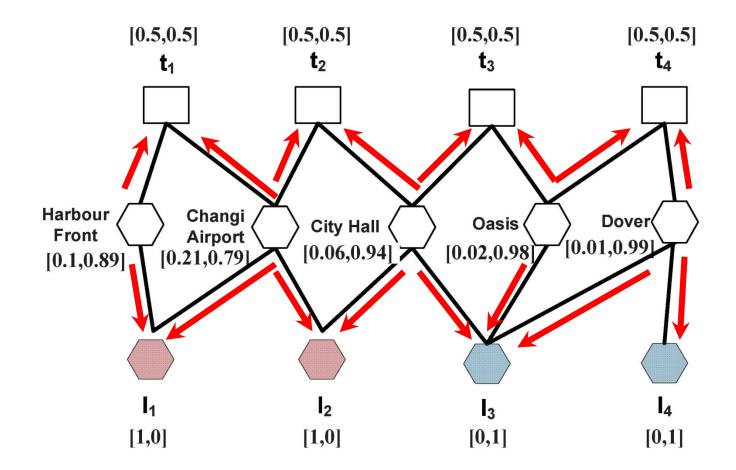
Name	$s_{m_i}$		
Changi Airport	0.213668		
Marina Bay	0.145012		
Clarke Quay	0.144702		
Bayfront	0.128008		
Little India	0.118879		
Chinatown	0.113837		
HarbourFront	0.106443		
Bras Basah	0.104787		
Esplanade	0.099637		
Orchard	0.098623		
Lavender	0.093104		
Farrer Park	0.081844		
Promenade	0.079080		
Bugis	0.070973		
City Hall	0.064815		

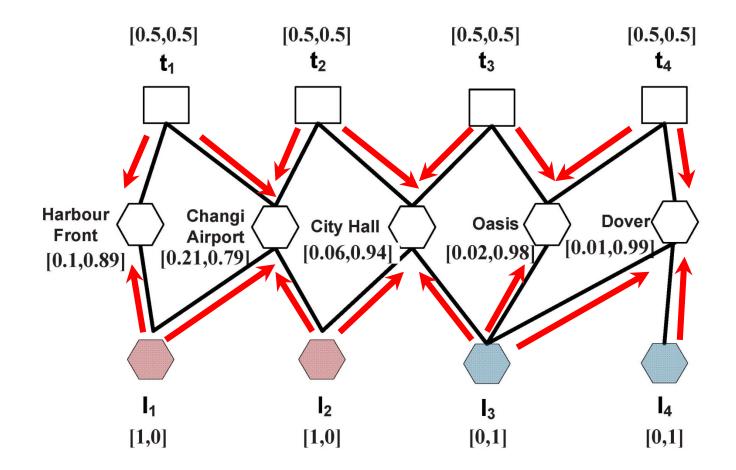
#### **Top Ranked stations based on attractiveness**



#### A toy Station-Commuter Relationship graph

- While # of iterations < predefined threshold (e.g 150) :
  - Update the class distribution of each commuter based on its current class distribution and the class distributions of stations that they visited
  - Update the class distribution of each station based on its current disribution and the class distributions of commuters who visit them





• Updating functions:

$$\phi_{l_i}^k \leftarrow \alpha \cdot \phi_{l_i}^{k-1} + (1-\alpha) \cdot \frac{\sum_{m \in N(l_i)} w_{l_im} \cdot \phi_m^k}{\sum_{m \in N(l_i)} w_{l_im}}$$
 Update for commuters 
$$\phi_{t_i}^k \leftarrow \beta \cdot \phi_{t_i}^{k-1} + (1-\beta) \cdot \frac{\sum_{m \in N(t_i)} w_{t_im} \cdot \phi_m^k}{\sum_{m \in N(t_i)} w_{t_im}}$$

• Final class assignment:

$$\hat{C} = \underset{c}{argmax} \frac{P(t_i|c)}{P(t_i)} = \underset{c}{argmax} \frac{P(c|t_i)}{P(c)}$$

### For $c \in \{\text{Tourist, Non-Tourist}\}$

### **Experiments**

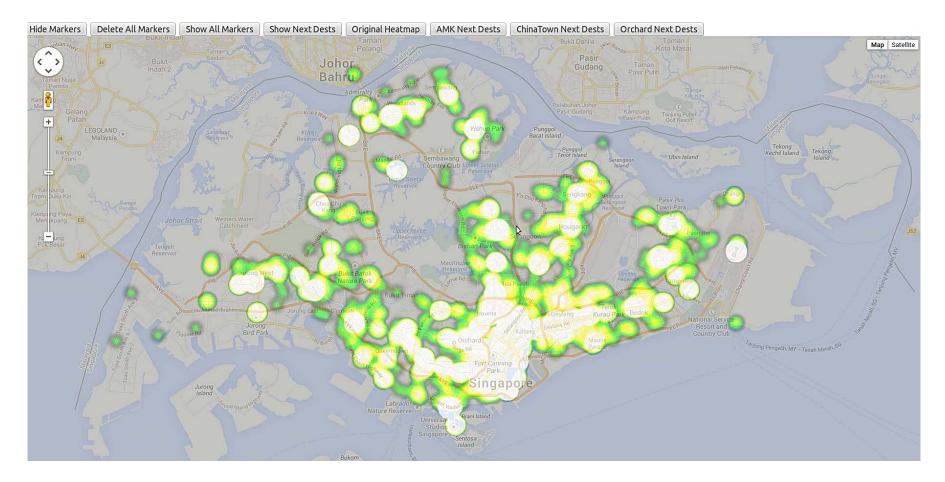
- One-month EZ-link records from LTA
- Preprocessing:
  - Exclude commuters with less than 6 records
- Data description:
  - 1.7 million commuters
  - 49.5 million records
  - Training set: 1000 tourists and 250,000 locals
- Competitors:
  - FTF (Fast Transversal Filter): a state-of-the-art iterative inference algorithm
  - SVM
- Evaluation metric:
  - F1 score:  $F1 = \frac{2 \times Precision \times Recall}{Recall + Precision}$

### **Experiments**

	SVM		FTF		$I^2$	
p%	Macro F1	Micro F1	Macro F1	Micro F1	Macro F1	Micro F1
5%	0.57984	0.8415	0.6109	0.8419	0.6267	0.8504
10%	0.5917	0.8420	0.6263	0.8464	0.6572	0.8538
15%	0.6144	0.8411	0.6441	0.8433	0.6677	0.8560
20%	0.6199	0.8480	0.6758	0.8504	0.6962	0.8575
25%	0.6286	0.8402	0.6956	0.8459	0.7154	0.8549

### **Comparison Results**

### **Case Study**



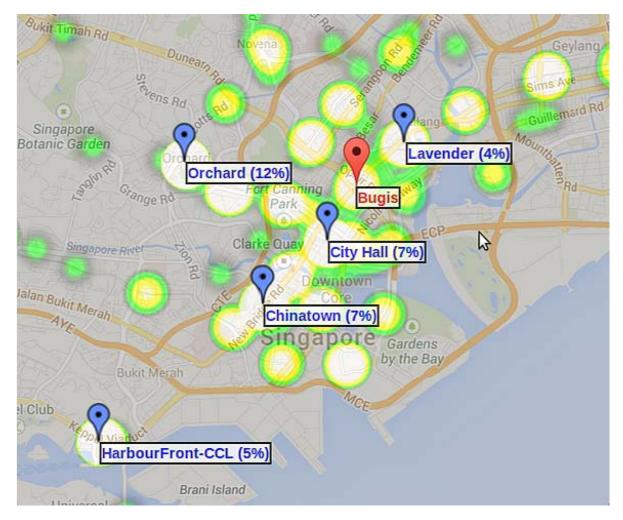
#### Places visited by tourists by popularity

### **Case Study**



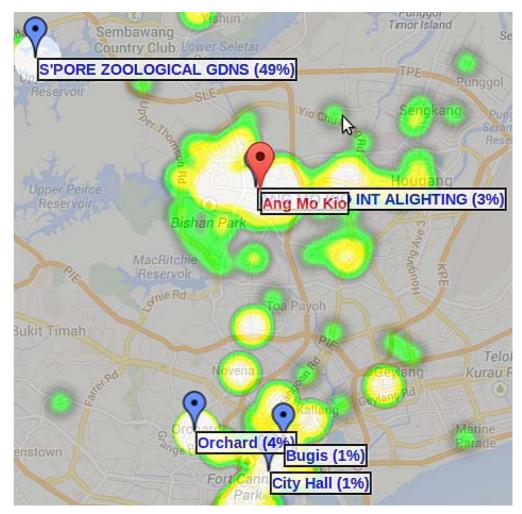
#### Where do tourists go from the airport?

### **Case Study**



#### Where do tourists go from bugis?

### **Cast Study**



#### Why do tourists visit Ang Mo Kio?

### **Related Work**

- Mining public transport data
  - Improve public transport in a city
  - Behaviors of populations (what's the popular shopping places)
  - Behaviors of individuals (what's one's home, work place)
- Mining tourists data
  - Travelling patterns of tourists (e.g based on Geo-tagged images)

### Conclusions

- Extract tourists records from public transport data
  - Meaningful to stakeholders, both private and government
- Proposed an algorithm based on:
  - Station scoring and iterative score refinement
- Verified findings with experiments
- Hope to attract interest to solve similar problems in other cities, e.g. Hong Kong, NYC, London etc.

# Thank you