

Enriching Traffic Information with a Spatiotemporal Model based on Social Media

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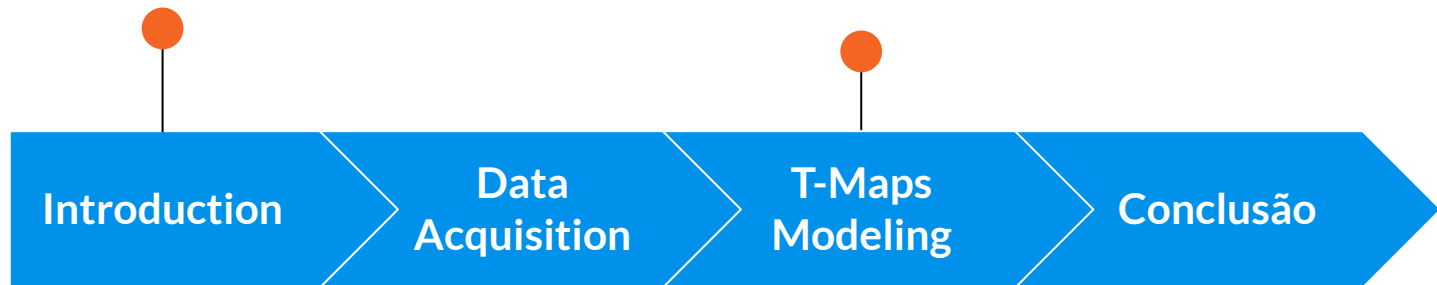
DCC **UF** *m* **G**

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Agenda

- Contextualization
- Motivation
- T-MAPS
 - A case Study



- Data sources
- Spatiotemporal coverage
- Twitter as a traffic sensor

- Related work
- Future directions

Introduction

- ◎ The **quality of life** in a city is, in part, a **reflection** of the **mobility** which the city offers
- ◎ It implies in the **constant** need for **planning** and **management** of the transportation system.

Introduction

- ◎ Who are interested in?
 - Governments
 - Researchers
 - Industries
- ◎ How are they studying and planning the Intelligent Transportation Systems (ITS)?
 - Using raw data sources
 - ◎ Inductive loops (velocity, density, and flow)
 - ◎ Traffic cameras
 - ◎ Origin-destination matrix

Introduction

◎ Who are interested in?

○ Governments
○ Researchers
○ Industries
◎ How are they studying and planning the ITS?
○ Raw Data sources
◎ Inductive loops (velocity, density, and flow)
◎ Traffic camera
◎ Origin-destination matrix

✘ Unfortunately, the **access** to these **data** sources **is**, in general, **limited** to those who are connected to *governmental entities or large corporations.*

Introduction

- ◎ The Location-Based Social Media (LBSM)
 - Ex: Twitter, Instagram, and Foursquare

- ◎ LBSM as an alternative
 - Low cost
 - Users sharing their
 - ◎ Thoughts
 - ◎ Viewpoints
 - ◎ Their feelings
 - ◎ **Traffic conditions**

Introduction

- ① In this work, we **investigated** the **traffic scenario** from the **lens** of **LBSM**
- ① We conducted a study to understand better the **relationship** between the **real traffic** scenario and the **data** provided by **Twitter**

Introduction

Goals

- **LBSM data collection and its characterization** as a data source to describe the traffic scenario
- **Twitter MAPS (T-MAPS):** we propose a low-cost spatiotemporal model to improve the description of traffic conditions based on tweets.

Data collection

◎ Ordinary users X Specialist users

Data collection

⊙ Ordinary users X **Specialist users**

| Acc name | # Tweets |
|--------------------------|-------------|
| @511NYC | 126925 |
| @TotalTrafficNYC | 20267 |
| @WazeTrafficNYC | 7850 |
| ... | ... |
| @NYC DOT | 3680 |
| Total of 21 accs: | 655K |



Total Traffic NYC

@TotalTrafficNYC

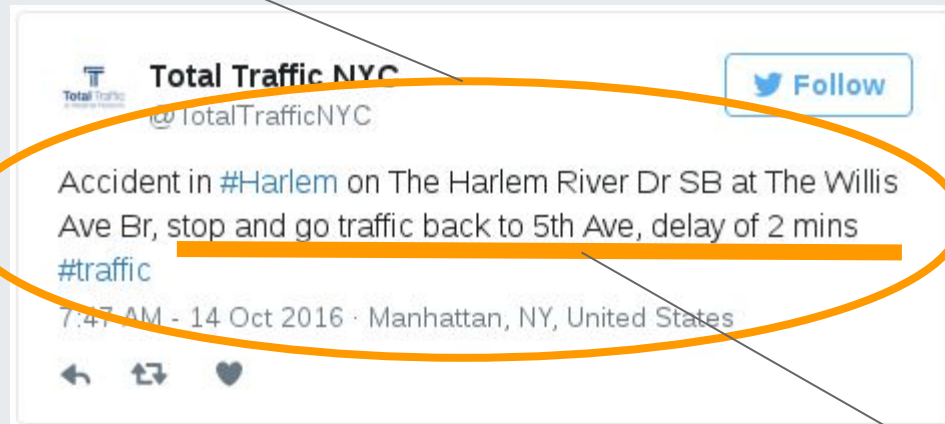
 Follow

Accident in [#Harlem](#) on The Harlem River Dr SB at The Willis Ave Br, stop and go traffic back to 5th Ave, delay of 2 mins
[#traffic](#)

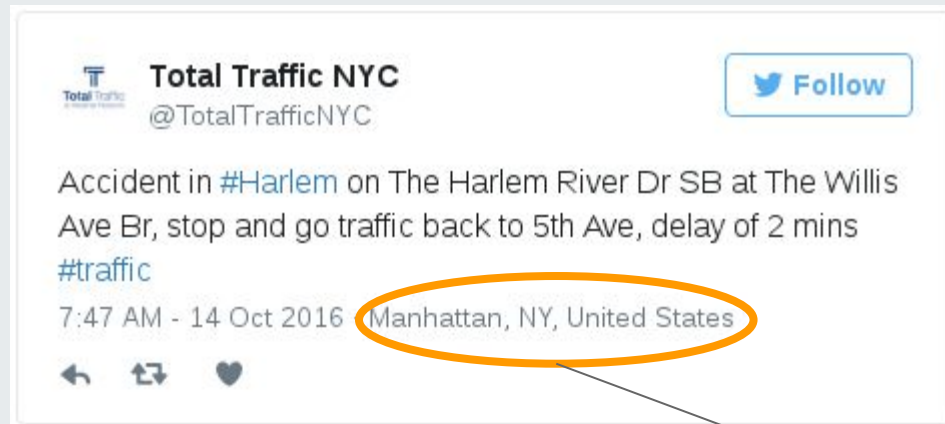
7:47 AM · 14 Oct 2016 · Manhattan, NY, United States



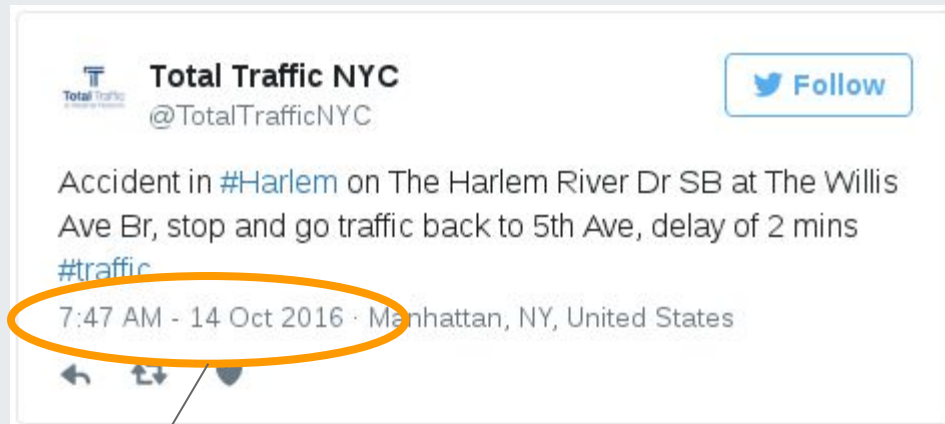
Traffic event description



Traffic condition



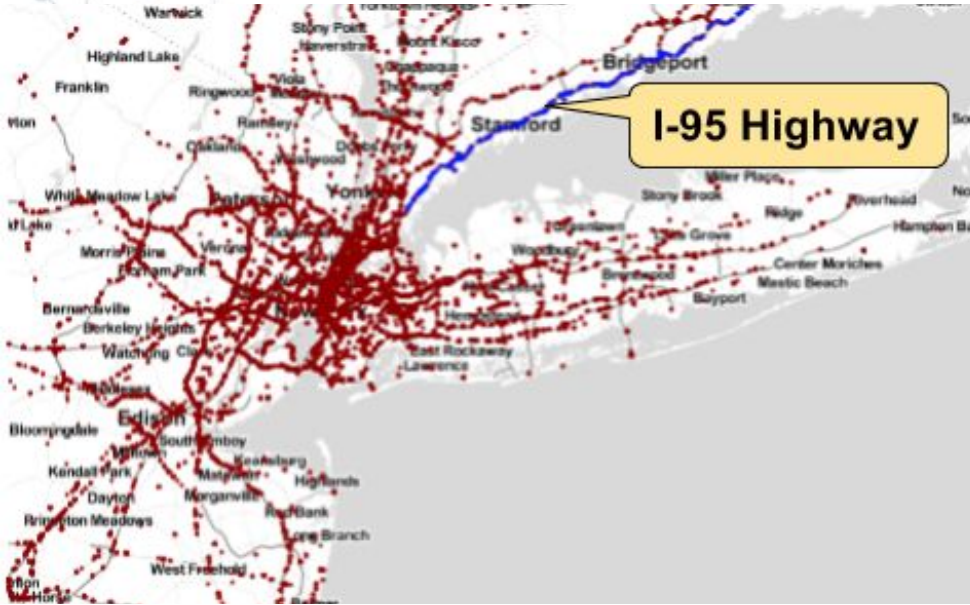
Location description. Some Tweets have geotag.



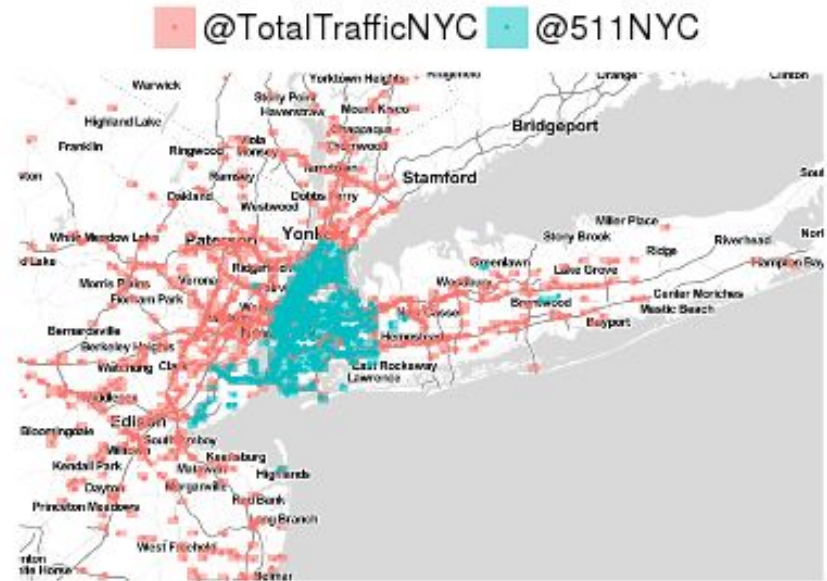
Tweet input hour

Data collection

Spatial coverage



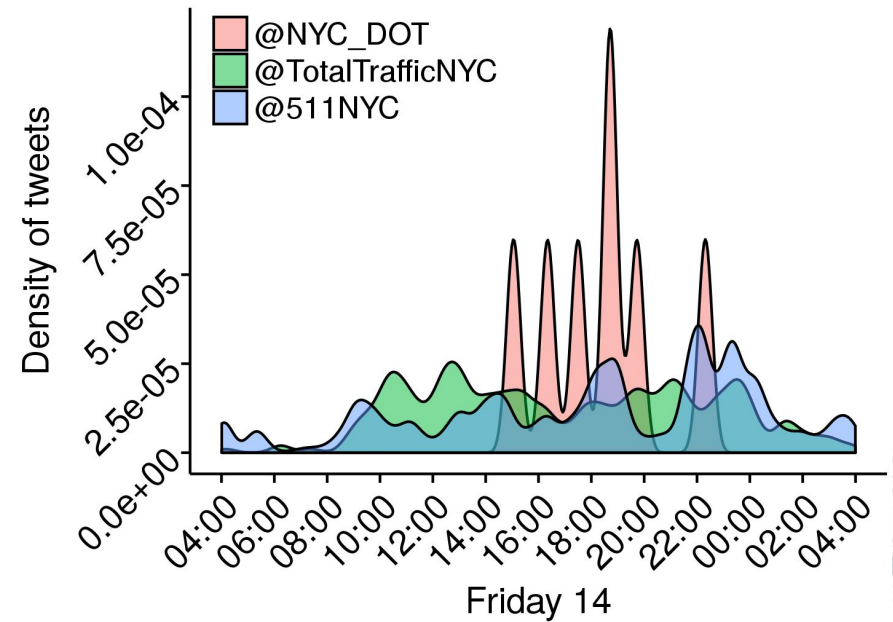
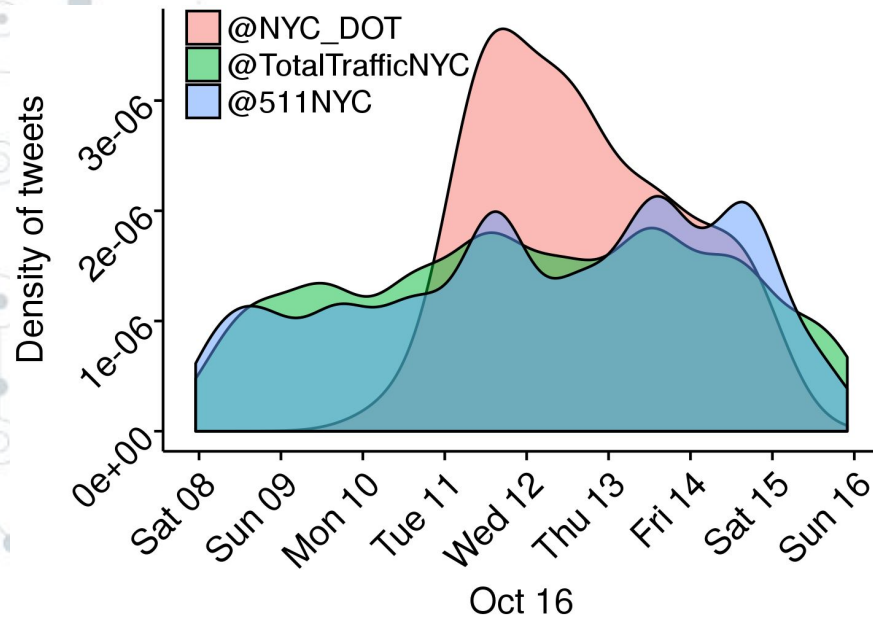
Tweets in NY



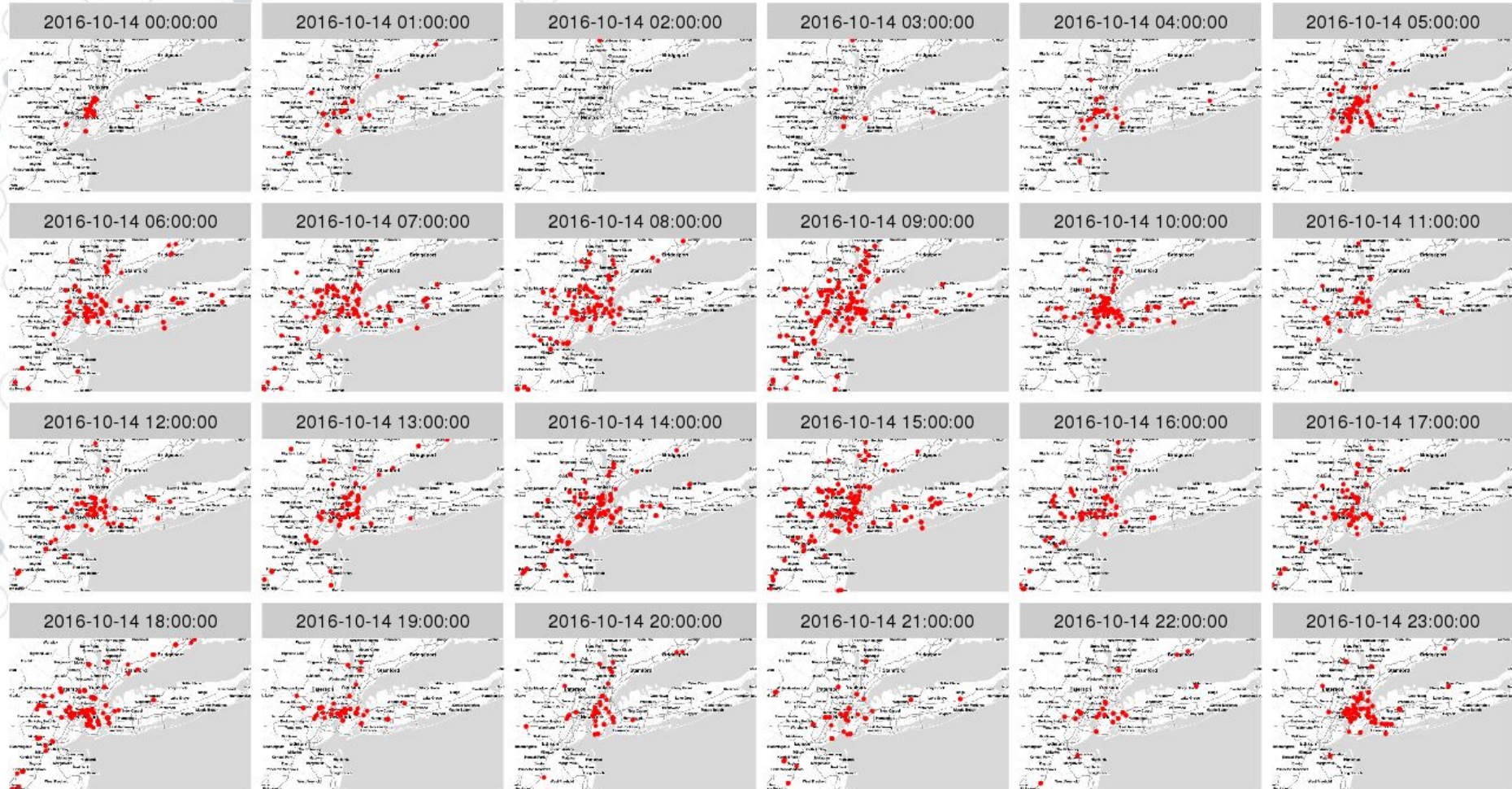
Spatial coverage in NY of two specialist accs

Data collection

Temporal coverage



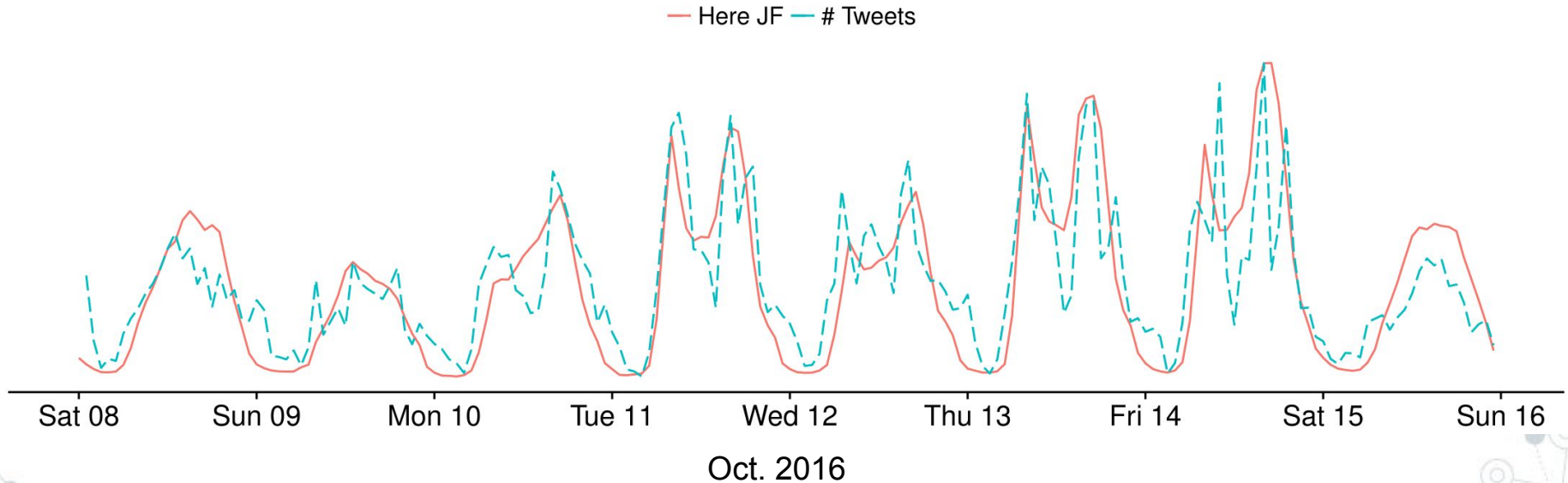
**Temporal coverage of
three accs**



Twitter as a traffic sensor

- ① How related are the tweets to the traditional traffic sensor?

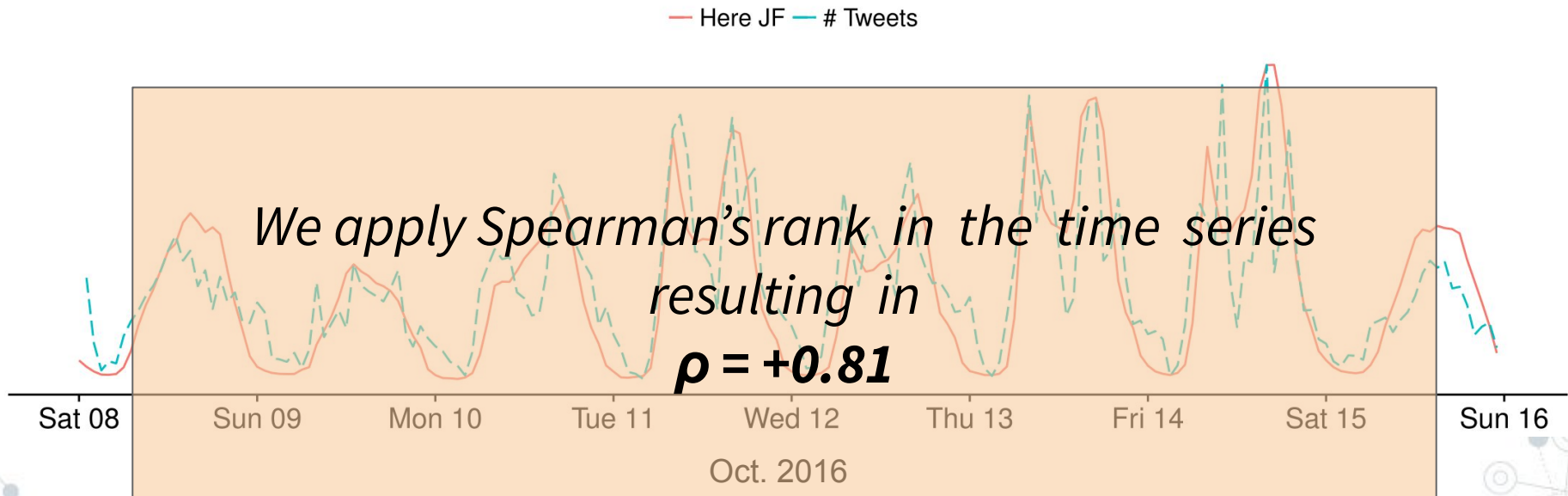
Twitter as a traffic sensor



Data:

- Jam Factor (Here developer API)
- # tweets

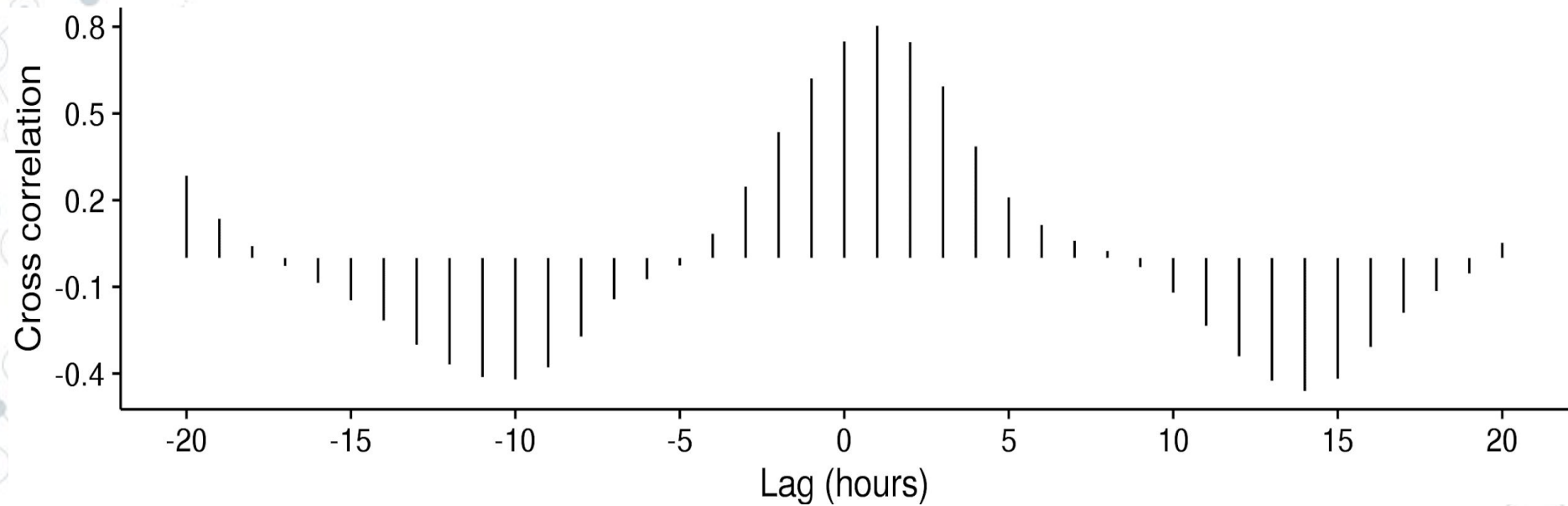
Twitter as a traffic sensor



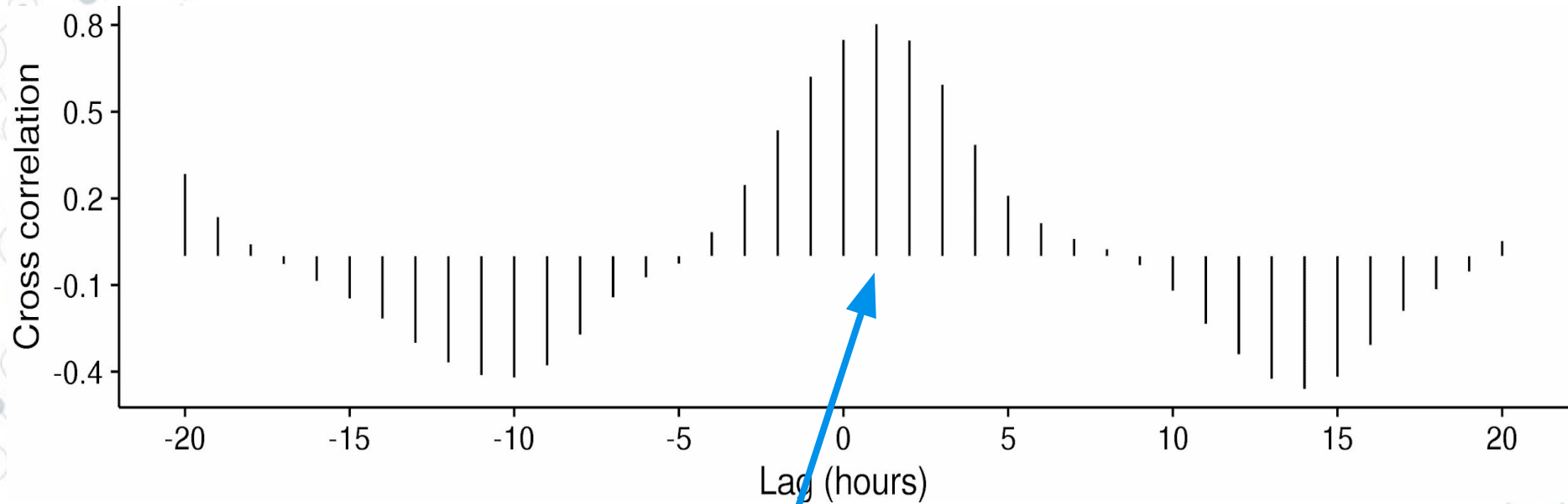
Data:

- Jam Factor (Here developer API)
- # tweets

Twitter as a traffic sensor



Twitter as a traffic sensor



The highest correlation (0.8) appears when the lag is +1 meaning
#tweets curve is 1 hour ahead of JF

Twitter MAPS (T-MAPS)

◎ Modeling Process

1. Data acquisition
2. Filtering and data fusion process
3. Metrics

T-MAPS

Step 1 - Data Acquisition



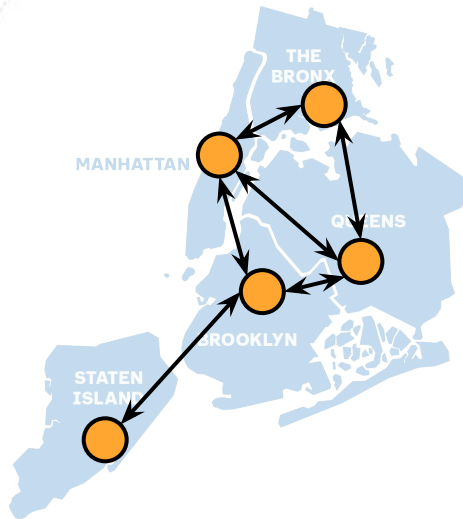
New York City
boundaries



Data from LBSM

T-MAPS

Step 2 - Filtering and Data fusion



$G(V,E)$

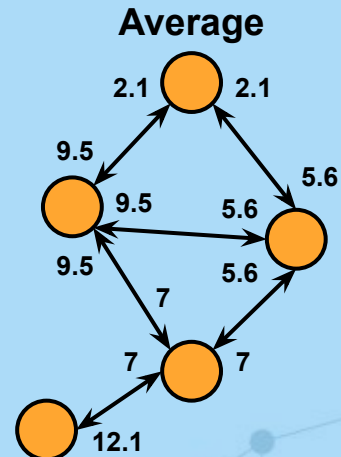
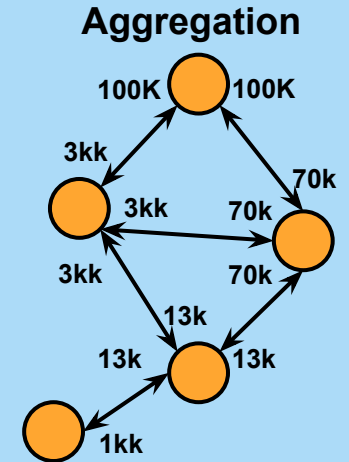
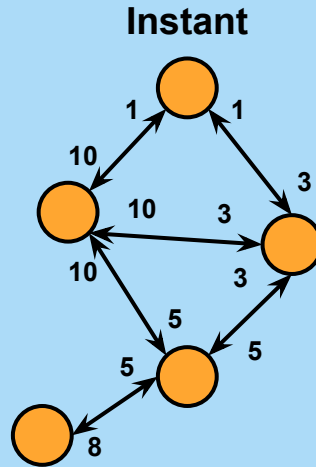
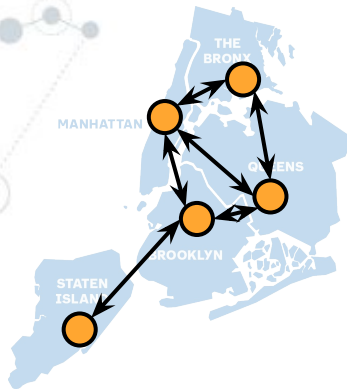
- $V(G)$ = map sub-regions
- $E(G)$ = adjacent regions



- Spatiotemporal assignment
- Filtering and bind data to regions
- Remove data inconsistent

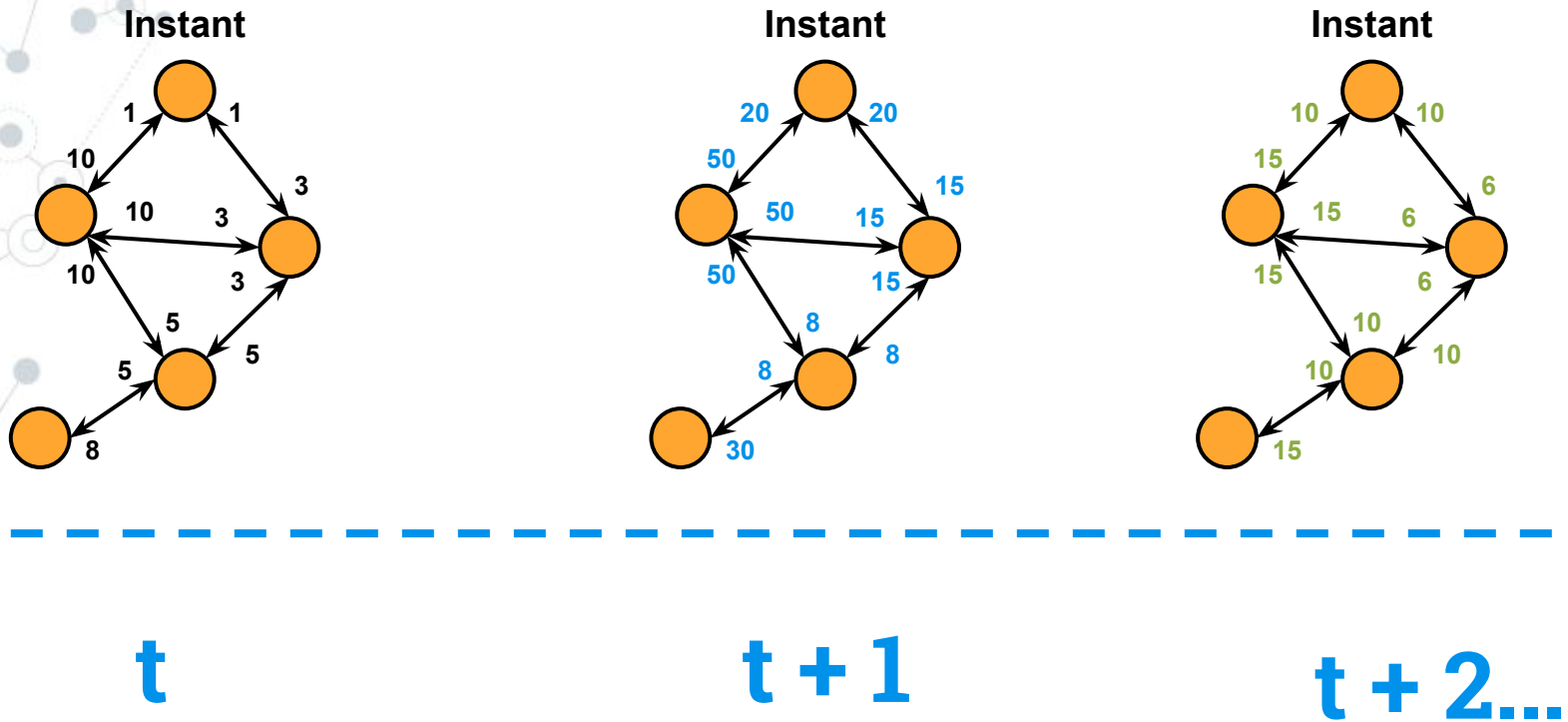
T-MAPS

Step 3 - Data Fusion and Metrics



T-MAPS

Time Discretization - metric - instant



A Case Study - T-MAPS



Manhattan

- 29 official borough
- 21 specialist accounts from Twitter.
- ~ 280 K geotagged *tweets*
 - Oct - Dec 2016

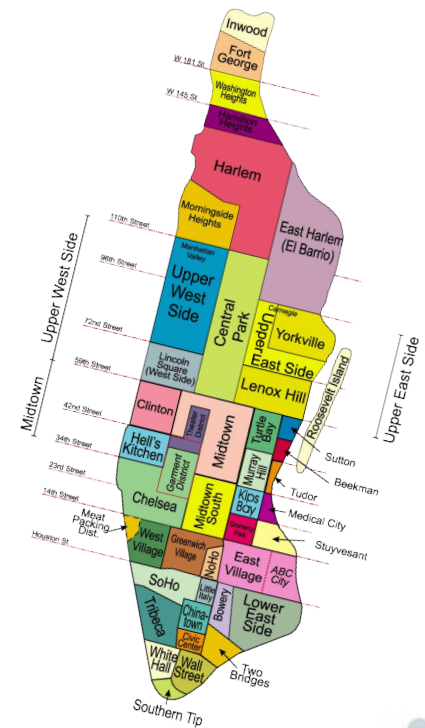


T-MAPS

- Shortest Path - Dijkstra Algorithm

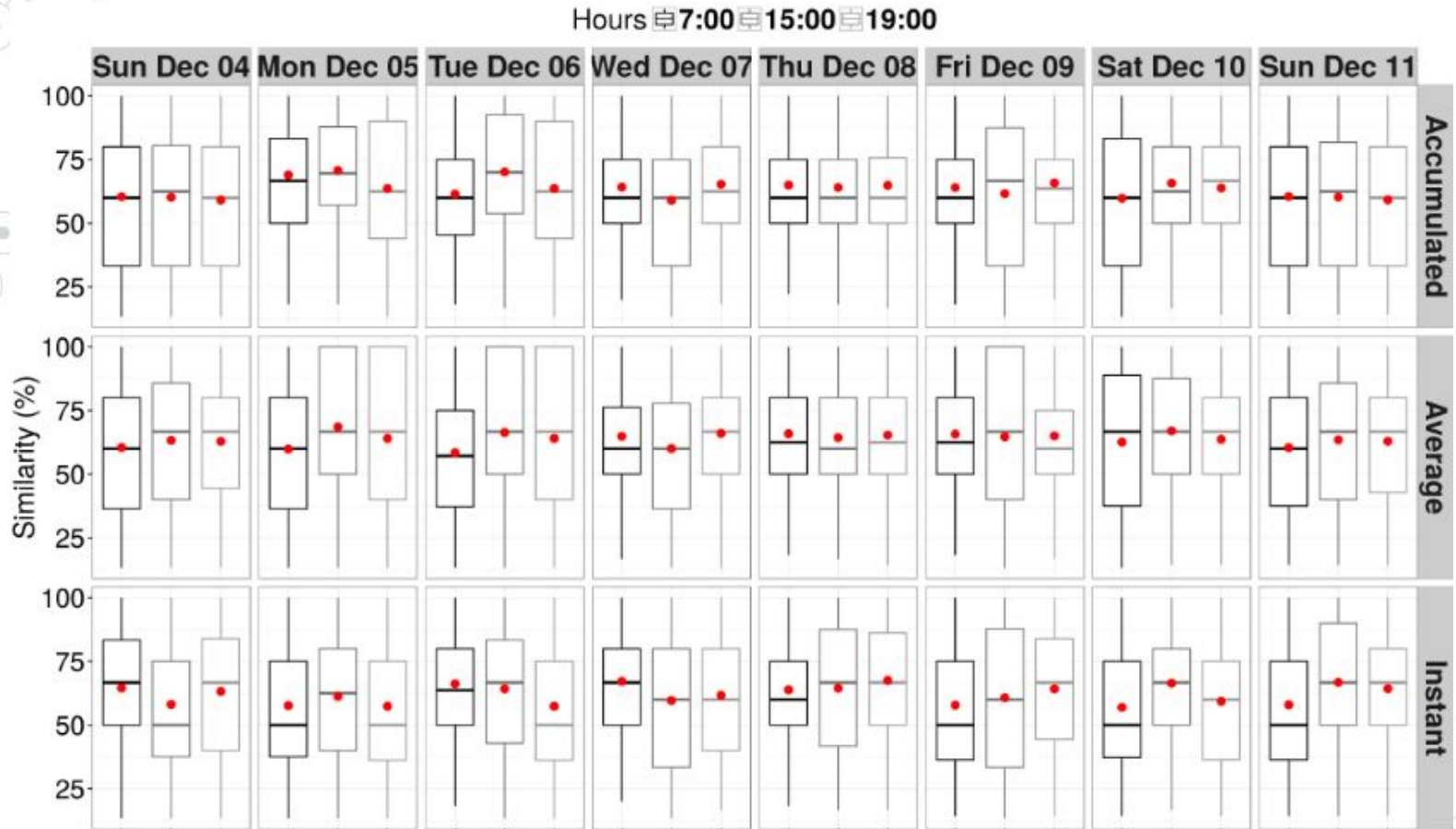


Google Directions



A Case Study

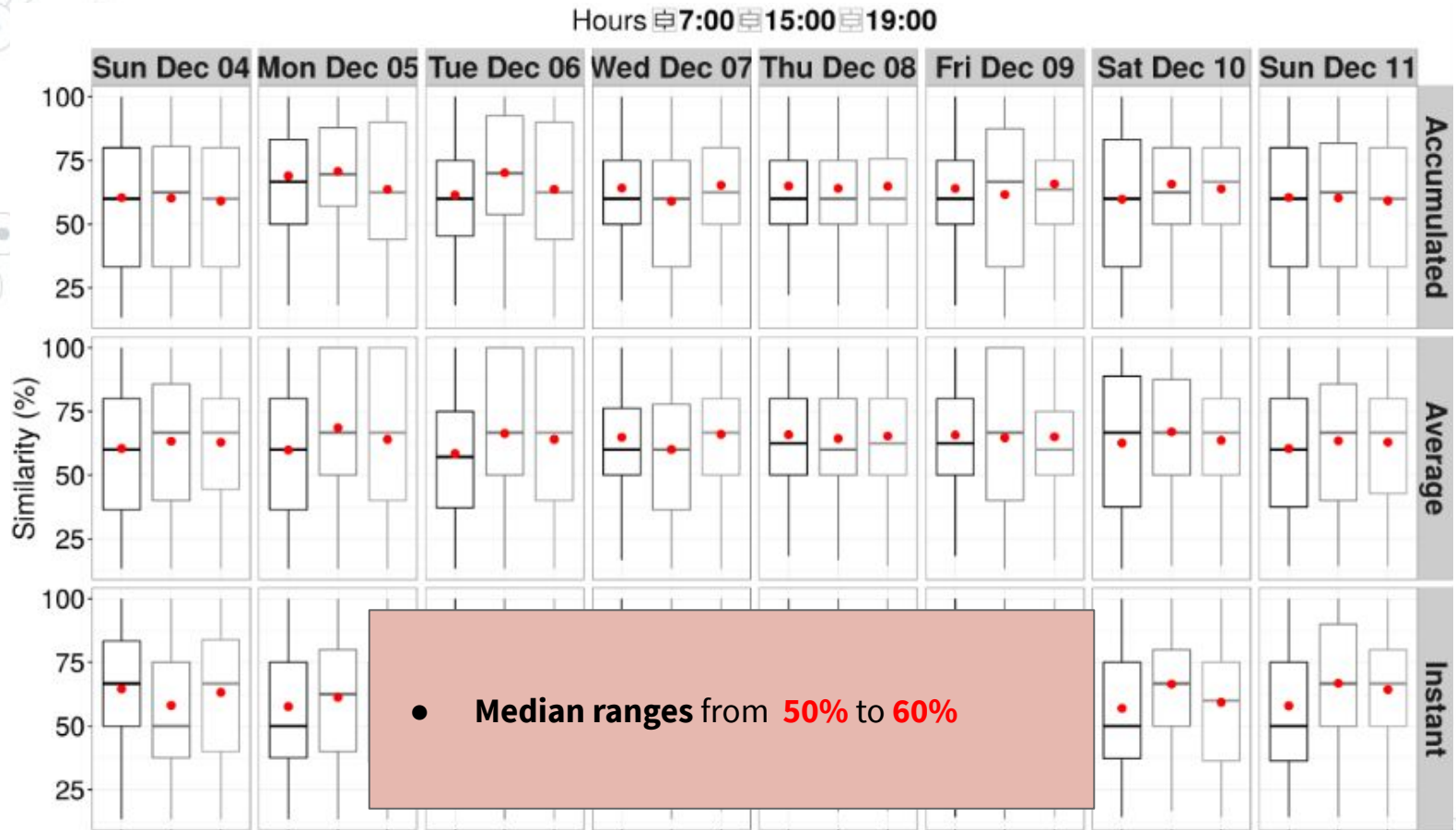
T-MAPS Applicability



Route similarity between T-MAPS and Google Directions (dots represent the mean)

A Case Study

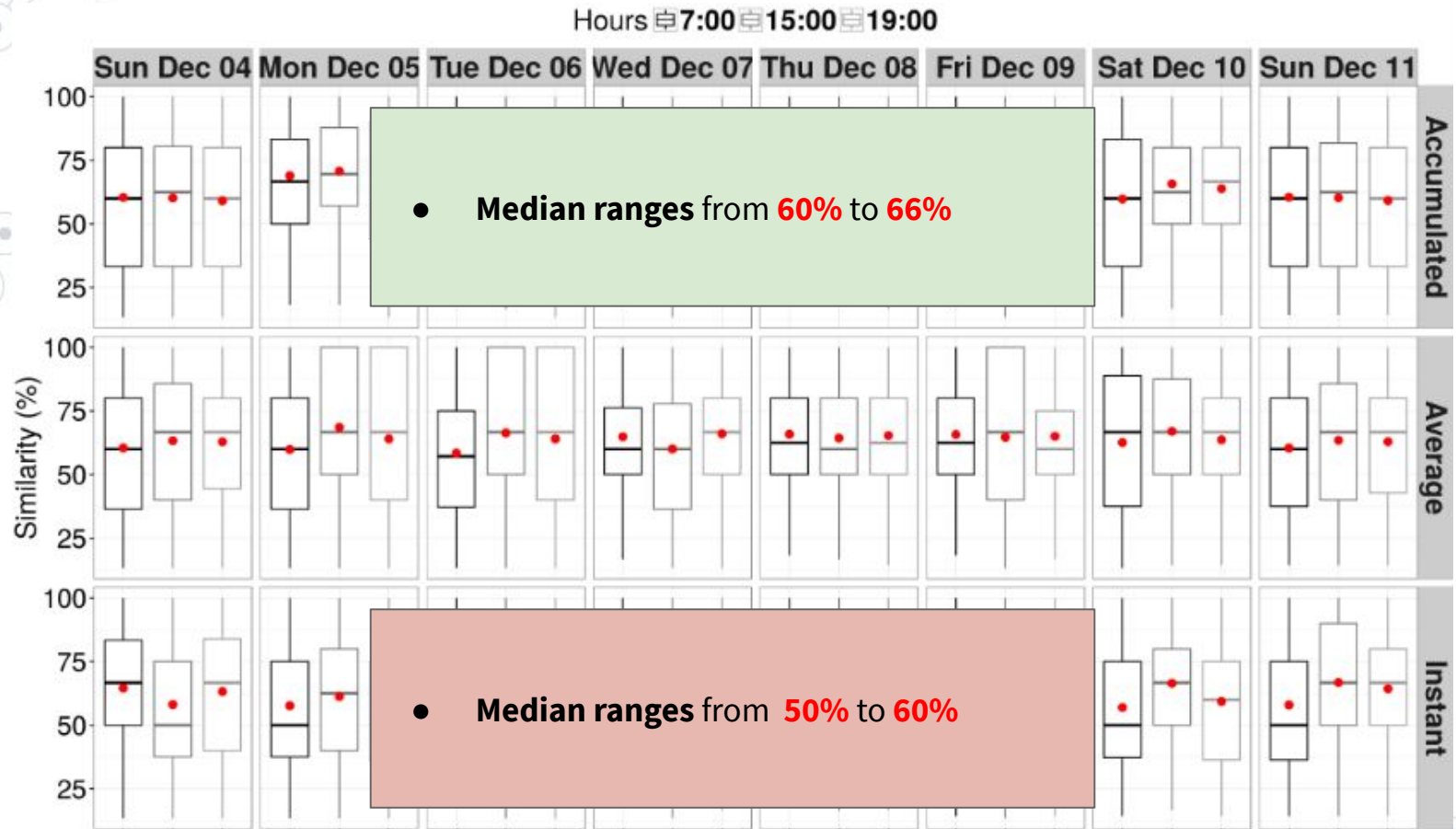
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A Case Study

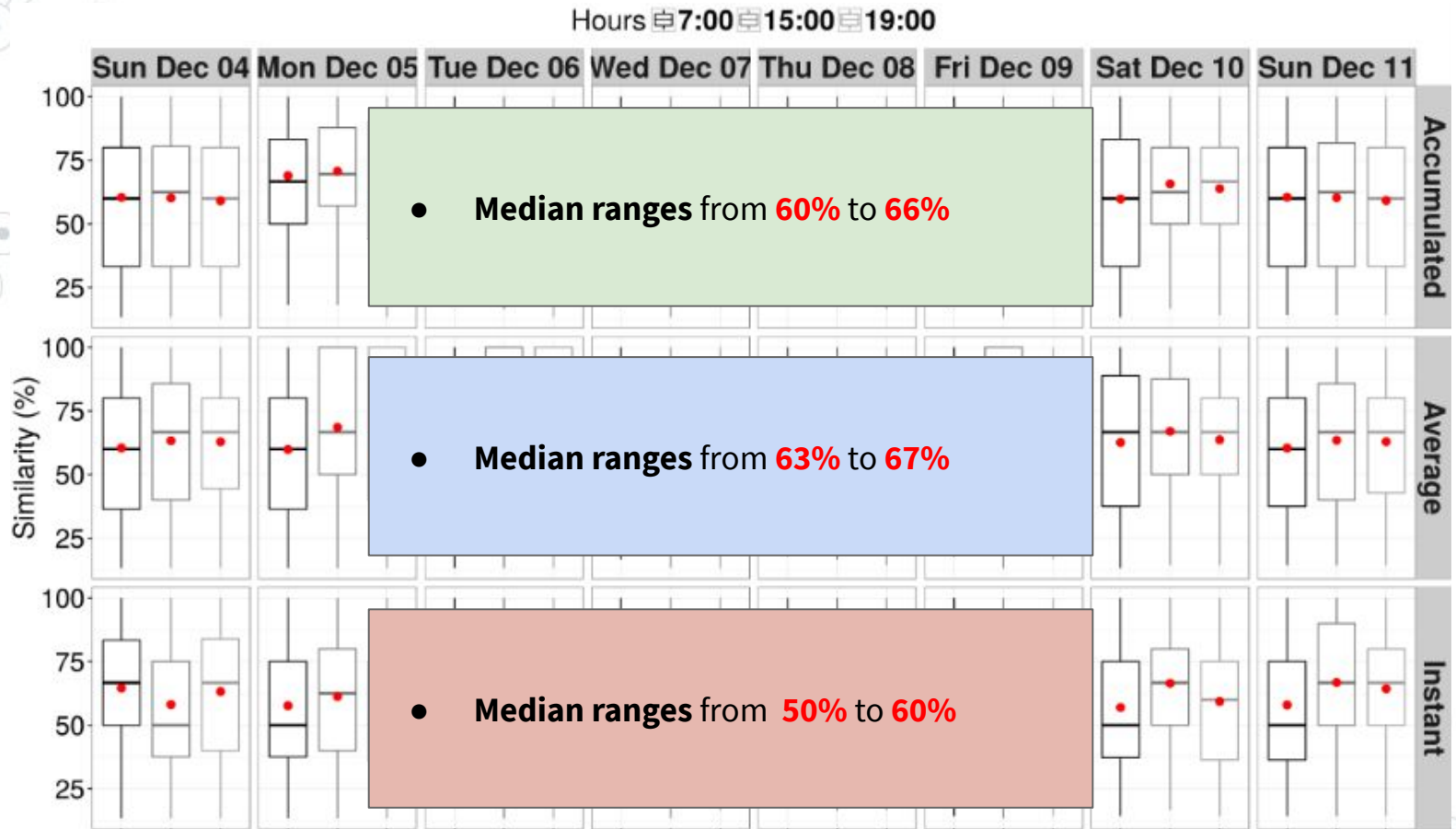
T-MAPS Applicability



Route similarity between T-MAPS and Google Directions (dots represent the mean)

A Case Study

T-MAPS Applicability



Route similarity between T-MAPS and Google Directions (dots represent the mean)

T-MAPS ROUTE DESCRIPTION SERVICES

 LBSM data collection

 RM punctuation

 RM stop words

✗ ‘/,.,:*”?!/...

✗ the, is, at, which...

R library:
[syuzhet, tm, stringr, wordcloud]

T-MAPS ROUTE DESCRIPTION SERVICES

 **LBSM data collection**

 RM punctuation

 RM stop words

 **Stemming**

Jamming, jammed → **Jam**
Ave, Av → **Avenue**
St → **Street**

T-MAPS ROUTE DESCRIPTION SERVICES

 **LBSM data collection**

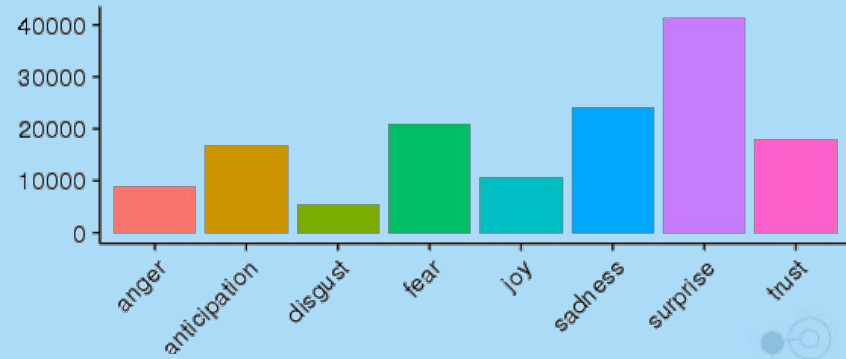
 RM punctuation

 RM stop words

 **Stemming**



 **Score**



T-MAPS ROUTE DESCRIPTION SERVICES

 **LBSM data collection**

 RM punctuation

 RM stop words

 **Stemming**










 **Score**

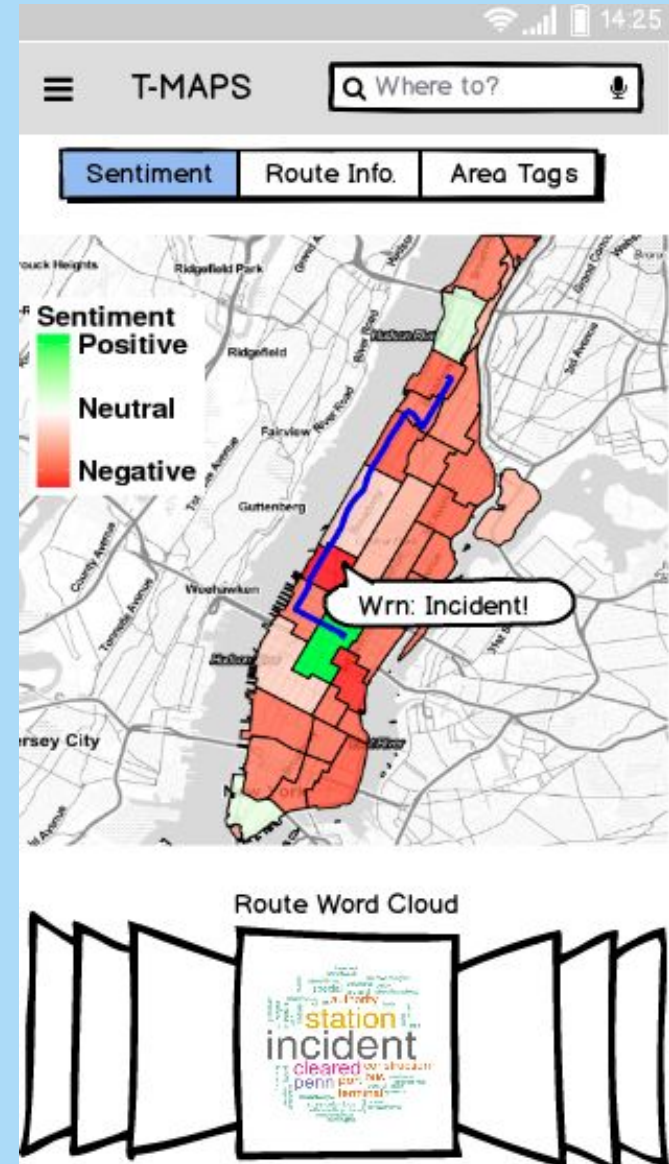


 **Pos ou Neg?**

| ## | Ang. | Anticip. | Disg. | Fear | Joy | Sad. | Surpri. | Trust | Neg. | Pos. |
|------|------|----------|-------|------|-----|------|---------|-------|------|------|
| ## 1 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 1 |
| ## 2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| ## 3 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| ## 4 | 0 | 1 | 1 | 0 | 1 | 1 | 0 | 2 | 1 | 2 |
| ## 5 | 0 | 1 | 0 | 0 | 1 | 0 | 1 | 2 | 0 | 2 |
| ## 6 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

T-MAPS ROUTE DESCRIPTION SERVICES

-  **LBSM data collection**
-  **RM punctuation**
-  **RM stop words**
-  **Stemming**
-  **Score**
-  **Pos ou Neg?**
-  **Routes and Map**



T-MAPS ROUTE DESCRIPTION SERVICES

 **LBSM data collection**

 RM punctuation


 RM stop words

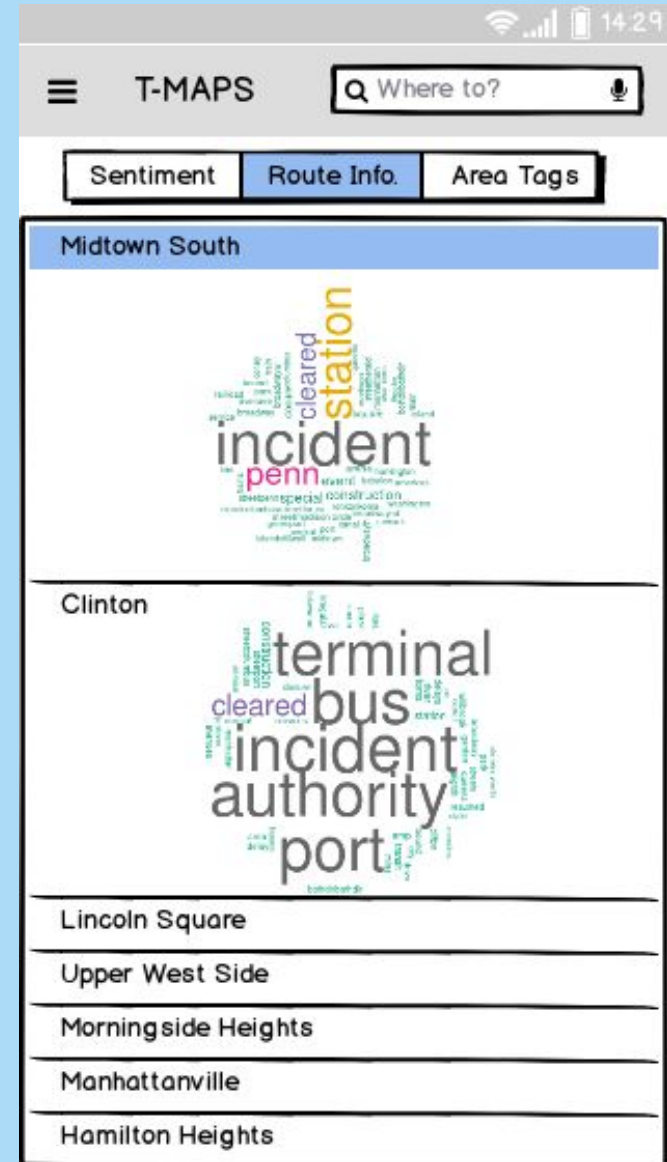
 **Stemming**

 **Word cloud**

 **Score**

 **Pos ou Neg?**

 **Routes and Map**



Conclusions

- ◎ We presented the T-Maps, a low-cost spatiotemporal model to enhance traffic and transit navigation context, using tweets
 - Three route description services, Route Sentiment, Route Information, and Area' Tags.
 - The similarity reached **62%**, and for a quarter of the evaluated trajectories, the similarity achieved up to **100%**. Compared with Google Direction route recommendation

Conclusions

- ◎ As future work
 - Extend the T-Maps applying strategies to process the data and offer more valuable information
 - Employ regular users accounts from LBSM and uses reputation models to handle conflicting information
 - Extend T-Maps to larger regions, taking into account the computational problem

Thanks!

Questions?

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heitor@ic.ufal.br