A CLUSTER-BASED TRIP PREDICTION GRAPH NEURAL NETWORK FOR BIKE SHARING SYSTEMS

By

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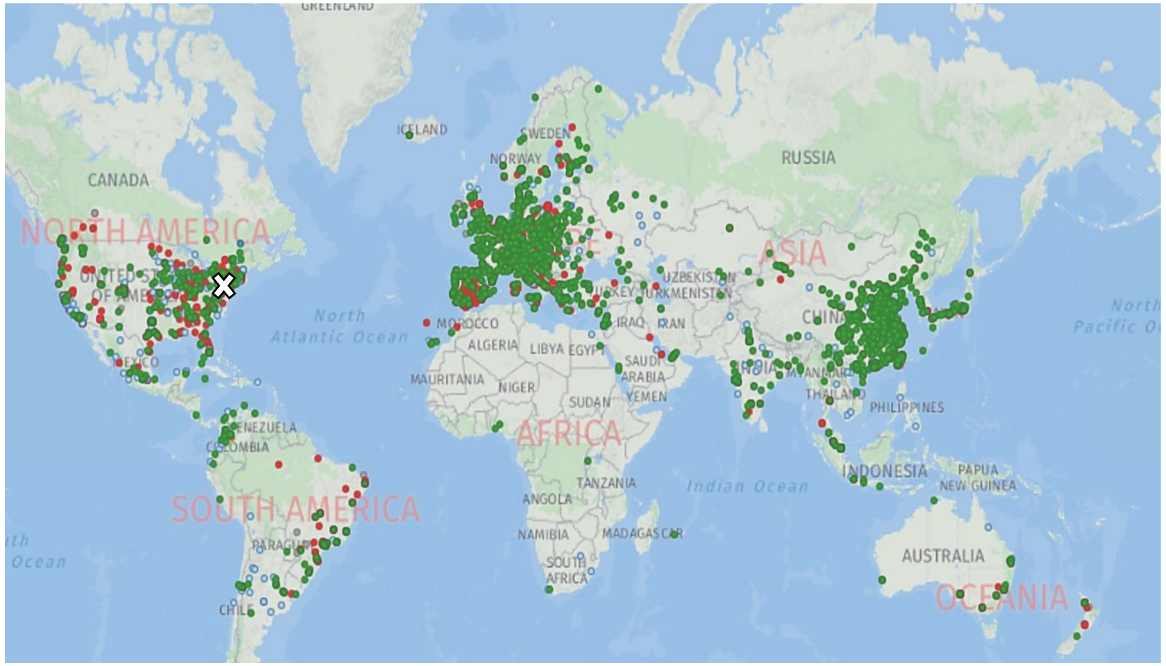
BSS: A MOBILITY SYSTEM EMERGING WORLDWIDE

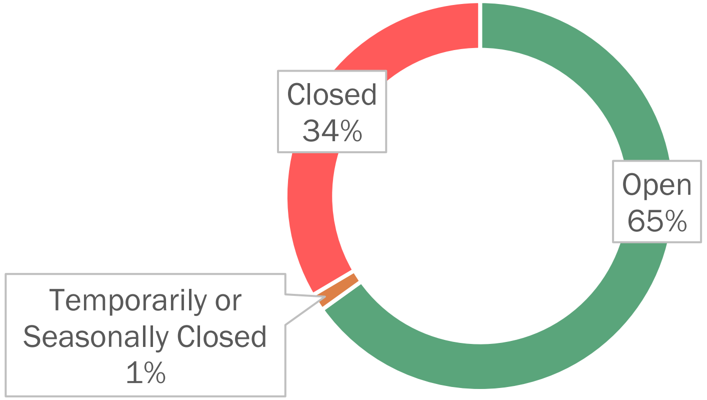
Usage

- Rent a bike on the departure local/station
- Ride to the destination local/station
- Return the bike to the destination local/dock

SBSS

DBSS





THE CURRENT BSS PROBLEM & PRESENTATION OUTLINE

Bike Imbalance

Analogous Transition Patterns →

↓

Customer Loss In The Long Term

System Operation ⇄ **System Prediction**

Rebalancing Strategies

We Propose: An Accurate Prediction of Bike Traffic

citi bike

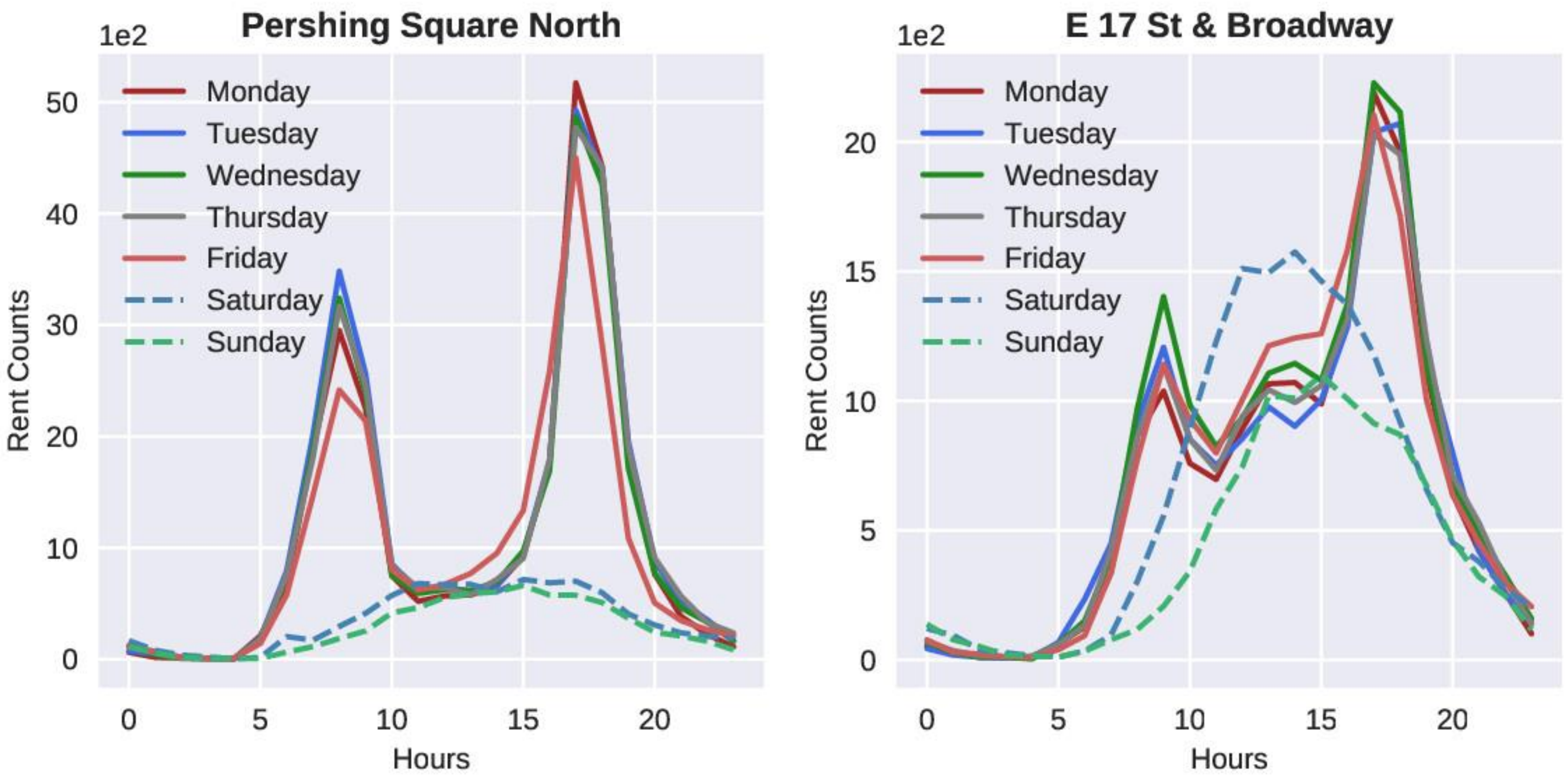
1. Main Challenges
2. **Proposed Solution**
   - **AdaTC** to Cluster the Stations
   - Bicycle Trips Predictor with GNN Embeddings
3. Experimental Results
   - Clustering Pertinence
   - Best Technique for the Problem

Main Challenges

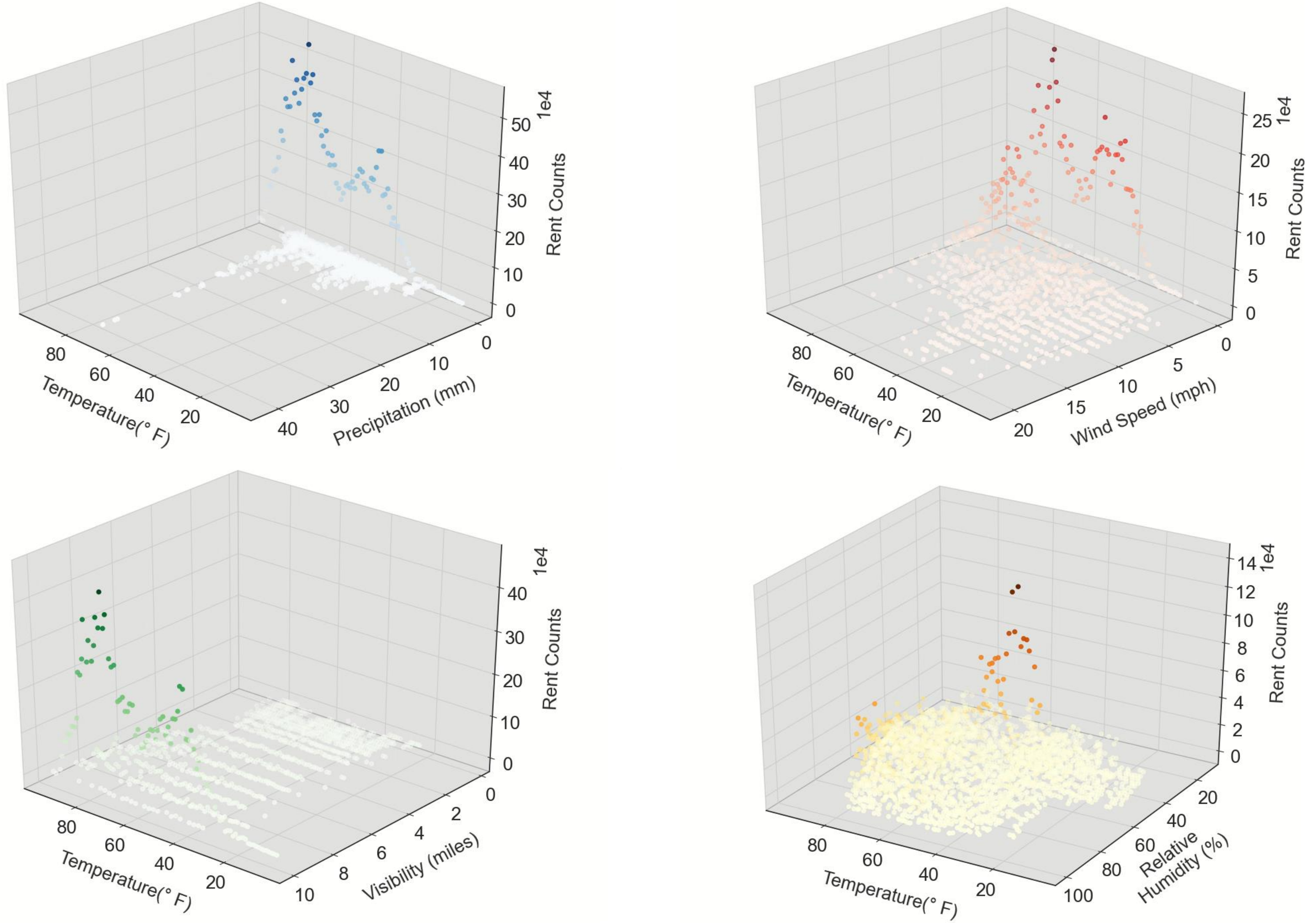
when Predicting Bike Traffic

DEMAND CHANGES TEMPORALLY AND SPATIALLY

Weekly And Hourly Seasonality In Different Locations



DEMAND IS INFLUENCED BY WEATHER CONDITIONS



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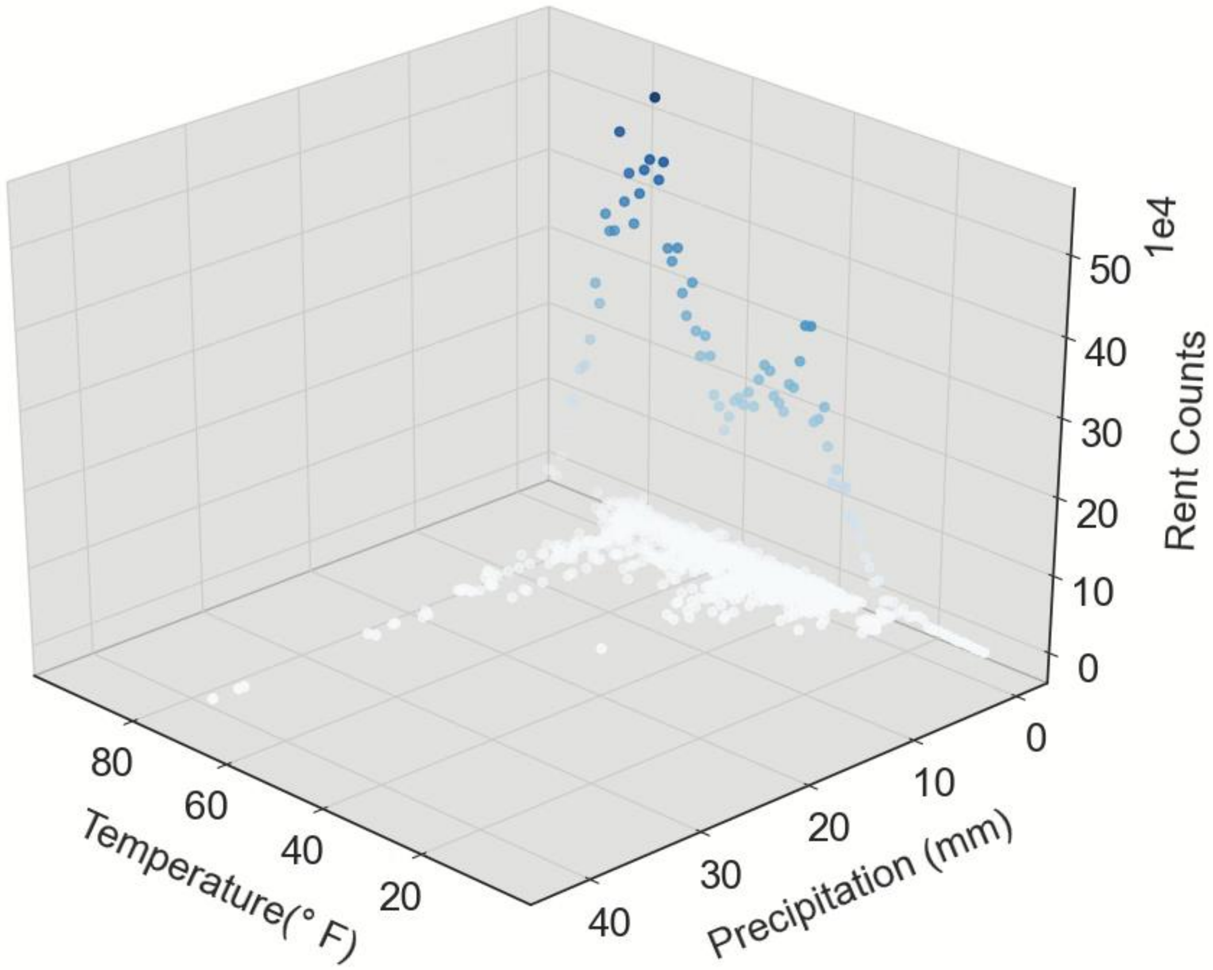


Temperature and Precipitation

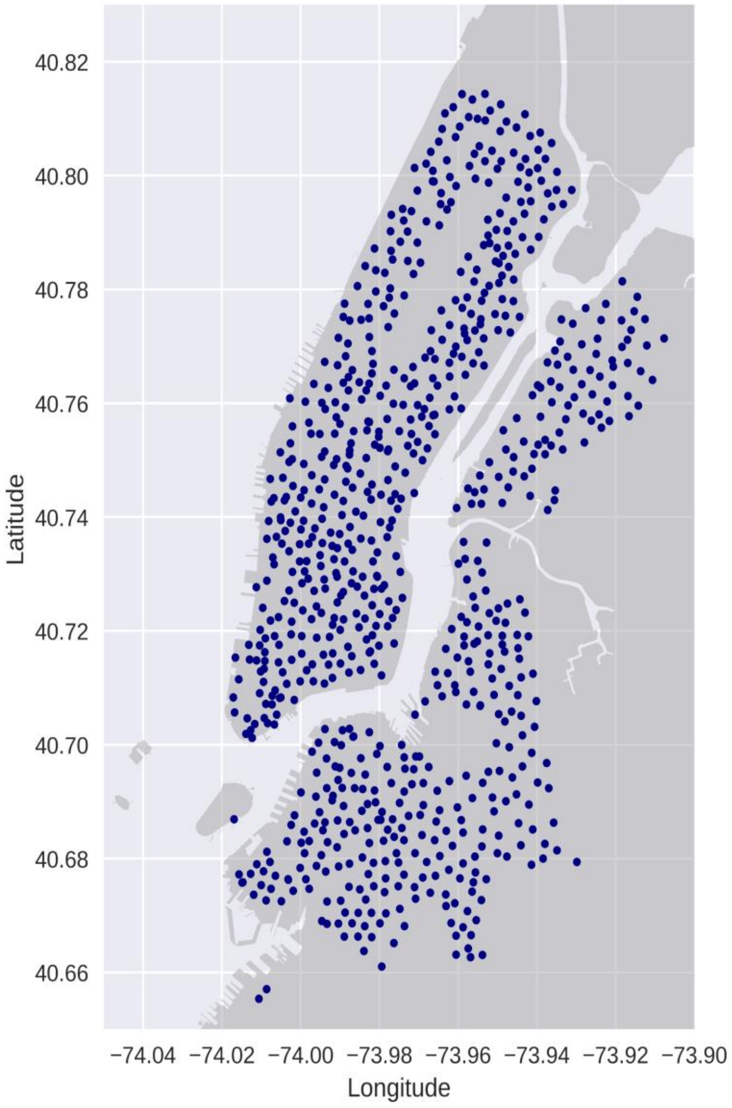
Conducive to Cycling

- Precipitation $\approx 0\ mm/h$
- **Precipitation $\approx 0\ mm/h$ & $\uparrow$ Temperature**

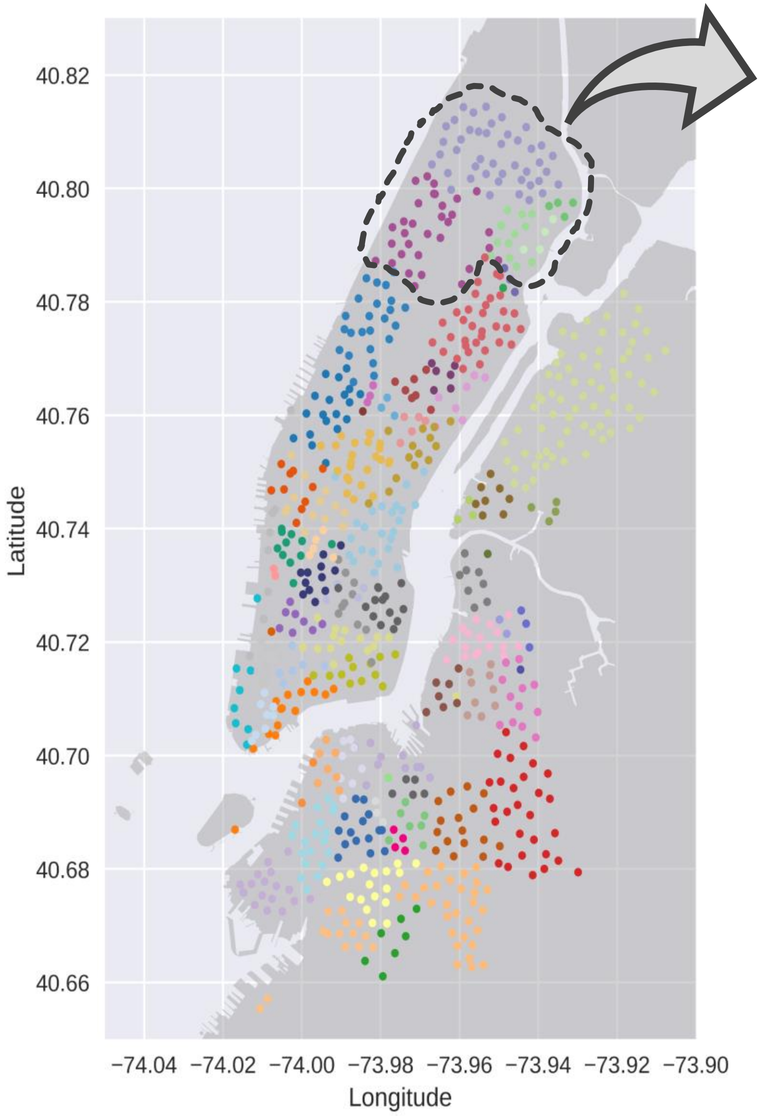
Not Conducive to Cycling

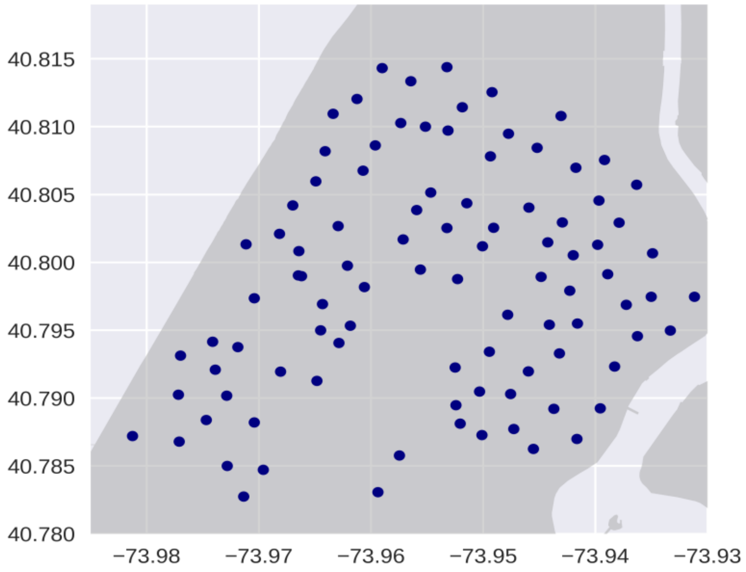
- Precipitation $> 10\ mm/h$
  - Residual # Trips
  - $\uparrow$ Temperature

RIDES RANDOMNESS



RIDES RANDOMNESS





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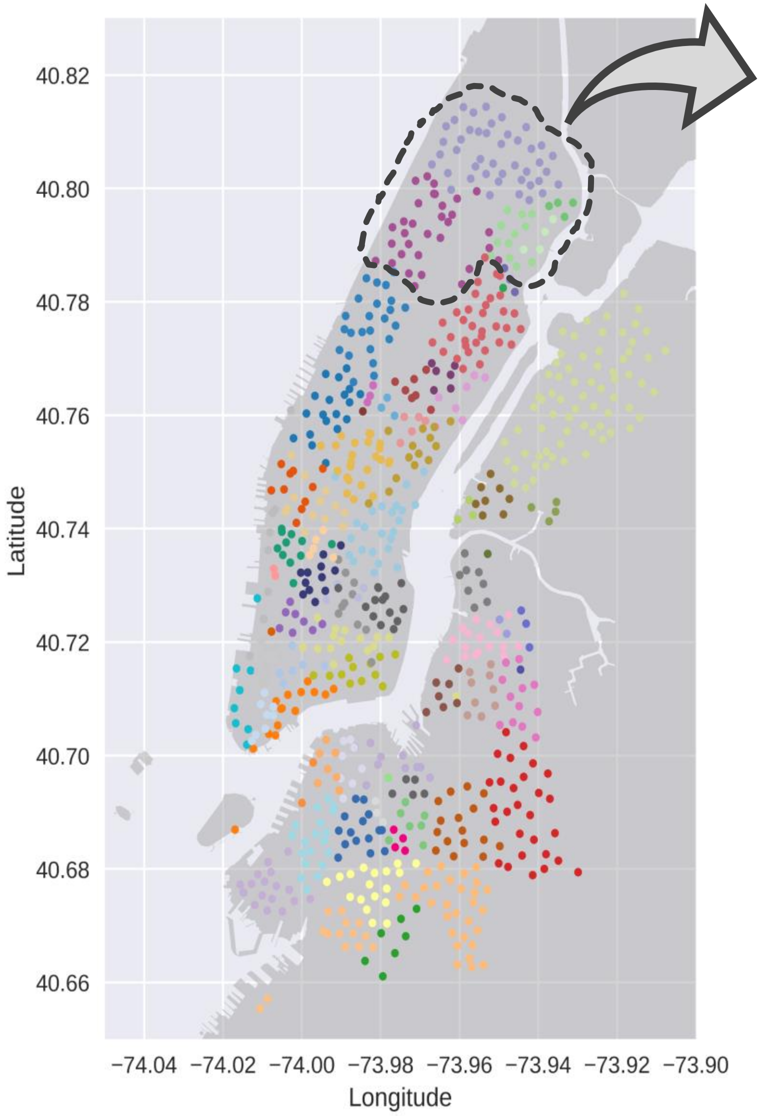
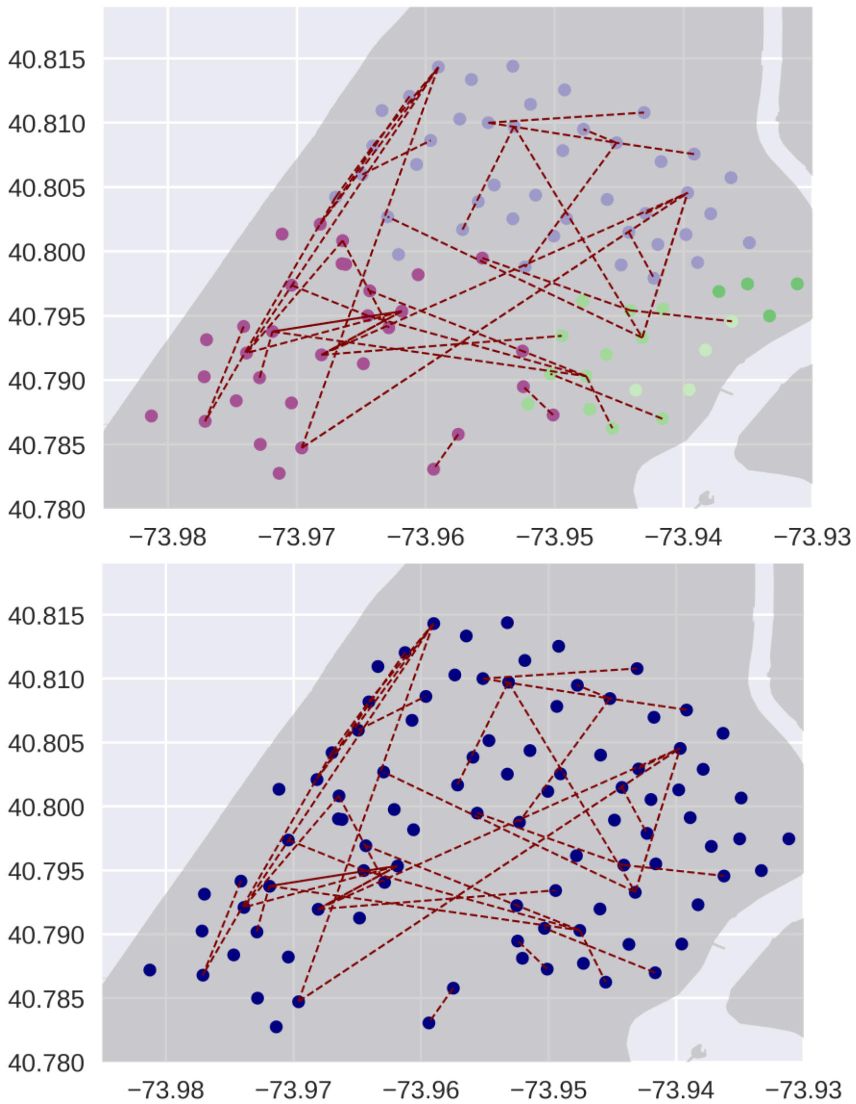
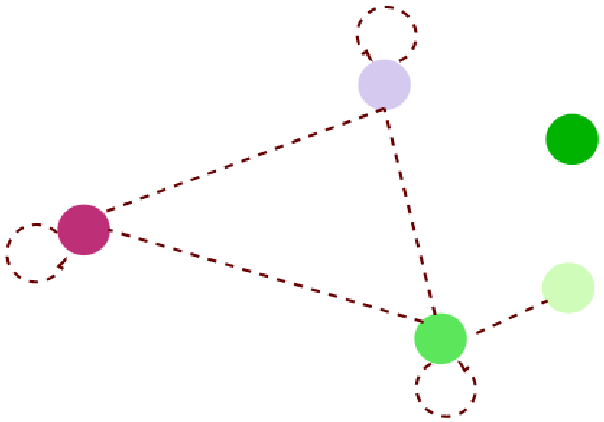


January 1, 2018
7:00 am – 12:00 pm





Inter-Station Random Trips → Inter/Intra-Cluster Frequent Trips

Apparently Random Trips Between Individual Stations show a Pattern when Stations are Clustered

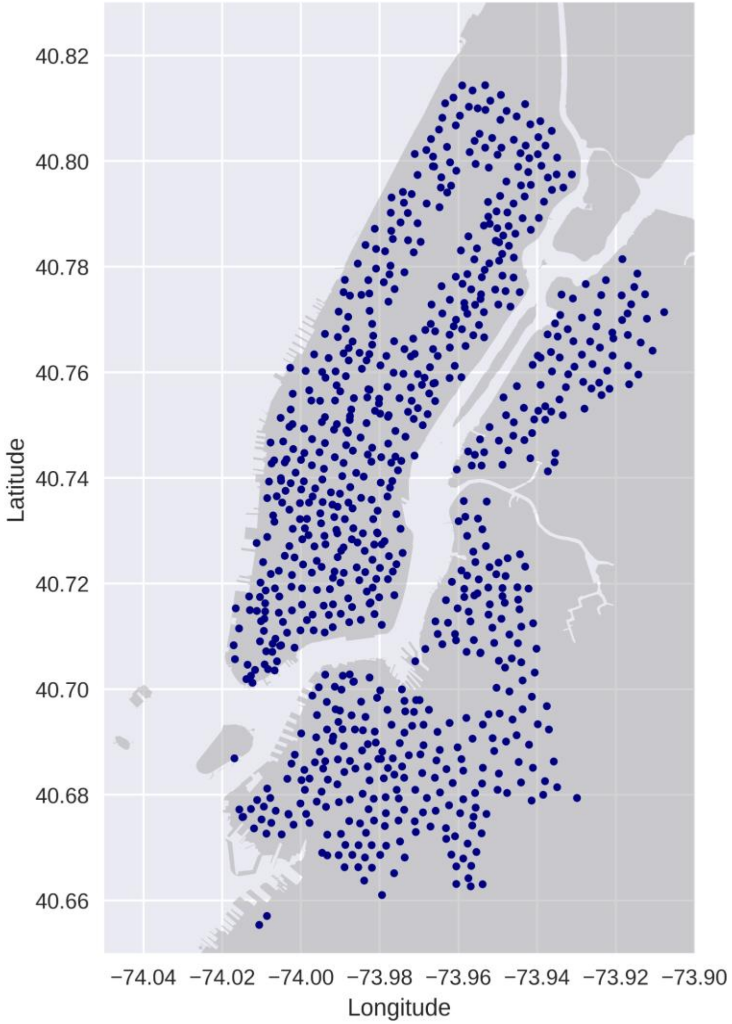
WHY IS CLUSTERING CRUCIAL?

Reduce the Complexity of Random Trips

System Prediction

Traffic Prediction

- Consider the Station Similarity to Neighbor Stations
- Bike Usage more Stable and Regular



System Operation

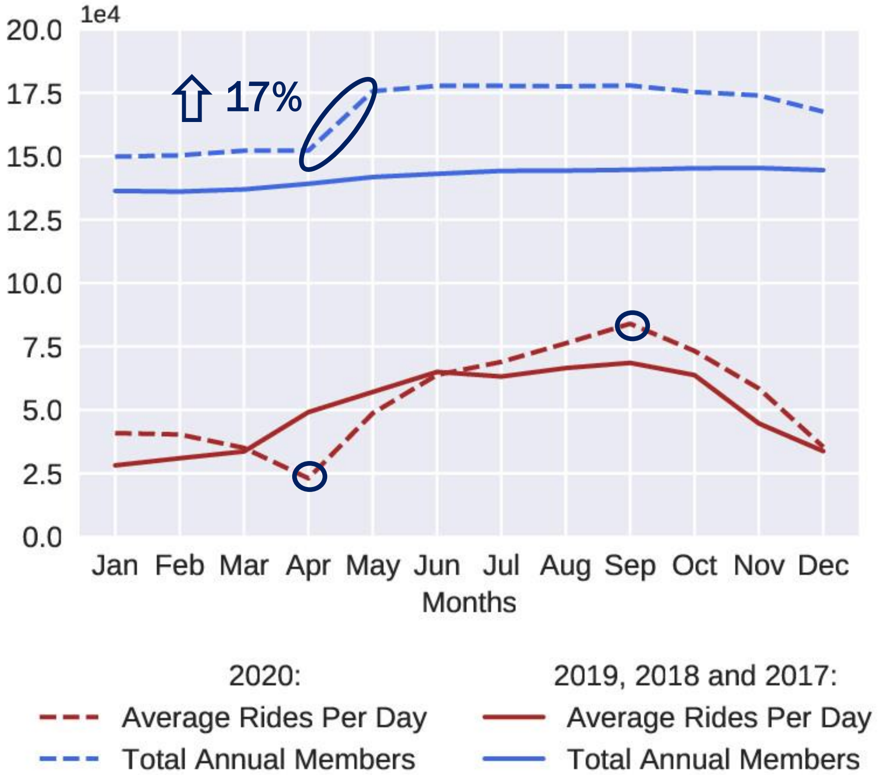
Bike Reposition

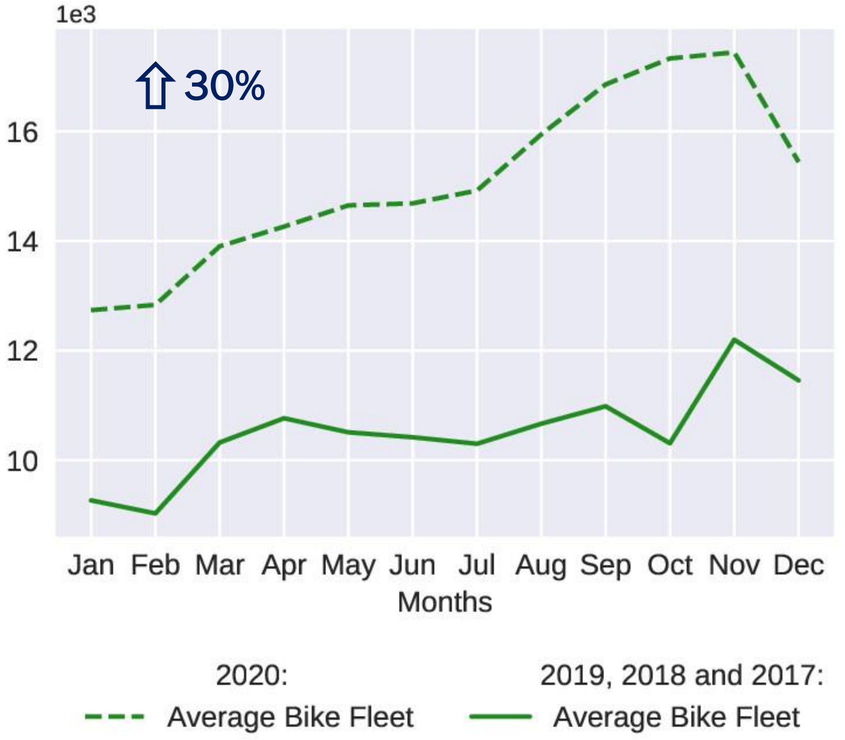
- Inter/Intra-Cluster Dynamics
- Derive Efficient Rebalancing Strategies

COVID-19 IMPACT ON CITIBIKE

2020

March	March – April	April – July	October
WHO declares the COVID-19 Pandemic	Full Lockdown in NY	Four-phase Reopening Plan by Region	Micro-cluster Strategy Introduced





Proposed Solution

Grouping Stations: AdaTC

Before clustering…

- Remove Potential Outlier Stations

$$S^g = \{s_i : s_i \in S, \%\, t_{s_i} \geq 0.001\%\},$$

such that, $\# S^g = 801$

- Assess Cluster Tendency

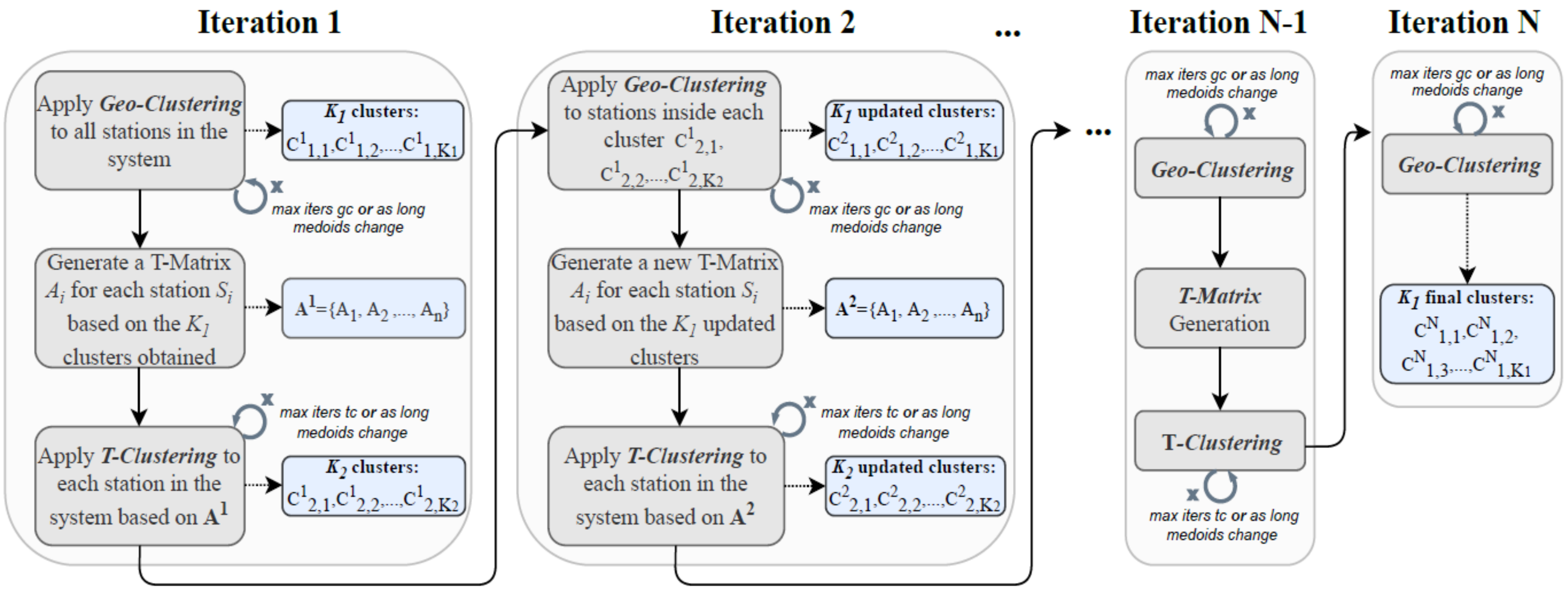
H_0: the data is uniformly distributed

- Define 5 Time Slots

ADAPTIVE TRANSITION CONSTRAINT CLUSTERING

Stations in the same cluster **are expected to:**

- Be Geographically Close
- With Similar Check-outs <u>and</u> Inter-cluster Transitions



AdaTC: GEO-CLUSTERING

$$diss_{GC}(S_h, S_k) = \rho_1 \times gd_{hk} + out_{hk}$$

Trade-off Parameter

Geographical Distance between S_h and S_k

Check-out Difference between S_h and S_k

where

- $$out_{hk} = \|U_h - U_k\|_2$$

where

- $$U_h = \left(\frac{u_1}{\sum_{j=1:3} u_j}, \frac{u_2}{\sum_{j=1:3} u_j}, \frac{u_3}{\sum_{j=1:3} u_j}, \frac{u_4}{\sum_{j=4:5} u_j}, \frac{u_5}{\sum_{j=4:5} u_j}\right)$$ (Check-out Pattern at S_h)

Estimate the Number of Bikes Available at S_h

where

- $$u_i = \frac{1}{TL_i} \times \underbrace{|t|}_{\substack{= \\ \text{60 min.}}} \times r_i$$ (Check-out Pattern at S_h in ts_i)

(Average Time Length that S_h has Bikes Available in ts_i)

$$TL_i = \frac{1}{np_i} \sum_{t=0}^{np_i - 1} \widehat{TL}_{i,t}$$

ts_1

t ... t

$$r_i = \frac{1}{np_i} \sum_{t=0}^{np_i - 1} r_{i,t}$$

(Average Number of Bikes Rented from S_h in ts_i)

AdaTC: GEO-CLUSTERING (cont.)

$\widehat{TL}_{i,t}^{S}$ Estimation

⇩ INFER

<u>Number of Bikes Available</u>:

1

Exact Flow:
Using CitiBike Historical Trips and Open Bus

2

“Offset” Method:
Using only CitiBike Historical Trips

$$\hat{u}_i^S = \frac{1}{\overline{TL_i^S}} \times \underbrace{|t|}_{=\,60\text{ min.}} \times \overline{r_i^S} \qquad (4)$$

(Check-out Pattern at S_h in ts_i)

(Average Time Length that S_h has Bikes Available in ts_i)

$$\boxed{\overline{TL_i^S} = \frac{1}{np_i}\sum_{t=0}^{np_i-1}\widehat{TL}_{i,t}^S}$$

$$\widehat{TL}_{i,t}^S = \begin{cases} \dfrac{1}{\#\,weekdays^{*}} \displaystyle\sum_{weekday\ dates^{*}} \widehat{TL}_{i,t,d}^S & for\ i = 1,2,3 \\[2ex] \dfrac{1}{\#\,weekend\ days^{*}} \displaystyle\sum_{weekend\ dates^{*}} \widehat{TL}_{i,t,d}^S & for\ i = 4,5 \end{cases}$$

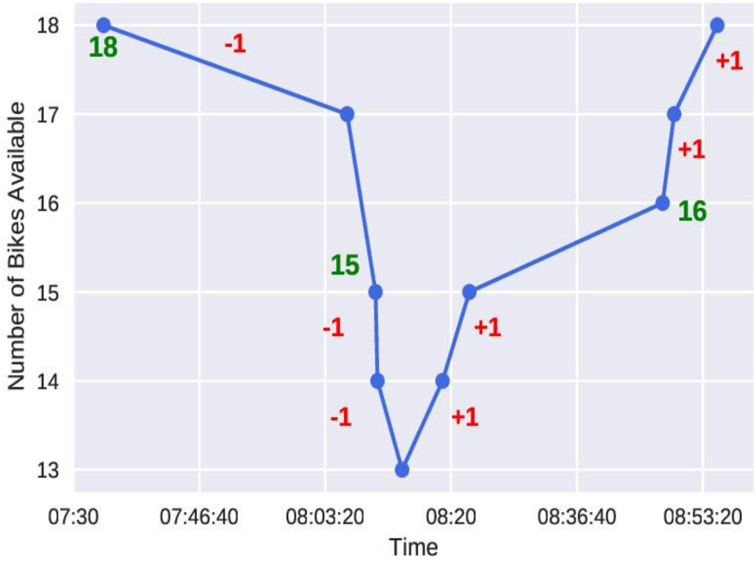
≤ 60 min.

date

≤ 60 min.

* in 2018

1



OpenBus

CitiBike Historical Trips Scores:

- -1 for rents
- +1 for returns

Number of Bikes Available

2

avail_bikes_cum + |min.|

$\underbrace{}_{\text{offset}}$

	station_id	balance	dock_time_time	dock_time_date	avail_bikes_cum	avail_bikes_cum_offset
0	3536.0	-1	09:08:01.358000	2018-01-01	-1	2855
1	3536.0	1	09:18:34.010000	2018-01-01	0	2856
2	3536.0	1	11:23:17.156000	2018-01-01	1	2857
3	3536.0	-1	11:31:55.385000	2018-01-01	0	2856
4	3536.0	1	12:58:13.333000	2018-01-01	1	2857
...	...	...	...	...	...	...
22461	3536.0	-1	13:24:09.036000	2018-12-31	-2854	2
22462	3536.0	1	13:48:14.227000	2018-12-31	-2853	3
22463	3536.0	1	13:48:15.943000	2018-12-31	-2852	4
22464	3536.0	-1	14:07:47.898000	2018-12-31	-2853	3
22465	3536.0	1	16:49:42.485000	2018-12-31	-2852	4

min.

AdaTC: TRANSIT-MATRIX GENERATION

Transit-Matrix: Describes the intra and inter-cluster transitions patterns of a specific station in all time slots

Ride-To-Cluster $(\boldsymbol{rt})$ Return-From-Cluster $(\boldsymbol{rf})$

$$\mathbf{A_s} = \begin{array}{c} \begin{array}{cccccccccc} C_{1,1} & C_{1,2} & C_{1,3} & \cdots & C_{1,K_1} & C_{1,1} & C_{1,2} & C_{1,3} & \cdots & C_{1,K_1} \end{array} \\ \begin{bmatrix} rt_{1,1,1} & rt_{1,2,1} & rt_{1,3,1} & \cdots & rt_{1,K_1,1} & rf_{1,1,1} & rf_{1,2,1} & rf_{1,3,1} & \cdots & rf_{1,K_1,1} \\ & & & \cdots & & & & & \cdots & \\ \vdots & \vdots & \vdots & \cdots & \vdots & \vdots & \vdots & \vdots & \cdots & \vdots \\ & & & \cdots & & & & & \ddots & \\ rt_{1,1,5} & rt_{1,2,5} & rt_{1,3,5} & \cdots & rt_{1,K_1,5} & rf_{1,1,5} & rf_{1,2,5} & rf_{1,3,5} & \cdots & rf_{1,K_1,5} \end{bmatrix} \end{array} \begin{array}{c} ts_1 \\ ts_2 \\ ts_3 \\ ts_4 \\ ts_5 \end{array}$$

Time Slots

Dimensions: $5 \times 2K_1$

where for a given $i = 1, \dots, 5$

- $\boldsymbol{rt}_{1,j,i} = \dfrac{\#\ trips\ starting\ in\ S\ ending\ in\ C_{1,j}}{\#\ trips\ in\ ts_i}$, with $\sum_{j=1}^{K_1} rt_{1,j,i} = 1$

- $\boldsymbol{rf}_{1,j,i} = \dfrac{\#\ trips\ ending\ in\ S\ starting\ in\ C_{1,j}}{\#\ trips\ in\ ts_i}$, with $\sum_{j=1}^{K_1} rf_{1,j,i} = 1$

AdaTC: TRANSIT-MATRIX GENERATION (cont.)

Transit-Matrix Generation Step

Iteration $\boldsymbol{n_{it}}$

↓ Geo-Clustering

$C_{1,1}^{n_{it}}, C_{1,2}^{n_{it}}, \dots, C_{1,K_1}^{n_{it}}$

↓

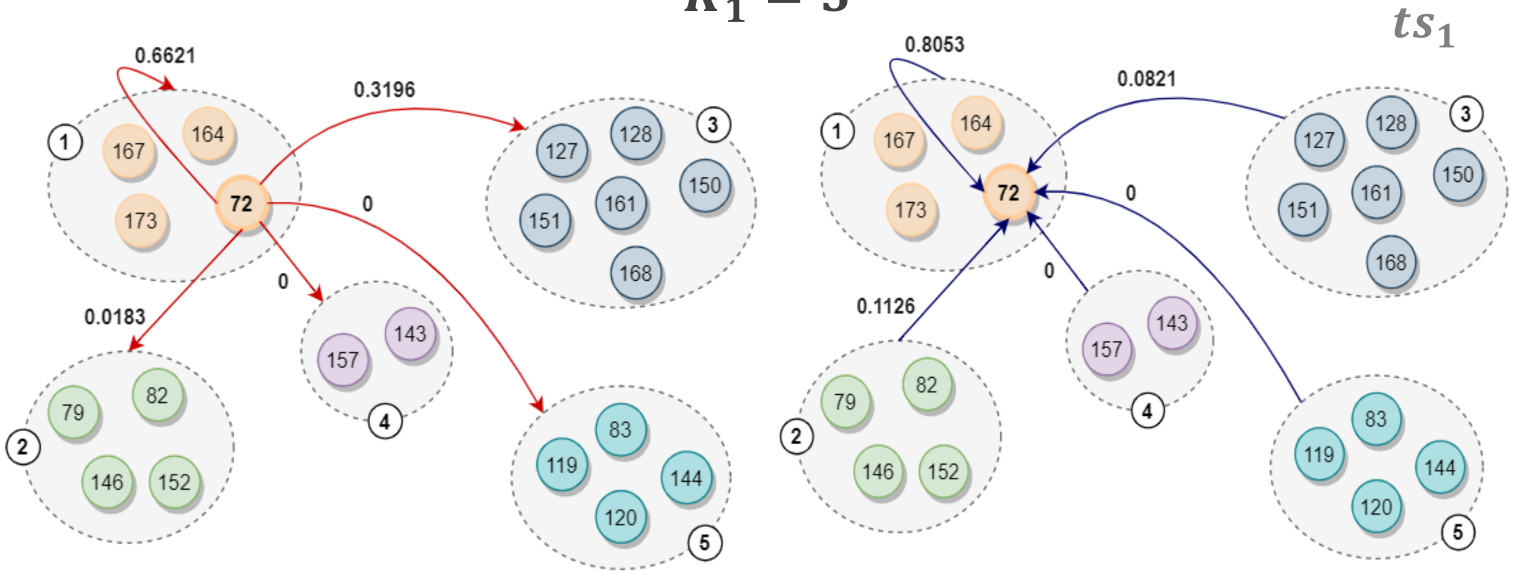
$\mathbb{A}^{n_{it}} = \{A_1, A_2, \dots, A_n\}$, with $n = \#$ stations

↓ Transit-Clustering

W 52 St & 11 Ave $(\boldsymbol{id = 72})$

$\boldsymbol{n = 20}$

$\boldsymbol{K_1 = 5}$



Ride-To-Cluster ⟷ Return-From-Cluster

$$
\mathbf{A}_{72} = \begin{array}{cccccccccc|c}
C_{1,1} & C_{1,2} & C_{1,3} & C_{1,4} & C_{1,5} & C_{1,1} & C_{1,2} & C_{1,3} & C_{1,4} & C_{1,5} & \\
\end{array}
$$

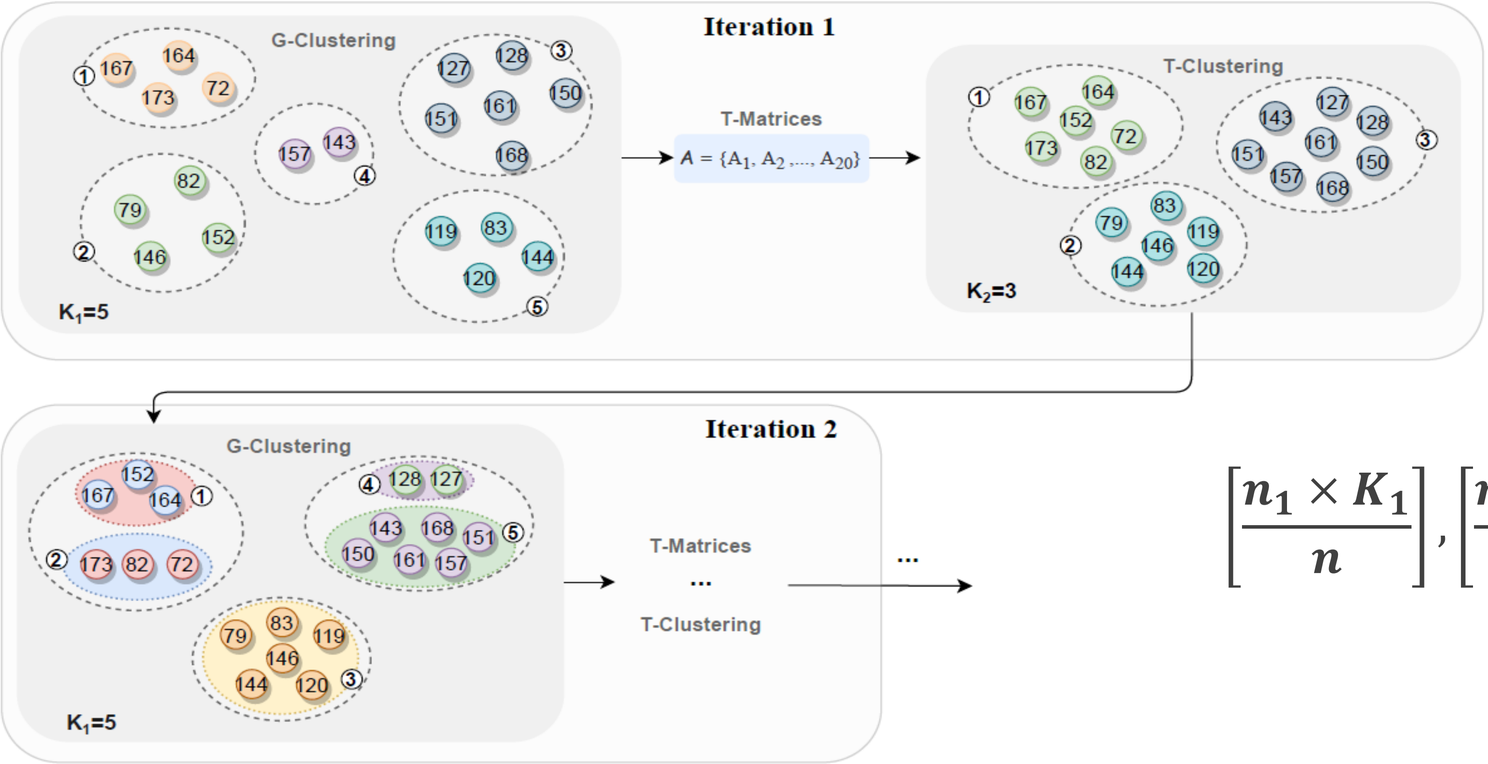
$$
\mathbf{A}_{72} = \begin{bmatrix}
0.6621 & 0.0183 & 0.3196 & 0 & 0 & 0.8053 & 0.1126 & 0.0821 & 0 & 0 \\
0.8360 & 0.0299 & 0.1395 & 0 & 0 & 0.8525 & 0.0354 & 0.1121 & 0 & 0 \\
0.7519 & 0.0611 & 0.187 & 0 & 0 & 0.5443 & 0.085 & 0.3689 & 0.0018 & 0 \\
0.6451 & 0.0444 & 0.3106 & 0 & 0 & 0.6862 & 0.0691 & 0.2394 & 0.0053 & 0 \\
0.8 & 0.0214 & 0.1786 & 0 & 0 & 0.8035 & 0.0173 & 0.1676 & 0.0116 & 0
\end{bmatrix}
\begin{array}{c} ts_1 \\ ts_2 \\ ts_3 \\ ts_4 \\ ts_5 \end{array}
$$

Time Slots

AdaTC: TRANSIT-CLUSTERING

Clusters stations into K_2 groups by *K-Medoids*, such that $K_1 \geq K_2$

$$diss_{TC}(S_h, S_k) = \underbrace{||A_h}_{\text{T-Matrix of Station } S_h} - \underbrace{A_k}_{\text{T-Matrix of Station } S_k}||_F = ||A_{\underbrace{(h-k)}_{\text{Element-By-Element Subtraction of } A_h \text{ with } A_k}}||_F$$



$$\left[\frac{n_1 \times K_1}{n}\right], \left[\frac{n_2 \times K_1}{n}\right], \ldots, \left[\frac{n_{K_2} \times K_1}{n}\right]$$

AdaTC: INTRINSIC PARAMETERS VALIDATION

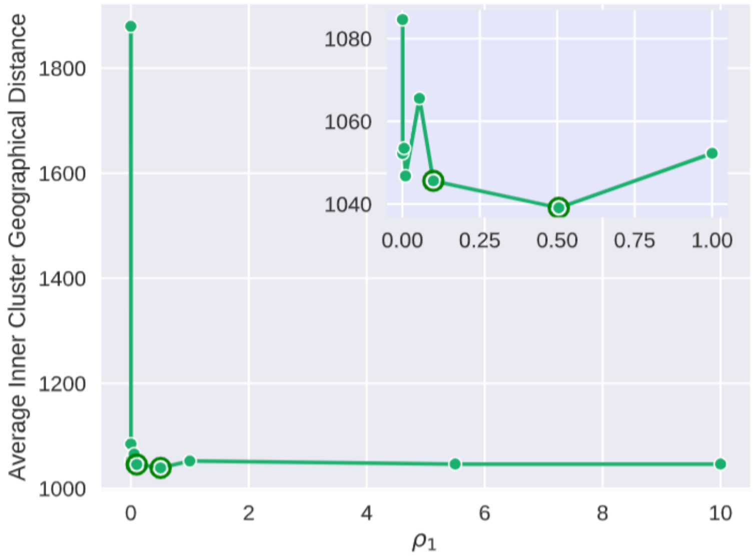
Intrinsic Parameters

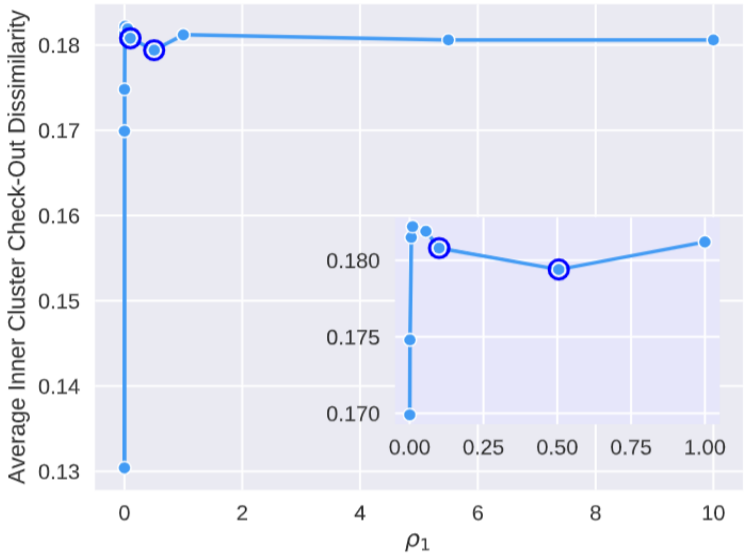
- ρ_1: $\rho_1 \in \{0, 5\times10^{-4}, 10^{-3}, 5.5\times10^{-3}, 10^{-2}, 5.5\times10^{-2}, 10^{-1}, 5.05\times10^{-1}, 1, 5.5, 10\}$
- K_1: $K_1 \in \{50, 60, 70, 80, 90, 100\}$
- K_2: $K_2 \in \{10, 20, 30, 40, 50\}$

VALIDATION METRICS

$\mathbf{AGD}_{\text{inner}}, \mathbf{ACOD}_{\text{inner}}, \mathbf{AGD}_{\text{inter}}, \mathbf{ACOD}_{\text{inter}}$

Average Inner Cluster Geographical Distance	Average Inner Cluster Check-Out Dissimilarity	Average Inter Cluster Geographical Distance	Average Inter Cluster Check-Out Dissimilarity



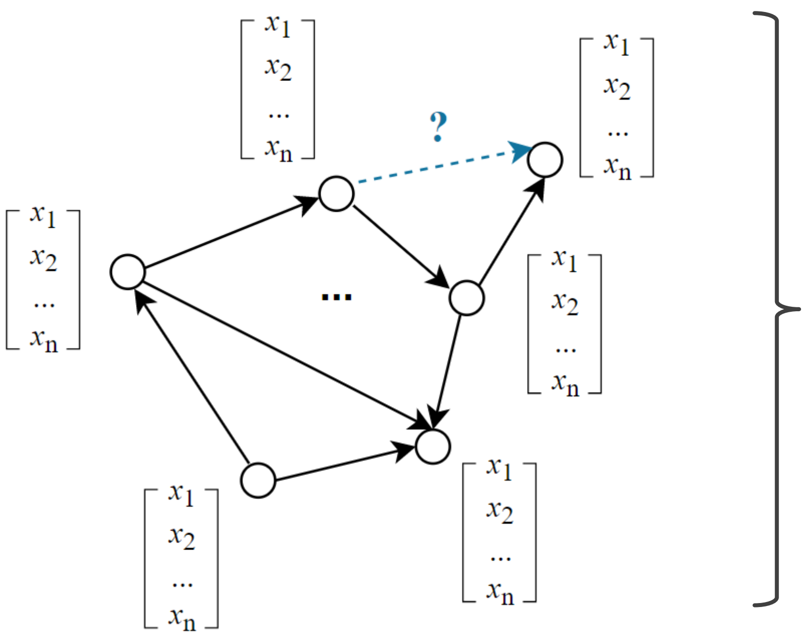


		$K_2 = 10$	$K_2 = 20$	$K_2 = 30$	$K_2 = 40$	$K_2 = 50$
$\rho_1 = 0.1$	$K_1 = 50$	1, 2, 4, 5 *1	3, 4, 2, 2	3, 5, 1, 3	5, 3, 3, 1	2, 1, 5, 4
	$K_1 = 60$	1, 2, 5, 2	4, 5, 3, 1	2, 4, 1, 2	3, 3, 2, 5	4, 1, 4, 3
	$K_1 = 70$	2, 4, 4, 3	1, 1, 5, 2	4, 4, 2, 1	5, 3, 1, 5	3, 2, 3, 4
	$K_1 = 80$	1, 1, 5, 3	5, 5, 1, 5	2, 3, 3, 4	3, 4, 4, 2	4, 2, 2, 1
	$K_1 = 90$	2, 3, 2, 2	4, 1, 3, 1	5, 5, 1, 2	3, 4, 2, 1	1, 2, 5, 3
	$K_1 = 100$	1, 1, 5, 3	3, 4, 4, 2	2, 3, 2, 5	4, 2, 2, 1	5, 5, 1, 3
$\rho_1 = 0.505$	$K_1 = 50$	1, 3, 4, 1	2, 5, 1, 4	2, 4, 2, 2	5, 2, 3, 5	1, 1, 5, 3
	$K_1 = 60$	2, 3, 4, 4	1, 1, 5, 1	5, 3, 2, 3	3, 2, 3, 5	3, 5, 1, 4
	$K_1 = 70$	1, 3, 4, 4	4, 5, 1, 1	3, 4, 3, 3	2, 2, 2, 2	5, 1, 5, 5
	$K_1 = 80$	1, 1, 5, 3	2, 2, 3, 1	3, 5, 1, 1	4, 3, 4, 4	5, 4, 2, 5
	$K_1 = 90$	1, 2, 2, 2	4, 1, 1, 1	2, 2, 3, 1	3, 1, 5, 4	5, 2, 2, 1
	$K_1 = 100$	1, 2, 5, 5	4, 1, 1, 1	2, 2, 4, 1	3, 5, 1, 5	5, 2, 2, 1

Proposed Solution

Bike Trips Predictor

A GNN BICYCLE TRIP PREDICTOR



Ride

Station

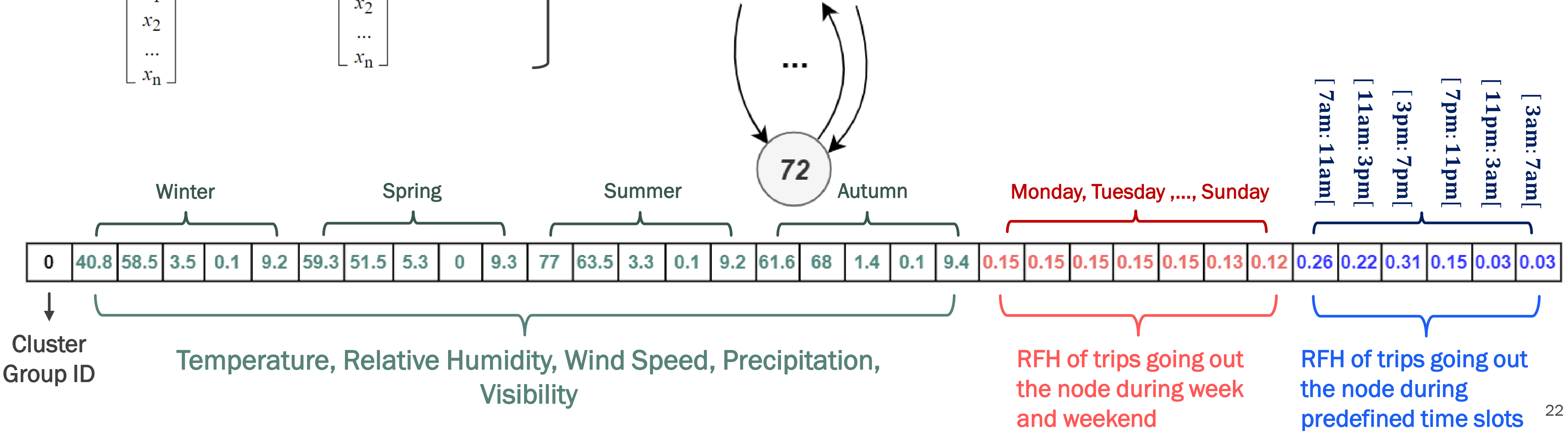
Features

Create the Multigraph Network Structure

+

GraphSAGE Algorithm: an *inductive* node embedding framework

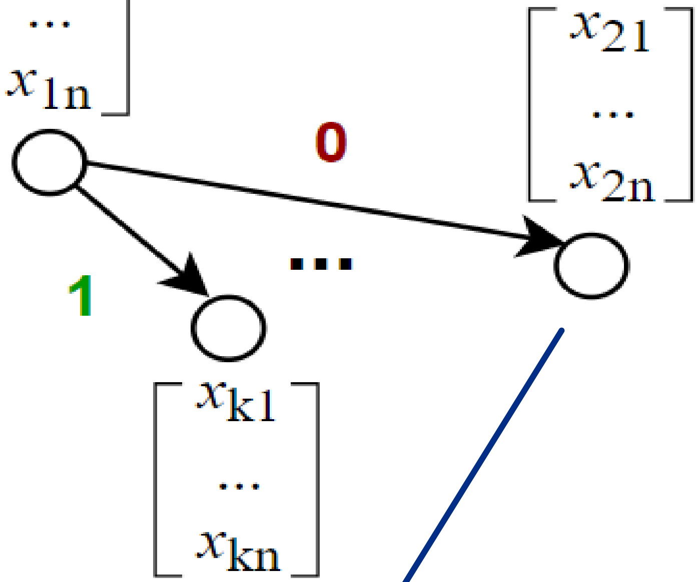
Predict Links (*Bike Trips*) BASED ON → Learning of the Node Features



GNN ARCHITECTURE

Node Embedding

$$\underbrace{\begin{bmatrix} mean(x_{21}, x_{k1}) \\ \dots \\ mean(x_{2n}, x_{kn}) \end{bmatrix} \begin{bmatrix} x_{11} \\ \dots \\ x_{1n} \end{bmatrix}}_{\sigma\,(W \times \mathrm{CONCAT}\,)}$$



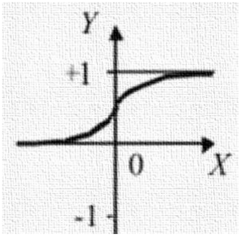
GraphSAGE Embedding Generation

Link Embedding

Link Classification Layer

Inner Product of Node Embeddings

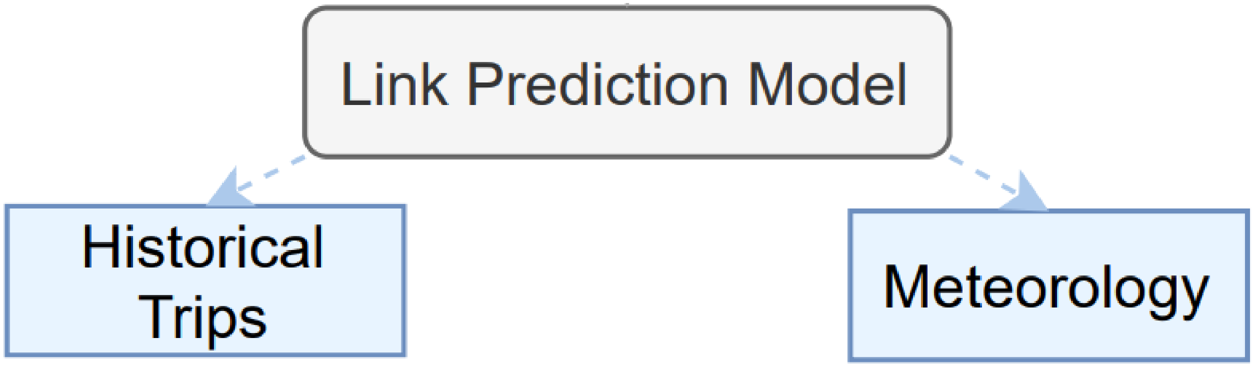
$$ip(u, v) = \sum_i u_i \times v_i$$



Dense Link Classification Layer

PROBLEM SETUP: DATA

2018



Four Clustering Configurations

↓

AdaTC and *three* baselines:

- K-Medoids (**KM**)
- Spectral Clustering (**SC**)
- Geo-Clustering (**GC**)

Train *Five* LP Models

↓

Four Cluster-Based:

- **AdaTC**, **KM**, **SC** and **GC**

One Without Clustering:

- No Clustering (**NC**)

Evaluate Performance on test held out data

2019 NETWORK

2019

Infer Generalization on test data, trained on 2018 data

↓

KEEPING

- Clustering Results
- Weather

UPDATING

- Historical CitiBike Trips

ACCURACY IN THE TEST SET AFTER CALIBRATION. ADATC$_+$ OUTPERFORMS THE BASELINES AND WHEN IN MISMATCH, THE PERFORMANCE DOES NOT DEGRADE SIGNIFICANTLY.

	AdaTC$_+$	GC	SC	KM	NC
2018	88%	87%	86%	83%	83%
2019 (Mismatch)	85%	86%	85%	83%	84%

ENTIRE GRAPH DIMENSIONS IN 2018 AND 2019. $2019_{\text{restricted}}$ REPRESENTS THE 2019 GRAPH RESTRICTED TO THE STATIONS (AND CORRESPONDING TRIPS) IN THE 2018 SETTING.

2018		$2019_{\text{restricted}}$		2019	
# nodes	# links	# nodes	# links	# nodes	# links
801	17.526.058	762	18.674.518	1333	20.551.697

AdaTC + GRAPHSAGE AS A BETTER PERFORMANT MODEL

Best Model ⟶ Performance on the Prediction Task

2018

Cluster-Based				Without Clustering
Our Predictor	Baselines			
AdaTC	GC	SC	KM	NC
88%	87%	86%	83%	83%

- Cluster Relevance
- AdaTC Outperforms all the Baselines in the 2018 setting

AdaTC + GRAPHSAGE MODEL PERCENTAGE ERROR

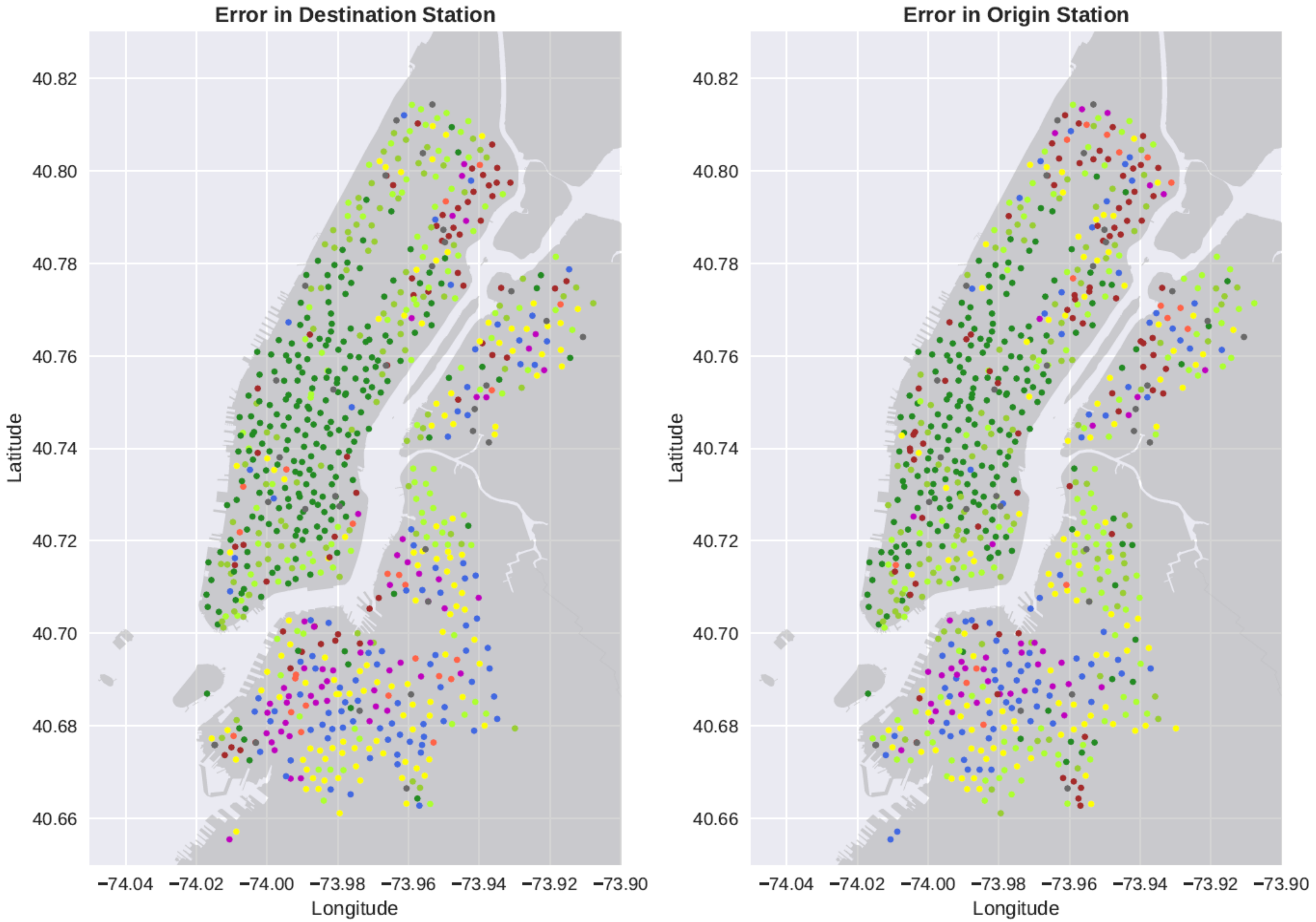
$$PE = \frac{1}{x_t}\left|x_t - x_p\right| \times 100 \ (\%)$$

Number of True Rides

Number of Positive Rides Predicted

citibike_station_id	start_true	start_pred_true	stop_true	stop_pred_true	error_start	error_stop
72.0	4.0	9.0	4.0	6.0	125.00	50.0
120.0	54.0	20.0	0.0	2.0	62.96	inf
127.0	359.0	356.0	8.0	15.0	0.84	87.5

AdaTC + GRAPHSAGE MODEL PERCENTAGE ERROR



$$PE = \frac{1}{x_t}\left|x_t - x_p\right| \times 100\ (\%)$$

Number of True Rides

Number of Positive Rides Predicted

- 0% ≤ Percentage Error ≤ 5%
- 5% < Percentage Error ≤ 15%
- 15% < Percentage Error ≤ 30%
- 30% < Percentage Error ≤ 45%
- 45% < Percentage Error ≤ 60%
- 60% < Percentage Error ≤ 75%
- 75% < Percentage Error ≤ 90%
- Percentage Error > 90%
- Stations Removed

AdaTC + GRAPHSAGE MODEL PERCENTAGE ERROR

\# Trips

↓↑

Error

Stations with Stable Transitions Patterns

↓

PE is on average $\approx 20\%$

12% of Error

↓

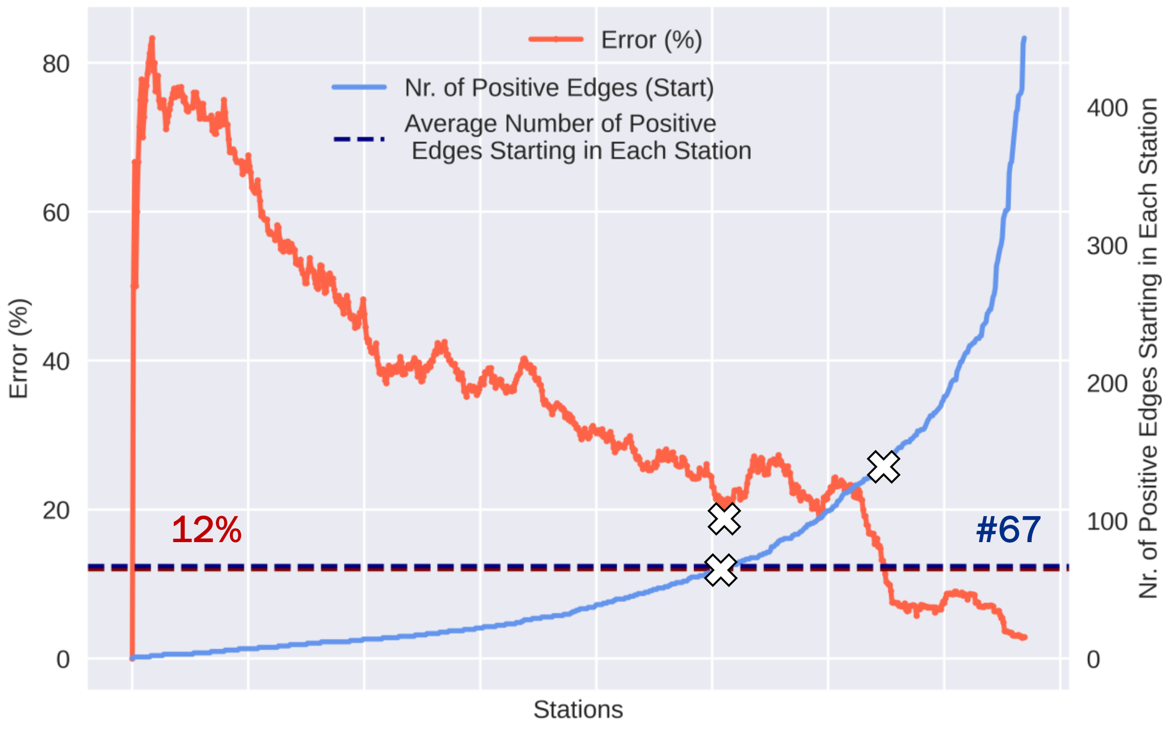
- Stations with ≥ 120 trips starting
- Stations with ≥ 100 trips ending

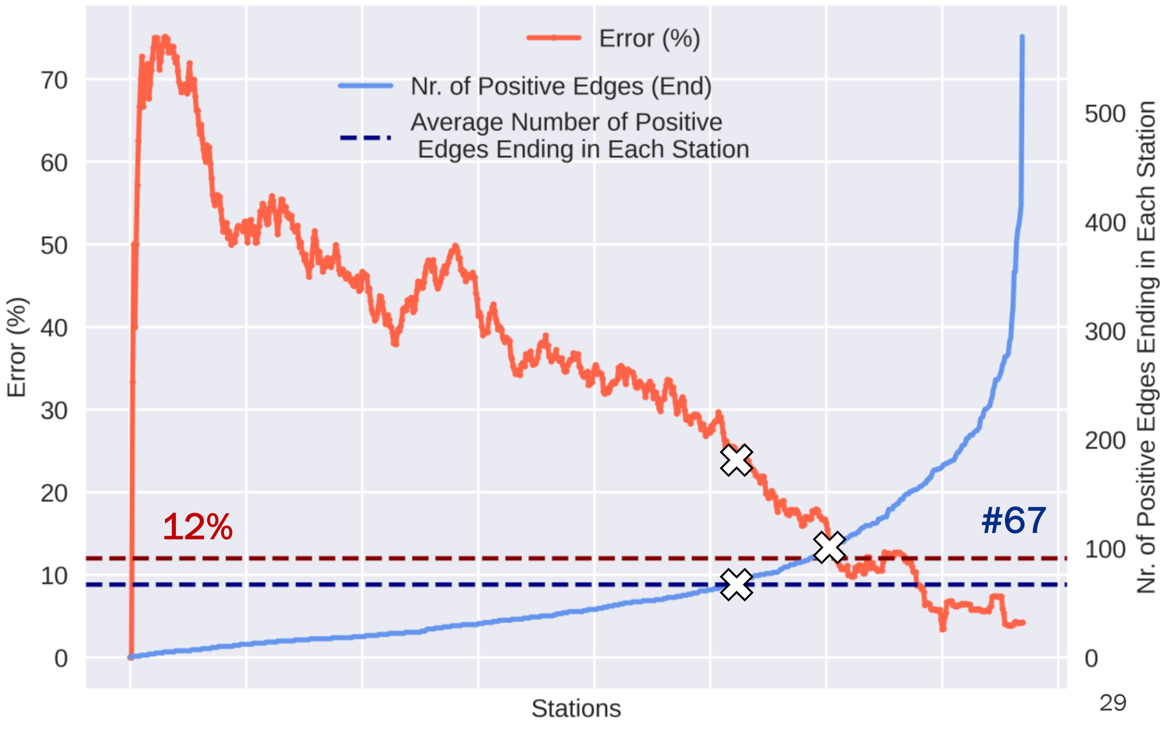
Larger PE → **Outlier Stations**

Stations with a smaller number of trips

64% of Stations are atypical

(below the average)





CONCLUSIONS AND LIMITATIONS

- We Provide a Lower Bound on the Accuracy for the Model in this Predictive Task

- Limitation: We cannot take advantage of the *Indutive Nature* of the Model

Future Work Redefine the Loss or *Continual Learning* Strategy