Introduction/ Background

Our Research Topic: Deciphering Traffic Dynamics: Insights from the Los Angeles Highway Network

Motivation: Want to study the data of car traffic in California's state highway systems to further understand the traffic network that California is infamously known for due to its high population density.

Our Datasets

Used the data set and computational methods for further network measurements from the research paper ***Predicting Los Angeles Traffic with Graph Neural Networks*** by Amelia Woodward.

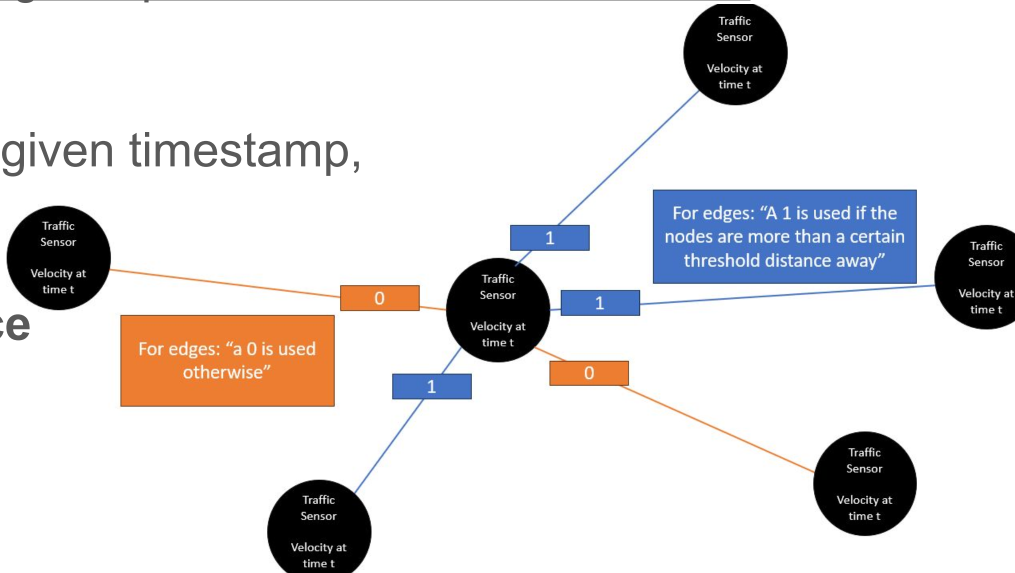
<u>nodes are locations, distance-based edges, speed at each node over time</u>

PeMSD7(M) and **PeMSD7(L):**

(M: 228, L: 1026) sensor's speed at a given timestamp,

PeMSD7(M) has location coordinates

From **caltrans: PeMSD7 (Performance Measurement System, District 7)**



Summary of our research areas

- Graph Structure Analysis
- Traffic Data Analysis
- Network Traffic Relationship
- Creation of a Predictive Model

Graph Structure Analysis - Graph Connections

- Geographical view of sensors
- Connectivity throughout the network
- Dense or Sparse in network?

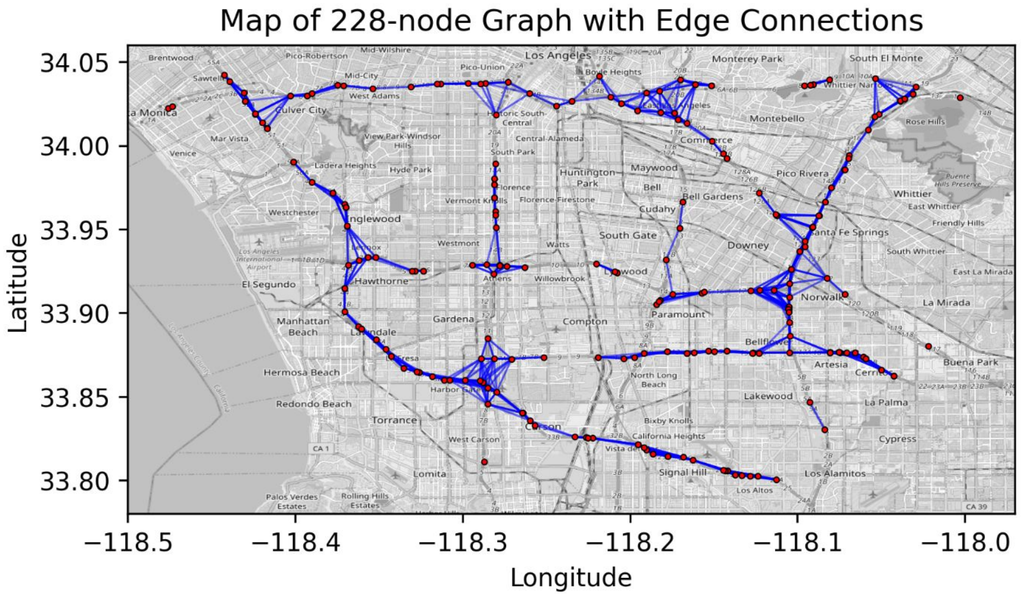


Fig. 2: Diagram of graph connections for the 228-node dataset.

Graph Structure Analysis - Adjacency Matrix

- Rough view of distinct groups
- Connections between groups
- Density/ Sparsity of network

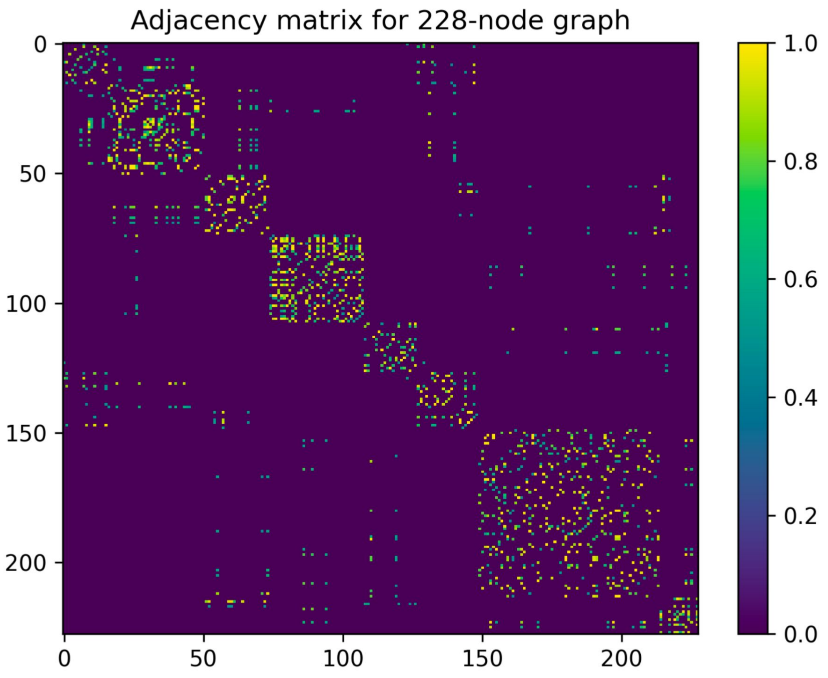
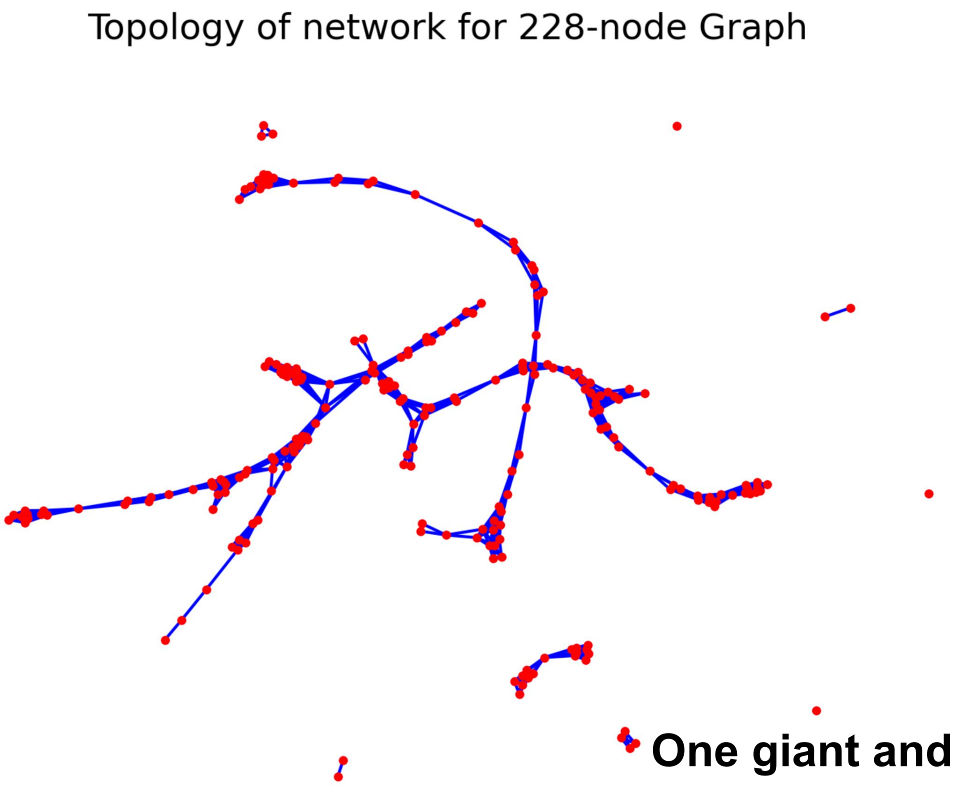
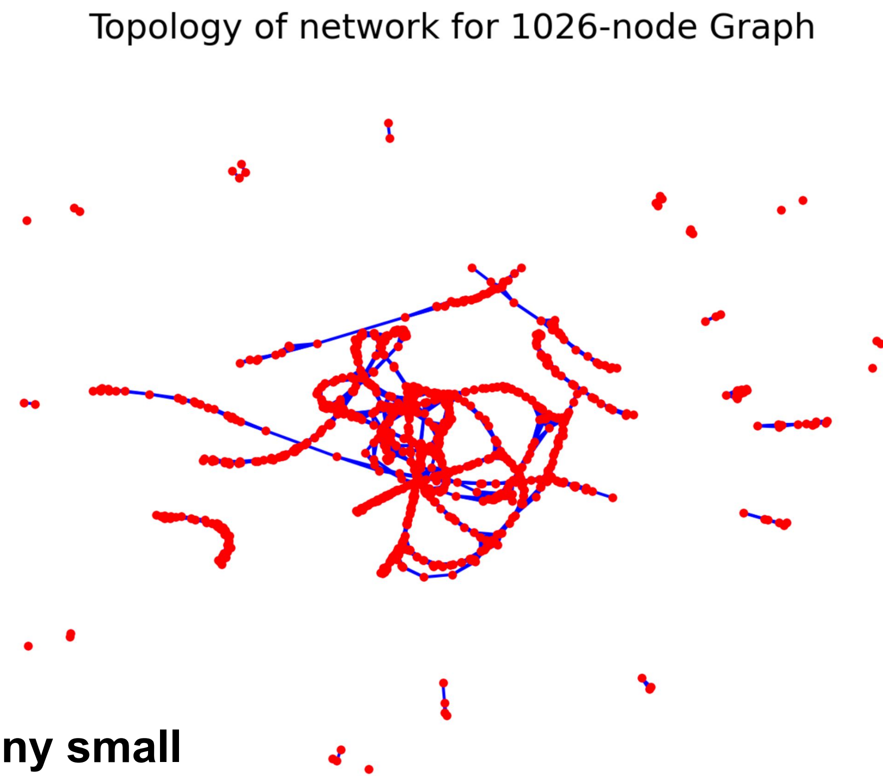


Fig. 3: Adjacency matrix for the 228-node dataset.

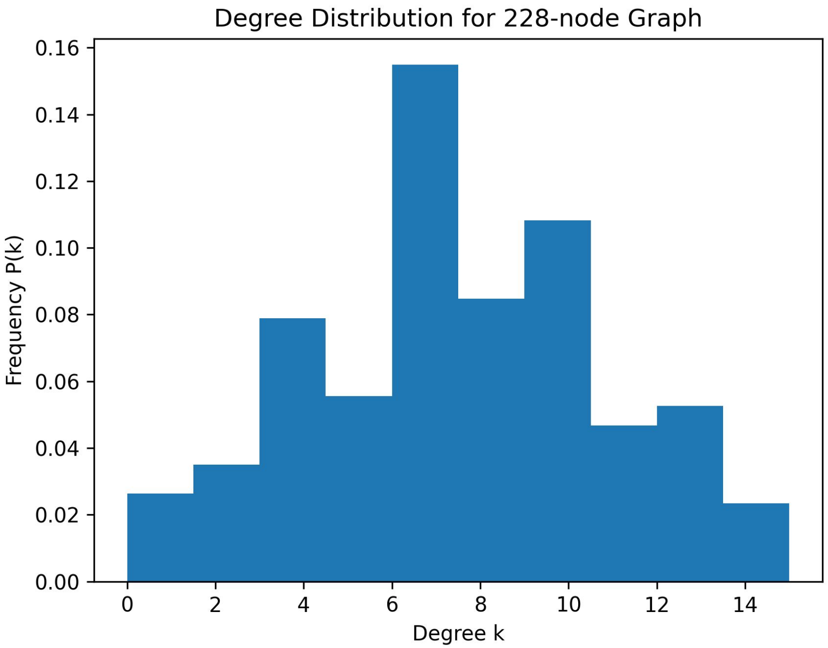
Graph Structure Analysis - Network Topology

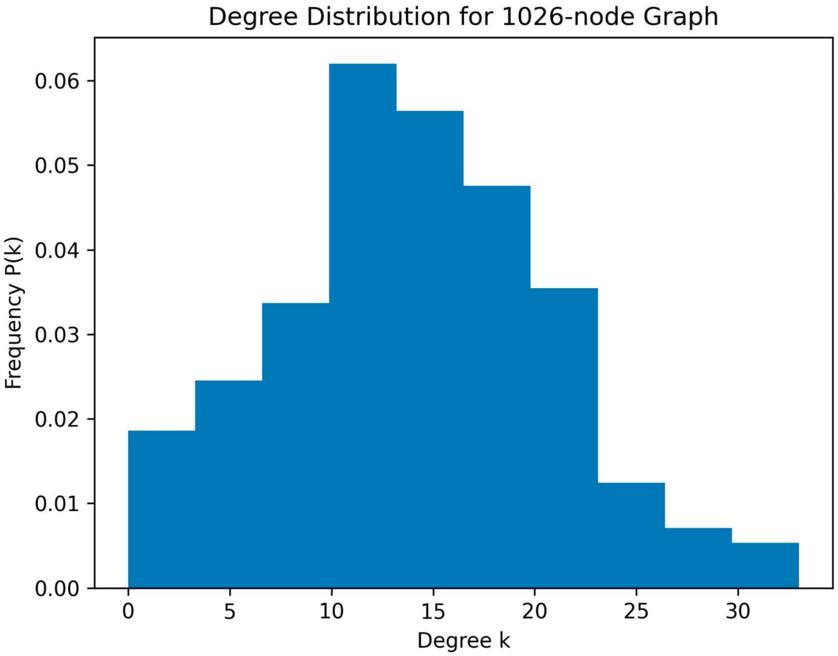




One giant and many small connect components

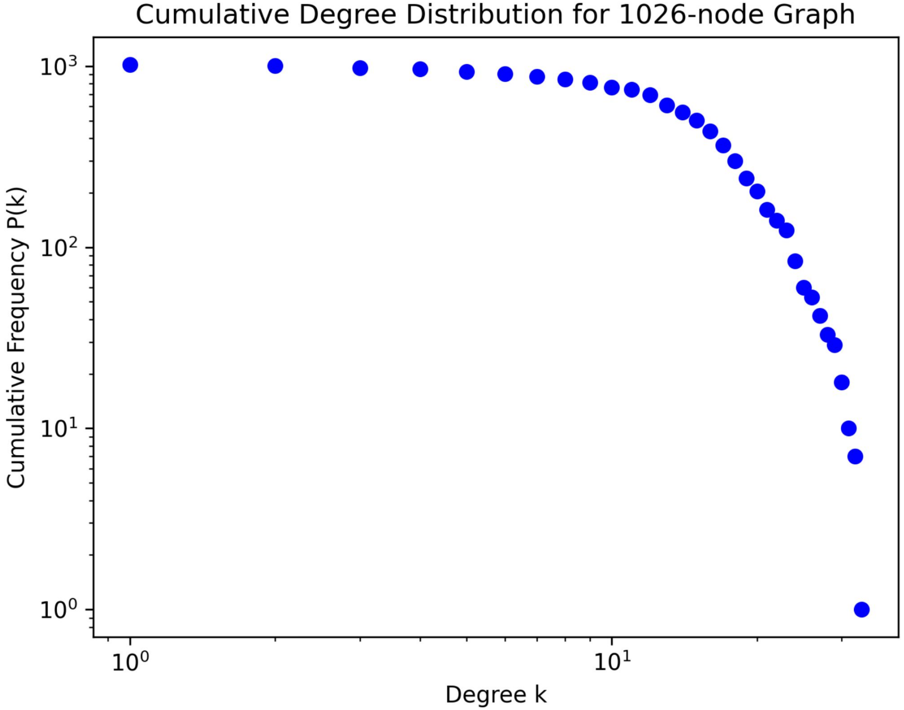
Graph Structure Analysis - Degree Distribution





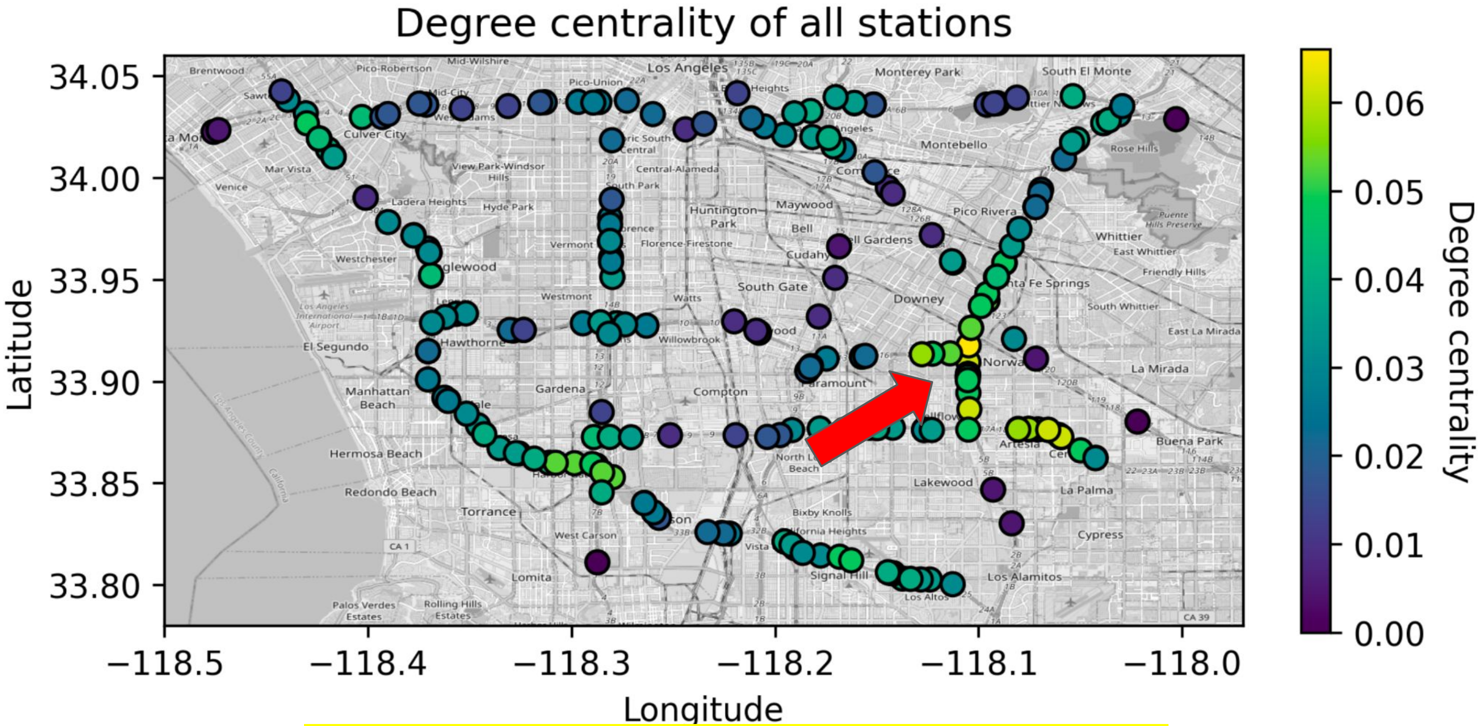
Approximately normal distribution in both data sets

Graph Structure Analysis - Cumulative Degree Distribution



Non-linear which implies not scale free
No large hubs in network

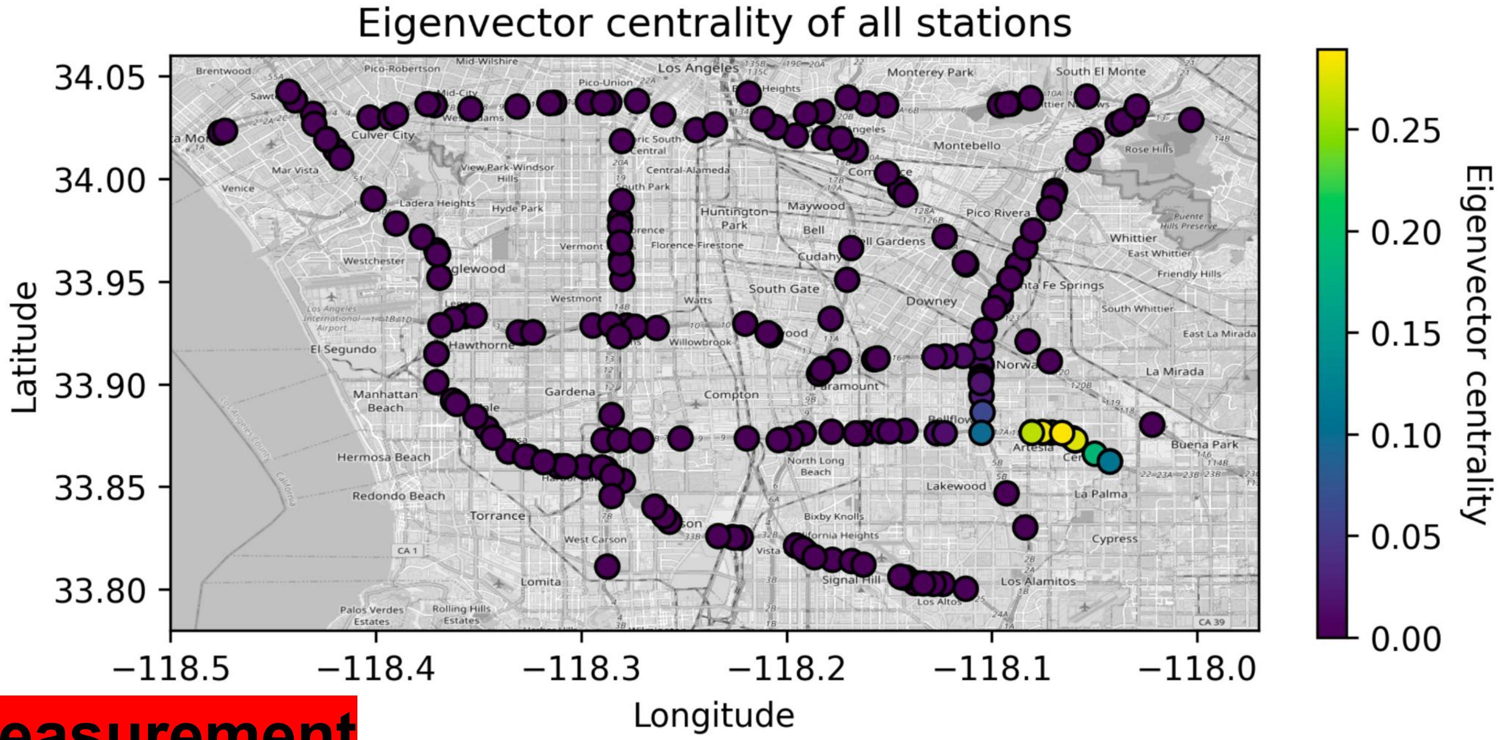
Graph Structure Analysis - Degree Centrality



Assuming certain properties of nodes

(b) Geographic map of each node's degree centrality.

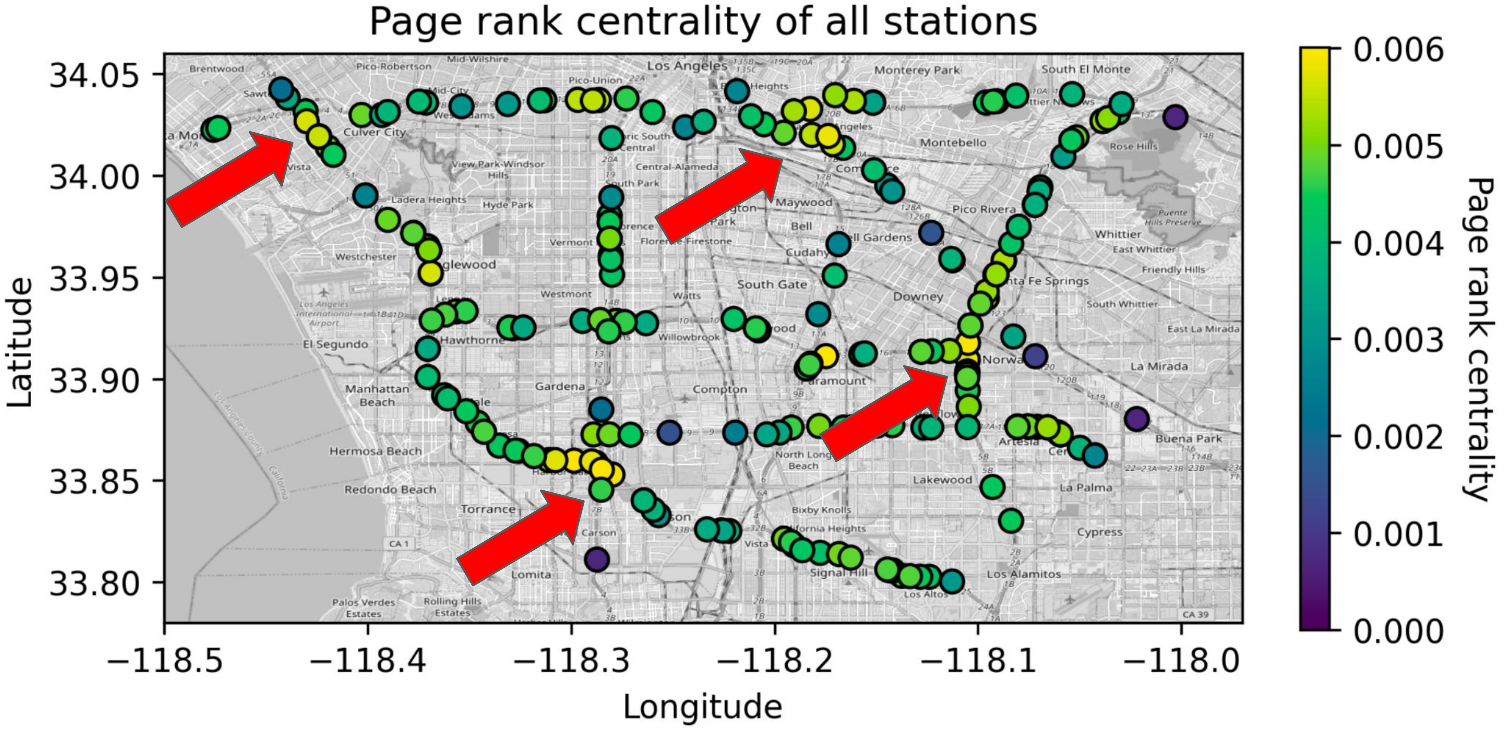
Graph Structure Analysis - Eigenvector Centrality



Bad Measurement

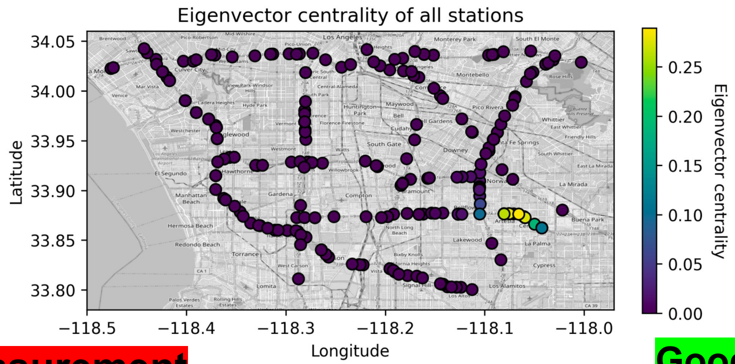
(a) Geographic map of each node's eigenvector centrality.

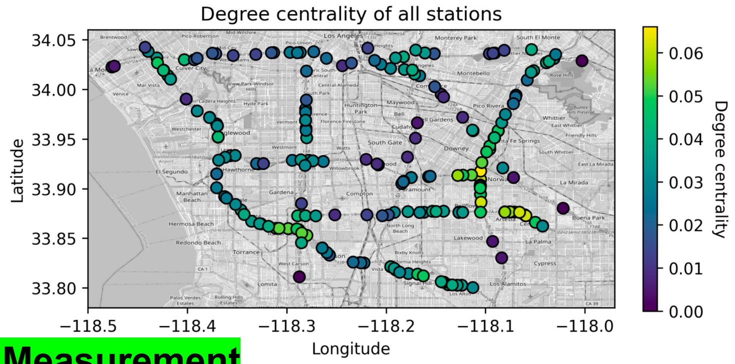
Graph Structure Analysis - PageRank Centrality



(c) Geographic map of each node's PageRank centrality.

Graph Structure Analysis - All Centrality Measures



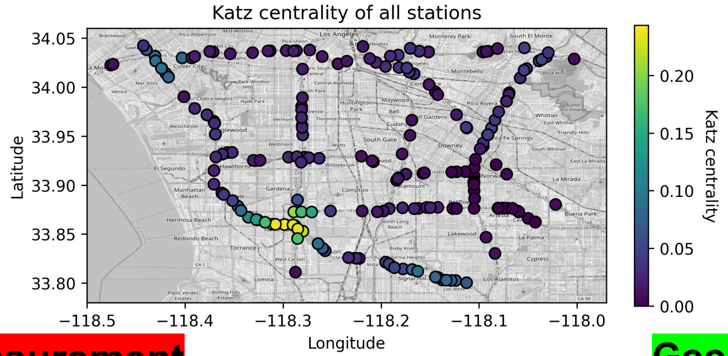


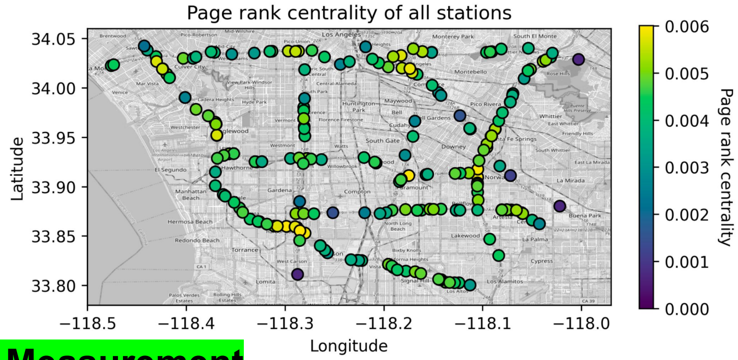
Bad Measurement

Good Measurement

(a) Geographic map of each node's eigenvector centrality.

(b) Geographic map of each node's degree centrality.



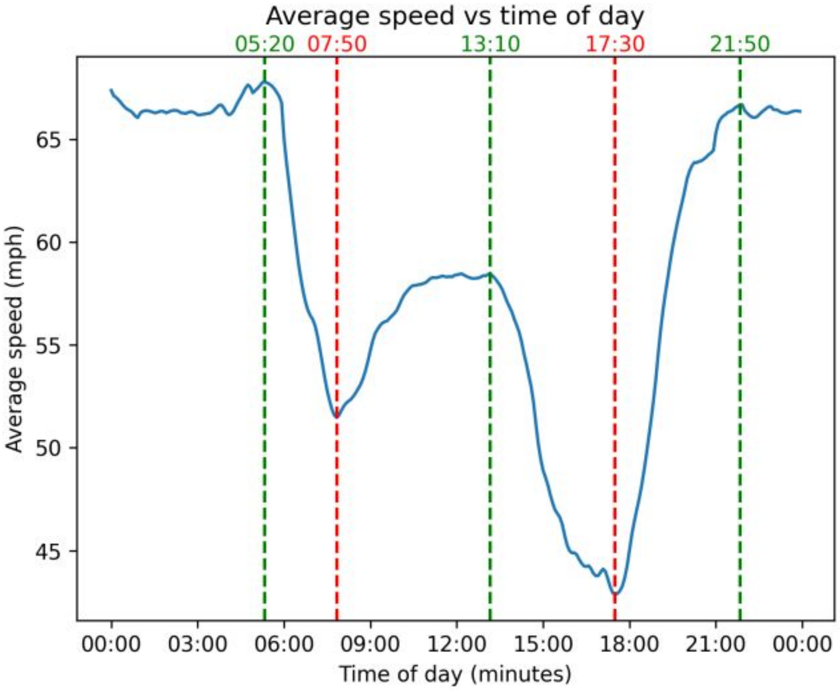


Bad Measurement

Good Measurement

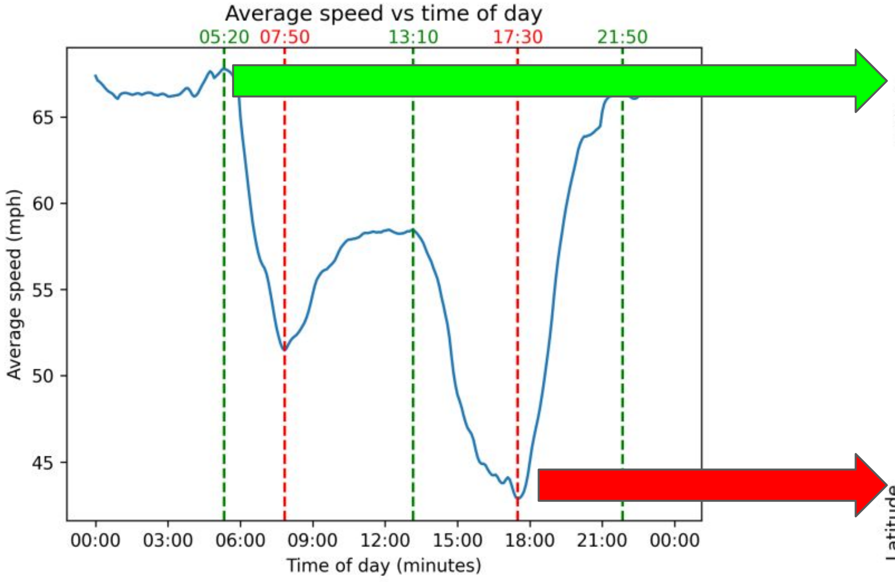
(c) Geographic map of each node's PageRank centrality.

Traffic Data Analysis - Average speed vs time of day

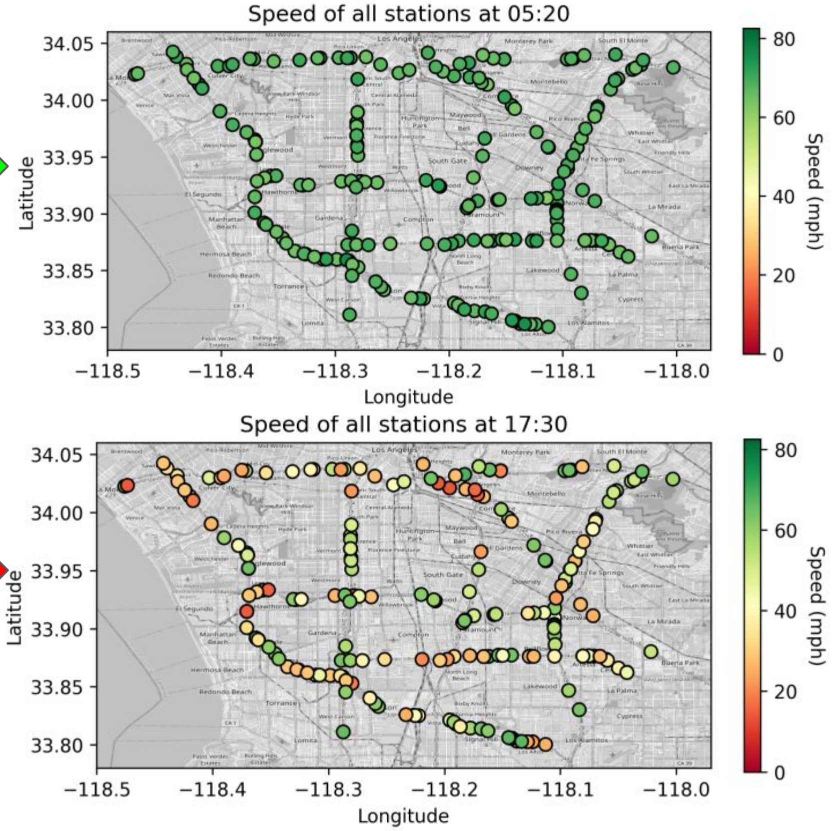


(a) Average speed of all sensors in the network at a given time of day, averaged across all 44 days in the dataset.

Traffic Data Analysis - Speed maps at local extrema



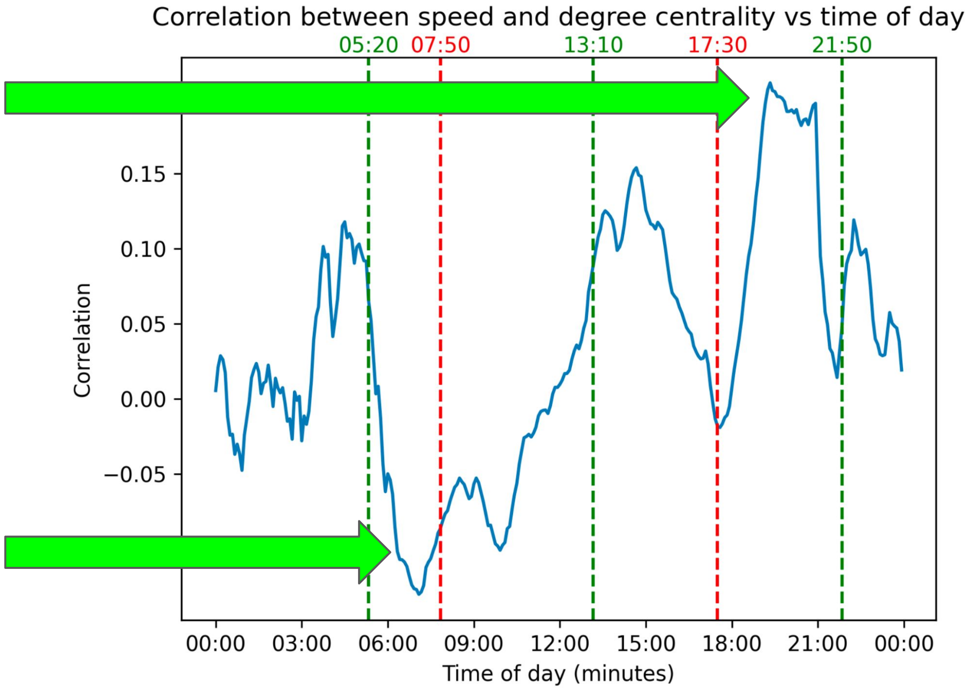
(a) Average speed of all sensors in the network at a given time of day, averaged across all 44 days in the dataset.



Network Traffic Relationship - Correlation vs time of day

Positive Correlation

Negative Correlation

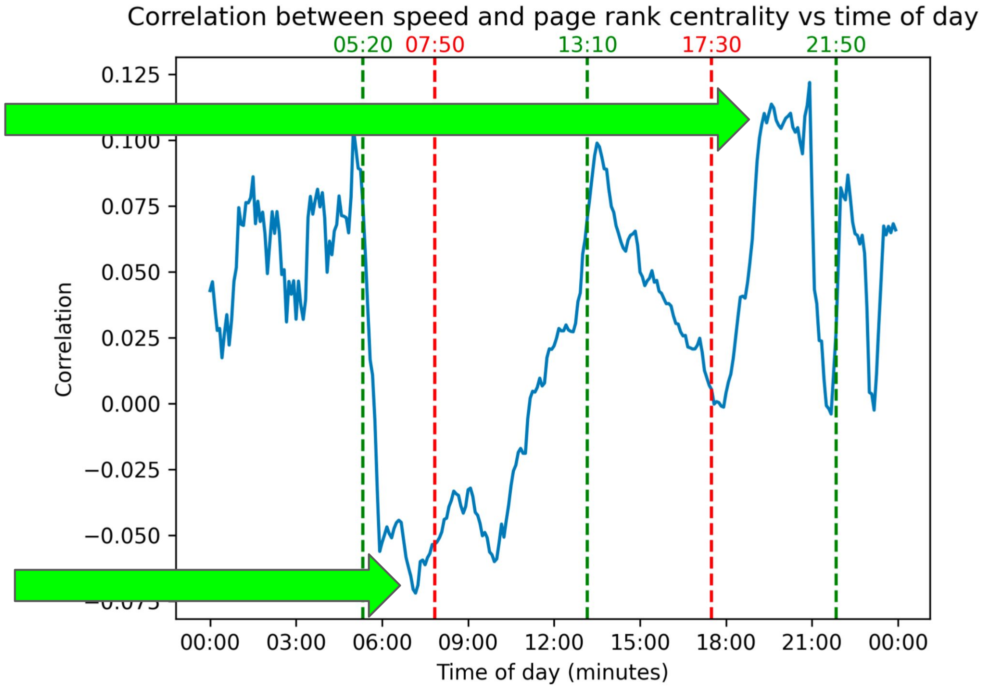


(a) Pearson correlation coefficient between each station's average speed and degree centrality, computed at each time of day.

Network Traffic Relationship - Correlation vs time of day

Positive Correlation

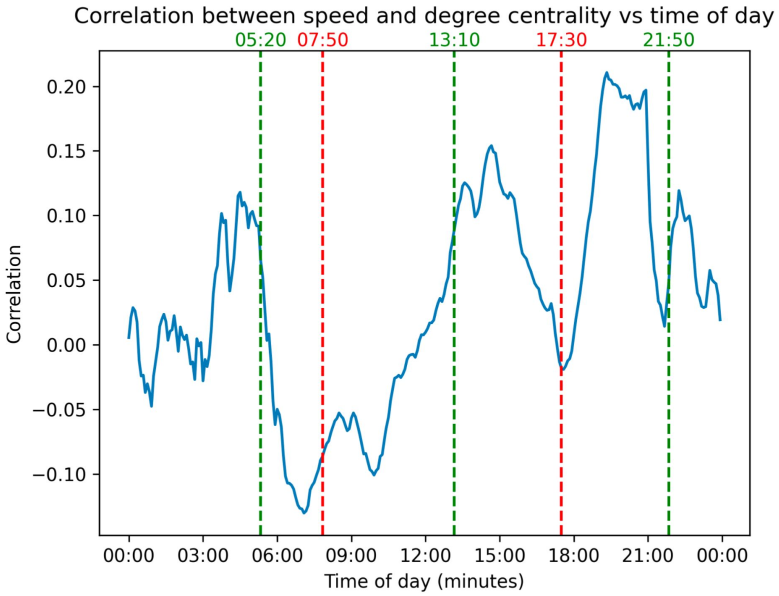
Negative Correlation



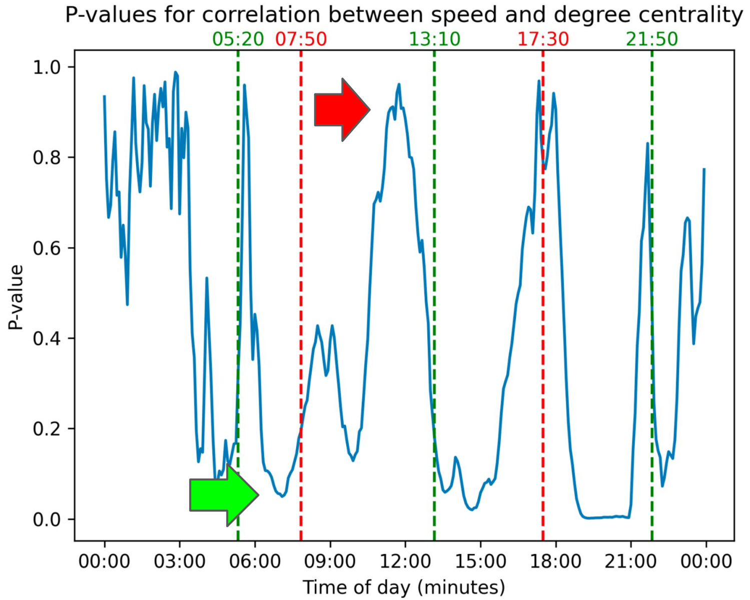
(b) Pearson correlation coefficient between each station's average speed and PageRank centrality, computed at each time of day.

Network Traffic Relationship - Correlation p-values

No Statistical Significance



(a) Pearson correlation coefficient between each station's average speed and degree centrality, computed at each time of day.



(c) The corresponding p-values for the Pearson correlations between speed and degree centrality in subfigure (a).

Predictive Model - Linear Dynamical System on a Network

$$\frac{dv_i}{dt} = b_i + w_{ii}v_i + \sum_{j \in N(i)} w_{ij}v_j$$

- "The acceleration of traffic at each node is linearly proportional to its neighbors traffic"
- W, b general parameters

Predictive Model - Linear Dynamical System on a Network

$$\frac{dv_i}{dt} = b_i + w_{ii}v_i + \sum_{j \in N(i)} w_{ij}v_j$$

$$\frac{d\mathbf{v}}{dt} = \mathbf{b} + \mathbf{W}\mathbf{v}$$

Predictive Model - Linear Dynamical System on a Network

$$\frac{d\mathbf{v}}{dt} = \mathbf{b} + \mathbf{W}\mathbf{v}$$

$$\frac{d\mathbf{v}}{dt} = \mathbf{b} + (\mathbf{A} \odot \mathbf{W})\mathbf{v}$$

- Force (1-A)⊙W=0 in computational experiments

Predictive Model - “Logistic” Dynamical System on Network

$$\frac{dv_i}{dt} = b_i + w_{ii} v_i (c_i - v_i) + \sum_{j \in N(i)} w_{ij} v_j (c_j - v_j)$$

- “The acceleration of traffic at each node is dependent on its neighbors traffic”
- Neighboring traffic > c $\rightarrow$ negative contribution to acceleration
- More representative of traffic flow on a network

Predictive Model - “Logistic” Dynamical System on Network

$$\frac{dv_i}{dt} = b_i + w_{ii} v_i (c_i - v_i) + \sum_{j \in N(i)} w_{ij} v_j (c_j - v_j)$$

$$\frac{d\mathbf{v}}{dt} = \mathbf{b} + \mathbf{W}\mathbf{v} \odot (\mathbf{c} - \mathbf{v})$$

Predictive Model - Loss Function to Learn the Parameters

$$
\begin{aligned}
\hat{\mathbf{v}}^{(t+1)} &= \mathbf{v}^{(t)} + dt\,\frac{d\mathbf{v}}{dt} \\
&= \mathbf{v}^{(t)} + dt(\mathbf{b} + \mathbf{W}\mathbf{v})
\end{aligned}
$$

- Using dv/dt, we can approximate the traffic speeds at the next timestep

Predictive Model - Loss Function to Learn the Parameters

$$\mathscr{L}(b, W, c) = \sum_{t=0}^{N-1} \|\hat{\mathbf{v}}_{b,W,c}^{(t+1)} - \mathbf{v}^{(t+1)}\|^2$$

- Penalize the difference between predicted speed and ground truth speed at each timestep

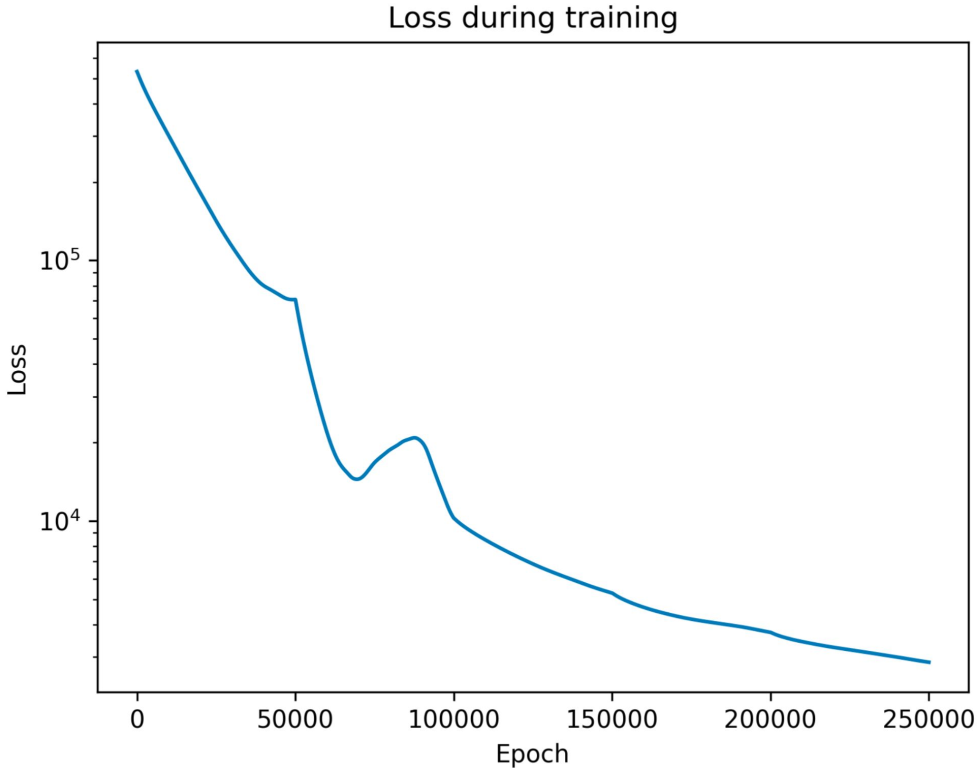
Predictive Model - Gradient Descent

$$b^*, W^* = \mathrm{argmin}_{b,W} L(b, W)$$

- Learn the optimal parameters for this model using gradient descent
  - W,b initialized uniform gaussian random
  - using Adam optimizer and cosine annealing LR scheduler

Predictive Model - Gradient Descent

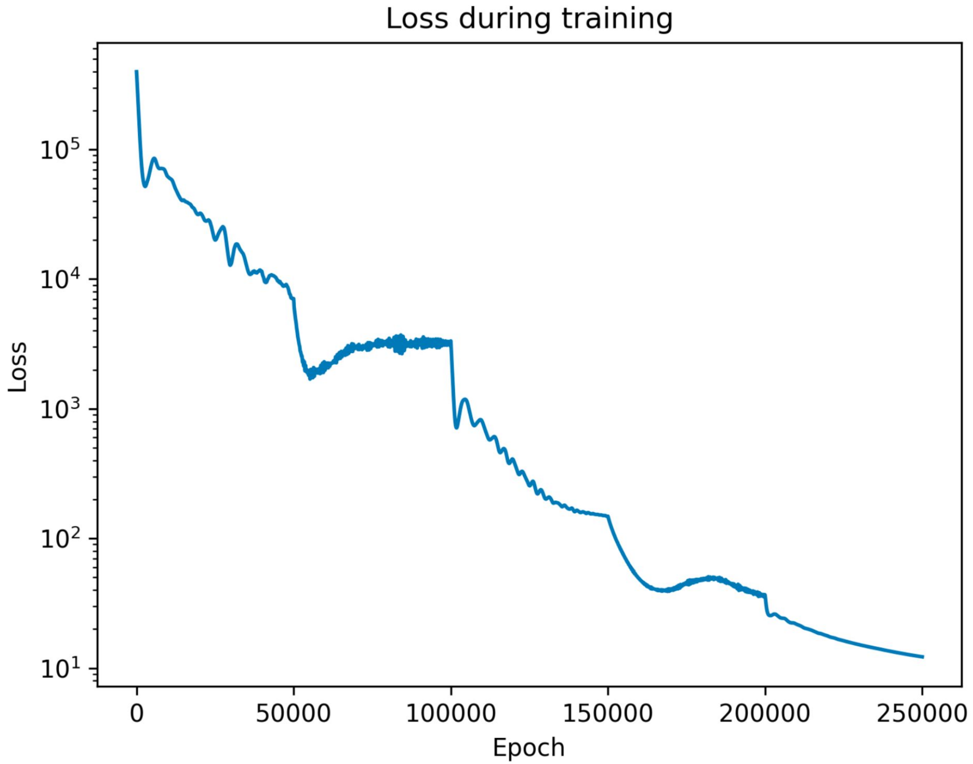
- 250,000 epochs
- Final loss: **2.86e3**



(a) Loss curve for training the linear dynamical system.

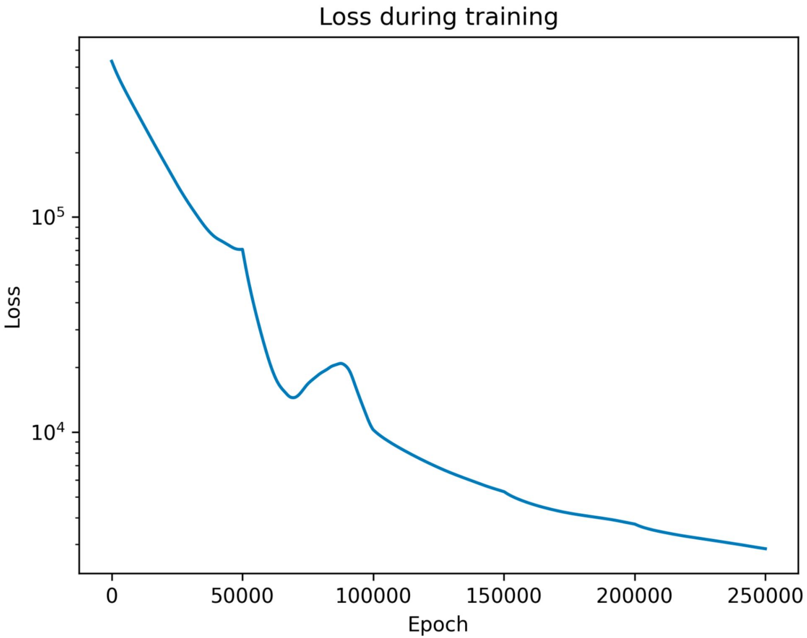
Predictive Model - Gradient Descent

- 250,000 epochs
- Final loss: **1.22e1**

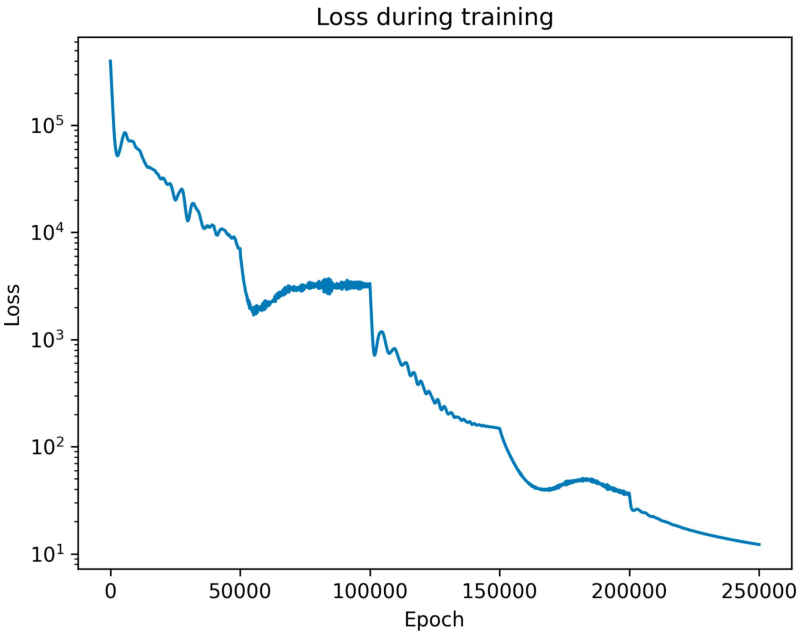


(b) Loss curve for training the logistic dynamical system.

Predictive Model - Gradient Descent

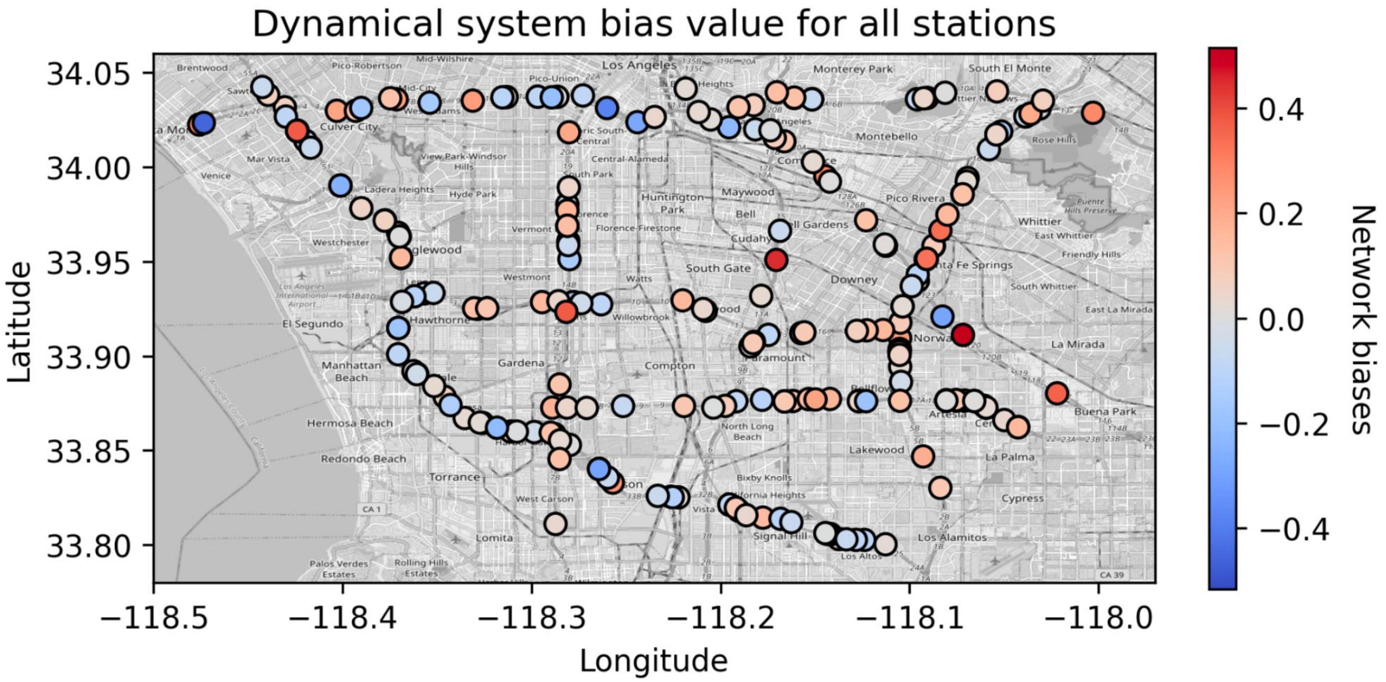


(a) Loss curve for training the linear dynamical system.



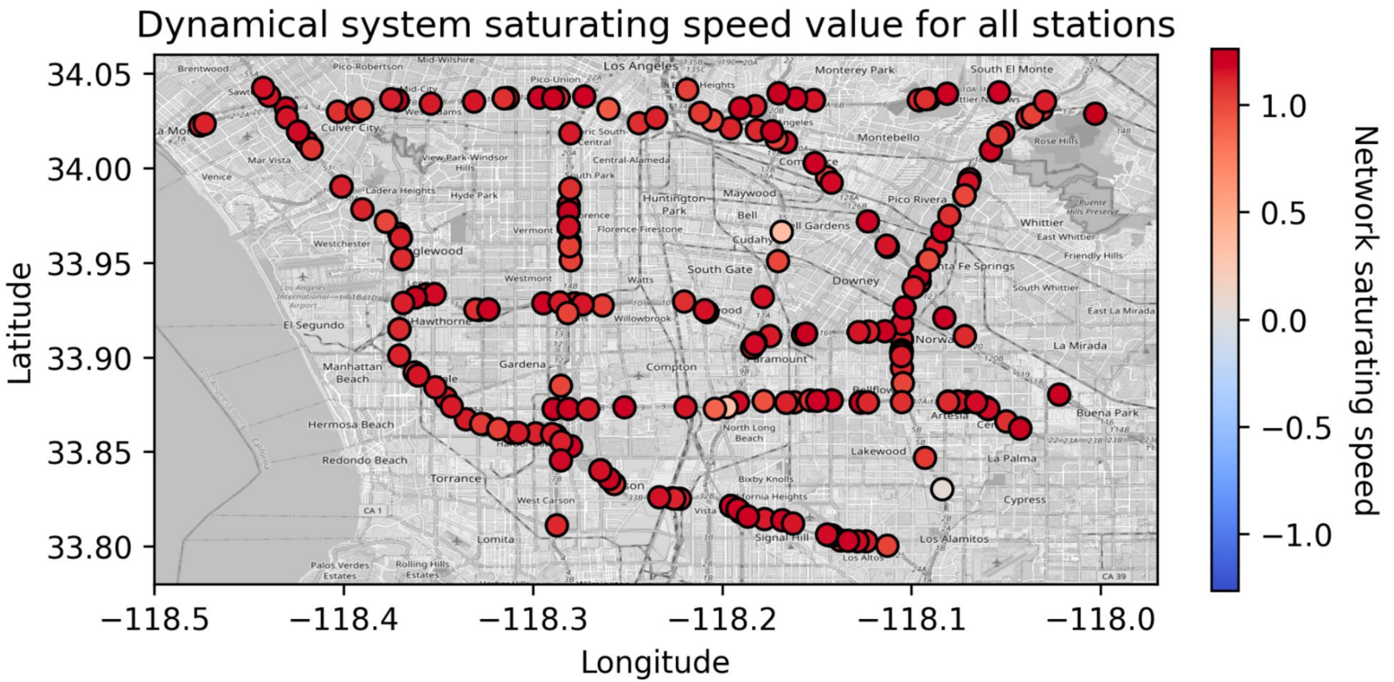
(b) Loss curve for training the logistic dynamical system.

Predictive Model - Learned bias parameters (b)



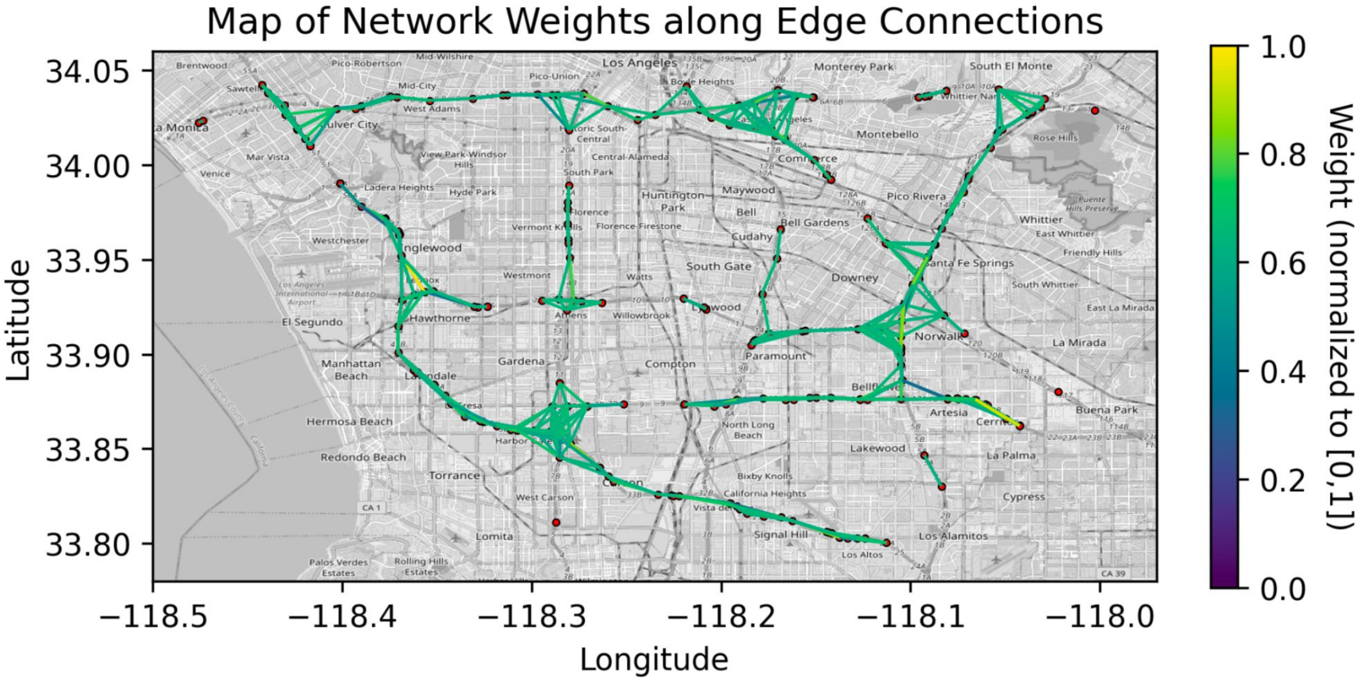
(a) Geographic map of bias parameter learned for each station.

Predictive Model - Learned saturating speed parameters (c)



(b) Geographic map of speed limit parameter learned for each station.

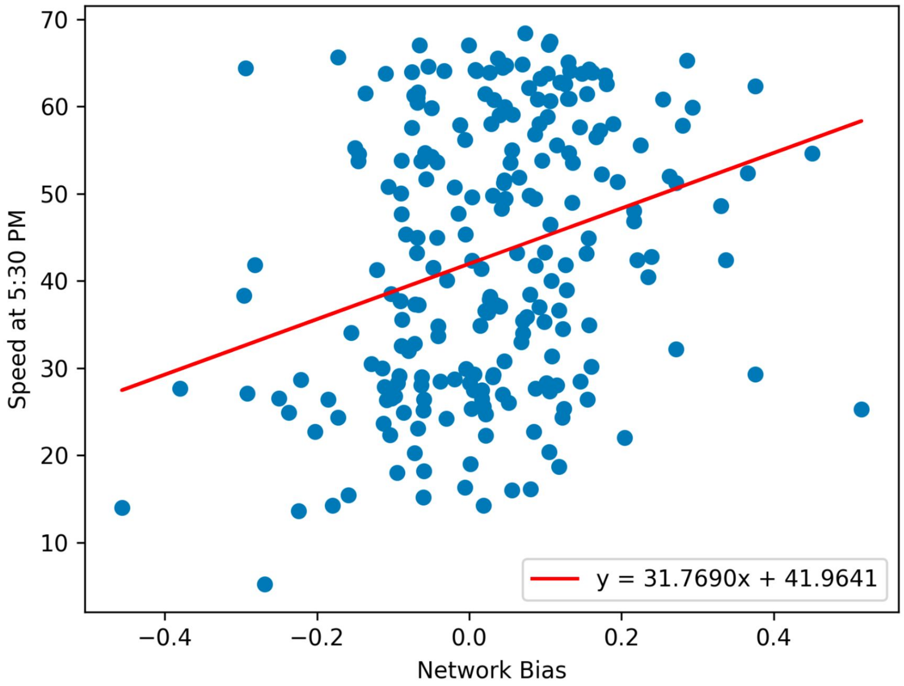
Predictive Model - Learned edge weights (W)



(c) Geographic map of weight parameter learned for each edge between stations.

Predictive Model - Correlation for bias parameter and speed

- Pearson correlation
  - r-value: 0.15
  - p-value: 0.02



(d) Correlation between speed at ”rush-hour“ (5:30 PM) and learned bias parameters for each station.

Future Research

Want to research more real world correlations/ causations that are causing this traffic behavior and how they can be changed/ controlled to help optimize traffic flow and limit traffic congestion.

We also hope to research and find a way to build a reliable model to challenge that can challenge and compare to other predictive models.