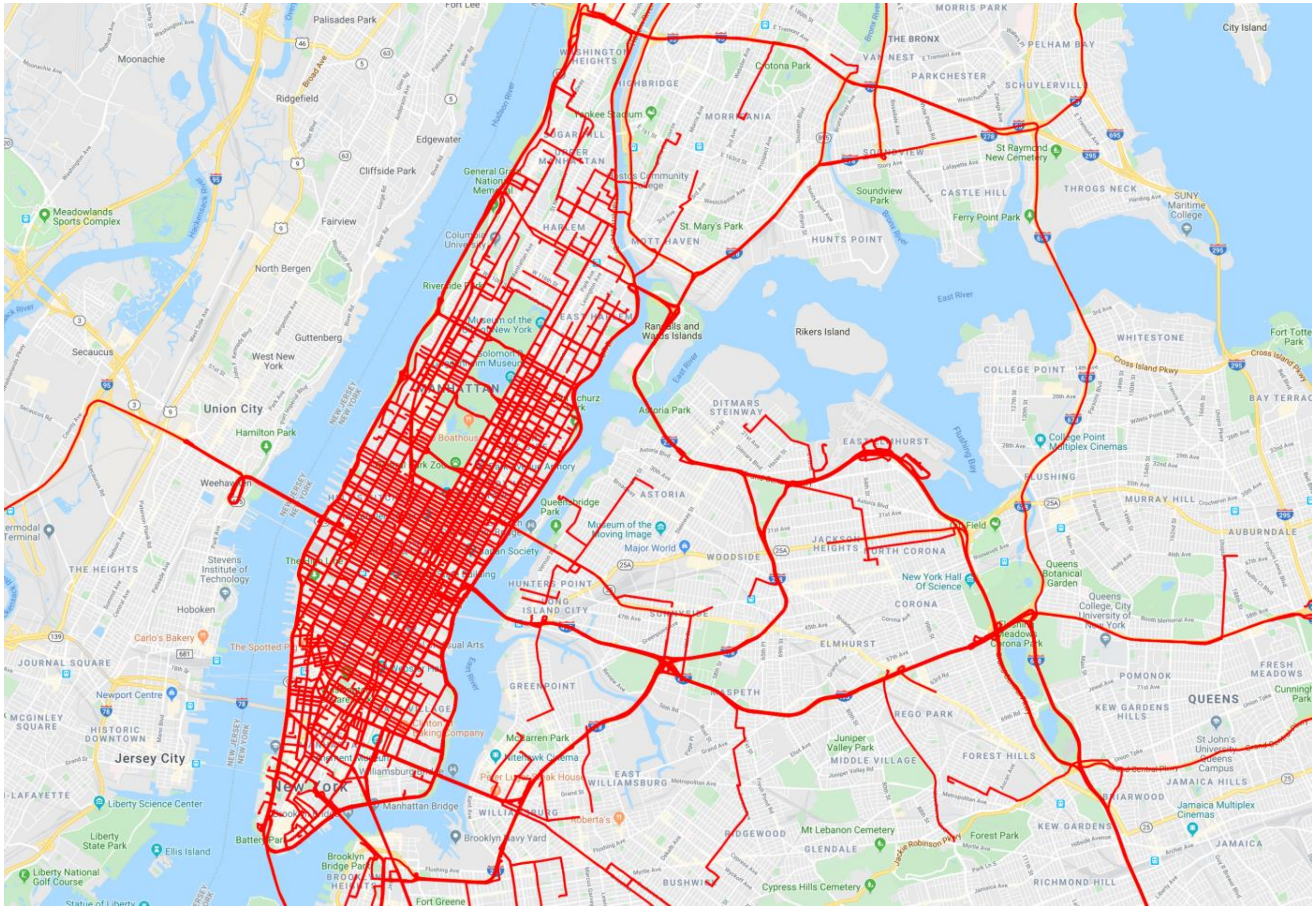
# Learning Semantic Relationships of Geographical Areas Based on Trajectories

Presenter: Saim Mehmood



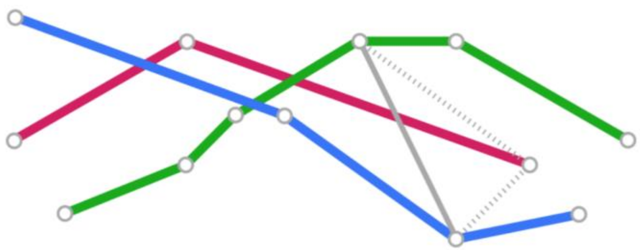

trajectories $(x, y, t)$

(spatiotemporal information of moving objects)

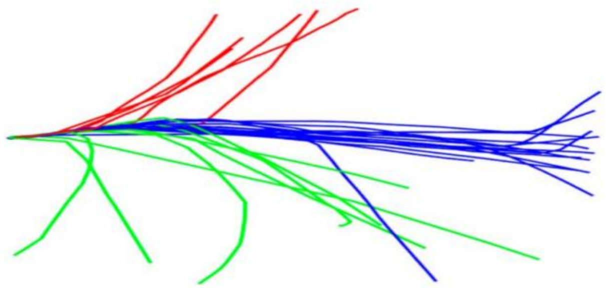
# Trajectory Data Mining

discovering patterns in trajectories to inform critical real-world applications

# Trajectory Data Mining Tasks



trajectory similarity



trajectory clustering

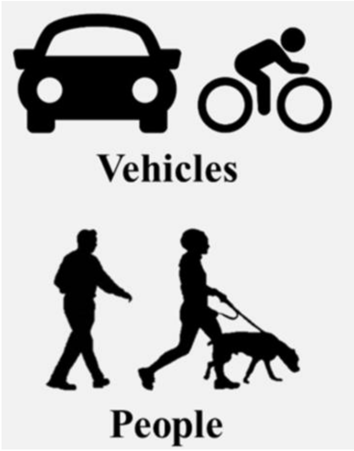
trajectory anomaly detection

trajectory classification

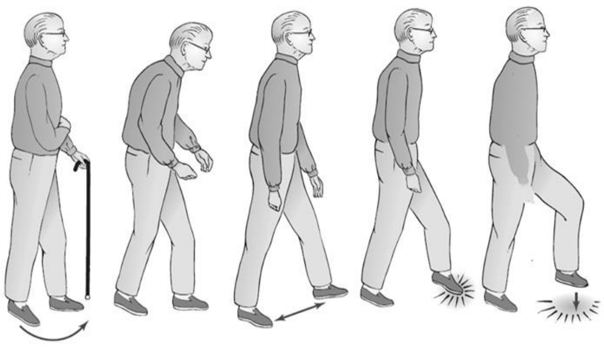
trajectory prediction

etc…

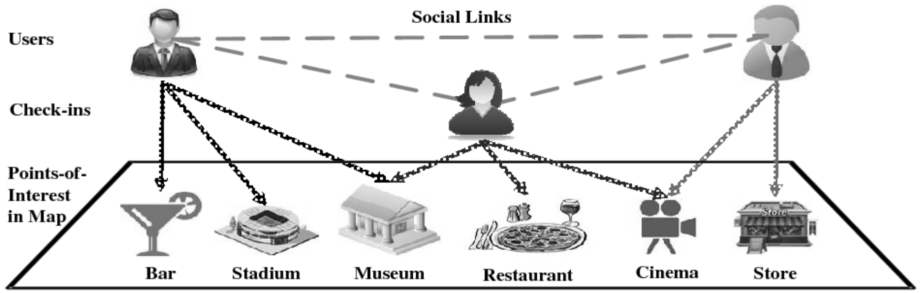
# Trajectory Applications




human mobility understanding



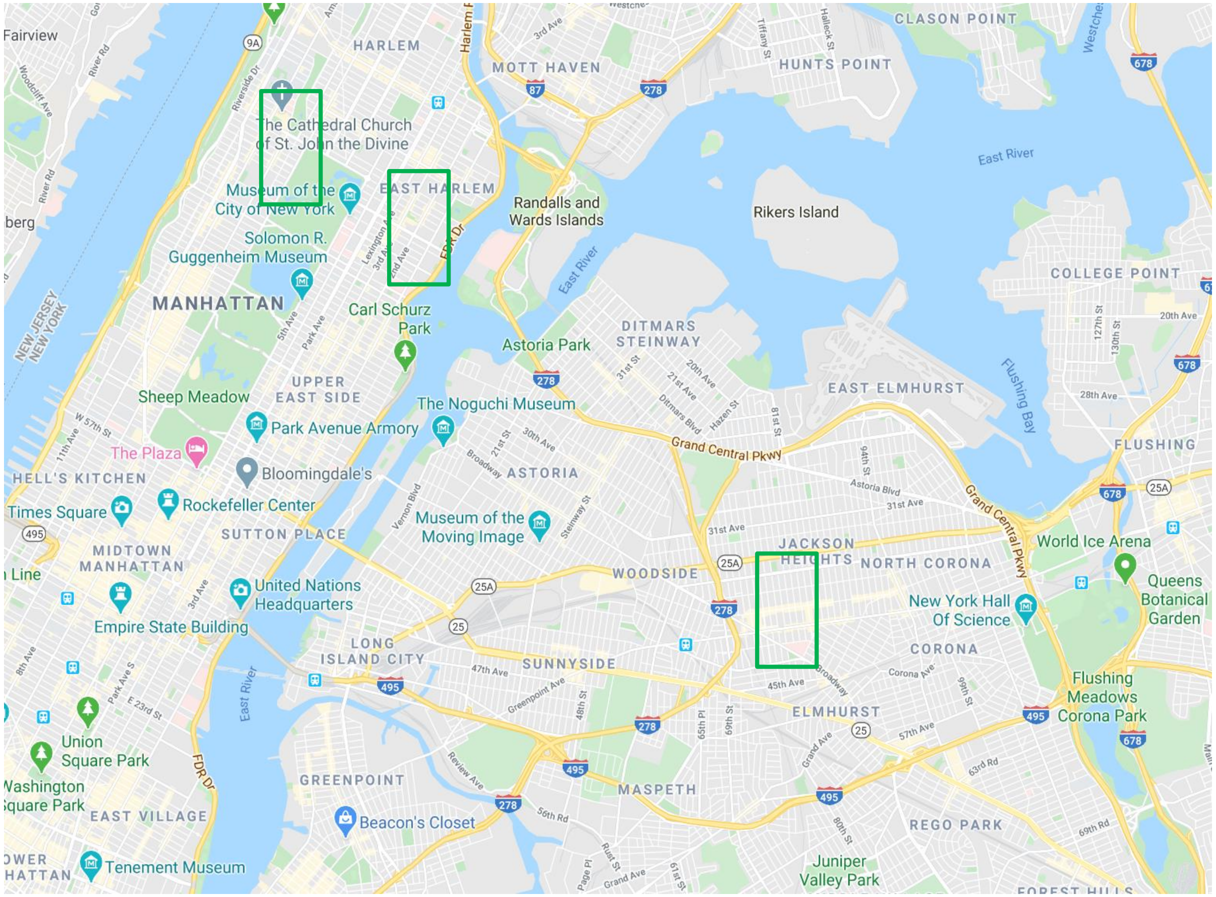
healthcare (detecting change in gait pattern of seniors)




location-based services (e.g., recommendation of points-of-interest)

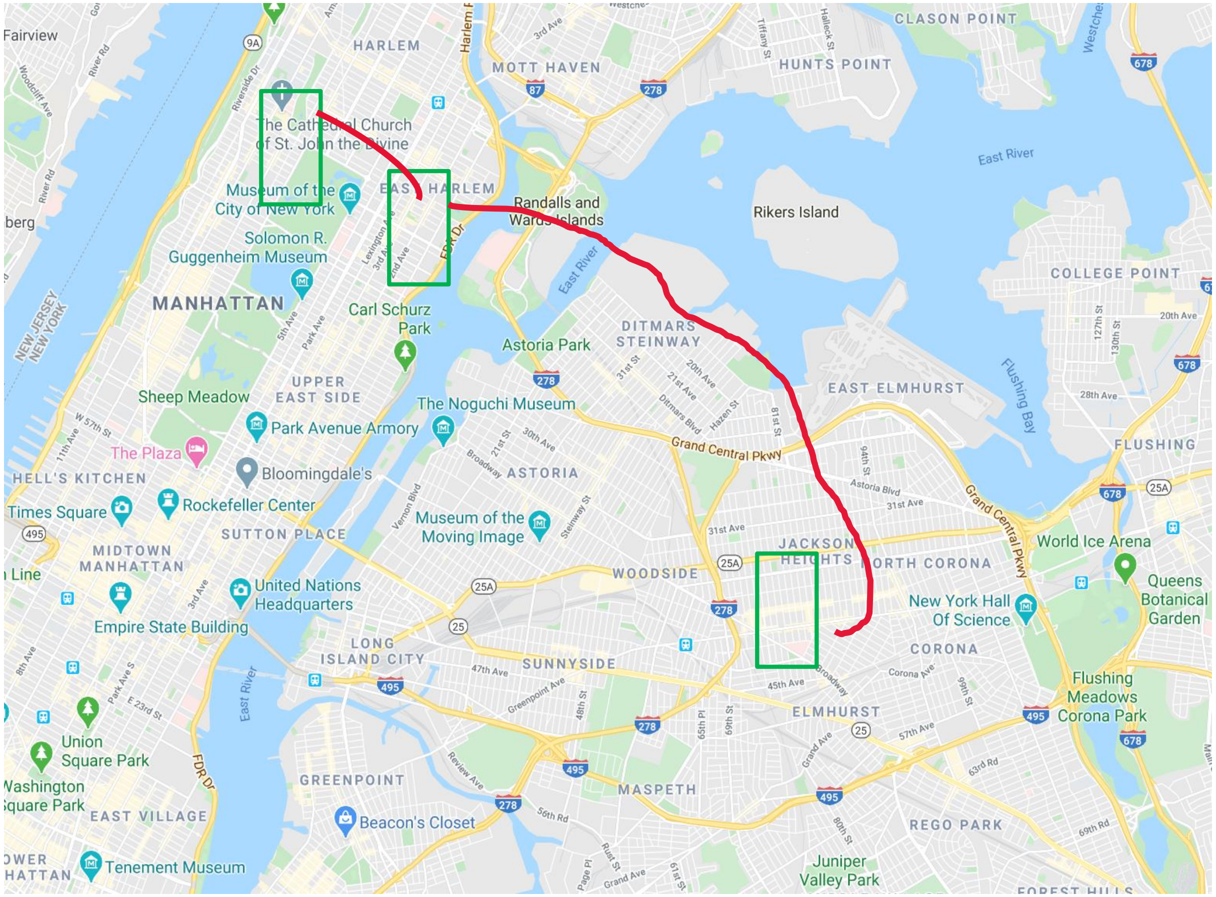
# Research Questions

# Research Question I



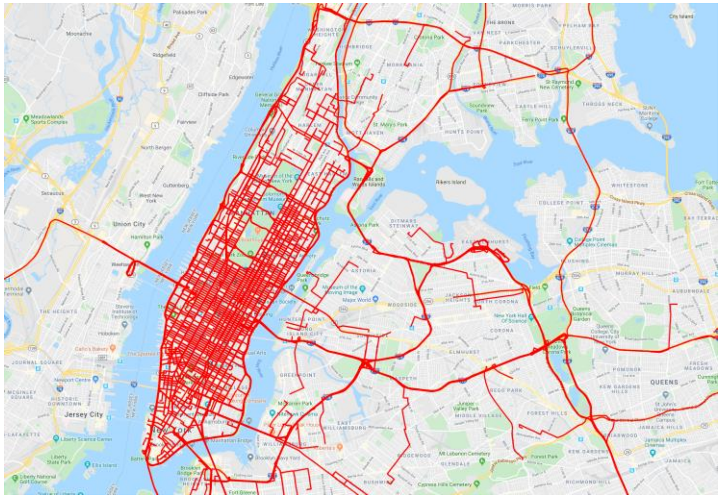

How people perceive different areas of their city?

# Research Question II

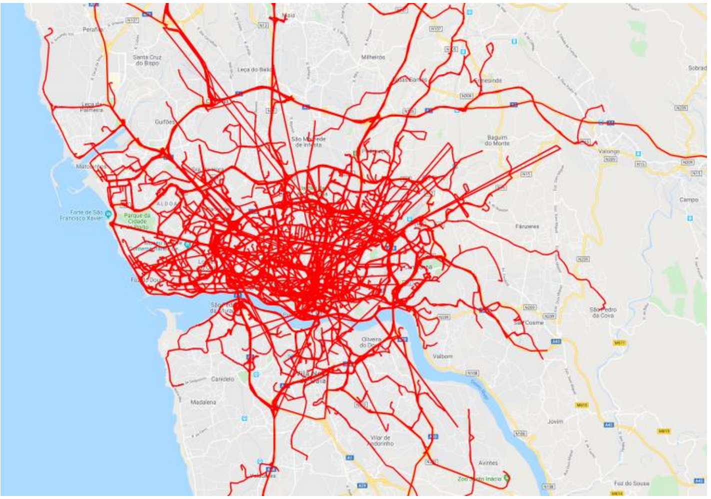



To what extent people rely on geographical proximity of areas?

# Research Question III



New York



City of Porto

How the behavior of people compare in different geographical space?

# Overview

**Method 1**

Learning Semantic Relationships of Geographical Areas

**Method 2**

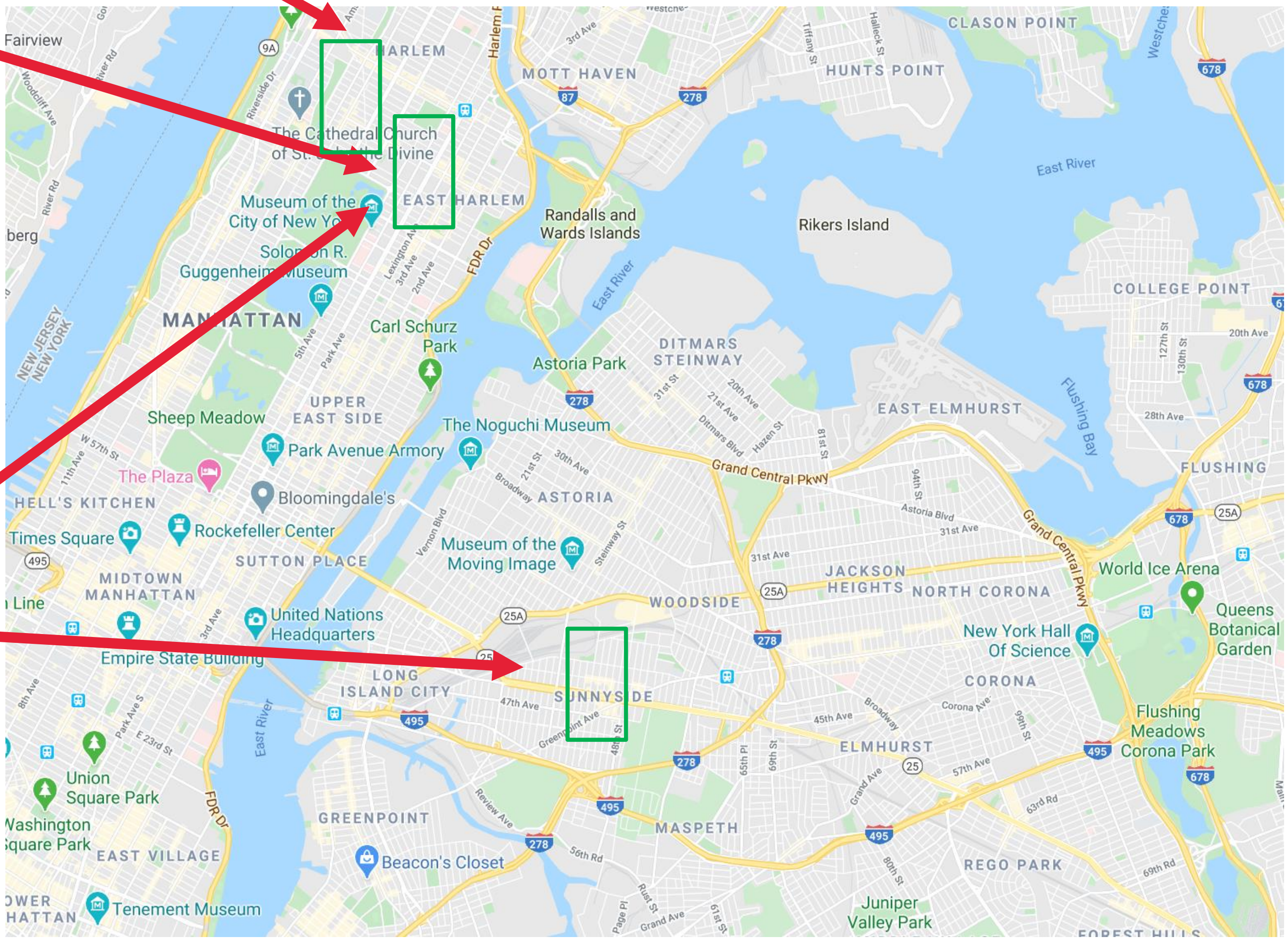
Statistical Method for Distinguishing Geographical Proximity to Semantic Proximity

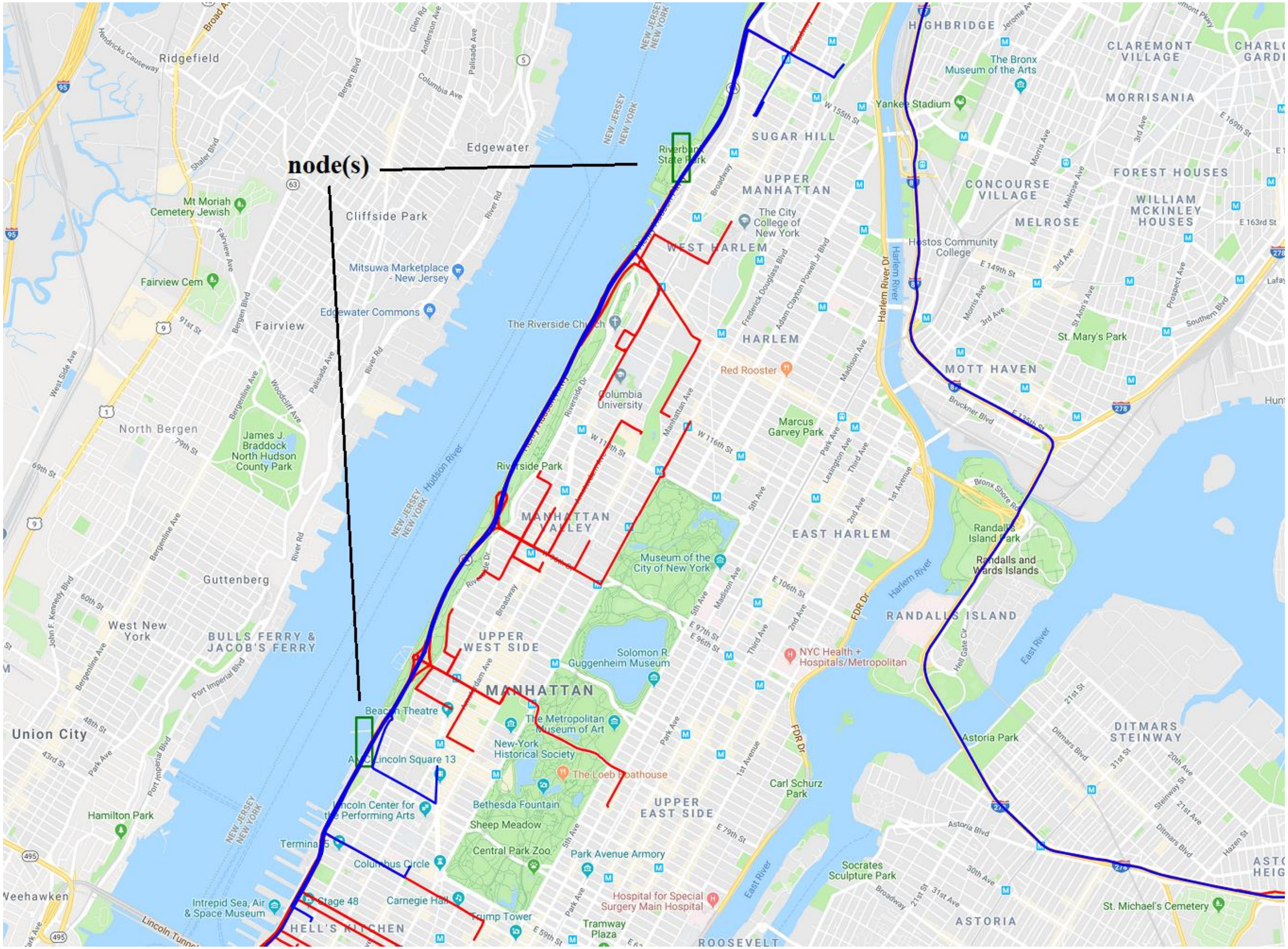
# Learning Semantic Relationships of Geographical Areas

How can we learn latent semantic relationships between geographical areas using trajectories?

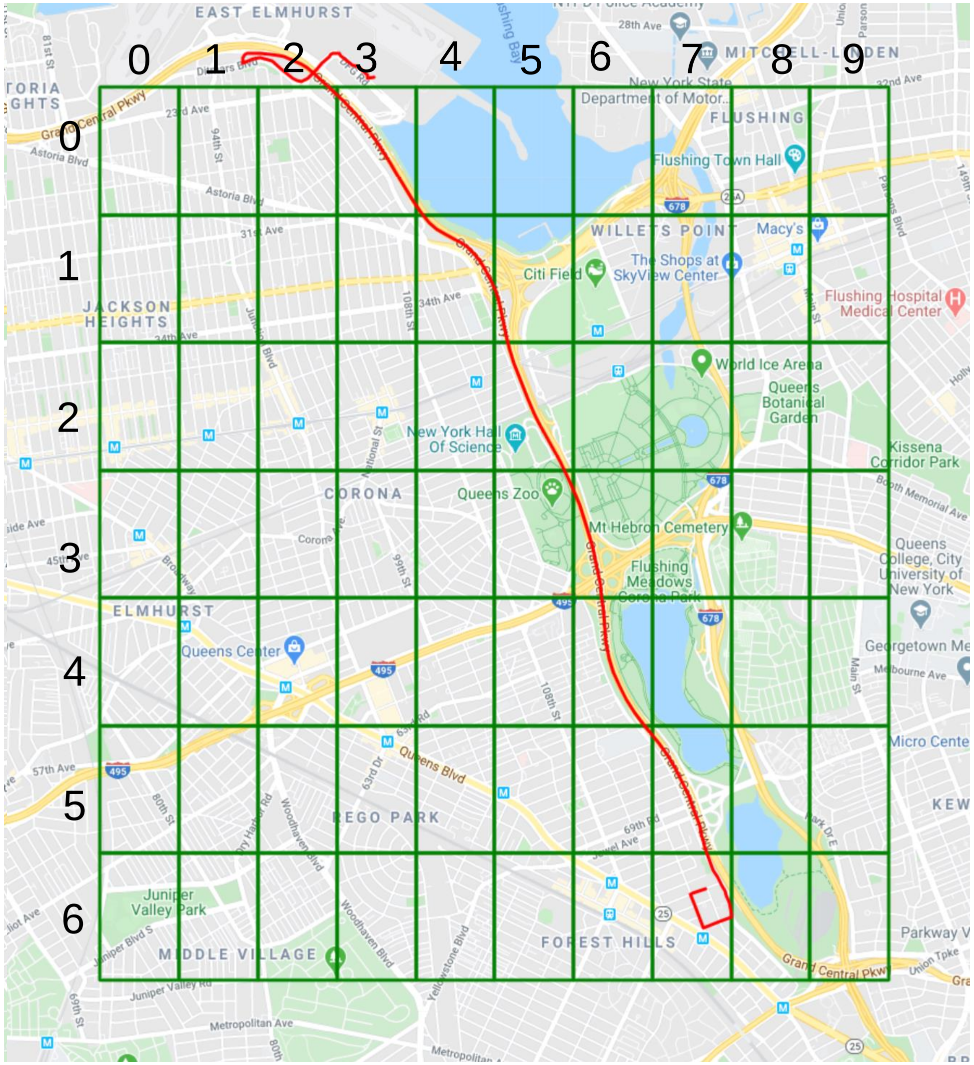
Geographical Proximity

Semantic Proximity

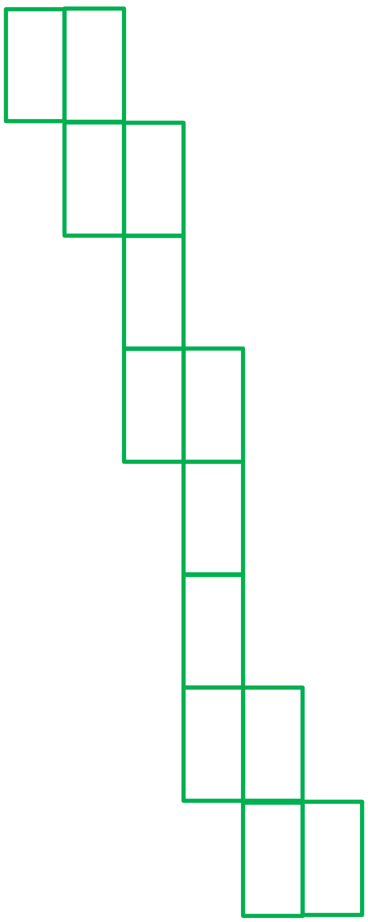



node(s)

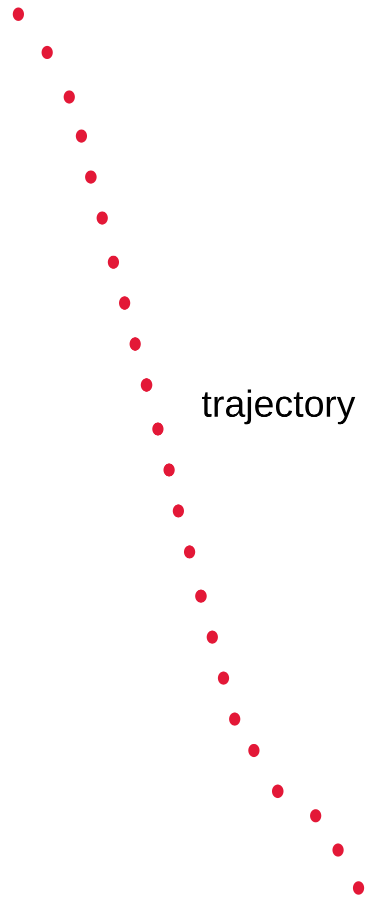
# Construction of a Uniform Grid



# How I Convert Trajectory Into Grid Cells?

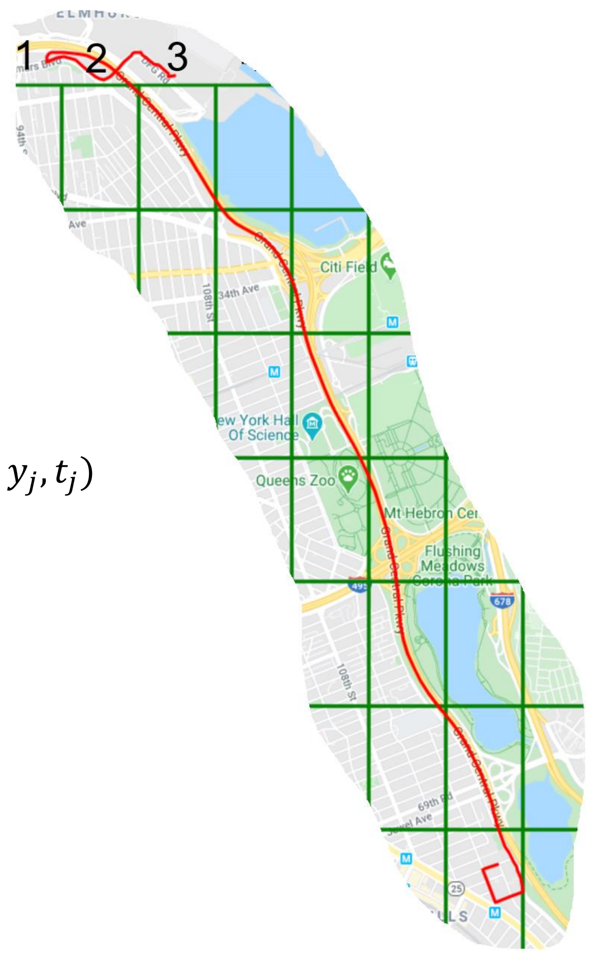


trajectory $(x_i, y_i, t_i)$



trajectory $(x_j, y_j, t_j)$

trajectory $(x_k, y_k, t_k)$

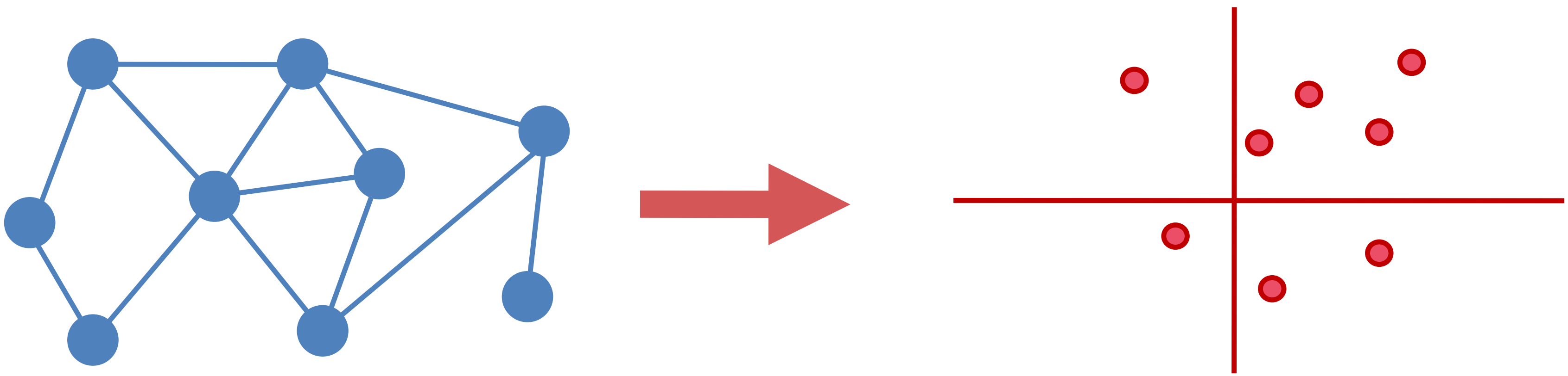


# Our Approach

learn relationships using
network representation learning
(NRL)

# Network Representation Learning (NRL)

# Network Representation Learning (NRL)

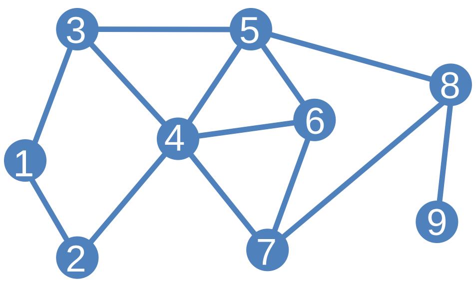


Network/Graph

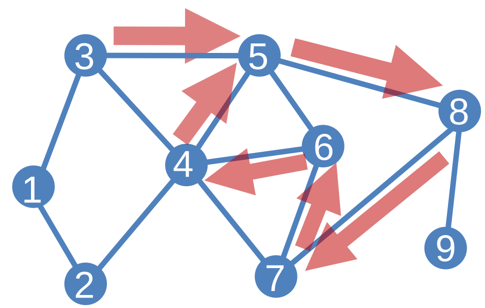
Low-dimension space

**several network structural properties can be learned/embedded**
**(nodes, edges, subgraphs, graphs, …)**

# Random Walk-based NRL




Input graph

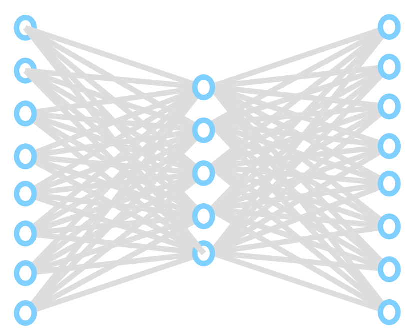



Obtain a set of random walks

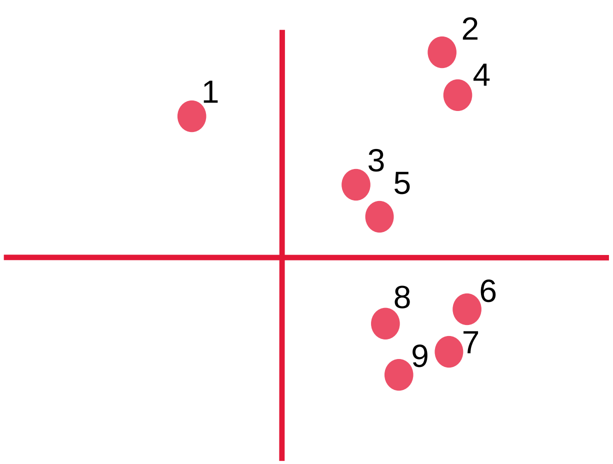
3 5 8 7 6 4 5

| | |
|---|---|
| 1 | 3 5 8 7 6 4 5 |
| 2 | 1 3 5 8 7 6 5 |
| . | . |
| . | . |
| . | . |
| . | . |
| 87 | 8 5 4 3 5 6 7 |
| 88 | 4 5 6 7 8 9 |
| 89 | 2 1 3 5 6 7 8 |
| 90 | 7 4 2 1 3 5 6 |

Treat the set of random walks as sentences



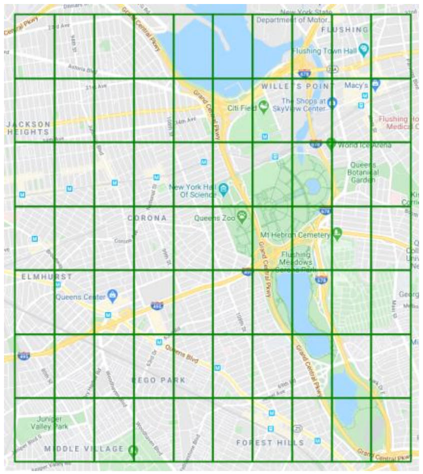
Feed sentences to Skip-gram NN model

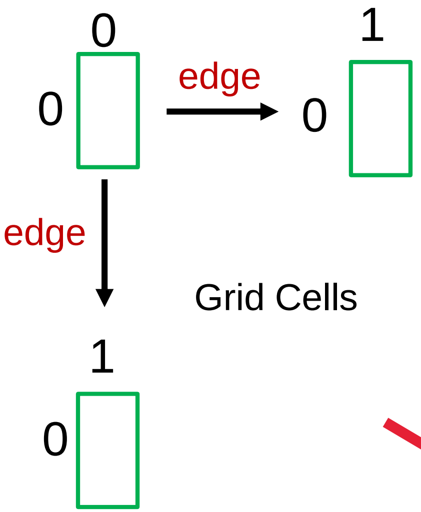



Learn a vector embedding for each node

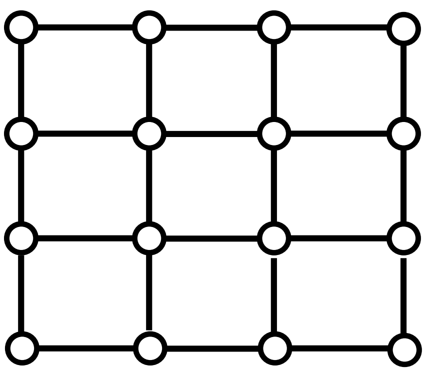
# NRL in our Approach

# Construction of a lattice graph



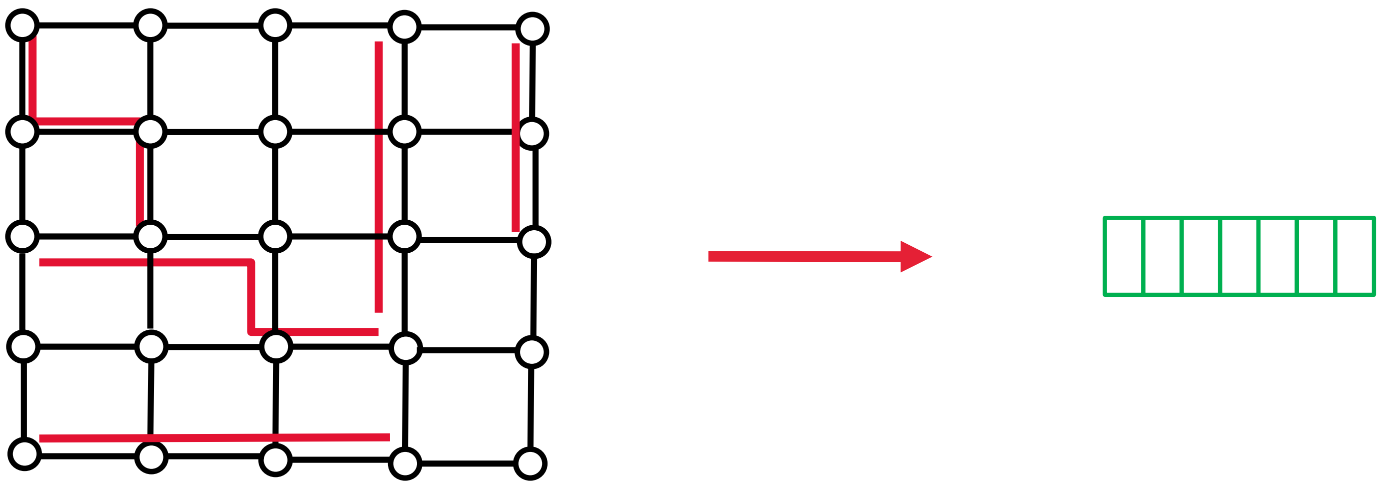



Grid Cells



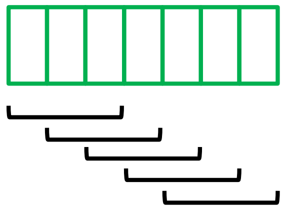
lattice graph

# Trajectory as walks



lattice graph

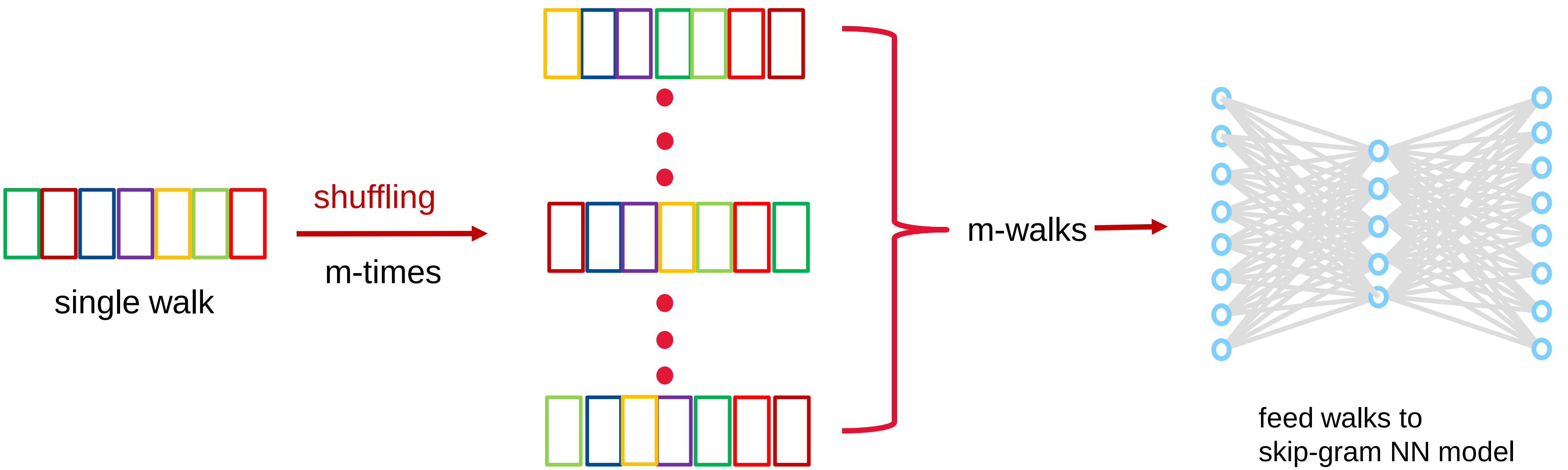
# Trajectory Permutations



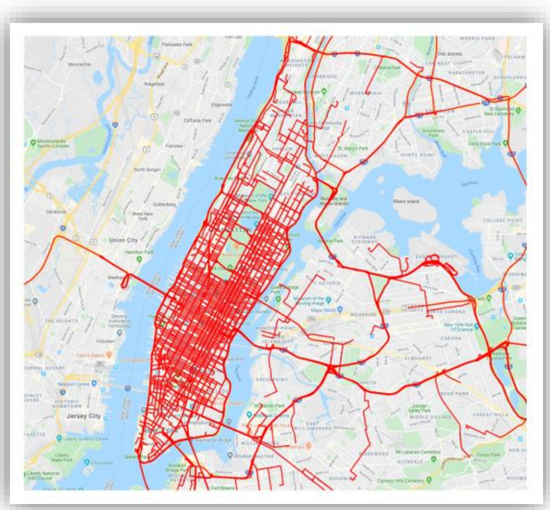
Skip-gram (context window)

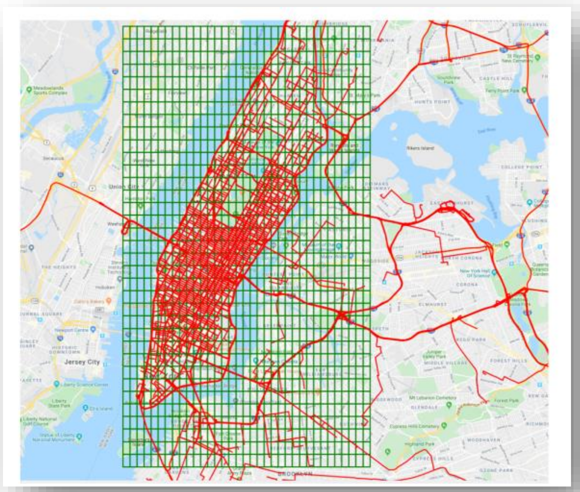
nodes appearing in same context window are more similar

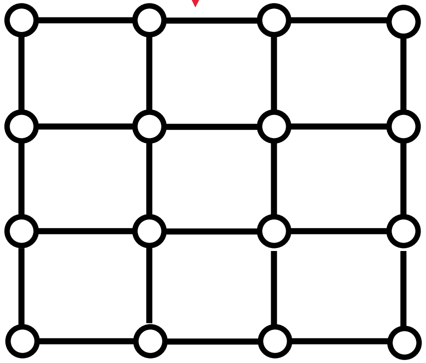
for trajectories, every node should be in the context of every other node

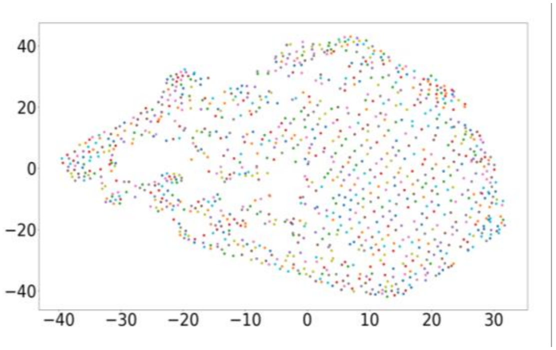


# Method 1 Overview





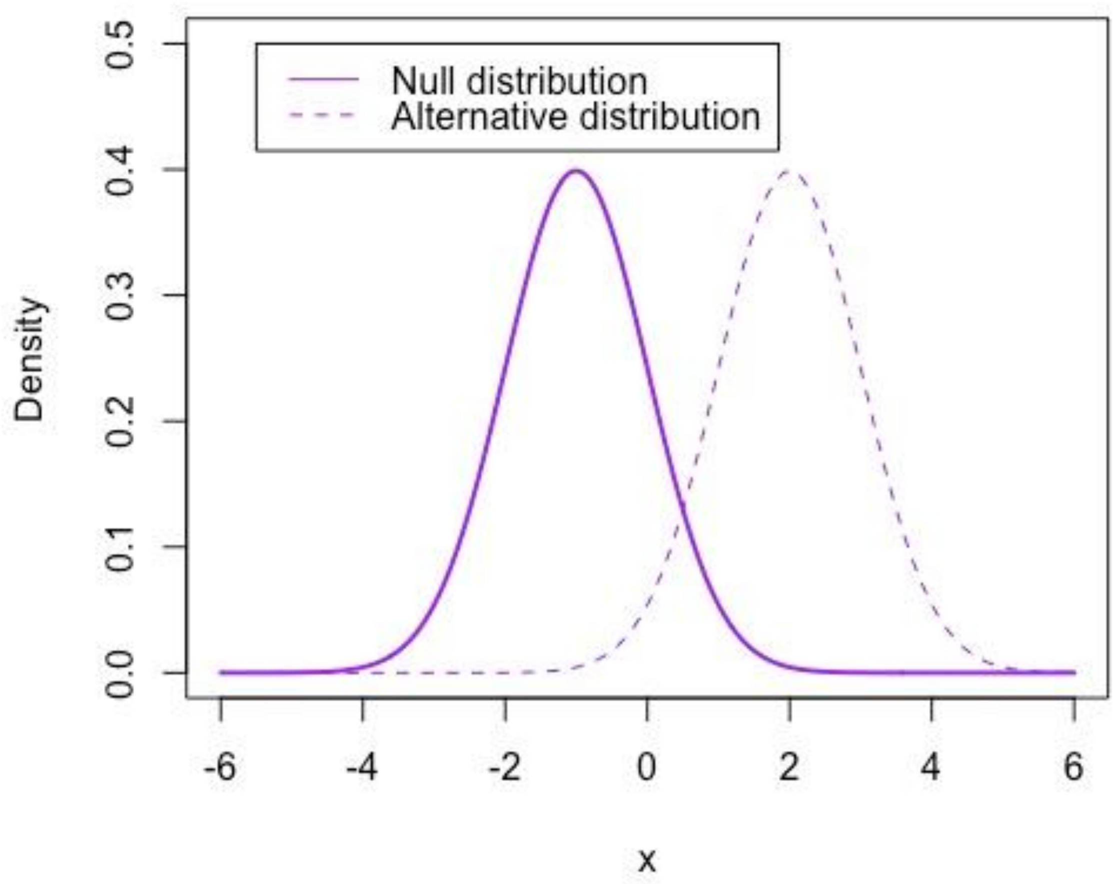




# Statistical Method for Distinguishing Geographical Proximity to Semantic Proximity

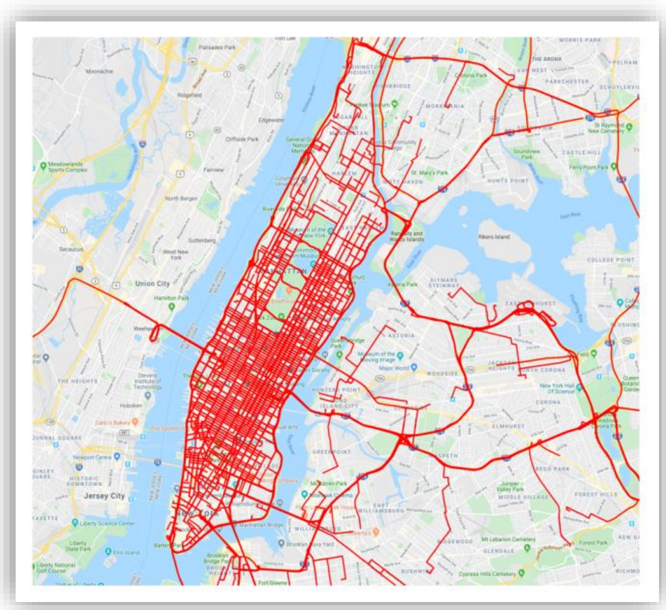
YORK UNIVERSITÉ UNIVERSITY

# Real vs Null Hypothesis

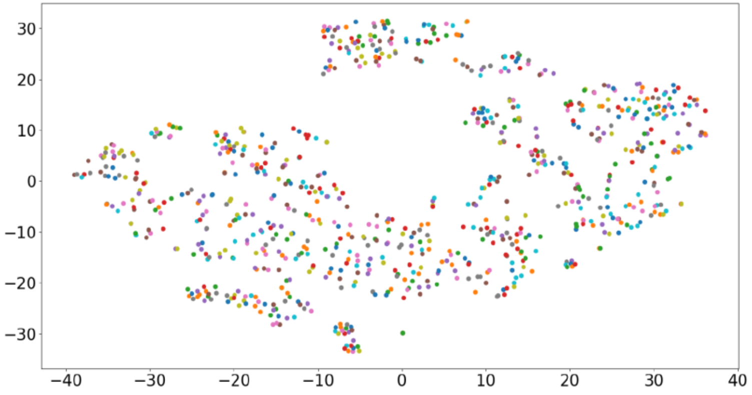


# Real Model

Real model is based on real trajectory movements over lattice graph

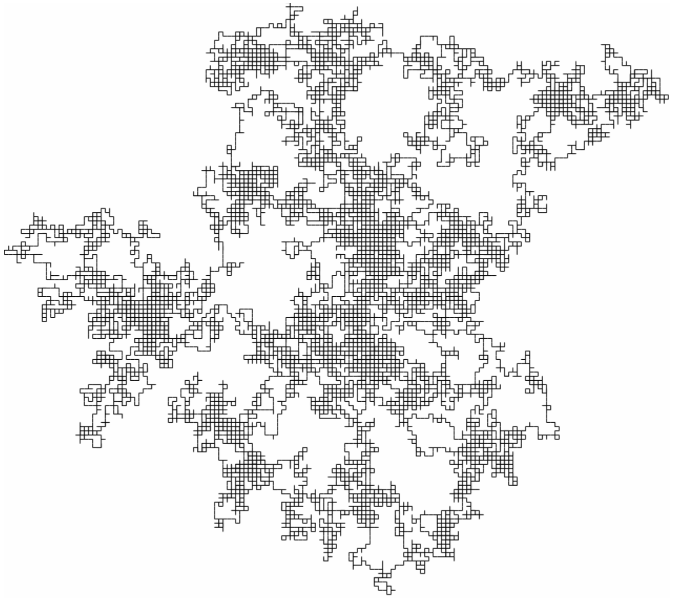


method 1

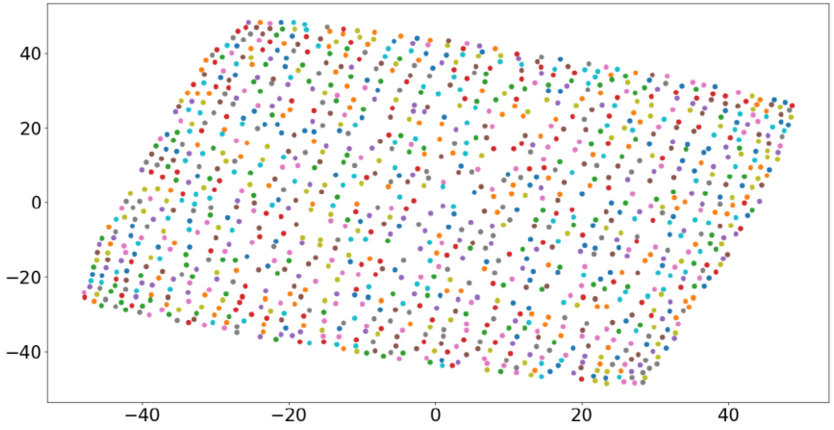


# Null Model

Null Model is based on random walks but satisfies the size constraint

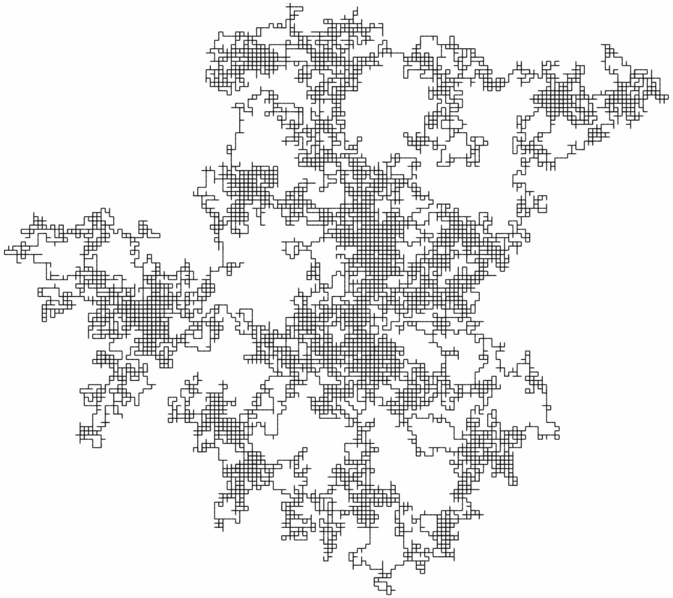


method 1

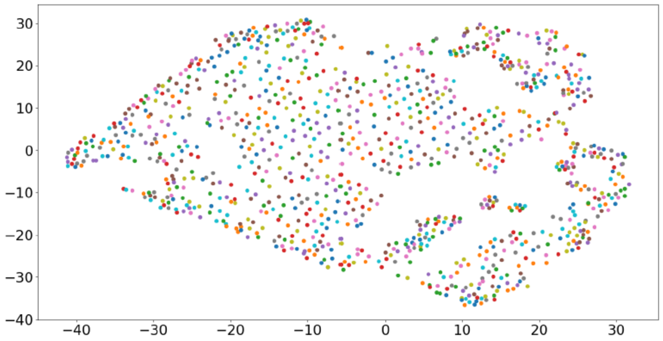


# Alternate Null (Intermediate) Model

Intermediate model is like Null model but satisfies the constraint for each walk starting from the same node $u$ as Real model walks



method 1



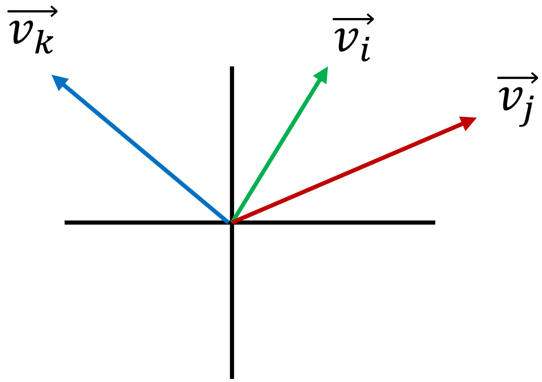
# Model Comparative Analysis

how can we compare the
real vs the null model?

metrics for both quantitative and visual comparison

# Quantitative: Cosine Similarity

$\overrightarrow{v_i}$ (128D) $\overrightarrow{v_j}$ (128D) $\overrightarrow{v_k}$ (128D)




$cos\theta(\overrightarrow{v_i}, \overrightarrow{v_j}) \geq \lambda_a$ ***"similar"***

$cos\theta(\overrightarrow{v_i}, \overrightarrow{v_k}) < \lambda_a$ ***"not similar"***

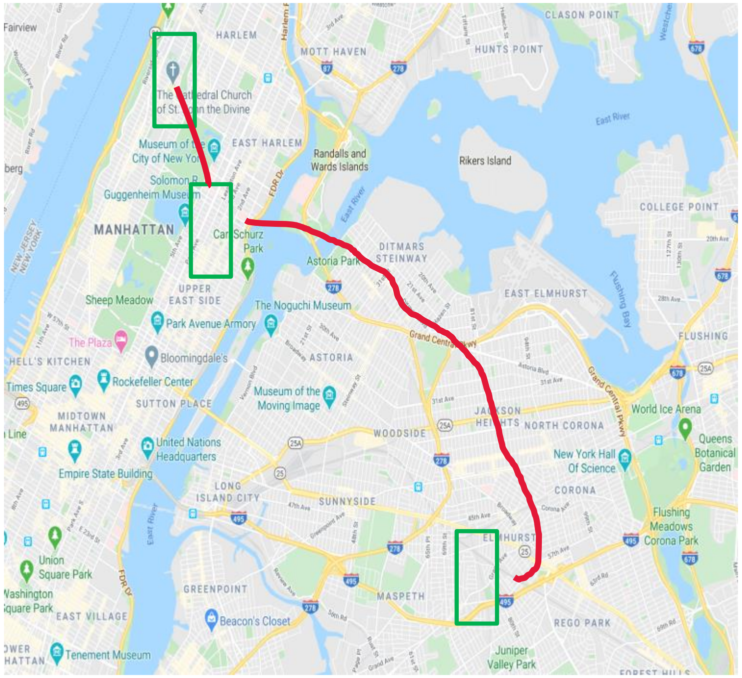
# Quantitative: Interesting Pairs of Nodes

Let's say we have two models $(X\ and\ Y)$

$$cos_{\theta_X}(\overrightarrow{v_i}, \overrightarrow{v_j}) \qquad cos_{\theta_Y}(\overrightarrow{v_i}, \overrightarrow{v_j})$$

$$d_{X,Y}(\vec{\mathbf{v_i}}, \vec{\mathbf{v_j}}) = |cos\theta_X(\vec{\mathbf{v_i}}, \vec{\mathbf{v_j}}) - cos\theta_Y(\vec{\mathbf{v_i}}, \vec{\mathbf{v_j}})|$$

$$d_{X,Y}(\vec{\mathbf{v_i}}, \vec{\mathbf{v_j}}) \geq \lambda_b$$ ***"similar"***

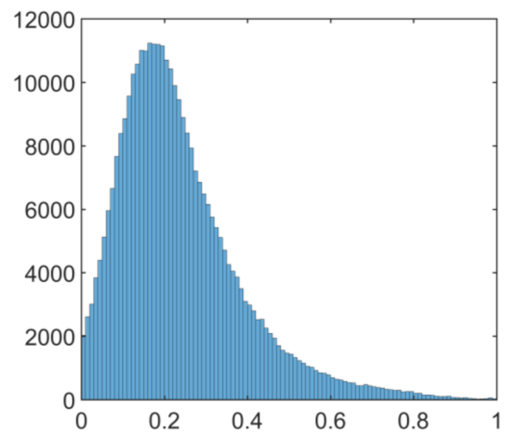


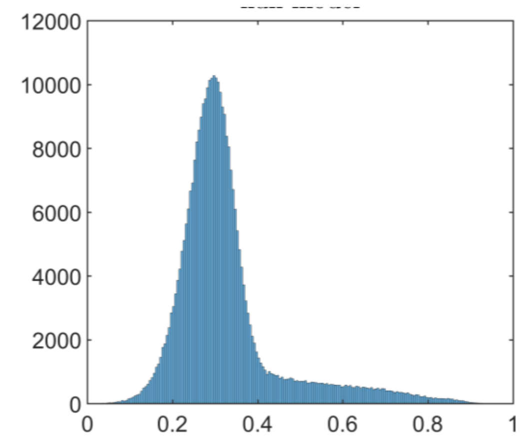
# Comparing Distributions of Models

Let’s say we have two Histograms $(H^A\ and\ H^B)$

$$\chi^2 = d(H^A, H^B) = \sum_{i=1}^{b} \frac{(H_i^A - H_i^B)^2}{H_i^A}$$

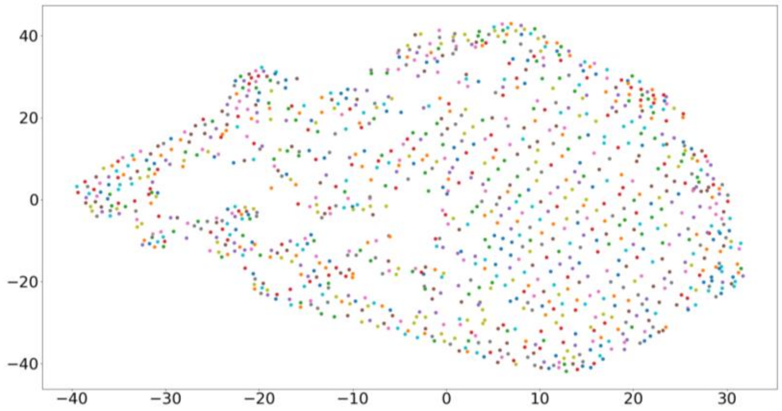
Where $b$ is the number of bins



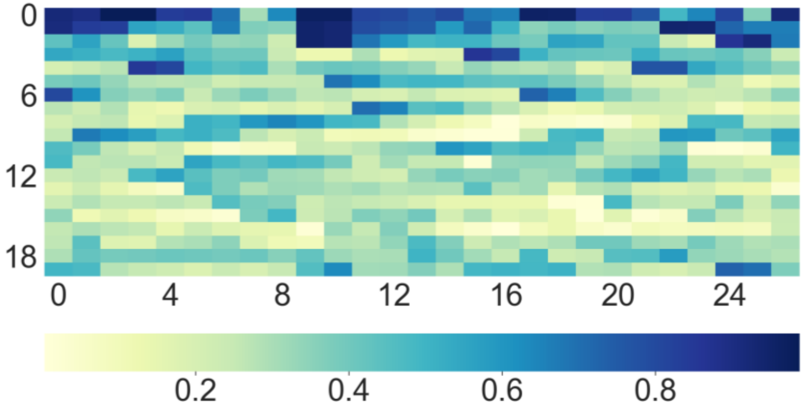



# Exploratory Analysis of Models

A many-to-many visualization

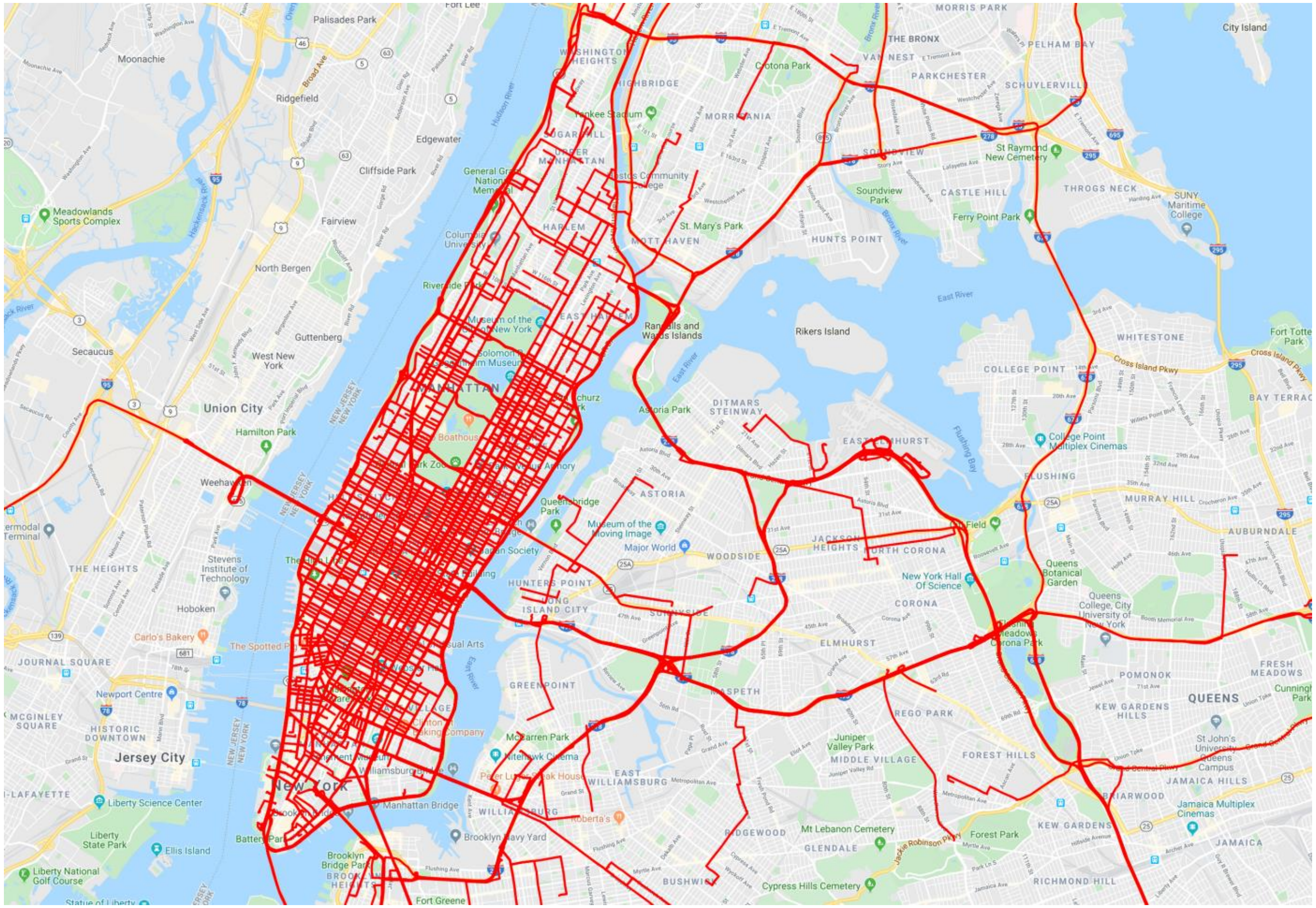



One-to-many visualization

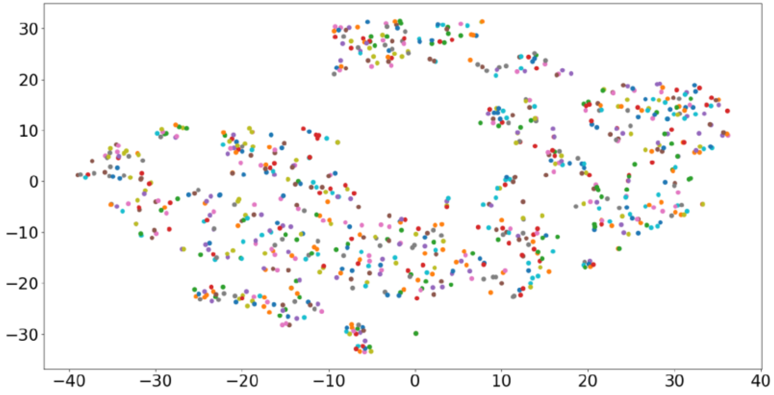


# Evaluation

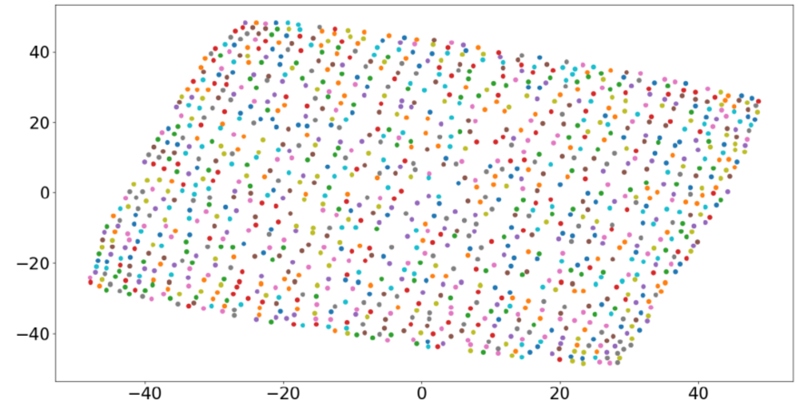
# Case Study I: New York City (NYC)



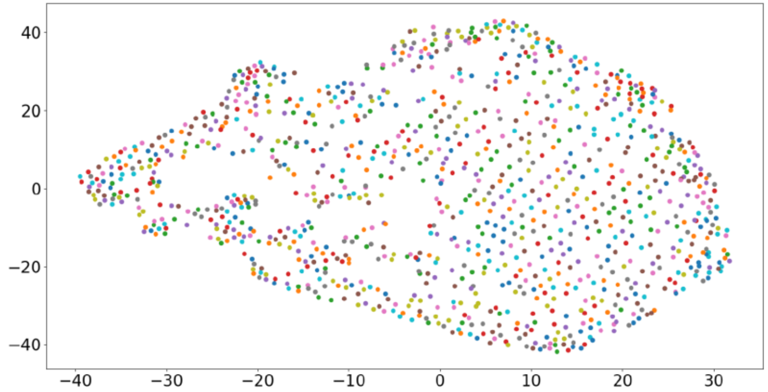
# Exploratory Analysis: Many-to-Many




real

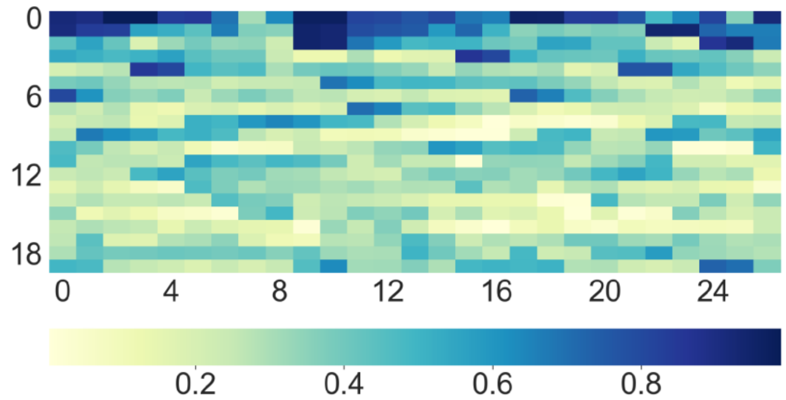



null

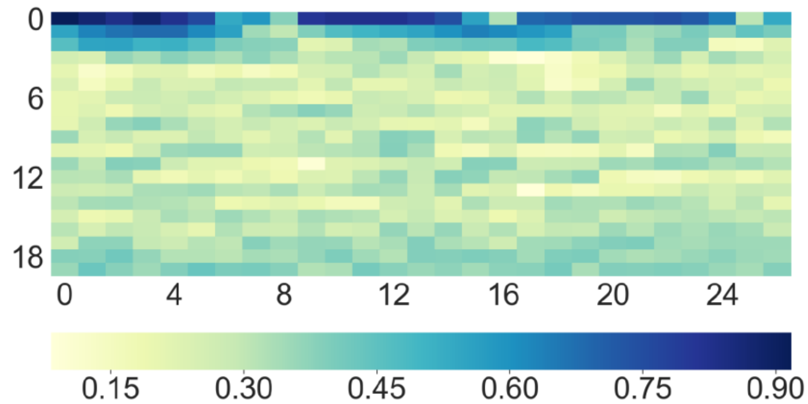



intermediate

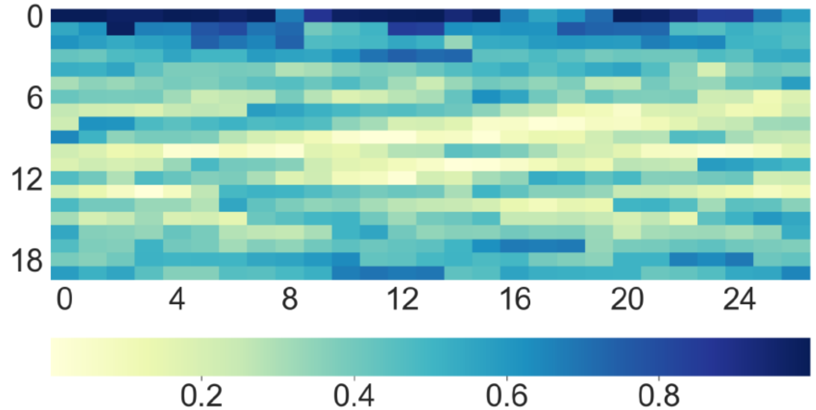
# Exploratory Analysis: One-to-Many




real

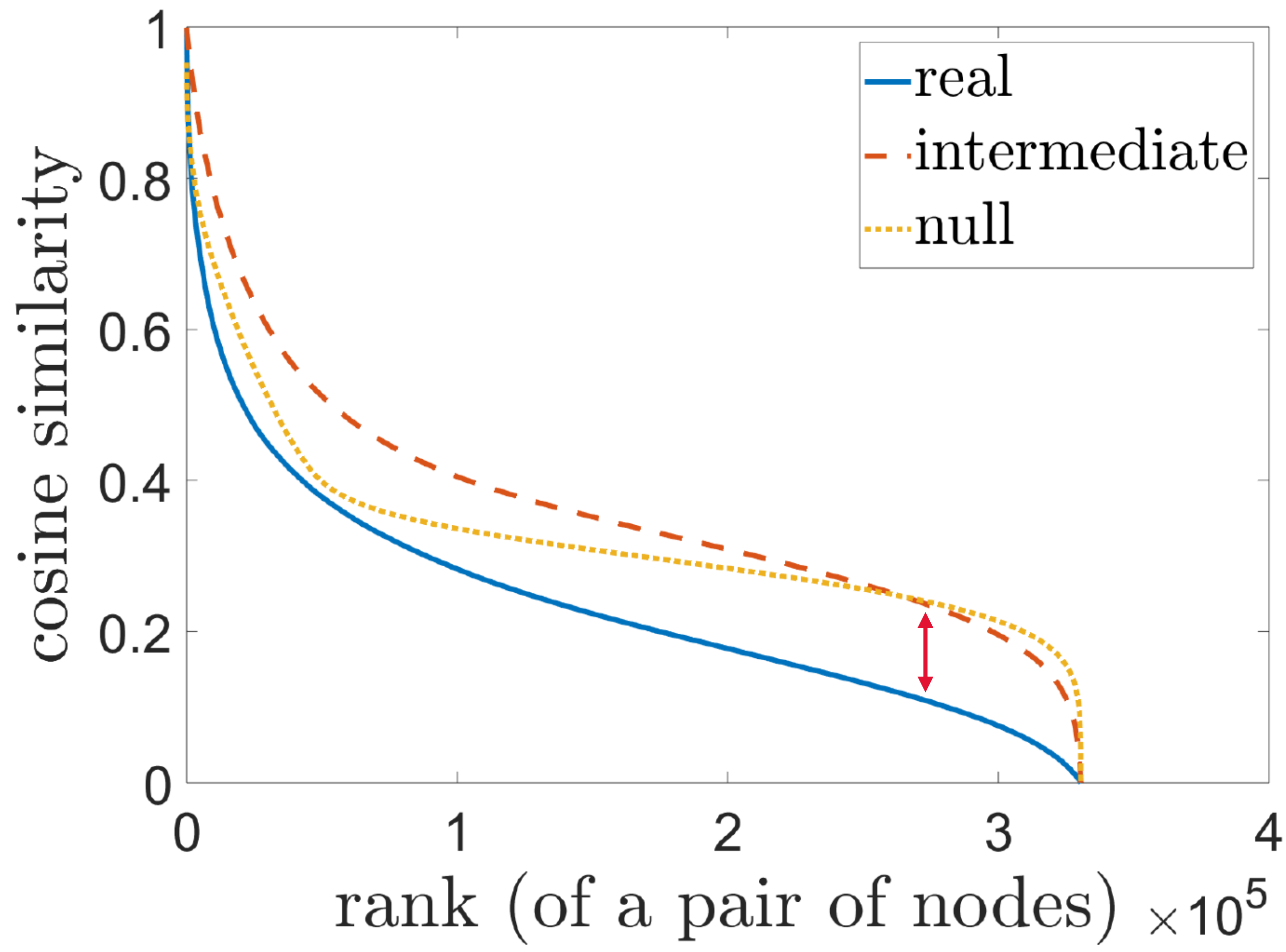



null

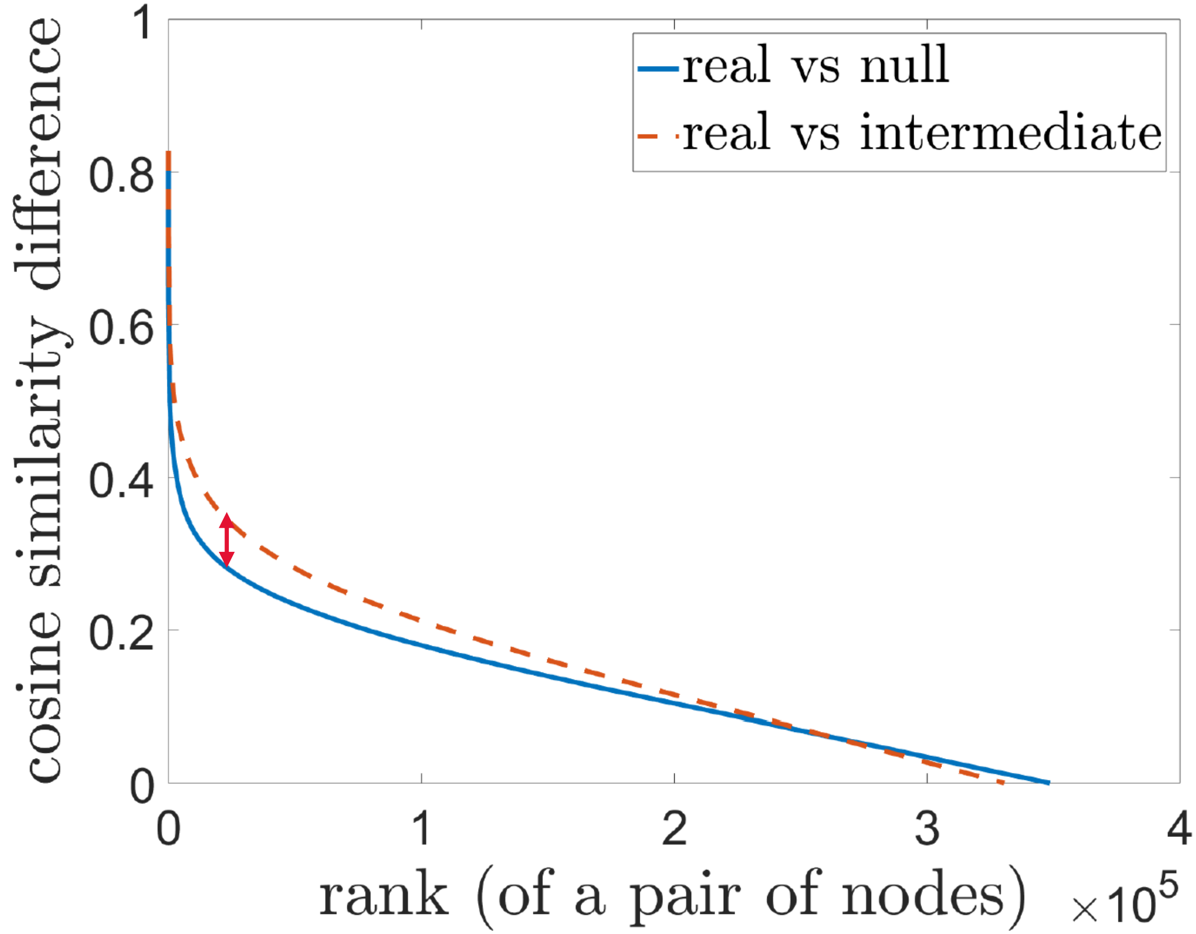



intermediate

# Quantitative: Cosine Similarity



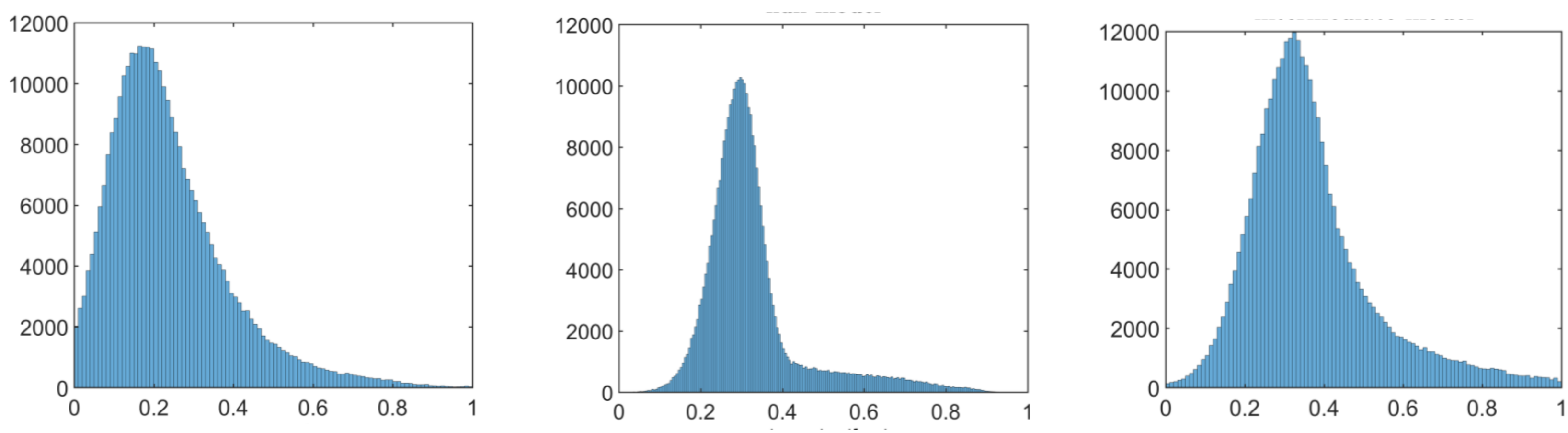
# Quantitative: Interesting Pairs of Nodes



# Distribution of Pair-wise Similarities

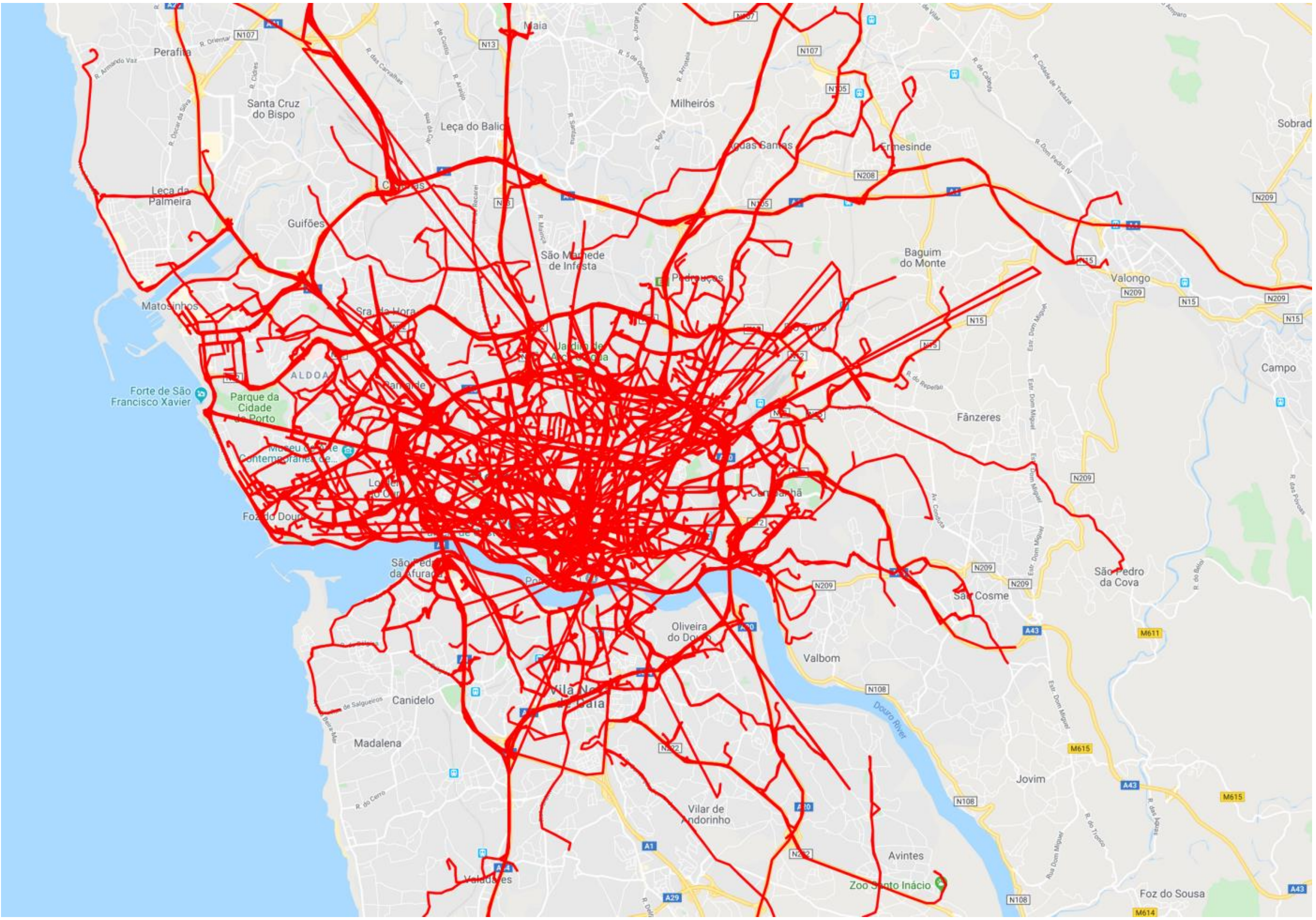
real null intermediate

no of pairs of nodes

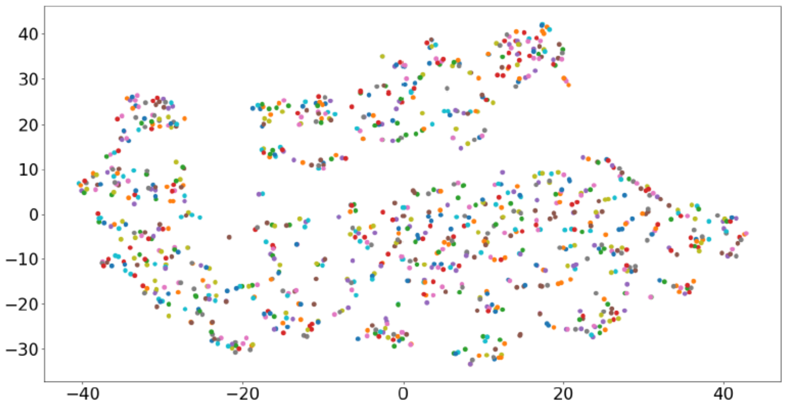



cosine similarity

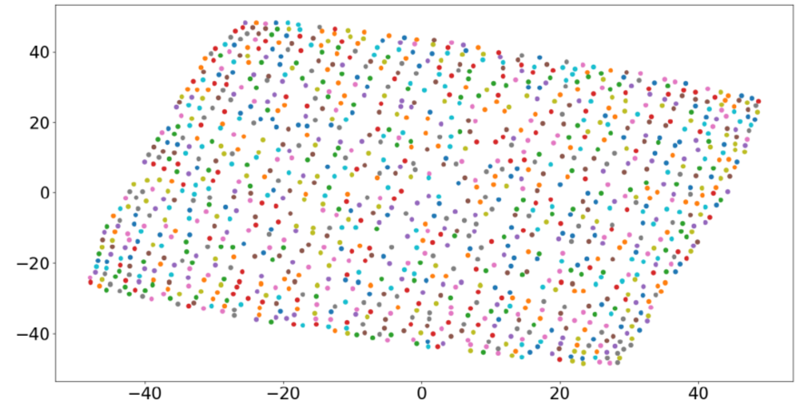
# Case Study II: City of Porto



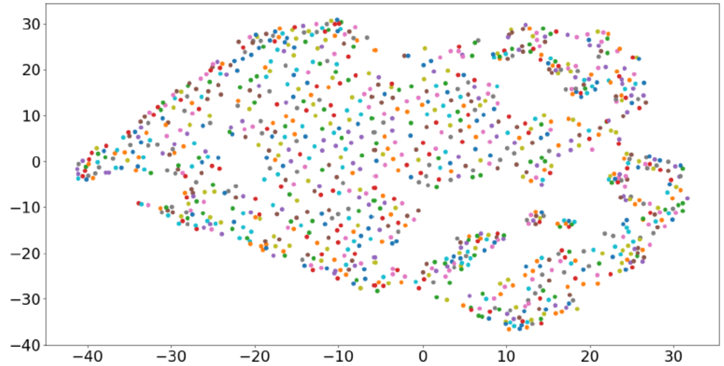
# Exploratory Analysis: Many-to-Many




real

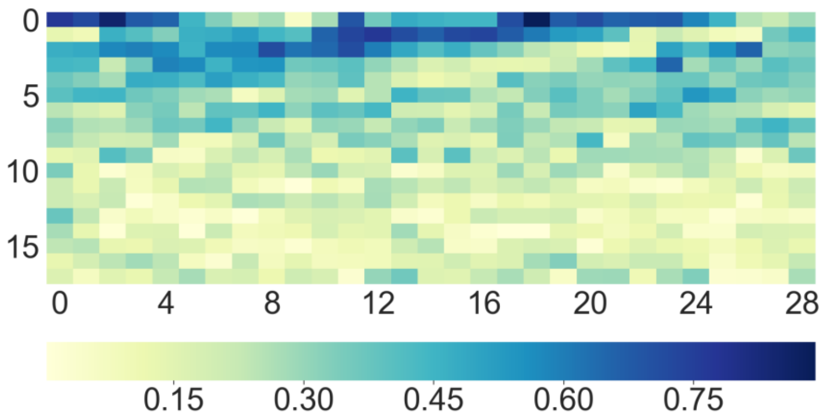



null

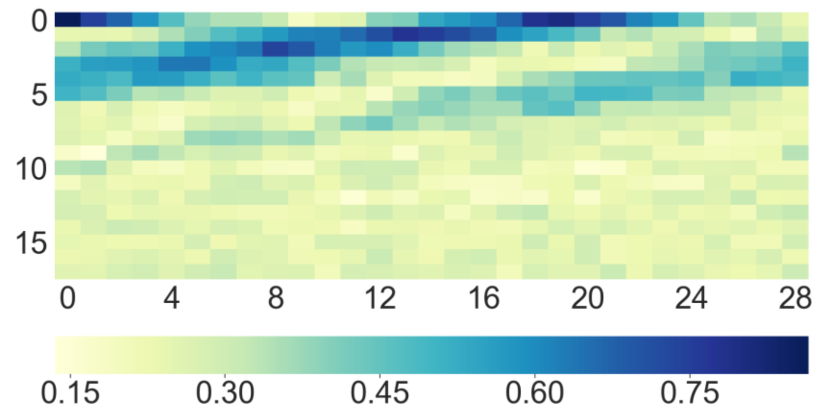



intermediate

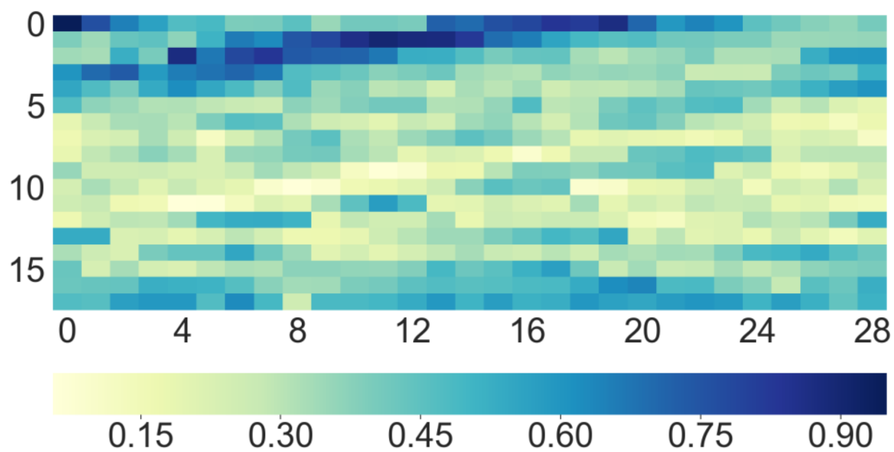
# Exploratory Analysis: One-to-Many




real

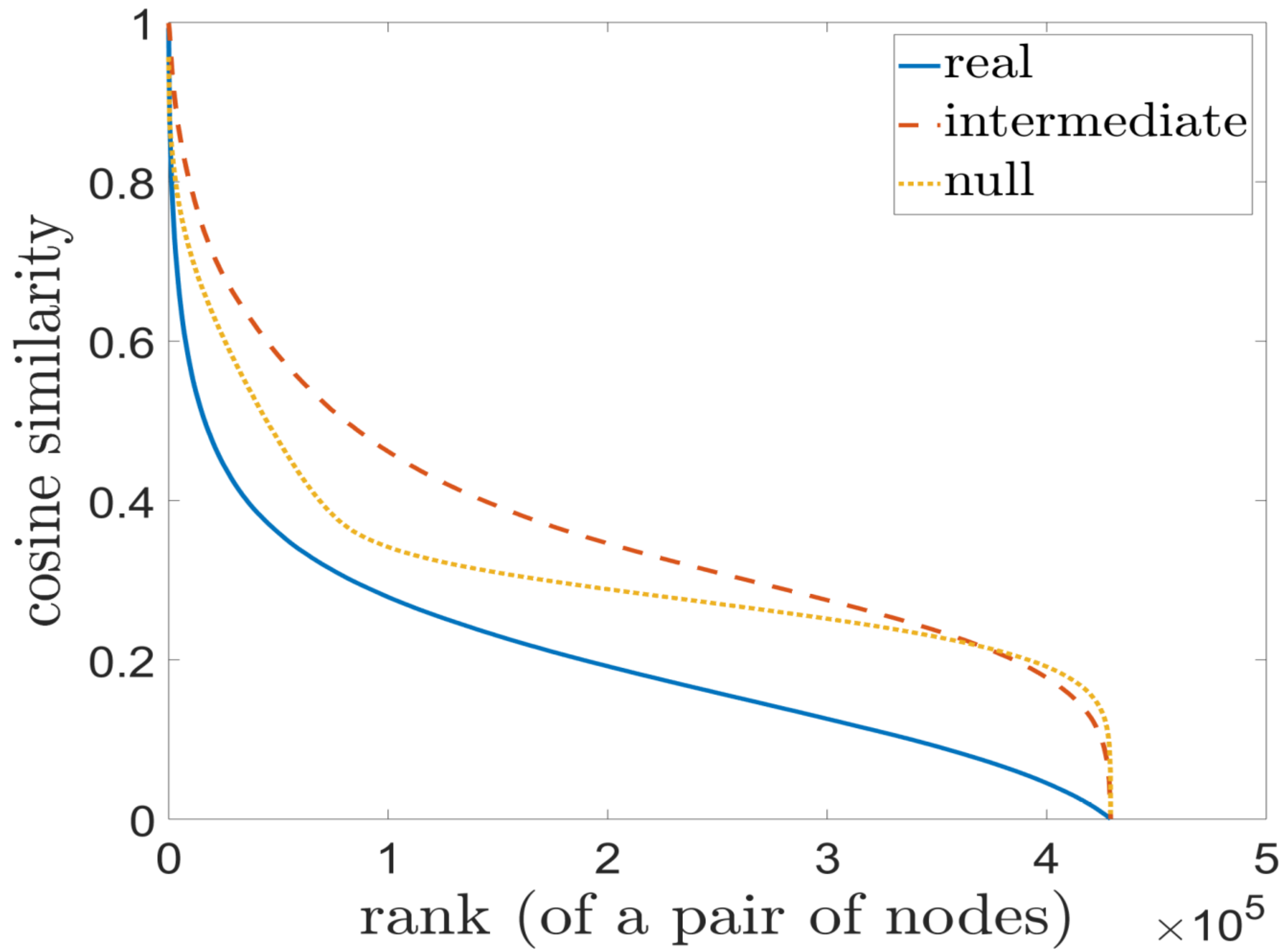



null

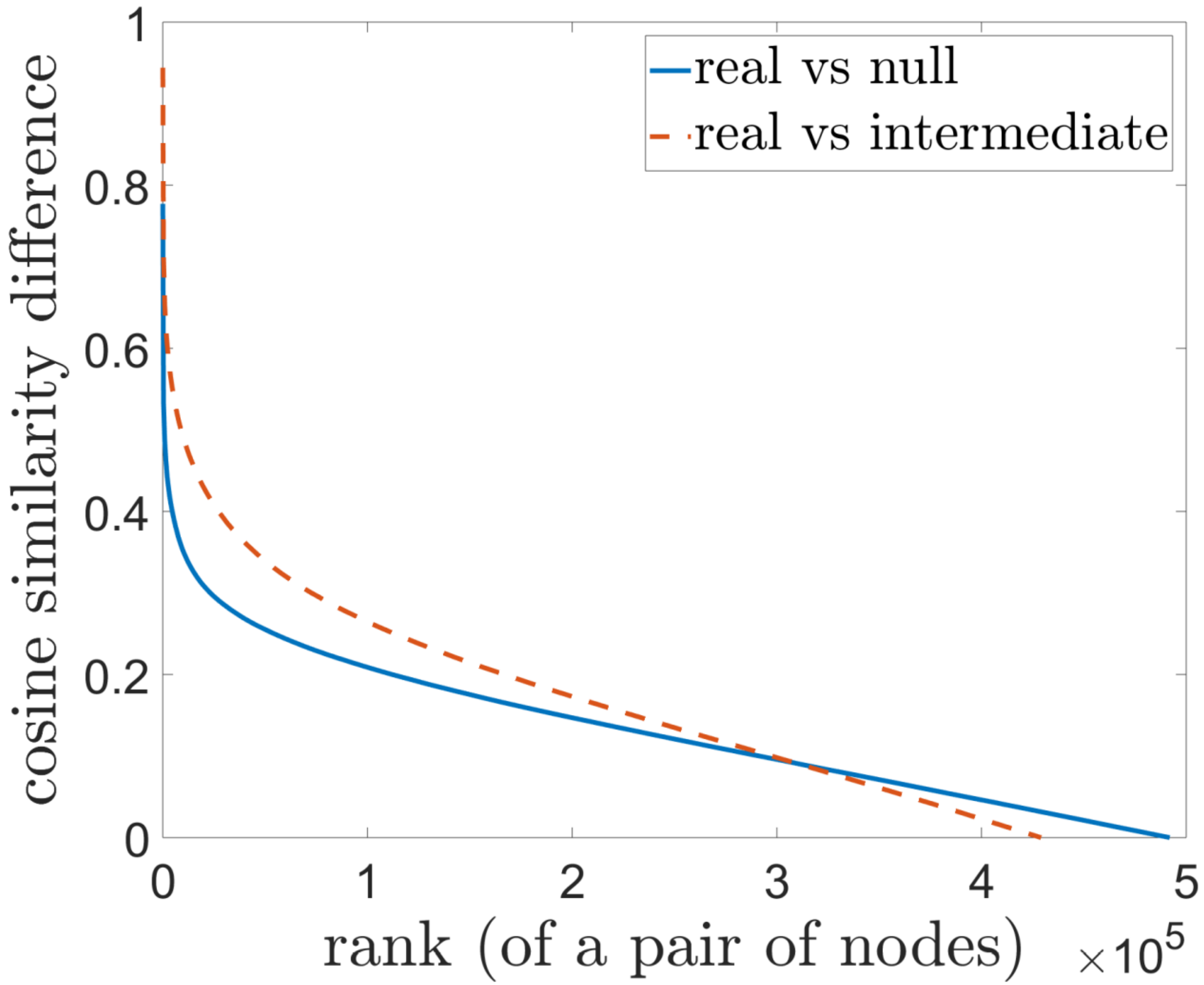



intermediate

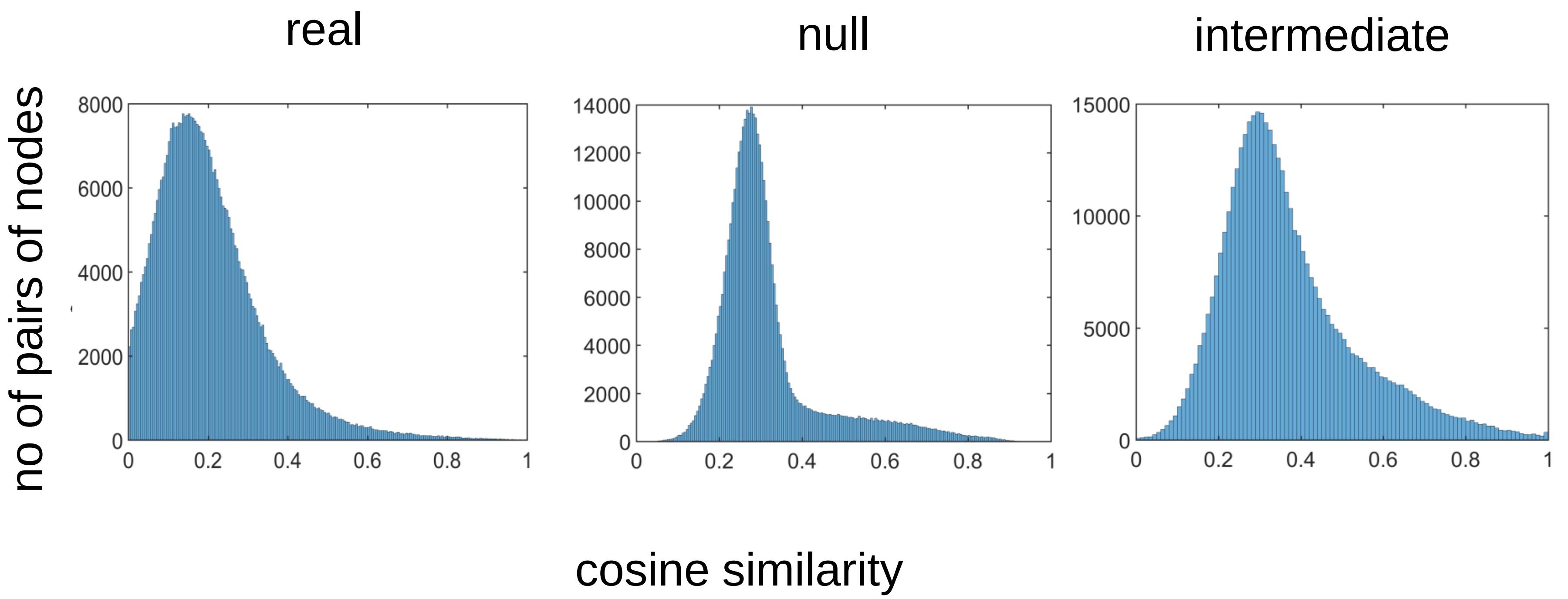
# Quantitative: Cosine Similarity



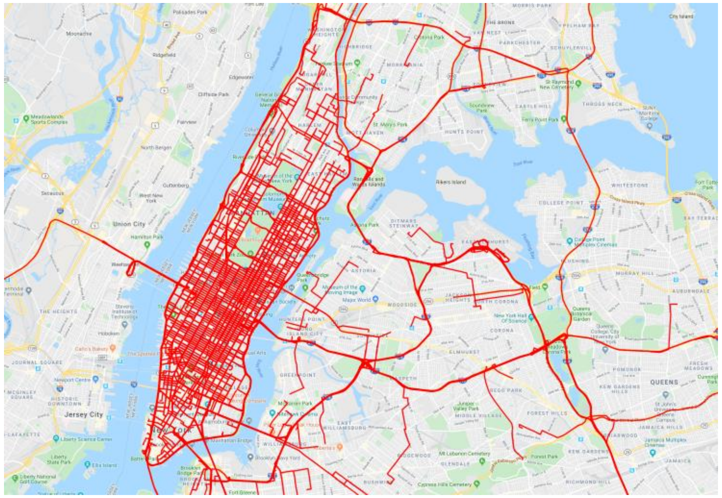
# Quantitative: Interesting Pairs of Nodes



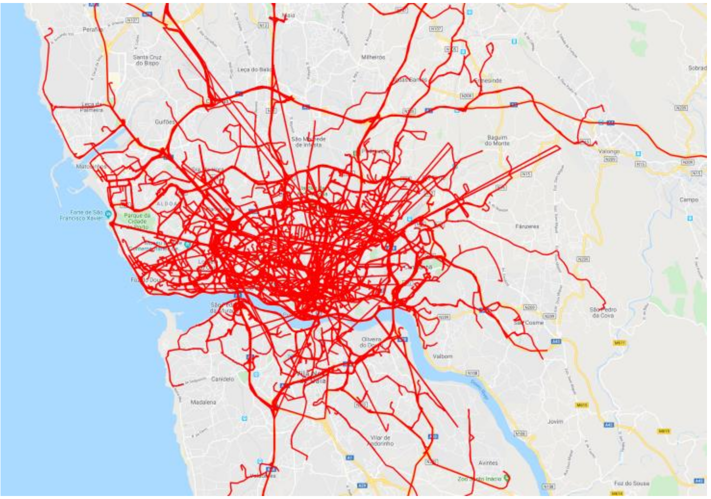
# Distribution of Pair-wise Similarities



# Research Questions



New York



City of Porto

How the behavior of people compare in different geographical space?

# Chi-Square

$$\chi^2 = d(H^A, H^B) = \sum_{i=1}^{b} \frac{(H_i^A - H_i^B)^2}{H_i^A}$$

City of New York

real distance from null: $\chi^2 = 4.0854e + 05 \gg 0$

real distance from intermediate: $\chi^2 = 3.0426e + 05 \gg 0$

City of Porto

real distance from null: $\chi^2 = 6.1697e + 05 \gg 0$

real distance from intermediate: $\chi^2 = 7.8492e + 05 \gg 0$

# Summary

# Summary of Contributions


learned nodes embeddings for real and null models

performed statistical analysis to distinguish geographical to semantic proximity

**Learning Semantic Relationships of Geographical Areas based on Trajectories**
Saim Mehmood and Manos Papagelis
IEEE Mobile Data Management 2020

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Thank you!