

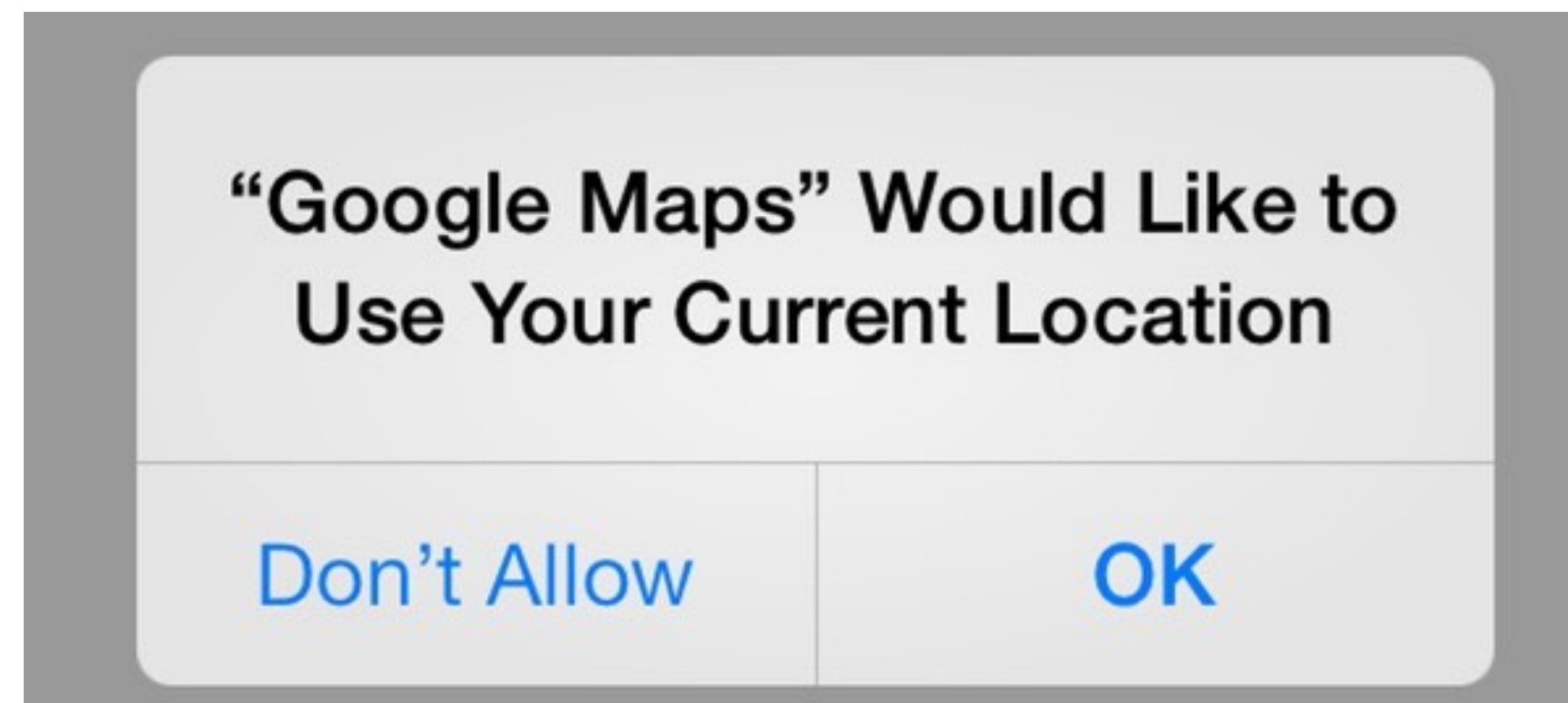
# walk2friends: Inferring Social Links from Mobility Profiles

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joint work with Michael Backes, Mathias Humbert, and Jun Pang







7:25

yelp

hot+new nearby

Novela 0.08 mi  
41 review \$\$  
662 Mission St, Financial Distric  
Cocktail Bars

Sushirrito 0.28 mi  
57 review \$  
226 Kearny St, Financial District  
Japanese, Sushi Bars,...

MKT Restaurant... 0.14 mi  
7 reviews \$\$\$\$  
Four Seasons Hotel 757 Market  
American (New)

Via Moto 0.18 mi  
7 reviews \$  
Metreon 135 4th St, Financial D  
Pizza, Italian, Sandwiches

Si  
th

Search icons: magnifying glass, checkmark, and menu.



# Location Privacy

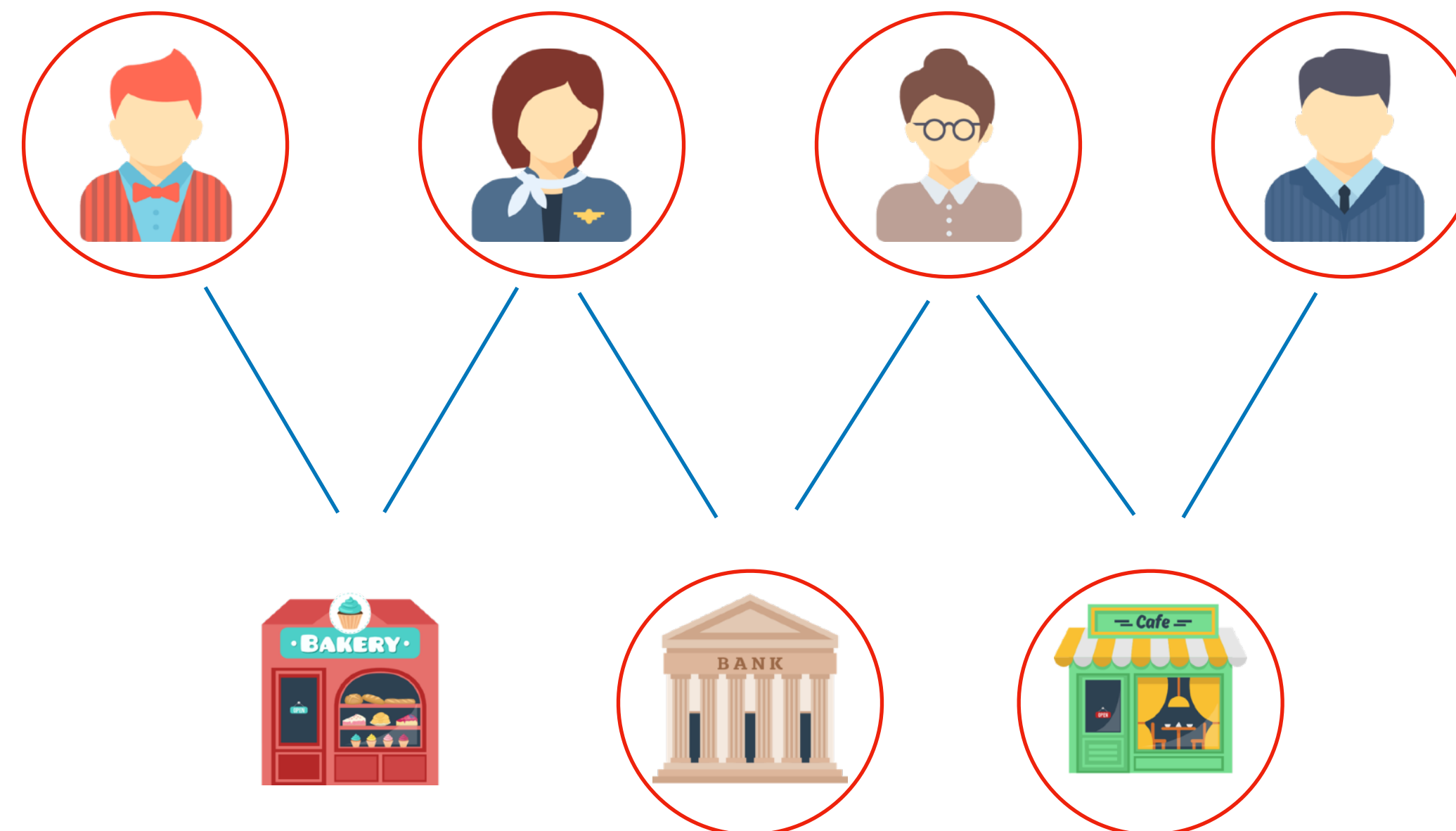
- 4 spatial-temporal points can identify 95% of the individuals
- Mobility traces can be effectively de-anonymized
- You are where you go
  - Demographics
  - Social relations

# Social Relation Privacy

- Social relations can be sensitive, e.g., office romance
- 17.2% -> 56.2% (Facebook users in New York)
- NSA's co-traveler program

Predict whether two users are friends based on the  
locations they have visited

- Solution 1: common locations two users have visited
  - Almost all data mining approaches take this way
    - Location entropy
  - Can't work when two users share no common locations





- Solution 2: mobility profiles/features
  - Summarize each user's mobility profiles
  - Friends share similar mobility profiles than strangers
  - Feature engineering
    - Tedious efforts and domain expert knowledge
    - Time consuming **Every Single Time!!!**

# Representation Learning

- Learning features (representation/deep learning)
  - Follow a general object (unsupervised)
- Graph representation learning (graph embedding)
  - Preserve each user's neighbors in a social network
- Mobility feature learning

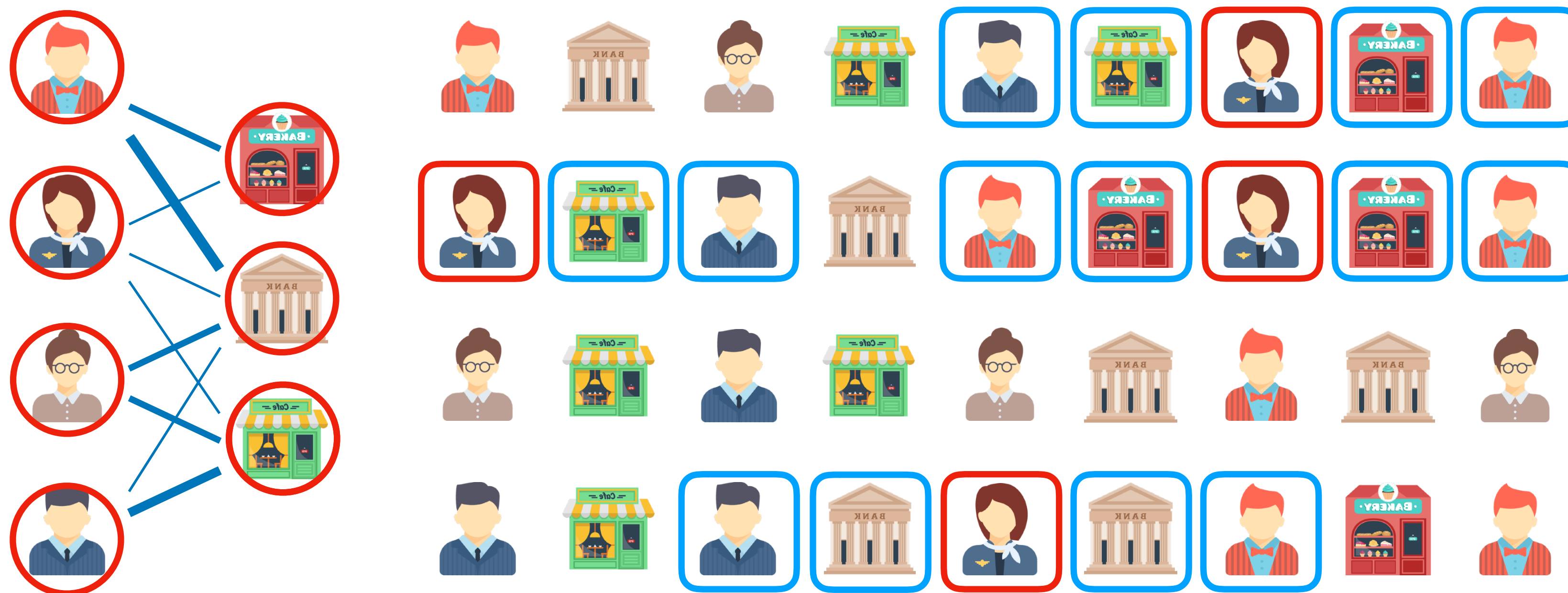
Assumption: A user's mobility neighbors can reflect his mobility profile/features

- Define each user's mobility neighbors
- Learn mobility features/profiles
- Infer two users' social relation

# Mobility Neighbors

- A user's mobility neighbors include
  - Locations a user has visited
  - Others who have visited similar locations and their locations
- Breadth first search
  - Not considering the visiting frequencies
- Random walk sampling

# Mobility Neighbors



# Feature Learning



- Learn a function:  $\theta : \mathcal{U} \rightarrow \mathbb{R}^d$
- Each node to predict it's neighbors
- $p(\cdot | \cdot ; \theta)$  Softmax

$$\arg \max_{\theta} p(\text{Bank} | \text{Red Hair}; \theta) \cdot p(\text{Glasses} | \text{Red Hair}; \theta) \cdot p(\text{Suit} | \text{Red Hair}; \theta) \cdot$$

$$p(\text{Red Hair} | \text{Suit}; \theta) \cdot p(\text{Bank} | \text{Suit}; \theta) \cdot p(\text{Cafe} | \text{Suit}; \theta) \cdot p(\text{Woman} | \text{Suit}; \theta) \cdot$$

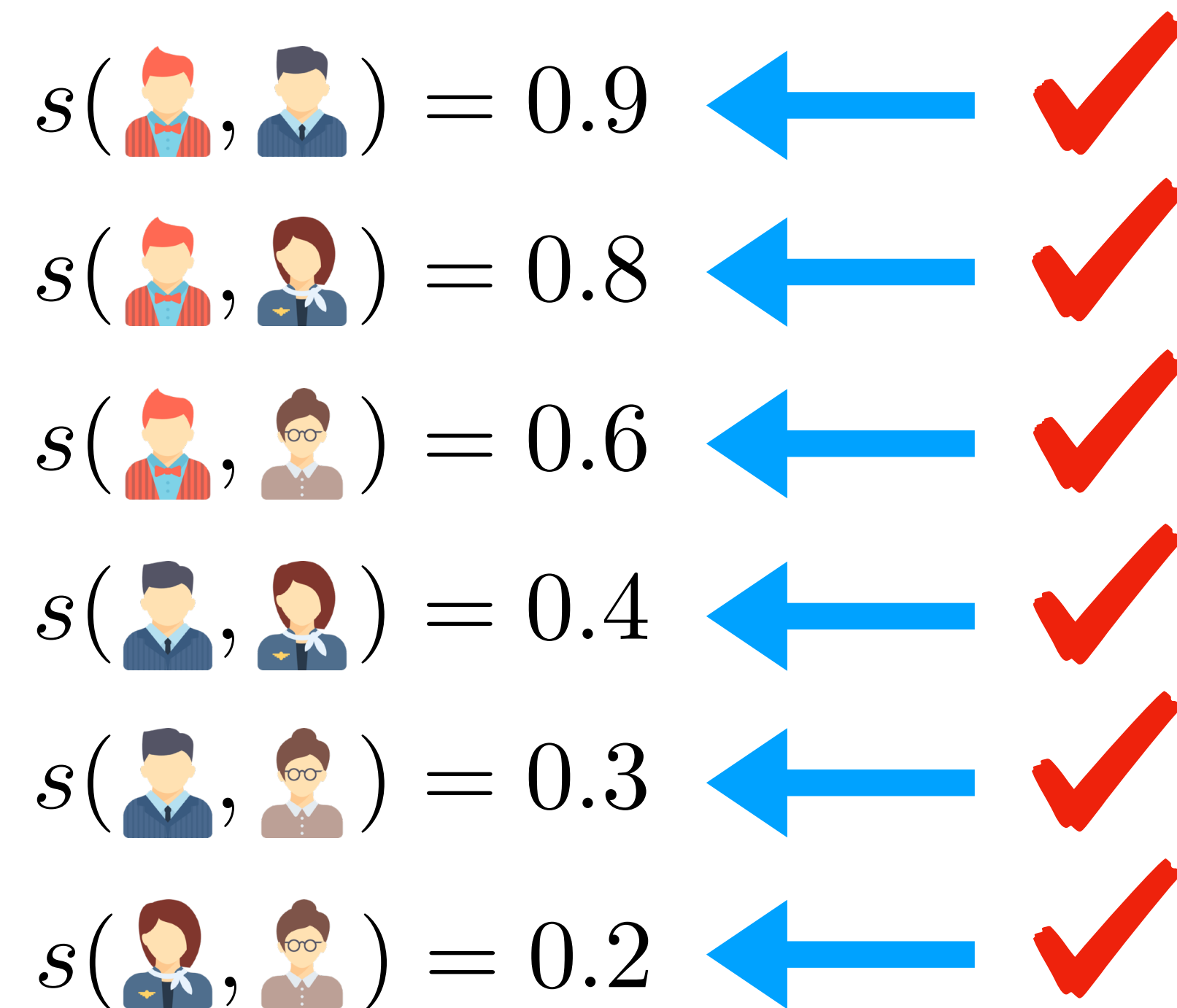
$$p(\text{Red Hair} | \text{Glasses}; \theta) \cdot p(\text{Bank} | \text{Glasses}; \theta) \cdot p(\text{Cafe} | \text{Glasses}; \theta) \cdot p(\text{Glasses} | \text{Glasses}; \theta) \cdot$$

$$p(\text{Cafe} | \text{Woman}; \theta) \cdot p(\text{Suit} | \text{Woman}; \theta) \cdot$$

$$p(\text{Red Hair} | \text{Bank}; \theta) \cdot p(\text{Glasses} | \text{Bank}; \theta) \cdot p(\text{Cafe} | \text{Bank}; \theta) \cdot p(\text{Suit} | \text{Bank}; \theta) \cdot$$

$$p(\text{Bank} | \text{Cafe}; \theta) \cdot p(\text{Glasses} | \text{Cafe}; \theta) \cdot p(\text{Suit} | \text{Cafe}; \theta) \cdot p(\text{Woman} | \text{Cafe}; \theta)$$

# Social Relation Inference



- Cosine similarity
- Unsupervised
- Predict any social relation

# Evaluation: dataset



- Instagram users' check-ins
  - New York, Los Angeles and London

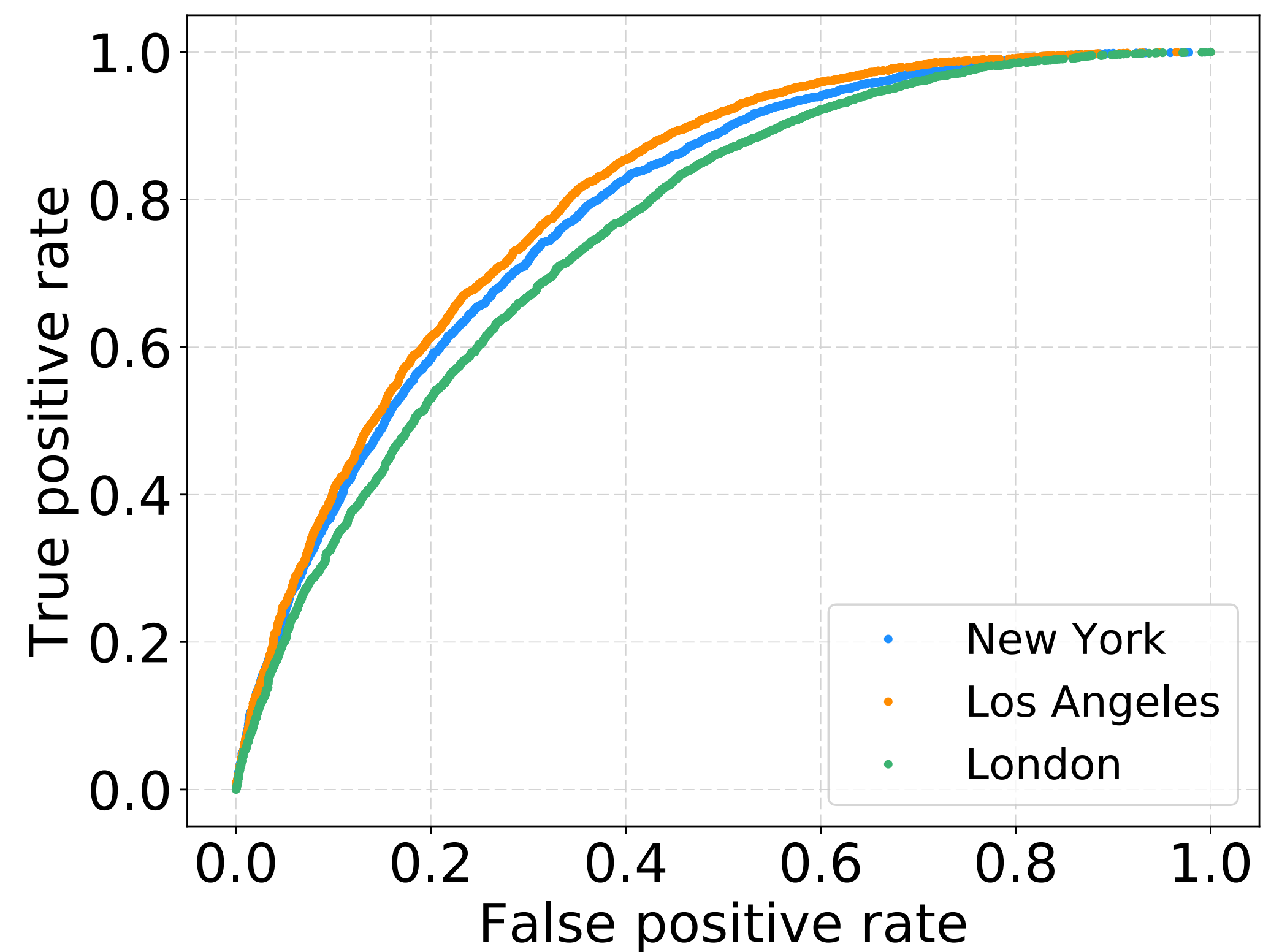


- Foursquare (location semantics)
- Social relations (two users follow each other)

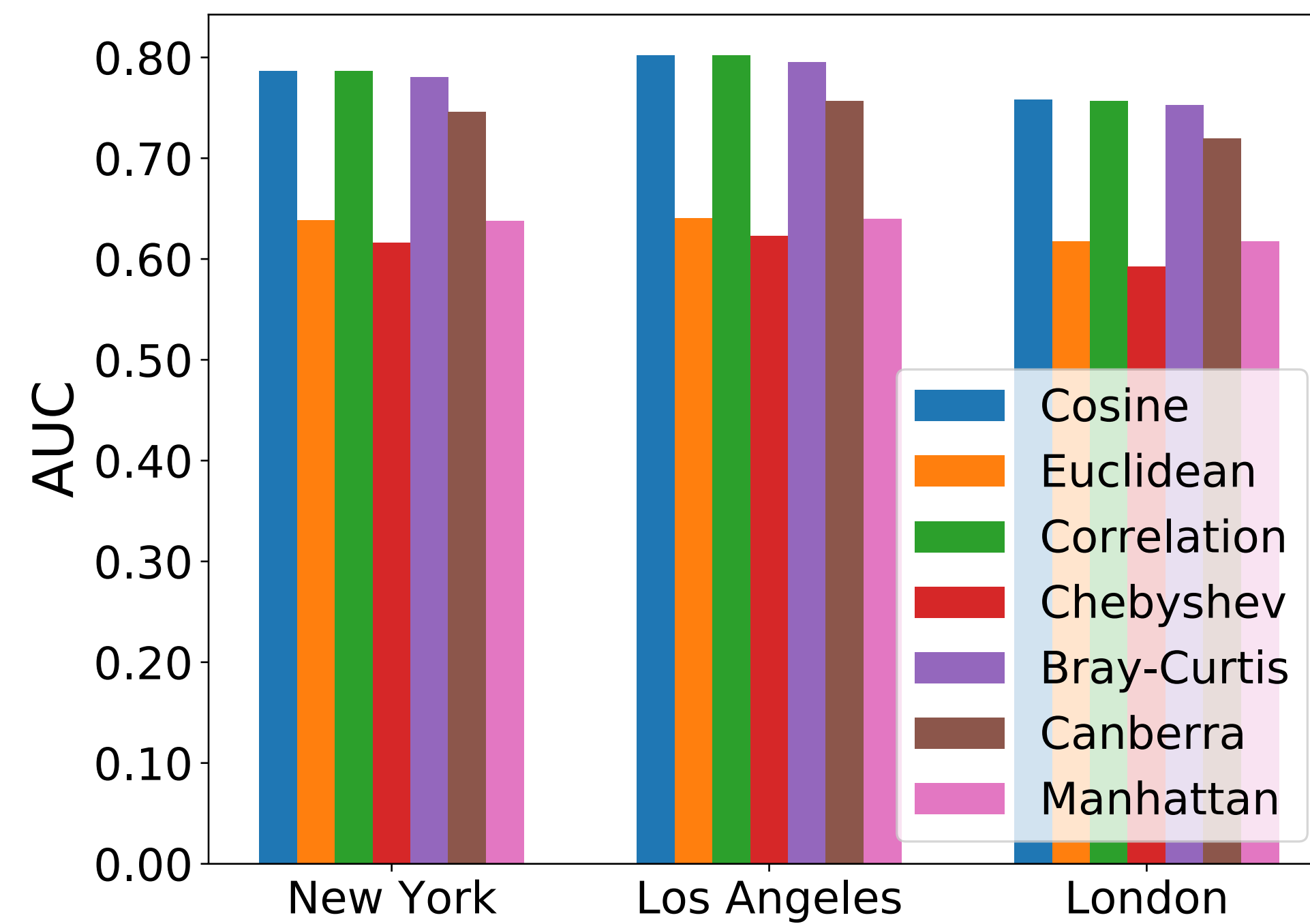
	New York	Los Angeles	London
No. check-ins	1,843,187	1,301,991	500,776
No. locations	25,868	22,260	10,693
No. users	44,371	30,679	13,187
No. social links	193,995	129,004	25,413



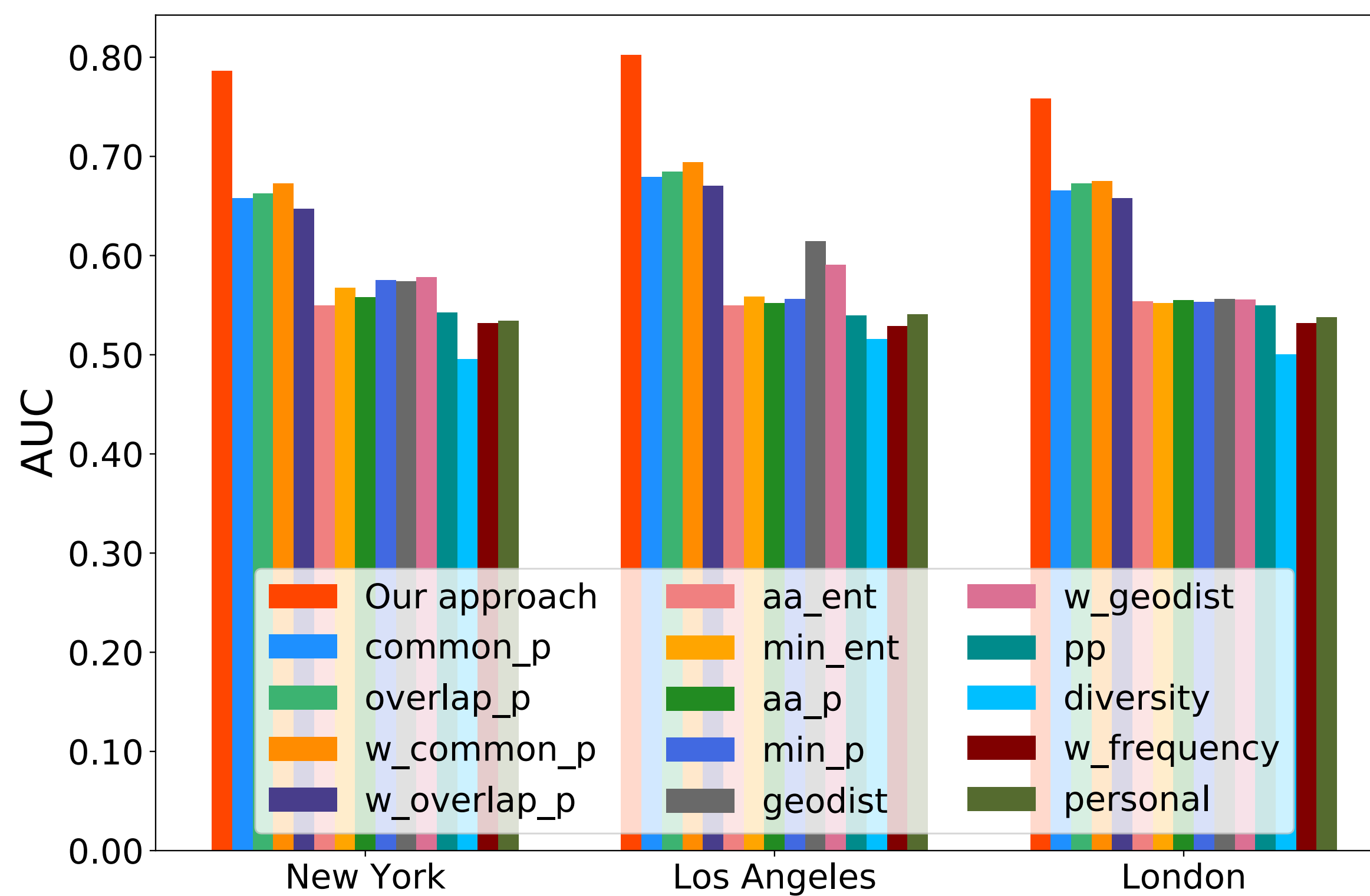
# Evaluation: ROC curve



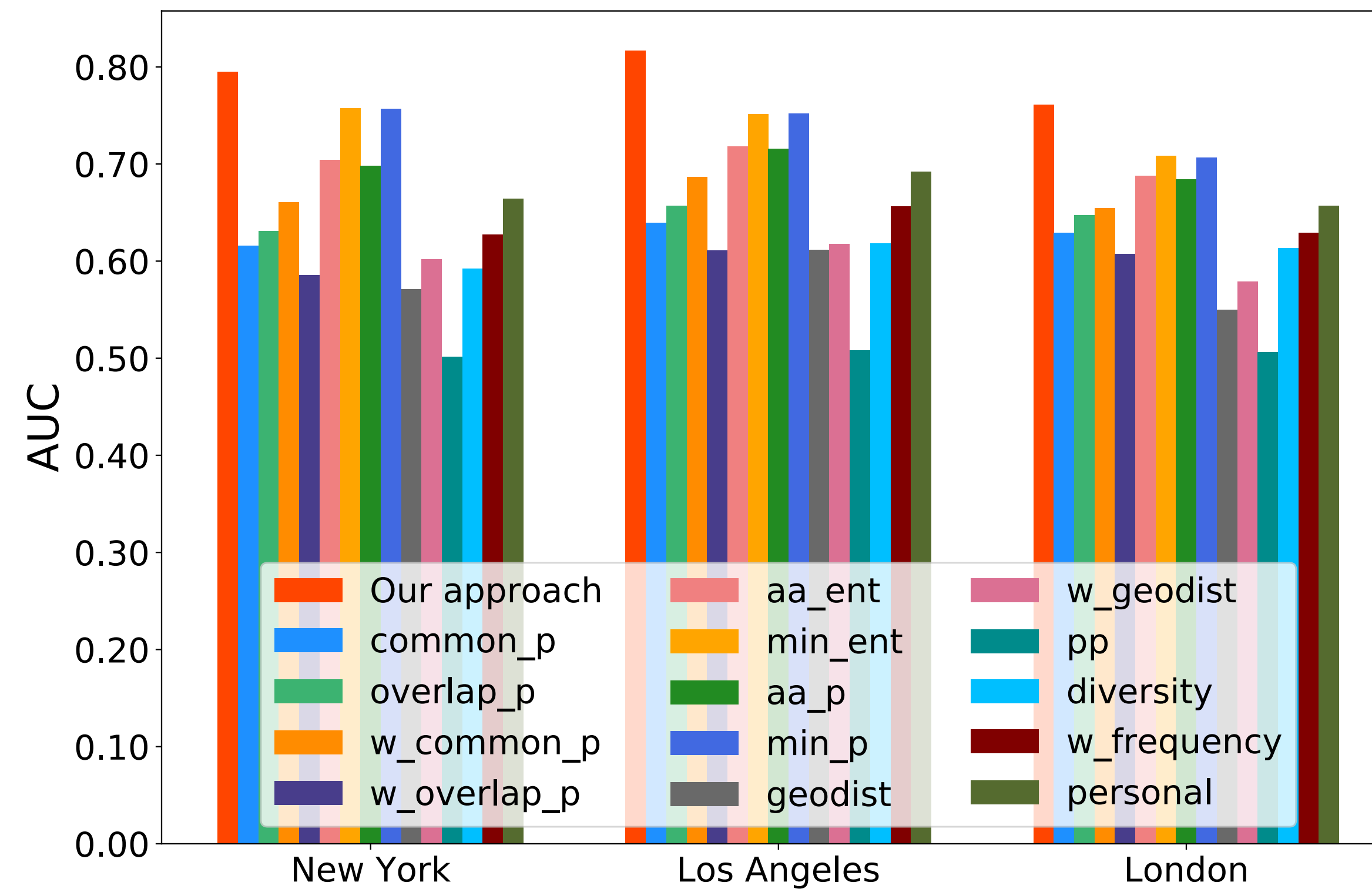
# Evaluation: distance metric



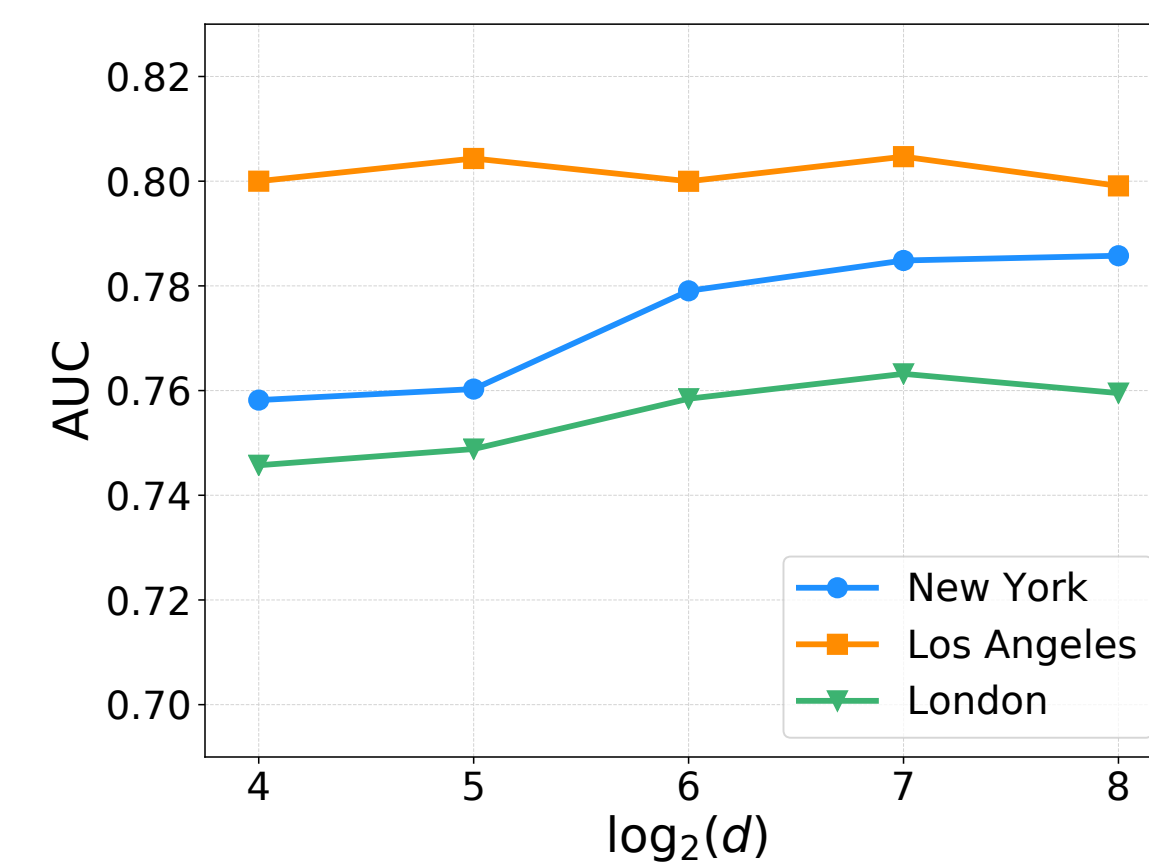
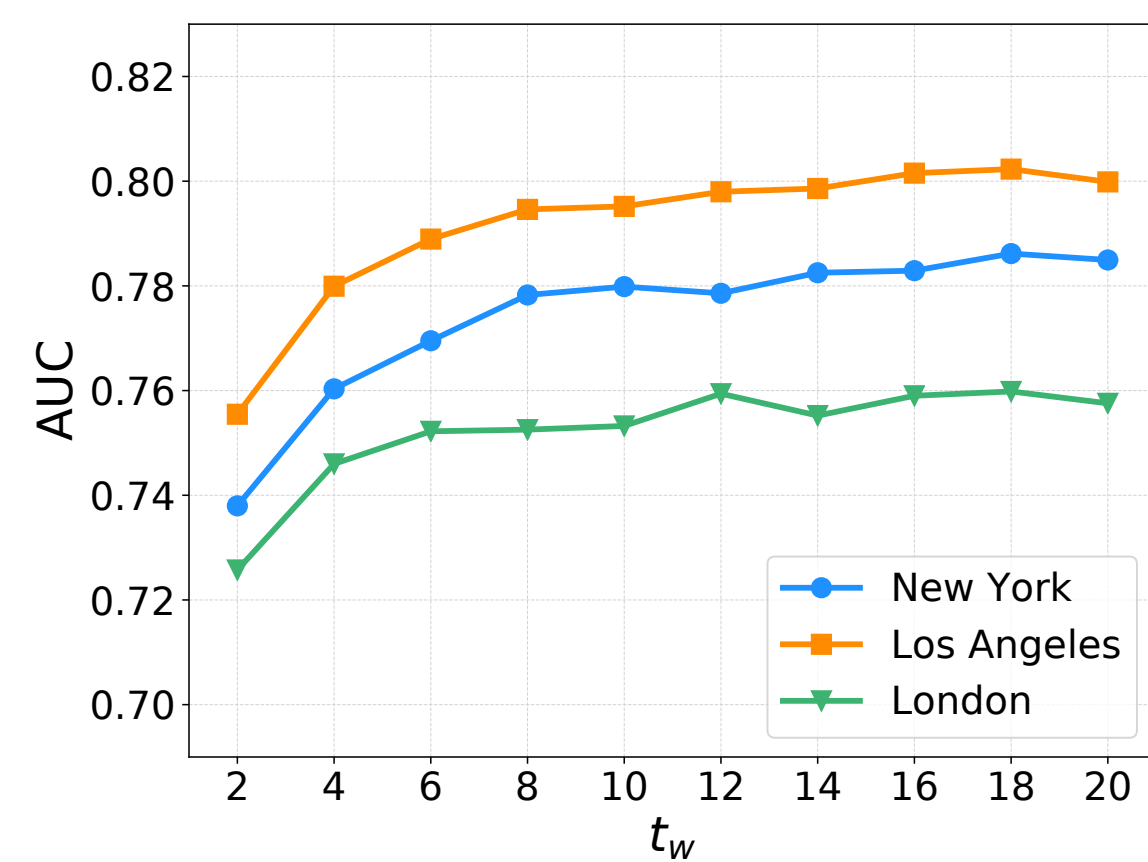
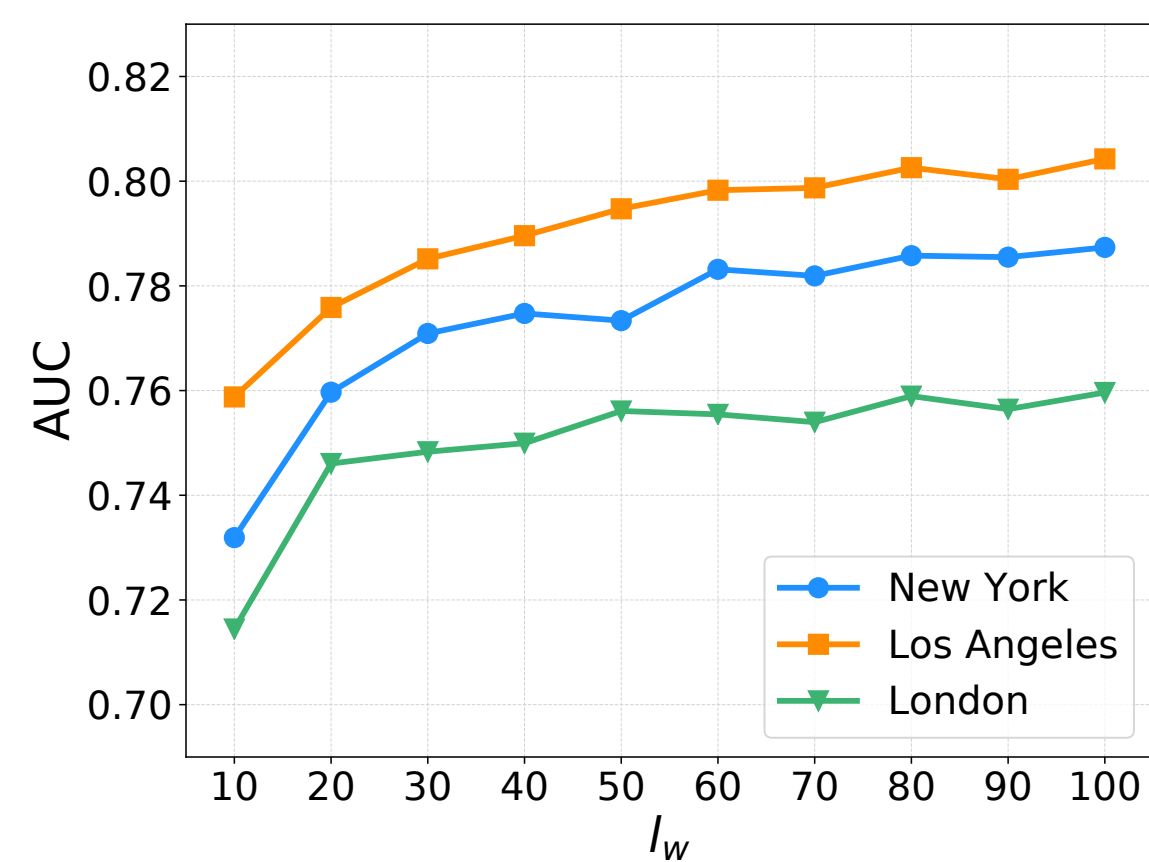
# Evaluation: baseline models



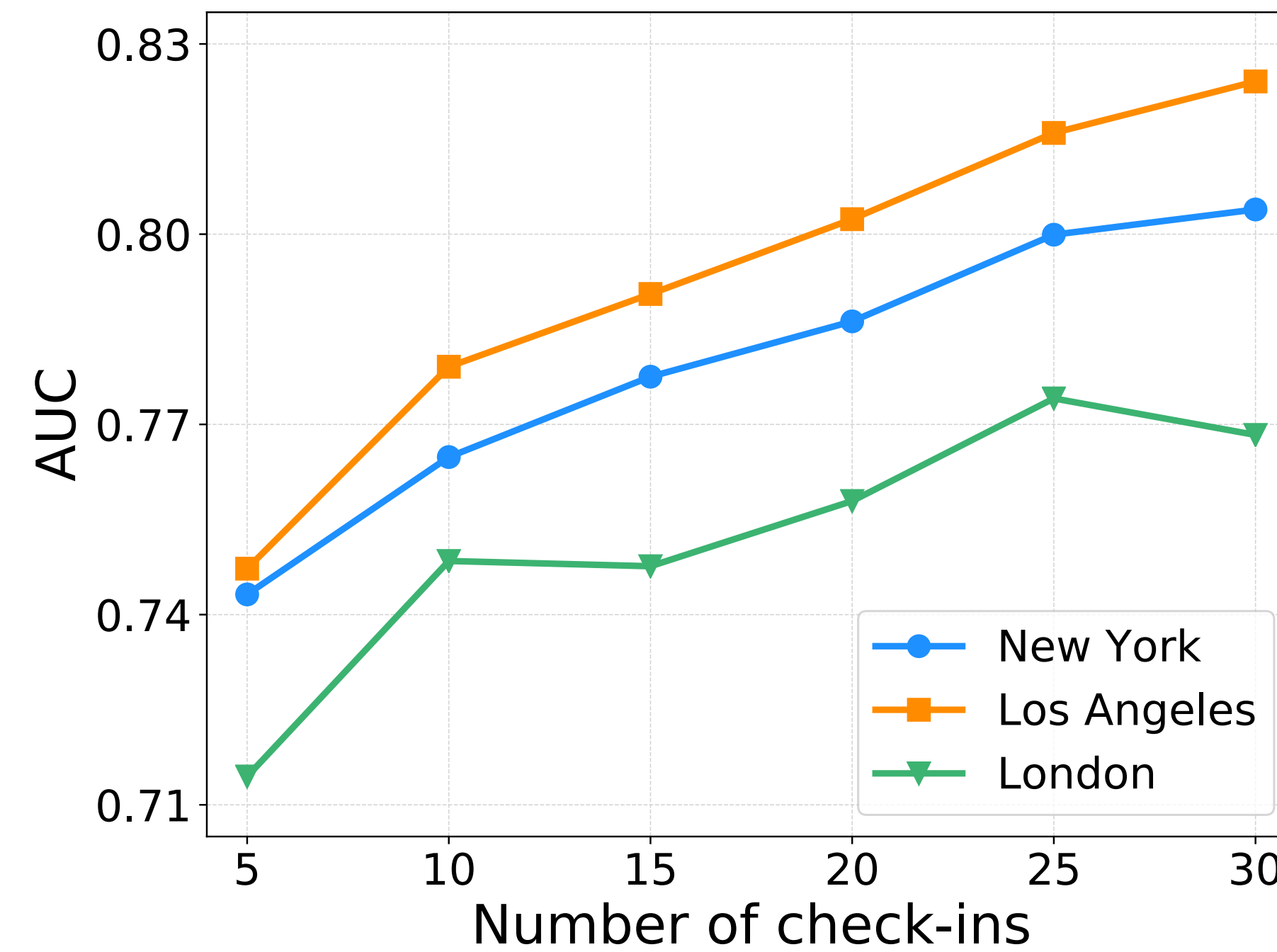
# Evaluation: baseline models



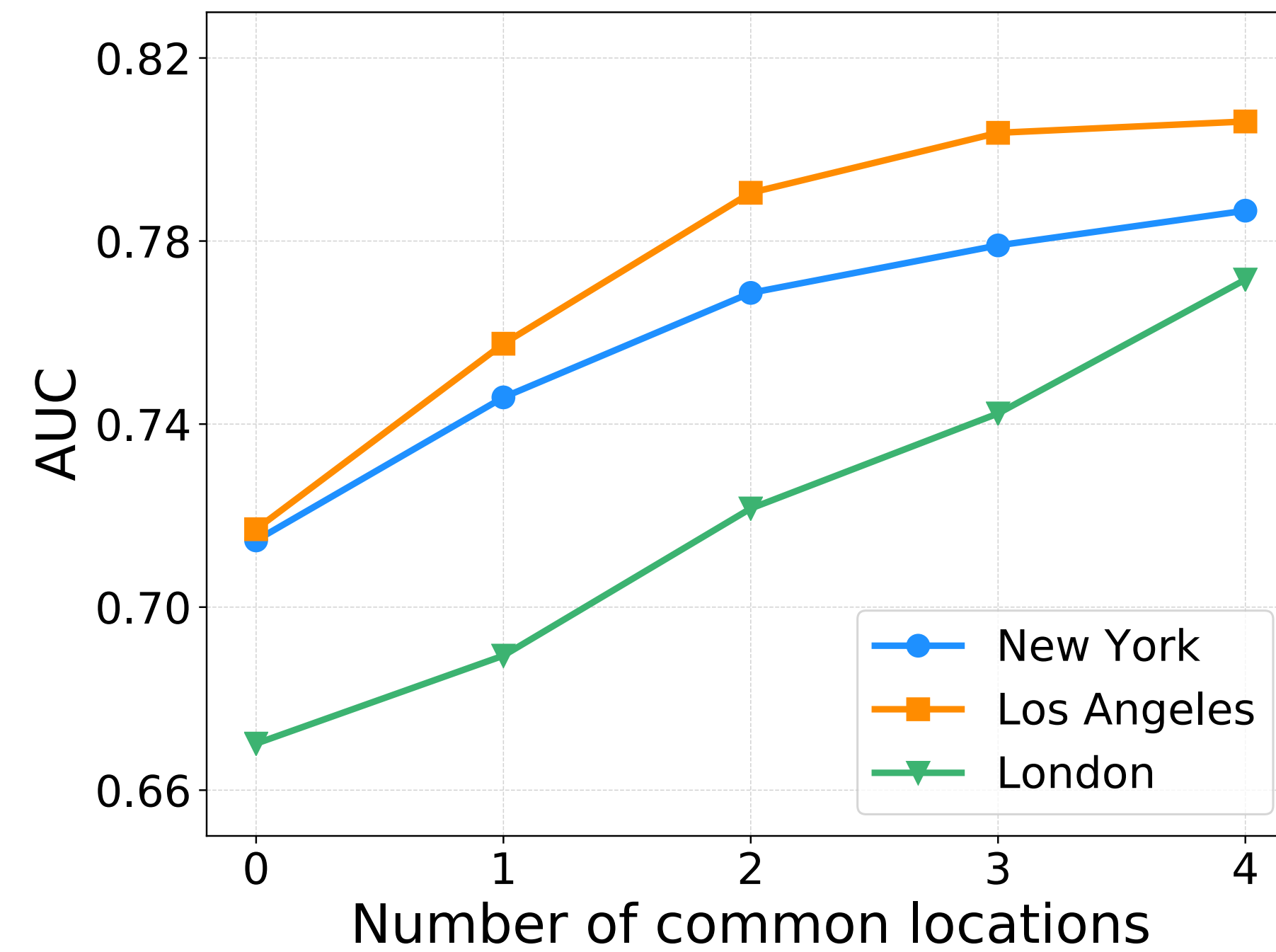
# Evaluation: hyperparameters



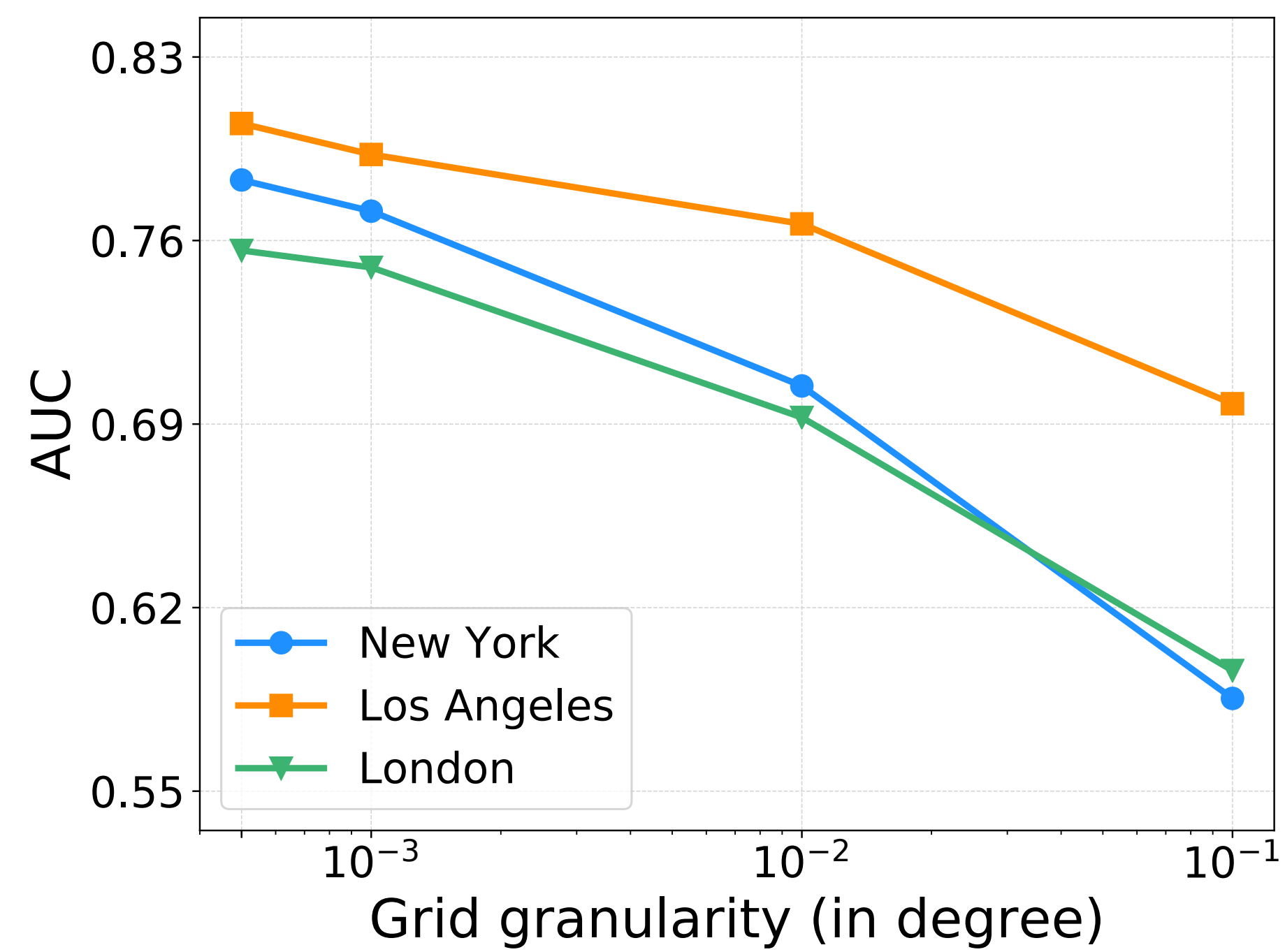
# Evaluation: check-in numbers



# Evaluation: common locations



# Evaluation: geo-coordinates





# Defense Mechanisms

- Hiding
  - Delete certain proportion of check-ins
- Replacement
  - Random walk to replace locations

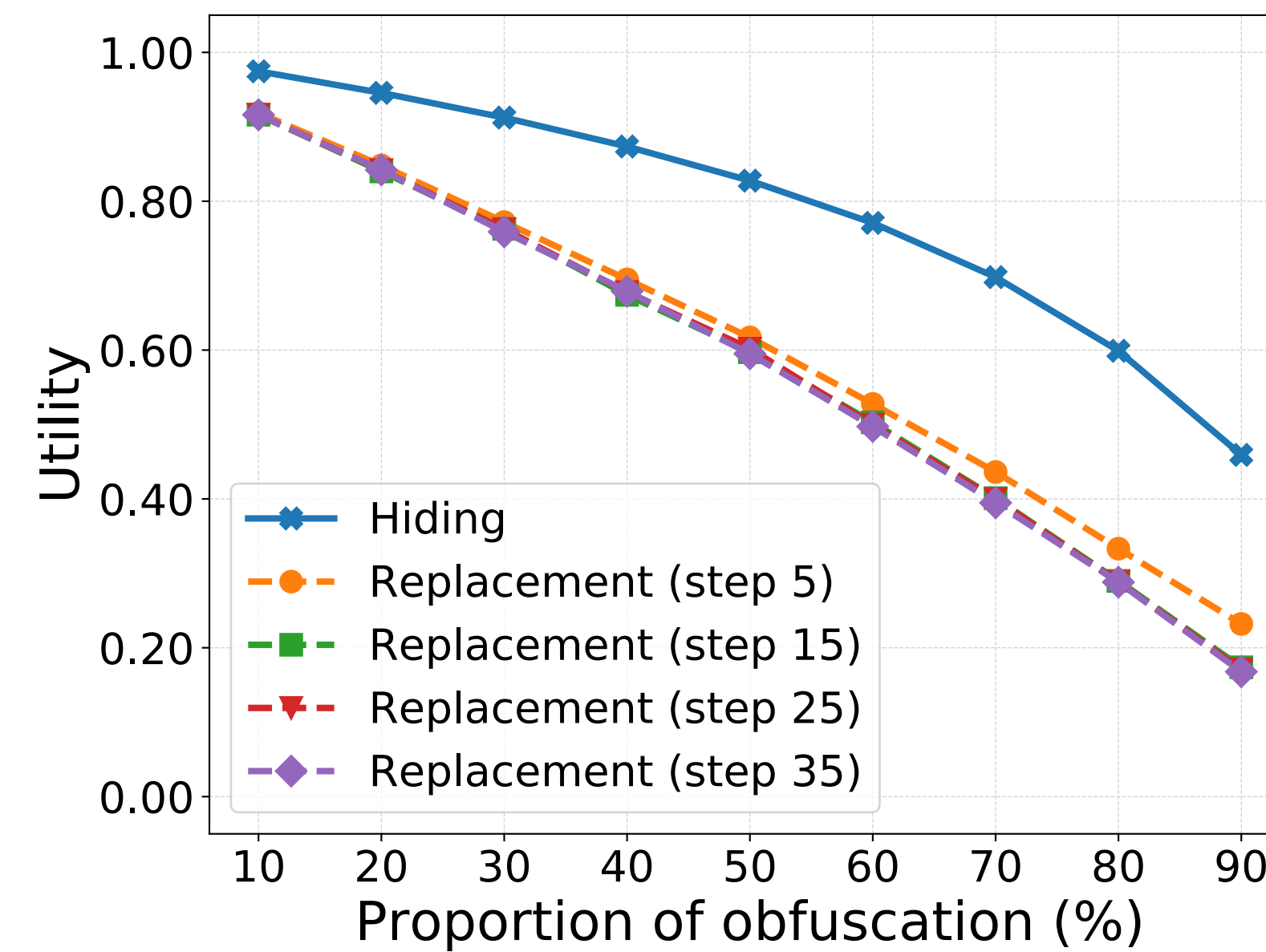
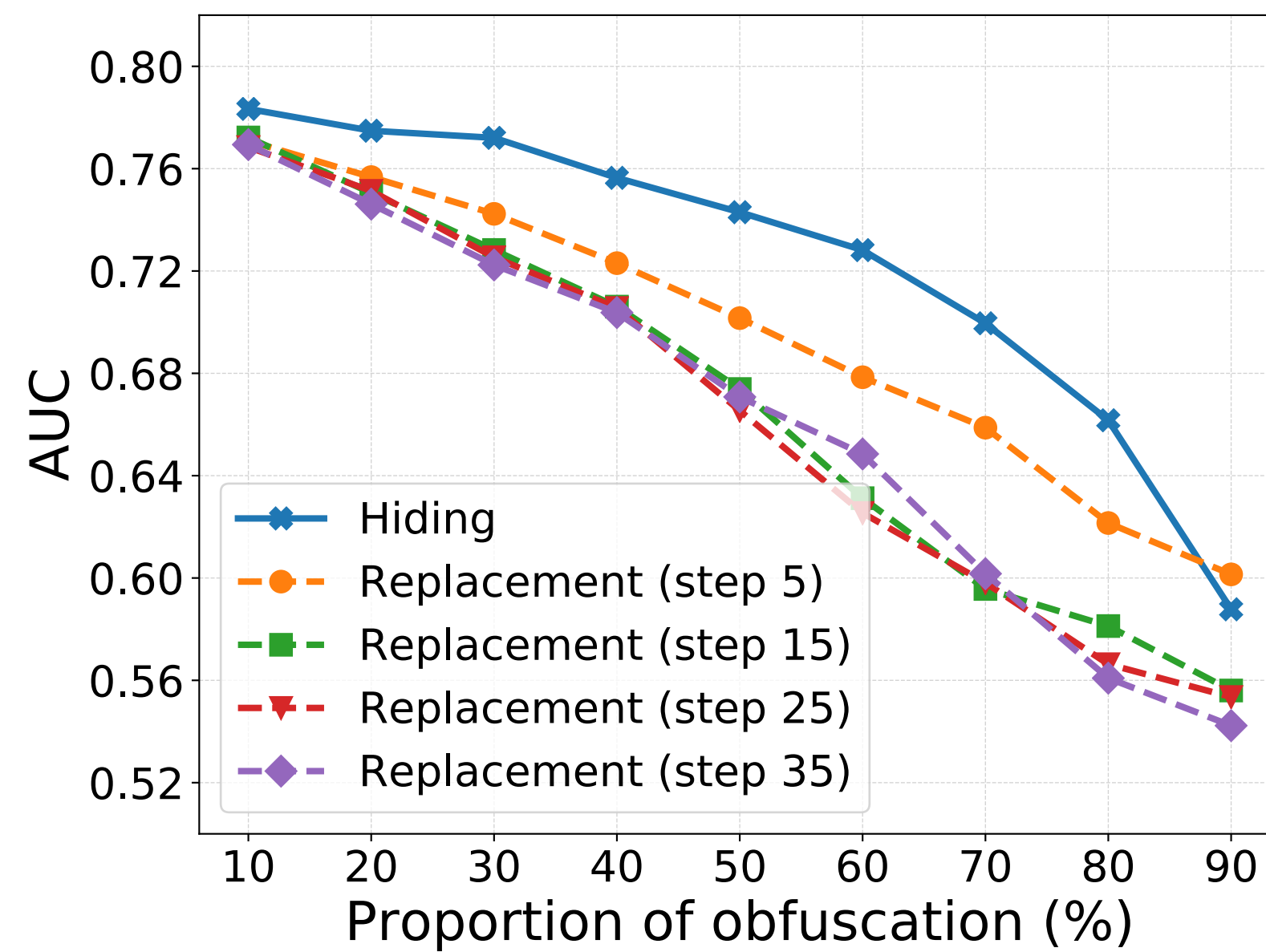
# Defense Mechanisms

- Generalization
  - Geo-coordinate and location semantics
    - MoMA -> art (40.76N, -73.97W)
  - Recover location first
    - art (40.76N, -73.97W) -> MoMA or Tom Otterness Frog?

# Utility Metric

- Each user's check-in distribution
  - Both original and obfuscated
- Jensen-Shannon divergence
- Average over all users

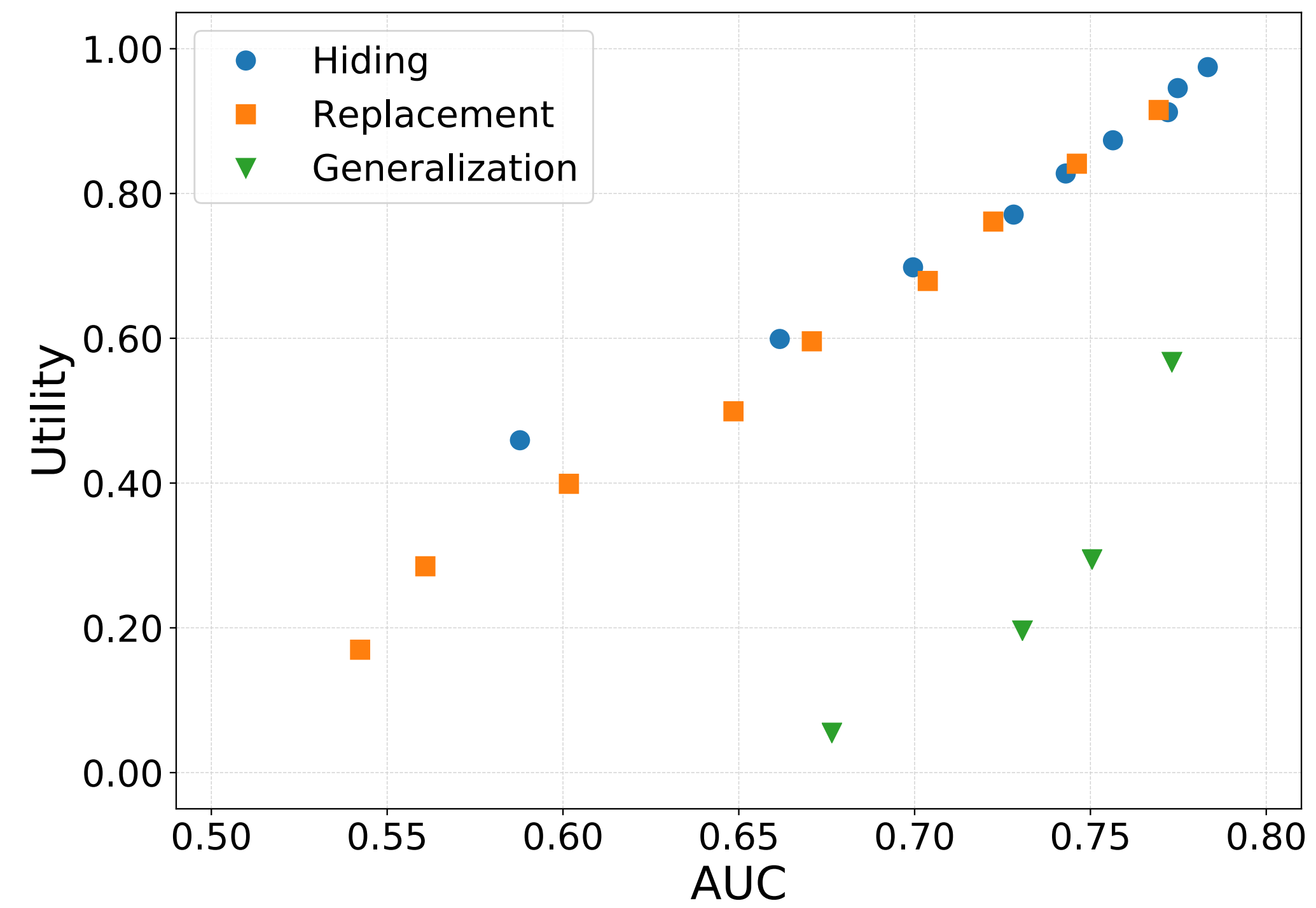
# Defense Evaluation



# Defense Evaluation

	AUC		Utility		Recovery rate	
	<i>ls</i>	<i>hs</i>	<i>ls</i>	<i>hs</i>	<i>ls</i>	<i>hs</i>
<i>lg</i>	0.77	0.75	0.57	0.30	52%	23%
<i>hg</i>	0.73	0.67	0.20	0.06	14%	2%

# Defense Evaluation



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# Conclusion

- A new social relation inference attack with mobility profiles
  - Learning user profiles
  - Unsupervised and predict any social relations
- Three general defense mechanisms
  - Replacement and hiding outperform generalization