Exploring Frequency-based Approaches for Efficient Trajectory Classification

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Outline

- Introduction and Motivation
- Problem Definition
- Objective and Contributions
- Proposal
- Experimental Evaluation
- Conclusion and Future Work

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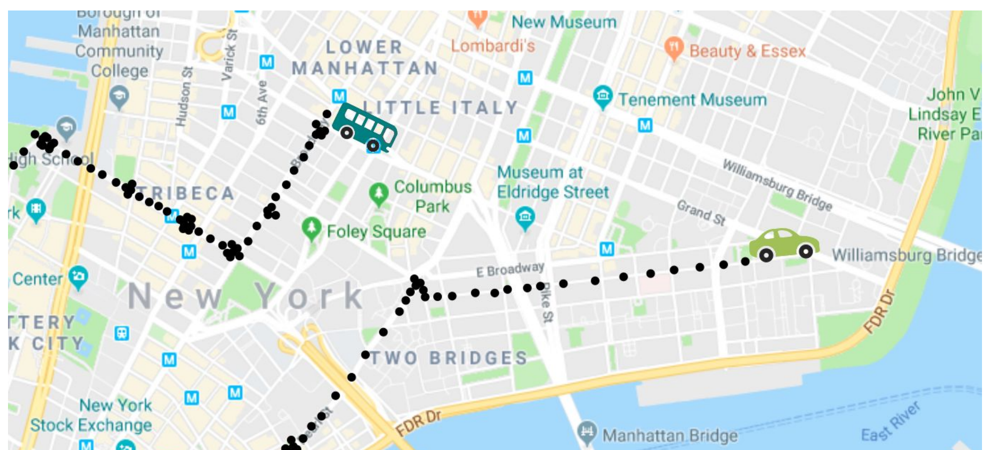
Introduction

- ➢ Era of movement tracking, and with the Corona virus, tracking people became important, urgent, and easy as never before in human history

For many years, moving object traces were called Raw Trajectories

- Sequence of points located in space and time
- Data are dense and have so semantics



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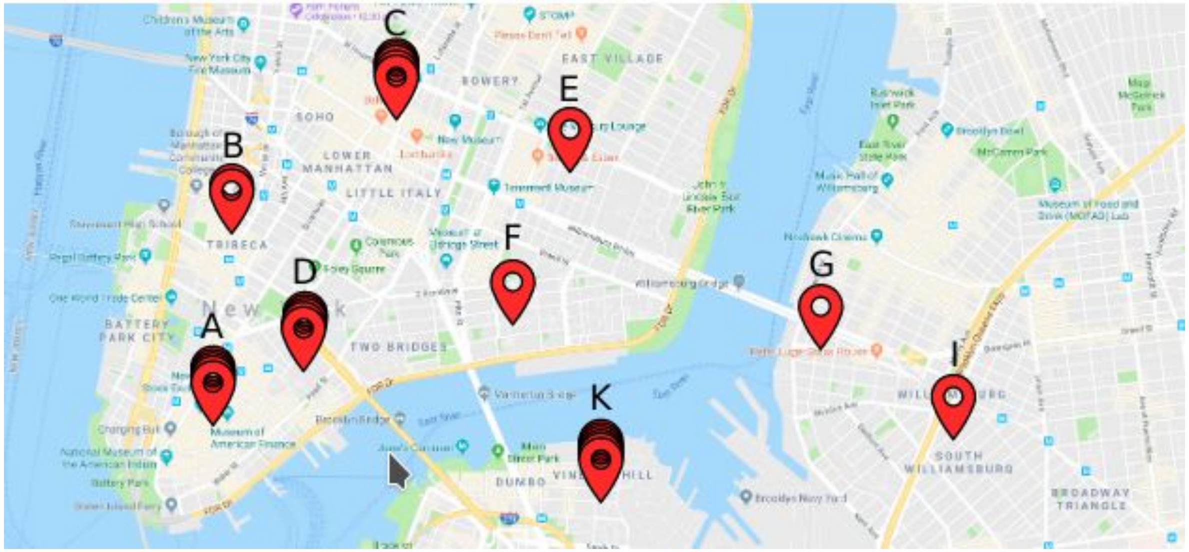
Introduction

After 2007 emerged the concept of *Semantic Trajectory*

- Sequence of points located in space and time enriched with **semantic** information
- The figure shows examples of social media trajectories, where each point is a visited place (called Point of Interest (POI)), and POI related attributes as *place category*, *price* and *rating*,



Introduction

An important task in trajectory data mining is *Classification*

It consists of categorizing a moving object based on its trajectories.

Applications

- Classifying animal species
- Transportation mode inference (car, bus, taxi, etc);
- Profiling human behavior
- Individuals that are potential virus spreaders

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Problem Definition

Given a large dataset of trajectories, how can we ***efficiently*** classify the moving objects based on their trajectories?

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Related Work

Work	Space	Time	Semantics	Frequency -based	Trajectory features used as input for the classifier
TraClass (Lee et al. 2008)	✓			✓	Subtrajectories
Patel et al. (2012)	✓	✓		✓	Subtrajectories
Dodge et al. (2009)	✓	✓			Features (speed, acceleration, ...)
Soleymani et al. (2014)	✓	✓			Space partitions + Temporal descriptive statistics
Etemad et al. (2018)					Features (speed, acceleration…)
Lee et al. (2011)			✓		Frequent segments (street names)
Bi-TULER (Gao et al. 2017)			✓		POI embeddings
TULVAE (Zhou et al. 2018)			✓		POI embeddings
Movelets (Ferrero et al. 2018)	✓	✓	✓	✓	Subtrajectories

- **All methods extract features from trajectories and use traditional classifiers**
- **Some are limited to a specific application, as transportation mode inference**
- **Movelets is generic for any application and is the best method so far in terms of accuracy**

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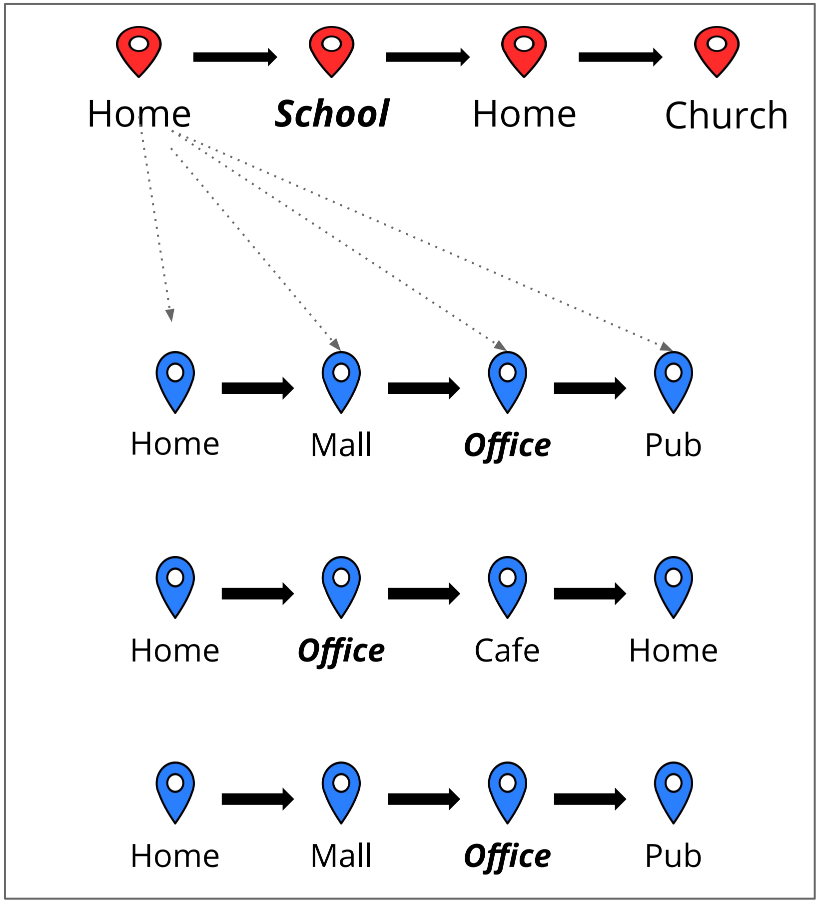
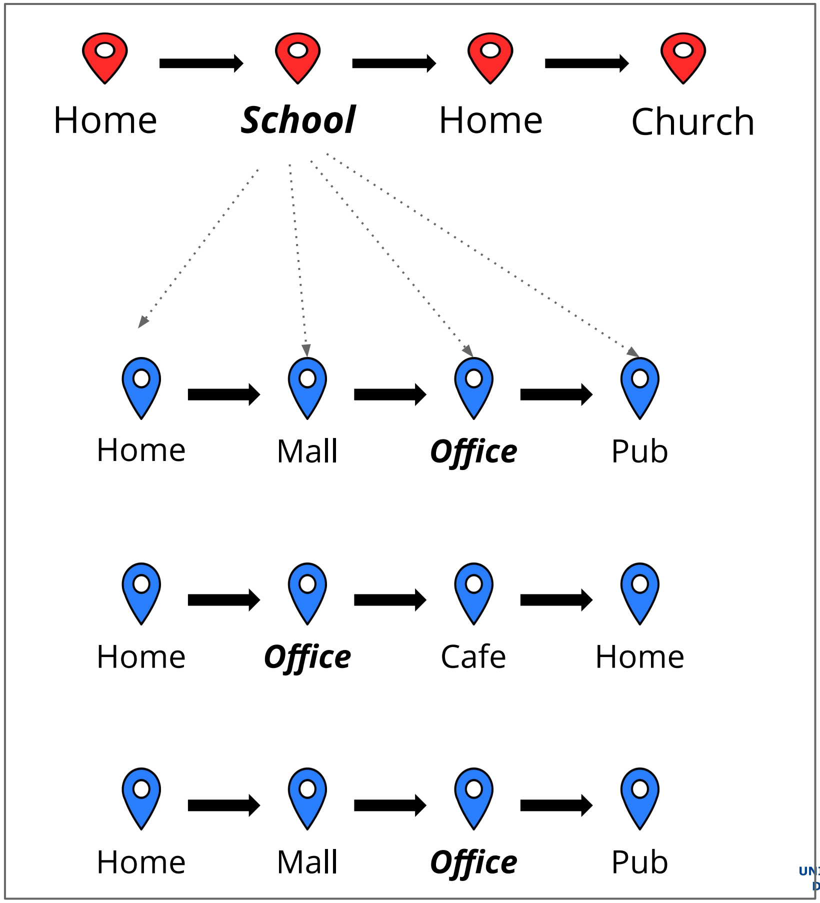
Problem definition

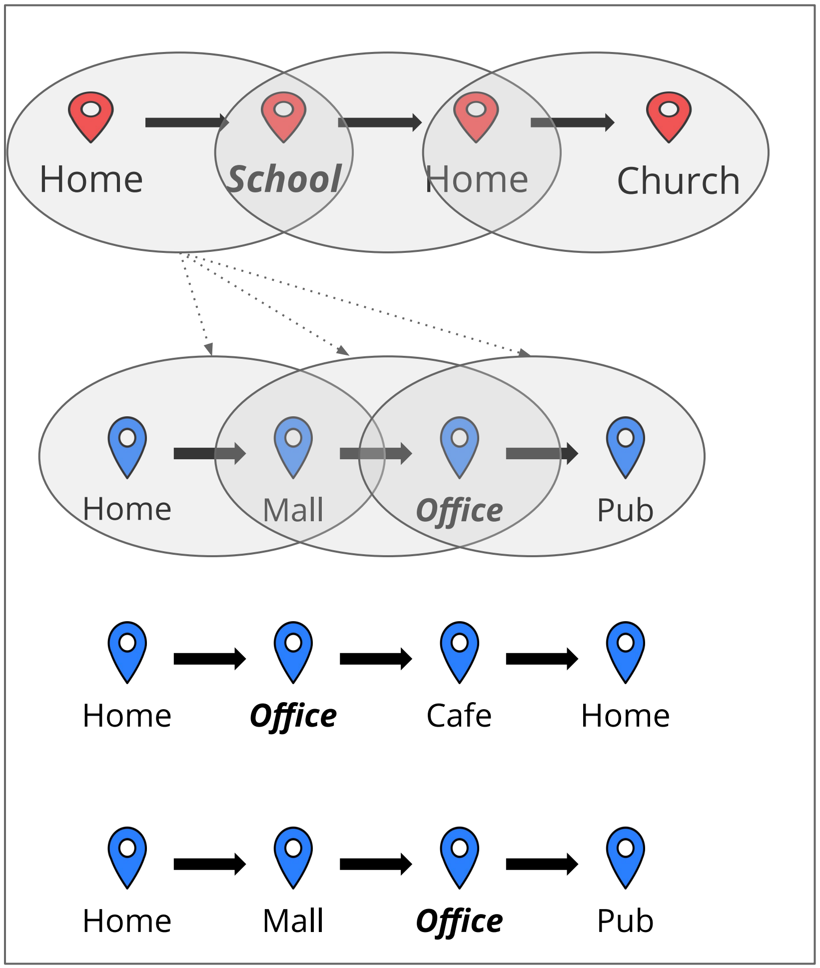
Movelets extracts every possible subtrajectory and computes the distance to all trajectories in the dataset to find the most discriminant subtrajectories

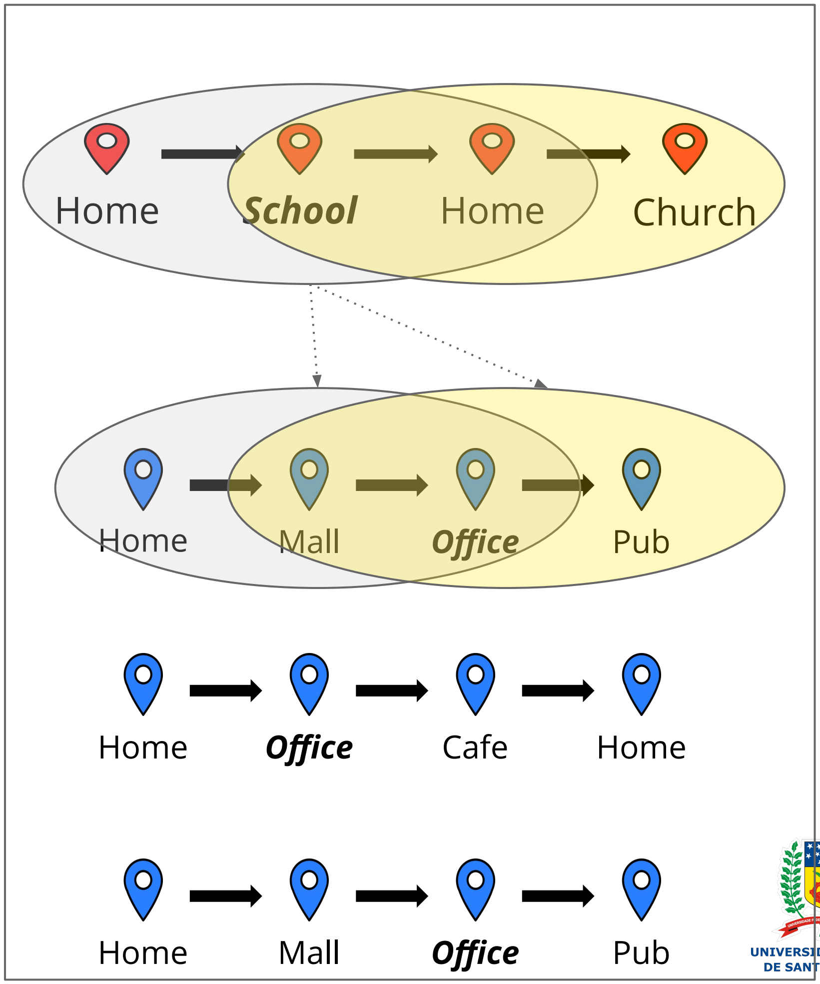




Problem definition

The approach is not scalable for big data





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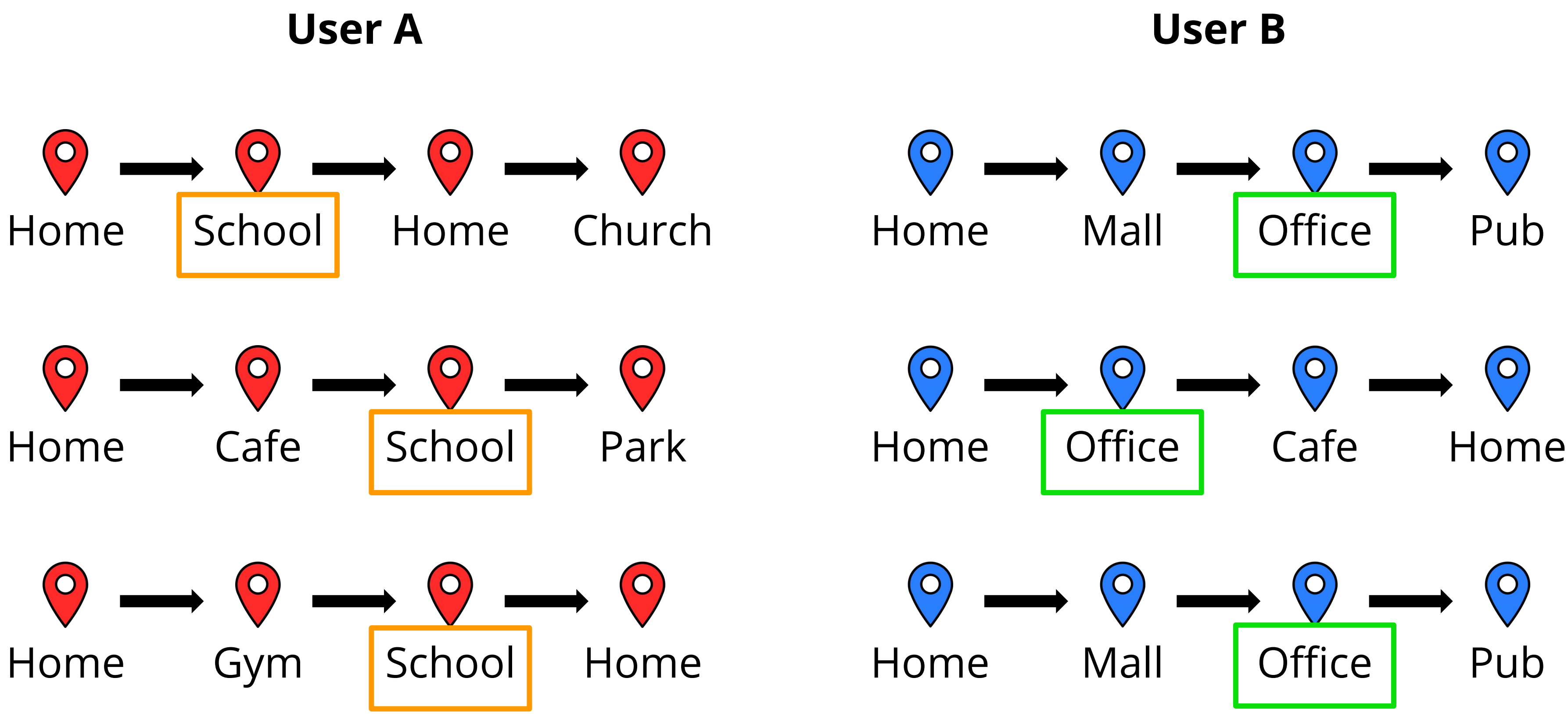
Problem Definition



Users show a certain frequency of some visited POIs

Objective

Propose frequency-based methods for semantic trajectory classification that are faster and achieve similar or better results than the state of the art

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Contributions

Three complementary fast approaches based on the **frequency** of **visits**:

- **POI-F** (POI Frequency)
- **NPOI-F** (Normalized POI Frequency)
- **WNPOI-F** (Weighted Normalized POI-Frequency)

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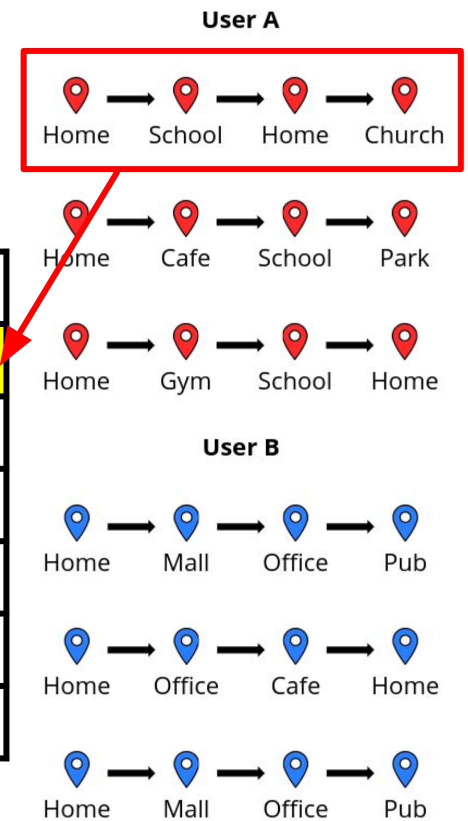
Proposal

POI-Frequency (POI-F): Given a trajectory *T* and a POI *P*, the frequency of *P* in *T* is computed as

$$\text{POI-F}(P, T) = \text{the number of visits of P in T.}$$

	Home	School	Church	Cafe	Park	Gym	Mall	Office	Pub	Class
A1	**2**	**1**	**1**	**0**	**0**	**0**	**0**	**0**	**0**	**A**
A2	1	1	0	1	1	0	0	0	0	**A**
A3	2	1	0	0	0	1	0	0	0	**A**
B1	1	0	0	0	0	0	1	1	1	**B**
B2	2	0	0	1	0	0	0	1	0	**B**
B3	1	0	0	0	0	0	1	1	1	**B**



The trajectories become a frequency matrix, where each row is a trajectory and the columns are all POIs in the database

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Proposal

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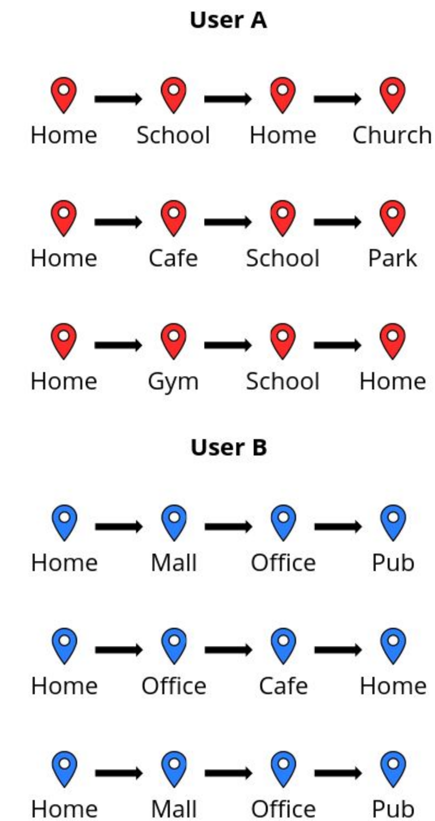

	Home	School	Church	Cafe	Park	Gym	Mall	Office	Pub	Class
A1	**2**	**1**	**1**	0	0	0	0	0	0	**A**
A2	**1**	**1**	0	**1**	**1**	0	0	0	0	**A**
A3	**2**	**1**	0	0	0	**1**	0	0	0	**A**
B1	**1**	0	0	0	0	0	**1**	**1**	**1**	**B**
B2	**2**	0	0	**1**	0	0	0	**1**	0	**B**
B3	**1**	0	0	0	0	0	**1**	**1**	**1**	**B**

The red cells represent the POIs visited by user A and the blue ones represent user B

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Proposal

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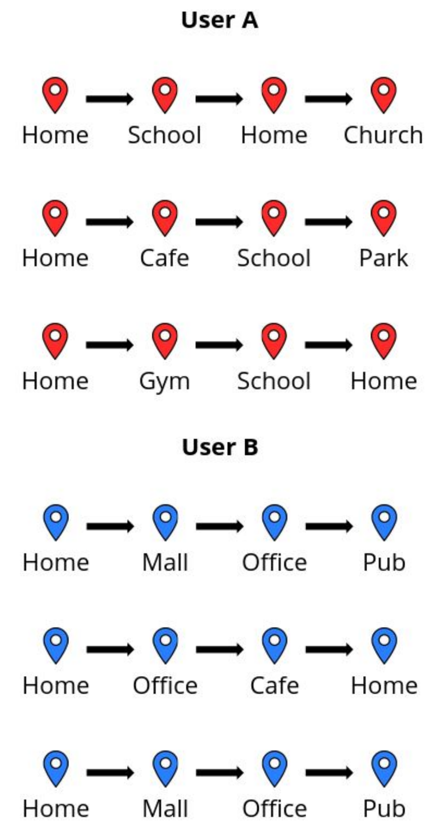
	Home	School	Church	Cafe	Park	Gym	Mall	Office	Pub	Class
A1	2	**1**	1	0	0	0	0	0	0	**A**
A2	1	**1**	0	1	1	0	0	0	0	**A**
A3	2	**1**	0	0	0	1	0	0	0	**A**
B1	1	0	0	0	0	0	**1**	**1**	**1**	**B**
B2	2	0	0	1	0	0	0	**1**	0	**B**
B3	1	0				0	**1**	**1**	**1**	**B**

Discriminative patterns



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Proposal

Normalized POI Frequency (NPOI-F). Given by the proportion of the frequency of a POI (P) in a trajectory (T) and the size of the trajectory

$$\text{NPOI-F}(P,T) = \frac{\text{POI-F(P,T)}}{\text{\# of points in T}}$$

- Useful for comparing the behavior of users in trajectories of different lengths.

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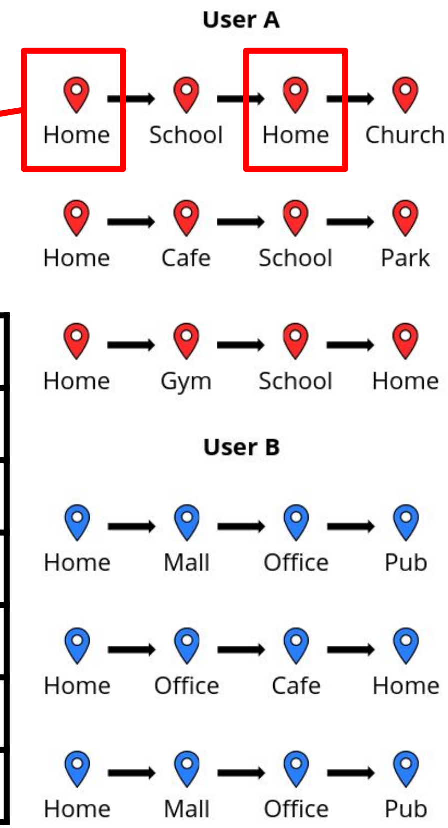
Proposal

Our previous example computing the **NPOI-F**:

$$\text{NPOI-F}(P,T) = \frac{\text{POI-F(P,T)}}{\#\text{ of points in T}}$$

$$\text{NPOI-F}(Home, A1) = \frac{2}{4} = 0.5$$



	Home	School	Church	Cafe	Park	Gym	Mall	Office	Pub	Class
A1	$\boxed{0.50}$	0.25	0.25	0	0	0	0	0	0	A
A2	0.25	0.25	0	0.25	0.25	0	0	0	0	A
A3	0.50	0.25	0	0	0	0.25	0	0	0	A
B1	0.25	0	0	0	0	0	0.25	0.25	0.25	B
B2	0.50	0	0	0.25	0	0	0	0.25	0	B
B3	0.25	0	0	0	0	0	0.25	0.25	0.25	B

Visits now are given as percentages according to the whole trajectory (each line sums up to 1)

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Proposal

Weighted Normalized POI Frequency. Considers the frequency wrt the number of users in the database and the number of users that have visited a place.

$$\text{WNPOI-F}(P, T, D) = \text{NPOI-F} * log\left(\frac{\text{\# of users in D}}{\text{\# of users that have visited P}}\right)$$

Useful for penalizing visits that many users (classes) have in common.

In the previous example, the frequencies of the POI Home would become zero because they do not discriminate the users.

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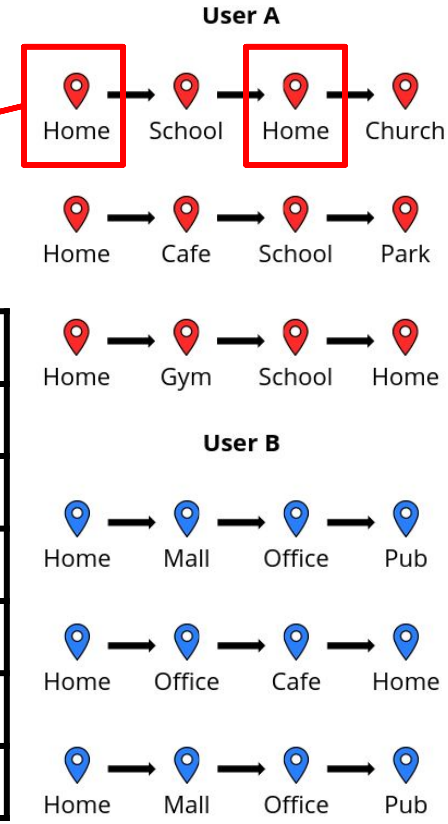
Proposal

Our previous example computed by using **WNPOI-F**:

$$\text{WNPOI-F}(P,T,D) = \text{NPOI-F} * log\left(\frac{\text{\# of users in D}}{\text{\# of users that have visited P}}\right)$$

$$\text{WNPOI-F}(Home, A1, 6) = \frac{2}{4} * log\left(\frac{2}{2}\right) = 0.5 * 0 = 0$$



	Home	School	Church	Cafe	Park	Gym	Mall	Office	Pub	Class
A1	0	0.07	0.07	0	0	0	0	0	0	A
A2	0	0.07	0	0	0.10	0	0	0	0	A
A3	0	0.07	0	0	0	0.07	0	0	0	A
B1	0	0	0	0	0	0	0.07	0.07	0.07	B
B2	0	0	0	0	0	0	0	0.07	0	B
B3	0	0	0	0	0	0	0.07	0.07	0.07	B

They are penalized because they do not discriminate the classes

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Experimental Evaluation

- ➢ Evaluation with three real **datasets** from three location-based social networks: Brightkite, Gowalla, and Foursquare;
- ➢ **Comparison** with Bi-TULER, TULVAE, and Movelets;
- ➢ **Metrics**: ACC@1, ACC@5 and Macro-F1;
- ➢ Classification algorithm: MultiLayer Perceptron (MLP) - determined by preliminary experiments;
  - Hidden layer with 100 units;
  - Trained with Adam optimizer and a learning rate of 10^{-3};
  - batch size of 64;
  - dropout rate of 0.5.

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Datasets

Datasets used by previous methods and that have lat, lon, time and semantic dimensions

Dataset	Description	
Brightkite	Min - Max Traj. Size	10 - 50
	Number of Trajectories	7911
	Number of Points	130494
	Attributes	Lat, Lon, POI, Time, Weekday, Class
	Class	Users (300)
Gowalla	Min - Max Traj. Size	10 - 50
	Number of Trajectories	5329
	Number of Points	98158
	Attributes	Lat, Lon, POI, Time, Weekday, Class
	Class	Users (300)
Foursquare NYC	Min - Max Traj. Size	10 - 144
	Number of Trajectories	3079
	Number of Points	66962
	Attributes	Lat, Lon, POI, Time, Weekday, Weather, Price, Rating, Class
	Class	Users (193)

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Results with the three datasets (Accuracy)

Brightkite

Method	ACC@1	ACC@5	Macro-F1
Bi-TULER [Gao et al., 2017]	90.64	95.55	87.92
MOVELETS [Ferrero et al., 2018]	90.55	93.79	89.41
TULVAE [Zhou et al., 2018]	88.41	92.15	83.63
POI-F	<u>95.29</u>	**97.98**	<u>93.80</u>
NPOI-F	**95.34**	**97.98**	**93.91**
WNPOI-F	95.13	<u>97.94</u>	93.68

Gowalla

Method	ACC@1	ACC@5	Macro-F1
Bi-TULER [Gao et al., 2017]	66.15	78.36	63.26
MOVELETS [Ferrero et al., 2018]	91.44	94.04	90.25
TULVAE [Zhou et al., 2018]	67.94	78.76	64.91
POI-F	<u>93.22</u>	<u>97.62</u>	**92.54**
NPOI-F	**93.46**	**97.68**	<u>91.91</u>
WNPOI-F	93.11	97.45	91.66

Foursquare

Method	ACC@1	ACC@5	Macro-F1
Bi-TULER [Gao et al., 2017]	48.20	67.38	40.56
MOVELETS [Ferrero et al., 2018]	97.66	98.93	96.45
TULVAE [Zhou et al., 2018]	54.33	73.81	46.54
POI-F	<u>98.05</u>	**99.41**	97.29
NPOI-F	**98.24**	**99.41**	<u>97.37</u>
WNPOI-F	**98.24**	**99.41**	**97.54**

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Results with Generalized Foursquare (Accuracy)

Making the classification problem more difficult - Generalizing the **POI name** to **POI category (e.g. Ibis Hotel → Hotel)**

Method	ACC@1	ACC@5	Macro-F1
Bi-TULER [Gao et al., 2017]	33.50	60.76	28.29
MOVELETS [Ferrero et al., 2018]	35.34	65.43	29.39
TULVAE [Zhou et al., 2018]	32.81	61.15	28.14
POI-F	**36.22**	**67.96**	**31.12**
NPOI-F	35.24	67.47	28.30
WNPOI-F	34.07	67.47	30.26

Significant accuracy reduction of ACC@1

36,22 % best

Generalized Foursquare considering **additional attributes**

Method	Attributes	ACC@1
MOVELETS [Ferrero et al., 2018]	POI Category + Time	44.59
POI-F	POI Category + Rating	71.56
NPOI-F	POI Category + Price + Rating	**74.09**
WNPOI-F	POI Category + Price + Rating	**74.09**

Accuracy increased to 74,09%

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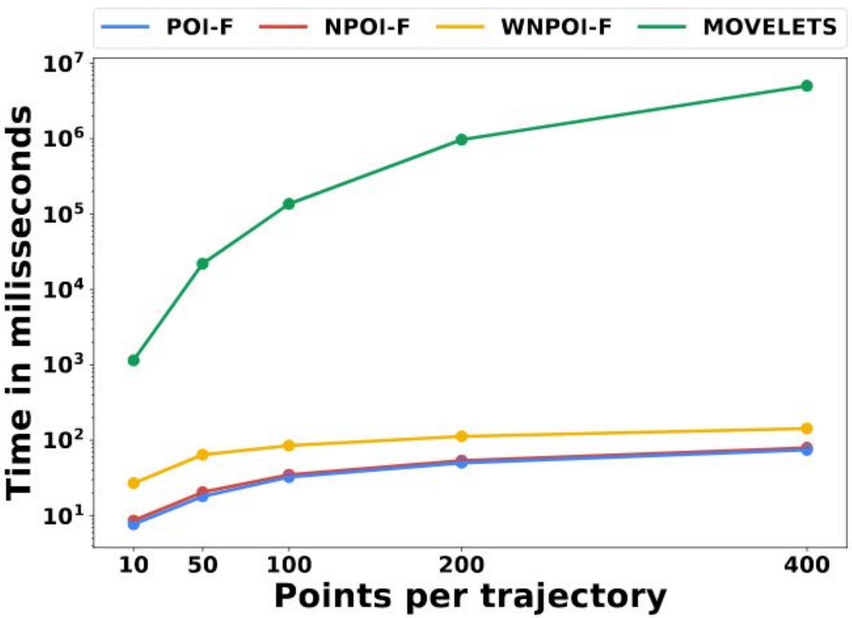
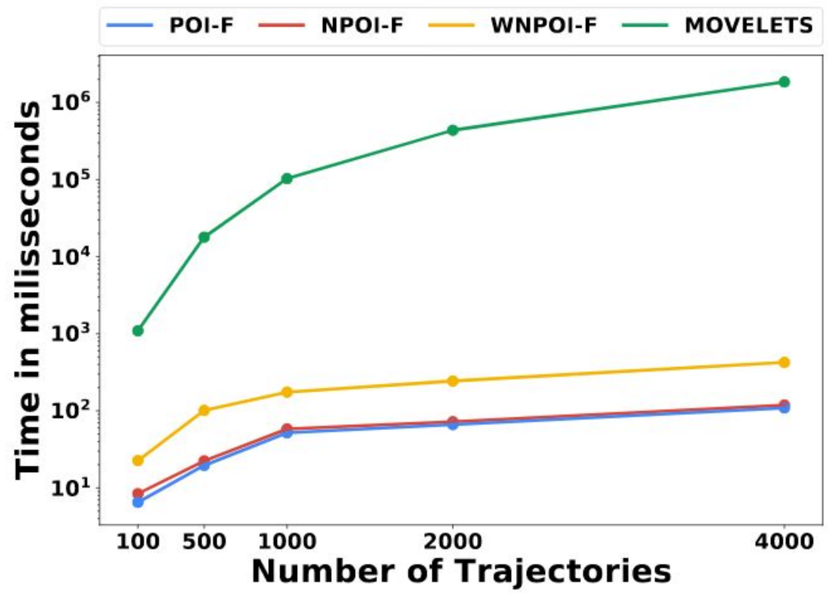
Scalability Analysis

Increasing the number of trajectory points

Increasing the number of trajectories





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Conclusion and Future Work

- ➢ Simple, effective and efficient method for **semantic trajectory classification**;
- ➢ Much higher **accuracy** than Bi-TULER and TULVAE, and equal or higher than MOVELETS;
- ➢ Approach feasible to be used for **big semantic trajectory data** due to its efficient processing time;
- ➢ **Future works**: consider the sequence of POIs.

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Thank You!

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