



# Trajectory Data Mining in the Age of Big Data and AI

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Ontario Database Day  
(OnDBD 2023)

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Wed, Dec 13, 2023  
McMaster University

YORK U

# Background & Motivation

# Trajectory/Mobility Data

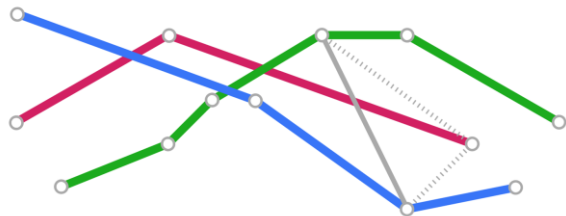
Trajectory: A Sequence of (Spatiotemporal) Points



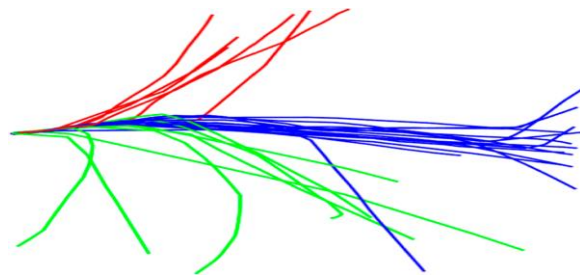
Vast Amounts of Trajectory/Mobility Data



# Trajectory Data Mining



trajectory similarity



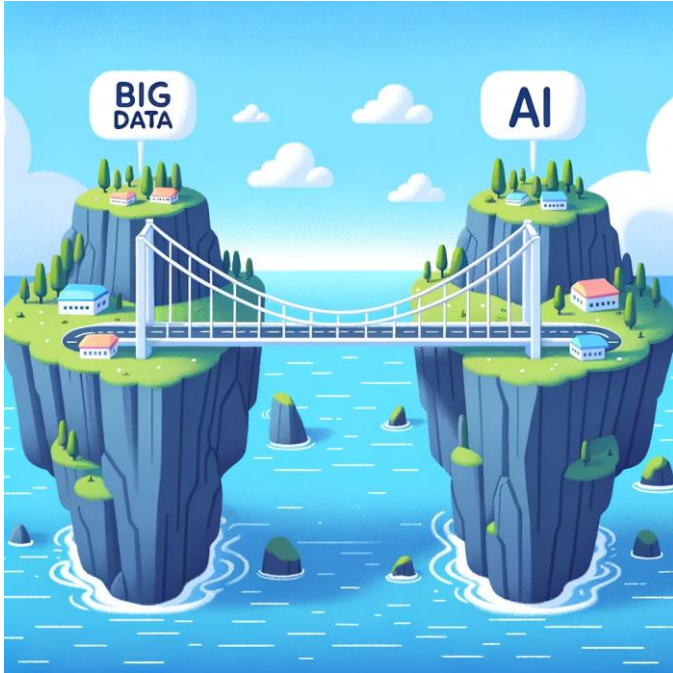
trajectory clustering

trajectory anomaly detection  
trajectory network mining  
trajectory classification

...

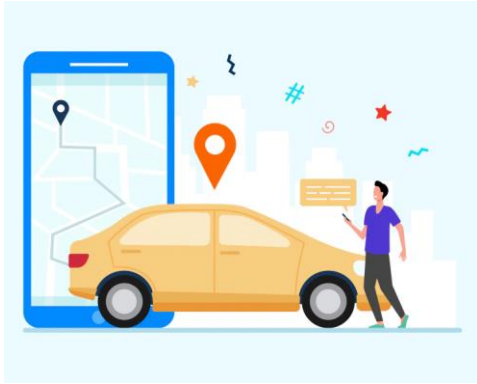
**challenging computational problems**

# Trajectory Data Mining in the Age of Big Data and AI



a symbiotic relationship that presents a new strategy for addressing complex problems in trajectory data mining

# Plethora of Applications



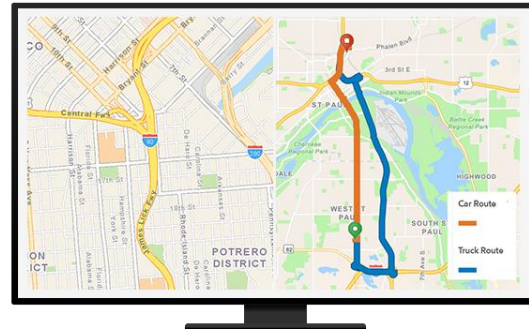
ridesharing



trip/POI (point-of-interest) recommendation



traffic analysis



route planning and optimization

# Data Mining Lab @ YorkU's Journey on Trajectory Data Mining

- Trajectory simplification [ACM SIGSPATIAL '23]
- Trajectory similarity [Submitted]
- Trajectory dataset and resources [ACM SIGSPATIAL '23]
- Trajectory prediction [Submitted]
- Trajectory classification [IEEE MDM '23]
- Trajectory network analysis [Big Data Research, IEEE MDM '20, Geoinformatica, IEEE BigData '18, 2 x IEEE MDM '18]
- Mobility + epidemics [ACM SIGSPATIAL/SpatialEpi '24, ACM SIGSPATIAL/SpatialEpi '23, IEEE MDM '22]
- Transportation optimization [ACM SIGSPATIAL '22, ACM SIGSPATIAL '22]

# Trajectory Simplification

The Trajectory Pathlet Dictionary Construction Problem



# Trajectories on the Road Network

- **Trajectory**

- Denoted by  $\tau$
- Represented as:

object's geo-location      specific time instance

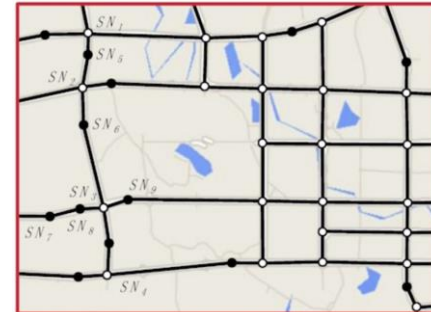
$$\tau = \langle ((x_1, y_1, t_1), \dots, (x_{|\tau|}, y_{|\tau|}, t_{|\tau|})) \rangle$$



- **Road Network**

Modelled as a **graph**  $\mathcal{G}(\mathcal{V}, \mathcal{E})$

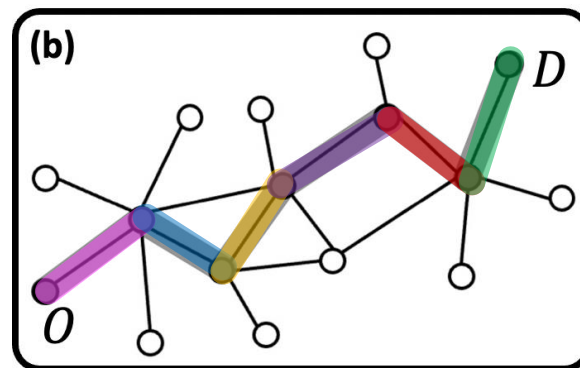
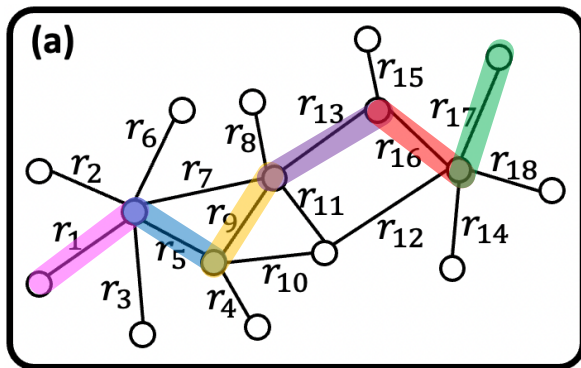
- $\mathcal{V}$  : **Nodes** (set of road intersections)
- $\mathcal{E}$  : **Edges** (set of road segments)



**Image Source:** "Updating Road Networks by Local Renewal from GPS Trajectories" [Wu et al, MDPI '16]

## Road Segment-based Representation

- Each trajectory  $\tau$  can be expressed as a set of road segments  $R_s \subseteq R$
- This special representation is denoted by  $\mathfrak{R}(\tau)$



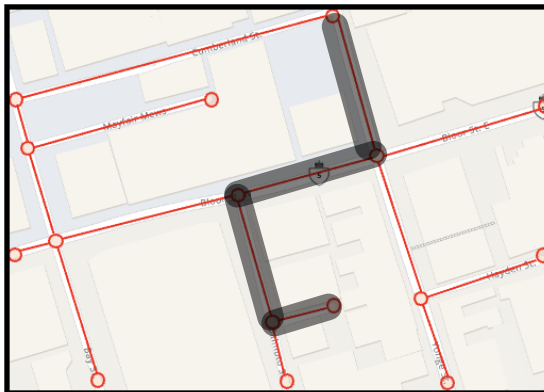
$$\mathfrak{R}(\tau) = \{r_1, r_5, r_9, r_{13}, r_{16}, r_{17}\}$$

# Trajectory Pathlet Dictionary (PD) Construction

- **Pathlet Dictionary:** A small set of basic building blocks that can represent a wide range of trajectories
- Many names in the literature

[Panagiotakis et al – TKDE '12, Chen et al – SIGSPATIAL '13, Sankararaman et al – SIGSPATIAL '13, Agarwal et al – PODS '18, Li et al – TSAS '18, Zhao et al – CIKM '18]

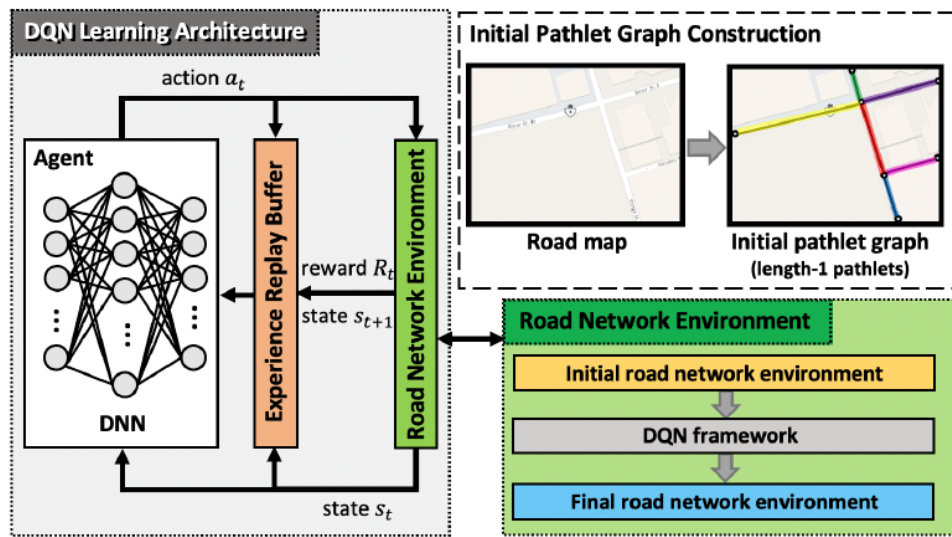
- Pathlet
- Subtrajectory
- Trajectory Segments
- Fragments
- ...



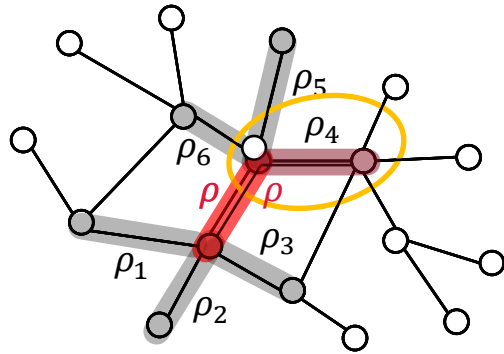


# PathletRL - Overview

- Extracting candidate pathlets
- Deep Reinforcement Learning framework



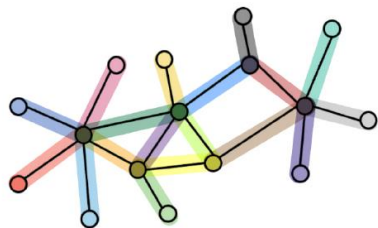
# Extracting Candidate Pathlets - Example



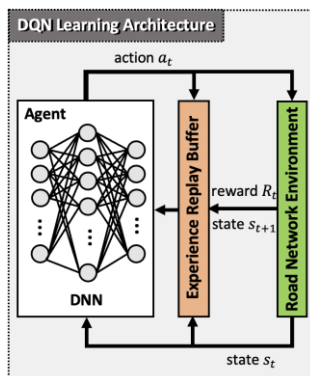
Original network  
 Candidate pathlets for merge  
 Utility

$\rho_{merge}$	Utility
MERGED( $\rho, \rho_1$ )	+0.7
MERGED( $\rho, \rho_2$ )	+1.8
MERGED( $\rho, \rho_3$ )	-1.6
⇒ MERGED( $\rho, \rho_4$ )	+5.5
MERGED( $\rho, \rho_5$ )	-3.2
MERGED( $\rho, \rho_6$ )	+2.9

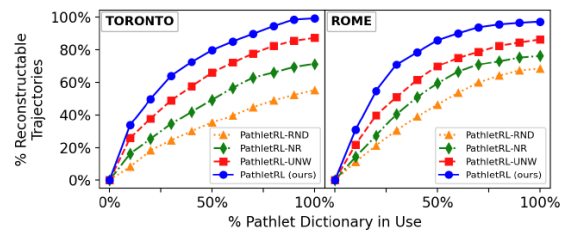
# Approach & Contributions



Edge-disjoint pathlets



Deep Reinforcement Learning (DQN)



Partial trajectory reconstruction  
~85%

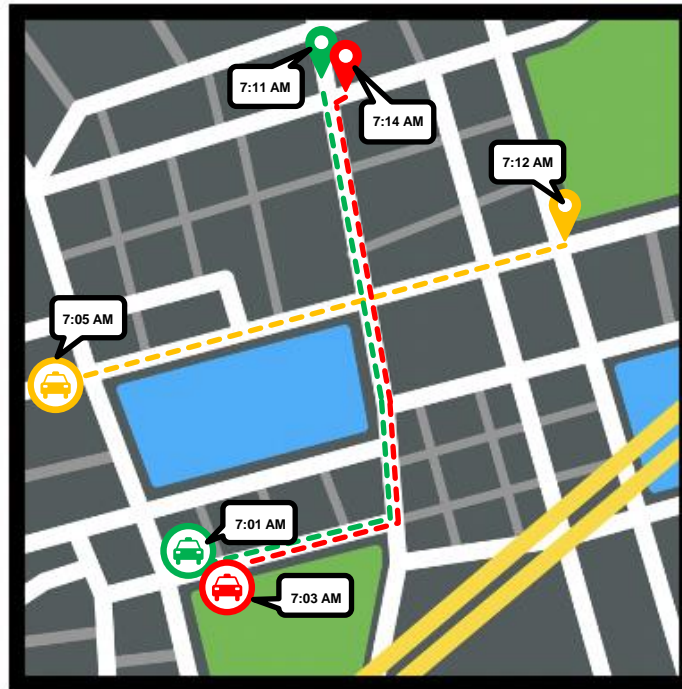
# Trajectory Similarity

The Top-k Trajectory Similarity Search Problem

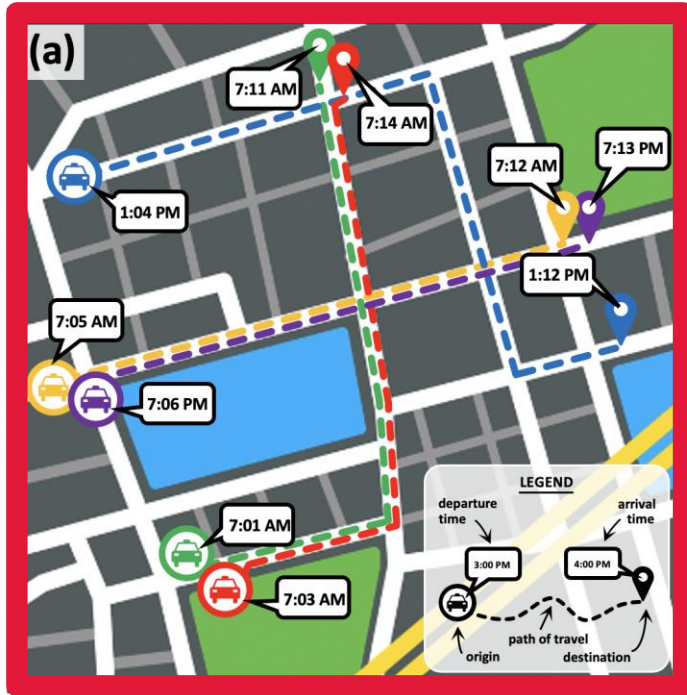


# Trajectory Similarity

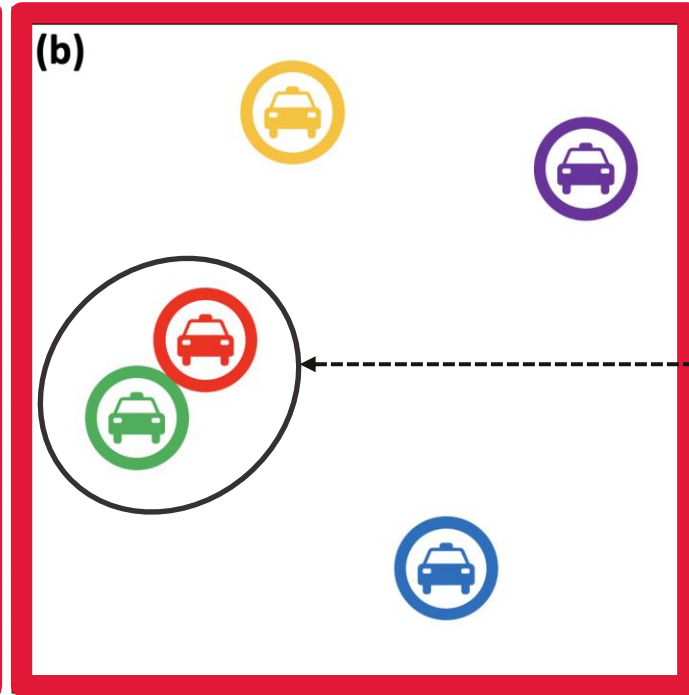
- How similar two trajectories are
- Several ways to define



# Spatiotemporal Similarity – Example



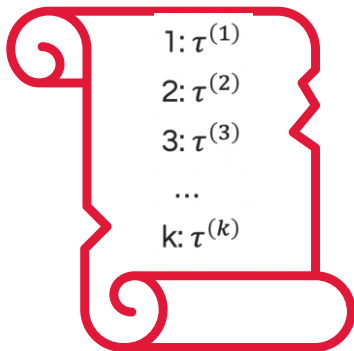
Taxi Trajectories



Embedding Space

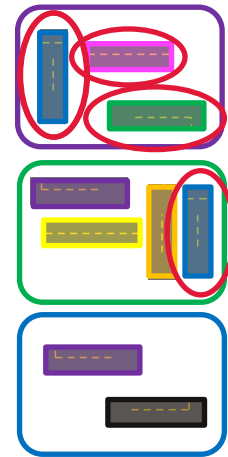
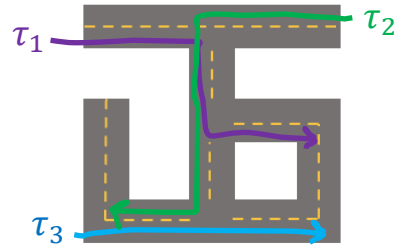
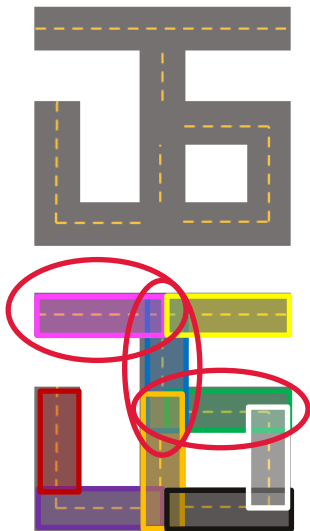
# Problem Statement

- Top- $k$  Trajectory Similarity Search Task
  - **Given:** Trajectory set  $\mathcal{T}$   
Query trajectory  $\tau_q$   
Positive integer  $k \geq 1$
  - Find the (ranked) list of top  $k$  trajectories in  $\mathcal{T}$ :
  - **Criterion:** Similarity with  $\tau_q$



# Approach: Reducing Trajectory Similarity to Set Similarity Problem

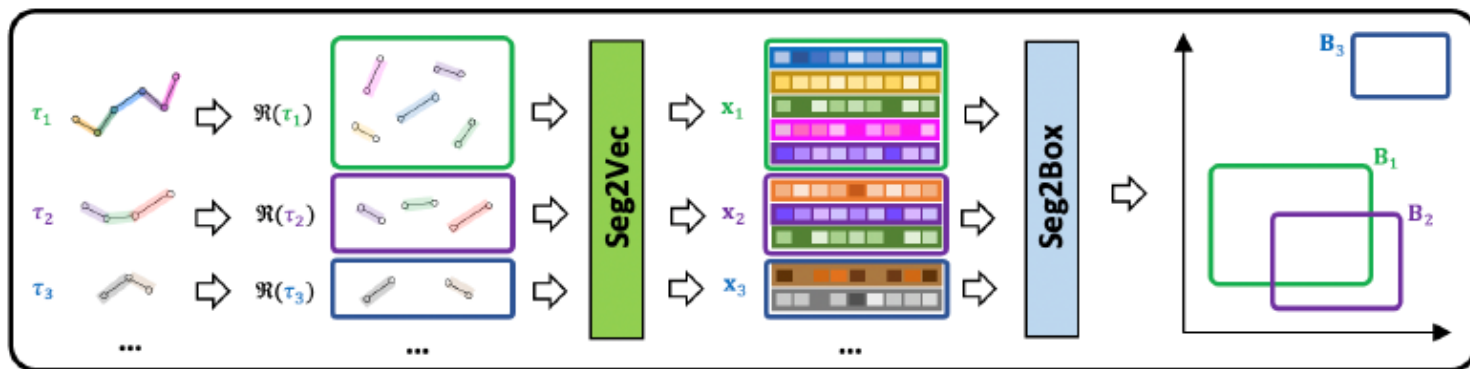
- Treat **each trajectory** as a **set**; its **elements** are the **road segments** it has traversed (road-based representation  $\mathfrak{R}(\tau)$ )
- Similar (Dissimilar) trajectories map to similar (dissimilar) sets



Trajectories  $\tau_1$  and  $\tau_2$  are similar!

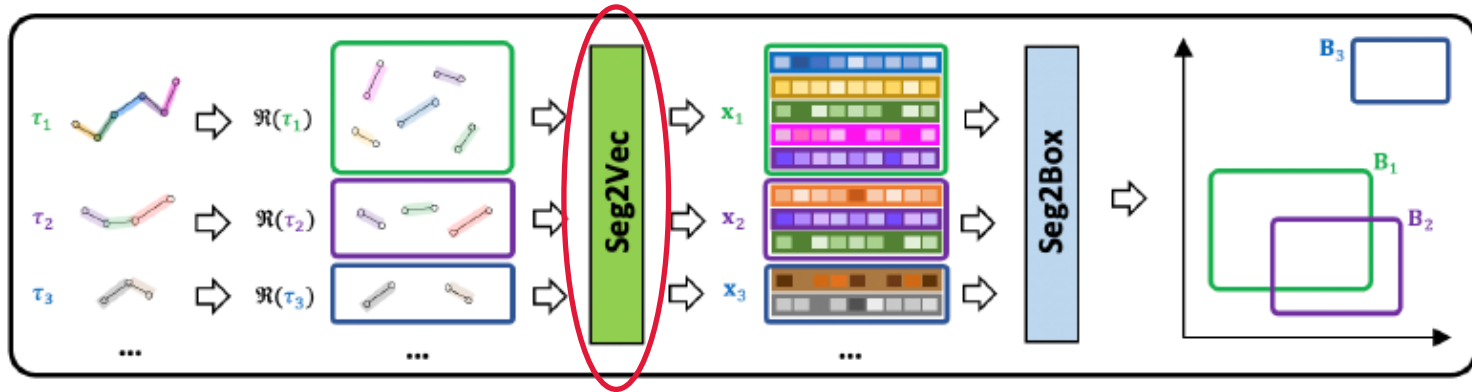
# ST2Box Overview

- Spatiotemporal Trajectories to Box Embeddings for Similarity Learning



# ST2Box Overview

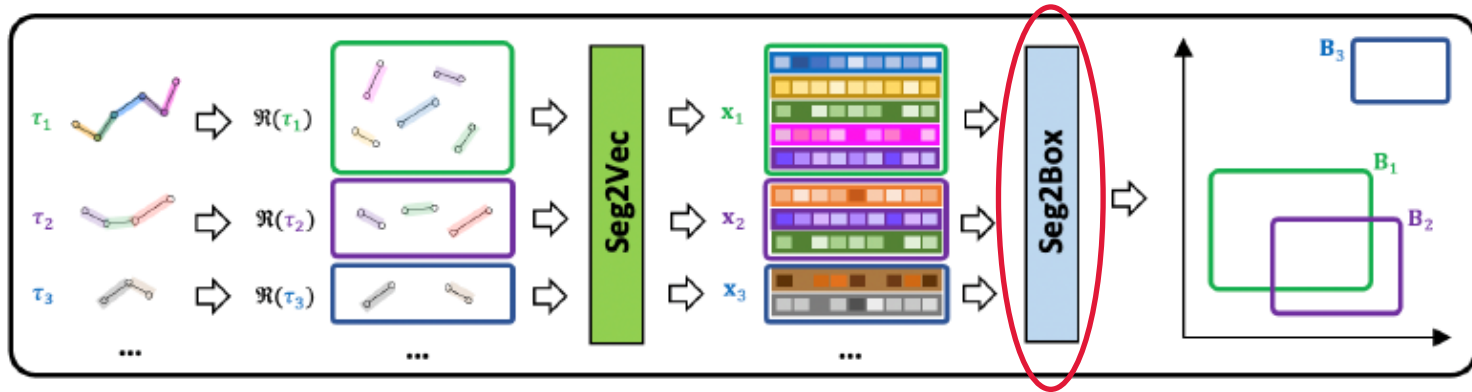
- Spatiotemporal Trajectories to Box Embeddings for Similarity Learning



- **Seg2Vec** – spatiotemporal vector representations of road segments

# ST2Box Overview

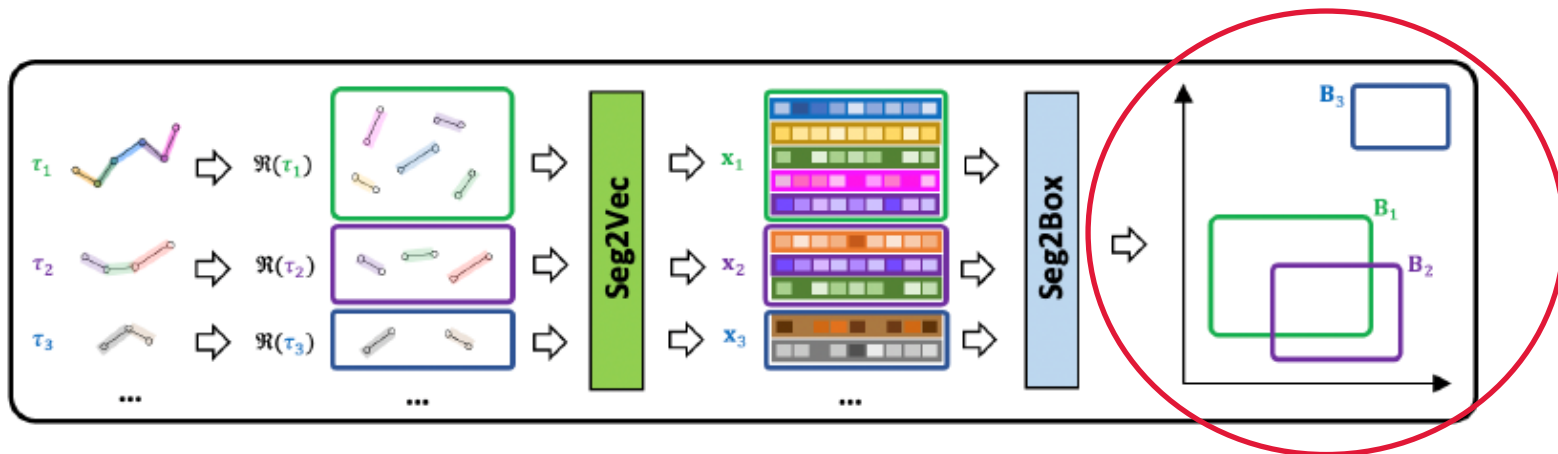
- Spatiotemporal Trajectories to Box Embeddings for Similarity Learning



- Seg2Box** – box representations of sets of road segments

# ST2Box Overview

- Spatiotemporal Trajectories to Box Embeddings for Similarity Learning



- Overlapping boxes  $\Rightarrow$  Similar sets  $\Rightarrow$  Similar trajectories

## ST2Box Properties

Accurate, Versatile, Generalizable, Robust, Fast, Scalable

Up to ~30% Performance Gain

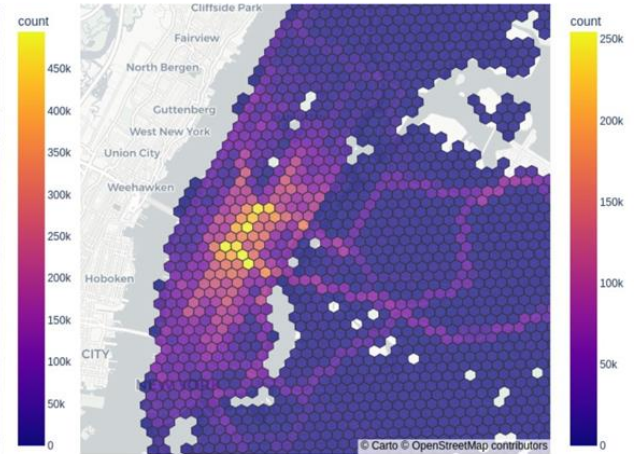
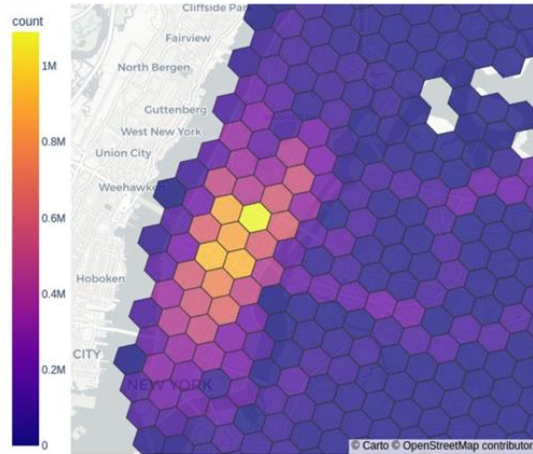


# Higher-order Mobility Flow Data

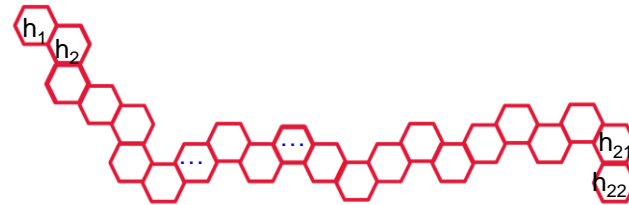
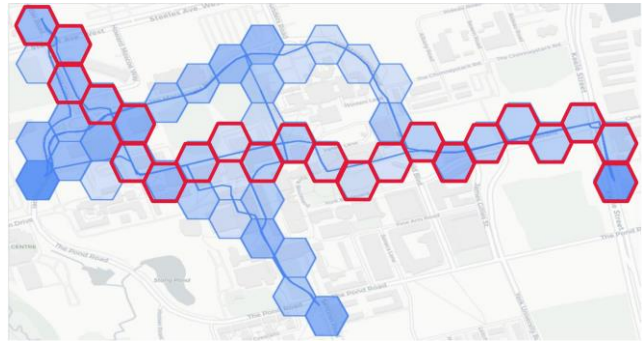
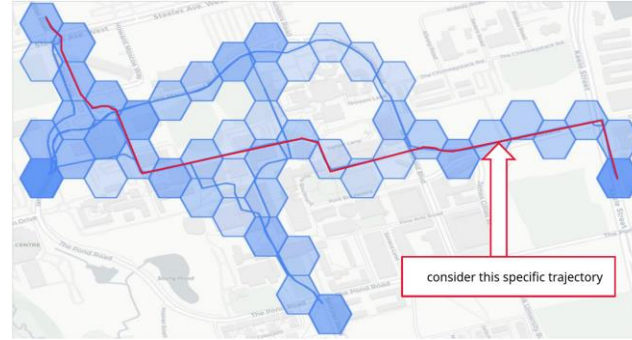
# Map Tessellation

lower  
resolution

higher  
resolution



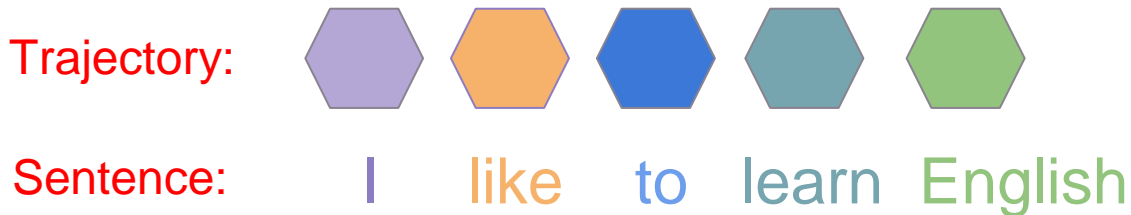
# Trajectories: Sequences of Hexagons



Trajectory:  $h_1, h_2, h_3 \dots h_{20}, h_{21}, h_{22}$

# Treat Trajectories as Language Statements

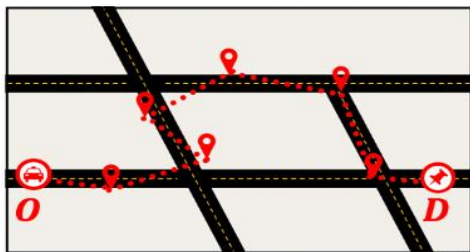
Hexagons represent 'tokens' & trajectories represent 'sentences'



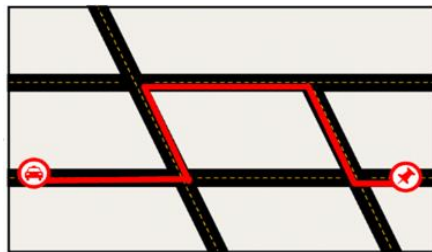
## Advantages:

- Reduced data sparsity
- More compatible with well-known ML models (e.g., sequence models, LLMs)

# Point2Hex: Overview of the Pipeline



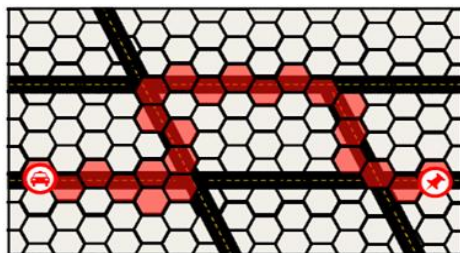
GPS Traces or POI  
Check-Ins  
(input)



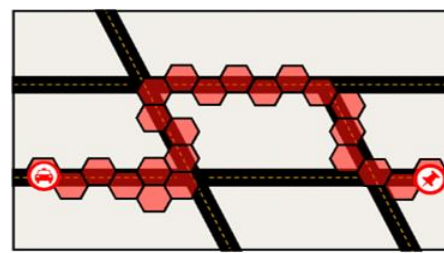
Linestring of  
Trajectories  
(Map-matching)



Map Tessellation with  
Trajectories  
(Hexagon-shaped cells)



Intersection of Linestrings and Polygons  
(Computational Geometry)



Higher-order Mobility Flow  
(Output)

# Higher-order Mobility Flow: Datasets and Data Generator

Dataset	Trajectories	Time Period	Resolutions
HO-T-Drive	65,117	02/02/08 - 02/08/08	{6,...10}
HO-Porto	1,668,859	07/01/13 - 06/30/14	{6,...10}
HO-Rome	5,873	02/01/14 - 03/02/14	{6,...10}
HO-GeoLife	2,100	04/01/07 - 10/31/11	{6,...10}
HO-FourSquare-NYC	49,983	04/12/12 - 02/16/13	{6,...10}
HO-FourSquare-TKY	117,593	04/12/12 - 02/16/13	{6,...10}
HO-NYC-Taxi	2,062,554	01/01/16 - 06/30/16	{6,...10}



Datasets @ [Zenodo](#)

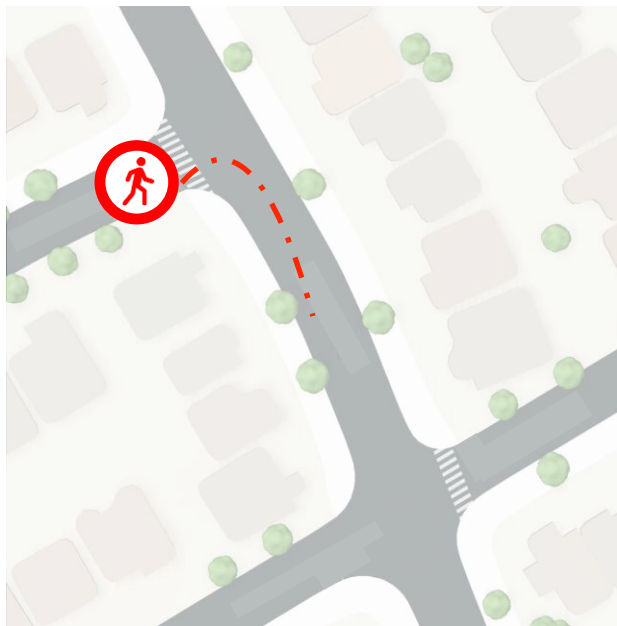


Data Generator @ [GitHub](#)

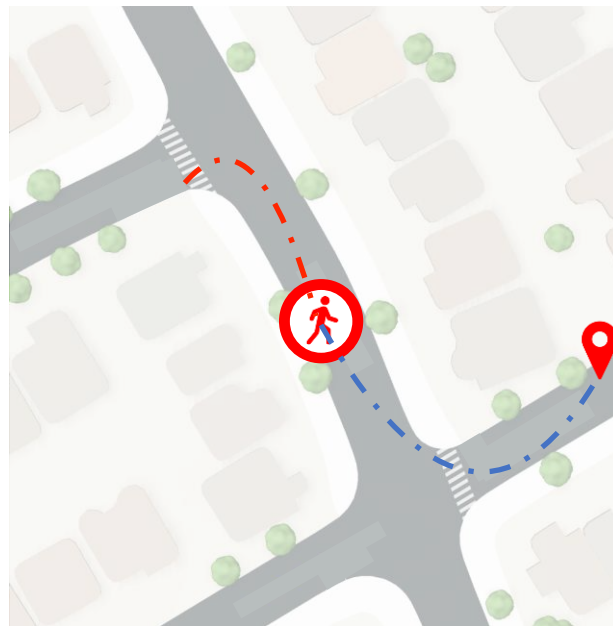
# Trajectory Prediction

Predict the Next-k Trajectory Steps Problem

## Problem of Interest: Trajectory Prediction



History trajectory



Predict future trajectory



# Trajectory Prediction (Revisited)

## Let

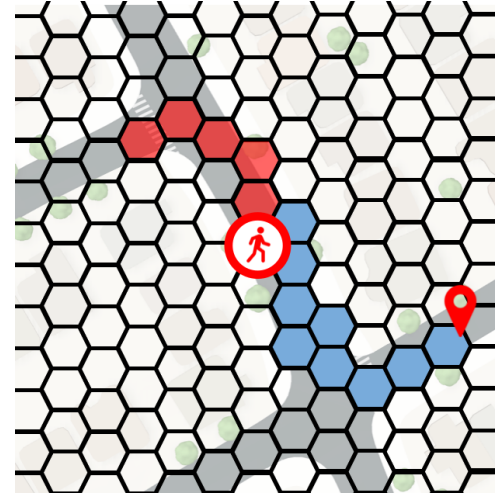
- an observation area
- a set of objects and their history trajectories
- an observation period

## Input: Given

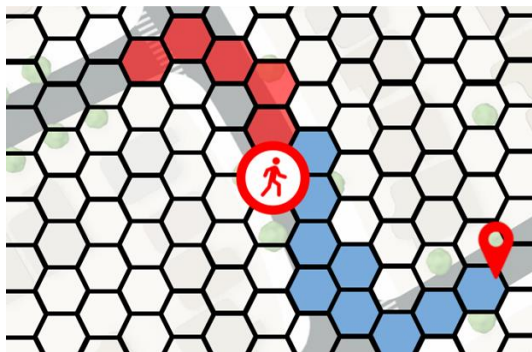
- a moving object  $n$
- a partial trajectory =  $\langle p_1, p_2, \dots, p_t \rangle$
- a prediction horizon  $k > 0$

## Output: We want to

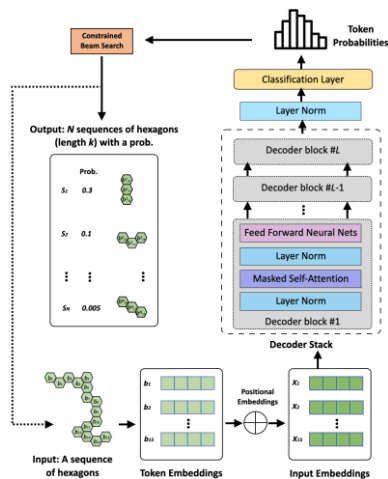
predict the **next  $k$  hexagons** of the input partial trajectory



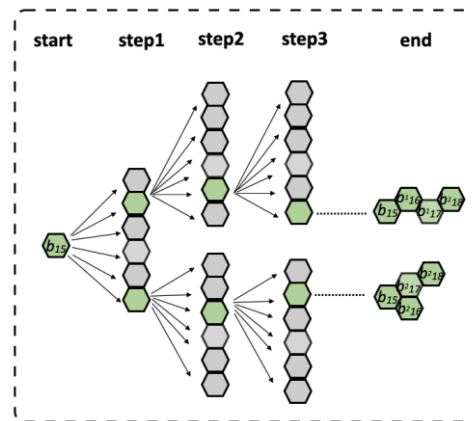
# Approach & Contributions



Trajectory Prediction  
(Revisited)



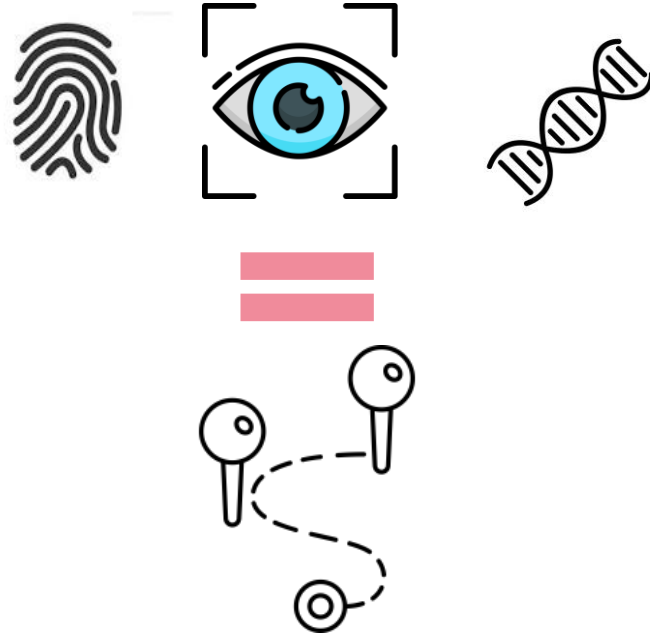
TrajLearn: Trajectory  
Deep Generative Model



Beam search

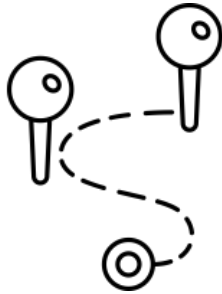
# Trajectory Classification

The Trajectory-User Linking Problem



can trajectories  
help to **identify** a person?

# Trajectory-user Linking (TUL)



trajectory-user linking **aims at linking** anonymous trajectories to users who generate them

## Problem Definition

Trajectory-user linking aims at linking anonymous trajectories to users

Given:

$\mathcal{U} = \{u_1, u_2, u_3, \dots, u_c\}$  – users

$\mathcal{T} = \{Tr_1, Tr_2, \dots, Tr_n\}$  – unlinked trajectories

TUL is defined as **a multiclass classification problem**

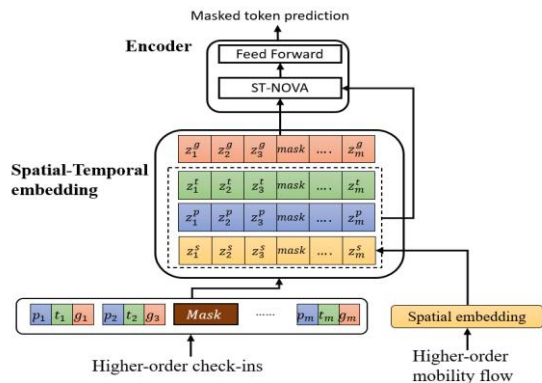
$$\min_{f \in \mathcal{F}} \mathbb{E}[\mathcal{L}(f(Tr_i), u_i)] \text{ over } \mathcal{F}$$

*where  $\mathcal{F}$  is the set of all classifiers in the hypothesis space  
 $\mathcal{L}(\cdot)$  is the loss between the predicted label  $f(Tr_i) \in \mathcal{U}$  and the true label  $u_i \in \mathcal{U}$*

# Approach & Contributions



Higher-order mobility flow data generation



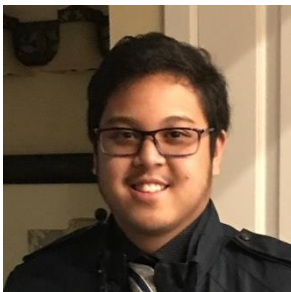
**TULHOR**: A spatiotemporal model that deals with sparsity and low data quality of the TUL problem

**TULHOR** **outperforms** baselines by up to 8%

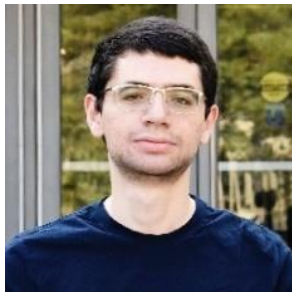
# Questions



# Credits



Gian Alix



Mahmoud Alsaeed



Ali Faraji



Jing Li



Nina Yanin



Amirhossein Nadiri

**PathletRL: Trajectory Pathlet Dictionary Construction using Reinforcement Learning.** G. Alix, M. Papagelis. **ACM SIGSPATIAL 2023.**

**Trajectory-User Linking using Higher-order Mobility Flow Representations.** M. Alsaeed, A. Agrawal, M. Papagelis. **IEEE MDM 2023.**

**Point2Hex: Higher-order Mobility Flow Data and Resources.** A. Faraji, J. Ling, G. Alix, M. Alsaeed, N. Yanin, A. Nadiri, M. Papagelis. **ACM SIGSPATIAL 2023.**

**St2Box: Trajectory Similarity Learning using Set to Box Representations.** G. Alix, M. Papagelis. **Submitted.**

**TrajLearn: Leveraging Generative Models for Trajectory Prediction Learning.** A. Nadiri, A. Faraji, J. Ling, M. Papagelis. **Submitted.**

Thank you!