

All-Scale Trajectory Clustering for Moving Behavior Detection with Spatiotemporal Recurrent Convolutional Neural Networks¹

Yao-Yi Chiang*

Associate Professor

Computer Science and Engineering

University of Minnesota

yaoyi@umn.edu

¹An NGA Boosting Innovative GEOINT (BIG) project

*With Cyrus Shahabi and Mingxuan Yue, University of Southern California; slides adopted from Mingxuan Yue

OUTLINE

- Overview
- Approach: DETECT
 - Convert trajectories to sequences of contexts
 - Fixed-size representation (embedding) with RNN
 - Embedding Clustering and Optimization
- Experiments
- Future Work

Motivation

Mobility behavior:

travel activity describing a user's movements, e.g., work commute, shopping, school commute, dining



Mobility Behavior



COVID 19



User Profiling



Recommendations



Ads targeting

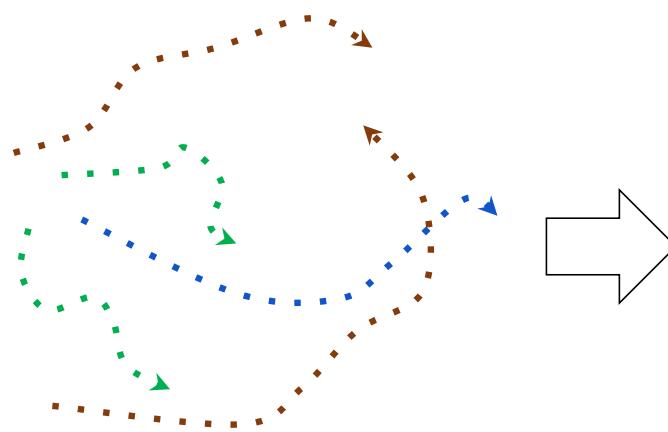
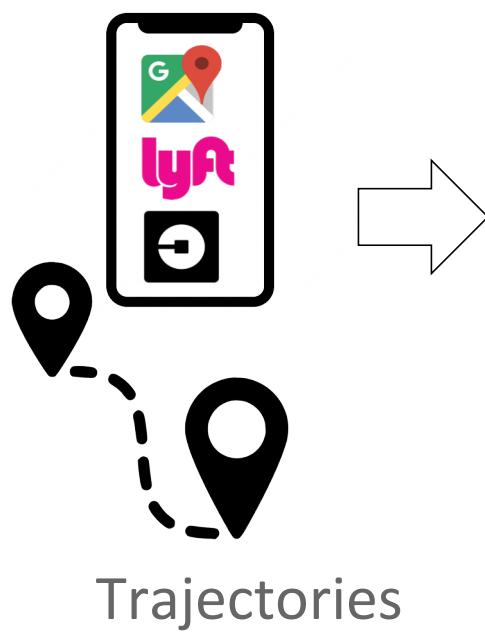


Insurance

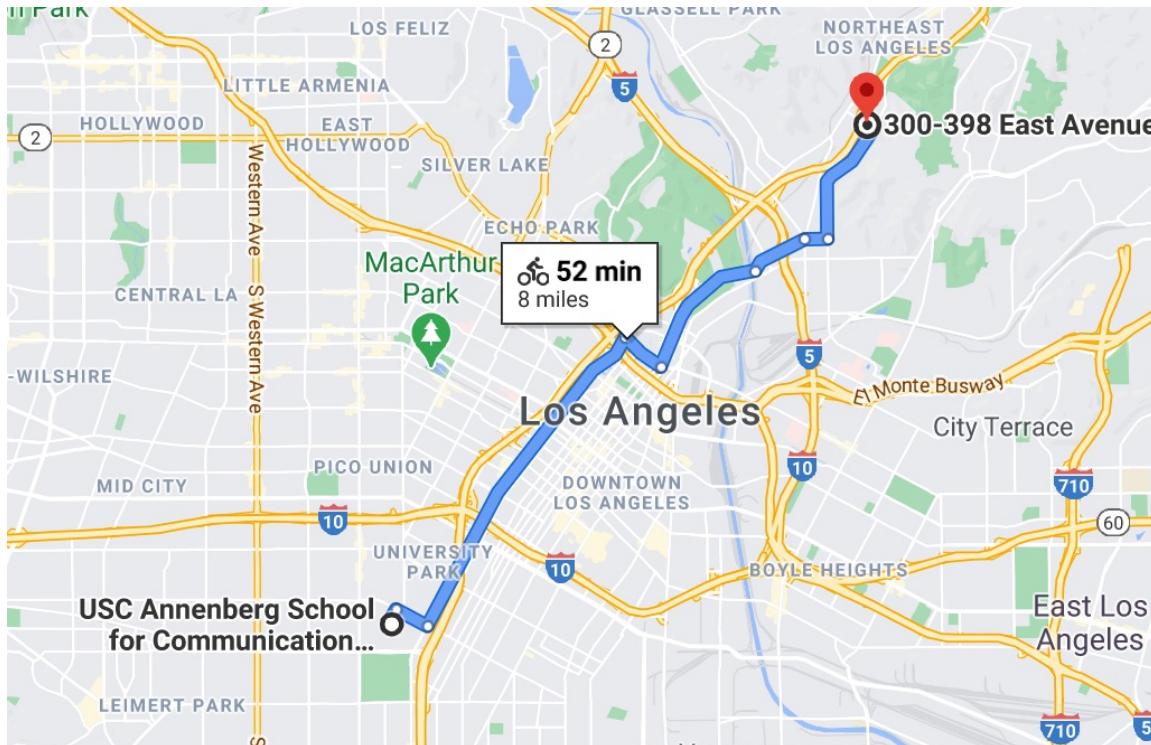


Threats Detection

Idea



Challenge: Multi-scale Trajectories



- Various temporal and spatial scales may represent the same mobility behavior
- 50 minutes work commute:
 - 14 miles, 44 miles, 8 miles
- 14 miles work commute
 - 20 min, 50 min, 1.5 hour

Trajectory Clustering Techniques

- Based on similarity of raw spatiotemporal features [AIR'17]
- Sequence distance measurement
 - Dynamic Time Warping (**DTW**), Longest Common SubSequence (**LCSS**)
- Clustering based on the distances
 - kMeans-DBA [ICDM'14], DBSCAN [CVPR'09], Hierarchical Clustering

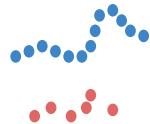
Limitations of Traditional Trajectory Clustering Techniques



Prone to scales & noises 



No activity context information 



Pre-defined similarity vs. data-driven 

DETECT: Deep Trajectory Clustering for Mobility-Behavior Analysis

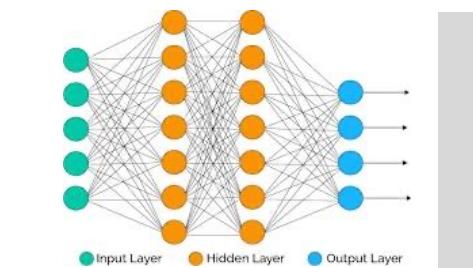


Traditional:

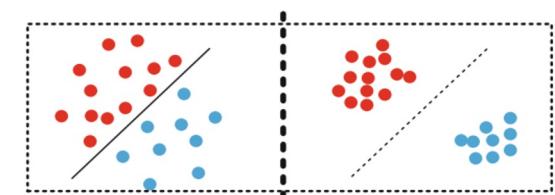
Proposed:

Convert trajectories to
sequences of contexts

- Address varying spatial & temporal scales
- Aware of geographical context
- Work for variable lengths of sequences
- Learn useful properties driven by data
- Avoid expensive manual labeling



Fixed-size representation
(embedding) with RNN



Embedding Clustering and
Optimization

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Approach

DETECT [BigData 19]



All-scale



Context-aware



Sequence Dynamics



Yue, M., Li, Y., Yang, H., Ahuja, R., **Chiang, Y.-Y.**, and Shahabi, C. (December 2019). DETECT: Deep Trajectory Clustering for Mobility-Behavior Analysis. In *Proceedings of the 2019 IEEE International Conference on Big Data (Big Data)*, pp. 988–997, Los Angeles, CA, USA

All-scale: Stay Points

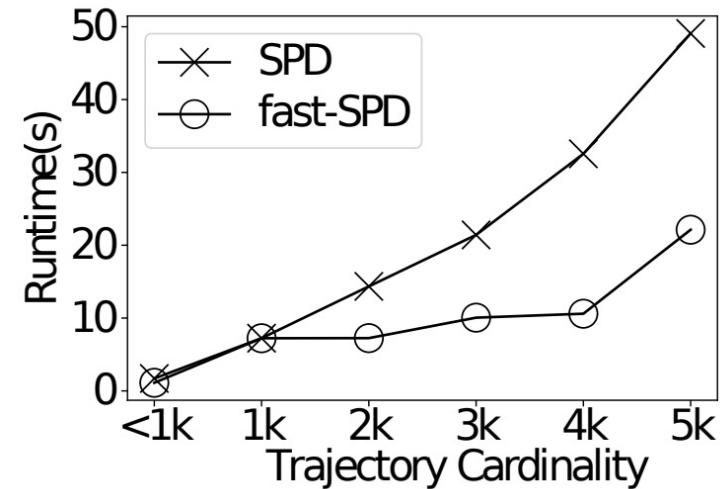
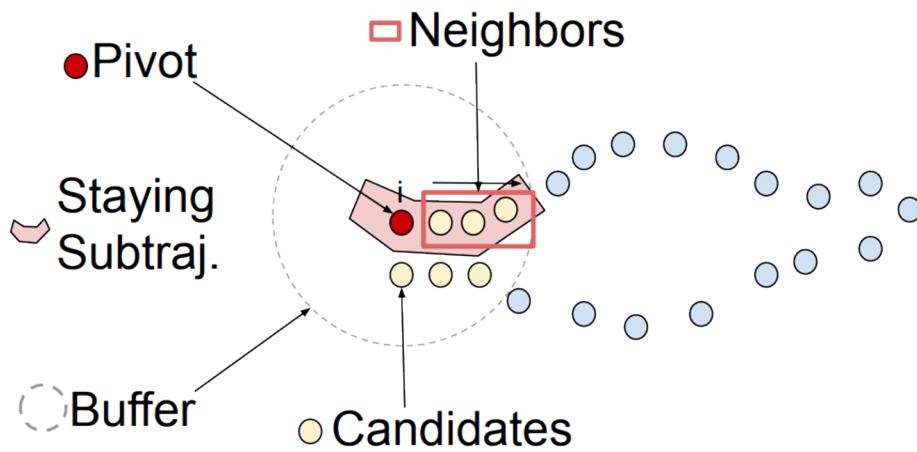
Stay points [SIGSPATIAL'08] are meaningful locations where:

1. the user travels within a small range of space
2. the user stays in this range for some time



All-scale: Fast Stay Point Extraction

- Fast-SPD:
 - Scan each trajectory to find consecutive sub-trajectories that the user travel within a limited range but stay for a long time
 - Use the centers of such sub-trajectories as stay points



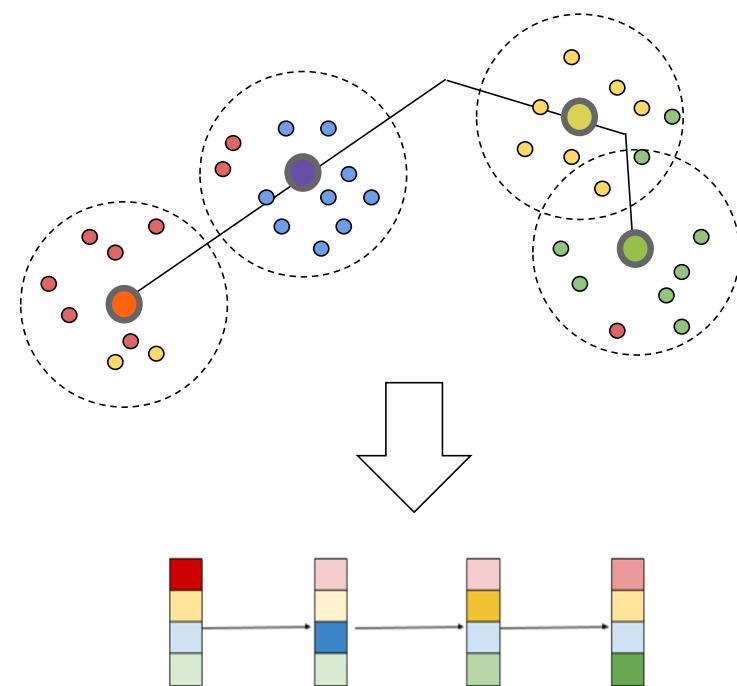
Context-aware: Geographical Augmentation

For each extracted stay point $\dot{s}^{(t)}$:

1. create a spatial buffer $b(r_{poi}, \dot{s}^{(t)})$
2. search a gazetteer for POI's in the buffer
3. count POIs in the buffer
4. generate a normalized vector

$$x^{(t)} = \{0.3, 0.09, \dots, 0.55\}$$

Normalized number of POI categories,
e.g., business area

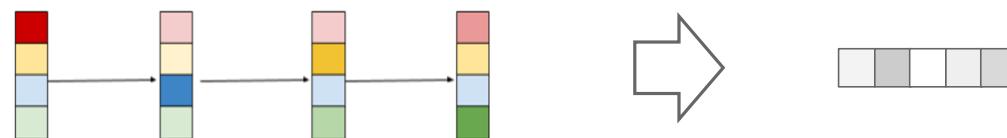


OUTLINE

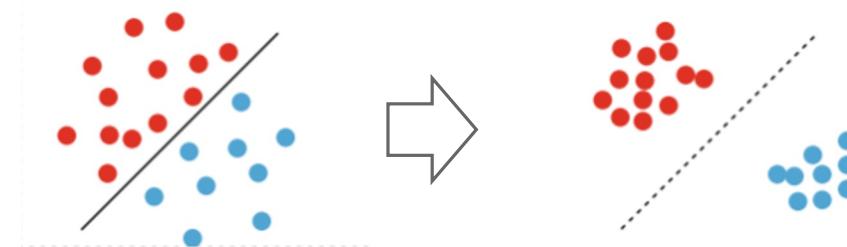
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Sequence Dynamics: RNN-AE + Clustering

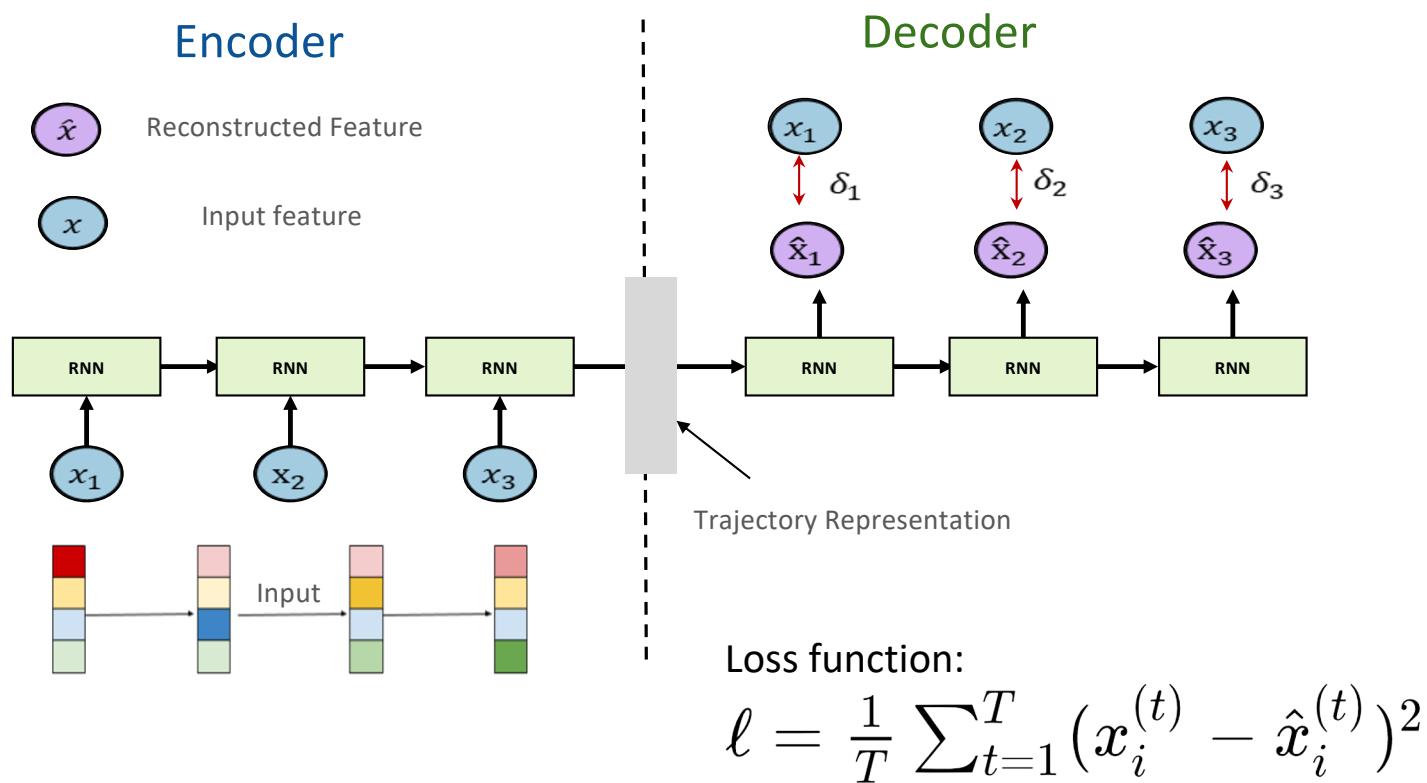
Phase I:



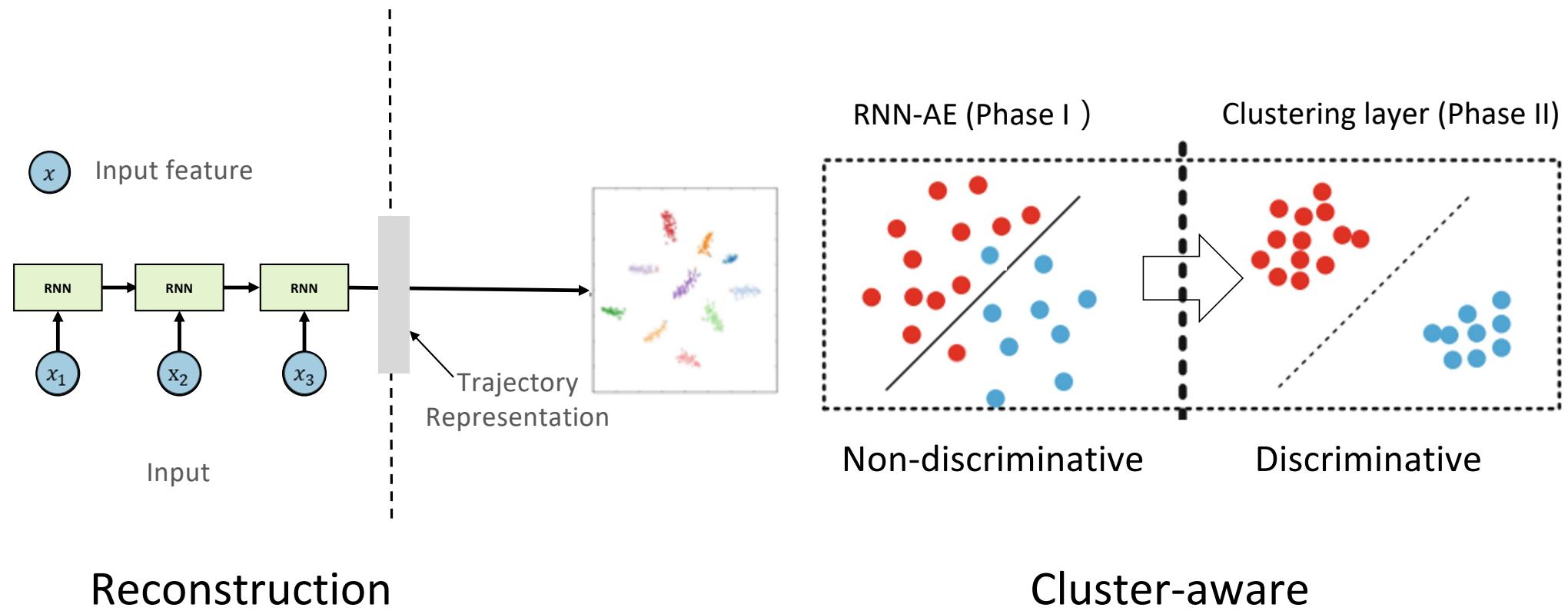
Phase II:



Phase I: RNN Autoencoder



Phase II: Refine for clean clusters



Phase II: Unsupervised clustering

p_{ij} and q_{ij} could be interpreted as the probability of trajectory i is assigned to cluster j

Current t-distribution:

$$q_{ij} = \frac{(1 + \|z_i - \mu_j\|^2)^{-1}}{\sum_{j'} (1 + \|z_i - \mu_{j'}\|^2)^{-1}}$$

Auxiliary distribution:

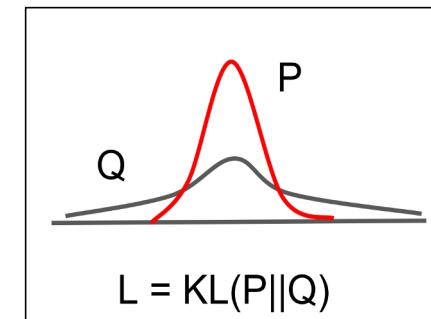
$$p_{ij} = \frac{q_{ij}^2 / \sum_{i'} q_{i'j}}{\sum_{j'} (q_{ij'}^2 / \sum_{i'} q_{i'j'})}$$

Loss function:

$$\ell = KL(P||Q) = \sum_i \sum_j p_{ij} \log \frac{p_{ij}}{q_{ij}}$$

If q_{ij} is small, q_{ij}^2 will be even smaller

- punish uncertain cluster assignments
- high certain cluster assignments remain high



Minimizing the KL distance to compact the clusters

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Experimental settings

- Dataset: GeoLife
 - 17,621 trajectories (601 labeled).
 - 6 labels: “dining activities”, “working commutes”, etc.
 - 14,000 POIs in Beijing
- Evaluation Metrics
 - With label: Rand Index (RI), Mutual Information (MI), Purity Fowlkes-Mallows Index (FMI)
 - Without label: Silhouette Score, Dunn index, Within-like Criterion, Between-like Criterion

Labeling Platform

About Us
GeoLife
Instruction
Contact

✓ The map showing the trajectory.
✓ You may use this map to get a general idea of how this person travels.

Distance from the Origin

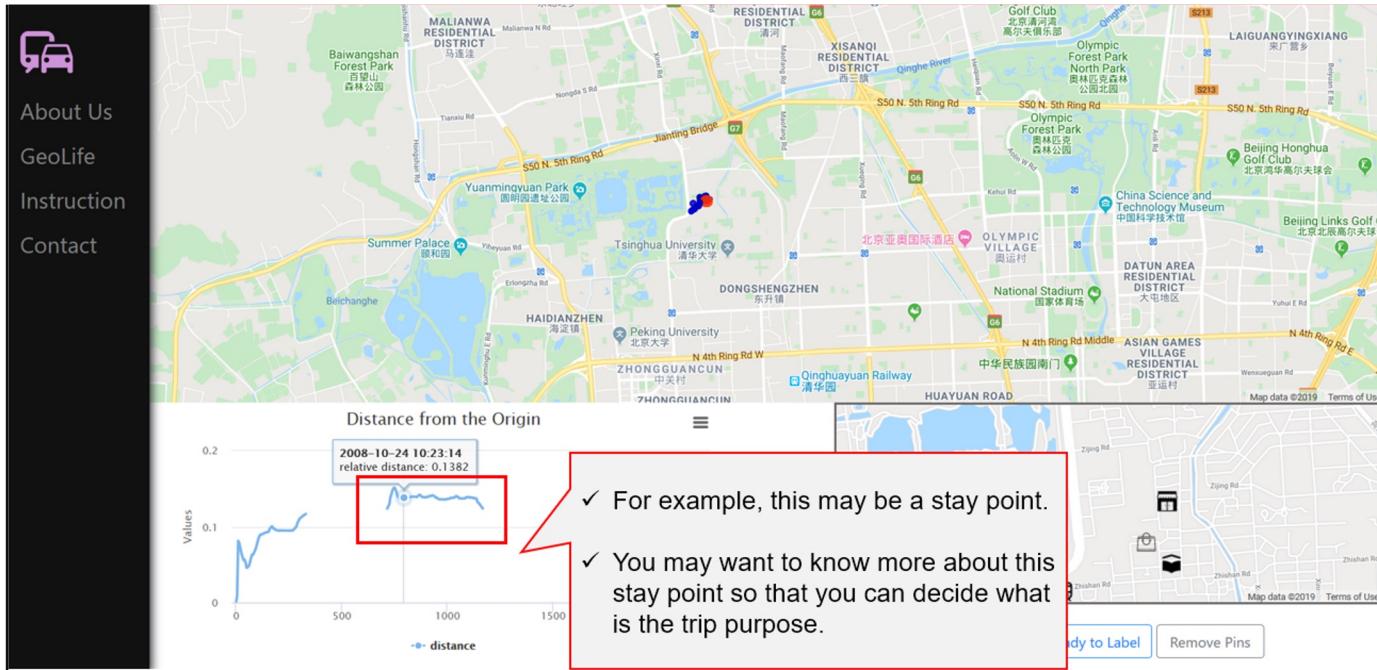
Values

distance

0 5k 10k 15k 20k 25k

Prev Next Ready to Label Remove Pins

Labeling Platform



With-label: quantitative results

Distance	Clustering
DTW	K-Means
LCSS	DBSCAN
SSPD	Hierarchical clustering



Method	RI	MI	Purity	FMI
KM-DBA	0.33	0.64	0.58	0.58
DB-LCSS	0.22	0.55	0.51	0.56
RNN-AE	0.39	0.46	0.56	0.53
SSPD-HCA	0.52	0.93	0.66	0.67
KM-DBA*	0.51	0.91	0.74	0.63
DB-LCSS*	0.5	0.95	0.64	0.66
DETECT Phase I	0.65	1.06	0.84	0.73
DETECT	0.76	1.26	0.89	0.81

RI (Rand Index) (0,1)

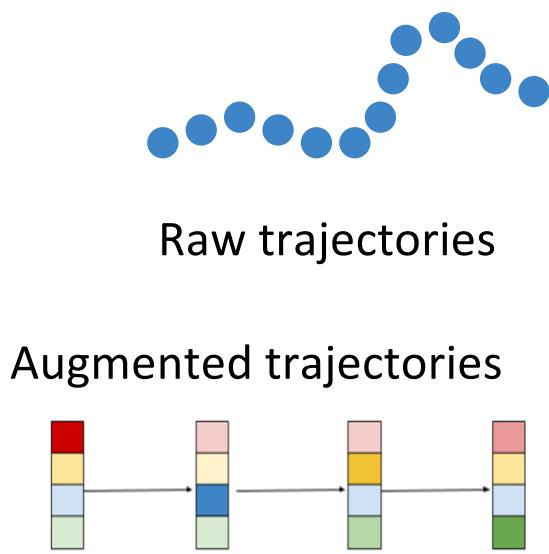
MI (Mutual Information) (0, inf)

Purity (0,1)

FMI (Fowlkes-Mallows Index) (0,1)

Higher values for all metrics mean better results.

With-label: quantitative results



Method	RI	MI	Purity	FMI
KM-DBA	0.33	0.64	0.58	0.58
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RI (Rand Index) (0,1)

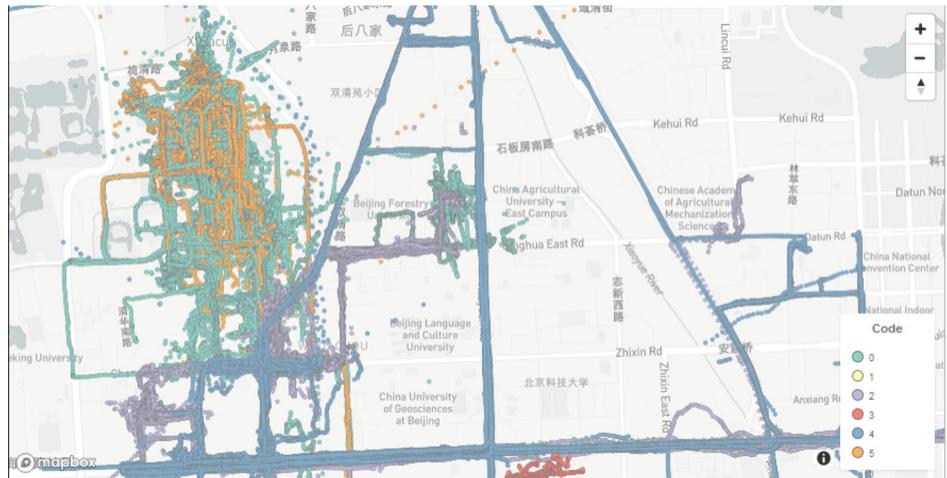
MI (Mutual Information) (0, inf)

Purity (0,1)

FMI (Fowlkes-Mallows Index) (0,1)

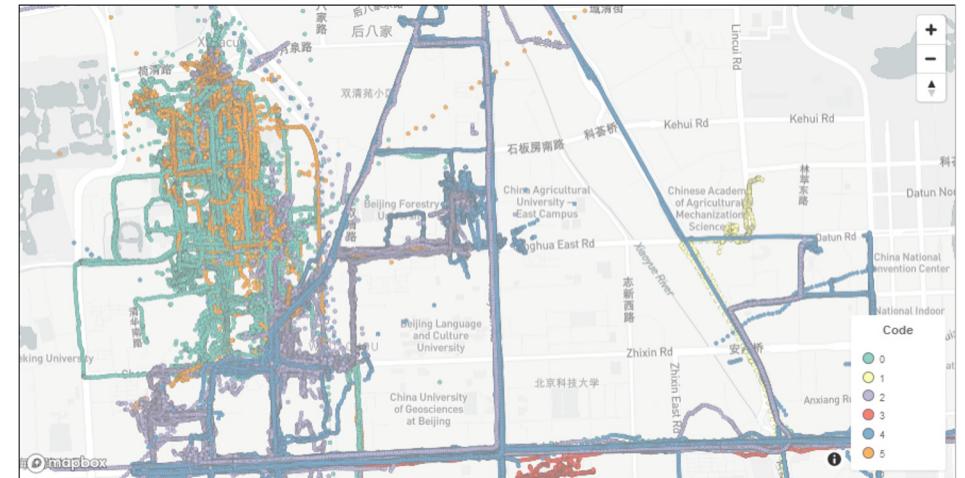
Higher values for all metrics mean better results.

With-label: qualitative results



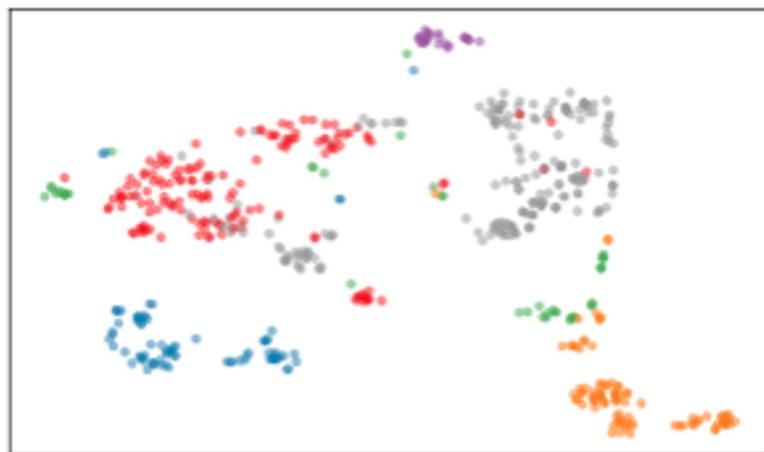
Ground Truth

Colors indicate different clusters.

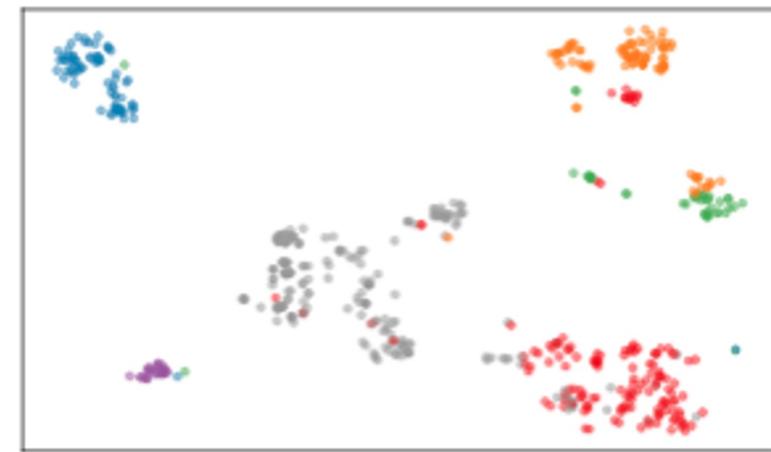


Our Results

With-label: qualitative results

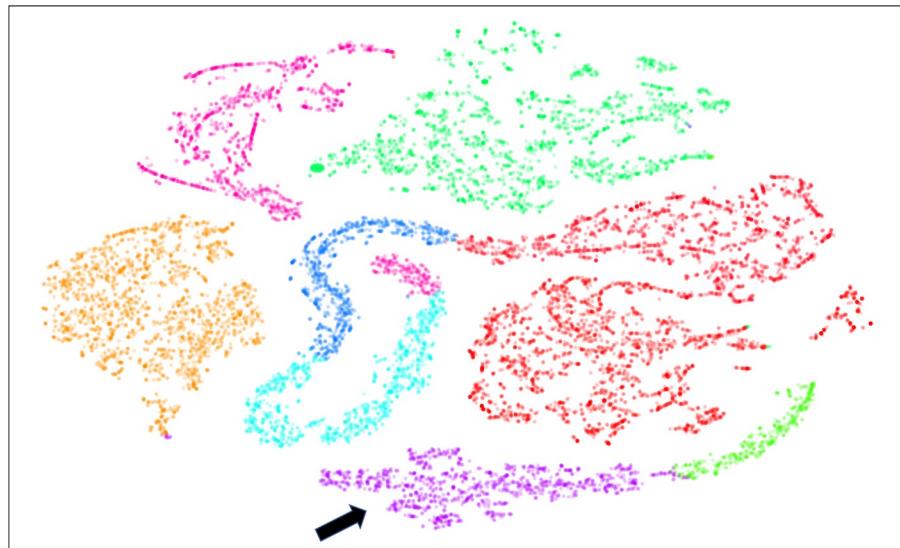


Embedding after Phase I

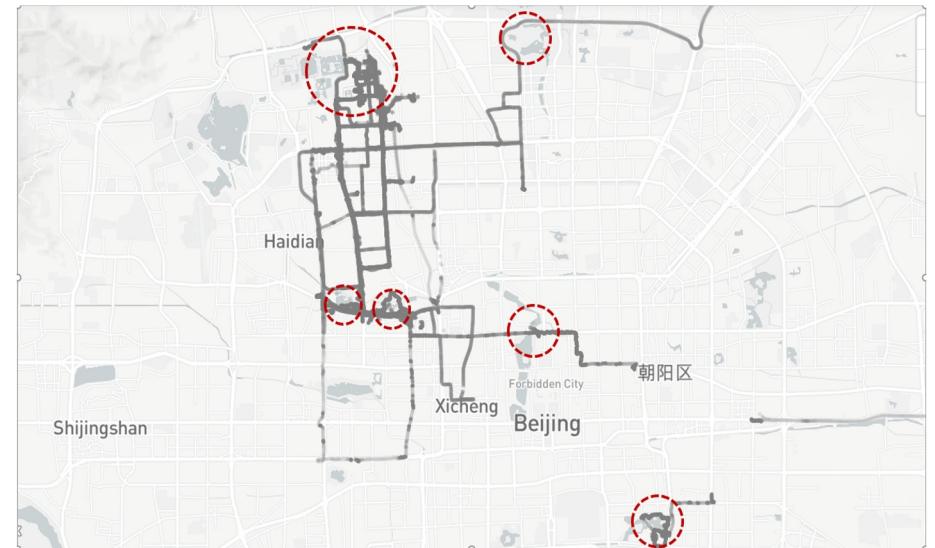


Embedding after Phase II

Without-label: qualitative results



Embedding of the full dataset



Recreation Activities

DETECT Extension: context learning

- What if we don't have a gazetteer for the area, e.g., boat trajectories?
- Idea: Learn the context from trajectories. [ECML 20]

Target Word
Deep Learning is very hard and fun
Context word Context words

Target Word
Deep Learning is very hard and fun
Context words Context words

Target Word
Deep Learning is very hard and fun
Context words Context words

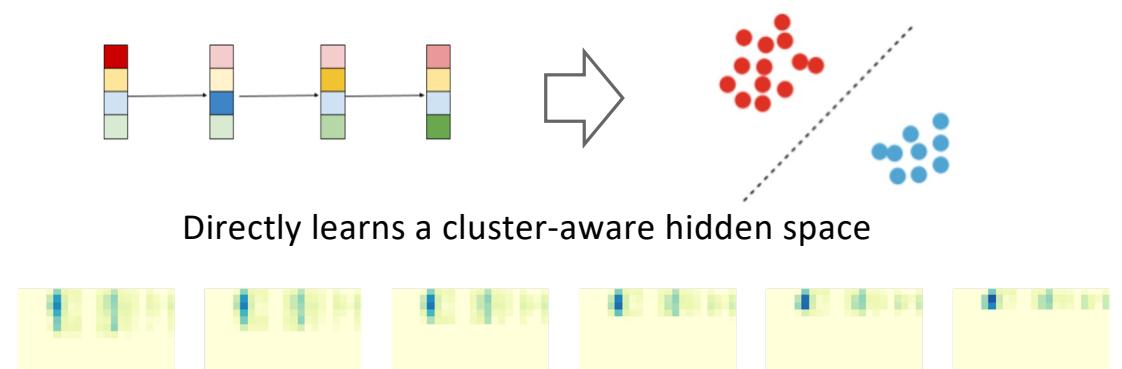
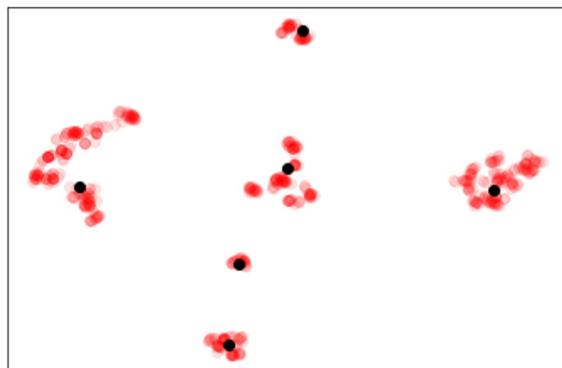
Sequence of words



Sequence of locations

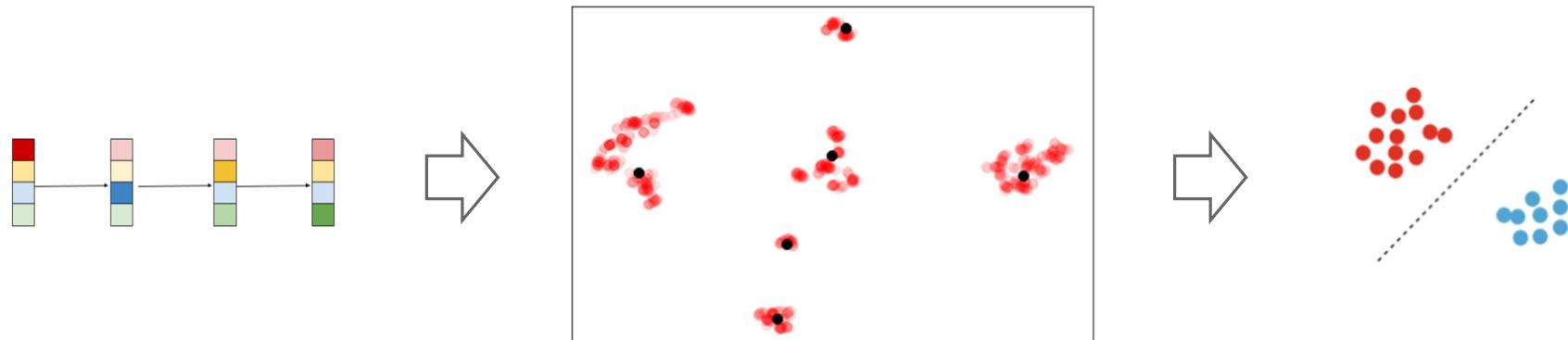
Also, one-phase generative model

- Using a generative model to directly learn a cluster-aware hidden space rather than a 2-phase procedure
- Can also be used for synthetic trajectory creation and anomaly detection



Future Work: Explainability

- How to generate meaningful (explainable) embeddings to explain the clustering results
 - provide semantic meanings of individual clusters
 - understand outlier trajectories



References

- [BigData 19] **Yue M**, Li Y, Yang H, Ahuja R, **Chiang YY**, **Shahabi C**. DETECT: Deep Trajectory Clustering for Mobility-Behavior Analysis. In Big Data 2019.
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- [ITS 16] Besse, Philippe C., et al. "Review and perspective for distance-based clustering of vehicle trajectories." IEEE Transactions on Intelligent Transportation Systems 17.11 (2016): 3306-3317.
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- [SIGSPATIAL 08] Li, Quannan, et al. "Mining user similarity based on location history." Proceedings of the 16th ACM SIGSPATIAL international conference on Advances in geographic information systems. ACM, 2008.

Acknowledgements

- Gil, Yolanda (Ed.) Introduction to Computational Thinking and Data Science. Available from <http://www.datascience4all.org>



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