Mobility Behavior Representation & Clustering

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OUTLINE

- Mobility Behavior Clustering
  - DETECT
  - VAMBC
- Synthetic Trajectory Generation
  - CSGAN
  - MPGAIL

Motivation

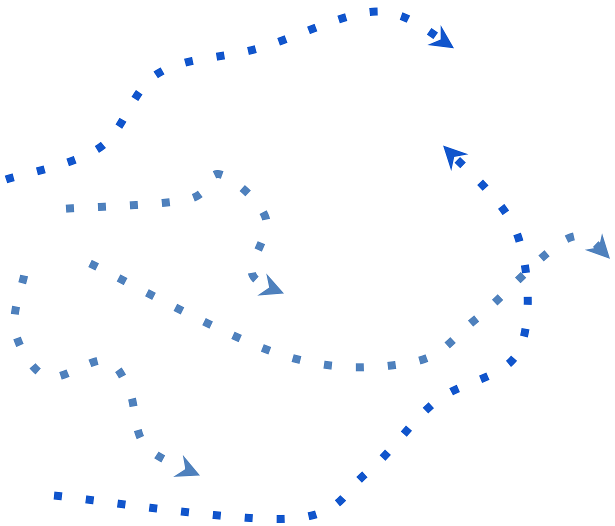
Mobility behavior: the travel activity that describes a user's movements, e.g., work commute, shopping, school commute, dining

Mobility Behavior

- COVID 19
- User Profiling
- Recommendations
- Ads targeting
- Insurance
- Threats Detection

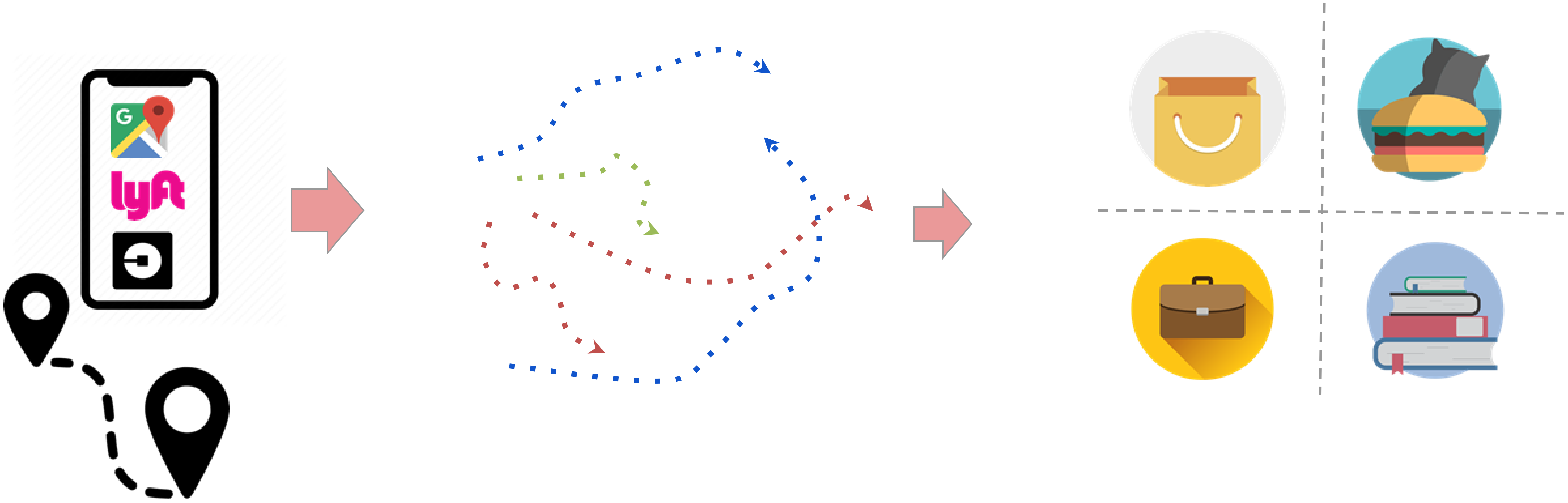
Idea: Trajectory Data → Mobility Behavior

Trajectories



Mobility Behavior

Idea: Trajectory Data → Mobility Behavior

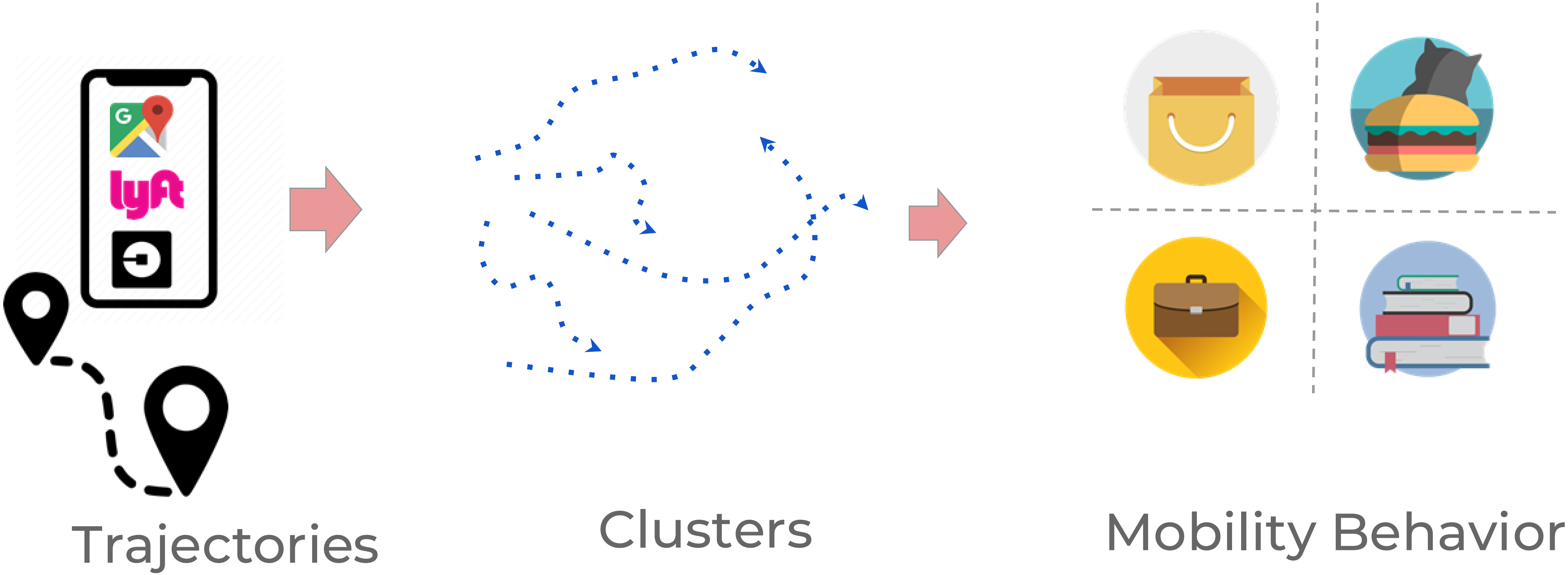


Trajectories

Clusters

Mobility Behavior

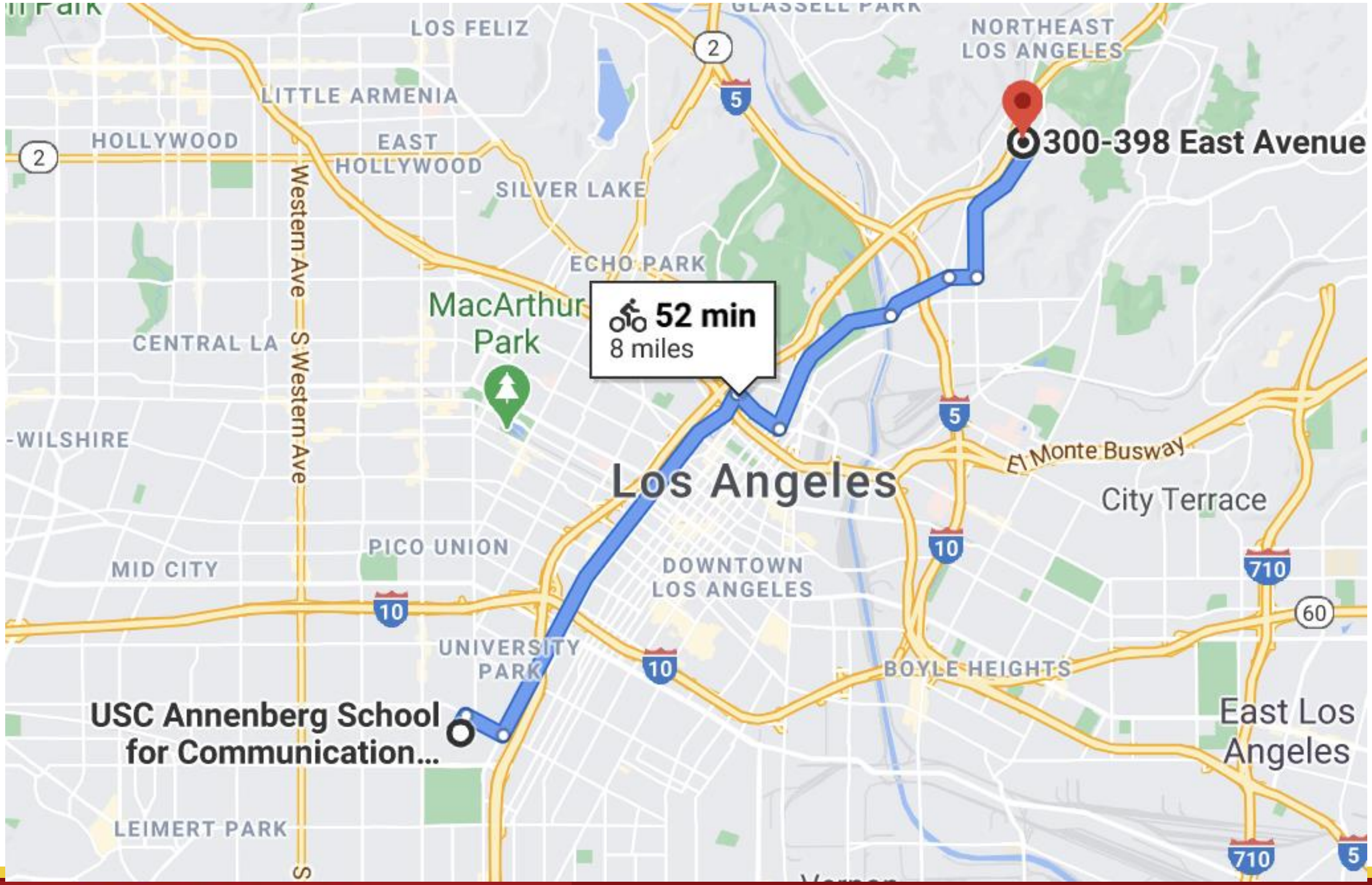
Idea



Trajectory Clustering Techniques

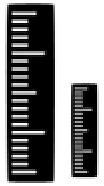
- Raw spatio temporal features [AIR’17]
- Sequence distance measurement
  - Dynamic Time Warping (**DTW**), Longest Common SubSequence (**LCSS**), Symmetrized Segment-Path Distance (**SSPD**)[ITS’16]
- Clustering based on the distances
  - kMeans-DBA[ICDM’14], DBSCAN[CVPR’09], Hierarchical Clustering

Challenge: Multi-scale Trajectories



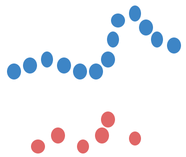
- Different temporal and spatial scales may represent the same mobility behavior
- 50 minutes work commute:
  - 14 miles, 44 miles, 8 miles
- 14 miles work commute
  - 20 min, 50 min, 1.5 hour

Limitations of Traditional Trajectory Clustering



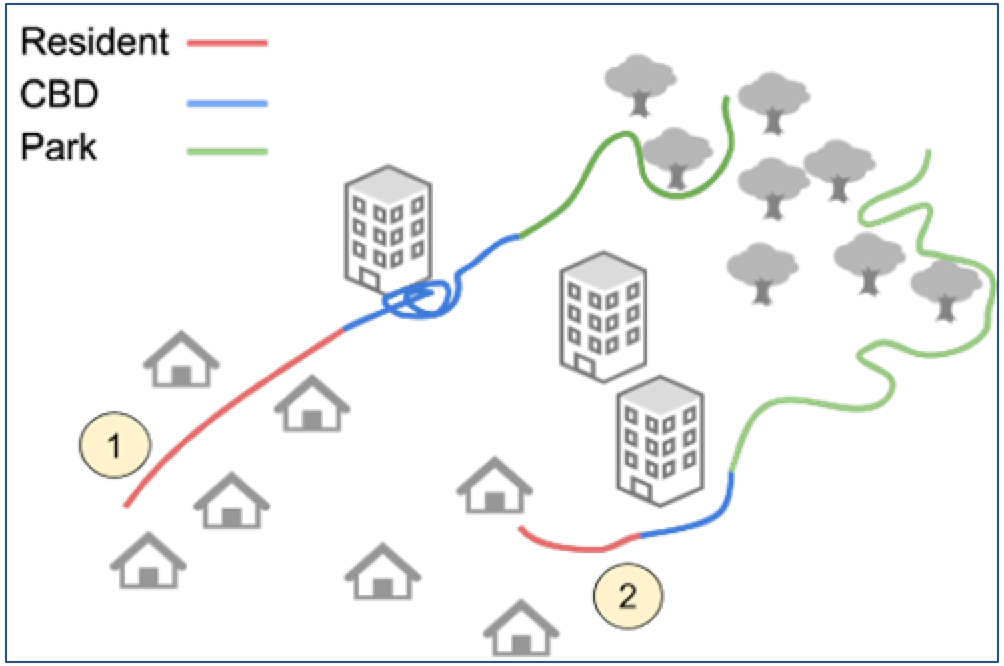
Prone to scales & noises

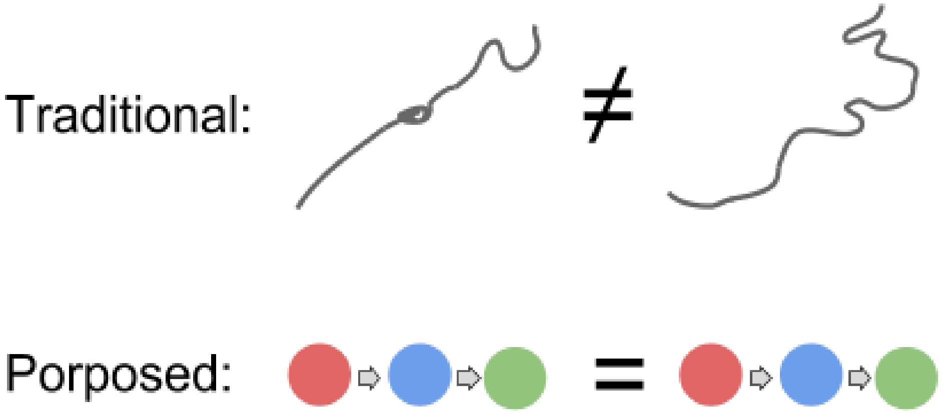
No activity context information



Pre-defined similarity vs. data-driven

Intuition





From trajectories to sequences of contexts

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  - Compact fixed-size representation with RNN
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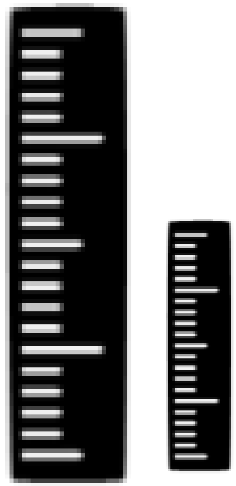
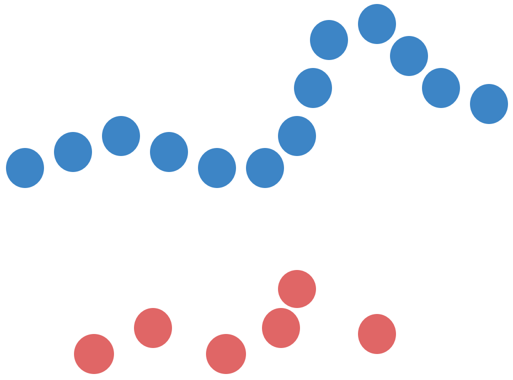
Approach

DETECT [BigData 19]



All-scale

Context-aware

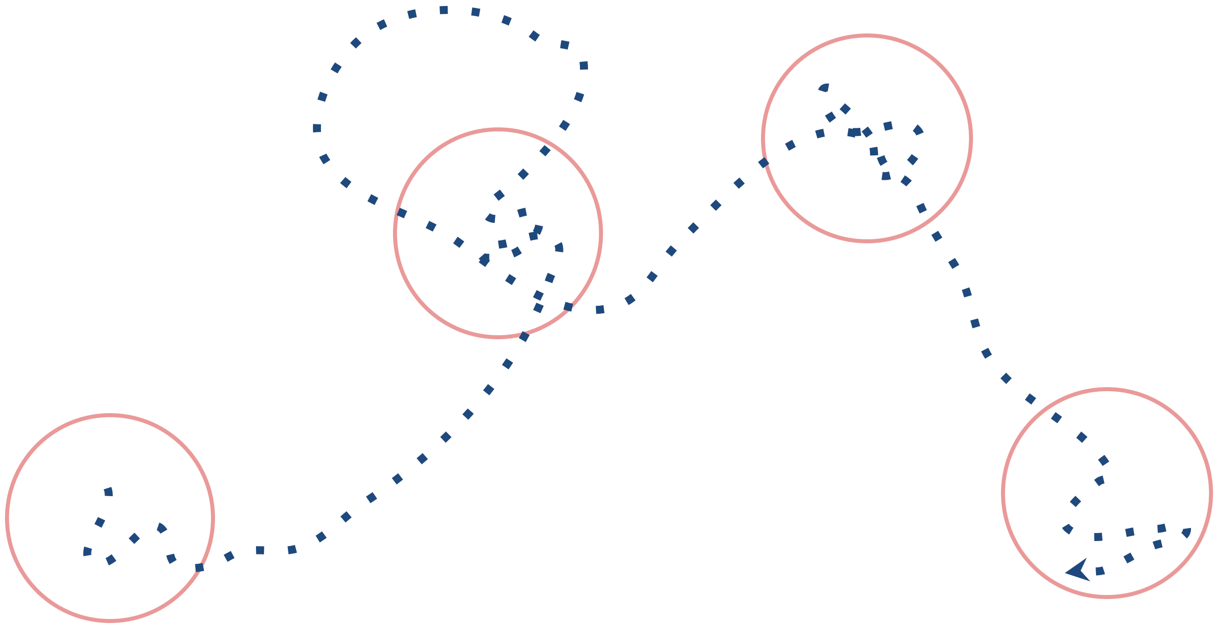


Sequence Dynamics

All-scale: Stay Point Extraction

Stay points [SIGSPATIAL'08] are representative points that:

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



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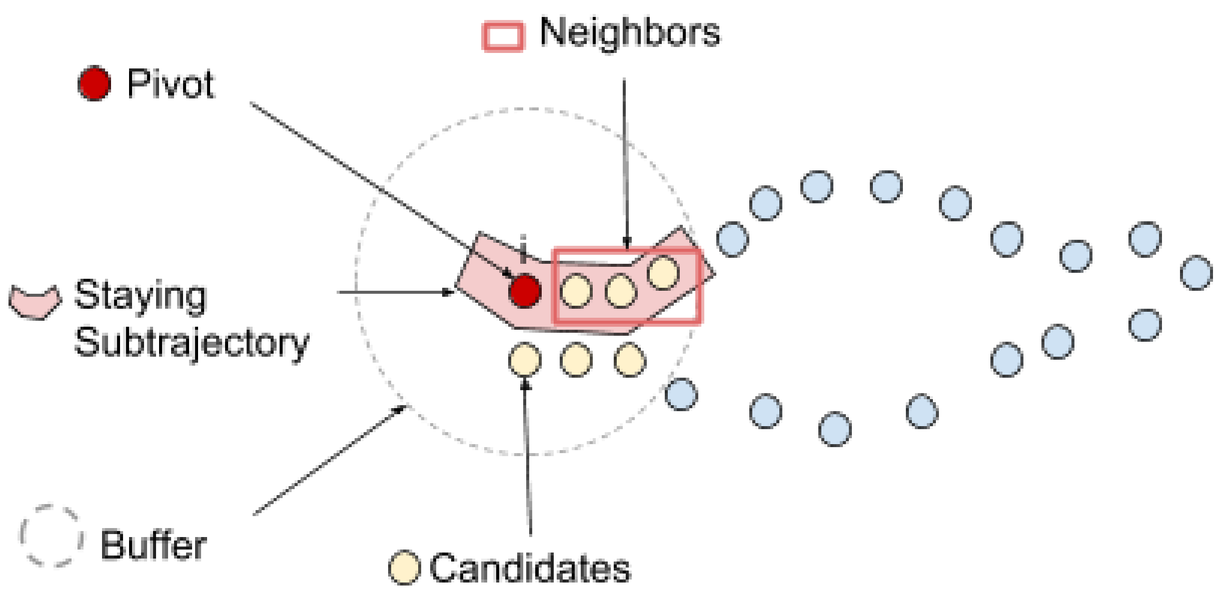

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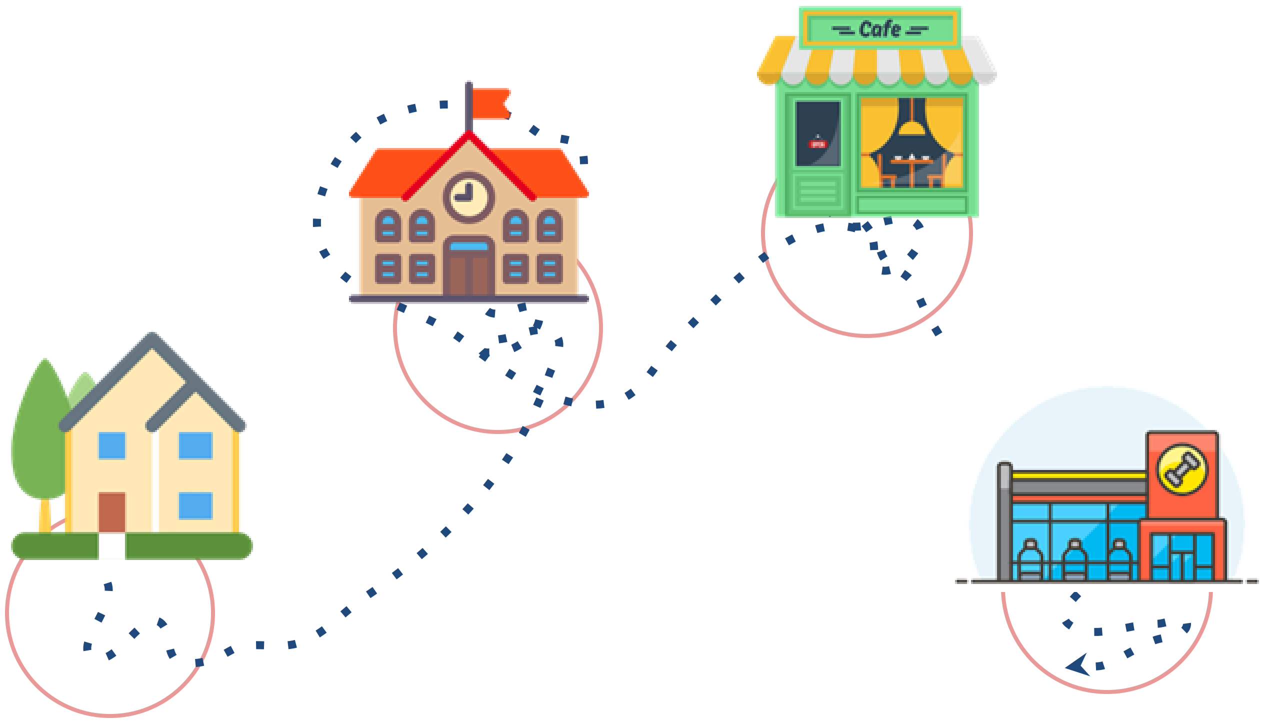


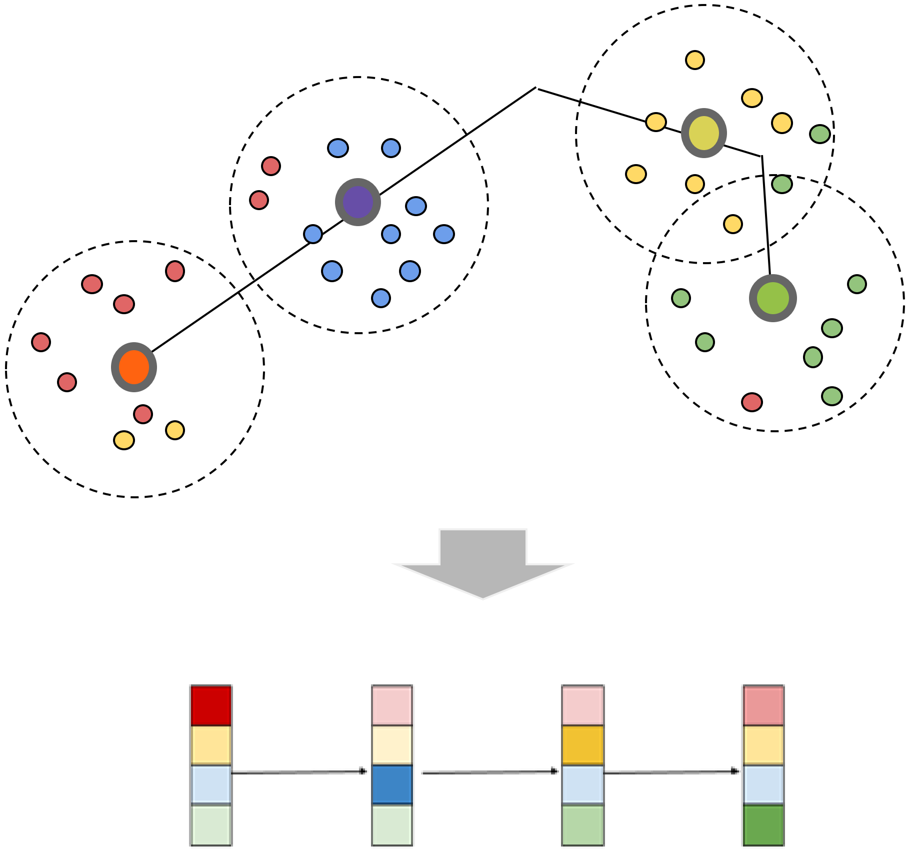
Context-aware: Geographical Augmentation

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

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

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



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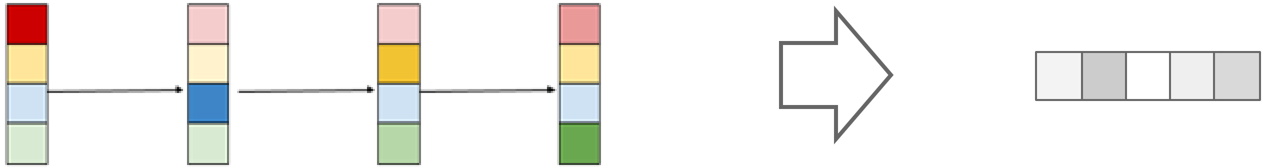
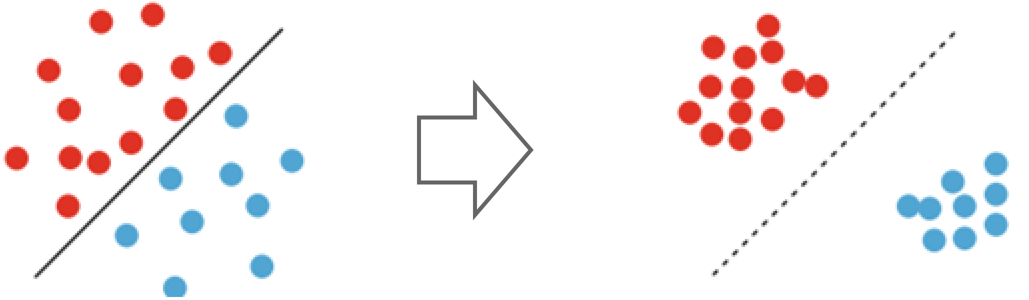
Sequence Dynamics: RNN-AE + Clustering

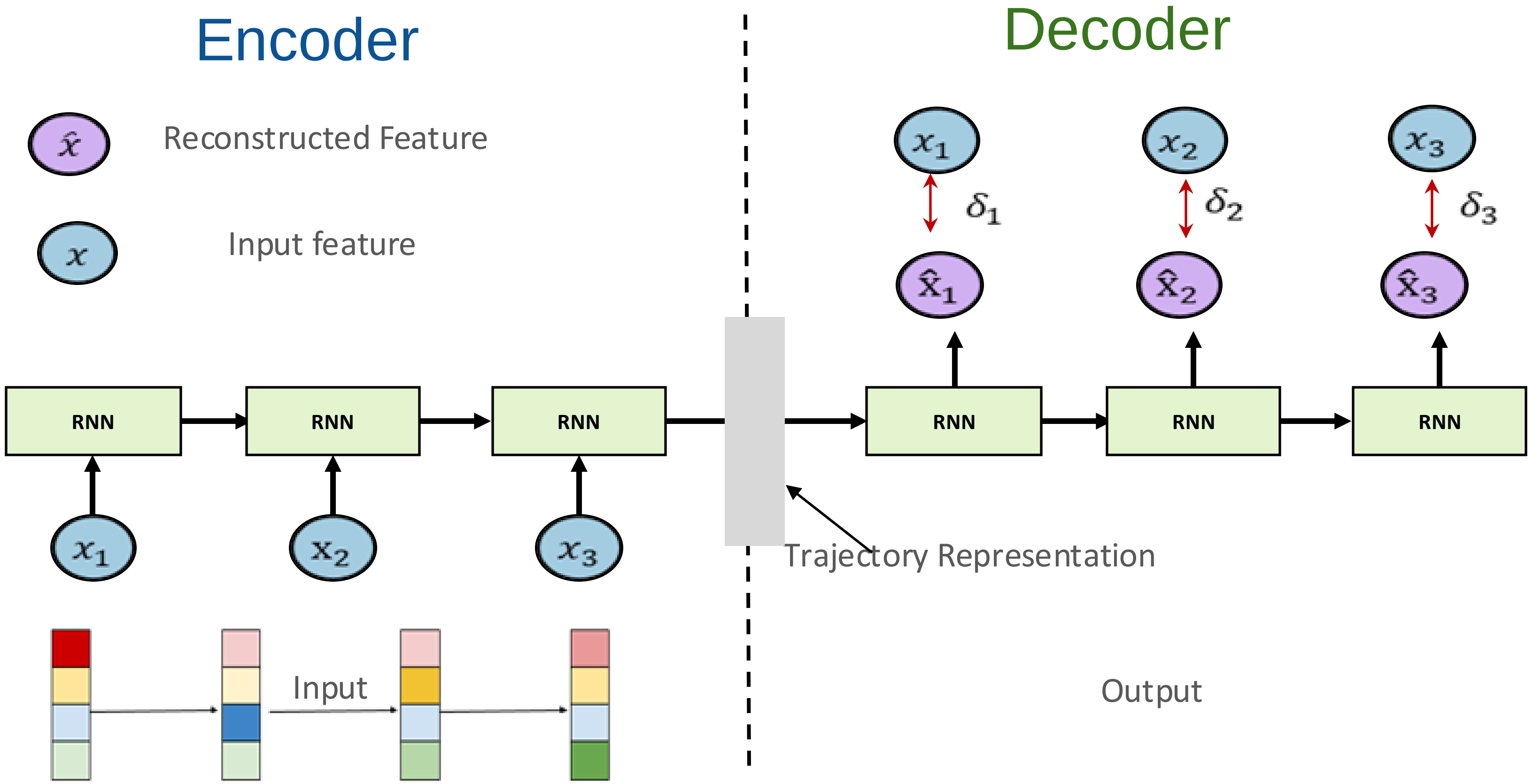
Phase I:



Phase II:



Phase I: RNN Autoencoder

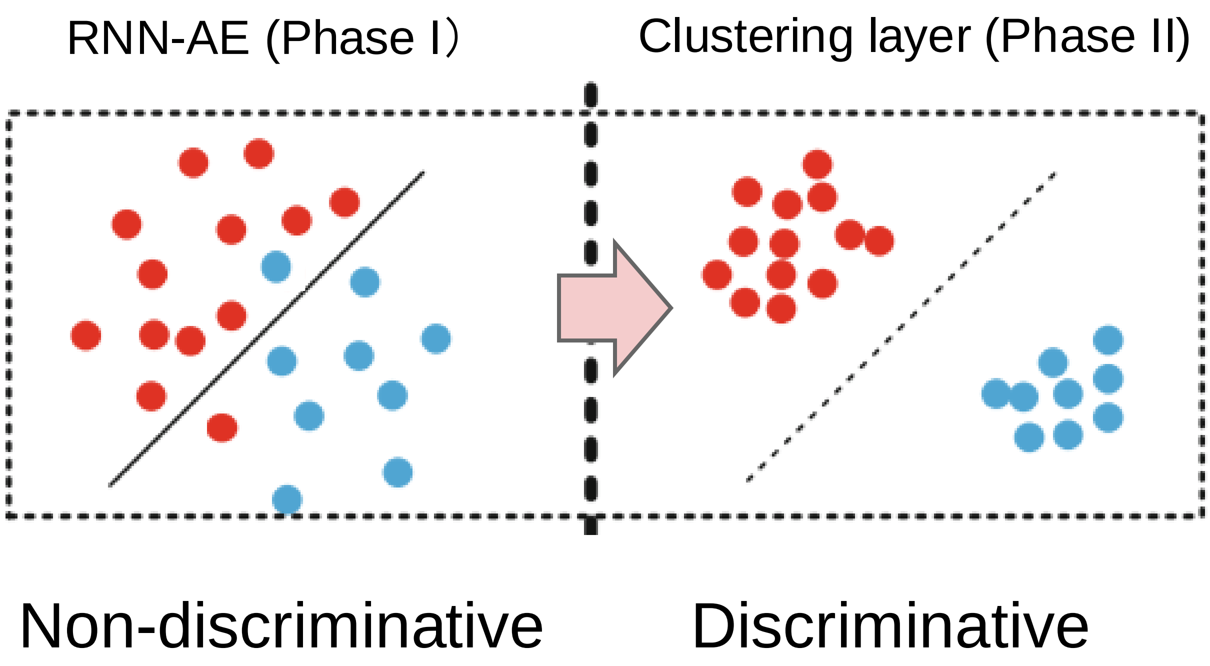


Intuition: Last hidden states of RNN → Sequence dynamics

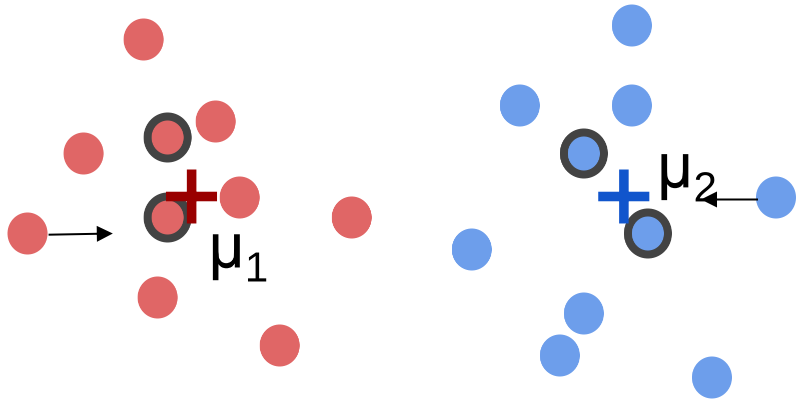
Phase II: Refine for clean clusters

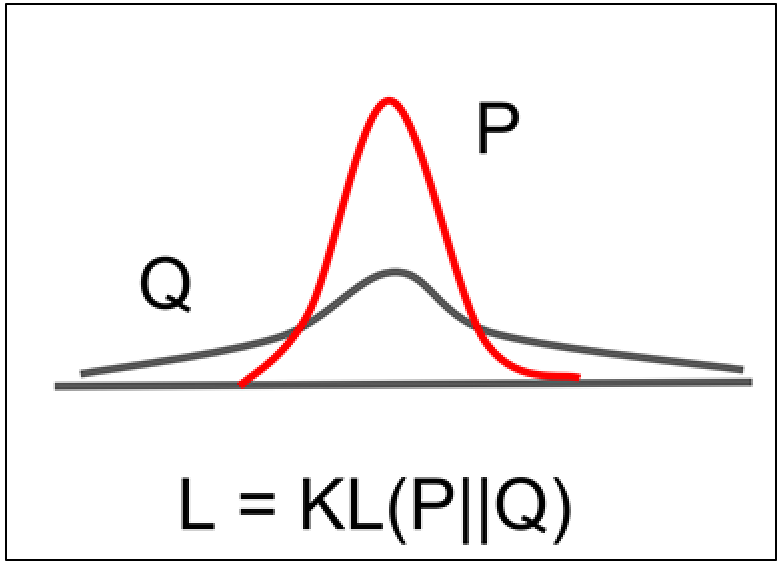
Reconstruction

Cluster-aware



Phase II: Cluster layer





Auxiliary Distribution P(q): hardened probability, trust high-confidence points

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

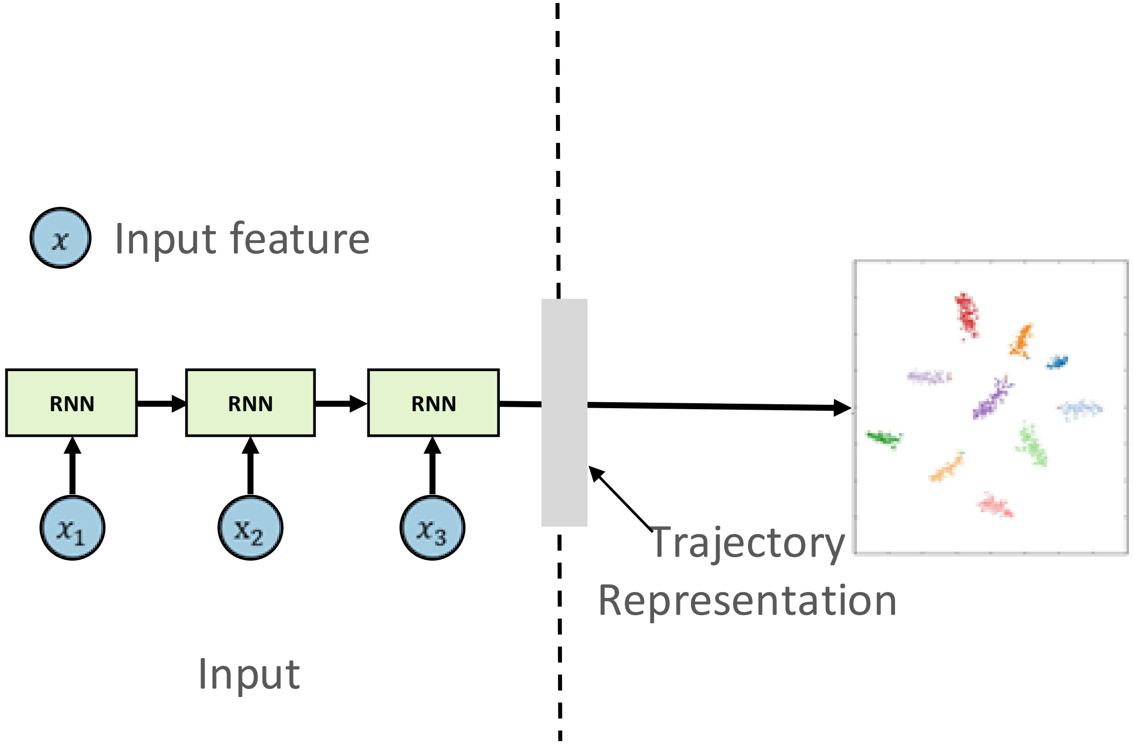
Phase II: Unsupervised optimization

Repeat:

1. Update z (encoder) and μ based on loss:

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

1. After a few batches, update Q and P. Stop if the assignment converges.



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Experimental settings

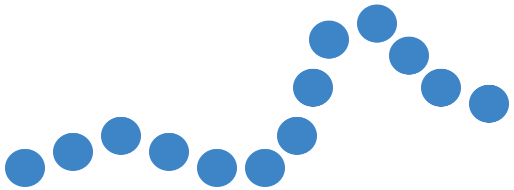
- Dataset: GeoLife
  - 17,621 trajectories (601 labeled).
  - 6 labels: “dining activities”, “working commutes”, etc.
  - 14,000 POIs in Beijing
- Evaluation Metrics
  - With label: Rand Index (RI), Mutual Information (MI), Purity Fowlkes-Mallows Index (FMI)
  - Without label: Silhouette Score, Dunn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

With-label: quantitative results

Distance		Clustering
DTW		K-Means
LCSS	+	DBSCAN
SSPD		Hierarchical clustering

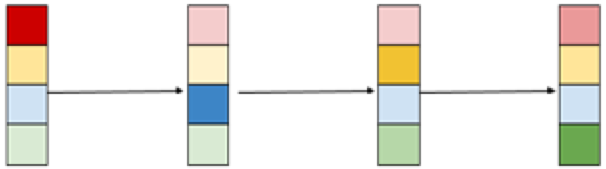
Method	RI	MI	Purity	FMI
KM-DBA	0.33	0.64	0.58	0.58
DB-LCSS	0.22	0.55	0.51	0.56
RNN-AE	0.39	0.46	0.56	0.53
SSPD-HCA	0.52	0.93	0.66	0.67
KM-DBA*	0.51	0.91	0.74	0.63
DB-LCSS*	0.5	0.95	0.64	0.66
DETECT Phase I	0.65	1.06	0.84	0.73
DETECT	**0.76**	**1.26**	**0.89**	**0.81**

With-label: quantitative results



Raw trajectories

Augmented trajectories



Method	RI	MI	Purity	FMI
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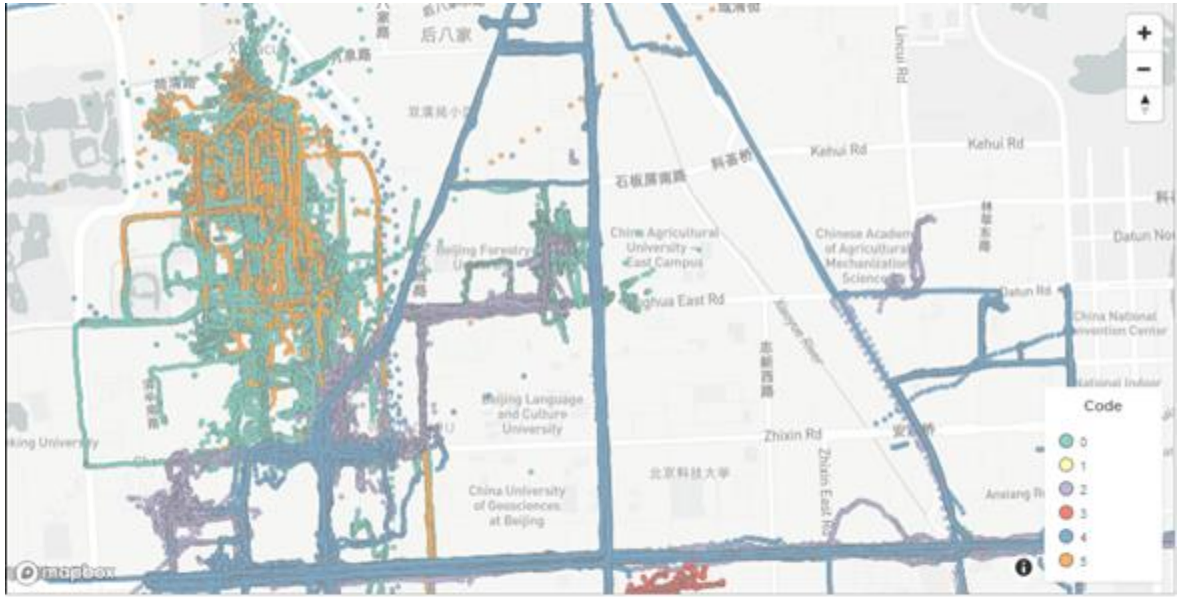
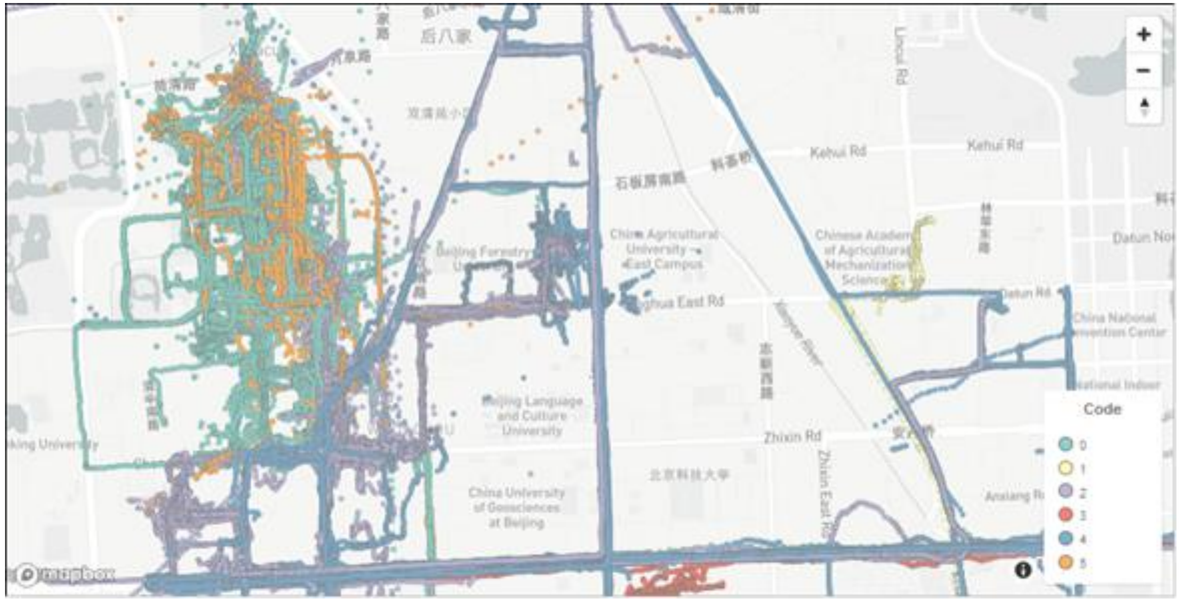
With-label: qualitative results



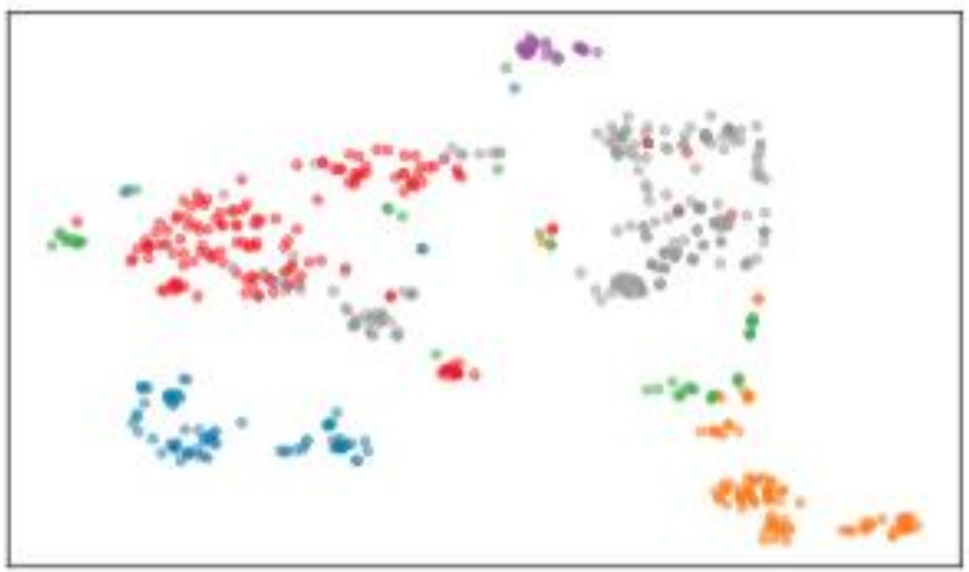
Ground Truth



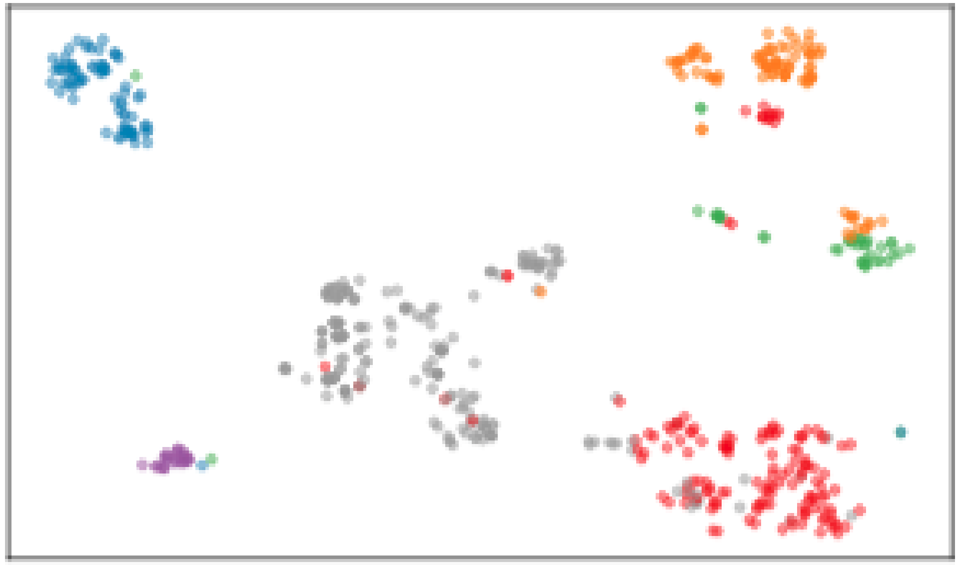
Our Results

Note: Different colors indicate different clusters.

With-label: qualitative results

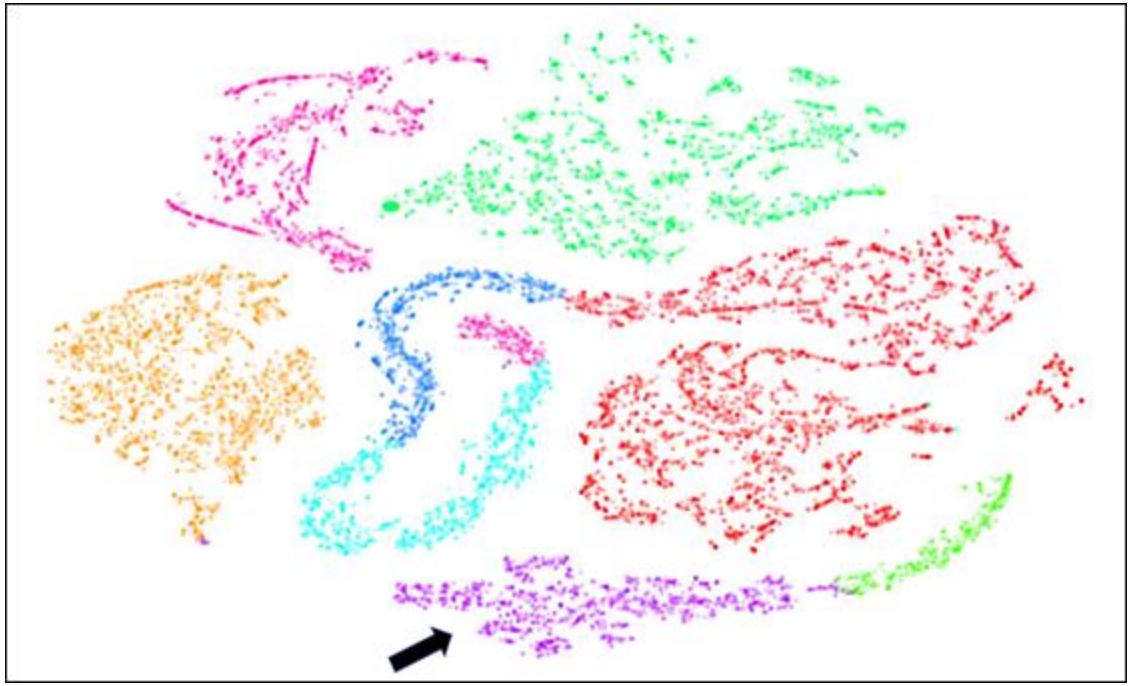


Embedding after Phase I



Embedding after Phase II

Without-label: qualitative results



Embedding of full dataset

Recreation Activities

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- Mobility Behavior Clustering
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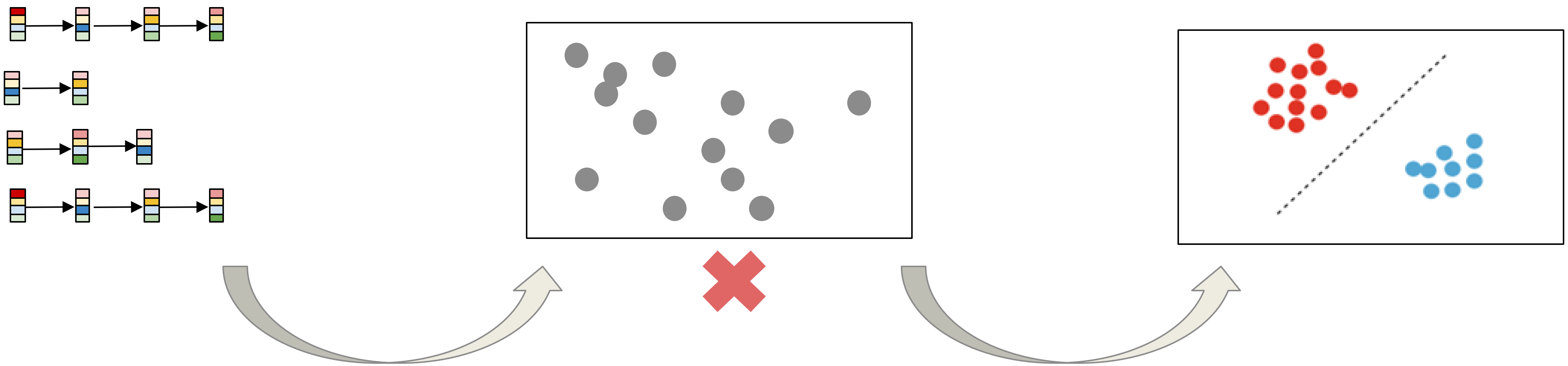
Shortcoming: Separate Embedding from Clustering

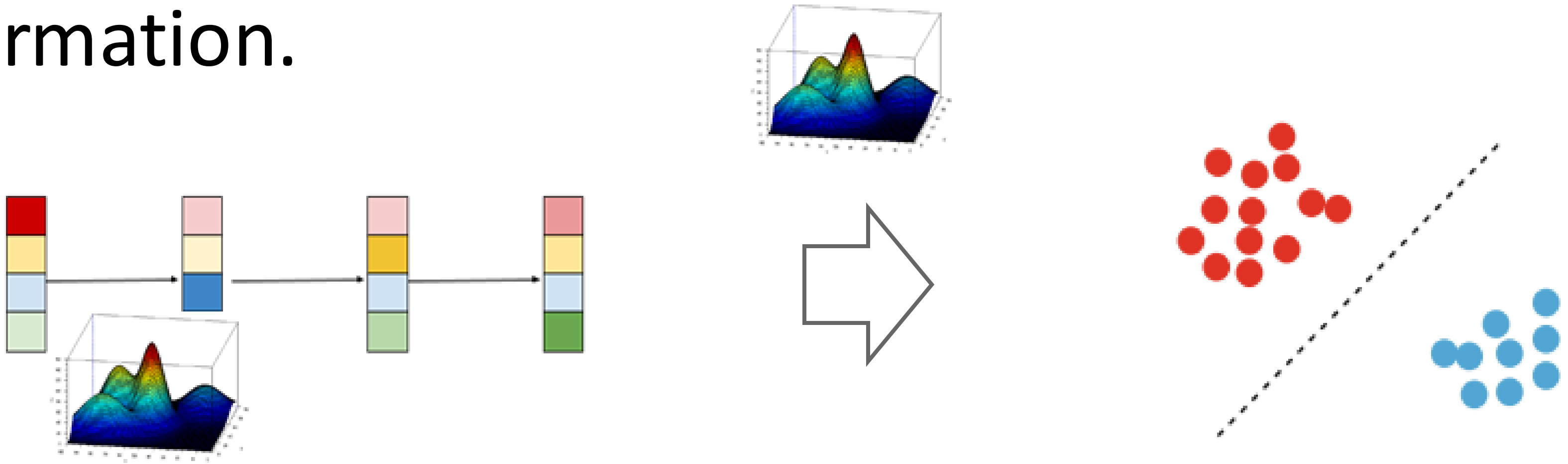
Two-phase: sub-optimal since the first phase is not aware of clustering.



Phase I: embedding Phase II: Clustering

Solution: A single phase

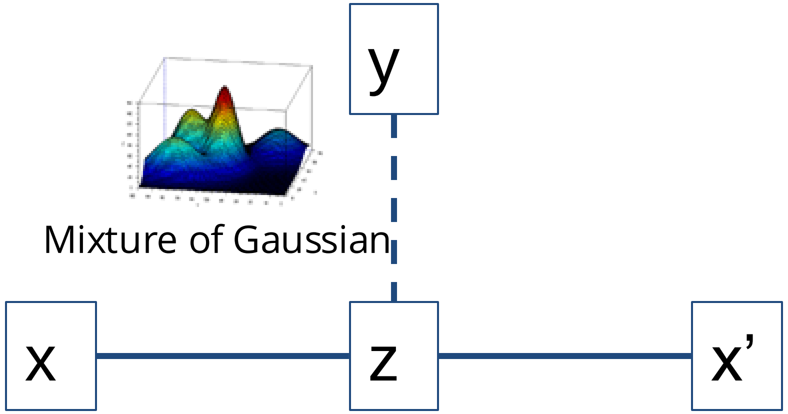
Assume the pre-existence of clusters in the latent space and jointly learn the hidden representation for reconstruction and cluster formation.



VAE: Variational AutoEncoders

VAE-based (1 phase) for images VaDE **[IJCAI 17]**, GMVAE **[ArXiv 16]**, JointVAE **[NIPS 18]**

$$y \sim Cat(1/K), z \sim \mathcal{N}(\mu_y, \sigma_y^2 I)$$
$$x \sim \mathcal{N}(\mu_x(z), \sigma_x^2(z) I)$$



y: discrete(onehot) variable indicating cluster

z: continuous variable denoting embedding

x: input context sequences

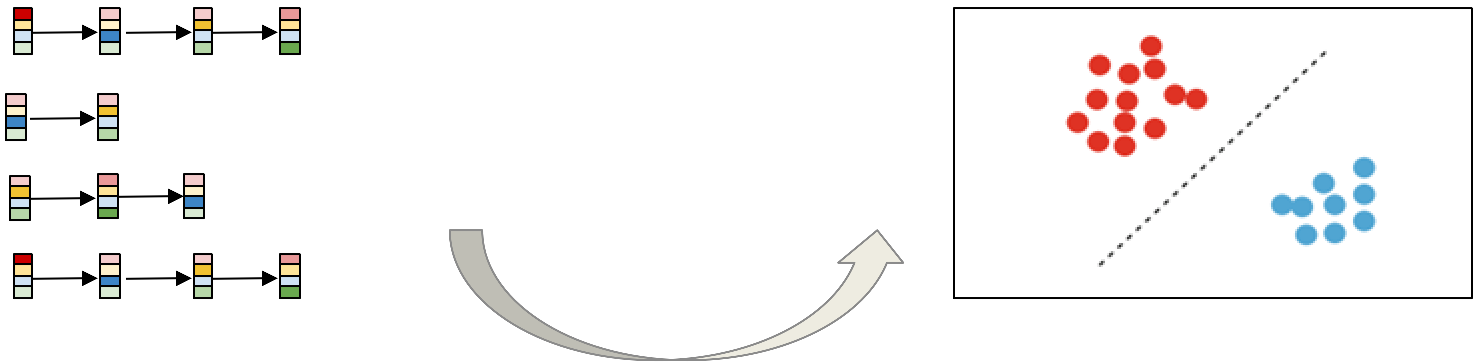
x’: reconstructed context sequences

The hidden space z will be restricted by a cluster variable y which try to regularize the hidden space to be a mixture of gaussian

Challenge: Sensitive Training of Clustering

Two-phase: sensitive since the first phase is not aware of clustering.

One-phase: produce trivial solutions as the model could ignore the cluster involvement.



Embedding + Clustering

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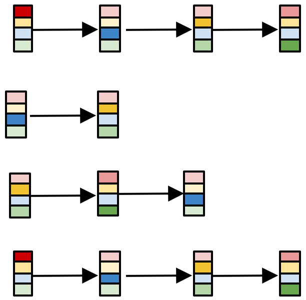
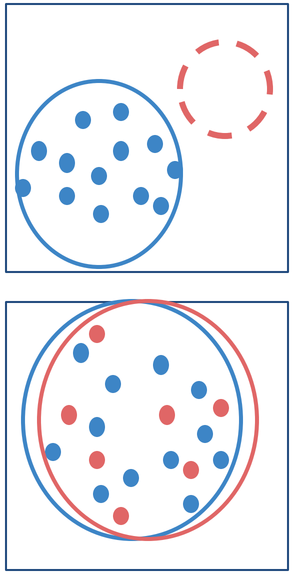
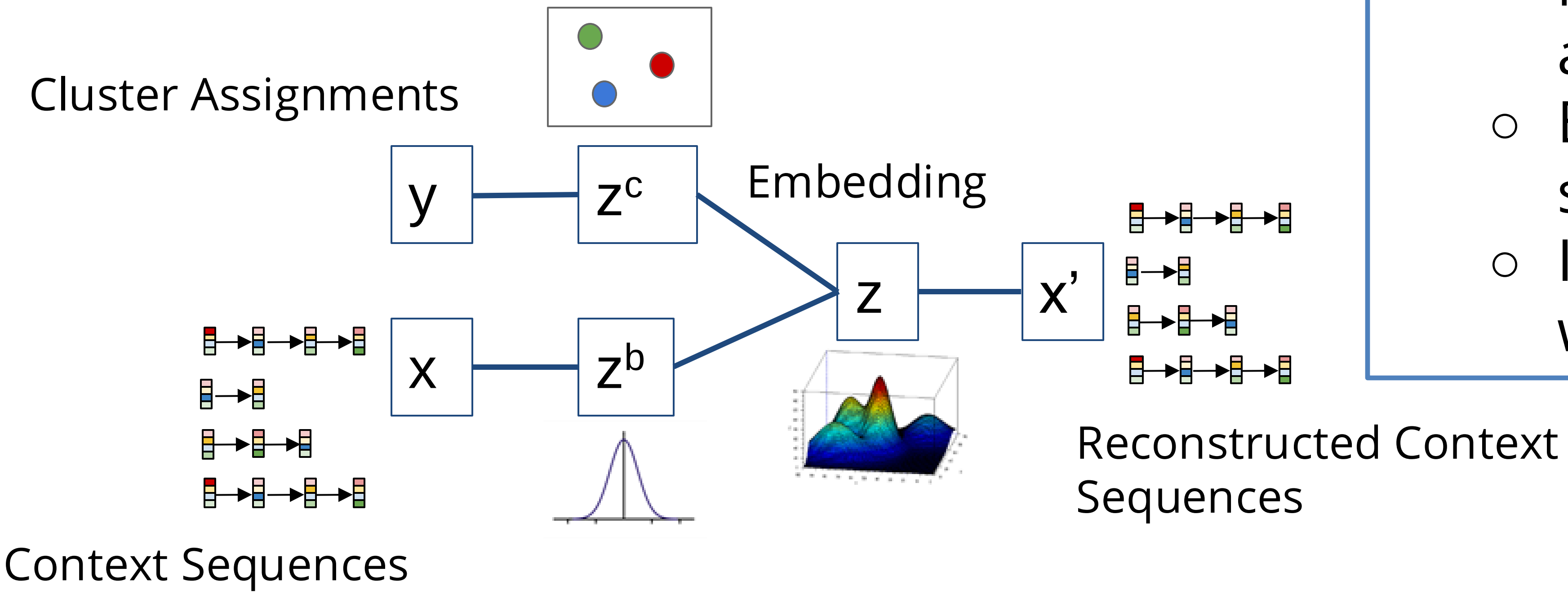


Embedding + Clustering



VAMBC: A Variational Approach for Mobility Behavior Clustering



- Increase the involvement of cluster assignments y.
- Encourage the cluster separation
- Improve the cohesion within each cluster

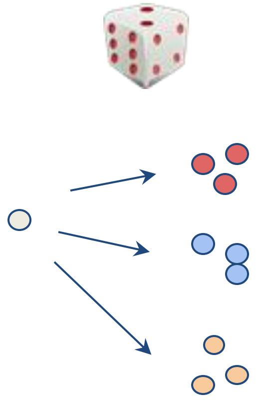
VAMBC

$$\mathcal{L}_{ELBO} = \mathbb{E}_{y,z\sim q(y,z|x)}\Big(\underbrace{\log\frac{p(y)}{q(y|x)}}_{L_{NE}} + \underbrace{\log\frac{p(z^b)}{q(z^b|x)}}_{L_{KL}} + \log p(x|y,z)\Big)$$

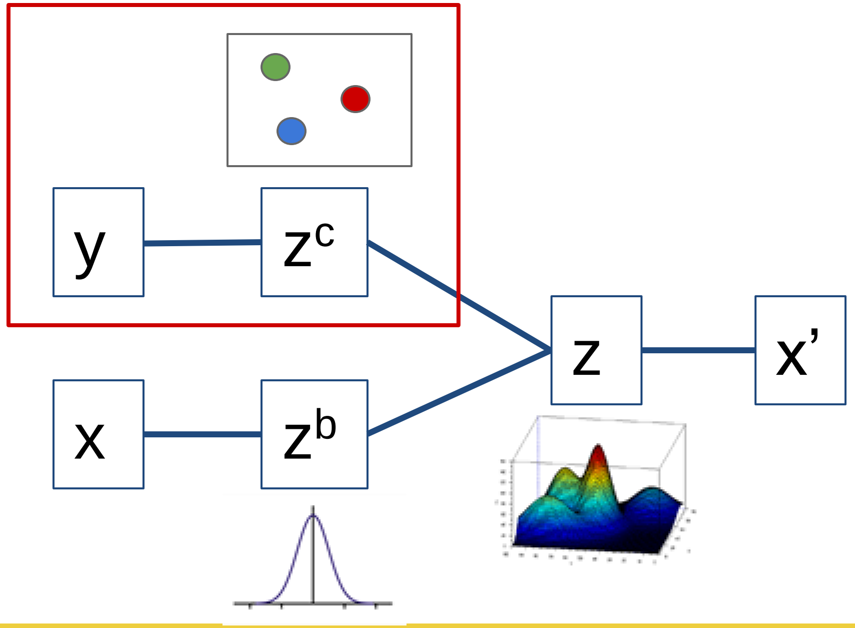
$$= -\underbrace{\boxed{D_{KL}(q(y|x)||p(y))}}_{L_{NE}} - \underbrace{\boxed{D_{KL}(q(z^b|x)||p(z^b))}}_{L_{KL}} + \underbrace{\boxed{\mathbb{E}_{y\sim q(y|x),z^b\sim q(z^b|x),z^c=f(y;W)}\log p(x|y,z^b,z^c)}}_{L_{recon}}$$

L_{NE}: Negative Entropy

Gumbel-Softmax



- Bring randomness to y
- Allow cluster adjustment
- Share z^c



VAMBC

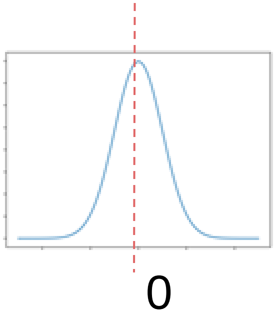
$$\mathcal{L}_{ELBO} = \mathbb{E}_{y,z\sim q(y,z|x)}\left(\log \frac{p(y)}{q(y|x)} + \log \frac{p(z^b)}{q(z^b|x)} + \log p(x|y,z)\right)$$

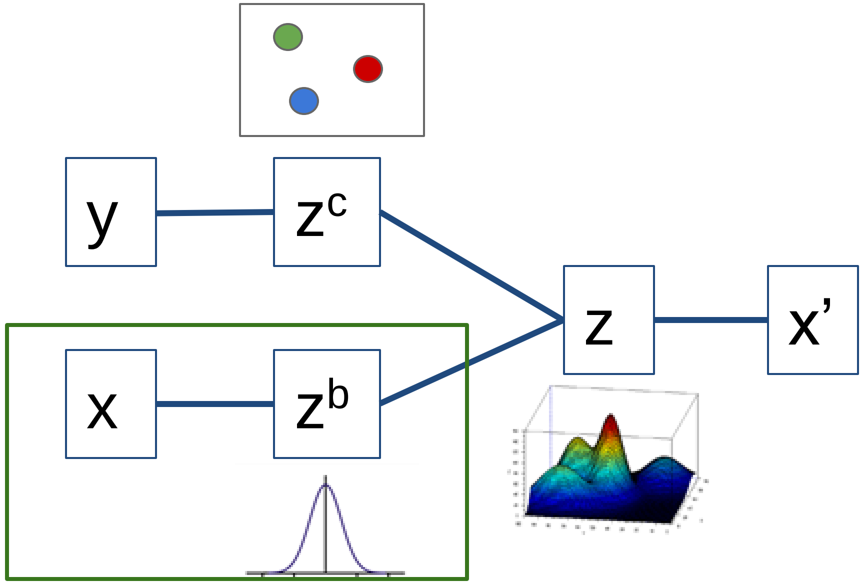
$$= -\underbrace{\boxed{D_{KL}(q(y|x)||p(y))}}_{L_{NE}} - \underbrace{\boxed{D_{KL}(q(z^b|x)||p(z^b))}}_{L_{KL}}$$

$$+ \underbrace{\boxed{\mathbb{E}_{y\sim q(y|x), z^b\sim q(z^b|x), z^c = f(y;W)} \log p(x|y, z^b, z^c)}}_{L_{recon}}$$

L_{KL}: KL loss

- A regularizer limits z^b.
- z^b only carries unique information of x.





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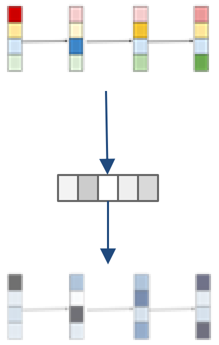
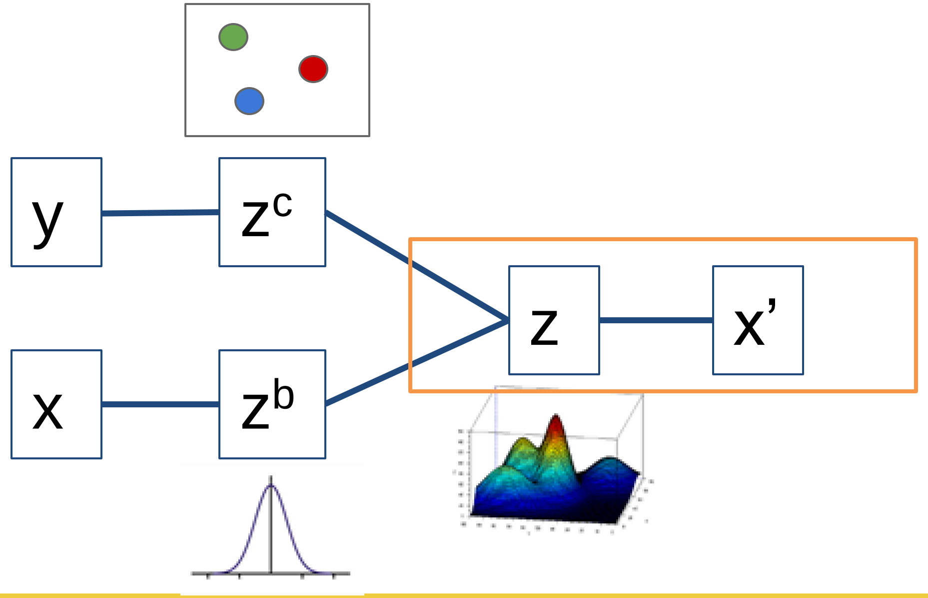
L_{recon}: Reconstruction

- Supervise the entire model
- learn the embedding z





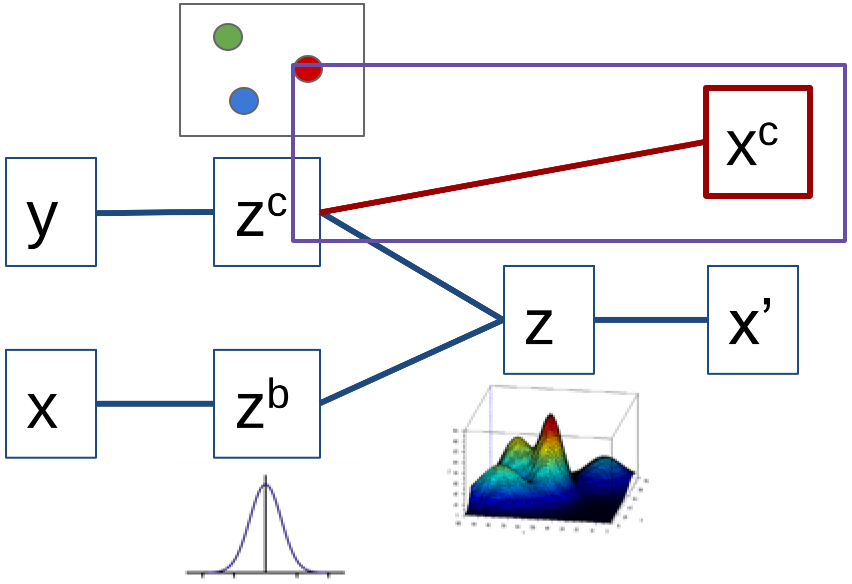
VAMBC

$$L = L_{NE} + L_{KL} + L_{recon} \boxed{+ L_{center}}$$

L_{center}: Center loss

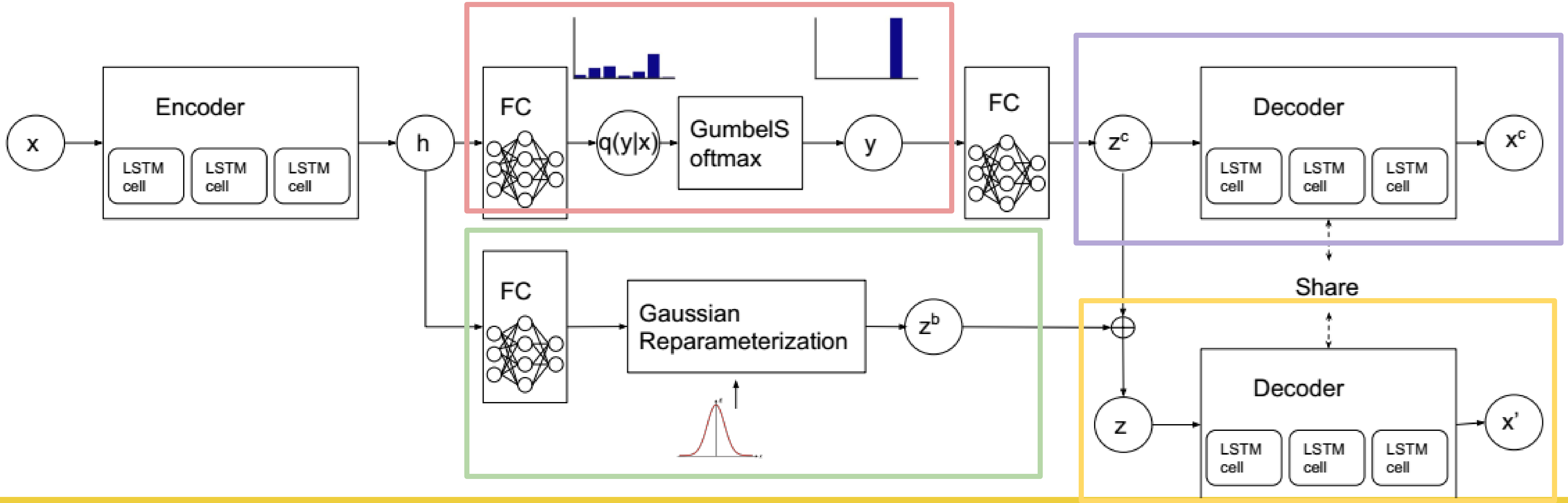
- Force z^c meaningful
- More involvement of y

$$L_{center} = ||x - x^c||_2^2$$



VAMBC Architecture

Loss = L_{NE} + L_{KL} + L_{recon} + L_{center}



Experiment: setting

- Dataset:
  - GeoLife trajectories and POI data
  - DMCL trajectories and POI data
- Baselines:
  - Classical TS: KM-DTW, KM-GAK, kShape, DB-LCSS
  - Autoencoder-based: DTC, DETECT, IDEC*, DCN*
  - VAE-based: VaDE*, GMVAE*, JointVAE*
  - Discrete Sequence Clustering: SGT, MHMM

- Metrics:
  - NMI: Normalized Mutual Information
  - ARI: Adjusted Rand Index
  - Accuracy

Experiment: result

Method	NMI (aver)	NMI (best)	NMI (worst)	ARI (aver)	ARI (best)	ARI (worst)	ACC (aver)	ACC (best)	ACC (worst)
KM-DTW	0.610±0.021	0.645	0.579	0.635±0.019	0.656	0.617	0.742±0.031	0.763	0.655
KM-GAK	0.591±0.057	0.657	0.507	0.505±0.076	0.573	0.392	0.737±0.033	0.770	0.688
K-Shape	0.229±0.033	0.272	0.174	0.220±0.046	0.271	0.102	0.522±0.015	0.551	0.495
DB-LCSS	0.547	0.547	0.547	0.412	0.412	0.412	0.697	0.697	0.697
SGT	0.419±0.024	0.454	0.371	0.216±0.036	0.277	0.149	0.628±0.029	0.694	0.579
MHMM	0.530±0.047	0.611	0.486	0.403±0.057	0.495	0.344	0.627±0.017	0.649	0.607
IDEC*	0.605±0.035	0.673	0.572	0.465±0.097	0.664	0.404	0.67±0.08	0.819	0.596
DCN*	0.646±0.051	**0.725**	0.594	0.635±0.065	0.693	0.503	0.782±0.061	0.840	0.624
DTC	0.500±0.027	0.550	0.474	0.483±0.028	0.512	0.451	0.682±0.032	0.737	0.655
DETECT	0.644±0.037	0.691	0.589	0.646±0.044	0.688	0.582	0.8±0.013	0.822	0.780
GMVAE*	0.132±0.267	0.501	0.250	0.098±0.128	0.351	0.000	0.411±0.079	0.551	0.346
VaDE*	0.631±0.053	0.669	0.502	0.603±0.078	0.658	0.440	0.783±0.037	0.822	0.720
JointVAE*	0.459±0.056	0.556	0.408	0.227±0.123	0.442	0.161	0.519±0.062	0.597	0.473
VAMBC	**0.697±0.015**	0.699	**0.692**	**0.7±0.019**	**0.719**	**0.682**	**0.825±0.01**	**0.842**	**0.810**

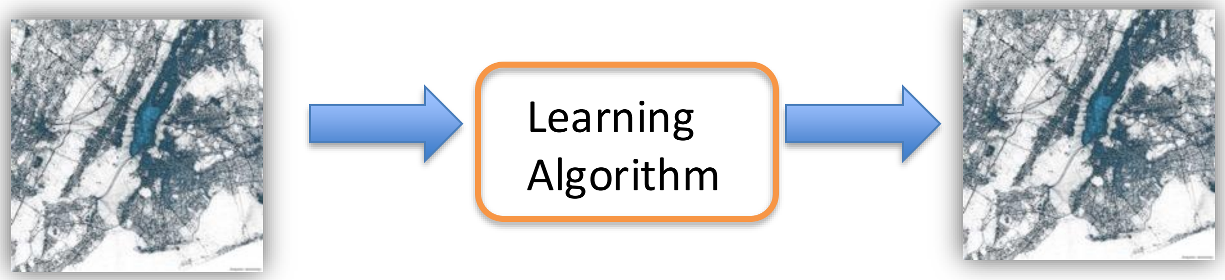
Conclusion

- Proposed a novel variational model VAMBC that clusters the context sequences in a single phase
- The VAMBC model decomposes the hidden embedding into individualized embedding and cluster embedding with a novel design.
- The VAMBC model achieves significantly better robustness and improved accuracy than existing approaches.

OUTLINE

- Mobility Behavior Clustering
  - DETECT
  - VAMBC
- Synthetic Trajectory Generation
  - CSGAN
  - MPGAIL

Synthetic Trajectory Generation – Why?



Real Data

Generated Data

- **Scale-up:** The input set is small and we need more realistic trajectories for the downstream task or when
- **Privacy preservation:** The privacy of the input set must be preserved
- **Diversification:** To generate trajectories for one geographical area (e.g., city, neighborhood) from the training set of trajectories belonging to a different geographical area

Background

<u>Computational algorithms</u>

- Moving-object generators (e.g., Brinkhoff)
  - Travel surveys and Handcraft-rules

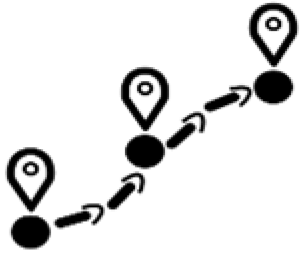
- Micro agent simulators
  - Lots of parameter setting

Limitation: Require human labor and domain knowledge to convert real-world data into the parameters/rules of the closed (artificial) environment.

<u>Data-Driven algorithms</u>

- Learn directly from the Real data distribution

Discretize



Latitude, longitude, timestamp

Mobility Trajectory

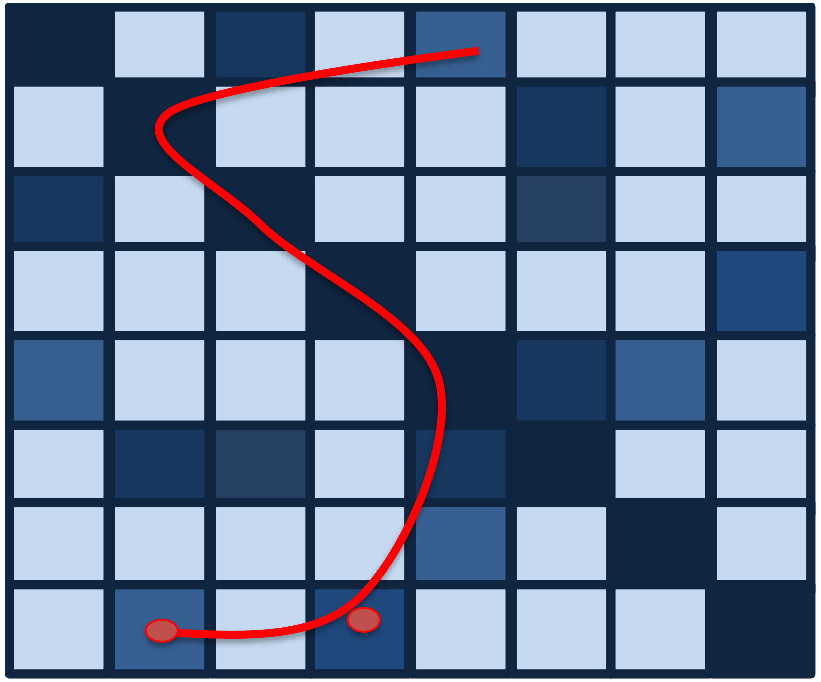
[1 , 3 , 7, 8 , 8]

8:00, 8:05, 8:10, 8:15, 8:20…

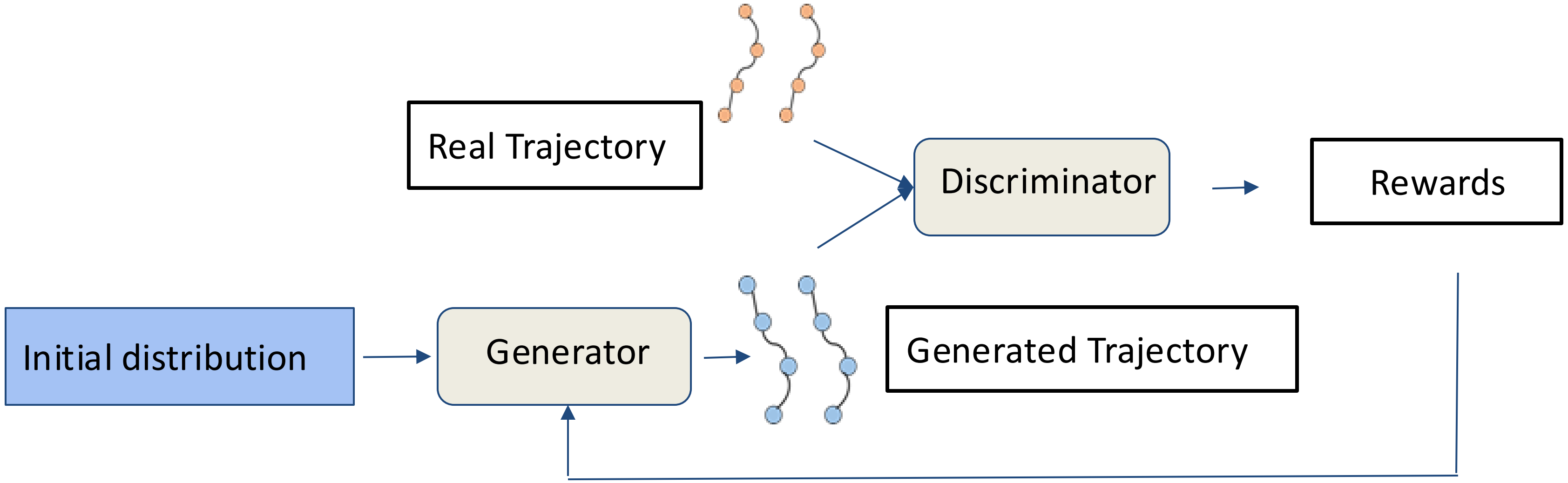
- Discrete Trajectory in space and time

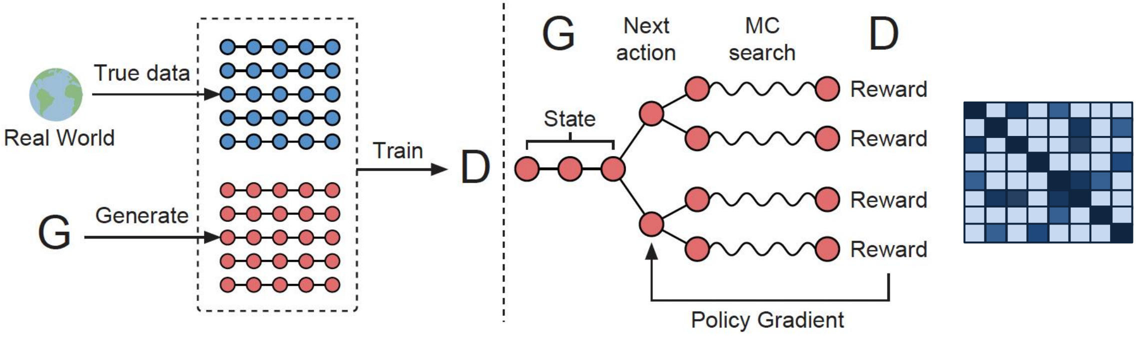
Generative AI Idea

- *Model human movements as state transitions and formulate trajectory generations as a decision-making process*
- *Follow a generator-discriminator structure to learn the underlying mechanism (e.g., policy) behind the state transitions.*



Background: Seq Generative Adversarial Network





$$\min_{G_\theta} \max_{D_\phi} E_{Y\sim p_d(Y)}[log(D_\phi(Y))]+E_{\hat{Y}\sim G_\theta(\hat{Y})}[log(1-D_\phi(\hat{Y}))]$$

Compete with each other in a zero-sum game framework.

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L. Yu, W. Zhang, J. Wang, and Y. Yu, "Seqgan: Sequence generative adversarial nets with policy gradient," in Proceedings of the AAAI conference on artificial intelligence, vol. 31, no. 1, 2017.

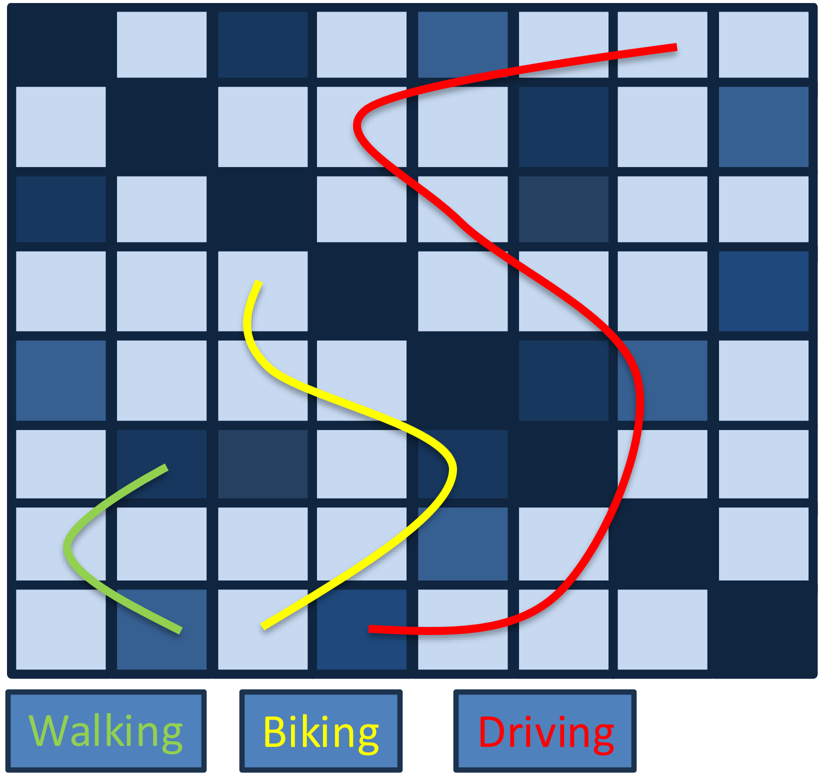
Related Work

	Name	Methods	Dataset
Non Deep Learning Model	TimeGeo [PNAS16]	Statistics modeling	CDR(Boston)
DNN Methods	TrajGAN [IJCAI18]	GAN	Nokia Lausanne location
	MoveSim [KDD 20]	GAN	GeoLife (Beijing)
	TrajGAIL [ICDM20]	GAIL	Taxi data (Shenzhen)
	DeltaGAN [ICLR 21]	GAN	GeoLife (Beijing)
	NEXTGAIL [SIGSPATIAL21]	GAIL	Taxi data (Shenzhen)
	ActSTD [KDD 21]	GAIL	Mobile Network (Beijing) Foursquare
	FVAE [SIGSPATIAL22]	VAE	Taxi data (Porto) Gowalla

Limitations: Cannot control the generation process to generate trajectories with specific semantics (e.g., different modality / moving behavior)

Our Main Hypothesis

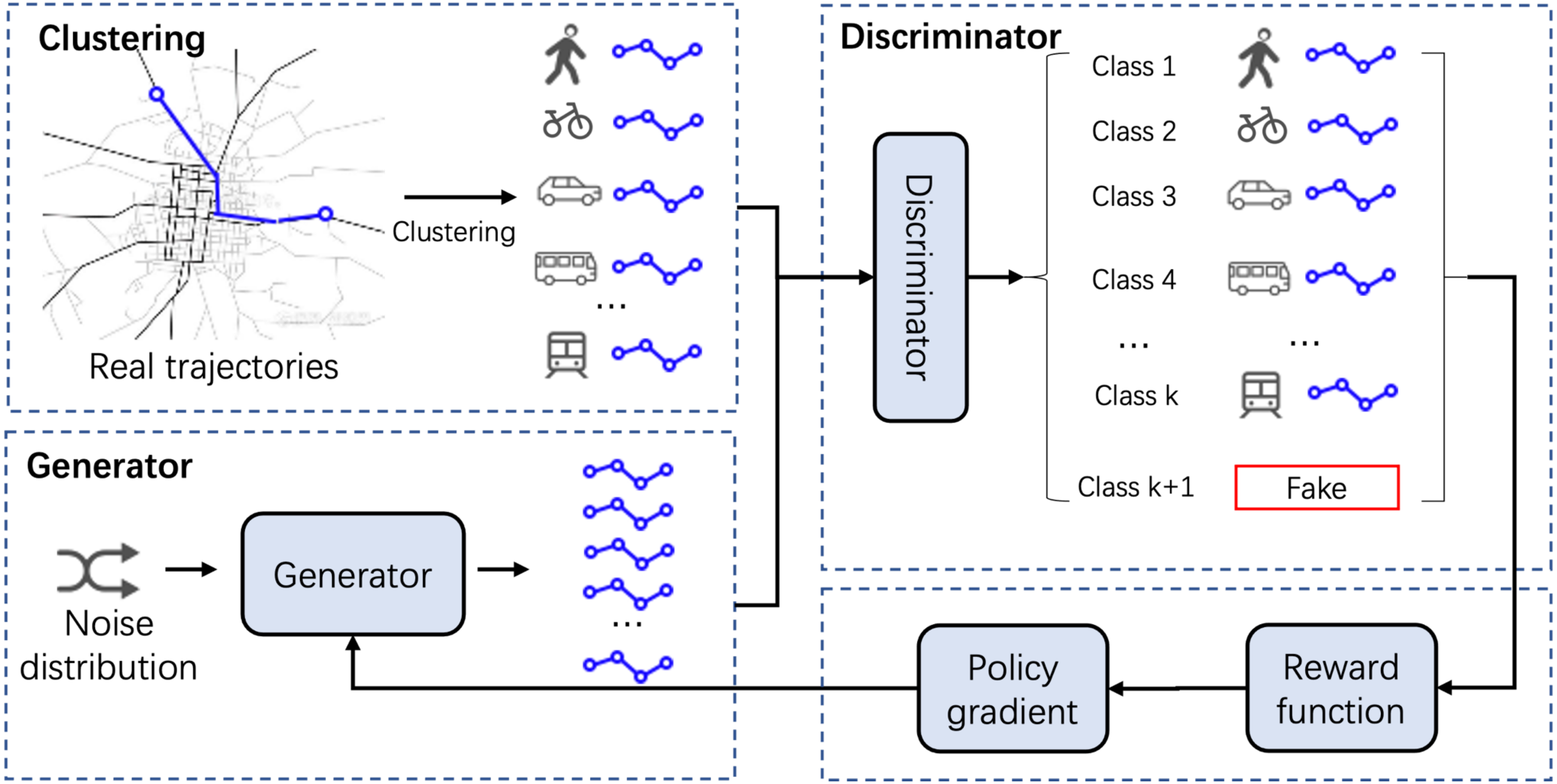
- *While common mobility regularity and transition patterns are shared across transportation modalities and moving behaviors, there are also modality/behavior-specific characteristics and patterns.*
  - *E.g., different speeds, distances traveled, number of distinct visits, and transition patterns (e.g., transitions on walkways vs. bikeways vs. roads).*
- *By including modality/behavior, the generated trajectories will be*
  - *Diverse and representative of different modalities*
  - *Realistic, corresponding to the real-world modalities*



OUTLINE

- Mobility Behavior Clustering
  - DETECT
  - VAMBC
- Synthetic Trajectory Generation
  - CSGAN
  - MPGAIL

CSGAN:
Clustering-based Sequence Generative Adversarial Network



- Classify the trajectory into k + 1 classes
- Rewards of the generator is the summation of any real modalities

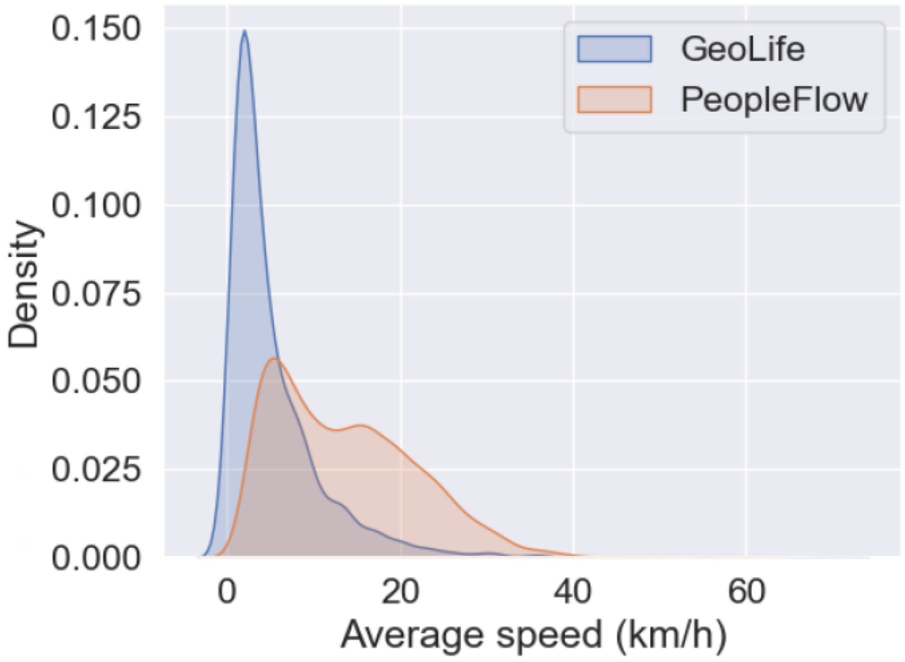
$$R_D(\hat{Y}) = \sum_{c \in C_r} p_D^c(\hat{Y})$$

M. Zhang, H. Lin, S. Takagi, Y. Cao, C. Shahabi, L. Xiong:
CSGAN: Modality-Aware Trajectory Generation via Clustering-based Sequence GAN.
MDM 2023: 148-157

Datasets

- GeoLife
  - Collected by Microsoft Research Asia from 182 users
- PeopleFlow
  - Tokyo Metropolitan Area
  - Transportation mode for each visit is available

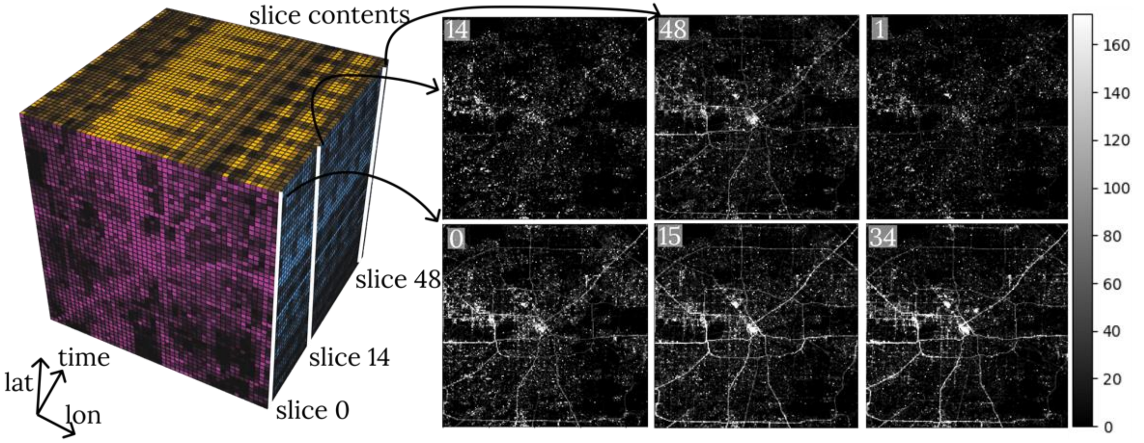
Characteristics	GeoLife	PeopleFlow
Number of Trajectories	2756	6183
Period	1 year (2008)	1 year (2008)
Visit Interval	every 15 minutes	every 15 minutes
Average Speed (km/h)	5.324±5.744	13.592±8.303
Average Accumulated Distance (km)	8.401±9.340	27.662±26.494
Average Distinct Visits	7.713±4.558	7.123±3.895



PeopleFlow has more diverse speeds due to mix-modalities

Evaluation Metrics

- Geographical density-based statistics
  - Probability of visiting location r, probability of visiting location r at time t
- Individual trajectory-level statistics
  - Distance traveled P(d), number of distinct visits P(v)



$$JSD(P_{re}||P_{gen}) = H(\frac{P_{re} + P_{gen}}{2}) - \frac{H(P_{re}) + H(P_{gen})}{2}$$

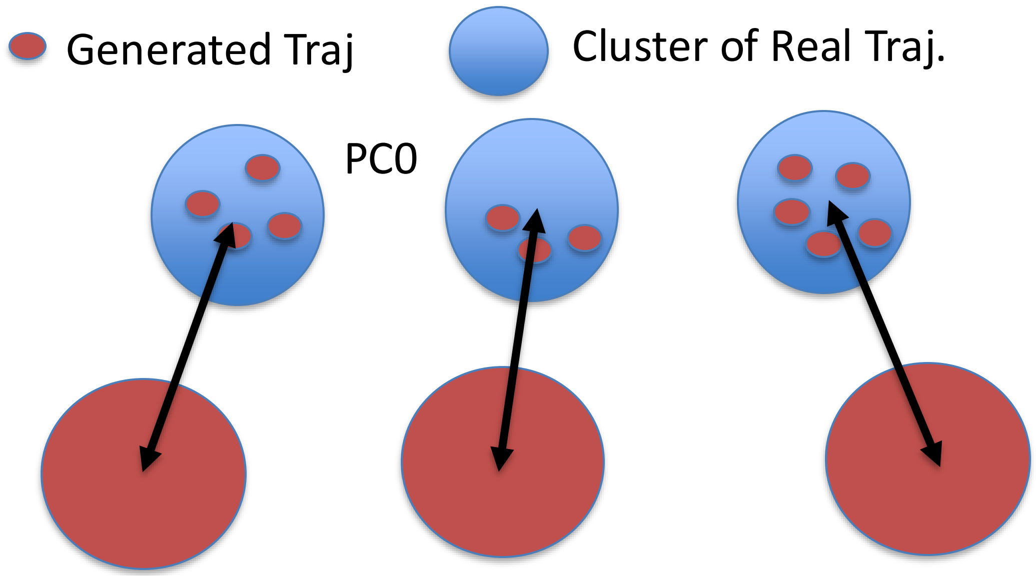
Jensen-Shannon Divergence (JSD) between the probability distribution of the real trajectories and the generated trajectories for each distribution.

Our Newly Proposed Evaluation Metrics

- Transition statistics
  - Probability of transitioning from location r_1 to r_2
- Modality level statistics
  - PC0: The proportion of trajectories within the correct cluster (clustering based on centroids of real trajectories)
  - **PC1:** Clustering separately (for both real and generated trajectories) and performing centroid matching and JSD of the two distributions is reported.
  - **C:** Given the vector of k centroids from real trajectories and generated trajectories, we compute the minimum total pair-wise distance among all permutations (closest match). The lower the value, the better the generated trajectories preserve the modality representatives.

Frobenius norm of the difference between the two transition matrices

$$||P_r - P_g||_F = \sqrt{\sum_{r_1=1}^{Q} \sum_{r_2=1}^{Q} |P_r(r_1, r_2) - P_g(r_1, r_2)|^2}$$



SeqGAN on each cluster

Learning Global Patterns: More realistic trajectories, per traditional metrics

Much better transition (e.g., walking vs driving)

More diverse & representative trajectories

TABLE II: Global comparison with baselines on GeoLife and PeopleFlow data with different clustering techniques. The table shows the average statistics of 5 experiments. The best performance is in boldface. The second-best is underlined.

	GeoLife							
	Geographical density-based statistics		Individual trajectory level statistics		Transition statistics	Modality level statistics		
Methods	P(r)	P(r,t)	P(d)	P(v)	P(r1, r2)	$P(c_i^0)$	$P(c_i^1)$	C
SeqGAN-S	0.407	0.478	0.208	0.288	0.100	0.162	0.220	18.682
Cluster-wise SeqGAN-S	0.506	0.562	0.313	**0.234**	0.082	0.402	0.298	83.441
Movesim-S	0.522	0.579	0.263	0.390	0.116	0.303	0.209	**7.934**
CSGAN-S	**0.319**	**0.439**	**0.195**	0.258	**0.047**	**0.147**	**0.058**	17.128

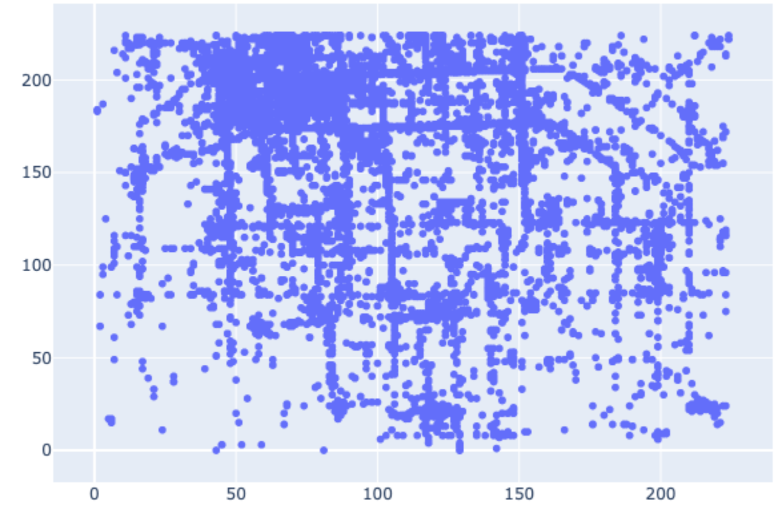
	PeopleFlow							
SeqGAN-S	0.378	0.437	0.368	0.275	0.092	0.406	0.167	29.694
Cluster-wise SeqGAN-S	0.344	0.406	0.363	0.317	0.105	0.311	0.194	31.046
Movesim-S	0.344	0.396	0.524	0.602	0.100	0.289	0.151	23.420
CSGAN-S	**0.284**	**0.376**	**0.218**	**0.215**	**0.050**	**0.146**	**0.070**	**13.136**

Cluster SeqGAN: Not enough data per cluster to learn global mobility patterns. It outperforms SeqGAN with PeopleFlow bc the modality is more diverse (vs GeoLife) and hence it is more important to learn modality-specific patterns within each cluster.

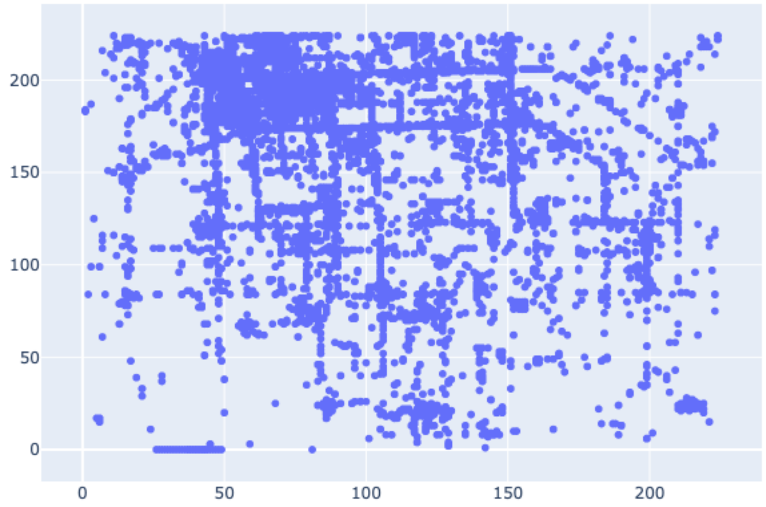
Discriminator's Spatial & temporal regularities check

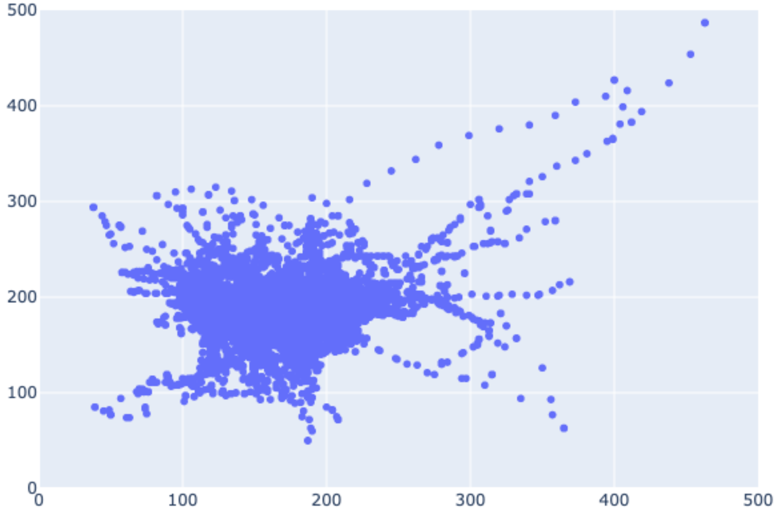
Density

Real (GeoLife)

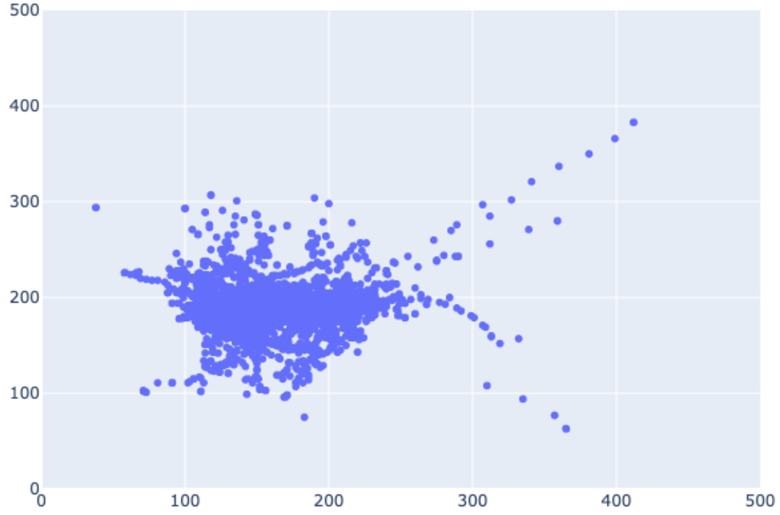


CSGAN (GeoLife)





Real (PeopleFlow)



CSGAN (PeopleFlow)

The population density --
The aggregate density from 6:00 am to 8:00 pm

OUTLINE

- Mobility Behavior Clustering
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Motivation

Mobility behavior: the travel activity that describes a user's movements, e.g., work commute, shopping, school commute, dining

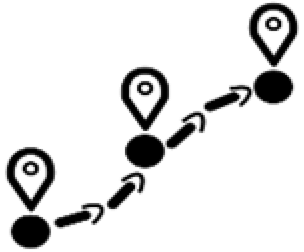
Mobility Behavior

- COVID 19
- User Profiling
- Recommendations
- Ads targeting
- Insurance
- Threats Detection

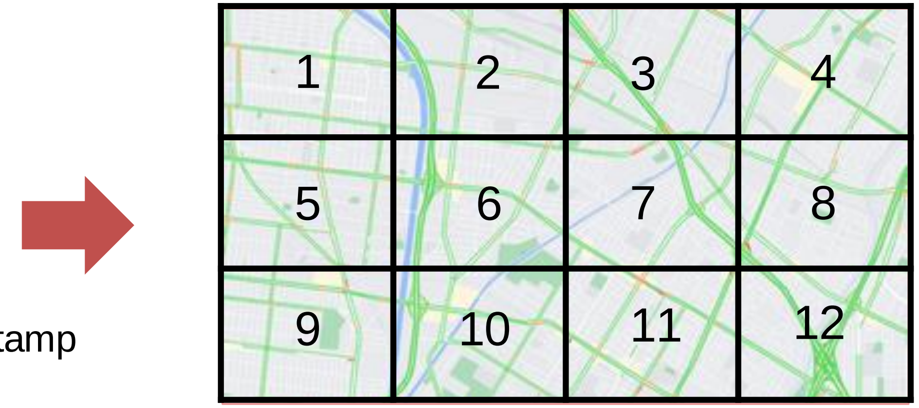
Mingxuan Yue, Yaguang Li, Haoze Yang, Ritesh Ahuja, Yao-Yi Chiang, Cyrus Shahabi: DETECT: Deep Trajectory Clustering for Mobility-Behavior Analysis. IEEE BigData 2019: 988-997

Context Trajectory

- Discretizing mobility trajectory
  by grid/time Partition



Latitude, longitude, timestamp



Mobility Trajectory

[1 , 3 , 7, 8 , 8]

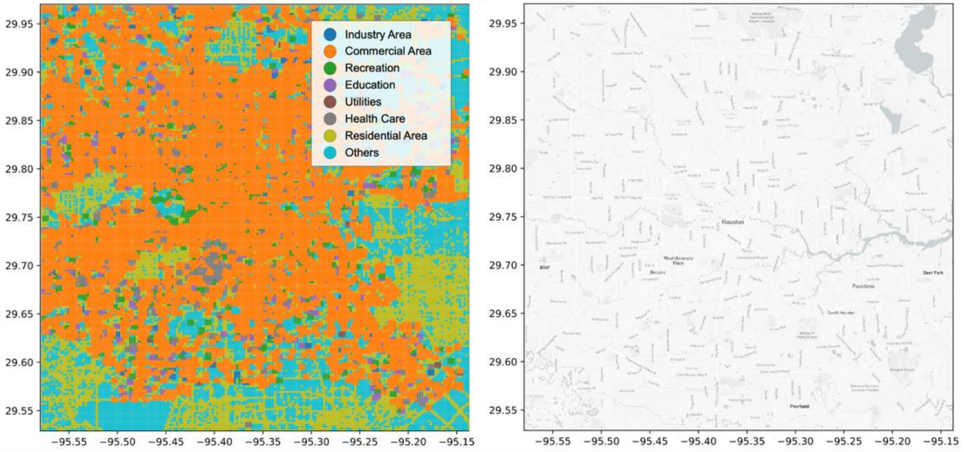
Context Trajectory

- Augment location with context

  - Decide by the number of Point of Interests (POIs)

  - Industry, Commercial Area, Entertainment, Education Services, Utilities, Health Care, Residential Areas, and Others

- Similar Moving Behavior has similar context



(a) The Context Type of Each Location Grid in Houston

(b) The Raw Map of Houston

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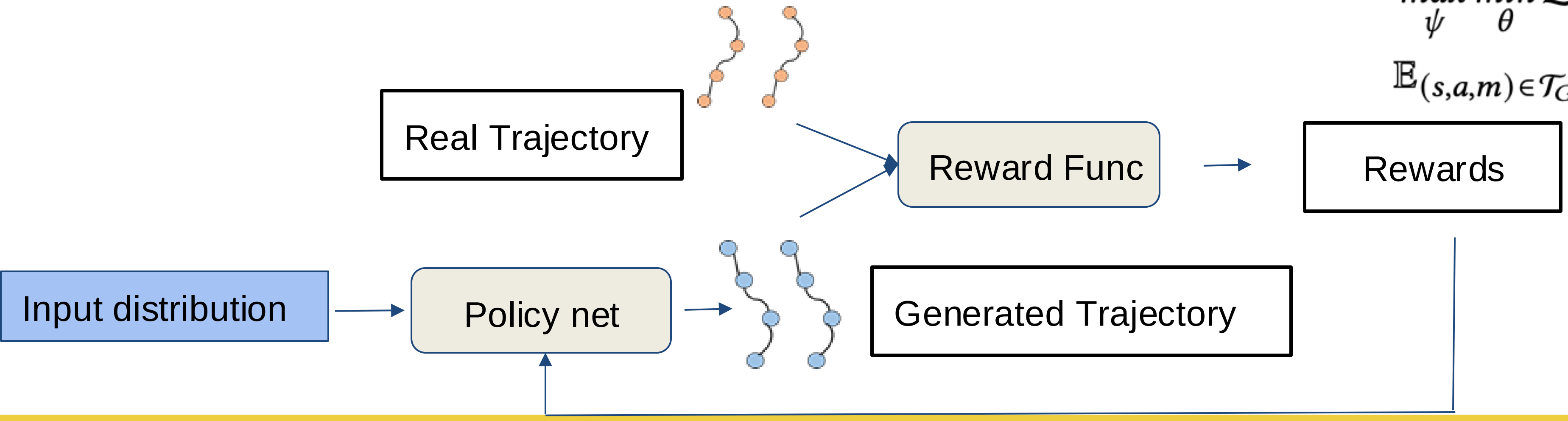
Preliminaries & Overview

Problem : Given a set of real-world trajectories and their moving behavior labels, how to generate synthetic trajectories while retaining moving behavior properties

GAIL : Generative Adversarial Imitation Learning

- Goal : modeling human agent decision-making process from real-data
  - policy: the underlying strategy to generate the trajectory
  - reward: ways to evaluate the generated trajectory

$$\max_{\psi} \min_{\theta} \mathcal{L}(\theta, \psi) = \mathbb{E}_{(s,a,m)\in\mathcal{T}_E} \log \mathcal{D}_{\psi}(s, a, m) + \mathbb{E}_{(s,a,m)\in\mathcal{T}_G} \log(1 - \mathcal{D}_{\psi}(s, a, m)) - \beta H(\pi_{\theta})$$

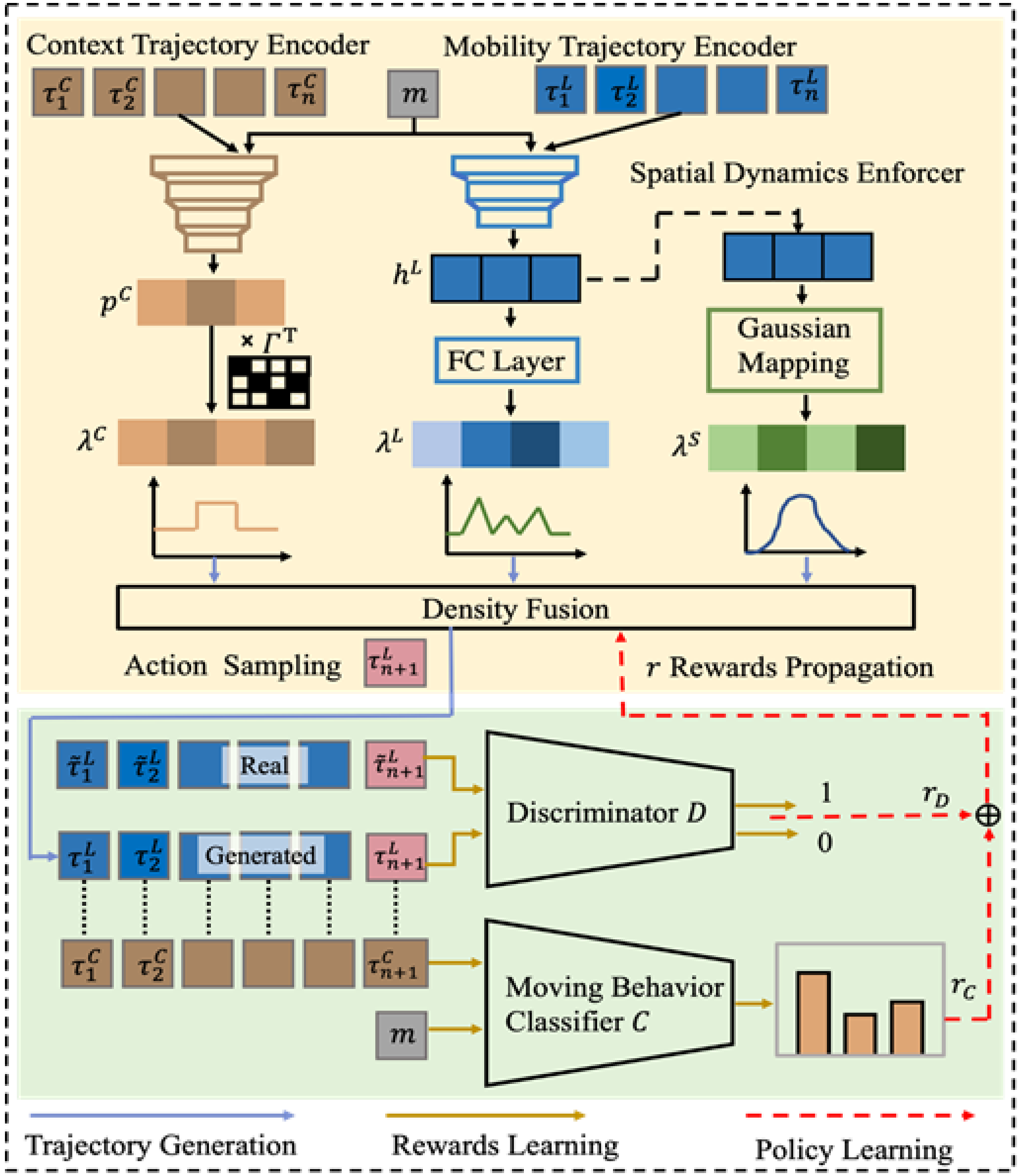


Preliminaries & Overview

Problem : Given a set of real-world trajectories and their moving behavior labels, how to generate synthetic trajectories while retaining moving behavior properties

- State: the history of the generated trajectory until the last step
- Action: which location to go next
- State transition: update the mobility trajectory with the chosen location
- Policy network: characterizes how to choose the following action, given the moving behavior
- Reward: evaluate the decision of chosen action based on the current state

MBP-GAIL Framework



MBP-GAIL Framework

Context Trajectory Encoder:

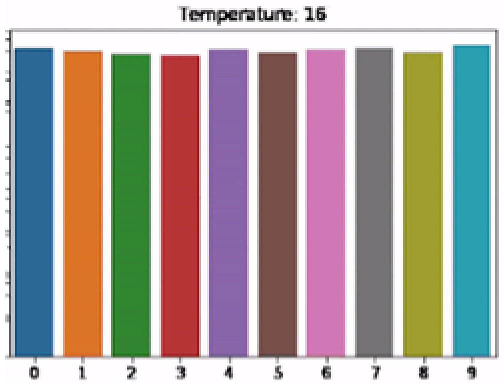
$$p_i^C = Softmax(\phi(W_h^C \times h_i^C + b_h^C), \gamma)$$

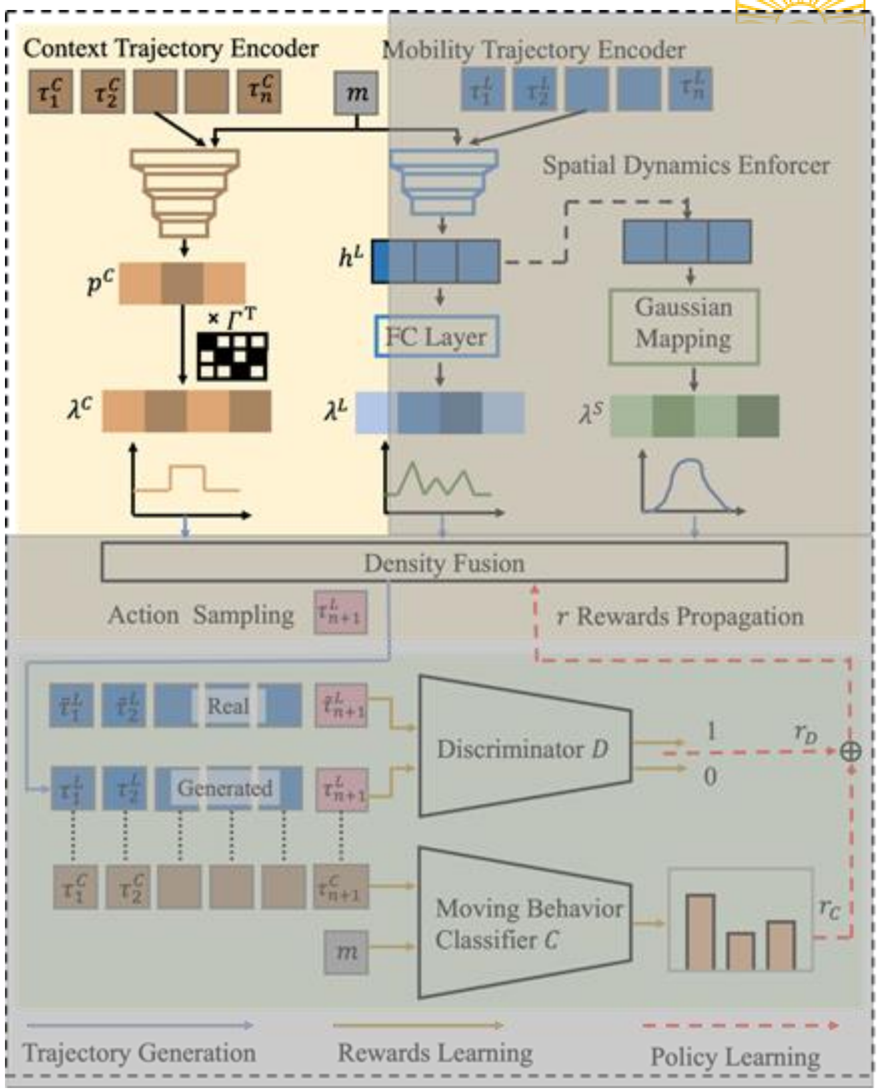
predict the next context type based on the history with temperature γ

Map to each location

$$\lambda_i^C = \Gamma^\intercal \times p_i^C$$

As we set the temperature higher, the context has less influence on our final generation

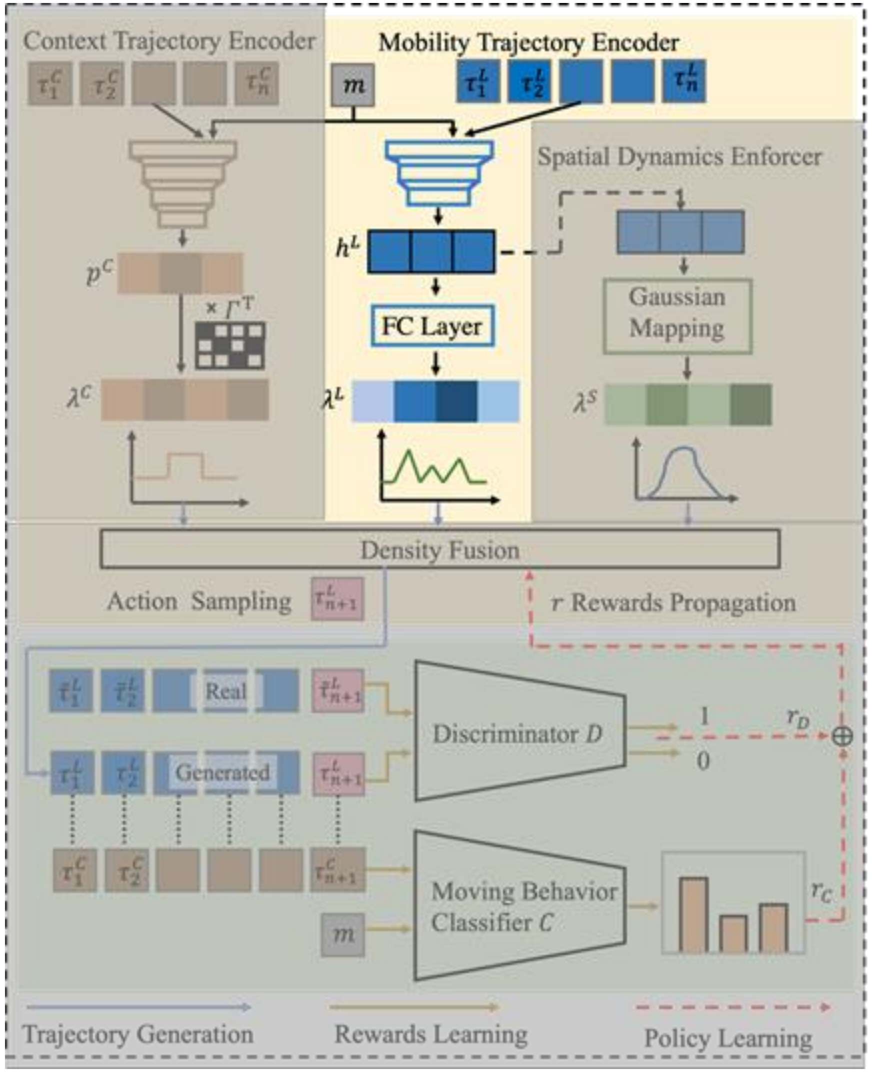




MBP-GAIL Framework

Mobility Trajectory Encoder:

predict the next location based on the history



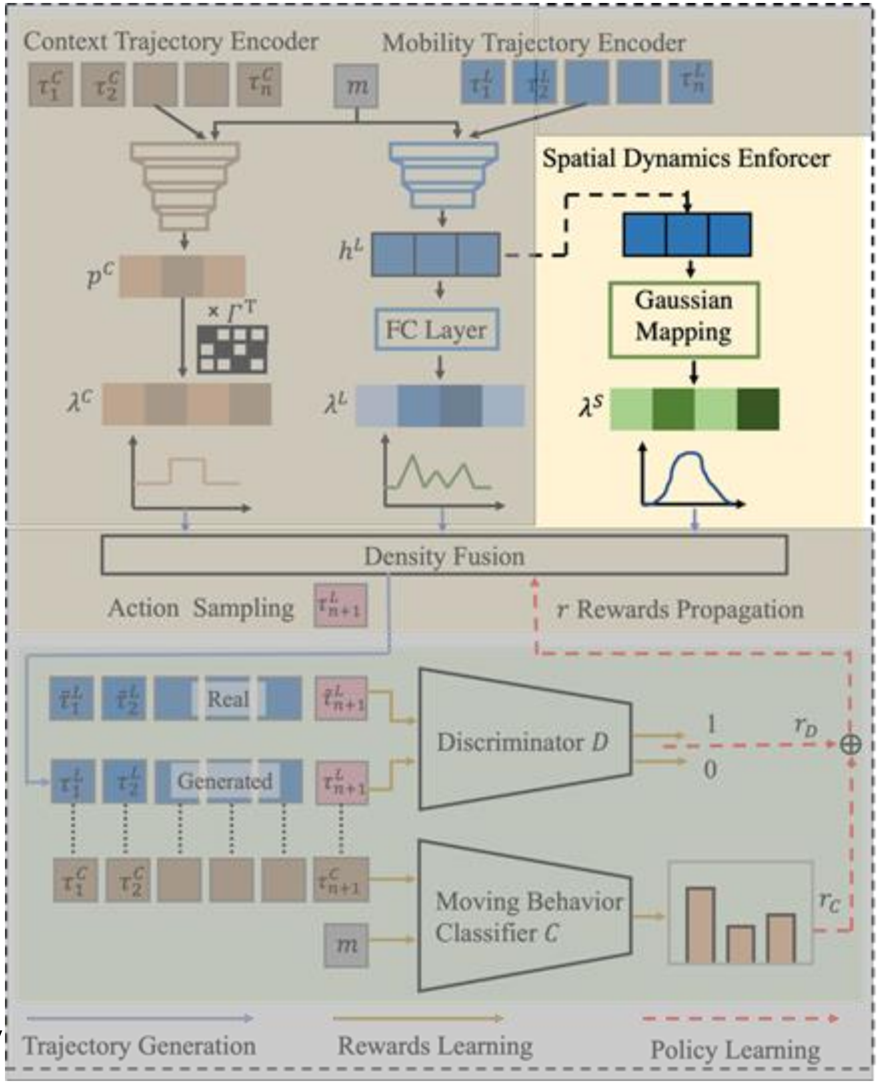
MBP-GAIL Framework

Spatial dynamic enforcer $\lambda_i^S = exp(-\frac{(\Delta \times OneHot(l_i))^2}{(\alpha\sigma_i^S)^2})$

trajectory should be physically feasible

Higher probability

Lower probability

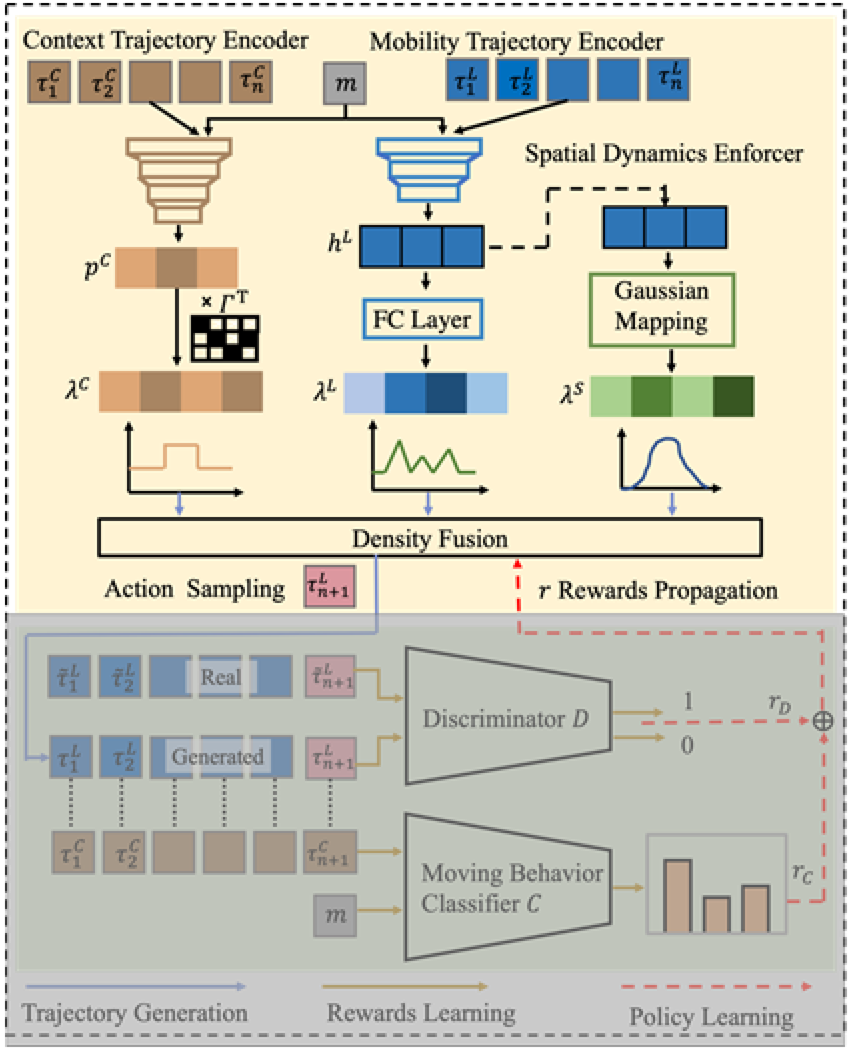


✗ fixed constraint due to variety transportation mode

MBP-GAIL Framework

Fusion

element wise multiplication



MBP-GAIL Framework

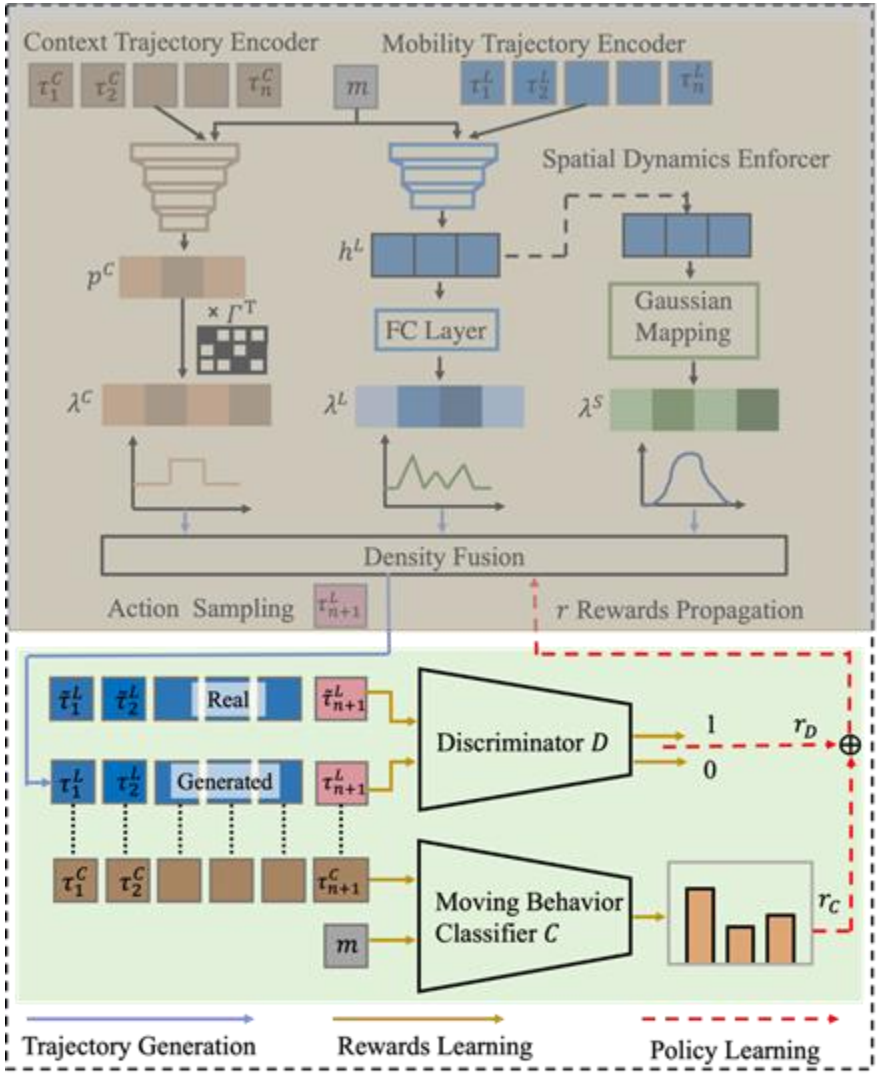
a discriminator differentiates real/fake trajectory

a classifier evaluates moving behavior pattern

$$r = (1 - v) * r_C + v * r_D$$

Reward from moving behavior

Reward from discriminator



Experimental Evaluation

Much better in distance-related metrics due to spatial dynamic enforcer

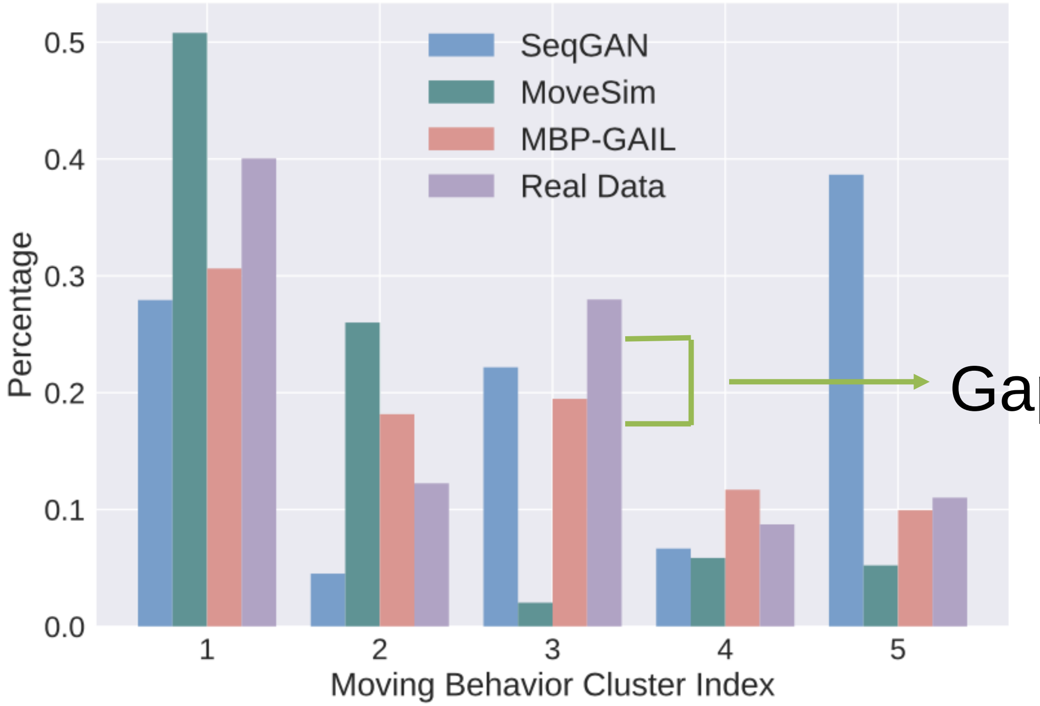
Much better transition due to context clustering modeling

	Houston					Los Angeles				
	Distance	Radius	Duration	$P(r)$	$P(r_1, r_2)$	Distance	Radius	Duration	$P(r)$	$P(r_1, r_2)$
Markov Model	0.5098	0.5032	0.4428	0.0028	0.3280	0.4086	0.4122	0.4332	0.0046	0.3073
LSTM	0.4865	0.4050	0.3748	**0.0023**	0.0881	0.3855	0.3050	0.3830	0.0032	0.1044
TransVAE	0.4662	0.3942	0.3276	0.0034	0.1537	0.3872	0.3443	0.3539	0.0042	0.1462
SeqGAN	0.3318	0.2908	0.2160	0.0074	0.1055	0.2948	0.1913	<u>0.1490</u>	0.0025	<u>0.0910</u>
MoveSim	<u>0.2413</u>	<u>0.2402</u>	<u>0.1520</u>	0.0025	<u>0.0924</u>	<u>0.0922</u>	**0.1274**	0.1617	**0.0021**	0.0932
MBP-GAIL	**0.0744**	**0.1215**	**0.1311**	<u>0.0024</u>	**0.0874**	**0.0667**	<u>0.1305</u>	**0.1452**	<u>0.0023</u>	**0.0891**

- For realistic evaluation (utility compared with original trajectory), MBP-GAIL outperforms almost all the JSD metrics evaluation, especially for the distance over the best baseline.

Experimental Evaluation

- **RQ2:** Can MBP-GAIL preserve the moving behavior patterns in its generation?
  - Compare with movesim / seqggan which also knows the moving behavior information
  - Clustering on the generated context trajectories
  - Closer to the real-world data distribution, the better



Gap is small

MBP-GAIL preserves the mobility trajectory patterns and achieves the lowest gap compared with real-data

Thank you!