ICLR

TRIDENT: Cross-Domain Trajectory Spatio-Temporal Representation via Distance-Preserving Triplet Learning

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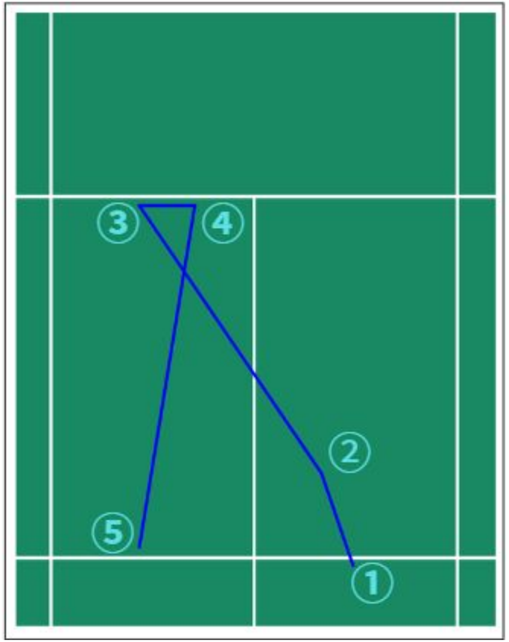
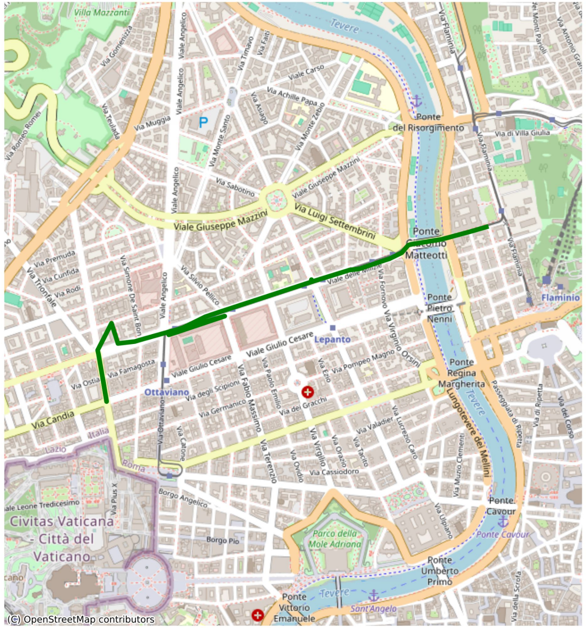
Unified Trajectory Representation Framework

From **Badminton Movement**



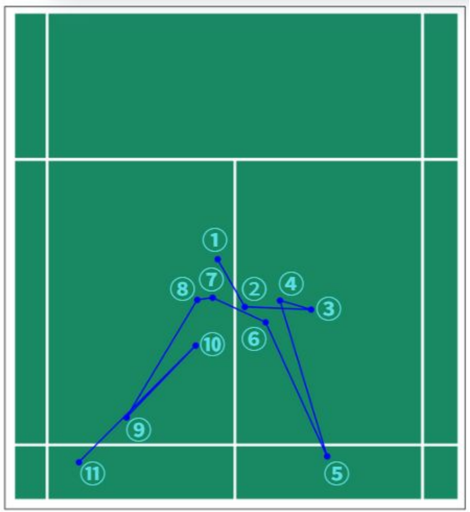
To **Urban Mobility**



Discrete vs Continuous Trajectories Characteristics

Discrete Trajectories

Badminton Movement



High tortuosity vs Low tortuosity

Event-triggered vs Ongoing

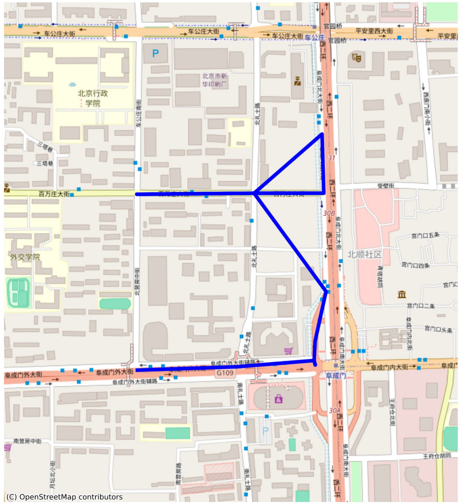
Reset-oriented vs No Reset

Episodic temporal vs Constantly adjusted

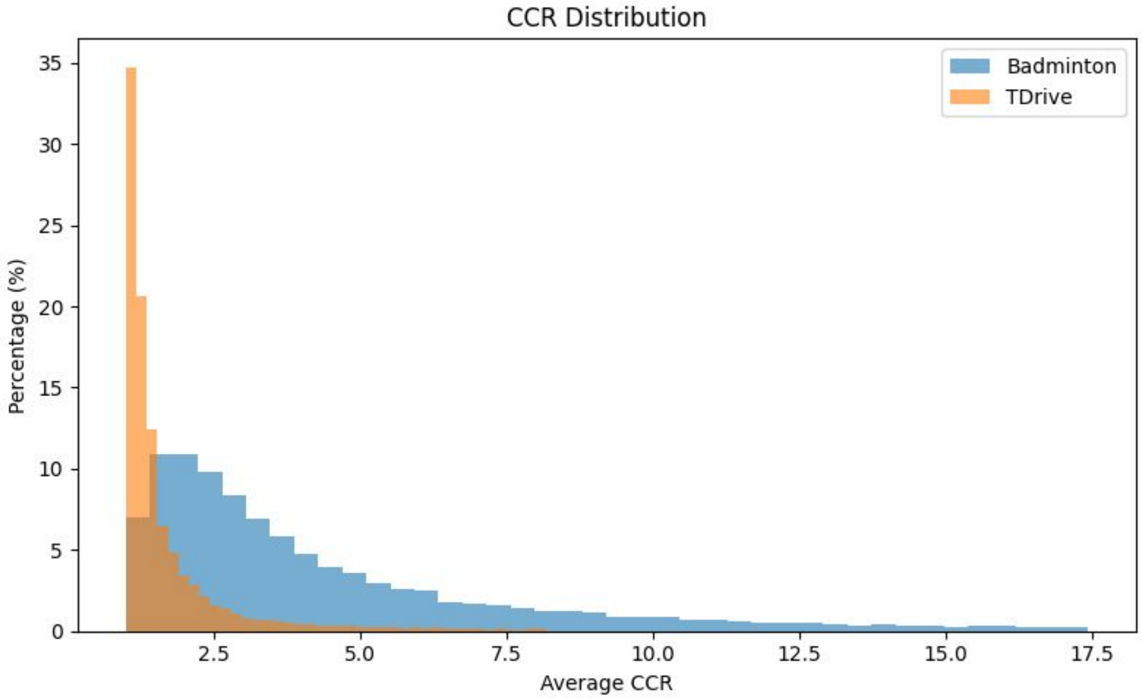
No spatial topology vs Spatial topology

Continuous Trajectories

Urban Mobility



Discrete vs Continuous Trajectories Tortuosity



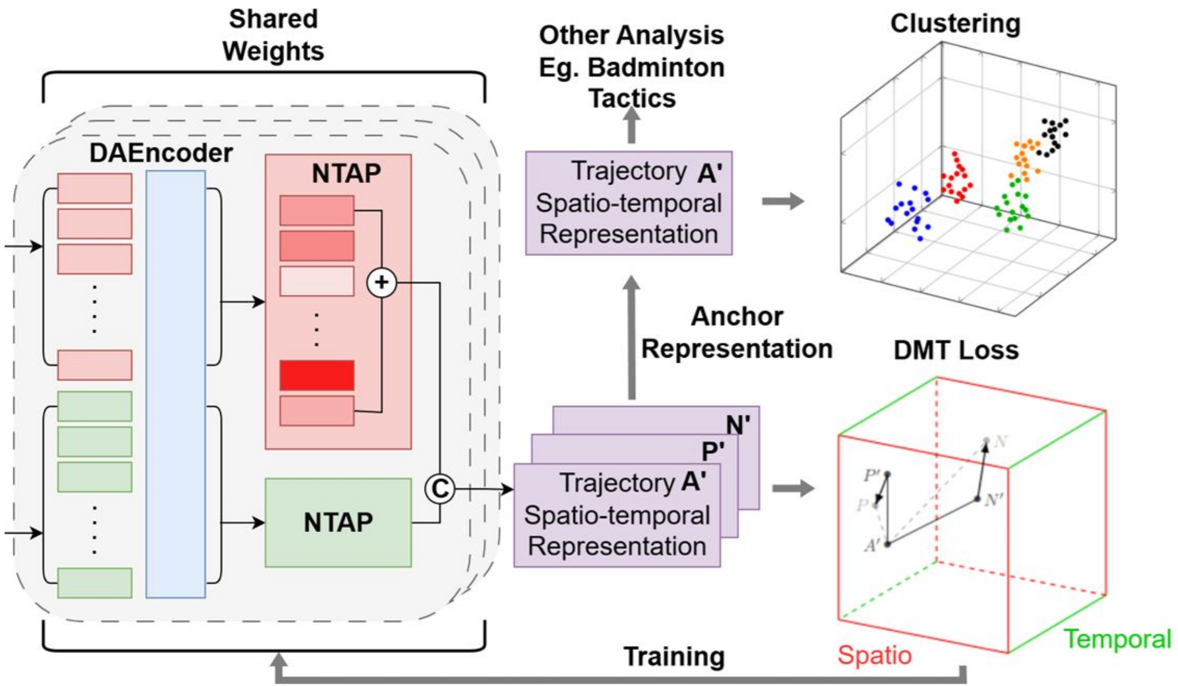
$$Average\ CCR = \frac{1}{N}\sum_{i=1}^{N}\frac{L_i}{D_i}$$

Adapted from, **Sliding Performance Evaluation with Machine Learning-Based Trajectory Analysis for Skeleton**, Yu et al, 2025

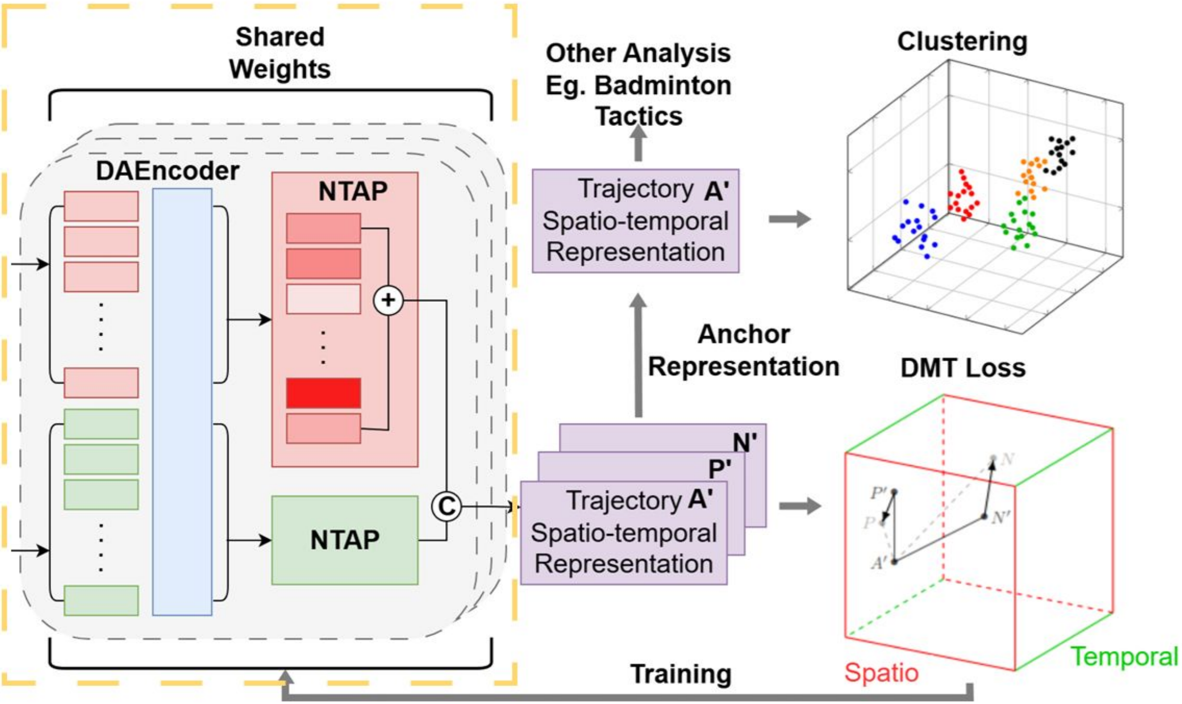
- Badminton dataset overall high tortuosity, high average CCR.
- T-Drive dataset overall low tortuosity, low average CCR.

TRIplet-based Distance-preserving Embedding Network for Trajectories (TRIDENT)

Why TRIDENT?

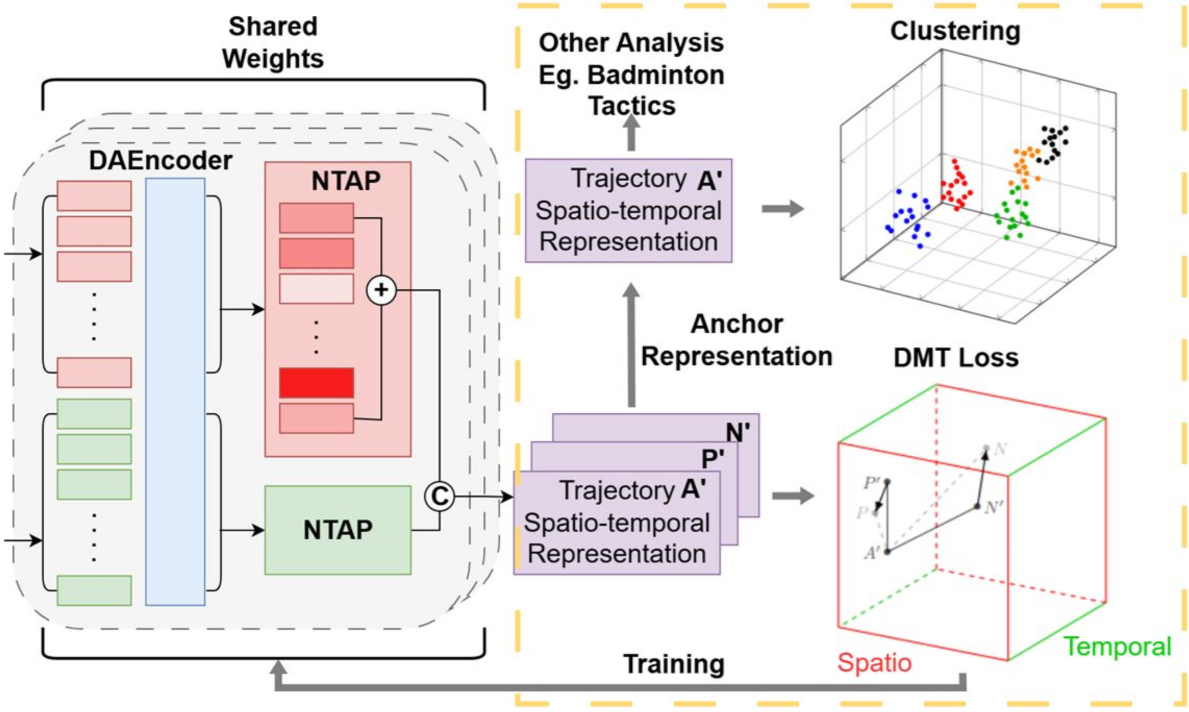


TRIplet-based Distance-preserving Embedding Network for Trajectories (TRIDENT)

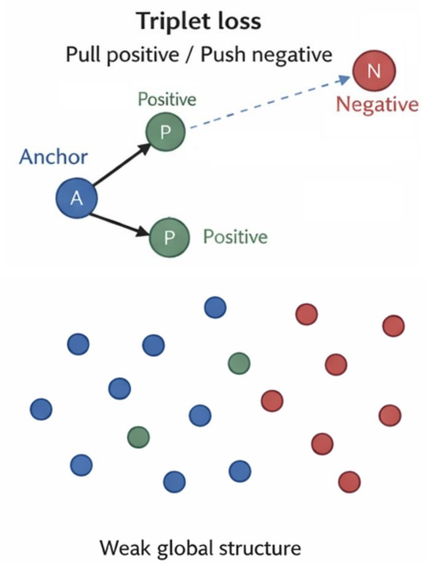


- Fuse spatial/temporal information with dual attention and handle discrete/continuous trajectories via NTAP.

TRIplet-based Distance-preserving Embedding Network for Trajectories (TRIDENT)

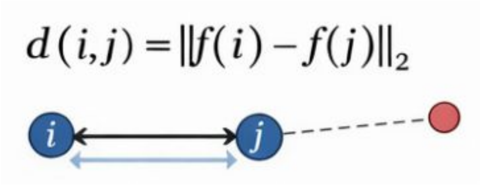


- Geometry preserving representation via DMT Loss, prevents classic triplet loss limitations on trajectories. Which enables better clustering and retrieval results.

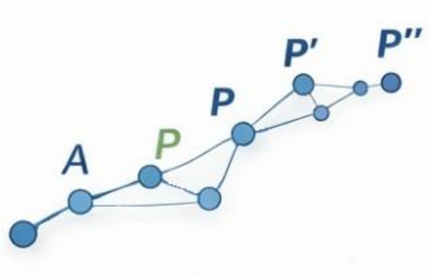


TRIDENT: Training Strategy with DMT Loss

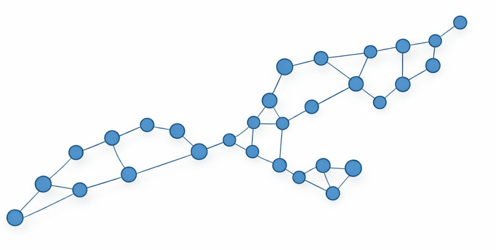
Align embedding-space distances with native trajectory-space distances to preserve representation distances.



Chain of Positive reused as Anchor with small σ Gaussian kernels to **define local relations**.

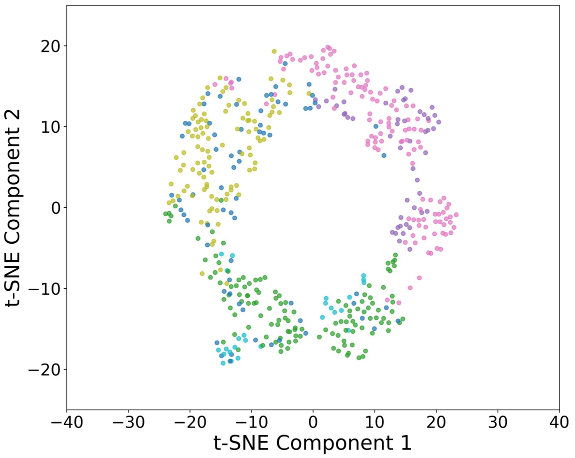


Diverse multiple Negatives with large σ Gaussian kernels to **explore global structure**.

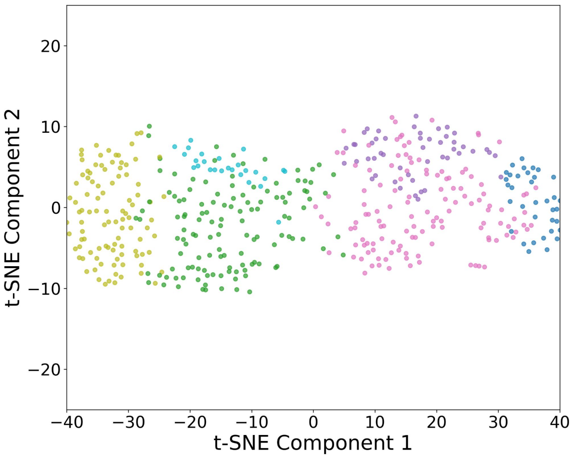


TRIDENT Learning Process (Badminton)

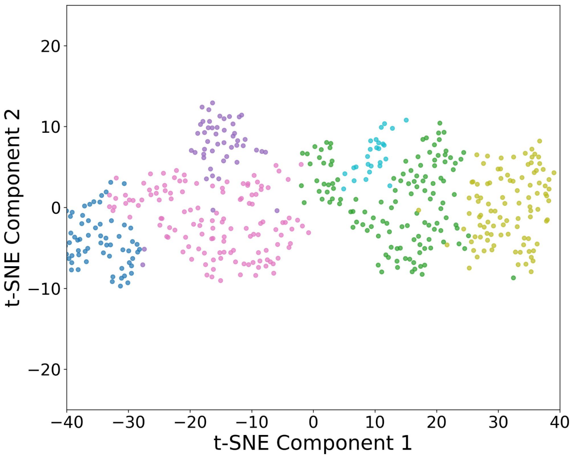
Initial Stage



Middle Stage

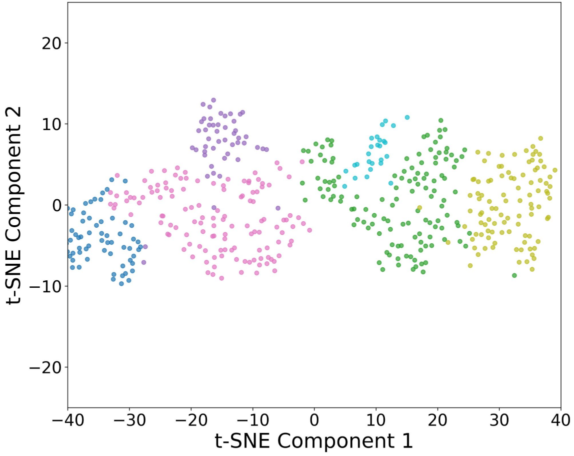


Convergent
Stage

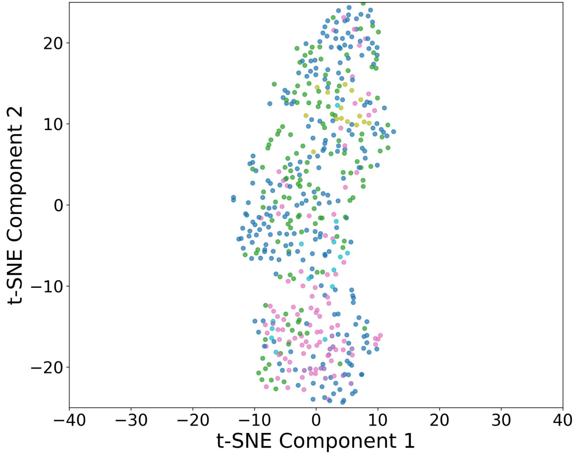


Representation Structure Comparisons (Badminton)

TRIDENT

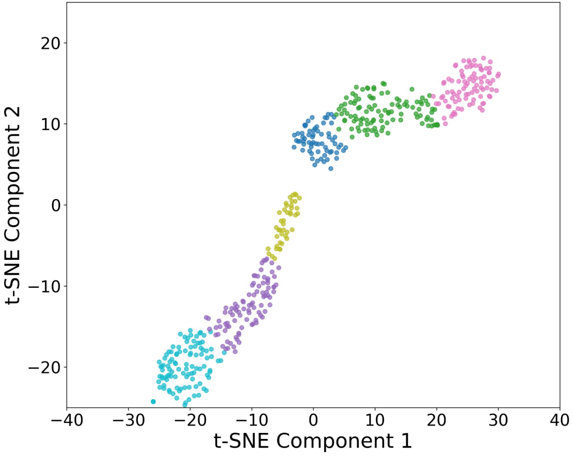


TrajCL



- **Mixed single mass**

ST2Vec



- **Poor inter-class separation**
- **Dense structure**

Representation Quality (Dist. to Ground Truth Medoids)

Model	Head@100	Median	Tail@100
ST2Vec	2337.8393 +- 321.7158	4472.35 +- 782.2841	9580.4514 +- 1017.76
E2DTC	3922.62 +- 417.9006	4690.325 +- 665.6507	8439.8795 +- 1334.2951
TrajCL	7002.83 +- 583.4479	7024.12 +- 570.1261	11877.985 +- 1044.7291
ConDTC	3672.0796 +- 20.2265	5122.15 +- 18.1173	10076.2385 +- 938.8144
START	4269.3658 +- 819.347	5778.7328 +- 1088.5665	10966.9708 +- 974.3519
TRIDENT	**1462.4336 +- 41.1869**	**3549.8059 +- 218.4169**	**7454.2774 +- 208.4266**

Representation Quality (Retrieval)

Framework	Badminton			T-Drive			Rome		
	HR@10	HR@50	R10@50	HR@10	HR@50	R10@50	HR@10	HR@50	R10@50
NeuTraj (ICDE)	0.009	0.036	0.041	0.177	0.222	0.270	0.123	0.217	0.261
ST2Vec (KDD)	0.073	0.178	0.212	0.496	0.593	0.844	0.479	0.598	0.830
TrajCL (ICDE)	0.084	0.243	0.197	0.241	0.369	0.359	0.094	0.293	0.260
ConDTC (IEEE)	0.009	0.021	0.047	0.139	0.348	0.343	0.091	0.279	0.323
Our method	**0.190**	**0.347**	**0.484**	**0.564**	**0.661**	**0.916**	**0.535**	**0.664**	**0.913**

TRIDENT exceeds the mean of all baselines by **271%** on Badminton, **96%** onT-Drive, and **127%** on Rome.

Conclusion

Remarks

- TRIDENT shows strong performance on badminton singles and single urban taxi data.
- TRIDENT preserves trajectory geometry in the embedding space, improving cluster separation.

Limitation & Future work

- Extend TRIDENT to more interactions multi-agent trajectories.
- Improve cluster structure automatically and hierarchically.