Graph Neural Network-based Clustering Enhancement in VANET for Cooperative Driving

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Outline

- Motivation and Background
- GNN-based Clustering Algorithm
- Evaluation Results
- Conclusions and Future Works

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Motivation and Background

- VANET clustering benefits [1]
  - Transportation network: traffic capacity, safety, and cooperative driving enhancement
  - Air Environment: fuel efficiency improvement and exhaust emissions reduction

Platooning improves traffic capacity, fuel economy, and safety

Cooperative driving facilitates safety in autonomous driving

[1] D. Jia, K. Lu, J. Wang, X. Zhang, and X. Shen, “A Survey on Platoon-Based Vehicular Cyber-Physical Systems,” IEEE Communications Surveys & Tutorials, 18(1), 2016, pp.263-284.

Challenges of VANET Clustering

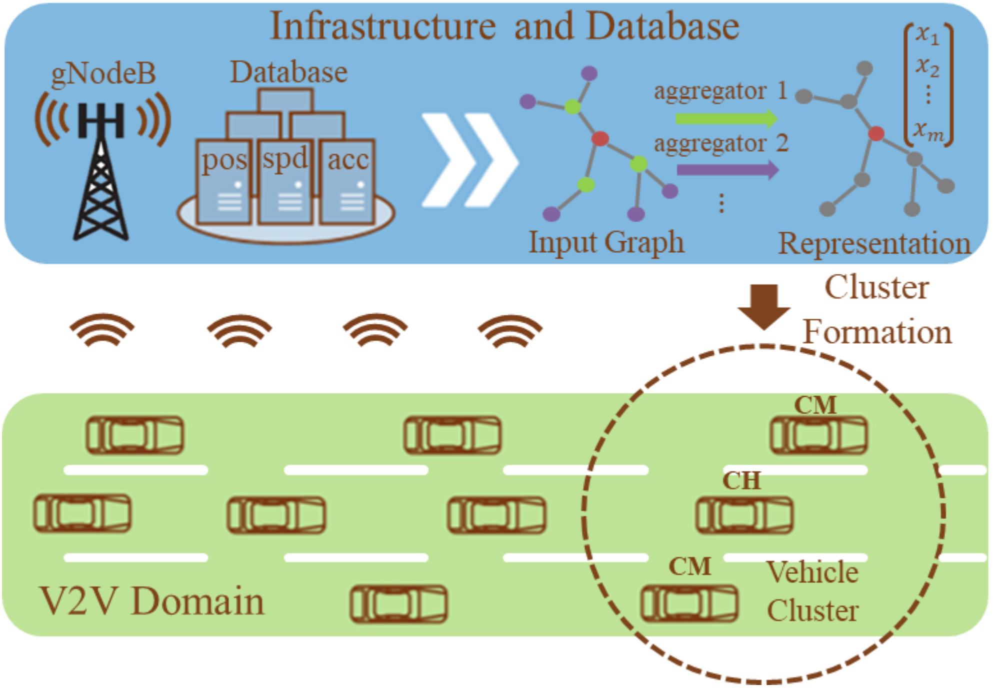
- State-of-the-art VANET clustering Algorithms
  - Distributed clustering approaches
    - High control message overhead
    - Manually select hyperparameters
    - Not intelligent and learnable
  - Machine learning-based clustering approaches
    - Leverage only a single feature
    - Not learnable

Clustering Algorithm	Weight-based Clustering [1]	ML-based Clustering [2]	GNN-based Clustering
Formation Strategy	Distributed	Centralized	Centralized
Complexity	High	Low	Low
Information Utilization	Node Feature	Node or Graph Feature	Node and Graph Feature
Learnability	No	No	Yes

[1] A. Bello Tambawal, et al., "Enhanced weight-based clustering algorithm to provide reliable delivery for VANET safety applications," PloS one, 14(4), 2019, e0214664.
[2] G. Liu, et al., "Enhancing clustering stability in VANET: A spectral clustering based approach. China Communications," 17(4), 2020, pp. 140-151.

Goal and Proposal Summary

- Goal: enhance the vehicle system's stability and optimize the average lifetime of all clusters
- Why we choose GNN
  - Fits naturally to solve clustering type of graph problem
  - Uses both node feature and graph information
  - Centralized approach and offloads the computation to BS
  - It's the very first attempt to apply GNN to solve the clustering problem in VANET



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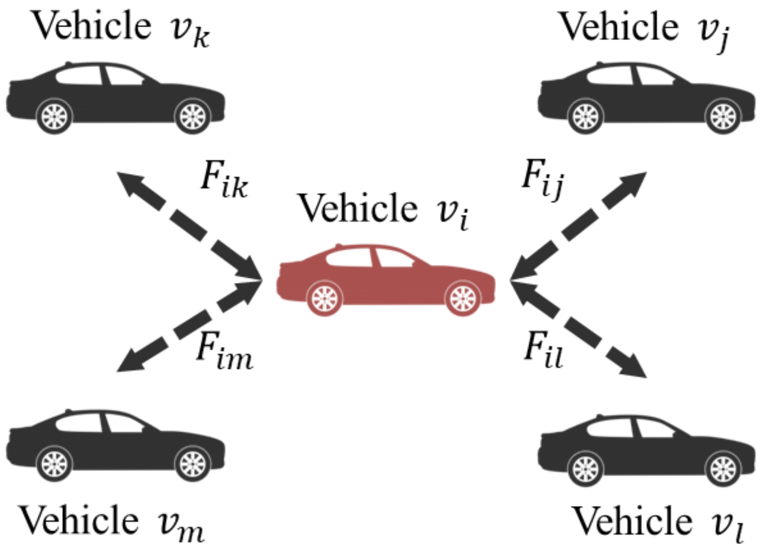
Graph Construction

- Graph is modeled by force-directed algorithm [1]
  - Relative force among vehicle interconnection weighs the similarity between the movement patterns of 2 vehicles
  - The greater the positive forces among nodes are, the more similar the moving pattern is



$$F_{ijx} = k_{ijx}\frac{q_i q_j}{D_{ij}^2}; F_{ijy} = k_{ijy}\frac{q_i q_j}{D_{ij}^2} \quad (1)$$

$$D_{ijx}(t) = x_i - x_j; D_{ijx}(t+dt) = x_i + dx_i - x_j - dx_j \quad (2)$$

$$D_{ijy}(t) = y_i - y_j; D_{ijy}(t+dt) = y_i + dy_i - y_j - dy_j \quad (3)$$

$$k_{ijx} = \frac{1}{1 + |D_{ijx}(t+dt) - D_{ijx}(t)|dt} \quad (4)$$

$$k_{ijy} = \frac{1}{1 + |D_{ijy}(t+dt) - D_{ijy}(t)|dt} \quad (5)$$

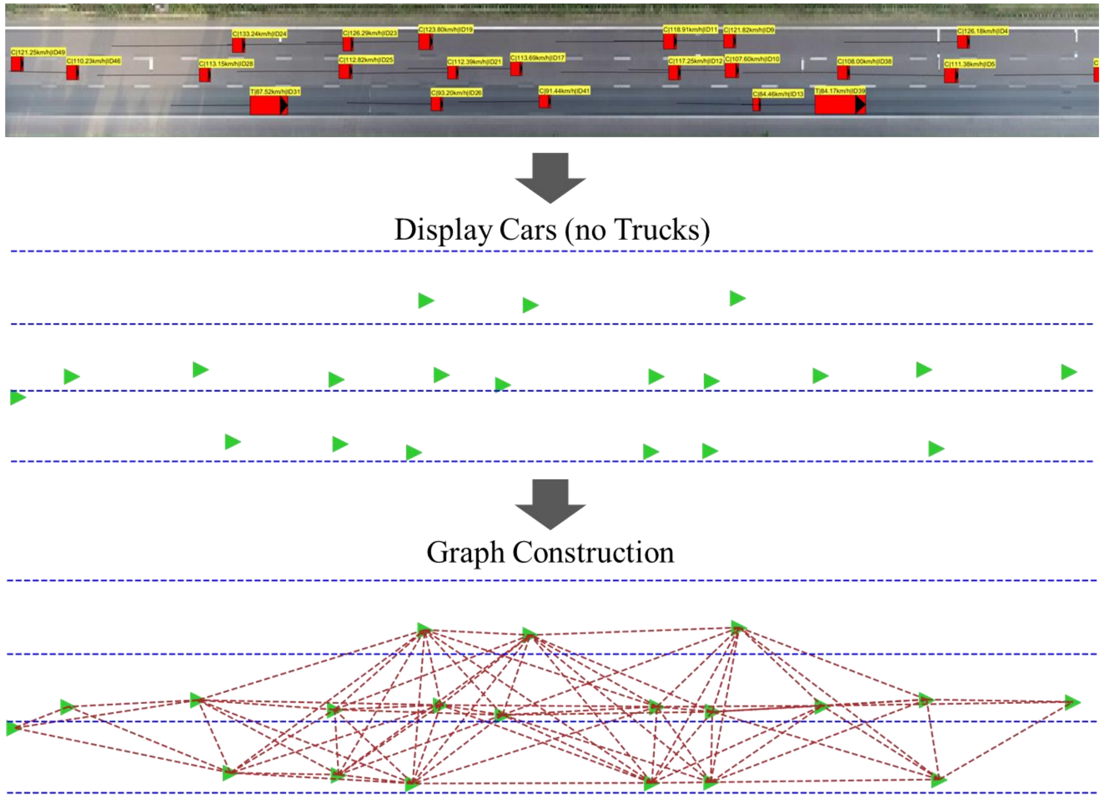
$$q_i = q_j = \begin{cases} R - D_{ijx}(t), & \text{if } D_{ijx}(t) \le D_{ijx}(t+dt) \\ R + D_{ijx}(t), & \text{if } D_{ijx}(t) > D_{ijx}(t+dt) \end{cases} \quad (6)$$

$$||\boldsymbol{F}_{ij}||_2 = \sqrt{F_{ijx}^2 + F_{ijy}^2} \quad (7)$$

[1] L. A. Maglaras, and D. Katsaros, “Distributed clustering in vehicular networks,” IEEE 8th international conference on wireless and mobile computing, networking and communications (WiMob), 2012, pp. 593-599.

Graph Construction Visualization

- Open-source highD traffic dataset [1]
  - Naturalistic vehicle trajectory recordings on German highways
  - Cover about 420 m road segment. The median duration of visible vehicles is13.6s
  - Traffic information includes vehicle trajectory, type, size, etc. The Position error is typically less than 10 cm
- Apply force-directed algorithm to highD dataset to customize our graph dataset

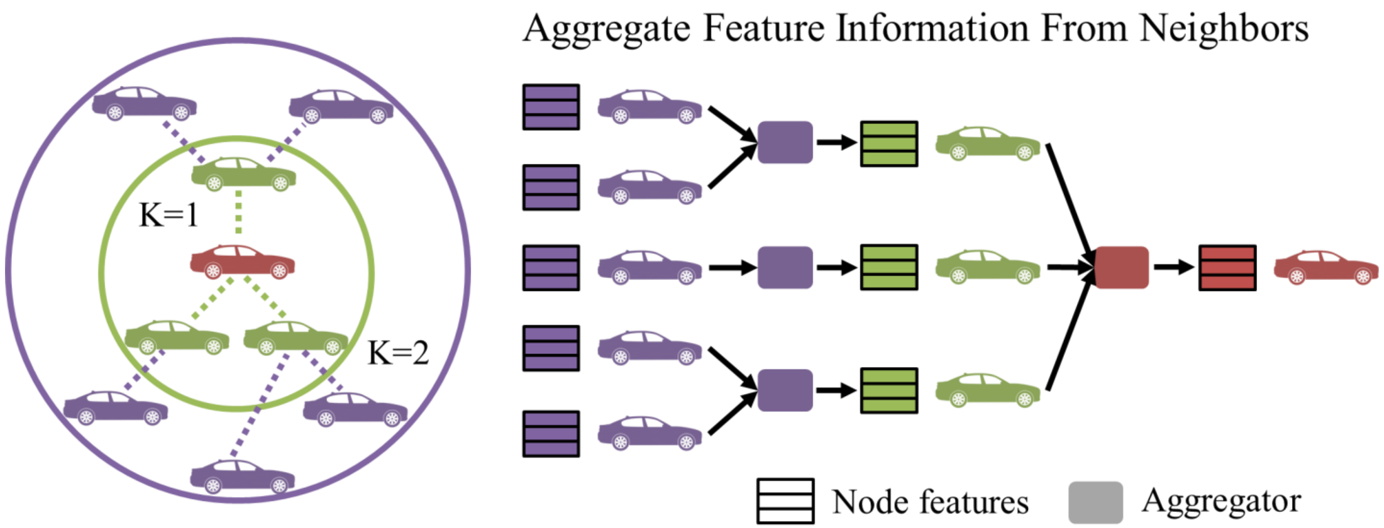


[1] R. Krajewski, et al., “The highd dataset: A drone dataset of naturalistic vehicle trajectories on german highways for validation of highly automated driving systems,” International Conference on Intelligent Transportation Systems (ITSC), 2018, pp. 2118-2125.

Design of GNN Clustering Algorithm

- Spatial-based convolutional graph neural network
  - Input is vehicle feature and graph; output is useful node embedding
  - Apply SAGE convolutional layer [1]
  - Apply Mean aggregator and search depth $K = 2$

$$h_i^k = \sigma\left(W^k \cdot \frac{1}{|N_i|} \sum_{j \in N_i} (h_j^{k-1} \cdot F_{ij})\right)$$



[1] W. L. Hamilton, R. Ying, and J. Leskovec, “Inductive representation learning on large graphs,” In Proceedings of the 31st International Conference on Neural Information Processing Systems, 2017, pp. 1025-1035.

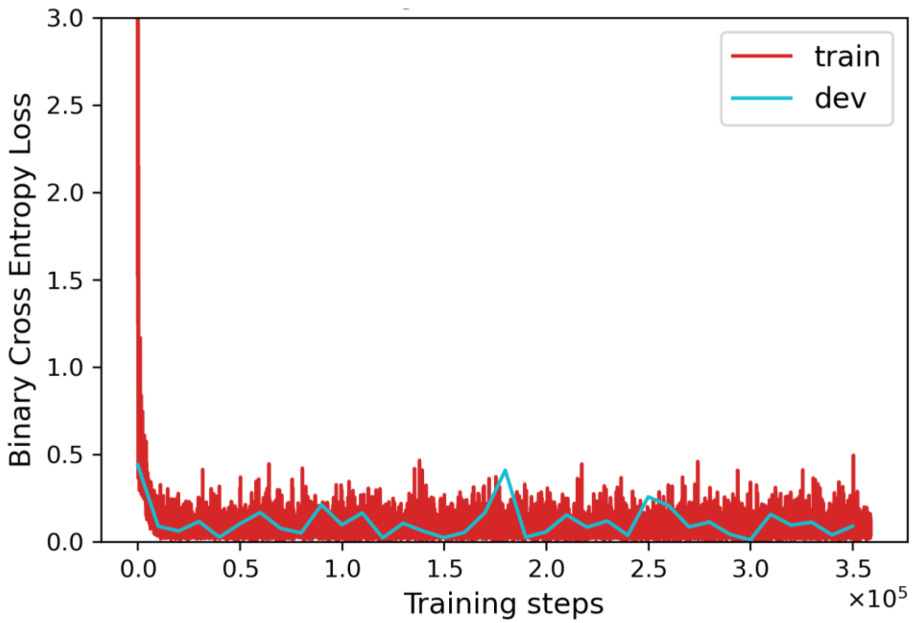
Model Training

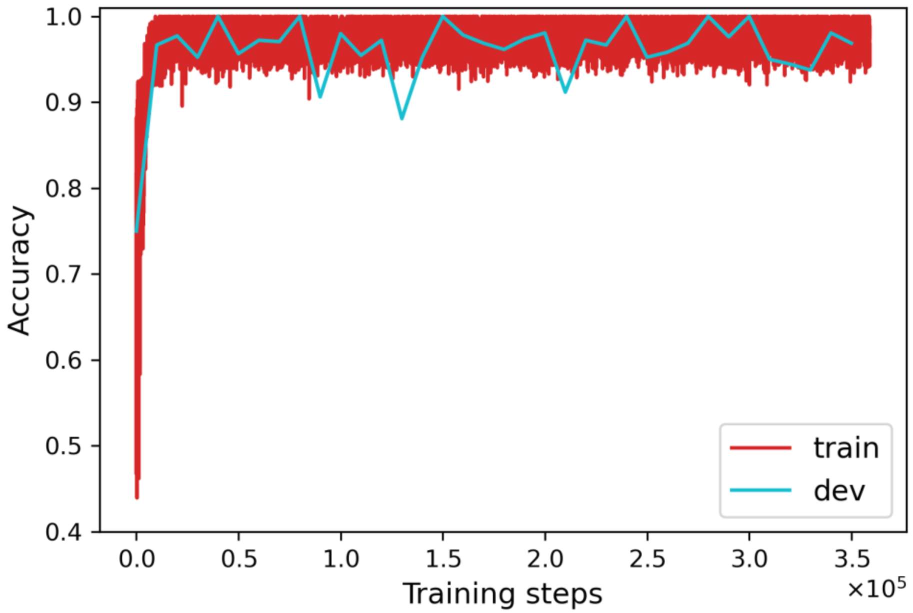
- Graph-based loss function in unsupervised learning
  - Guidance is the edges existent or non-existent
  - Forward propagation
    - Calculate node representations via GNN model
    - Apply node embeddings to compute pairwise probability among nodes
  - Backward propagation
    - Calculate loss and update model parameters via stochastic optimization

$$J_G(z_i) = -\sum_{i,j \in V} \left(y_{ij} \log\left(\hat{y}_{ij}\right) + \left(1 - y_{ij}\right) \log(1 - \hat{y}_{ij})\right)$$

Model Training Results

- 1000 training graphs (train:dev=9:1) and 210 testing graphs





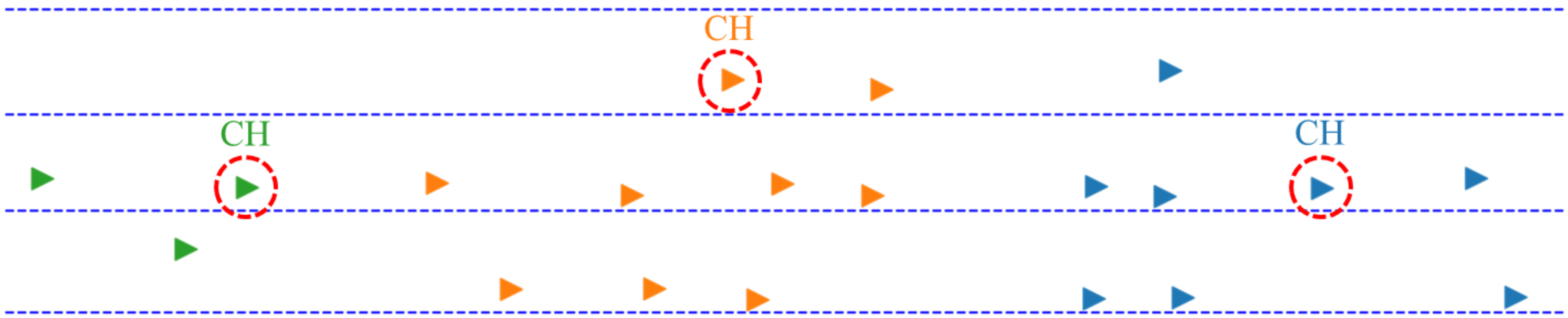
	Training Set	Validation Set	Testing Set
Loss	0.041	0.084	0.063
Acc	0.986	0.969	0.978

*Trained GNN model can learn useful and effective node representation

Clustering Visualization

- GNN-based clustering steps
  - Apply the trained GNN model on a graph to calculate node embeddings
  - Obtain the clustering results by running k-means on node embeddings
- A visual example of clustering results

$$n = \left\lceil \frac{L}{2R} \right\rceil$$



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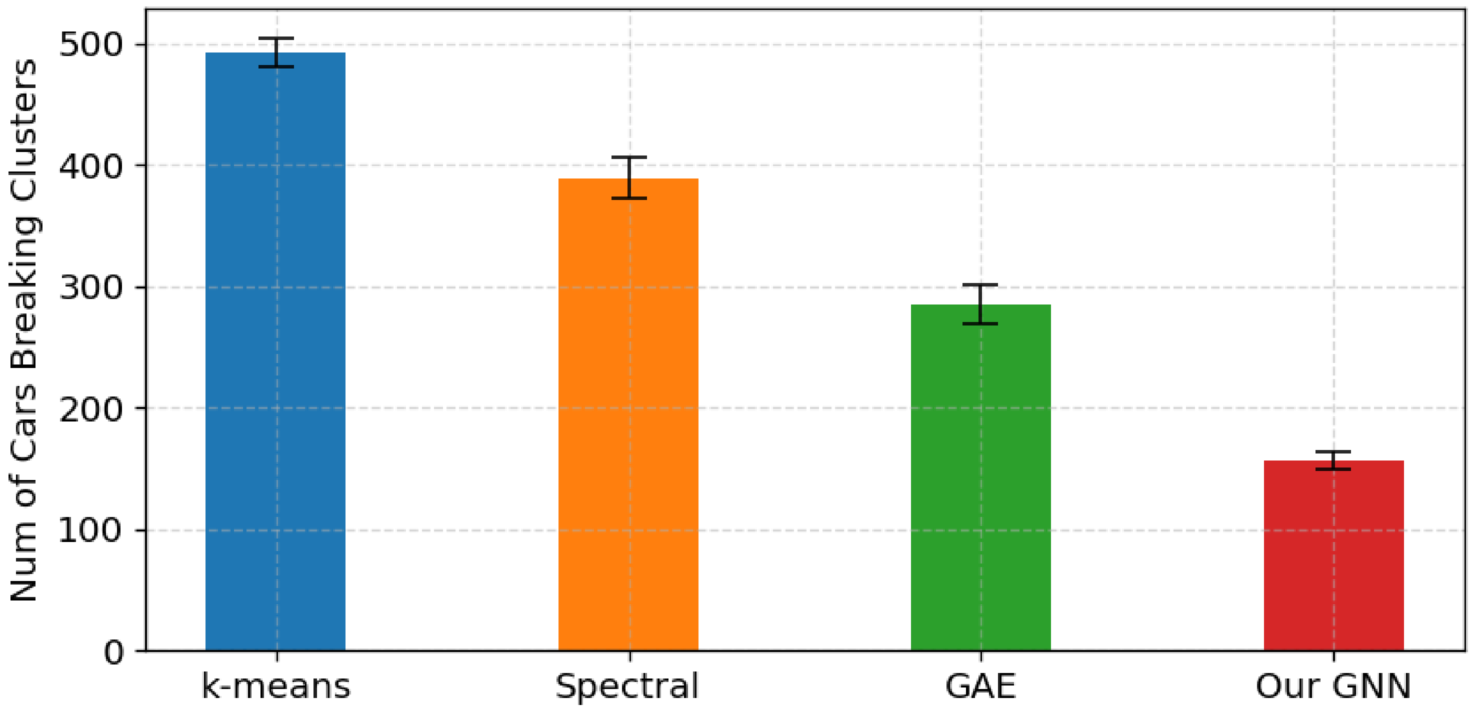
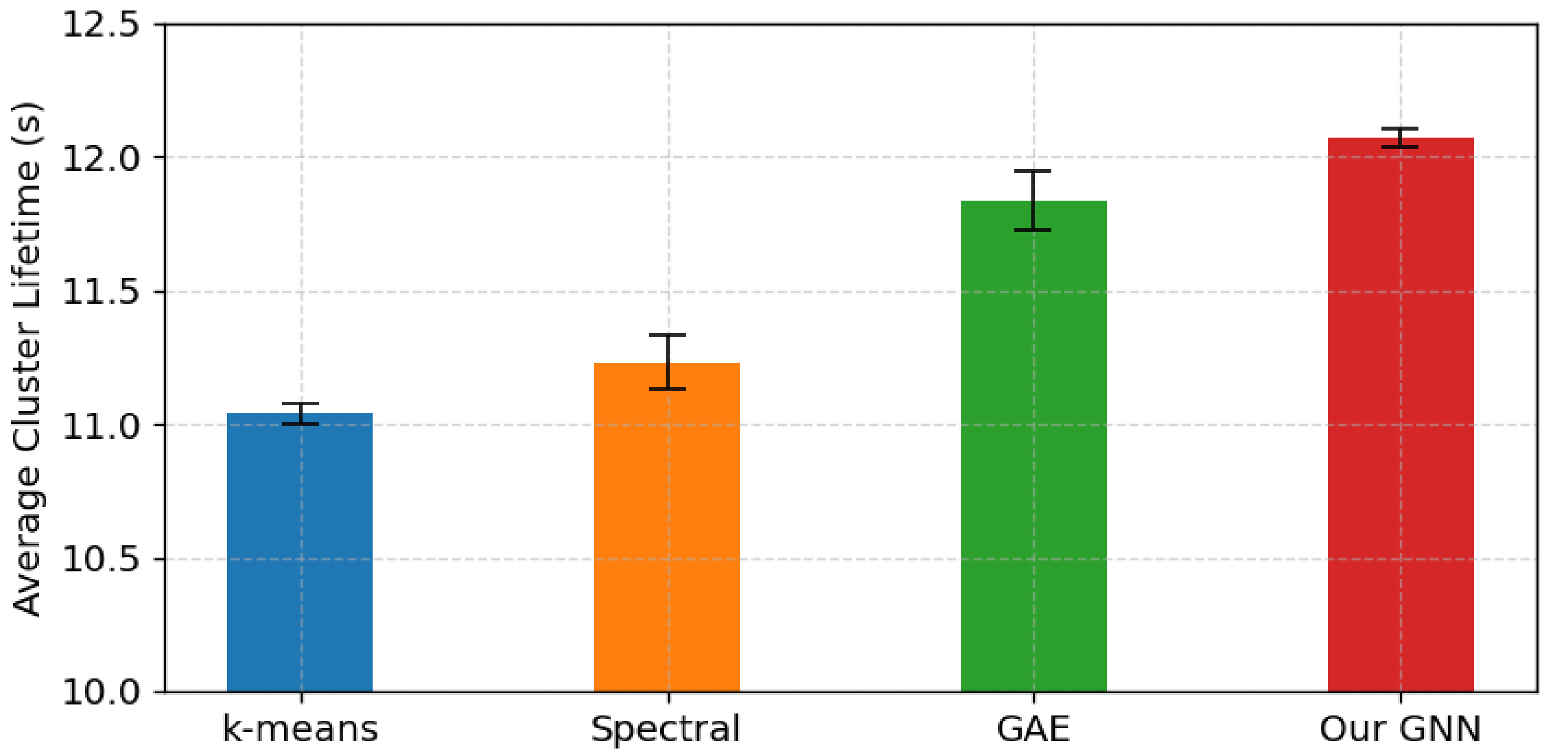
Performance Evaluation

- GNN-based algorithm corresponds to the minimum number of vehicles breaking the initial clusters



Average Cluster Lifetime Evaluation

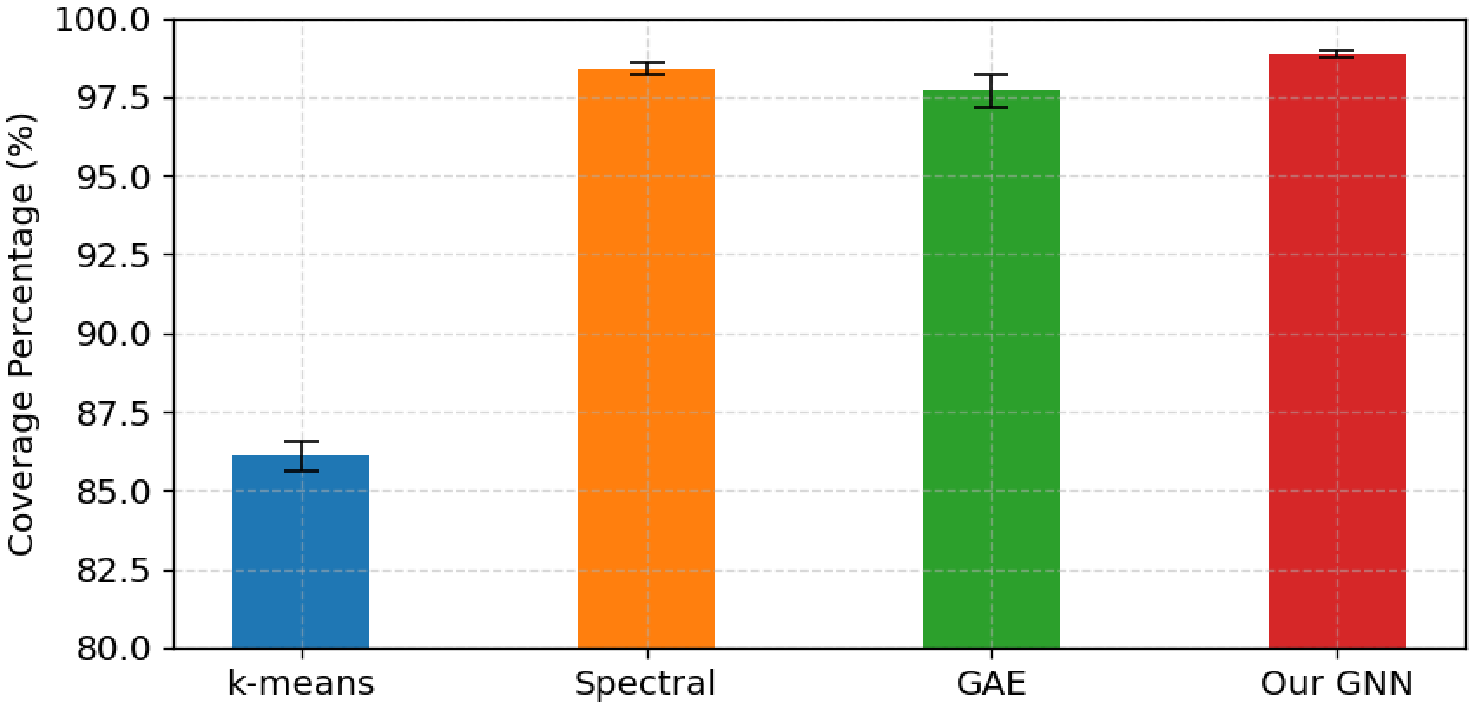
- Average cluster lifetimes of GNN-based method is 12.069±0.037s with confidence 95%. Compared with baseline algorithms, it has the longest average cluster lifetime



Coverage Percentage Evaluation

- Cluster efficiency of GNN-based algorithms achieve 98.927±0.111% with confidence 95%

$$CP = \frac{N - N_{Iso}}{N}$$



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Conclusions and Future Works

- High performance GNN-based VANET clustering on open-source highD traffic dataset
  - Average cluster lifetime (12.069±0.037s)
  - Coverage percentage (98.927±0.111%)
- Future works
  - Study other traffic scenarios like urban environment
  - Simulation of Urban Mobility (SUMO) for long-term performance

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Thank You!

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