REAL TIME RISK PREDICTION AT SIGNALIZED INTERSECTION USING GRAPH NEURAL NETWORK

Abhijit Sarkar, Akash Sonth, Hirva Bhagat, Sparsh Jain, Zachary Doerzaph

Virginia Tech Transportation Institute

INTERSECTION SAFETY IS A GROWING ISSUE

Intersection Crashes

Each year, roughly one-quarter of traffic fatalities and about one-half of all traffic injuries in the United States are attributed to crashes at intersections.[1]

Rising Vulnerable Road User Deaths

Vulnerable road user fatalities are on the rise, with pedestrian fatalities up 13% and pedalcyclist fatalities up 2% in 2021 compared to 2020.[2]

[1] https://highways.dot.gov/safety/intersection-safety/about

2 https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/813435

Image credit: https://its.dot.gov/isc/pdf/USDOT_IntersectionSafetyWebinar3.pdf

TECHNOLOGY CAN HELP

Sensing

Safety metric assessment

Countermeasures

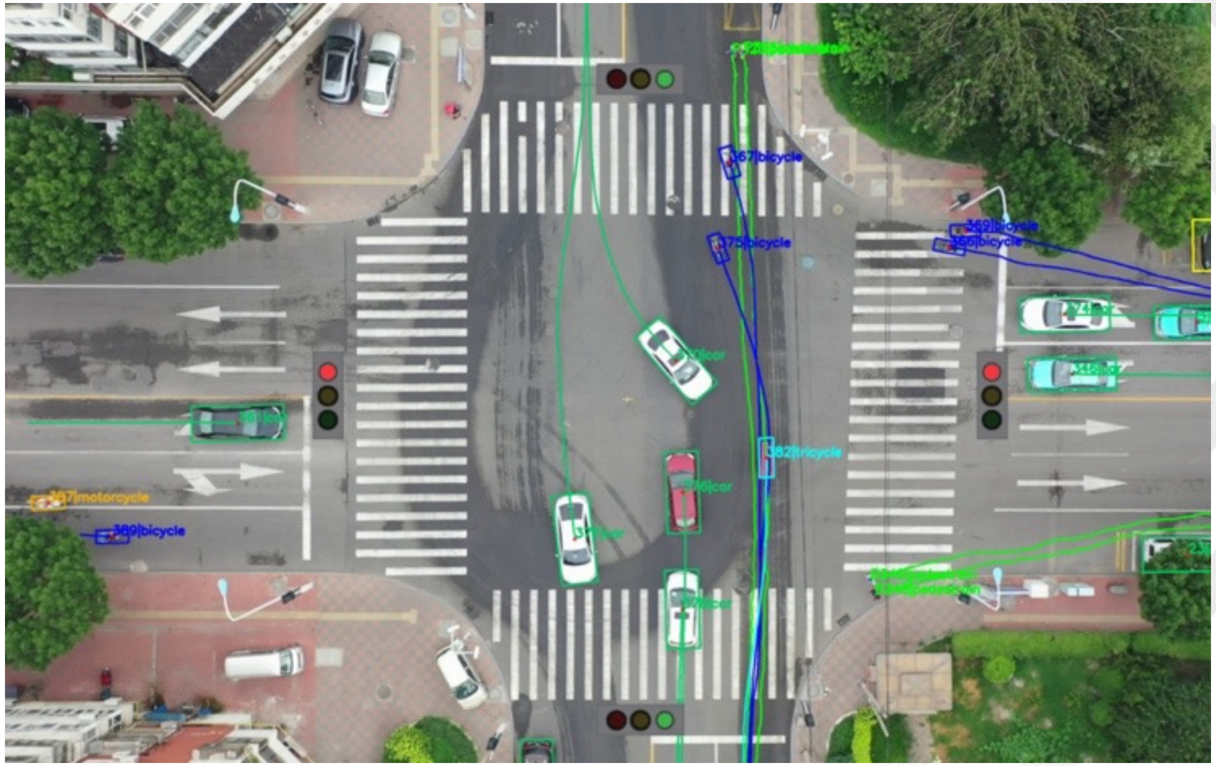
- Traditional methods largely depends on police accident report
- We need to move from after-event diagnosis to prognosis
- We need continuous monitoring of intersection

Continuous Assessment Using AI

- Artificial intelligence and machine learning has shown promises in recent years
  - Sensor processing can be performed real time on edge devices
- Continuous assessment can benefit safety
  - Improved sensing of vulnerable road user
  - Improve situational awareness
  - Highlight near crash areas
  - Determine traffic demand
  - Facilitate multimodal transportation
  - Emergency response
  - V2I

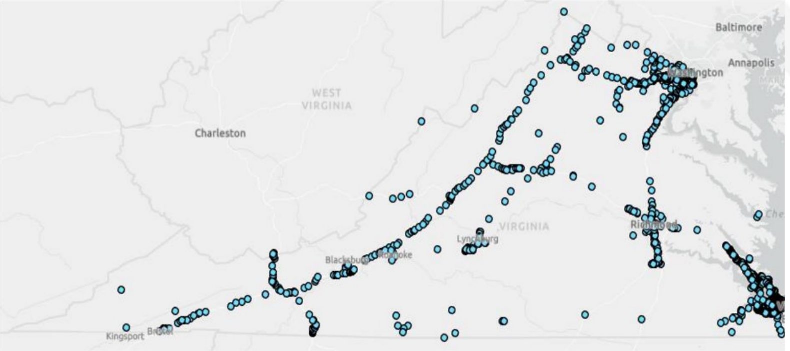
INTERSECTION IS COMPLEX

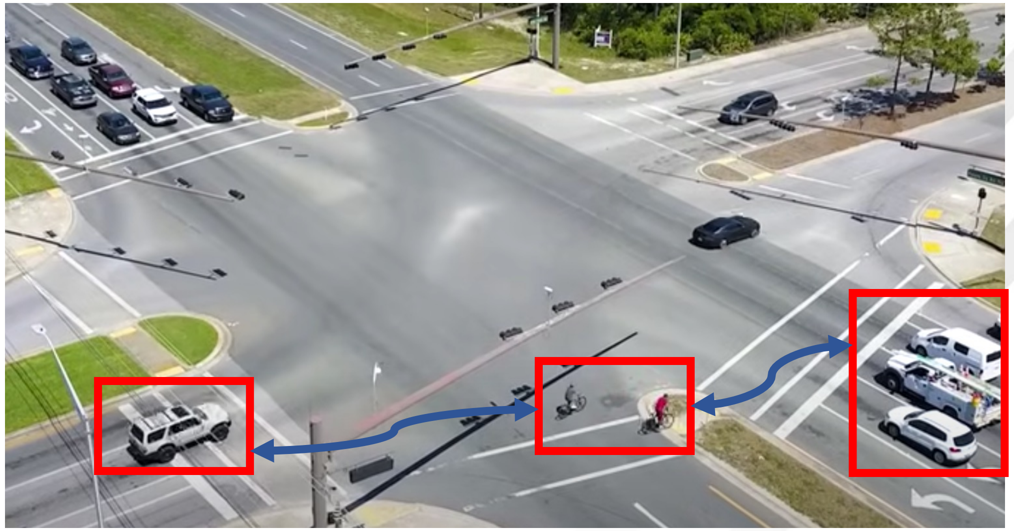
- It is a special infrastructure
  - Variable speed
  - Multimodal actors
- Maneuver
  - Lane change
  - Unprotected left turn
  - Right turn at pedestrian crossing



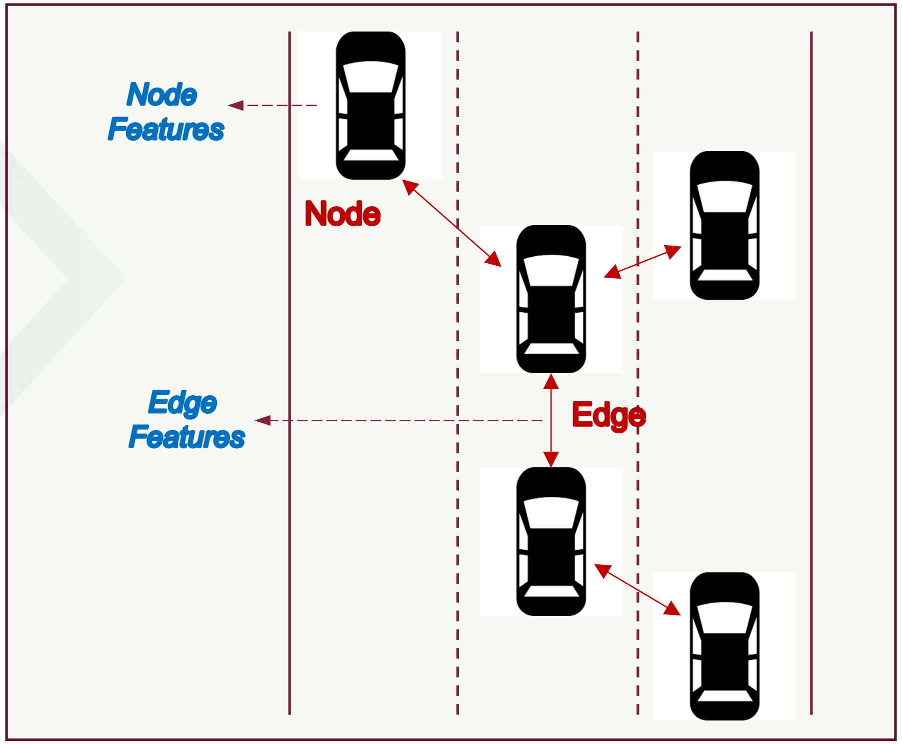
PROJECT SCOPE AND OBJECTIVES

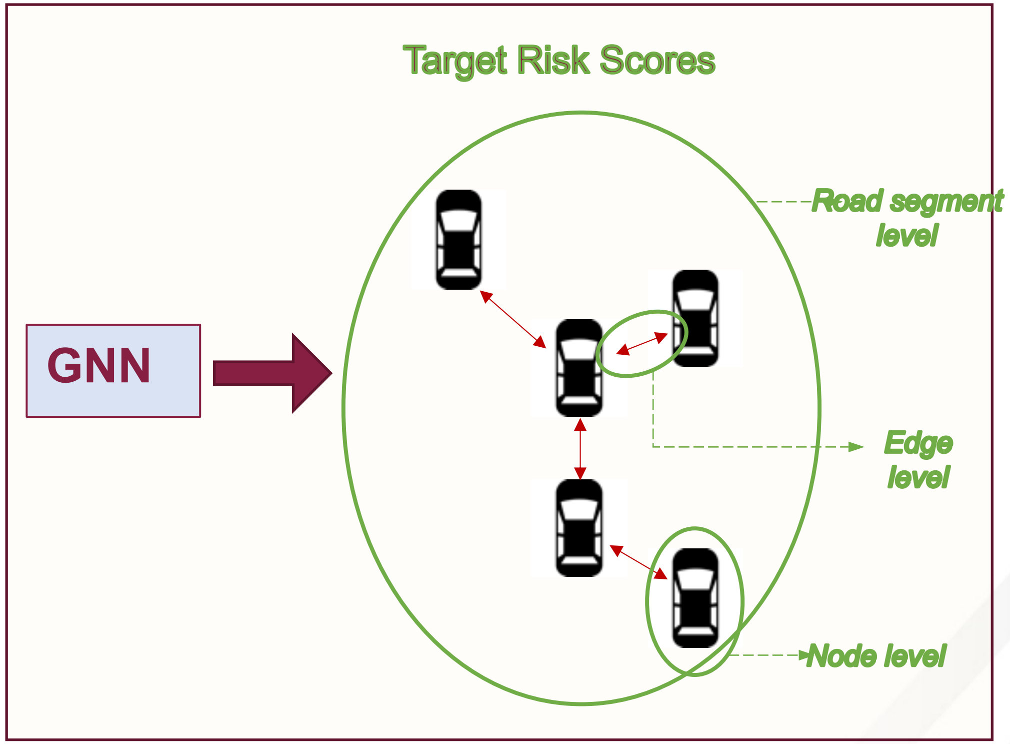
- Can we leverage intersection cameras?
- How the behavior of all actors collectively effects the overall safety of the intersection?
  - How graph can help?
- Can we study relative safety for each participant?
- Graph-based representation of traffic scenes for safety analysis.



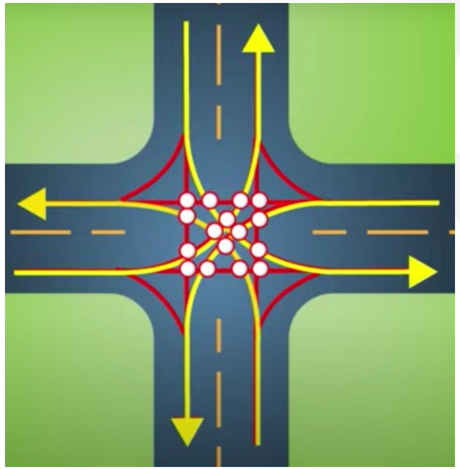


TRAFFIC AS GRAPH

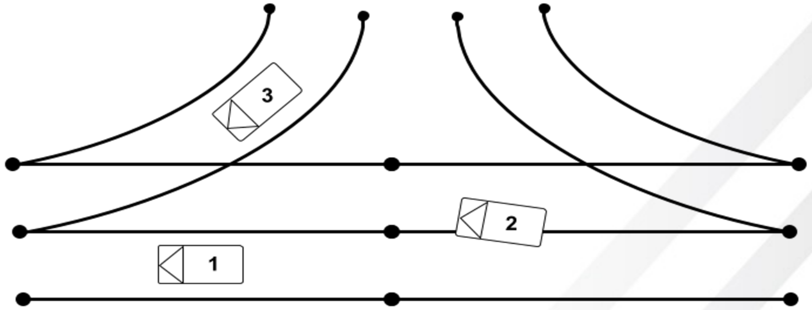




CHALLENGES



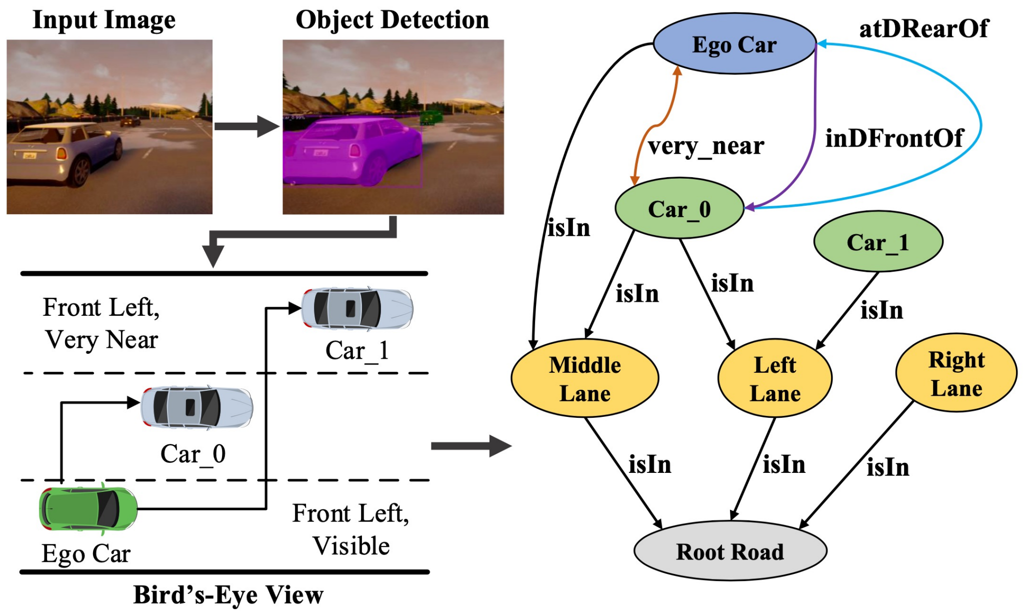
- Every intersection is different, some of them are similar
  - How to develop a common algorithm that can be generalized for each intersection?
- Crashes can happen within a distance to intersections
- How to model different intersection and maneuvers?



https://safety.fhwa.dot.gov/intersection/signal/fhwasa13027.pdf
https://safety.fhwa.dot.gov/intersection/about/index.cfm

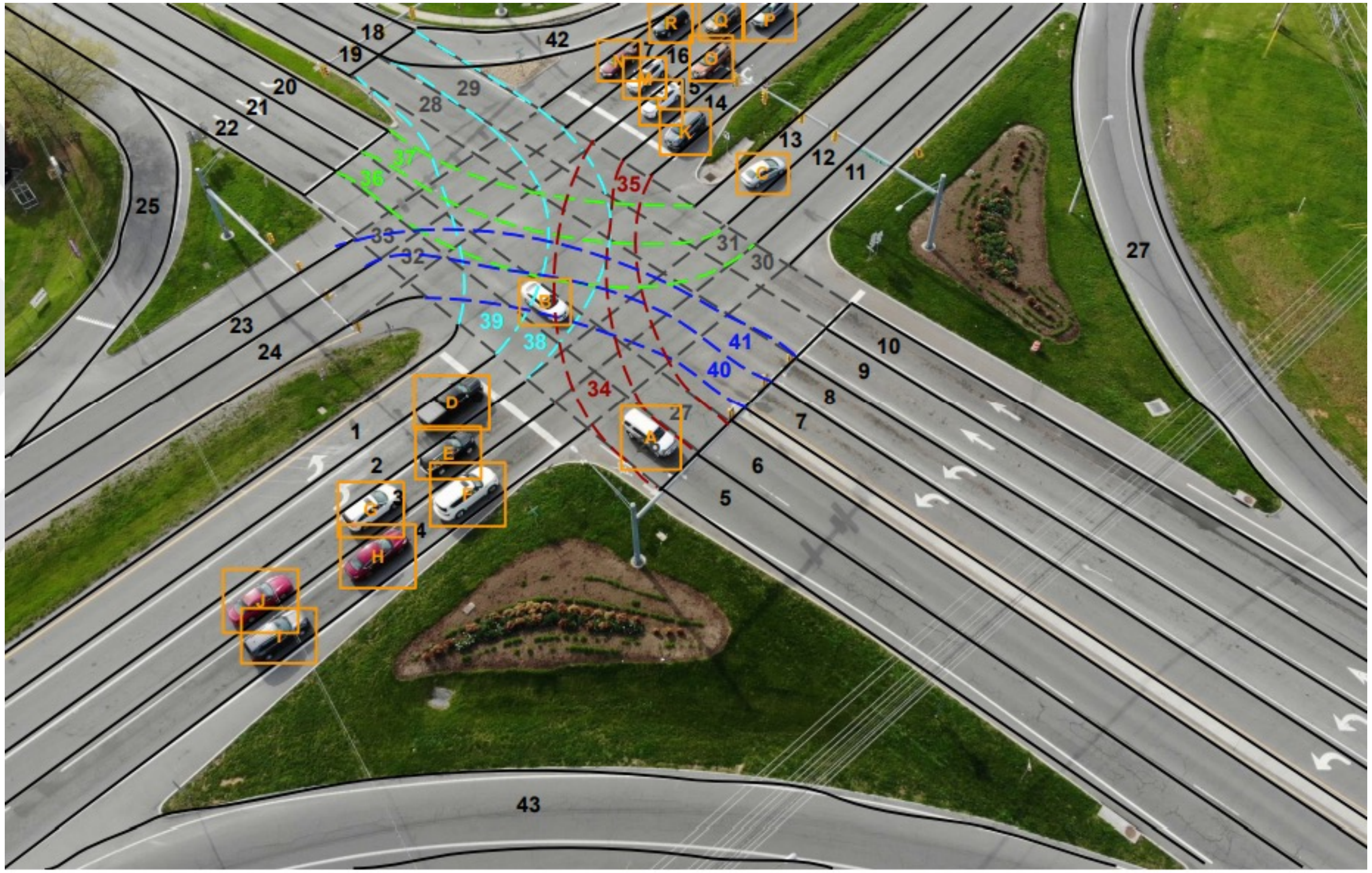
THE POWER OF GRAPH AND GNN

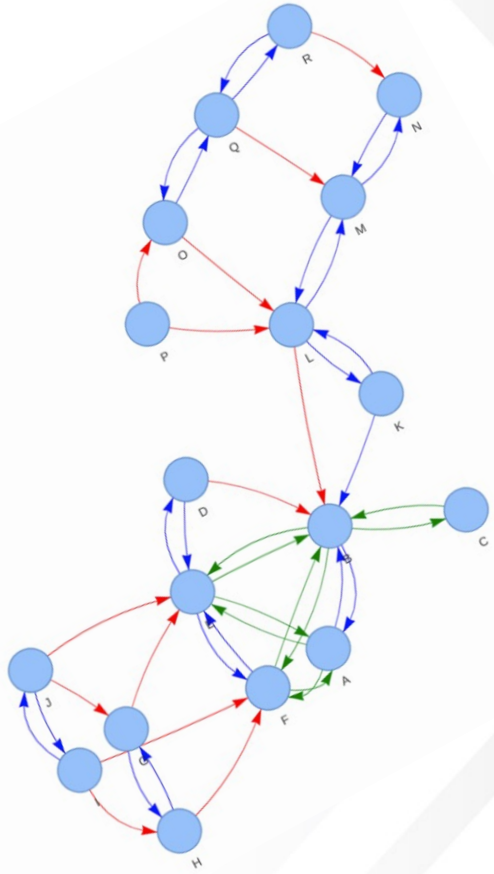
- We can integrate information from all vehicles, VRUs, and infrastructure
- Graph theory is a matured field
  - Encodes structural complexity and dependancies
- Graph neural network has revolutionized how we can process graph at scale
  - Information fusion
  - Information propagation
  - Transferability



Malawade, A. V., Yu, S. Y., Hsu, B., Muthirayan, D., Khargonekar, P. P., & Al Faruque, M. A. (2022). Spatiotemporal scene-graph embedding for autonomous vehicle collision prediction. *IEEE Internet of Things Journal*, *9*(12), 9379-9388.

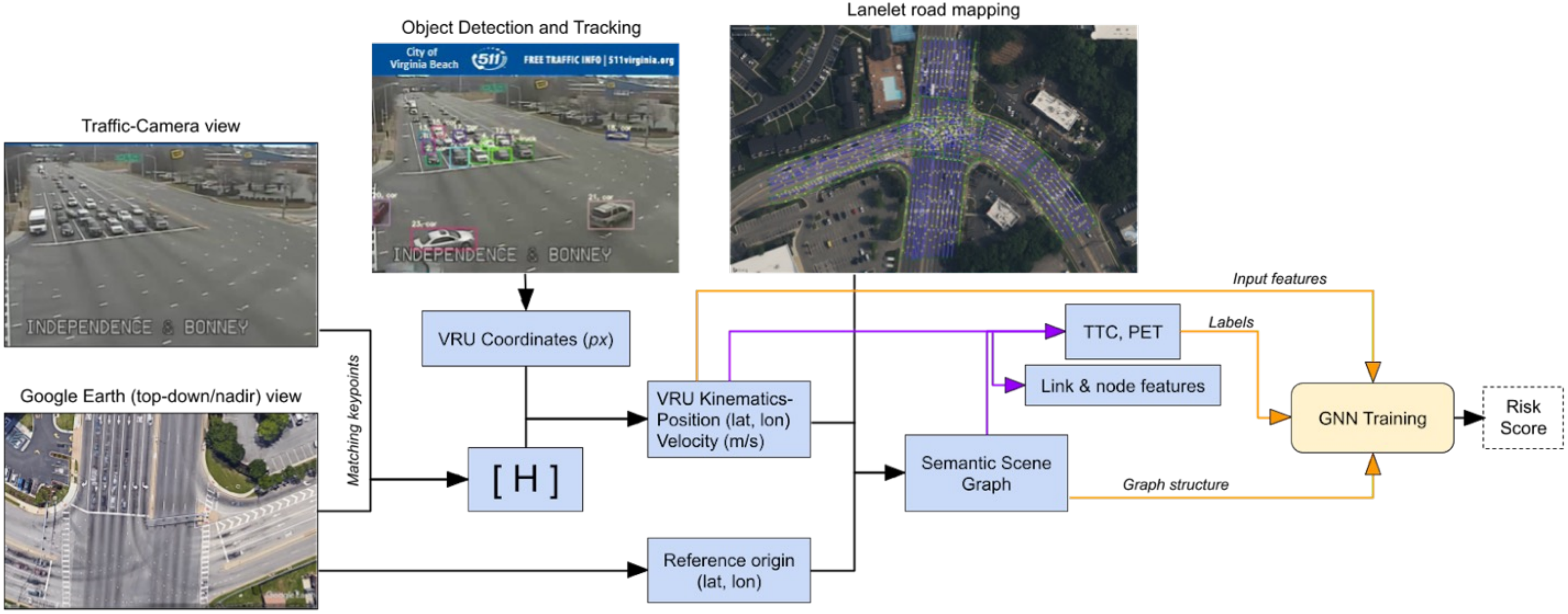
GRAPH REPRESENTATION OF INTERSECTION





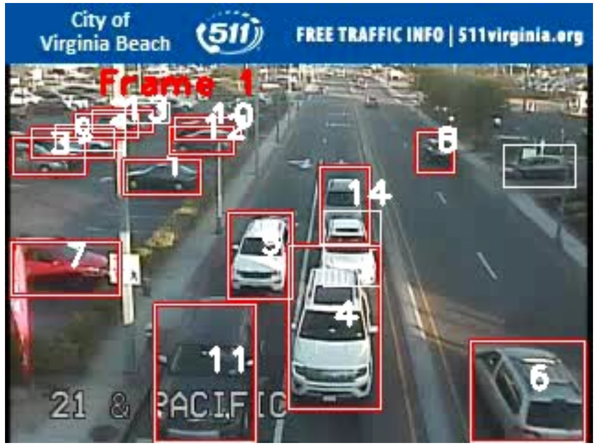
WORKFLOW AND PROCESS

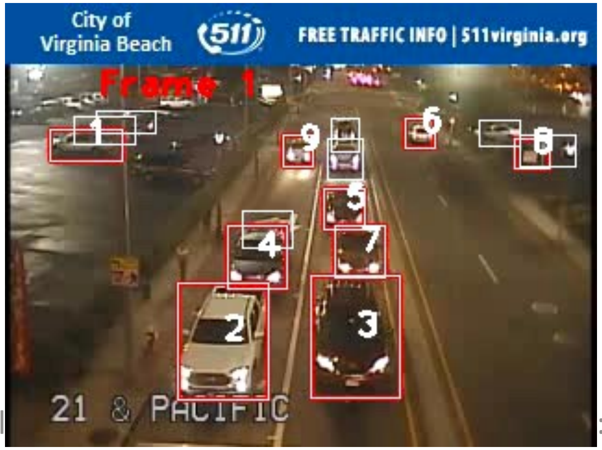
WORKFLOW

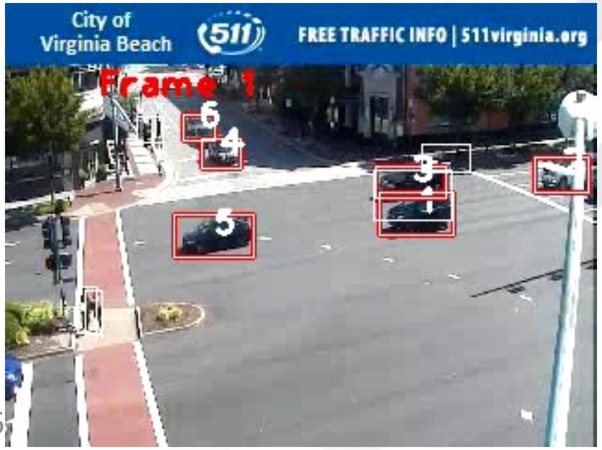

Object Detection and Tracking
Lanelet road mapping
Traffic-Camera view
INDEPENDENCE & BONNEY
Google Earth (top-down/nadir) view
Matching keypoints
VRU Coordinates (px)
[H]
VRU Kinematics-
Position (lat, lon)
Velocity (m/s)
Reference origin
(lat, lon)
Input features
TTC, PET
Labels
Link & node features
Semantic Scene
Graph
Graph structure
GNN Training
Risk
Score

TRAFFIC PARTICIPANT DETECTION AND TRACKING

- Use object detector that automatically detect objects (car, truck, pedestrians, bicycle, etc.)
- The multi object tracking helps to track objects across frames
- We tested multiple object detectors and tracker: BotSORT, YOLOv7, GCNNMatch

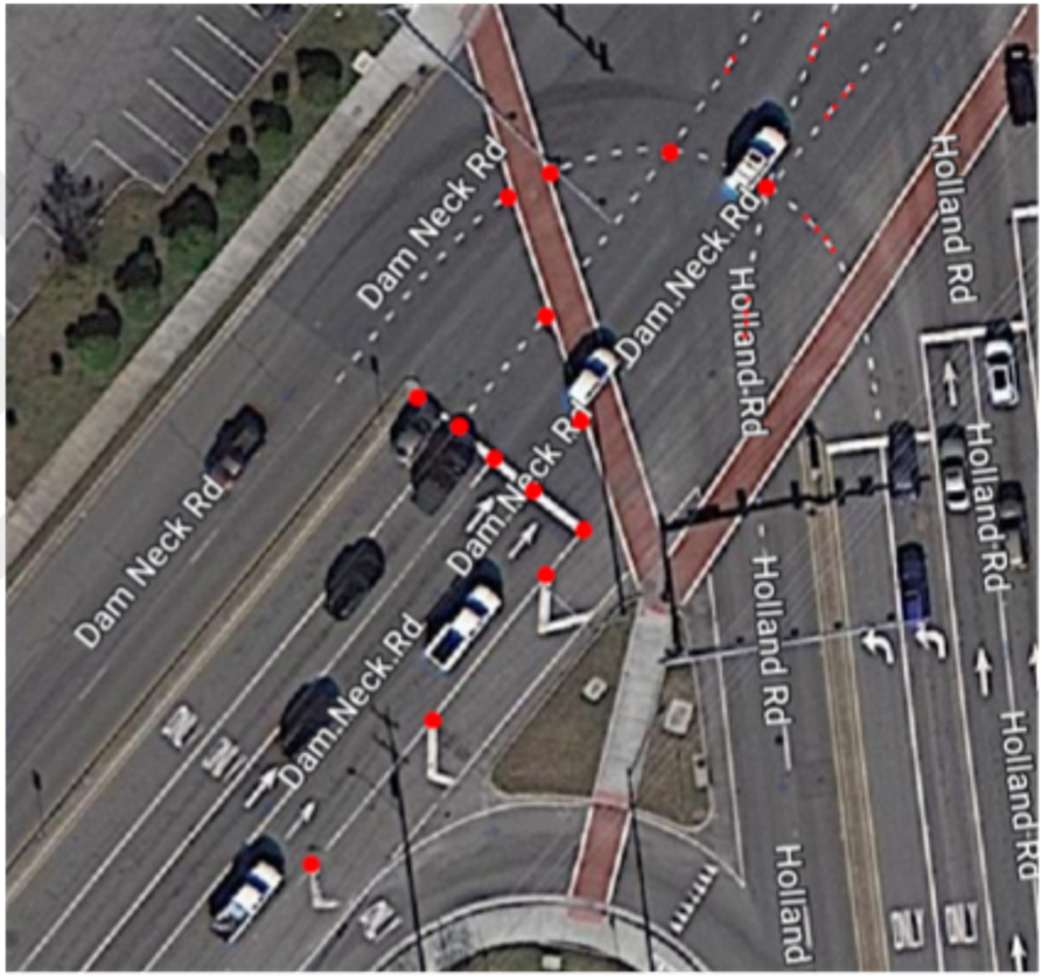






[5] Aharon, N., Orfaig, R., & Bobrovsky, B. Z. (2022). BoT-SORT: Robust associations mul :2206
[6] Wang C. Y., Bochkovskiy, A., & Liao, H. Y. M. YOLOv7: Trainable bag-of-freebies sets new state-of-the-art for real-time object detectors. CVPR 2023.
[7] Lin, Tsung-Yi, et al. "Microsoft coco: Common objects in context." ECCV 2014.

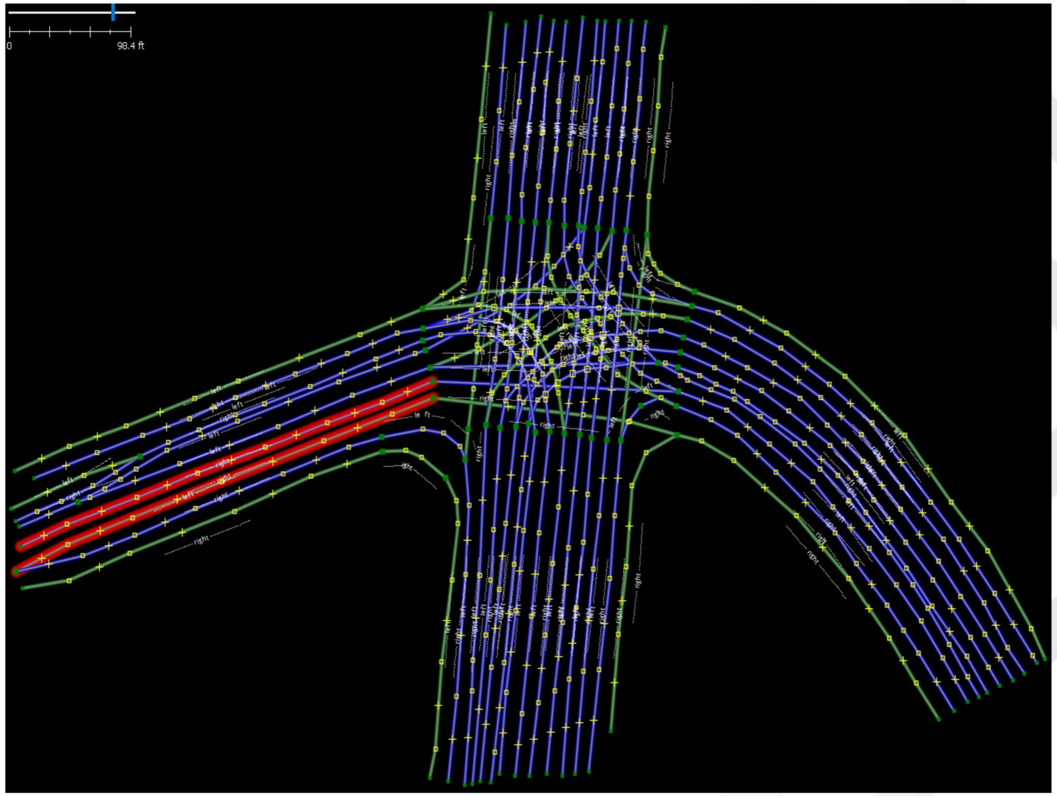
PIXEL TO GPS TRANSFORMATION



LANELET

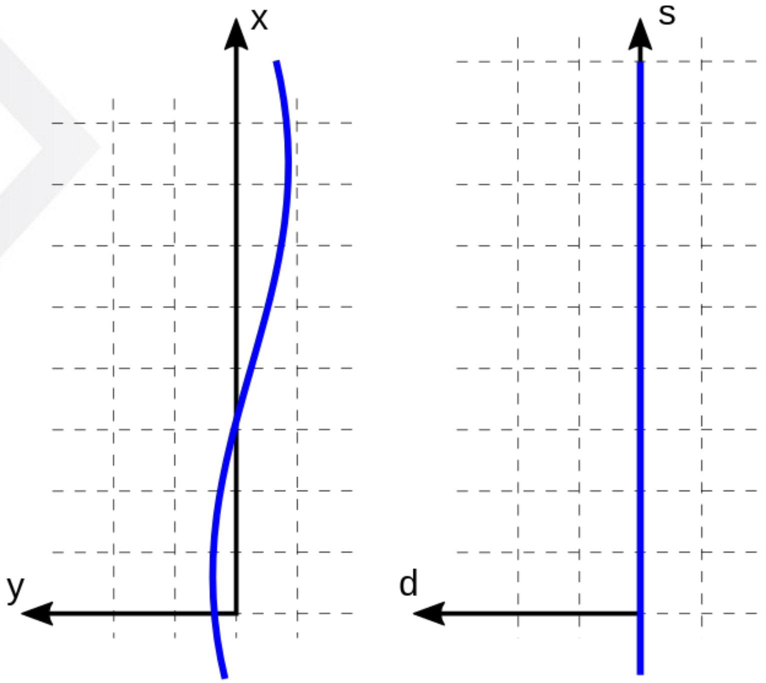
- Creating small segments of road that are homogeneous in nature
  - Each lanelet is a segment of the road that includes left and right boundaries.
  - Green: road & non-road
  - Blue: road & road

- Lanelet creation:
  - JOSM (Java OpenStreetMap Editor) software used for creating maps
  - OpenStreetMap (OSM) provides open-source platform to contribute geospatial data.



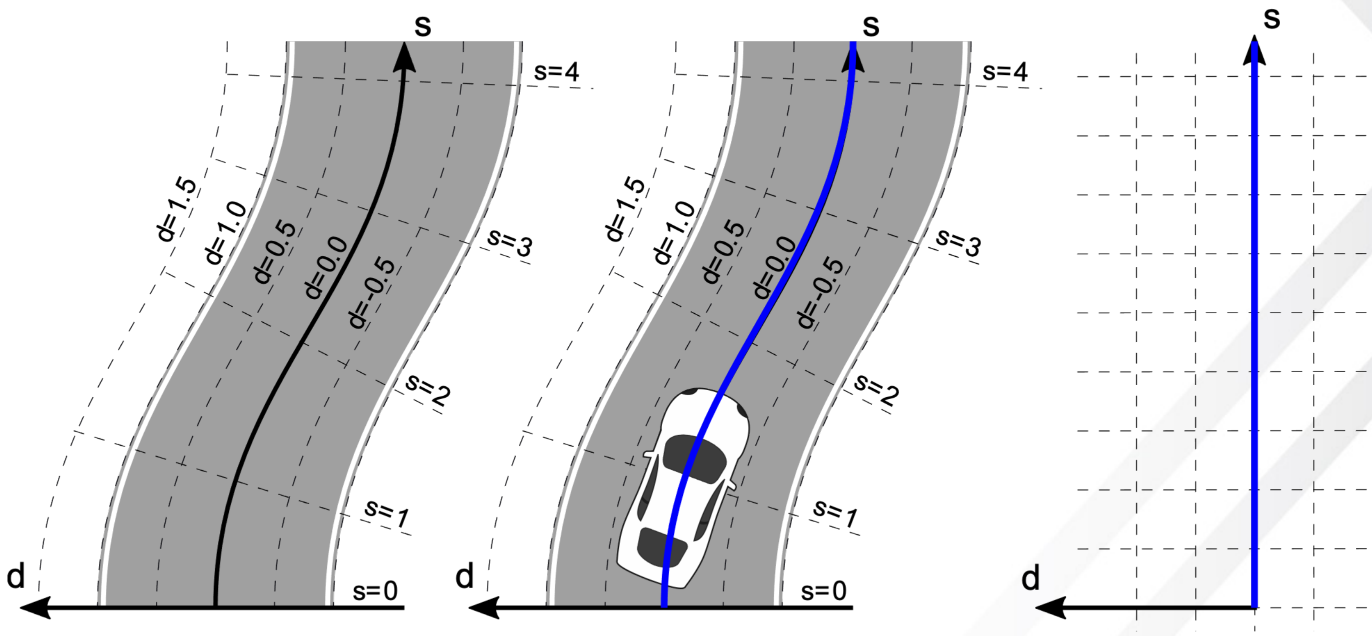
PROJECTION TO FRENET SPACE

Traffic participants described by objects in Cartesian space are projected onto the Frenet space



Cartesian Coordinate System

Frenet Coordinate System



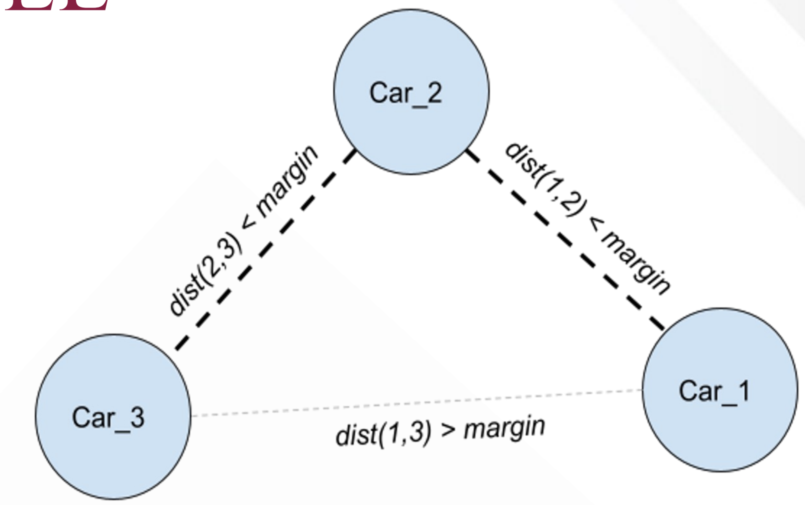
TRAFFIC SCENE GRAPH

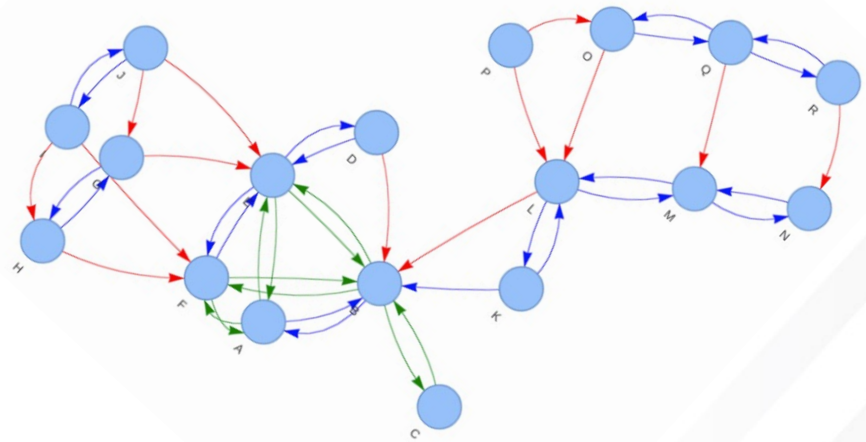
Elementary traffic model

Semantic scene graph

ELEMENTARY TRAFFIC MODEL

- Each participant in the scene is represented by a vertex in a graph.
- Euclidean distance based edge creation.
- Gives an idea of traffic density and flow.
- Does not take into account road structure.
- We can compute node level and edge level features

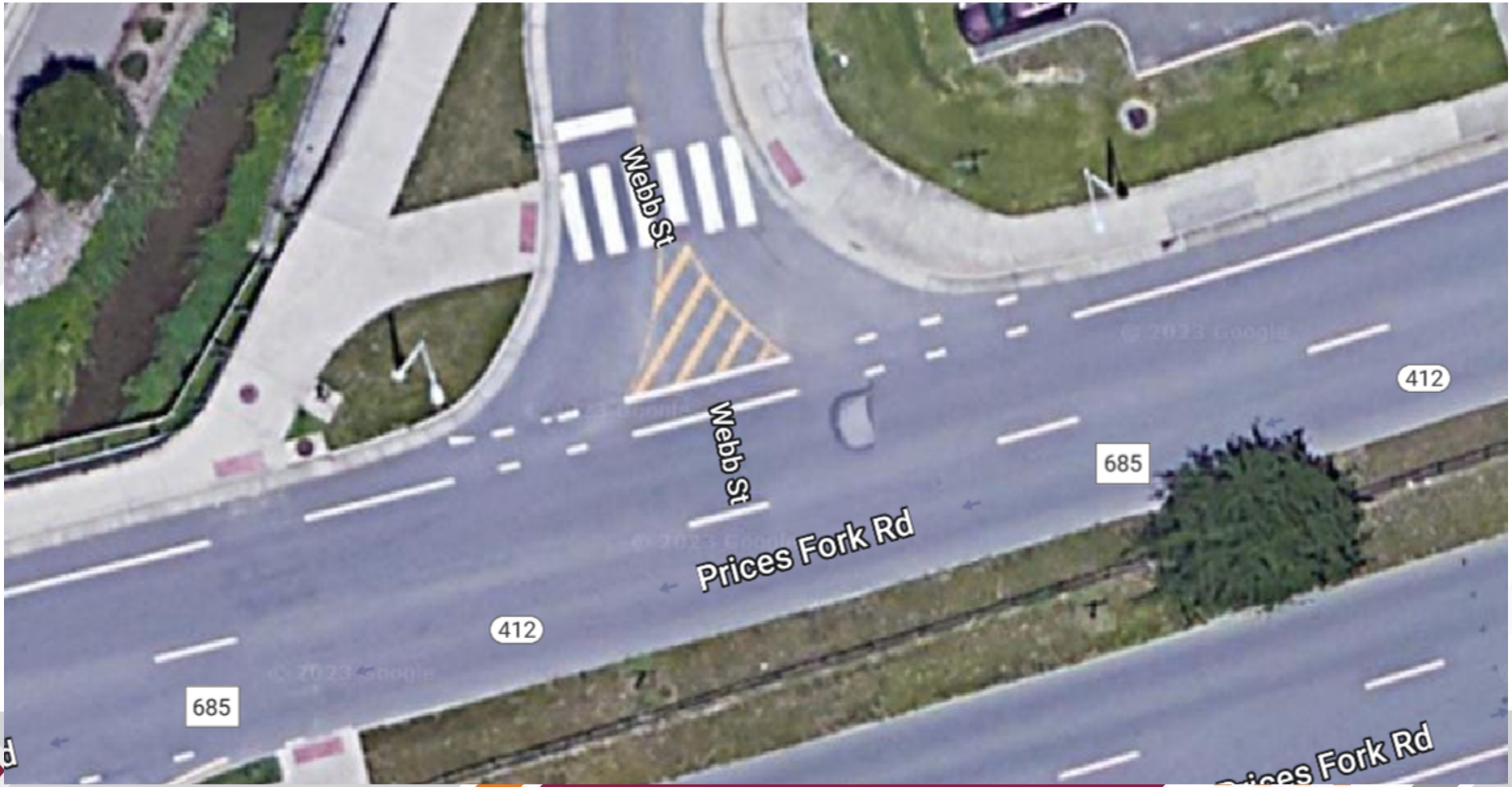




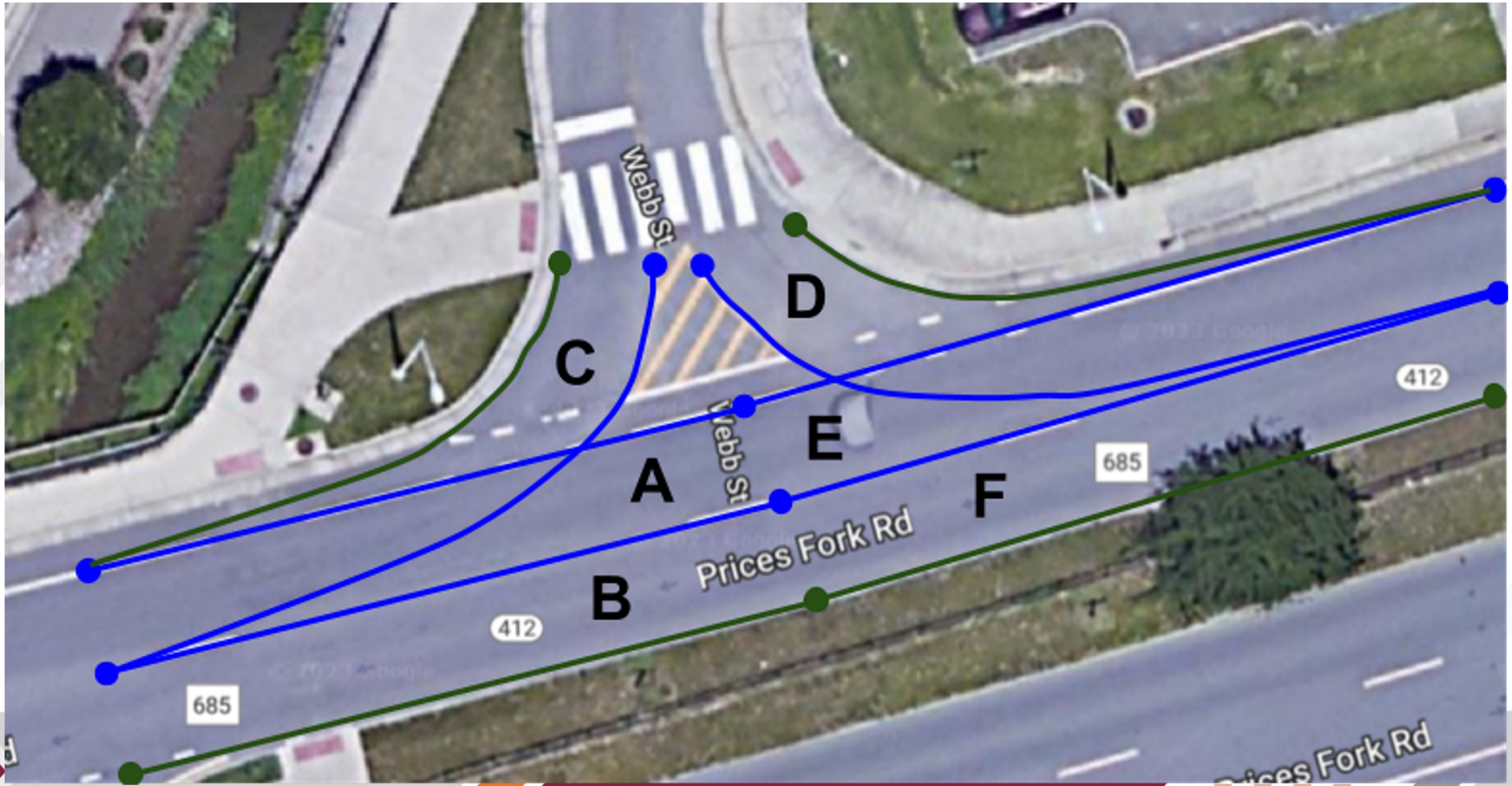
What is a semantic scene graph?

- A semantic scene graph represents a scene in terms of its semantic meaning. In a semantic scene graph, each node in the graph represents an object in the scene, and is labeled with a category or class of object (e.g., "car", "person", "bicycle", etc.).
- Semantic scene graph also captures information about the functional and semantic relationships between objects. For example, it might indicate that a "pedestrian" node is "adjacent" to a "car" node, or that a "truck" node is "behind" a "car" node.
- Why semantic scene graph?

EXAMPLE INTERSECTION

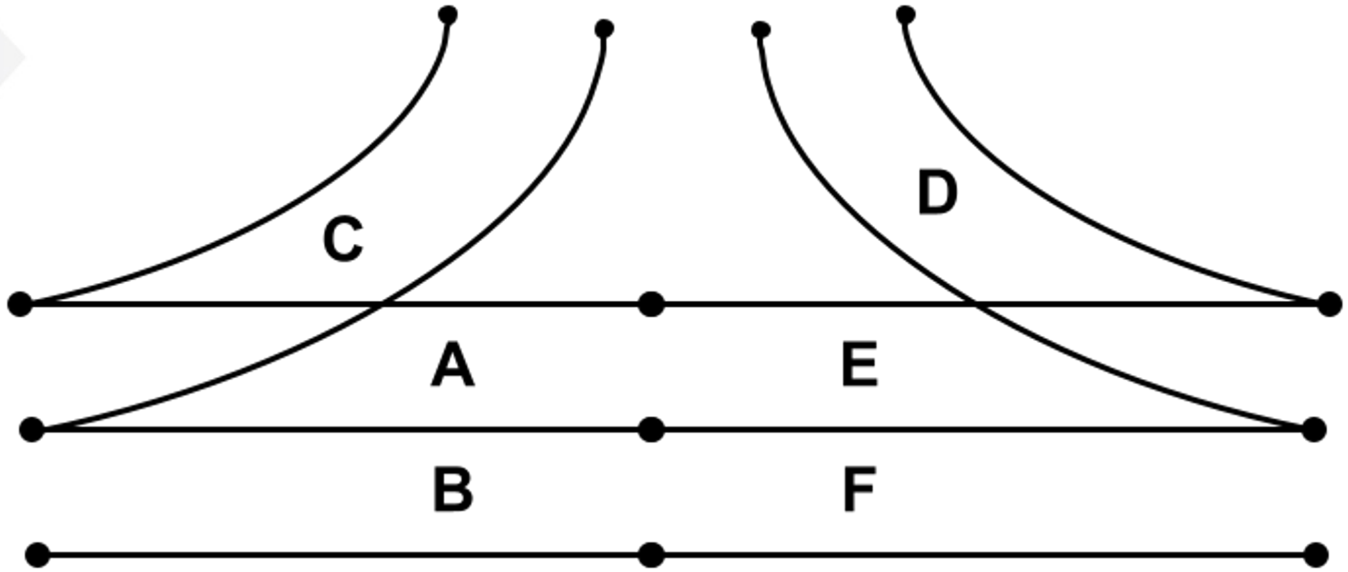


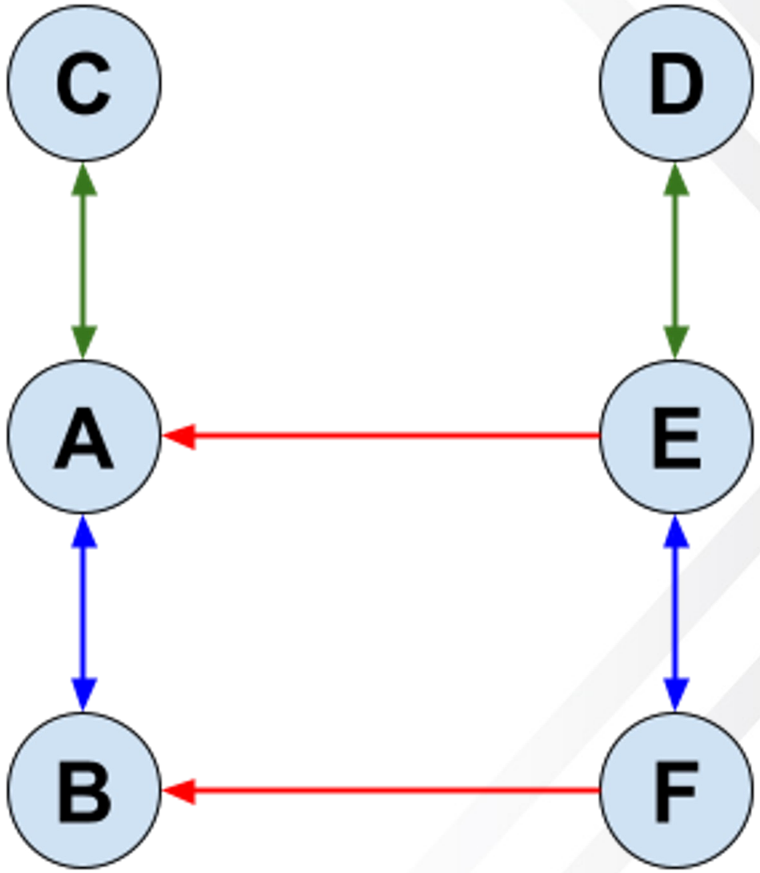
EXAMPLE INTERSECTION



EXAMPLE INTERSECTION: ROAD GRAPH

Road map is described by a directed graph G_{road} defined by (V_{road}, E_{road}). Method proposed for trajectory datasets by Zipfl et al. [8]



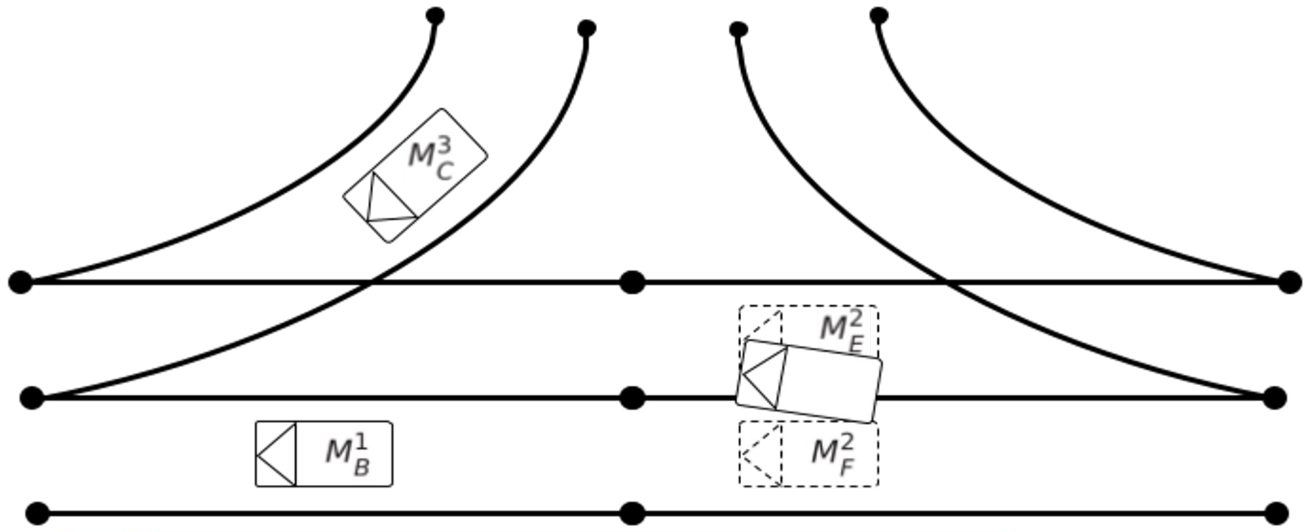


[8] Zipfl, Maximilian, and J. Marius Zöllner. "Towards traffic scene description: The semantic scene graph." 2022 IEEE 25th International Conference on Intelligent Transportation Systems (ITSC). IEEE, 2022.

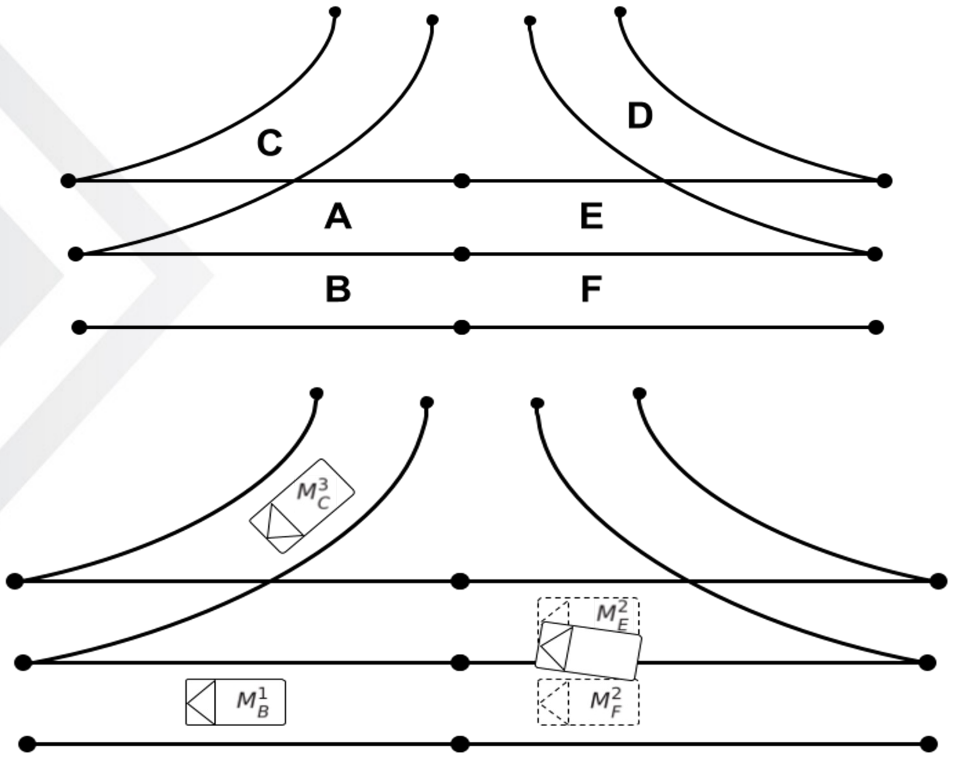
EXAMPLE SCENARIO: PROJECTION INTO LANELETS

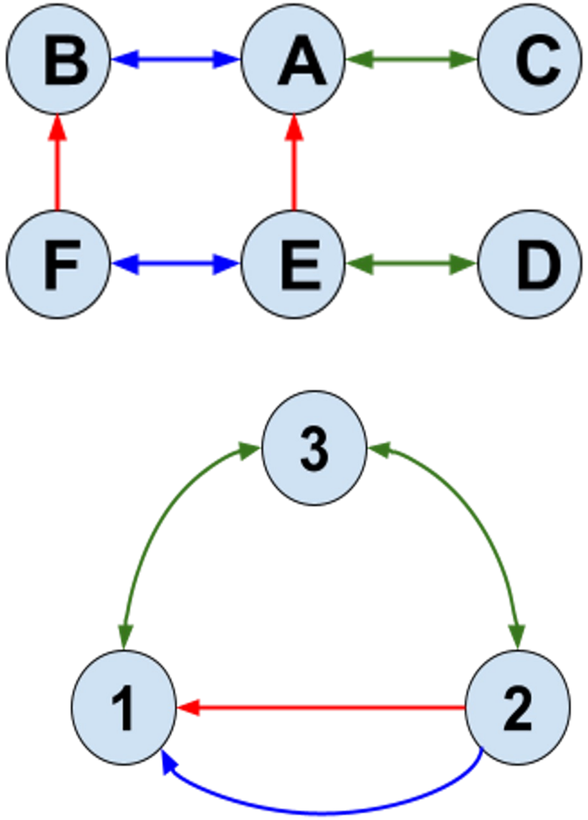
Vehicles projected onto the centerline of the lanelets to aid in creation of the scene graph

Traffic scenario showing three vehicles with their heading and position



EXAMPLE SCENARIO: SEMANTIC SCENE GRAPH

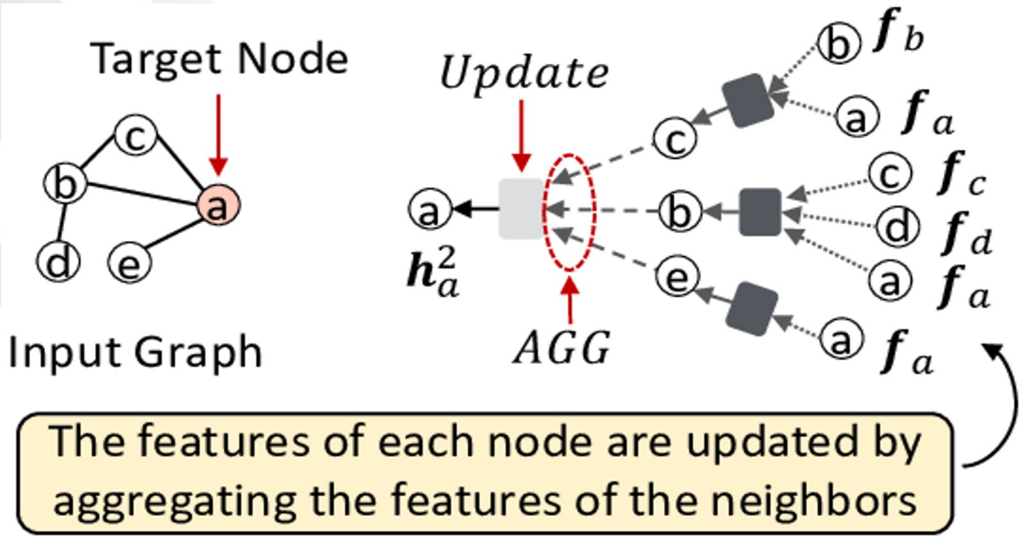


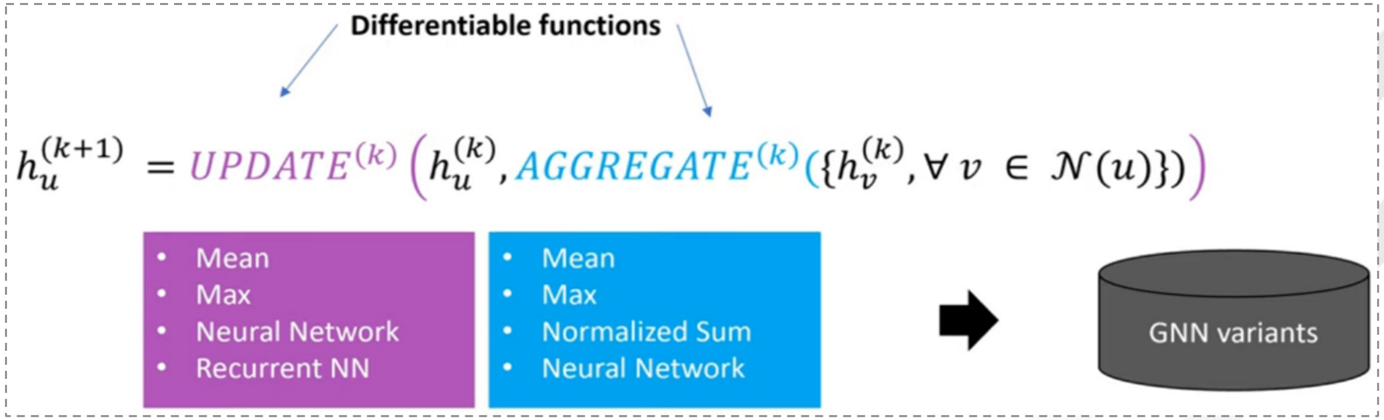


[9] Zipfl, Maximilian, and J. Marius Zöllner. "Towards traffic scene description: The semantic scene graph." 2022 IEEE 25th International Conference on Intelligent Transportation Systems (ITSC). IEEE, 2022.

GRAPH NEURAL NETWORK (GNN)

- Features of nodes and edges in the 1-hop neighborhood of target node are considered in every layer of the neural network. This is also called convolution.
- There are several GNN variants, and they all mostly differ in the AGGREGATE and UPDATE functions





GRAPH NEURAL NETWORK BASED SAFETY ANALYSIS

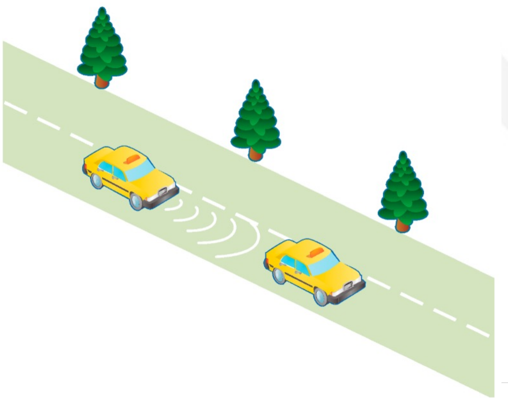
SAFETY

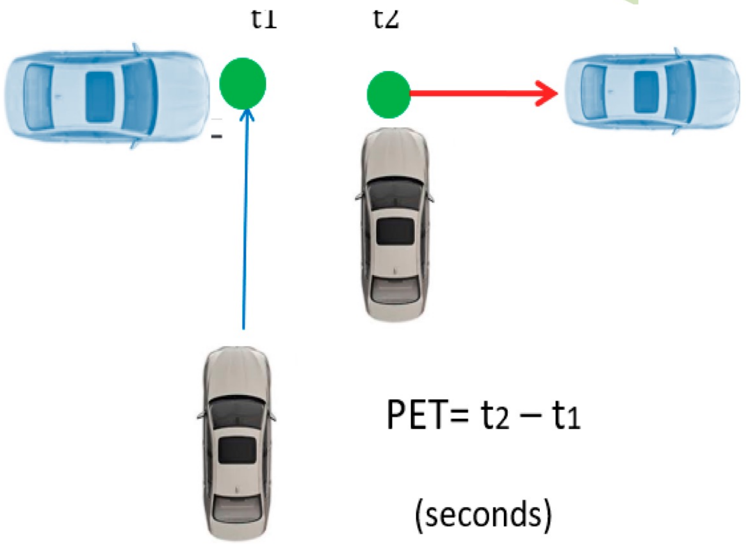
SAFETY METRIC: SPEED AND ACCELERATION

- Overspeeding & driving too slow are both dangerous
- Speed thresholded at speed limit + 10 mph (i.e. only overspeeding participants considered)
- Rapid acceleration and sudden braking are unsafe
- Acceleration & braking thresholded at 0.6g and 0.5g respectively

SAFETY METRIC

- Several safety metrics are used in research
  - TTC, PET, RSS
- Pairs of participants that exhibit longitudinal, or lateral, or intersecting relationship
- We used TTC threshold of 2 sec
- We used PET threshold as 1.5 secs for intersecting traffic

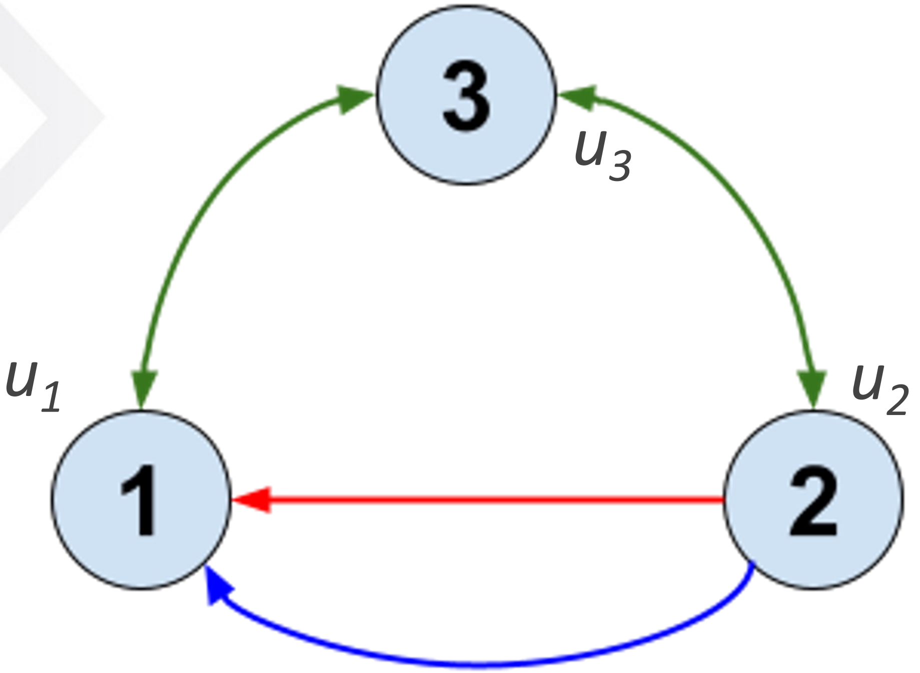




Example Intersection: Data Representation

Node feature: *u = [isPed, isBicycle, isCar, isTruckBus, isMotorbike,* $|v|$, v_x, v_y, *length, width]*

Edge feature: *e = [isLon,* $|d_{lon}|$, *isLat,* $|d_{lat}|$, *isInt,* $|d_{int}|$*]*



H \ T	1	2	3
1	-	-	e_{13}
2	e_{21}	-	e_{23}
3	e_{31}	e_{32}	-

SAFETY MODELING

Class label: $cf = \min(1, \text{floor}(\alpha_1\, n_{PET} + \alpha_2\, n_{TTC} + \alpha_3\, n_G + \alpha_4\, n_S))$

- n_{PET}: Number of vehicles with PET <= 1.5 seconds
- n_{TTC}: Number of vehicles with TTC <= 2 seconds
- n_G: Number of vehicles with acceleration >= 0.6g, and deceleration >= 0.5g
- n_S: Number of vehicles overspeeding >= 10 mph

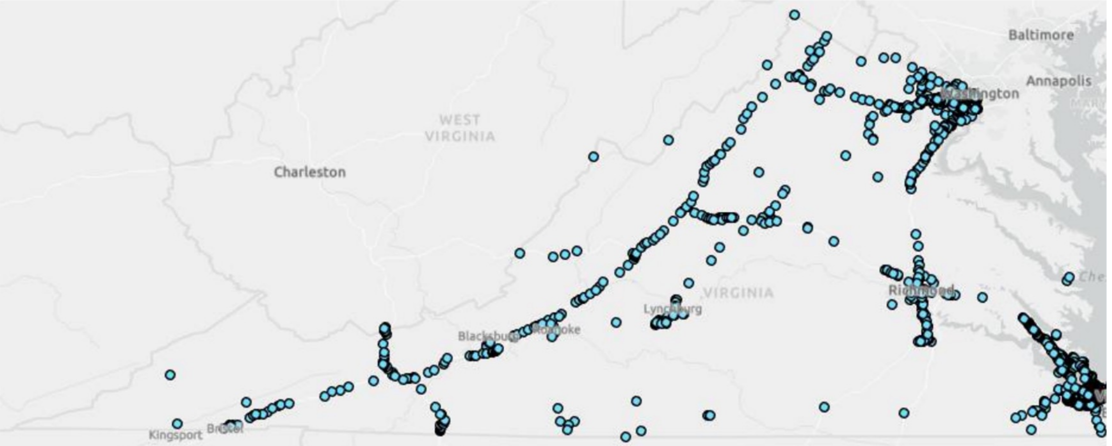
SAFETY METRIC EVALUATION

- For 10.5% of the frames, there a PET violation by a pair of vehicles in the high crash intersection, and around 7.9% of the time in the low crash videos.
- For 3.1% of the frames, there was a PET violation by two pairs of vehicles for the high crash intersection videos, and around 1.9% of the time for the low crash videos.
- When TTC is combined with speed and acceleration, we obtain violation in 15.2% of the frames for the high crash videos, and 13.8% for the low crash ones.

EXPERIMENT AND RESULTS

VT-CAST 2020 DATASET

- Traffic cameras throughout Virginia used to collect the dataset [4] VT-CAST (Virginia Traffic Cameras for Advanced Safety Technologies).
- Videos are usually 320x240 resolution at 15 fps.
- We chose 10 intersections in Virginia chosen- high crash history and low crash history
    - Similar traffic volume and number of lanes

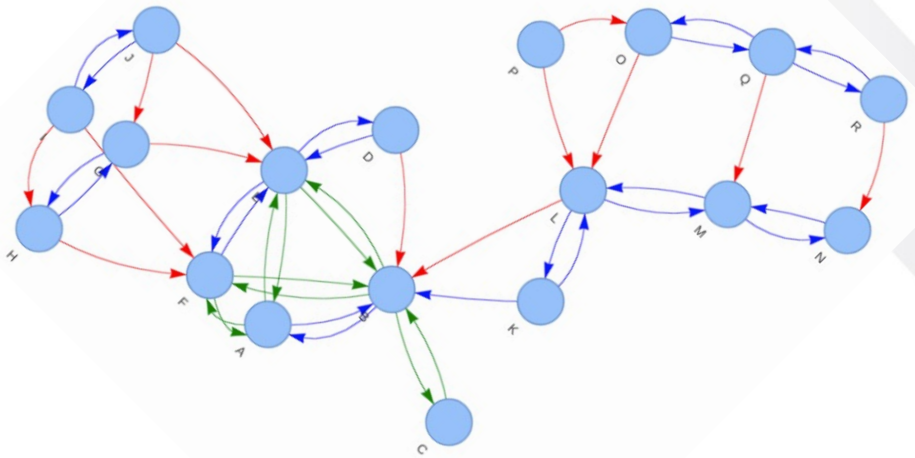


[4] Bareiss, Max G. A Dataset of Vehicle and Pedestrian Trajectories from Normal Driving and Crash Events in One Year of Virginia Traffic Camera Data. Diss. Virginia Tech, 2023

SAFE-D SAFETY THROUGH DISRUPTION

NODE-LEVEL FEATURES

- Provide information regarding the structure and position of nodes in the network.
- Understand the role and importance of individual nodes in the network, as well as identify patterns and trends in the network's overall structure and behavior.

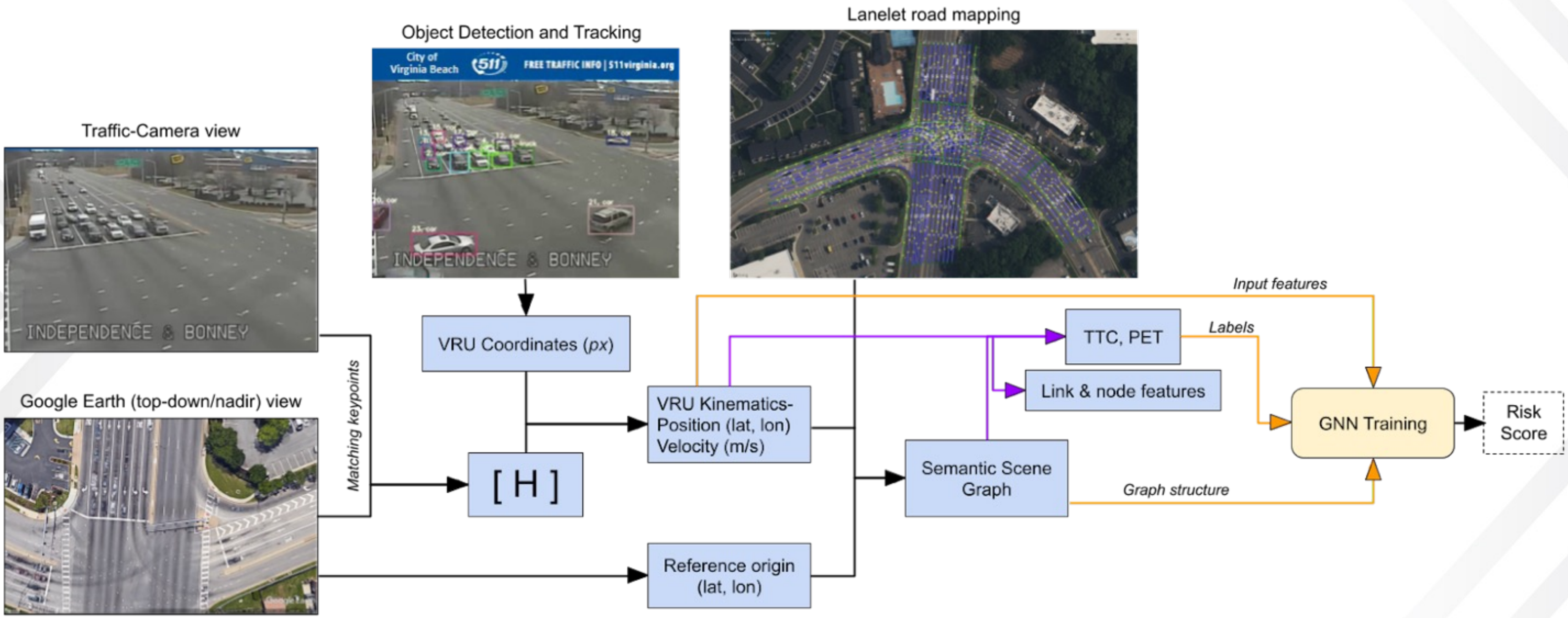


Node	Count	Degree	Centrality			Clustering coefficient
			Eigenvector	Betweenness	Closenness	
Car	8177	2.48659	0.18796	0.03496	0.24433	0.32658
Truck/bus	3110	2.57098	0.21295	0.02449	0.25161	0.3795
Pedestrian	120	1.46054	0.10737	0.016178	0.18812	0.25529
Bicycle	23	4.81395	0.19966	0.05233	0.41798	0.42497
Motorcycle	23	2.6279	0.24813	0.05588	0.3293	0.40337

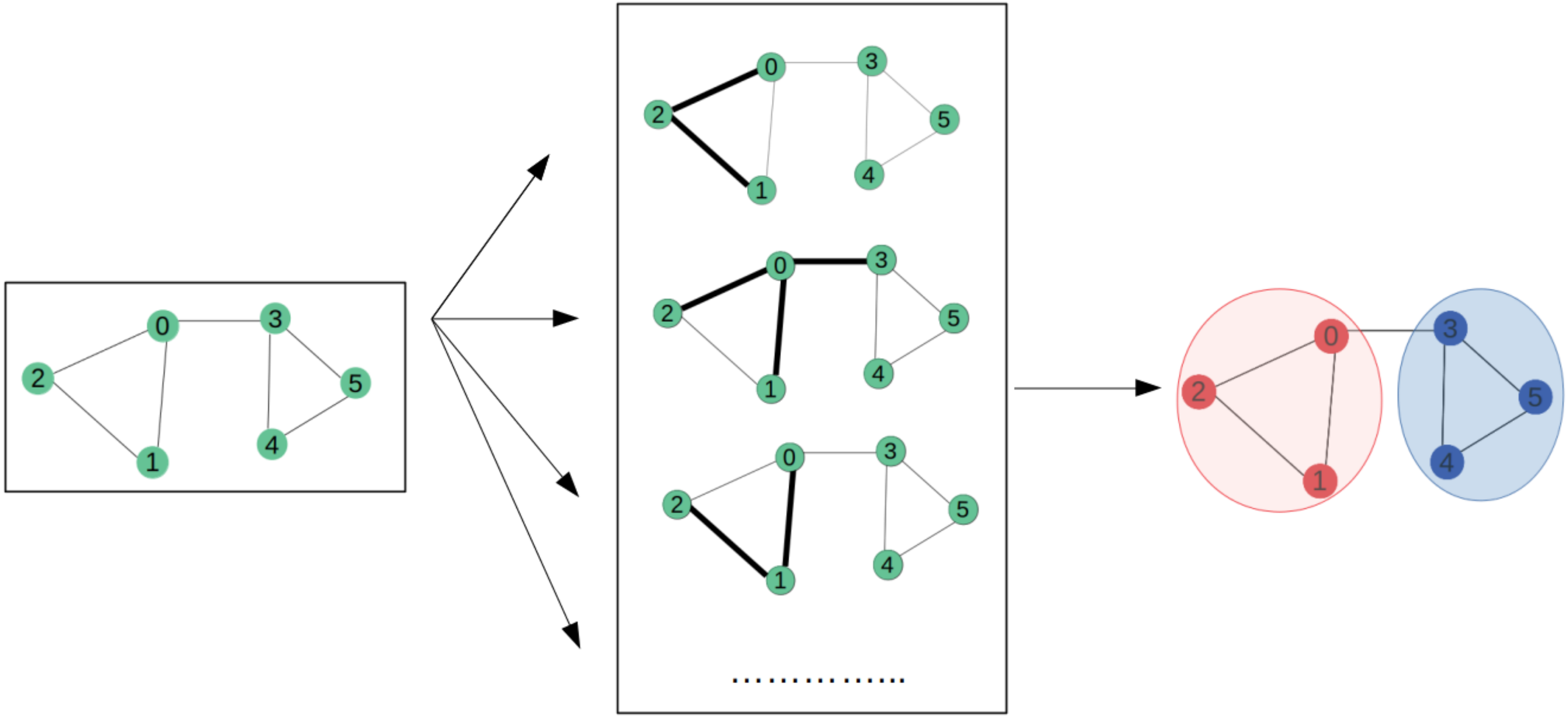
LINK-LEVEL FEATURES

- Provide information about individual edges/links, and can be used to understand the relationships between nodes.
- Patterns and trends of relatio nships between nodes in the network
- Identify influential edges and understand their role in the network's overall behavior.

Node1	Node2	Average	
		Jaccard	Adamic-Adar
Bicycle	Car	0.20755	0.85407
Bicycle	Pedestrian	0.05555	0.2103
Bicycle	Truck/Bus	0.19010	0.89363
Car	Car	0.2341	0.82552
Car	Motorcycle	0.21041	0.72338
Car	Pedestrian	0.191915	0.5831
Car	Truck/Bus	0.25405	0.89782
Motorcycle	Pedestrian	0.03809	0.16156
Motorcycle	Truck/Bus	0.2	0.63092
Pedestrian	Truck/Bus	0.12771	0.43341
Truck/Bus	Truck/Bus	0.29414	0.99186

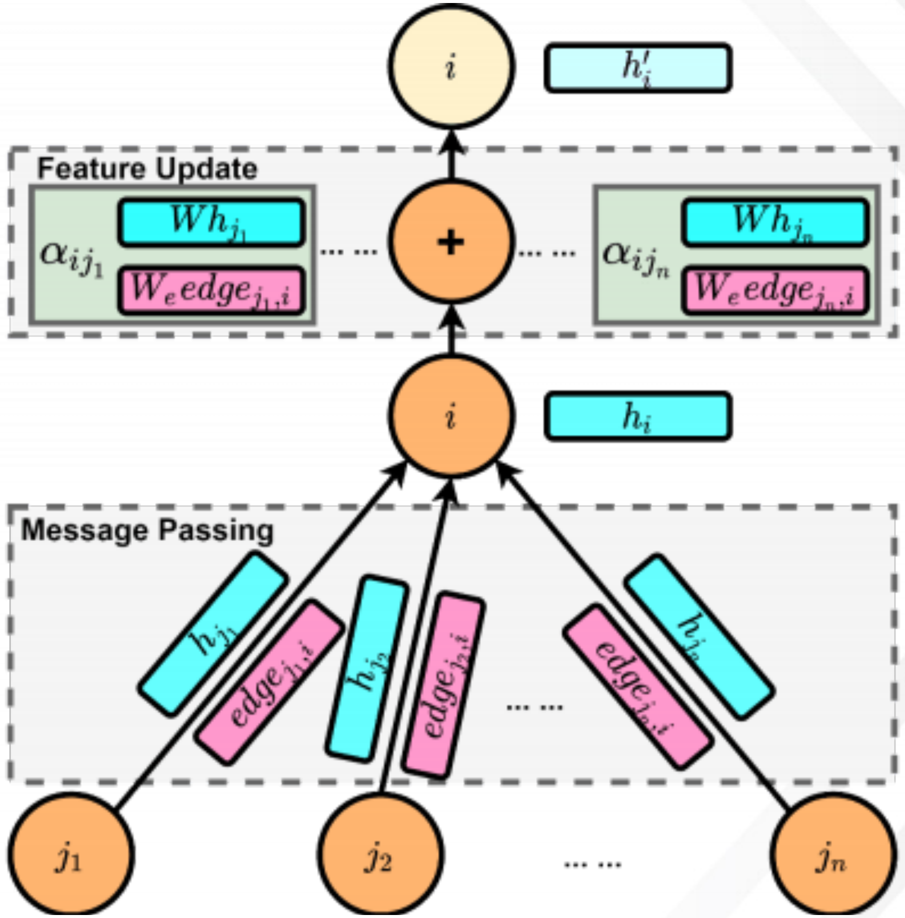

Lanelet road mapping
Object Detection and Tracking
City of Virginia Beach
511
FREE TRAFFIC INFO | 511virginia.org
INDEPENDENCE & BONNEY
Traffic-Camera view
Google Earth (top-down/nadir) view
Matching keypoints
VRU Coordinates (px)
[H]
VRU Kinematics-
Position (lat, lon)
Velocity (m/s)
Reference origin
(lat, lon)
Input features
TTC, PET
Labels
Link & node features
Semantic Scene
Graph
Graph structure
GNN Training
Risk
Score

GRAPH CONVOLUTIONAL NETWORK



GRAPH ATTENTION NETWORK

- While convolution aggregates information from neighboring nodes & edges,
- but applying specific different weights to these nodes & edges allows the network to focus on important information.



CLASSIFICATION BASED ON PET METRIC VIOLATIONS

Combining all data and training the models for predicting safe/unsafe based on the PET metric violations.

Trained model can be used to make predictions on new scenarios.

	Graph Attention [10]	Graph Conv [11]
Accuracy	72.9%	**79.85%**

Pred\GT	**P**	**N**
P	0.804	0.231
N	0.196	0.769

[10] Yunsheng Shi, Zhengjie Huang, Shikun Feng, Hui Zhong, Wenjin Wang, and Yu Sun. Masked label prediction: Unified message passing model for semi-supervised classification. arXiv preprint arXiv:2009.03509, 2020.
[11] Weihua Hu, Bowen Liu, Joseph Gomes, Marinka Zitnik, Percy Liang, Vijay Pande, and Jure Leskovec. Strategies for pre-training graph neural networks. arXiv preprint arXiv:1905.12265, 2019.

DISCUSSION

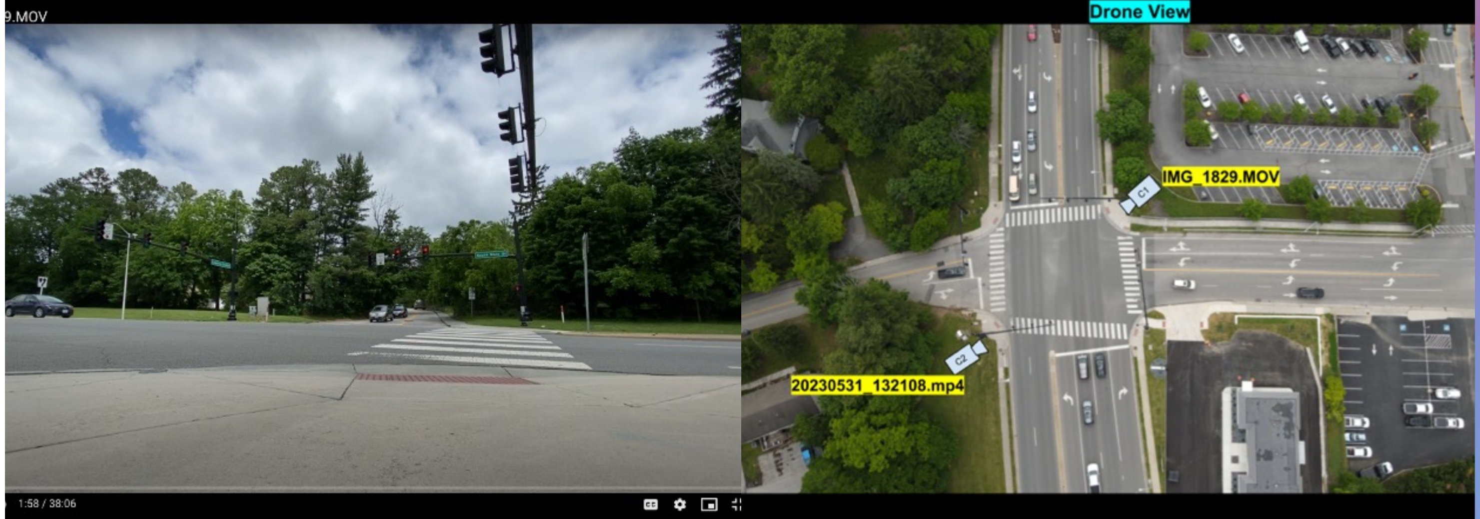
- Key takeaways
  - Graph based methods are being increasingly used for traffic analysis and safety measurement.
  - Infrastructure cameras can encode key information about the traffic dynamics
  - Graph based methods can encode both road way information and traffic information
  - We can perform safety prediction and analysis using GNN
  - Code will be available: https://github.com/VTTI/GNN-based-intersection-safety

DISCUSSIONS

- Practical limitations
  - The current camera infrastructure, characterized by its low resolution of 320x240 leads to cameras frequently losing focus in various situations.
  - Often only one camera is installed at an intersection. This does not provide complete information of the traffic dynamics.
  - Adequate annotations for safety events

DATASET


20230531_132108.mp4
Press Esc to exit full screen
8:47 / 33:00


9.MOV
Drone View
IMG_1829.MOV
20230531_132108.mp4
1:58 / 38:06

FUTURE SCOPE

- Upgrading the cameras to higher resolutions would greatly improve the clarity and level of detail in captured images and videos.
- The current project uses safety measures like TTC, PET, speed behavior. In recent years, more advanced safety features including RSS [12, 13] has been proposed. Future research can use these measures to create more detailed safety score.
- Intersection safety challenge
- Testing on a large scale data
  - We are currently processing 7 days of data from 10 intersections to record temporal analysis of safety

[12] Shalev-Shwartz, S., Shammah, S., & Shashua, A. (2017). On a formal model of safe and scalable self-driving cars. arXiv preprint arXiv:1708.06374.
[13] Sarkar, A., Krum, A., Hanowski, R., & Hickman, J. (2021, June). Responsibility Sensitive Safety Analysis of Truck Following in US Highway. In International Conference on Applied Human Factors and Ergonomics (pp. 119-126). Cham: Springer International Publishing.

THANK YOU

Contact: asarkar@vtti.vt.edu, asonth@vtti.vt.edu