

August, 2020

Training A Spatial Graph With Expert Human Driver Log Data

Summer 2020 Intern Project - Planning Team, Motional
Intern: Tianyi Gu

Content

The Problem

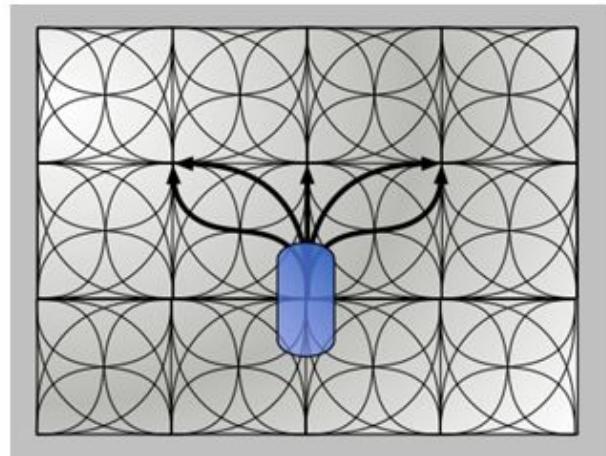
Our Approach

Results and Discussion

What's Next

The Problem - Background

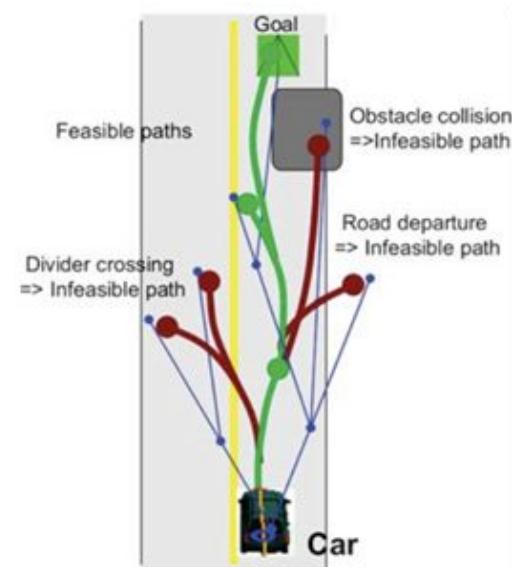
Lattice-based Planner



Pivtoraiko & Kelly 2005



Sampling-based Planner



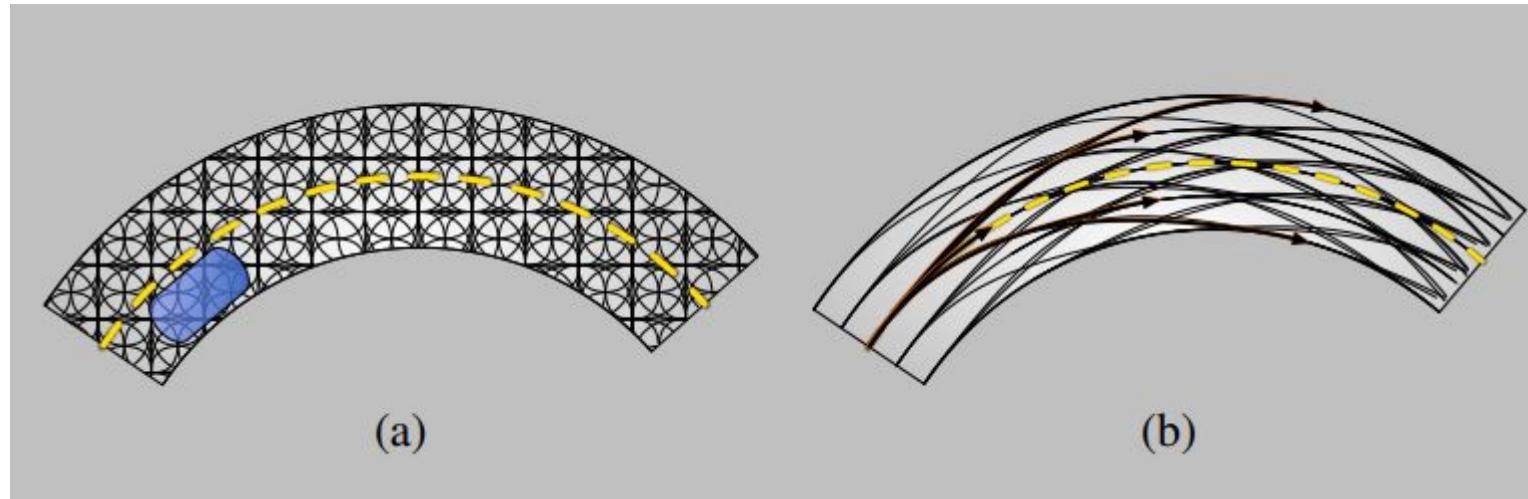
Leonard et al. 2008

The Problem - Background

Lattice-based Planner

Spatial-Temporal Graph Search

SE(2) Graph Generation



Many edges in the left lattice are not useful !

The Problem - SE(2) Graph Generation

In this project, we want to find a **principled** way to generate SE(2) graph.

We want to answer following questions:

1. How dense should the SE(2) graph be?
2. Where should we put the vertices?
3. How to connect vertices?

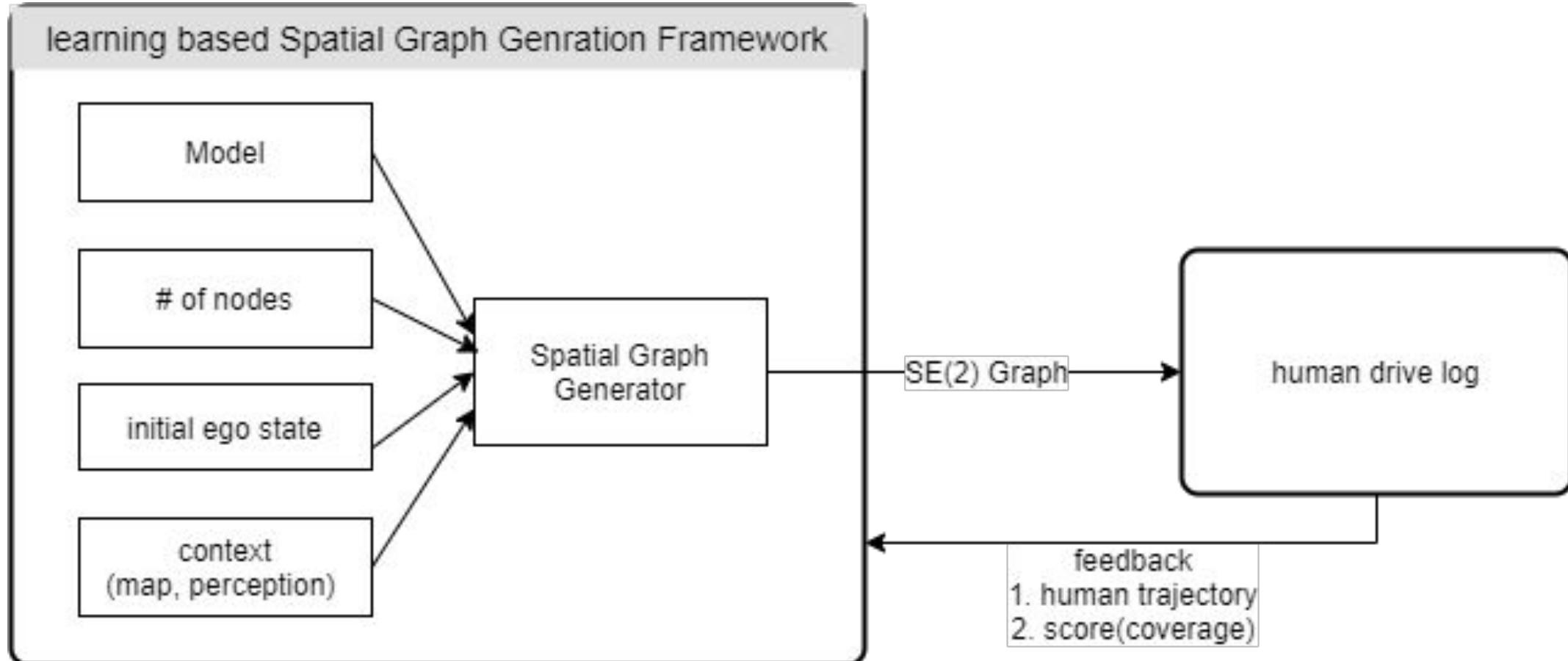
Maximize

Diversity / Coverage

Minimize

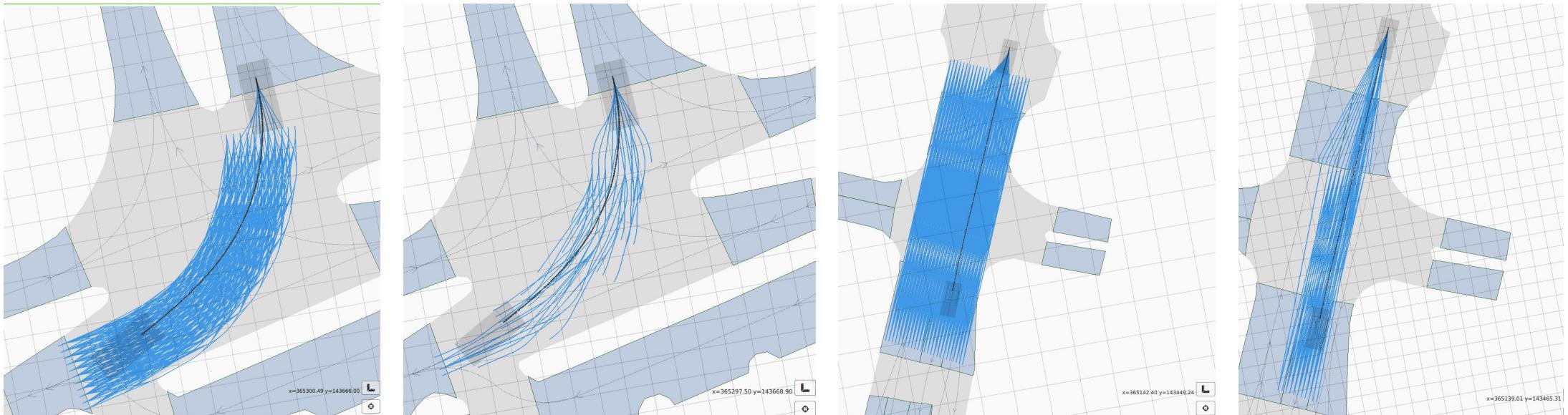
Node count / Edge count

Our Approach - Learning A SE(2) Graph From Human Driver



The Problem - SE(2) Graph Generation

- Less nodes, less edges
- High coverage on expert human trajectories

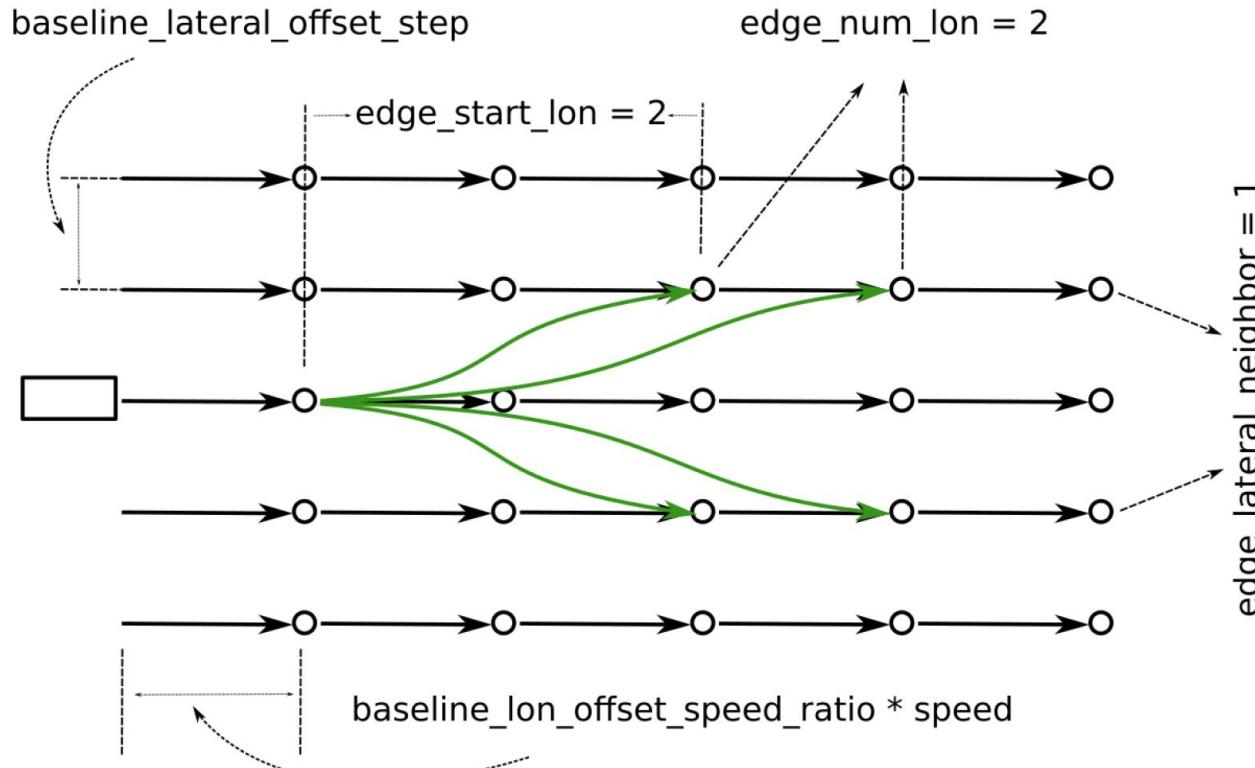


Our Approach - Learning A SE(2) Graph From Human Driver

- Initial Graph Generation
- Training Data Preparation
- Train a SE(2) Graph with Human Drive Data

Our Approach - Learning A SE(2) Graph From Human Driver

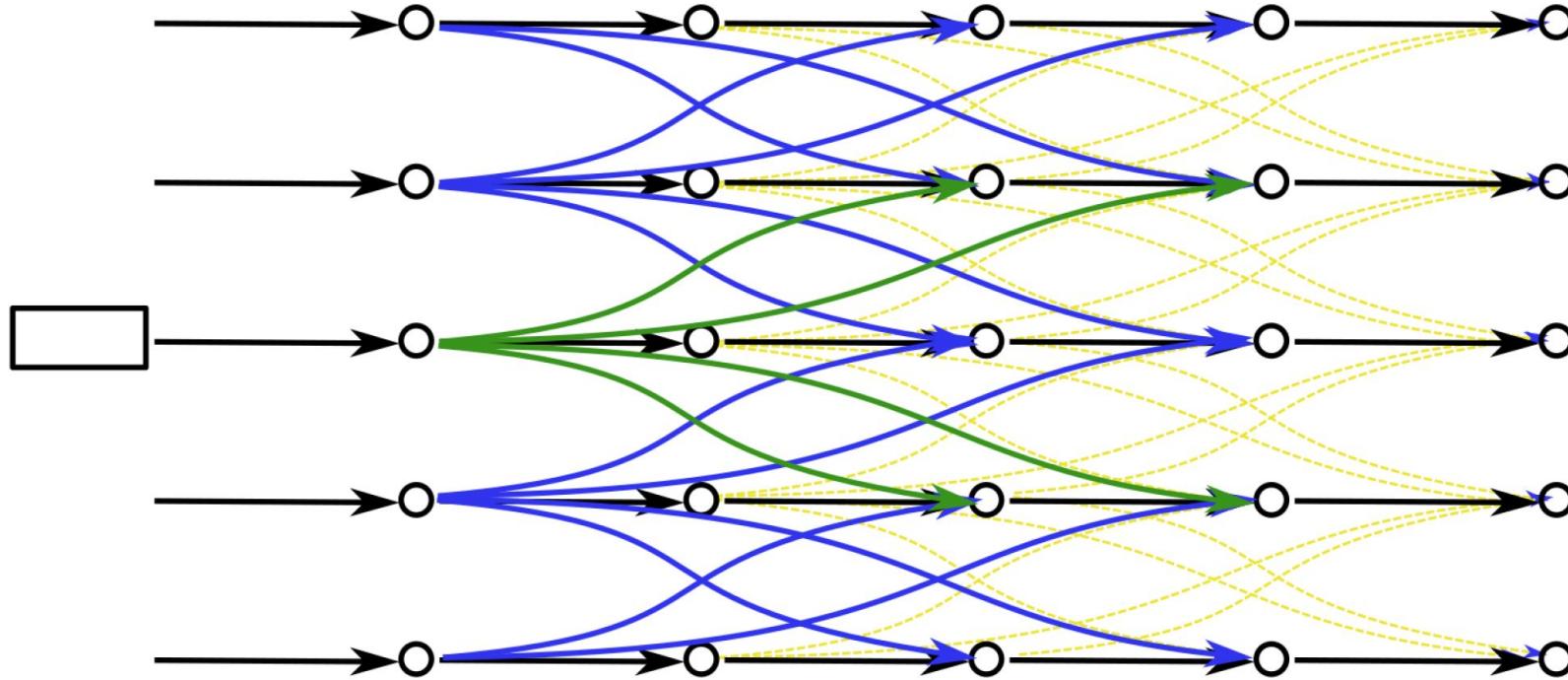
- Initial Graph Generation - **structured connection**



parameter	value	unit
baseline_lon_offset_speed_ratio	4	-
baseline_lateral_offset_step	0.5	m
edge_start_lon	2	vertices
edge_number_lon	2	vertices
edge_lateral_neighbor	1	neighbor lines each direction

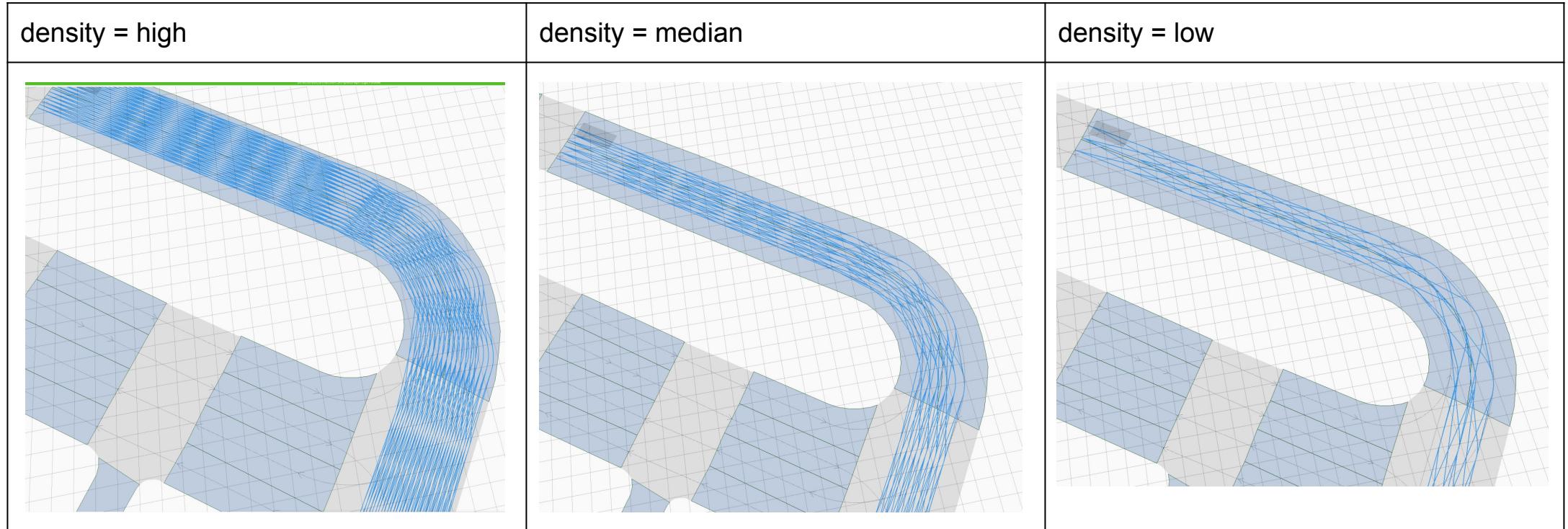
Our Approach - Learning A SE(2) Graph From Human Driver

- Initial Graph Generation - **structured connection**



Our Approach - Learning A SE(2) Graph From Human Driver

- Initial Graph Generation - How to choose **candidate graph?**

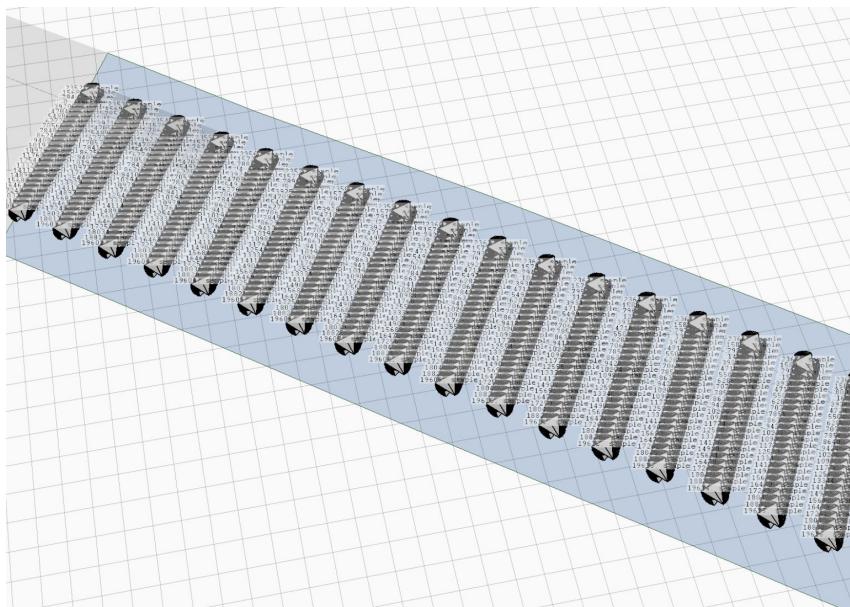


Our Approach - Learning A SE(2) Graph From Human Driver

- Initial Graph Generation - How to choose candidate graph?

uniform sample-based evaluator

cover samples as much as possible but still keep the **graph size small**



Our Approach - Learning A SE(2) Graph From Human Driver

- Initial Graph Generation - How to choose candidate graph?

uniform sample-based evaluator

SE2 distance function: Weighted SE2 distance

$$d(s, g) = w1 \cdot \|s_{linear} - g_{linear}\|_{L_2} + w2 \cdot \|s_{angular} - g_{angular}\|_{L_1}$$

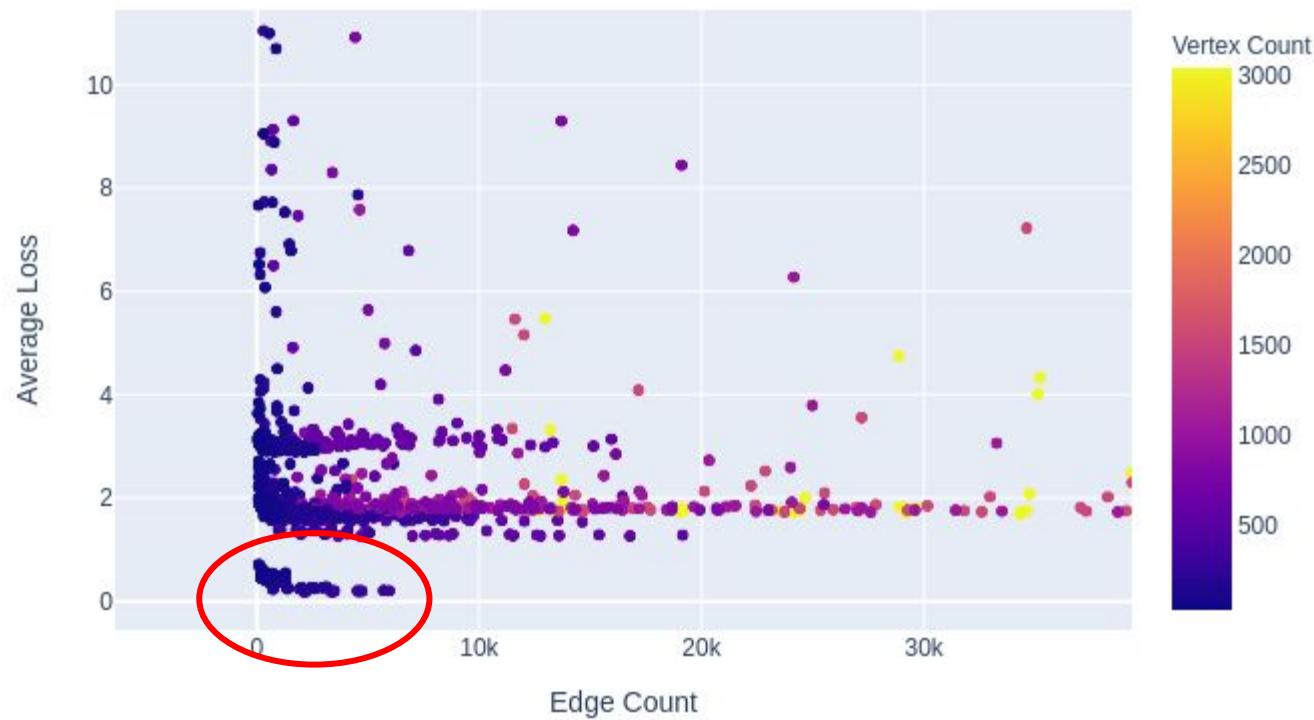
We set w1 = 1, w2 = 2.

This means 3 degree off on heading is about equally important as 10 cm off on 2D map.

(0.05 rad is as important as 0.1 m)

Our Approach - Learning A SE(2) Graph From Human Driver

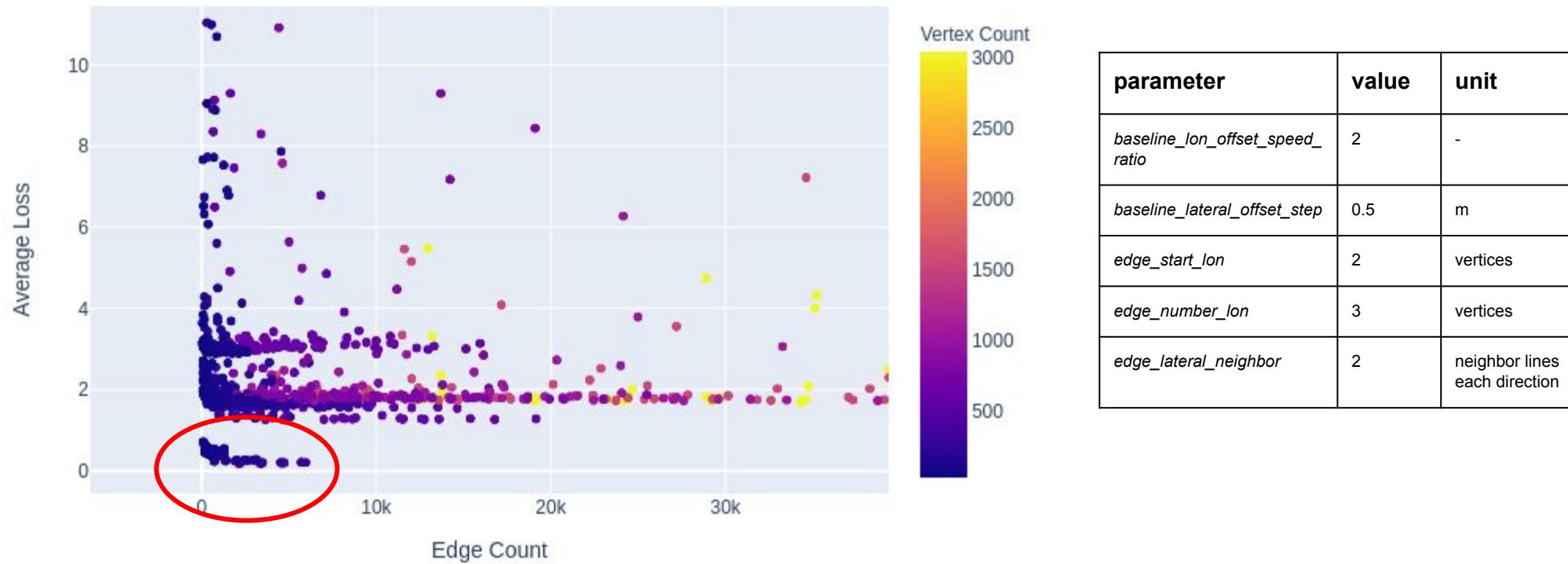
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parameter	tested value	unit
baseline_lon_offset_s speed_ratio	1, 2, 3, 4, 5	-
baseline_lateral_offset_step	0.1, 0.5, 1, 2	m
edge_start_lon	1, 2, 3	vertices
edge_number_lon	1,2,3,4,5	vertices
edge_lateral_neighbour	1,2,3,4,5	neighbor lines each direction

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Our Approach - Learning A SE(2) Graph From Human Driver

- Training Data Preparation

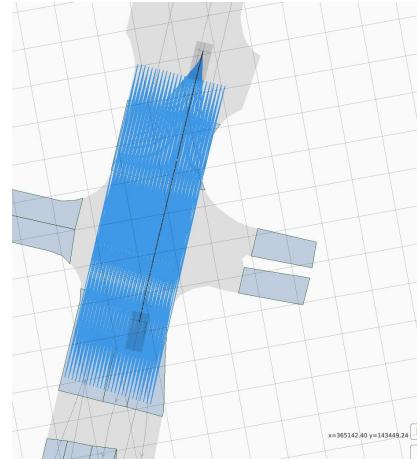
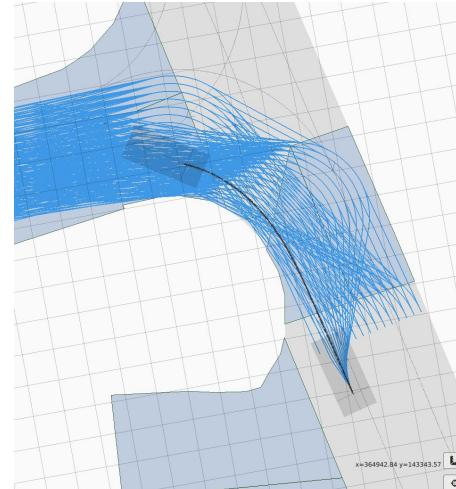
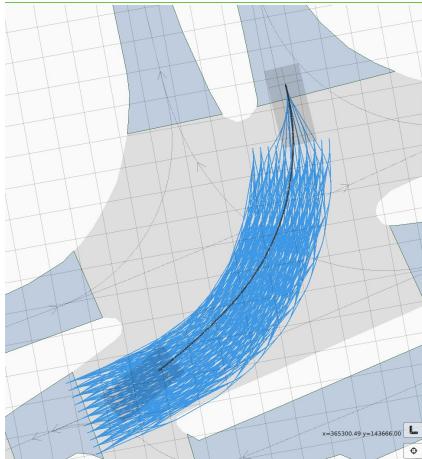
- [OneNorth Expert Driver Log](#)
- contain 30 hours of AV data in Singapore
- convert from legacy coordinates to UTM coordinates, so it can work with avmap and avtest
- split log into planning problem instances
- planning instances are saved as JSON files

```
{  
  "init_ego_pose": [  
    1151.808874255592,  
    393.97060909332663,  
    1.2096617576737891  
  ],  
  "init_ego_velocity": 3.3481582460510673,  
  "goal_ego_pose": [  
    1170.8830955458552,  
    414.6584417187234,  
    0.9328866715163339  
  ],  
  "log_name": "n013-2019-06-17-14-19-46+0800",  
  "init_timestamp": 1560752396183863,  
  "duration": 5,  
  "ego_path": [  
    [  
      1151.808874255592,  
      393.97060909332663,  
      1.2096617576737891  
    ],  
    [  
      1151.8681950012576,  
      394.09195137945943,  
      1.199778708367397  
    ],  
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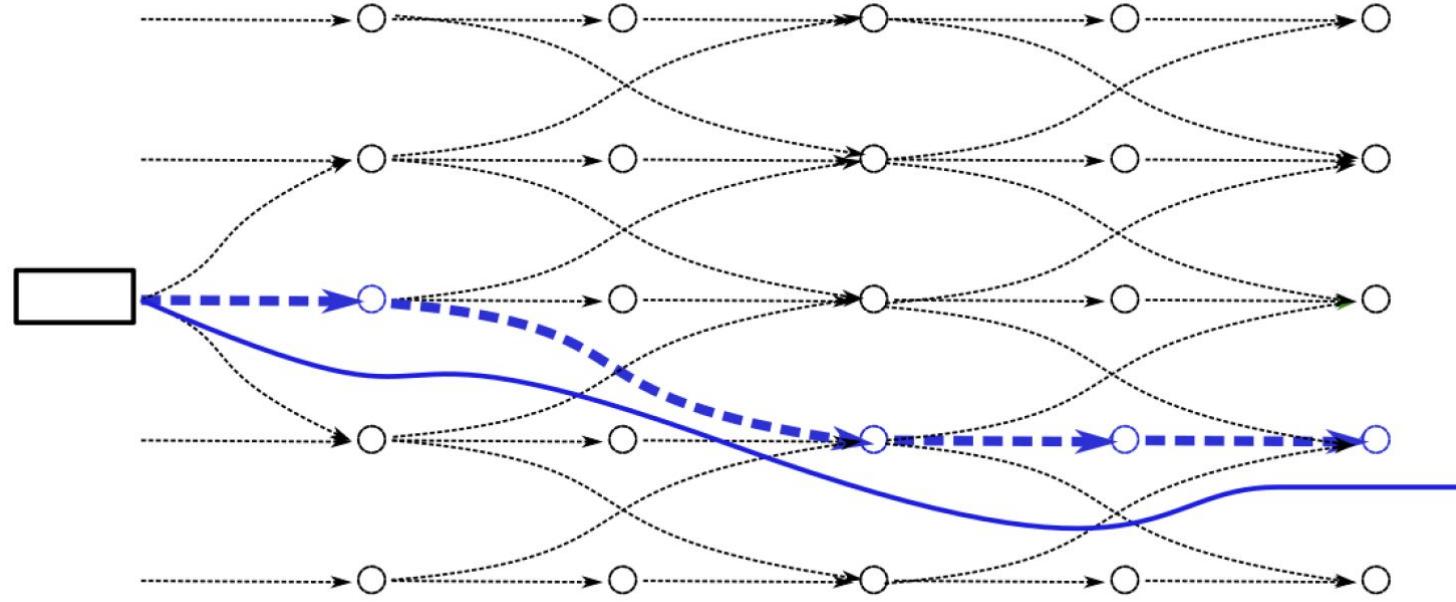
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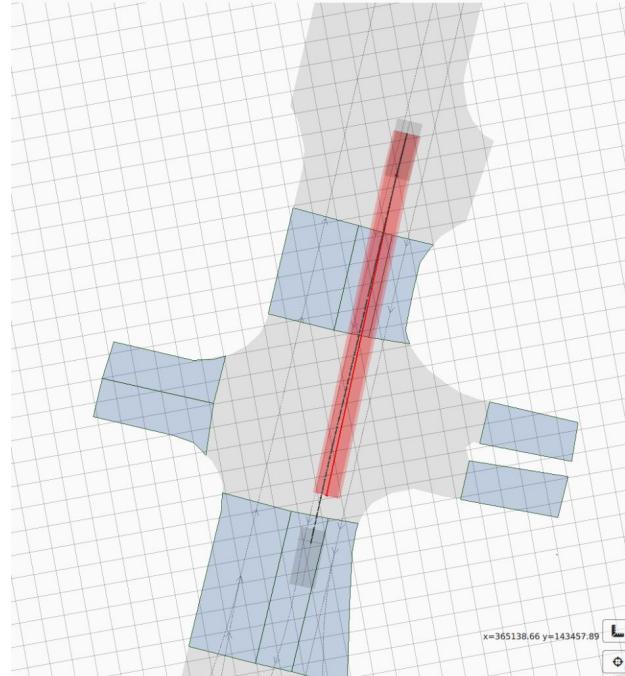
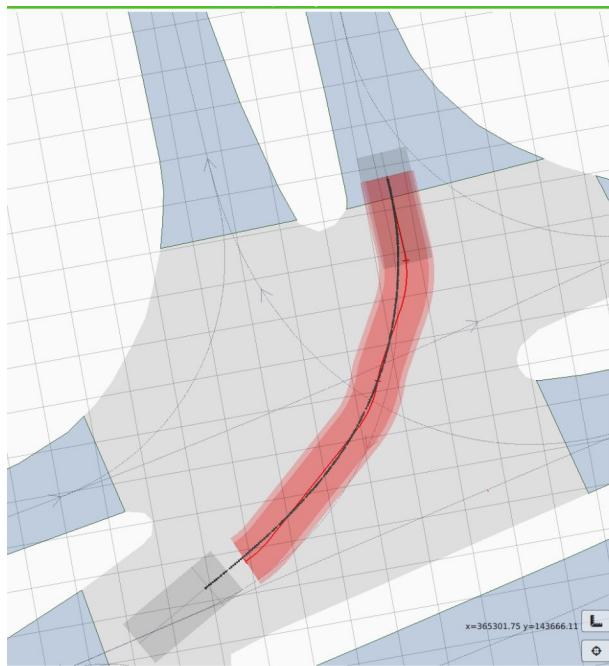
Our Approach - Learning A SE(2) Graph From Human Driver

- Train a SE(2) Graph with Human Drive Data
 - **Loss computator** : given a graph and a human trajectory, what is the loss between the best reproduced trajectory and the human trajectory?



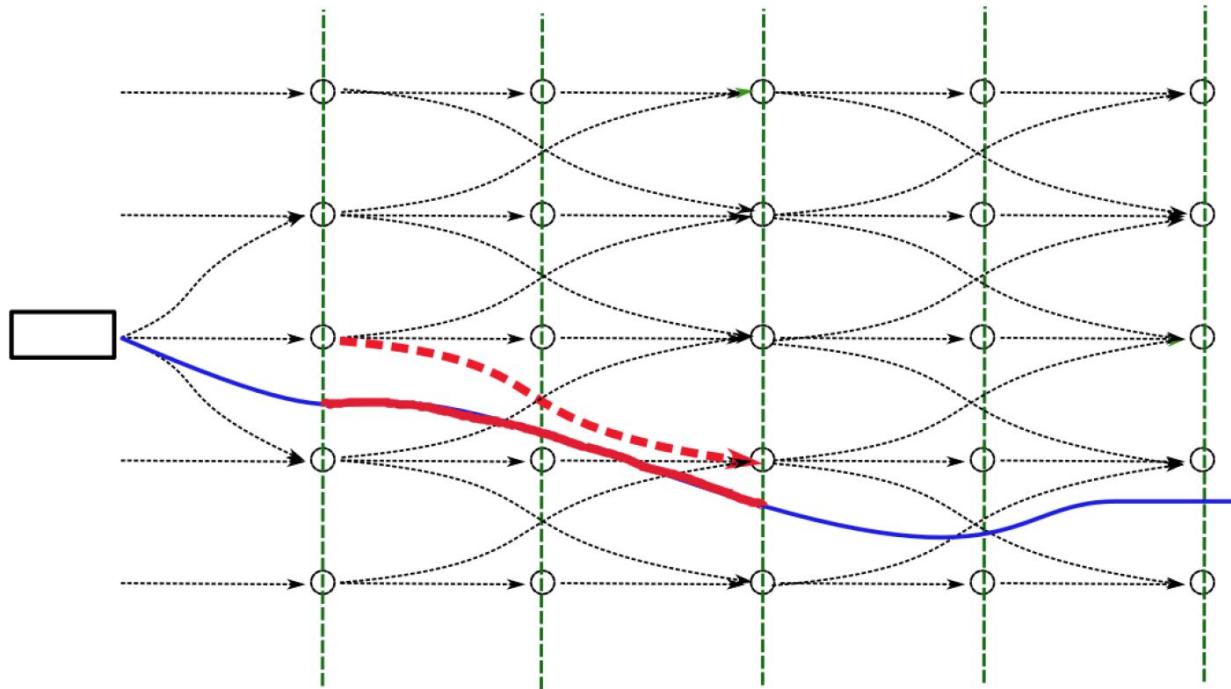
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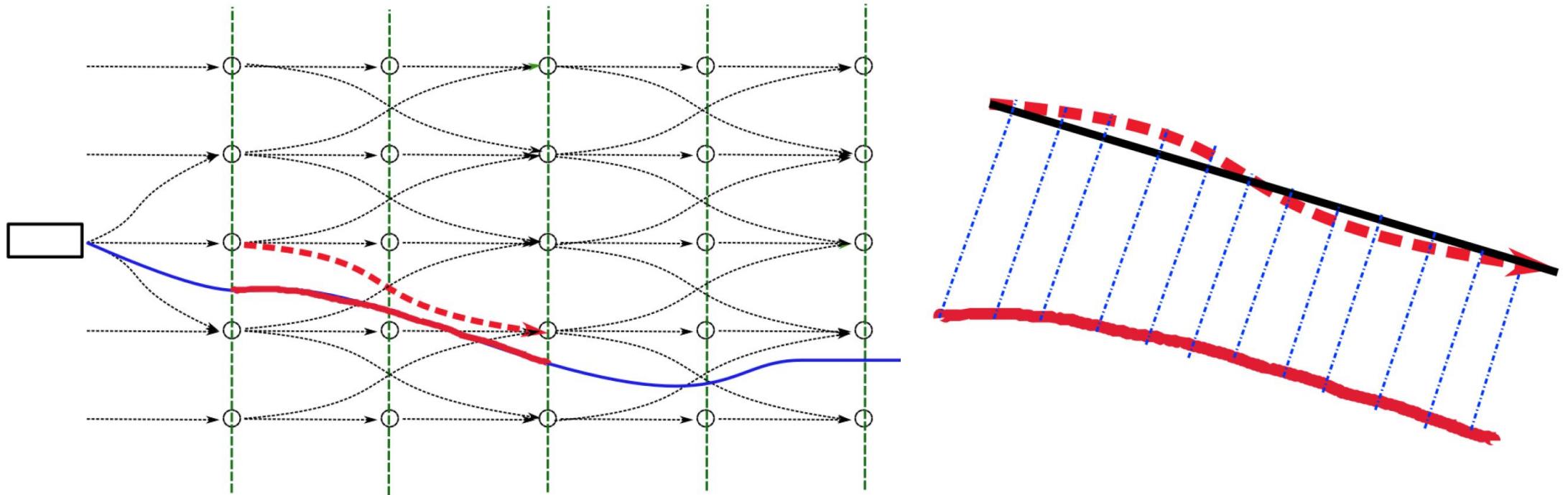
Our Approach - Learning A SE(2) Graph From Human Driver

- Train a SE(2) Graph with Human Drive Data
 - Loss computator : Dijkstra with edge loss as cost
 - Edge Loss:



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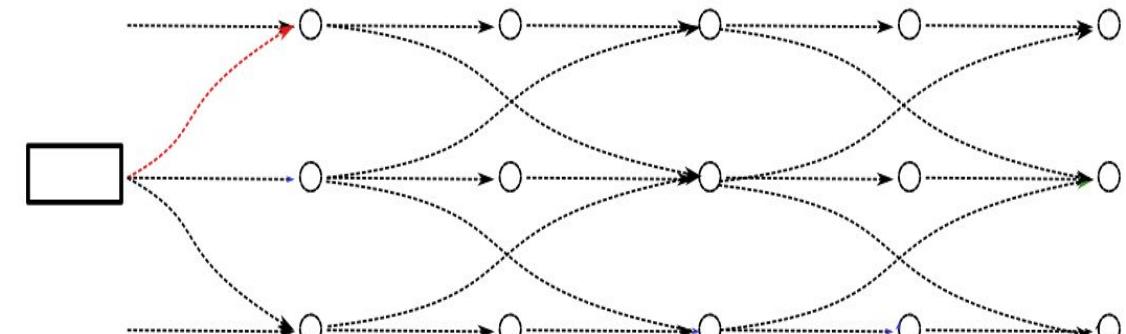
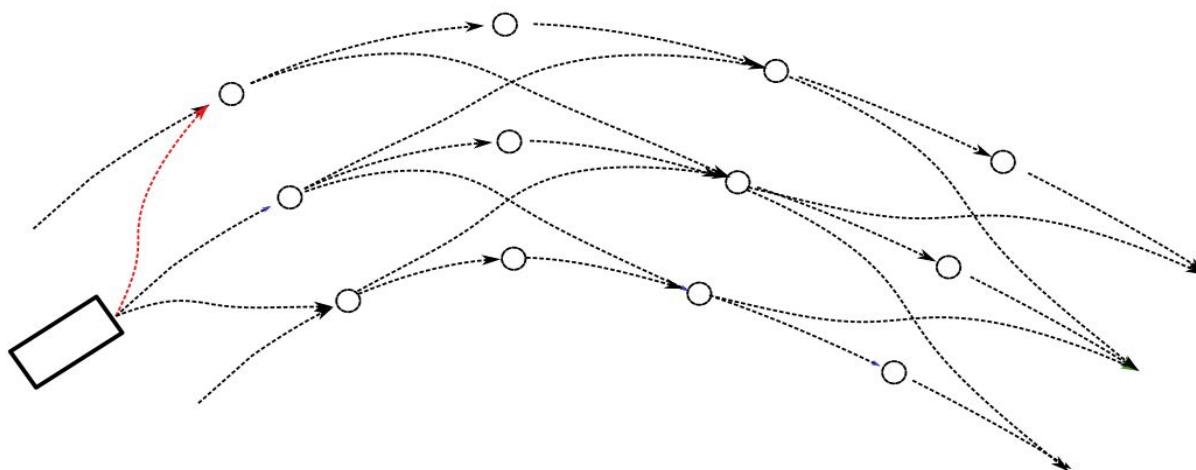


Our Approach - Learning A SE(2) Graph From Human Driver

- Train a SE(2) Graph with Human Drive Data
 - Loss computator : Dijkstra with edge loss as cost
 - Edge Loss
 - Score of the graph, Score of each edge

Our Approach - Learning A SE(2) Graph From Human Driver

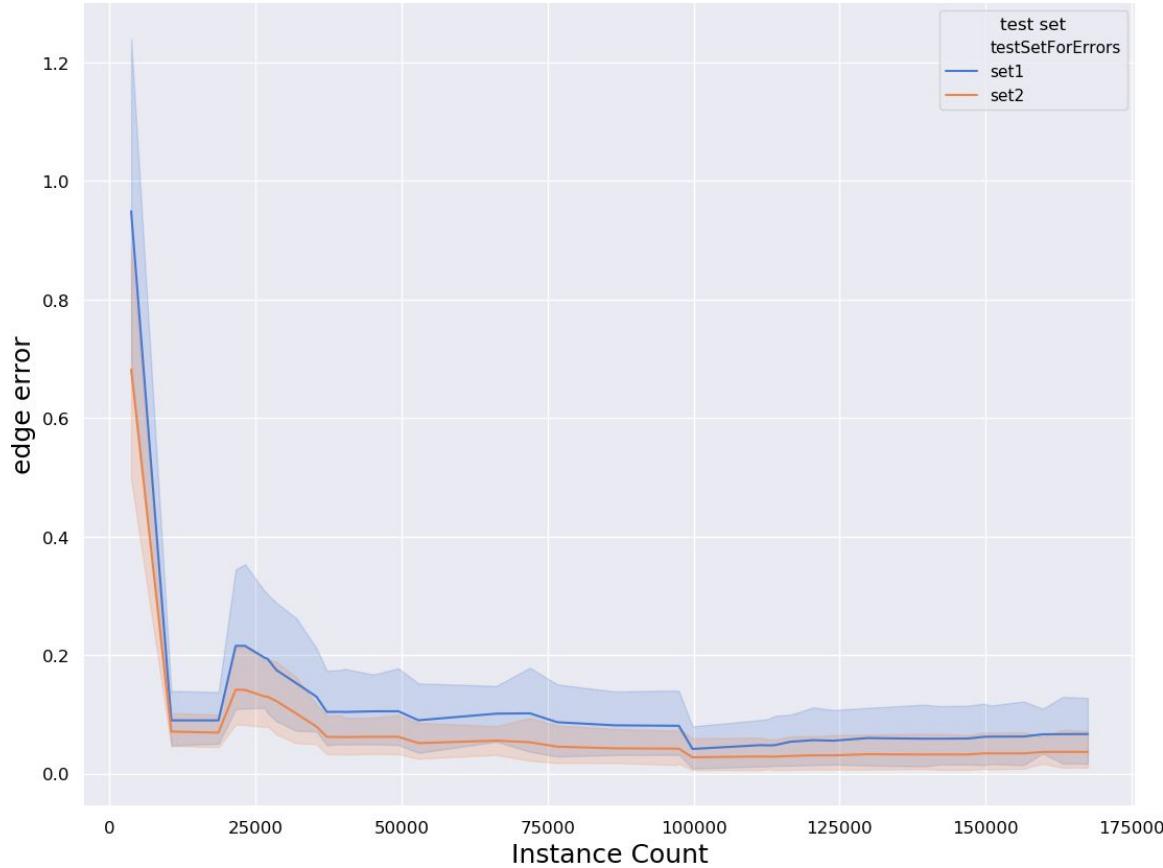
- Train a SE(2) Graph with Human Drive Data
 - Loss computator : Dijkstra with edge loss as cost
 - Edge Loss
 - Score of the graph, Score of each edge
 - Abstract graph



Results and Discussion

- Results
- Takeaways
- Limitations

Results - Edge Loss Prediction



Metrics:

mean

median

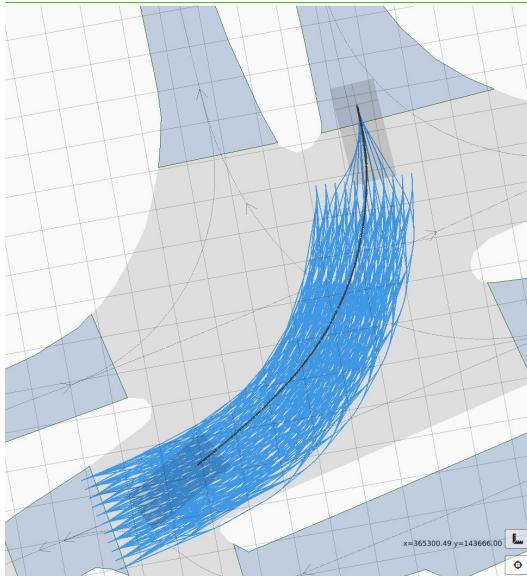
min

95 percentile

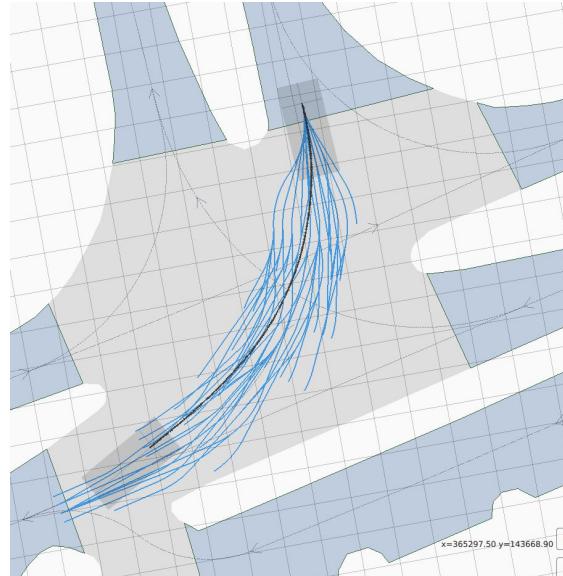
used in best trajectory

prediction error converge on test set

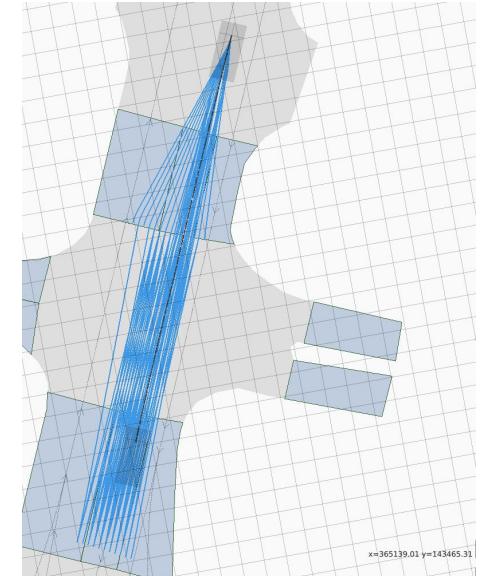
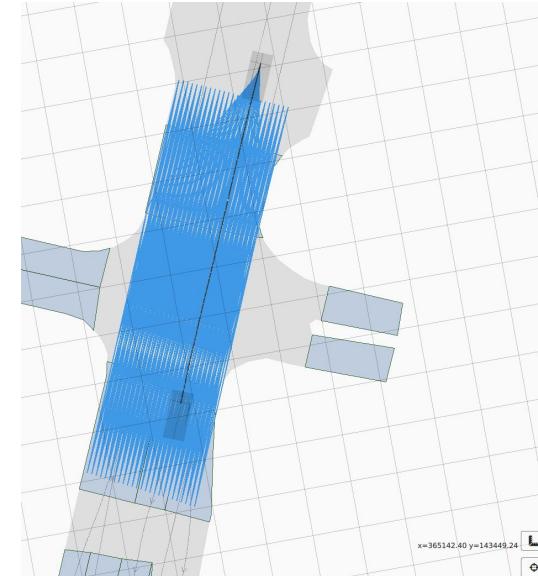
Results - Graph Pruning



90.5% pruned

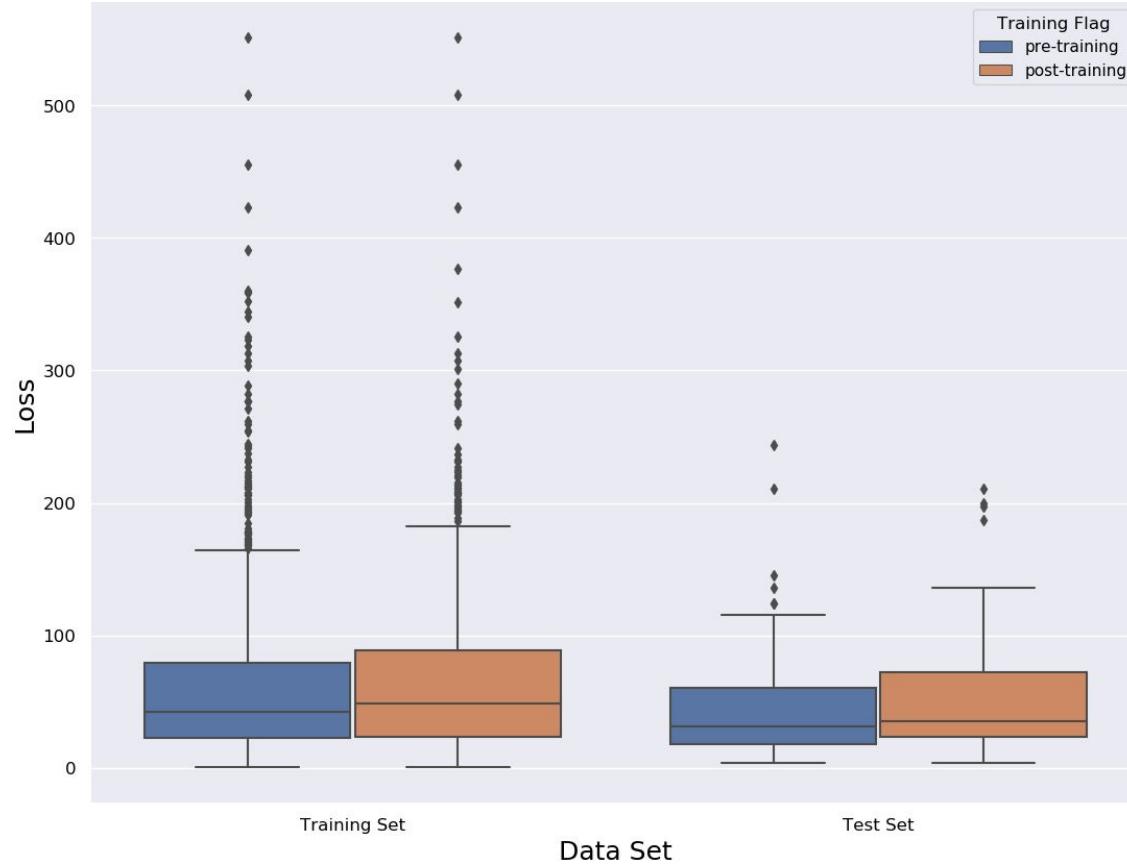


79.6% pruned



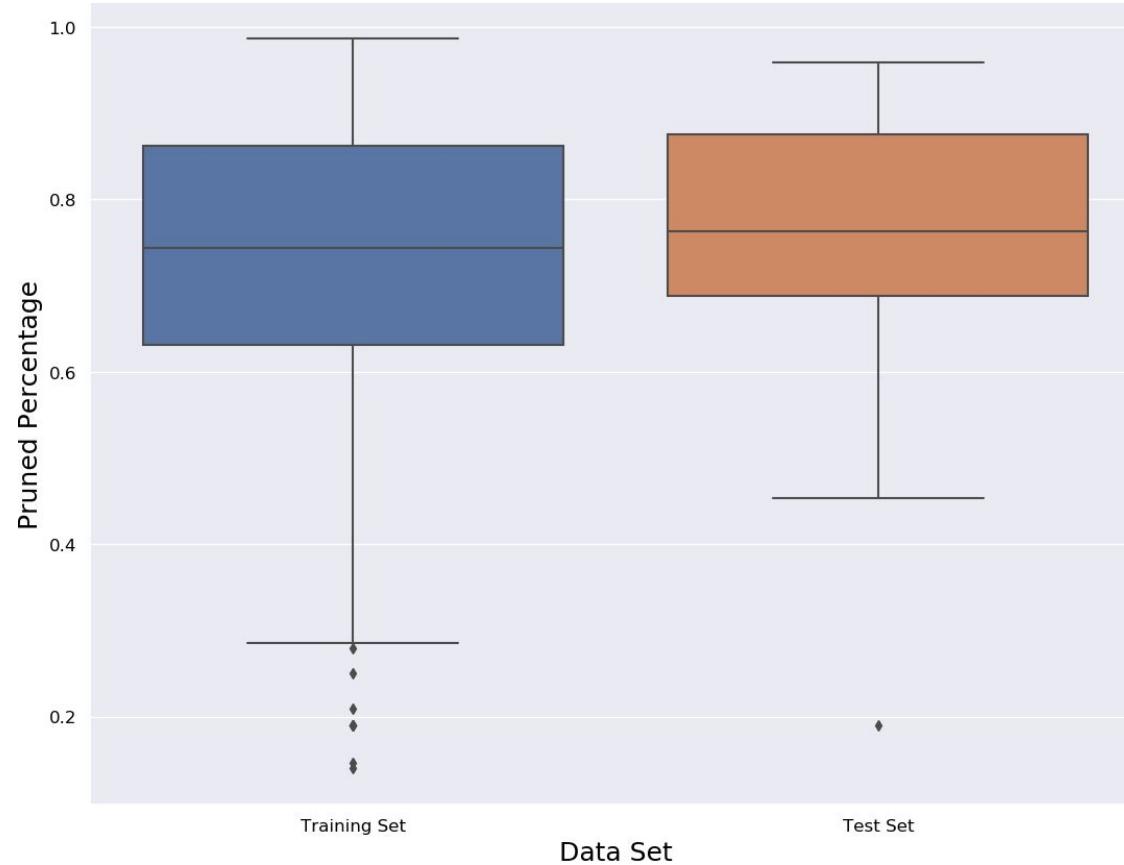
Many useless edges are pruned

Results - Overhead on Loss



Not much overhead on loss

Results - Graph Pruning



~78% of the edges are pruned

Results - Takeaways

- This approach enable the graph size reduction without compromising the performance
- Utilizing drive logs has the potential to inform the planner

Results - Limitations

- Low speed and stop scenarios are not supported
- The graph coverage is limited by the dataset
- Temporal dimension of the drivers' decision is learned implicitly

What's Next

- Test the graph generator with a S-T planner
- Write a patent/paper about the discovery