CSE 151B Project Final Report

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1 Task Description and Background

1.1 Problem A

1.2 Problem B

1.3 Problem C

2 Exploratory Data Analysis

2.1 Problem A

The task is to predict and forecast the motion of agents tracked by an autonomous vehicle. It is important to develop models to accurately predict the future positions of these agents for autonomous vehicles to work properly and safely.

Where the data is sampled at 10 timestamps per second, the input to the prediction task is an input array of 50 timestamps, with each time stamp having an (x, y) coordinate. Thus, the input array has shape $(50, 2)$. After processing through the model, output needs to predict the position of the agent for the next 60 timestamps, so the output array has shape $(60, 2)$.

Thus, the prediction task will consist of taking in 50 positional coordinates which are ordered in time (5 seconds), and output the next 60 predicted positional coordinates in time (6 seconds).

2.2 Problem B

The training data set has input shape $(203816, 50, 2)$ and output shape $(203816, 60, 2)$. The test data set has input shape $(29843, 50, 2)$ and output shape $(29843, 60, 2)$. For each trajectory, the model input dimension is $(50, 2)$ and its output dimension is $(60, 2)$.

The distribution of input positions for all agents is shown as a heatmap in Figure 1. The distribution of output positions for all agents is shown as a heatmap in Figure 2. The distributions of positions for each city is shown in the following heatmaps (Figure 3-8).

Preprint. Under review.

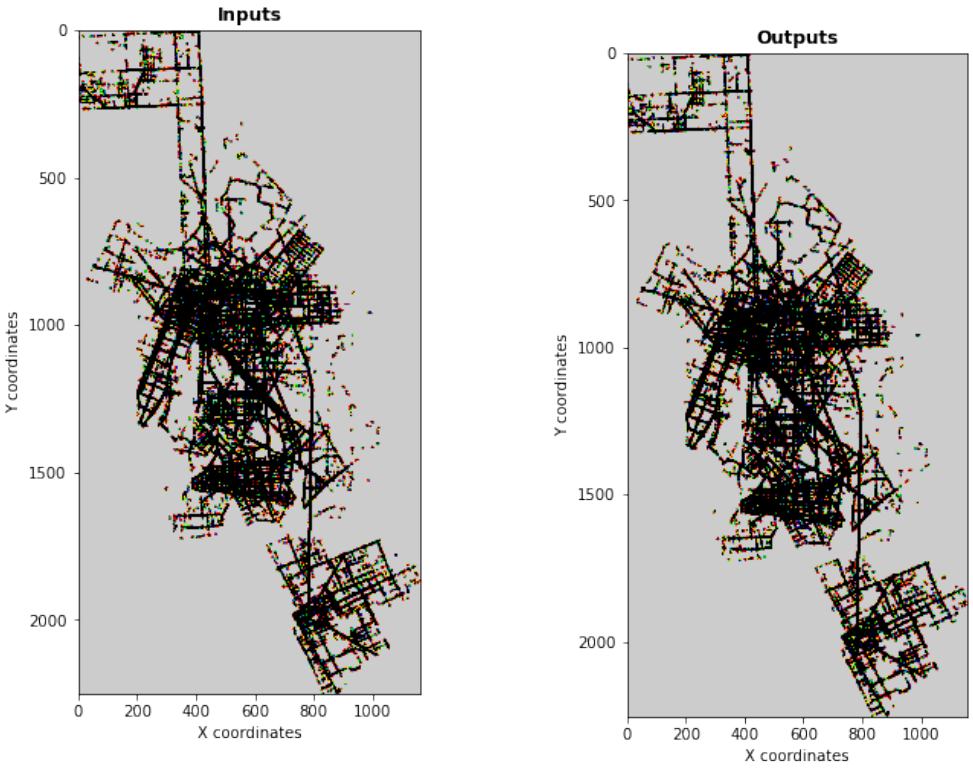
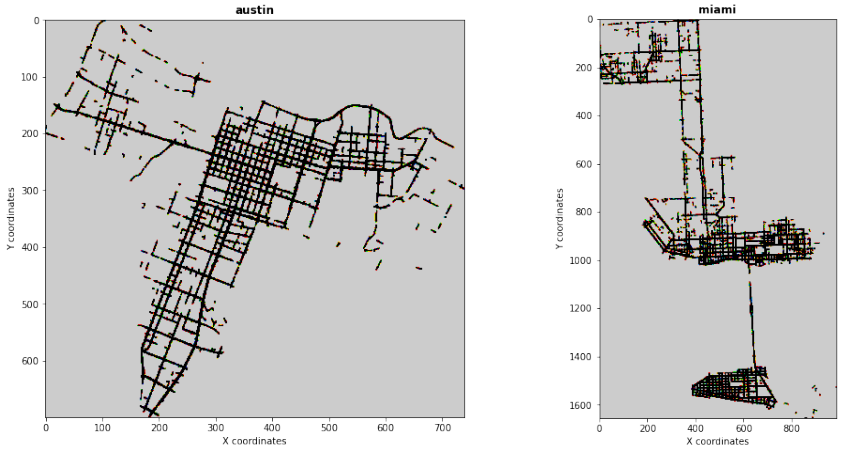
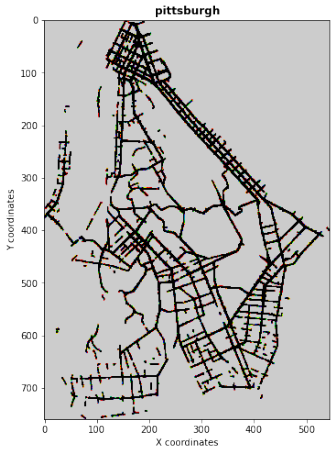
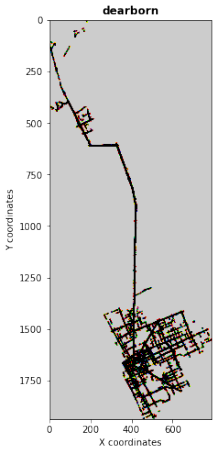
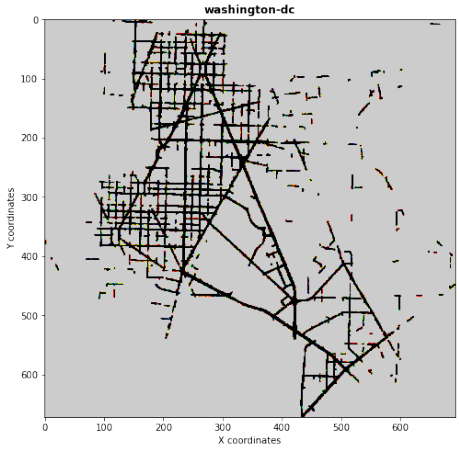


Figure 1: some more







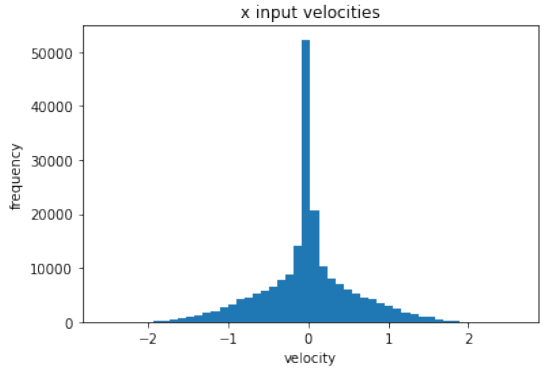


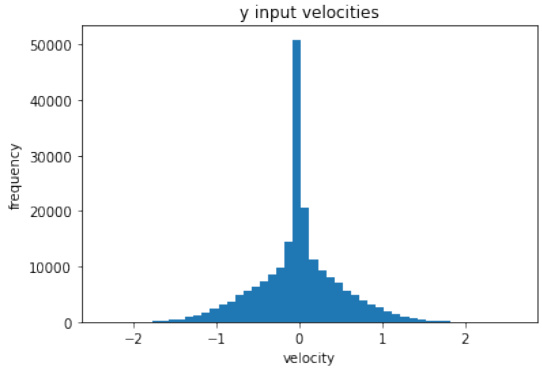
The positions shown in these heatmaps illustrate that the motion/direction of agents are generally very linear and straight. Thus, in the bonus exploratory analysis, I will dive into the information provided by the motion of the agents.

2.3 Problem C

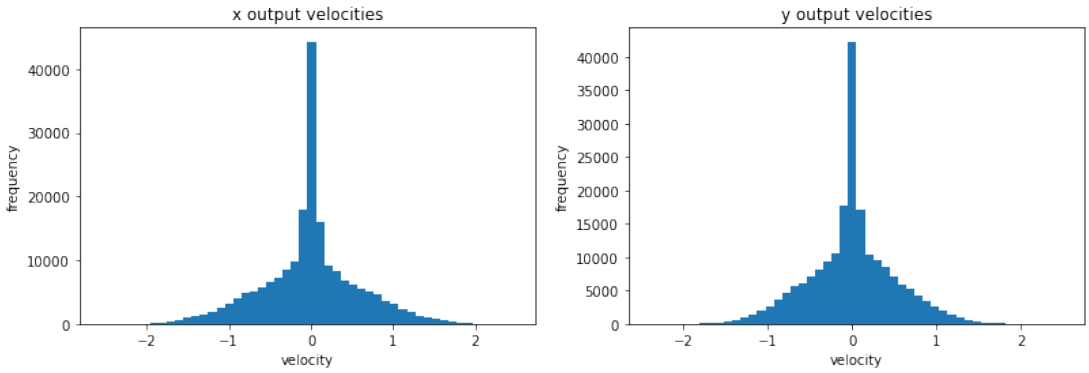
2.4 Bonus exploratory analysis

In figures 9-10, we visualize the frequency of average velocity in each input set.

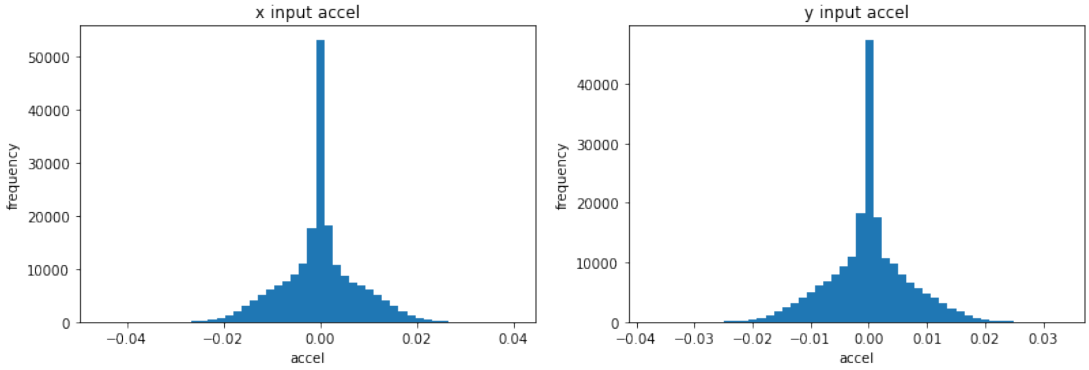




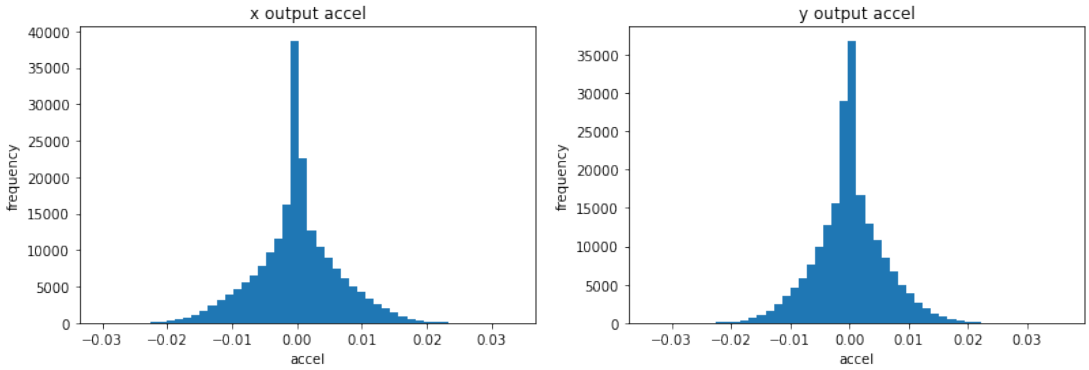
In figures 11-12, we visualize the frequency of average velocity in each output set.



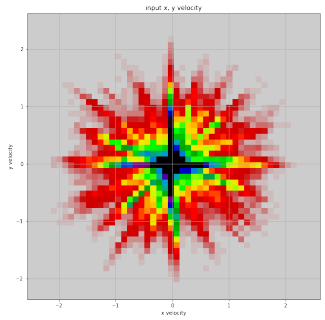
In figures 13-14, we visualize the frequency of average acceleration in each input set.

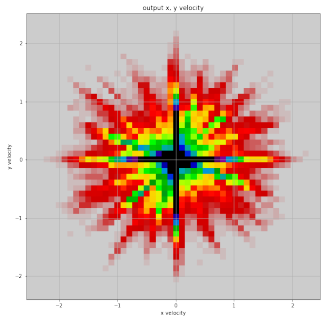


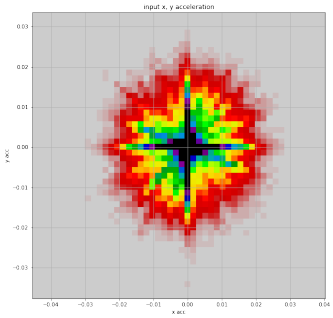
In figures 15-16, we visualize the frequency of average acceleration in each output set.

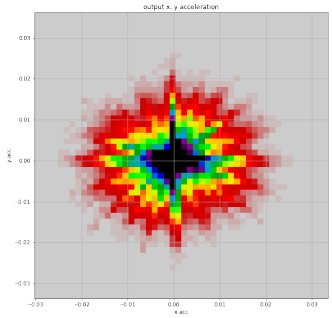


In figures 17-20, we take the the previous data and visualize them in 2D.

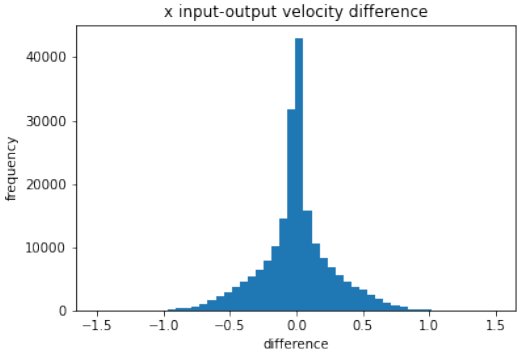


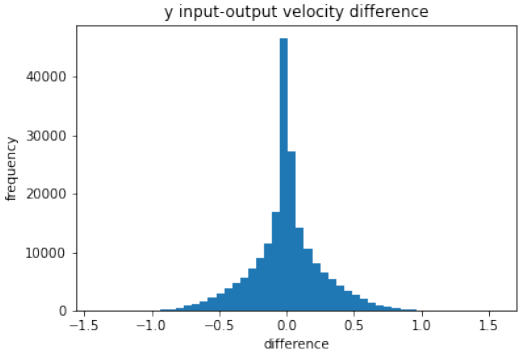


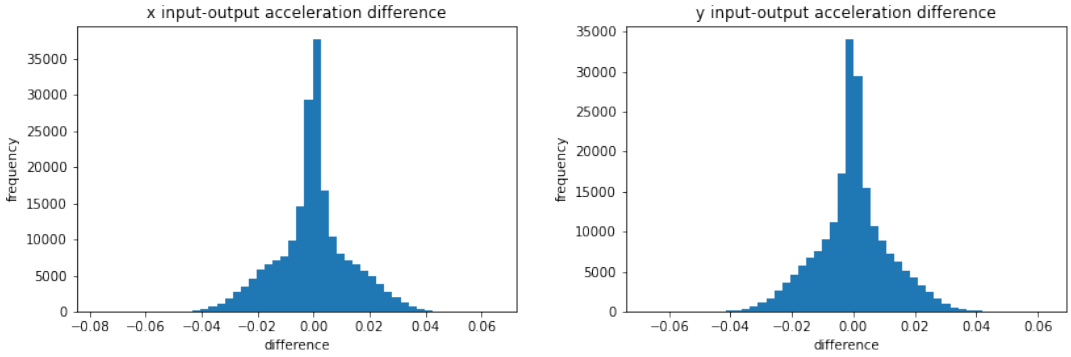




In figures 21-24, we show the frequency of differences between input and output data.







The further exploratory data analysis reveals that a linear prediction model will be very accurate for the data set, because we can see the density of velocity/acceleration is greatly concentrated near zero, and also the difference between the input and output data is typically zero. Thus, in general a straight linear prediction based on input data should accurately predict the output positions.

3 Machine Learning Model

3.1 Problem A

3.2 Problem B

3.3 Problem C

4 Experiment Design and Results

4.1 Problem A

4.2 Problem B

4.3 Problem C

5 Discussion and Future Work

5.1 Problem A

References

[1] Argoverse 2: Next Generation Datasets for Self-Driving Perception and Forecasting, Wilson et al. *Thirty-fifth Conference on Neural Information Processing Systems Datasets and Benchmarks Track (Round 2)*, 2021.

[2] What-If Motion Prediction for Autonomous Driving, Khandelwal et al. *arXiv preprint arXiv:2008.10587*, 2020.