

Multiple Future Prediction Leveraging Synthetic Trajectories

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Introduction

- The ability to forecast trajectories is essential to ensure safety in autonomous driving
- Unfortunately, the autonomous driving datasets required to train prediction models are extremely expensive to gather effectively
- We propose a data driven approach based on Markov Chains to generate synthetic trajectories, which are useful for training a multiple future trajectory predictor.
- We define a trajectory prediction model and we show that combining synthetic and real data we obtain prediction improvements, obtaining state of the art results.

Trajectory Generation

- Markov Chain whose parameters are estimated from real data
- Chain states correspond to vehicle position offsets from one timestep to the next

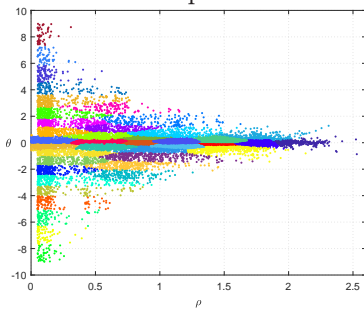


Figure 1: Clusterized offsets from the KITTI dataset in polar coordinates (ρ, Θ) .

Model

We developed a model specifically tailored to exploit synthetic samples with multimodal ground truth futures. The architecture is based on an encoder-decoder structure, which takes as input past trajectories and outputs multiple futures.

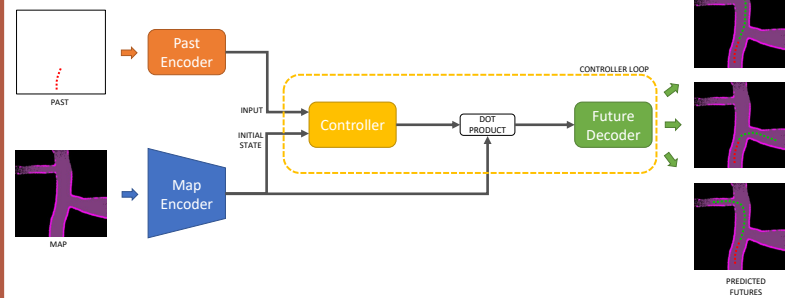


Figure 2: Architecture overview. Past trajectory and context map are encoded separately and used as input and initial state of the controller. The controller loops K times and at each iteration performs an attention with the map encoding via dot product. The resulting vector is fed to the decoder which emits a prediction. A diverse future is obtained for each iteration of the controller

Results

We trained three different variants of our method, varying the source of data: only real trajectories from KITTI, only synthetically generated trajectories, both real and synthetic trajectories. All variants are tested on the test set of KITTI, i.e. on real data.

| Method | ADE@4s | FDE@4s |
|-----------------------|-------------|-------------|
| Kalman | 3.03 | 7.41 |
| Linear | 1.64 | 4.73 |
| MANTRA | 0.94 | 2.48 |
| Ours (Synthetic data) | 1.31 | 3.44 |
| Ours (Real data) | 1.24 | 2.95 |
| Ours (Mixed data) | 0.89 | 2.27 |

Table 1: Average Displacement Error (ADE) and Final Displacement Error (FDE) in meters, computed for predictions at 4 seconds.

Using synthetic data, along with a model specifically tailored for multimodal predictions, has led to state of the art results on the KITTI dataset.

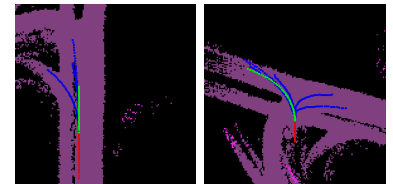


Figure 3: Predictions on real data. Green: GT, blue: predictions.



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