ICPR 2020

25th INTERNATIONAL CONFERENCE
ON PATTERN RECOGNITION

Milan, Italy 10 | 15 January 2021

Multiple Future Prediction Leveraging Synthetic Trajectories

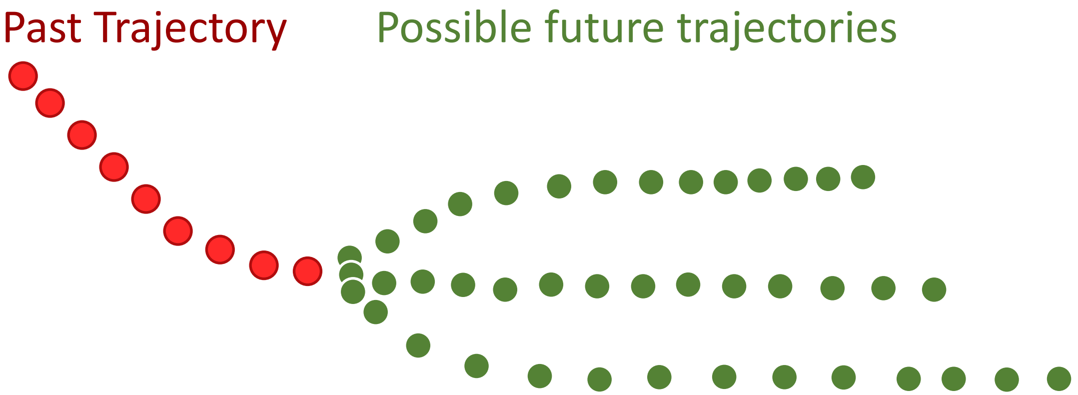
Lorenzo Berlincioni , Federico Becattini, Lorenzo Seidenari, Alberto Del Bimbo
MICC - Università degli Studi di Firenze
firstname.lastname@unifi.it

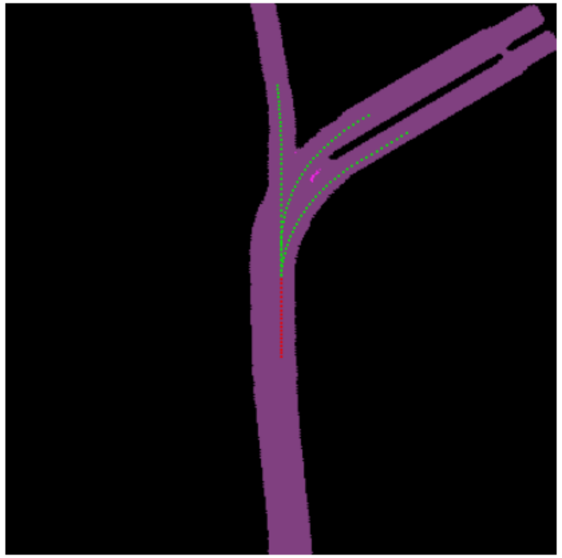
25th INTERNATIONAL CONFERENCE ON PATTERN RECOGNITION
Milan, Italy 10 | 15 January 2021

ICPR 2020
25th INTERNATIONAL CONFERENCE ON PATTERN RECOGNITION
Milan, Italy 10 | 15 January 2021

Trajectory prediction in autonomous driving

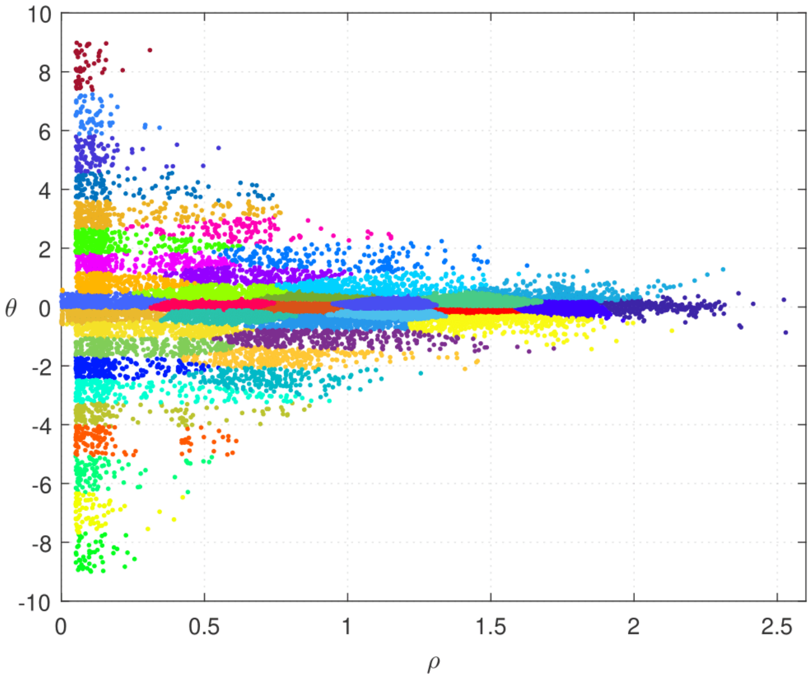
- **Multimodal** problem
- Learn a relation that maps *x* into one of K multiple outcomes $\{y_i\}$ i=1,...,K . In a supervised learning framework, real world data is able to provide only **a single supervision signal out of K**.
- Data collection is an **expensive** process
- We propose a method for synthetically generating trajectories for training prediction models





25th INTERNATIONAL CONFERENCE ON PATTERN RECOGNITION
Milan, Italy 10 | 15 January 2021

Synthetic trajectory generation



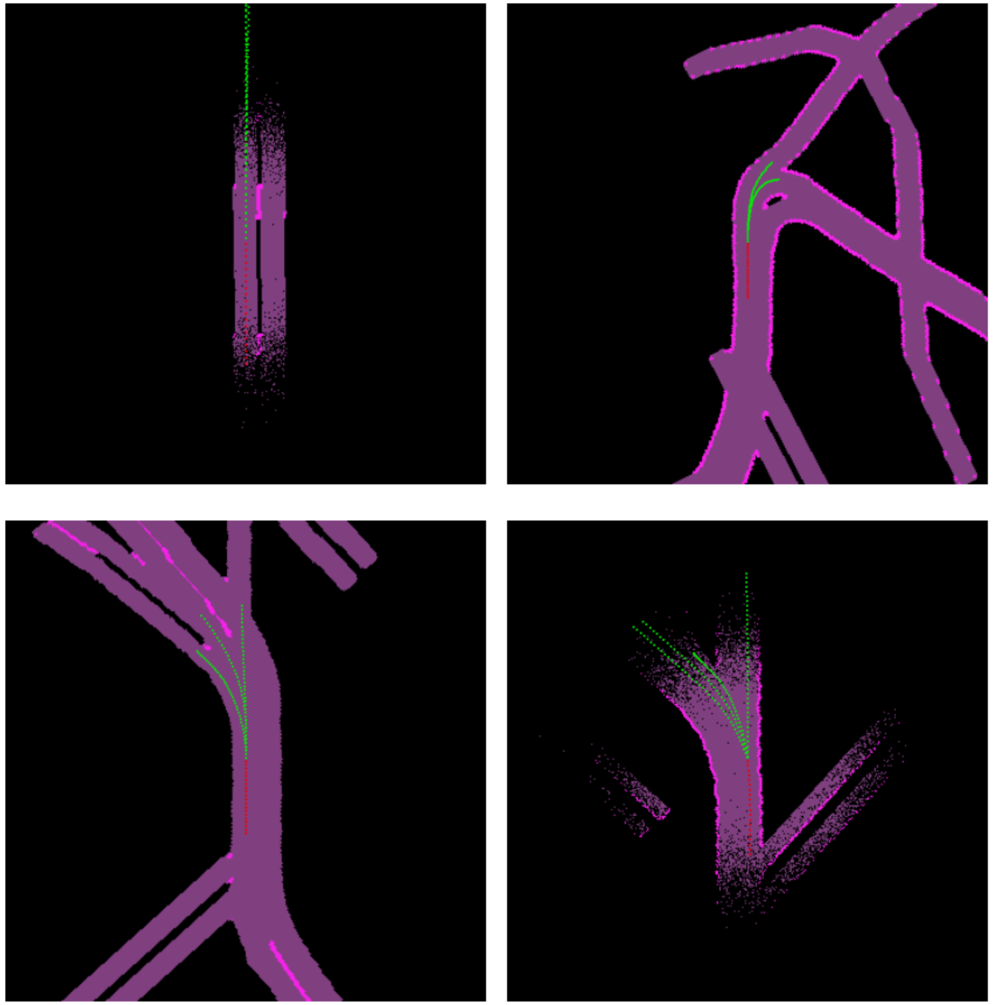
- We want to augment existing trajectory datasets with synthetic samples
- To generate synthetic trajectories we exploit a **Markov Chain** whose parameters are estimated from real data.
- The **states of the chain** correspond to vehicle position **offsets** in a polar coordinate system from one timestep to the next.
- To obtain a finite and compact set of states, we apply K-means to cluster all offsets

Synthetic map generation

- Maps are created by generating a set of trajectories and drawing roads around them.

- To obtain crossroads and forks we generate a new road starting from a random point along the previously generated

- To mimic realistic LiDAR artifacts we **randomly add noise** on map borders

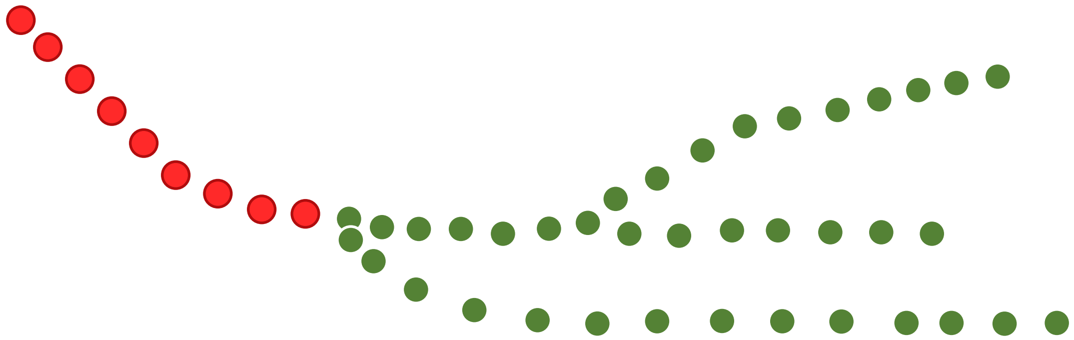


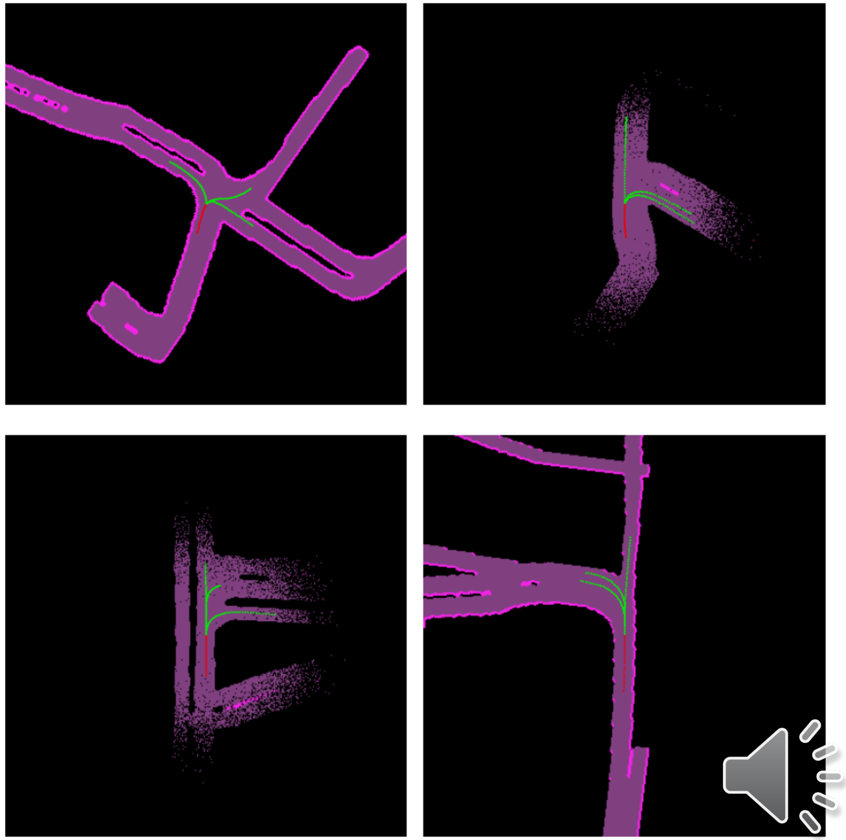
ICPR 2020
25th INTERNATIONAL CONFERENCE
ON PATTERN RECOGNITION
Milan, Italy 10 | 15 January 2021

Multimodal trajectories

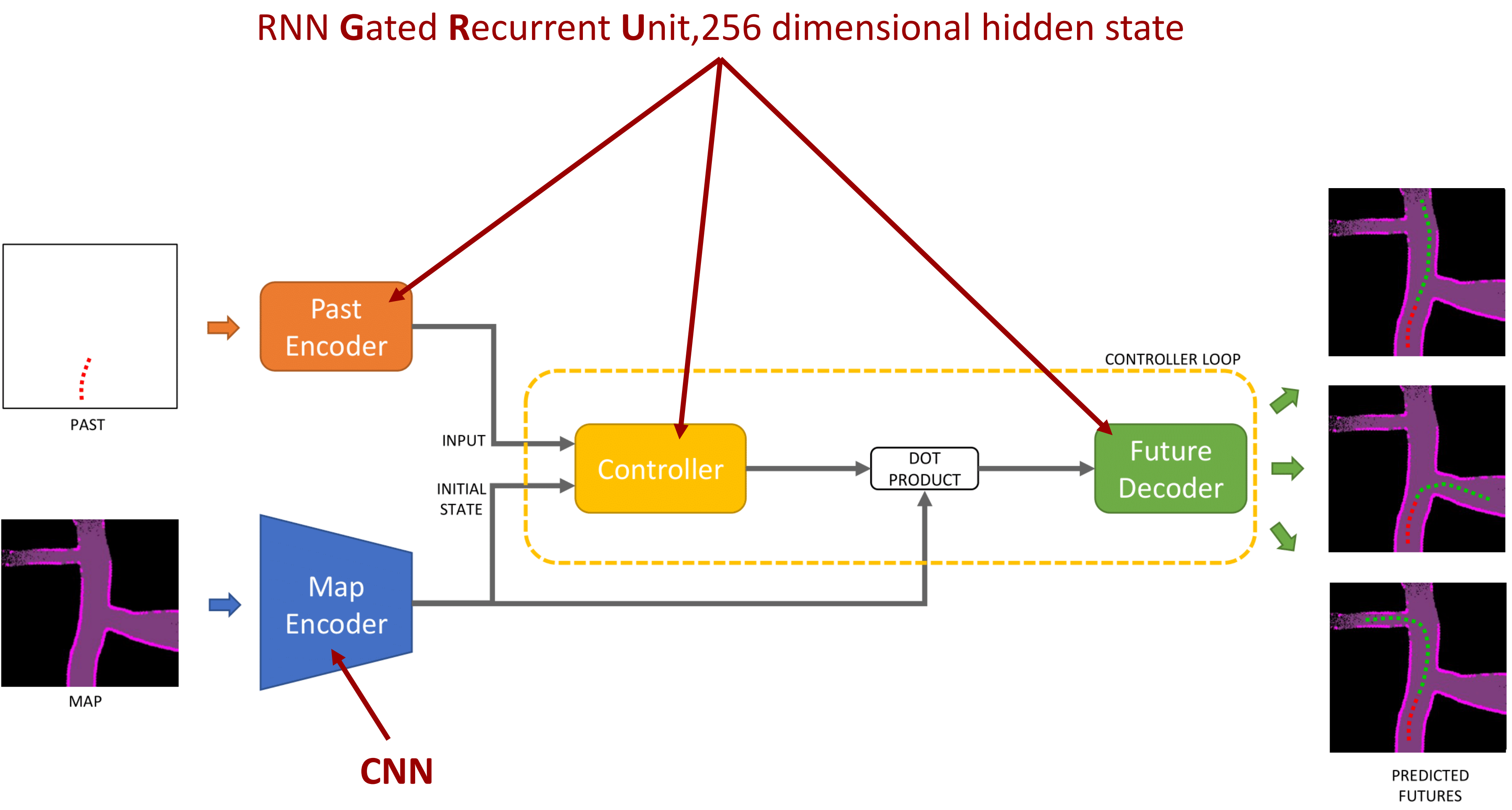
- A **sample** is made of:
  - a semantic map *m* centered in the present position of the vehicle;
  - the past trajectory of the vehicle *p*;
  - a set of ***N* possible futures *f*$_i$** with *i = 1,…,N* GT .

- To create multimodal trajectories, we select points in the future segment from which to initialize new trajectories and sample different transitions from the Markov Chain.





Model



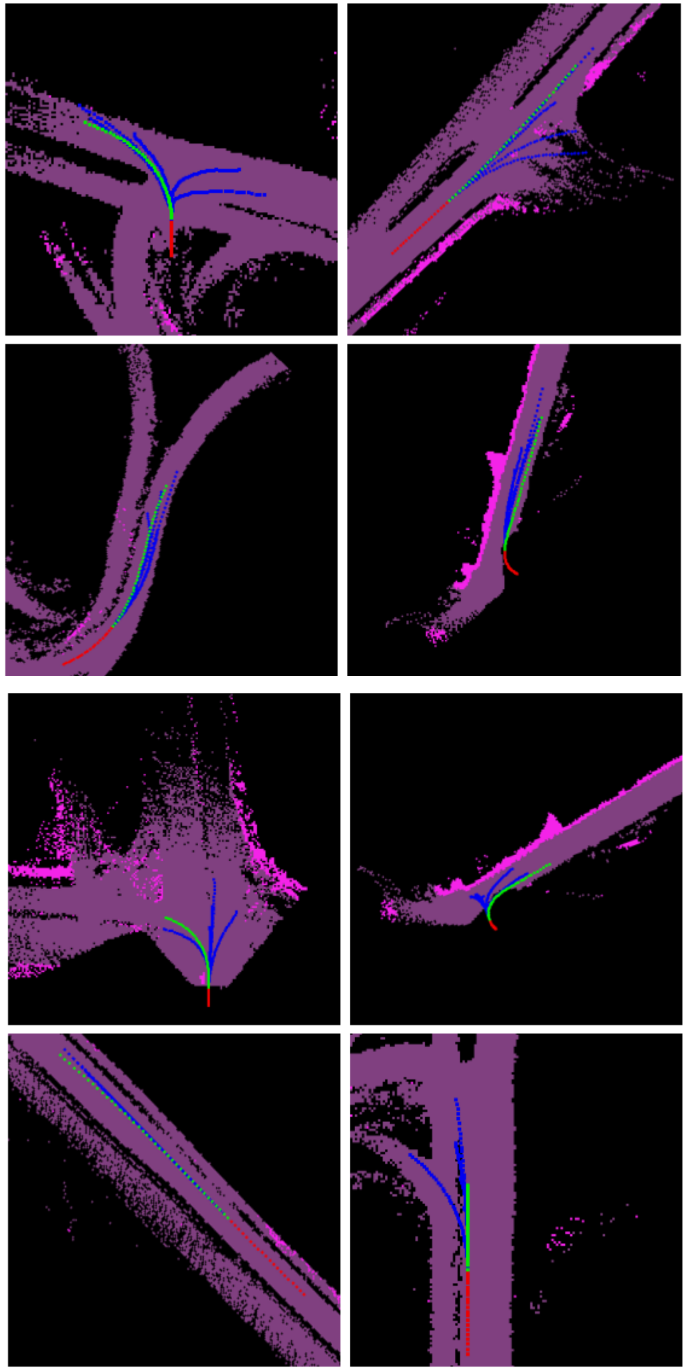
Multimodality Loss

- optimizes a prediction for each available ground truth.
- pairs minimum distance trajectories in order to assign to each future at least one prediction.

Experiments

TABLE I
AVERAGE DISPLACEMENT ERROR (ADE) AND FINAL DISPLACEMENT ERROR (FDE), COMPUTED FOR PREDICTIONS AT DIFFERENT TIME STEPS.

	ADE				FDE			
Method	1s	2s	3s	4s	1s	2s	3s	4s
Kalman [4]	0.51	1.14	1.99	3.03	0.97	2.54	4.71	7.41
Linear [4]	0.20	0.49	0.96	1.64	0.40	1.18	2.56	4.73
MLP [4]	0.20	0.49	0.93	1.53	0.40	1.17	2.39	4.12
MANTRA [4]	**0.17**	**0.36**	0.61	0.94	**0.30**	0.75	1.43	2.48
Ours (Synthetic data)	0.32	0.54	0.85	1.31	0.52	1.01	1.90	3.44
Ours (Real data)	0.31	0.53	0.78	1.24	0.51	0.95	1.63	2.95
Ours (Mixed data)	0.22	0.38	**0.59**	**0.89**	0.35	**0.73**	**1.29**	**2.27**



Conclusions

We presented a method to generate synthetic trajectory samples
This has shown two main advantages:

- Augment existing datasets and train better prediction models
- Couple past observations with multiple ground truths, with a new loss to train our model and address the intrinsic multimodality of the task

This allowed us to reach **state of the art results on the KITTI trajectory prediction benchmark**.

ICPR 2020

25th INTERNATIONAL CONFERENCE ON PATTERN RECOGNITION

Milan, Italy 10 | 15 January 2021

Multiple Future Prediction Leveraging Synthetic Trajectories

Lorenzo Berlincioni , Federico Becattini,
Lorenzo Seidenari, Alberto Del Bimbo
MICC - Università degli Studi di Firenze
firstname.lastname@unifi.it