WED-AM-134

JUNE 18-22, 2023 CVPR VANCOUVER, CANADA

Uncovering the Missing Pattern: Unified Framework Towards Trajectory Imputation and Prediction

Yi Xu[1,2] Armin Bazarjani[2,3] Hyung-gun Chi[2,4] Chiho Choi[2,5] Yun Fu[1]

[1]Northeastern University [2]Honda Research Institute, USA [3]University of Southern California
[4]Purdue University [5]Samsung Semiconductor US

➢ Motivation

- Existing trajectory prediction methods usually assume the observations are complete.
- Observed sequences are not complete due to object occlusion, scope limitation, sensor failure, etc.

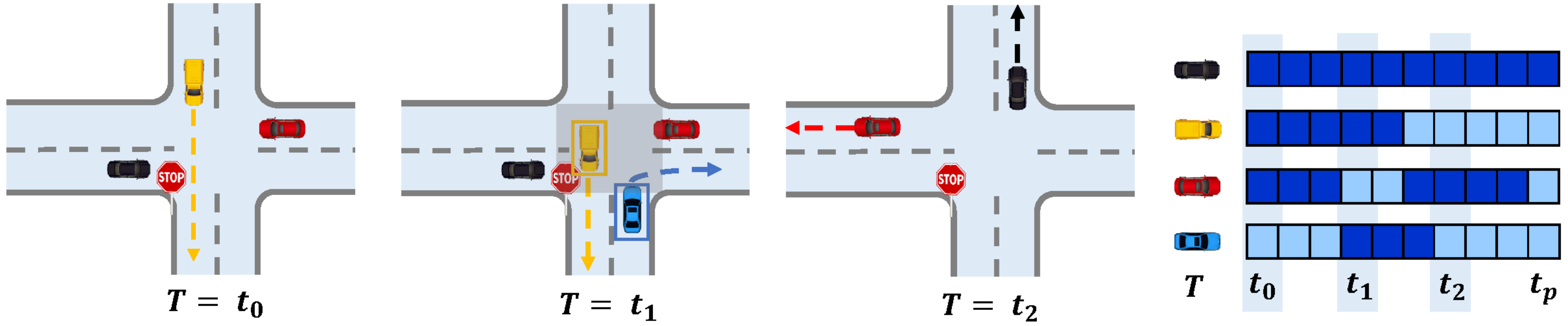


Fig 1. An example of incomplete observation situation in autonomous driving.

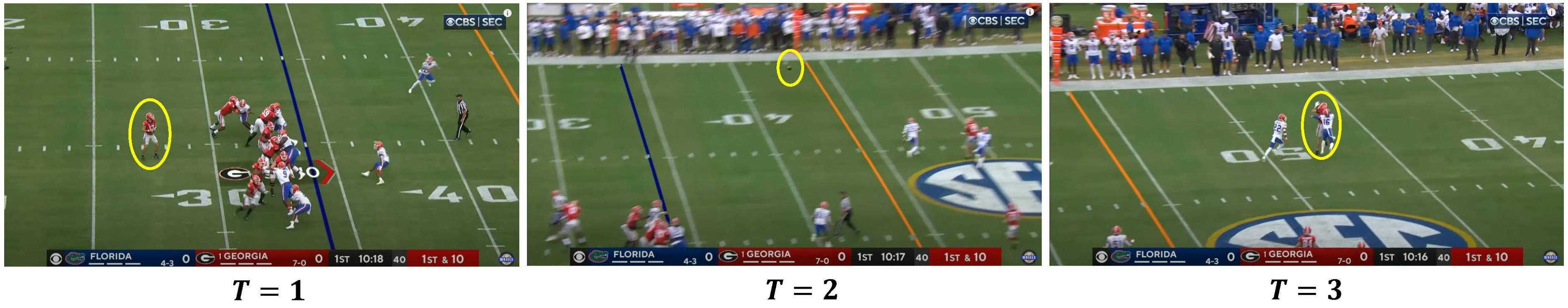


Fig 2. Another real-world case of incomplete observation in a live football match.

➢ Challenge

- How to predict when observations are **incomplete**.
- How to learn moving patterns from the **incomplete trajectories**.

➢ Existing Solutions and Drawbacks

- Straightforward approach: ***Impute first and then predict***.
  - → Treat imputation and prediction as two **separate** tasks
  - → Incomplete observations are generated via **random** masking → not practical

➢ Core Idea

- Unified framework for simultaneously imputation and prediction.

➢ Our Method

- We develop an MS-GNN for extracting spatial features from incomplete observations of multiple agents.
  - Design three different GCLs:
    1) Static Topology GCL → ***A*** is fixed
    2) Dynamic Learnable GCL → ***A*** is learnable
    3) Edge Conditioned GCL → edge category

- We propose a VRNN with a Temporal Decay (TD) module for temporal dependencies extraction.
  - TD module is designed to indicate the **relative distance** between the last observable time step and the current time step.
  - The temporal missing patterns are highlighted.

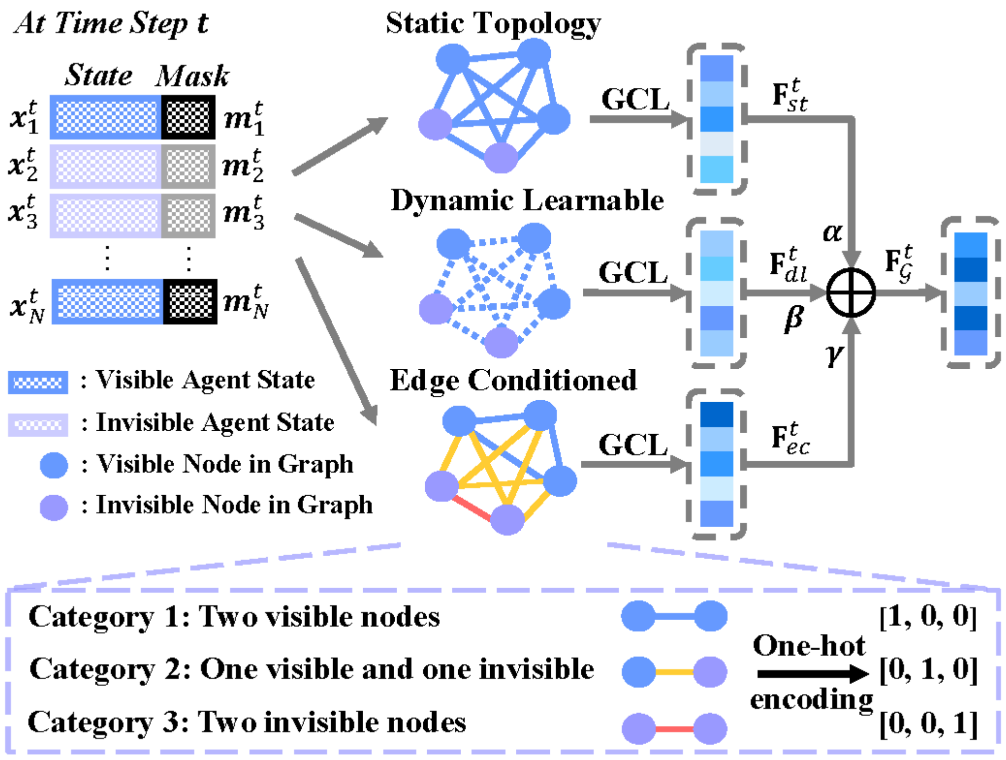


Fig 3. Diagram of our proposed MS-GNN.

➢ Our Method

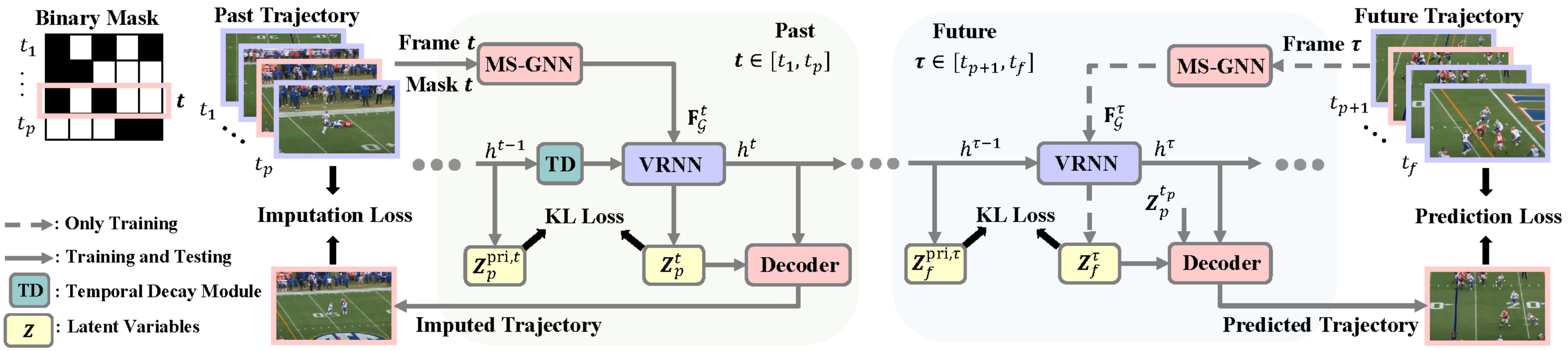


Fig 4. The overview of our proposed GC-VRNN method.

- ❑ Our model is trained via two parts of losses: **imputation** stream and **prediction** stream.
- ❑ In the inference phase, only the observable trajectories are accessible.

Experiments

Datasets

- Three datasets, ***Basketball-TIP***, ***Football-TIP***, and ***Vehicle-TIP***, are curated.
- Two strategies are applied in the dataset ***Basketball-TIP*** and ***Football-TIP***. We define three parameters to create three scenarios for each strategy.
- By thresholding the integrity value, we could determine if a vehicle was occluded or not, to create the dataset ***Vehicle-TIP***.

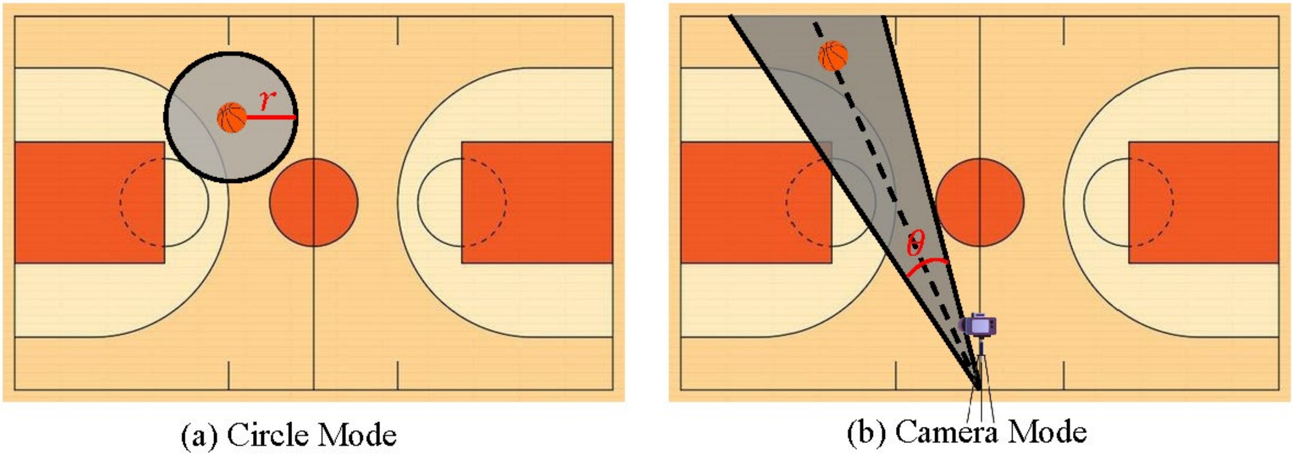


Fig 5. Two strategies of curating the datasets.

➢ Experiments

❑ Results

Datasets	Methods	$r=3$ ft. I-L_2	$r=3$ ft. P-L_2	$r=5$ ft. I-L_2	$r=5$ ft. P-L_2	$r=7$ ft. I-L_2	$r=7$ ft. P-L_2	$\theta=10°$ I-L_2	$\theta=10°$ P-L_2	$\theta=20°$ I-L_2	$\theta=20°$ P-L_2	$\theta=30°$ I-L_2	$\theta=30°$ P-L_2
Basketball-TIP (In Feet)	Mean	9.07	–	9.53	–	9.51	–	8.83	–	8.64	–	8.47	–
	Median	9.32	–	9.82	–	9.81	–	9.16	–	8.96	–	8.75	–
	GMAT [78]	7.36	–	6.89	–	6.73	–	6.42	–	5.99	–	6.01	–
	NAOMI [36]	7.68	–	7.08	–	7.04	–	6.33	–	6.11	–	5.91	–
	Linear Fit	14.90	21.14	14.06	20.36	13.58	18.94	12.78	21.01	11.47	16.38	11.26	14.40
	Vanilla LSTM [24]	7.33	20.07	6.73	14.91	6.51	10.07	6.28	9.34	6.01	7.52	5.67	6.10
	Vanilla VRNN [14]	7.43	12.26	6.90	11.38	6.68	10.07	6.38	8.49	6.09	7.47	5.92	7.36
	INAM [47]	7.35	8.93	6.93	8.24	6.80	7.68	6.50	7.32	6.13	7.10	5.92	6.96
	GC-VRNN (Ours)	**7.03**	**7.50**	**6.41**	**6.80**	**6.24**	**5.93**	**5.86**	**6.29**	**5.56**	**4.74**	**5.39**	**4.28**
		$r=2$ yd. I-L_2	$r=2$ yd. P-L_2	$r=4$ yd. I-L_2	$r=4$ yd. P-L_2	$r=6$ yd. I-L_2	$r=6$ yd. P-L_2	$\theta=2°$ I-L_2	$\theta=2°$ P-L_2	$\theta=6°$ I-L_2	$\theta=6°$ P-L_2	$\theta=8°$ I-L_2	$\theta=8°$ P-L_2
Football-TIP (In Yards)	Mean	8.94	–	9.28	–	9.69	–	8.74	–	9.12	–	9.27	–
	Median	8.99	–	9.39	–	9.86	–	8.80	–	9.23	–	9.39	–
	GMAT [78]	4.63	–	5.37	–	6.44	–	7.37	–	6.98	–	6.92	–
	NAOMI [36]	4.48	–	4.95	–	5.83	–	7.21	–	6.82	–	6.70	–
	Linear Fit	7.18	7.58	7.01	6.97	7.08	9.88	8.48	9.77	7.17	8.40	7.12	8.04
	Vanilla LSTM [24]	5.26	6.98	5.96	5.13	6.47	6.83	7.33	10.21	7.85	7.90	7.75	7.88
	Vanilla VRNN [14]	4.61	5.63	5.31	5.48	6.29	5.94	6.70	8.27	6.38	6.98	6.21	6.72
	INAM [47]	4.32	6.01	4.94	5.52	6.11	6.34	7.19	8.31	6.85	7.33	6.62	7.26
	GC-VRNN (Ours)	**3.95**	**4.50**	**4.68**	**4.42**	**5.19**	**4.66**	**5.54**	**7.58**	**5.37**	**5.88**	**5.42**	**5.71**

Tab 1. Results on ***Basketball-TIP*** and ***Football-TIP***.

Dataset	Methods	Easy I-L_2	Easy P-L_2	Ordinary I-L_2	Ordinary P-L_2	Hard I-L_2	Hard P-L_2
Vehicle-TIP (In Pixels)	Mean	337.38	–	282.24	–	319.68	–
	Median	336.94	–	281.58	–	318.82	–
	Linear Fit	100.53	139.86	86.69	97.24	106.43	113.61
	Vanilla LSTM [24]	83.50	125.05	75.23	82.76	87.59	91.61
	Vanilla VRNN [14]	88.36	103.21	70.89	73.54	95.66	104.34
	GC-VRNN (Ours)	**65.48**	**72.44**	**58.36**	**62.03**	**74.28**	**78.12**

Tab 2. Results on ***Vehicle-TIP***.

ID	GCL ST	GCL DL	GCL EC	$r=3$ ft. I-L_2	$r=3$ ft. P-L_2	$r=7$ ft. I-L_2	$r=7$ ft. P-L_2	$\theta=10°$ I-L_2	$\theta=10°$ P-L_2	$\theta=30°$ I-L_2	$\theta=30°$ P-L_2
1	✓			7.24	9.46	7.16	9.01	6.20	7.30	5.78	5.28
2		✓		7.16	9.44	6.74	8.93	6.15	7.27	5.70	5.19
3	✓	✓		7.11	9.33	6.55	8.54	5.98	7.18	5.51	5.08
4	✓		✓	7.10	9.09	6.30	7.08	5.90	6.96	5.41	4.90
5		✓	✓	7.07	8.10	6.26	6.04	5.87	6.32	5.88	6.09
Ours	✓	✓	✓	**7.03**	**7.50**	**6.24**	**5.93**	**5.86**	**6.29**	**5.39**	**4.28**

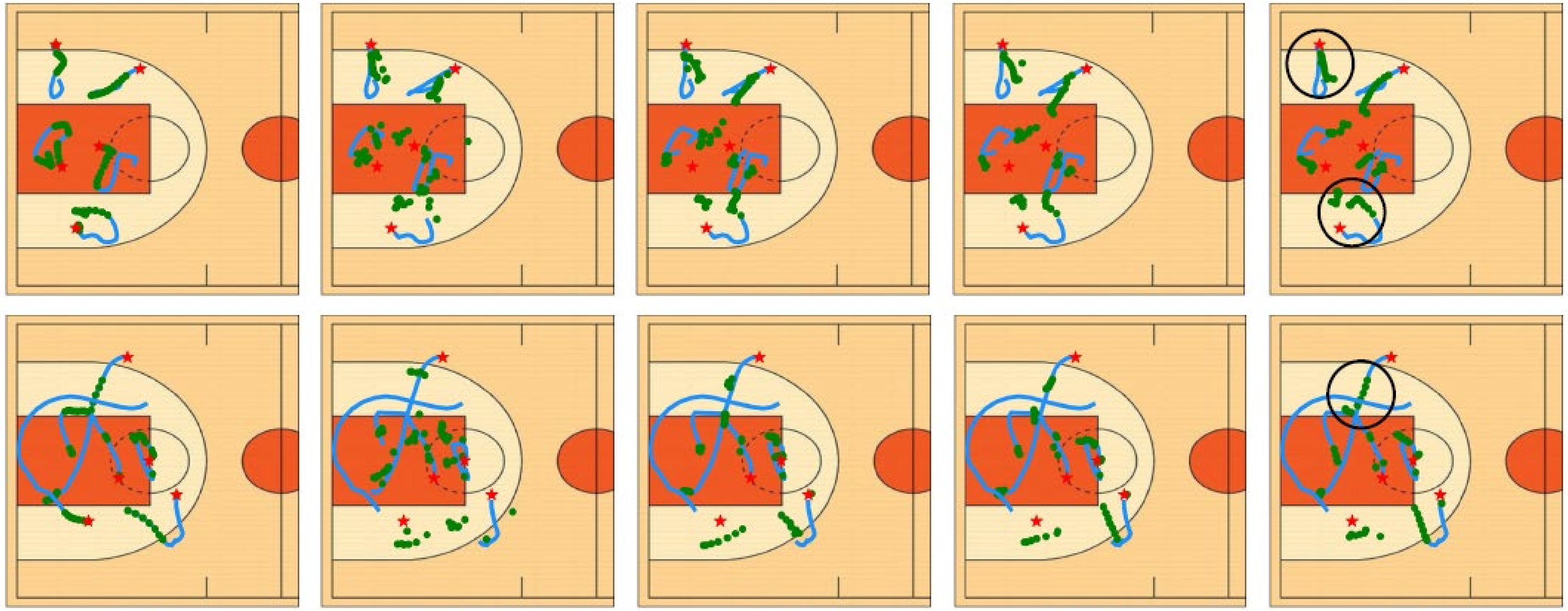
Tab 3. Ablation study on three GCLs.

Variants	$r=3$ ft. I-L_2	$r=3$ ft. P-L_2	$r=7$ ft. I-L_2	$r=7$ ft. P-L_2	$\theta=10°$ I-L_2	$\theta=10°$ P-L_2	$\theta=30°$ I-L_2	$\theta=30°$ P-L_2
w/ IMP	7.21	28.74	6.58	30.06	5.94	31.84	5.56	31.57
w/ PRE	29.15	7.78	29.07	6.48	30.61	6.83	32.35	4.76
wo/ CON	7.11	16.38	6.40	13.32	5.96	15.05	5.48	13.96
wo/ TD	7.25	7.70	6.37	6.26	5.98	6.61	5.51	4.52
Ours	**7.03**	**7.50**	**6.24**	**5.93**	**5.86**	**6.29**	**5.39**	**4.28**

Tab 4. Ablation study on TD and task connection.

➢ Experiments

❑ Results



(a) GT (b) GMAT (c) NAOMI (d) INAM (e) Ours

Fig 6. Visualizations on imputation results.

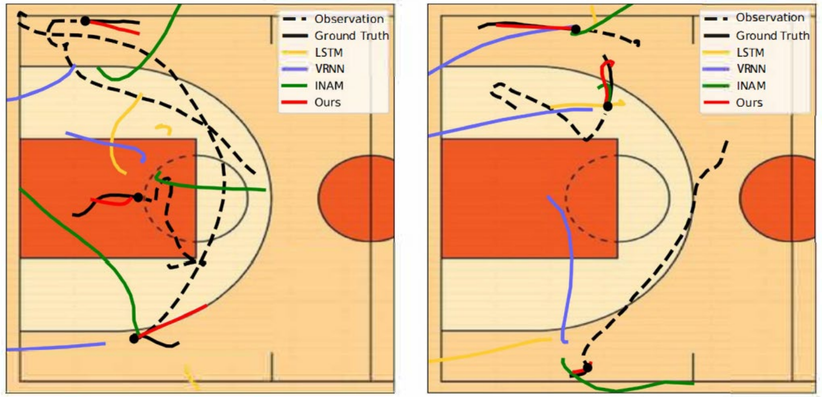


Fig 7. Visualizations on prediction results.

Contributions

- We delve into the trajectory prediction problem when the observations are incomplete.
- Three datasets are curated for the multiagent trajectory imputation and prediction problem.
- We develop a unified framework GC-VRNN for imputing missing observations and predicting future trajectories simultaneously.

Limitations and Future Work

- Extend it to a multi-modality method, which could enhance the accuracy and robustness.
- The imputation performance decreases when there is a long and continuous instance of missing data during the observed trajectory, particularly when it occurs at the beginning of the observation. We believe that exploring better solutions to address these situations would be a valuable direction for future research.

JUNE 18-22, 2023
CVPR
VANCOUVER, CANADA

Thank you for listening!