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Trajectory Imputation in Multi-Agent Sports with Derivative Accumulating Self-Ensemble

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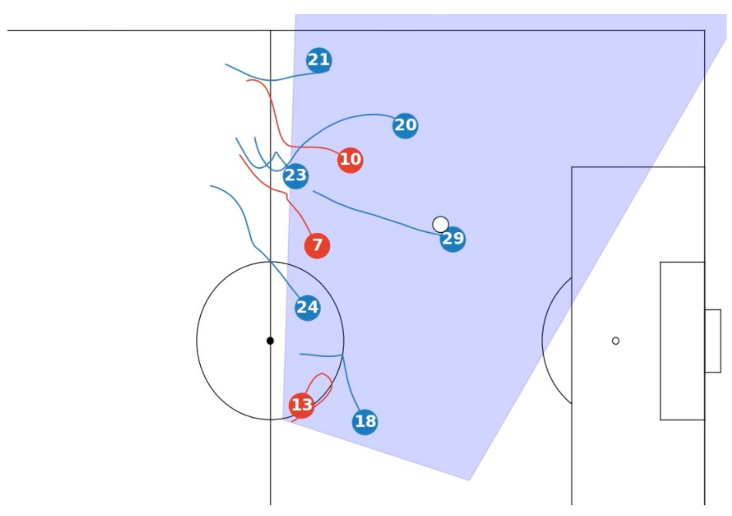
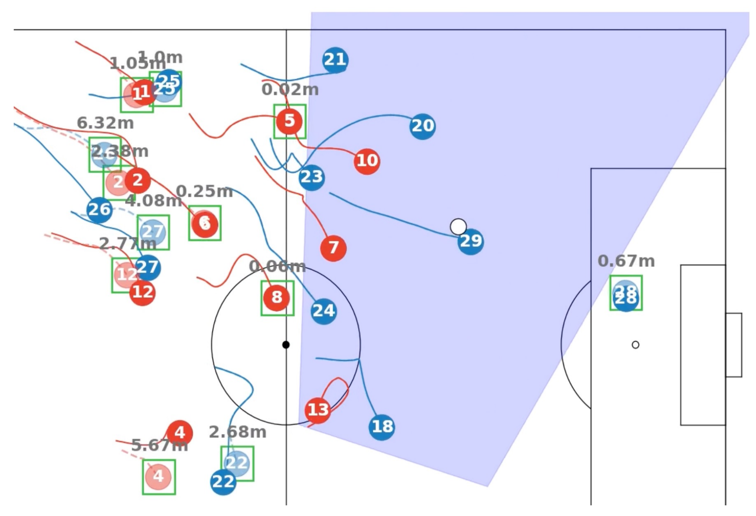
Background

- Sports tracking data often suffer from missing values due to various factors, such as player occlusion, frame drops, or low-quality sensor signals.
- Accurate and realistic imputation of missing trajectories is crucial for many downstream tasks in sports analytics.
- Existing time-series imputation methods performs poorly on sports data, as they do not account for the dynamic movements and interactions between players.

Proposed Framework: MIDAS



Incomplete input trajectories

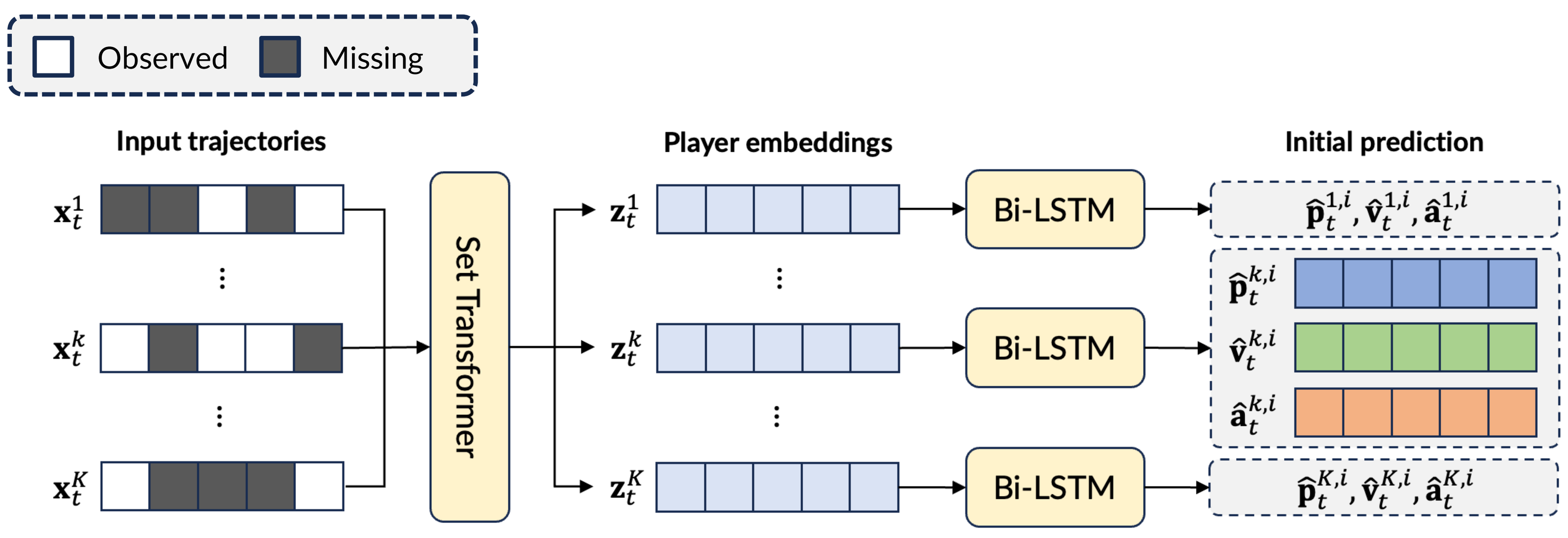


True and imputed trajectories

- **MIDAS: Multi-agent Imputer with Derivative-Accumulating Self-ensemble**
- Combines multiple predictions using a hybrid architecture

Neural Network-Based Initial Prediction (IP)

- **Set Transformer encoder** for permutation-equivariant player embeddings
- **Bi-LSTM** for player-wise temporal modeling
- Jointly predicts position, velocity, and acceleration for each time step

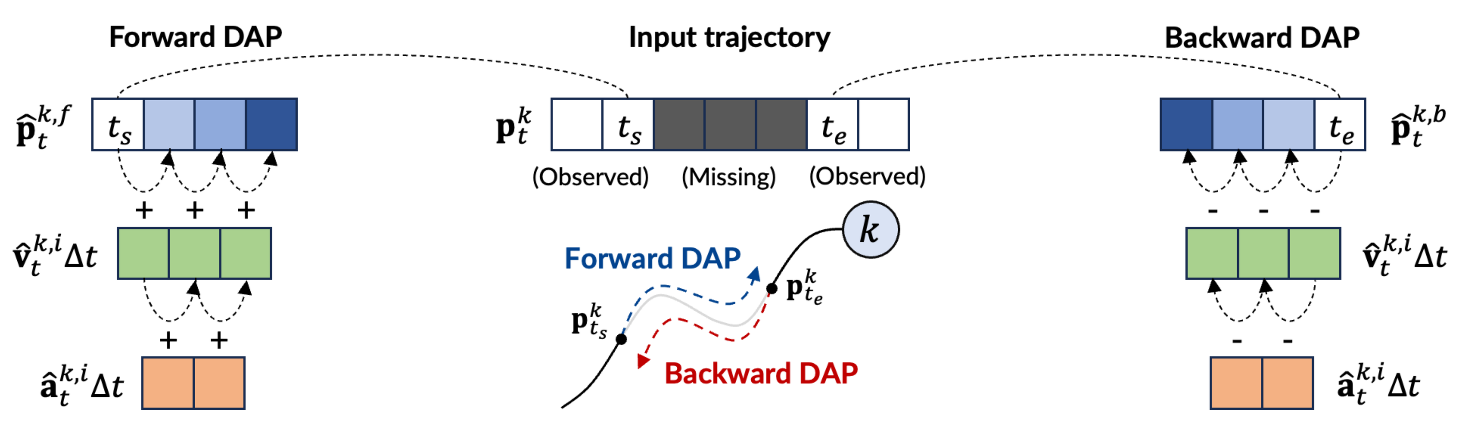


Derivative-Accumulating Predictions (DAP)

- Produces alternative predictions $\hat{\mathbf{p}}_t^{k,f}$ and $\hat{\mathbf{p}}_t^{k,b}$ by **accumulating velocity and acceleration from the observed endpoints** t_s and t_e:

$$\hat{\mathbf{p}}_{t_s}^{k,f} = \mathbf{p}_{t_s}^{k}, \quad \hat{\mathbf{p}}_{t+1}^{k,f} \approx \hat{\mathbf{p}}_t^{k,f} + (\hat{\mathbf{v}}_t^{k,i} + \hat{\mathbf{a}}_t^{k,i}\Delta t)\Delta t \;\; (t_s < t < t_e)$$

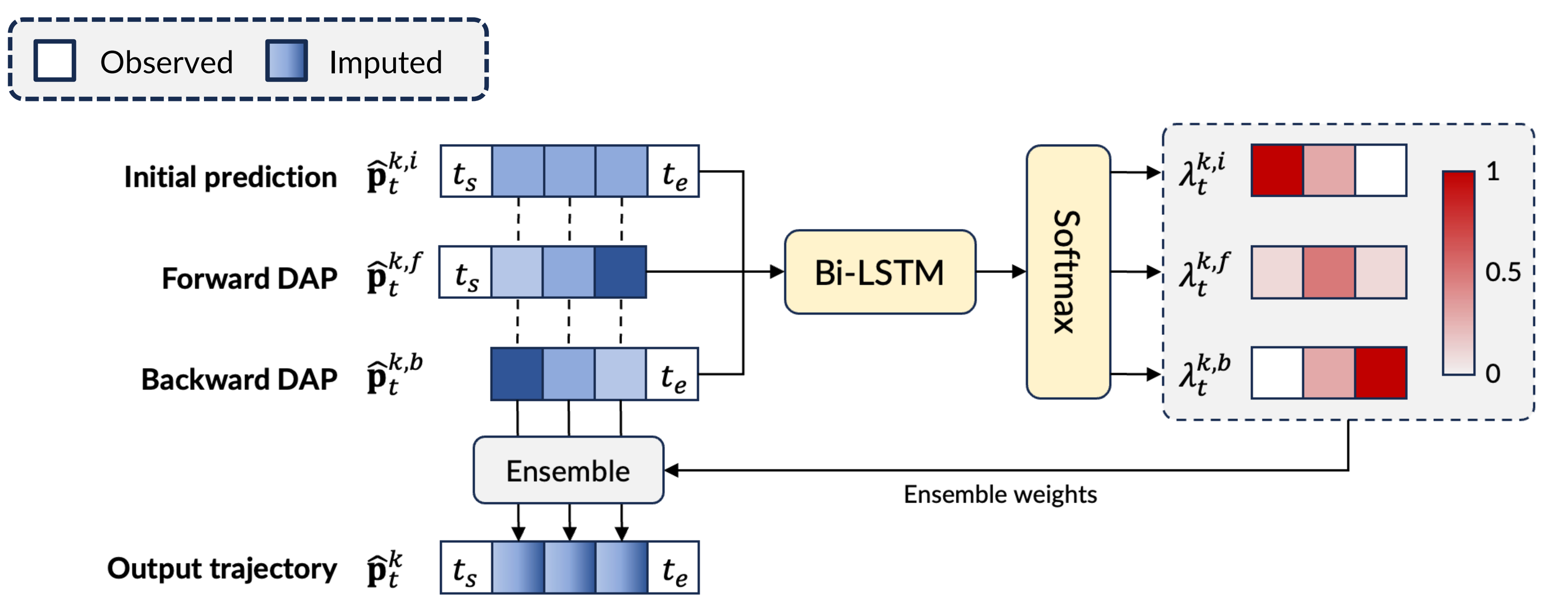
$$\hat{\mathbf{p}}_{t_e}^{k,b} = \mathbf{p}_{t_e}^{k}, \quad \hat{\mathbf{p}}_{t-1}^{k,b} \approx \hat{\mathbf{p}}_t^{k,b} - (\hat{\mathbf{v}}_t^{k,i} - \hat{\mathbf{a}}_t^{k,i}\Delta t)\Delta t \;\; (t_s < t < t_e)$$



Dynamic Ensemble of Multiple Predictions

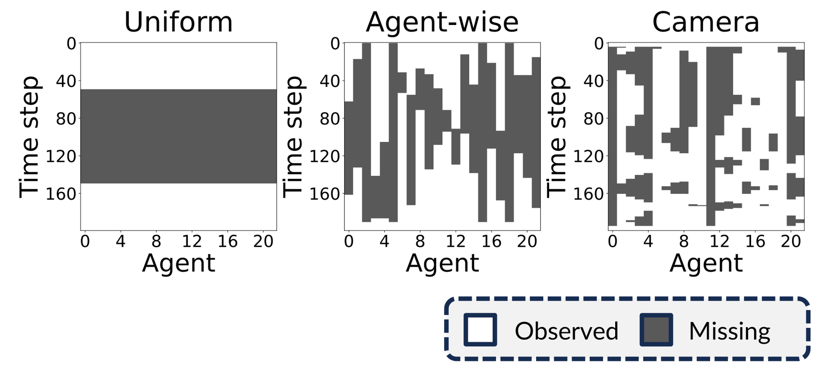
- Learns to dynamically weight and combine IP and forward/backward DAPs:

$$\hat{\mathbf{p}}_t^{k} = \lambda_t^{k,i}\hat{\mathbf{p}}_t^{k,i} + \lambda_t^{k,f}\hat{\mathbf{p}}_t^{k,f} + \lambda_t^{k,b}\hat{\mathbf{p}}_t^{k,b}$$



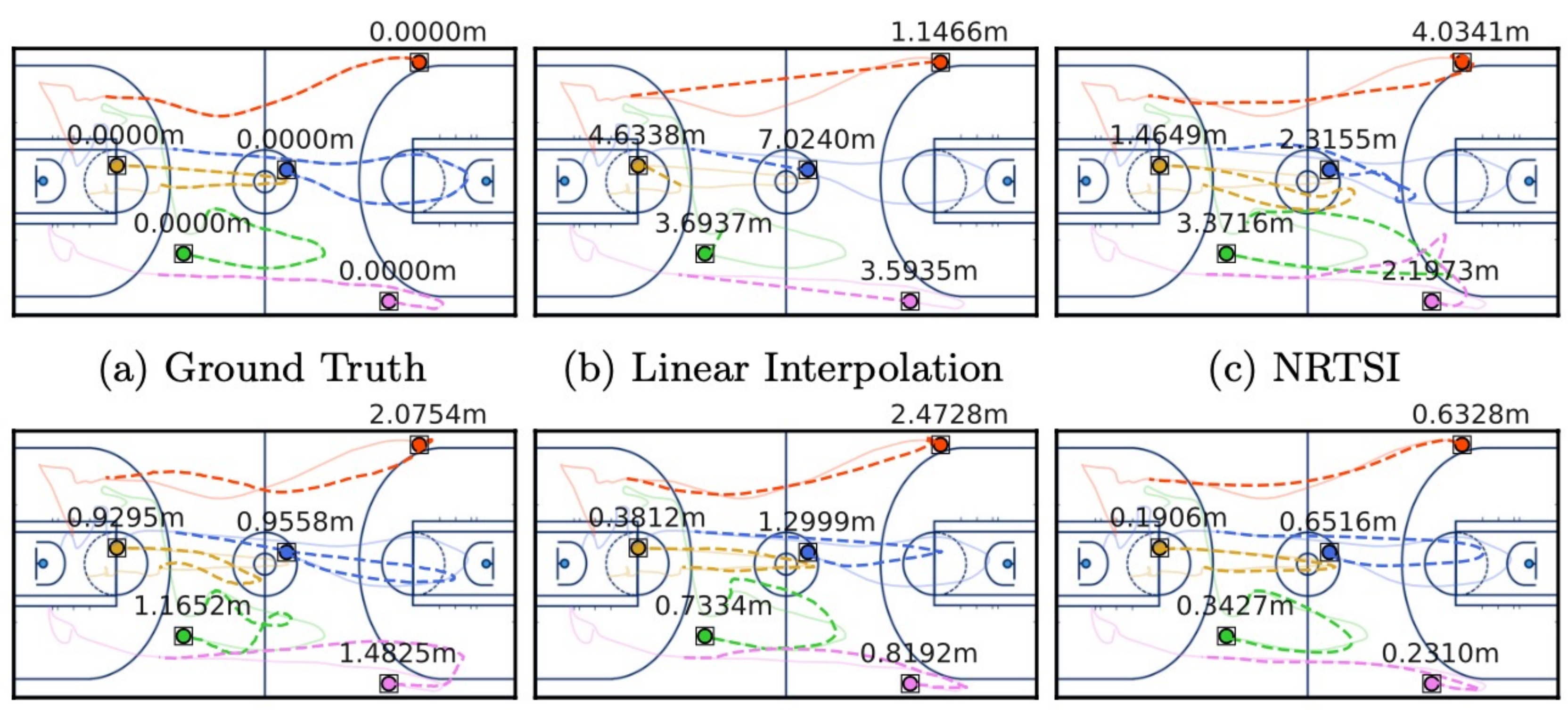
Experiments

- **Three sports datasets**
  - Soccer: 2/0.5/0.5 matches
  - Basketball: 70/10/20 matches
  - American football: Preprocessed 5-second sequences
- **Three missing scenarios**



- **Experimental results**

Scenario	Metric	LI	CS	BRITS	NAOMI	NRTSI	CSDI	GI	IF	IP	MIDAS
Soccer											
Uniform	PE	3.8406	2.2085	7.4859	4.5343	3.1791	3.4295	4.6511	2.0898	1.4563	**1.3205**
	SCE	0.1299	0.0867	3.9089	3.9793	0.0854	0.1586	0.1191	0.0815	0.1488	**0.0516**
Agent-wise	PE	5.0752	11.4647	5.7266	—	—	4.0279	5.6011	2.5798	2.0755	**1.9832**
	SCE	0.1631	0.2939	2.9627	—	—	0.1305	0.1508	0.0976	0.1057	**0.0535**
Camera	PE	3.1083	1.9209	7.4208	—	—	3.5181	3.6512	2.2151	1.4879	**1.2296**
	SCE	0.0993	0.0547	4.1967	—	—	0.2132	0.0934	0.3149	0.1554	**0.0374**
Basketball											
Uniform	PE	3.3481	2.3114	2.9085	1.5254	2.5291	2.2558	2.8305	1.3622	0.9801	**0.9727**
	SCE	0.1483	0.1025	1.0521	0.3230	0.0734	0.0631	0.1066	0.0531	**0.0432**	0.0438
Agent-wise	PE	4.4992	10.3857	2.4238	—	—	2.3471	2.5859	**1.3345**	1.3832	1.3862
	SCE	0.1787	0.2715	0.5397	—	—	0.0563	0.0700	0.0485	**0.0373**	0.0381
American Football											
Uniform	PE	0.8897	0.7448	1.7990	0.9692	0.5158	0.5558	0.8899	0.3673	0.2073	**0.1542**
	SCE	1.1063	0.9463	10.9459	2.3112	0.2989	0.4905	1.1023	0.2858	0.1990	**0.1126**
Agent-wise	PE	1.5128	1.2041	1.7527	—	—	0.6182	1.5128	0.3944	0.2383	**0.2104**
	SCE	1.0641	0.5306	10.6807	—	—	0.4288	1.0631	0.1869	0.1180	**0.0967**



(a) Ground Truth (b) Linear Interpolation (c) NRTSI

(d) CSDI (e) ImputeFormer (f) MIDAS (ours)

- **Analysis on missing length and ensemble behavior**

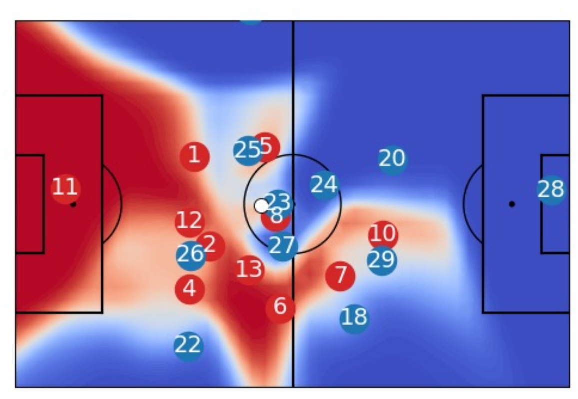
Sports	Category	Missing Frames	$\hat{\mathbf{p}}_t^{k,i}$ $(\hat{\lambda}_t^{k,i})$	$\hat{\mathbf{p}}_t^{k,f}$ $(\hat{\lambda}_t^{k,f})$	$\hat{\mathbf{p}}_t^{k,b}$ $(\hat{\lambda}_t^{k,b})$	$\hat{\mathbf{p}}_t^{k}$
Soccer	Short	33.30 ± 15.72	0.1379 (0.0001)	0.0742 (0.6501)	0.0783 (0.3498)	**0.0504**
	Medium	90.42 ± 19.17	0.7939 (0.0003)	0.7492 (0.6110)	0.7624 (0.3887)	**0.7004**
	Long	173.41 ± 21.70	2.7359 (0.0002)	2.7017 (0.5034)	2.7186 (0.4964)	**2.6082**
Basketball	Short	33.86 ± 16.11	0.0444 (0.1596)	0.0424 (0.5216)	0.0426 (0.3187)	**0.0376**
	Medium	90.65 ± 19.02	0.5395 (0.1783)	0.5483 (0.4809)	0.5482 (0.3406)	**0.5312**
	Long	172.60 ± 21.20	1.8104 (0.1801)	1.8288 (0.4313)	1.8258 (0.3985)	**1.8005**

Downstream Applications

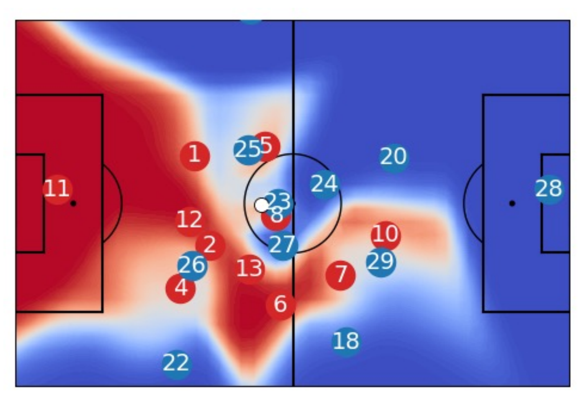
- **Estimating physical metrics**

Method	Distance (m) Mean	Distance (m) MAPE	Sprints Mean	Sprints MAPE
Ground Truth	11,093.5	—	41.49	—
Linear Interp.	10,167.8	8.46%	38.89	6.32%
Cubic Spline	10,686.3	3.73%	38.85	6.73%
BRITS	10,979.2	2.76%	59.89	53.62%
CSDI	11,343.0	2.77%	44.20	14.71%
Graph Imputer	8,972.1	19.15%	37.85	9.80%
ImputeFormer	11,441.7	3.22%	50.25	26.29%
MIDAS (ours)	**10,922.4**	**1.58%**	**40.71**	**4.95%**

- **Estimating contextual metrics**



True Pitch Control values



Estimated Pitch Control values