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

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Background: Sports Player Tracking

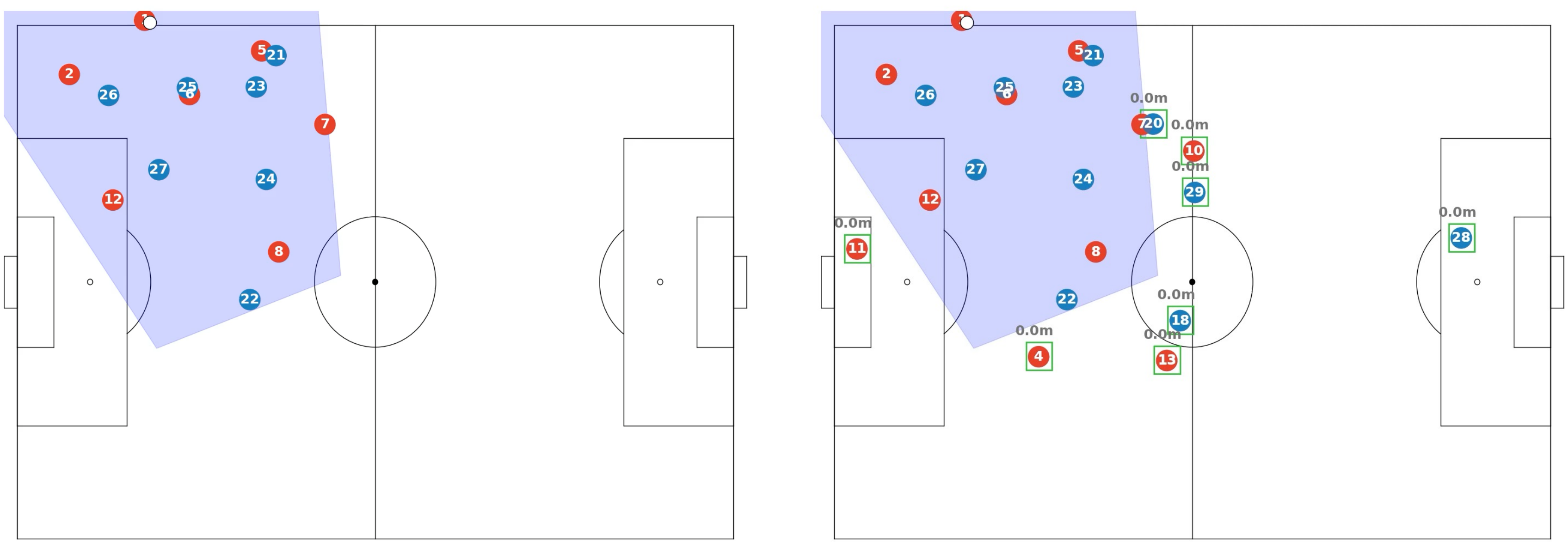
- Collected from wearable sensors or computer vision systems
- **Contain missing values for various reasons** (e.g., out-of-camera view, occlusion, etc.)
- Many downstream tasks require complete tracking data

Wearable tracking
(usually via GPS/IMU sensors)

Optical tracking
(usually via cameras and CV techniques)

Background: Sports Trajectory Imputation

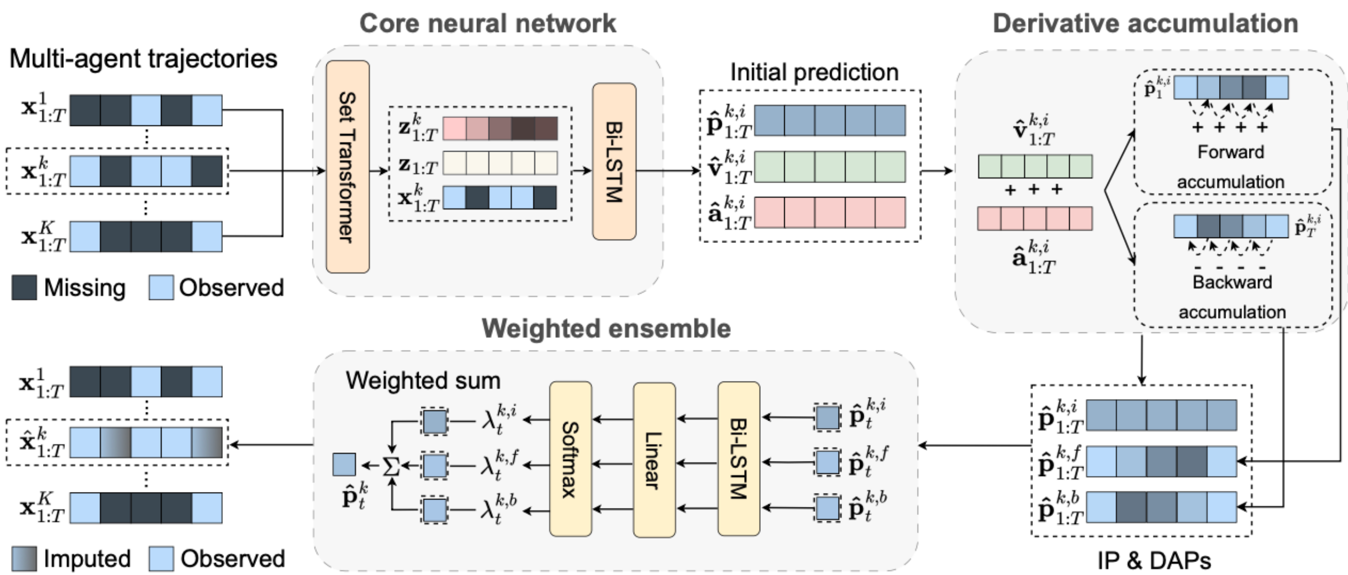
- **Goal: Impute missing player trajectories in multi-agent sports**
- Challenges compared to general time-series imputation
  - Dynamic inter-player relationships
  - Biomechanical constraints (e.g., limited speed and acceleration)
  - Data scarcity in real-world sports due to confidentiality and cost



Proposed Framework: MIDAS

MIDAS: Multi-agent Imputer with Derivative-Accumulating Self-ensemble

- **Initial prediction** of position, velocity, and acceleration using Set Transformer and Bi-LSTM
- **Alternative predictions** by forward/backward accumulation of velocity and acceleration values
- **Weighted ensemble** of the initial prediction and alternative predictions

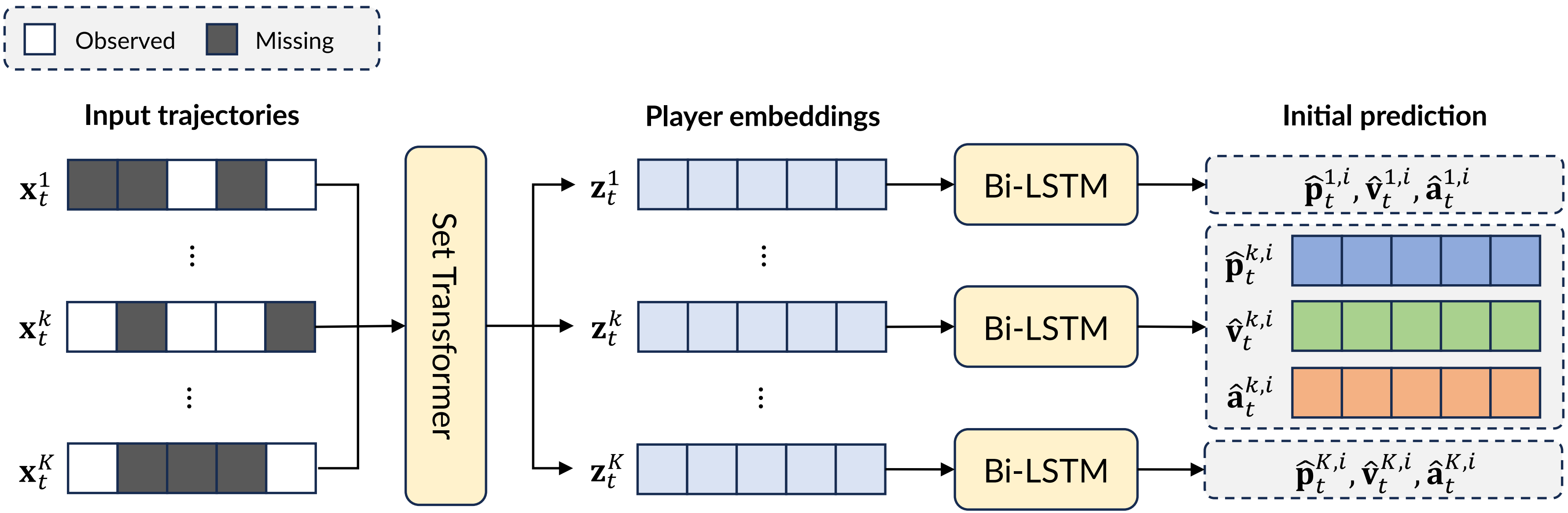


Lee et al., Set Transformer: A framework for attention-based permutation-invariant neural networks. ICML 2019.
Hochreither and Schmidhuber. Long short-term memory. Neural Computation 9(8), 1997.

Neural Network-Based Initial Prediction (IP)

- **Set Transformer encoder** for permutation-equivariant player embeddings
- **Bi-LSTM** for player-wise temporal modeling
- Joint prediction of position, velocity, and acceleration for each time step:

$$\hat{\mathbf{x}}_t^{k,i} = \left(\hat{\mathbf{p}}_t^{k,i}, \hat{\mathbf{v}}_t^{k,i}, \hat{\mathbf{a}}_t^{k,i}\right) = \left(\hat{p}_{t,x}^{k,i}, \hat{p}_{t,y}^{k,i}, \hat{v}_{t,x}^{k,i}, \hat{v}_{t,y}^{k,i}, \hat{a}_{t,x}^{k,i}, \hat{a}_{t,y}^{k,i}\right)$$



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Derivative-Accumulating Predictions (DAP)

- Physical relationships between position, velocity, and acceleration:

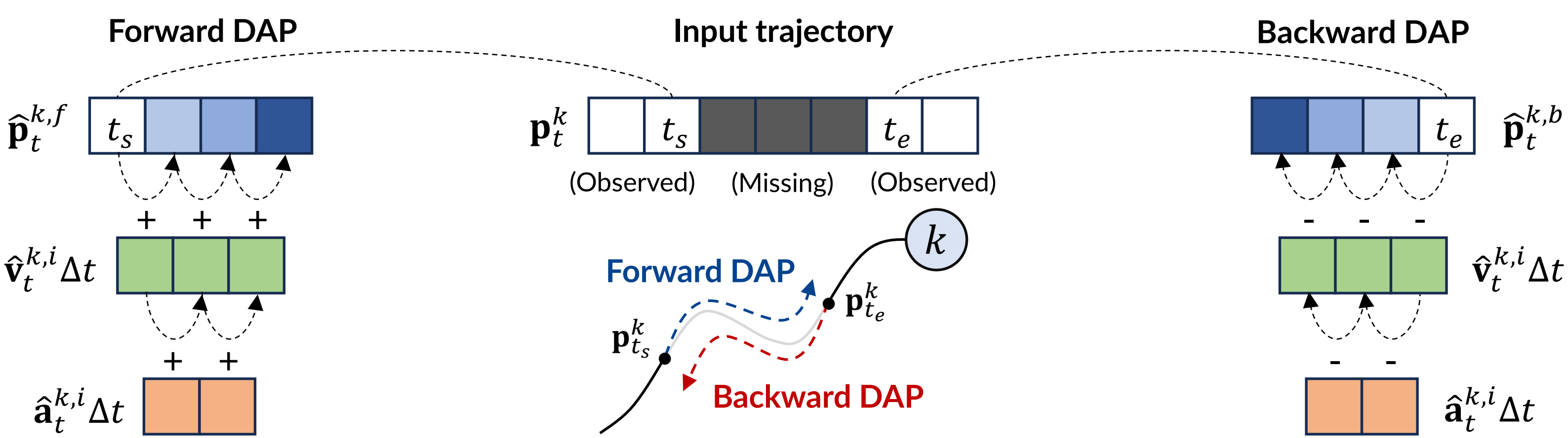
$$\mathbf{p}_{t+1}^{k} \approx \mathbf{p}_{t}^{k} + \mathbf{v}_{t+1}^{k}\Delta t \approx \mathbf{p}_{t}^{k} + (\mathbf{v}_{t}^{k} + \mathbf{a}_{t}^{k}\Delta t)\Delta t$$

- Initial prediction does not enforce this relationships.

- For each missing interval (t_s, t_e), the model produces alternative predictions $\hat{\mathbf{p}}_t^{k,f}$ and $\hat{\mathbf{p}}_t^{k,b}$ by **accumulating velocity and acceleration values on the position** at either observed endpoint.

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

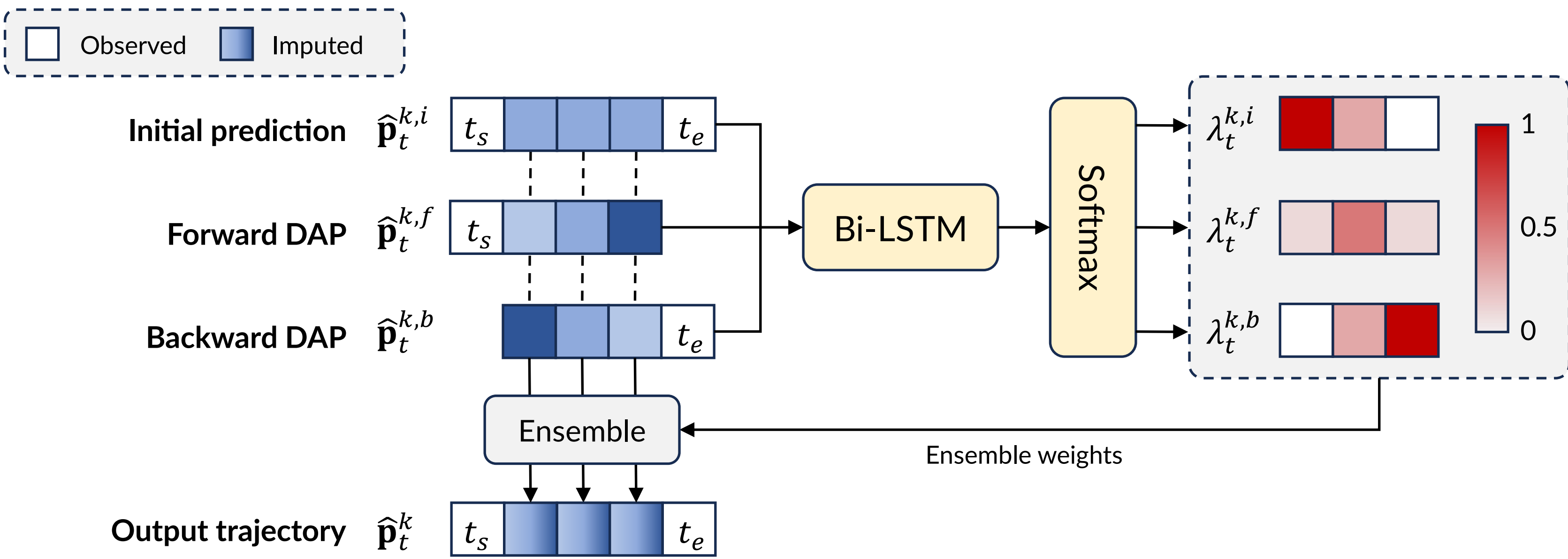
$$\hat{\mathbf{p}}_{t_e}^{k,b} = \mathbf{p}_{t_e}^{k}, \qquad \hat{\mathbf{p}}_{t-1}^{k,b} \approx \hat{\mathbf{p}}_{t}^{k,b} - \left(\hat{\mathbf{v}}_{t}^{k,i} - \hat{\mathbf{a}}_{t}^{k,i}\Delta t\right)\Delta t \;\; (t_s < t < t_e)$$



Dynamic Ensemble of Multiple Predictions

- Trade-off between IP and DAP
  - IP does not enforce relationships between physical quantities and thus lacks stability.
  - DAP suffers from error compounding problem, especially for long missing intervals.
- **Dynamic ensemble by learnable weights** to mix IP and forward/backward DAPs:

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



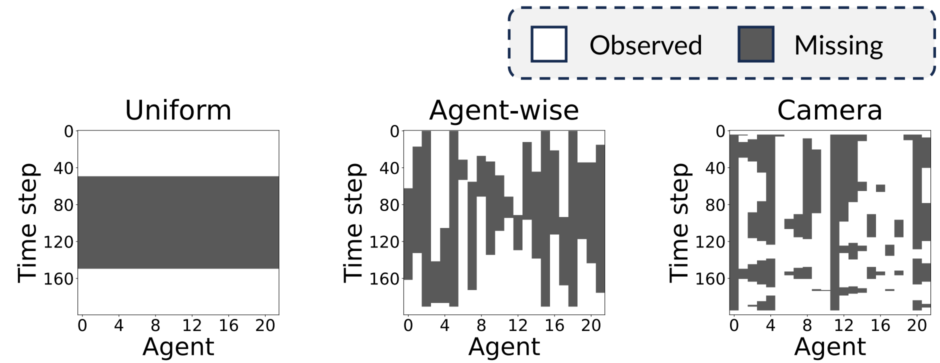
Experiments

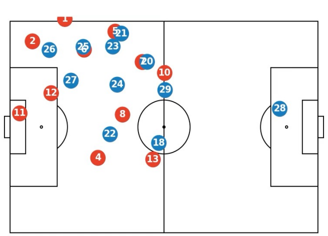
- **Datasets**
  - Soccer: 3 matches provided by Metrica Sports
  - Basketball: 100 NBA matches provided by SportsVU
  - American football: Preprocessed NFL sequences released with a Kaggle competition

- **Missing Scenarios**
  - Uniform: Same missing interval for all players
  - Agent-wise: Different missing intervals per player
  - Camera: Players outside camera view are missing

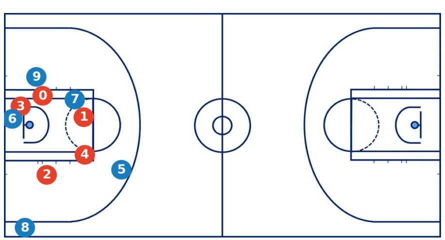
Table 1: Details on the three sports datasets.

Split	Soccer Matches	Soccer Frames	Basketball Matches	Basketball Frames	A. Football Matches	A. Football Frames
Training	2	65,014	70	1,621,835	—	425,000
Validation	0.5	20,104	10	216,118	—	52,150
Test	0.5	21,242	20	468,885	—	—

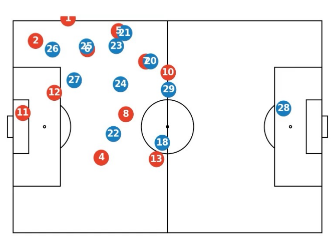




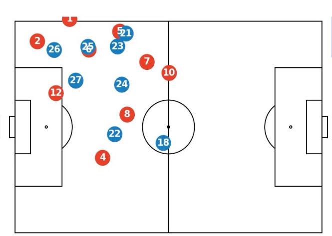
Soccer



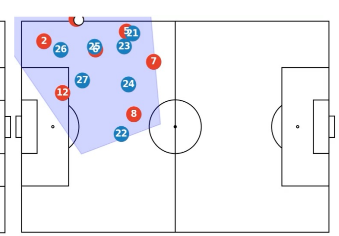
Basketball



Uniform missing



Agent-wise missing



Broadcasting camera

Experiments

- **Results**

Scenario	Metric	Method									
		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**

Limited Data		
IF	IP	MIDAS
1.6741	1.1868	**1.1438**
0.0628	0.1483	**0.0493**
1.8876	1.6414	**1.5994**
0.0645	0.0452	**0.0439**

Experiments

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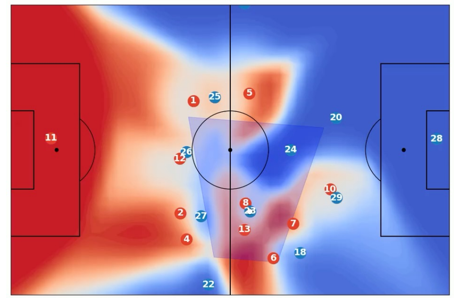
Applications

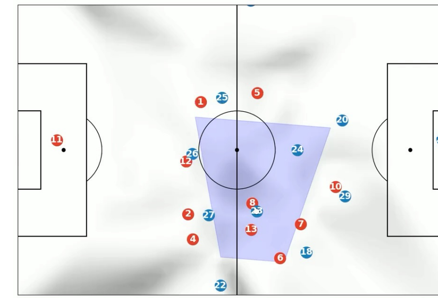
- **Estimating physical metrics**

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%**

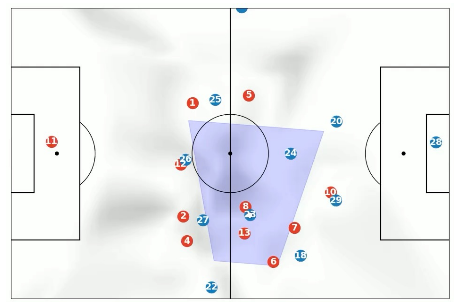
- **Estimating pass success probability maps (Pitch Control)**



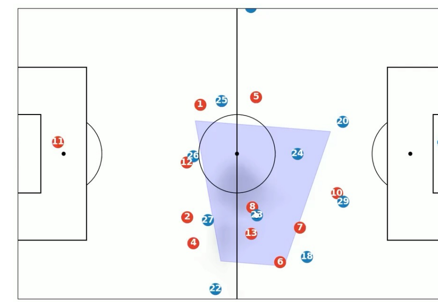
Ground truth



CSDI



ImputeFormer



MIDAS (ours)

Conclusions

- **Main contributions**
  - Imputation framework that exploits physical relationships
  - Experiments on various missing scenarios and datasets
  - Demonstrating applicability to real-world applications
- **Future work**
  - Adapting MIDAS to other domains
  - Developing metrics for quantitative evaluation in real-world applications
  - Applying MIDAS to downstream tasks in an end-to-end manner

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Thank you for listening!

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