Context-based Evaluation of Defensive Actions in Football

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Outline

- Introduction
- Related Work
- Research Motivation
- Methodology
- Experiments
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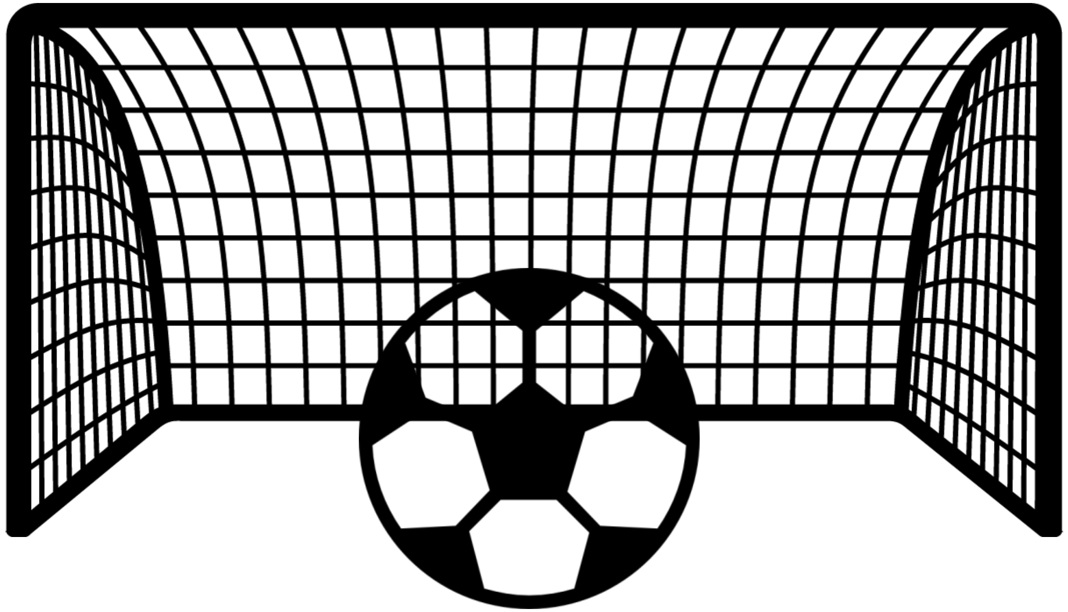
  - Evaluation Metrics
  - Experimental Results
- Conclusion

Introduction

Goal = Value



Introduction

Defense = ?

Location

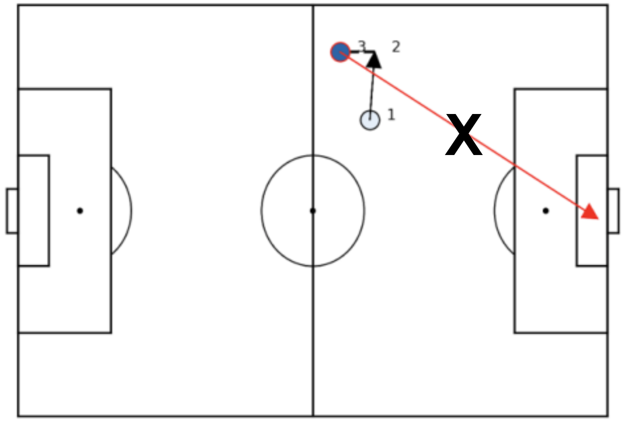
Player

Team

Interaction

Related works

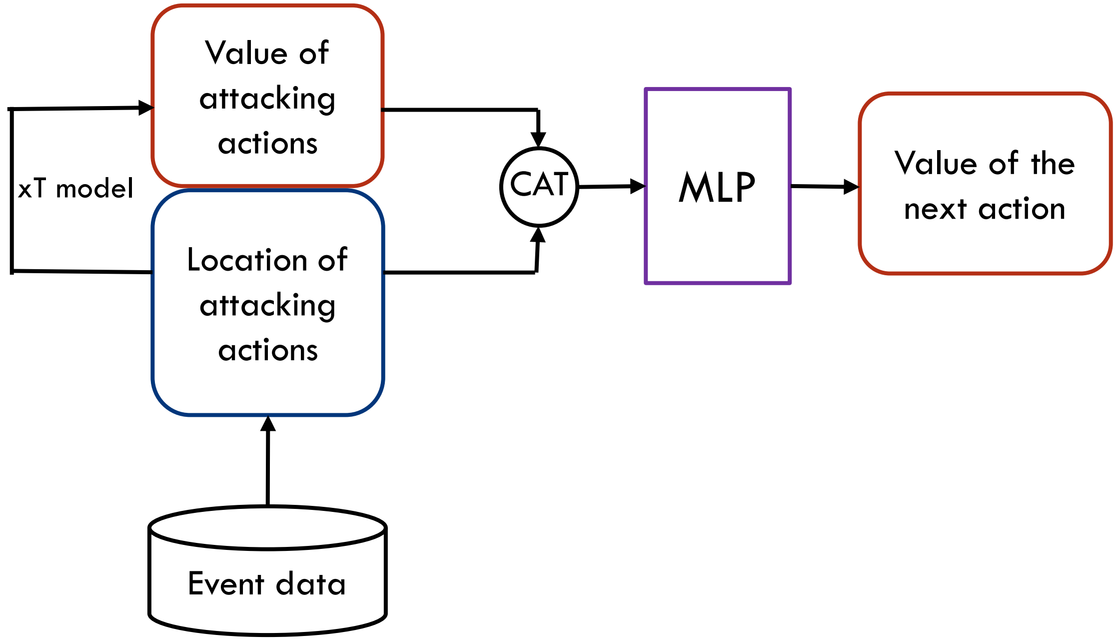
- **Defensive Actions Expected Threat (DAxT)**
  - Predict what was prevented by the defensive action
  - Assign value of the prevented action to the defensive action



	time	type_name	player	team_name	value
1	7m17s	pass	Romelu Lukaku	Manchester United	-0.001
2	7m18s	dribble	Alexis Sánchez	Manchester United	-0.002
3	7m20s	pass	Alexis Sánchez	Manchester United	~~0.215~~

Related works

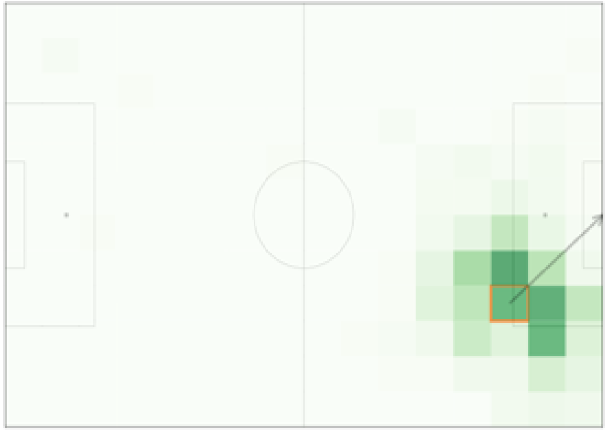
- **Defensive Actions Expected Threat (DAxT)**
  - Predict what was prevented by the defensive action
  - Assign value of the prevented action to the defensive action



Related works

- **Expected Threat (xT)**
  - Possession-based: only for consecutive, successful, attacking actions

$$\mathrm{xT}(z) = \overbrace{\underbrace{s_z}_{\text{Shooting probability}} \cdot \underbrace{\mathrm{xG}(z)}_{\text{Goal probability}}}^{\text{Probability of shooting and scoring}} + \overbrace{\underbrace{m_z}_{\text{Moving probability}} \cdot \sum_{z'=1}^{M \times N} \underbrace{T_{z \rightarrow z'}}_{\text{Transition matrix}} \cdot \mathrm{xT}(z')}^{\text{Probability of moving and having the threat at that zone}}$$



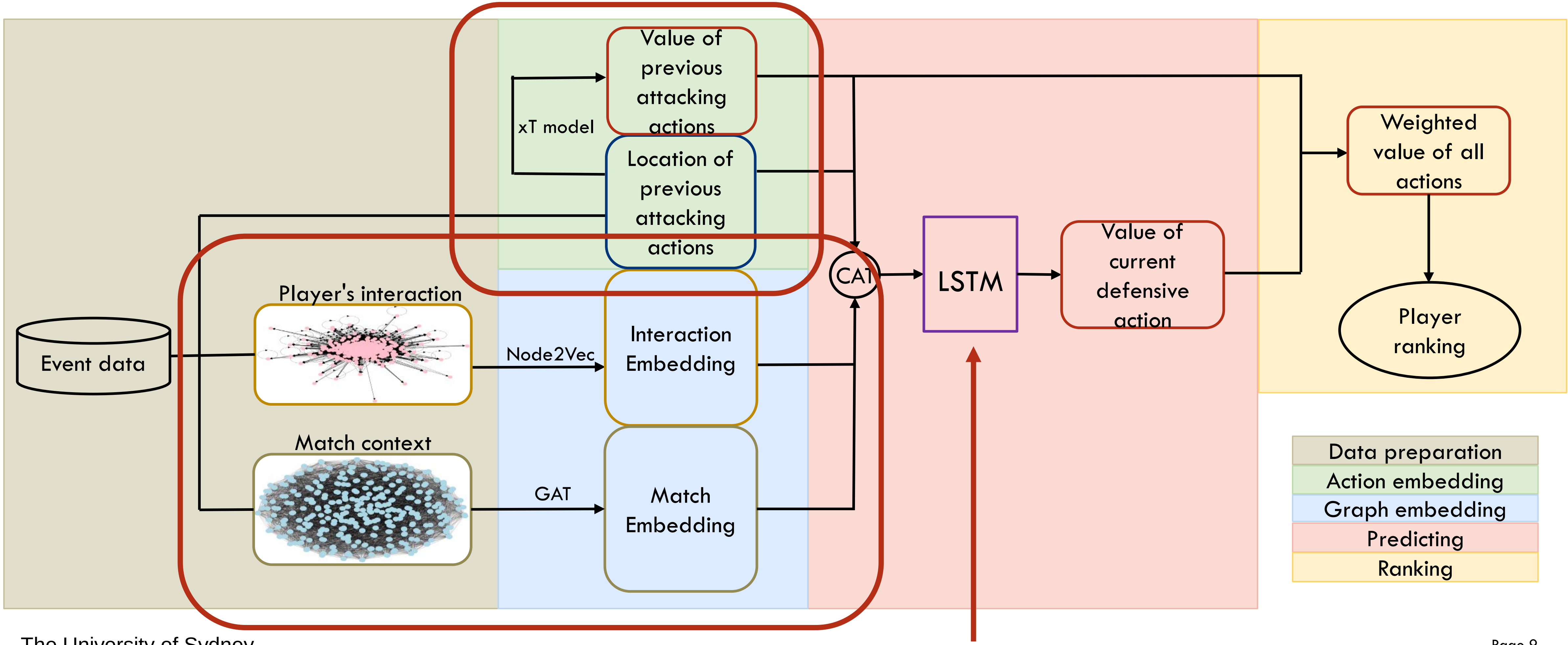
Shoot: **26%**, scoring **4%** of shots
Move: **74%** according to the map
(derived from real-life event data)

Motivation

- Existing models ignore the spatio-temporal relationships in the football actions.
- Values assigned to actions cannot be evaluated due to the lack of ground truth.

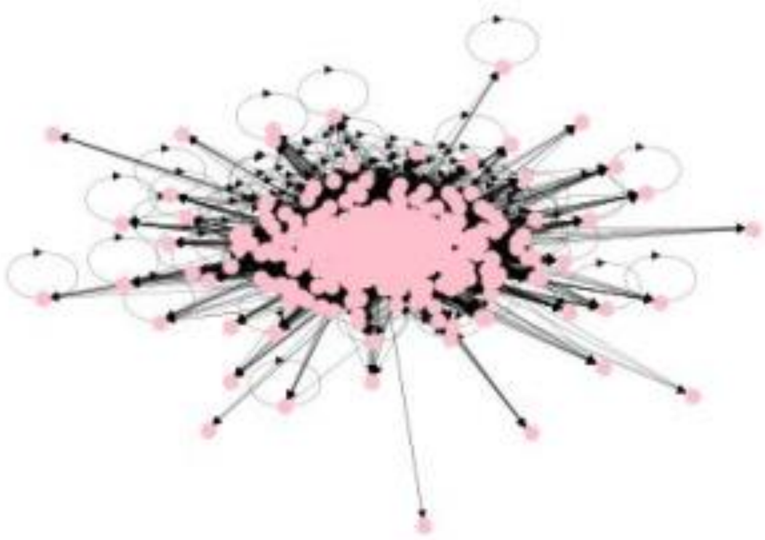
Methodology

– **Context-based Evaluation of Defensive Actions in Football**

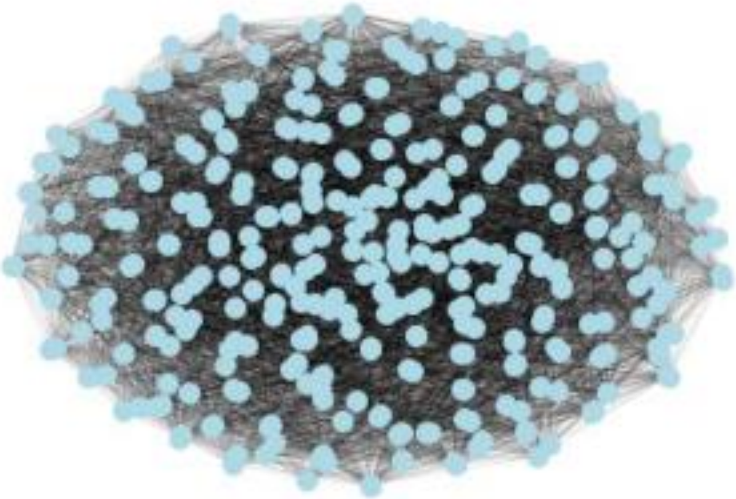


Methodology

– **Graph Construction**



Graph of player's interaction

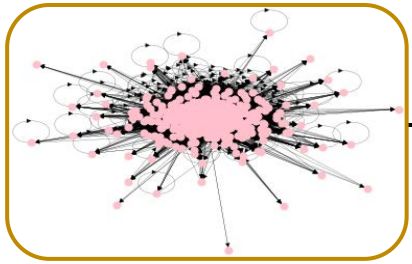


Graph of match context

Methodology

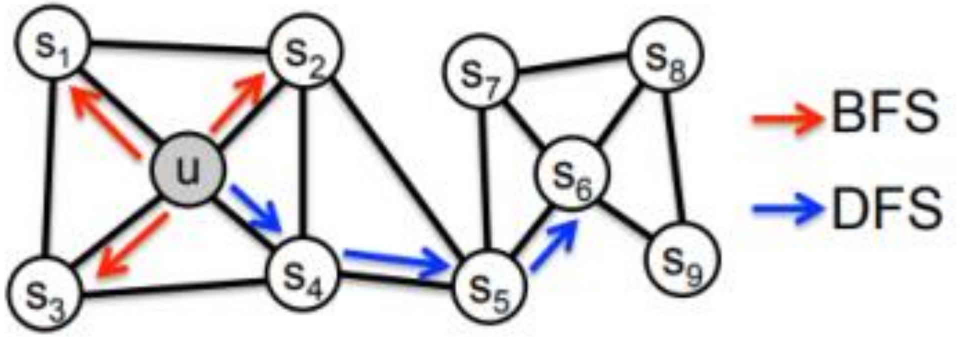
- **Graph Embedding**
  - Node2Vec: ensure that player features had a high similarity with both interacted players (Breadth-first Sampling) and structurally similar players (Depth-first Sampling)

Player's interaction



Node2Vec

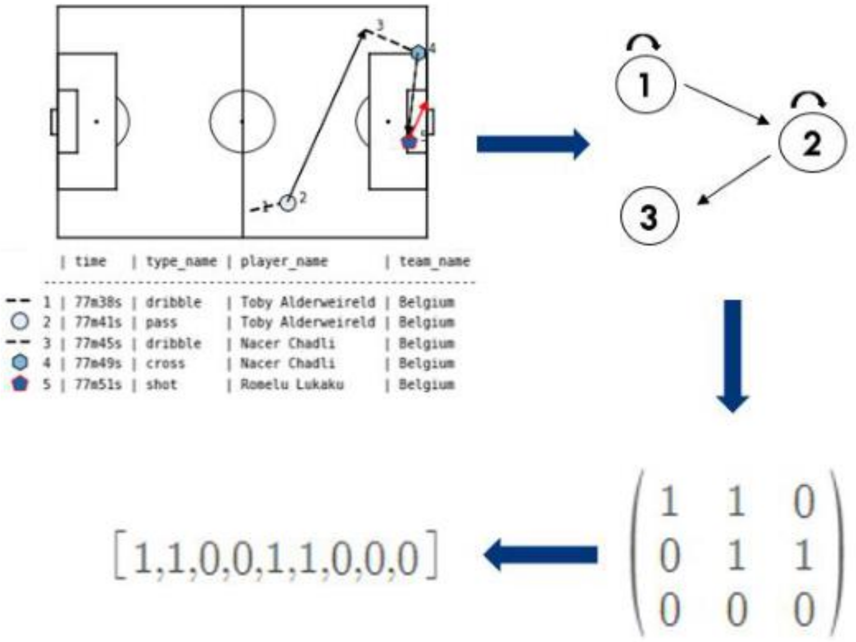
Interaction Embedding



BFS and DFS search strategies from node u

Methodology

- **Graph Embedding**
  - Relative Interaction: extract a fixed number of consecutive actions and generate adjacency matrix based on the change in players possessing the ball between the actions

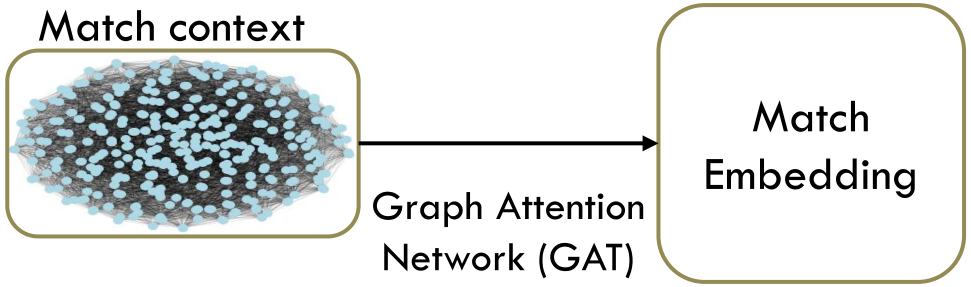


	time	type_name	player_name	team_name
1	77m38s	dribble	Toby Alderweireld	Belgium
2	77m41s	pass	Toby Alderweireld	Belgium
3	77m45s	dribble	Nacer Chadli	Belgium
4	77m49s	cross	Nacer Chadli	Belgium
5	77m51s	shot	Romelu Lukaku	Belgium

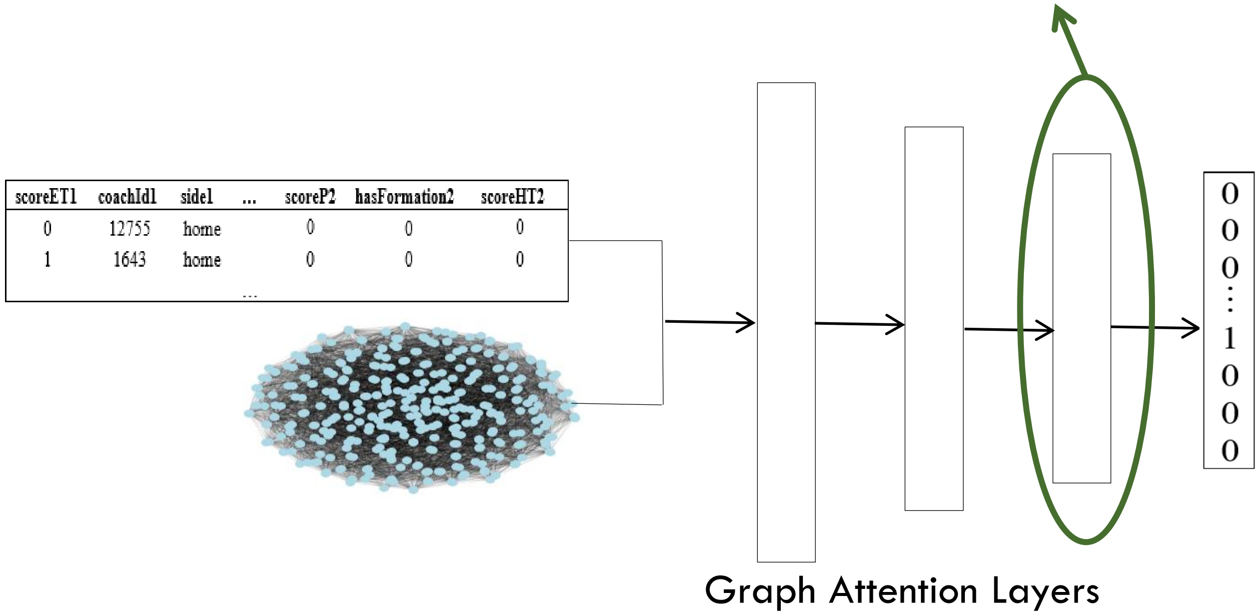
Methodology

– **Graph Embedding**

  – GAT: automatically learn the importance between nodes, which helped find the important matches

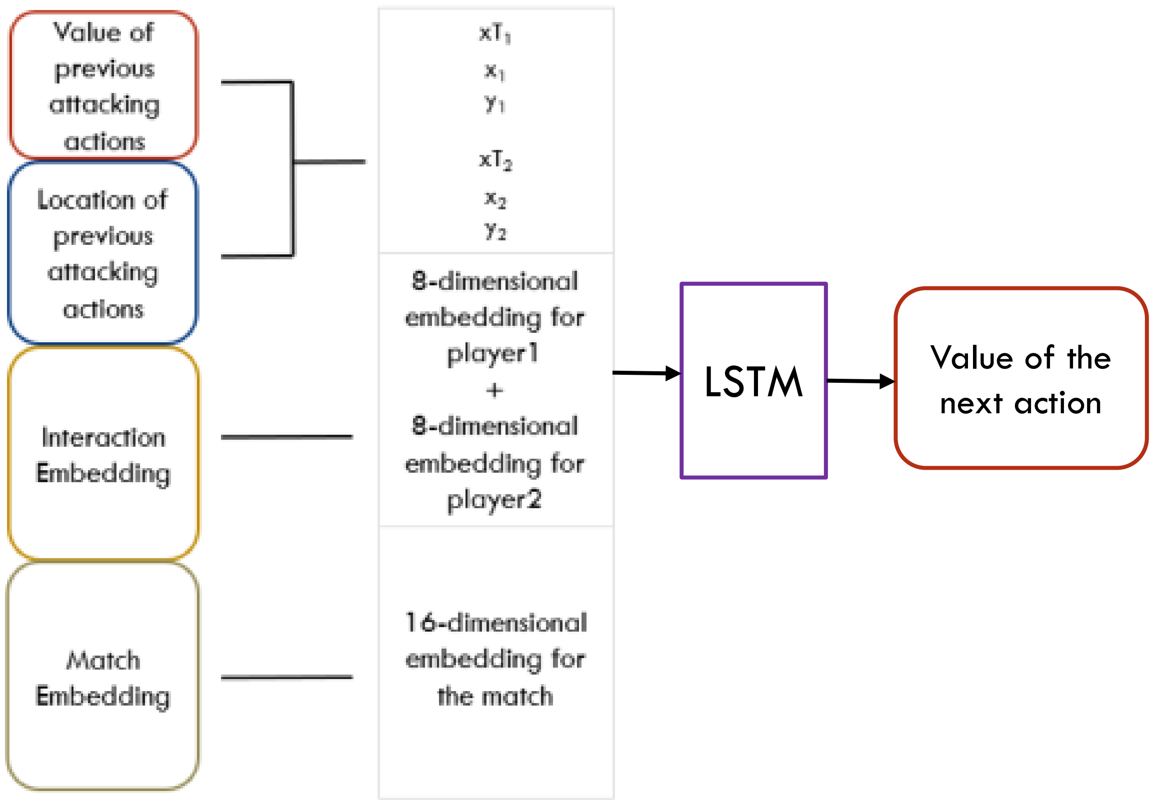


Graph Attention Network (GAT):



Methodology

– **Predicting**



Concatenated embeddings as input for the prediction model

Methodology

– **Ranking Distance**
  – The Euclidean distance between predicted players' ranking and actual players' ranking

$$d(\hat{r}, r) = \sqrt{\sum_{i=1}^{n} (\hat{r}_i - r_i)^2}$$

n: number of players
$\hat{r}_i$: predicted ranking for player i
r_i: actual ranking for player i

Experiment

- **Dataset**
  - Event data
  - 380 games during the 2017/18 season of English Premier League

Game ID	Period ID	Time	Team ID	Player ID	Start x	Start y	...	Type Name	Result Name	Bodypart
2500089	1	2.7635	1659	9637	52.50	34.00		pass	success	foot
2500089	1	4.7613	1659	8351	42.00	37.40		pass	success	foot
2500089	1	5.5330	1659	9285	40.95	57.80		pass	success	foot
2500089	1	7.7075	1659	239411	32.55	47.60		pass	success	foot

Experiment

– Experimental Results

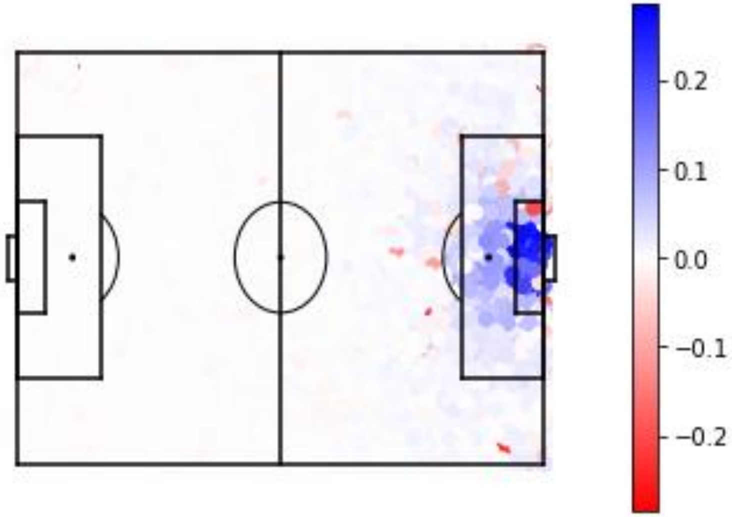
– Training Loss: Mean Absolute Error (MAE)

– Validation Loss: Mean Absolute Error (MAE)

	Training Loss	Validation Loss
Baseline DAxT (MLP)	0.0147	0.0148
Transformer	0.0111	0.0114
LSTM	0.0105	0.0107
LSTM+Node2Vec	0.0104	0.0106
LSTM+RelativeInteraction	0.0108	0.0110
LSTM+MatchEmb	0.0106	0.0109
LSTM+Node2Vec+MatchEmb (CTXT-DAxT)	0.0101	0.0103
LSTM+ReInter+Node+MatchEmb	0.0106	0.0108

Experiment

- **Evaluation for components**
  - xT model
    - observe the distribution of xT values



Actions coloured according to xT value plotting based on the ending location

Experiment

- **Evaluation for components**
  - Node2Vec
    - looked at similar players

Player	Similarity	Team	Role
Aaron Ramsey	0.9989	Arsenal	Midfielder
Nacho Monreal	0.9983	Arsenal	Defender
Granit Xhaka	0.9982	Arsenal	Midfielder
Héctor Bellerín	0.9982	Arsenal	Defender
Laurent Koscielny	0.9979	Arsenal	Defender
Alex Iwobi	0.9969	Arsenal	Midfielder

Players that are similar to Mesut Özil.

Experiment

- **Evaluation for components**
  - GAT
    - Evaluation metric: accuracy

Training accuracy	Validation accuracy	Testing accuracy
0.95	0.93	0.92

Experiment

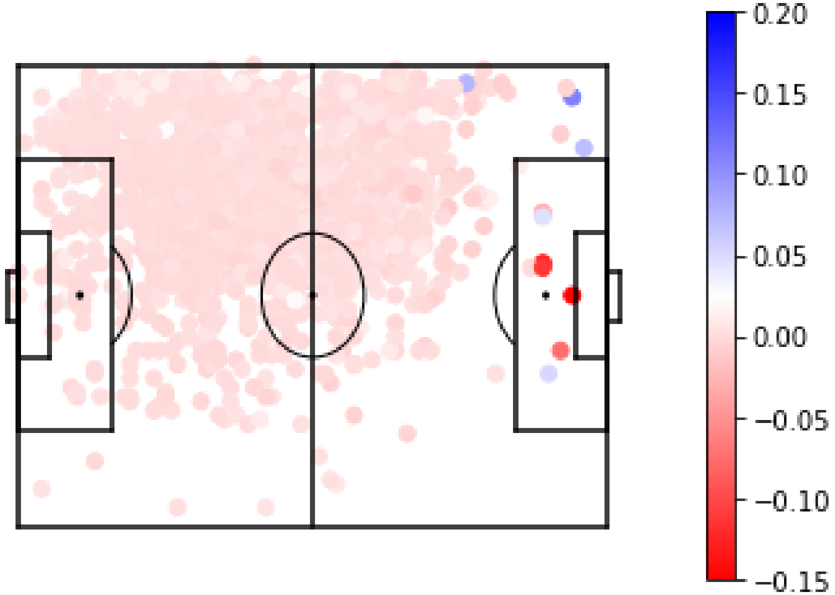
– Overall Evaluation

– Ranking Distance

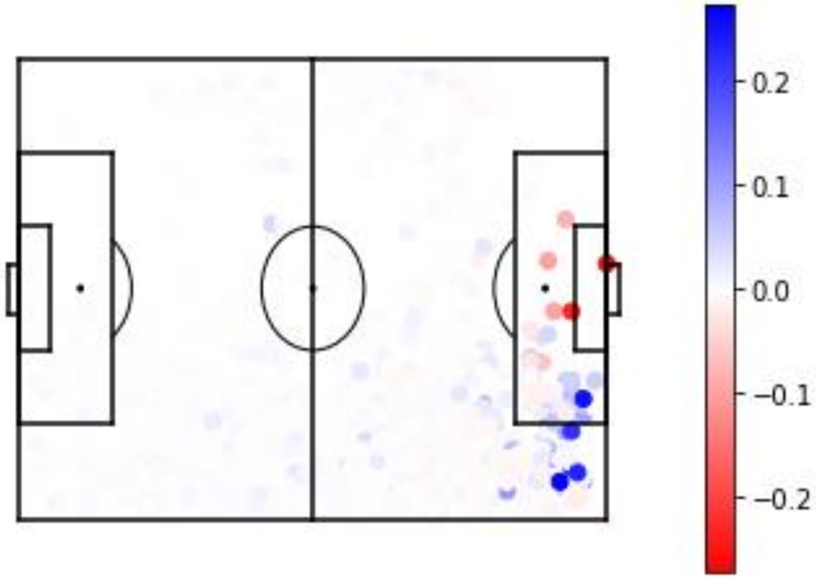
Player	Actual Ranking	Predicted Ranking from DAxT	Predicted Ranking from CTXT-DAxT
Jan Vertonghen	1	96	93
Nicolas Otamendi	2	1	1
Cesar Azpilicueta	3	20	20
Ben Mee	4	7	7
James Tarkowski	5	44	44
Euclidean Distance		104.14	101.41

Experiment

– **Visualisation**



Actions performed by Jan Vertonghen.



Actions performed by Hector Bellerin.

Conclusion

- **CTXT-DAxT**
  - A new approach valuing defensive actions based on spatio-temporal relationships
    - Player's interaction
    - Match context
    - Sequential model
- **Ranking Distance**
  - A metric evaluating the overall performance of models for quantifying football actions
    - Comparison of other models
- **Poor valuation of actions that are away from the goal**
  - Improvement is still required