The Wide Attack Battles

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1 Analysis Scope

Season: WSL 2023-2024

Object: Actions after a player receiving a pass in the Wide Attack Area.

- Wide Attack Area: outside of the box and in the attacking third.

Methods:

- Define the success of the attacking sequence following the initial pass.
- Quantify the difficulty of context as to gaining success
- Modeling to reveal the variance of result that can be explained by the context
- Extract cases where an attacker gained success under difficult to attack context, and where a defender prevent success under easy to attack context.
- Rank players accordingly

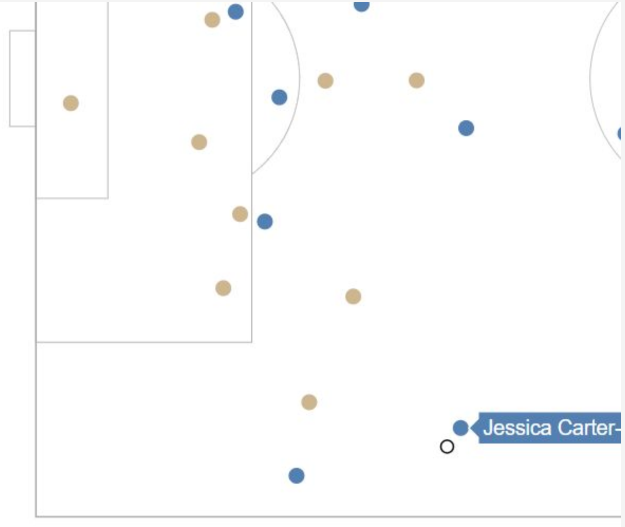
1.1 Define Success of Sequence

Start of sequence: The frame when the distance between the ball and the receiving player first becomes less than 2 meters.
End of sequence: When the second pass or shot event occurs after the sequence starts.

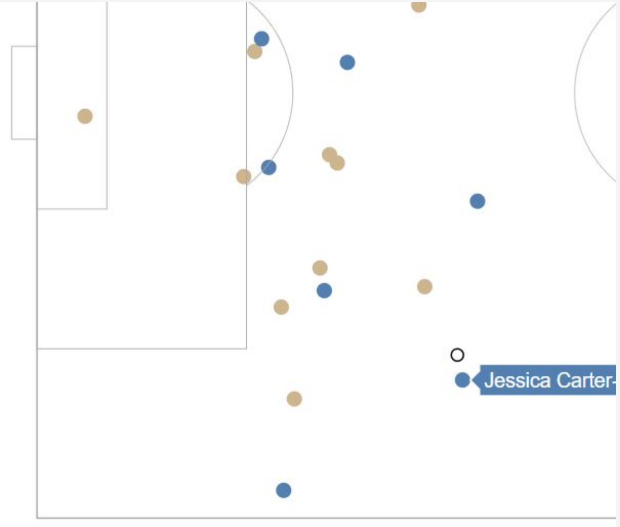
A sequence is considered successful if it meets the following criteria:

- The ball's new location is at least 2 meters closer to the goal compared to its position at the start of the sequence.
- The attacking team maintains continuous possession of the ball until it reaches the specified location.

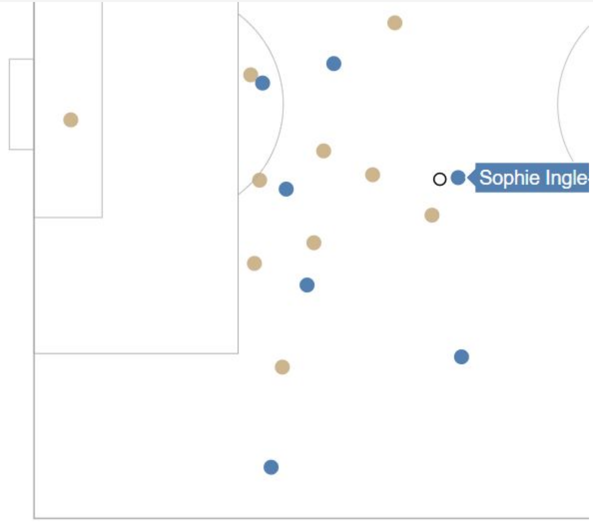
Start of sequence
Ball to goal distance: 42.04 m



1st event
Ball to goal distance: 40.38 m



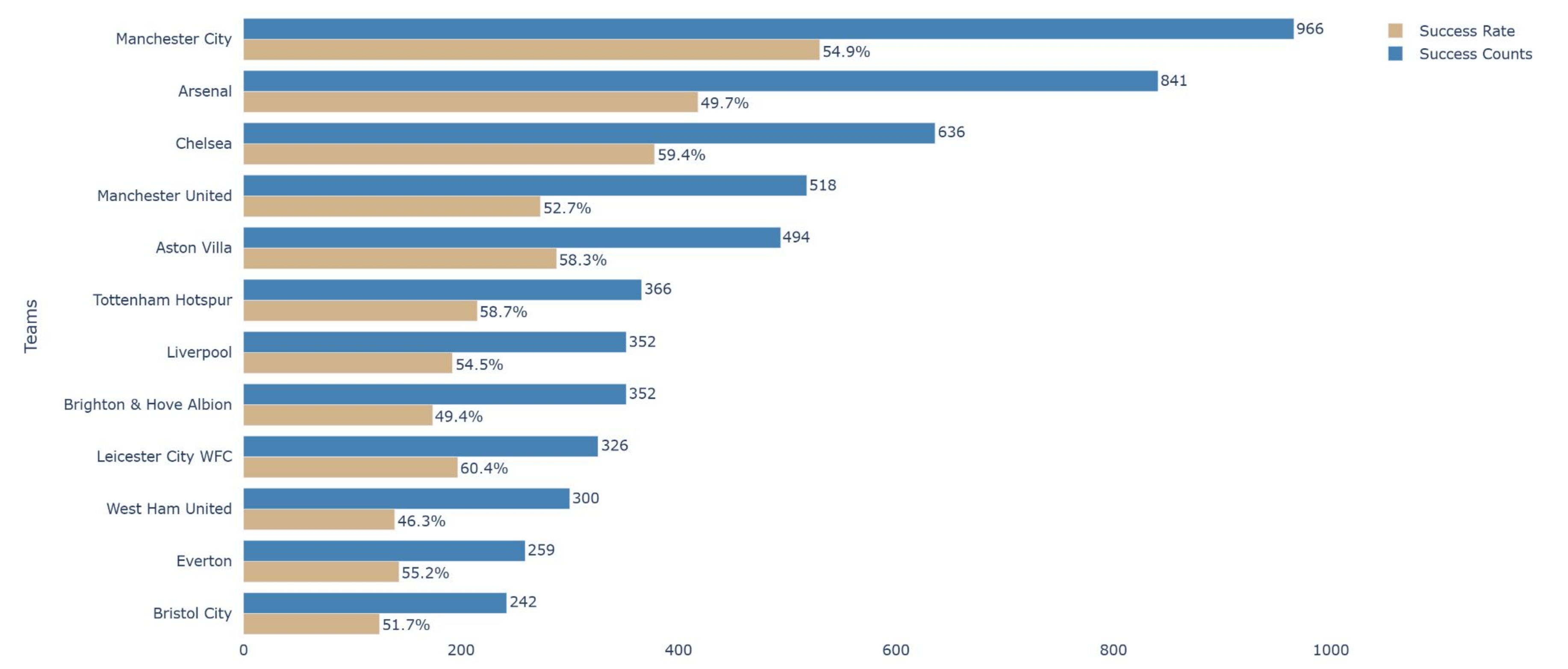
2nd event
Ball to goal distance: 34.68 m - Success



During this project, the location of possessing player was used to indicate the ball location, as event frames were marked during the passes at which the ball was away from where the player last possessed it.

1.2 Team Performance

Manchester City and Arsenal lead in the total number of successful sequences. However, some teams with much lower counts achieve impressive success rates—for instance, Leicester City succeeded in 60.4% of all their wide attack sequences, top of all teams..



2 Context Variables

As the team performance differs, each sequence faces difference attacking difficulties. Here are a few variables considered to have influences on the sequence result.

- **Score difference**
  The scoring situation at the start of sequence can affect players' aggressive levels. It may also reflect the skill disparity between the teams.

- **Count of defender in the box**
  With a sufficient number of defenders in the box, the main defender of the sequence has more freedom to leave certain space behind and press hard, thereby increasing the attacking difficulty.

- **Count of attacker** (beyond the attacking point)
  From the 2 meters behind ball location to the goal line, all the attackers within this zone are considered as potential helpers to assist the sequence.

- **Team**
  Playing at a home stadium is often believed to impact a team's performance positively.

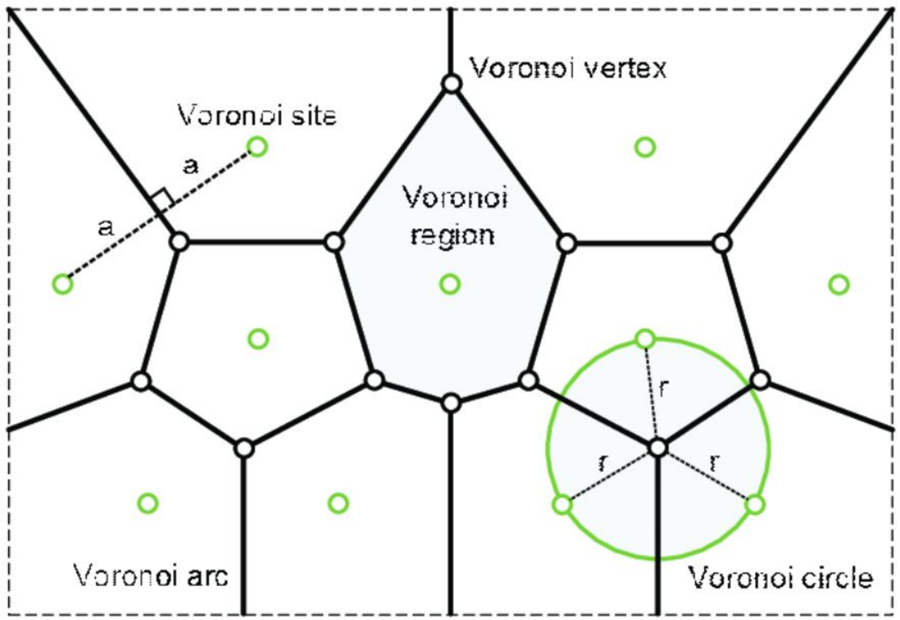
- **Sum of Freedom**
  The available space where an attacker can move with minimal threat. This is calculated using a Voronoi diagram, as detailed on the next page.

2.1 Sum of Freedom

[A Voronoi diagram is a type of tessellation pattern in which a number of points scattered on a plane subdivides in exactly n cells enclosing a portion of the plane that is closest to each point.]

Simply put, any point on the edge between two green dots in the image has equal distance to each circle. Any point within a green dot's Voronoi region is closer to this dot than to any other dots.

Voronoi diagram



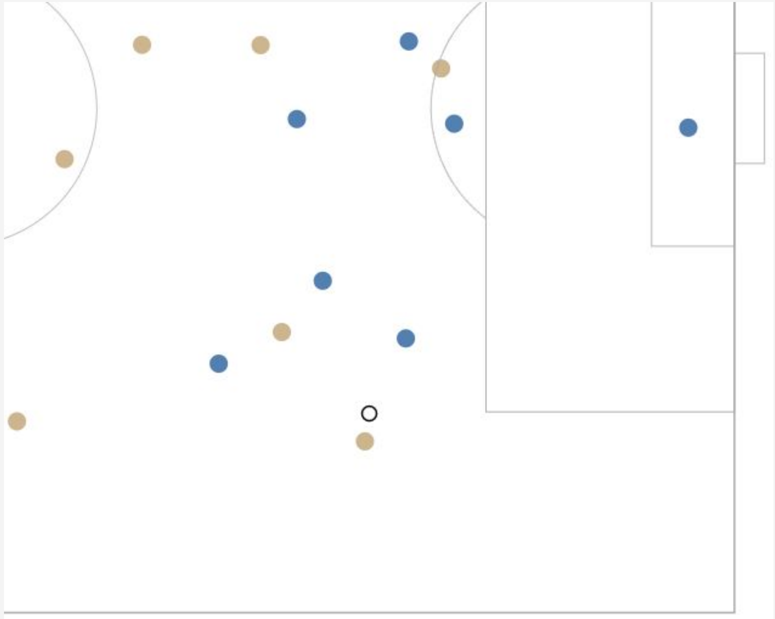
2.1 Sum of Freedom

For each sequence, a Voronoi site is generated for the ball and nearby defenders. The site is divided by a line perpendicular to the line connecting the ball and the center of the goal. The Sum of Freedom is defined as the sum of the site areas closer to and farther from the goal, with a heavier weight applied to the area closer to the goal

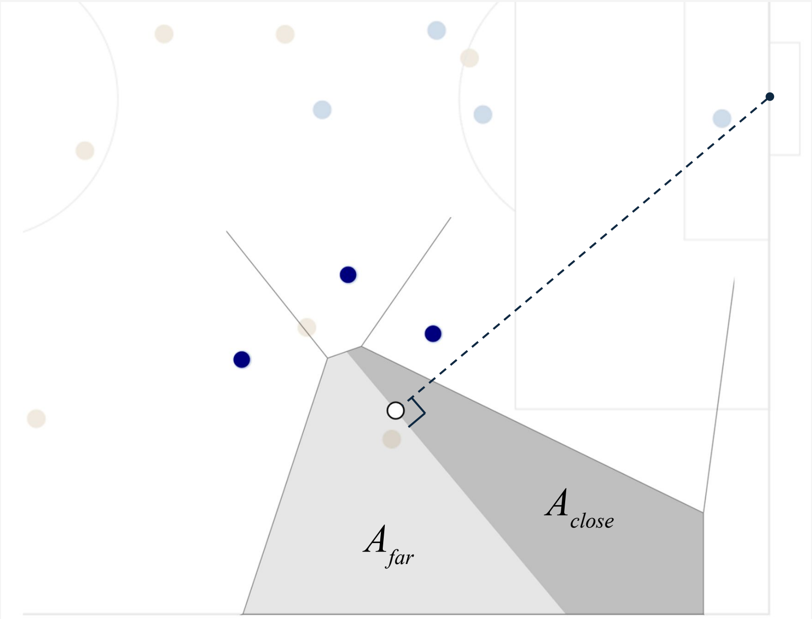
The boundary of the Voronoi diagram was the sidelines, the goal lines, and 20 m away from the ball to four directions.

$$SoF = log(A_{far} + 1) + A_{close}$$

Example 1 start of sequence



SoF = 166.9 m^2 Result: Success



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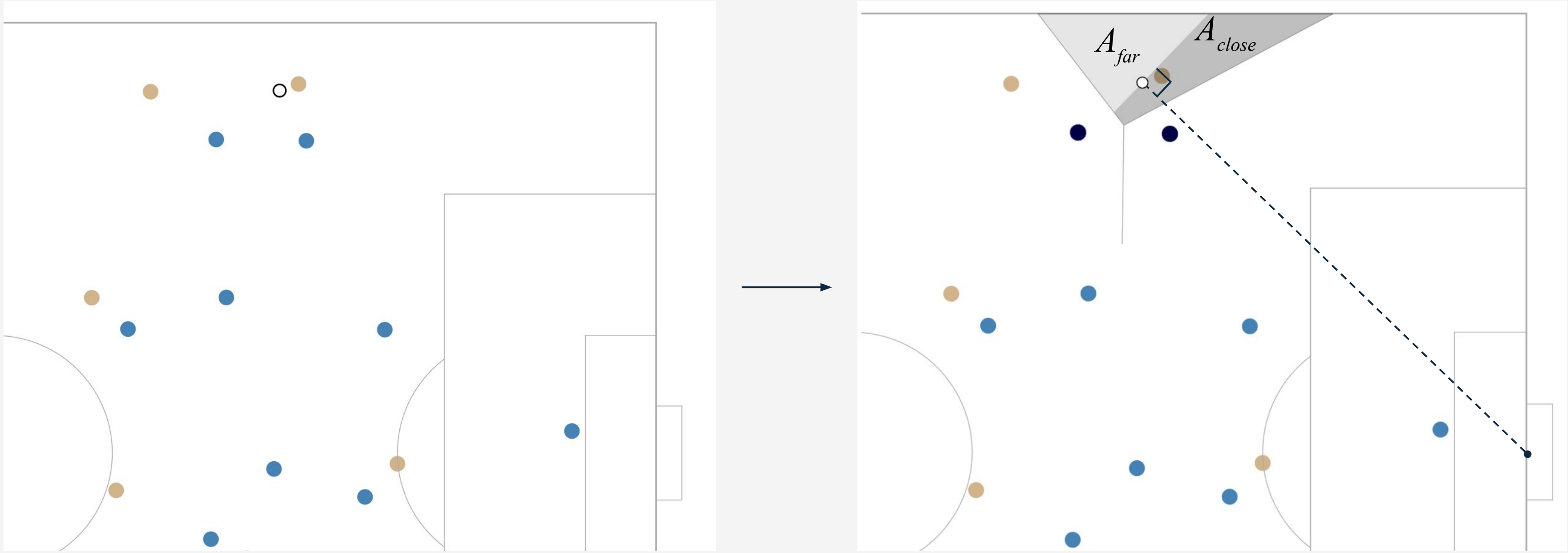
Example 2 start of sequence

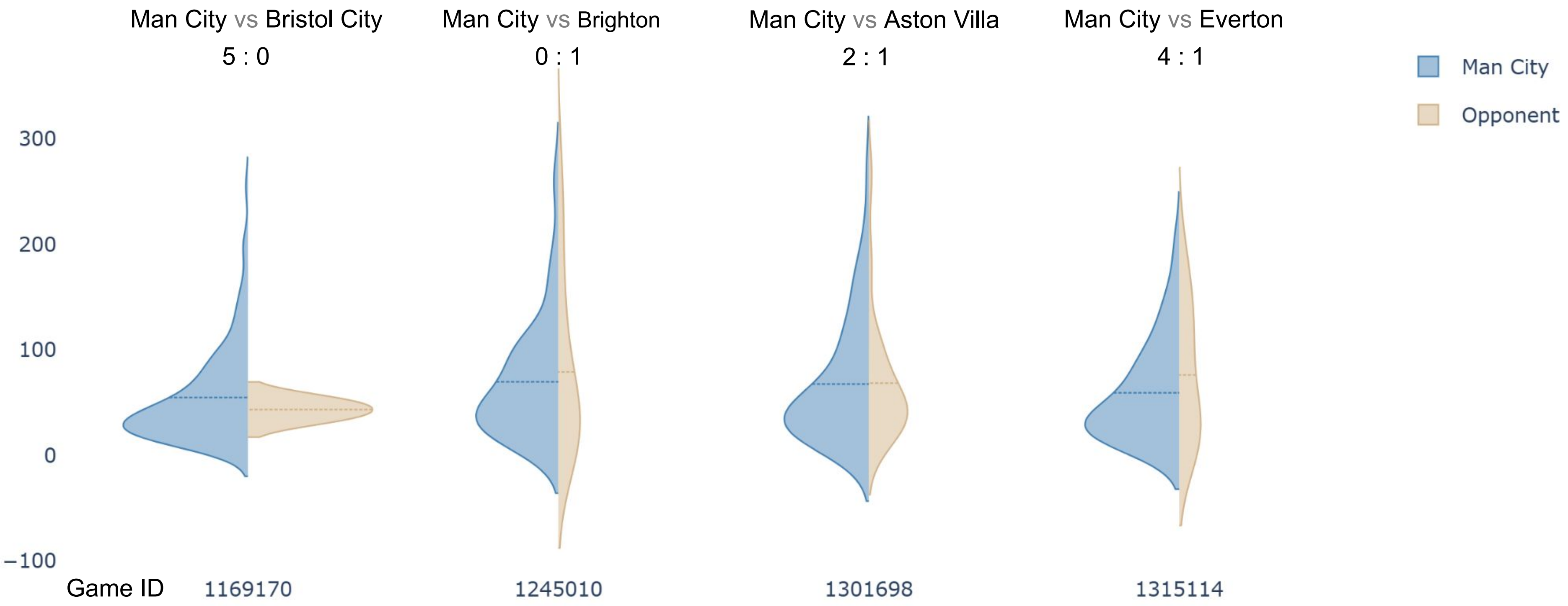
SoF = 51.3 m^2 Result: non-success



2.1 Sum of Freedom

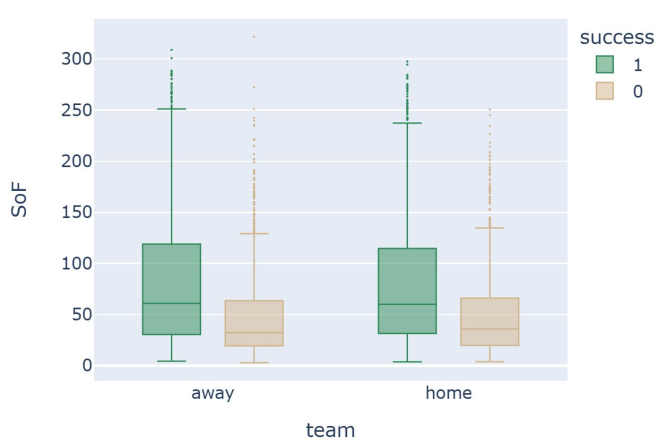
We can visualize the distribution of SoF to see pattern of teams.

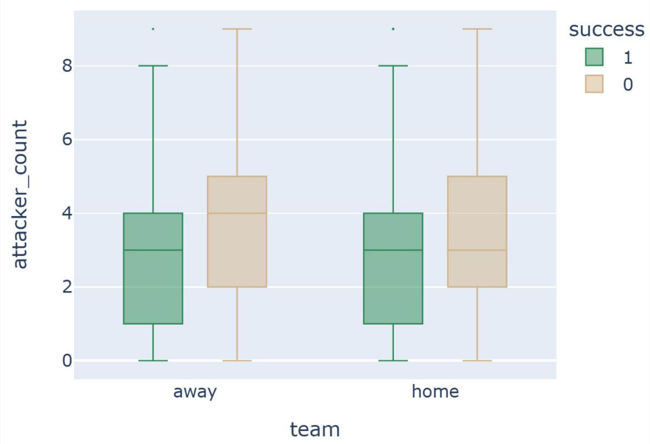
Manchester CIty SoF Distribution in Four Games

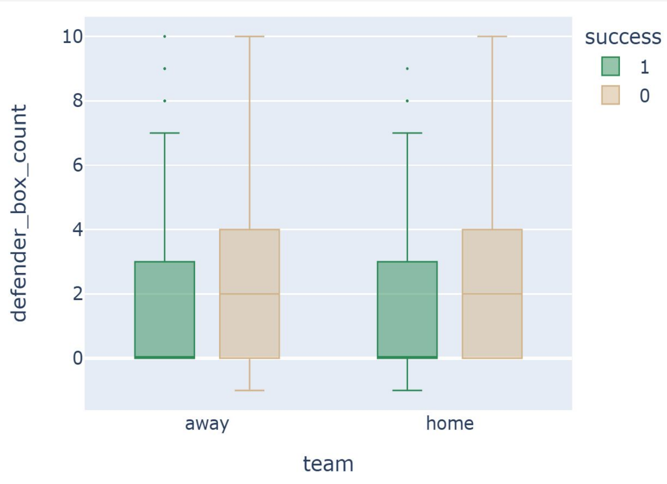


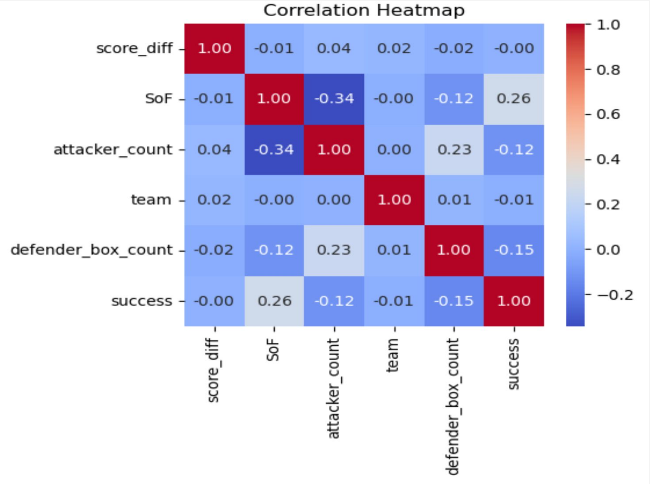
2.2 Feature exploration

A few feature exploration reveals the significance of SoF, defender_box_count, and attacker_count to the sequence result.









3 Models

Using the variables mentioned as features, a few classification models were trained to reveal how much variance of the sequence result can be explained by contextual influences.

In the report on the right, label 1 represents success, label 0 represent unsuccess.

```
Model: RandomForest
Accuracy: 0.6438
Classification Report:
              precision    recall  f1-score   support

           0       0.59      0.67      0.63       203
           1       0.70      0.63      0.66       249

    accuracy                           0.64       452
   macro avg       0.64      0.65      0.64       452
weighted avg       0.65      0.64      0.64       452

Confusion Matrix:
[[135  68]
 [ 93 156]]
```

```
Model: GradientBoosting
Accuracy: 0.6372
Classification Report:
              precision    recall  f1-score   support

           0       0.57      0.78      0.66       203
           1       0.75      0.52      0.61       249

    accuracy                           0.64       452
   macro avg       0.66      0.65      0.64       452
weighted avg       0.67      0.64      0.63       452

Confusion Matrix:
[[159  44]
 [120 129]]
```

```
Model: LogisticRegression
Accuracy: 0.6283
Classification Report:
              precision    recall  f1-score   support

           0       0.56      0.75      0.65       203
           1       0.72      0.53      0.61       249

    accuracy                           0.63       452
   macro avg       0.64      0.64      0.63       452
weighted avg       0.65      0.63      0.63       452

Confusion Matrix:
[[153  50]
 [118 131]]
```

```
Model: KNeighbors
Accuracy: 0.5774
Classification Report:
              precision    recall  f1-score   support

           0       0.53      0.52      0.52       203
           1       0.61      0.63      0.62       249

    accuracy                           0.58       452
   macro avg       0.57      0.57      0.57       452
weighted avg       0.58      0.58      0.58       452

Confusion Matrix:
[[105  98]
 [ 93 156]]
```

4 Player Evaluation

The variance that were not explained by contextual influences should be heavily influenced by the players' capabilities:

- Outstanding attackers would succeed on scenarios which the model considered to be difficult to succeed.
- Outstanding defenders would prevent an attacking success on scenarios considered to be easy to succeed.

3392 randomly selected sequences were left out before the model training and was used for player evaluation.

Among the four models, the GradientBoosting model was chosen to evaluate attacker, because of its better performance on label 0 (unsuccess), the RandomForest model chosen to evaluate defender, because of its better performance on label 1 (success).

4.1 Attacker Evaluation

Among attacker who have faced more 25 difficult scenarios from the evaluation set, Mary Fowler and Kirsty Hansen stood out with their over 0.6 success ratio.

pass_recipient_name	success_difficult_ratio	difficult_count
C. Kelly	0.569892	93
C. Foord	0.538462	65
L. Hemp	0.519231	52
S. Catley	0.404255	47
B. Mead	0.409091	44
Leila Ouahabi	0.465116	43
E. Toone	0.585366	41
N. Charles	0.512195	41
M. Fowler	0.628571	35
H. Blundell	0.375000	32
L. Galton	0.290323	31
K. Dali	0.483871	31
K. Hanson	0.607143	28
K. Casparij	0.370370	27
S. Mayling	0.518519	27
L. James	0.500000	26
K. Smith	0.384615	26
K. Robinson	0.400000	25
K. McCabe	0.240000	25

4.1 Defender Evaluation

Defender evaluation was focused on the 'paired players' who were the closest to the ball receiver at the start of sequence.

Among attacker who have faced more 20 difficult scenarios from the evaluation set, Ella Powell, Niamh Charles, Mayumi Pacheco, and Catherine Bott stood out with their over 0.4 prevent success ratio.

paired_player	unsuccess_easy_ratio	easy_count
Ella Mae Florence Powell	0.400000	55
Heather Payne	0.361702	47
Ffion Morgan	0.264706	34
Jamie-Lee Napier	0.303030	33
Hannah Blundell	0.193548	31
Emma Kullberg	0.266667	30
Sarah Emma Mayling	0.366667	30
Kirsty Smith	0.259259	27
Niamh Louise Charles	0.481481	27
Mayumi Pacheco	0.480000	25
Emma Koivisto	0.250000	24
Naomi Layzell	0.391304	23
Catherine Joan Bott	0.428571	21
Katie Robinson	0.285714	21
Clare Wheeler	0.250000	20