

### Abstract

Attaching values to actions performed by players is one of the great challenges in football analytics, as an extensive valuation model provides unbiased insight into how players perform and, more importantly, expresses it in numbers, which is priceless when comparing footballers. This project proposes a comprehensive model to value player contributions in counterattacks with four different metrics that employ both tracking and event data.

This project is dedicated to Dr. Garry Gelade, a leading football analytics pioneer that supported and encouraged many young data scientists and analysts.

### Filtering & Episodes

Because data consisted of full matches, relevant episodes of counterattacks had to be filtered out. To be filtered as a counterattack, the episode had to have finished in a chance or a goal and include an action by the opponents in their attacking half in 20 seconds before the goal/chance.

After filtering, 11 counterattacking episodes have been extracted from the tracking and event datasets of the 10 matches. They were manually tagged based on:

- Where the ball was won
- How many opponents were behind the ball when possession changed
- If the danger was increased using passes, dribbles or both
- Whether the episode resulted in a chance or a goal

No.	Start	Opps.	Actions	Result
Ep. 01	Back	5	Dribbles	No Goal
Ep. 02	Back	9	Passes	No Goal
Ep. 03	Back	6	Passes	No Goal
Ep. 04	Back	11	Passes	No Goal
Ep. 05	Back	3-4	Passes	Goal
Ep. 06	Back	8	Mixed	Goal
Ep. 07	Back	6-7	Mixed	Goal
Ep. 08	Back	10	Passes	Goal
Ep. 09	Back	8	Mixed	Goal
Ep. 10	Back	7	Mixed	Goal
Ep. 11	Back	6-8	Passes	Goal

Table 1. Manually tagged counterattacking episodes

### Visualizations

To make the proposed model more intuitive a visualization script was created. It is based on code by Ricardo Tavares on Medium[1]. The script takes the start and end times, event and tracking datasets as inputs and produces a visualization of that play. If needed, the visualization can include Voronoi cells of players, the line that depicts where the ball is and centroids of both teams.

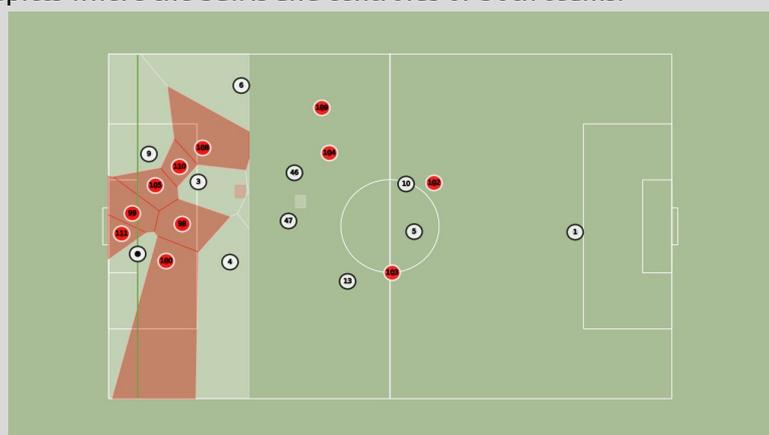
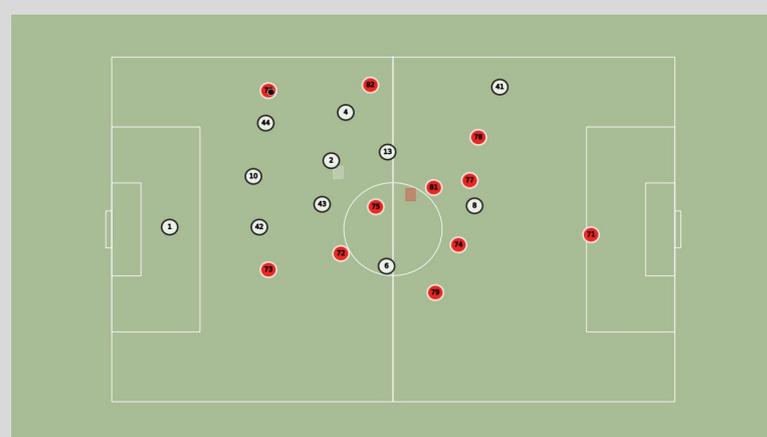
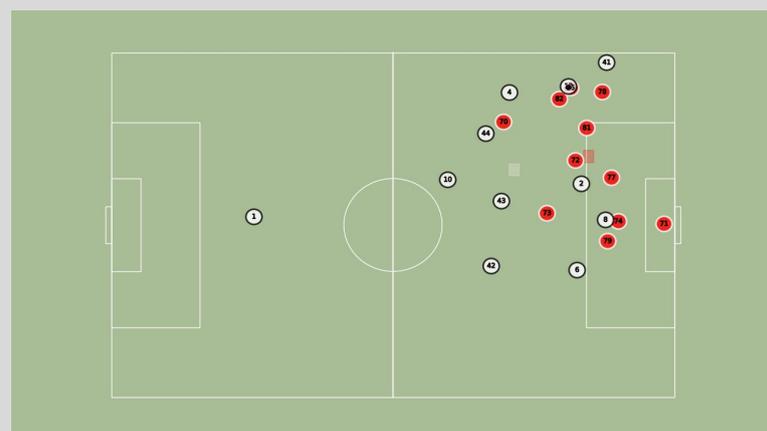


Figure 1. Screenshot from visualization

### Measure 1: Distance

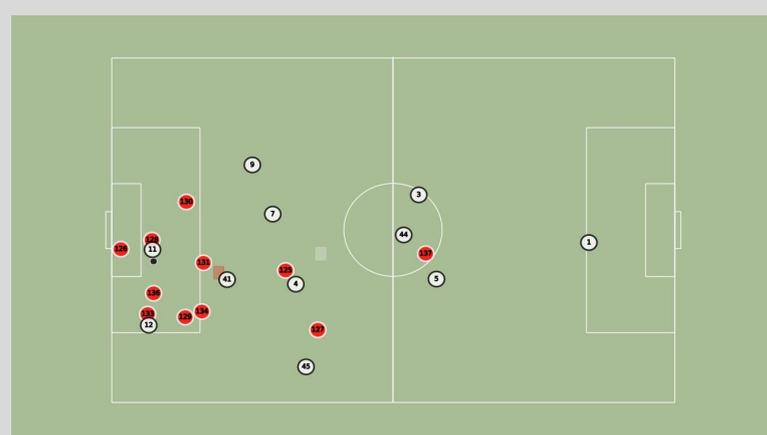
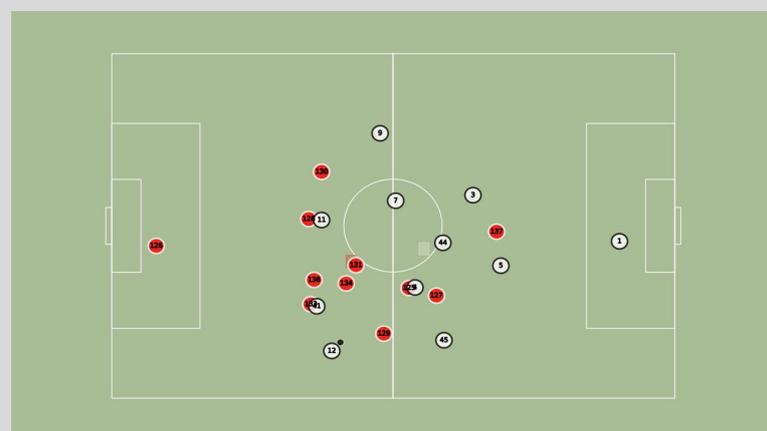
The first measure is likely the most obvious of the four - carrying the ball near the opponent's goal is sure to make the attack more dangerous, especially in counterattacks where the goal is to move the ball as quickly as possible. To reward players who do this, the model computes the difference of distances between the ball and the goal before and after player's actions.



Figures 2 and 3. The play before and after the contribution that had the highest distance metric - 49.6 meters

### Measure 2: Danger

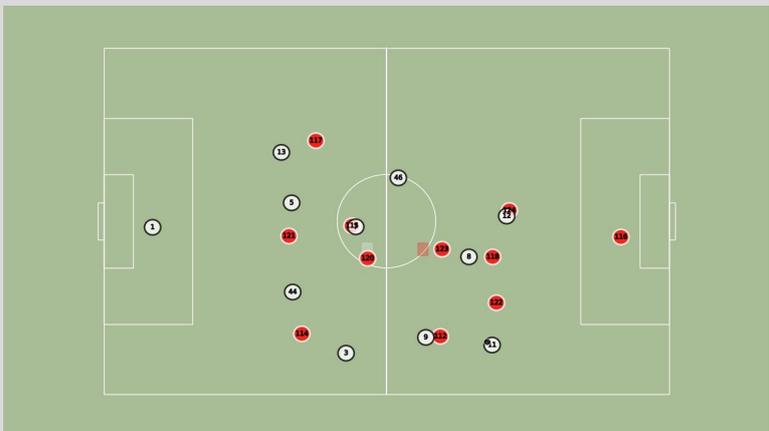
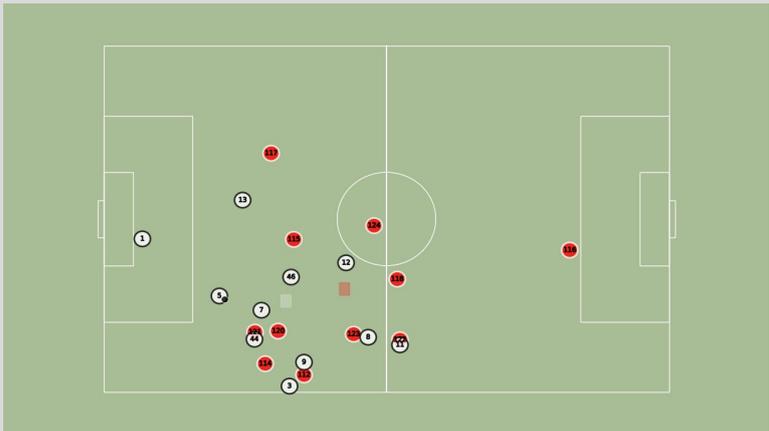
Although similar to the first, the second metric also takes into account how much more dangerous a player made the attack. Measuring how dangerous an attack is when the ball is at a certain position in the pitch was discussed in a paper on dangerousness by Daniel Link et al.[2]. The danger values for 2x2 meter spaces in the final 34 meters of the pitch proposed in the said paper were chosen for this project.



Figures 4 and 5. The play before and after the largest observed increase in danger in a contribution - 1.0, the maximum possible value

### Measure 3: Outplayed opponents

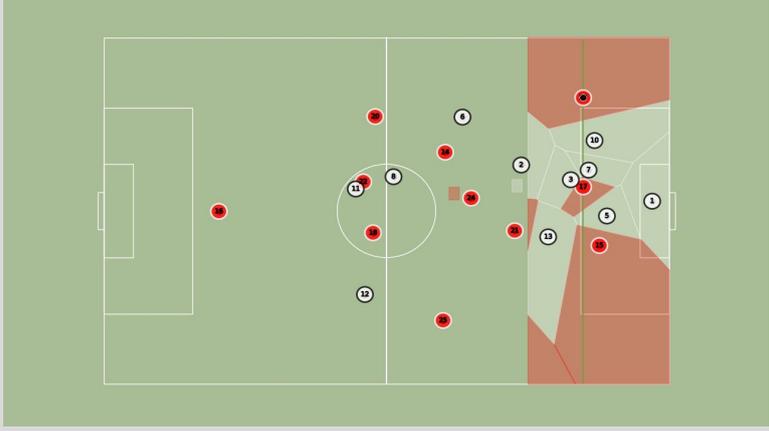
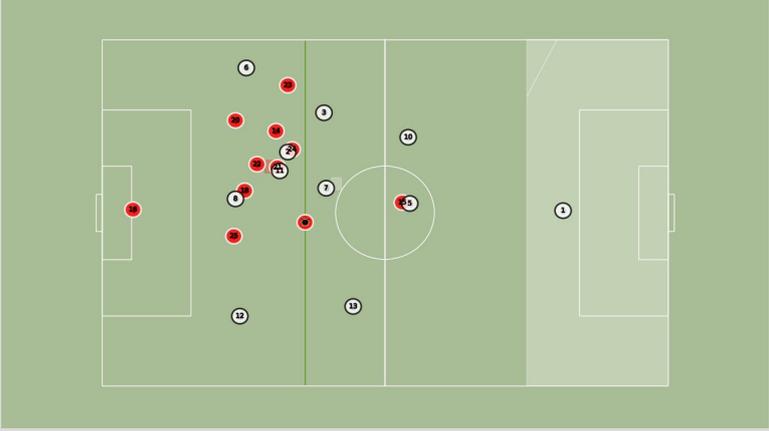
One could say the first two methods are limited as they only consider where the ball is on the pitch. To complement them, the third approach measures how many defenders were left behind the ball during player's actions. This particular approach was introduced in a research paper that focused on valuing passes by Rein et al.[3] This project extends it to include all the dribbles a player made before the pass.



Figures 6 and 7. Images before and after the contribution in which Player 5 outplayed 7 opposition defenders with dribbles and a long pass to Player 11 - the highest score observed

### Measure 4: Space control

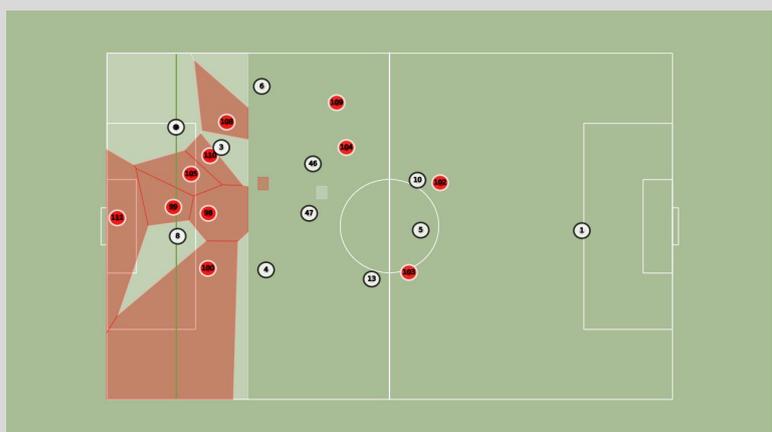
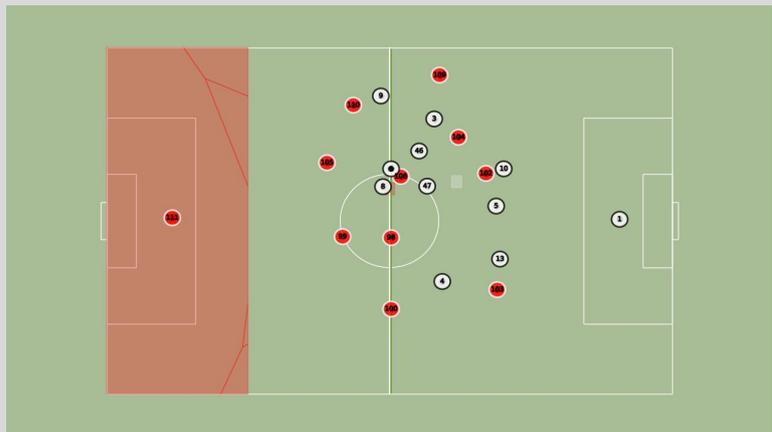
Likely the least obvious of the four, the third method to value player contributions focuses on space controlled by the attacking team before and after player's actions. Space control in attack was the focal point of a research paper by Perl and Memmert[4], they found that many successful teams control large areas in their opponent third of the pitch. Experiments have shown that replacing it with the final quarter of the pitch produces more volatile results, so it was chosen as the threshold for this project.



Figures 8 and 9. Visualizations of the contribution that increased the controlled space the most of all the observed contributions. The red team increased controlled space by 61.5%

### Counterattack score

To create a truly comprehensive valuation of a player's contribution, all of the measures explained above had to be combined together. It was implemented by normalizing all metrics to range [-1; 1] and adding them up. The sum would then be multiplied by 2.5 to achieve a complete Counterattack score with range [-10; 10].



Figures 10 and 11. The before and after images of the contribution with the highest combined score of all - Player 6's contribution to this counterattack was given a score of 4.9

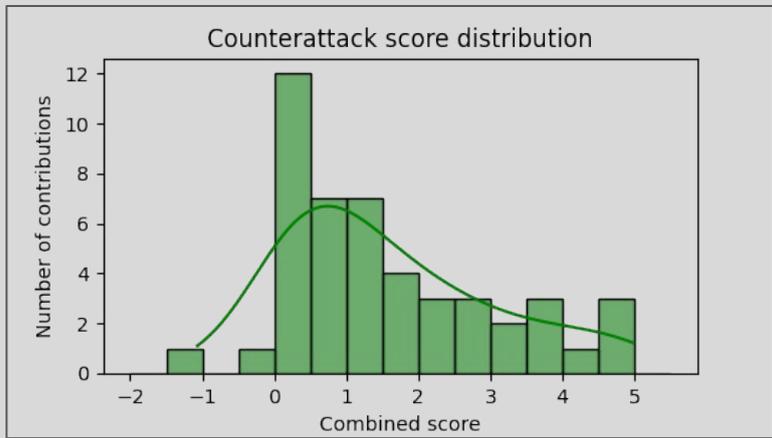


Figure 12. Histogram of all observed counterattack scores

From the figure above it is obvious that, similarly to the players themselves, there are lots of average contributions but they become more and more rare as they get better.

After experimenting it was found that the contributions with highest combined scores rarely have the largest values in each separate category - most of them have average to pretty good scores in all of them. This means that the proposed model is unbiased and comprehensive and promotes balanced contributions rather than the one-sided ones.

### References

[1] Tavares, Ricardo. (2019). Using Voronoi Diagrams in Football. <https://medium.com/football-crunching/using-voronoi-diagrams-in-football-ca730ea81c05>

[2] Link, D., Lang S., and Seidenschwarz P. 2016. Real Time Quantification of Dangerousity in Football Using Spatiotemporal Tracking Data. PLOS ONE <https://doi.org/10.1371/journal.pone.0168768>

[3] Rein, R., Raabe D., and Memmert D. (2017). "Which Pass Is Better?" Novel Approaches to Assess Passing Effectiveness in Elite Soccer. Human Movement Science 55. <https://doi.org/10.1016/j.humov.2017.07.010>

[4] Perl, J. & Memmert, D. (2017). A Pilot Study on Offensive Success in Soccer Based on Space and Ball Control – Key Performance Indicators and Key to Understand Game Dynamics. <https://doi.org/10.1515/ijcss-2017-0005>