Inter Milan Player Performance Report

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Mathematical Modelling of Football

ANALYSIS SUMMARY

The **Team Performance** group highlighted that Inter focused threat down both flanks during the 2017/18 Serie A season, creating chances through crosses.

The **Player Performance** group took a data-driven approach to:

- Identify high / low performing players within Inter squad;
- Identify transfer targets in key positions enabling Inter to:
  - Mitigate key losses;
  - Strengthen positions of vulnerability;
  - Add depth to the squad following CL qualification.

To identify players, we produced position-specific player performance metrics for a number of positions, combining KPIs that suit Inter's style of play along with a systematic framework to value player actions.

A. Analysis Highlights

Metrics were derived using the xT framework (section I), in addition to other complementary models and algorithms – finishing with more traditional metrics adjusted for possession (section III).

xT is a possession-based framework, meaning the only actions it provides values for are actions that move the ball between pitch zones (i.e. crosses, passes, dribbles). xT values are only attributed to successful actions, meaning an xT-based dribble metric summarises a player's tactical ability to identify threatening areas to move into, but lacks the context of dribble success rate and the dribbler's ability to beat a man to get there. To fill this gap, we created a bespoke mean ELO dribble system (section VII) after matching attackers and defenders within the Wyscout **duel** event taxonomy.

World Class Wingers

FIG. 1 showcases these ELO and xT-based metrics for wingers, with goals above expectation (with separate models and metrics for headers and non-headers, section II) and touches in the opponent's box metrics rounding out the proportional area radar (section VI). Our analysis showed Inter's Perišić (LW) and Candreva (RW) to be world class dribblers and crossers of the ball. Following Manchester United's attempted €45M transfer for Perišić the previous season, we present a systematically identified LW replacement candidate in Alexis Sanchez (out-of-form star at Manchester United) as well as strength-in-depth RW candidate Victor Moses (squad player at Chelsea). Should Manchester United come back in for Perišić, our analysis would support the recommendation to Inter management to attempt to swap Perišić for Sanchez, a superior passer to Perišić who seems to be able to do everything but score at Manchester United!

An Artist-Tank Partnership at Centre Back

An attractive property of our methodology is that the systematic construction of position-specific metrics would enable us to create a

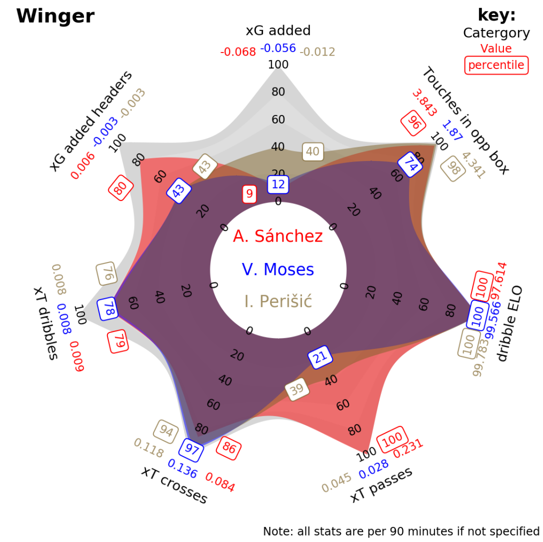

FIG. 1: Winger radar comparing star Inter winger Perišić with a systematically identified replacement candidate Alexis Sanchez and back-up candidate Victor Moses.

timeseries per metric per player with which to track rising stars and declining veterans. FIG. 2 shows another position covered by our analysis, centre halves, displaying the complementary *Artist-Tank* partnership between newly-signed Škriniar (the risk-taking *artist* capable of playing out from the back and scoring headed goals) and veteran Miranda (the experienced *tank* who dominates physically, whether it be in the air, on the ground against the dribble or a striker with back to goal). Our analysis would allow Inter management to track Škriniar's development and systematically identify when Miranda needs to be replaced.

Weaknesses at Left Back

An innovative piece of analysis that provides insight into a team's weak point (whether that team be Inter or an opponent) is our *Delta xT Strategy* analysis. The following methodology produces a *Delta xT* grid for Inter:

- Calculate the mean opponent threat per zone *excluding* Inter;
- Calculate the mean opponent threat per zone *versus* Inter;
- Sum the threat deltas (*versus* Inter − *excluding* Inter) for all opponents.

Delta xT intuitively shows where opponent's deviate from their usual threat strategy when playing against Inter, where the 2017/18 analysis can be seen in FIG. 4 (Real Madrid's *Delta xT* is also shown, as Real also show defensive frailty at left back). D'Ambrosio, a right-footed right back, was preferred over left backs Nagatomo, Santon, and Dalbert in the left back position towards the second half of the season. It's fascinating to see from FIG. 4 just *how wide* Inter were targeted on the left side of the defence, suggesting that opponents tactically attacked D'Ambrosio's weaker

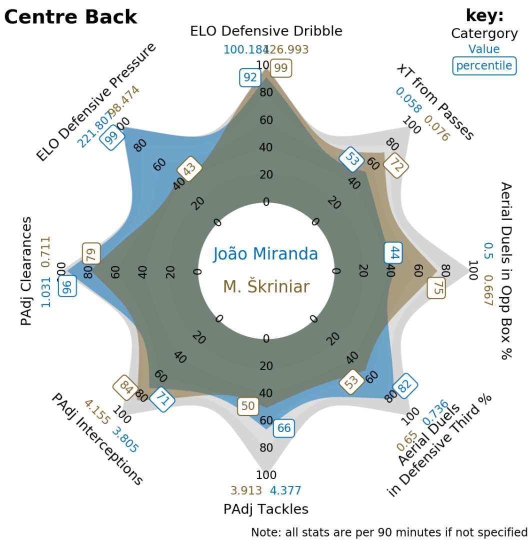

FIG. 2: Centre back radar highlighting the complementary *Artist-Tank* partnership between Škriniar and Miranda.

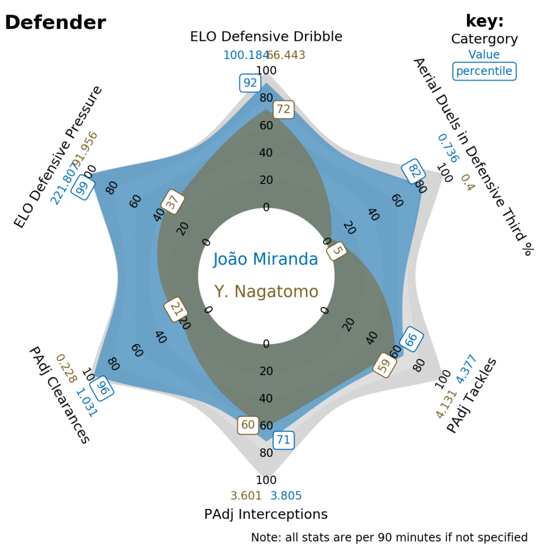

FIG. 3: Nagatomo – Inter's most played left back – compared with defensive powerhouse Miranda highlighting the chasm in quality between defensive positions.

foot to gain an advantage. FIG. 3 highlights the stark contrast in quality between Inter's most played left back, Nagatomo, and defensive powerhouse Miranda, showing Nagatomo to be average or below average in most defensive metrics. Not ideal for a first choice left back in a team looking to mount a domestic league and Champions League challenge.

Identifying Potential Replacement Left Backs

Using the off-ball defensive measures described in sections IV and V, we sought to identify attacking left backs who scored better in terms of opposition chances created against according to these measures. Some notable players who scored highly were:

- **Junior Firpo**, market value c. €100,000, a young talent, who joined Barcelona for €25 M in 2019,

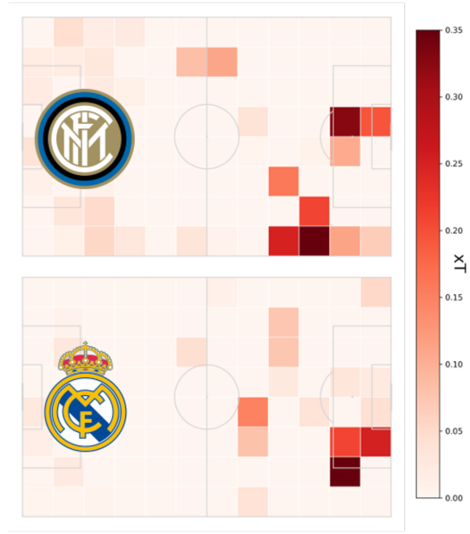

FIG. 4: *Delta xT Strategy* for Inter Milan and Real Madrid. On average, opponents against these two teams deviate from their usual strategy to target the left back.

- **Danny Rose**, market value c. €10M, ageing and perhaps suited for a move to Serie A, and
- **Alberto Moreno**, market value c. €10 M, who fell out of favour at Liverpool towards the end of the season, and signed for Villareal in 2019.

*Links to **Player Fitness** group*

A more complete picture of a player's performance would include fitness metrics in addition to our technical indicators. It would be useful to see acceleration, deceleration, and energy profiles for the specific players highlighted within this report, especially those moving into the twilight of their careers like Danny Rose.

B. Limitations of the Analysis

It was a practical decision to convert Wyscout events to SPADL format given the tight timeline for this project. It enabled the group to quickly train and apply Karun Singh's implementation of xT requiring SPADL formatted input, rather than developing the xT Markov chain model from scratch. Whilst the idea motivating SPADL is attractive in theory – to have a single representation of football events data taking either Opta, Statsbomb, or Wyscout data as inputs – in practice it reduces the events dataset you're working with down to the lowest common denominator shared by two other datasets that you may not have access to or be interested in. This significantly reduces the richness of the chosen dataset, with SPADL clipping around a third of all Wyscout events.

Naturally, there are a few limitations of the xT model even if it was fed with the ideal dataset. Since it's location-based, it fails to incorporate game context such as time of game, game score, and whether or not a team has received a red card and is a player light. There's also no mathematical machinery to penalise players for failed actions, as the model only applies threat values to successful actions.

TECHNICAL APPENDIX

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I. QUANTIFYING PLAYER'S PERFORMANCE THROUGH ON BALL ACTION

It is vital to look beyond the traditional metrics of shots taken, passes completed, assists etc. to evaluate the performance of the players. We can do so by using metrics built through models that use event-data to value player actions. Many of the currently available metrics focus on measuring the quality of shots and assists only, although these represent less than 1% of all on-the-ball actions. In our evaluation of the player's performance we used the expected threat (xT) model. This model depicts how the ball progressive actions increase or decrease the likelihood of yielding a goal.

Expected Threat (xT) Overview

The expected threat or xT model is a possession-based Markov model which is built using event-level data. The model overlays a 12×16 grid on the pitch in order to divide it into 192 zones. Each zone z is then assigned a value $\mathrm{xT}(z)$ that reflects how threatening teams are at that location. The contribution of the player's action in the buildup play is calculated by computing the difference in xT between the start and end locations of action, i.e. when the ball moves from zone z to zone z', the xT value for this action is $\mathrm{xT}(z')-\mathrm{xT}(z)$. This model uses a very limited game state representation that is purely location-based [5] [4].

Deriving the xT model

The Markov model view allows deriving these xT values from historical data by iteratively solving the following equation:

$$\mathrm{xT}(z) = s_z \cdot \mathrm{xT}(z) + m_z \cdot \sum_{z'=1}^{192} T_{z\rightarrow z'} \cdot \mathrm{xT}(z'), \tag{1}$$

where:

- s_z is the probability that a player will shoot when in zone z,
- $\mathrm{xT}(z)$ is the probability of a shot from zone z being converted into a goal,
- m_z is the probability that a player moves the ball another zone when in zone z, and
- $T_{z\rightarrow z'}$ is the transition matrix that defines the probability that the player moves the ball from zone z to zone z'.

Intuitively, solving the equation boils down to looking at another action ahead with each added iteration. In the first iteration, all $\mathrm{xT}(z)$ values are initialized to zero. After iteration i, $\mathrm{xT}(z)$ then represents the probability of scoring within the next i actions. Subsequently, the model values a successful action a_i that moves the ball from zone z to zone z' by computing the difference between the threat value before and after that action:

$$V_{\mathrm{xT}}(a_i) = \mathrm{xT}(z') - \mathrm{xT}(z)\,. \tag{2}$$

Key points about the model

- It can reward individual player actions in buildup play and not just based on goals and assists.
- Rewards actions independent of the end outcome of the possession as each action is assigned a score in isolation independent of the outcome at the end of the ball possession.
- Rewards moving the ball not just into high-xG shooting positions, but also into threatening positions that can in turn lead to high-xG shooting positions with high likelihood.
- Good for assessing the attacking threat posed through ball-progressive actions, i.e. actions in which the ball moves from one location of the pitch to another.

Limitations

- It ignores defensive actions like tackles and interceptions and offensive actions such as take-ons, short dribbles within the same zone on the pitch. As the zone does not change in these actions, the change in the xT values before and after the action is 0.
- Actions performed in the team's own half cannot be valued appropriately as all zones near a team's own goal are valued close to zero.

II. ASSESSING OVER-PERFORMING & UNDER-PERFORMING FINISHERS USING xG ADDED

The xG model (expected goals) is a powerful metric for evaluating chance creation and finishing skills on team-level as well as player-level. Based on a training data set that can contain thousands of shots, the xG model assigns each shot a probability that the shot results in a goal. The probability depends on the characteristics of the shot, such as the position from which the shot was taken.

Intuition

Our football knowledge tells us that the closer we get to the opposition's goal before taking a shot, the greater the chance is that the shot ends up in the back of the net. Similarly, it's easier to score from a central position, "making the goal big", compared to shooting from a very small angle. As such, we expect the distance from goal and the goal angle to be significant shot properties when evaluating the scoring probability.

Creating the model

As data for the model, we use the Wyscout data from the 2017/2018 season across five leagues. We look at headers and shots separately, picking different relevant characteristics such as the player's height (for headers) and whether the shot was taken with the player's stronger foot (for shots). In effect, we therefore generate two models - one for headers and one for shots - though the underlying method is the same in both cases.

To calculate the probability of a shot or header ending up in goal, we apply the logistic regression model to a training set consisting of 70% of the shots or headers in the data set. For shots, we filter out

Player	Shot Goals	xG Shots	xG Added / 90 mins
Icardi	19	16.28	0.08
Škriniar	2	1.14	0.02
Perišić	9	9.43	-0.01
Candreva	0	6.48	-0.23
Karamoh	1	2.87	-0.35

TABLE I: Inter xG Added over- and under-performers, for **shots**.

Player	Headed Goals	xG Headers	xG Added / 90 mins
Ranocchia	2	1.35	0.09
Icardi	4	1.92	0.06
Škriniar	2	2.53	-0.01

TABLE II: Inter xG Added over- and under-performers, for **headers**.

shots from more than 50 meters from the goal. For headers, we filter out headers from outside the penalty area.

Common features for shots and headers:

- Distance from goal line ($goal\_distance\_x$);
- Distance from goal ($goal\_distance$);
- Goal angle ($goal\_angle$)
- Whether the shot or header was taken in a counter attack ($counter\_attack\_flag$).

Additional features for shots:

- Distance from goal line squared ($goal\_distance\_x\_squared$);
- Distance from goal squared ($goal\_distance\_squared$);
- Whether the shot was taken with the player's stronger foot ($strong\_foot\_flag$).

Additional features for headers:

- How tall the player is ($player\_height$).

We use the remaining 30% of the data set as a test set. When happy with the selected features and model properties, we apply the two models to all the shots and headers in the data set.

xG and xG added for Inter players

With the xG metric calculated for every shot and header, we are able to analyse the goalscoring performance of the Inter Milan players. By calculating the difference of xG and the actual goals scored, we obtain the xG added metric. A player that scores more goals than expected has a positive xG added, while a player that scores less goals than expected has a negative xG added. To make the comparisons between players fair, we normalise the xG added metric per 90 minutes played.

Over-performers and under-performers for shots taken with foot can be seen in TABLE I, and likewise for headed shots in TABLE II.

Inter relied heavily on Icardi's finishing, and the model shows that he scored a few more goals than expected with his feet. Perišić managed to score nine goals, which is a good amount for a winger, but slightly less than expected considering the chances he got. The biggest underperformers were Candreva and Karamoh, who should have scored nine goals between them, but managed only one.

Icardi was the top scorer when it comes to headers too, and again scoring more than expected from the opportunities he got. The central defenders Ranocchia and Škriniar scored two headers each, with Ranocchia overperforming greatly when considering the xG added per 90 minutes played, and Škriniar underperforming slightly. It is worth noting that the sample size is much smaller for headers than for shots, and we shouldn't read too much into the data with just a few scored headers per player.

III. POSSESSION ADJUSTED METRICS

Introduction

Possession adjusting is a means to take into account the system a player's team uses. Teams which place emphasis on possession tend to play an attacking brand of football, whereas a counter attacking team are more defence-orientated. A player's level of opportunity to make defensive actions can therefore vary depending on the system they play in.

Technical description

To obtain a player's possession adjusted number of tackles in a match, we first calculate the number of successful tackles they made and the percentage possession of their team. A simple calculation then gives us the possession adjusted value (PAdj):

$$\text{PAdj} = \frac{\text{no. tackles}}{1\text{–possession }\%} \cdot 0.5 \tag{3}$$

Doing this for all of a player's matches and normalising per 90 minutes gives an average PAdj tackle value per match for the player.

Statistical motivation

This all sounds relatively sensible, but ideally we'd be doing something which is backed up by a sound statistical argument. A crude aim of a defensive unit could be to limit shots for opposition teams. So to establish a statistical reason behind this metric we can look at the correlation between number of tackles made and shots conceded, and observe how this differs from the correlation with possession adjusted tackles. We'd hope to see stronger correlation for the possession adjusted metric, with more possession adjusted tackles corresponding to fewer shots conceded.

In figure 5 we can see that players who make more possession adjusted tackles tend to concede fewer shots. The correlation is not strong, but is present. However, when we look at the relationship between tackles made and shots conceded we see no relationship.

Summary

In this brief explanation of possession adjusted defensive metrics, we have seen the logic behind calculating and using these. As part of comparisons for defensive players we included possession adjusted statistics for tackles, interceptions and clearances – three popular defensive metrics, each with more meaning attached than simple counts.

IV. OPPOSITION PROGRESS IN A DEFENDER'S ZONE

Introduction

It is difficult to capture the extent to which a defender is able to prevent an opposition team from making dangerous ball progression

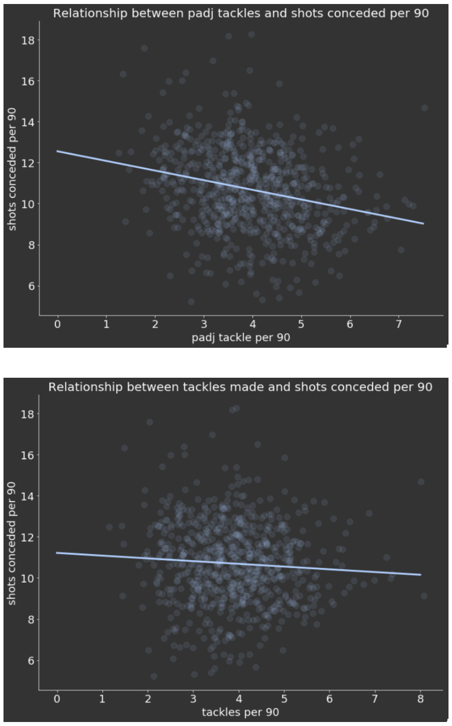


FIG. 5: Relationship between shots and tackles or possession adjusted tackles

in the area they are defending. We can use metrics like xT to look into how actions which are captured on the ball stop threat, but the reality of defending is slightly more nuanced: a lot of defending is about positioning and pressure – top defenders prevent dangerous opposition progression by not letting it be an option in the first place. One way in which we can attempt to capture this information is to calculate the area a defender operates in for a match and then look at how much the opposing team progresses the ball, and how quickly that ball progression happens, in that area: the less progression and the slower that progression the better from a defensive point of view. This concept is introduced by Thom Lawrence in a metric which he originally called PATCH (Possession Adjusted Territorial Control Held), and here we use a later iteration of this [3].

Technical description

We start by looking at the area each player occupies on the pitch. From a defensive point of view it makes sense to use the locations of defensive actions to calculate this, and we consider only the 70% of actions closest to the mean location for a player to prevent outliers from skewing the area. On its own, this is interesting – we have a purely data-driven way to find the areas each defensive player is largely responsible for in a team's system.

For example figure 6 shows Škriniar's defensive area and actions within it during Inter's 0-0 draw away to Juventus, and we can see he defends quite deep and occupies a compact area.

Looking beyond a simple area of action, you might consider that a high-level aim for a defender is to prevent the opposition from increasing their probability of scoring, which is linked to proximity to the goal. So, having calculated these areas, we look at the extent to which and the speed at which the opposition team progresses the ball through each player's territory.

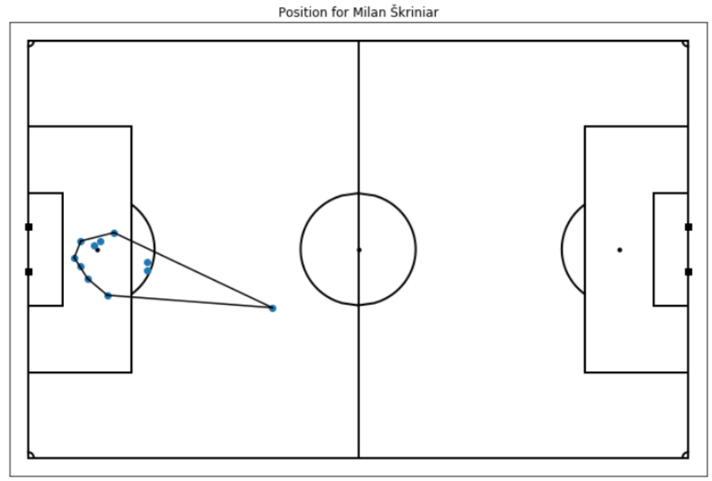


FIG. 6: Defensive area of Škriniar away against Juventus

We then calculate a score based on these features: We want a player's score to increase with the size of the area they occupy, and to decrease for allowing the opposition to progress within that zone at pace. After adjusting ball progression per 90, the formula we use is:

$$(k \times \text{area}) \div \left(\frac{\text{opponent ball progression}}{\text{progression duration}} \times \frac{90}{\text{minutes on field}} \right) \tag{4}$$

There are, of course, some limitations. Most notably in the implementation described above, the nature of the ball progression is not considered. This means that a passing move exploiting space left in a defensive zone will be no more detrimental to a defender's score than a hopeful punt to the striker made in desperation at the excellent job a defensive unit is doing to prevent incisive ball progression.

Summary

With this metric we try to move beyond measuring defensive play based purely on actions and instead attempt to put a number on how well players prevent danger in an area they control, which in theory can take into account off-the-ball movements.

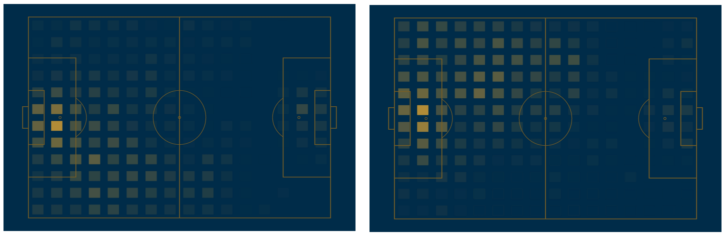
V. OPPOSITION xT IN A DEFENDER'S ZONE

Introduction

An xT-based approach to the problem in section IV, examines opposition xT created in a defender's zone. We again calculate the area a defender operates in (this time over all matches) and then look at how much xT the opposing team generates from actions in that area.

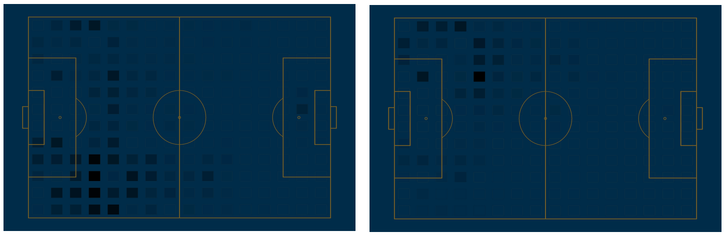
Technical description

We again start by looking at the area each player occupies on the pitch, but this time use the grid system inherent in the xT model. To define the defensive zone we count defensive actions (tackles interceptions fouls etc) and build a heat map for each player. As the



a) M. Škrinar b) J. Miranda

FIG. 7: The complementary defensive zones of Inter's centre-back pair.



a) M. Škrinar b) J. Miranda

FIG. 8: Defensive opposition xT allowed in defender's zone

sample size—one season—is quite small, we smooth the data a bit, and then normalise it so the sum over all squares is equal to 1. This normalisation is similar to the area adjustment in PATCH, giving us an xT-cell based version of the basis of the PATCH method. Again, this is already a nice way to examine a defenders playing area. We can see the complementary almost mirrored zones of the two inter centre-backs in figure 7.

We can then sum opponent xT for all minutes an Inter player is on the pitch an multiply each by the proportion that square represents in the players normalised defensive profile to apportion'blame' for these actions. We can see the the centre-backs concede more xT toward the outer edges of their defensive zones - which points towards Inter's weakness there.

As we use a whole season of data this method obviously only works well for players playing consistently in the same position in the same formation with the same tactics. An improved implementation would take into account these differences and slice the data with more care.

Summary

This alternative xT-based version of the PATCH metric is another way of using event data to try to infer of ball quality. In using xT, we have a quantitative measure of opposition action values, and there is a clear link to our other xT-based metrics.

VI. PROPORTIONAL AREA RADAR CHARTS

Radar charts (a.k.a. spider charts or radial charts) are visualisations where axes representing three or more variables are depicted radially around a central point, usually oriented to increase in value further from the centre. Throughout we use the analogy of a wheel and refer to these axes as *spokes* and the centre as the *hub*.

The Problem

The main criticisms of radar charts are in terms of legibility and interpretability. As the categories are distributed around a central point at differt angles, they are not directly comparable with the same ease as in e.g. bar charts (pie-charts are criticised for a similar reason). A further issue regarding interpretability is that most radar charts are not simply a bar-chart rearranged onto the spokes of a wheel, but have some area of the chart filled with colour. Typically, neighbouring values are joined by a straight line; we shall call this type a *join-the-dots radar chart*. The radar charts produced by football data company StatsBomb (see figure 9a) are an example of this type. Another type of radar chart is obtained by filling a sector for each variable bounded by an arc representing the described value; we will call this type a *sectoral bar chart* (e.g. figure 9b.)

Both types of radar chart have the problem that the length along the spoke does not correspond with the area enclosed[1], and so the viewer may interpret either the lengths or areas as representing the values, but only one, in fact, does. The question is—perceptually, intuitively—do we read and interpret based on area or length, or some combination of the two?

With the sectoral bar chart, either can be chosen. Tom Worville (now at the Athletic) was, until recently, adjusting his sectoral bar charts so that the area was proportional to the represented value, see figure 9b , but found this unsatisfactory and changed the design so that the bar length represented the described value, see figure 9c [6]. Figures 9b and 9c show that either choice can be misleading.

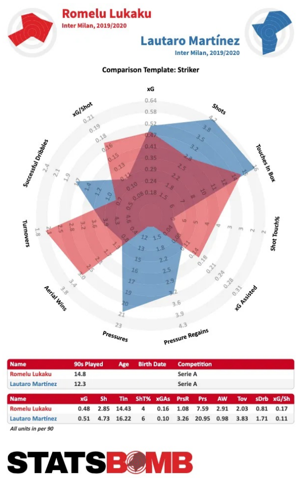
In the case of the join-the-dots radar the problem is worse: the area does not necessarily bear any relation to the lengths. With different values on each spoke, the area enclosed can change greatly between different orderings of the variables. Compare the visual effect of figure 10a and figure 10b. These charts both show the same data in a different configuration but one encloses a much greater area than the other, possibly suggesting a difference in overall value.

Despite these problems, the radar chart remains popular, especially in the football analytics community. Ted Kunutson (CEO of StatsBomb) argues for it, claiming they are the single visualisation which captures the attention an even that at some football clubs, "radars became accepted as a default visualization type." [2]. Radars have value in terms of engagement, and in an area where communication between analysts and practitioners is crucial, will remain popular.

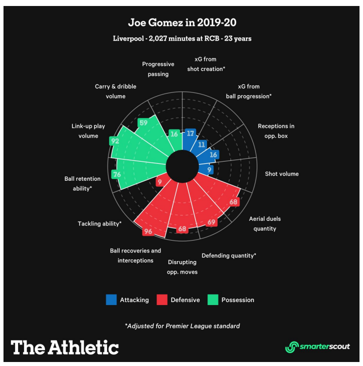
Improvements

We then ask if the radar chart can be improved, or its faults lessened. The ordering problem can be mitigated somewhat simply by moving the spokes away from the centre of the chart, thereby creating a central counter, as in figure 10. However, only in the limit (as the central counter approaches infinite size) does the issue of proportionality fully resolve. This is therefore not a satisfactory solution.

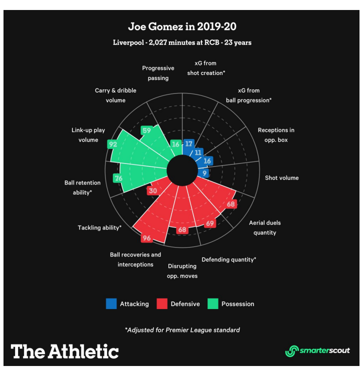
[1] for a sectoral bar chart they are proportional quadratically, but not linearly!



a) A 'join-the-dots' radar chart as used by StatsBomb.

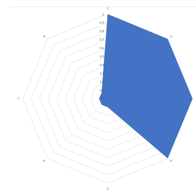


b) Tom Worville's sectoral barchart with values proportional to area.

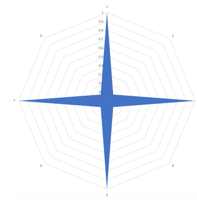


c) Tom Worville's sectoral barchart with values proportional to length.

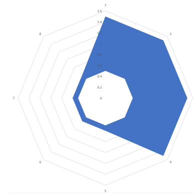
FIG. 9: Types of radar chart in use today



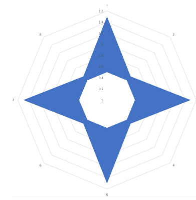
a) A radar chart.



b) A reordering.



c) A larger hub.



d) Reordered

FIG. 10: Join the Dots Radar Charts: four representations of the same data on a scale of 0 to 1: each radar chart represents four points of value 0.1, and four points of value 1

Towards a Solution

While the sectoral bar chart can be made to either scale with area or length, it remains a choice between those two. However, in the seemingly more flawed join-the-dots radar chart, the area/length issue can be directly addressed. If we use curves to join our values, the area *can* be made proportional to the values in a certain way.

Suppose our radar depicts n values, $v_i \in [0, 1]$, for $i = 1, \ldots, n$ on n spokes of a radar chart. Consider two values v_i, v_j on adjacent spokes of our radar chart. In order to choose a curve we first define a curve in Cartesian coordinates, which we will transform later. There are probably many viable candidates curves but, for the sake of control, and, importantly, so that we can find explicit solutions, we use the quadratic function

$$f(x) = a\left(-\sqrt{v_i}(1-x) + \sqrt{v_j}x\right)^2 + (1-a)\left(1 - \left(-\sqrt{1-v_i}(1-x) + \sqrt{1-v_j}x\right)^2\right) \tag{5}$$

defined on the interval $[0, 1]$ joining the points $(0, v_i)$ and $(1, v_j)$. The function f depends on these values and a further parameter a. This parameter, a, helps us adjust the area under the curve. The reason for choosing this function is that it has some desirable properties. Firstly, it is identically zero when $v_i = v_j = 0$. Secondly, for $a \in [0, 1]$, the curve is bounded above by 1 and below by 0, and achieves these values for $a = 0$ and $a = 1$, respectively, and its stationary point always lies in the interval of definition.

Defining $g(\theta) = f(\frac{n\theta}{2\pi}) + c$ for c a constant creates a central counter on the hub of the plot when this function is plotted in polar coordinates (r, θ), such that the values v_i and v_j lie on two adjacent spokes (an angle of $2\pi/n$ apart). We can then solve[2] for our parameter a such that the area enclosed between the line and counter is proportional to the average of the values, i.e.

$$\int_0^{\frac{2\pi}{n}} \frac{1}{2}\left(g(\theta)\right)^2 \, d\theta - \frac{\pi c^2}{n} = \frac{v_i + v_j}{2} p \tag{6}$$

where p is the constant of proportionality.

We can then plot $g(\theta)$ in polar coordinates and fill the area under the curve. Doing this in each sector between each pair of adjacent values produces what we will term *the proportional area radar chart*, shown in various guises in figure 11. Here we have used a counter offset of $c = 1/2$ and a constant of proportionality of 4. Any constant of proportionality $p > 0$ can be chosen; the resulting charts will be more 'bulbous' for larger p. Note that, in general, because the function f in equation (5) is identically zero when $v_i, v_j = 0$, two adjacent zeroes are always connected by an arc of the circle with radius $r = c$ and so no area is enclosed outside of the hub.

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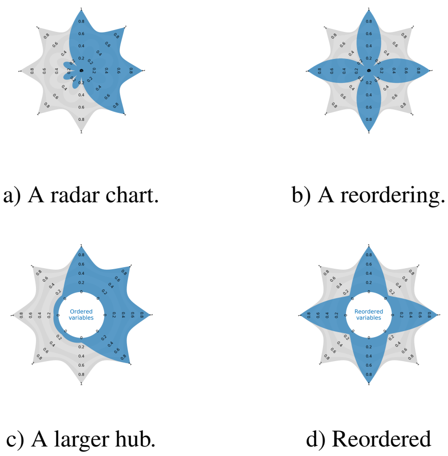
[2] I recommend using a computer! I originally solved this in Maple but rewrote it for python using the `sympi` package. Originally I used the function $f(x) = \left(x - \frac{1}{2} + (a+1)(v_j - v_i)\right)\left(x - \frac{1}{2} - (a-1)(v_j - v_i)\right)$, which results in simpler solutions, but the shapes were not as well behaved.



a) A radar chart.

b) A reordering.

c) A larger hub.

d) Reordered

FIG. 11: Equal Area Radar Charts: four representations of the same data on a scale of 0 to 1: each radar chart represents four points of value 0.1, and four points of value 1.

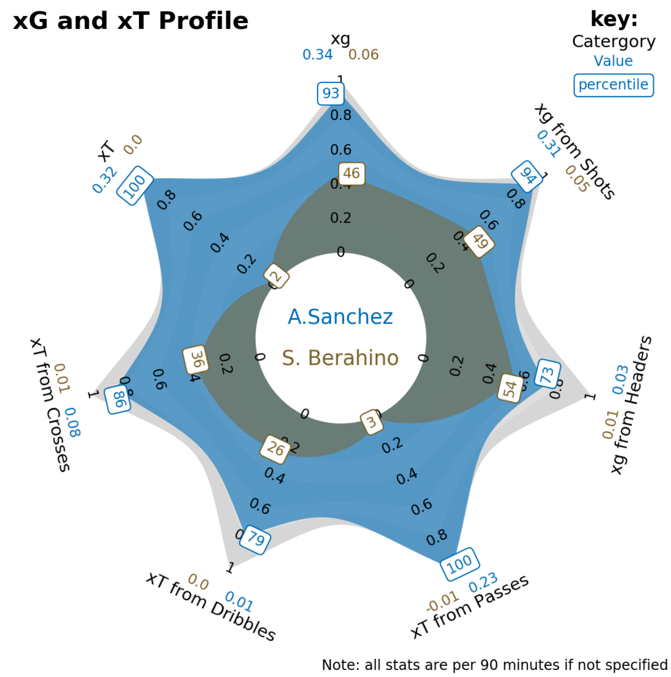


FIG. 12: A player comparison proportional area radar chart.

Interpretability and Aestetics

A comparison of the four radars in figure 10 and figure 11 shows that the area adjustment achieves visually what it does mathematically. Reordering has no effect on the area enclosed. The substitutions made in the conversion to polar coordinates and the range of the integral in equation (6) over which we solve for a ensures that for any given v_i, v_j , the value of a, and therefore the equation of the curve, is independent of the number of categories n. There is a different effect on the shape, though, depending on the number of variables. A possible future adjustment is to have the proportion, p, vary with the number of categories, n. For now, it suffices to select a suitable p once n is fixed. The constant of proportionality p can be chosen so as not to make the shapes too extreme, and the presence of a sizeable central counter ($c = 1/2$ is used here) helps to reduce the differences in shapes. Another effect of the use of different curves for higher or lower values is the different shapes produced. Curves connecting small values bulge out a little near the hub, whereas curves connecting high values dip in, creating a spiky effect. This means that higher and lower values are associated with different curves and so in addition to the overall shape profile of a radar being recognisable, even the shape profile of different values should be, given that the viewer has some experience in a consistent format.

If we use this visualisation for comparing football players, to take an example, an xT/xG profile of a player Inter signed following the 2017/18 season, Alexis Sanchez, and a player they did not, say Saido Berahino, one looks like a star, and the other doesn't—see figure 12 (for other examples see also figures 1 to 3). The presence of a central counter allows for design elements to be placed in the center. In this example we have the player's names centrally.

Conclusion

The proportional area radar chart seeks to address a major flaw in the intuitive reading of standard radar charts, while preserving their value. The area-vs-length disparity is solved by design, mathematically, and, it is claimed, this has desired effect perceptually. The varying contours may even aid in shape recognition, but this would need to be tested. Potential further improvements include the automatic selection of the optimal constant of proportionality p, based on the offset c and the number of categories n, and choosing such p for the best legibility.

VII. ELO RATING SYSTEM

The **duel** event type within the Wyscout dataset is the second most common within the Wyscout event taxonomy after passes. Duel events provide direct insight into the interactions between opposing players, where Wyscout provides the following sub-events at the second tier of the event taxonomy:

- Aerial duels;
- Loose ball duels (i.e. 50:50s with no clear attacking / defending player);
- **Attacking duels**;
- **Defending duels**.

Wyscout provides sub-events with attributes (tags) that provide additional granularity to enable a richer modelling of the interactions between players. Attacking **dribbles** can be modelled by combining attributes for direct "take on" actions and movement with the ball into "space" from the attacking duel sub-event. Non-dribble **physical pressure** duels – i.e. where an attacking player is shielding the ball – can then be inferred by all non-dribble attacking duels. It's also straightforward to label these dribbles and physical pressure duels as successful or failed using another of Wyscout's attributes.

When judging the dribbling (or physical pressure) ability of a player, it matters who that player is dribbling against, and the best dribbler shouldn't just be defined as the player who makes the most successful dribbles - a measure that would favour star players that attract more of the ball than others and would hinder the ability to find diamonds in the rough.

We implemented the **Elo ranking system**, originally conceived to rank chess players, to rank the dribbling (and physical pressure) ability of attacking players. With the Elo system, winners of duels are rewarded more handsomely the better the opponent they beat - and they're penalised when they suffer a loss.

In order to implement the Elo system, we first needed to match the attacking side of a duel with the defensive side (Wyscout does not provide this as part of their data product). When the Wyscout data is being collected, one data collector focuses on the home team, whilst a second, independent data collector focuses on the away team. Therefore the timestamps between the action of an attacking duelist and resulting reaction of the defensive duelist may not be perfectly synced. Wyscout applies computational post-processing to the manually tagged data to identify and automatically correct inconsistencies within the data. *Automatic corrections are applied to player positions, but not the action timestamps*. Using this information, we created the following algorithm to map attacking actions and defending reactions together, to enable the application of Elo rankings:

Algorithm 1 Mapping attack and defence duel actions

```
df_A → attacking dataframe
df_D → defending dataframe
df_C → candidate dataframe
for each attack in df_A do
    df_C = df_D[
        df_D.match = df_A.match
        df_D.team ≠ df_A.team
        df_D.period = df_A.period
        df_D.timestamp ≥ df_A.timestamp − 5
        df_D.timestamp ≤ df_A.timestamp + 5
        df_D.x = df_A.x
        df_D.y = df_A.y
    ]
    mapping = df_C.sort(closest timestamp)
    return mapping
end for
```

Usually, the two sides of an Elo competition are trying to achieve the same objective: to win a game. For dribbling, there are two objectives:

- The dribbler objective to beat the opposition player;
- The opponent objective to stop the dribbler,

thus we want to reward dribblers with points and penalise opponents if the first objective is achieved, and vice versa if the second is achieved, hence two scores.

Each player has an Elo rating initialised at 100 points for **four different Elo ratings**:

- Dribbling - attacker;
- Dribbling - defender;
- Physical pressure - attacker;
- Physical pressure - defender.

The expectation (a probability) of player A beating player B, E_A, is defined as:

$$E_A = \frac{1}{1 + 10^{(R_A - R_B)/400}}, \tag{7}$$

where R_A is the Elo rating of player A and R_B is the Elo rating for player B. As a general rule, player A having an Elo rating of 100 points higher than player B – i.e. $R_A - R_B = 100$ – is equivalent to player A having a 64% chance of beating B. Elo ratings are updated following each duel via:

$$R_A := R_A + k \times (d - E_A), \tag{8}$$

where $d = 1$ if player A wins the duel (otherwise 0 if they lose), and k is a coefficient that controls the sensitivity of how quickly ratings will change to reflect changes in player performance. We set the k-factor to be 20 in our analysis, following the conventional wisdom of how Elo is applied in chess.

A final consideration when applying the Elo system is that order of which the pairwise comparisons (the duels) are fed through the Elo update algorithm. **Order matters**, therefore to achieve robust player ratings for the quarter of a million attack Vs defence duel events throughout the 2017/18 season, we take the mean Elo rating (mElo, [1]) of 10,000 iterations of the Elo algorithm, randomising the duel order each time.

[1] Andy T. Woods Ian S. Penton-Voak Christof Neumann Andrew P. Clark, Kate L. Howard. Why rate when you could compare? using the "elochoice" package to assess pairwise comparisons of perceived physical strength.

[2] Ted Knutson. Revisiting radars, 18.5.2017. https://statsbomb.com/2017/05/revisiting-radars/.

[3] Thom Lawrence. Defending your patch, 7.2.2016. https://deepxg.com/2016/02/07/defending-your-patch/.

[4] Karun Singh. Introducing expected threat (xt). https://karun.in/blog/expected-threat.html.

[5] Maaike Van Roy, Pieter Robberechts, Tom Decroos, and Jesse Davis. Valuing on-the-ball actions in soccer: A critical comparison of xt and vaep.

[6] Tom Worville. Twitter thread on 'dataviz', 25.10.2020. https://twitter.com/Worville/status/1320409463971549184/.