Actions Speak Louder Than Goals: Valuing Player Actions in Soccer

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Actions Speak Louder Than Goals: Valuing Player Actions in Soccer

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Abstract

Assessing the impact of the individual actions performed by soccer players during games is a crucial aspect of the player recruitment process. Unfortunately, most traditional metrics fall short in addressing this task as they either focus on rare events like shots and goals alone or fail to account for the context in which the actions occurred. This paper introduces a novel advanced soccer metric for valuing any type of individual player action on the pitch, be it with or without the ball. Our metric values each player action based on its impact on the game outcome while accounting for the circumstances under which the action happened. When applied to on-the-ball actions like passes, dribbles, and shots alone, our metric identifies Argentine forward Lionel Messi, French teenage star Kylian Mbappé, and Belgian winger Eden Hazard as the most effective players during the 2016/2017 season.

1 Introduction

How will a player's actions impact his or her team's performances in games? This question is among the most relevant questions that needs to be answered when a professional soccer club is considering whether to sign a player. Nevertheless, the task of objectively quantifying the impact of the individual actions performed by soccer players during games remains largely unexplored to date. What complicates the task is the low-scoring and dynamic nature of soccer games. While most actions do not impact the scoreline directly, they often do have important longer-term effects. For example, a long pass from one flank to the other may not immediately lead to a goal but can open up space to set up a goal chance several actions down the line.

To help fill the gap in objectively quantifying player performances, we propose a novel advanced soccer metric that assigns a value to any individual player action on the pitch, be it with or without the ball, based on its impact on the game outcome. Intuitively, our action values reflect the actions' expected influence on the scoreline. That is, an action valued at +0.05 is expected to contribute 0.05 goals in favor of the team performing the action, whereas an action valued at -0.05 is expected to yield 0.05 goals for their opponent. Unlike most existing advanced metrics, our proposed metric considers all types of actions (e.g., passes, crosses, dribbles, take-ons, and shots) and accounts for the circumstances under which each of these actions happened as well as their possible longer-term effects.

Our metric was designed to take a step towards addressing three important limitations of most existing advanced soccer metrics (Routley, 2015). The first limitation is that existing metrics largely ignore actions other than goals and shots. The soccer analytics community's focus has very much been on the concept of the expected value of a goal attempt in recent years (Lucey et al., 2014; Caley, 2015; Altman, 2015; Mackay, 2016; Aalbers, 2016; Mackay, 2017). The second limitation is that existing approaches tend to assign a fixed value to each action, regardless of the circumstances under which the action was performed. For example, many pass-based metrics treat passes between defenders in the defensive third of the pitch without any pressure whatsoever and passes between attackers in the offensive third under heavy pressure from the opponents similarly. The third limitation is that most metrics only consider short-term effects and fail to account for an action's effects a bit further down the line. These limitations render many of the existing metrics virtually useless for player recruitment purposes.

Using our metric, we analyzed the 2016/2017 campaign to construct a *Team of the 2016/2017 Season*. When applied to on-the-ball actions like passes, dribbles, and shots alone, Barcelona's Lionel Messi unsurprisingly headlines the team as the highest-ranked player. His average action value per game last season was 26% higher than his nearest competitor's. Other members featuring on the team include forward Kylian Mbappé then playing for AS Monaco, Real Madrid midfielder Isco, Manchester City playmaker Kevin De Bruyne as well as Chelsea teammates Eden Hazard and Cesc Fàbregas. To identify young talent, we also ranked the best players under 21 years old from the 2016/2017 season according to our metric. Teenage star Mbappé, who moved to French giants Paris Saint-Germain last summer, tops this list. He appears ahead of his fellow countrymen Ousmane Dembélé, who moved to Barcelona from Borussia Dortmund over the summer, and midfielder Maxime Lopez of Olympique Marseille.

In summary, this paper presents the following four contributions:

1. SPADL: A powerful but flexible language for representing player actions, which is described in Section 2.

2. HATTRICS: A general framework for valuing player actions based on their contributions to the game outcome, which is introduced in Section 3.

3. HATTRICS-OTB: An algorithm for valuing on-the-ball player actions as a concrete instance of the general framework, which is outlined in Section 4.

4. A number of use cases showcasing our most interesting results and insights, which are presented in Section 5.

2 SPADL: A language for representing player actions

Valuing player actions requires a dedicated language that is *human-interpretable*, *simple* and *complete* to accurately define and describe these actions. The human-interpretability allows reasoning about what happens on the pitch and verifying whether the action values correspond to soccer experts' intuitions. The simpleness reduces the chance of making mistakes when automatically processing the language. The completeness enables to express all the information required to value actions in their full context.

Based on domain knowledge and feedback from soccer experts, we introduce SPADL (**S**occer **P**layer **A**ction **D**escription **L**anguage). SPADL represents each action as a tuple of nine attributes:

StartTime: the exact timestamp for when the action started;

EndTime: the exact timestamp for when the action ended;

StartLocation: the (x, y) location where the action started;

EndLocation: the (x, y) location where the action ended;

Player: the player who performed the action;

Team: the team of the player;

Type: the type of the action;

BodyPart: the body part used by the player for the action;

Result: the result of the action.

We distinguish between 21 possible types of actions including, among others, *passes*, *crossed corners*, *dribbles*, *runs without ball*, *throw-ins*, *tackles*, *shots*, *penalty shots*, *clearances*, and *keeper saves*. These action types are interpretable and specific enough to accurately describe what happens on the pitch yet general enough such that similar actions have the same type.

Depending on the type of the action, we consider up to four different body parts and up to six possible results. The possible body parts are *foot*, *head*, *other*, and *none*. The two most common results are *success* or *fail*, which indicates whether the action had its intended result or not. For example, a pass reaching a teammate or a tackle recovering the ball. The four other possible results are *offside* for passes resulting in an off-side call, *own goal*, *yellow card*, and *red card*.

We represent a game as a sequence of action sets, where each action set describes the actions performed by the players in between two consecutive touches of the ball. More formally, each action set A consists of one on-the-ball action and $n-1$ off-the-ball actions, where n is the total number of players on the pitch. Each game is a sequence of action sets $< A_1, A_2, \ldots, A_m >$, where m is the total number of touches of the ball.

In addition to being human-interpretable, simple and complete, SPADL has the added advantage of being able to naturally unify both event data and tracking data collected by providers such as Wyscout, Opta, and STATS. The representations used by these companies have multiple different objectives (e.g., providing information to the media or informing clubs) and are not necessarily designed to facilitate data analysis. Furthermore, each representation uses a slightly different terminology when describing the events that occur during a game. SPADL is an attempt to unify the existing description languages into a common vocabulary that enables subsequent data analysis. The following sections operate on data in the SPADL format.

3 HATTRICS: A framework for valuing player actions

Broadly speaking, most actions in a soccer game are performed with the intention of (1) increasing the chance of scoring a goal, or (2) decreasing the chance of conceding a goal. Given that the influence of most actions is temporally limited, one way to assess an action's effect is by calculating how much it alters the chances of both scoring and conceding a goal in the near future. We treat the effect of an action on scoring and conceding separately as these effects may be asymmetric in nature and context dependent.

In this section, we introduce the HATTRICS (**H**onest **Attri**bution of **C**redit in **S**occer) framework for valuing actions performed by players. In our framework, valuing an action boils down to estimating the probabilities that a team will score and concede a goal in the near future for both the game state before the action was performed and the game state after the action was performed.

Now, we will more formally define our metric. For ease of exposition, we will use h to denote the home team and v the visiting team, and will focus on the perspective of the home team. Given any game state $S_i =< A_1, \ldots, A_i >$, we need to estimate the short-term probability of a home goal (hg) and a visiting goal (vg), which we denote by:

$$\begin{aligned} P_{hg}(S_i) &= P(hg \in F_i^k | S_i) \\ P_{vg}(S_i) &= P(vg \in F_i^k | S_i) \end{aligned}$$

where $F_i^k =< A_{i+1}, \ldots, A_{i+k} >$ is the sequence of k action sets that follow action set A_i, and k is a user-defined parameter. These probabilities form the basis of our action-rating framework.

Valuing an action requires assessing the *change* in probability for both P_{hg} and P_{vg} as a result of action set A_i moving the game from state S_{i-1} to state S_i.[1] The change in probability of the home team scoring can be computed as:

$$\Delta P_{hg} = P_{hg}(S_i) - P_{hg}(S_{i-1}).$$

This change will be positive if the action increased the probability that the home team will score. The change can be computed in an analogous manner for P_{vg} as:

$$\Delta P_{vg} = P_{vg}(S_i) - P_{vg}(S_{i-1}).$$

Finally, before combining these two terms, we must contend with the subtlety that the ball may change possession as a result of A_i. To account for this, we always normalize the value to be computed

[1] The challenge of distributing the payoffs of the joint actions that a group takes across the individuals constituting the group goes beyond the scope of this paper but is a well-studied topic in the field of cooperative game theory (Driessen, 2013). The Shapley value is one possible solution to this challenge and has been successfully applied to soccer already (Altman, 2016).

from the perspective of the team that has possession after the i^{th} action set. If the home team has possession after action set A_i, then the value is calculated as:

$$V(A_i) = \Delta P_{hg} - \Delta P_{vg}$$

For this valuing scheme, higher scores represent more valuable actions so the change in P_{vg} is subtracted from the change in P_{hg} because it is advantageous for the home to decrease its chance of conceding. If the visiting team had possession after action set A_i, the two terms would be swapped.

The HATTRICS framework provides a simple approach to valuing actions that is independent of the representation used to describe the actions. The strength of the framework lies in the fact that it transforms the subjective task of valuing an action into the objective task of predicting the likelihood of a future event in a natural way. One possible limitation is that game-state transitions correspond to on-the-ball actions, whereas some off-the-ball actions (e.g., a smart overlap from a wing-back) can span several consecutive on-the-ball actions. As a result, accurately valuing such off-the-ball actions would require the additional step of aggregating the values of the constituting subactions.

4 HATTRICS-OTB: An algorithm for valuing on-the-ball actions

In this section, we describe the HATTRICS-OTB (**H**onest **Attr**ibution of **C**redit in **S**occer for **O**n-**t**he-**B**all Actions) algorithm for valuing on-the-ball player actions as an instantiation of our general framework. As a data source, we consider play-by-play event data, which means that each action set contains exactly one on-the-ball action and no other actions. We employ machine learning to estimate the probabilities P_{hg} and P_{vg} from the stream of actions. Consequently, we frame this as a binary classification problem and train a probabilistic classifier to estimate the probabilities. Our implementation involves three key tasks: (1) transforming the stream of actions into a feature-vector format, (2) selecting and training a probabilistic classifier, and (3) aggregating the individual action values to arrive at a rating for a player.

4.1 Constructing features

Applying standard machine learning algorithms requires converting the sequence of action sets $< A_1, A_2, \ldots, A_m >$ describing an entire game into examples in the feature-vector format. Thus, one training example is constructed for each game state S_i. A game state S_i is labeled positive if the team possessing the ball after action set A_i scored a goal within the next ten actions. A goal in this time frame could arise from either a converted shot by the team possessing the ball after A_i or an own goal by the opposing team.

For each example, instead of defining features based on the entire current game state $S_i =< A_1, ..., A_i >$, we only consider the previous three action sets $< A_{i-2}, A_{i-1}, A_i >$. Approximating the game state in this manner offers several advantages. First, most machine learning techniques require examples to be described by a fixed number of features. Converting game states with varying numbers of actions, and hence different amounts of information, into this format would necessarily result in a loss of information. Second, considering a small window focuses attention on the most relevant aspects of the current context. The number of action sets to consider in the approximation is a parameter of the approach, and three sets was empirically found to work well as shown in Section 4.2.

Since each action set A_i only consists of one on-the-ball action a_i in our data source, we denote the actions we consider as $< a_{i-2}, a_{i-1}, a_i >$. From these actions, we define features that will impact the probability of a goal being scored in the near future. Based on the SPADL representation, we consider three categories of features.

First, for each of the three actions, we define a number of categorical and real-valued features based on information explicitly included in the SPADL representation. There are categorical features for an action's $Type$, $Result$, and $BodyPart$. Similarly, there are continuous features for the (x, y)-coordinates of its start location, the (x, y)-coordinates of its end location, and the time elapsed since the start of the game.

Second, we define a number of complex features that combine information within an action and across consecutive actions. Within each action, these include (1) the distance and angle to the goal for both the action's start and end locations, and (2) the distance covered during the action in both the x and y directions. Between two consecutive actions, we compute the distance and elapsed time between the start position and time of an action, and the end position and time of the next action. These features provide an intuition about the current speed of play in the game. Additionally, there is also a feature indicating whether the ball changed possession between these two actions.

Finally, to capture the game context, we add as features (1) the number of goals scored in the game by the team possessing the ball after action a_i, (2) the number of goals scored in the game by the defending team after action a_i, and (3) the goal difference in the game after action a_i.

4.2 Estimating probabilities

We investigated which learner to use as well as the number of actions prior to the action of interest to consider. To properly evaluate our classifiers, we used play-by-play event data for Europe's top five competitions. We trained models on all game states for the 2012/2013 through 2014/2015 seasons and predicted the goal probabilities for all game states for the 2015/2016 season.

First, we investigated which learner to use for this task. Logistic Regression is the prevalent method in the soccer analytics community, while Random Forest and Neural Network are popular choices for addressing machine-learning tasks. We compared the performance of these three learners as implemented in the H2O software package[2] on three commonly-used evaluation metrics in probabilistic classification (Ferri et al., 2009): (1) logarithmic loss, (2) area under the receiver operating characteristic curve (ROC AUC), and (3) Brier score. A Random Forest classifier with 1000 trees won on all metrics and achieved a ROC AUC of 79.7%. Furthermore, it was the best calibrated classifier as shown in Figure 1. Our observation that Random Forest outperforms Logistic Regression on the task of probabilistically predicting goals is in line with earlier work Decroos et al. (2017a).

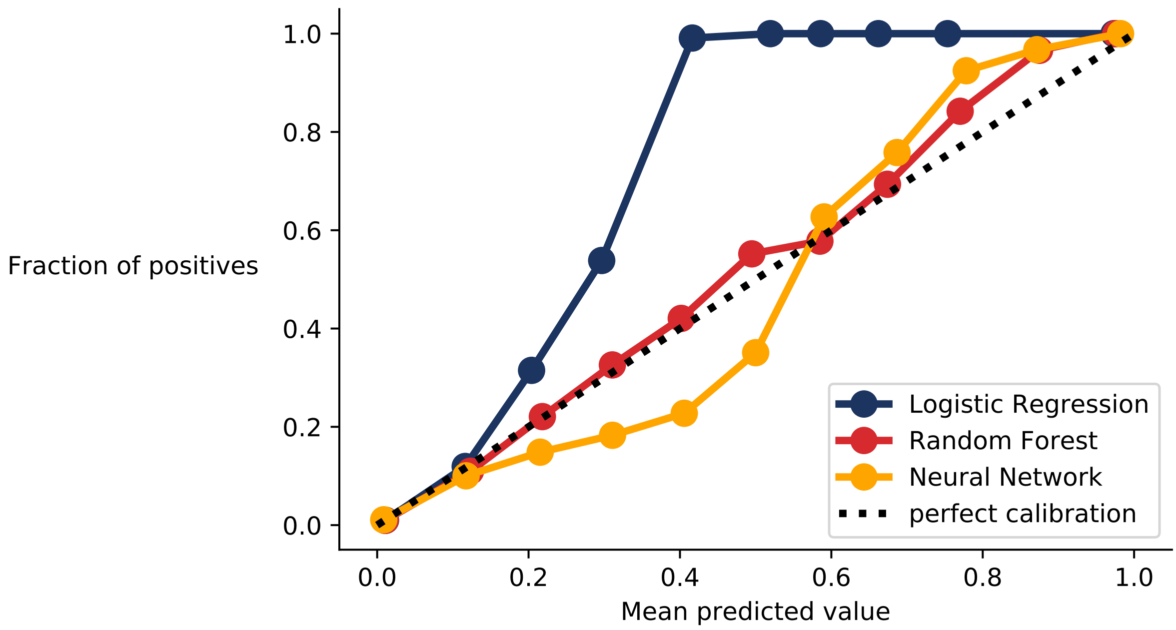

Figure 1: Calibration curves of the three classifiers under consideration. The probabilities produced by the Random Forest model are calibrated better than the probabilities produced by the other two models.

Second, we investigated the number of previous actions to consider. Adding too few actions might leave valuable contextual information unused, while adding too many actions can make the feature set unnecessarily noisy. We trained five different Random Forest classifiers ranging the number of previous actions from one through five as shown in Table 1. We found that three actions is the best number, which is in line with earlier work by Mackay (2017).

[2] `https://www.h2o.ai`

Actions	Logarithmic loss	ROC AUC	Brier score
1	0.0548	0.7955	0.0107
2	0.0546	0.7973	0.0107
3	**0.0546**	**0.7977**	**0.0107**
4	0.0546	0.7970	0.0107
5	0.0547	0.7965	0.0107

Table 1: Comparison of five Random Forest models taking into account a varying number of actions prior to the action of interest. For the logarithmic loss and the Brier score a lower value is better, while for the ROC AUC a higher value is better. The best results are in bold.

4.3 Rating players

To this point, our method assigns a value to each individual action. However, our method also allows aggregating the individual action values into a player rating for multiple time granularities as well as along several different dimensions. A player rating could be derived for any given time frame, where the most natural ones would include a time window within a game, an entire game, or an entire season. Regardless of the given time frame, we compute a player rating in the same manner. Since spending more time on the pitch offers more opportunities to contribute, we compute the player ratings per 90 minutes of game time. For each player, we first sum the values for all the actions performed during the given time frame, then divide this sum by the total number of minutes he played and finally multiply this ratio by 90 minutes.

Players can also be compared along several different axes. First, players have different positions, and the range of values for the rating may be position dependent. Therefore, comparisons could be done on a per-position basis. Similarly, some players are versatile and what position they play may vary depending on the game. Therefore, it may be interesting to examine a player's rating for each position he or she plays. Second, instead of summing over all actions, it is possible to compute a player's rating for each action type. This would allow constructing a player profile, which may enable identifying different playing styles.

5 Use cases

In this section, we present a number of use cases to demonstrate the possible applications of our proposed metric. We focus our analysis on the English Premier League, Spanish Primera Division, German 1. Bundesliga, Italian Serie A, and the French Ligue 1. We apply the HATTRICS-OTB algorithm to 9582 games played since the start of the 2012/2013 season. We only include league games and thus ignore all friendly, cup, and European games. We train the predictive models on the games in the 2012/2013 through 2015/2016 seasons and report results for the 2016/2017 season as well as the ongoing 2017/2018 season until Sunday November 5th 2017. We represent each game as a sequence of roughly 1750 on-the-ball-actions. The most frequently occurring actions in our dataset are passes (53%) and dribbles (24%). In contrast, shots are much rarer and represent just 1.4% of the actions with only 11% of them resulting in a goal.

The remainder of this section is structured as follows. Section 5.1 explains the intuition behind our metric by means of Kevin De Bruyne's goal for Manchester City against Arsenal on Sunday November 5th 2017. Section 5.2 provides insights into the distribution of the action values. Section 5.3 shows the best possible line-up for the 2016/2017 season based on our metric. Section 5.4 discusses the five highest-rated players born after January 1st 1997 for the 2016/2017 season. Section 5.5 identifies a number of players who stood out at smaller clubs during the 2016/2017 season. Section 5.6 explains how our metric can be used to compare players in terms of their playing styles. Section 5.7 shows how the performances of Manchester City, Real Madrid, and Barcelona have evolved since the start of the 2016/2017 season. Section 5.8 discusses how our metric is used by SciSports, a Dutch data analytics company providing expertise to soccer clubs.

5.1 Intuition behind the action values

Figure 2 visualizes the goal from Manchester City midfielder Kevin De Bruyne against Arsenal on Sunday November 5th 2017. The table at the top of the figure shows the action values assigned to the shot that resulted in the goal as well as the twelve prior actions.

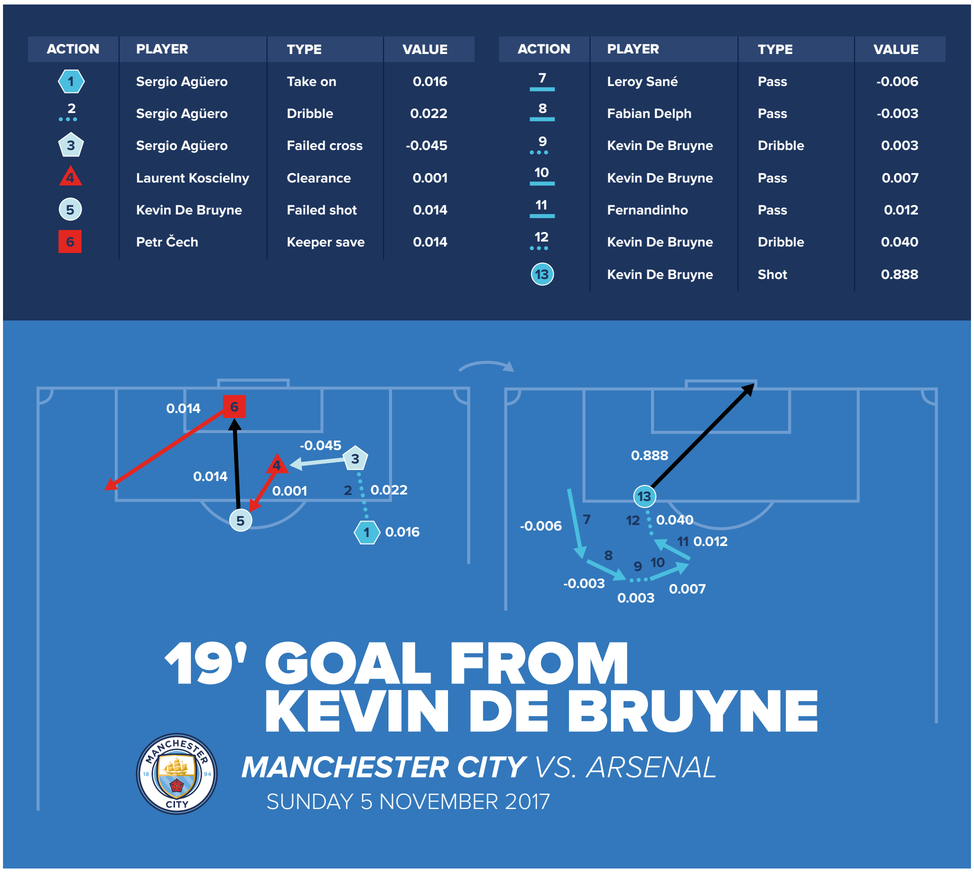

Figure 2: Visualization of Kevin De Bruyne's 19th-minute goal for Manchester City against Arsenal on Sunday November 5th 2017. The table at the top shows the values assigned to each of the actions performed in the build-up to the shot.

The attack starts with Argentine forward Sergio Agüero who first takes on an opponent (Action 1), then dribbles into the box (Action 2), and finally delivers a cross that fails to reach a teammate (Action 3), which gets a negative value of -0.045. The clearance from Arsenal defender Laurent Koscielny (Action 4) is collected by De Bruyne, who attempts a shot on target (Action 5). The Belgian midfielder sees his shot saved by Arsenal goalkeeper Peter Cech (Action 6), whose save gets a positive value of 0.014. However, Manchester City are able to recover the ball, which returns to De Bruyne following passes from Leroy Sané (Action 7) and Fabian Delph (Action 8). De Bruyne first dribbles a bit towards the middle of the pitch (Action 9) and sets up a one-two pass with teammate Fernandinho (Actions 10 and 11), then dribbles into the box (Action 12), and finally sends the ball into the lower-right corner of the goal with a powerful driven shot (Action 13). The dribble into the box and the shot get positive values of 0.040 and 0.888, respectively.

The attack leading to De Bruyne's goal is a clear example of how our metric works. Actions increasing a team's chances of scoring (e.g., a dribble or pass to a more dangerous location on the pitch like Actions 11 and 12) or decreasing the opponent's chances of scoring (e.g., a clearance and a save by the goalkeeper like Actions 4 and 6) receive positive values, whereas actions decreasing a team's chances of scoring like the failed cross from Agüero (Action 3) receive negative values. In this particular game, the 19th-minute goal from De Bruyne is the highest-valued action, while a 47th-minute foul from Arsenal's

Nacho Monreal causing a penalty is the lowest-valued action.

5.2 Distribution of the action values

Figure 3 shows the number of actions that players execute on average per 90 minutes and the average value of their actions for those players who played at least 900 minutes during the 2016/2017 season. Naturally, there is a tension between these two quantities. If a player performs a high number of actions, then it is harder for each action to have a high value. The 15 highest-rated players according to our metric are highlighted in red.

The grey dotted isoline shows the gap in total contribution between Messi and other players. This isoline is curved since a player's total contribution is computed as the average value per action (*x-axis*) multiplied by the number of actions per 90 minutes (*y-axis*).

The plot shows that strikers like Harry Kane (Tottenham Hotspur), Luis Suárez (Barcelona), Kylian Mbappé (AS Monaco), and Pierre-Emerick Aubameyang (Borussia Dortmund) are less involved in the game as they perform a relatively low number of actions on average. However, the actions they do perform tend to be highly valued. In contrast, players like Arjen Robben (Bayern Munich), Eden Hazard (Chelsea), and Philippe Coutinho (Liverpool) perform more actions although the average value of their actions is considerably lower. Cesc Fàbregas (Chelsea), Isco (Real Madrid), and James Rodríguez (Real Madrid) perform more actions per 90 minutes than them while maintaining a higher average value per action. Finally, as shown by the isoline and more traditional statistics,[3] Lionel Messi is clearly in a class of his own.

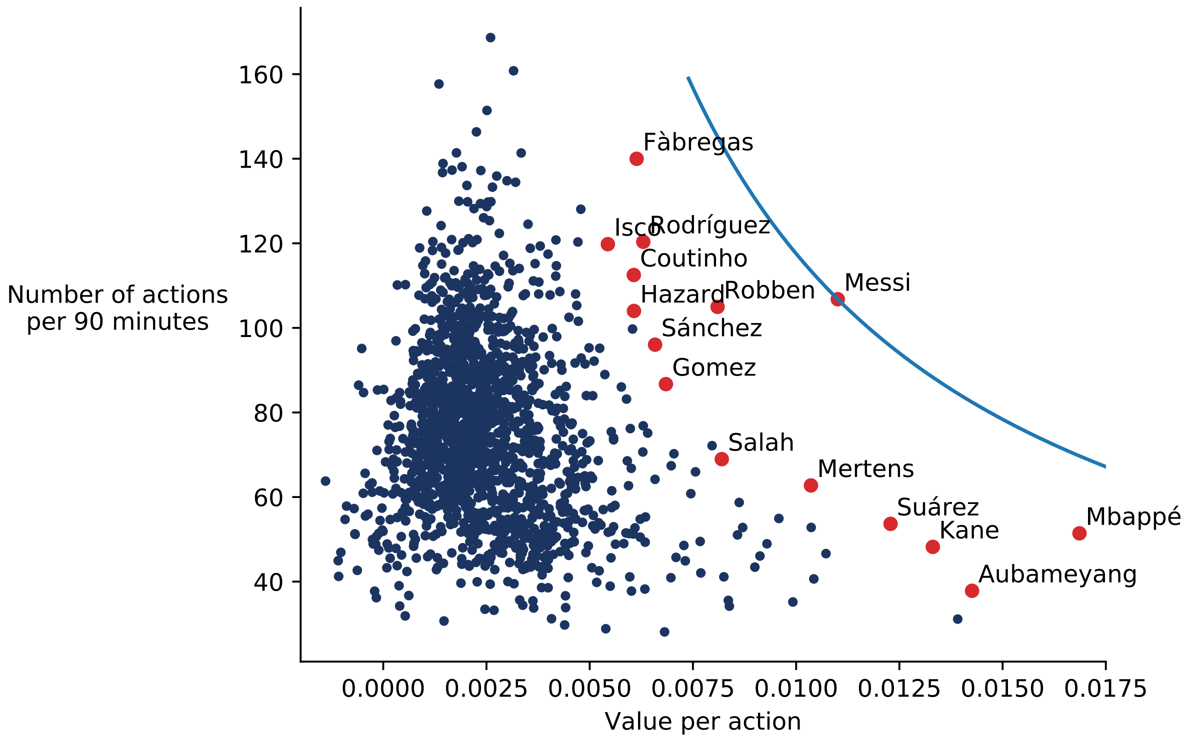

Figure 3: Scatter plot that contrasts the average number of actions performed per 90 minutes with the average value of these actions for each player who played at least 900 minutes during the 2016/2017 season. The 15 highest-rated players according to our metric are highlighted in red.

For nine positions on the pitch, Figure 4 shows the distribution of the average ratings per game for

[3] https://fivethirtyeight.com/features/lionel-messi-is-impossible/

those players who played at least 900 minutes during the 2016/2017 season. The highest-rated player for each position is highlighted in red.

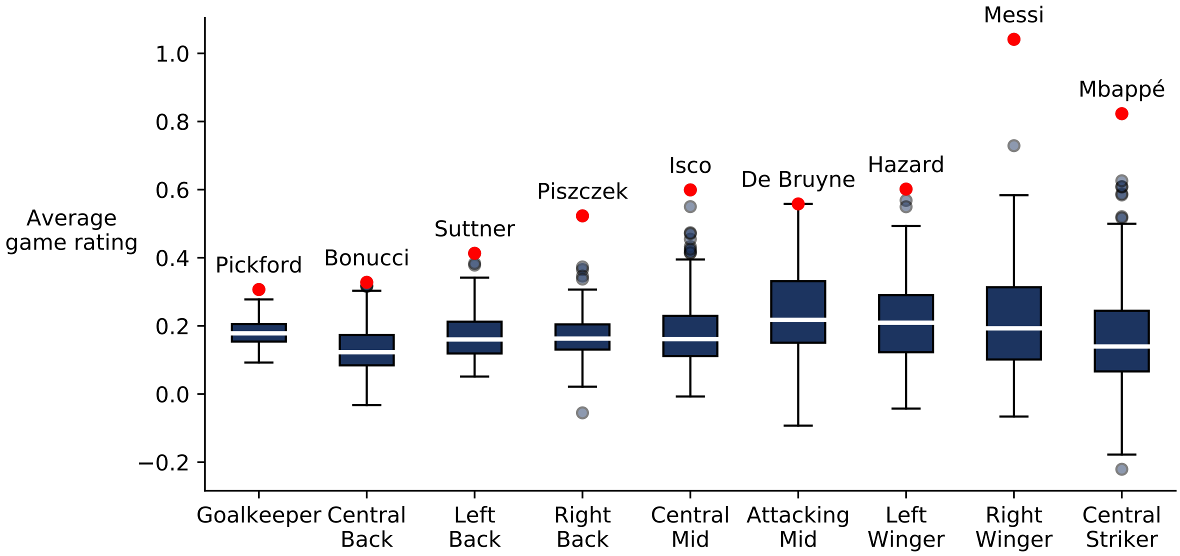

Figure 4: Distribution of average per game rating for players who played at least 900 minutes in the 2016/2017 season.

5.3 Selection of 2016/2017 team of the season

Figure 5 shows the best possible line-up for the 2016/2017 season according to our metric. For each position, the line-up includes the highest-ranked player who played at least 900 minutes, which is the equivalent of ten full games, in that particular position. The offensive line features the likes of Eden Hazard (Chelsea), the inevitable Lionel Messi (Barcelona), and teenage star Kylian Mbappé, who joined Paris Saint-Germain on a loan from AS Monaco last summer. The French striker will move to the French giants on a permanent basis next summer for a transfer fee rumoured to be around 90 million euros.[4] The midfield consists of Kevin De Bruyne (Manchester City), Isco (Real Madrid), and Cesc Fàbregas (Chelsea), who were all key figures for their respective teams during the previous campaign. However, the composition of the defensive line is somewhat more surprising. Serie A centre backs Vlad Chirices (Napoli) and Leonardo Bonucci (Juventus) combine their strength with excellent passing abilities. Bundesliga wing-backs Markus Suttner (FC Ingolstadt 04) and Lukasz Piszczek (Borussia Dortmund) are known for overlapping and providing support in offense. Goalkeeper Jordan Pickford got relegated with Sunderland last season but moved to Everton over the summer nevertheless. These somewhat surprising names in the defensive line reveal one limitation of HATTRICS-OTB. That is, the algorithm only values on-the-ball actions, while defending is often more about preventing your opponent from gaining possession of the ball by clever positioning and anticipation. More specifically, goalkeepers are rewarded for their interventions but not punished for the goals they concede.

The inclusion of Eden Hazard in our *Team of the 2016/2017 Season* shows the strength of our metric at identifying impactful players. The Belgian winger, who had a crucial role in Chelsea's Premier League title, is the seventh-highest rated player on our metric but ranks only 133rd in terms of goals and assists per 90 minutes with 10 goals and 3 assists. Similarly, wing-back Lukasz Piszczek ranks 19th on our metric but only appears in 292nd position for goals and assists per 90 minutes with 5 goals and 1 assist. In contrast, notable omissions from the team are high-profile players like Robert Lewandowski (54th), Álvaro Morata (61st), Edinson Cavani (77th), and Edin Dzeko (265th), who were all directly involved in more than one goal or assist per 90 minutes in the 2016/2017 season.

[4] https://www.transfermarkt.com/kylian-mbappe/profil/spieler/342229

Figure 6 shows the best possible line-up for the 2017/2018 season up through November 5th 2017 according to our metric. For each position, the line-up includes the highest-ranked player who played at least 450 minutes in that particular position. The average rating for the players for the 2017/2018 season (0.659) is significantly higher than the average rating for the players on the 2016/2017 season (0.551). However, we expect the average rating to regress towards the average for last season as the season progresses.

Appendix B lists the five highest-rated players in each position for the 2016/2017 season. Appendix C lists the five highest-rated players in each position for the 2017/2018 season until November 5th 2017.

Figure 5: The best possible line-up for the 2016/2017 season according to our metric. For each position, the line-up includes the highest-ranked player who played at least 900 minutes in that particular position.

Figure 6: The best possible line-up for the 2017/2018 season until November 5th 2017 according to our metric. For each position, the line-up includes the highest-ranked player who played at least 450 minutes in that particular position.

5.4 Identification of young talents

Table 2 shows the five highest-rated players born after January 1st 1997 who played at least 900 minutes during the 2016/2017 season. Kylian Mbappé, who is recognized as one of the biggest talents in the world, tops this list with a rating nearly twice as high as his nearest competitor. He has seamlessly transitioned from Monaco to Paris Saint-Germain this season, and has continued to gain acclaim for his play. Allan Saint-Maximin who played midfielder for Bastia in the French Ligue 1 last season is second-ranked. His play earned him both a transfer to Nice after the season and plaudits from the soccer intelligensia.[5] Ousmane Dembélé is also a huge talent, who parlayed his outstanding season for Borussia Dortmund into a summer move to FC Barcelona, where he was injured early in the season.

[5]http://www.squawka.com/news/allan-saint-maximin-the-monaco-wonderkid-you-havent-heard-of-yet-and-europes-take-on-king/919430

Maxime Lopez and Malcom play in the Ligue 1 and remained with their respective clubs where they continue to play well and are attracting significant interest from bigger clubs.

Rank	Player	Team	Age	Position	Rating
1	Kylian Mbappé	AS Monaco	18	Central striker	0.82
2	Allan Saint-Maximin	Bastia	20	Winger	0.46
3	Ousmane Dembélé	Borussia Dortmund	20	Winger	0.38
4	Maxime Lopez	Olympique Marseille	19	Attacking midfielder	0.30
5	Malcom	Girondins Bordeaux	20	Winger	0.26

Table 2: The highest-ranked players born after January 1st 1997 during the 2016/2017 season according to our metric.

Next, we consider a slightly larger age range and also consider players under 23 years old. Figure 7 shows the 15-game moving average for our metric for Leroy Sané, Mikel Oyarzabal, and Karol Linetty. Leory Sané was a big signing for Pep Guardiola in the summer of 2016, and is widely recognized for his high level of play this season with Manchester City. Mikel Oyarzabal currently plays for mid-table Primera Division team Real Sociedad. However, the 20-year-old winger, who debuted for the Spanish national team last year, is being linked with big clubs throughout Europe. Karol Linetty is a 22-year-old central midfielder playing for Sampdoria in Serie A. He is much less well known than the other two players, but our metric suggests he is playing at a level commensurate with these more highly touted youngsters, and hence the Pole may be one to watch.

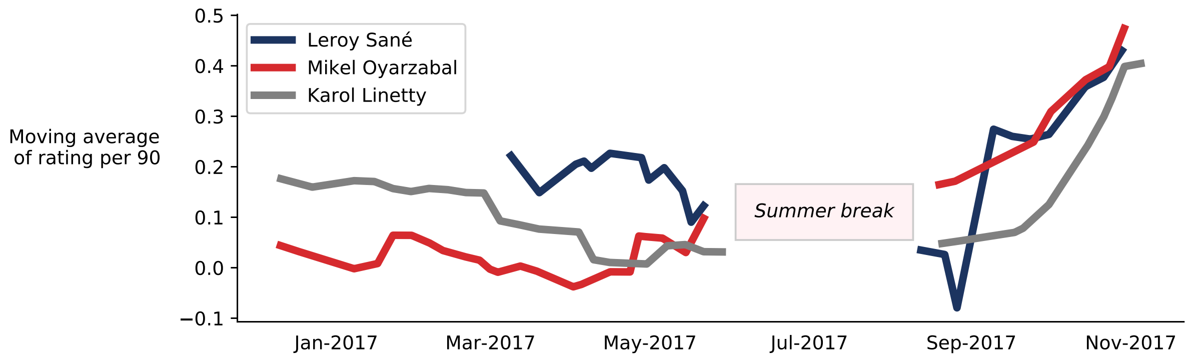

Figure 7: The 15-game moving average for our metric for Leroy Sané (Manchester City), Mikel Oyarzabal (Real Sociedad), and Karol Linetty (Sampdoria) since the start of the 2016/2017 season.

5.5 Identification of the players who stand out

One talent pipeline often exploited by larger clubs is identifying the players on less successful top division clubs whose skills have the potential to flourish in a more competitive environment. Thus, a natural question to ask is: Can our player rating metric help identify promising talent toiling at lesser clubs that larger clubs could target in the transfer market? When scouting such players from an objective perspective, one challenge is that the value of a metric often will partially reflect the team context. In this case, that means being surrounded by less-talented players, which may adversely affect a player's rating. Therefore, to find players that stand out compared to their teammates' performances, we look at the highest-ranked players on teams who finished outside the top 5 in their respective league. Table 3 lists the players who stood out at smaller clubs during the 2016/2017 season.

Rank	Player	Team	Position	Rating
1	Junior Stanislas	Bournemouth	Winger	0.58
2	Dimitri Payet	West Ham United	Winger	0.55
3	Iago Aspas	Celta de Vigo	Central striker	0.52
4	Max Kruse	SV Werder Bremen	Central striker	0.50
5	Ryad Boudebouz	Montpellier	Attacking midfielder	0.47
6	Fin Bartels	SV Werder Bremen	Central striker	0.46
7	Allan Saint-Maximum	Bastia	Winger	0.46
8	Ross Barkley	Everton	Winger	0.44
9	Romelu Lukaku	Everton	Central striker	0.44
10	Federico Viviani	Bologna	Central midfielder	0.43

Table 3: The highest-ranked players on teams who finished outside the top 5 in their respective league during the 2016/2017 season according to our metric.

Table 3 contains a number of interesting names. Junior Stanislas plays winger for Bournemouth in the English Premier League, and he is especially strong at shooting. Bournemouth performed exceptionally well in the 2016/2017 season, finishing 9th after finishing 16th the previous season. Another interesting player is Ryad Boudebouz, an attacking midfielder for Montpellier last season. He has since been transferred to Real Betis, but was on the wish list for a number of other clubs as well. The list also contains a number of recognized talents such as Dimitri Payet, who was a key performer for France at EURO 2016, Romelu Lukaku, who moved to Manchester United after the 2016/2017 season and is playing well there, and Ross Barkley, who moved to Chelsea in the previous winter transfer window.

5.6 Characterization of playing styles

Clubs are beginning to consider player types during the recruitment process in order to focus on identifying those players who best fit a team's preferred style of play (e.g., short passes and high defending vs. long balls and defensive play). Currently, scouts and experts are typically tasked with judging playing style. These experts' time is almost always the limiting resource in the player recruitment process, which makes it difficult to consider the entire pool of players. Therefore, advanced metrics offer the potential to help select a set of players that are worthy of additional attention. The metrics can be used to assess a player's ability at performing different types of actions. With our metric, this can be accomplished by computing a player's total value per 90 minutes for each type of action.

To showcase this use case, we analyze the playing styles of Lionel Messi, Harry Kane, and Kylian Mbappé, who are all counted among the best forward players in the world. Figure 8 shows the total contributions per 90 minutes for the passes, crosses, dribbles, and shots performed by these three players. Messi rates excellent at all four aspects and is an *allrounder*. In comparison to Messi, Kane rates poorly at passing, dribbling and particularly crossing. However, he outperforms Messi in shooting and is clearly a *finisher*, which is also reflected in the fact that he has scored 23 goals while providing only one assist in the ongoing season. In comparison to Messi, Mbappé only rates poorly at passing and even outperforms him in crossing.

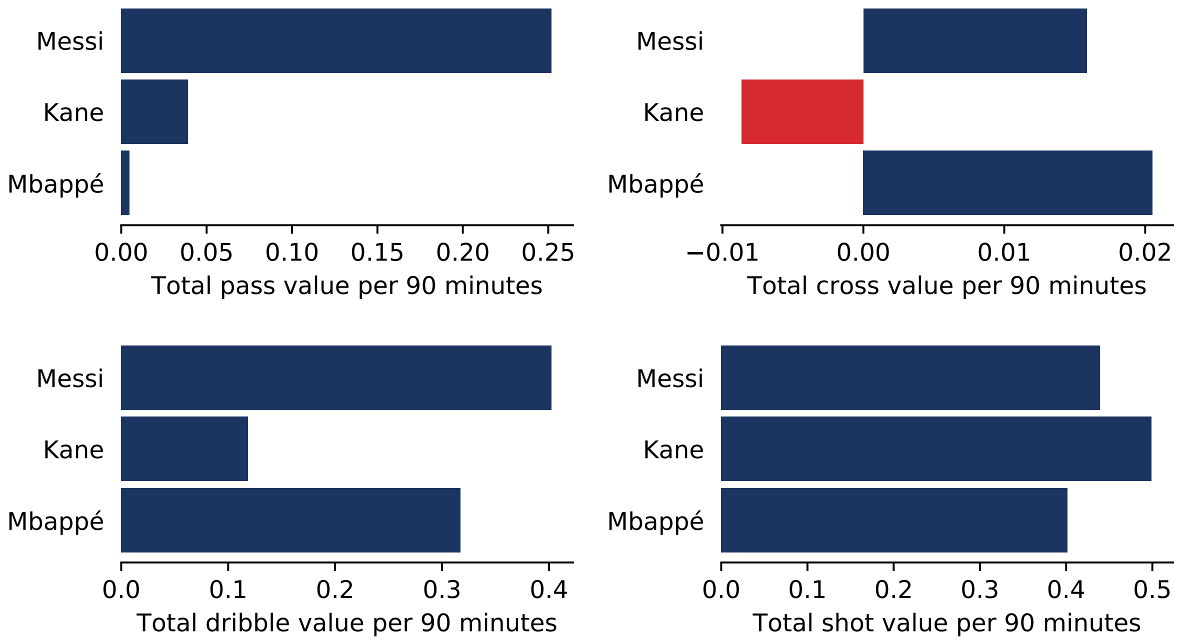

Figure 8: Overview of the total contribution per 90 minutes for different types of actions for Lionel Messi, Harry Kane, and Kylian Mbappé.

As another use case, consider FC Barcelona's attempts to offset the loss of Neymar by acquiring Borussia Dortmund's Ousmane Dembélé and Liverpool's Philippe Coutinho. Figure 9 compares Dembélé, Coutinho and Neymar's total values per 90 minutes for four action types. According to our metric, both Dembélé and Coutinho's passes receive a much higher value than Neymar's. Dembélé is the best crosser, with Neymar and Coutinho receiving nearly identical values for this skill. Neymar is a superior dribbler, and is ranked as the third best dribbler out of all players we analyzed in the 2016/2017 season. However, Dembélé is also exceptionally strong at dribbling and is ranked as the tenth best dribbler, whereas Coutinho is ranked thirty fourth. From a stylistic perspective, this breakdown suggests that Dembélé was a reasonable target in that he comes close to replicating Neymar's signature skill of dribbling.

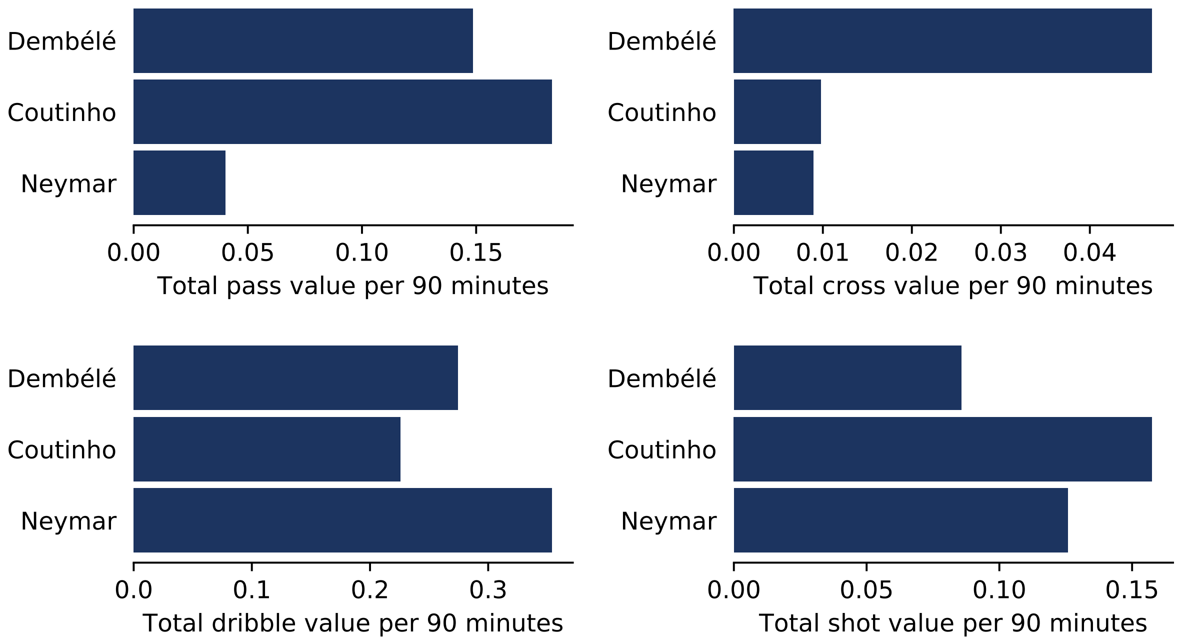

Figure 9: Overview of the total contribution per 90 minutes for different types of actions for Neymar, Ousmane Dembélé, and Philippe Coutinho.

5.7 Evolution of team performances

Figure 10 shows the evolution of the game ratings for Manchester City, Real Madrid, and Barcelona computed as a 15-game moving average since the start of the 2016/2017 season. We compute a team's game rating by summing the values for all the team's actions, which corresponds to summing the ratings for all the team's players in a particular game. The average game rating for Manchester City has been steadily increasing since the end of the 2016/2017 season, which was their first under the management of Pep Guardiola. Manchester City seem unbeatable and topped the Premier League table with 43 points from a possible 45 in their opening 15 games of the 2017/2018 season.

In contrast, Real Madrid had a poor start to the 2017/2018 season and ranked only fourth in the Primera Division after 14 games with 28 points from a possible 42. Their Portuguese star player Cristiano Ronaldo seems to be completely out of shape and does not appear near the top of our rankings. Rivals Barcelona finished their 2016/2017 season on a high with seven consecutive victories in their final league games of the season. The *Blaugrana* also had an excellent start to their 2017/2018 season but have been struggling to convincingly win games more recently. The evolution of their game ratings suggests Barcelona might have been overperforming and are now regressing towards their regular level.

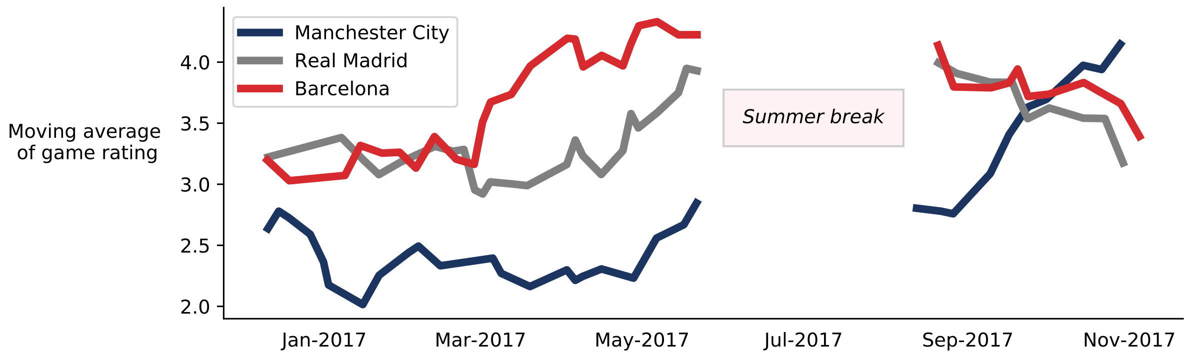

Figure 10: The evolution of the game ratings for Manchester City, Real Madrid, and Barcelona computed as a 15-game moving average since the start of the 2016/2017 season. A team's game rating is computed by summing the values for all its actions.

Figure 11 shows the average contribution per game for the goalkeepers, defenders, midfielders, and strikers of Barcelona, Real Madrid, and Manchester City during the 2016/2017 season. Barcelona's front line, which consisted of Neymar, Luis Suárez, and Lionel Messi in most games, was responsible for the largest share of their average contribution per game. In contrast, Real Madrid's midfielders contributed more than their strikers, while Manchester City's midfielders and strikers contributed roughly equally.

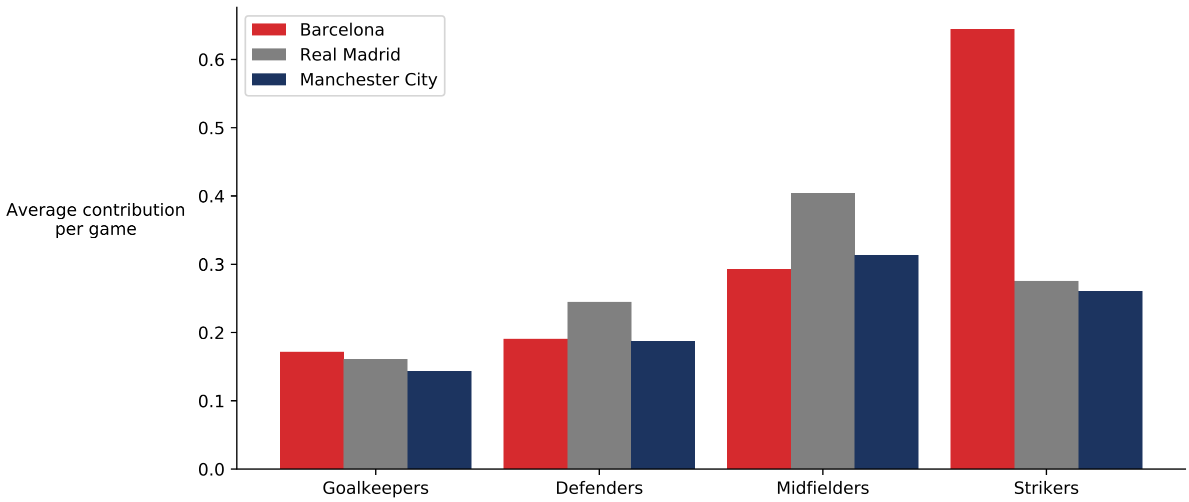

Figure 11: The average contribution per game for the goalkeepers, defenders, midfielders, and strikers of Barcelona, Real Madrid, and Manchester City during the 2016/2017 season.

Similarly, Figure 12 shows the average contribution per game for each line of Barcelona, Real Madrid, and Manchester City during the 2017/2018 season. Despite their loss of Neymar to Paris Saint-Germain, Barcelona still have the strongest attack by far. Real Madrid have seen their average contribution per game go down in midfield and offense, while Manchester City have seen notable increases in both those lines.

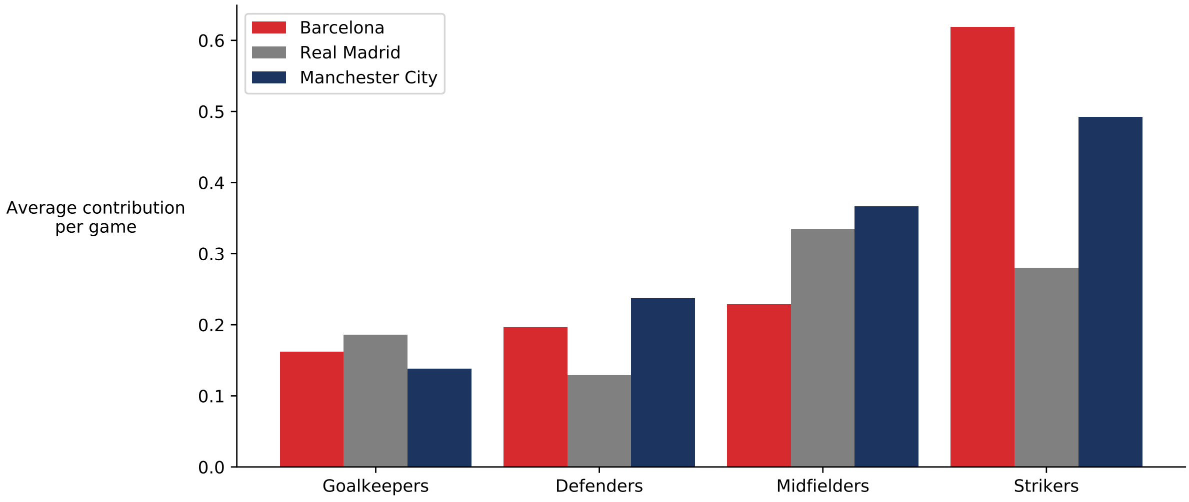

Figure 12: The average contribution per game for the goalkeepers, defenders, midfielders, and strikers of Barcelona, Real Madrid, and Manchester City during the 2017/2018 season.

5.8 Deployment in the soccer industry

The SciSports Datascouting department leverages our action values for providing data-driven advice to soccer clubs and soccer associations with respect to player recruitment and opponent analysis. Until recently, the SciSports datascouts almost exclusively relied upon more traditional metrics and statistics as well as the company's SciSkill Index, which ranks all professional soccer players in the world in terms of their actual and expected future contributions to their teams' performances. The SciSkill Index provides intuitions about the general level of a player, whereas our action values offer more insights into how each player contributes to his team's performances. While our action values are currently only available for internal use by the SciSports datascouts, they will also be made available in the SciSports Insight[6] online scouting platform.

6 Related work

Although the valuation of player actions is an important task with respect to player recruitment and valuation, this subject has remained virtually unexplored in the soccer analytics community due to the challenges resulting from the dynamic and low-scoring nature of soccer. The approaches from Nørstebø et al. (2016) for soccer, Routley (2015) for ice hockey, and Cervone et al. (2014) for basketball come closest to our framework. They address the task of valuing individual actions by modeling each game as a Markov game (Littman, 1994). In contrast to Nørstebø et al. (2016) and Routley (2015), which divide the pitch into a fixed number of zones, our approach models the precise spatial locations of each action. Unlike Cervone et al. (2014), which is restricted to valuing only three types of on-the-ball actions, our approach considers any relevant on-the-ball action during a game. However, our definitions of player actions, action sets and games are similar to those used by these works as well as earlier research for soccer (Rudd, 2011; Hirotsu et al., 2002), American football (Goldner, 2012), and baseball (Tango et al., 2007).

Most of the related work on soccer either focuses on a limited number of player-action types like passes and shots or fails to account for the circumstances under which the actions occurred. Decroos et al. (2017b), Knutson (2017), and Gregory (2017) address the task of valuing the actions leading up to a goal attempt, whereas Bransen (2017) addresses the task of valuing individual passes. The former ap-

[6] `https://insight.scisports.com`

proaches naively assign credit to the individual actions by accounting for a limited amount of contextual information only, while the latter approach is limited to a single type of action only.

Furthermore, this work is also related to the work on expected-goals models, which estimate the probability of a goal attempt resulting into a goal (Lucey et al., 2014; Caley, 2015; Altman, 2015; Mackay, 2016; Aalbers, 2016; Mackay, 2017). In our framework, computing the expected-goals value of a goal attempt boils down to estimating the value of the game state prior to the goal attempt.

7 Conclusion

This paper introduced an advanced soccer metric named HATTRICS-OTB that quantifies the performances of players during games. Our metric values any individual player action on the pitch based on its expected influence on the scoreline. In contrast to most existing metrics, our metric offers the benefits that it (1) values all types of actions (e.g., passes, crosses, dribbles, and shots), (2) bases its valuation on the game context, and (3) reasons about an action's possible effect on the subsequent actions. Intuitively, the player actions that increase a team's chance of scoring receive positive values while those actions that decrease a team's chance of scoring receive negative values.

We presented HATTRICS-OTB as a concrete instantiation of our more general action-valuing framework named HATTRICS for use with play-by-play event data. Several illustrative use cases based on an analysis of the data for the top five European leagues highlighted the inner workings of HATTRICS-OTB. Furthermore, we also proposed a language for representing play-by-play event data that is designed with the goal of facilitating data analysis.

A limitation of HATTRICS-OTB is its focus on valuing on-the-ball actions whereas defensive skill often manifests itself through positioning and anticipation abilities that are used to deny certain action possibilities. Therefore, including full optical tracking data would be an interesting direction for future research.

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A Action types

Table 4 provides an overview of the action types in the dataset alongside their descriptions.

Action type	Description	Successful?	Special result
Pass	Normal pass in open play	Reaches teammate	Offside
Cross	Cross into the box	Reaches teammate	Offside
Throw-in	Throw-in	Reaches teammate	-
Crossed corner	Corner crossed into the box	Reaches teammate	Offside
Short corner	Short corner	Reaches teammate	Offside
Crossed free-kick	Free kick crossed into the box	Reaches teammate	Offside
Short free-kick	Short free-kick	Reaches team mate	Offside
Take on	Dribble past opponent	Keeps possession	-
Foul	Foul	Always fail	Red or yellow card
Tackle	Tackle on the ball	Regains possession	Red or yellow card
Interception	Interception of the ball	Always success	-
Shot	Shot attempt not from penalty or free-kick	Goal	Own goal
Shot from penalty	Penalty shot	Goal	Own goal
Shot from free-kick	Direct free-kick on goal	Goal	Own goal
Save by keeper	Keeper saves a shot on goal	Always success	-
Claim by keeper	Keeper catches a cross	Does not drop the ball	-
Punch by keeper	Keeper punches the ball clear	Always success	-
Pick-up by keeper	Keeper picks up the ball	Always success	-
Clearance	Player clearance	Always success	-
Bad touch	Player makes a bad touch and loses the ball	Always fail	-
Dribble	Player dribbles at least 3 meters with the ball	Always success	-
Run without ball	Player runs without the ball	Always success	-

Table 4: Overview of the action types in the data set alongside their descriptions. The *Success?* column specifies the condition the action needs to fulfill to be considered successful, while the *Special* column lists additional possible result values.

B Five best-ranked players per position for the 2016/2017 season

This section lists the five best-ranked players per position for the 2016/2017 season.

CENTRAL STRIKERS SEASON 16/17

	PLAYER	TEAM	RATING
1	Kylian Mbappé	Monaco	0.823
2	Harry Kane	Tottenham Hotspur	0.626
3	Papu Gomez	Atalanta	0.609
4	Dries Mertens	Napoli	0.608
5	Alexis Sánchez	Arsenal	0.588

WINGERS SEASON 16/17

	PLAYER	TEAM	RATING
1	Lionel Messi	Barcelona	1.041
2	Arjen Robben	FC Bayern Munchen	0.729
3	Eden Hazard	Chelsea	0.602
4	Mohamed Salah	AS Roma	0.584
5	Junior Stanislas	Bournemouth	0.580

MIDFIELDERS SEASON 16/17

	PLAYER	TEAM	RATING
1	Isco	Real Madrid	0.599
2	Kevin De Bruyne	Manchester City	0.558
3	Cesc Fàbregas	Chelsea	0.550
4	Éver Banega	Internazionale	0.529
5	David Silva	Manchester City	0.498

WING BACKS SEASON 16/17

	PLAYER	TEAM	RATING
1	Lukasz Piszczek	Borussia Dortmund	0.523
2	Markus Suttner	FC Ingolstadt 04	0.413
3	Aleix Vidal	Barcelona	0.391
4	Marcelo	Real Madrid	0.384
5	Christian Fuchs	Leicester City	0.378

CENTRE BACKS SEASON 16/17

	PLAYER	TEAM	RATING
1	Leonardo Bonucci	Juventus	0.328
2	Vlad Chiriches	Napoli	0.319
3	Thiago Silva	PSG	0.317
4	Aleksandar Kolarov	Manchester City	0.316
5	Daniele Rugani	Juventus	0.303

GOALKEEPERS SEASON 16/17

	PLAYER	TEAM	RATING
1	Jordan Pickford	Sunderland	0.307
2	Tom Heaton	Burnley	0.278
3	Oliver Baumann	TSG 1899 Hoffenheim	0.266
4	Ørjan Nyland	FC Ingolstadt 04	0.263
5	Benjamin Lecomte	Lorient	0.255

C Five best-ranked players per position for the 2017/2018 season

This section lists the five best-ranked players per position for the 2017/2018 season.

CENTRAL STRIKERS SEASON 17/18

	PLAYER	TEAM	RATING
1	Lionel Messi	Barcelona	1.283
2	Sergio Agüero	Manchester City	0.884
3	Falcao	Monaco	0.823
4	Antonio Sanabria	Real Betis	0.688
5	Cédric Bakambu	Villarreal	0.669

WINGERS SEASON 17/18

	PLAYER	TEAM	RATING
1	Neymar	PSG	1.005
2	Memphis Depay	Lyon	0.661
3	Goncalo Guedes	Valencia	0.645
4	Malcom	Bordeaux	0.625
5	Leroy Sané	Manchester City	0.598

MIDFIELDERS SEASON 17/18

	PLAYER	TEAM	RATING
1	Nabil Fekir	Lyon	0.857
2	Luis Alberto	Lazio Roma	0.681
3	Enis Bardhi	Levante	0.617
4	Nuri Sahin	Borussia Dortmund	0.608
5	Paulo Dybala	Juventus	0.601

WING BACKS SEASON 17/18

	PLAYER	TEAM	RATING
1	Thomas Meunier	PSG	0.551
2	Aleksandar Kolarov	AS Roma	0.540
3	Ben Davies	Tottenham Hotspur	0.446
4	Faouzi Ghoulam	Napoli	0.426
5	Philipp Max	FC Augsburg	0.394

CENTRE BACKS SEASON 17/18

	PLAYER	TEAM	RATING
1	Bastos	Lazio Roma	0.510
2	Kalidou Koulibaly	Napoli	0.444
3	Nacho Monreal	Arsenal	0.413
4	Willi Orban	RB Leipzig	0.406
5	Sokratis	Borussia Dortmund	0.402

GOALKEEPERS SEASON 17/18

	PLAYER	TEAM	RATING
1	Vid Belec	Benevento Calcio	0.260
2	Alexander Schwolow	SC Freiburg	0.255
3	Lukás Hrádecky	Eintracht Frankfurt	0.252
4	Kasper Schmeichel	Leicester City	0.248
5	Alisson	AS Roma	0.243