How does context affect player performance in football?

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Football professionals are faced with many challenges. In order to make the best possible decision in each situation, they need to consider the contexts that may impact their decisions. Although technological advances are increasingly providing insights from data, many widely-used performance metrics still struggle to capture important contextual information. As a result, the focus in the football analytics community has recently shifted to developing methods that better capture the circumstances in which players perform their actions. This chapter overviews recent approaches that quantify player performance and to what extent these approaches account for relevant technical, tactical and mental aspects that affect player performance.

1. Introduction

Football professionals and fans are faced with a multitude of important questions on a daily basis. Managers and coaches are tasked with fielding the best possible line-up in their teams' matches, scouts and recruitment analysts are concerned with identifying potential transfer targets that suit their teams' playing styles, player representatives and agents aim to sign emerging youngsters at the starts of their careers, and football fans aim to compose the best-performing fantasy football teams. For all these tasks, it is crucial to consider the relevant contexts in order to make the best possible decision. For instance, in scouting, the quality of the opposition that potential transfer targets played against is one relevant context. Hence, a scout must evaluate their performances in this light and reason about how these performances would relate to the quality of opposition they would face at their new club.

Football professionals and fans nowadays have access to insights from data that enable them to make better-informed decisions. Technological advances have enabled capturing more fine-grained information about the context in which football players perform their actions, which has spurred the development of novel metrics for quantifying player performance. Attention has gradually shifted from simply counting *how often* players perform certain actions to also accounting for *how well* players perform those actions. While quantity-based metrics usually treat all actions of a particular type equally (e.g., number of shots on target), quality-based metrics consider additional *contextual information* in order to differentiate among actions of the same type (e.g., expected-goals or xG values for shots). Furthermore, attention has gradually shifted from evaluating mostly offensive actions such as shots and passes, where the impact is relatively easy to quantify, to other types of actions such as interceptions and tackles where the impact is much harder to quantify.

To satisfy the desire of practitioners to better understand the game, the recent focus in the football analytics community has been on better capturing the context in which players perform their actions. The increasing granularity of football data has enabled metrics to account for technical, tactical and mental aspects that impact the performances of football players. Examples include the consideration of players' finishing abilities (Gregory, 2017; Kwiatkowski, 2017), teams' playing styles (Decroos et al., 2018), and players' mental resilience in performance metrics (Bransen et al., 2019).

This chapter overviews how context affects the performances of football players by addressing the following four questions in turn in the following sections:

1. How to quantify the impact of a single action?
2. How do technical aspects affect a player's performance?
3. How do tactical aspects affect a player's performance?
4. How do mental aspects affect a player's performance?

2. How to quantify the impact of a single action?

Due to the low-scoring nature of football, the impact of the many actions that a player performs in a match is hard to quantify in isolation. As a result, the focus in the football analytics community has gradually shifted from quantifying each action's impact on the goals that were scored (e.g., counting assists or pre-assists) to quantifying each action's impact on increasing or decreasing the likelihood of scoring a goal from a particular game situation (e.g., computing xG values for shots). By doing so, the performance of a player can be assessed from a much larger, more representative set of actions.

To adequately measure an action's impact, it is crucial to reason about the context in which the action was performed. For example, a foul committed in the penalty box increases the odds of conceding a goal in most situations but avoids an almost certain goal in situations where the goalkeeper is out of position. Inspired by the richness of present-day football data, the field of football analytics has shifted towards devising performance metrics that incorporate the relevant contextual information to quantify player performance in recent years. The remainder of this section outlines the most relevant approaches to quantify the impact of shots, passes, other on-the-ball actions as well as off-the-ball actions.

Shots

Shot-based performance metrics have quickly evolved from context-free metrics such as the shot conversion rate (i.e., the fraction of a player’s shots that finds the net) to context-heavy metrics such as xG values. Since finishing a close-range shot with no defenders around is typically easier than scoring from a long-range shot with a crowded penalty box, a player usually deserves more credit for scoring the long-range shot than for scoring the easy shot from close to the goal. Traditionally, the impact of a shot is quantified by contrasting its xG value (i.e., the likelihood of a shot yielding a goal) with its actual outcome (i.e., goal or no goal). As a result, a player is positively rewarded for scoring a difficult long-range shot and negatively rewarded for missing a sitter.

xG models have evolved over time from considering little contextual information such as the location of the shot (Green, 2012) to more sophisticated models that account for the locations of opponents and the height of the ball at the time of the shot (Knutson, 2020). The early xG models mostly include characteristics of the shot such as the distance to the goal, the shot angle and whether the shot was headed or not (Green, 2012; Pollard & Reep, 1997). These models distinguish between short- and long-distance shots and recognize that shots with the foot are easier to finish than shots with the head. However, they do ignore important contextual information such as the build-up to the shot. For instance, scoring from a fast counter attack is often easier than scoring from a slow build-up when the defense has more time to get organized. Therefore, most early xG models comprise an ensemble of regression models that each address particular types of situations such as footed open-play shots, headed open-play shots, and direct freekicks (Caley, 2015; Ijtsma, 2015). The introduction of more granular match event data and spatio-temporal tracking data has eventually led to models that can identify, for instance, shots taken under pressure of defenders, shots where the goalkeeper is out of position and shots that require difficult body movements from the goalkeeper to reach the ball (Knutson, 2018, 2020; Lucey et al., 2015).

Although xG models are primarily used to evaluate the performances of attackers, they are also increasingly used to evaluate the performances of goalkeepers. While xG values provide insights into how many goals an attacker should have scored, expected-saves values (xS values) provide insights into how many on-target shots a goalkeeper should have saved. Attackers are typically positively rewarded for scoring more goals than expected, whereas goalkeepers are typically positively rewarded for conceding fewer goals than expected. However, two important differences exist between evaluating attackers and goalkeepers. First, unlike attackers, goalkeepers are only evaluated based on the shots that hit the target and could possibly be saved. Second, while xS models are similar in spirit to xG models, they usually also take relevant post-shot information into account such as the direction of the shot (Lawrence, 2015; Ruiz et al., 2017; Trainor, 2014).

Passes and other actions

Since shots constitute less than 2% of the on-the-ball actions in a match and primarily involve attacking players and goalkeepers, assessing the performances of defenders and midfielders remains hard using the aforementioned xG and xS models. Other types of on-the-ball actions happen much more often with passes being the most frequent type of action (Decroos et al., 2019). As a result, quantifying the impact of other types of on-the-ball actions, including passes, dribbles, interceptions and tackles among others, has gained more attention in recent years. Widespread count-based metrics are limited as they ignore important contextual information. For example, metrics such as passing accuracy and number of completed passes ignore the circumstances in which passes are executed. For example, a lateral pass from one central defender to the other is different from a perfect through ball from a midfielder that puts the striker in a one-on-one with the goalkeeper. While both passes would be counted as accurate, the latter pass has a considerably higher positive impact on the team's scoring chances than the former pass.

Analogous to shots, the general approach to quantifying the quality of an arbitrary on-the-ball action is to measure to what extent the action increases or decreases the likelihood of scoring a goal in the near future. The commonality among most of these approaches is that they value the game states right before and after the action. Intuitively, the game state can be thought of as the current situation in the match, which may include the locations of the players and the ball, the scoreline, and the time remaining in the match. Since an action transitions a match from one game state to another, its value corresponds to the difference in value between the game states before and after the action. Hence, an action that transitions the match to a more favorable game state is positively rewarded, whereas an action that transitions the match to a less favorable game state is negatively rewarded.

Different approaches have been proposed to value game states with the key difference being the amount of contextual information that each approach takes into account. Some approaches solely consider the sequence that an action belongs to (Lawrence, 2018; Decroos et al., 2017), whereas other approaches also consider the location of the ball (Singh, 2019; Gyarmati & Stanojevic, 2016). However, these approaches cannot distinguish between, for example, a forward pass on the own half after regaining possession that initiates a counter-attack on one hand and a dribble in the build-up phase without any other players around the ball on the other hand. Therefore, several approaches that leverage more contextual information to determine the game state value have been proposed. These approaches can differentiate between different match situations (e.g., penalty, corner, free kick; (Rudd, 2011; Yam, 2019)), type of action (Kothari, 2020) and include the trajectory and speed of play to describe the game state (Michalczyk, 2018; American Soccer Analysis, 2020; Bransen, 2017; Bransen & Van Haaren, 2018; Decroos et al., 2019; Liu et al., 2020; Mackay, 2017, 2019). These approaches can better differentiate between the aforementioned actions, but still have difficulties to capture contextual information such as pressure on the ball and players possibly blocking the pass lane.

To account for this contextual information, (Power et al., 2017) introduce an approach to measure the impact of single passes using spatio-temporal tracking data. They account for factors such as the pressure on the player in possession of the ball, and whether any players are between the passing player and the intended recipient. Moreover, they consider tactical concepts such as whether the pass is part of a counter-attack. Similarly, (Goes et al., 2018) use spatio-temporal tracking data to value passes. They introduce a defensive disruptiveness score to value the effectiveness of passes in disrupting the opponent's defensive organization. Fernandez et al.'s EPV metric (Fernández et al., 2019) and Link et al.'s Action Value (Link et al., 2016) use spatio-temporal tracking data to value actions besides passes. In their work, Fernandez et al. state that "a critical aspect to properly evaluate soccer situations is to have a clear understanding of the ongoing context". Both approaches account for the locations of all players to value on-the-ball actions.

The aforementioned approaches have shown to identify players who contribute much value to their teams and at the same time are also considered to be impactful players by the public and on the transfer market. Decroos et al.'s VAEP ratings identify Marcus Rashford, Trent Alexander-Arnold, Mason Mount, Kylian Mbappé and Frenkie de Jong as emerging talents in the 2017/2018 season (Decroos et al., 2019), and, similarly, (Gyarmati & Stanojevic, 2016) identify Lucas Vázquez, Antoine Griezmann and Lionel Messi among others as the top-ranked attackers in terms of pass contribution in the 2015/2016 Spanish LaLiga season. In addition, Lawrence's xGChain identifies Lionel Messi, Mohamed Salah and Arjen Robben as top contributors in the 2016/2017 season (Lawrence, 2018) and Mackay's xG Added identifies Eden Hazard, Alexis Sánchez and David Silva as the top contributors in the 2016/2017 English Premier League season (Mackay, 2017).

Off-the-ball actions

The strong focus on on-the-ball actions is mainly driven by the widely available match event data's restriction to only registering on-the-ball actions. However, the availability of spatio-temporal tracking data describing all movements of the players and the ball has enabled also considering the impact of players' actions without the ball. For example, a player might create space for a team mate with a run or a player marks his opponent close in a situation where the team is out of possession. However, little work has been done in this area due to the limited availability of spatio-temporal tracking data and the complexity of the problem. It is hard to divide the credit among all 22 players on the pitch when multiple players are responsible for moving the game from one game state to the other.

The EPV framework (Fernández et al., 2019) mentioned in the previous subsection enables to rate players' off-the-ball impact. When looking at EPV added one can credit players for the off-the-ball movements they make, even when not receiving the ball.
(Dick & Brefeld, 2019) use deep reinforcement learning techniques to rate player positioning. (Robberechts, 2019) introduces the VPEP (Valuing Pressure decisions by Estimating Probabilities) metric that values players' pressure actions when not in possession of the ball.

Little work has been done in measuring the defensive impact of player movement without the ball (Llana et al., 2020; SciSports, 2020). This is partly due to the limited availability of tracking data, but even more so because of the complexity of determining who deserves credit for preventing an opponent from performing well. Consider the example where an opponent striker scores from a cross. Who is to blame? The defender who let the opponent give the cross, the two central defenders who let the striker tip in the cross or the goalkeeper who failed to prevent the ball from finding the net?

To objectively measure players' performances in matches, more and more contextual information could be incorporated in the metrics. However, to understand how and in what situations a player performs in a certain way we will describe three different types of context that could affect players' performances: technical, tactical and mental aspects. The next three sections discuss each of these types of context and their impact on player performance.

3. How do technical aspects affect a player's performance?

One crucial contextual piece of information to consider is which player performed a certain action. Each player has different technical abilities, and this will affect his or her ability to execute a particular action. For example, Kevin De Bruyne is an outstanding passer and is able to attempt and complete passes that others cannot. While not purely technical skill, players such as Eden Hazard, James Milner and Bruno Fernandes are known as excellent penalty takers who convert a higher proportion of their penalties than the typical player.

Considering the context of a player's technical skills has been most explored and hotly debated when considering finishing skills. That is, if two players could repeatedly take the same shot (i.e., the shot occurs in an identical match situation), would one player convert more chances? Intuitively, this would reflect a player's technical ability to hit the ball such that it is (a) on target and (b) placed in a location that optimizes the chance of scoring (i.e., the ball is not saved by the keeper). Unfortunately, there are two big challenges related to investigating finishing. First, it is impossible to collect such data as few, if any, shots occur in identical circumstances. The standard proxy is to use an xG model, which accounts for some aspects of a shot's context. Second, very few individual players take a large number of shots, even when aggregating across different seasons. One way to identify good finishers is to look for players who score more goals than predicted by an xG model. Kwiatkowski (2017) approached the problem by training an xG model that included a set of variables representing which player took the shot. The intuition is that the weight associated with a player's variable captures his finishing skill. This is reflected in the model by the fact that if two players take an identical shot, the model will assign a higher xG to the one that is a better finisher. He found a small but noticeable effect with players like Antoine Griezmann, Lionel Messi, and Luis Suárez topping the list.

The inverse of the question can be asked about goalkeepers: How does a keeper's technical skill affect the chance a shot will result in a goal? Here, technical skills could include executing a dive or the ability to time a jump. This is a challenging question to address for exactly the same reasons that arise when trying to assess finishing skill. First, keepers face different shots. Second, keepers face relatively few on-target shots in a season. Power et al. addressed this problem by training an expected saves (xS) model. The model captures the context of the scoring attempt by using the location of the shot and keeper at the start of the attempt as well as the score, time and location of the ball when it crosses the line or is saved. Finally, the model is augmented by considering properties of the keeper such as save percentages for various types of shots. Such a model allows answering counterfactual questions such as what is the expected number of goals a team would have conceded with a different goalkeeper? For example, it enables estimating how many goals Real Madrid would have conceded in the 2019-2020 season if they did not have Thibaut Courtois in goal, which in turn allows assessing if his absence would have affected their chance of winning the title.

More recently, (Bransen et al., 2019) proposed an execution rating metric that attempts to answer the question: How well did the player perform the chosen action? This extends the idea of investigating finishing ability to other on-the-ball actions. Intuitively, their metric attempts to reward players who successfully perform difficult actions such as completing a through ball or dribbling through pressure. Similarly, we want to punish players who flub an easy action such as having a lateral pass to an open teammate under no pressure. To this end, they train a model to predict the probability that an action will be successful (e.g., did the cross reach a teammate or did the player retain possession after a take-on) based on the context under which the action was performed. Here, the context is captured by features such as the player's current location on the pitch, the body part used to execute the action, and information about the previous action. The execution rating is then simply the difference between the result of the action (i.e., success such as completing a pass or connecting on a shot or failure such as having a pass intercepted or missing the shot) and the predicted probability that the action would be successful. As an example, the model assigns a high execution rating to Lionel Messi's perfect freekick in the 2018/2019 Champions League semi-final against Liverpool. Table 1 shows the field player on teams that reached the knock-out rounds of the 2018/2019 Champions League that had the highest average pass execution ratings. The table is dominated by well-known deep-lying playmakers Toni Kroos, Axel Witsel, Steven N'Zonzi, Sergio Busquets and Rodri. These players are known for dictating the game from the midfield and their strong passing skills. The list is completed by offensive wing backs Noussair Mazraoui, Alex Sandro and Sergi Roberto, striker Karim Benzema and centre back Matija Nastasic.

	Player	**Club**
1	Toni Kroos	Real Madrid
2	Axel Witsel	Borussia Dortmund
3	Noussair Mazraoui	AFC Ajax
4	Karim Benzema	Real Madrid
5	Alex Sandro	Juventus FC
6	Steven N'Zonzi	AS Roma
7	Sergio Busquets	FC Barcelona
8	Sergi Roberto	FC Barcelona
9	Rodri	Atlético Madrid
10	Matija Nastasic	FC Schalke 04

Table 1. *The top 10 field players in terms of the highest average pass execution rating that played on teams that reached the knock-out rounds of the 2018/2019 Champions League.*

4. How do tactical aspects affect a player's performance?

Most performance metrics aim to assess individual players although their performances are often strongly influenced by tactical concepts. Ideally, performance metrics would account for the tactical instructions that the players received. For instance, a player who is instructed to play a direct type of football should not necessarily be punished for sending risky long balls into their opponent's penalty box. However, the teams' game plans are usually not publicly known, which has inspired football analytics researchers to develop data-driven methods to automatically detect tactical concepts and playing styles from data.

Since detecting tactical concepts in a data-driven fashion is extremely challenging due to the fluid nature of football, the contextualization of player performance with respect to tactics has received little attention to date. Instead, the focus has mostly been on detecting frequently occurring patterns of play in the data and measuring players' involvement in those patterns (Bekkers & Dabadghao, 2017; Decroos et al., 2018; Perdomo Meza, 2017). Some of those approaches do account for high-level relevant context (e.g., whether a team plays at home or on the road; whether a team plays a stronger or weaker opponent). Extracting recurring patterns from football data is challenging on its own and would be further complicated by accounting for player-level context (e.g., the players' playing styles).

Despite the challenges, a number of approaches addressing several tactics-related tasks have appeared to date, including techniques to automatically detect formations (Bialkowski, Lucey, Carr, Yue, & Matthews, 2014; Bialkowski, Lucey, Carr, Yue, Sridharan, et al., 2014a) as well as playing styles of players and teams (Aalbers & Van Haaren, 2018; Bialkowski, Lucey, Carr, Yue, Sridharan, et al., 2014b; Decroos et al., 2020; Decroos & Davis, 2019). (Bialkowski, Lucey, Carr, Yue, & Matthews, 2014) introduce an approach to automatically detect and visualize team formations. They show that teams tend to play higher up the field at home than on the road, giving merit to the common saying that teams try to win at home and draw away. (Decroos et al., 2020) introduce an approach to capture the playing style of a team or player within a single match. They showed how Liverpool adopts a different playing style against Manchester City than against lesser opposition.

In addition, a number of approaches have appeared to quantify team balance by capturing each player's performance with respect to their teammates. (Beal et al., 2020) present a method that values the contributions of players to their team and automatically forms the optimal team by leveraging frequently appearing patterns in the team's passing network. (Bransen & Van Haaren, 2020) present a method to quantify the chemistry between a pair of players by measuring the impact of their joint actions on their team's chances of scoring and preventing goals. Furthermore, they introduce a method that predicts the mutual chemistry between a pair of players who has never played together before. Inspired by (Beal et al., 2020), they also present a method to automatically assemble a starting line-up that maximizes the mutual chemistry between pairs of players for a given squad of players. They found that Mesut Özil's performances for Arsenal rapidly declined after Alexis Sánchez' departure to rivals Manchester United in the winter of 2018. The pair had gelled particularly well in the preceding seasons and had a considerable joint impact on Arsenal's performances at the time.

5. How do mental aspects affect a player's performance?

While most existing football performance metrics focus on players' physical, technical and tactical performances, they typically ignore the mental aspect. Yet, there are various mental factors that can affect a player’s performance. These factors can range from mental fatigue due to the quick succession of games (Russell et al., 2019), to mental pressure in crucial game situations (Schweickle et al., 2020), to frustration when things do not go according to plan (Cowden & Worthington, 2019). In short, anything that affects the cognitive thoughts of a player would come under the mental factor. To gain a better insight in the performance of football players, it is important to recognise and develop an understanding of how these factors are presented and how they affect performance.

The vast majority of research on these mental aspects appears in the cognitive sciences’ literature (Hill et al., 2010). This research is mostly experimental and induces cognitive stress through artificial manipulation, distraction and self-focus. For example, Williams et al. (2002) showed that anxiety is thought to affect detrimentally sporting tasks which rely heavily on decision making by measuring variables such as reaction time, visual search data, and arm kinematics in an artificial table tennis setting. The remaining body of research in this domain is qualitative and predominantly involves interviewing athletes.

In a sports analytics setting, it is much harder to quantify the mental context. While teams are able to inquire about the mental well-being of their own players, they are certainly not able to do this for opponents and future transfer prospects. Therefore, the focus is entirely on the effect of mental pressure, which is most straightforward to measure by means of proxies. With these, two groups of factors that affect the pressure level can be distinguished (Bransen et al., 2019):

1. The **in-game context** or the events in the game itself. Pressure mounts in close games, particularly as time winds down because a goal would increase the chances of a favorable outcome. Conversely, pressure decreases when the score differential is high as a goal would only have a small impact on the expected outcome.
2. The **pre-game context** or the context surrounding the game. For example, a rivalry game or a game directly impacting relegation will be more tense than a typical end-of-season game with little to nothing at stake.

We now discuss each of these in more detail.

In-game context

In the field of sports analytics, people have mainly focused on the effect of crucial game situations (often referred to as “clutch situations”) with a presumed high level of mental pressure on performance. A clutch situation, according to Hibbs (2010), is ‘a point in a competitive sport where the success or failure of the participants has a significant impact on the outcome of the contest'. Examples of such situations are Michael Jordan scoring with five seconds remaining to win the 1998 NBA Championship, Sergio Agüero's injury time goal to win Manchester City's first Premier League title in over 40 years in 2012, and the fifth-set tiebreaker between Djokovic and Federer in the 2019 Wimbledon final.

While these are clear examples of clutch situations, questions remain over how to adequately define clutch performance, as well as the situations in which such performances occur. Typically, one defines clutch situations by hand (e.g., in the NBA, one defines the last five minutes of games separated by five points or fewer as clutch situations), and then computes performance metrics (both traditional and advanced) for players in such situations. Although, these approaches are not directly transferable to football. Since up to 75% of all football games end with a goal difference below one, it often depends on a combination of multiple factors whether a team is truly under pressure or not.

An alternative approach is to give a player a certain amount of positive or negative credit, according to how much his involvement advanced or reduced his team's chance of winning the game. Naturally, clutch situations will carry more weight, because those moments produce the largest swings in win probability. This approach was introduced as early as 1977 in baseball (Cramer, 1977), but only recently found its way into football along with the first in-game win probability models. Such in-game win probability models estimate a sports team's likelihood of winning at any given point in a game, based on the current game state (i.e., the current score line, time remaining, red-carded players, relative team strength, etc.).

Based on an in-game win probability model, Robberechts et al. (2019) introduced the Added Goal Value (AGV) metric. This metric computes the average boost in expected league points due to a player's goals as the sum of the change in win probability multiplied by three and the change in draw probability. Figure 1 shows the relation between goals scored per 90 minutes and AGVp90 for the 2017/2018 and 2018/2019 seasons. The diagonal line denotes the average AGVp90 for a player with similar offensive productivity. Players below this line such as Neymar, Robert Lewandowski, Edinson Cavani and Luka Jovic have a relatively low added value per goal; while players above the line such as Robert Beric, Harry Kane, Paco Alcacer and Mauro Icardi add more value per goal than the average player.

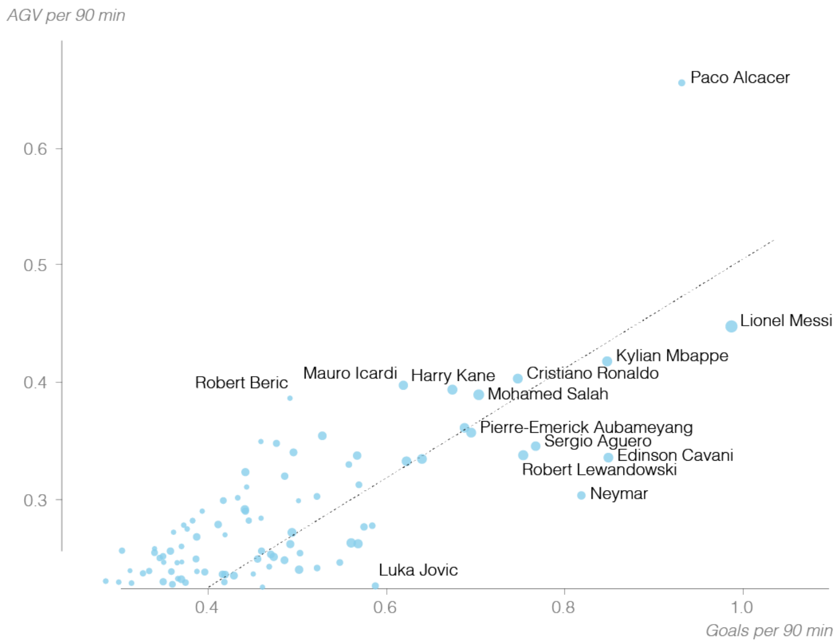

Figure 1. *The relation between goals scored per 90 minutes and AGVp90 for the most productive Bundesliga, Ligue 1, Premier League, LaLiga and Serie A players in the 2017/2018 and 2018/2019 seasons.*

This approach works well for goals and red cards, which have a measurable effect on win probability. Most other actions will have an infinitesimal effect. However, win probability can still be used to measure the 'crucialness' of game episodes by taking the difference in win probability between the current game state and the two hypothetical game states where the home or away team has scored an additional goal. This approach was taken by Bransen et al. (Bransen et al., 2019) and is illustrated in Figure 2 for the game between Real Madrid and Barcelona on April 23, 2017. Barcelona's pressure level drops when they scored the 1-2 late in the game and Sergio Ramos got sent off. However, after Madrid's equalizer, the pressure level sharply increases again and only cools down after Messi's winning goal in the final minute of the game.

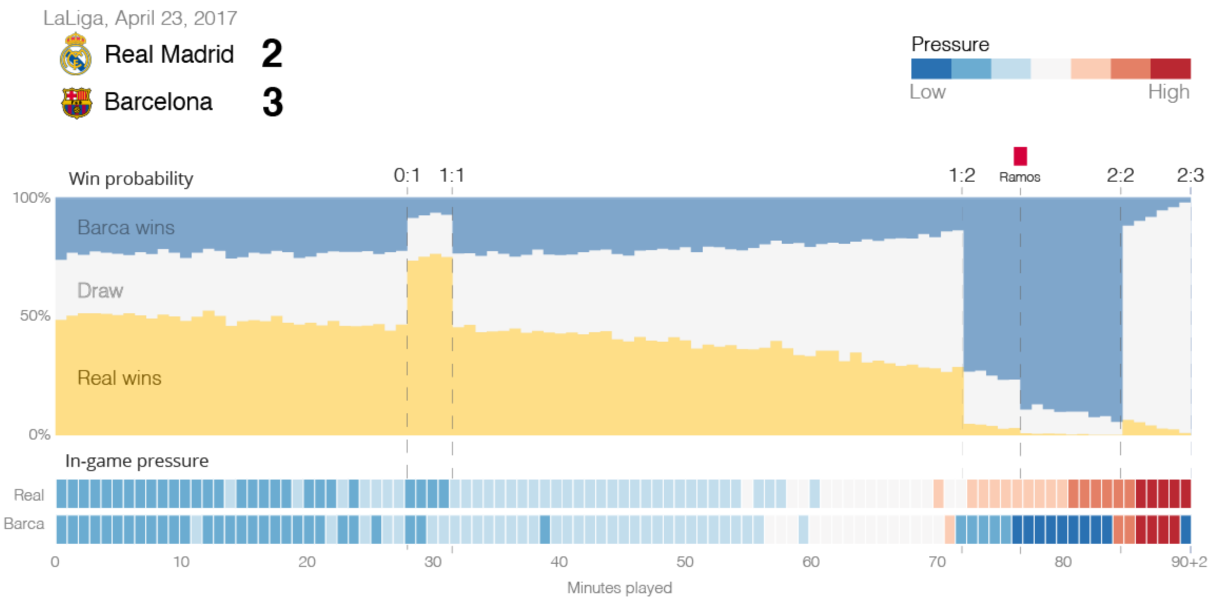

Figure 2. *Evolving pressure levels (bottom) and win probabilities (top) in Barcelona's 2-3 win against Real Madrid in the 2016/2017 LaLiga season. Pressure mounts when scoring increases the chance of a favorable match outcome, and subsides when a goal would only have a small impact on the expected outcome. At the start of the game, each team has a low pressure level since there is still enough time left to overcome the other team scoring and win the game.*

Pre-game context

To get an overall picture of the mental context, one cannot see the in-game situation apart from the context surrounding the match. Players will experience a different level of mental pressure ahead of a cup final, relegation battle or rivalry, compared to an end-of-season game with nothing at stake. This pre-game pressure will either fade or increase as the match progresses, depending on the in-game scenario.

The magnitude of the stakes and the importance of achieving success are the most important pre-game pressure facilitators. However, as for the in-game context, there exists no clear definition of what constitutes a big game. Some people have solved this by focussing on a category of games which are undeniably "big", such as elimination games in NBA playoffs (Morgulev & Galily, 2018) or games in the latter stages of the UEFA Champions League (Dawson, n.d.). This approach, however, limits the number of games that can be analysed.

Bransen et al. (2019) used an alternative approach based on machine learning to estimate the pre-game pressure of football games. While it is hard to provide a general definition for what makes one game more pressure-packed than another one, football fans typically have a good intuition about which of two games has the higher pre-game pressure. Therefore, they first asked football experts to assess for pairs of matches which one has higher stakes and subsequently used these pairwise rankings to train a machine learning model. The model learns to reproduce the judgments of the experts by assigning scores to matches, such that a higher score is assigned to the match with the higher pre-game pressure. These scores define the pre-game pressure metric. To be able to rank games that were never rated by the experts, the model describes each game by a set of general features that capture the following factors:

1. **Team ambition**: Each team has different ambitions for the season – such as winning the league or simply staying up – that affect its pre-game pressure level. This ambition is captured by clustering the teams in each league into four groups using each team's result in previous seasons, transfer value of its top-20 players, spending on loans and Football Manager's reputation score, which reflects how prestigious a club is.
2. **Game importance**: Capturing how much a game will affect a team's chance to achieve its ambitions requires estimating how the current match's outcome will affect the probability that the team reaches a certain season outcome (e.g., avoiding relegation). This game importance is measured as the association between each possible game result (win-draw-loss) and each expected final league outcome (e.g., relegated, league champion) by simulating the remainder of the season.
3. **Recent performance**: Football clubs are also subject to pressure based on recent form. Particularly for a big club, several consecutive poor performances will ratchet up the pressure. This is captured using the number of points obtained and the deviation from the expected performance over the last five games.
4. **Game contex**t: Specific characteristics of a game will affect pressure, namely: game location (i.e., home or away), the rivalrousness of the opponent, the match attendance, and how long ago the coach was appointed.

6. Conclusion

This section outlined the techniques that have been developed to value the actions that players perform. In particular, this section discussed how technical, tactical and mental aspects affect player performance and to what extent player performance metrics account for relevant contextual information. The existing metrics focus on evaluating player performance in a given context, but the important application of projecting player performance into a novel context (e.g., different tactics at a new club) has remained virtually unexplored to date and presents an interesting avenue for further research.

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