un-xPass: Measuring Soccer Player's Creativity

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Introduction

The best soccer players are often described as being "creative". For example, Kevin De Bruyne is widely regarded as an unparalleled genius when it comes to bringing creativity to the pitch: he sees the options that other players don't and his sparks of creativity have frequently turned a closed game around. Hence, media and fans often discuss a player's creativity. Moreover, clubs and analysts view this as a valuable trait and thus look for it when scouting for new players. Yet, it remains unclear how creativity can be concisely captured and quantified.

The current advanced metrics typically quantify player decisions along two dimensions, namely their risk and reward. For example, Power et al. [15] and Goes et al. [8] evaluate passes based on how likely they are to be successfully completed to a teammate (i.e., risk), and also by how much they would increase the chance of something good happening (e.g., scoring) if successful (i.e., reward). Neither aligns with what one would intuitively label as capturing creativity.

Discussions around creativity differ from risk and reward in that being creative entails going beyond just doing something obvious but useful, to accomplishing something useful but in a unique or atypical way. Based on these intuitions, a player performs a creative action when it (1) differs from the typical action that most players would have selected in the given game state, and (2) has more promising results than this typical choice. We capture this idea in a single value per action and define the creative decision rating (CDR) for passes as a composition of three estimates: the likelihood of each possible pass destination, the long-term reward of each passing option and the success probability of each passing option. Eventually, the creativity of a pass is quantified by the difference between the expected values of the chosen pass option and the predicted typical pass.

We use machine learning methods to learn models for each of these components from StatsBomb 360 event stream data. While each of the three components has previously been implemented for traditional event stream data and spatio-temporal tracking data, the hybrid 360 data poses unique challenges. We evaluate two approaches to learning each of the separate models: a gradient-boosted trees model based on handcrafted features and a deep-learning model based on the SoccerMap architecture [6].

We compute our creativity metric for the 2021/22 English Premier League season and show that Kevin De Bruyne is indeed the most creative player, followed by Tariq Lamptey and Trent Alexander-Arnold. When looking at pairs of players, we found that the interactions between Mohammed Salah and Sadio Mané exhibited the highest creativity. Additionally, we found that the average level of creativity is not affected by the game state (i.e., time remaining and goal difference), but that the variance of creativity increases as time progresses.

To summarize, this paper makes the following contributions:

1. We propose a novel metric for capturing the complex notion of creativity in soccer;
2. We compare deep learning and feature-based approaches for estimating (i) the likelihood of each possible pass destination, (ii) the long-term reward of each passing option, and (iii) the success probability of each passing option from snapshots of player positioning in StatsBomb 360 data;
3. We provide a number of use cases showcasing our most interesting results and insights;

The remainder of this paper is organized as follows. Section 2 presents our metric for measuring the creativity of a player's pass selection. Next, section 3 presents our experimental framework for learning the machine learning components that underlie our metric. Section 4 provides insights into how our metric performs in practice and presents our most interesting findings. Finally, section 5 concludes the paper and discusses directions for future work.

Measuring Creative Passing

In psychology, creativity is commonly defined as "the ability to produce work that is both novel (i.e., unexpected, original) and appropriate (i.e., useful)" [12]. Creativity thus goes beyond just doing something useful, to accomplishing something useful but in a unique or atypical way. For example, a cutback pass almost always puts a player in a good scoring position. Yet, it is typically not perceived as being creative as it is generally the most straightforward option when the game state allows it. Hence, creative actions should (1) differ from the typical action that the vast majority of players would select in a given game state, and (2) have more promising results than this typical choice. In the remainder of this section, we first describe how one can measure an action's expected usefulness and originality. Next, we show how both can be combined to measure creativity.

Valuing the usefulness of actions

When considering event stream data, a soccer match can be viewed as a sequence of *n* consecutive actions $a_1, a_2, \ldots, a_n$. Each action $a_i \in$ *{pass, dribble, shot, ...}* with outcome $o_i \in$ *{success, fail}* moves the game from state $S_{i-1} = \{a_1, \ldots, a_{i-1}\}$ to state $S_i = \{a_1, \ldots, a_{i-1}, a_i\}$.

Consequently, a logical approach to capture the usefulness of actions is by measuring the difference in quality between the pre-action game state S_{i-1} and post-action game state S_i. In recent years, several performance metrics have been introduced based on this idea (e.g., *xT, VAEP, g+, PV, OBV*). At a high level, they all quantify the usefulness (U) of actions according to the following equation:

$$U(A = a, O = o \mid S) = Q(S \mid A = a, O = o) - Q(S)$$

where Q captures the value or quality of a particular game state. Generally, this quality is expressed in terms of the likelihood of scoring or conceding a goal.

Whether or not the action was successful has a large impact on the eventual value of the action. However, creativity concerns the conception of an action, rather than its execution. Therefore, creative actions do not necessarily have to succeed. To quantify the creativity of a player's decision, we thus abstract away from the actual result of the action. Therefore, we compute the expected usefulness of an action as the weighted sum of the value of both outcomes:

$$E[U(A = a \mid S)] = \sum_{o \in \{o^+, o^-\}} P(O = o \mid A = a, S) \, . \, U(A = a, O = o)$$

where $P(O = o^+ \mid A = a, S)$ is the probability that action a succeeds in game state S, and $P(O = o^- \mid A = a, S)$ is the probability that it fails.

Valuing the originality of actions

The second aspect of creativity concerns originality with respect to the choice of actions. Generally speaking, in soccer, there are three possible high-level actions a player can perform with the ball. A player can try to shoot at the goal, pass it to another teammate, or drive with the ball up the pitch. In this paper, we restrict the space of possible actions A to passes, since these are the type of action that is mostly linked to creativity.

More concretely, we characterize a pass $a_i \in A$ by its origin and destination. The origin corresponds to the current ball location and is included in the current game state. The destinations can be defined in terms of player identities (i.e., passing to a specific player) or in terms of locations of the field. To be able to distinguish between simple passes to a specific player's location and (often more creative) through balls that a player should run into, we opt for the second approach in this research. Thus, let L be the set of all the possible locations in a soccer field. Then, we can define D_i to be the selected pass destination location of pass a_i and $P(D = l \mid S)$ to be a transition probability model for passes to any location $l \in L$. Finally, the originality of a player's pass selection decision can be defined as the complement $1 - P(D = l \mid S)$.

Valuing the creativity of actions

By comparing the expected usefulness of the chosen pass with that of other typical passes that the game state allowed, we can now assess whether a player is performing unexpected actions that lead to more promising results, thereby indicating a notion of creativity. Our intuition is that there is seldomly more than one obvious high-value pass option in any game state and that professional soccer players are all experts at selecting such options. Therefore, it is generally sufficient to compare the selected pass with the predicted most likely pass option $l_{typical} = \arg\max_{k \in L} P(D = k \mid S)$.

Combining these insights, we define the creative decision rating (CDR) of a pass to a location $D = l$ in a game state S as:

$$CDR(D = l \mid S) = E[U(D = l \mid S)] - E[U(D = l_{typical} \mid S)]$$

where $E[U(D = l \mid S)]$ is the pass' expected usefulness. Since the chosen action and most typical action have the same pre-action game state, this reduces to

$$\begin{aligned} & CDR(D = l \mid S) \\ & = E[U(D = l \mid S)] - E[U(D = l_{typical} \mid S)] \\ & = (E[Q(S \mid D = l)] - E[Q(S)]) - (E[Q(S \mid D = l_{typical})] - E[Q(S)]) \\ & = E[Q(S \mid D = l)] - E[Q(S \mid D = l_{typical})] \\ & = \sum_{o \in O} P(O = o \mid D = l, S) * [Q(S \mid D = l, O = o) - Q(S \mid D = l_{typical}, O = o)] \end{aligned}$$

This leads us to the task of estimating three components that produce a single estimation of pass creativity when combined:

- Pass selection $P(D = l \mid S)$: an estimate of the likelihood of a pass being made to every other location on the field.
- Pass success $P(O = o \mid D = l, S)$: an estimate of pass success probability for a pass to every other location on the field.
- Pass value $Q(S \mid D = l, O = o, S)$: an estimate of the game state value following a successful or unsuccessful pass to every other location on the field.

Each component can be estimated utilizing a standard supervised learning pipeline, where given some input features describing the game state, we can train a classifier to yield a probability between 0 and 1 for each location on the pitch. The next two sections provide a detailed description of our approach to train these classifiers.

Experimental Framework

In this section, we describe the dataset used and experimental settings for the inference and evaluation of each model component.

Data

We build our datasets based on StatsBomb 360 event stream data. This type of data is extracted from broadcast video and consists of the regular human-annotated event stream data enhanced with snapshots of player positioning. The event stream describes on-the-ball actions such as passes, dribbles and shots observed during the match. These are described by their time of occurrence in the match, the origin and destination location, the player who performs the action, the outcome of the action, and the body part used to execute the action. We work with the SPADL representation of this event stream.[1] The 360 snapshots are recorded at the time of each on-the-ball action and include the location and relationship to the ball carrier (i.e., teammate or opponent) of all players visible in the video.

Following our model design, we focus exclusively on passes. Additionally, we discard passes not performed by foot, passes from dead-ball situations (i.e., we discard corners, free-kicks, goal-kicks, kick-offs, and throw-ins), and passes for which the origin or destination location falls outside the 360 snapshot. Using these criteria, we construct a training dataset of 118,758 passes from the data of the 2020 European Championship, and the top-10 teams in the 2020/21 seasons of the English Premier League. A random sample of 20% of these passes is used as a validation set for model selection. A dataset of 93,631 passes extracted from the top-10 teams in the 2021/22 season of the English Premier League is set apart for evaluating the models and developing the use cases.

Model settings

For each component, we train two classes of models: an XGBoost model based on hand-crafted features and a deep-learning SoccerMap model [6]. For all XGBoost models, we applied the Tree-structured Parzen Estimator (TPE) algorithm for optimizing the max tree depth ([1, 9]), learning rate ([1e-2, 0.25]), L1 regularization ([1e-8, 100]), L2 regularization ([1e-8, 100]), and the minimum loss reduction required to make a further partition on a leaf node ([1e-8, 1]). We use early stopping with patience set to 100 boosting rounds.

We train the SoccerMap models using the PyTorch Lightning framework with the adaptive moment estimation (ADAM) algorithm. We perform a grid search on the learning rate ({1e−3, 1e−4, 1e−5, 1e−6}), and batch size parameters ({16, 32, 64}). We use early

[1] https://github.com/ML-KULeuven/socceraction

stopping with patience set to 10 epochs and a delta of 1e−3 for the pass success probability model, and 1e−5 for the pass selection and pass value models.

The SoccerMap-based models naturally produce a $l \times h$ probability surface covering the full extent of a soccer field. We use a 104 x 68 grid. To obtain a similar surface for the XGBoost models, we simulate a pass to each of the $l \times h$ grid cells and compute the corresponding feature representation. The prediction for each simulated pass is then mapped to the corresponding grid cell. For computational reasons, we use a coarser 26 x 17 grid, which we then upscale using bilinear interpolation.

Inference of model components

In this section, we provide a detailed description and evaluation of the approaches followed for estimating each of the components required to estimate the creative decision rating of an action.

Pass selection

To estimate the most typical pass in a given game situation, our model requires a component that produces a selection probability distribution over all possible pass destinations. Learning the full pass selection surface is not straightforward, though. For each pass, one typically only has ground truth selection information about one location on the pitch (i.e., the pass end location). In order to learn a calibrated probability surface over all pitch locations, Fernandez et al. [6] proposed the SoccerMap deep learning architecture which can propagate this sparse information to the entire pitch. Therefore, our approach uses a similar SoccerMap-based deep learning model to learn the pass selection surface.

As the target output, we use a sparse matrix where a value of 1 is given for every observed pass in its corresponding destination location. As the input, we use the following nine channels:

- Channel A & B: Two sparse matrices with the locations of the players in the attacking and defending team, respectively.
- Channel C & D: Two dense matrices with the distance to the ball and the goal for every location.
- Channel E & F: Two dense matrices with the sine and cosine of the angle between every location and the ball location.
- Channel G: One dense matrix with the angle between every location and the goal.
- Channel H & I: Two sparse matrices with the two components of the velocity vector of the ball, derived from the timestamps and ball location in the event data during the two preceding actions. These channels give an indication of the direction in which the ball is moving.

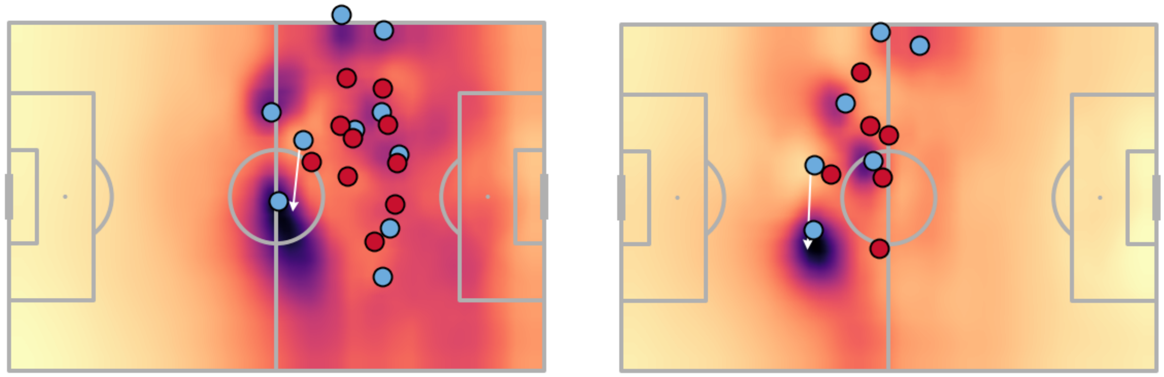


Figure 1: Pass selection probability surface on a logarithmic scale for two example game situations where purple colors represent more likely pass destinations. Blue and red circles represent the player's location of the attacking and defending team respectively. The blue team is in possession and plays left to right. The white arrow represents the selected pass.

Due to the lack of other approaches for estimating the full pass selection surface, we compare our results against approaches that predict the most likely receiver. First, we establish a naive baseline that consistently predicts the nearest teammate as the most likely receiver. Second, we train an XGBoost ranking classifier predicting the likelihood that a given player is effectively the receiver of a possible pass based on the following set of handcrafted features for each pass option in the 360 snapshot: origin and destination location, pass distance, pass angle, angle to goal at origin and destination, distance to the nearest defender at the destination, and distance of the nearest defender to a straight line between origin and destination. Per pass, one data point receives a positive label, the effective receiver, and all the other data points are labeled zero.

Table 1 presents the results for the baseline models and the SoccerMap model on the test data. To allow for a comparison between the location-based SoccerMap model and the receiver-based baseline models, we compute the most likely receiver from the prediction surface of the SoccerMap model as the teammate closest to the most likely pass destination and compute the accuracy as the percentage of passes for which the receiver was predicted correctly. The SoccerMap model is only slightly less accurate than the feature-based model. Although, it should be noted that mapping the location-based predictions to players introduces an additional error. In particular for passes that are played at a distance from the player's current location. Hence, the difference in accuracy between the XGBoost and SoccerMap models is likely smaller in reality than what the metrics reflect.

Table 1: The average loss and accuracy of three alternative implementations for the pass selection component: (1) a naive baseline predicting the nearest teammate as the most likely receiver, (2) an XGBoost model based on handcrafted features and (3) a deep-learning model based on the SoccerMap architecture.

Model / Feature set	LogLoss	Accuracy
Closest teammate	-	0.395
XGBoost	-	**0.538**
SoccerMap	6.277	0.513

Pass success probability

For estimating pass success, we define a binomially distributed outcome, according to the definition of success used by StatsBomb. That is, passes that reach a teammate on-side are labeled as "successful". All passes that go out of bounds or that are intercepted are labeled as "failed".

One important caveat with respect to modeling pass success is that the intended target location of a pass is only known for successful passes. The end location of failed passes is recorded as the location where the ball was intercepted or went out of bounds. Hence, it is impossible to construct an accurate feature representation for attempted passes. Previous work has addressed this issue in two ways: (1) by ignoring the problem and assuming that most passes will be intercepted near their intended destination [6], and (2) by estimating the intended receiver based on the direction of the pass and the positions of potential receivers [1,15]. Approaches to estimate the intended receiver range from simple distance-based rules to advanced physics-based approaches that model the ball trajectory and player movement [1]. As the 360 snapshots lack information about the velocity of players and the ball, we follow the approach of Power et al. [15] and estimate the intended receiver as the one closest to where the ball was intercepted and with the smallest angle to the line of the pass:

$$Expected\ receiver = \frac{Min\ Distance}{Distance} \times \frac{Min\ Angle}{Angle}$$

If the predicted receiver is positioned outside the field's boundaries, we clip its coordinates to the field's nearest boundary. If no player is within 20° of the pass line, we assume that the intended receiver is not included in the snapshot and we proceed with the observed end location. Figure 2 illustrates this procedure.

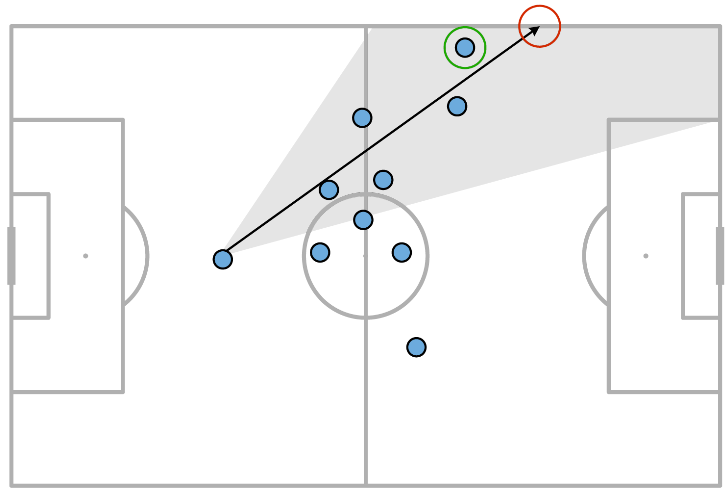


Figure 2: The intended receiver (green circle) is identified as the teammate closest to where the ball was intercepted or went out of bounds (red circle) and has the smallest angle to the line of the pass. Only players within 20° of the pass line (gray area) are considered as potential intended receivers.

Estimating the intended receiver has some obvious limitations though. First, the estimate will be inaccurate when the intended receiver is not included in the 360 snapshot, when the ball is blocked early in its flight path, when the ball is deflected, or when two players are close to each other. In addition, the end location of attempted passes is replaced by the (x,y) coordinates of the expected receiver at the time of the pass. In reality, a pass is often played in front of the receiver to run onto.

We implemented three simple location-based gradient-boosted trees models to evaluate whether the advantages of identifying the intended receiver outweigh the limitations: *i) receiver-agnostic*: a baseline model in which we use only the origin of the pass; *ii) observed end location*: we use both the observed origin and end location of the pass; and iii) *intended end location*: we replace the end location of the pass by the coordinates of the most likely receiver. Instead of the raw coordinates, we use the distance and angle to the goal and the distance to the sideline as features in each of these models. Additionally, we describe the relationship between the start and end location of a pass by the pass distance (total and along both axes) and angle.

Our results show that using the intended end location provides little to no advantage. First, we can observe that using the observed end location is more accurate (Table 2). Although, we hypothesize this is because the observed end location often gives away the outcome of a pass. For example, passes with an observed end location on the sideline or within a 1 meter radius of the origin are most likely failed passes. More importantly, using the intended end location produces inaccurate estimates for through balls, because these are mapped to player locations when they fail. For example in Figure 3, the model using the intended end location predicts the prior probability for a large part of the opponent's penalty box, since there are no examples with a potential receiver on that location in the training data. The main downside of using the observed end location is that locations near the pass origin are assigned very low success probabilities, which is probably due to blocked passes.

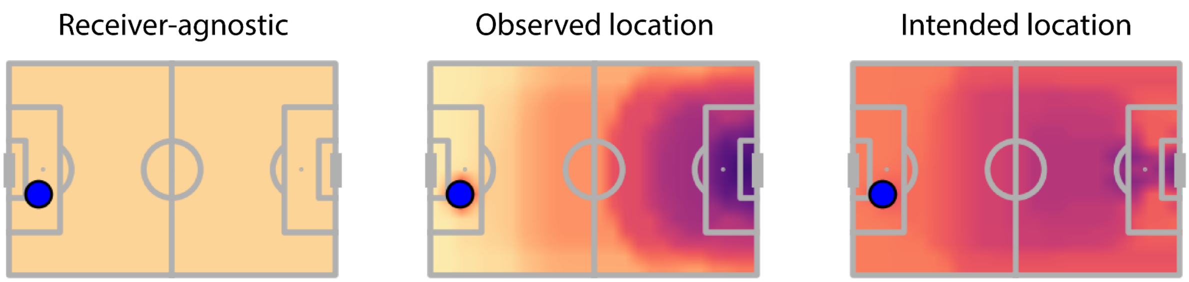


Figure 3: Pass success probability surface for a pass starting at the location of the blue circle to all other locations using a receiver-agnostic model, a model trained on the observed end location of each pass, and a model trained on the estimated intended end locations.

Given these results, we build further upon the observed end location and extend the location-based feature set with attributes available in the event stream:

1) The ball height (ground, shoulder level, above shoulder level);
2) The speed (distance covered / time) during the two preceding actions in the possession sequence;
3) The time the passer was in ball possession before attempting the pass.

Furthermore, we craft features from the 360 snapshots that describe the situation around the passer, receiver and ball trajectory:

4) The distance of the nearest defender to the passer and receiver;
5) The distance of the nearest defender to a straight line connecting the pass location and the receiver's location;
6) The number of opposing players in the passing path, where the path is defined as a triangular corridor between the pass origin and the receiver's location with a base of 1 meter at the receiver's location.

These features are inspired by recent work of Szczepański and McHale [19], Anzer and Bauer [1], Goes et al. [8] and Power et al. [15].

Next to the feature-based models, we again learn a SoccerMap deep learning model. As the input, we use channels A through G as defined in the previous section. Finally, we establish a naive baseline that assigns the average pass completion to all passes. As shown in Table 2, the XGBoost model using the full set of handcrafted features generally performs best.

Table 2: The performance of three alternative implementations for the pass success probability component: (1) a naive baseline predicting the average pass completion, (2) an XGBoost model based on handcrafted features and (3) a deep-learning model based on the SoccerMap architecture.

Model / Feature set	Precision	Recall	F_1	AUC	Brier
Avg pass completion	0.858	1.000	0.924	0.500	0.122
XGBoost					
Receiver agnostic	0.871	0.988	0.926	0.704	0.110
Intended end location	0.901	0.980	0.939	0.849	0.131
Observed end location	0.916	0.975	0.945	0.886	0.075
+ event data attributes	0.925	0.970	0.947	0.916	0.068
+ 360-based features	**0.936**	0.966	**0.951**	**0.939**	**0.062**
SoccerMap	0.926	**0.975**	0.950	0.930	0.065

Pass value

The final two components correspond to the expected usefulness of completed and failed passes, which reduces to estimating the value of a game state. Several approaches have been introduced to capture the value of game states, but generally they estimate the likelihood of scoring (i.e., the offensive value) or conceding (i.e., the defensive value) a goal in the near future. Unlike some other approaches [7,10], we train two separate models for these offensive and defensive components of game state value; however, we use an equivalent architecture for both cases. This allows us to inspect the model's predictions at a higher level of granularity. The total game state value is then obtained as the difference between both model's estimates.

We define the offensive value as the probability of scoring a goal in the next 10 actions; and correspondingly the defensive value as the probability of conceding a goal in the next 10 actions [5]. However, goals are rare and provide a weak learning singal. As a solution, previous work has proposed the use of expected goals (xG) values to train possession value models [10,18]. Therefore, we make use of StatsBomb's xG values to determine the likelihood of scoring from any shot in the next 10 actions. If this sequence of 10 actions contains multiple shots, we combine their xG value as

$$xG_{seq} = 1 - \prod_{shot \in seq} 1 - xG_{shot}$$

This corresponds to taking the complement of the probability that the defending team does not allow a goal from a sequence of shots.

The key difference between various game state value models is the amount of contextual information they take into account. The most basic approaches only consider the location of the ball [16,17,22], while intermediate approaches leverage more contextual information that can be extracted from traditional event stream data [5,10,18,21], and the most advanced approaches extract a detailed spatial representation from tracking data accounting for the locations of all players [7]. However, to the best of our knowledge, no public models exist for estimating the game state value based on 360 data,[2] which can be seen as a limited version of the full spatio-temporal tracking data as it provides only a partial view of the player's locations and lacks information about the velocity and acceleration of players and the ball. Again, we experiment with a set of XGBoost models based on handcrafted features and a deep-learning model based on the SoccerMap architecture. As baselines, we consider the location-based Expected Threat (xT)[3] [17] and event data-based VAEP [5] frameworks.

For the XGBoost, we extend VAEP's game state representation with features extracted from the 360 data that capture the number of outplayed players and the ball interceptability. The number of outplayed players is computed using a simplified version of Impect's Packing Rate: a defender is considered to be packed if he is positioned between the ball and the goal before a forward pass, but would be further from the goal than the ball after the pass. For interceptability, we use the number of defenders in a 3 meter and 5 meter radius around the pass' end location. For the SoccerMap models we use the seven input channels described earlier (A- G), as well as two dense matrices with the number of players of the team in possession and the opposing team that would be packed after a pass to each location.

We need the expected value of both completed and failed passes. Since the outcome of the pass is a feature in VAEP's game state representation, a value for completed and failed passes can be obtained by modifying the feature value. For the SoccerMap models, we learn separate models on completed and failed passes. For simplicity we only report the performance of all offensive game state value models on completed passes in Table 3. Also, we evaluate the performance on a binary goal / no goal label rather than the xG values to allow comparison with the xT and VAEP baselines.

[2] It is unclear whether StatsBomb's own On Ball Value (OBV) metric uses the 360 snapshots.
[3] We use the xT grid provided at https://karun.in/blog/data/open_xt_12×8_v1.json

Table 3: The performance of five alternative implementations for the offensive pass value component: (1) the location-based expected threat (xT) framework, (2) the event data-based VAEP framework trained on binary goal/no-goal labels, (3) the event data-based framework trained on xG values, (4) the VAEP framework with features extracted from 360 snapshots trained on xG values, and (3) a deep-learning model based on the SoccerMap architecture. All models are evaluated on completed passes only using binary goal/no-goal labels.

Model / Feature set	AUC	Brier	LogLoss
xT	0.741	0.012	0.062
VAEP	0.757	0.011	0.056
VAEP-xG	0.766	0.011	0.056
VAEP360	**0.776**	**0.011**	**0.055**
SoccerMap	0.743	0.011	0.064

Use Cases

We now present a number of observations that result from computing the Creative Decision Rating metric for the 2021/22 Premier League season. First, we present a ranking of the most creative players and quantify how their creativity pairs with their technical abilities. Second, we look at the creativity of interactions between pairs of players. Third, we look for a relationship between a player's position and creativity. Fourth, we look at the effect of the game state on creativity.

Most creative players

Table 4 shows the top-10 players in terms of Creative Decision Rating per 90 minutes (CDR90) in our dataset. To obtain a robust ranking, we only include players who performed at least 250 passes according to the criteria defined in section 3. Kevin De Bruyne tops the ranking, closely followed by Tariq Lamptey. Liverpool's right-back Trent Alexander-Arnold completes the top three.

Table 4: The top-10 players who completed at least 250 passes in the 2021/22 English Premier League season in terms of our Creative Decision Rating (CDR), normalized for minutes played.

	Player	Team	CDR90
1	**Kevin De Bruyne**	Manchester City	0.0834
2	**Tariq Lamptey**	Brighton & Hove Albion	0.0817
3	**Trent Alexander-Arnold**	Liverpool	0.0584
4	**Raphinha**	Leeds United	0.0563
5	**Hakim Ziyech**	Chelsea	0.0527
6	**Martin Ødegaard**	Arsenal	0.0480
7	**Lucas Moura**	Tottenham Hotspur	0.0473
8	**Harry Kane**	Tottenham Hotspur	0.0472
9	**Bukayo Saka**	Arsenal	0.0415
10	**Mason Mount**	Chelsea	0.0413

There is a natural tension between the creativity and quantity of a player's passes. This is illustrated in Figure 3, which shows the number of passes that players execute on average per 90 minutes (quantity) in function of the average creativity of these actions. The reason is twofold. First, players who perform more passes generally play in a more defensive position, from which it requires less creativity to progress the ball. For example, Harry Kane has a very high average CDR, but attempts relatively few passes as a striker. Second, if a player performs a high number of passes, then it is harder for each pass to have a high value. However, as shown by the dotted isoline, players like De Bruyne, Lamptey, Alexander-Arnorld, Raphina and Ziyech pair a high creativity with a large quantity of passes.

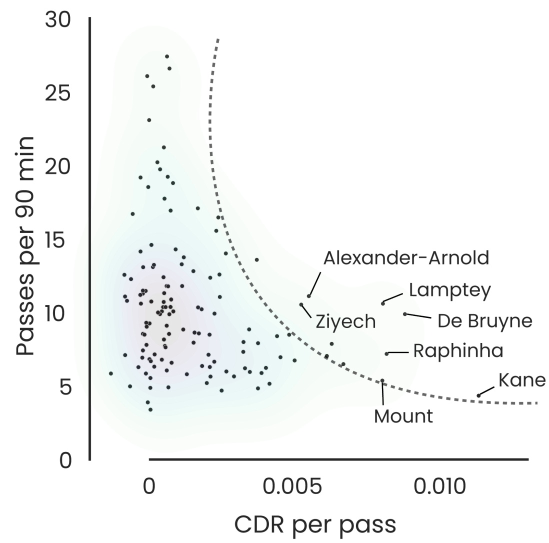


Figure 3: Scatter plot contrasting a player's average Creative Decision Rating (CDR) with the average number of passes performed per 90 minutes. The dotted isoline shows the gap between the top-ranked players and the rest. Only players who completed at least 250 passes in the 2021/22 English Premier League season are included.

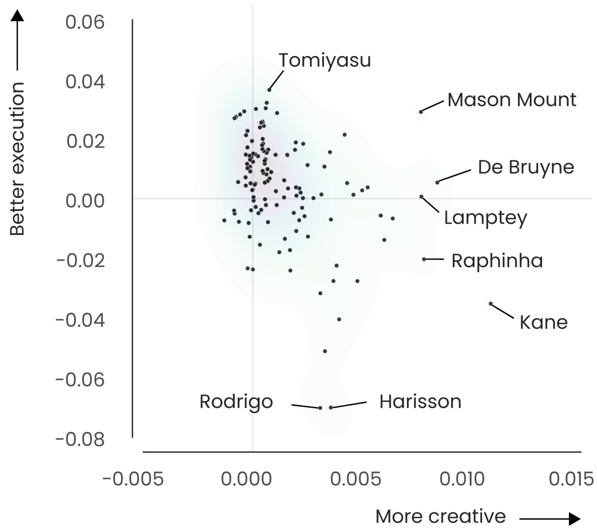
Combining creativity and technical skills

Our creativity metric rewards players who attempt atypical passes, regardless of the result of the pass. While this enables a fine-grained evaluation of a player's creativity, it omits an important piece of a player's performance evaluation. To assess whether a player pairs vision with the technical abilities to successfully complete the passes he attempts, we apply the execution rating metric proposed by Bransen et al. [3]. Their metric measures the technical execution quality of a pass as the difference between the observed outcome of the pass (e.g., did the cross reach a teammate) and the predicted probability that the pass would be successful based on the context under which it was performed. Formally, the Execution Rating (ER) is defined as

$$ER(O = o, D = l \mid S) = [o^{+}] - P(O = o \mid D = l, S)$$

where $[o^{+}]$ takes the value of one if the pass succeeds and is zero otherwise, and $P(O = o \mid D = l, S)$ is given by the action success predictor from the previous section. Intuitively, the metric rewards players who successfully perform difficult passes and punishes players who flub an easy pass.

Figure 4 compares the average CDR and ER of passes, grouped by player. In general, we found no strong relationship between the creative and technical abilities of players. The execution rating is mainly determined by a player's position, with defensive midfielders scoring the highest and strikers scoring the lowest. We assume this is because the consequences of losing possession are less detrimental for attacking players. Hence, they can afford more mistakes.



	Player	ER
1	**Kevin De Bruyne**	0.0054
2	**Tariq Lamptey**	0.0007
3	**Trent Alexander-Arnold**	0.0038
4	**Raphinha**	-0.0203
5	**Hakim Ziyech**	0.0028

Figure 4: The relation between average creative decision rating and execution rating for each player in the 2021/22 English Premier League season (left) and average execution rating for the top-5 most creative players (right). Only players who completed at least 250 passes are included.

Most creative duos

A limitation of our creativity metric is that it gives all credit to the player who gives the pass. Yet, it is often the player on the receiving end who enables the pass by slipping into a pocket of space. Therefore, Table 5 looks at the pairs of players who exhibited the highest creativity with mutual passes. Unsurprisingly, the pairs that rank highest have spent many minutes together on the pitch and are fully attuned to each other. Mohamed Salah and Sadio Mane have led Liverpool's attack for five seasons, while Harry Kane and Heung-Min Son are a sterling duo at Tottenham Hotspur.

Table 5: Player pairs with the highest Creative Decision Rating (CDR) per interaction in the 2021/22 English Premier League season. Only pairs with at least 50 interactions are included.

	Player	Team	CDR
1	**Mohamed Salah** **Sadio Mané**	Liverpool	0.0387
2	**Harry Kane** **Heung-Min Son**	Tottenham Hotspur	0.0202

3	**Leandro Trossard** **Neal Maupay**	Brighton & Hove Albion	0.0132
4	**Bernardo Silva** **Kevin De Bruyne**	Manchester City	0.0126
5	**Kevin De Bruyne** **Philip Foden**	Manchester City	0.0125
6	**Marc Cucurella** **Neal Maupay**	Brighton & Hove Albion	0.0114
7	**Raphinha** **Rodrigo**	Leeds United	0.0114
8	**João Cancelo** **İlkay Gündoğan**	Manchester City	0.0096
9	**Bruno Fernandes** **Cristiano Ronaldo**	Manchester United	0.0095
10	**Jordan Henderson** **Sadio Mané**	Liverpool	0.0079

The link between creativity and position

Being creative is most often associated with the role of a playmaker or "number 10", who typically operates from the position of an attacking midfielder. Figure 5 shows that players who operate from this position indeed score high on our creativity metric. However, we found that wingers are on average the most creative players in the 2021/22 Premier League. This position has become more common for offensive playmakers to carry out in recent years. For example, Messi typically operates from a wide offensive position. Another trend is to use a wingback as a playmaker. This is illustrated by Tariq Lamptey and Trent Alexander-Arnold, who both rank among the top creative players according to our metric.

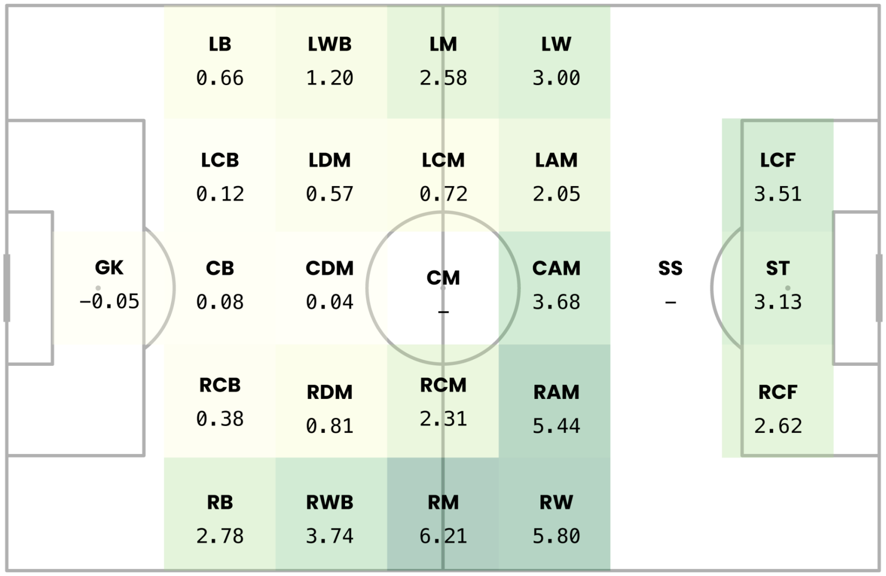


Figure 5: The average creative decision rating per pass, grouped by a player's position on the field. Darker green colors reflect higher creativity. Not enough data was available for the CM and SS positions. For a definition of each position, we refer to StatsBomb's data specification guide.

Interestingly, we found a large imbalance between the left and right wings, with the right wing being significantly more creative. Further research on other leagues should be carried out to determine whether this could be generalized or should be attributed to the player selection in the 2021/22 Premier League season.

The link between creativity and game state

Both the time remaining and the goal difference have no clear effect on the average CDR (Figure 6). However, the variance in creativity increases as time progresses, particularly in injury time. Possibly, this could be attributed to fatigue and teams taking more defensive risks near the end of the game. This creates extra space, which could be exploited with creative passing. However, as players get more tired, this also gives rise to more "missed" creative opportunities.

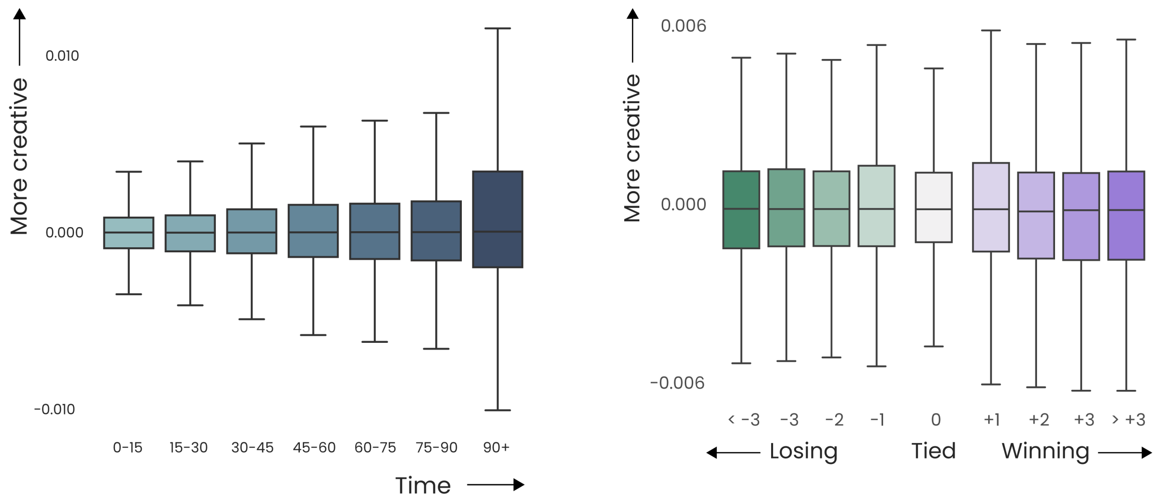


Figure 6: The distribution of the creative decision rating grouped by 15-minute time intervals (left) and goal difference (right). A negative goal difference corresponds to the team in possession being behind.

Related Work

In team sports, creativity has been emphasized as an important factor of success by both researchers [12] and practitioners [2]. Specifically for soccer, Kempe and Memmert [9] showed that successful teams use more highly creative actions to score goals. However, the evaluation of creativity in these studies is mostly conducted via psychological assessments [14,20] or experts rating each action of a player [11,13]. Obviously, this approach does not scale.

Despite being a highly desired attribute, no previous research has looked at statistical models to objectively quantify creativity. That is because creativity is generally seen as an intangible quality, something which cannot be analyzed through statistics. Yet, creativity can be seen as an aspect of decision-making, which is typically evaluated as a trade-off between an action's risks and rewards [4,8,15]. Our creativity metric builds on these risk-reward frameworks, adding a notion of originality and making an abstraction of the actual result of the action [3].

Conclusions

The above-outlined metrics are a first step towards capturing the complex notion of the creative abilities of soccer players. In conclusion, with these metrics, it will be possible to compare different players on their creative abilities in general as well as in various different scenarios. This can provide clubs and analysts with valuable information during the scouting process.

In the future, we plan to extend our creativity metric to other action types, in particular shots and dribbles. Currently, our metric generally undervalues the creativity of passes in game states where a shot or dribble would be the most typical action instead of a pass. Generalizing the pass selection model to an action selection model would solve this problem. Also, it would allow valuing the creativity of other action types. Second, we aim to experiment with alternative approaches for evaluating the value of typical actions. While taking the most likely pass works well in practice, this approach would provide an inaccurate result when multiple passes are equally likely. Finally, we aim to incorporate spatio-temporal tracking data to obtain more accurate estimates for our pass selection, pass success and pass value components.

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