On Ball Value

March 17, 2021

Introduction

Since the team that scores the most goals wins a football match, it is natural and understandable that historically, a lot of emphasis has been placed on goalscorers as primary contributors of value to a team. However, the shortcomings of focusing primarily on goals as a way to assess players became increasingly evident over time as this fails to account for the fact that the opportunity for goalscorers to shoot arises predominantly from contributions by their teammates, without which goalscorers are unlikely to be able to score goals.

Over time, the idea of tracking assists as a statistic started gaining some traction and ended up being the first recognition of the importance of non-goal events with a meaningful contribution to gameplay. This development is relatively recent, though. It was only in 1994 that FIFA started officially tracking assists as part of the World Cup. While a key step in recognising that events that lead to goals are worthy of monitoring, assists are far from a comprehensive solution to the problem of tracking players' contribution to their team's performance.

Since the advent of assists, analysts have developed numerous alternate approaches to attempt to extend the idea of crediting players for valuable events that lead to goals being scored (directly or indirectly) or improving a team's potential for goals being scored. Some examples of these include the idea of key passes, secondary assists, xG Buildup, xT, and several variants/implementations of a possession state value models (PSVM).

The premise of possession state value models is to attempt to objectively and quantitatively measure the value of each event on the pitch by assessing the change in probability of a team scoring and/or conceding as a direct result of the event. There are 2 key benefits to PSVM that other common build-up metrics are unable to adequately take into account. They are:
(a) An ability to differentiate between the value of different passes or actions within a possession chain that leads to a goal.
(b) More importantly, appropriate consideration of the opportunity cost of attempting high-risk actions and losing the ball.

Many of the traditional opportunity creation metrics such as assists, key passes, secondary assists or xG-Buildup all credit players for successful events that lead to goals or goal-scoring opportunities, but don't penalise players for losing possession of the ball, thereby losing the opportunity for the team to score a goal. PSVM are able to value the impact of losing possession of the ball and appropriately penalise players for turnovers of possession based on the loss of probability of scoring a goal, and in most cases go a step further to penalise players for giving the opposition an opportunity to score a goal.

By evaluating each action based on how much they increase or decrease the team's chances of scoring/conceding, we can obtain objective and quantitative player-level assessments of players' contributions to a team's overall performance in matches.

Background and state of the art

Most existing Possession State Value models are trained on event-level data. This is a series of data entries describing events/actions on the pitch, many of which refer to actions taken by players who are in control of the ball and result in the ball moving from one location to another.

Most existing Possession State Value models choose to value possession states instead of actions. This means that instead of trying to infer the value of each action directly, the models aim to assess the value of having possession of the ball the instant immediately before and after each action. The events/actions then serve as a way to transition between these possession states and are generally assigned a value based on the difference in possession value of the possession states they transition from/to.

Existing Possession State Value Models generally follow one of 2 broad approaches:
The first is a Markov Decision Process (MDP), a reinforcement learning model, where we start by considering some objective reward (in most cases goals or xG) and work backwards from the events to see where the actions that resulted in this reward came from. We then look back a step further to see where the events that led to those possession states came from, and so on iteratively until we end up with a convergent estimate of the net overall likelihood of each possession state resulting in a goal.

The other general approach is a supervised machine learning model. This involves describing a possession state (or event) using a set of features and then using one of a number of established regression or other supervised machine learning techniques to best reproduce some target variable, usually the observation of a goal within a certain time or event window, based on the possession state features.

Specific approaches taken by other popular models on event-level data are:

Sarah Rudd: MDP model (at least this is what it was around 2012, it may have changed since)

Karun Singh - xT model: MDP model based on pitch location (discretised). Only considers Goals For. No consideration of Goals Against.

SciSports / KU Leuven - VAEP: Supervised machine learning: Separate CatBoost models trained on the likelihood of scoring and conceding in the next N events. Possession state features include possession history - up to 3 events.

American Soccer Analysis - G+: Supervised machine learning: xgboost trained on the 2-possession net xG. Features include possession chain length until the event and prior event type.

Opta - Possession Value Framework: Supervised machine learning: xgboost trained on the likelihood of scoring in the next 10 seconds

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Model Design Decisions

High-level modelling approach

Similar to many of the other approaches, we decide to value the possession states rather than actions directly. The feature space complexity of possession states is considerably smaller than the complexity of the action feature space, which needs to include information that describes both the start and end states of the action. Because of this, models trained to learn the value of possession states can be trained with a much better fit for the same amount of data than the equivalent action value model. Actions/events are then valued as a transition between possession states based on the difference in value of the possession states immediately preceding and following the action/event.

Model choice

A supervised learning approach was chosen over a reinforcement learning approach. The main reason for this is that MDP-type models handle discrete states, not continuous states. To make MDP models work in football, we generally group together similar events (by location of the pitch in a grid, for example) and treat them as discrete states. This is not a bad approximation but limits the complexity of the feature space that can be used to describe these states, due to the combinatorial explosion in the number of distinct Markov decision state nodes that arises when we combine features. Supervised learning models are much better suited to features that are continuous variables rather than discrete ones, and handle larger and more complex features well. There are several supervised learning models that are able to consider non-linear relationships between the features and the target variable as well as complex interaction terms between features. One example of such a model is the gradient-boosted decision tree model, which is the model we will be using.

Event time window

The value of possession for any given state is approximated as the probability of scoring within a chain of possession and the likelihood of conceding in the opposition's next possession. Since the value of most build-up actions in football are generally contained within the possession chain, we believe this to be an appropriate timeframe to consider. To be able to model the likelihood of scoring and conceding from each possession state, we consider the likelihood of scoring and conceding over 2-possessions (the current possession and the opposition's next possession). Reinforcement learning approaches are generally found to converge within 5-6 events from goal. This is well within the 2 possessions window chosen for our model, which substantiates our timeframe choice as an appropriate one.

However, this choice requires a careful consideration of what we define as a possession. If a series of actions result in a foul being won and a free kick being taken, there are many analytics contexts for which the free kick would usually be defined as the start of a new possession. For the specific case of valuing states, however, all events that led to the free kick being given are directly associated with the outcome of the free kick. Similarly, actions that result in a penalty being won are usually considered beneficial or favourable in football, so events that lead to the penalty being won should be considered part of the possession that led to the penalty. As such, all contiguous possessions from the same team are merged, which links plays interrupted by set-pieces. This allows all events within a build-up play that result in set pieces to be associated with the outcome of the set piece or any goals that may occur downstream from it.

Separate GF and GA models

In addition, unlike some other approaches that train a single supervised model on the net 2-possession xG, we opt to train 2 separate models for the Goals For (GF) and Goals Against (GA) components of possession value. This allows us to understand and visualise the model behaviour better as well as retain a higher level of granularity in the assessments of actions of the pitch, since we can track each event's impact on increasing the team's chances of scoring and decreasing the chances of conceding separately to resolve between attacking and defensive contributions instead of just net Goal Difference (GD).

Training to xG instead of binary goal / no-goal

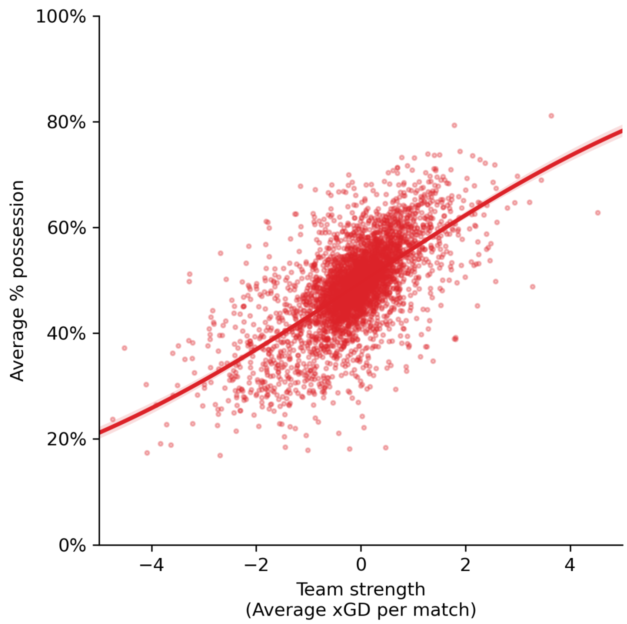
Goals are a relatively rare occurrence in football (only ~1% of possessions result in a goal). Instead of treating our model as a binary classification problem to relate each possession state's features to whether or not a goal was scored later in that possession, we can make use of StatsBomb's xG model to determine the likelihood of each shot downstream in the possession resulting in a goal. The model is then trained on the expected downstream xG within the possession. For cases where multiple shots are taken within a possession chain, we can accurately estimate the xG within that possession as the likelihood of scoring from any of those individual shots, which is given by:

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

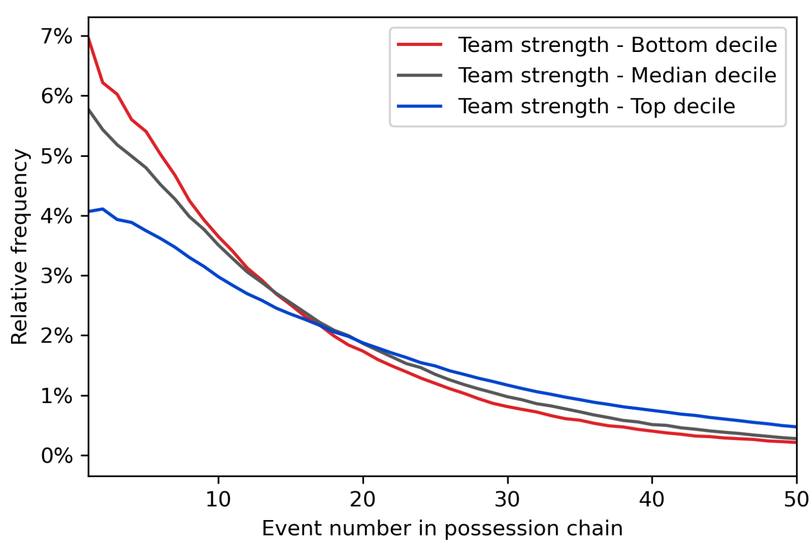
Possession state features

One of the next critical decisions that needs to be made is the selection of features that are included in the model to estimate the possession state's value. We have chosen to include features describing the pitch location (x and y coordinates as well as distance to goal, angle to goal, and angle subtended by goalposts), action context (Free kick, open play, etc.), whether the event was carried out while pressured from an opposition player, and body part used for the event (Head, Foot, etc.).

An active decision was made to exclude possession history features. This is because none of the possession features are intrinsically linked to an increase in likelihood of scoring downstream within the possession. Some other implementations of GVA/OBV include possession history features with the justification that these features stand in as proxies for contextual information that we don't have more direct data for e.g. markers for counterattacks to provide some indication of likely opposition defensive structure. This is an enticing idea since inclusion of some possession history features does improve the log-likelihood of the model fit. However, we have little control of what the proxy variables are actually acting as a proxy for. It would be elegant and desirable for these variables to act as proxies for the availability and location of teammates as well as defensive structure of the opposition but, in practice, many possession history features correlate strongly with other factors such as team play style and more importantly, team strength, as shown below.

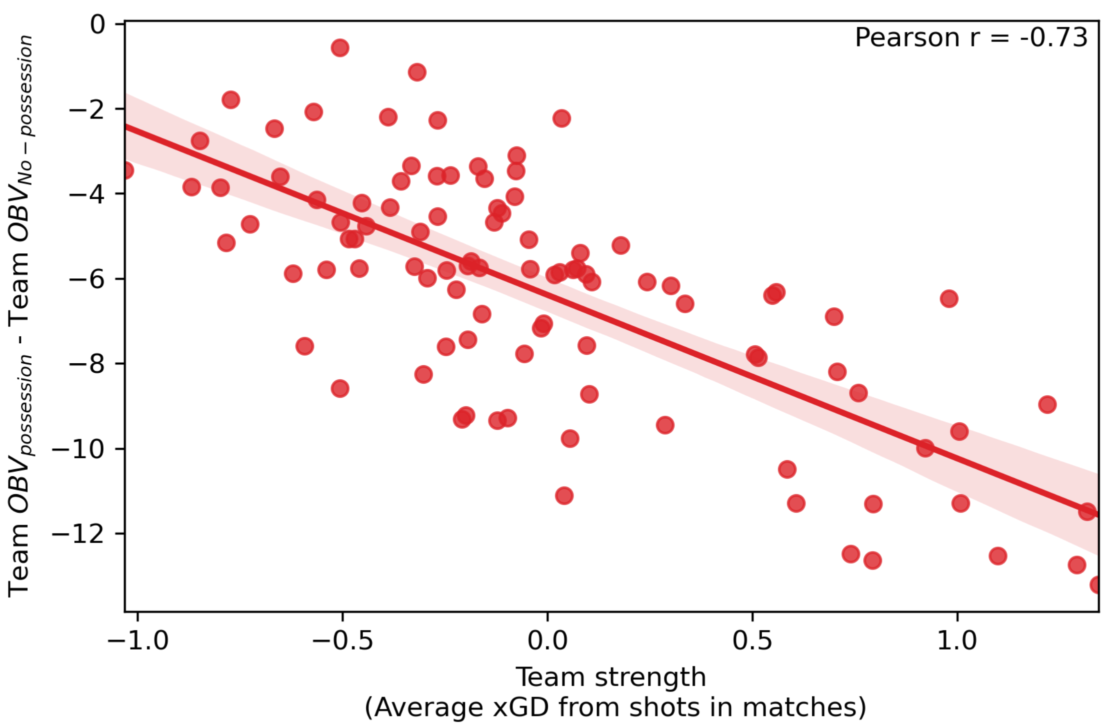


Let us consider possession chain length. We can see from the plot above that stronger teams tend to hold on to possession for longer, on average, than weaker teams do, so will have longer possession chains. This means that events with possession history associated with a ball recovery many events in the past, a relatively large amount of time in the past or from further away on the pitch are likely to be disproportionately representative of the possession xG from stronger teams (a case of censorship/survival bias).



The inclusion of these features in the model would therefore act as an indirect proxy for team strength, leading to a systematic bias in the model that shifts xG values for teams with longer possessions as a consequence, and an apparent better fit in the model from leaking team strength information into the xG model with possession duration as a proxy. Using a model that includes possession history features would then drift away from a "like-for-like" evaluation of events.

Such a model's assessment of a particular player's actions on the pitch then becomes invariably tied to the strength of the team. So the value associated with a forward pass following a long possession will differ to that of an identical pass in the same area of the pitch under similar conditions but with a shorter possession history (high possession teams are more likely to convert from any given state). So, a player that plays any given selection of successful passes for a team like Man City will therefore be assessed differently in general than a player who plays the exact same passes successfully for a team whose possession histories tend to be shorter. Losses of possession will also be penalised more aggressively in high possession teams for giving away the ball from a higher PV state. We have tested the impact of including possession features in the OBV model, and found that there is indeed a strong relationship between team strength and the impact of including possession features in the model, as shown below.



The lower OBV observed for strong teams when possession features are included are the result of a second order effect. The possession value will be higher for stronger teams across the entire pitch, but this increase is not necessarily even. Because stronger teams expect to face lower possession attrition during build-up than weaker teams, the difference in possession value between strong and weak teams is more evident further back in the pitch, where weaker teams are expected to lose the ball in the buildup. The difference in PV between strong and weak teams therefore diminishes as you get closer to the opposition goal. Since OBV for actions are associated with the change in PV, the OBV for successful attacking events will generally be lower for high possession or stronger teams than weaker teams.

The team-strength-dependence is an undesirable characteristic for a model whose objective it is to assess players objectively and to compare players' skill levels. In addition to the observation above, the OBV models that included possession features led to less self-consistent assessments of players. The latter observation is consistent with research that has shown that player assessments using KU-Leuven's VAEP model (which includes possession features) is less robust than player assessments using the xT model.

Despite the better model fit metrics on inclusion of possession features, we believe that a possession value as a true state function rather than a path function (i.e. the possession value of a given snapshot in time in the game is consistent regardless of how a team got to that particular state) is a more appropriate representation of the factors that describe the intrinsic possession value of a possession state.

It is important to note that we are not suggesting that additional contextual information is not important for OBV models. Factors such as teammate positions and opposition defensive structure and player velocities and directions should all be taken into account, if possible. However, we believe that possession features are a poor proxy for these since they have the unintended consequence of serving as proxies for team strength and playing style, leading to models with systematic bias aligned with team strength and certain playing styles.

After some deliberation on the impact of including proxy features and the results of preliminary experiments, we hold the view that the most appropriate way to incorporate the contextual information in OBV models is to include features derived from tracking data or similar data sources at the point in time of the possession state that are able to capture the contextual information more directly instead of using possession history information as a proxy to attempt to fill-in for the absence of a more direct representation of this information.

Crediting shots based on xG or PS xG.

From the perspective of goal-scoring likelihood, a player's decision to shoot is associated with a change in probability of scoring from the Goals For component of Possession Value (PV-GF) to the shot xG from the location of the shot, taking into account all characteristics of the shot including location of all players. The shot execution (primarily placement) is then associated with a transition from xG → post-shot xG. The actual outcome of the shot beyond post-shot xG is then a function of the goalkeeper's positioning, ability, and to some extent, random chance and other factors not captured by the models. As such, the overall OBV-GF associated with shots for the players taking the shot should be PSxG – PV-GF. For cases where the shot is blocked, no PS xG information is available. For these cases, the best estimate for the likelihood of scoring from the shot is given by the shot xG. Our approach therefore assigns OBV-GF for these cases as xG – PV-GF.

From a goalkeeper's perspective, the likelihood of conceding (PV-GA) when facing a shot is the PS xG of the shot. Any goals conceded lead to a GV-GA of 1. Any saves lead to a transition in likelihood of conceding from PS xG to the PV of the subsequent possession state. This corresponds to the value of the goalkeeper having possession if a controlled save is made, or the possession value of whoever has possession of the ball, if the ball is parried.

Other approaches to this problem typically resort to crediting the shot-taker by either xG, which just credits the decision to shoot, and disregards the shot execution characteristics, or outcome - xG, which conflates the role the shot-taker and the goalkeeper play in the shot sequence, and leads to a higher variance in player shooting ability estimates. We believe that partitioning the value of shots between the shot-taker and goalkeeper based on post-shot xG strikes the best balance between these other extremes, and takes into consideration the role each player plays in altering the goal -scoring or -conceding likelihoods.

True possession states and transition states

Since the approach we propose is centred around possession states, we must carefully consider the appropriate way to handle events that aren't true possession states. Some examples of this are fouls committed, tackles (which may or may not subsequently lead to control of possession), blocks, etc. These differ from events like passes or carries that are much more robust indicators that the team carrying out the event is in firm control of possession. To handle this difference, we distinguish event types into true possession states and transition states and assign event rewards differently for true possession and transition states.

Value of actions at true possession states are assigned a value based on their start and end true possession state values. In most cases, this simply means that the value of an event corresponds to the difference in value between start and event states. However, if an action is interrupted by a touch of the ball that does not represent control of possession (i.e. transient possession state), then the event's value is based on the value of the next true possession state i.e. the possession state following the transient possession state. As an example: If a pass is blocked but that block results in the ball going out for a throw-in, the touch that led to the ball going out is considered a transient state and the passer is assigned a value based on having possession at the point where the pass was made to the resulting value of the throw-in, rather than the value of turning over possession to the opposition. The player is thus assigned a reward based on the net effect of the action, so even if the action was considered unsuccessful, the net effect still involves the player's team being in possession of the ball from a throw in. This plays out in a similar way for other transient states to allow attacking players to be credited for winning corners, fouls, etc. if the next true possession state has a higher Possession Value than the state preceding it. For most successful events, this plays out in a more intuitive manner than if we were to associate the value of all actions to the difference in the possession value between start and event states for all cases.

Actions associated with transient possession states are valued as the difference in possession value from the last known true possession state and next known true possession state. The events could be associated with the recovery of the ball, but can also be associated with an immediate turnover of possession (hence the term Transient state).

As an example, if a defender blocks a shot, but the ball immediately falls to another attacker, then the value of the defensive action (transient state) is determined by the difference in the value of the possession states immediately preceding and following it i.e. PV of the attacker if falls to - Shot1 xG. This credits defenders for defensive actions that suppress the opposition's chances of scoring, even if they do not recover ball possession.

If the ball ends up being recovered by the defending team following a transition state, then the event would be valued in a similar manner to a true possession state since the next true possession state will be the defending team in possession of the ball in a similar area of the pitch.

Ball-receipt credit

We have chosen not to credit pass recipients. While there can be some value to receiving the ball and holding up play, most of that benefit comes from movement of players off-the-ball. This is very challenging to quantify with event-level data. From the perspective of the ball location and event data, there is no intrinsic value to receiving a ball. If players go on to lose the ball every time they receive it, the outcome is largely indistinguishable from the players not receiving it in the first place, which indicates that the ball receipt itself does not add value. However, players that are able to put themselves in good positions to receive the ball give themselves an opportunity to follow that up with an action. Players that are good at receiving the ball are therefore rewarded (or penalised) indirectly based on the outcome of the subsequent event, which would not have occurred if the player had not successfully received the ball. This approach differs from ASA's G+ approach where recipients are credited with a fraction of the pass's OBV based on the pass difficulty.

Summary of key merits and limitations of the approach

Key merits of the approach:

• **Careful consideration of the implications of using conventional definitions of possession:** How other models treat possessions is generally under-documented, but it's likely that treatment of possessions is handled in ways that lead to set pieces being considered the start of a new possession (e.g. the default possession definition in SBD).

• **PV model trained on StatsBomb xG:** Many other models train directly on the observation of goals. Using xG to estimate the goals scored from each possession allows us to train models more accurately with the same amount of data by reducing the variance and class imbalance of the otherwise binary target variable. The only other model known to be using xG is ASA's G+ model, but our approach should be an improvement due to the xG model considering the shot freeze frame and being known as the most performant xG model.

• **Statistically robust treatment of xG within a possession chain:** In order to estimate downstream xG within a possession, we use a statistically robust xG aggregation method within possession chains. There is little documentation or explanation on how xG is aggregated within possession chains, if any, for other models that use a similar approach (e.g. ASA's G+ model)

• **We retain the GF and GA components forward:** The GF and GA components of each event's value are retained instead of folding them into GD early in the process. This allows us to obtain the net defensive and attacking contributions from each player. ASA's G+ is known to merge these early in the process, thereby losing some assessment fidelity. VAEP appears to retain them, but none of the output indicates that the separate GF and GA components are being used.

• **Introduction of the concept of transient states:** This allows us to differentiate between events indicative of robust control of possession (e.g. Passes, Carries) and transient states to represent touches of the ball that are not themselves makers of having firm control of possession, but may lead to control of possession. Introducing the concept of transient states allows us to reward attacking players for events that are blocked by the opposition, but lead to corners, throw-ins, etc. Transient states also allow us to reward defenders more accurately based on the net effect of their actions on the state of the game.

• **Value shots and GK events based on xG and post-shot xG:** In order to maximise fidelity of goalscoring likelihood estimates for shots, we use our state of the art xG and post-shot xG models. These should be an improvement over other models based on the inclusion of shot freeze-frame data.

Key limitations of the approach:

• **Valuation of unobserved events:** This approach is able to value any observed action sequences in matches because they're all real transitions between observed states, each of which can be directly valued by the model. However, the model is unable to properly value hypothetical or unobserved events i.e. how much OBV would this pass have added, had it been successful? Or which is the most valuable action from the range of actions available? unless some large assumptions are made on the likely end positions and circumstances of those hypothetical events

• **Valuation of defensive actions:** Defensive actions are valued based on how they change the pitch location and team in possession of the ball. They do not take into account the value of the dribble or carry that would have been made had the tackle not occurred. Similarly interceptions are valued based on the transition from the passer to the player recovering the ball. There is no consideration of the value of the state that would have been observed had the pass been completed i.e. if the interception prevents an attacking player who is in a very dangerous position from receiving the ball, that is not taken into account. Since the defensive actions are valued based on events, defensive players are also not penalised for allowing opposition attacking events to happen.

Methodology

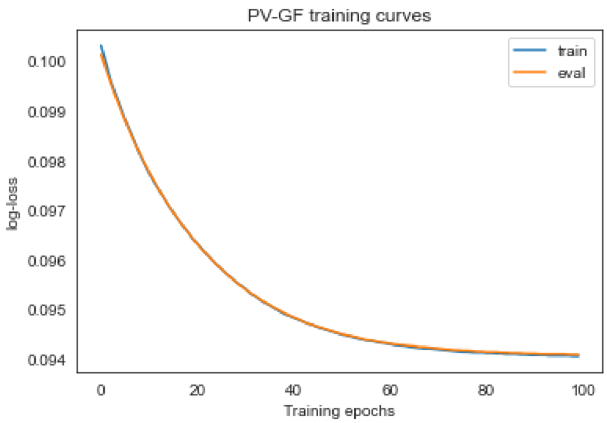
Two xgboost models are trained to estimate the likelihood of scoring in the current possession chain, and conceding in the next possession chain respectively based on the xG within the possession chain. The features used for these models are outlined in the previous section. We refer to these models as the PV-GF and PV-GA models.

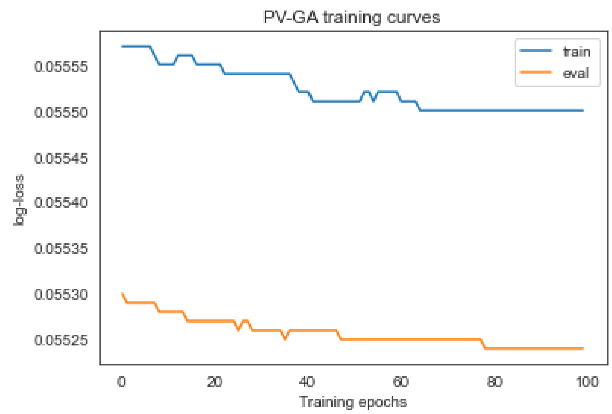
Actions are valued based on the difference in possession values in the possession states they transition between, with a reversal of PV-GF and PV-GA for cases where possession is recovered or given away. Transient states are valued based on the transition from the possession state prior to the transient state to the possession state following the transient state. Transient states include Block, Tackles, Interceptions, Clearances, GK Sweep and GK Save events.

Model Evaluation

Model performance characteristics

Model Training curves

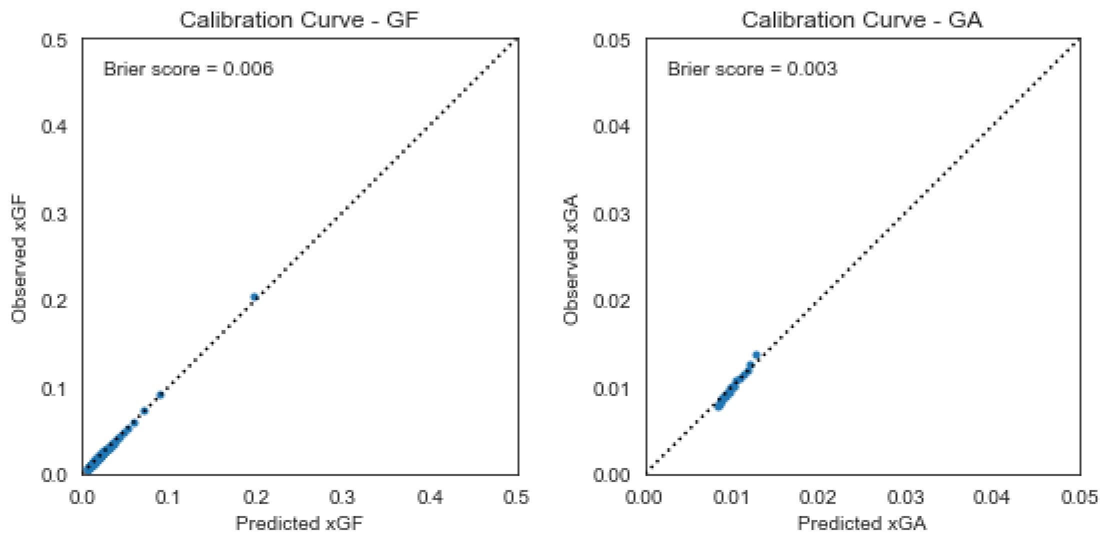




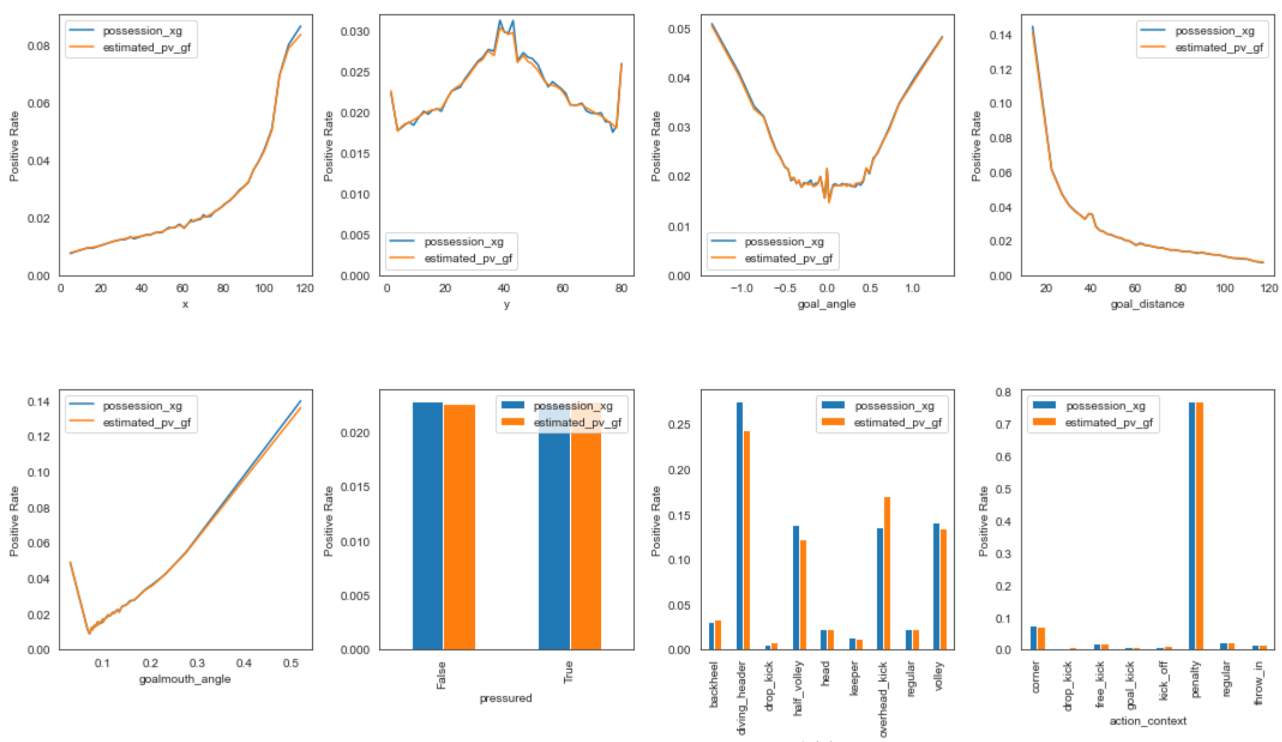
Log-loss table

	Training	Evaluation
Possession Value - Goals For (PV-GF)	0.09405	0.09408
Possession Value - Goals Against (PV-GA)	0.05551	0.05525

PV-GF and PV-GA probability calibration curves

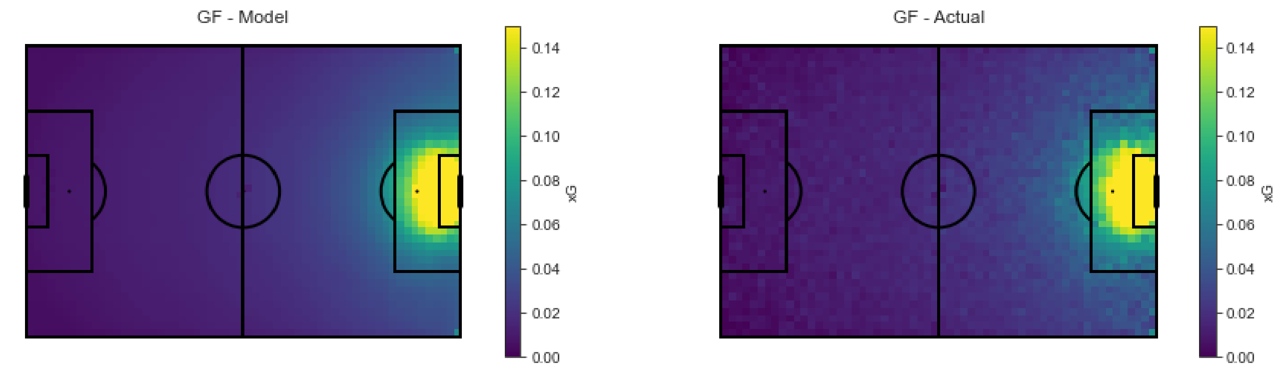


Sensitivity to state features



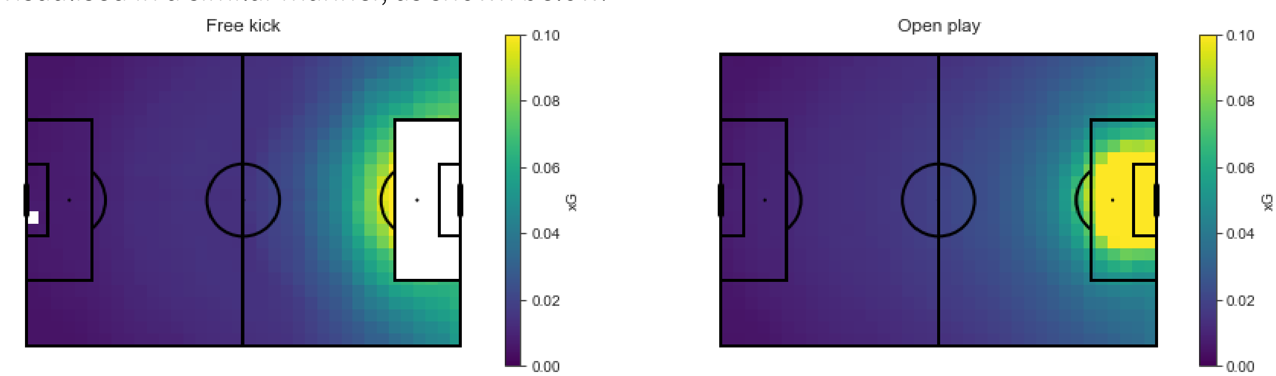
The plots above are a useful way to verify the model's sensitivity and response to the input features, and indicate a good level of sensitivity to all features included in the model. Some categorical features with a low incidence rate e.g. diving headers and overhead kicks exhibit a greater level of discrepancy between predictions and observations, but higher levels of discrepancy are expected naturally for groups with lower sample sizes based on random sampling.

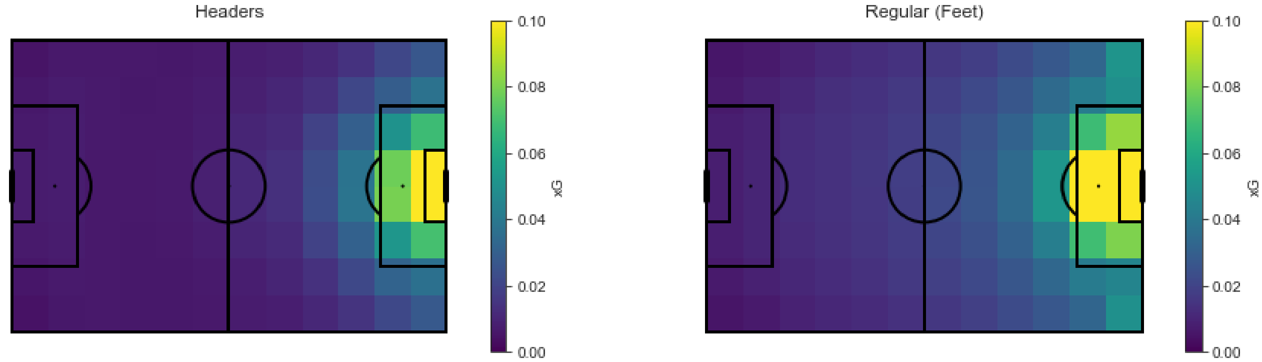
Below are plots comparing the PV-GF surface from the model and the average observed downstream possession xG for each observed location.



The plots indicate that the model represents a smoother version of the actual downstream expected GF surface, as expected. Moreover, the shape and magnitude of the surfaces are consistent with other models trained to estimate similar surfaces e.g. Karun Singh's xT model.

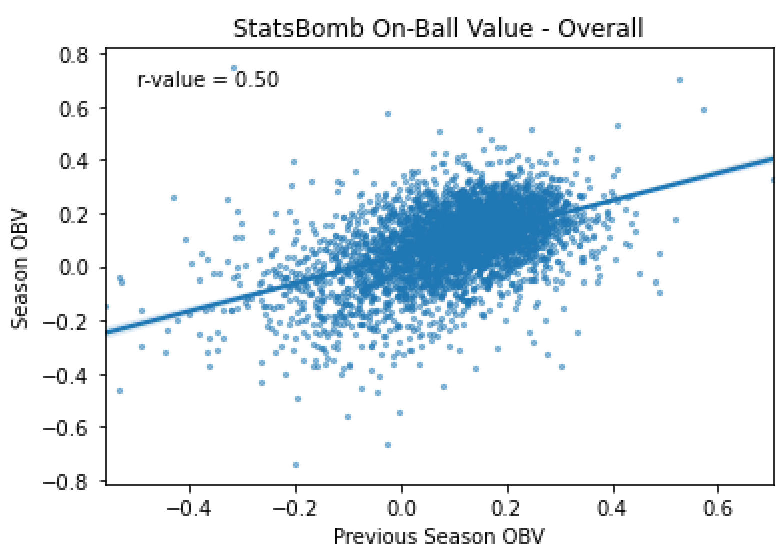
The model's sensitivity to the body part used for the event and the action context can also be visualised in a similar manner, as shown below.



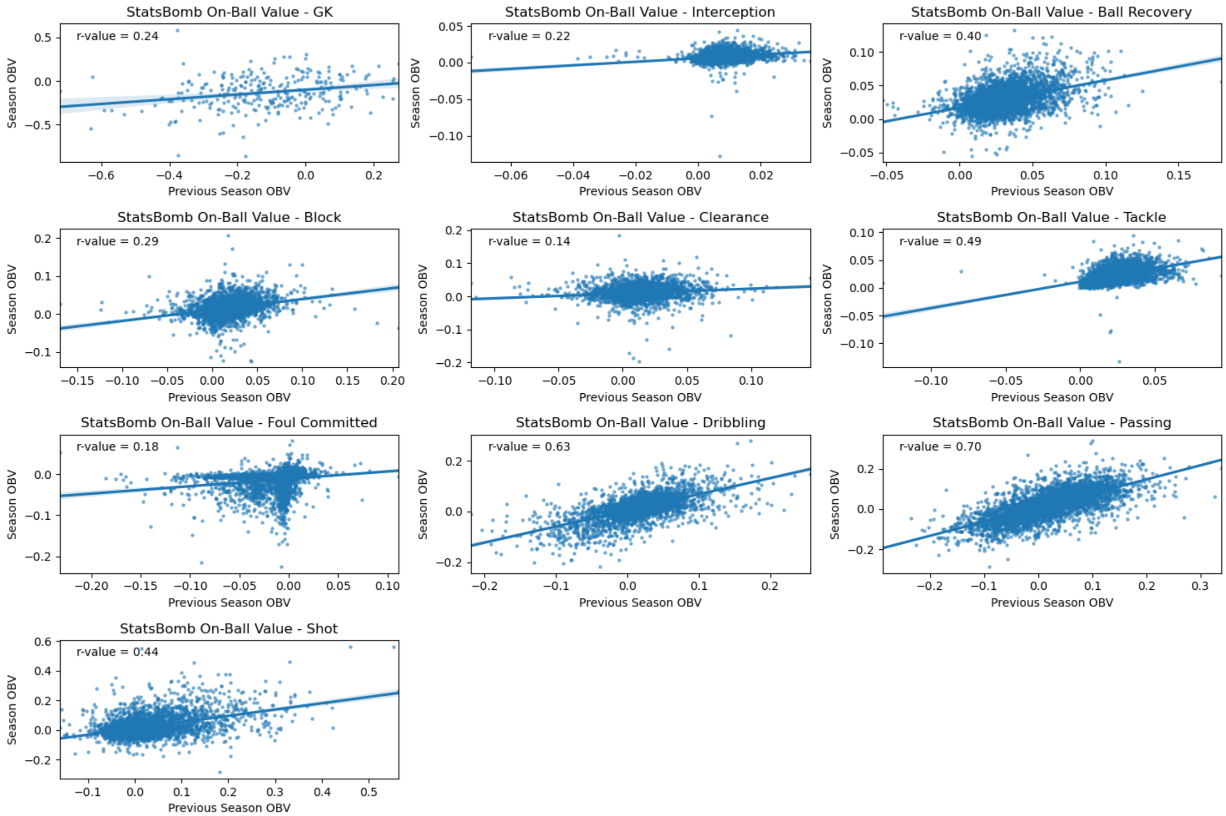


Robustness and Autocorrelation

One way to measure the robustness of the OBV metric is to look at the seasonal autocorrelation (correlation of player assessments between successive seasons) for players that meet a minimum threshold of 500 minutes played across both seasons. The extent to which the values are self-consistent across successive seasons can be summarised using the r-value of the seasonal correlation. Doing this shows that there is a reasonable level of self-consistency with which the model assess players.



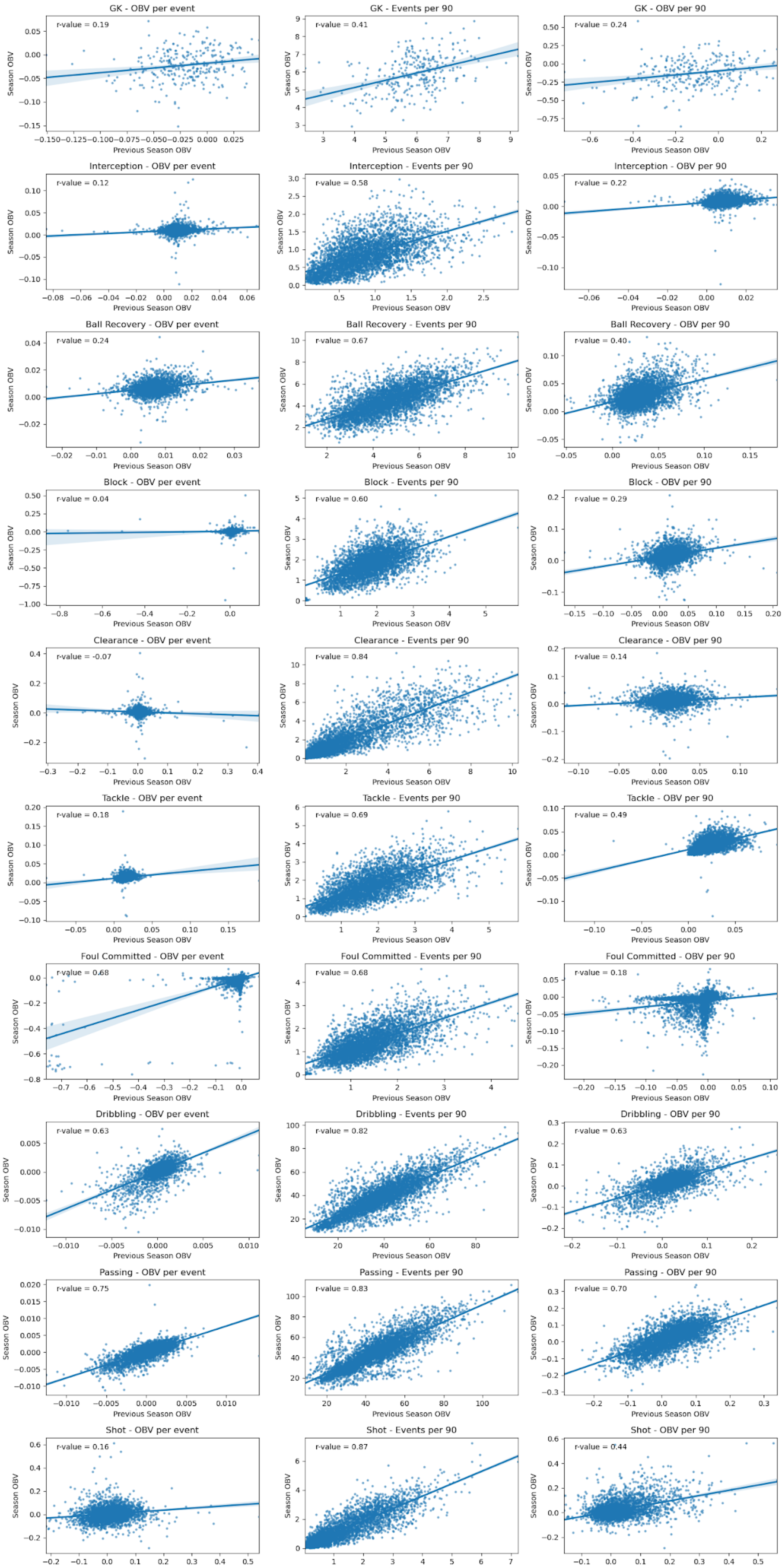
This assessment can be deconstructed at an event level to obtain a better understanding of the robustness of the individual OBV rating components.



Events with a high number of observations such as passes and progressive ball movements (carries + dribbles) are the most robust, as expected, since higher sample sizes reduce the uncertainty in the mean of the skill metric estimate. Ball recoveries and tackles also have relatively robust measures. Most other event types have lower robust estimates largely due to the lower sample sizes observed for those events.

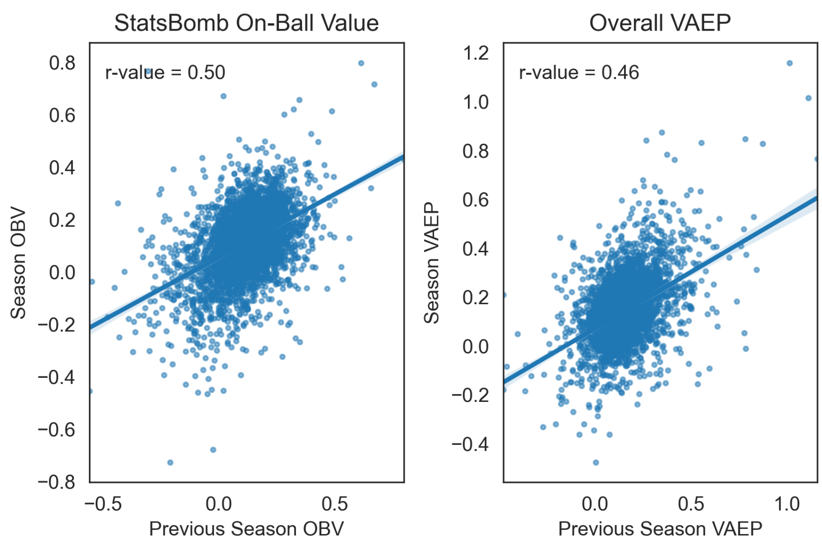
Since the overall OBV for a player is a product of their ability at the event type (Average OBV per event) and how often they play that event in a match, we can also deconstruct the OBV autocorrelations to mean OBV per event and events per 90 to obtain a better understanding of when variations in OBV arise from differences in event rates rather than underlying ability (OBV per event).

The results show that there is a significant skill component (average OBV per event) to Overall OBV measures, rather than just measuring event volumes. This is particularly true for events such as passing and dribbling (which include carries). Using discrepancies in measures such as OBV per event and overall OBV allows us to identify players that excel at a particular event type, even when their overall contribution isn't very high due to a lack of participation in events of that type.


GK - OBV per event
r-value = 0.19
GK - Events per 90
r-value = 0.41
GK - OBV per 90
r-value = 0.24
Interception - OBV per event
r-value = 0.12
Interception - Events per 90
r-value = 0.58
Interception - OBV per 90
r-value = 0.22
Ball Recovery - OBV per event
r-value = 0.24
Ball Recovery - Events per 90
r-value = 0.67
Ball Recovery - OBV per 90
r-value = 0.40
Block - OBV per event
r-value = 0.04
Block - Events per 90
r-value = 0.60
Block - OBV per 90
r-value = 0.29
Clearance - OBV per event
r-value = -0.07
Clearance - Events per 90
r-value = 0.84
Clearance - OBV per 90
r-value = 0.14
Tackle - OBV per event
r-value = 0.18
Tackle - Events per 90
r-value = 0.69
Tackle - OBV per 90
r-value = 0.49
Foul Committed - OBV per event
r-value = 0.68
Foul Committed - Events per 90
r-value = 0.68
Foul Committed - OBV per 90
r-value = 0.18
Dribbling - OBV per event
r-value = 0.63
Dribbling - Events per 90
r-value = 0.82
Dribbling - OBV per 90
r-value = 0.63
Passing - OBV per event
r-value = 0.75
Passing - Events per 90
r-value = 0.83
Passing - OBV per 90
r-value = 0.70
Shot - OBV per event
r-value = 0.16
Shot - Events per 90
r-value = 0.87
Shot - OBV per 90
r-value = 0.44
Season OBV
Previous Season OBV

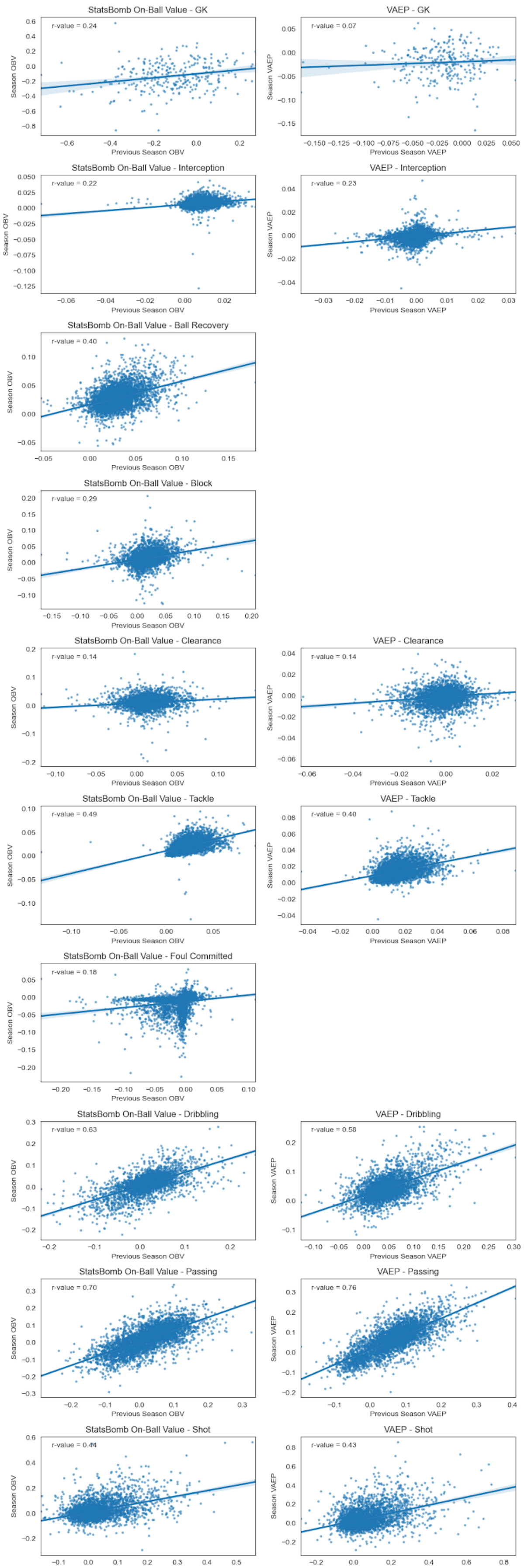
Comparison with VAEP

The autocorrelation values can be difficult to interpret on their own. It can often be helpful to have a benchmark model to compare against. In this section, we compare OBV autocorrelations to its analogous VAEP values determined using StatsBomb data, for the Euro top 5 leagues from 2016/2017 to 2019/2020 (inclusive). The plot below indicates that the overall autocorrelation of the StatsBomb OBV model is slightly more robust season-to-season, on average, than the VAEP model.



VAEP has its own internal handling of event types that don't correspond perfectly to the event type categorisation used in the OBV model. Nonetheless, we have grouped VAEP's event types in ways that most closely match OBV's event types to obtain as close to a like-for-like comparison of the event-type rating robustness as possible.

The assessment of player contribution by event type is more self-consistent with our model compared to VAEP for most event types. One notable exception to this is passes, where the self-consistency is greater with VAEP than OBV. The exact cause for this difference remains unclear, but it is likely that the team-strength bias built into the VAEP model as a result of including possession history features plays a part in artificially increasing the player-level value contribution assessments since the abundance of pass events allows that systematic bias to surface more reliably.


StatsBomb On-Ball Value - GK
r-value = 0.24
VAEP - GK
r-value = 0.07
StatsBomb On-Ball Value - Interception
r-value = 0.22
VAEP - Interception
r-value = 0.23
StatsBomb On-Ball Value - Ball Recovery
r-value = 0.40
StatsBomb On-Ball Value - Block
r-value = 0.29
StatsBomb On-Ball Value - Clearance
r-value = 0.14
VAEP - Clearance
r-value = 0.14
StatsBomb On-Ball Value - Tackle
r-value = 0.49
VAEP - Tackle
r-value = 0.40
StatsBomb On-Ball Value - Foul Committed
r-value = 0.18
StatsBomb On-Ball Value - Dribbling
r-value = 0.63
VAEP - Dribbling
r-value = 0.58
StatsBomb On-Ball Value - Passing
r-value = 0.70
VAEP - Passing
r-value = 0.76
StatsBomb On-Ball Value - Shot
r-value = 0.44
VAEP - Shot
r-value = 0.43
Season OBV
Previous Season OBV
Season VAEP
Previous Season VAEP

Results

The tables below list the top performers according to the OBV model, at an overall level as well as based on some specific event types.

Top 20 overall player performances by season for players in the Euro Top 5 leagues between 2016-17 and 2019-20, according to the OBV model:

Player	Team	Season	OBV p90
Lionel Messi	Barcelona	2018/2019	0.80
Kylian Mbappé	Paris Saint-Germain	2019/2020	0.72
Kylian Mbappé	Paris Saint-Germain	2018/2019	0.67
Neymar	Paris Saint-Germain	2017/2018	0.66
Josip Iličić	Atalanta	2019/2020	0.62
Lionel Messi	Barcelona	2017/2018	0.61
James Rodríguez	Bayern Munich	2018/2019	0.60
Kylian Mbappé	AS Monaco	2016/2017	0.53
Riyad Mahrez	Manchester City	2019/2020	0.53
Marcel Halstenberg	RB Leipzig	2018/2019	0.50
Arjen Robben	Bayern Munich	2017/2018	0.50
Philippe Coutinho	Liverpool	2017/2018	0.49
Lionel Messi	Barcelona	2016/2017	0.49
Dimitri Payet	Marseille	2017/2018	0.48
Cesc Fàbregas	Chelsea	2016/2017	0.48
James Rodríguez	Real Madrid	2016/2017	0.47
Łukasz Fabiański	West Ham United	2018/2019	0.47
Philipp Max	Augsburg	2017/2018	0.46
Ashley Young	Inter Milan	2019/2020	0.46
Franck Ribéry	Bayern Munich	2017/2018	0.45

These results appear to be consistent with professional consensus of who the best players in the last 5 years have been, with most entries in this list aligning with players in the UEFA team of the year for their respective seasons. The list does, however, exhibit a bias towards attacking positions. A more balanced ranked list can also be obtained by looking at player OBV z-scores relative to other players in their position. For a more robust assessment of the top players, we can also aggregate data across several league seasons to obtain a more comprehensive and less temporal view of the best players in top 5 leagues in Europe across the last 5 years. The results of the top players by z-score (by position) since 2016/2017 are shown below:

Player	OBV p90 z-score
Lionel Messi	5.59
Kylian Mbappé	3.36
Papu Gómez	3.23
Kevin De Bruyne	3.11
Toni Kroos	2.90
Riyad Mahrez	2.49
Mohamed Salah	2.39
Mats Hummels	2.36
Pierre-Emerick Aubameyang	2.31
Aleksandar Kolarov	2.13

Besides being able to rank players by overall OBV contribution, we can also rank players by OBV contribution from specific event types to identify players that excel at specific aspects of the game. The tables below show some examples of this for shots, dribbles (including carries) and tackles.

Top 20 **finishers** by season for players in the Euro Top 5 leagues between 2016-17 and 2019-20, according to the OBV model:

Player	Team	Season	OBV p90
Kylian Mbappé	Paris Saint-Germain	2019/2020	0.57
Lionel Messi	Barcelona	2018/2019	0.56
Kylian Mbappé	Paris Saint-Germain	2018/2019	0.55
Lionel Messi	Barcelona	2017/2018	0.46
Kylian Mbappé	AS Monaco	2016/2017	0.42
Nils Petersen	Freiburg	2016/2017	0.42
Erling Haaland	Borussia Dortmund	2019/2020	0.39
Álvaro Morata	Real Madrid	2016/2017	0.38
Ante Rebić	AC Milan	2019/2020	0.38
Mohamed Salah	Liverpool	2017/2018	0.37
Josip Iličić	Atalanta	2019/2020	0.36
P-E Aubameyang	Arsenal	2017/2018	0.36
James Rodríguez	Bayern Munich	2018/2019	0.36
Luis Suárez	Barcelona	2016/2017	0.34
Edinson Cavani	Paris Saint-Germain	2017/2018	0.33
Gabriel Jesus	Manchester City	2017/2018	0.33
Neymar	Paris Saint-Germain	2017/2018	0.33

Lionel Messi	Barcelona	2016/2017	0.33
Olivier Giroud	Arsenal	2016/2017	0.32
Luis Muriel	Atalanta	2019/2020	0.32

Top 20 **dribblers** by season for players in the Euro Top 5 leagues between 2016-17 and 2019-20, according to the OBV model:

Player	Team	Season	OBV p90
Eden Hazard	Real Madrid	2019/2020	0.28
Riyad Mahrez	Manchester City	2019/2020	0.27
Diego Perotti	AS Roma	2016/2017	0.26
Neymar	Barcelona	2016/2017	0.23
Ismaïla Sarr	Metz	2016/2017	0.20
Arjen Robben	Bayern Munich	2016/2017	0.20
Arjen Robben	Bayern Munich	2017/2018	0.20
Joaquín Correa	Lazio	2019/2020	0.19
Ryan Fraser	AFC Bournemouth	2016/2017	0.18
Diego Farias	Cagliari	2016/2017	0.18
Franck Ribéry	Bayern Munich	2018/2019	0.18
Yevgen Konoplyanka	Schalke 04	2017/2018	0.18
Vinícius Júnior	Real Madrid	2019/2020	0.18
Kingsley Coman	Bayern Munich	2017/2018	0.18
Anthony Martial	Manchester United	2018/2019	0.18
Franck Ribéry	Bayern Munich	2017/2018	0.18
Paulo Dybala	Juventus	2019/2020	0.17
Youcef Atal	OGC Nice	2018/2019	0.17
Raheem Sterling	Manchester City	2017/2018	0.17
Eden Hazard	Chelsea	2018/2019	0.17

Top 20 **tacklers** by season for players in the Euro Top 5 leagues between 2016-17 and 2019-20, according to the OBV model:

Player	Team	League	OBV p90
Valon Behrami	Udinese	2017/2018	0.08
Emiliano Velázquez	Rayo Vallecano	2018/2019	0.08
Marash Kumbulla	Hellas Verona	2019/2020	0.08
Ozan Kabak	Schalke 04	2019/2020	0.07
Gojko Kačar	Augsburg	2016/2017	0.07

Casemiro	Real Madrid	2016/2017	0.07
Benjamin Hübner	Hoffenheim	2016/2017	0.07
Gabriel Mercado	Sevilla	2017/2018	0.07
Valon Behrami	Udinese	2018/2019	0.07
Tom Trybull	Norwich City	2019/2020	0.07
Daniele Rugani	Juventus	2016/2017	0.07
Eric Bailly	Manchester United	2016/2017	0.07
Ander Herrera	Manchester United	2017/2018	0.07
Federico Ricca	Málaga	2017/2018	0.07
Lucas Biglia	AC Milan	2018/2019	0.07
Paul Baysse	OGC Nice	2016/2017	0.07
Luca Kilian	Paderborn	2019/2020	0.07
Jordi Amat	Swansea City	2016/2017	0.07
Gelson Fernandes	Rennes	2016/2017	0.07
Pablo Zabaleta	Manchester City	2016/2017	0.06

Conclusion

We have developed an approach to quantitatively and objectively value all events that occur on the pitch in football based on how they change teams' likelihood of scoring and conceding goals within the subsequent parts of the possession chain. The event probability estimates are well calibrated and the model is responsive to the event start and end locations as well as contextual information such as the part of the body used to perform actions, the play context (open play, set piece, etc.) and whether the event was performed whilst under pressure from the opposition. Using this approach to value and rank players yields player lists that include numerous UEFA team of the year members at the top of the list. The approach is flexible enough to value all event types separately to break down a player's assessment into arbitrary sub-divisions and sub-classifications e.g. value lost from unsuccessful passes, value added from passes to a particular other player, etc. and allows for a more accurate, flexible and granular way to value both teams and players in football.