Boot It: A Pragmatic Alternative To Build Up Play

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Introduction

A player wins possession deep in their own half, and immediately, shouts echo from the sideline: “BOOT IT!”… Up until the early 2000s, this was a common refrain at soccer matches across all levels and age groups. Back then, the only responsibility of a defender was to ensure goals were not conceded—passing skills were hardly a concern. Likewise, when a goalkeeper gained control of the ball or took a goal kick, the most frequent expectation was to "send it long".

Today, however, it is increasingly rare to see players kick a long ball to escape pressure and gain a positional advantage on the field at the cost of losing possession. A well-known trend in modern soccer is for teams to patiently build up play from deep within their own half or even from within their defensive box [1]. This strategy is often favored even when facing intense pressure from nearby opponents, where one might expect a more pragmatic approach of clearing the ball to avoid losing possession in a dangerous area.

Nevertheless, even when there is no immediate risk of losing the ball, sacrificing possession in exchange for a positional advantage seems more effective than stalling in long possession chains where no chances are created. Moreover, the odds of scoring from a possession originating in the defensive zone decrease with the duration of the possession [2]. The rise of counter-pressing—where teams immediately apply pressure after losing possession—further highlights the potential benefits of turning over the ball in advanced areas.

Therefore, the underlying hypothesis of this research is that—in certain situations—it might be both less dangerous and more effective to try regaining possession close to the opponent’s goal and score from there, rather than building up an offensive play from the back at the risk of losing the ball in a vulnerable location.

Specifically, we will investigate the trade-off between diligently constructing an offensive play from the back and directly kicking a long ball out of bounds in the opponent's defensive third. While the latter option may seem unconventional, intentionally playing the ball out is not an entirely radical idea—regularly you see teams employing it as a kick-off strategy.[1] The underlying belief is that an opponent throw-in in the corner of the pitch is worth more than established possession in the center of the pitch.

We see three reasons why kicking the ball out of bounds might be a valuable option, more so than just launching the ball forward. First, professional players should consistently be able to clear the ball out of play near the final third from the midfield area. Second, a throw-in provides the attacking team ample time to regroup and establish an organized press. Third, previous research has shown that possession is more likely to be lost than retained for throw-ins taken within 20 yards (~18m) of a team's own goal [3].

In this work, we empirically evaluate the trade-off between trying to retain possession versus intentionally putting the ball out of play near the opponent's goal for a throw-in using a mix of basic statistical analysis and machine learning. First, we perform a simple analysis that divides the pitch into coarse-grained bins based solely on location (i.e., all other context is ignored). This analysis indicates that there is a slight benefit to the throw-in strategy over a long backwards pass. Second, we develop a framework based on machine learning to give more nuanced estimates of the payoffs associated with different action choices. By employing machine learning, we can reason about a much richer set of contextual information about the game state such as locations of players for a pass model and whether a team is able to apply pressure during the throw-in. Concretely, this enables us to simulate the expected chance of scoring if a team would have kicked the ball out of bounds in certain situations (i.e., that is, we can value a counterfactual action choice). The experimental results of our more nuanced analysis also confirm our original hypothesis that booting a long ball out of bounds is a valid strategy when compared to trying to maintain possession by recycling the ball using a (long) backward pass.

Data and Definitions

Our datasets consist of StatsBomb 360 event stream data. This contextualized event stream data is extracted from broadcast video and contains 1) event stream data, and 2) snapshots of player positioning at the moment of each event. The event stream data describes semantic information about the on-the-ball actions, such as which actions are performed, their start and end location, the outcome of the action, which players performed them, and the time in the match they were performed at. To facilitate the analysis, we work with the SPADL representation of this event stream data.[2] The snapshots include the positions of the players that were visible at the moment of the action, as well as their relationship to the ball carrier (i.e., teammate or opponent).

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[1] See for example https://youtu.be/6svu2FDDbWo?t=710 and https://www.youtube.com/watch?v=5j-lj5_3Cs8&t=481s

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

This study investigates the trade-off between patiently building up play and kicking a long ball out of bounds, following the clearance with a high pressing on the opponents' throw-in. We choose to specifically focus on backward passes as a proxy for conservative or patient build-up play. In practice, a player may have other options for useful progressive passes in addition to a backward pass and a long kick; however, we make the assumption that if such an option is present, a professional soccer player will select it. We are interested instead in the trade-off between a backward pass and a long ball in those situations where the opponents are preventing all other options.

We define backward passes by computing the angle between start and end location of a pass and filtering passes whose angle is $<-5/6 * \pi$ or $> 5/6 * \pi$. We also consider whether the defending team is applying pressure on a throw-in and only include throw-ins with pressure. We avoid unpressured throw-ins as they do not fit our assumed scenario of kicking a long ball and immediately trying to regain possession by pressing the upcoming throw-in. To divide the throw-ins, we leverage StatsBomb's provided "*under_pressure*" feature: a throw-in is considered as pressured if (1) the ball is stolen immediately after the throw-in or (2) the team keeps possession, but the first or second pass after the throw-in is labeled "*under_pressure*" (except in cases where the first pass is a long ball, where we ignore the second pass).

Our training dataset consists of 1,466,942 passes (of which 351,247 backward), 32,392 long kicks, and 63,414 throw-ins (of which 31,300 pressured). These are extracted from StatsBomb's open source 360 data[3], which include all games from the 2020 and 2024 European Championships, the 2022 World Cup, plus Bayer Leverkusen's title winning matches from the 2023/24 German Bundesliga, together with data from the 2020/21 season of the English Premier League, the Spanish LaLiga and the German Bundesliga, and the 2021/22 + 2022/23 Premier League seasons. A random sample of 20% of passes and throw-ins is used as a validation set when training pass and throw-in value models. In addition, a dataset of 504,962 passes (of which 118,395 backward) and 21,851 throw-ins extracted from the 2022/23 and 2023/24 Italian Serie A seasons has been set aside for the purpose of evaluating the models and developing the use cases.

Elementary Analysis

We first use a simple binning and counting approach to investigate whether kicking a long ball out of play—and applying pressure on the opponent's throw-in—leads to a higher probability of scoring compared to making a (possibly risky) backward pass. To simplify our analysis, we assume that kicking the ball out always results in an opponent throw-in.

To compare the two options, we count the number of times a goal is scored within 10 actions of each backward pass or pressured throw-in. In the latter case, we look at goals

[3] https://github.com/statsbomb/open-data

scored by the team that conceded the throw-in (i.e., the “booting” team recovers the ball and scores from the opponent’s throw-in). For a more fine-grained analysis, we divide the passes and throw-ins into five bins according to their end location.

The results presented in Table 1 provide an initial comparison that frames the trade-off of this paper. Namely, the analysis suggests that the probability of scoring from an opponent throw-in in the last bin of the pitch (0.34%) is higher than the probability of scoring as the result of a backward pass in a team’s defensive bins (0.18%, 0.20%). Figure 1 shows that a throw-in in the last bin of the pitch (and therefore the long kick that originates it) are more likely to result in a goal compared to a conservative backward pass in the three closest regions to a team's own goal.

Table 1. Probability of scoring in next 10 actions following a throw-in, or pass out from the back.

Location: X/Touchline Coordinate as the Distance From a Team’s Own Goal	From Opponent Throw-in: Probability of Scoring	From Pass: Probability of Scoring
0-21m	0.01%	0.18%
21-42m	0.09%	0.20%
42-63m	0.17%	0.33%
63-84m	0.16%	0.73%
84-105m	0.34%	2.06%

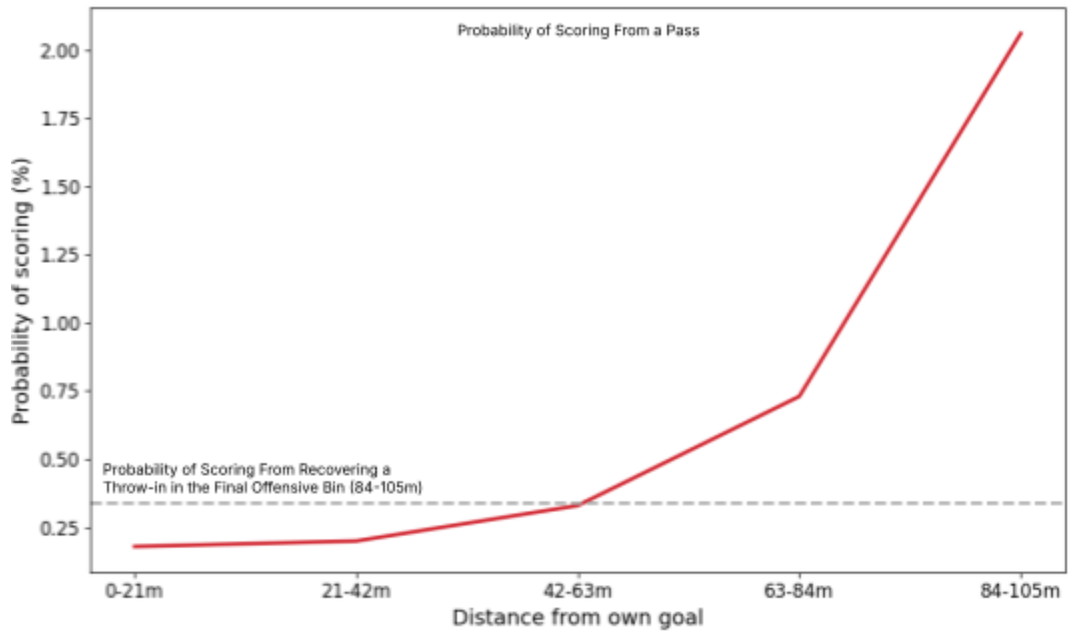

Figure 1. Comparison of scoring probabilities as a result of pass (red line) or throw-in (dashed line) from different regions of pitch.

Model-based Analysis

The elementary analysis suggests that, in certain situations, kicking a long ball out of bounds is a viable alternative to backward passes in areas of the pitch that are either dangerous or do not improve a team's chances of scoring.

To verify this claim and provide more nuanced estimates of the payoffs associated with different action choices, we employ machine learning techniques to assign a value to each of the two possible choices: 1) a standard backward pass to a teammate, or 2) a long clearance that results in a throw-in for the opponents. Employing machine learning techniques allows us to reason about a much richer set of contextual information about the game state and provide more nuanced analyses of the trade-offs.

Model choice and settings

Recent literature proposed two main alternatives to value game states by means of machine learning models, where the key design choice revolves around how we represent a game state, i.e., a snapshot of the ongoing match.

On one hand, deep learning architectures that leverage full spatial tracking data effectively capture a good representation of the game state (e.g., SoccerMap) and are applied to prediction tasks such as pass selection, pass success and pass value [4], [5].

On the other hand, we can handcraft features exploiting domain knowledge and use them to train feature-based models. Tree ensemble models such as XGBoost [6] achieve state-of-the-art performance on tabular and event-stream data, which typically makes them the chosen option when one can only work with event stream data [5], [7], [8], [9].

While it remains unclear what the best option is for the hybrid 360 data, we follow the work of Robberechts et al. [5], where the authors tried both approaches to build a pass value model and ultimately found that the second option can offer slightly better performances.

For all XGBoost models, we tune the parameters through a grid search optimizing the max tree depth in {3, 5, 7}, learning rate in {1e–2, 0.1, 0.3}, number of estimators in {50, 100, 200}. We use early stopping with patience set to 10 boosting rounds.

Valuing Actions

Intuitively, the value of any game state in a match is related to how likely it is for a team to score and concede a goal in the near future. We therefore employ machine learning methods to learn models that estimate the likelihood of scoring and conceding in the near future of a pass or a throw-in, following state-of-the art approaches proposed in the literature [7], [8].

We train two separate XGBoost models that assign an offensive and a defensive value to a game state. The overall game state value is then the difference between the offensive and the defensive value. Following the common approach proposed by [7], we define the offensive value as the probability of scoring a goal in the next 10 actions, and the defensive value as the probability of conceding a goal in the next 10 actions.

Given that goals are rare, multiple works including [5] use xG values to train possession state value models on a stronger learning signal. We do the same and exploit StatsBomb's xG values to quantify the probability of scoring/conceding from any shot in the next 10 actions. If multiple shots are contained in a sequence, we extract their combined xG as:

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

which evaluates to one minus the probability that no shot in the sequence ends in a goal.

Pass Value Model

Following [5], we start by training a model to specifically value passes. We represent the game state with the best set of features crafted by [4] for their pass value model using 360 event stream data. This consists of the traditional set of features used by VAEP [7] with event stream data, which means:

- action type and result

- time of occurrence in the match
- origin and destination location
- the body part used to execute the action
- the team performing the action
- the current goal difference.

We also add features extracted from the 360 frames that capture:
- the number of outplayed players
- the ball interceptability.

The former is computed using a simplified version of Impect's Packing Rate, where a defender is 'packed' if located between the ball and the goal before a forward pass, but further from the goal than the ball after the pass. For the latter, we extract the number of defenders in a 3 meter and 5 meter radius around the pass' start and end location. Note that differently from [5], we do not train a model for completed passes and a model for failed passes, as we incorporate the pass result as a feature in our game state representation.

Table 2 shows the performance of our pass value models. The offensive pass value model's performance is comparable to the performance of the offensive pass value model from Robberechts et al. [5].

Table 2. The performance of our offensive and defensive pass value components. Both models are XGBoost ensembles trained on xG values using features from the VAEP framework and additional features extracted from 360 data.

Model	AUC	LogLoss	Brier Score
Offensive pass value model	0.790	0.043	0.008
Defensive pass value model	0.763	0.010	0.001

Throw-In Value Model

We adopt a similar approach to value throw-ins. We train our models on a set of historical throw-ins, and we use a tailored feature set made of:
- the throw-in's start and end location
- the current time in the match
- the time elapsed since the previous action (i.e., a proxy for the time to put the ball back in play)
- a Boolean indicator of whether the opponent team is applying pressure on the receiver of the throw-in (see Data section for the definition).

Table 3 reports the performance of the throw-in value models.

Table 3. The performance of our offensive and defensive throw-in value components. Both models are XGBoost ensembles trained on xG values.

Model	AUC	LogLoss	Brier Score
Offensive throw-in value model	0.727	0.027	0.004
Defensive throw-in value model	0.744	0.008	0.001

Simulating long kick + throw-in as alternative to a pass

The final goal of the model-based approach is to exploit the learned models to answer practical questions around the trade-off between passing the ball backwards and kicking it out of bounds in proximity of the opponents' goal. Given that only one of the two events happens each time a player has the opportunity to choose, our idea is to approach this by starting from an executed backward pass and, together with assigning a value to the pass, simulating a long ball cleared out of bounds towards the opponents goal. We then evaluate the subsequent throw-in as the alternative option. Note that while possible in theory, it is hard to make an opposite analysis where we start from an executed "boot it" + throw-in scenario and simulate a backward pass, simply because the "boot it" pattern is rare and harder to pinpoint (often clearances are not a choice, but a necessity).

We therefore need to describe the missing piece from the puzzle, i.e., a way to simulate a long clearance out of bounds and the subsequent throw-in. Specifically, we start from a snapshot where a player is about to perform a backward pass. Instead of such a pass, we create two new events, a *clearance* ending out of bounds and a *throw-in* for the opponent team.

Long kick out of bounds

We first generate a synthetic *clearance* event starting from the same location as the backward pass. The key point here is how far forward the players are able to kick the ball. However, defining what constitutes a deliberate long kick out of bounds is challenging. It is difficult to understand from 360 data whether a player's intention is to simply kick the ball away or to reach a teammate far up the pitch. Therefore, since we are mainly interested in how far players can kick the ball away without aiming for a specific target, we use goal kicks from goalkeepers as a proxy for long kick length. Namely, we extract goal kicks longer than 40 meters (assuming shorter kicks are not at full power or aim for a specific teammate), and use their distribution as a proxy for the length of the simulated clearances.

Throw-in

After the clearance has been simulated, we create a synthetic throw-in event at the location where the ball went out of bounds. However, we must account for the time spent between the ball going out of bounds and the throw-in being taken. This is particularly relevant as it is also a feature in the throw-in value model. Similarly to what we do for the clearance length, we sample the time needed to take the throw-in from its distribution gathered from the training data (i.e., we extract the time since the previous action from event stream data). We do the same for the end location of the throw-in, which is sampled from the set of historical throw-ins close enough to the current one (10 meters tolerance).

Since we are studying the trade-off between passing the ball and kicking it long to recover it closer to the opponents' goal, in our basic setting we assume that the simulated throw-in is always pressured. However, in the following section we also experiment with two more scenarios where the throw-in is pressured 50% and 75% of the time. This is to mitigate the (at times unrealistic) assumption that the defending team is always able to apply pressure on the opponents' throw-in after kicking the ball out of bounds.

Finally, note that while we assume that a player will kick a long ball out towards the closest touchline, this simplification does not have a large effect on the analysis. Indeed, while the starting y location of the subsequent throw-in is included in the throw-in model, its weight is null as the model learns that it is not a discriminative feature. The only difference is that a clearance of the same length to the further touchline would result in an end location that is slightly further from the opponent's goal.

Use Cases

We use the described models and simulation procedure to compare observed backward passes with simulated clearances+throw-ins for each of the top ten Serie A teams in the 2023/24 season.

Analyzing a single match

A first, immediate application of our framework consists in rating all backward passes performed in a match and the corresponding simulated clearances+throw-ins. This allows highlighting a few game states where the choice of passing was not ideal and it would have been preferable to boot the ball. We provide an example in Figure 2. In the presented game state, the team in possession of the ball chose to pass the ball backwards. According to our models, however, the team should have avoided the risk of such a pass and should have kicked a long ball out of bounds.

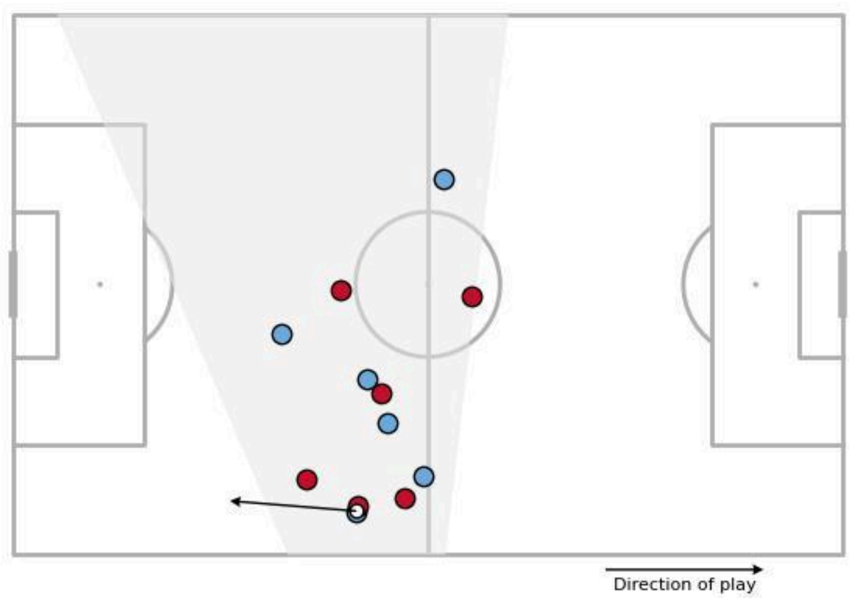

Figure 2. Backward pass extracted from the 2023/24 Inter Milan-AC Milan match. This is the pass in the match where the difference between the two options is maximum, i.e., the value assigned to the simulated clearance+throw-in is higher than the value of the executed pass.

Analyzing a full season

Figure 3 shows the distributions of the values attributed to all observed backward passes and throw-ins in our test set: if we exclude passes in a team's opponent third, it is rare for an event to be valued more than 0.01. This is not entirely unexpected: in general the values are low for passes and throw-ins because the vast majority of these occur far from a goal when the near-term chance of scoring is low.

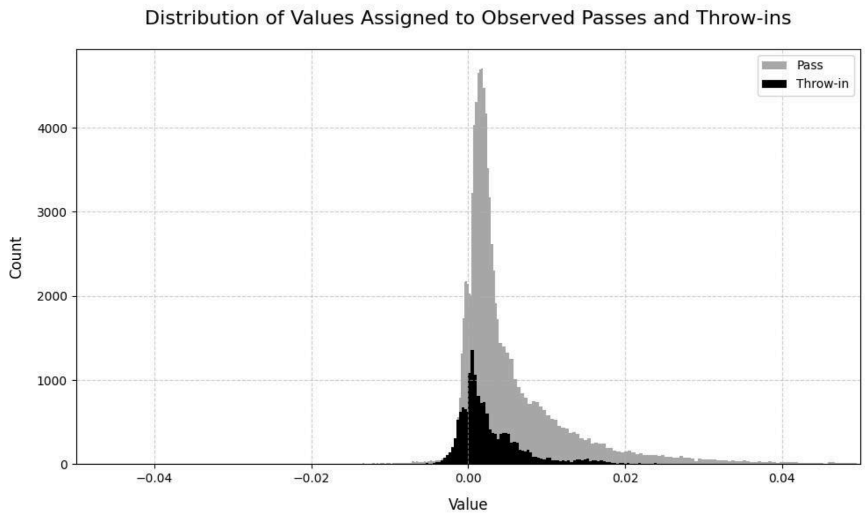

Figure 3. Ratings of backward passes and throw-ins taken from the 2023/24 Serie A season.

Next, we consider all observed backward passes in the defensive third on a team level for the top ten teams in the 2023/24 Serie A season. For each such pass, we simulate booting the ball out of bounds for a throw-in. Figure 4 shows the aggregated difference between the total value generated by (1) simulated boots and (2) observed passes. In this first analysis, we exclusively focus on passes in a team's defensive third of the pitch. Intuitively, losing the ball there puts the team in danger as the opponents gain possession close to the goal. At the same time, possessing the ball in the defensive third is not a highly-valued game state per se, as the ball is still far away from the opponent's goal.

Figure 4 shows that kicking the ball long and out of bounds instead of playing it in the defensive area is indeed advantageous. The trade-off is in favor of the "booting" option for all teams: on average, the difference in possession value over the full season is around +1.08 (i.e., booting results in a bigger reward). Or in other words, this strategy increases a team's expected goal differential for the season by about 1 goal. If we look at such a difference in terms of expected points, previous works [10] showed that one goal corresponds to approximately one expected point in the league table, which can actually be a relevant difference impacting (for example) a team's chances to qualify for European competitions or to avoid relegation.

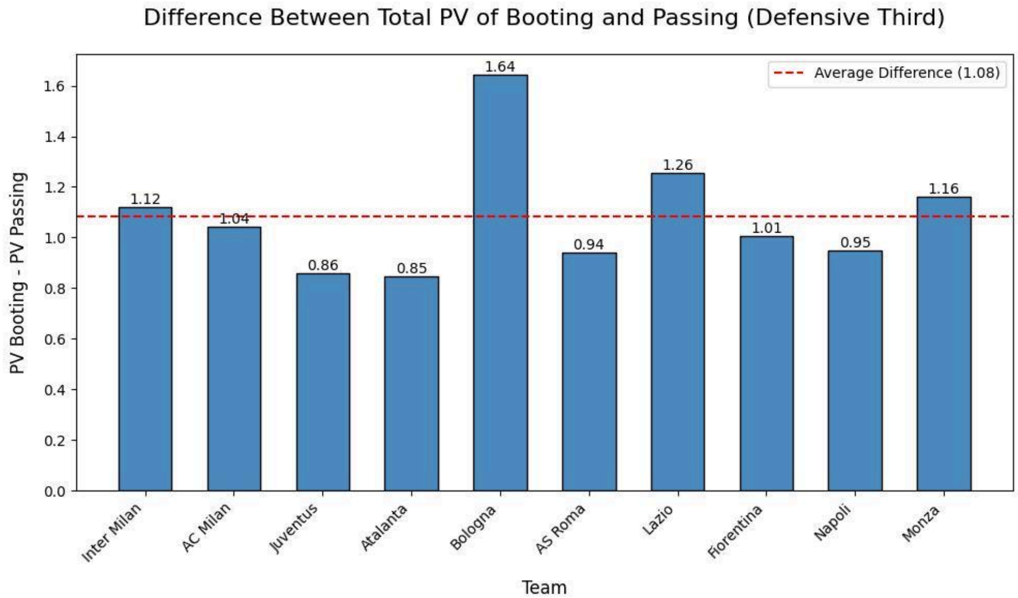

Figure 4. Difference over a season in the total possession value generated by always booting the ball vs always passing it backwards, for the top 10 teams and considering all attempted backwards passes of the 2023/24 Serie A season. A positive value indicates that booting is better.

We then perform the same analysis dividing the full pitch in six bins according to the x-location, and report the average difference between booting and passing for the top ten Serie A teams in each of the bins. Figure 5 shows that as expected, booting the ball is not advantageous when the team has the ball in the offensive midfield: at that point, it is better to retain possession and orchestrate offensive play. However, before the halfway line booting seems to be the preferable option.

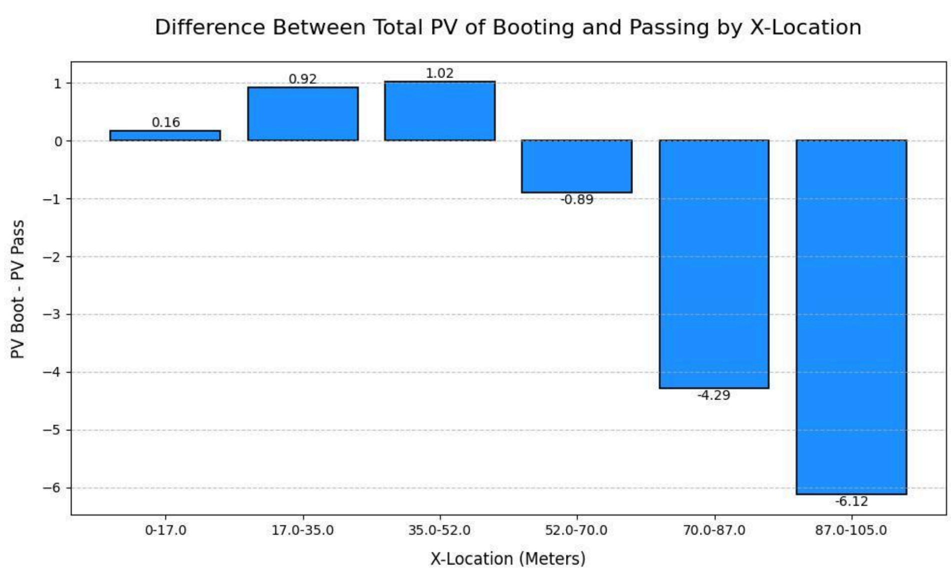

Figure 5. Difference over a season in the total possession value generated by always booting the ball vs always passing it backwards. Passes are divided in six bins according to the x-coordinate, and we report the average value for the 10 best teams of the 2023/24 Serie A. A positive value indicates that booting is better.

Comparing different pressing intensities

In these first experiments, we assume that a team is always able to apply pressure on the opponents' throw-in after kicking the ball out of bounds. This could sometimes be challenging to execute in practice, e.g., due to the opponents putting the ball back in play very quickly. Table 4 presents results for three different fractions of pressured throw-ins. In short, the "100% pressing" column reports the approach from Figure 3 for all three thirds of the pitch. In the other two columns, we see that as the defending team struggles to consistently apply pressure, the "booting" option loses some value. However, in the defensive third it remains clearly advantageous even if the team is only able to apply pressure in one out of two throw-ins.

Table 4. Average difference in total possession value between always booting and always passing for the ten best teams of the 2023/24 Serie A season, for different values of the fraction of pressured throw-ins (proxy for how aggressive the booting team manages to be after clearing the ball).

Area	50% pressing	75% pressing	100% pressing
Defensive third	+ 0.73	+0.91	+1.08
Middle third	-0.90	-0.38	+0.13
Offensive third	-10.88	-10.65	-10.41

Custom policy

While our analysis indicates that booting the ball is a valid option when a team has the ball in its own half, always choosing the same option is clearly a suboptimal choice. Trade-offs like this are usually better addressed using a mixed policy that selects the option based on the game context (possibly with some randomness for game-theoretic reasons).

We approach this by training an XGBoost policy that predicts which of the two options is best, given a set of historical ratings of passes and throw-ins. Specifically, we:

- Rate all observed backward passes and simulated throw-ins of the 2022/23 Serie A season with the previously trained pass value model and throw-in value model.

- Use these ratings to train a new XGBoost ensemble to predict which of the two options will receive a higher rating - using the same features of the pass value model.

The ensemble policy achieves 82% accuracy on the test season (2023/24 Serie A). That is, it selects what our models consider to be the best option more than four times out of five.

We compare the performance of the learned policy with respect to our naive simulated boot-only policy and the observed policy (i.e., the team always passes backwards), by re-aggregating values of the chosen actions over the course of the 2023/24 season. In essence, in Table 5 we are adding the ensemble policy to the results of the previous section.

Table 5. Average total possession value for different policies: always passing (what we observe in practice), always booting (our naive simulation), and the learned ensemble policy. Values are aggregated for the ten best teams of the 2023/24 Serie A season.

Area	Observed Policy (Pass-only)	Naive Policy (Boot-only)	Learned Policy
Defensive third	-0.17	+0.91	+1.00
Middle third	+5.77	+5.90	+7.71
Offensive third	+13.18	+2.78	+13.27

In all three zones of the pitch, the learned mixed policy improves over the baselines. In the defensive third, it still seems that always booting the ball is also a valid option. The main difference arises in the middle third of the pitch, where the learned policy is able to consistently improve over the two baselines, generating a possession value difference of around +2 over the course of a season. Instead, as expected, the “booting” option loses value in the offensive third, and the learned policy almost always chooses to pass.

Related Work

Several recent works have investigated specific trade-offs in sports decision making [10], [11], [12], [13], [14], [15].
In parallel, a lot of interest has been devoted to studying soccer set pieces, but the focus is typically on penalty kicks [16], [17] and corner kicks [18], [19].

Throw-ins are an underexplored area as their impact on the game is more limited [20]. However, [3] studied throw-ins providing insights on what the expected value of throw-in is, and on how likely it is to retain possession after a throw-in. Plus, the authors studied how features such as the start/end location and the time to put the ball in play influence these values, and used the study to provide some high-level recommendations. Recently, [21] also analyzed throw-ins from the ongoing 2023/24 Premier League season to study whether some teams are exploiting them better than others to create dangerous situations.

Conclusions

The presented work argues that the modern emphasis on build-up play might be excessively demonizing long balls out of bounds. Our analysis is based on action value models and an ad-hoc simulation procedure to compare backward passes with long balls out of bounds. The reported results show that in certain situations, a long kick out of bounds can be a useful move to gain some positional advantage and move the play away from dangerous areas of the pitch. Namely, this appears to be the better alternative in a team's defensive third of the pitch, and a valid option when the ball is in the middle third.

Future work should follow up on this study by addressing a few key limitations. The proposed framework compares observed passes with simulated throw-ins. This is justified by a clear imbalance in the data (there are many more passes than throw-ins), which means that we cannot only work with the observed throw-ins. However, this approach limits the contextual information at disposal of the throw-in value model, whose performance could be improved, e.g., using the location of the players at the time of the throw-in. The simulation approach could also be fine-tuned by considering multiple scenarios when simulating a throw-in, as the current procedure simply samples once from the training data distributions.

Acknowledgments

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