**Advancing Expected Goals (xG) Models in Football: A Hybrid Feature Engineering Approach Leveraging Spatiotemporal StatsBomb Data**

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**Abstract**

The use of data in sports, particularly football, is not a new concept. Since the early 1960s, clubs have leveraged analytics for recruitment and injury prevention, though these insights rarely reached public audiences. In recent years, however, data integration has surged, transforming fan engagement and tactical discourse. Among these advancements, Expected Goals (xG)—a metric quantifying shot quality based on contextual variables—has emerged as a cornerstone of modern analysis since its popularization by OPTA in 2012. In this study, we develop an xG model using machine learning and spatiotemporal feature engineering, trained on a decade of StatsBomb’s open men’s competition data. By synthesizing traditional variables (distance, angle) with advanced metrics (defender positioning, pressure), our model achieves a robust ROC-AUC of 80%–82%, outperforming baseline benchmarks given the dataset’s scale and complexity. These results highlight the practical utility of incorporating detailed defensive metrics, such as defender positioning and pressure, into xG frameworks, while offering fans and analysts an accessible, interpretable tool to evaluate shot outcomes in professional football.

**1 Introduction**

Football’s relationship with data has evolved significantly over the decades, transitioning from rudimentary manual observations to sophisticated, algorithm-driven insights powered by technological advancements. The journey began in the 1950s with Charles Reep, a British analyst who manually collected match data to develop his controversial “long ball” strategy. While his conclusions were flawed, Reep’s work underscored the potential of data in football. Decades later, the publication of *Moneyball: The Art of Winning an Unfair Game* by Michael Lewis in 2003 inspired football clubs to embrace data-driven approaches, challenging traditional scouting and tactical methods. Clubs like Liverpool F.C., Brentford F.C., FC Midtjylland, and AZ Alkmaar have since demonstrated the competitive edge that data analytics can provide when applied effectively.

This study focuses on constructing an Expected Goals (xG) model using the Hudl StatsBomb open-access dataset, a rich resource containing detailed event-level match data. Our approach incorporates advanced and engineered features such as the shooter’s preferred foot, defensive pressure, and dynamic player positioning.

Expected Goals (xG) quantifies the probability of a shot resulting in a goal based on historical data of similar shots, considering factors such as shot location, angle, and contextual variables. Ranging from 0 to 1, an xG value of 0 indicates no chance of scoring, while 1 represents a certainty.

While xG cannot predict match outcomes or player performance, it is a powerful tool for assessing chance quality, creative play, and player efficiency (e.g., identifying players who consistently outperform their xG).

**Resources and Tools**

This project utilized a variety of tools and resources for data analysis and processing. The computational environment was set up using WSL 2 Ubuntu for seamless integration with Linux-based tools.

Key software and libraries included:

* **Python 3.12.3**: The primary programming language for analysis and processing.
* **Hadoop 3.3.6**, **Spark 3.5.3**, and **PySpark 3.5.4**: For handling and processing large-scale data efficiently.
* **statsbombpy 1.14.0** and **mplsoccer 1.4.0**: Libraries specifically used for football analytics and visualizations.
* **Kaggle**: A resource for accessing datasets and hosting analysis.

The computations were performed on:

* HP Victus 16 Intel Core i5-11400H 2.70 GHz, 16 GB RAM, NVIDIA GeForce RTX 3060 6 GB

**2 Dataset**

The data used for this study was sourced from the publicly available StatsBomb Open Data repository, accessible via the following link: [Hudl StatsBomb Open Data](https://github.com/statsbomb/open-data).

The repository includes **JSON** files containing the dataset, which is regularly updated whenever StatsBomb announces new free data. Additionally, a documentation folder is provided, offering detailed explanations of the dataset and its features.

The dataset covers the last 10 years (2014–2024) and includes data exclusively from men's competitions. This decision aligns with a prior study demonstrating that mixing data from men’s and women’s competitions for expected goals (xG) modelling is not fair to either group due to inherent differences in playstyle and context. (1)

To extract and utilize this data, Hudl StatsBomb offers an API that supports Python and R, enabling efficient access to the free data.

**Role of the Dataset in Research**

Since 2019, Hudl StatsBomb has been hosting an annual conference at the beginning of the football season (September to October). The conference invites speakers and participants who have contributed to research over the past year. As part of the event, a research competition is held, ensuring at least nine studies are conducted using the StatsBomb dataset each year. Additionally, the dataset is actively utilized by StatsBomb’s partners, including professional football clubs such as Clube Atlético Mineiro, Club Brugge KV, and AZ Alkmaar.

Research papers from the StatsBomb conferences can be accessed through the following links:

* [StatsBomb Conference 2019](https://statsbomb.com/news/statsbomb-conference-research-papers-1/)
* [StatsBomb Conference 2021](https://statsbomb.com/news/statsbomb-conference-2021-research-papers/)
* [StatsBomb Conference 2022](https://statsbomb.com/articles/soccer/statsbomb-conference-2022-research-papers/)
* [StatsBomb Conference 2023](https://statsbomb.com/news/statsbomb-conference-2023-research-papers/)
* [StatsBomb Conference 2024](https://statsbomb.com/news/statsbomb-conference-2024-research-papers/)

**Researches used in this project**

**1. FOOTBALL DATA ANALYSIS: THE PREDICTIVE POWER OF EXPECTED GOALS**

This research used StatsBomb data from UEFA Euro 2020 to evaluate the predictive accuracy of Expected Goals (xG). By employing Kolmogorov-Smirnov testing, it demonstrated that xG-based rankings were statistically equivalent to goal-based rankings, validating xG as a reliable long-term performance metric.

**2. An xG of Their Own: Using Expected Goals to Explore the Analytical Shortcomings of Misapplied**

This research examined the transferability of xG models across genders using StatsBomb data, revealing significant performance differences when women's data were applied to models built on men's football. It highlighted the need for gender-specific xG models to avoid biases and improve evaluation accuracy. Based on these findings, we opted to use data from men's football over the last 10 seasons to ensure the reliability of our model.

**3. Footedness: How important is it? Which is better, a brilliant right footer or an average left footer?**

This research examined the role of footedness in football performance, using StatsBomb data to analyze left- and right-footed players' contributions to match outcomes. It highlighted the tactical and positional advantages of deploying left-footed players in left-sided roles, particularly for attacking plays and switches. Inspired by this study, we built a "Favorite Foot" variable in our model to capture the influence of a player's dominant foot on performance.

**Dataset Structure**

**Competitions** table provides information about the competition, including details such as the competition's ID, season, country or continent, and whether the competition is international. It contains 6 features and 26 unique values.

**Matches** table contains data on individual matches, including match dates, the teams involved, scores, match week, competition stage, stadium, referee, and the managers of both teams. It includes 14 features and 2,450 records.

|  |  |
| --- | --- |
| Competition | Matches |
| La Liga | 590 |
| Ligue 1 | 435 |
| Serie A | 380 |
| Premier League | 380 |
| Bundesliga | 340 |
| FIFA World Cup | 128 |
| UEFA EURO | 102 |
| Africa CAN | 52 |
| Copa America | 32 |
| MLS | 6 |
| Champions League | 5 |

Table 01: Number of matches per competition

**Lineups** table provides information about the players in each match, including details such as the player’s identity, team, jersey number, the cards received, and the positions they played during the match, along with the transitions in tactics and the minutes in which these occurred. It contains **7** features and **95,630** records.

**Events** table is the most comprehensive and critical table in the dataset, containing detailed event-by-event data for each match. It includes **122** features and a total of **8,710,714** records. The table captures various match events such as passes, shots, dribbles, tackles, fouls, ball recoveries, goalkeeper actions, and substitutions. Most of the features are stored in a dummy-like structure, where values like *True* or *Null* indicate whether a specific event detail is relevant (e.g., the 50\_50 feature is True if the event involves a 50-50 duel). A ";" separator was used due to the presence of dictionary-like fields that PySpark couldn't read directly.

|  |  |  |  |
| --- | --- | --- | --- |
| index | match\_id | play\_pattern | type |
| 37 | 3943077 | From Kick Off | Shot |
| 182 | 3943077 | From Keeper | Shot |
| 241 | 3943077 | From Throw In | Shot |
| 474 | 3943077 | From Corner | Shot |

Table 02: Example of events data

**Frames** table provides a view of the stadium field during each event, capturing the positions of all players involved in that specific moment. Each row corresponds to one player and their position during an event, enabling detailed spatial analysis. The table includes **7** features and a total of **10,259,434** records. Key features include player roles such as teammate, actor (the player performing the action), and keeper, as well as their exact locations on the field.

|  |  |  |  |
| --- | --- | --- | --- |
| match\_id | teammate | actor | location |
| 3942819 | true | false | [22.96, 41.02] |
| 3942819 | false | false | [46.54, 46.65] |
| 3942819 | true | false | [70.01, 41.18] |
| 3942819 | true | true | [60.00, 40.00] |

Table 03: Example of frames data

**Dataset Limitations**

The dataset has several limitations that may affect its comprehensive analysis. One of the primary issues is the lack of continuity for free data, as it is only available from sporadic years, such as 2015, 2016, and 2018, with no data for certain years, creating gaps in the timeline. The dataset also lacks player details such as height, weight, footedness, which are critical for understanding player performance in different contexts. Lastly, while the dataset provides detailed event information, the granularity of these events can complicate the analysis, especially due to the use of dummy-like structures and dictionaries in some fields, which may be challenging to parse for less experienced users.

**3 Feature Selection and Engineering**

There are many variations of an xG model, often determined by the selected features. Some models are more sophisticated, incorporating extensive details. In this section, we will identify relevant features from our dataset, explore their meaning and values, and assess their importance within the context of xG.

The simplest xG models typically rely on two key features: distance to goal and shot angle. In our dataset, this information is embedded within the location data.

**1. Numerical Variables**

**a. Location** is the most critical feature in an xG model, as it directly represents the position from which a shot was taken. It provides valuable insights, such as the player's proximity to the goal and the angle of the shot.

In the dataset, location is captured as a pair of values: the first value corresponds to the horizontal coordinate (x), while the second represents the vertical coordinate (y). The StatsBomb field dimensions range from 0 to 120 for the x-axis (horizontal distance from the goal line) and 0 to 80 for the y-axis.

|  |  |  |
| --- | --- | --- |
| type | location | statsbomb\_shot\_xg |
| Shot | [105.6, 44.0] | 0.07213958 |
| Shot | [98.6, 25.2] | 0.02977089 |
| Shot | [105.5, 47.3] | 0.07589752 |
| Shot | [113.4, 38.7] | 0.15686217 |
| Shot | [106.2, 36.8] | 0.15133068 |

Table 03: Example of location values in the dataset

A football field with orange and green dots

Description automatically generated

Figure 01: Sampled Distribution of 1,000 Shots on the Pitch Using Clustering

**2. Categorical Variables**

**a. Play pattern** indicates the type of play during the event leading to the shot. This information helps to distinguish the context in which the shot occurred, providing insight into whether the shot was made during open play, a set piece, or from a counterattack, among other scenarios. The values in the play pattern column can help us understand how different game situations influence shot outcomes.

In the dataset, the "play pattern" is represented by categorical values, with 9 distinct types:

* **Regular Play:** Shots taken during normal game flow.
* **From Free Kick:** Shots originating from free kick situations.
* **From Throw In:** Shots taken after a throw-in.
* **From Counter:** Shots made following a counterattack.
* **From Goal Kick:** Shots taken after a goal kick.
* **From Keeper:** Shots made after the goalkeeper’s play.
* **From Kick Off:** Shots right after a kick-off.
* **Other:** Other types of plays.

This feature represents the tactical context of the shot and can reveal how the situation impacts shot quality and conversion likelihood. For example, shots from "Regular Play" may generally have more dynamic and varied angles and distances, whereas shots from a "Free Kick" might be more controlled or involve a set strategy.

A graph of blue rectangular bars with white text

Description automatically generatedA graph of a number of blue rectangular bars with white text

Description automatically generated

Figure 02: Distribution of play patterns for goals

**b. Shot Type** refers to the category of play in which the shot was taken. This feature helps to distinguish between shots based on the nature of the play or situation leading to the shot. Understanding the shot type is important as different shot types typically have different expected goal (xG) values associated with them. For example, penalties often have a higher chance of scoring than shots taken during open play.

In our dataset, the shot type is represented by a categorical variable with four possible values:

* **Open Play** – A shot taken during the flow of the game, without any set-piece situation.
* **Corner** – A shot that is taken from a corner kick.
* **Free Kick** – A shot that results from a free kick awarded during the game.
* **Penalty** – A shot taken from the penalty spot, usually awarded after a foul in the box.

A blue circle with orange and green segments

Description automatically generated

Figure 04: Proportion of shot types resulting a goal

**c. Shot Body Part** refers to the part of the body used by the player to execute the shot. This feature provides valuable insight into the mechanics of the attempt, as certain body parts are generally more accurate or powerful when taking a shot. For instance, shots taken with the foot are typically more precise, while headers are often used in aerial duels or set-piece situations.

The dataset contains the following values for this feature:

* **Right Foot**: The shot was taken using the player's right foot.
* **Left Foot**: The shot was taken using the player's left foot.
* **Head**: The shot was taken using the player's head.
* **Other**: The shot was taken using another body part or a unique situation.

A pie chart with different colored circles

Description automatically generated

Figure 05: Proportion of Shot Body Parts resulting a goal

**d. Shot Technique** refers to the specific method or style employed by the player to take the shot. This feature highlights the diversity in shot execution, from creative and skilful techniques to standard attempts. Each technique carries implications for accuracy, power, and difficulty, adding valuable context to the shot data. The dataset includes the following values for this feature:

* Backheel
* Diving Header
* Half Volley
* Overhead Kick
* Volley
* Lob
* Normal

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| type | play\_pattern | shot\_type | shot\_body\_part | shot\_technique | xg |
| Shot | From Corner | Open Play | Right Foot | Half Volley | 0.072139 |
| Shot | From Free Kick | Free Kick | Right Foot | Normal | 0.039566 |
| Shot | Regular Play | Open Play | Right Foot | Half Volley | 0.075897 |
| Shot | From Corner | Open Play | Head | Normal | 0.156862 |
| Shot | From Penalty | Penalty | Left Foot | Normal | 0. 783500 |

Table 07: Example of shot technique values in the dataset

A graph with blue squares

Description automatically generated

Figure 08: Distribution of shot techniques for goals

**3. Boolean Variables**

**a. Under Pressure** indicates whether the player was being directly pressured by an opponent at the time of taking the shot. This feature provides insight into the external challenges faced by the shooter, reflecting the defensive pressure applied by the opposing team. Shots taken under pressure often result in reduced accuracy and power due to limited time and space, making it a critical variable for evaluating shot difficulty and understanding the influence of defensive actions on scoring probability.

**b. Shot First Time** refers to whether the shot was taken immediately on the player’s first touch, without any prior control or adjustment. This feature highlights the ability of players to react quickly and capitalize on opportunities. First-time shots are often faster, surprising goalkeepers and defences, but they can also sacrifice accuracy due to the lack of preparation time. Including this variable sheds light on the balance between speed and precision in shooting.

**c. Shot Aerial Won** captures whether the shot was the result of an aerial duel won by the attacking player. This feature emphasizes physicality, positioning, and aerial dominance, particularly in situations like set pieces and crosses. Aerial shots, such as headers, generally have lower accuracy compared to ground shots but can be critical in capitalizing on key opportunities during a match.

**d. Shot One on One** indicates whether the shot occurred during a direct one-on-one situation between the shooter and the goalkeeper. This feature represents high-quality scoring chances where defenders are absent, but the outcome often depends on the composure, skill, and decision-making of the shooter. These situations usually have a high xG value, making this a crucial variable for modelling goal-scoring opportunities.

**e. Shot Open Goal** refers to whether the shot was taken at an unguarded net with no goalkeeper present. This feature represents the highest probability scoring opportunities, as there is no obstacle preventing the ball from crossing the goal line. Open goal scenarios are often associated with very high xG values and are pivotal in determining clear-cut chances.

**f. Shot Follows Dribble** captures whether the shot immediately followed a dribbling action by the player. This feature highlights the ability of a player to create their own scoring opportunity through skilful ball control and manoeuvring past opponents. Shots following dribbles can reflect individual brilliance and often occur in dynamic, high-pressure situations.

**Preprocessing and Feature Engineering**

The features discussed in the previous section are directly available in the dataset. In this section, we will focus on features that are not explicitly present but are instead derived or calculated from the existing data and on the transformations made on the previous variables.

The engineered features provide additional insights and can enhance the predictive power of the model by capturing underlying patterns and relationships.

**1. Splitting Shot Location** as the original dataset includes a single column representing the shot location. To enable more granular analysis and calculations, this column was split into two separate features: **shot\_location\_x** and **shot\_location\_y**. These coordinates provide a detailed spatial representation of where each shot was taken on the pitch, forming the basis for several other engineered features described in the next section.

**2. Distance to goal** measures the straight-line distance between the shot location and the center of the goal. This feature is calculated using the Pythagorean theorem, where the x-coordinate of the goal is set at 120 (the farthest end of the pitch) and the y-coordinate is set at 40 (the center of the goal on the StatsBomb field).

Distance to goal is one of the most critical factors influencing shot success in an xG model. Shots taken closer to the goal are statistically more likely to result in goals due to better angles, reduced reaction time for the goalkeeper, and increased shooting precision. By including this feature, we can capture spatial factors affecting shot quality, which serves as a foundational input for the model.

The formula for calculating the distance is:

A football field with a green and orange line

Description automatically generated

Figure 09:

**3. Angle to goal** measures the angle formed between the two goalposts and the location of the shot on the pitch. This feature provides a geometric perspective on the scoring opportunity by quantifying the shooting angle available to the player.

The calculation involves determining the vectors pointing from the shot location to the left and right goalposts, then computing the angle between these vectors using the dot product formula:

Where:

* and are the vectors to the left and right goalposts, respectively.
* and are the magnitudes of these vectors.
* is the angle, later converted to degrees.

The angle to goal is a vital feature for an xG model because larger shooting angles generally increase the likelihood of scoring. A wider angle indicates a more significant portion of the goal is visible, making it harder for the goalkeeper to cover all possible trajectories. Conversely, narrower angles tend to be more challenging to convert into goals.

A football field with a blue line and orange dots

Description automatically generated with medium confidence

Figure 10:

**4. Preferred Foot Shot** feature determines whether a shot was taken using a player's dominant foot (i.e., the foot they use most frequently for passing and shooting). The calculation is based on a footedness research approach, which suggests that players who use one foot more than 66% of the time are considered to have a dominant foot (Right Foot or Left Foot). This approach considers both passing and shooting data, as passes are frequent actions that provide insight into a player's foot preference.

To determine if a shot was taken with the preferred foot:

A player's foot preference is determined by analyzing both passes and shots. The player’s dominant foot is assigned if they use it more than 66% of the time.

After identifying the player’s preferred foot, we compare it with the shot body part. If they match, the shot is considered as being taken with the preferred foot.

This feature is crucial for xG models because shots taken with the preferred foot are often more accurate, powerful, and likely to result in goals. Knowing whether a shot is made with the player's dominant foot provides additional context to evaluate the quality of the shot and its likelihood of scoring. The research-based approach of using a player's foot preference across multiple actions (passes and shots) offers a more reliable indicator of footedness, improving the robustness of the analysis.

**5. Number of Players Inside Shooting Area** quantifies how many players (obstacles) are within the triangular shooting area formed by the shot location and the two goalposts. This calculation evaluates the potential obstructions between the shooter and the goal, providing a measure of defensive density in the critical shooting zone.

To calculate it:

I. Shooting Area Triangle between the shot location, the left goalpost and the right goalpost.

II. Check if player is inside the triangle for each player on the pitch

* 1. Calculate the area of the shooting triangle .
  2. For the player’s position , calculate the areas of three smaller triangles:

1. Between the shot and the left goalpost .
2. Between the shot and the right goalpost .
3. Between the two goalposts and the player .
4. Sum the areas of the smaller triangles .

A player is inside the triangle if:

(The sum of the smaller triangles matches the full triangle's area within a small margin of error.)

III. Count the players: Repeat the above check for all players’ positions to determine how many are inside the shooting area.

IV. Penalty Shots Exception: If the shot is a penalty, only the goalkeeper is considered inside the area, and the value is set to 1.

A football field with red and green dots

Description automatically generated

Figure 11:

This feature captures defensive pressure in the form of obstructions between the shooter and the goal. Its inclusion in an xG model is crucial because the density of players in the shooting area impacts the likelihood of the shot being successful.

* **Higher count**: Indicates greater defensive density, making scoring more difficult.
* **Lower count**: Implies fewer obstacles, increasing the chance of scoring.

**6. Categorical Features Encoding**

To prepare the categorical features for modelling, each variable mentioned in the previous sections will be converted into dummy variables using one-hot encoding. This process transforms each category within a feature into a separate binary column, where a value of 1 indicates the presence of the category, and 0 indicates its absence. For example, a feature such as Shot Type with categories like "Open Play," "Set Piece," "Counterattack," and "Penalty" will be converted into separate columns for each category. To avoid the dummy variable trap—where multicollinearity arises due to redundant information—we will drop one dummy variable for each feature. This ensures that the features remain linearly independent while retaining the information needed for accurate and unbiased modelling.

**Target Variables**

**1. Shot Outcome** variable has multiple categories, such as Goal, Saved, Off Target, Blocked, Wayward, Saved to Post, Saved Off Target, and Post. We simplify this feature by converting it into a binary outcome for classification purposes:

* Goal is considered 1 (indicating a successful shot).
* All other outcomes are considered 0 (indicating an unsuccessful shot).

This binary encoding allows the model to focus on predicting whether a shot results in a goal or not.

**2. StatsBomb Shot xG** variable provides the expected goal (xG) value, ranging from 0 to 1, representing the likelihood of a shot resulting in a goal. To evaluate our model’s performance against StatsBomb’s xG model, we round this value to the nearest integer.

* xG >= 0.5 will be considered as 1 (goal).
* xG < 0.5 will be considered as 0 (no goal).

This rounding provides a clear match-up between the predictions from our model and StatsBomb’s xG, making it possible to calculate the accuracy and compare the models' predictions on goal vs. non-goal events.

**Preprocessing Time**

The preprocessing tasks, including feature engineering, splitting shot locations, calculating distances, and encoding categorical variables, took **2 hours and 51 minutes** to complete. This time reflects the effort required to handle a dataset of considerable size and complexity while ensuring the transformations were accurate and aligned with the modelling requirements.

**Model Training**

In this section, we will explore the training of classification models to predict whether a shot results in a goal or not, which serves as a binary classification task. The models will be trained using various features from the dataset, including shot type, body part, distance, and others, with the target variable being goal or no goal. While the initial approach might suggest using linear regression, we opted for classification models due to the nature of the target variable being binary. Furthermore, linear regression was excluded as a potential model due to its tendency to return negative values, which are not meaningful in this context. Instead, classification models, such as logistic regression, random forest, gradient boosting, and support vector machines, were utilized.

The output from these classification models will be treated as the predicted probabilities of scoring (expected goals or xG), which we can further evaluate using both classification and regression metrics, such as accuracy, F1 score, mean squared error, and matching rate between our predictions and the StatsBomb xG values.

**Splitting Dataset**

For model training and evaluation, the dataset was split into **training** and **test** sets using **PySpark’s MLlib**. The split ensures that the model is trained on one subset and tested on another, assessing its ability to generalize to unseen data.

The dataset was split as follows:

* **Training Set**: 70% of the data was used for training the model. This subset contains the data used to fit the model’s parameters.
* **Test Set**: 30% of the data was reserved to evaluate the final model's performance on unseen data.

**Model Selection**

**1. Logistic Regression:** A simple, interpretable model for binary classification. Outputs probabilities, which are used as expected goals (xG). It serves as a baseline model.

**2. Random Forest:** An ensemble method that combines multiple decision trees to improve prediction accuracy. Captures complex, non-linear relationships in the data.

**3. Multilayer Perceptron:** A neural network model that can capture complex patterns through multiple layers of neurons. Suitable for non-linear relationships between features and target.

**4. Gradient-Boosted Trees:** An ensemble method that builds trees sequentially, each correcting the previous tree’s errors. Effective for improving accuracy and handling imbalanced data.

**5. Naive Bayes:** A probabilistic model based on Bayes’ theorem. Simple, fast, and effective when features are independent, but may not capture complex relationships.

**6. Decision Tree:** A non-linear model that splits data into subsets based on feature values. Easy to interpret but prone to overfitting without regularization.

**7. Support Vector Machine:** A classification model that finds the best hyperplane to separate data. Effective in high-dimensional spaces and non-linear classification tasks.

**Training**

After completing the traditional machine learning training with models like logistic regression, random forest, and others, we followed up by applying the RDD-based API for ensemble methods, specifically with Gradient Boosting Trees (GBT) and Random Forest (RF). This allowed us to compare the performance of the classic models with the ensemble models, ensuring a thorough evaluation of the model’s predictive power.

Training Time

**Evaluation**

To evaluate the performances, we used a combination of classification and regression metrics, given that we treated the task as both a classification problem (goal vs. no goal) and a regression task (predicting the expected goal value, xG). The key metrics used were:

1. **ROC-AUC**: Evaluated the ability of the models to discriminate between goals and non-goals. A higher ROC-AUC indicates better performance in distinguishing between the two classes.
2. **Accuracy**: Measures the percentage of correctly predicted goal outcomes.
3. **Precision, Recall, and F1-Score**: Evaluated how well the models identified goals, with a balance between precision (how many predicted goals were actually goals) and recall (how many actual goals were predicted correctly).
4. **Root Mean Squared Error (RMSE)**: Used to assess the performance on predicting xG, measuring how far the predicted xG values were from the actual values.
5. **Matching Rate**: Specifically, we calculated the matching rate between the predicted goals (based on model probabilities) and StatsBomb's xG predictions, checking how often both the model and StatsBomb predicted a goal or non-goal.

This evaluation allowed us to assess each model's overall performance in both classification and regression contexts and select the best-performing one for further analysis.

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Appendix A