**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 78%–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. Unlike traditional xG models, which rely on basic variables like shot distance and angle, our approach incorporates advanced and engineered features such as the shooter’s preferred foot, defensive pressure, and dynamic player positioning. By leveraging these nuanced factors, we aim to bridge the gap between professional analytics and public research, demonstrating how accessible tools and open data can yield insights comparable to those driving decisions at elite clubs.

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. Popularized by OPTA, xG has become a cornerstone of modern football analysis, used in post-match evaluations and even fan discussions. 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).

In Section 2, we explore the StatsBomb dataset, review related research, and outline the methodology for selecting our study range. We then identify and justify critical features—such as shot distance, angle, and defensive pressure—through exploratory visualizations, followed by preprocessing steps to engineer variables like “favorite foot,” dynamic player density, and geometric shot angles.

Section 3 details the training of machine learning models on the preprocessed dataset, incorporating cross-validation and hyperparameter tuning to enhance robustness. In Section 4, we evaluate the models using a dual approach: as a regression model with RMSE and as a classification model with accuracy and other metrics.

Finally, we discuss the results, including model performance and computational efficiency, before concluding with the broader implications of our work. By democratizing advanced analytics through open-data models, this study aims to inform tactical, scouting, and developmental decisions in football, making high-level insights accessible to a wider audience.

**2 Dataset**

**Source**

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) modeling is not fair to either group due to inherent differences in playstyle and context.

To extract and utilize this data, Hudl StatsBomb offers an API that supports Python and R, enabling efficient access to the free data. The data scraping process, which took approximately **2 hours and 51 minutes**, is detailed in the Jupyter Notebook, *statsbomb\_data.ipynb*, demonstrating the use of the StatsBomb API for extracting and preparing the dataset.

**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/)

**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.

The **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.

# References

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