Skor-xG: SKeleton-ORiented Expected Goal Estimation in Soccer

Supplementary Material

A. Details of Relevant Area

Here we detail the relevant area used to filter out irrelevant players during preprocessing, as introduced in Section 3.1. In the coordinate system centered at the center of the left goal, the positions of the two goalposts are given by: $(x_{\text{left-post}}, y_{\text{left-post}}) = (0, -3.66), (x_{\text{right-post}}, y_{\text{right-post}}) =$ (0, 3.66). Given the 2D ball location (x, y), we define the relevant area as a rectangle with boundaries $(x_{\min}, x_{\max}, y_{\min}, y_{\max})$ as follows:

$$x_{min} = -\infty$$

$$x_{max} = x + d_{margin}$$

$$y_{min} = \min(y_{left_post}, y) - d_{margin}$$

$$y_{max} = \max(y_{right_post}, y) + d_{margin}$$
(7)

where d_{margin} represents an additional margin to ensure sufficient coverage around the ball's position. In this study, we set $d_{\text{margin}} = 5$. $x_{min} = -\infty$ indicates that players are not filtered out even if they are out of the goal line. More intuitively, Figure 9 illustrates how the relevant area adapts based on the ball position. For inputs with multiple frames, the relevant area is derived based on the shot frame. A player is excluded if any of their joints fall outside the relevant area in any frame.

B. Details of Baseline Methods

B.1. Feature Extraction

In this section, we introduce the details of our feature extraction for training Logistic Regression and XGBoost. For a shot with the ball at (x, y, z), we construct a shot triangle in the 2D plane by connecting the 2D ball location (x, y)to the two goalposts for feature extraction, as illustrated in Figure 10. The features used to build our baseline models are as follows:

Distance to Goal We define the distance to goal as the minimum of three distances on the 2D plane: the distance from the ball to the left post, the distance from the ball to the right post, and the perpendicular distance from the ball to the goal line.

Angle to Goal We define the angle to goal as the angle at the ball's vertex in the shot triangle (Figure 10).

Goalkeeper Position We extract the goalkeeper's 2D pelvis position from the 3D skeleton tracking data, ignoring the z-coordinate.

3D Ball Position We use the 3D ball position (x, y, z).

Pressure A value ranging from 0 to 1 indicating the pressure on the shooting player, derived from an internal model.



Figure 9. *Illustration of the relevant area used to filter out irrelevant players*. The red-shaded region is the relevant area, determined by the ball position, goalposts, and a margin.



Figure 10. *Shot triangle for feature extraction*. This triangle helps compute the shot angle and identify players within its area.

Ball Speed 3D ball speed is calculated using the previous and next frames:

$$\mathbf{v}_{ball}^{(t)} = \frac{\mathbf{x}_{ball}^{(t+1)} - \mathbf{x}_{ball}^{(t-1)}}{2\Delta t},$$



(a) The player faces a decision: either take a direct shot or pass to a teammate. In reality, the player chose to pass, but our Skor-xG can estimate the xG of a hypothetical shot at this moment, which is 0.34.



(b) The teammate received the pass and took a shot, with an xG of 0.43 according to Skor-xG.

Figure 11. What if the player shoots instead of passing? In (a), the player has two options: pass or shoot. They chose to pass to a teammate, leading to (b), where the teammate took the shot. By comparing the xG of the actual shot in (b) (0.43) and the xG of the hypothetical shot in (a) (0.34), our model confirms that passing was the better choice.

where $\mathbf{x}_{ball}^{(t-1)}$ and $\mathbf{x}_{ball}^{(t+1)}$ represent 3D ball position in the previous and next frames, respectively, and Δt is the time interval between frames.

Number of Players in the Shot Triangle The number of players inside the shot triangle (Figure 10), including players from both teams and their goalkeepers.

Number of Defenders in the Shot Triangle The number of defenders inside the shot triangle (Figure 10), including the goalkeeper, but excluding the shooting player's teammates.

Body Part Used A categorical feature derived from fbref.com indicating the body part used for the shot, such as Right Foot, Left Foot, or Head.

Previous Action A categorical feature derived from fbref.com indicating the action preceding the shot, such as Pass(Live), Pass(Dead), Shot, Fouled, or Take-on.

B.2. Implementation

Logistic Regression We use the scikit-learn² implementation. Our Logistic Regression model is trained with an L2 regularization penalty and optimized using the L-BFGS solver. The maximum number of iterations is set to 1000.

XGBoost We use the official implementation from the xgboost³ Python package. Our XGBoost model is trained with 1000 trees, a maximum depth of 3, a learning rate of 0.2, and a minimum sum of instance weight (hessian) needed in a child (min_child_weight) set to 6. Early stopping rounds is set to 10 to prevent overfitting.

C. Extra What-if Case

One key benefit of using skeletons is that we eliminate the need for human annotations and enable computing xG for 'what-if' scenarios. In addition to simulating player poses, we can evaluate xG for alternative in-game actions, providing valuable insights into different strategies.

What if I shoot instead of pass? To pass or to shoot, that is the question. This is a common dilemma on the soccer field, particularly during a counterattack, where a player must decide between taking a shot from a tight angle or passing to a better-positioned teammate while risking defenders closing in. With Skor-xG, we can compute xG values for both options easily without manual annotations, providing a quantitative evaluation of the decision-making process. As shown in Figure 11, we present a real-game scenario where a player must decide between shooting or passing. In this case, the player chose to pass to a teammate rather than take the shot. However, the teammate's shot went off target, with an xG of 0.43 assigned by Skor-xG, as shown in Figure 11b. This raises the question of whether the passing player in Figure 11a should have taken the shot instead. Although this player didn't choose to shoot, Skor-xG can still estimate its xG as if they had attempted the shot. The xG for this hypothetical shot is 0.34, which is lower than the actual shot taken by their teammate. By comparing xG values, we confirm that even though the teammate missed the opportunity, the decision to pass was not a poor choice. This case demonstrates that Skor-xG can provide tactical insights by quantitatively evaluating decision-making, helping players and coaches assess and optimize in-game choices.

²https : / / scikit - learn . org / stable /
modules / generated / sklearn . linear _ model .
LogisticRegression.html

³https://xgboost.readthedocs.io/en/stable/ python/