Action-Evaluator: A Visualization Approach for Player Action Evaluation in Soccer

Anqi Cao, Xiao Xie, Mingxu Zhou, Hui Zhang, Mingliang Xu, and Yingcai Wu

Abstract—In soccer, player action evaluation provides a fine-grained method to analyze player performance and plays an important role in improving winning chances in future matches. However, previous studies on action evaluation only provide a score for each action, and hardly support inspecting and comparing player actions integrated with complex match context information such as team tactics and player locations. In this work, we collaborate with soccer analysts and coaches to characterize the domain problems of evaluating player performance based on action scores. We design a tailored visualization of soccer player actions that places the action choice together with the tactic it belongs to as well as the player locations in the same view. Based on the design, we introduce a visual analytics system, Action-Evaluator, to facilitate a comprehensive player action evaluation through player navigation, action investigation, and action explanation. With the system, analysts can find players to be analyzed efficiently, learn how they performed under various match situations, and obtain valuable insights to improve their action choices. The usefulness and effectiveness of this work are demonstrated by two case studies on a real-world dataset and an expert interview.

Index Terms—Soccer Visualization, Player Evaluation, Design Study

1 Introduction

Evaluating player performance is crucial in soccer match data analysis. It can provide valuable insights for various decision-making tasks, such as arranging team tactics and adjusting player strategies, to increase the winning chance of upcoming matches. In particular, action evaluation is a fine-grained player performance evaluation method that precisely evaluates players' indirect contributions to winning goals reflected in their actions [3]. It calculates a score for each action performed by a player. Based on the scores, analysts could learn how the player contributed to the whole team on each action [10]. For instance, a player who is good at passing threatening balls but seldom immediately creates shots and goals would be highlighted with high action scores.

Analyzing soccer player performance through action scores is a complicated task. Analysts need to link each action to its context among a large volume of match data and compare the action scores under different contexts to summarize the players' strengths and weaknesses. These match contexts are not limited to action attributes such as locations and types, but also other complex spatio-temporal match situations that affect players' action choices such as team tactics. A series of data-driven models have been developed to estimate objective action scores in soccer matches [3]. However, without an interactive exploration tool, analysts often encounter difficulties in investigating action scores with match situations of interest and comparing player performance in diverse match situations. Meanwhile, lacking the explanation of meaningful performance patterns, analysts also face challenges in understanding the reasons behind player performance and obtaining guidance for improving players' actions. Thus, it is difficult for professional soccer analysts to adopt these models to their daily analysis directly. Several interactive visualization tools have been proposed for in-depth soccer player performance analysis [40]. However, those studies mainly evaluate players with summarized statistical indicators [8, 24, 45–47], which hardly support the investigation of fine-grained player action scores integrated with different match situations.

In this work, we collaborated closely with professional soccer analysts and coaches to develop a visual analytics system for player action evaluation. The system supports flexible exploration, comparison, and explanation of soccer player actions and its scores. We tackled two major challenges during the system development. The first challenge is to integrate essential match situations into the visualization of soccer actions and their scores. When investigating action scores, analysts need to view the various match situations that the actions belong to, including team tactics and player locations, to understand the tactical intentions of the action choices. It can be seen as visualizing a function that maps complicated match situations and action choices to the scores. Existing studies usually display actions from match situations separately [38, 65], which is hard for analysts to directly connect actions and their scores to the match situations. It is difficult to characterize the match situations and visualize such a function that is over a multi-dimensional mixed domain. The second challenge is to design visualization tools for effective action score comparison and explanation. To evaluate the strengths and weaknesses of a player, analysts need to compare how the player performed with different action choices under various match situations. However, identifying heterogeneous match situations that the actions should belong to could overwhelm them in the analysis. Besides, it is non-trivial to explain the scores provided by the complicated models to players and figure out how to improve player performance through action choices. The visualization tools should also provide such an effective explanation for the action scores.

To address the first challenge, we design a pitch-based visualization for soccer actions that places the action choices with the match situations in the same view. The visualization presents the action choice, the team tactic it belongs to, and the player locations in the same pitch to facilitate comprehension of the tactical intention of the action choice. To address the second challenge, we design a visual analytics system, Action-Evaluator, for a comprehensive soccer player action evaluation. Users can navigate players of interest through the player view. The action view supports the exploration of essential match situations and multiple comparisons of player action scores. Users can further turn to the explanation view to acquire guidance for player actions.

The main contributions of this work are as follows:

- A **characterization of domain problems** that summarizes the description of match situations and the criteria of player action evaluation from soccer experts.
- A **tailored visualization** to integrate complicated soccer match situations into soccer actions and their scores.
- A **visual analytics system** to support the comprehensive evaluation of player actions in soccer matches.

- *A. Cao, M. Zhou, and Y. Wu are with the State Key Lab of CAD&CG, Zhejiang University. E-mail: {caoanqi, zhoumingxu, ycwu}@zju.edu.cn.*
- *X. Xie and H. Zhang are with the Department of Sports Science, Zhejiang University. E-mail: {xxie, zhang_hui}@zju.edu.cn.*
- *M. Xu is with the School of Computer and Artificial Intelligence, Zhengzhou University, Engineering Research Center of Intelligent Swarm Systems, Ministry of Education, and National Supercomputing Center in Zhengzhou. E-mail: iexumingliang@zzu.edu.cn.*
- *X. Xie is the corresponding author.*

Manuscript received xx xxx. 201x; accepted xx xxx. 201x. Date of Publication xx xxx. 201x; date of current version xx xxx. 201x. For information on obtaining reprints of this article, please send e-mail to: reprints@ieee.org. Digital Object Identifier: xx.xxxx/TVCG.201x.xxxxxxx

2 Related Work

In this section, we review previous studies related to our work, including soccer player performance evaluation and soccer data visualization.

2.1 Soccer Player Performance Evaluation

Evaluating player performance objectively has attracted considerable research attention during recent years, especially in team sports such as ice hockey [29,49] and basketball [9]. In soccer, traditional methods for evaluating player performance usually calculate an overall score for a player based on statistics, as seen in soccer analysis websites like WhoScored [60]. Generally, a straightforward method is to rate players through a weighted sum calculated by features on match statistics and feature weights learned with match outcomes. For instance, McHale et al. defined essential performance indices of soccer players and assigned the weights based on domain knowledge [32]. Brooks et al. constructed features by the start and end regions of a pass and trained the weights by whether the possession ended in a shot [7]. Pappalardo et al. improved the rating framework by extracting fine-grained passing features and integrating player roles into the player ranking process [36].

Soccer is a complicated sport, and player performance is difficult to be evaluated precisely with simple statistical indicators. Thus, the player evaluation methods have been extended to estimate a fine-grained score for each detailed action based on the match features. Power et al. measured the risk and reward of the soccer passes on the basis of trajectory features [44]. Moreover, the expected possession value (EPV) framework is widely adapted to further involve match context features within a possession in soccer action evaluation. It predicts expected match results at the end of the possession for each action by its context features and calculates the score of an action based on the change in the results caused by the action. Specifically, Decroos et al. [10, 12] and Bransen et al. [4–6] have presented a series of representative work to value actions by the change of goal probabilities before and after the action. Recently, deep learning techniques have been introduced to the EPV framework because of their outperformed ability to describe complicated hidden relationships in a large amount of data. Fernández et al. proposed a deep learning framework to estimate the expected outcome at the end of the possession for each moment [15, 16]. Liu et al. formulated the soccer action evaluation problem as a deep reinforcement learning task and valued each action through the reward function trained by a reinforcement learning algorithm [28].

Although these studies can provide valuable insights for soccer player performance, they hardly support interactive analysis to investigate action scores by complex spatio-temporal match situations and reveal how to improve players' action choices. The position of our work is to develop a visualization system to help with a flexible and comprehensive analysis for soccer player action scores.

2.2 Soccer Data Visualization

Visualization techniques have been widely adopted for the analysis of diverse sports data [14, 40], including basketball [18, 19, 31, 59, 63], baseball [13, 25, 34, 35], ice hockey [41], rugby [23], and racket sports [26, 42, 43, 58, 61, 62]. Specifically, numerous visualization studies have paid attention to soccer match data to solve different analysis tasks such as ranking table analysis, tactic discovery, and player evaluation. In soccer ranking table analysis, Perin et al. designed visualizations to illustrate the change of team rankings along with the round of matches [37, 39]. As for soccer tactic discovery, player passing behaviors and movement behaviors are most extensively analyzed by existing visualization studies. On the aspect of player passing behaviors, SoccerStories [38] is a pioneering visualization system to extract and show player passing patterns in a soccer match. PassVizor [65] visualized the dynamics of passing patterns under different soccer match situations. To facilitate summarizing team tactics from soccer player movements, Stein et al. proposed a video enhancement technique by embedding player movement visualizations into soccer match videos [53, 54]. Shao et al. [51] and Sacha et al. [48] developed trajectory search methods and trajectory aggregation methods to identify soccer player movement patterns, respectively. Andrienko et al. revealed soccer team tactics through the coordination of player movement trajectories [1]. Seebacher et al. [50] and Stein et al. [55] further integrated visual what-if analysis into detecting and improving soccer player movement patterns. Besides, significant methods have also been proposed to address other important soccer team tactic analysis tasks, such as visualizing player defense [2] and the change of team formations [64].

In particular, soccer player evaluation is an essential analysis task and also attracts the interest of visualization researchers [40]. For instance, Rusu et al. proposed a metaphor-based visualization named Soccer Scoop to compare statistical indicators of different players [45, 46]. Janetzko et al. presented soccer player performance through the change of multiple features of players under certain match contexts, such as a movement pattern and a passing pattern [24]. Ryoo et al. developed a pixel-based visualization to demonstrate the critical statistical indicators of multiple soccer players [47]. These studies focus on visualizing player performances based on statistical indicators along soccer match contexts. However, it is insufficient for fine-grained action score analysis because the visual exploration of important actions and the integration of action choices with match situations remain unsolved. Thus, we develop a visualization system to assist soccer analysts in evaluating player performance from action scores in various aspects.

3 Background and System Overview

In this section, we introduce the basic domain concepts used in our work. We further provide the problem characterization of soccer player action evaluation together with domain experts.

3.1 Background and Term Definitions

Soccer is a highly dynamic sport that involves two teams competing with each other. During the match, each team of players tries to steal the ball from the opponent, pass or take the ball forward, and finally finish a shot to win a goal. In this work, we focus on evaluating and improving the basic player actions in soccer matches. The definitions of terms used in our study are as follows.

- An **action** is a match event that describes how a player performed with the ball [10, 17]. It indicates the transition of the ball created by a player, which most directly affects the development of a soccer match [3]. An action is usually denoted with a tuple of six attributes: the player, the start location, the end location, the occurring time, the action type, and the action result [10, 12] (Table 1).
- A **possession** refers to a sequence of successive actions that begin with a team regaining control of the ball and end with losing it [11, 15]. It denotes a complete ball-controlling process in soccer matches, and the player action choices within it are highly interrelated [15]. The description of possession comprises a sequence of actions and the possession result (i.e., shot, goal, and losing the ball).
- A **tactic** is a frequent player behavior pattern occurs in soccer matches [3]. In our analysis, we take one of the mostly adopted definitions of tactic, the representative frequent sequential pattern in a group of similar possessions [11], because it reflects player action choice patterns such as attacking from the left wing. We follow the previous work [11] to calculate the similarity among the possessions, cluster the possessions into groups, and choose the frequent sequential pattern to represent the tactic. The tactic is denoted by a list of actions that consist of this frequent sequential pattern.
- A **match situation** includes the team tactic and players' locations when an action is conducted [10, 15]. We use this definition because the action choices of a player are mainly affected by the locations of his/her teammates and opponents, as well as how the ball is passed to him/her. For instance, a player is likely to take the ball forward when his/her teammate has passed a long ball to him/her while passing the ball back when closely defended by opponents.

3.2 Requirement Analysis

We collaborated with three soccer experts for one year to develop a visual analytics system for soccer player action evaluation and improvement. The experts include a professor from sports science who has worked as a senior sports analyst for decades (E1), a continental top soccer coach (E2), and a Ph.D. student from sports science who was a professional player in a top soccer league (E3).

We surveyed related work to summarize the problem of soccer player action evaluation and discussed it with the experts through meetings. The experts agreed that the basic problem is to calculate objective scores for player actions by data-driven models. Then, we interviewed the experts individually to understand their own analysis workflow and faced challenges. In the interview, the experts mentioned that the exact same player locations and action locations would hardly repeat in soccer matches. Thus, they seldom directly examine the action scores one by one. They often categorize the actions of certain players and aggregate the scores by interested categories to evaluate player performance in various aspects. However, the experts faced challenges in both action evaluation models and action score analysis. E1 mentioned that previous action evaluation models [6, 10, 28] provide one score for each action rather than evaluate multiple aspects such as risk and reward. Besides, E1 and E2 stated that they need to investigate action scores under different match situations, which is laborious to manually identify and summarize with current analysis workflow. Based on the results, we summarized the initial requirements for system design.

We held weekly meetings during the system development and iteration process. As for the action evaluation framework, we discussed with the experts which action evaluation models meet their knowledge. They indicated that the principle of the EPV framework [3] matches their experiences, but a simple action score is limited to evaluate the action comprehensively. Thus, we decided to extend the original EPV framework by providing action scores on both risk and reward based on the suggestions from E1. As for the visual design, we designed a system prototype that supported displaying action scores by match situations and presented it to the experts to collect their comments. E1 mentioned that comparing action choices in the same match situation is also important to evaluate which action choice is better. E3 also denoted that explaining the action scores to players is helpful to improve their performance on action choices. We iterated the visual design with the comments and synchronized the design requirements accordingly.

We finally developed the following six design requirements in three aspects, including player navigation (**R1**, **R2**), action investigation (**R3**, **R4**), and action explanation (**R5**, **R6**).

R1 *Navigate important players for evaluation and improvement.* To improve team performance effectively, experts often pay attention to the players who play important roles in matches. They usually learn the importance of players through the number of actions and the action results. Efficient navigation tools should be provided to help discover important players by these indicators.

R2 *Identify similar players on decision styles for comparison.* Experts also demand to obtain references on player action improvement from comparing to other players with better performance. Particularly, experts would focus on those players with similar decision styles because their action choices are practical to learn from. It is necessary to support the identification of such players.

R3 *Explore player action scores by match situations.* Players usually perform differently according to the match situations, including the current team tactics and the locations of their teammates and opponents. Evaluating performance by match situations can assist experts in understanding the players' strengths and weaknesses and whether the players suit the match situations well. The system should present action scores among different match situations.

R4 *Investigate player action scores of different action choices.* Under the same match situation, players would perform variously with different action choices because of the dynamic nature of soccer matches. Providing action scores of different action choices on risk and reward can help evaluate if the choices are successful under such a match situation and find the actions that need to be improved. The system should illustrate these detailed scores.

R5 *Compare action choices and their scores from different players under similar match situations.* After the evaluation, experts need to compare action choices to those of other well-performed players under similar match situations to seek guidance for improving the action choices. Besides, comparing the action scores on risk and reward would facilitate players to understand where their action choices are not as good enough as the well-performed players.

R6 *Display the individual action and the results of its alternative actions.* Experts need to inspect each action and the results of its alternatives to explain to the players why the action is not the best choice. The results for an alternative action refer to the change of action scores on risk and reward after adjusted end location or action type. For instance, with such results, players can realize that passing forward would gain more reward on winning shots and goals, which is better than their actual actions.

3.3 Data Processing

The data used in our analysis is from an open-sourced soccer event dataset provided by StatsBomb [52] with all matches in *EURO 2020*, one of the top European soccer tournaments. It is a fine-grained soccer event dataset that contains not only the locations of the ball controllers but also those of other players closely focused by the ball controllers. In detail, each event in the dataset is described by categorical attributes, spatio-temporal attributes, and fine-grained contextual information. The primary event attributes are presented in Table 1. In total, the dataset contains 51 matches, 24 teams, 487 players, and 112,556 actions. Our analysis mainly focuses on offensive actions that the type is pass, dribble, or shot. The data processing consists of two steps: the conversion of terms and the extraction of features and labels. To convert the original data to the terms in Section 3.1, we divide event streams in each match into possessions based on the definition, detect tactics from the possessions following the previous work [11], and match the tactics to actions to complete the description of the match situation. The construction of features and labels for training the action evaluation framework will be introduced in Section 4.2.

Table 1: The event attributes

Attribute	Description
Event Type	Technique used to process the ball (*i.e., pass, dribble, shot, etc.*).
Event Result	Result of the event (*i.e., succeeded or failed*).
Player	Player who acts on the ball.
Time	The match time when the event occurred.
Event Locations	The start and end coordinates of the event.
Player Locations	The coordinates of all players who are visible in the live match video.
Visible Area	The area of the pitch that is visible in the live match video.

3.4 System Overview

Action-Evaluator is a web application comprising three components: data processing, action evaluation, and visualization (Fig. 1). The data processing component constructs the action features and labels from the dataset for model training and detects team tactics within the actions for match situation characterization. The action evaluation component contains the improved EPV framework trained with the action features and labels to calculate each action's risk and reward scores and provide the results of its alternative actions. The visualization component is the user interface for interactive action evaluation and consists of three views: the player view (Fig. 4(A)), the action view (Fig. 4(B)), and the explanation view (Fig. 4(C)). The data processing component and action evaluation component are implemented via Python. The visualization component is implemented via React.

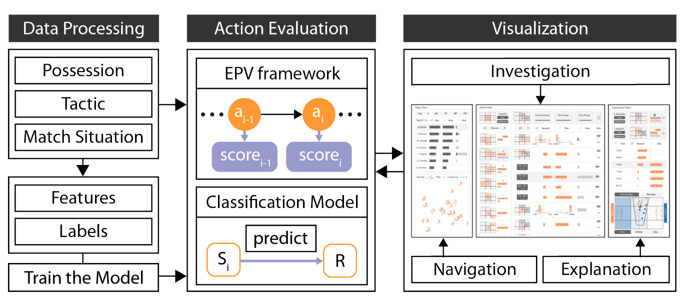

Fig. 1: The overview of the system. The system includes three components: the data processing component, the action evaluation component, and the visualization component.

4 Framework for Action Evaluation

In this section, we define the soccer action evaluation task and introduce the expected possession value (EPV) framework. Then, we provide our action evaluation framework based on the EPV framework.

4.1 Task Definition

The major task of soccer player action evaluation is to calculate a score $score_i$ for each action a_i to indicate its performance. We choose the expected possession value (EPV) framework [3] for action score calculation because its principle is widely accepted by analysts, and the calculated action scores are meaningful. The intuition of the EPV framework is to regard the effect of an action on the expected result at the end of the possession as the action score. Specifically, it measures the effect of an action through the change of the expected possession result before and after the action. The detailed definition is as follows.

The EPV framework focuses on player actions in a possession $P = \{a_1, \cdots, a_n\}$ because actions in the same possession reflect the tactic intention of a team, providing more relevant context information than other actions. A match state at action a_i in a possession is a subsequence of the possession, represented as $S_i = \{a_1, \cdots, a_i\}$, where $i \leq n$. The expected result at the end of the possession, such as the chance of creating a shot, is denoted as the team performance indicator I, which can be calculated by the prediction results of a probabilistic classification model given each current match state. Thus, the effect of a_i is modeled through the change of a certain team performance indicator I from match states $S_{i-1} = \{a_1, \cdots, a_{i-1}\}$ to $S_i = \{a_1, \cdots, a_i\}$. The action score $score_i$ of action a_i can be calculated as follows (Fig. 2):

$$score_i = I(S_i) - I(S_{i-1}). \tag{1}$$

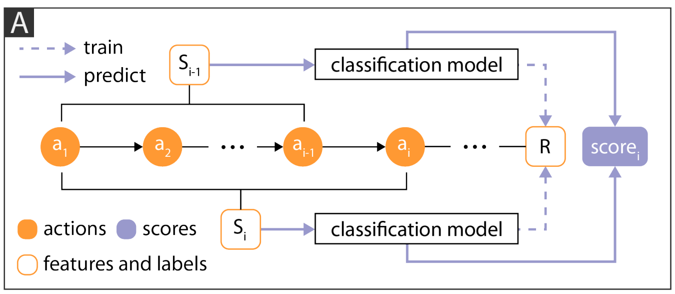

Fig. 2: The structure of the EPV framework. a_i and R refer to the actions and the result in the possession. S_i refers to the match state. $score_i$ refers to the score of action a_i.

4.2 The Probabilistic Classification Model Architecture

We build our action evaluation framework based on the EPV framework. Our framework considers both the reward of creating goal chances and the risk of losing control of the ball by a probabilistic classification model. The model takes the action features and player identifications within a possession as input, and outputs the probability distributions of the two aspects of results for each action.

Input action features. The action feature vector AF_i for an action a_i consists of the spatio-temporal features, the categorical features, and the context features. The spatio-temporal features contain the two-dimensional coordinates of the start and end locations and the occurring time of the action. The categorical feature includes the action type. The context features are the two-dimensional coordinates of all players' locations. To deal with the players who are not visible in the live match video, we consider those players seldom affect the ball controller and assign them their average location in the match. Those action features can cover most of the relevant factors that affect the match result [10].

Output result labels. We define two result labels, l_{risk} and l_{reward}, to identify the outcomes on maintaining the ball possession and winning a goal chance. In detail, we assign a positive label for l_{risk} if the ball is under the control of the same team after the action a_i is finished. Besides, we assign different labels for l_{reward} by which result has occurred within a temporal window of k actions in the same possession, including a shot, a goal, and none of them. We introduce a hyperparameter k to measure the impact of an action on the match result in the relevant future. We choose $k = 5$ based on domain knowledge.

The model architecture. The probabilistic classification model contains a player embedding component and a sequence prediction component. We integrate the learning of player embedding vectors into the probabilistic classification model for a precise action evaluation [29]. The player embedding component transforms the player one-hot encoding e_i to an n-dimensional embedding vector E_i [33]. We set the embedding dimension $n = 10$ as a hyperparameter according to preliminary experiments. The sequence prediction component includes an LSTM network [22] to extract the feature vector SF_i of each match state $S_i = \{a_1, \cdots, a_i\}$ throughout the possession (Fig. 3(D)). The input of each LSTM cell I_i is the concatenation of the player embedding vector E_i and the action feature vector AF_i (Fig. 3(B)). The state feature vectors SF_i are used for the classification tasks of l_{risk} and l_{reward} (Fig. 3(C)). The player embedding vectors E_i are also jointly learned through the backpropagation of the two kinds of loss. In this method, players who contribute similarly to the risk and reward through their actions would have similar embedding vectors learned by the model.

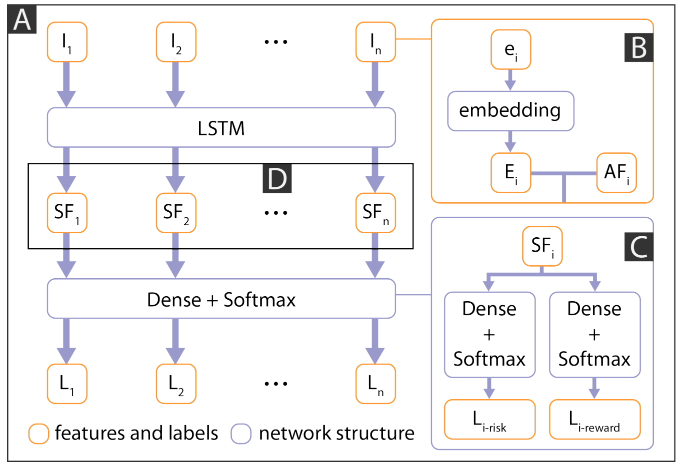

Fig. 3: The architecture of the probabilistic classification model (A). (B) and (C) present the model input and the classification layers.

4.3 The Calculation of Action Score

Through the probabilistic classification model, we obtain the probability distributions of l_{risk} and l_{reward} for each match state S_i. We define two team performance indicators that denote the successful outcomes of an action, $I_{risk}(S_i)$ and $I_{reward}(S_i)$, by the two probability distributions. The calculation of the two team performance indicators is as follows:

$$I_{risk}(S_i) = P(l_{risk} = same|S_i), \tag{2}$$

$$I_{reward}(S_i) = \lambda_1 \cdot P(l_{reward} = shot|S_i) + \lambda_2 \cdot P(l_{reward} = goal|S_i), \tag{3}$$

where $\lambda_1 + \lambda_2 = 1$. $P(l_{risk} = same|S_i)$ indicates the probability of the ball being controlled by the same team immediately after the action a_i. $P(l_{reward} = shot|S_i)$ and $P(l_{reward} = goal|S_i)$ denote the probabilities of occurring a shot or goal in the near future within the possession after the action a_i, respectively. λ_1 and λ_2 are adjustable weights that represent the importance of the result types to win a match. The two scores $risk_i$ and $reward_i$ of action a_i are calculated as follows:

$$risk_i = I_{risk}(S_i), \tag{4}$$

$$reward_i = I_{reward}(S_i) - I_{reward}(S_{i-1}). \tag{5}$$

Thus, the score $risk_i$ indicates the chance of the possession still maintained after the action a_i, and the score $reward_i$ means the chance increment of winning a shot or goal caused by the action a_i.

4.4 Model Evaluation

The EPV framework estimates the action scores with the change of expected results at the end of possessions. Thus, an accurate probabilistic classification model can lead to a precise evaluation of the effects of the actions on expected possession results. To evaluate the effect of player embedding on prediction accuracy, we compare our model with the baseline model that removed the player embedding component. In the evaluation, we select the last 15% of actions in the dataset according to the occurring time as the test data and others as the training data. We use the standard metrics to evaluate the two models, including precision, recall, and F1-score. The detailed results are shown in Table 2.

As for the prediction of the reward label, all three metrics are higher than those of the baseline model, meaning that the player embeddings can improve the model performance. As for the newly concerned risk label, our model also performs well on these metrics, indicating that our model can also provide a precise evaluation for risk.

Table 2: The model evaluation results

	Reward (Baseline)	Reward (+ Embedding)	Risk (+ Embedding)
Precision	0.52	**0.65**	0.98
Recall	0.78	**0.79**	0.83
F1-score	0.58	**0.71**	0.90

5 Visual Design

In this section, we introduce the visual encoding and interaction in our system according to the previously summarized domain requirements.

5.1 Overview of Visual Design and User Interface

In Action-Evaluator, we design a player view for player navigation (**R1**, **R2**), an action view for action investigation (**R3**, **R4**), and an explanation view for action explanation (**R5**, **R6**). In the player view, analysts can navigate the target player through action frequency and results with the player ranking list (**R1**) (Fig. 4(A1)). Besides, they can also select players similar to the target player for comparison by the player projection component (**R2**) (Fig. 4(A2)). After the player selection, analysts can inspect the actions of the player in the action view. They can choose actions by match situations with the match situation list (**R3**) (Fig. 4(B1)), and further investigate the scores of each action choice with the action score list (**R4**) (Fig. 4(B2)). During the investigation, analysts can add action choices of interest to the explanation view. In the explanation view, analysts can compare the action choices from different players (**R5**) (Fig. 4(C1)) and observe individual action choices to explain the scores to players (**R6**) (Fig. 4(C2)). We choose orange and blue to encode positive values and negative values of the action scores throughout the whole user interface.

5.2 Player View

The player view (Fig. 4(A)) consists of a player ranking list to navigate the target player for further analysis (**R1**) and a player projection component to present the similarity among the players (**R2**).

Player ranking list. The player ranking list presents players in a sortable list to assist the navigation of the target player (**R1**) (Fig. 4(A1)). Each row of the list indicates a player, which consists of the name label to denote the player and the indicators to represent the player's importance, including the total action number and the succeeded action number for each action type (Fig. 4(A3)). The indicators in the same action type are encoded together by a stacked bar chart for effective sorting and comparing, where the dark bar represents the number of succeeded actions, and the whole bar indicates that of all actions.

Justification. The number of actions performed by the players and those that succeeded are usually used to reveal the importance of players to the matches. Thus, the list contains the two indicators for each action type. We provide the two indicators by different action types because analysts need to select important players on multiple aspects.

Player projection component. The player projection component is a scatterplot presenting similarities among the players on the aspects of competence and style (**R2**) (Fig. 4(A2)). Each player in the scatterplot is represented by a glyph, and the player similarity is encoded by the distance between glyphs. The glyph contains three metrics to indicate the overall performance of the player. In detail, we use the radius of the inner circle to encode the total action number, the length of the inner arc to encode the overall risk score, and the length of the outer arc to encode the overall reward score. The two-dimensional locations of the glyphs in the scatterplot are projected by the t-SNE algorithm [56] that takes the learned high-dimensional player embedding vectors as input.

Justification. We define player similarity as the Euclidean distance among the player embedding vectors because similar embedding vectors mean the players contribute similarly to their teams through actions. We choose the t-SNE algorithm for projection because it preserves local similarity, which can help efficiently distinguish similar players.

Interaction. The interaction in the player view is as follows.

- *Filtering.* Analysts can filter the players appearing in the player view according to their teams and roles with the drop list and the switch button. Besides, analysts can also filter out the top n players with the top-n drop list to focus on important players.
- *Sorting.* Analysts can click the three buttons on the top of the player ranking list to sort players by the numbers of all actions or succeeded actions of pass, dribble, and shot, respectively.
- *Selecting players.* Analysts can click the item in the player ranking list or the glyph in the player projection component to select the player to be analyzed in the action view.

5.3 Action View

The action view (Fig. 4(B)) is composed of a match situation list and an action score list. Analysts can choose actions by spatial regions and specify the match situation they are interested in through the match situation list (**R3**). Then, the scores of different action choices under the selected match situation are presented in the action score list (**R4**). We also design a set of pitch-based diagrams to display the match situation and the action choices together with the match situation (Fig. 6).

Pitch-based diagrams. The pitch-based diagrams include a match situation diagram (Fig. 6(A)) and an action choice diagram (Fig. 6(B)) to present match situations and action choices in soccer matches.

The match situation diagram comprises a pitch-based tactic representation and a pressure bar to describe the tactic and player locations, respectively (**R3**). According to its definition, a tactic can be denoted by a sequence of actions discretized by regions on the pitch [11] (Fig. 5(C)). Thus, we design a pitch-based tactic representation to visualize the tactic through links between the regions on the pitch. The pitch is divided into nine spatial regions, including the defensive third, the middle third, and the attacking third, because it is one of the most common pitch division method in soccer analytics [21] (Fig. 5(A)). We also highlight the pitch regions involved in the tactic with orange color and diminish others with gray color. The pressure bar is a gray bar chart placed along the pitch to encode the average defense pressure in the match situation.

To identify the tactics that the actions belong to, we find the possessions that the actions belong to and calculate the distances among the possessions with the dynamic time warping (DTW) algorithm [11]. Then, we cluster the possessions into groups through hierarchical agglomerative clustering (Fig. 5(B)). Finally, we discretize the actions of each possession in the cluster and obtain the representative sequential pattern as the tactic by the pattern mining algorithm (Fig. 5(C)). The defense pressure value is calculated based on the average distance between the ball controller and the opponent players [2].

The action choice diagram is derived from the match situation diagram, containing a pitch-based action representation, and a pressure bar identical to that in the match situation diagram (**R4**). An action choice indicates how the ball is processed by a player under a certain match situation, which can be determined by the start and end regions and the type of this action. In the pitch-based action representation, we use orange color to highlight the start and end regions of the action and link the regions by a link that encodes the action type. To integrate tactics into the action representation, we divide each possession into three parts, the action sequence before the action, the action, and the action sequence after the action, and utilize the pattern mining algorithm to obtain the representative frequent sequential patterns for the action sequences before and after the action choice, respectively [11]. We link the sequences of pitch regions before and after the action choice to the action choice. Those regions are marked with dark gray color to be distinguished from the start and end regions of the action choice.

Justification. We choose links between regions on the pitch rather than other widely used visualizations, such as pitch region sequence [65] and heatmap [1], to illustrate the tactic in the match situation because it remains the trace of the action sequence in a concise view, which enables an effective comparison. Besides, different from previous work that displays action choice from match situation separately [38, 65], we place the action choice together with the tactic it belongs to in the same view to attach the context information to the action choice directly. The defensive pressure value reflects the extent that the action choice of the ball controller is affected by the locations of other players [2], which is usually adopted to comprehend why an action choice was made under such a circumstance. Thus, in the two

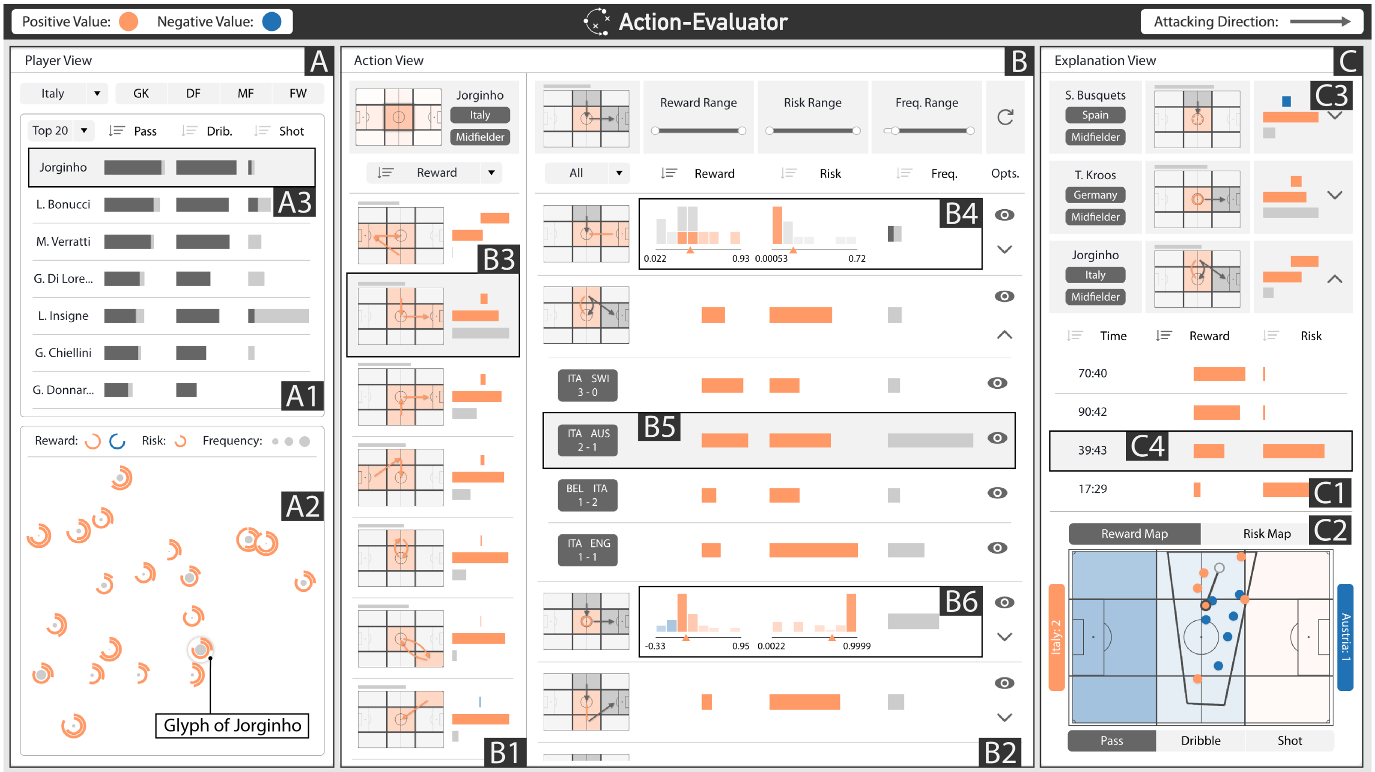

Fig. 4: System user interface. The interface contains three views: a player view (A), an action view (B), and an explanation view (C). The player view consists of a player ranking list (A1) to navigate players by importance and a player projection component (A2) to navigate players by similarity. The action view includes a match situation list (B1) to investigate action scores by match situations and an action score list (B2) to present those of different action choices. The adjustment view is composed of a record list (C1) and a ghost pitch (C2) to explain action scores to players.

kinds of pitch-based diagrams, we abstract the player locations to the defensive pressure value to simplify their representation.

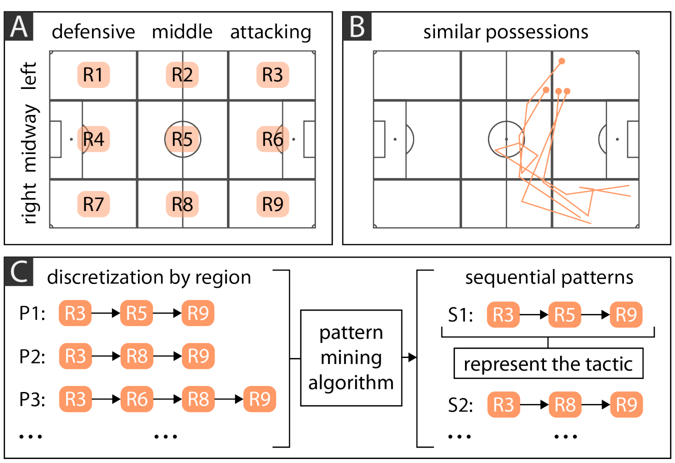

Fig. 5: The tactic detection process in the system [11]. (A) shows the pitch division method [17] used in our system. (B) presents a group of similar possessions after clustering. (C) demonstrates the process of finding the sequence of actions to represent the tactic.

Match situation list. The match situation list presents the action scores in multiple match situations with a sortable list (**R3**) (Fig. 4(B1)). At the top of the list, we provide a player action heatmap that enables selecting actions by start region for further analysis. Each row of the list indicates the actions conducted in the same match situation, containing a match situation diagram that denotes the match situation, the average reward and risk scores, and the frequency of the actions (Fig. 4(B3)). The two kinds of action scores and the action frequency are encoded by three bar charts, respectively, to facilitate comparison.

Justification. Selecting actions by start region is supported because analysts usually inspect actions that players conducted in their familiar locations on the pitch. The match situations in the list can be sorted by the three metrics because analysts need to learn the player's strengths and weaknesses under different match situations in diverse aspects.

Action score list. The action score list is a sortable list of all action choices conducted under the selected match situation (**R4**) (Fig. 4(B2)). Each row of the sortable list represents an action choice and consists of an action choice diagram and three bar charts that encode the same three metrics as those in the match situation list. Moreover, the bar charts that encode the average risk and reward scores can be unfolded into histograms to display the detailed distribution of the scores among different actions (Fig. 4(B4, B6)). Both the length and the saturation of the bar encode the numbers of the actions that fall into the interval, and the triangle indicator denotes the average score value. Each row in the list can also be unfolded to a sub-list that shows the scores and frequency of the action choice by matches (Fig. 4(B5)).

Justification. We utilize histograms to display the distributions of the two action scores because analysts also need to inspect the variation of scores for the same action choice. The detailed scores and frequency of the action choice by matches are provided to help analyze the action performance when facing different opponents.

Interaction. The interaction in the action view is as follows.

- *Selecting action region.* Analysts can click the region in the action heatmap to select the actions started from it for further analysis.
- *Filtering.* Analysts can click the region in the match situation diagram or drag the sliders at the top of the action score list to focus on a specific group of action choices by filtering.
- *Sorting.* Analysts can click the buttons on the top of the match situation list or the action score list to sort the items in the lists.
- *Unfolding details.* In the action score list, analysts can click an item to unfold the bar charts for the two scores into histograms. The same actions within different charts in an item can also be simultaneously highlighted by clicking a bar in a histogram. They can also click the unfold icon to unfold the sub-list in each item.
- *Selecting actions.* Analysts can click the view icon of the item in the action score list to add the actions to the explanation view.

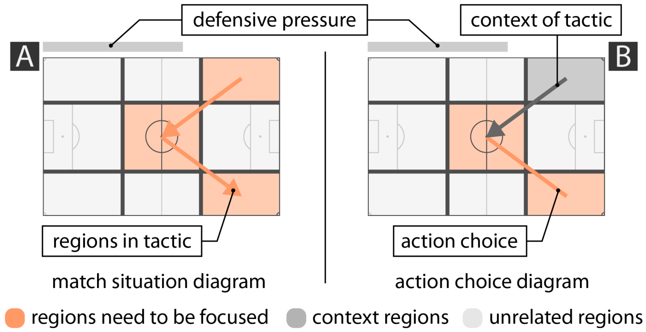

Fig. 6: The design of the two pitch-based diagrams in the system. (A) presents the design of the match situation diagram. (B) presents the design of the action choice diagram.

5.4 Explanation View

The explanation view (Fig. 4(C)) contains a record list to compare actions from different players (**R5**) and a ghost pitch to display individual actions and the results of alternative actions (**R6**).

Record list. The record list records the selected actions to compare action choices from different players (**R5**) (Fig. 4(C1)). It supports comparing action choices from multiple players by continuously selecting action choices from the action view of different players. Each row in the list consists of a player label, an action choice diagram to illustrate the action choice that the actions belong to, and three bar charts that encode the average reward and risk scores and the frequency of the actions (Fig. 4(C3)). A certain row can be unfolded to a sub-list to represent individual actions contained in this row by their occurred time and the reward and risk scores encoded by bar charts (Fig. 4(C4)).

Justification. The record list only supports comparing several players because analysts usually focus on one or two players who played similarly to but more well-performed than the target player to seek the most effective action improvement guidance. The action choice diagram is included in the list to facilitate the comparison of action choices from different players under similar match situations.

Ghost pitch. The ghost pitch displays detailed information about individual actions and illustrate the results of alternative actions based on the ghosting method [27] (**R6**) (Fig. 4(C2)). The pitch provides the player locations when the action occurred, where the orange circles indicate the players of the offensive team, and the blue ones denote those of the defensive team. The ball controller is highlighted with a border around the circle, and the action is presented by a link that encodes the action type. The increment of the scores that the actions end up with different locations on the pitch is shown by a heatmap.

Justification. We use a heatmap to present the score increments to facilitate analysts to understand why the current action choice is not the best one by a familiar view. The score increments are aggregated by regions to be consistent with the discretization of action choices.

Interaction. The interaction in the explanation view is as follows.

- *Sorting.* Analysts can click the buttons on the top of the sub-list to sort the actions by occurred time and action scores.
- *Selecting individual action.* Analysts can click the item in the sub-list to select the action displayed in the ghost pitch.
- *Switching score or action types.* Analysts can switch between the reward and risk scores or among the alternative action type by clicking the two groups of switch buttons in the ghost pitch.

6 System Evaluation

In this section, we evaluate the system usability on different kinds of users with two case studies conducted by our experts respectively. We interviewed the experts after the case studies to collect their feedback.

6.1 Case Study

The case studies are based on the open-sourced soccer event dataset [52] used in our analysis with all matches in *EURO 2020*. We invited two experts who did not participate in the requirement analysis to conduct the case study, including a senior sports analyst (E1) and a professional soccer coach (E2). Before the case studies, we introduced the visual encodings and a typical workflow of the system to the experts, and helped them get familiar with the system through freely exploring. Then, the experts respectively analyzed player actions with their own interests. During the case studies, we recorded the analysis process of the experts as well as their comments and valuable insights.

6.1.1 Case 1: Inspecting the Excellent Performance of the Italian Midfielder Jorginho

The first case study is finished by E1, which aims to analyze the action choices of the important players of Italy. Italy has entitled the champion of *EURO 2020* and won all matches during the tournament. E1 stated that the outstanding performance of Italy had attracted extensive attention from soccer analysts. Therefore, E1 was interested in analyzing their performance through the actions conducted by them.

In the beginning, E1 selected Italy from the drop list in the player view and selected the top 20 from the top-n drop list to focus on important players (Fig. 4(A)). In the player ranking list, E1 noticed that Jorginho ranked at the top of the team on both the total number and the succeeded number of pass and dribble actions, meaning that Jorginho is one of the core players of Italy and played an important role in the whole team (Fig. 4(A1)). Besides, in the player projection component, E1 found that compared with the teammates, the overall risk score of Jorginho is relatively higher, while the overall reward score is relatively lower (Fig. 4(A2)). Such scores indicated that Jorginho mainly contributes to the team by controlling the ball instead of key attacking actions. Then, E1 selected Jorginho for further analysis.

After the player navigation, E1 turned to the action view to evaluate the actions of Jorginho. E1 first explored the action scores of Jorginho by match situations in the match situation list. In the player action map, E1 selected the actions started in the central region because almost all actions are included (Fig. 4(B1)). Then, E1 sorted the match situation list with action frequency to inspect how Jorginho performed in the match situations that occurred most. E1 examined the list and summarized that Jorginho mainly participated in the tactics of transiting the ball from wings to midway for attack when under high pressure (Fig. 7(A)). As for the action scores under those match situations, E1 noticed that the average reward scores are positive and higher than most of the other match situations. The average risk scores are similar to other match situations and near the maximum value of 1 (Fig. 7(A)). Based on such observations, E1 concluded that **Jorginho tends to keep control of the ball in the midfield and slightly increase the goal chance at the same time in transiting the ball to midway when under high pressure**. It also indicated that as a midfielder, Jorginho is good at keeping the balance between risk and reward in his actions.

To analyze action scores by action choices, E1 selected the match situation of Jorginho that he occurred most, transiting the ball from the left wing to midway when under high pressure (Fig. 7(A1)), and moved to the action score list. E1 filtered out the action choices whose frequency is less than 10 and sorted the action score list with action frequency to examine the frequent actions. Then, E1 inspected the list and found that under such a match situation, the action choices of Jorginho concentrate on short passes or dribbles within the midfield (Fig. 7(C2)). Besides, the action choices for passes to wings and direct forward passes are also occasionally conducted (Fig. 7(B1)). As for the action scores, E1 noticed that those action choices are mainly with a relatively low average reward score and high average risk score, while the action choice for direct forward passes is an exception (Fig. 7(B2)). E1 explained that it is reasonable since passing forward would usually increase the goal chance but are likely to fail due to the defense from the opponents. Through this process, E1 concluded that **the critical action choices of Jorginho under the match situation that occurred most are controlling the ball through short passes or dribbles within the midfield**. E1 also commented that such kind of actions is essential in organizing build-up attacks because it takes the ball out of the high defensive pressure to start an effective attack.

Furthermore, E1 noticed that the average reward score of short dribble within the midfield is slightly less than 0, meaning that the goal chances were mainly decreased after those actions (Fig. 7(C3)). E1 tried to find out whether such an action choice of Jorginho could be further improved. Thus, E1 clicked to unfold the histograms of action scores and found that most actions have a negative reward score and a near 1 risk score. It indicated that those actions aimed to control the ball under high pressure and find other chances of attack, although the goal chances would be temporarily decreased. Then, E1 inspected the action scores by matches and found that the average reward score in the match against Belgium, which usually defended at a high position with five defenders, is the lowest among all matches (Fig. 7(D)). E1 added these actions to the explanation view for improvement. In the explanation view, E1 sorted the sub-list of this item with the reward score and selected the action with the lowest reward score as an example action. With the ghost pitch, E1 found that the selected action is a short backward dribble, and passing the ball to the wings would slightly increase the reward score and decrease the risk score (Fig. 7(E1, E2)). Through this process, E1 concluded that **as for the action choice on short dribble within the midfield of Jorginho, passing the ball to teammates not closely defended by opponents might be an improvement if he is required to increase the goal chance**.

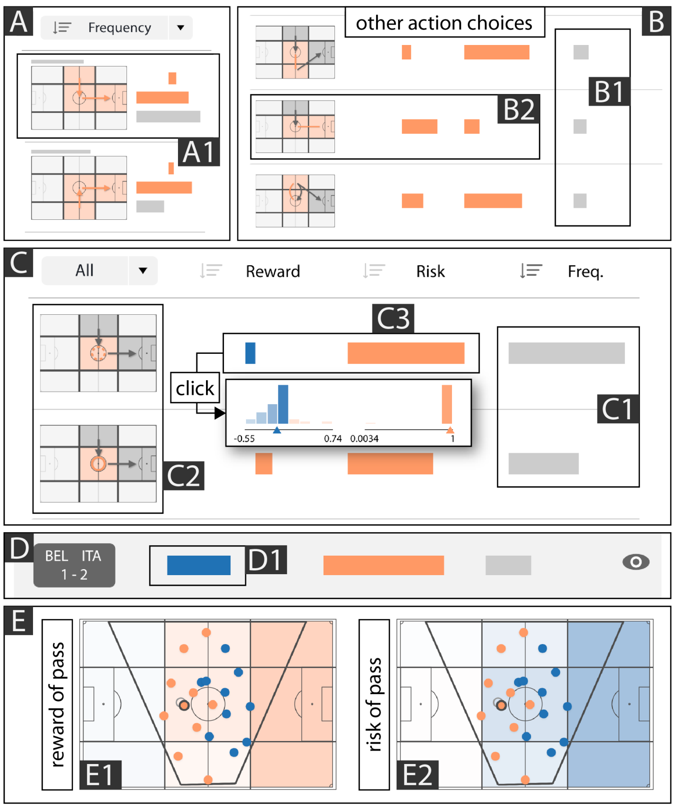

Fig. 7: The analysis process of case 1. (A) presents the match situations of Jorginho that he occurred most. (B) and (C) present the frequently used action choices of Jorginho under the selected match situation (A1). (D) and (E) present the action improvement process.

6.1.2 Case 2: Improving the Performance of the French Forward Kylian Mbappé

The second case study is conducted by E2, which focuses on improving the action choices for the important players of France. France was seen as one of the teams that most likely to win the championship in *EURO 2020*. However, France only won the first match during the tournament and stopped their step at the round of 16. Thus, E2 was interested in discovering improvement guidance on action choices for them.

E2 started from the player view by selecting France from the drop list and switching to the forwards to try to improve the action choices of the forwards. In the player ranking list, E2 found that Kylian Mbappé finished the most shot but did not obtain a goal (Fig. 8(A1)). Besides, in the player projection component, E2 noticed that the overall reward score of Mbappé is only 0.017, which is lower than those of other main forwards. E2 indicated that as one of the most important forwards of France, the performance of Mbappé on increasing the goal chance for the team did not meet the expectation. Thus, E2 added Mbappé to the action view to analyze and improve his action choices on reward scores.

In the action view, E2 selected the actions conducted in the left wing and near the opponent's goal as Mbappé is well known for his effective breakthrough from wings, and the actions on the left wing are more than those on the right wing (Fig. 8(C)). Then, E2 sorted the match situation list with the average reward score and found that the actions that Mbappé conducted in the match situation that he occurred most, attacking from the left wing when under medium pressure, are with the lowest average reward score (Fig. 8(C1)). Therefore, E2 selected this match situation and turned to the action score list to find out the action choices that could be further improved. E2 sorted the action score list with the average reward score and filtered out the action choices with a frequency of less than 10 to focus on the frequent actions with unsatisfying reward scores. E2 noticed that action choices of Mbappé under such a match situation mainly include short dribbles within the left wing and passes to the opponent's goal, and both the average reward and risk scores of the latter action choice are lower than the former one (Fig. 8(D)). Through this process, E2 concluded that **passing to the opponent's goal when attacking from the left wing under medium pressure is an essential action choice for Mbappé that needs to be improved**. Thus, for such an action choice, E2 further clicked to unfold the histograms of action scores, selected the actions with the lowest reward score near 0, and added them to the explanation view for further investigation and improvement (Fig. 8(D2)).

To obtain references on action improvement from other players, E2 returned to the player view and selected forwards from all countries whose shot number is ranked top 20 as important forwards around the tournament. In the player projection component, E2 noticed a player, Harry Kane from England, who played similarly to Mbappé, but the overall reward score is 0.077, much higher than that of Mbappé (Fig. 8(B)). E2 added Kane to the action view, selected a similar match situation from the match situation list, and filtered the action choices from the action score list with the same procedure as before. Then, E2 found two critical action choices of Kane, including short passes and dribbles within the left wing, and added both action choices to the explanation view as the action improvement references. In the record list, E2 noticed that the average reward score of the short pass within the left wing of Kane is much higher than that of the action choice to be improved for Mbappé (Fig. 8(E2)). Moreover, E2 took the action that Mbappé conducted in the match against Germany at 07:05 as an example to verify whether the improvement would be effective (Fig. 8(E4)). In the ghost pitch, E2 found that passing the ball within the left wing would increase both the reward and risk scores (Fig. 8(F)). E2 also agreed that short passes in the attacking third might be more effective as they could help players get rid of defense and organize the attack in an unexpected way. Through this process, E2 concluded that **Mbappé could improve his action choices by short passing within the left wing instead of directly passing to the opponent's goal**.

6.2 Expert Interview

After the case studies, we interviewed the experts separately to collect their feedback. Before the interviews, we showed each expert the analysis procedure of the case study conducted by another expert. During the interviews, we asked the experts three questions for their own opinions on the system usability, including whether the system could fulfill the requirements on player action evaluation (**R1**-**R6**), what new insights were discovered by the system, and where the system could be further improved. Their answers are summarized as follows.

Usability. Both experts appreciated our system and agreed it could meet the requirements for evaluating player actions. E1 thought highly of the analysis workflow of our system, *"The action view can help me quickly learn how the players performed with their actions under different match situations, which is laborious with manual identification and summarization in the traditional workflow."* E1 was also impressed by our action evaluation model, *"Most of the action scores meet my expectations. Moreover, I can still discover new insights through the comparison among the exact score values, such as how the players try to strike a balance between risk and reward in their actions."* As for the visual design, E1 liked the pitch-based diagrams, *"Such representations are familiar to me. I can notice the match situation when the action choices were conducted just at a glance."* E2 was impressed by the navigation of similar players, *"I can obtain inspiration on improving the action choices of players in my team from similar but well-performed players."* E2 also favored explaining action scores to players, *"It would

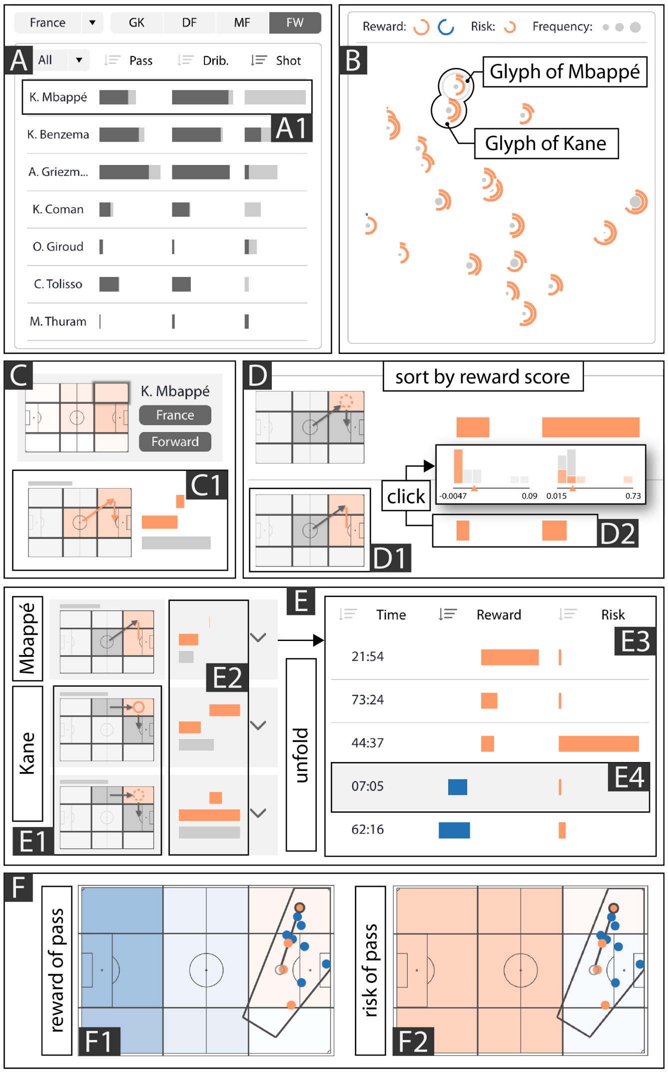

Fig. 8: The analysis process of case 2. (A) and (B) present the player navigation. (C) presents the match situation selection for Kylian Mbappé. (D) presents the action choices of Mbappé under the selected match situation (C1). (E) and (F) present the action improvement process.

be extremely useful in the player training process, especially when I explain to the players why their action choices are not good enough."

Suggestion. The experts proposed several suggestions for our system. First, E1 hoped to improve the action evaluation model by integrating fine-grained action features, *"Including more detailed context information, such as the movements of all players between two consecutive actions, in the action evaluation model may estimate the performance of the actions more precisely."* Second, E2 focused on the interactions in the match situation list and suggested that searching match situations would be useful, *"Sometimes I need to investigate how a player performed under a certain team tactic, such as attacking from the wings. Under such circumstances, directly searching for the match situation would be more effective than finding it in the list by myself."*

7 Discussion

Significance. Evaluating player performance on fine-grained actions is essential in team sports [3]. Existing work on player action evaluation aims to calculate scores for each action to indicate player performance on it. However, it falls short of revealing the dynamics of player action scores under different match situations and providing guidance for improving action choices. We solve such problems in soccer through a visualization approach incorporating an action evaluation framework and a visual analytics system supporting player navigation, action investigation, and action explanation. With our approach, analysts can evaluate player actions by match situations and gain insights for improving player performance on action choices in future matches.

Generalizability. Our approach can be extended to other team sports where the match structure is similar to soccer. The player action evaluation framework treats action effects as the change of expected results at the end of the possession between two consecutive states. As a possession means successive actions of the same team, the framework can be easily adapted to team sports where two teams of players possess the ball alternately, such as basketball and ice hockey, by extracting action features and defining risk and reward caused by the action. The analysis workflow and visual design in our system can also be applied to other sports after simply modifying the domain-specific definitions.

Design lessons. We have learned two lessons in the design study. The first lesson is about the soccer pitch division method used in our pitch-based diagrams. In our system, the pitch division would affect how the tactics and actions are displayed in the diagrams, and how the action scores are aggregated by start and end regions. During the visual design iteration, our experts found that dividing the soccer pitch into too few regions would lead to the same frequent sequential pattern to represent different tactics, while too many regions would cause heavy visual clutter on the diagrams and ineffective action score aggregation. Applying various pitch division methods based on action characteristics [49] or user preferences would be helpful to support different analysis scenarios. The second lesson is about the integration of context information when visualizing action choices. Compared with presenting the match situation and the action choice separately, integrating them in the same view would avoid switching between two diagrams frequently. Thus, in our action choice diagram, we draw how the ball was passed before and after the action as the context information of the tactic, facilitating the understanding of the match situation when the action is conducted. The design can also be generalized to similar tasks for visualizing the context of spatio-temporal trajectories [30, 57].

Limitations. The limitations of our work mainly lie in two aspects. First, the scalability of the record list is limited. In our system, the record list only supports comparing no more than five players because it could fulfill the analysis requirements of our experts. In the future, we plan to improve the scalability of player comparison to a cluster of more than five similar players. In detail, we will develop an algorithm to detect similar match situations among all the players automatically. Then, analysts can indicate a certain match situation and compare the action frequency and scores of a cluster of players directly in the scatterplot. Second, the verification of alternative action outcomes is not provided. In the explanation view, we use a heatmap to illustrate the outcomes of alternative actions compared with the actual action. Further verification of alternative action results may require understanding the inner process of how the outcomes are changed through the different development of subsequent actions. We will develop a model to predict the subsequent actions and their results given a certain action and design visualizations to support the verification process in the future.

8 Conclusion

In this work, we characterize the domain problem of visual analytics for soccer player action evaluation. To provide an effective action illustration, we propose a tailored visualization for soccer actions to place essential match situations with the actions in the same view. Based on the visualization, we develop a visual analytics system, Action-Evaluator, to facilitate action evaluation through player navigation, action investigation, and action explanation, and gain valuable insights for improving player performance on action choices in future matches.

We plan to improve our work in two aspects. First, we will try to collect fine-grained match data such as player trajectory and take them into the action score estimation. It can improve the accuracy of the prediction model and lead to a more precise action score measurement. Second, we plan to extend our system to other team sports like basketball and ice hockey. We aim to summarize the common player action evaluation pipeline and integrate a database such as data cube [20] with multiple team sports data to build a general visual analytics system.

Acknowledgments

The work was supported by National Key R&D Program of China (2022YFE0137800) and NSFC (U22A2032, 62202424), and the Collaborative Innovation Center of Artificial Intelligence by MOE and Zhejiang Provincial Government (ZJU).

References

[1] G. L. Andrienko, N. V. Andrienko, G. Anzer, P. Bauer, G. Budziak, G. Fuchs, D. Hecker, H. Weber, and S. Wrobel. Constructing Spaces and Times for Tactical Analysis in Football. *IEEE Transactions on Visualization and Computer Graphics*, 27(4):2280–2297, 2019. doi: 10.1109/TVCG.2019.2952129 2, 5

[2] G. L. Andrienko, N. V. Andrienko, G. Budziak, J. Dykes, G. Fuchs, T. von Landesberger, and H. Weber. Visual Analysis of Pressure in Football. *Data Mining and Knowledge Discovery*, 31(6):1793–1839, 2017. doi: 10.1007/s10618-017-0513-2 2, 5

[3] R. Beal, T. J. Norman, and S. D. Ramchurn. Artificial Intelligence for Team Sports: A Survey. *The Knowledge Engineering Review*, 34, 2019. doi: 10.1017/S0269888919000225 1, 2, 3, 4, 9

[4] L. Bransen, P. Robberechts, J. Van Haaren, and J. Davis. Choke or Shine? Quantifying Soccer Players' Abilities to Perform Under Mental Pressure. In *2019 MIT Sloan Sports Analytics Conference*, 2019. 2

[5] L. Bransen and J. Van Haaren. Measuring Football Players' On-the-Ball Contributions from Passes During Games. In *International Workshop on Machine Learning and Data Mining for Sports Analytics*, pp. 3–15, 2019. doi: 10.1007/978-3-030-17274-9_1 2

[6] L. Bransen, J. Van Haaren, and M. van de Velden. Measuring Soccer Players' Contributions to Chance Creation by Valuing Their Passes. *Journal of Quantitative Analysis in Sports*, 15(2):97–116, 2019. doi: 10.1515/jqas-2018-0020 2, 3

[7] J. Brooks, M. Kerr, and J. Guttag. Developing a Data-Driven Player Ranking in Soccer using Predictive Model Weights. In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pp. 49–55, 2016. doi: 10.1145/2939672.2939695 2

[8] A. Cao, J. Lan, X. Xie, H. Chen, X. Zhang, H. Zhang, and Y. Wu. Team-Builder: Toward More Effective Lineup Selection in Soccer. *IEEE Transactions on Visualization and Computer Graphics*, pp. 1–16, 2022. doi: 10.1109/TVCG.2022.3207147 1

[9] D. Cervone, A. D'Amour, L. Bornn, and K. Goldsberry. POINTWISE: Predicting Points and Valuing Decisions in Real Time with NBA Optical Tracking Data. In *Proceedings of MIT Sloan Sports Analytics Conference*, 2014. 2

[10] T. Decroos, L. Bransen, J. Van Haaren, and J. Davis. Actions Speak Louder than Goals: Valuing Player Actions in Soccer. In *Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pp. 1851–1861, 2019. doi: 10.1145/3292500.3330758 1, 2, 3, 4

[11] T. Decroos, J. Van Haaren, and J. Davis. Automatic Discovery of Tactics in Spatio-Temporal Soccer Match Data. In *Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pp. 223–232, 2018. doi: 10.1145/3219819.3219832 2, 3, 5, 6

[12] T. Decroos, J. Van Haaren, V. Dzyuba, and J. Davis. STARSS: A Spatio-Temporal Action Rating System for Soccer. In *Proceedings of the 4th Workshop on Machine Learning and Data Mining for Sports Analytics co-located with 2017 European Conference on Machine Learning and Principles and Practice of Knowledge Discovery in Databases (ECML PKDD 2017)*, pp. 11–20, 2017. 2

[13] C. A. Dietrich, D. Koop, H. T. Vo, and C. T. Silva. Baseball4D: A Tool for Baseball Game Reconstruction and Visualization. In *Proceedings of IEEE Conference on Visual Analytics Science and Technology*, pp. 23–32, 2014. doi: 10.1109/VAST.2014.7042478 2

[14] M. Du and X. Yuan. A Survey of Competitive Sports Data Visualization and Visual Analysis. *Journal of Visualization*, 24(1):47–67, 2021. doi: 10.1007/s12650-020-00687-2 2

[15] J. Fernández, L. Bornn, and D. Cervone. Decomposing the Immeasurable Sport: A Deep Learning Expected Possession Value Framework for Soccer. In *2019 MIT Sloan Sports Analytics Conference*, 2019. 2

[16] J. Fernández, L. Bornn, and D. Cervone. A Framework for the Fine-grained Evaluation of the Instantaneous Expected Value of Soccer Possessions. *Machine Learning*, 110(6):1389–1427, 2021. doi: 10.1007/s10994-021-05989-6 2

[17] J. Fernandez-Navarro, L. Fradua, A. Zubillaga, P. R. Ford, and A. P. McRobert. Attacking and Defensive Styles of Play in Soccer: Analysis of Spanish and English Elite Teams. *Journal of Sports Science*, 34(24):2195–2204, 2016. doi: 10.1080/02640414.2016.1169309 2, 6

[18] A. Franks, A. Miller, L. Bornn, and K. Goldsberry. Counterpoints: Advanced Defensive Metrics for NBA Basketball. In *MIT Sloan Sports Analytics Conference*, 2015. 2

[19] K. Goldsberry. Courtvision: New Visual and Spatial Analytics for the NBA. In *Proceedings of MIT Sloan Sports Analytics Conference*, 2012. 2

[20] J. Gray, A. Bosworth, A. Layman, and H. Pirahesh. Data Cube: A Relational Aggregation Operator Generalizing Group-By, Cross-Tab, and Sub-Totals. In *Proceedings of the 12th International Conference on Data Engineering*, pp. 152–159, 1996. doi: 10.1109/ICDE.1996.492099 9

[21] J. Gudmundsson and M. Horton. Spatio-Temporal Analysis of Team Sports. *ACM Computing Surveys*, 50(2):1–34, 2017. doi: 10.1145/3054132 5

[22] S. Hochreiter and J. Schmidhuber. Long Short-Term Memory. *Neural Computation*, 9(8):1735–1780, 1997. doi: 10.1162/neco.1997.9.8.1735 4

[23] Y. Ishikawa and I. Fujishiro. TideGrapher: Visual Analytics of Tactical Situations for Rugby Matches. *Visual Informatics*, 2(1):60–70, 2018. doi: 10.1016/j.visinf.2018.04.007 2

[24] H. Janetzko, D. Sacha, M. Stein, T. Schreck, D. A. Keim, and O. Deussen. Feature-Driven Visual Analytics of Soccer Data. In *2014 IEEE Conference on Visual Analytics Science and Technology (VAST)*, pp. 13–22, 2014. doi: 10.1109/VAST.2014.7042477 1, 2

[25] M. Lage, J. P. Ono, D. Cervone, J. Chiang, C. A. Dietrich, and C. T. Silva. StatCast Dashboard: Exploration of Spatiotemporal Baseball Data. *IEEE Computer Graphics and Applications*, 36(5):28–37, 2016. doi: 10.1109/MCG.2016.101 2

[26] J. Lan, J. Wang, X. Shu, Z. Zhou, H. Zhang, and Y. Wu. RallyComparator: Visual Comparison of the Multivariate and Spatial Stroke Sequence in Table Tennis Rally. *Journal of Visualization*, 25(1):143–158, 2022. doi: 10.1007/s12650-021-00772-0 2

[27] H. M. Le, P. Carr, Y. Yue, and P. Lucey. Data-Driven Ghosting using Deep Imitation Learning. In *2017 MIT Sloan Sports Analytics Conference*, 2017. 7

[28] G. Liu, Y. Luo, O. Schulte, and T. Kharrat. Deep Soccer Analytics: Learning an Action-Value Function for Evaluating Soccer Players. *Data Mining and Knowledge Discovery*, 34(5):1531–1559, 2020. doi: 10.1007/s10618-020-00705-9 2, 3

[29] G. Liu, O. Schulte, P. Poupart, M. Rudd, and M. Javan. Learning Agent Representations for Ice Hockey. In *Proceedings of the 34th Conference on Neural Information Processing Systems*, pp. 18704–18715, 2020. 2, 4

[30] H. Liu, X. Chen, Y. Wang, B. Zhang, Y. Chen, Y. Zhao, and F. Zhou. Visualization and Visual Analysis of Vessel Trajectory Data: A Survey. *Visual Informatics*, 5(4):1–10, 2021. doi: 10.1016/j.visinf.2021.10.002 9

[31] A. G. Losada, R. Therón, and A. Benito. BKViz: A Basketball Visual Analysis Tool. *IEEE Computer Graphics and Applications*, 36(6):58–68, 2016. doi: 10.1109/MCG.2016.124 2

[32] I. G. McHale, P. A. Scarf, and D. E. Folker. On the Development of a Soccer Player Performance Rating System for the English Premier League. *Interfaces*, 42(4):329–420, 2012. doi: 10.1287/inte.1110.0589 2

[33] T. Mikolov, K. Chen, G. Corrado, and J. Dean. Efficient Estimation of Word Representations in Vector Space. *arXiv Preprint*, arXiv:1301.3781, 2013. doi: 10.48550/arXiv.1301.3781 4

[34] B. Moon and R. Brath. Bloomberg Sports Visualization for Pitch Analysis. In *Workshop on Sports Data Visualization*, 2013. 2

[35] J. P. Ono, C. A. Dietrich, and C. T. Silva. Baseball Timeline: Summarizing Baseball Plays Into a Static Visualization. *Computer Graphics Forum*, 37(3):491–501, 2018. doi: 10.1111/cgf.13436 2

[36] L. Pappalardo, P. Cintia, P. Ferragina, E. Massucco, D. Pedreschi, and F. Giannotti. PlayeRank: Data-Driven Performance Evaluation and Player Ranking in Soccer via a Machine Learning Approach. *ACM Transactions on Intelligent Systems and Technology*, 10(5):1–27, 2019. doi: 10.1145/3343172 2

[37] C. Perin, J. Boy, and F. Vernier. Using Gap Charts to Visualize the Temporal Evolution of Ranks and Scores. *IEEE Computer Graphics and Applications*, 36(5):38–49, 2016. doi: 10.1109/MCG.2016.100 2

[38] C. Perin, R. Vuillemot, and J.-D. Fekete. SoccerStories: A Kick-off for Visual Soccer Analysis. *IEEE Transactions on Visualization and Computer Graphics*, 19(12):2506–2515, 2013. doi: 10.1109/TVCG.2013.192 1, 2, 5

[39] C. Perin, R. Vuillemot, and J.-D. Fekete. A table!: Improving Temporal Navigation in Soccer Ranking Tables. In *CHI Conference on Human Factors in Computing Systems*, pp. 887–896, 2014. doi: 10.1145/2556288.2557379 2

[40] C. Perin, R. Vuillemot, C. D. Stolper, J. T. Stasko, J. Wood, and S. Carpendale. State of the Art of Sports Data Visualization. *Computer Graphics Forum*, 37(3):663–686, 2018. doi: 10.1111/cgf.13447 1, 2

[41] H. Pileggi, C. D. Stolper, J. M. Boyle, and J. T. Stasko. SnapShot: Visualization to Propel Ice Hockey Analytics. *IEEE Transactions on Vi-

sualization and Computer Graphics, 18(12):2819–2828, 2012. doi: 10.1109/TVCG.2012.263 2

[42] T. Polk, D. Jäckle, J. Häußler, and J. Yang. CourtTime: Generating Actionable Insights into Tennis Matches Using Visual Analytics. *IEEE Transactions on Visualization and Computer Graphics*, 26(1):397–406, 2020. doi: 10.1109/TVCG.2019.2934243 2

[43] T. Polk, J. Yang, Y. Hu, and Y. Zhao. TenniVis: Visualization for Tennis Match Analysis. *IEEE Transactions on Visualization and Computer Graphics*, 20(12):2339–2348, 2014. doi: 10.1109/TVCG.2014.2346445 2

[44] P. Power, H. Ruiz, X. Wei, and P. Lucey. "Not All Passes Are Created Equal": Objectively Measuring the Risk and Reward of Passes in Soccer from Tracking Data. In *Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pp. 1605–1613, 2017. doi: 10.1145/3097983.3098051 2

[45] A. Rusu, D. Stoica, and E. Burns. Analyzing Soccer Goalkeeper Performance Using a Metaphor-Based Visualization. In *2011 15th International Conference on Information Visualisation*, pp. 194–199, 2011. doi: 10.1109/IV.2011.57 1, 2

[46] A. Rusu, D. Stoica, E. Burns, B. Hample, K. McGarry, and R. Russell. Dynamic Visualizations for Soccer Statistical Analysis. In *2010 14th International Conference on Information Visualisation*, pp. 207–212, 2010. doi: 10.1109/IV.2010.39 1, 2

[47] M. Ryoo, N. Kim, and K. Park. Visual Analysis of Soccer Players and a Team. *Multimedia Tools and Applications*, 77(12):15603–15623, 2018. doi: 10.1007/s11042-017-5137-4 1, 2

[48] D. Sacha, F. Al-Masoudi, M. Stein, T. Schreck, D. A. Keim, G. L. Andrienko, and H. Janetzko. Dynamic Visual Abstraction of Soccer Movement. *Computer Graphics Forum*, 36(3):305–315, 2017. doi: 10.1111/cgf.13189 2

[49] O. Schulte, Z. Zhao, M. Javan, and P. Desaulniers. Apples-to-Apples: Clustering and Ranking NHL Players Using Location Information and Scoring Impact. In *2017 MIT Sloan Sports Analytics Conference*, 2017. 2, 9

[50] D. Seebacher, T. Polk, H. Janetzko, D. A. Keim, T. Schreck, and M. Stein. Investigating the Sketchplan: A Novel Way of Identifying Tactical Behavior in Massive Soccer Datasets. *IEEE Transactions on Visualization and Computer Graphics*, pp. 1–1, 2021. doi: 10.1109/TVCG.2021.3134814 2

[51] L. Shao, D. Sacha, B. Neldner, M. Stein, and T. Schreck. Visual-Interactive Search for Soccer Trajectories to Identify Interesting Game Situations. *Electronic Imaging*, (1):1–10, 2016. doi: 10.2352/ISSN.2470-1173.2016.1.VDA-510 2

[52] StatsBomb. StatsBomb Open Data. `https://github.com/statsbomb/open-data`, 2022. 3, 7

[53] M. Stein, H. Janetzko, T. Breitkreutz, D. Seebacher, T. Schreck, M. Grossniklaus, I. D. Couzin, and D. A. Keim. Director's Cut: Analysis and Annotation of Soccer Matches. *IEEE Computer Graphics and Applications*, 36(5):50–60, 2016. doi: 10.1109/MCG.2016.102 2

[54] M. Stein, H. Janetzko, A. Lamprecht, T. Breitkreutz, P. Zimmermann, B. Goldlücke, T. Schreck, G. L. Andrienko, M. Grossniklaus, and D. A. Keim. Bring It to the Pitch: Combining Video and Movement Data to Enhance Team Sport Analysis. *IEEE Transactions on Visualization and Computer Graphics*, 24(1):13–22, 2018. doi: 10.1109/TVCG.2017.2745181 2

[55] M. Stein, D. Seebacher, R. Marcelino, T. Schreck, M. Grossniklaus, D. A. Keim, and H. Janetzko. Where to Go: Computational and Visual What-if Analyses in Soccer. *Journal of Sports Sciences*, 37(24):2774–2782, 2019. doi: 10.1080/02640414.2019.1652541 2

[56] L. van der Maaten and G. Hinton. Visualizing Data using t-SNE. *Journal of Machine Learning Research*, 9(Nov):2579–2605, 2008. 5

[57] H. Wang, Y. Ni, L. Sun, Y. Chen, T. Xu, X. Chen, W. Su, and Z. Zhou. Hierarchical Visualization of Geographical Areal Data with Spatial Attribute Association. *Visual Informatics*, 5(3):82–91, 2021. doi: 10.1016/j.visinf.2021.09.001 9

[58] J. Wang, J. Ma, K. Hu, Z. Zhou, H. Zhang, X. Xie, and Y. Wu. Tac-Trainer: A Visual Analytics System for IoT-based Racket Sports Training. *IEEE Transactions on Visualization and Computer Graphics*, 29(1):951–961, 2023. doi: 10.1109/TVCG.2022.3209352 2

[59] W. Wang, J. Zhang, X. Yuan, and S. Liu. MatchOrchestra: A Generalized Visual Analytics for Competitive Team Sports. *Journal of Visualization*, 19(3):515–528, 2016. doi: 10.1007/s12650-015-0337-3 2

[60] WhoScored. WhoScored.com: Football Statistics | Football Live Scores. `https://www.whoscored.com/`, 2022. 2

[61] J. Wu, D. Liu, Z. Guo, and Y. Wu. RASIPAM: Interactive Pattern Mining of Multivariate Event Sequences in Racket Sports. *IEEE Transactions on Visualization and Computer Graphics*, 29(1):940–950, 2023. doi: 10.1109/TVCG.2022.3209452 2

[62] J. Wu, D. Liu, Z. Guo, Q. Xu, and Y. Wu. TacticFlow: Visual Analytics of Ever-Changing Tactics in Racket Sports. *IEEE Transactions on Visualization and Computer Graphics*, 28(1):835–845, 2022. doi: 10.1109/TVCG.2021.3114832 2

[63] Y. Wu, D. Deng, X. Xie, M. He, J. Xu, H. Zhang, H. Zhang, and Y. Wu. OBTracker: Visual Analytics of Off-ball Movements in Basketball. *IEEE Transactions on Visualization and Computer Graphics*, 29(1):929–939, 2023. doi: 10.1109/TVCG.2022.3209373 2

[64] Y. Wu, X. Xie, J. Wang, D. Deng, H. Liang, H. Zhang, S. Cheng, and W. Chen. ForVizor: Visualizing Spatio-Temporal Team Formations in Soccer. *IEEE Transactions on Visualization and Computer Graphics*, 25(1):65–75, 2019. doi: 10.1109/TVCG.2018.2865041 2

[65] X. Xie, J. Wang, H. Liang, D. Deng, S. Cheng, H. Zhang, W. Chen, and Y. Wu. PassVizor: Toward Better Understanding of the Dynamics of Soccer Passes. *IEEE Transactions on Visualization and Computer Graphics*, 27(2):1322–1331, 2021. doi: 10.1109/TVCG.2020.3030359 1, 2, 5