ScoutBall: The Ultimate World Cup Visualization Tool

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1 Abstract

This comprehensive report explores ScoutBall, an innovative football scouting tool meticulously crafted to cater specifically to club scouts. With a primary focus on visualization, ScoutBall seamlessly integrates sophisticated data analytics with compelling visualizations, placing a strong emphasis on key performance metrics for both outfield players and goalkeepers. The meticulously organized dataset provides in-depth visual insights into defensive and offensive contributions, empowering scouts to identify well-rounded players, conduct intricate comparative analyses, and unravel nuanced goal-scoring dynamics. Implemented in Python using Dash and Plotly, ScoutBall stands as a powerful and adaptable solution, showcasing the pivotal role of visualization in facilitating streamlined and comprehensive football player analysis.

2 Introduction

Football scouting is a meticulous and systematic process that involves identifying and evaluating potential football players for recruitment by clubs. In the contemporary era, scouting has evolved beyond traditional methods such as live observations, incorporating advanced techniques like data analytics and visualizations to comprehensively assess a player's performance [3].

For clubs, scouting is paramount as it enables them to unearth talented players who can significantly contribute to the team's success. Informed decision-making on player acquisitions is crucial, ensuring that the individuals align with the team's strategy and goals. The FIFA World Cup, being a global showcase of top football talent, provides a unique opportunity for scouting, allowing experts to evaluate players under intense competition and gain insights into their abilities, strengths, and weaknesses on an international stage.

In the realm of football scouting, our specialized visualization tool is exclusively designed for club scouts. Unlike relying solely on statistics, this tool merges advanced data analytics with user-friendly visualizations to provide a comprehensive understanding of player performance.

The primary aim is to empower club scouts by offering a clear view of player performance patterns and facilitating direct comparisons of statistics. The tool goes beyond data presentation, allowing scouts to interact with and filter information based on specific criteria. This personalized approach ensures that scouts can tailor their analysis to their club's unique needs.

The goal of our visualization tool is to enhance decision-making in player recruitment. While statistics can identify top-performing players, visualization adds clarity by presenting complex data in an easily digestible format. This visual approach provides a more nuanced evaluation of potential recruits, contributing to more informed decisions by club scouts.

This tool is designed to streamline talent evaluation. From pinpointing standout performers through statistical extremes to analyzing metrics for a balanced player profile, it covers key aspects. Geographical exploration provides regional insights, while player comparisons unveil shared characteristics, offering a comprehensive solution for efficient football scouting.

3 Data Analysis

3.1 Domain Data Specification

We chose to utilize the "FIFA World Cup 2022 Player Data" dataset (`https://www.kaggle.com/datasets/swaptr/fifa-world-cup-2022-player-data/data`), which offers a multi-faceted perspective of all 829 players who participated in the tournament and their statistics. This rich dataset serves as the foundation for our analysis, allowing us to have a more detailed look into player performance.

The data is represented by 11 tables with players as items (represented by rows) and a variable number of attributes (represented by columns).

The necessary dataset attributes can be divided into two categories: general player statistics and position-specific metrics.

3.1.1 General Player Statistics

The general attributes we are interested in are *player* (name), *age*, *position*, *team* (nationality), *club* and *minutes* (played throughout the tournament).

Considering the dataset encompasses players from various countries, we introduced a new attribute (*cont*) by converting each player's country of origin to their corresponding continent. This modification facilitates a broader understanding of the geographic distribution of players and aids in potential regional insights.

The key attribute is *name*. It is possible to choose this attribute as the key because there are no duplicates (two or more players with the same name) in the dataset. In the case of replacing, expanding or updating the dataset, care must be taken to maintain the uniqueness of this attribute.

These attributes are not inherent to player performance and are relevant to every player, regardless of their role on the field.

3.1.2 Position Specific Performance Data

The attributes used to represent player performances differ depending on the position considered. This is necessary to evaluate and compare the performance of all players in a given position. In fact, some attributes are suitable for quantifying a player's abilities in a certain position, but are not very significant for others. For example, in the analysis of defenders, attributes that measure contributions to the defensive phases of the game are much more significant than those that measure offensive ability. For midfielders, however, the balance between offensive and defensive skills is important, while for attackers offensive skills are of primary importance. Furthermore, the choice to use position-specific attributes is motivated by the fact that it makes no sense for scouters to compare players who play different roles on the pitch. Therefore, there will never be a need to view data from players with different positions at the same time. The position-specific performance attributes we have chosen are represented in Table 1, together with the general ones.

It is important to note that since the FIFA World Cup is an elimination tournament, the number of matches played by teams is different,

Dataset			
Goalkeepers	Defenders	Midfielders	Forwards
Player (name) Age Position Club Team (nationality) Cont (continent) Minutes			
Clean Sheets Pct	Tackles Won Pct	Goals-Assists per Match	Goals-Assists per Match
Saves Pct	Dribble Tackles Pct	SCA per Match	SCA per Match
Pens Saved Pct	Aerial Won Pct	Dribbles Completed Pct	Dribbles Completed Pct
Passes launched Pct	Passes Blocked per Match	Tackles Won Pct	Shots on Target Pct
Crossed Stopped Pct	Shots Blocked per Match	Interceptions per Match	Tackles Interceptions per Match
Passes Pct	Passes Pct	Passes Pct	Passes Pct

Table 1: Dataset Description

therefore considering the absolute statistics of the players throughout the tournament is not adequately representative of their actual performances. For this reason, relative data is necessary. The "FIFA World Cup 2022 Player Data" dataset provides many statistics expressed in percentages. However, this is only possible if the statistic in question can be represented in the form $\frac{favorable\ cases}{total\ cases}$ (for example $\frac{number\ of\ shots\ on\ target}{total\ number\ of\ shots\ attempted}$). For other statistics, however, this form is meaningless. For example, in the case of blocked shots, it is easy to quantify the number of successes, but measuring the player's attempts to block a shot is not. Attributes of this type are normalized by dividing their values by the total minutes the player has played divided by 90 (duration of a match). The dataset used makes the results of this normalization available for some attributes, but not for all. Therefore, when necessary, normalization was applied manually, as described in Section 3.1.3.

3.1.3 Data Preprocessing

The data preprocessing phase is divided into four steps:

Normalization As explained previously, some attributes are not present in normalized form in the original dataset. Therefore, using the *minutes* attribute (minutes played throughout the tournament), the following normalization is applied:

$$value = \frac{value}{minutes/90}$$

Simplifying, we can say that the data in this form represents the values *per match*.

Derived attributes To achieve the objectives introduced in Section 2 and represent the overall performance of the players, an additional attribute is required. The *overall_score* attribute was therefore defined, of a sequential quantitative type, using the following formula:

$$overall\_score = \sum_{i \in I} \frac{value_i - min_i}{max_i - min_i} \times 100$$

Where I is the set of attributes used to evaluate the player, which depends on the player's position, as can be seen in Table 1.

Data Cleaning We apply the following data cleaning steps to the dataset:

- To refine the handling of missing data in our dataset, we systematically removed players with a significant number of missing values, such as *Ismail Mohamad* from Qatar, *Kevin Rodríguez* from Ecuador, and *Yahya Jabrane* from Morocco. This decision was made due to the substantial presence of *NaN* values in the majority of their statistical entries. Recognizing the importance of precision in individual player performance data, we opted against imputing missing values with averages or statistical placeholders, as such an approach could introduce inaccuracies.

- We applied a prudent inclusion criterion excluding from the dataset players who participated for less than 50 minutes in total throughout the entire tournament. This decision stems from the understanding that drawing meaningful conclusions about players with such minimal playing time is nearly impossible and would not be representative. This meticulous data pruning ensures that our analyses and visualizations are based on a reliable and relevant dataset, providing more accurate insights for football scouting experts. Thus, the total number of players is reduced from 829 to 572.

- To ensure uniformity, we made some adjustments to the attribute *age*, such as converting it from a year-day format to years only.

Separation of Tables Since all the identified goals require the analysis and comparison only of players covering the same position on the pitch, it was decided to use 4 separate tables, one for each position. In each table there are the general statistics of the players and their performances, expressed by the position-specific metrics and by the *overall score*.

3.2 Data Abstraction

By doing Data Abstraction we can clearly see that the data we are dealing with is static tabular data. An overview of the Data Abstraction with all attributes that we choose to use can be seen in Table 2.

4 TASK ANALYSIS

4.1 Domain Specific Tasks

In the dynamic world of football scouting, the pursuit of identifying exceptional talent and constructing a winning team requires a nuanced understanding of player performance, statistical analysis, and geographical insights. Let us explore the four key questions that serve as guiding principles for a football scout aiming to make informed decisions in this complex landscape.

Who are the top-performing players based on their overall score, and are there any outliers that significantly stand out from the rest? This question delves into the meticulous task of identifying the top-performing players in a specific position based on their overall score. Beyond a mere statistical exercise, this query forms the cornerstone of talent evaluation, guiding scouts towards

Attribute	Data Type
Player (name)	Categorical
Age	Quantitative Sequential
Position	Categorical
Club	Categorical
Team (nationality)	Categorical
Cont (continent)	Categorical
Minutes	Quantitative Sequential
Clean Sheets Pct	Quantitative Sequential
Saves Pct	Quantitative Sequential
Pens Saved Pct	Quantitative Sequential
Passes Launched Pct	Quantitative Sequential
Tackles Won Pct	Quantitative Sequential
Dribble Tackles Pct	Quantitative Sequential
Aerial Won Pct	Quantitative Sequential
Passes Blocked per Match	Quantitative Sequential
Shots Blocked per Match	Quantitative Sequential
Passes Pct	Quantitative Sequential
Goals-Assists per Match	Quantitative Sequential
SCA per Match	Quantitative Sequential
Dribbles Completed Pct	Quantitative Sequential
Interceptions per Match	Quantitative Sequential
Shots on Target Pct	Quantitative Sequential
Tackles Interceptions per Match	Quantitative Sequential

Table 2: Data Abstraction

players who consistently demonstrate excellence in their respective roles. Furthermore, the exploration of outliers becomes imperative, as it opens avenues for discovering unconventional talents that may bring unique strengths to the team.

How do individual metrics contribute to a player's overall performance, and can we determine if a player possesses balanced stats? Moving on to the second question, the focus shifts to understanding how individual metrics contribute to a player's overall performance. Here, the scout seeks to unravel the intricacies of a player's skill set, discerning the specific qualities that define their success on the field. The goal is not only to identify star players but also to assess whether a player possesses a well-rounded set of skills, a crucial factor in achieving team balance. The scout aims to go beyond surface-level analysis, deciphering the nuanced interactions between various parameters to evaluate the player's strengths and weaknesses, to determine his versatility and adaptability on the pitch.

Which countries or continents have a concentration of high-performing players, and can this information confirm existing hypotheses about scouting bases? The third question propels the scout into the realm of global football dynamics by exploring the concentration of high-performing players across countries and continents. This geographical perspective is instrumental in confirming or challenging existing hypotheses about the predefined scouting areas that teams and scouts have established across the world. The scout endeavors to uncover patterns that may indicate emerging football powerhouses or regions with a consistent track record of producing top-tier talent. This insight becomes invaluable for scouting strategies, helping teams tap into diverse reservoirs of skill and potential.

In comparing two or more players of the same position, what details differentiate their performance, and can we discover players with similar characteristics in terms of their playing style or skill set? The final question narrows the focus to player comparison within the same position. Here, the scout seeks to unearth the nuanced details that differentiate players' performances, aiming to discover those with similar characteristics in terms of playing style or skill set. This detailed analysis enables the scout to recommend players who not only fulfill positional requirements but also complement each other seamlessly, contributing to a harmonious and effective team dynamic.

In conclusion, these four questions serve as guiding lights for a football scout navigating the intricacies of talent identification and team composition. By addressing these queries, the scout aspires to contribute to the construction of a formidable and balanced team that can thrive in the competitive landscape of football.

To summarize, the following tasks can be formulated:

- **Task 1:** Identifying Best Performing Players
- **Task 2:** Cultivating a Balanced Player Profile and Analyzing Metrics' Impact on Overall Performance
- **Task 3:** Exploring the Geographical Distribution of Players of Interest
- **Task 4:** Comparing Players and/or Discovering Similar Characteristics

Several attributes are involved for these tasks. Task 1 requires the Overall Score of the players, Tasks 2 and 4 the position-specific metrics (see Table 1), while Task 3 is based on the Team attribute, which represents the nationality.

4.2 Task Abstraction

Based on the above Task Analysis, the following Task Abstraction, presented in Table 3, is derived.

Task	Action	Target
Task1	Browse	Extremes
Task2	Discover	Trends
Task3	Summarize	Distribution
Task4	Compare	Similarity

Table 3: Task Abstraction

Task 1 involves browsing through player statistics to identify the best performers, focusing on extremes in performance metrics. In Task 2, the goal is to discover trends in player profiles, cultivating a balanced approach and analyzing how specific metrics impact overall performance. Task 3 shifts the focus to summarizing and exploring the geographical distribution of players of interest. Finally, Task 4 aims to compare players or discover similar characteristics, utilizing a methodology centered around comparing and highlighting similarities in player attributes.

5 CURRENT SOLUTION

In response to the challenges posed by the wealth of personal statistics of FIFA World Cup players, our team developed "ScoutBall", a visualization tool designed to present both general and position-specific metrics. By focusing on player statistics and position-specific metrics, ScoutBall seeks to facilitate informed decision-making in the scouting process. Our football scouting visualization tool embodies a thoughtful approach to player analysis, driven by a deep understanding of the scouting process. When creating the dashboard, we conscientiously aligned visual elements to key tasks, prioritizing functionality and user experience.

This section provides an analytical breakdown of our implementation choices, in relation to the tasks described in Section 4.

5.1 Task 1: Identifying Best Performing Players

The Swarm Plot (Figure 1) places each point (representing a player) on the graph so that the points do not overlap, allowing each individual value to be identified, despite the large number of elements to be displayed. Since each point is clearly visible, extremely high scores, which we are interested in, become immediately noticeable and can be easily identified by users. Furthermore, thanks to the

Swarm Plot it is possible to visualize the distribution of the scores and so it is immediately clear where the data accumulate and where they are scattered, allowing the user to understand how the scores are distributed around the median and quartiles.

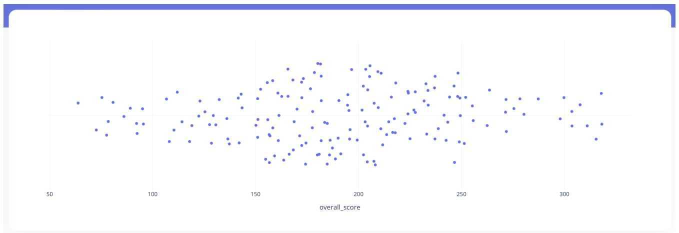

Figure 1: Swarm Plot.

In the interim report, a Scatterplot was chosen for the task of identifying the players with the best performances. However, in the final version of our tool we added the Overall Score attribute to complete this task, thus moving to a one-dimensional context, for which a Scatterplot is not suitable. Another possibility that has been evaluated is a bar chart, which is ideal for comparing quantities in discrete categories. However, the large number of elements (players) in our dataset would have compromised readability. A Stripchart was also considered, but it may have less optimized point placement and points may overlap. For this reason the choice of the Swarm Plot is the best [1].

5.2 Task 2: Cultivating a Balanced Player Profile and Analyzing Metrics' Impact on Overall Performance

The Parallel Coordinates Plot (Figure 2) facilitates the exploration of multivariate relationships, providing a holistic view of player profiles and metric interaction. Chosen for its ability to handle multiple dimensions, it aligns with the goal of cultivating a balanced player profile and understanding its metric impact.

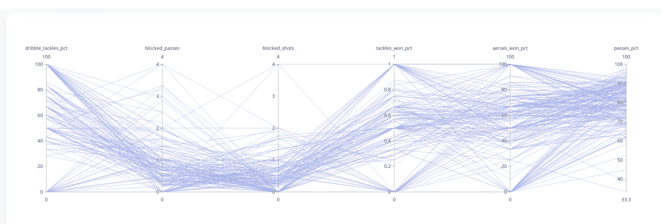

Figure 2: Parallel Coordinates Plot.

Again, in the interim report, a similar task was completed by means of a Scatterplot. The limitation of this solution has proven to be the number of attributes it can display simultaneously. A Scatterplot, in fact, allows us to represent two attributes, while for this task we are interested in simultaneously examining all the position-specific metrics of the players. The parallel coordinate chart proved to be suitable for this purpose, allowing multiple parameters to be displayed and analyzed simultaneously. Additionally, the parallel coordinate chart facilitates the identification of balanced player profiles, as lines that cross the axes evenly indicate consistent performance across all metrics. This multidimensional approach to data visualization highlights the impact of each metric on overall performance and allows analysts to grasp the nuances that lead to optimal performance.

Even the bar chart described in the interim report to view individual player metrics is no longer necessary. The parallel coordinate chart, in fact, displays all metrics simultaneously for all players, thus allowing immediate and overall analysis. Each player is represented as a line spanning multiple axes, each representing a different metric, making relative performance evident at a glance. This not only replaces the need to individually select each player to analyze their performance on a bar chart, but also offers the unique ability to spot trends, anomalies and correlations across the entire dataset. However, it is possible to select a single player to highlight their metrics, as described in Section 5.5.

5.3 Task 3: Exploring the Geographical Distribution of Players of Interest

Geographic representation improves understanding of player distribution. The Choropleth Map, depicted in Figure 3, is effective in visually conveying regional disparities. Supported by geographic information systems (GIS) principles, the Choropleth Map helps summarize and explore the spatial distribution of players. Since the geographical areas in our case are only 32 states, a bar chart was also evaluated. However, a Choropleth Map maintains geographic context, showing exact locations and spatial patterns. This is particularly useful because it allows viewers to quickly recognize areas of high and low player density in relation to their real-world location.

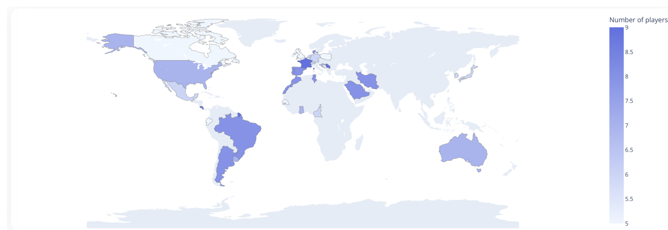

Figure 3: Choropleth Map.

5.4 Task 4: Comparing Players and/or Discovering Similar Characteristics

The Radar Chart, depicted in Figure 4, provides a comprehensive overview of position-specific metrics, aiding in player comparisons. The values of each statistic in the radar chart have been normalized to a scale ranging from 1 to 100 using the min-max normalization technique, ensuring that each metric is proportionally scaled according to its minimum and maximum observed values for more equitable visual comparison. This creates a shape or area that can be quickly analyzed and compared to that of another player with similar position, making similarities and differences in performance evident. Chosen for its ability to display multivariate data in a radial format, the radar chart aligns itself with the task of comparing players with various attributes. The multi-selector integrates seamlessly for analysis, allowing you to quickly add and remove players of interest to the graph.

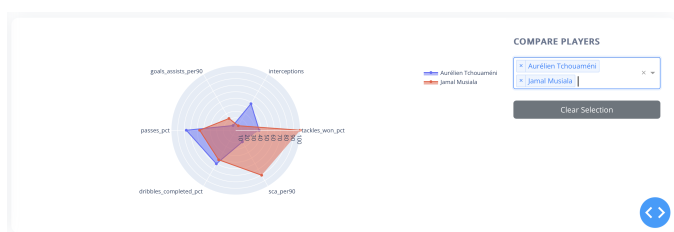

Figure 4: Radar Chart.

5.5 Interactivity and Graph Relationships

The interaction component involves dialogue between the user and the system as the user visualizes data to amplify cognition helping uncover detailed information [4].

A key feature is linked highlighting: by clicking on a player in the Swarm Plot or selecting an interval intersected by a player's line in an axis of the parallel coordinates chart, the player is immediately highlighted in both views. This interaction changes the color of the point in the plot or the line in the chart, facilitating visual tracking of the selected athlete through the different views. In the swarm plot the color of the highlighted player is red, easily distinguishable from the other points (blue) even by color blind people [2]. In the parallel coordinates chart, however, the selection causes a darkening of all the lines except the selected one, making it identifiable at a glance. At the same time, selecting a player activates the display of his details in the Player Card section (Figure 5), creating a focused and personalized flow of information.

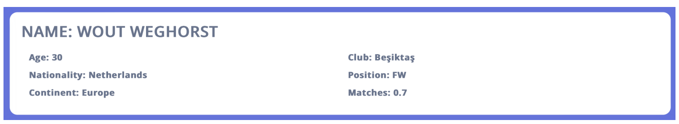

Figure 5: Player Card.

The dynamic manipulation of the Swarm Plot is also made possible by the geometric zoom, which allows the clusters of points representing the players to be enlarged and examined more precisely, which is essential for isolating and analyzing performances in sectors densely populated with data.

The sliders in the Side Bar (on the left side of the example of Figure 6) add a further layer of customization, providing the user with data reduction tools that allow players to be filtered not only by general statistics but also by performance attributes, refining the analysis to the desired detail. These filters, once applied, simultaneously influence the Swarm Plot, the Parallel Coordinates Chart and also the Choropleth Map, ensuring data consistency (shared data) across different display modes.

Finally, the interactivity of the Parallel Coordinates Chart is enhanced by the possibility of reorienting and exchanging the axes at will. This allows the user to customize the analysis according to priorities and particular interests, highlighting different correlations or patterns between the metrics taken into consideration. This flexibility enables sophisticated data exploration, transforming data processing into a highly adaptable, user-centric process.

6 Implementation

We implemented ScoutBall using Python and the Dash and Plotly frameworks. Python's versatility, along with the capabilities offered by Dash and Plotly, allows us to create an interactive and visually appealing scouting tool. Dash facilitates the development of web-based applications, while Plotly provides powerful visualization tools, making them ideal choices for our project. The mockups and the phases of our implementation can be seen in the Figures at the end of the report.

7 Use Cases

Use Case 1: Uncovering Promising Defenders

In the scouts' quest to identify promising under 24yo defenders with a well-rounded skill set for potential inclusion in the B team of the club as future prospects for the first team, they can utilize our tool to analyze player data. One standout prospect uncovered through such an analysis is Alidu Seidu. As we can see in Figure 6, by employing some filtering we can reveal Seidu as one of the top performers among his peers, boasting commendable stats across various categories. Notably, our tool enables the scouts to ascertain crucial details about Seidu, including his age, nationality, and current club affiliation. Such information proves invaluable for strategic planning, particularly in understanding whether Seidu would necessitate a non-EU slot in our team and estimating potential transfer costs based on his club's league market.

This use case exemplifies the capabilities of our tool in efficiently identifying promising young talents like Seidu who possess a balanced skill set and have the potential to be groomed for future integration into the first team. The scouts are not only able to pinpoint standout performers but also gain insights into their background and market valuation, thus facilitating informed decision-making processes within our club's talent acquisition and development strategies.

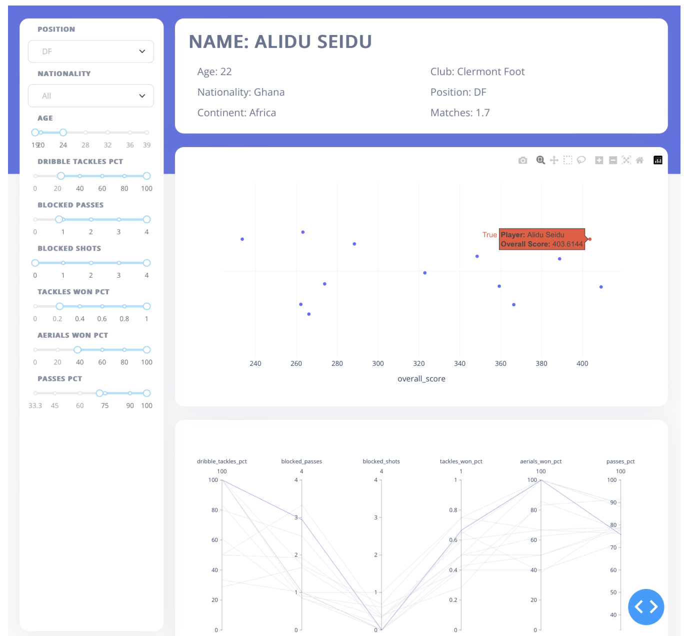

Figure 6: Discovering Alidu Seidu.

Use Case 2: Geographical Analysis in Scouting

In the realm of scouting, hypotheses regarding specific geographical regions can be both verified and falsified with ease. For instance, a common assumption among scouts is that Latin American players, particularly midfielders, tend to exhibit a more offensive-minded playstyle, demonstrating a desire for scoring. Through the application of filters based on statistical metrics like 'Shot-Creating Actions per 90 minutes' (SCA per 90mins), these hypotheses can be put to the test.

Consider a scout's hypothesis that Latin players are more proactive in generating scoring opportunities. By filtering player data based on SCA per 90mins and analyzing the results, as depicted in Figure 7, the scout can discern whether this assumption holds true. The data may reveal that indeed, Brazilian and Argentinian players exhibit a higher frequency of shot-creating actions compared to players from other regions.

The versatility of available filters and the ability to combine them offer scouts a myriad of possibilities to investigate similar hypotheses. This analytical approach empowers scouts to make informed assessments and refine their understanding of player characteristics across different geographical regions, ultimately enhancing the efficacy of talent identification and recruitment strategies.

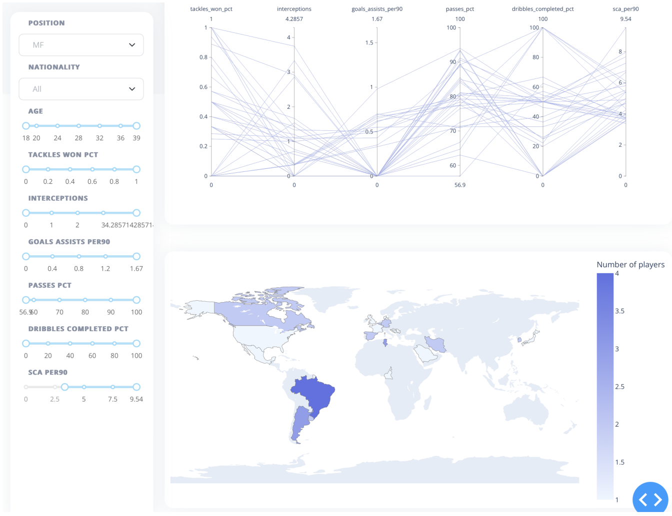

Figure 7: Evaluating Offensive Trends.

Use Case 3: Identifying Young Talents to Replace Key Veterans

As one of the best players on a team approaches retirement, the need to find a suitable replacement becomes paramount for maintaining competitiveness in the long term. To ensure a seamless transition, the scouting team embarks on a quest to identify a young player with similar performance and attributes to the retiring veteran.

The existing swarm and parallel coordinates plots provide the initial intuition for potential candidates who share similarities with the veteran player. However, it is the radar chart that offers a clear and concise comparison of various players' attributes, enabling the scouting team to pinpoint the most suitable replacements.

For instance, let's consider the scenario where the scouting team of Paris Saint-Germain seeks to replace Messi (Figure 8), one of the best forwards in their squad, for the long term. By leveraging radar charts to compare Messi's performance metrics and playing style with those of other attackers, the scouting team can identify young footballers (like Rafael Leao or Vinicius Jr.) who exhibit similar traits and potential for recruitment.

Through this strategic succession planning approach, the scouting team can ensure a smooth transition by identifying and grooming young talents who possess the necessary attributes to fill the void left by the retiring veteran. This proactive approach not only maintains the team's competitiveness but also fosters a culture of continuous renewal and development within the organization.

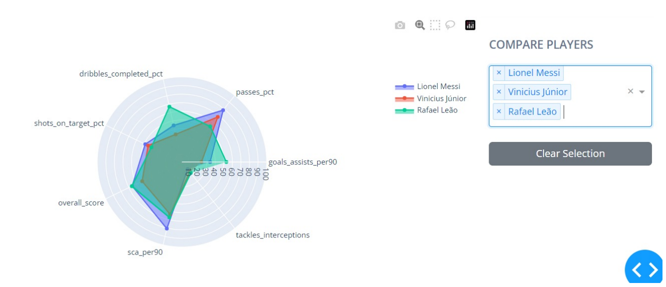

Figure 8: Strategic Succession Planning.

8 Conclusion

The creation of ScoutBall is driven by the goal of improving sports analytics, offering scouts a powerful and intuitive environment for evaluating performance. The effective combination of advanced interactivity and high-definition data visualizations leads to deeper insights and informed decisions. Looking to the future, our commitment will focus on updating the dataset with future sports competitions. It will also be possible to expand the dataset considering new types of competitions, such as national leagues, to increase the number of players that can be analysed. Additional performance metrics may also be introduced, to further enrich our analysis with an even broader skill spectrum. In parallel, we will place great importance on the scalability of the solution, ensuring that the system constantly evolves to handle growing volumes of data without compromising performance or user experience. For example, a large number of elements in the dataset may make it impossible to avoid overlapping points in the Swarm Plot and may compromise the readability of the Parallel Coordinate Chart. A more careful study of the use of color and transparency may be necessary in this case, as well as an even more advanced filtering and data reduction system. This continuous iteration will guide us towards an even more robust and versatile platform, capable of adapting to changes in the sporting landscape and user needs, perpetuating our commitment to providing a state-of-the-art tool for discovering the best talents in the world of football.

References

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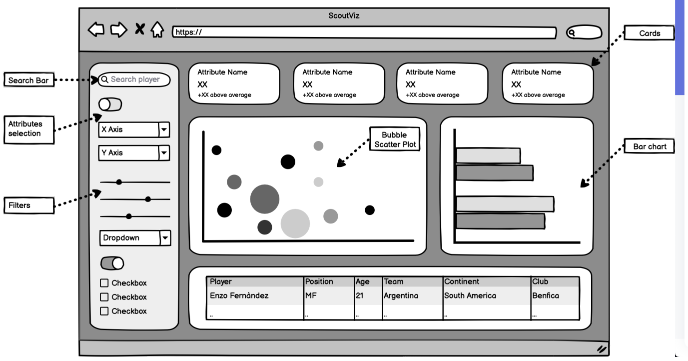

Figure 9: First Mockup.

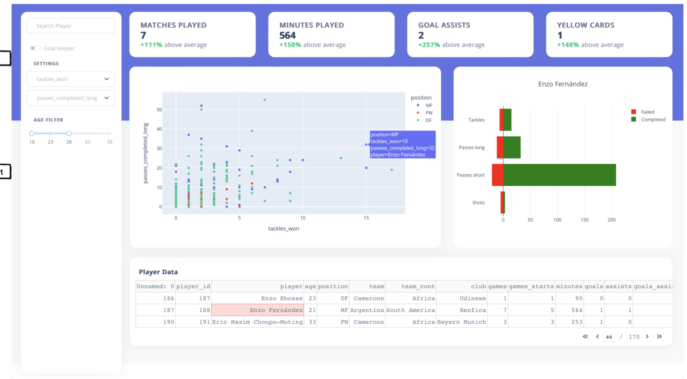

Figure 10: First Implementation.

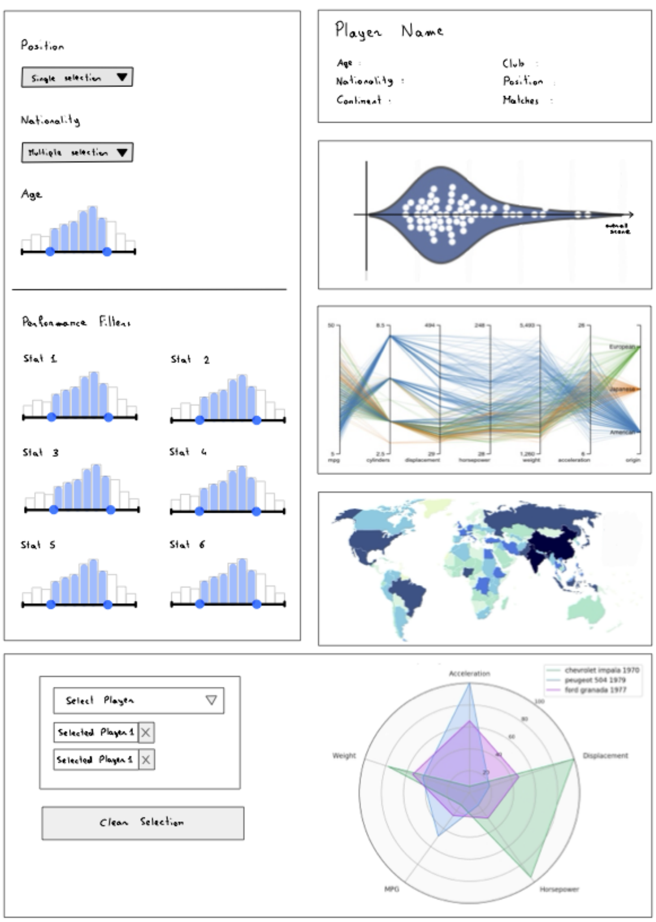

Figure 11: Second Mockup.

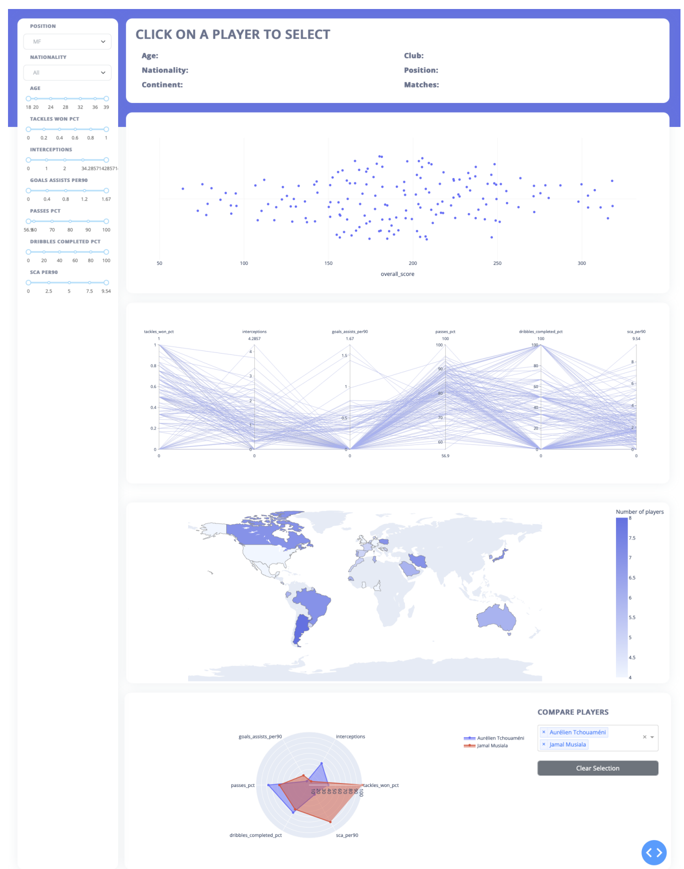

Figure 12: Final Implementation.