The Big Three: a practical framework for designing Decision Support Systems in Sports and an application for basketball

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Abstract. In a world full of data, Decision Support Systems (DSS) based on ML models have significantly emerged. A paradigmatic case is the use of DSS in sports organisations, where a lot of decisions are based on intuition. If the DSS is not well designed, feelings of unusefulness or untrustworthiness can arise from the human decision-makers towards the DSS. We propose a design framework for DSS based on three components (ML model, explainability and interactivity) that overcomes these problems. To validate it, we also present the preliminary results for a DSS for rival team scouting in basketball. Finally, we propose some lines of research for DSS design using our framework and for team scouting in basketball.

Keywords: Machine Learning · Explanability · Interactivity · Basketball · Understanding winning

1 Introduction

In the realm of sports, the strategic decisions made by coaches and analysts play a crucial role in the success of a team. With the advent of modern data science technologies, there is a growing opportunity to leverage these advancements to aid in the design and optimization of team strategies.

Nevertheless, the adoption of new decision support systems (DSS) in high-performance sports organizations can be challenging. In fact, it is hard to incorporate data-based decision-making in the daily operations of the team. A considerable number of decision-making processes in sports are intuitive and the cognitive processes to understand such kinds of systems are mainly analytical. This makes cognitive biases appear [5]. This is especially relevant for DSS that use Machine Learning (ML) algorithms. In most cases, ML algorithms are *black-boxes* and it is difficult for humans to understand the system's output based on the inputs. Therefore, human decision-makers are left with a sensation of untrustworthiness, uselessness and even falsehood towards those systems [48].

As a matter of fact, in this world full of data, DSS are vastly common and these kinds of challenges exist in other fields as well. Frameworks consisting of an ML model, an explanation for that model and some kind of interactivity between the user and the data have proven useful to improve trust in them.

1.1 Contributions

Past work in sports has explored model explanation and interactivity with data separately. There is a lack of work that uses both tools together to enhance understanding of DDS that use ML. In this paper, we present a preliminary framework that closes that gap. The framework consists of three components: model, explanation and interactivity. It has the potential to be used for any task in any statistical sport. However, as an application for this workshop paper, we focus on team scouting in basketball to propose a novel methodology to understand why teams win to show that it is beneficial to improve trust in DDS. We also propose new lines of research that this framework could potentially be applied to.

2 Literature Overview

Past literature in sports analytics builds upon the fact that transitioning from observational analysis to automatic statistical analysis based on data provides huge opportunities [9, 38]. This has been a reality for physical conditioning for quite some time [25, 22]. Nevertheless, with the advent of modern data collection techniques, almost all aspects of the game can be studied nowadays. Everything from tactical analysis [12, 3] to even mental aspects [11].

Not only in sports but, as the use of data has increased overall, an increasing number of human decision-makers without any background in statistics are exposed to DSS based on ML. Particularly interesting is the work of Kayande et al. [20], which proposes a framework to understand the potential problems of DDS in general. Specifically in sports, there has been past work highlighting the challenges of adding these kinds of systems in professional organisations [40, 48]. There have also been some attempts of proposing frameworks to facilitate the incorporation of such systems into sports organisations [44, 2]. However, these frameworks mainly focus on organisations and not on how DDS should be designed in order to overcome those challenges. Other papers focus on the development of DSS for specific tasks [43, 34]. Our work closes this gap by proposing a general framework to design DSS based on ML in sports by adding two components (model explanation and interactivity) to the traditional analysis (only composed by a model). With these three components (ML model, explanation, interactivity), we aim to close the 3 gaps pointed out by Kayanda et al. [20].

For the rest of the section, we look at ML Explainability and Human-Computer interaction in sports to understand how both components have already been used individually in the field. We also focus on basketball analytics and predicting winning in basketball as a background for our application.

Data-Model Explainability in Sports Machine Learning explainability has proven essential when an ML system needs to satisfy certain requirements such as scientific understanding, safety or ethics [6]. From these, past literature in sports has focused in scientific understanding. ML models could be a tool for generating hypotheses to find correlations between the input and the output. Particularly for tactical analysis.

Song et al. [46] tried to explain American football defence using a visual explanation (saliency maps). In the work done by Fernandes et al. [18], they helped American football coaches with their decision on their next play (pass or rush) with the use of decision trees for explainability because of their transparency. In volleyball, Lalwani et al. [24] trained a Neural Network to predict the result of matches and then use SHAP and ProtoDash to find the most relevant factors. Silver and Huffman [45] also use Shapley values for identifying the most relevant factors when predicting the outcome of a batter versus pitcher in baseball with a Neural Network. Finally, Wang et al. [50] apply LIME (Local Interpretable Model-agnostic Explanation) on Neural Networks and Random Forests to analyze the game style based on the boxscore.

As can be seen, the state-of-the-art mainly uses a predictive ML and then applies a standard explainability method.

Human-Computer Interaction in Sports Interactivity has been a more prolific field than explainable ML in sports. Past work has focused mainly on data visualization [15, 37, 7]. Also important is the effort of practitioners.

In basketball, journalist's works like Goldsberry's *shotmaps* [13] or Whitehead's *bubbles map* with players and teams [53] tried to incorporate a storyline into data. In addition, Fu and Stasko [10], Chen et al. [4], and Losada et al. [27] have proposed interactive dashboards for exploring basketball data.

One work that uses ML techniques in addition to data visualization is [51], where they use infographics to visualize the results of a Neural Network to provide tactical decision support to rugby coaches. Nevertheless, there is a lack of research regarding interactivity with ML models beyond visualization, where the human decision-maker can interact directly with the model.

Sports Analytics in Basketball Obviously, the proliferation of data science techniques within the field of sports has also permeated basketball analytics. The field began studying the concept of possessions and how to optimize them, as shown in the works by Oliver [35], and Kubatko et al. [23]. With the appearance of new data collection systems, new data sources have emerged, allowing a more complete quantitative analysis of a game. Current literature such as Page et al. [36], and Mandic et al. [33], uses box-score data, where basic statistics in a game are summarized. Play-by-play data is used by Grassetti et al. [14], and Vracar et al. [49], where a series of events composing the game is specified. Lastly, tracking data has been used by Sampaio et al. [42], Reina et al. [39], and Abdelkrim et al. [1], where the locations of every player in each moment can be consulted.

Although there are plenty of tasks that have been tried to be solved with data, in this paper we will focus on predicting winning.

Studying Winning in Basketball Predicting winning has been one of the most traditional perspectives to studying the game of basketball using data. In fact, the seminal work [35] proposed 4 factors to predict winning. The literature can be divided between pre-game prediction [17, 26] and in-game prediction [52, 31, 47]. One consequence of this kind of research is studying what factors are key to winning a game [19, 41, 32]. Nevertheless, these studies are general for the sport and not team specific, which is not practical for scouting specific teams.

3 The Big Three: model, explanation and interactivity

As proposed in Kayanda et al. [20], there are three potential gaps when using a DSS (See Figure 1). We propose a framework for designing DSS in the context of sports analytics consisting of 3 components (ML model, model explanation and interactivity) where each one closes one gap. This technique can potentially be applied to any sport that is statistically quantifiable. In order to practically articulate the framework, designing each component separately is essential.

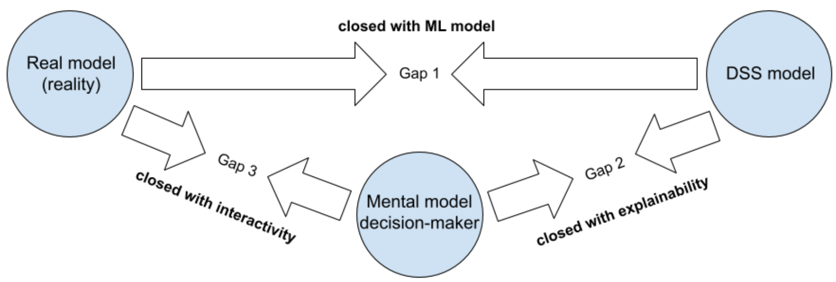

Fig. 1. Gaps proposed by [20] and solutions from our framework.

- Gap 1: closed with **ML model** component. In ML, it is commonly observed that models with higher performance tend to be more opaque, such as Neural Networks. However, with the addition of interaction and explainability components, the necessity for transparent models diminishes. Consequently, any superior performing model can be employed to enhance performance.
- Gap 2: closed with **explainability** component. Accordingly, to past literature, model transparency is key when adopting machine learning-based DSS within the sports domain [16]. We contend that incorporating an explainability method into the process will lead to increased user trust in the DSS. The type of explanation needed will depend on the task [8].
- Gap 3: closed with **interactivity** component.Running what-if analyses is crucial for coaches to gain insights into various scenarios and understand the reality of their team or game. By incorporating an interactive component, such as a dashboard, the coach's mental model can closely align with the actual circumstances. This enables them to make informed decisions based on a more accurate representation of the situation at hand.

A useful tool for designing each component can be interviews with domain experts. In order to do that, we suggest to identify the most relevant person within the organisation. Also, co-creating the solution together with experts could potentially be more engaging for them.

4 BasketXplainer: a DSS for basketball.

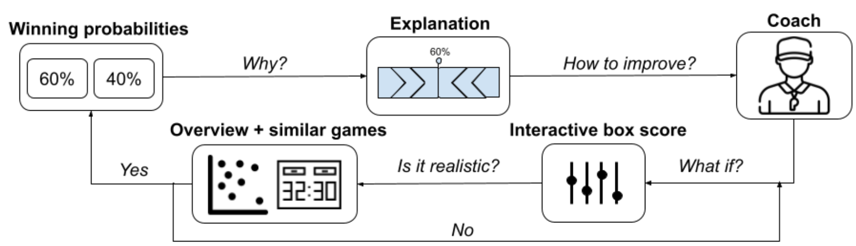

Fig. 2. Workflow from a user of our solution

To illustrate our framework we present an application of it. The application[1] is used for scouting teams in basketball games and designing a game plan. It has had promising acceptance by domain experts.

Model We identified the need for a predictive model that can predict the chances of winning a game. This information is useful for coaches to have a first realistic idea of how difficult the game is going to be and if they can design a risky game plan or if it should be more conservative. For this preliminary design of the solution, we have trained the model with the simplest data available, boxscore data, and decided to use LightGBM [21] to train on the boxscores of the NBA from the 2004 season till December 2020[2]. The box score statistics data chosen in the end are assists (AST), blocks (BLK), defensive rebounds (DREB), 3-point attempts (FG3A), field goal attempts (FGA), free throw attempts (FTA), offensive rebounds (OREB), steals (STL), and turnovers (TO). LightGBM is a gradient-boosting framework that uses tree-based learning algorithms.

Explainability n order to present some useful information for coaches to come up with a game plan, understanding what factors are the most important in order to win the game can be helpful. As professional teams do not have a lot of time between games, focusing on just the most important aspects of the next game can be crucial. From an ML perspective, this can be done using SHAP

[1] Publicly accessible in http://b5-winning-in-basketball.course-xai-iml23.isginf.ch/
[2] Accessible at https://www.kaggle.com/datasets/nathanlauga/nba-games

(SHapley Additive exPlanations) [29] values to explain the factors that were important for our model's decisions. SHAP assigns each feature an importance value for a particular prediction based on how much it contributes to moving the model output from the baseline prediction. For its implementation, we used of TreeExplainer [28] for the LightGBM model and a force plot [30] for visualisation.

Interactivity: Dashboard For this component, we have focused on what-if analyses. We hypothesize that for coaches it is important to run several scenarios to see how potential game plans would transfer to tangible results.

Interactive Box Score Data. The core piece of the dashboard is an interactive parallel coordinates plot of the box score data. When choosing an existing team to start an analysis, the pre-computed box score data for this team is displayed in parallel coordinates. However, using the sliders in each parallel line users can change the box score data and thereby simulate what-if scenarios to see how changes in the box score will impact the predicted outcome of the matchup.

Winning Probability. The pre-trained ML model is used to infer the winning chances of the two teams based on the provided box score data. Every change to the box scores displays new winning probabilities. Users can use this to understand how changes in the box score will influence the predicted outcome.

Similar Matchups. Though we are providing predictions for the outcome of future games, it is also helpful for users to be able to look back at past games of teams to see how they previously performed. When users manually adapt the box score from an existing team, we calculate the distance of this new, custom box score to all the existing teams and provide the user with the closest matching one. That way, even with a custom box score, users can look at the closest matching historic matchups and what the outcomes of those games were.

Feature Importance. We use SHAP as an explainability tool for users to understand the ML model's outcomes. The contribution of each input feature to the output is displayed graphically and intuitively, even without any technical knowledge of the underlying theory. Like all the other elements, it dynamically adapts whenever users make any changes to the input box score data.

League Overview The offensive performance and defensive performance of a team are calculated and visualized to show how the team performs in the league compared to all other teams. To represent offensive performance, an Offensive Performance (OP) statistic is calculated. The calculation of OP is similar to the calculation of offensive rating. For each team,

$$OP = 100 * PTS/(poss_{team} + mean(poss_{opponents}))$$

The Defensive Performance (DP) statistic is calculated as

$$DP = 100 * (BLK + DREB + STL)/(poss_{team} + mean(poss_{opponents}))$$

which represents how well the team is guarding other teams on average.

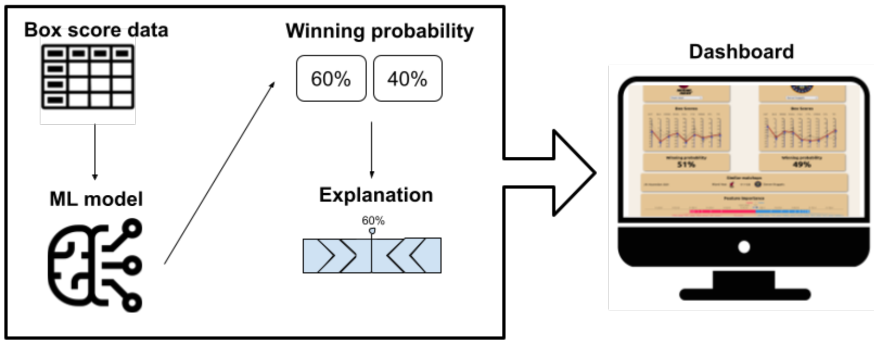

Fig. 3. ML pipeline from our solution

5 Analysis

To understand how our solution is useful as a DSS and whether it closes the gaps proposed by Kayanda et al. [20], we have conducted interviews with domain experts. The domain experts are three people from the coaching staff from teams in the Spanish men's first league and women's first league. These coaches are responsible to their staff for collecting data in order to help the head coach to come up with a game plan. We proposed a practical interview: they were presented with a use case where they had to come up with a game plan just using the dashboard. The main takeaways from their interviews were the following:

The decisions of the model made sense. Before anything else, the first thing that two of the interviewees did was select different teams to determine if the model's output made sense based on the box score statistics. Thus, it was confirmed that Gap 1, which deals with the performance of the DSS, is crucial for its acceptance. Moreover, it was validated that in our system the model performance is a key factor to close that gap.

The explainability component was key to improving trust in the model. During the use case of the interview, this component was used as a guideline to discover what factors were key to the model's decision, they sought confirmation later with the what-if analysis by modifying those factors. It seemed that this guided two-step discovery improved the trust in the system a lot (Gap 2). There was one person that did not quite get what the plot of Feature Importance meant due to confusing colouring that has to be improved in future iterations of the dashboard. This made him more reluctant to believe the model's output and just performed more what-if analysis to come up with a game plan.

They could pour their mental model thanks to the interactivity. The most popular component of the dashboard was the interactive box score. The interviewees spent most of their time focusing on it. They were impressed with the what-if analysis and they used it to perform simulations. To do that, two of them divided the box score statistics into several categories: rebound, shooting and turnovers. Then, they modified all the statistics of one category imagining different scenarios and seeing their impact on the winning probabilities. For example, one of them thought that increasing the three-point attempts would give them more possibilities, so he increased the FG3A and FGA and decreased FTA because if you shoot three-pointers a basketball team receives fewer fouls in general. All these modifications were qualitative (i.e. increase or decrease), and none of them focused on how much exactly. All of them highlighted that the interactive part was really useful to explore what was happening. And, therefore, decreasing the gap 3 of the framework which was between the manager's mental model and the reality.

They were expecting a tool with information that could be quickly transferred to the court. Before the use case was proposed, one thing that came up recurrently during the expectations check was the usefulness of the data of the DSS. Their notion of usefulness had to do a lot with how easy it was to transfer data onto decision-making for a game plan. They were expecting some kind of data that could give them a couple of headlines about what was important for the next game. After the use case, they all said that our solution fulfilled this. Our system allowed rapid decision-making and could potentially save them a lot of time, which, under their impression, was one of the most important factors to decide whether to use a DSS or not. Normally, teams in a European competition (two of the three teams of the interviews) have two games per week and the opponent's scouting has to be done even faster.

6 Conclusion and future work

In this paper, we have made an approach to defining a general framework for designing Decision Support Systems based on ML models in the context of sports. We have proposed a 3-component framework that closes all the potential gaps that produce user mistrust when using a DSS. This framework opens new lines of research (see next section) regarding DSS design. In addition, we have illustrated our framework with a DSS used for coming up with a game plan in basketball. Our solution allows coaches to scout the rival team using an ML model for predicting winning, SHAP values to explain the model prediction and an interactive dashboard to perform what-if analysis and check if the potential game plan is realistic. We have obtained excellent preliminary feedback from domain experts. The majority of domain experts were keen on the application and ended up thinking about how to integrate it into their team operations as soon as possible.

6.1 Research opportunities

Regarding the Big Three: our framework. To further understand the benefit of our framework, a good option would be to conduct a review of ML-based DSS used in sports and see if they have characteristics that fit into our three components. Another research opportunity would be what kind of models (i.e. predictive, clustering, generative, anomaly detection...) would be useful for what kind of task. The same applies to the kind of explanation (deductive, inductive, comparative) and interaction.

Regarding BasketXplainer and scouting rival teams in basketball.

Improving the model to make it specific. According to one domain expert, one of their main concerns in this kind of task is how relevant the data used to train the model for their prediction i.e. out of distribution shifts. For example, it would not be logical to train the model with NBA data and apply it to the *Liga Femenina Challenge* (Spanish second women league). Nevertheless, there might be not enough data to train an ML model for a specific league or team and, therefore, the model could learn useful representations learnt from basketball games in other leagues. Ideas like fine-tuning, weighted training or ensemble training could be explored to solve this problem.

Adding players stats Another important point made by our interviewees was that our solution was great for understanding the team's overall performance. Nevertheless, another dimension of the analysis that they normally make when using data to prepare a game plan is the individual contribution of each player. This opens a new research line about how to integrate individual performance in team sports while maintaining quality interactions.

Adding advanced metrics One wish that appeared in every interview was the possibility of adding personalized metrics. In other words, to use a deductive workflow for the dashboard so they can integrate their knowledge into the system. This could be possible but lack of data is one of the biggest challenges. Normally, the collection of this personalized data is specific to each team and its objectives. What teams do is collect, which takes a lot of time this data by rewatching the game in video. For example, the number of shots in each zone of the field. Nevertheless, the coaches quickly saw that this information could be integrated into our application. This could potentially initiate an area of investigation about how good the personalised metrics for describing winning in basketball are. Nevertheless, two of them asked for more, they wanted to include other metrics that were important for their teams so they could use their mental model even more. For example, one expert proposed dividing the assists into assists for three-pointers and assists for two-pointers.

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