Introduction

The group is interested in identifying profitable bets given historical professional basketball data scraped from the NBA API, at the player and team levels. Once this data is gathered, the team is interested in training a model to output a probability distribution of the five main player stats, which are points (PTS), assists (AST), rebounds (REB), blocks (BLK) and steals (STL), given the model outputs a predicted value for each of these measures. This will help us compute a probability that a player will score more or less than a particular value. With these attributes computed in the backend, the team seeks to display these insights in a digestible, interactive format. These visualizations include the results of the model's training, probability distributions for current predictions, and sliders and inputs that help the player identify profitable bets.

Problem Definition

We seek to provide an interactive dashboard meant to inform statistically optimal basketball betting strategy and provide visually appealing descriptions of trends in player-level data. We hope that our final product will be a necessary companion for any NBA fan interested in watching basketball and sports betting. The use of interactive visualization around machine learning prediction should help to distill advanced data science concepts for everyone to receive data-driven advice to assist their intuition.

Literature Survey

(Ref. 1) Professors Yu and Stasko design and evaluate two interactive NBA statistic visualization systems, primarily to aid journalists. Many interesting visualization styles are presented, which will be inspirational for our representation. Our project addresses the visualization of predicted statistics, while this paper only addresses previous game data. **(Ref. 2)** The authors analyze various daily fantasy basketball predictions. We seek to perform similar predictive capabilities to the models referenced in the paper. Hence the regression based testing of forecasts presented in the paper would be a good method to validate our own predictions. **(Ref. 3)** The authors of this paper provide many interesting NBA visualizations, primarily at the game level. Taking inspiration, we can display player statistics as a similar time series to team win/loss. In terms of improvement, we will focus on player-level data and also seek to provide simpler visuals, even if at the expense of information quantity. **(Ref. 4)** This paper is a broad review of advances in predicting outcomes of sporting events. It includes data for a broad range of sports and shows that American Football and Basketball had the highest accuracies for outcome prediction. This paper provides excellent insight into what has worked in the past and what might be useful information to include in examining *specific* players' performances. **(Ref. 5)** This paper uses Support Vector Machines (SVMs) to classify the outcome of basketball games. This paper gives detailed methodology on data preprocessing as well as a top-down mathematical explanation on why Hybrid-Fuzzy SVMs are particularly well-equipped to handle problems like this. This is a very narrow paper in terms of the models examined, though. **(Ref. 6)** This paper examines the use of CART and Random Forest techniques to predict basketball outcomes. This shows how to use the Box Score statistics of a team to accurately make informed predictions about the outcome of the game, similar to what the team plans on doing. **(Ref. 7)** This paper talks about different methods for using machine learning to make predictions from the large wealth of data that is available from the NBA. It focuses on predicting a player's future performance, which is very similar to what our group wants to achieve with this project. This paper lacks on the visualization front, which we aim to make a focus of our project. **(Ref. 8)** This paper focuses on methods for the visualization aspect of modeling NBA team and player data. This paper will be very useful for our project, as there are few papers that focus on the visual representation of NBA data. We aim to improve on this by future outcomes of NBA player statistics. **(Ref. 9)** This paper focuses on applying machine learning to three areas with professional basketball: All-Star Prediction, Playoff Prediction and Hot Streak Fallacy. This article gives us helpful information on how to handle NBA data for modeling. We aim to go one step further than this paper and predict player success on a game-by-game level. **(Ref. 10)** This paper provides an interesting machine learning perspective in fusing convolutional networks and random forests in

game prediction. We can seek to use a similar ML structure on player prediction. **(Ref. 11)** The author presents a variety of models to use in game prediction. Notably, the use of player statistics as variables is important towards our goal. The paper shortcomings revolve around a lack of data-specific visuals. **(Ref. 12)** The authors implement a strong ML pipeline for game level prediction that could influence our modeling stage, but fall short in describing the techniques used. **(Ref. 13)** This paper showcases the enhancement of predictive models for soccer match outcomes through domain-specific knowledge, focusing on recency feature extraction and rating feature learning. These methodologies emphasize the importance of considering sport-specific dynamics, like team form and opposition strength, to improve model accuracy. Adapting these approaches to basketball could significantly benefit NBA player performance predictions. **(Ref. 14)** This reference provides an example of domain-specific knowledge we could incorporate into our model. Using match data, the authors built a weighted directed graph of players to analyze the offensive behaviors of basketball teams, a method we could utilize to engineer a feature that provides information on the quality of player teams. **(Ref 15.)** This study identified several features that have the greatest predictive power of player performance. The authors found that minutes played, usage percentage, and difference in team quality were the main factors of variance in individual point scores. **(Ref 16.)** This paper compares present data of football teams and their matchups to similar matchups in the past to predict game outcomes. This is useful as in our project we can try comparing past players and current players with similar styles of play to make specific predictions regarding the player. One of the drawbacks of the paper is that it makes a broad prediction of who will win the game compared to our in depth predictions of the specific statistics of each player. **(Ref 17.)** The authors predict soccer match outcomes by assigning ratings based on algorithms for each team. The GAP method that assigns a rating for offense, defense, and home or away games to predict success in a matchup can be a useful way to organize our statistics for each player as it has seen success. The drawback of this paper is that it focuses on overall team statistics and does not take into account specific players that could make a difference. Our data will be player-specific as well. (**Ref 18.)** This paper predicts the rating of a basketball player based on how their team performs when they are and are not on the floor. This idea will be useful to our project as we will need to take into account which players are on the floor as that will affect a player's numbers based on who is injured or not. However, this approach has only been proven to be accurate for offensive statistics. We will need to take into account the opposing team's offensive statistics to predict defensive numbers for players.

Proposed Method

1. Intuition - This project seeks to combine team and player-level statistics as well as state-of-the-art calibration methods to create a more holistic, probability-based model that focuses on individual statistics, implement an algorithm to identify profitable bets based on expected value maximization, and utilize visualization methods within a statistical context to display these insights in a novel way.

2. Description - We describe our data collection and processing, model building, training, and selection, and visualization approaches.

A. Data Collection - The data used for this project comes from the NBA statistical database and is accessed via the `nba_api` python module. This module came with its share of challenges as often the server became overloaded and the connection timed out making data collection time-consuming and unreliable. The api also didn't have functions to gather large amounts of player-data at one-time, meaning that the team had to query the database individually for each active player. Improvement in this area would certainly streamline the team's performance and make the finished product more reliable.
B. Data Processing - Once the player and team-level data was gathered from the API, the following manipulations were performed:
    a. The player data was grouped by player and season, and a running average of quantitative statistics was calculated for each game a player participated in. This helped give a "snapshot"

of a player's performance at a particular point in time. The first game of each season was disregarded.

b. The team data was grouped by team and season, and a similar running average of quantitative team box score statistics was calculated for each game the team participated in to help give a snapshot of the team performance at a particular point in time.
c. Once these running average calculations were made, the player and team data were merged into one dataframe where the player's running average statistics, the player's team running average statistics, and the opposing team's running average statistics formed the features which were fed into the model.
d. The model-selection was performed via cross-validation and model performance was evaluated with Mean Squared Error (MSE). Because of its computational efficiency and universal function approximation of nonlinear relationships, the team trained a simple regularized neural network model with 30 hidden neurons and Rectified Linear Unit (ReLU) activation.
e. From this training data, the team synthesized a conditional probability distribution based on true variability of an individual statistic given what the model outputs.

C. Data Visualization/User Interface - We are building a multifaceted app that displays a select player's historical stats and trends as well as our predictions for the next game. This will allow the user to have a look into where the player is trending and make an informed prediction for themselves, as well as see what our model is predicting. The user will also have an opportunity to input a player's over/under for a certain statistic, the odds for the bet, and the amount wagered. The expected return will then be displayed based on predictions from our model. There are few tools that allow for interactive visualizations for NBA statistics and predictions, which is what we plan to achieve.

Experiments and Evaluation [Under Construction]

We seek to answer two questions in our model design. First, how can we best collect and model player and team level data to predict player statistics. We expect that a running average for a player, their team, and their opponent can provide the best results. With these results, the next question becomes whether our model can predict with a high enough accuracy to be confident in odds against a sportsbook in the long run. While this question will be harder to answer within the timeframe of the project, we hope that our advanced visualizations provide enough innovation to make our product useful, even if the model does not measure up to those deployed by sportsbooks.

The model was evaluated using cross-validation and holding out a 20% test-set of data to see how well the model generalized to new data. The model's accuracy in predicting quantitative player statistics was assessed using Mean Squared Error. **Figure 1** depicts the results of a regression of the previously described features and the number of points a player will score in a given game. The black dots represent the training data and the yellow dots represent the validation/holdout/testing data. Clearly, there is a positive, linear relationship between what the model predicts and what the player ends up scoring.

Further, the team was able to approximate probability distributions of the actual counts of a particular statistic, say points, for example, given the model outputted a certain value. For example, the distribution of points a player is likely to score when the model predicts a player will score 5 points is very different from when the model outputs 20 points. Generally speaking, a large number of players score zero points and hence there is a spike at zero for the lower predictions. This will allow the team to effectively produce a CDF against which to test betting lines using the following formula:

$$\mathbb{E}[\text{Bet}] = P_w \cdot W + (1 - P_w) \cdot L$$

where W is the proportion of a bet if the outcome is a win, L is the loss incurred if a bet is lost, and P_w is the probability of the bet winning, which will be calculated from the aforementioned CDFs. If the expected value of a bet is positive, this indicates that, on average, a particular line will be profitable. In our initial tests, simpler machine learning paradigms performed similarly to more sophisticated ones—Lasso Regression

worked just about as well as a many-layered regularized neural network. This is desirable for the low-number and interpretability of its parameters.

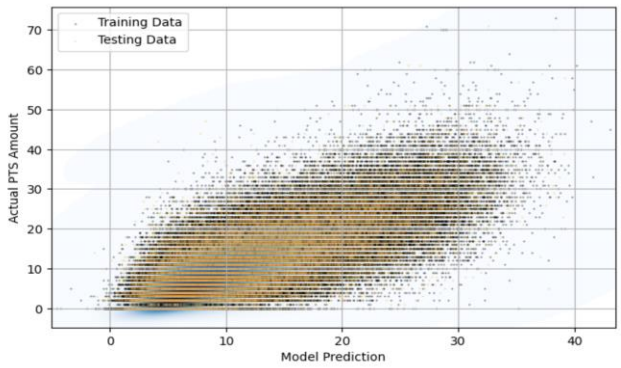

Figure 1: Performance plot of neural network moc in predicting individual players' point totals f separate games. On the X-Axis is the amount points the model predicts the player to score given t features it has access to, and on the Y-Axis is t actual amount of points the player scored.

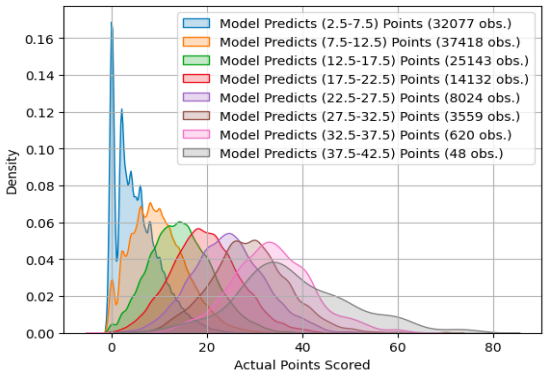

Figure 2: Kernel Density plots of actu observed points a player scored given the moc predicted a certain interval. When the moc predicts a low amount of points scored, t distribution tends to be bimodal, with a hi likelihood of a player scoring zero points.

Conclusions and Discussion [Under Construction]

Plan of Activities

Former Plan (March 2, 2024)

	2/19-2/25	2/26-3/3	3/4-3/10	3/11-3/17	3/18-3/24	3/25-3/31	4/1-4/7	4/8-4/19
Sahil	Presentation	Data Collection		Progress Report		Visualization		Final Report
Josh	Lit Review	Heilmeier	Model Building/Selection			Visualization	Final Report	
Avery	Activity Plan	Data Collection		Model Training		Visualization		Presentation
Oliver	Lit Review	Proposal	Data Processing		Progress	Visualization		Presentation
Hardik	Lit Review	Presentation	Model	Progress Report		Visualization		Presentation
Atticus	Innovations	Data Collection	Data Processing			Moral Support	Final Report	

Updated Plan (March 29, 2024)

	2/18-2/24	2/25-3/2	3/3-3/9	3/10-3/16	3/17-3/23	3/24-3/30	4/1-4/7	4/8-4/19
Sahil	Presentation	Data Collection		Progress Report		Visualization		Final Report
Josh	Lit Review	Heilmeier	Visualization/UI			Visualization	Visualization/Final Report	
Avery	Activity Plan	Data Collection			Progress Report		Visualization	Presentation
Oliver	Lit Review	Proposal	Data Processing		Web Scraping Functionality			Presentation
Hardik	Lit Review	Presentation	Model	Progress Report		Web Scraping		Presentation
Atticus	Innovations	Data Collection	Data Processing		Profitability Analysis		Final Report	

All team members have contributed a similar amount of effort.

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