Mining NCAA basketball data to inform March Madness predictions

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1 INTRODUCTION

Over the last decade, sports betting has experienced a meteoric rise in popularity. In 2021 alone, March Madness—the annual NCAA Basketball Tournament—garnered approximately $ 3.1 billion in bets on platforms such as FanDuel, DraftKings, and BetMGM (Fortune). With this incredible amount of participation, increasing rates of sports betting legality, and the ample amount of historical data available on NCAA teams, predicting the winner NCAA basketball matches is a prime subject for investigation.

March Madness matches are renowned for their unpredictability. In fact, it is one of the main reasons the tournament ganrers so much attention from fans. Factors such as volatile player contribution on the court, streaks in game-play, buzzer beaters, and more all come together to form "Cinderella Stories" - situations in which teams achieve far greater successes than spectators could have reasonably expected. These dynamic aspects of the game engage fans and present a rewarding challenge—that of predicting game winners—for data miners to approach.

2 RELATED WORK

There exists a myriad of related work in the NCAA data mining genre from fanatics who are tracking their college teams to research papers on predicting game outcomes based on past team performance.

Contributions to the current literature on NCAA tournament prediction focuses primarily on model and feature selection, with an emphasis on mining historical data for predictive features. These predictive features are leveraged for the outcome of classification which has several methodologies available in the literature for this purpose.

With reference to model selection, Yuan, et al. recently published with The 5th International Conference on Big Data Research (ICBDR) on different classification models such as decision tree, random forest, Linear Discriminant Analysis, QDA, Support Vector Machines, and Naïve bayes were used to predict the result of a game (2).

Variable/feature selection is varied among the models available because NCAA data is in abundance. However, Lo-Hua Yuan et al. found that parsimonious feature sets and relatively simple algorithms tend to outperform more complicated models with numerous features which will be taken into consideration (3).

Many models use averages over seasons to calculate feature metrics. Given the spontaneous nature of NCAA seasons, we wish to bring new team insights based on sequential game performance. Student researcher Bryce Brown leverages 5-game averages in on logistic regression model to perform NCAA predictions (1).

In this paper, we branch out from the existing classification literature to investigate how such models can be leveraged to place moneyline bets on NCAA games by accounting for recent team performance over game averages.

3 PROPOSED WORK

3.1 Data

For the purpose of training and testing our models, we will use the dataset from NCAA 2022 machine learning competition on Kaggle.com. The dataset includes historical performance metrics (statistics), game-by-game stats at a team level (free throws attempted,

defensive rebounds, turnovers, etc.) for all regular season, conference tournament, and NCAA tournament games since the 2002-03 season. A few data points we intend to include when training our model are:

- WFGM3 - three pointers made (by the winning team)
- WFGA3 - three pointers attempted (by the winning team)
- WFTM - free throws made (by the winning team)
- WFTA - free throws attempted (by the winning team)
- WOR - offensive rebounds (pulled by the winning team)
- WDR - defensive rebounds (pulled by the winning team)
- WAst - assists (by the winning team)
- WTO - turnovers committed (by the winning team)

As part of evaluating the effectiveness of our model, we will also be using historical NCAA betting odds data. Specifically, we will be gathering the Vegas moneyline odds for each match. In sports betting, a moneyline bet is a bet on the winner of the game. For each bet, the casino/bookmaker releases odds for users to bet on. Moneyline odds can be positive or negative and have different implications. For positive odds, the odds number represents how much a user could win off a $100 bet. For example, a moneyline bet on team A with odds of +150 indicate that a user would win $150 off a $100 bet if team A won. For negative odds, the odds number represents how much a user would need to bet in order to win $100. For example, a moneyline bet on team B with odds of -150 indicate that a user would win $100 off a $150 bet if team B won.

From these Vegas moneyline odds, we can compute the bet's implied probability of a team winning via the following formula:

$$P(win) = \begin{cases} \frac{|odds|}{|odds|+100} & \text{if } odds < 0 \\ \frac{100}{odds+100} & \text{if } odds > 0 \end{cases} \quad (1)$$

From our examples earlier, a bet having odds of +150 has implied probability of $\frac{100}{250} = 40\%$ and a bet having odds of -150 has implied probability of $\frac{150}{250} = 60\%$. We will use the implied probability from each match to inform our betting strategy.

3.2 Approach

We have planned to implement a selection of models in order to compare them against one another to see which one performs best. These include:

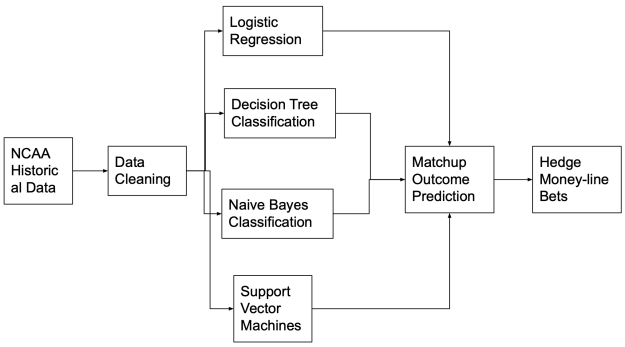
- Logistic Regression
- Decision Trees
- Support Vector Machines
- Bayesian Classifiers

After training our models, we will compare the computed probability of winning to the implied probability from the moneyline Vegas odds. The difference between these two figures—a.k.a. our edge—will determine whether or not we bet, and if so, how much. For example, if we predict the probability of team A winning a match against team B to be 45% but derive that the implied probability from the Vegas moneyline odds to be only 40%, we would want to make a bet as our computed probability is greater than the bets probability.

One of the challenging aspects of this project will be fine tuning our betting strategy based on our edge. Intuitively, we know that the higher our edge, and thus greater difference between our computed probability and Vegas probability, the higher we should bet. However, determining the most effective relationship between edge and bet amount will require extensive testing.

3.3 Process

To outline the general process we plan to follow, we have provided the following diagram:



3.4 Feasibility

Seeing as our team only has two members (both being undergraduate students), we recognize this is an ambitious project. However, we believe that we will be able to implement and compare the results of at least two models and can take on additional work as time permits.

4 EVALUATION

Our models will be evaluated on two metrics. First, we will evaluate our prediction accuracy on correctly identifying wins and losses for specific NCAA tournament matchups. This includes the optimal selection of features to include in the model to confidently predict game outcomes.

Second, we will test our model through a sports betting application. Specifically, we will leverage our model's predictions and confidence levels to inform our betting strategy. In the end, the total amount of money won/lost will be reflective of the success of the model. We see this as more relevant test for the model and believe it will provide a meaningful contribution to the space.

5 DATA CLEANING AND INTEGRATION

The first stage of our project consisted of importing, cleaning, and combining our various data sources into an accessible and integrated format. In order to do this, we first set out to determine a methodology to connect the data set containing historical Las Vegas odds and the Kaggle data set containing game-specific stat lines. As is often the case, our two data sources did not share a common format. For example, the team names in the Las Vegas data and Kaggle data rarely matched one another. In order to develop a key that would connect the two data sources, we leveraged an open source string similarity library to compare the two lists and make a "best guess" of which were referring to the same team. Another issue we had to resolve was the differentiated date formats wherein

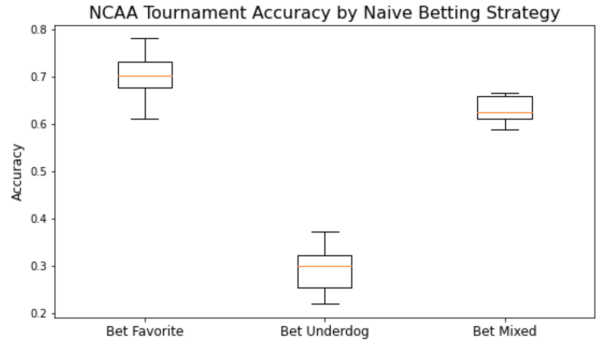
the Las Vegas data set listed the month and day of a match while the Kaggle data set listed the number of days since the beginning of the season. After some developing a few complex data parsing approaches, we were able to convert the data into a uniform, connectable format. Once we finished pre-processing our data we were then able to join the two sources together while minimizing both incorrect and incomplete matches.

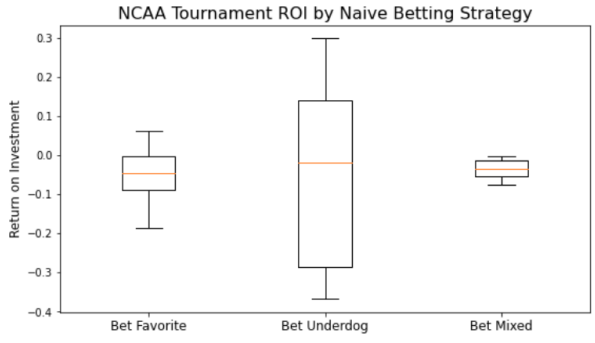
6 EXPLORATORY DATA ANALYSIS

The second stage of our project was comprised of preliminary exploration into our data. The primary focus of our efforts was to determine baseline performance measures of basic betting strategies against which we could later compare our model to. The three baseline/naive strategies—which relied on the implied win probability calculated from the Vegas moneyline odds—we tested were:

(1) **Bet Favorite:** Always bet on the team with the higher implied win probability
(2) **Bet Underdog:** Always bet on the team with the lower implied win probability
(3) **Bet Mixed:** Bet in alignment with random choice based on implied win probability.

We computed the average accuracy and return on investment (ROI) for each betting strategy across years with available data (after 2007) and display a summary of the results below.





Strategy	Avg. Accuracy	Avg. ROI
Bet Favorite	70.04%	-5.49%
Bet Underdog	29.35%	-4.35%
Bet Mixed	62.85%	-3.83%

From these results, we can draw a few observations. First, although betting on the favorite has the highest performance in terms of accuracy, it also has the *lowest* return on investment (i.e., loses the most money). This is interesting because it highlights the fact that a model that optimizes on accuracy alone may not be suited for the task of informing bets. Second, we notice that our second strategy—always betting on the underdog—has the most upside (highest max ROI) but is also the most variable having the largest distribution of outcomes relative to the other two. Intuitively, this makes sense as strategies with high reward are likely to necessitate high risk. Finally, we see that all three strategies yield a negative return on investment, that is that they would lose money. This is primarily because of the edge the casino holds on bettors. And so, based on our analysis we seek to develop a model that returns better than a -3.83% ROI.

7 ATTRIBUTE SELECTION

Dean Oliver, an American statistician and assistant coach for the NBA's Washington Wizards, wrote a paper on four factors that contribute to a winning basketball team based on box score data an how impactful these are to the win (4). The four factors each have an associated weight to ascertain information gained with regards to a win for a team. The four factors and their associated information gain weights are: Shooting (40%), Turnovers (25%), Rebounding (20%), and Free Throws (15%).

These factors optimize the amount of information in any given model by leveraging several different box scores to output one more concise marker on each of the factors. These factors also identify a team's strategic strengths and weaknesses. These can be calculated for the winning and loosing teams.

A team's own Effective Field Goal Percentage measures the shooting factor, and is the most important factor to a teams success. Effective Field Goal Percentage puts emphasis on the accuracy of shots made out of all shots taken and positively weights 3-pointers made. The equation to calculate Effective Field Goal Percentage is

$$\frac{(FieldGoalsMade) + (0.5 * 3 - PointerFieldGoalsMade)}{(FieldGoalAttempts)} \tag{2}$$

A team's own Turnover Percentage is the percentage of a team's or possessions that end in a turnover. Winning teams in theory will have low turnover meaning they hold and complete possessions. The equation to calculate Turnover Percentage is

$$\frac{Turnovers}{(FieldGoalAttempts + (0.44 * FreeThrowAttempts) + Turnovers)} \tag{3}$$

A team's own Offensive Rebound Percentage is an estimate of the percentage of available offensive rebounds a team grabbed. The equation to calculate Offensive Rebound Percentage is

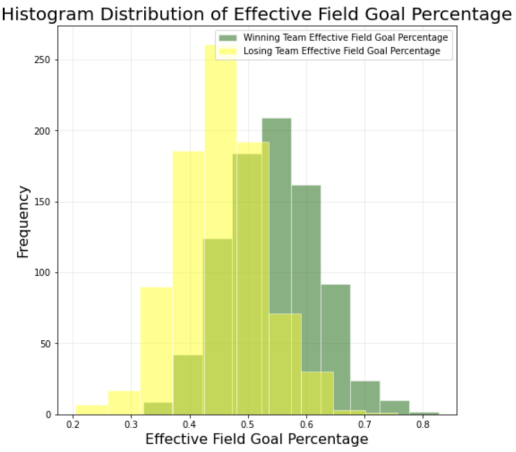
$$\frac{(OffensiveRebounds)}{(OffensiveRebounds + Opponent'sDefensiveRebounds)} \tag{4}$$

A team's own Free Throw Rate is a measure of both how often a team gets to the line and how often they make them. The equation to calculate Free Throw Rate is

$$\frac{FreeThrowsMade}{FieldGoalsAttempted}. \tag{5}$$

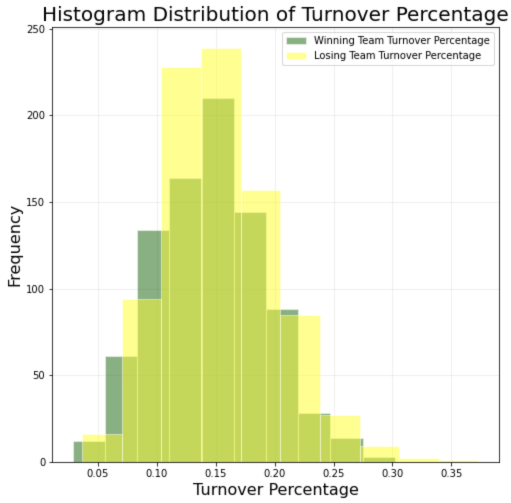
7.1 Attribute Calculations and Trends

From these attributes we gained new insights on the differences between a winning team and a loosing team. Effective Field Goal Percentage as an attribute leverages Field Goals Made, 3-Pointers Made, Field Goals Attempted to output a comprehensive shooting score. This attribute typically has 40% weight contribution to a winning team.



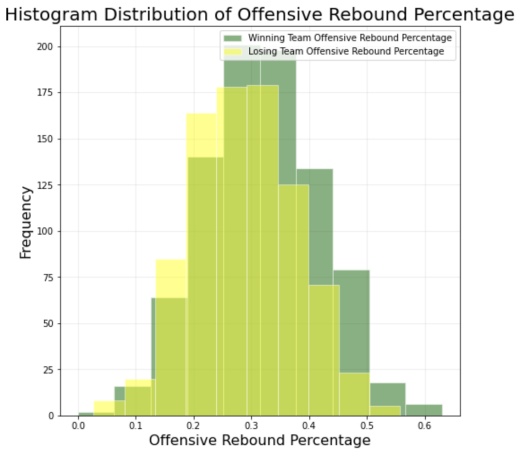
From the figure above a learned insight is that winning teams from the data set have a clear greater Effective Field Goal Percentage. These teams are not only completing a greater number of field goals, but also following through on a greater number of 3-point field goals made.

Turnover Percentage as an attribute leverages Turnover Count, Field Goals Attempted, Free Throws Attempted to output a comprehensive turnover score. This attribute typically has 25% weight contribution to a winning team. From the figure above a learned



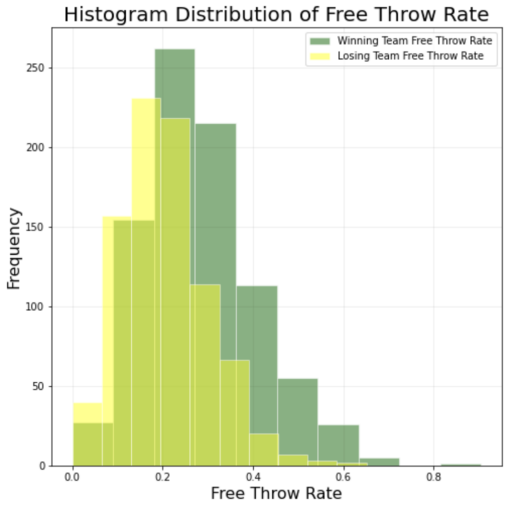
insight is that losing teams from the data have greater turnover frequency.

Offensive Rebound Percentage as an attribute leverages Offensive Rebound and Opposing Team's Defensive Rebounds to output a comprehensive rebounding score. This attribute typically has 20% weight contribution to a winning team.



From the figure above a learned insight is that winning teams grab offensive rebounds with greater frequency than losing teams.

Free Throw Rate as an attribute leverages Free Throws Made and Field Goals Attempted to output a comprehensive free throw score. This attribute typically has 15% weight contribution to a winning team.



From the figure above a learned insight is that winning teams take and make free throws at a greater rate than losing teams.

8 MILESTONES

(1) **Data Cleaning & Integration (Oct. 13):** Importing data into local environment and joining from multiple sources. Due to the sheer amount of data, we will be splitting data sets up by seasons. A training and test set are needed for the implementation of an accurate model meaning we are able to use all years of data if need be. The money line data is limited to odds from the 2007 season on with intention of testing betting practices on the most recent seasons.

(2) **Exploratory Data Analysis (Oct. 20):** Exploring data to identify relationships between team statistics (specifically recent performance) and tournament game outcomes
(3) **Attribute Subset Selection (Nov. 10):** Narrowing in on informative features from large dataset. As mentioned, smaller feature subset selection has demonstrated better model performance.
(4) **Model Creation, Examination, and Revision (Nov. 17):** Implementing, testing, and comparing multiple classification models (Logistic Regression, Bayesian Classification, Decision Trees, Random Forests, Support Vector Machine). Fine-tuning models to increase performance. Model selection is flexible and scope to the models is bigger than anticipated output.
(5) **Result Synthesis (12/6):** Compiling results from work into written project report and video describing which features and methods created the most profitable prediction in betting. Highlighting key findings, insights, and applications.

Completed

- Data Cleaning Integration: 100%
- Exploratory Data Analysis: 100%

In Progress

- Attribute Subset Selection: 70%
- Model Creation, Examination, and Revision: 20%
  - Four Factor Model

To Do

- Result Synthesis: 0%

8.1 Risks Issues

(1) **Data Integration**
- Unanticipated challenges regarding connecting data sources
- Resolved, but has delayed other aspects of project

(2) **Feature Computation**
- Underestimated difficulty of navigating Kaggle data structure (very granular)

(3) **Defining Betting Strategy**
- Not yet certain how to optimize betting strategy based on model's predictions
- Little available research on this

(4) **Model Creation**
- Using the same factors on different models vs using different factors in different models

9 REFERENCES

(1) Brown, Bryce, "Predictive Analytics for College Basketball: Using Logistic Regression for Determining the Outcome of a Game" (2019). Honors Theses and Capstones. 475.
(2) University, Yuan Liu Georgetown, et al. "Prediction for NCAA Championship: 2021 the 5th International Conference on Big Data Research (ICBDR)." ACM Other Conferences, 1 Sept. 2021
(3) Y, et al. A Mixture-of-Modelers Approach to Forecasting NCAA Tournament Outcomes.
(4) Al Baghal, Tarek. (2012). Are the Four Factors Indicators of One Factor? An Application of Structural Equation Modeling Methodology to NBA Data in Prediction of Winning Percentage. Journal of Quantitative Analysis in Sports. 8. 10.1515/1559-0410.1355.

10 HONOR CODE PLEDGE

On my honor, as a University of Colorado Boulder student, I have neither given nor received unauthorized assistance.