Forecasting the 2023 NCAA Basketball Tournament

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***Abstract*** — **Predicting the winner of individual tournament games and the ultimate champion of the NCAA Basketball Tournament is a fun, yet challenging endeavor. The Kaggle 2023 March Machine Learning Mania competition is a considerably more complex with an objective to predict the probabilistic outcome of a hypothetical matchup of each team matched against all other teams in their league. We sought to tackle this challenge using machine learning predictive analytics. In this work we show that several machine learning algorithms are appropriate to accomplish this task. However, trying to accurately predict outcomes that show so much unpredictability proved to be very difficult.**

***Keywords— College Basketball; NCAA Tournament; Predictive Analytics; Machine learning; Kaggle***

I. INTRODUCTION

**Background**

We sought to predict the winner of every individual game of the NCAA Men’s and Women’s Basketball Tournaments.

Predicting the winner of individual tournament games and the ultimate champion of the NCAA Basketball Tournament is a fun, yet challenging endeavor many individuals around the world attempt each March-April when the tournament is held. According to the American Gaming Association, in 2017 as many as 70 million brackets were completed[1] (and an estimated 45 million people last year[2]) competed through some verifiable online sports websites (such as ESPN, CBSSports, NCAA, Yahoo!, etc.).

To date, no one has ever completed a 'perfect bracket' - correctly predicting the winner of each of the 63 total games in the NCAA Tournament. In fact, the odds of completing a 'perfect bracket' are truly absurd. If you were to just guess or flip a coin the odds of all of your picks being correct are 1 in (9.2 quintillion) 9,223,372,036,854,775,808 - that's 1 in 9.2 quintillion. Or if you know a little something about basketball, the odds are estimated to be around 1 in 120.2 billion[3]. Although many people complete their bracket in private (and never share them), to date, the longest (verifiable) streak of correct picks in an NCAA tournament bracket is at 49 games - which is at the start of the third round (by Greg Nigl of Columbus, Ohio in 2019)[4]. Each year, there is a team with 'no chance' who manages to beat a higher seeded team; or a team with a great regular season winning percentage who manages to be upset, unexpectedly, by another team. Hence, the popular reference to the tournament as 'March Madness'. Out of the popularity for the tournament itself and the rising popularity of predictive machine learning algorithms, many data enthusiasts have entered into competitions to try to use predictive analytics to forecast the NCAA tournament.

For our project, we decided to use the provided data and competitive structure of the Kaggle 2023 March Machine Learning Mania competition, – now into its ninth annual edition[5]. For the millions of people fill out brackets predicting the ultimate Champion of the tournament, the objective is to consider each game individually, predict who will continue and who will not; then repeat this for all 63 games - declaring one team as the Champion. For the Kaggle competition (and our project), the task was considerably more complex with an objective to predict the outcome of a hypothetical matchup of each team matched against all other teams in their league. There are 363 men's Division-I teams this season, thus a submission for the Kaggle competition would need to include predictions for all possible pairs of those 363 teams (leading to over 65,000 total possible combinations), and there are 363 \* 362/2 = 65,703 possible combinations. We also needed to repeat this exercise for the women's league, as well. There are 361 women's Division-I teams this season - which corresponds to 64,980 possible combinations. So our final submission file must have 65,703 + 64,980 = 130,683 predictions. An additional layer of complexity for the Kaggle competition requires that we not just submit a winner for each matchup, rather we were tasked to submit a probability for each outcome.

Therefore, we simplified our problem definition for this project. We defined our problem as predicting the probability for all possible matchup between the 64 teams selected for the 2023 Men's NCAA College Basketball Tournament. We divided our problem into a men’s competition and a women’s competition for each of us to tackle separately; then we combined our results.

**Goal:** Predict the probability that each team selected for the NCAA tournament will win a hypothetical matchup between all other teams in the tournament (64 \* 63/2 = 2,048 combinations).

**Related Work**

In 2012, Chris Wright[6] provided a statistical analysis of the predictors of for success in March Madness. He found that win percentage and defensive efficiency had a large positive impact one outcome. Overall, he concluded that is very difficult to predict the winners of March Madness matchups. And that with even an unbiased model, the error term is large enough to create a lot of outcomes that were not predicted.

In 2014, Alex Tran and Adam Ginzberg[7] reported in their Stanford final project paper, that nearly all of the game statistics were useless except for FG%, FT%, and 3PT%, which were marginally helpful. Also in 2014, Levi Franklin[8] found in his project paper that margin of victory, difference between seeding, and performance previous tournament were useful features for training a machine learning model.

And finally, in 2018, Cody Kocher and Tim Hoblin[9], used generalized linear, random forest, and decision tree models to perform predictive analytics on the NCAA Tournament. They found that the correlation between the statistical variables used for analysis tended to be high among several variables. "A team’s win-loss record has a strong positive correlation to its average margin of victory." "Seed and strength of schedule are also highly correlated because teams who play more difficult schedules are usually rewarded with better seeds." They used principal component analysis to reduce related statistics with limited success.

We took these considerations into account when we performed our analysis.

Today's millions of online documents and social media are common sources of Big data. Twitter is one of the most popular microblogging social media platforms, where users can communicate with each other using short messages of up to 140 characters. These text messages are known as *tweets*. Users can track other users by "following" them on twitter. Every second, 6000 tweets are sent, or 500 million tweets per day on average. Because of the large and fast growing number of tweets being generated daily, tweet analytics is viewed as one of the fundamental problems of Big data stream.

II. DATASET AND FEATURES

The dataset we used included 31 well structured csv files containing various items of information and statistics. These files were completely organized without missing values. We are not going to run through all the data files in great detail, but I will just mention each one to give you a complete understanding of the data and features we were working with.

The first set of files (see Table 1) contains the main files we used for our analysis. The data includes a file that list all of the seasons beginning from 1985 through 2023 and the date the season started, ‘DayZero’.

Table 1: Dataset and features – main files

|  |  |
| --- | --- |
| **Data Section 1 Main Files** | |
| **Seasons** | Season, DayZero, RegionW, RegionX, Region Y, Region Z |
| **Teams** | TeamID, TeamName, FirstD1Season, LastD1Season |
| **Regular Season Detailed Results** | Season, DayNum, WTeamID, WScore, LTeamID, LScore, WLoc, NumOT, WFGM, WFGA, WFGM3, WFGA3, WFTM, WFTA, WOR, WDR, WAst, WTO, WStl, WBlk, WPF |
| **Tourney Detailed Results** | Season, DayNum, WTeamID, WScore, LTeamID, LScore, WLoc, NumOT, WFGM, WFGA, WFGM3, WFGA3, WFTM, WFTA, WOR, WDR, WAst, WTO, WStl, WBlk, WPF |
| **Tourney Seeds** | Season, Seed, TeamID |
| **Sample Submission** | ID, Pred (e.g. 2018\_3181\_3314,0.516) |

The data includes a file containing all of the teams listed by season. The number of division schools varies from season to season.

The data includes a files containing detailed game-by-game matchups for entire seasons. Each game included the number of days from ‘DayZero’ the game took place, team id, scores, as well as other statistics for both the winning and loosing teams. The detailed game-by-game data was also provided for the NCAA tournament games for previous years. These detailed game results only went back as far as 2003. But, we found these files to be the most beneficial.

The data also includes files providing the seeding for each team in the tournament; and a sample of how the submission file should look.

The next set of files (see Table 2) includes some extra files such as the cities where the games are played - this could be beneficial as teams tend to perform better in a friendlier home crowd.

Table 2: dataset and features – extra files

|  |  |
| --- | --- |
| **Data Section 2 Extra Files** | |
| **Cities** | CityID, City, State |
| **Game Cities** | Season, DayNum, WTeamID, LTeamID, CRType, CityID |
| **Compact Season Results** | Season, DayNum, WTeamID, WScore, LTeamID, LScore, WLoc, NumOT |
| **Compact Tourney Results** | Season, DayNum, WTeamID, WScore, LTeamID, LScore, WLoc, NumOT |
| **Compact Secondary Tourney Results** | Season, DayNum, WTeamID, WScore, LTeamID, LScore, WLoc, NumOT, SecondaryTourney |
| **Tourney Slots** | Season, Slot, StrongSeed, WeakSeed |

It includes game-by-game statistics (similar to the detailed files) but with only a smaller set of features. The files includes a file containing game-by-game statistics for secondary tournaments.

And the last set of files (see Table 3) includes some supplementary files such as coaches (which could be useful as some more experienced coaches show better team success in tournament games where the stakes are all-in. Other files included in this set are the conferences the teams play in (some conferences perform better than other during tournament). Other files include team rankings for a number of different ranking systems, and team spelling (which provides alternate forms of the spelling of the team name).

III. METHODS

One of the feature sets we developed was by taking the regular season data, and splitting it so that one dataframe represented the winning teams’ metrics, and another dataframe represented the losing teams’ metrics. These data frames were then used to develop average, median and count metrics grouped by season and team. In this way, each team had a datapoint representing their performance in each season (2023 - 2022). These two data frames were then merged together as they were originally and the columns representing the winning and losing teams were randomized so that not all the winning teams were listed in the same column. In this final version of the dataset, each datapoint represented a match (Team A vs. Team B) and the relevant metrics of both teams. And each of these matchups were represented twice (A vs. B, and B vs. A) to give the models more information about the matchups. The final dataset representing tournaments since 2003 had 1,181 rows and 70 columns. This dataset was then used to determine the outcome of the team in the first team column (team\_1) winning the game. (In this dataset team\_0 was listed after team\_1 in the order of the columns).

Table 3: Dataset and features – supplementary files

|  |  |
| --- | --- |
| **Data Section 3 Supplements** | |
| **Team Coaches** | Season, TeamID, FirstDayNum, LastDayNum, CoachName |
| **Conferences** | ConfAbbrev, Description |
| **Team Conferences** | Season, TeamID, ConfAbbrev |
| **Conference Tourney Games** | ConfAbbrev, Season, DayNum, WTeamID, LTeamID |
| **Secondary Tourney Teams** | Season, SecondaryTourney, TeamID |
| **Massey Ordinals** | Season, RankingDayNum, SystemName, TeamID, OrdinalRank |
| **Team Spellings** | TeamNameSpelling, TeamID |
| **Seed Round Slots** | Seed, GameRound, GameSlot, EarlyDayNum, LateDayNum |

For feature selection, we used the scikit learn Sequential Feature selector and forward selection and time series cross validation to reduce the feature set. This reduced our features to 15. We then ran this feature set through Ridge Regression and SVM models. Then we used scikit learn’s GridSearchCV() to tune the parameters. For logistic regression, the data was scaled before fitting to the model. Then we evaluated the different models using the accuracy\_score function. Again, we are testing to see if the team listed as “team\_1” is the winner (signified by a ‘1’ in the data frame’s ‘winner’ column which was our target variable).

IV. EXPERIMENTS AND RESULTS

Chart, line chart

Description automatically generated

Figure 1: Number of teams per year

Table

Description automatically generated Figure 2: Comparison of seed vs win in team\_1 and team\_0

We also wanted to test the models against the accuracy prediction of always choosing the team with the seed with the lower value (which is the higher ranking, Seed 1 is the top seed, Seed 16 is the lowest) as the winning team. If you always chose the seed with the lower numeric value as the winning seed, you would have 33% accuracy. This is fairly low, but it is one of the metrics we could test our models against, and all of the models tested higher than 33% accuracy.

Diagram

Description automatically generated

Figure 3: Sequential feature selector and forward selection

In using the sequential features selector (Figure 3) across the RidgeRegression, Logistic Regression, and SVM models, there were some variables that appeared in more often in the selection processes: the seed number for team 1 (the winning team) - this variable was used in all eight models; the team id number - these variables were used in six of the models; the median of personal fouls for team 1 over the selected seasons; and the median defensive rebounds for team 0 (the loosing team). These variables have significant weight in determining whether or not ‘team\_1’ wins in our tournament predictions when using the outlined models. There could be more exploration into why these variables are significant.

Table 3: Example model tuning

|  |  |  |
| --- | --- | --- |
| **Model** | **# Features** | **Tuning** |
| SVM | 19 | kernel = 'linear', probability = True |
| KNN | 19 | k = 5 |
| GNB | 19 |  |
| DT | 19 | max\_depth = 5 |
| RF | 19 | n\_estimators = 10 |
| MLP | 19 | alpha = 1, max\_iter = 1000 |

Table 4: Example model training accuracy

|  |  |  |  |
| --- | --- | --- | --- |
| **Model** | **# Features** | **Tuning** | **Accuracy** |
| SVM | 15 | Linear Kernel | 0.69 |
| 10 | Linear Kernel | 0.69 |
| 10 | RBF Kernel | 0.71 |
| Ridge Regression | 15 | Alpha = 1 | 0.7 |
| 15 | Alpha = 1 | 0.7 |
| 10 | Alpha = 0.01 | 0.69 |
| Logistic Regression | 15 | Data Scaling | 0.7 |
| 10 | Data Scaling | 0.7 |

What we see from these models in Table 4 is that they all perform similarly on the data set, and the lower number of features is a better option for developing our model. In training, the Support Vector Machine with the RBF kernel model performs slightly better, which may be due to its complexity and ability to project data into higher-dimensional space allowing better separation and thus classification. However, the Ridge Regression model performed slightly better on the testing set. The small size of the dataset may be one contributor to the performance of the models on this dataset.

This feature set and model selection would have to be further improved, because in the real-world setting we would not have the actual Team vs Team matchups. But it provides a basis for a model. We actually implemented our model development in the 2023 Kaggle March Madness competition. In this case, instead of predicting a limited number of matchups, we made predictions for all possible combinations of teams in the tournament.

Table 5: Example model testing accuracy

|  |  |  |  |
| --- | --- | --- | --- |
| **Model** | **# Features** | **Tuning** | **Accuracy** |
| SVM | 10 | RBF Kernel | 0.66 |
| Ridge Regression | 10 | Alpha = 0.01 | 0.69 |
| Logistic Regression | 10 | Scaling Data | 0.64 |

V. CONCLUSION AND FUTURE WORK

Using the sequential features selector across the RidgeRegression, Logistic Regression, and SVM models, there were some variables that appeared in more often in the selection processes, in particular, seed\_1 - the seed number for team 1 - was used in all eight models. This means this variable has significant weight in determining the outcome and should be considering in future predictive modeling that undertakes this task of tournament prediction.

There needs to be a way to account for the randomness of the matchups, what kind of metric can be used for this? (i.e. a player is hurt, team’s lack of sleep due to travel schedule, etc.). Especially considering this is a single-elimination tournament, which means any aberration in performance could mean a top team losing or a bottom team winning. This type of unpredictability is the ‘madness’ of March Madness.

This project was fun, but very challenging. Trying to accurately predict outcomes that show so much unpredictability proved to be very difficult.

One learning point from this project was that we should have provisioned our time at the onset (to allow sufficient time for model and hyperparameter tuning). Another learning point, feature engineering is very important. It would have been better to establish ‘hot team’ and ‘tired team’ features - for streaking teams; bring in time-series.

We believe using a convoluted neural network model with transfer learning from regular season data might be a better approach. The brier score metric was new for us, fully understanding this metric and using this metric to optimize model may also prove to be a smarter tactic.

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