**How to not Blow a 3-1 Lead in this Year’s Bracket Predictions**

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**Abstract (Damir)**

As of recent, the NCAA March Madness tournament has piqued the interests of the computing and machine learning community. The tournament’s seemingly unpredictable nature questions whether tournament brackets and the associated upsets can be accurately predicted. In this document, we will explore the existence of upset indicators, success of various models in predicting brackets, and impact of mixing raw team statistics with various measures of team rankings. First, we describe the results of regular season data manipulation and model performance of Logistic Regression, Random Forest, Multilayer Perceptron, and K-Nearest Neighbors models, of which Random Forest consistently outperformed others. Next, we outline data and model improvement to cater towards the nature of March Madness Tournament play. Our model’s success in prediction is then quantified – we estimate that it has an accuracy of about 70 and 60 percent accuracy in predicting regular and tournament games respectively. Our techniques in tuning our model provides a 25% and 20% increase in correctness from tournament game predictions made by non-experts increase from experts respectively [1].

**1 Project Outline (Damir)**

**1.1 NCAA March Madness Tournament**

The NCAA Division I Men’s Basketball (nicknamed March Madness) is a single elimination basketball tournament played by 68 Division I collegiate basketball teams. The tournament consists of 32 teams who win Division I conferences and 36 teams awarded positions via committee choice [2]. It has become tradition for fans to predict the tournament bracket given initial team slots. Due to the nature of single elimination, game outcomes are highly unpredictable. Additionally, there are 9.2 quintillion valid bracket combinations. Thus, the prediction of the correct bracket combination is highly improbable.

**1.2 Workflow**

Our first goal was to determine the best model for predicting NCAA basketball game results. Although there are differences between tournament and regular season play, we operated under the assumption that model success would reflect across all forms of NCAA basketball games. Using regular season data from 2003–2016 we tested the success of Logistic Regression, Random Forest, Multilayer Perceptron, and K Nearest Neighbors models. Once Random Forest was determined as the most successful model, we adjusted our tournament data set to reflect teams’ yearly performance, tournament seeding, and Las Vegas point spreads for each game and weighted upset games more heavily. Our models were then run on tournament data on a March Madness tournament simulator which provided the most probable bracket based on our models’ predictions.

**1.3 Key focuses**

The following questions were central to formulating our workflow and model/data manipulation techniques:

* Do predictable indicators of an upset exist?
* Is there a correlation between tournament seeding and the Las Vegas Point Spread?
* Is it possible to combine team statistics with seeding and the Las Vegas point spread to predict more accurately than the spread/seeding on their own?
* How does performance during the regular season transfer to tournament performance?

**1.4 Hypothesis**

As discussed by Lopez and Matthews, the “rules of efficient gambling markets” state that it is impossible to beat the spread of the Las Vegas sports books in the long run [3]. We believe that it is possible to train our model to predict upsets more accurately than the spread through weighting upsets more heavily. The negative aspect of this, though, is that our ability to predict “straightforward” results will suffer. Additionally, we expect that our model prediction performance will drop from regular season to tournament games as tournament games are considered to be more unpredictable due to a variety of extraneous factors.

**2 Data Overview (Damir)**

**1.1 Original dataset**

Kaggle’s March Machine Learning Mania 2017 challenge provided data for all NCAA basketball regular season and tournament games from 2003 – 2016 [4]. Each data point contained a game’s statistics pertaining to game information such as the year, location, and participating team IDs. Additionally, each point provided game statistics for both participating teams (e.g. points scored, field goals made, steals, etc.). Teams for each game were marked as team1 and team2 where team1 was the winner of each matchup.

The Kaggle challenge also provided a table mapping team IDs to the school name. Other data was provided, but not used. We used Python’s SQLite library to format and modify data as necessary.

**1.2 Regular Season Games**

To experiment with various models on the success of predicting regular season games we needed to reformat team statistics to reflect the strength of participating teams rather than their actual performance during that game. Obviously, in its original format the model would simply choose the winner of the game as whoever scored more points, this was not the function of our intended model.

To reformat data, we replaced each team’s statistics for a game with the average of their statistics for an entire year. This way, the averages reflected the team’s strength in that statistic and the model could use this as a factor in impacting game evaluation. Additionally, we added an indicator value to classify the games, where 1 meant team1 won and 0 meant otherwise. Since team1 won each game in the original dataset, each classifier value was 1 for the original data. In this given format, the model would simply predict that team1 for any game and feature values would be irrelevant. Thus, for each data point, we created a copy with a team1 and team2 flipped and an indicator value of 0. We had hoped, as well, that this would completely remove any bias towards weights in team1 over team2 and that those weights would ultimately have an inverse relationship.

**1.3 March Madness Games**

The March Madness games were reformatted to contain the same averages found in the regular season for each team during a given year. This made sense to us, as a team’s performance during the regular season is presumably an accurate reflection of the same team playing in the tournament. In addition, we added the tournament seed of each team and the Las Vegas point spread for the game.

**1.3.1 Seeding**

Tournament seeds are preliminary rankings. For March Madness purposes, these values are determined by the NCAA tournament committee [2]. For each region, there are seeds given 1-16, but the NCAA also releases an all-inclusive 1-68 ranking of all participants. For each game in the March Madness dataset we added the participating teams’ tournament seed. The intuition is that the highest seeded teams consistently make it to the final rounds of the tournament. Thus, the seed is an accurate representation of more qualified teams. Additionally, although raw statistics provide insight on individual strength of each team, the seed provides an all-encompassing team ranking which we believed would holistically strengthen our model. These values were entered manually and due to time constraints, we entered values for 2012-2016, all other values were 0.

**1.3.2 Las Vegas Point Spread**

The Las Vegas Point Spread “provides the predicted difference in total points scored between the visiting and the home team; a spread of – 5.5, for example, implies that the home team is expected to win by 5.5 points” [3]. In our case, team1 was considered the home team as all games were in neutral locations. Our intuition for adding these values comes from Lopez and Matthews who argue that it is impossible to beat the Las Vegas Point Spread in the long run due to normalization associated with the large number of bets made [3]. Lopez and Matthews cite that “should act as the standards on which to judge any pre-game predictions” [3]. These values were entered by hand from Odds Shark [5].

We ran into numerous issues with Odds Shark. Firstly, we simply did not have the resources to gather data for every game (naming conventions between our name-to-ID and Odds Shark were different therefore data scraping was ruled out). Additionally, Vegas odds did not exist for all games between 2003-2016 and no odds exist for this year as the bracket has not been finalized. Therefore, we a built an L2 Normalized Linear Regression model to find a relationship between tournament seeding and Las Vegas odds. For games with seeds, but no Las Vegas Odds we used the relationship to guess the Las Vegas odds. Our intuition was that both values are based on overall perceived team strength and thus must be at least loosely correlated. Our model found the following weights:

0.29599983 for the higher team seed

-0.37982249 for the lower team seed

These values are consistent as the Las Vegas odds are negative towards the better (lower seeded) team. But, since the higher seed values are larger than the lower seed values, the weight must be lower in magnitude for higher seeds.

**1.4 Feature selection results**

The tournament data originally used contained 35 features including both raw statistics as well as seeding and Las Vegas odds. We ran L1 Regularized Linear Regression feature selection to determine the most impactful features. After running feature selection, our model contained between 17 and 20 features depending on the run. The results are as follows:

Figure 1.2: Scores for Features after Feature Selection on Regular Season Data

Figure 1.1: Scores for Features after Feature Selection on Regular Season Data

Figure 1.2: Scores for Features after Feature Selection on Tournament Data

Regular Season Data

* Location was the most impactful feature for determining the winner of regular season games. All March Madness games are played from a neutral location and could account for some of the unpredictability in games results.
* As expected, average score and score difference were the most impactful raw team statistics.

Tournament Data

* Average score difference was the most important feature for prediction.
* Vegas odds were the second most important feature and this supports our claim that Vegas odds should be a standard for pre-game indication.
* Seeding plays very little role in the result of the tournament games. This may be because we did not have seeds for all games, but if this was the case our Vegas odds would have a similar score (as we have the same number of Vegas odds and seeds statistics). Thus, this implies that our assumption that Las Vegas odds and tournament seeds are correlated is incorrect.

**3 Model Selection (Jason)**

**4 Tournament Adjustments (Damir)**

As mentioned above, tournament seeds and Las Vegas odds were added to our dataset to provide a holistic indicator of team strength. Additional data manipulation and simulation of tournament play was implemented to address differences between regular season and tournament play.

**4.1 Upset Weight**

The March Madness tournament is popularly known for tournament “upsets” where a team perceived to be considerably worse than their competitor wins a matchup. Upsets of various degree have occurred every year and pose the greatest challenge for prediction models. A key interest we had during these experiments was to find any indicators of a possible upset if they exist. The intuition for our focus on upsets is due to the rules of efficient gambling markets. Since it is impossible to beat Las Vegas odds in the long run, our model would simply converge towards Las Vegas predictions if provided enough raw team statistics and tournament prediction data.

Our solution to predicting upsets was to weight upset data points more heavily. Using news reports from previous years, we found for each year and repeated the corresponding data points in our set 3-5 times in our dataset. We had hoped that this would influence our model to search for a correlation between upset games. Our measure for the success of this method was to determine how many (if any) tournament upsets our model predicted. This method obviously has the potential for overfitting our model towards making upset predictions. But, if provided more time we would be interesting in experimenting with various upset weights and other models of data manipulation to make our model to predict upsets accurately (rather than over fit). Additionally, there are unquantifiable factors which contribute to upsets such as how team operates under tournament pressure. As these factors are unquantifiable, it would be impossible to train our model to account for them.

**4.2 Simulated Tournament Play**

**5 Results (Jason)**

**6 Conclusions (Jason)**

**References**

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