Project Final Report
DSO 579
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Exploring the Causes of March Madness Upsets

Objective: The objective of this study is to investigate the underlying factors that contribute to upsets in the March Madness tournament and to develop a predictive model for future tournaments

Problem: March Madness often experiences upsets where lower-seeded teams defeat higher-seeded teams. These upsets present challenges for individuals attempting to predict tournament outcomes.

Research Questions: What factors have contributed to the increase in upsets during March Madness, and can these factors be effectively predicted to anticipate upsets in the tournament?

Null Hypothesis:
H0: There is no significant data that can predict the cause of upsets in March Madness.
H1: There is significant data that can predict the cause of upsets in March Madness.

Report Structure

1. Datasets
2. Defining "Upset"
3. Upset by Round
4. Methods
    a. Feature Selection
    b. Predictive Models
        i. Logistic Regression
        ii. Random Forest
        iii. Gradient Boosting
5. Analysis of Barthag and Wins Above Bubble
6. Limitations
7. Conclusion
8. Relevant Literature
9. Feature Glossary

Datasets

Downloaded two datasets from Kaggle

1. Tournament_Scores_1981-2021.csv (URL)
   This dataset includes team names, seeds, and scores of each March Madness game.

YEAR	ROUND	WSEED	WTEAM	WSCORE	LSEED	LTEAM	LSCORE	…
2021	6	1	Baylor	73	1	Gonzaga	68	…
2021	5	1	Gonzaga	71	11	UCLA	63	…

2. Tournament_Team_Data_2008-2022.csv (URL)
   This dataset includes team data of the season participating in March Madness.
   On top of basic stats like FG% and REB%, advanced stats from KemPon Rankings and BartTorvik

Rankings are also featured.

YEAR	SEED	TEAM	OF EFF	DF EFF	…	WIN %
2022	1	Kansas	1.17	0.85	…	0.760
2022	1	Arizona	1.16	0.86	…	0.729

For predictive analysis, merge these datasets and create Merged_Data_2008-2021.csv
Prior to merging datasets, standardize school names, e.g. USC -> Southern California, so that the datasets can merge by using the school name as a key.
Add suffix _F for favorite team data and _U for underdog team.
Add a binary value column UPSET and drop unnecessary columns.

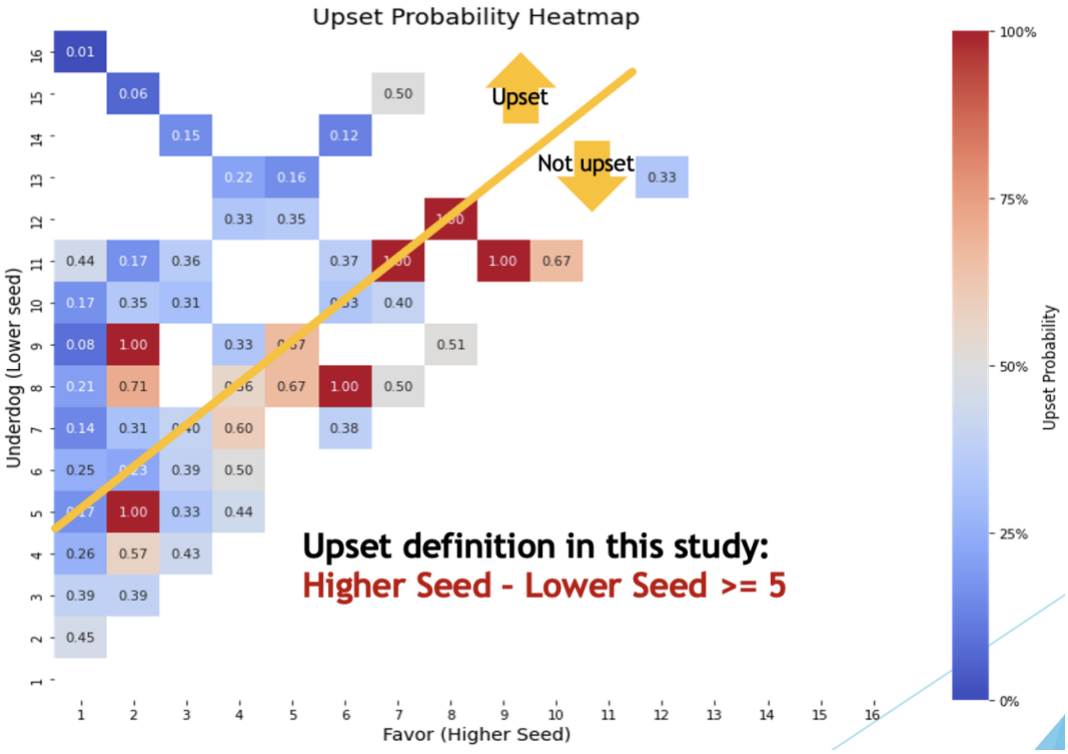
YEAR	ROUND	TEAM_F	SEED_F	OF EFF_F	DF EFF_F	…	TEAM_U	SEED_U	OF EFF_U	DF EFF_U	…	UPSET
2021	6	Baylor	1	1.12	0.771	…	UCLA	11	1.05	0.910	…	0
2021	5	Gonzaga	1	1.19	0.698	…	Houston	6	1.09	0.830	…	1

Defining "Upset"
Upset should not be a phenomenon that occurs frequently, and definitions in different studies are inconsistent.

The study Predicting March Madness using Machine Learning simply defines upset as lower seed beating a higher seed

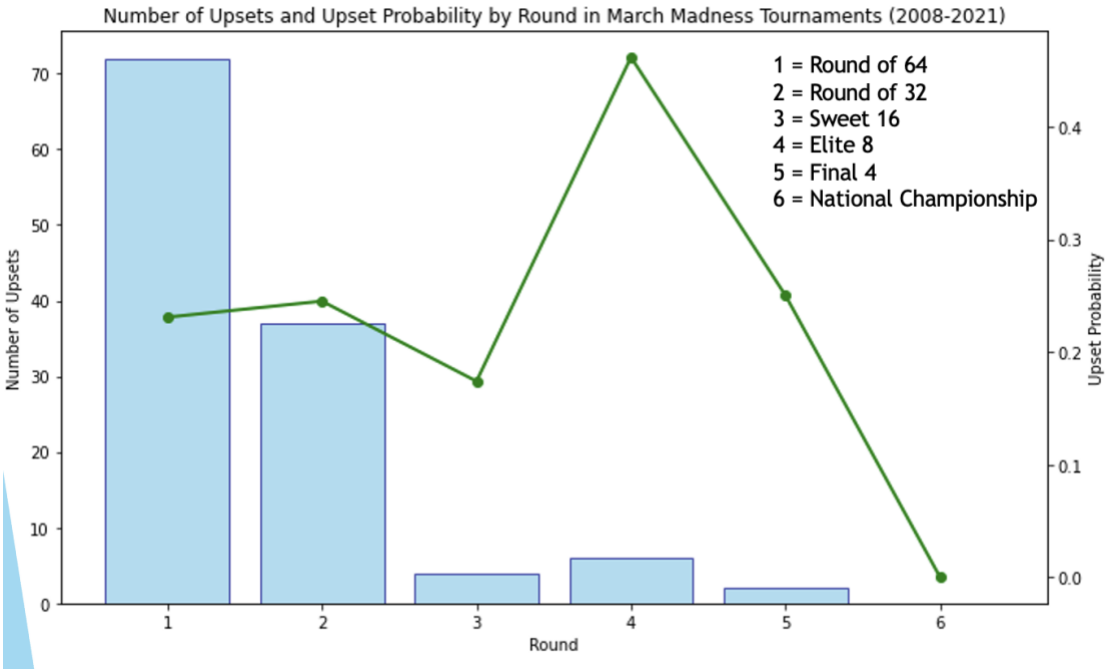
The study Use my upset prediction model to pick underdogs in your NCAA tournament bracket define upset as a win by an underdog team seeded at least 4 slots lower than their opponent

Due to the inconsistency, this study is defining a new definition of upset based on historical probability.



In the above image, notice that most of the upset probability of each combination decreases significantly above the yellow line.
That tiles above the line are the games where underdog team seeded at least 5 slots lower than their opponent.
Therefore, upset definition in this study is defined as a win by underdog team against a team that's seeded 5 slots or higher.

Upset by Round



- Most upsets occur in 1st round. However, provability is not as high
- Upset probability increases in the 4th round. This indicates that once an underdog makes it to the 3rd round, they have the momentum to advance further
- There are no upsets in the championship within the data period. The last championship upset was in 1988, Kansas (6) vs Oklahoma (1)

Feature Selection

Performed ANOVA and selected top 30 important features (high F-Score and low p-value) to before training predictive models.

Started out with selecting top 50, and then top 40 features but the high number of features did not improve predictive model performance at all. Top 30 seems to be a good cut off point where it can provide a good performance for the models and save computing power.

	Feature	F-Score	p-value
10	BARTHAG_F	44.735574	6.899160e-11
7	BARTTORVIK ADJUSTED EFFICIENCY_F	43.040659	1.515662e-10
3	KENPOM ADJUSTED EFFICIENCY_F	37.841246	1.732121e-09
44	BARTTORVIK ADJUSTED EFFICIENCY_U	37.252041	2.287699e-09
47	BARTHAG_U	36.902496	2.698781e-09
40	KENPOM ADJUSTED EFFICIENCY_U	35.701817	4.766732e-09
72	WINS ABOVE BUBBLE_U	31.272375	3.953434e-08
48	ELITE SOS_U	24.470318	1.077659e-06

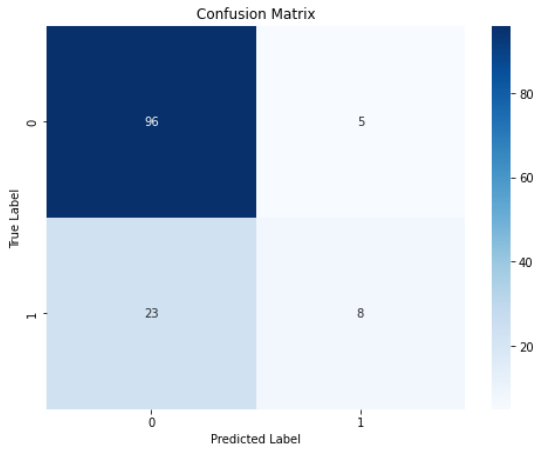
35	WINS ABOVE BUBBLE_F	23.860049	1.455085e-06
46	BARTTORVIK ADJUSTED DEFENSE_U	22.929026	2.303543e-06
42	KENPOM ADJUSTED DEFENSE_U	22.804567	2.449733e-06
2	SEED_F	22.348260	3.070432e-06
39	SEED_U	21.344945	5.052015e-06
36	WIN %_F	20.246293	8.735209e-06
37	POINTS PER POSSESSION OFFENSE_F	19.796110	1.094031e-05
45	BARTTORVIK ADJUSTED OFFENSE_U	18.063276	2.612758e-05
4	KENPOM ADJUSTED OFFENSE_F	17.800780	2.982834e-05
8	BARTTORVIK ADJUSTED OFFENSE_F	17.317324	3.808664e-05
41	KENPOM ADJUSTED OFFENSE_U	15.639963	8.933405e-05
38	POINTS PER POSSESSION DEFENSE_F	10.979723	9.976003e-04
20	OFFENSIVE REBOUND %_F	10.533068	1.262502e-03
32	OP D REB %_F	10.533068	1.262502e-03
9	BARTTORVIK ADJUSTED DEFENSE_F	8.339414	4.071594e-03
13	2PT %_F	7.057030	8.183798e-03
5	KENPOM ADJUSTED DEFENSE_F	6.199591	1.314782e-02
16	EFG %_F	5.294752	2.185859e-02
57	OFFENSIVE REBOUND %_U	5.201907	2.304161e-02
69	OP D REB %_U	5.201907	2.304161e-02
24	2PT % DEFENSE_F	4.818724	2.867620e-02
59	BLOCK %_U	4.765842	2.956005e-02

Logistic Regression Model

Reason for choosing this model: Logistic regression model is a simple and widely-used linear classification algorithm that works well for binary classification like predicting the outcome of a sports game

Cross-validation results
[0.81818182, 0.79545455, 0.72727273 0.79545455, 0.75, 0.79545455, 0.72727273, 0.68181818, 0.79545455, 0.77272727]

Average cv accuracy: 0.76590



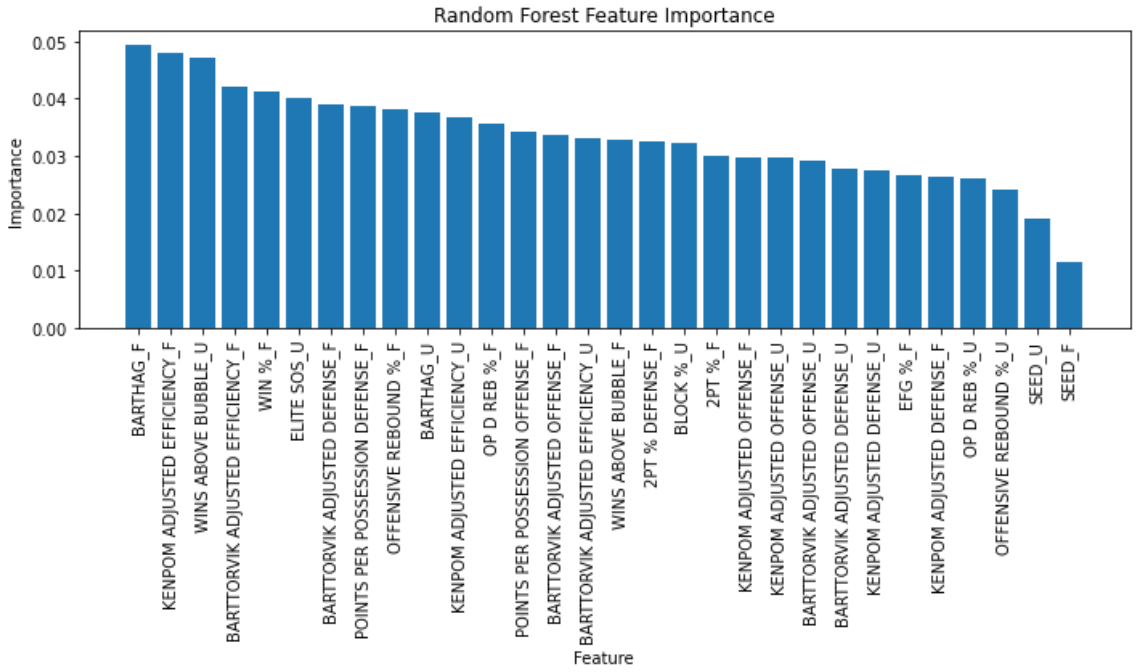
Based on the confusion matrix, the model predicted non-upset games 81% (96 out of 119) right. And it predicted the upset games 38.5% (5 out of 13) right.

Random Forest Model

Reason for choosing this model: Random forest model is an ensemble model which can provide high accuracy and reduce overfitting

Cross-validation results
[0.81818182, 0.79545455, 0.72727273 0.79545455, 0.75, 0.79545455, 0.72727273, 0.68181818, 0.79545455, 0.77272727]

Average cv accuracy: 0.74545



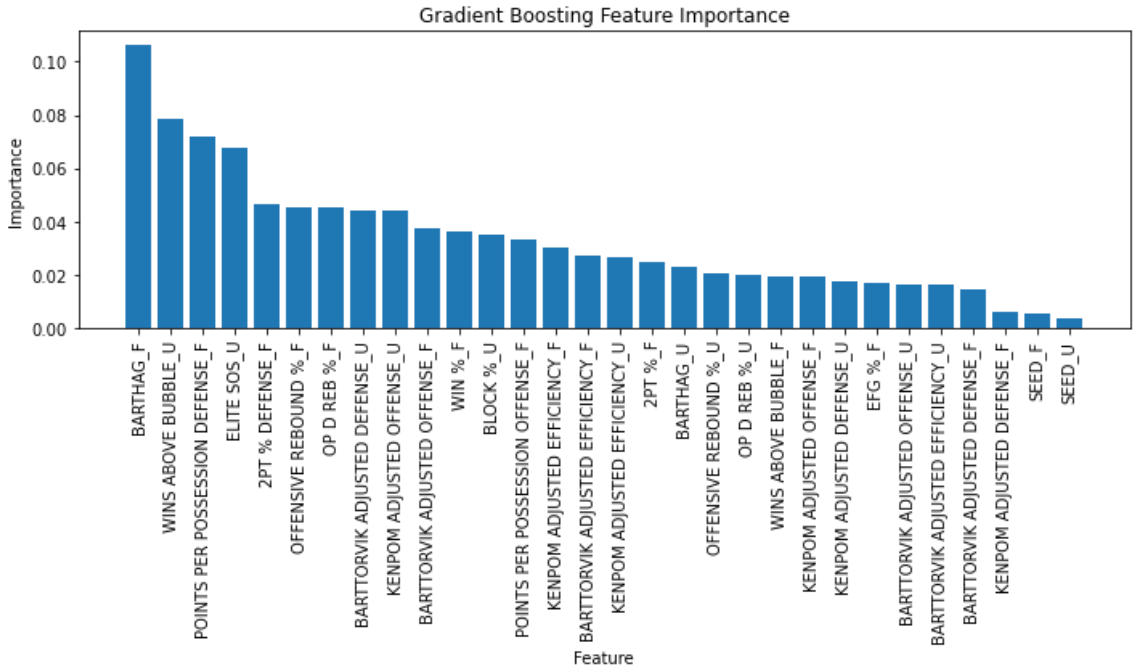
Top 3 important features in Random Forest Model are BARTHAG_F, KENPOM ADJUSTED EFFICIENCY_F and WINS ABOVE BUBBLE_U

Gradient Boosting Model (GBM)

Reason for choosing this model: A model using GBM won the *NCAAW March Madness Kaggle Competition* in 2022. Therefore, this model can be applied to predict Men's Tournament

Cross-validation results
[[0.81818182, 0.77272727, 0.79545455, 0.72727273, 0.68181818, 0.77272727, 0.65909091, 0.70454545, 0.79545455, 0.70454545]

Average cv accuracy: 0.74318



Top 3 important features in GBM are BARTHAG_F, and WINS ABOVE BUBBLE_U and POINTS PER POSSESION DEFENSE_F

Out of the three models, Logistic Regression has the highest accuracy at 0.76590. This means that this model can predict the outcome of potential upset games (where an underdog team is 5 slots or lower than the favorite team) 76.6% of the time. The result of all three models was close and the order could easily change with some additional data or analysis from different angles/perspectives. However, the reason why Logistic Regression won may be because it is specialized in predicting a binary outcome. On the other hand, Random Forest and GBM are well-rounded ensemble models that are not necessarily made exactly for binary outcomes.

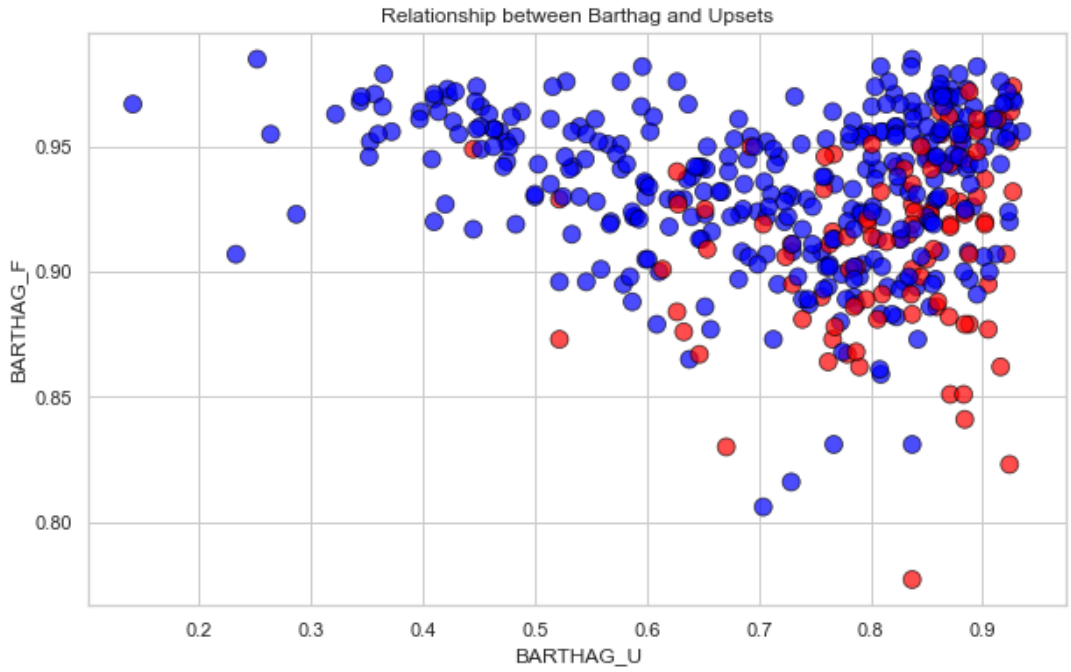
Analysis of Barthag and Wins Above Bubble

Decided to investigate Barthag and Wins Above Bubble deeper because they were both in the top 3 of important features of Random Forest and GBM.

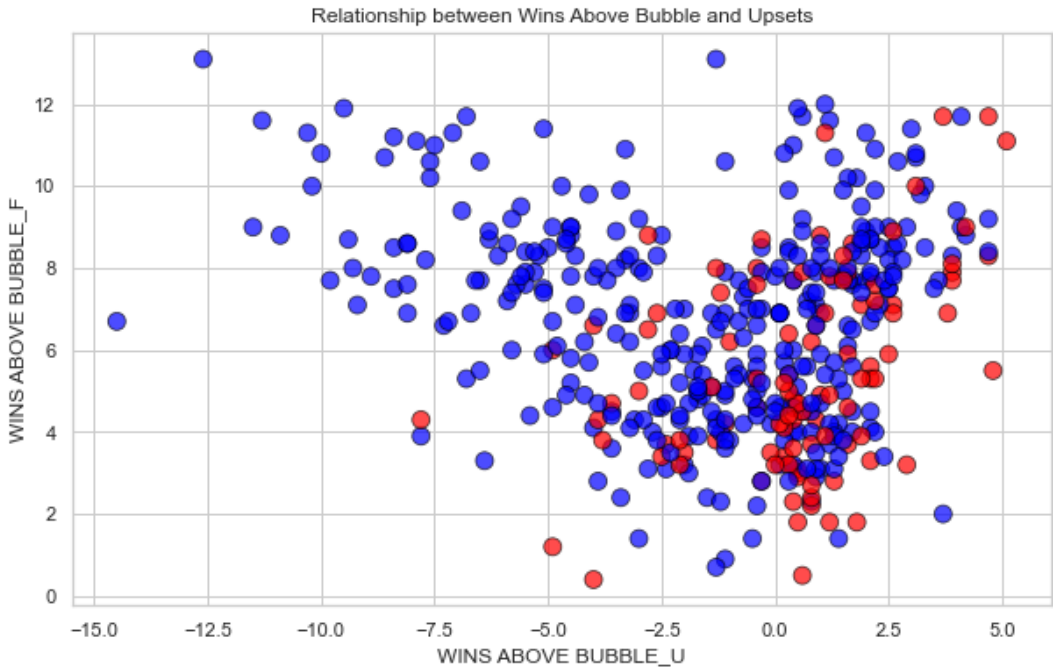
Barthag definition: Power Rating (Chance of beating the average Division I basketball team).

Wins Above Bubble definition: The expected winning percentage for an average *bubble team in each game of a team's schedule subtracted from the total of the team's actual wins. The bubble teams for the NCAA tournament are on the cusp of making the field of 68, but an invitation isn't guaranteed

Below is the relationship between Barthag and Upsets. Blue dots are non-upset games and red dots are upset games. We can see that a game of favorite team with barthag < 0.95 and underdog with barthag > 0.75 has a higher concentration of upsets.



Below is the relationship between Wins Above Bubble and Upsets. We can see that a game of favorite team with WAB < 6 and underdog with WAB > 0 has a higher concentration of upsets



Limitations

- Data period

    - Used 2008-2021 data for this project. March Madness has a long history since 1939
- Alternative data
    - Did not use data outside of team stats. It could produce a model with higher accuracy if able to collect alternative data e.g. coach experience, travel distance
- Recency data
    - No data that takes recency into account. There is something to be said about peaking at the right time in the season
- Resource and time
    - If there were more time and resources, it would be interesting to deep dive into the data more by testing additional prediction models or looking into the trends through different rounds

Conclusion

The objective of this study was to investigate the underlying factors that contribute to upsets in the March Madness tournament and to develop a predictive model for future tournaments. The problem is March Madness often experiences upsets where lower-seeded teams defeat higher-seeded teams. These upsets present challenges for individuals attempting to predict tournament outcomes. Through this study, the created model proved to be able to predict with a fairly high accuracy. For next year's tournament, we can download data from KenPom and BartTorvic Rankings and apply those metrics to the model to predict upsets.

Below are key takeaways:

- Upset is defined as an underdog win in a game where **Higher Seed – Lower Seed >= 5**
- Round 4 (Elite 8) has the highest probability of upsets
- Out of the three tested models (logistic regression, random forest and gradient boosting) **logistic regression has the highest accuracy**
- **Barthag** and **Wins Above Bubble** features are important to the random forest and gradient boosting models

References

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