Forecasting the 2023 NCAA Basketball Tournament

Final Project Presentation | MSDS 565, Spring 2023

20 March 2023

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Agenda

- Introduction – **Problem Understanding** and Definition
- Dataset and Features – **Data Collection** and Preparation
- Methods – Data Understanding using **EDA**
- Experiment and Results – **Model Building**
- Experiment and Results – **Model Evaluation**
- Conclusions – **Communication** (and Deployment)
- Questions

Introduction

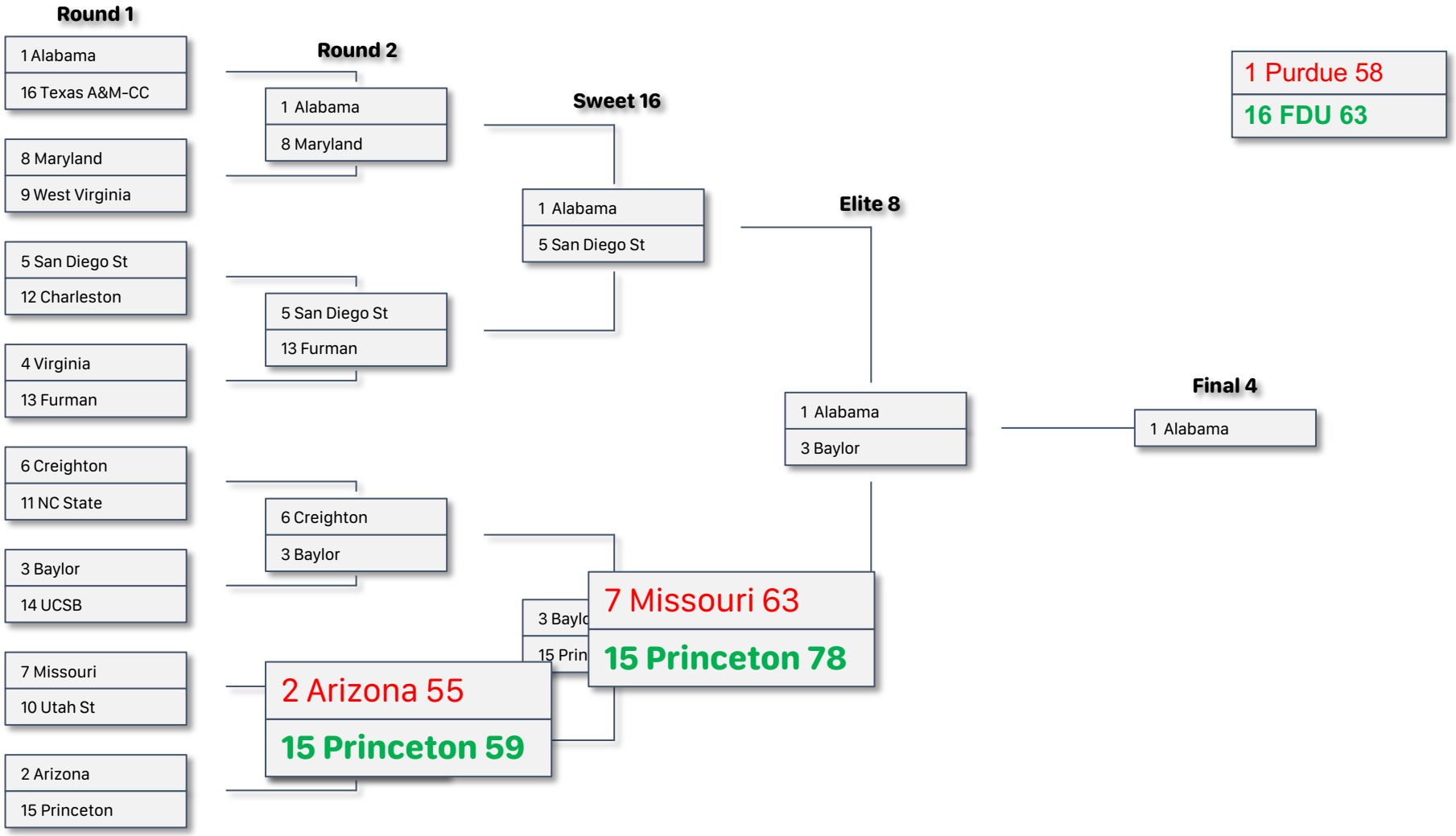
Introduction – Problem Understanding

- **predict the winner** of every individual game of NCAA College Basketball Tournaments
- according to the AGA, up to **70 million brackets** in 2017[1]; an estimated **45 million people** in 2022[2]

Source : [1] David Purdum (2017) | [2] American Gaming Association (2022)

How the brackets work.

How the brackets work.



Introduction – Problem Understanding

- **predict the winner** of every individual game of NCAA College Basketball Tournaments
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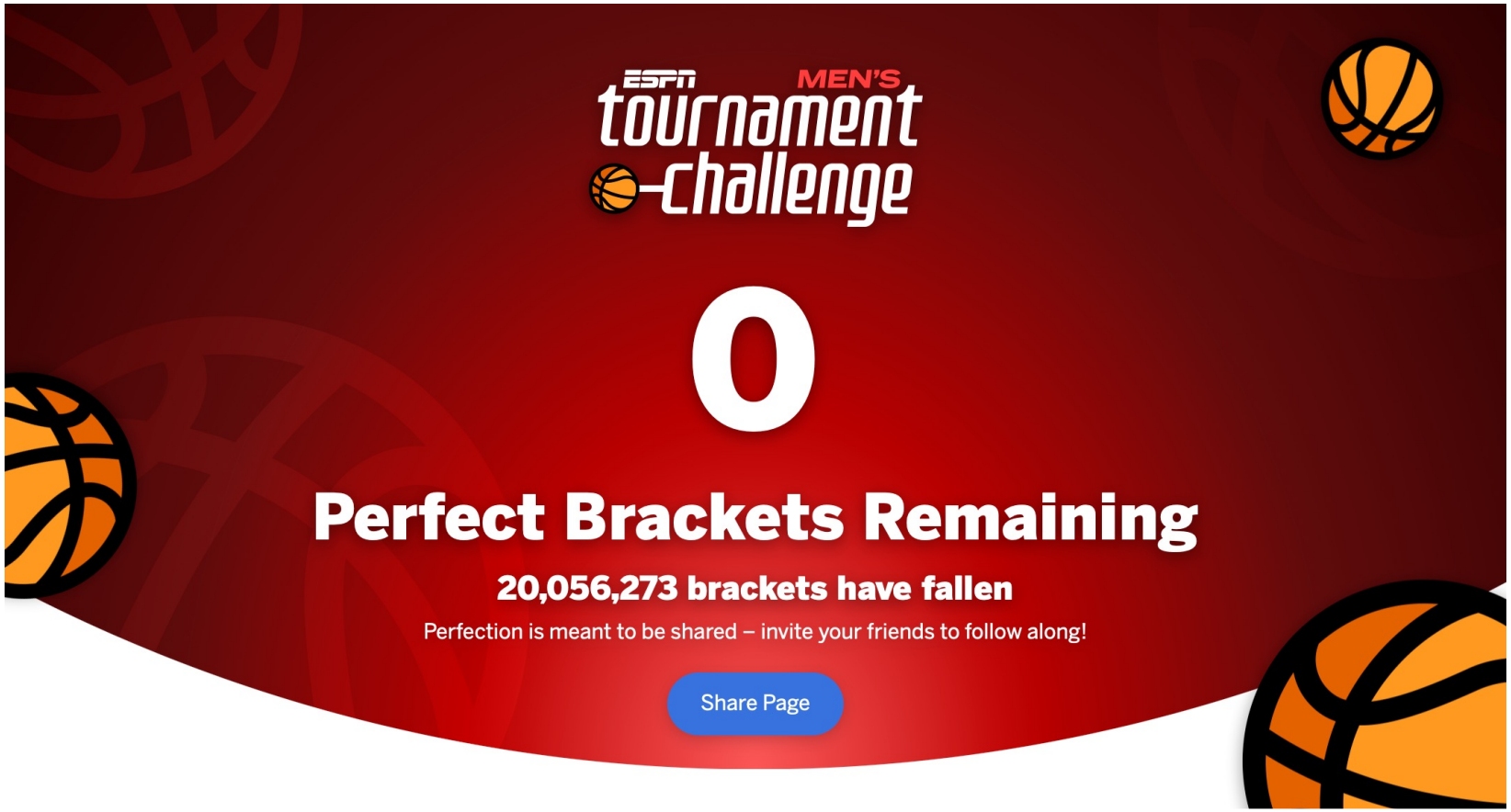
- no one has ever completed a **'perfect bracket'**

Source : [1] David Purdum (2017) | [2] American Gaming Association (2022)

Perfect brackets



Introduction – Problem Understanding

- **predict the winner** of every individual game of NCAA College Basketball Tournaments
- according to the AGA, up to **70 million brackets** in 2017[1]; an estimated **45 million people** in 2022[2]
- no one has ever completed a **'perfect bracket'**
- odds of completing a 'perfect bracket' are 2^{63} or 1 in 9,223,372,036, 854,775,808 - **1 in 9.2 quintillion** [3]
- streak of correct bracket picks is at **49 games** [4]
- used provided data and competitive structure of the Kaggle **2023 March Machine Learning Mania** competition[5]

Source : [3] Daniel Wilco (2023) | [4] Brian Budzynski (2022) | [5] J. Sonas, et al (2023)

Introduction – Problem Definition

- millions of brackets predicting Champion for 63 tournament games
- more complex task with an objective to predict the outcome of a hypothetical matchup between each team against all other teams
  - 363 men teams, thus 363 * 362/2 = **65,703** combinations
  - 361 women teams, thus 361 * 360/2 = **64,980** combinations
  - final submission file must have 65,703 + 64,980 = **130,683** predictions
- additional complexity to submit a probability for each outcome

Source : J. Sonas, et al (2023)

Introduction – Problem Definition

- we simplified our problem definition for this project
- we divided our problem into men's and women's predictions for each of us to tackle, and we combined our results.

- **Goal:** Predict the probability of all possible matchup between the 64 teams selected for the College Basketball Tournament (64 * 63/2 = 2,048 predictions)

Source : J. Sonas, et al (2023)

Introduction – Related Work

- in **2012**, Chris Wright provided a statistical analysis of predictors for March Madness [6]
- in **2014**, Alex Tran and Adam Ginzberg reported nearly all of the game statistics were useless except for FG%, FT%, and 3PT% [7]
- in **2014**, Levi Franklin found margin of victory, seeding, and previous tournament performance were useful features [8]
- in **2018**, Cody Kocher and Tim Hoblin found that the correlation between the statistical variables used for analysis tended to be high among several variables[9]

Source : [6] Chris Wright (2012) | [7] Tran and Ginzberg (2014) | [8] Levi Franklin (2014) | [9] Kocher and Hoblin (2018)

Dataset and Features

Dataset and Features – 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)

Dataset and Features – Data Section 2 Extra Files

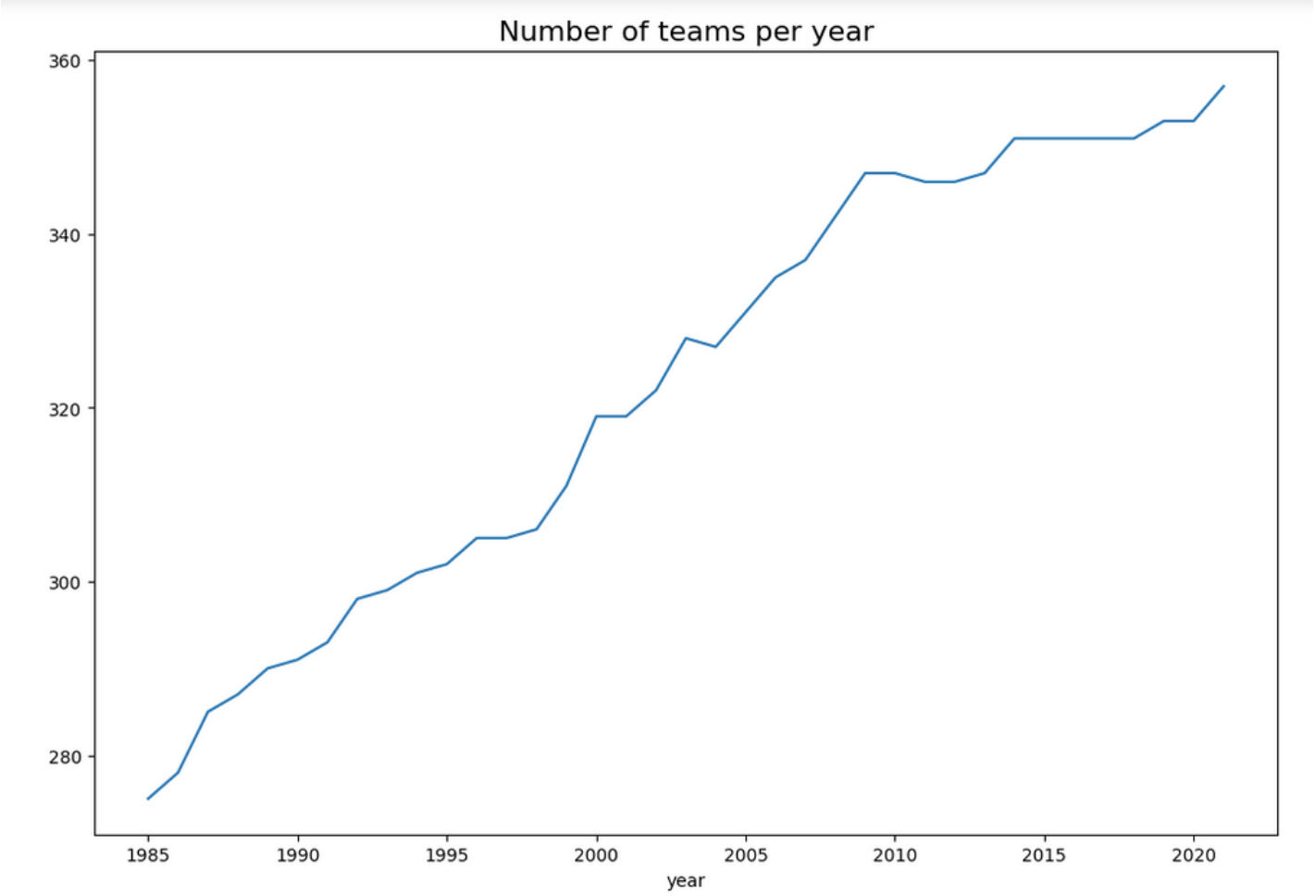
- **Cities :** CityID, City, State
- **Game Cities :** Season, DayNum, WTeamID, LTeamID, CRType, CityID
- **Compact Season Results :** Season, DayNum, WTeamID, WScore, LTeamID, LScore, WLoc, NumOT
- **Compact Tourney Results :** Season, DayNum, WTeamID, WScore, LTeamID, LScore, WLoc, NumOT
- **Compact Secondary Tourney Results :** Season, DayNum, WTeamID, WScore, LTeamID, LScore, WLoc, NumOT, SecondaryTourney
- **Tourney Slots :** Season, Slot, StrongSeed, WeakSeed

Dataset and Features – 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

Methods

Methods – Data Understanding using EDA



Methods – Data Understanding using EDA

Number of tournament wins by seed (for years 2003 - 2021):

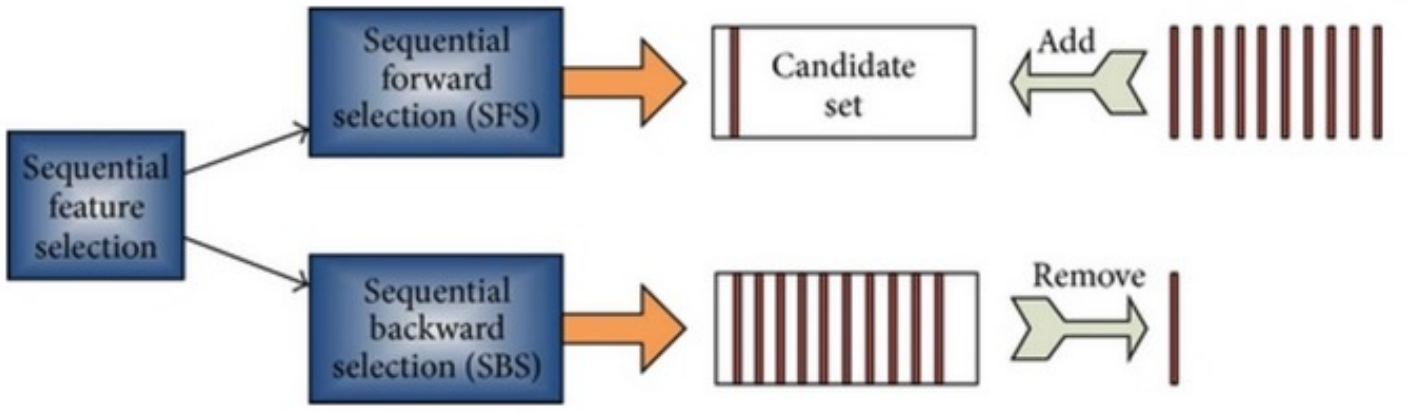
	wincount
1	158
2	108
3	99
4	92
5	83
6	65
7	62
8	64
9	59
10	45
11	81
12	62
13	41
14	33
15	33
16	57

In this dataset, if you look at at the seeds for team_1 and team_0, and you were to guess that team_1 won every time they had a lower seed number (which is a higher ranking) than team_0, then you would be right 33% of the time. We want our models to perform better than that.

	team_1	Seed_1	team_0	Seed_0	winner
0	1411	16	1421	16	0
1	1400	1	1421	16	1
2	1112	1	1436	16	1
3	1112	1	1211	9	1
4	1153	8	1211	9	0
...	...	...	...	...	...
1176	1325	13	1438	4	1
1177	1222	2	1333	12	1
1178	1329	4	1333	12	0
1179	1260	8	1333	12	0
1180	1234	2	1332	7	0

Methods – Data Understanding using EDA

- For feature selection, we used the scikit learn Sequential Feature selector and forward selection and time series cross validation to reduce the feature set.



Two variants of sequential feature selection: the sequential forward selection and sequential backward selection.

Source : [10] Zhang, et al. (2013)

Experiments

Experiment – Testing and Training Split

- Because this is a time series dataset, we had to make sure our training dataset was entered into the model sequentially.

In [222]:
```
def backtest(data, model, predictors, start=2, step=1):
    all_predictions = [] # list odf dataframe, each dataframe is the prediction for a single seasons
    seasons  = sorted(tournaments["season"].unique()) #list of seasons tha texist in data

    for i in range(start, len(seasons), step): #we progress with step parameter (one season at a time)
        season = seasons[i] # pull out the season number / 2013 will be the first season

        train = tournaments[tournaments["season"] < season] #for 2013, training will be 2012 and 2011
        test = tournaments[tournaments['season'] == season] #test will be 2013 (or whatever the current season is)

        model.fit(train[predictors], train['winner']) #this will take training data, all the predictors
        preds = model.predict(test[predictors]) #generate predictions from the test set we want

        #by default model.fit  will return numpy array, but we want to convert it to a pandas series, keep index the
        preds = pd.Series(preds, index=test.index)

        combined = pd.concat([test['winner'], preds], axis=1) #axis=1 means treats target and preds as two columns,
        combined.columns = ['actual', 'predictions'] #renaming columns

        all_predictions.append(combined) #this will be a list of five dataframes, one for each season, then we will

    return pd.concat(all_predictions)
```

Experiment – Model Building

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

Experiment – Model Building

Built stacked model using 5 or 6 trained models as estimators; and using Logistic Regression as algorithm

```
# Define estimators
from sklearn.ensemble import StackingClassifier
from sklearn.linear_model import LogisticRegression

estimator_list = [ ('svm', svm), ('knn', knn), ('gnb', gnb), ('rf', rf), ('mlp', mlp) ]

# Build stack model
model = StackingClassifier(estimators=estimator_list, final_estimator=LogisticRegression())
```

Results – Model Evaluation

Model	# Features	Tuning	Accuracy
SVM	15	Linear Kernel	.69
	10	Linear Kernel	.69
	10	RBF Kernel	.71
Ridge Regression	15	Alpha = 1	.70
	15	Alpha = 1	.70
	10	Alpha = 0.01	.69
Logistic Regression	15	Data Scaling	.70
	10	Data Scaling	.70

Results

Results – Model Evaluation

Model	# Features	Tuning	Accuracy
SVM	10	RBF Kernel	.66
Ridge Regression	10	Alpha = 0.01	.69
Logistic Regression	10	Scaling Data	.64

- Smaller feature sets performed better
- All models performed similarly (which may be due to the small data set size)
- SVM with radial basis function kernel, which may be because it can better pick up nonlinearity in data by projecting the data into more dimensions
- Ridge Regression performed best in testing data

Results – Model Evaluation

Scikit Learn Metrics

```
from sklearn.metrics import brier_score_loss, accuracy_score, matthews_corrcoef, f1_score
from keras.metrics import binary_accuracy
from keras import backend as K
```

Brier Score Metric

```
# Define Brier score function
def brier_score(y_true, y_pred):
    return K.mean(K.square(y_true - y_pred), axis=-1)

# Define custom metric function wrapper
def brier_metric(y_true, y_pred):
    return 1 - brier_score(y_true, y_pred)

# Define Brier score function
def brier_score_metric(y_true, y_pred):
    return K.mean(K.square(y_true - y_pred))
```

Results – Model Evaluation

Stacked Model

```
Model performance for Training set
- Brier: 4.087152605165435e-07
- Accuracy: 1.0
- MCC: 1.0
- F1 score: 1.0
----------------------------------
Model performance for Test set
- Brier: 6.749724411646529e-07
- Accuracy: 1.0
- MCC: 1.0
- F1 score: 1.0
```

Summary Table

	Brier	Accuracy	MCC	F1
svm	2.748182e-05	1.000000	1.000000	1.000000
knn	2.823448e-02	0.969051	0.938038	0.969049
gnb	2.758299e-02	0.962047	0.924020	0.962047
rf	4.619970e-04	1.000000	1.000000	1.000000
mlp	2.369699e-04	1.000000	1.000000	1.000000
model	4.087153e-07	1.000000	1.000000	1.000000

Conclusions

Conclusions – Communication (and Deployment)

- 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.

Conclusions – Communication (and Deployment)

- 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.

Conclusions – Communication (and Deployment)

- 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**.

Conclusions – Communication (and Deployment)

- I think 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.

References

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Questions?