NCAA BRACKET PREDICTIVE ANALYSIS - QUERY QUEENS

(Synthetic Version)

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AGENDA

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ABOUT US

Introduction to our team and project goals

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TABLEAU INSIGHTS

Key data visualizations and trends from our analysis

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Foundational analysis of bracket predictions

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ADVANCED MODEL

Deeper predictive insights

TABLEAU INSIGHTS



PERFORMANCE VS. AFFILIATION IN BRACKET PICKS



What influences their choices: Performance or Loyalty?



School Size



Team Performance



Affiliation

HOW SCHOOL SIZE & FAN BASE IMPACT BRACKET PICKS

Number of Enrollment by Institution



- Top schools with the most enrollment: **Houston** (2.16K), **Purdue** (1.85K), **UConn** (1.74K), and **Arizona** (1.53K)
- Larger institutions tend to appear in the semifinals or finals more often.

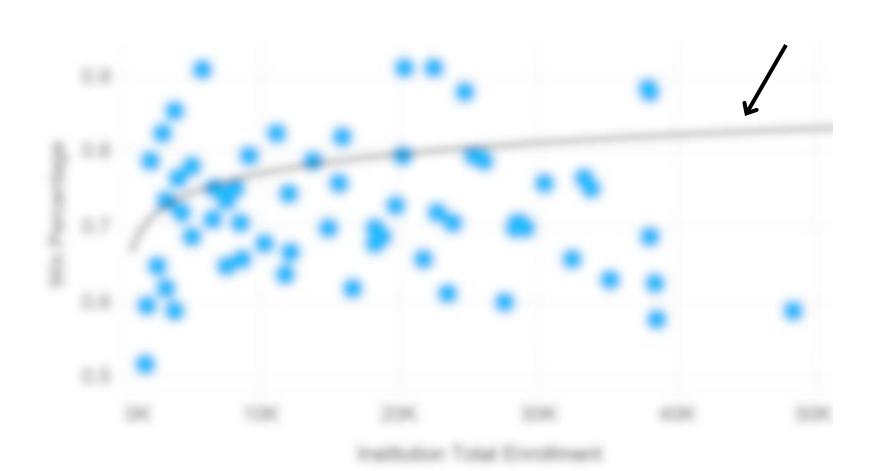
Top 5 Attendance by Institution



- Top 5 institutions with the highest attendance are **UConn**, **UNC**, **Purdue**, **Arizona**, and **Kentucky**.
- More students = More potential fans and alumni attending games.

DOES SCHOOL SIZE PREDICT SUCCESS?

Team Performance vs. Enrollment Size



- For **small schools** (<5K), resources significantly impact win percentage.
- But for **large schools**, additional enrollment doesn't strongly correlate with better performance.

Top 5 Win Percentage by State



- CT (91%), LA (88%), and IN (88%) have the highest win rates, showing strong basketball traditions in these states.
- Connecticut's high percentage is largely driven by UConn's success.

WHAT INFLUENCES PICKS: PERFORMANCE OR AFFILIATION?



1.Bracket Submission Trends

- March 20 saw 22% of all bracket submissions.
- Most fans wait until the last moment to make picks.

3.Team-Picked by Institution

- Shows which teams are most picked within each state.
- Purdue ranks high in its home state, but UConn (15%) is still #1.

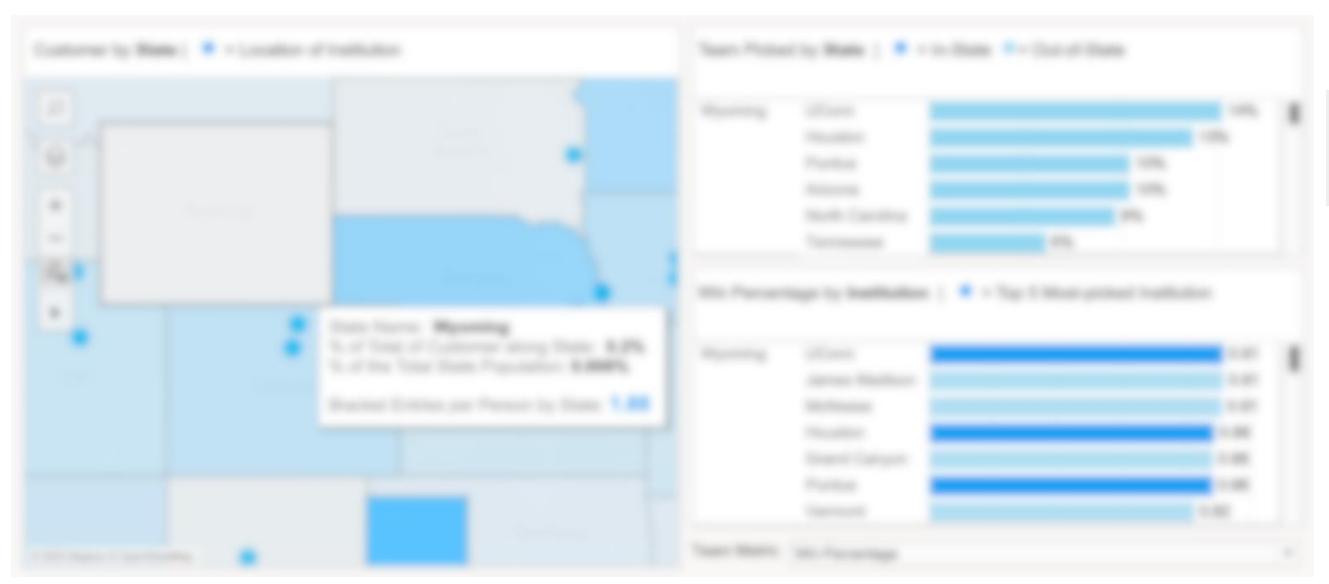
2.*M*ap

Texas (7% total bracket participation) has a high number of participants, likely due to Houston's presence.

4.Win Percentage by Institution

UConn, Houston, and Purdue are among the top teams in win percentage and also rank in the top 5 mostpicked teams in brackets.

STATES WITHOUT ANY INSTITUTIONS--- WYOMING



All of the most-picked teams are out-of-state.

Among the top 7 highperforming schools, 3 are within Wyoming's top 5 most-picked teams.

Performance is the primary factor influencing team selection, as there is no local affiliation.



STATES WITHOUT STRONG INSTITUTIONS--- IOWA: IOWA ST.



One of the most-picked teams is in-state.

Among the top 7 highperforming schools, 3 are within Iowa's top 5 mostpicked teams.

In states without strong schools, affiliation has a certain level of influence, but performance remains the primary factor in team selection.



STATES WITH STRONG INSTITUTIONS--- INDIANA: PURDUE

In states with high-performing schools, bracket challenge participation tends to be higher.



One of the most-picked teams is in-state.

Among the top 7 highperforming schools, 3 are within Indiana's top 5 mostpicked teams.

STATES WITH STRONG INSTITUTIONS--- TEXAS: HOUSTON

In states with high-performing schools, bracket challenge participation tends to be higher.



One of the most-picked teams is in-state.

Among the top 7 highperforming schools, 3 are within Texas' top 5 mostpicked teams.

In states with strong schools, performance remains the primary factor influencing team selection. However, highly ranked in-state schools tend to have a higher pick percentage within their state.



STATES WITH STRONG INSTITUTIONS--- CONNECTICUT: UCONN

Connecticut shows a relatively high rate of participation compared to its population size, especially when compared with larger states like Indiana and Texas.



UConn is the top-picked team in Connecticut, with 20% of participants selecting them.

Among the top 7 highperforming schools, 3 are within Connecticut's top 5 most-picked teams.

Compared to other states, Connecticut shows a relatively stronger in-state preference, as evidenced by lower pick rates for out-of-state teams like Houston and Purdue.

CONCLUSION



Key Insights

- Larger schools boost engagement, leading to more bracket submissions.
- Team selection is primarily influenced by team performance.
- Affiliation remains a key factor in decision-making, especially in states with strong teams.



Bracket Strategy

- Team Performance
- Affiliation & Loyalty
- School Size

Based on these insights, we developed our predictive model.

BASIC MODELING



DATA PREPROCESSING

Feature Engineering



Win Percentage (Wins/Total Games)



Tenure (This Year – The year the institution joined NCAA)

Merge institution data

Region Choices

West

East

South

Midwest

Institution ID



Institution Data

Average Score

Tenure

Win Percentage

Institution Enrollment

MODELING METHODOLOGY

Why 3 separate models?



Performance

- Win Percentage
- Average Score
- Tenure
- Average Attendance



Geographic

- Latitude
- Longitude
- DMA Code



Scale

- Institute Enrollment(Total)
- Institute Enrollment(Male)
- Institute Enrollment(Female)



Diverse characteristics improve ensemble model effectiveness

BASIC MODEL

XGBOOST Ensemble Model

SOFT VOTING



Parameters

N Iteration: 100 Learning Rate: 0.05 Max Depth: 6

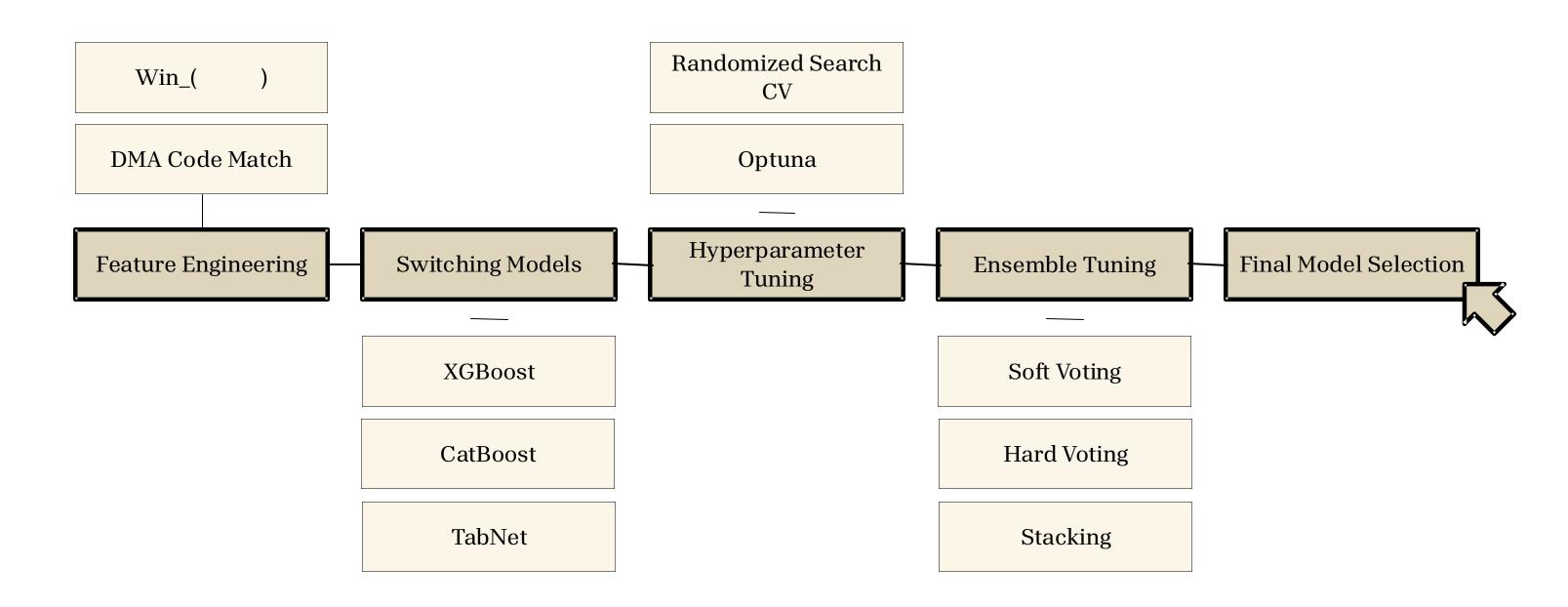
ADVANCED MODELING



ADVANCED MODEL

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Approach Overview





FEATURE ENGINEERING

Enhance Feature Impact

01

If Customer DMA Code is same with Institution DMA Code or not?

02

Does Win_Percentage have interactions with other team performance features?

DMA Code Match

- DMA_East_Match
- DMA_West_Match
- DMA_South_Match
- DMA_Midwest_Match
- DMA_Total_Match

Win_(

- Win_Tenure: Win_Percentage * NCAA_Tenure
- Win_Attendance: Win_Percentage * RegularSeasonAverageAttendance
- Win_Score: Win_Percentage * RegularSeasonAverageScore

HYPERPARAMETER TUNING

RandomizedSearchCV

- Selects random 'integer' hyperparameter combinations from a predefined range (manual specification of parameter)
- No adaptive tuning: Does not learn from previous trials
- Works well with smaller search spaces but inefficient for large search spaces, using with 5 cross-validation

#integer #simple #crossvalidation

Optuna

- Select and explore random 'float' hyperparameter from a predefined range
- Adaptively explore best hyperparameters: Learns from previous trials to narrow the search space efficiently
- More efficient for complex and high dimensional search spaces
- Define **optimization function** to find optimal

#float #complex #optimization

BEST MODEL

XGBoost Ensemble Model

OPTUNA TUNIG





HARD VOTING

Ensemble

Performance

Geographic

Scale

Parameters Search Scope

N-Iteration: 500~1500 Learning Rate: 0.01~0.1 Max Depth: 4~10

Voting Weight

Performance: 2 Geographic: 3 Institution Scale: 1

FEATURE IMPORTANCE

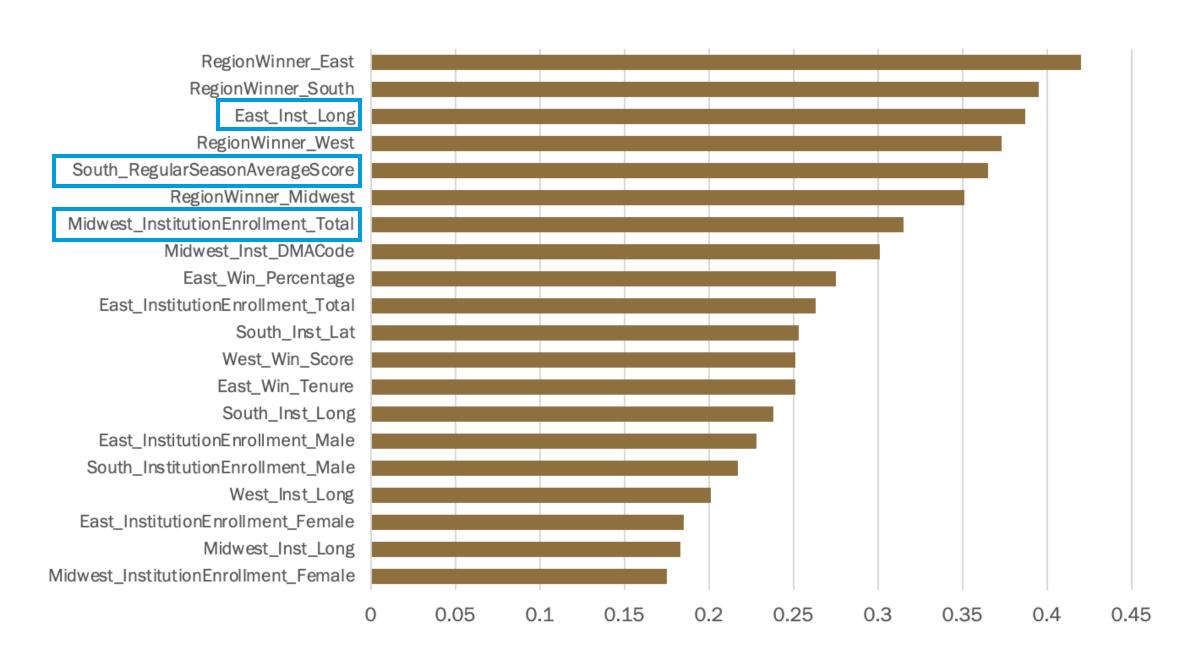
Top 20 Most Important Features in Best Ensemble

- The three aspects of features are evenly distributed in top 20 list
- In terms of dominance, feature importance follows the order:

1.geographic

2.performance

3.institution scale



RESULTS

- Accuracy (NationalChampion): 0.4624
- Accuracy (SemiFinal East/West): 0.6915
- Accuracy (SemiFinal South/Midwest): 0.6412

ex) Optimal Parameters for National Champion Bracket Prediction

Team Performance XGBoost Model				
N-estimators: 1287	Learning Rate: 0.0342	Max Depth: 8		
Geographical Factor XGBoost Model				
N-estimators: 1436	Learning Rate: 0.0388	Max Depth: 6		
Institution Scale XGBoost Model				
N-estimators: 1079	Learning Rate: 0.0303	Max Depth: 6		

KEY TAKEAWAYS

Previous Assumption from Tableau Dashboard

- Larger schools boost engagement, leading to more bracket submissions.
- Team selection is primarily influenced by team performance.
- Affiliation remains a key factor in decision-making, especially in states with strong teams.

Final Conclusion

- Multiple model experiments revealed that the three aspects geographical, performance, and scale contribute in a well-balanced manner to the predictions.
- Addition to school affiliation, geographical affinity is also a key factor.

THANK YOU

Look Forward to Further Discussion!



APPENDIX

Code Chunk Detailed Results

PARAMETER OPTIMIZATION

```
def objective(trial, X_train, y_train, X_val, y_val, start_time, total_trials):
    "XGBoost Hyperparameter Optimization Function with Optuna"
    params = {
        'objective': 'multi:softmax',
        'num_class': len(np.unique(y_train)),
        'learning_rate': trial.suggest_float("learning_rate", 0.01, 0.1),
        'max_depth': trial.suggest_int("max_depth", 4, 10),
        'n_estimators': trial.suggest_int("n_estimators", 500, 1500),
        'subsample': trial.suggest_float("subsample", 0.5, 1.0),
        'colsample_bytree': trial.suggest_float("colsample_bytree", 0.5, 1.0),
        'gamma': trial.suggest_float("gamma", 0.0, 0.5),
        'reg_lambda': trial.suggest_float("reg_lambda", 1.0, 10.0),
        'reg_alpha': trial.suggest_float("reg_alpha", 0.0, 5.0),
        'random_state': 42
```

OPTIMAL PARAMETER VALUES

Optimal Parameters				
Team Performance XGBoost Model				
National Champion	N-estimators: 1287	Learning Rate: 0.0342	Max Depth: 8	
Semi Final E/W	N-estimators: 560	Learning Rate: 0.0238	Max Depth: 5	
Semi Final S/M	N-estimators: 543	Learning Rate: 0.0111	Max Depth: 10	
Geographical Factor XGBoost Model				
National Champion	N-estimators: 1436	Learning Rate: 0.0388	Max Depth: 6	
Semi Final E/W	N-estimators: 792	Learning Rate: 0.0855	Max Depth: 7	
Semi Final S/M	N-estimators: 1035	Learning Rate: 0.0749	Max Depth: 4	
Institution Scale XGBoost Model				
National Champion	N-estimators: 1079	Learning Rate: 0.0303	Max Depth: 6	
Semi Final E/W	N-estimators: 507	Learning Rate: 0.0213	Max Depth: 5	
Semi Final S/M	N-estimators: 1417	Learning Rate: 0.0610	Max Depth: 4	

DETAILED FEATURE IMPORTANCE

