# Spotting Cinderella at the Dance: Predicting Upsets in the NCAA Men's Basketball Tournament

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# Presentation Outline

Introduce and define the problem

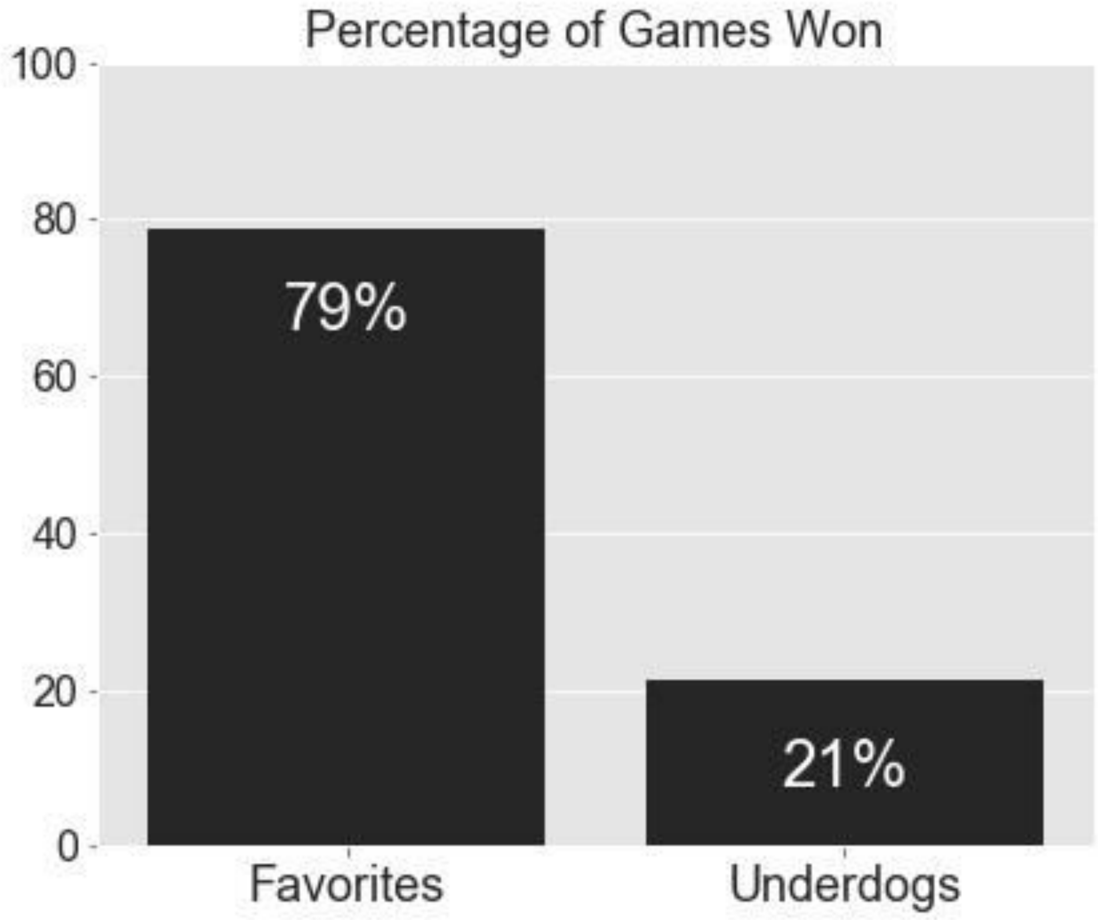
Performance: Metrics and Real-World

Adding value and iterating to improve

# The Problem

Most games are an uneven matchup between a favored team expected to win and an "underdog"

Around one-fifth of the time, underdogs "upset" the favorites



# Upsets bust brackets

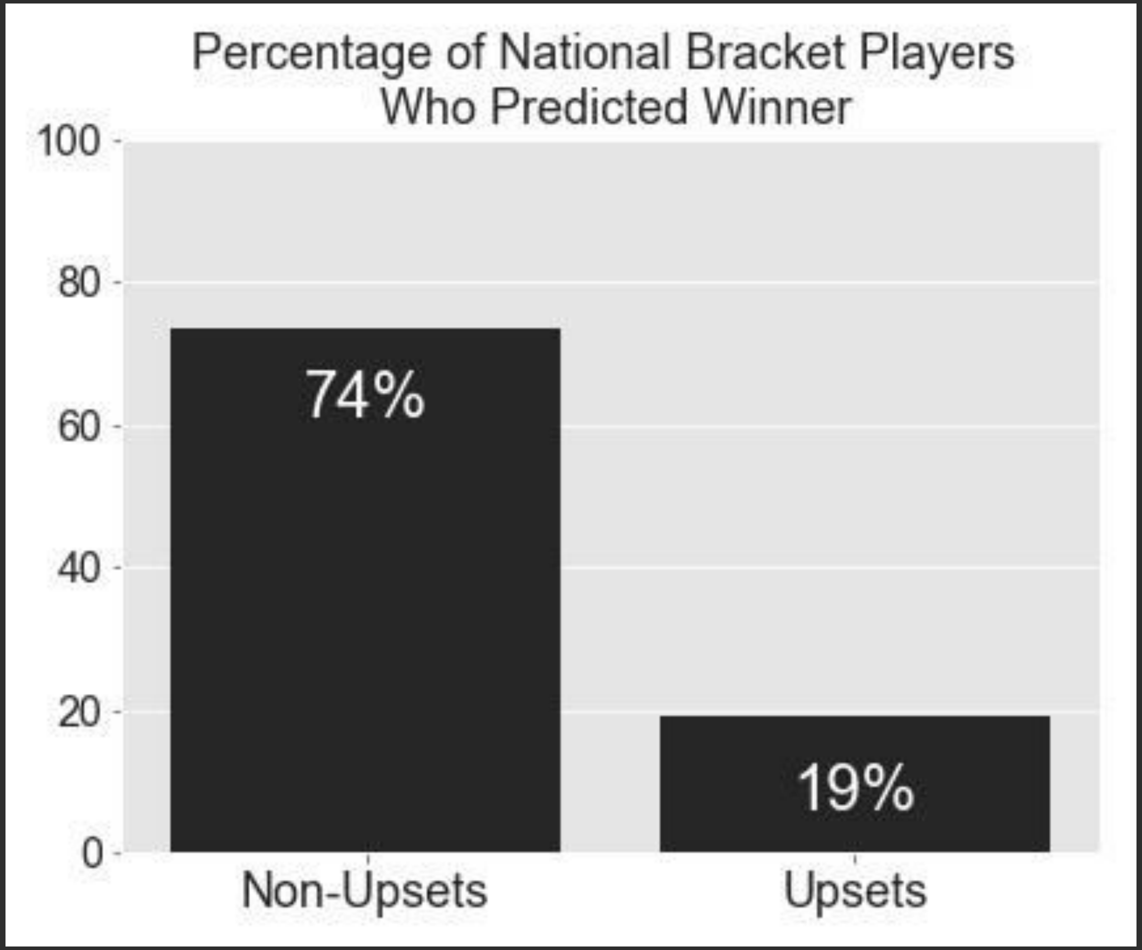
Upsets cause bracket pool players to lose points

Future matchups are eliminated

# Which upsets to predict?

Bracket players have worse accuracy for upsets

Know they occur, but lack guidance on which to pick



# “Experts” or Algorithms?

# The Solution

Use machine learning to provide better upset guidance for bracket contests and game wagers

# Project Pipeline

**Data Processing and Exploration** → **Create and Compare Models** → **Test Models**

## Data Processing and Exploration

- Download and web-scrape data
- Build characteristics for each tournament team
- Label games as upsets or not

## Create and Compare Models

- Train classification models to predict upsets from features of teams in each game

## Test Models

- Use best models to classify held-out games
- Provide estimate of future performance

# Strategy: Broad range of team features

## Player Statistics

## Coach History

## Distance Traveled

## Team Season Performance

**GAME STATISTICS**

| Player | GP | MIN | PPG | RPG |
|---|---|---|---|---|
| Frank Mason III | 36 | 36.1 | 20.9 | 4.2 |
| Josh Jackson | 35 | 30.8 | 16.3 | 7.4 |
| Devonte' Graham | 36 | 35.3 | 13.4 | 3.1 |
| Sviatoslav Mykhailiuk | 36 | 27.3 | 9.8 | 3.0 |
| Landen Lucas | 35 | 25.6 | 8.0 | 8.3 |

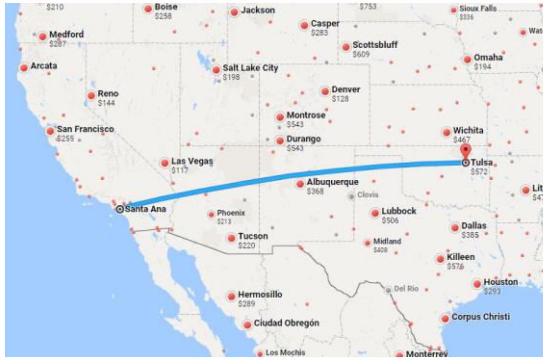

| Rank | Team | Conf | W-L | AdjEM |
|---|---|---|---|---|
| 6 | Kansas 1 | B12 | 31-5 | +27.45 |

1 Kansas (28-4)

16 UC Davis (23-12)

**GAME STATISTICS**

| Player | GP | MIN | PPG | RPG |
|---|---|---|---|---|
| Brynton Lemar | 36 | 33.0 | 16.1 | 3.3 |
| Chima Moneke | 36 | 27.3 | 14.6 | 9.5 |
| Siler Schneider | 36 | 23.2 | 10.3 | 3.3 |
| Lawrence White | 36 | 27.3 | 7.7 | 3.6 |
| Darius Graham | 36 | 28.9 | 7.3 | 1.8 |




| Rank | Team | Conf | W-L | AdjEM |
|---|---|---|---|---|
| 218 | UC Davis 16 | BW | 23-13 | -4.41 |

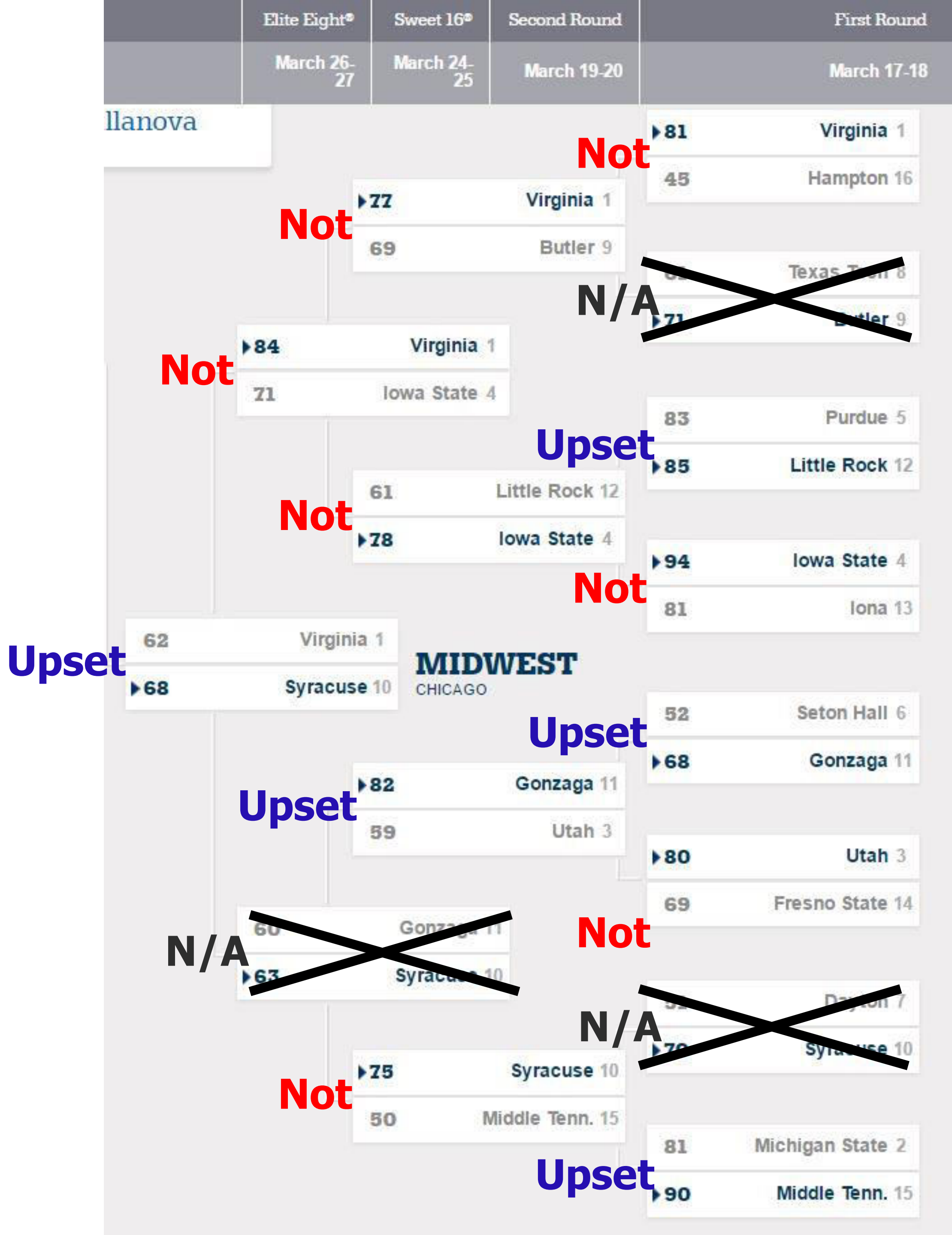
# Focus only on upsets

Games with "upset potential" involve a "favorite" vs. an "underdog"

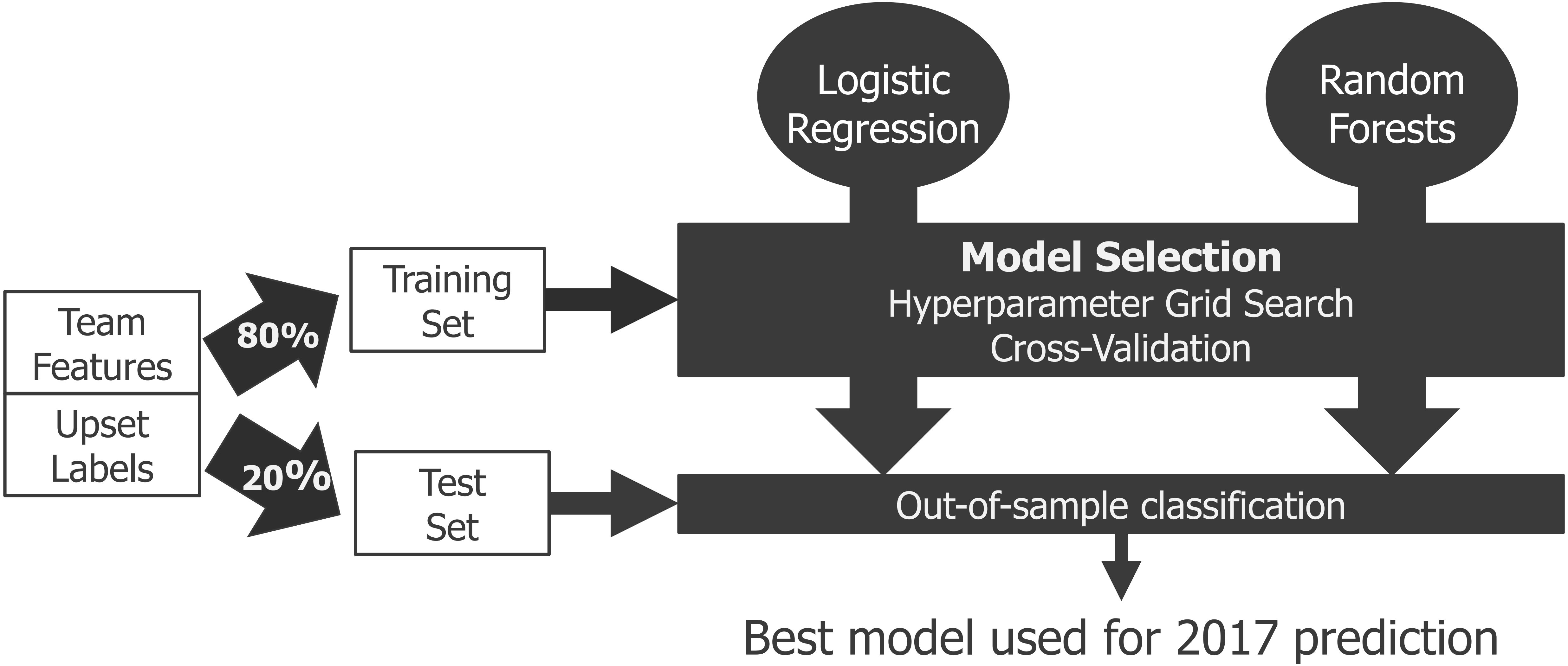
Criteria: Seed difference > 3

Labels for games that meet criteria:

**"Upset" - Underdog wins**
**"Not upset" - Underdog loses**
**"N/A" – Game not used**



# Machine Learning Process



# Use Case: 2017 NCAA Tournament

## Use model to classify future games

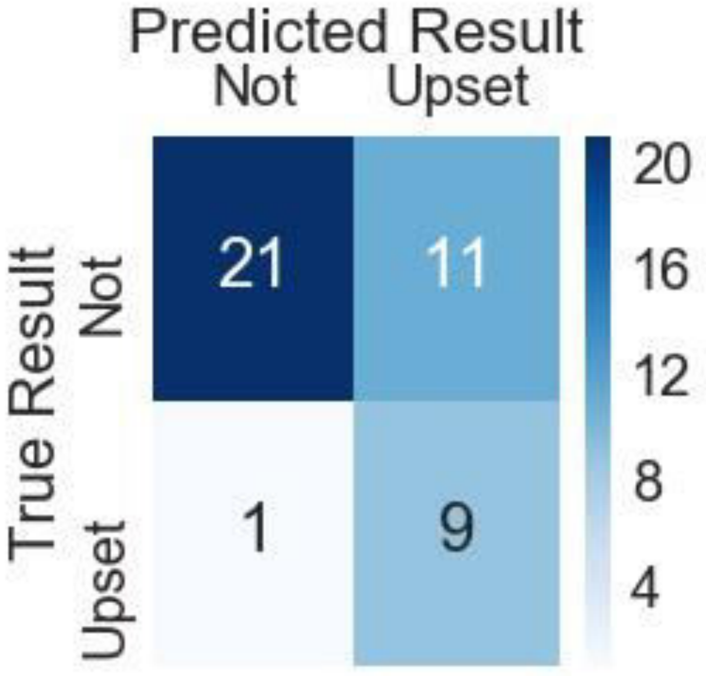
90% Upset Recall

Predicted 9 of 10 true upsets

45% Upset Precision

9 true upsets in 20 upset predictions

*F1* = 0.60

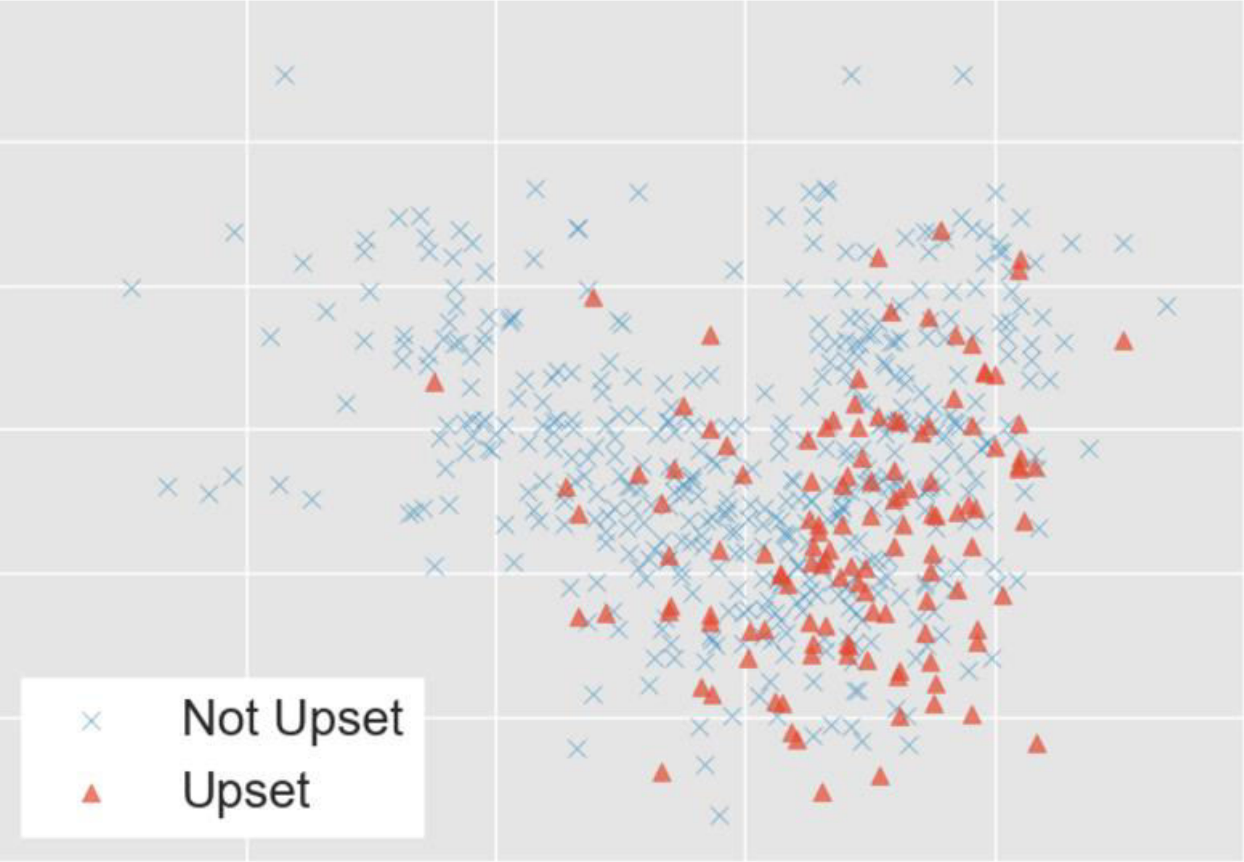


# 17% return on wagers using predictions

**Scenario: Place $100 money line bet on each game**

| | | | |
|---|---|---|---|
| 30 Correct Predictions | $1900 | Net Profit | $700 |
| 12 Incorrect Predictions | - $1200 | Total Investment | ÷ $4200 |
| Net Profit | $700 | ROI | 17% |

# Iteration: Addressing Label Imbalance




Only ~20% of games are an upset

Most classification algorithms perform better with more balanced labels

# The Solution

Use “resampling” to reduce the label imbalance in training sets

### Random Undersampling

Randomly remove non-upsets

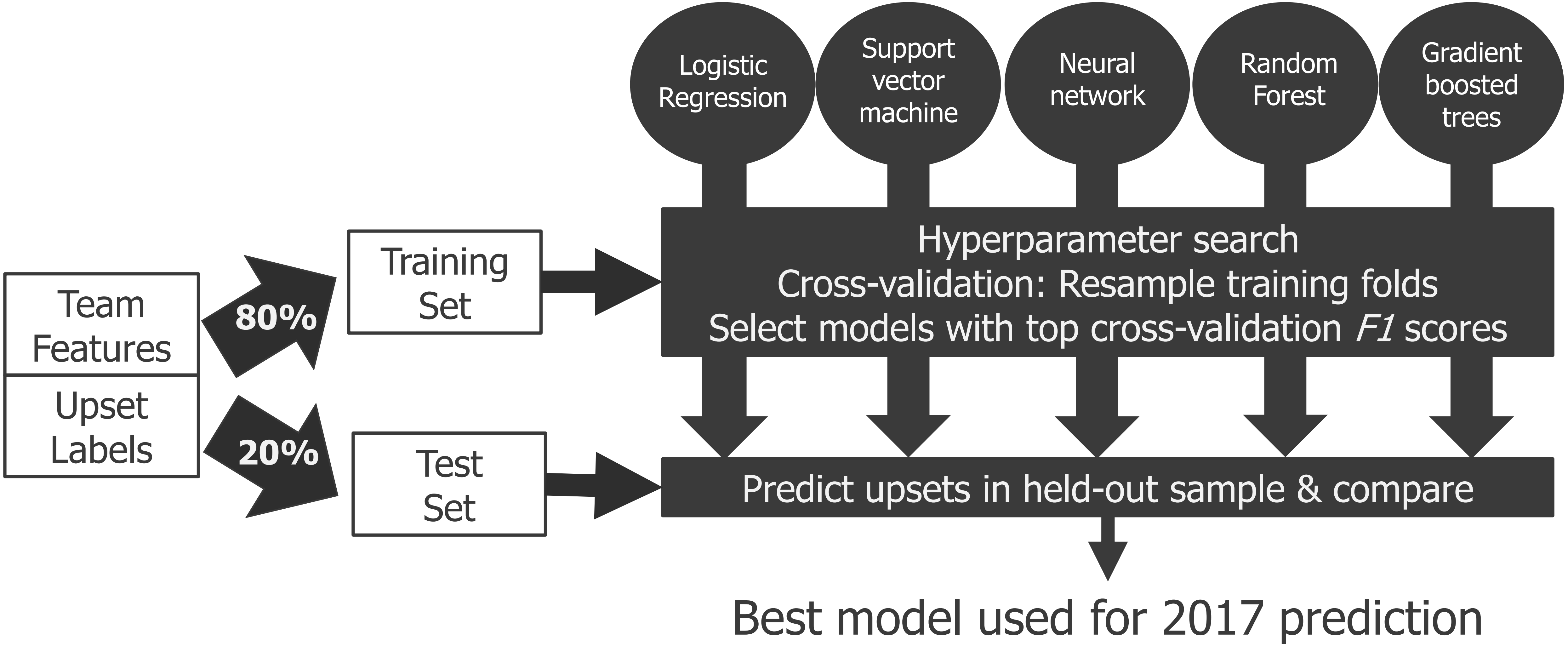
### Random Oversampling

Randomly repeat upsets

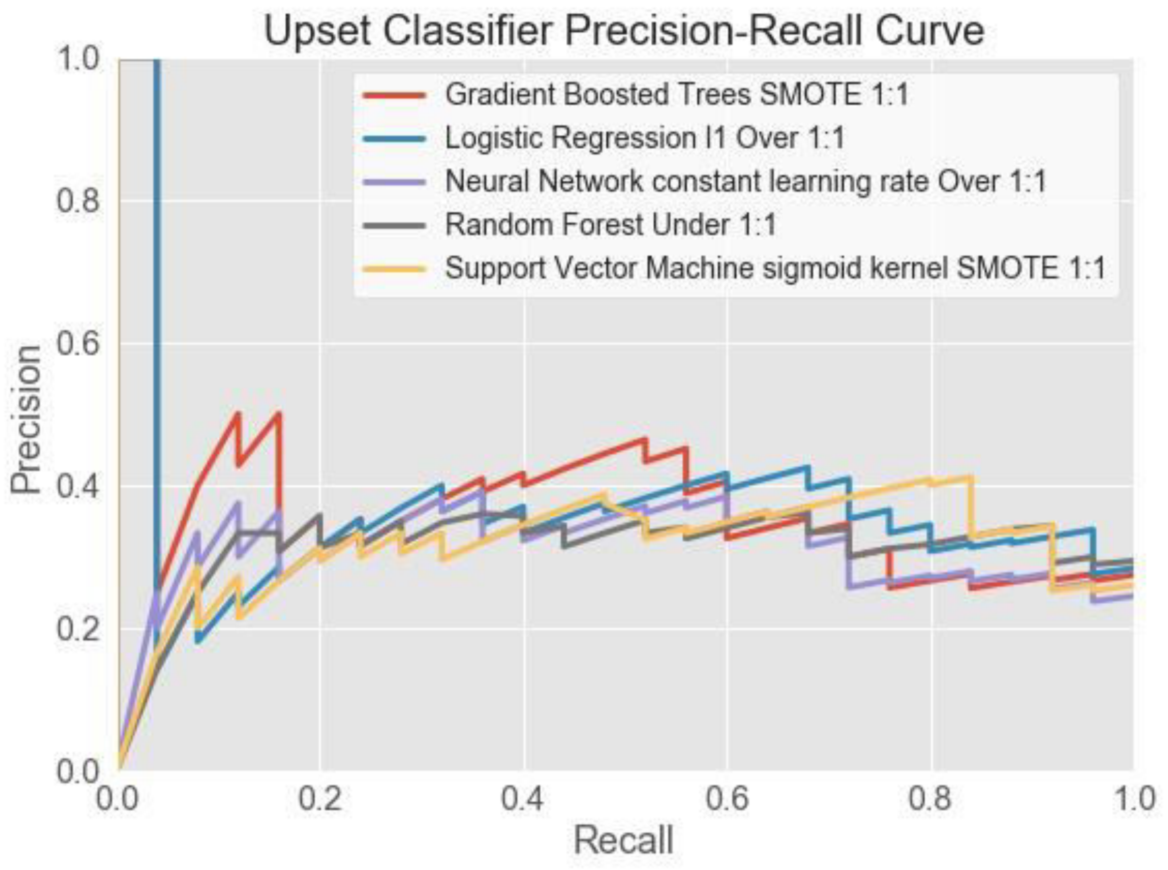
### Synthetic Oversampling

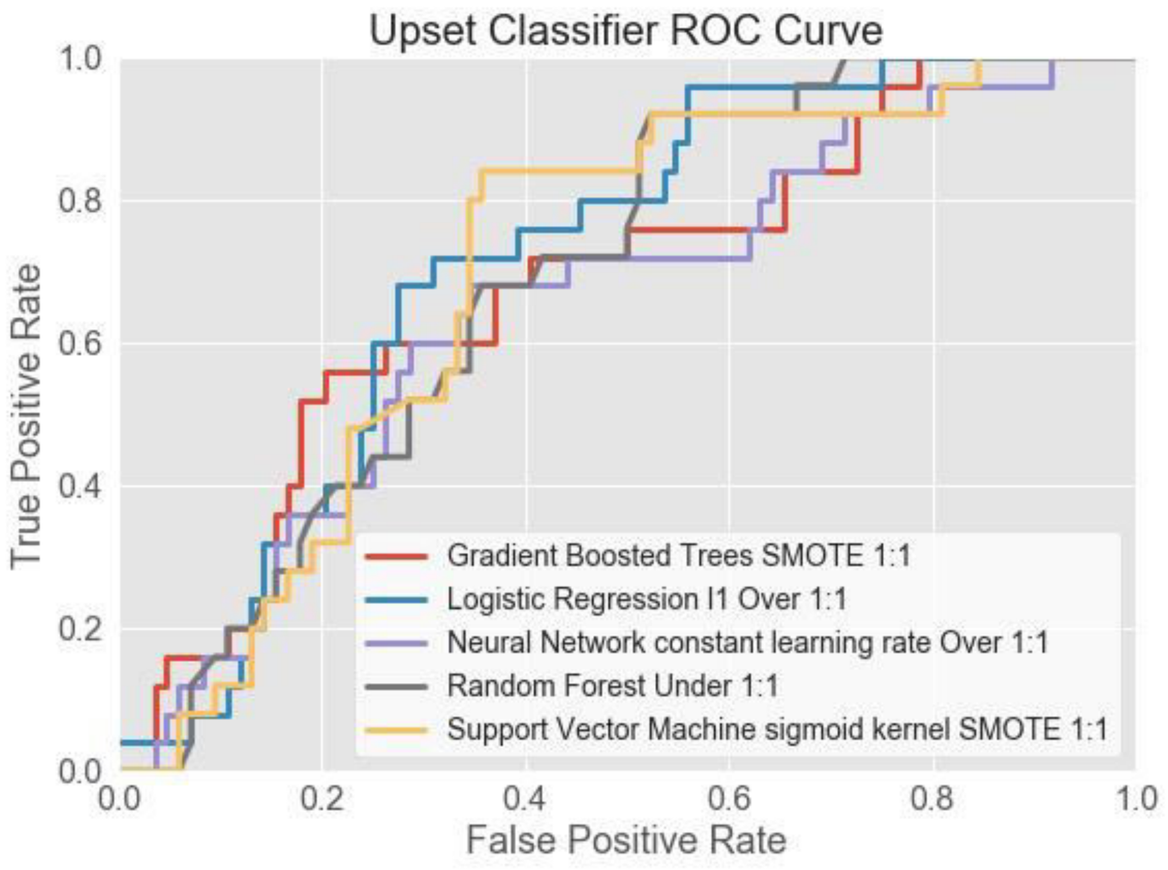
Create new upsets similar to authentic ones

# Resampling in Machine Learning



# Model Selection: Test set performance



# Use Case: 2017 NCAA Tournament

## Resampling improved upset classification

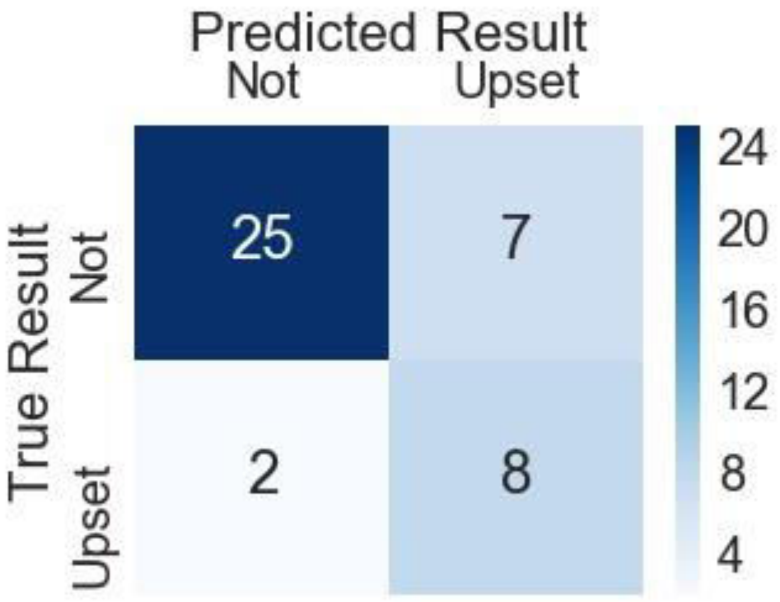
80% Upset Recall

Predicted 8 of 10 true upsets

53% Upset Precision

8 true upsets in 15 upset predictions

*F1* = 0.64

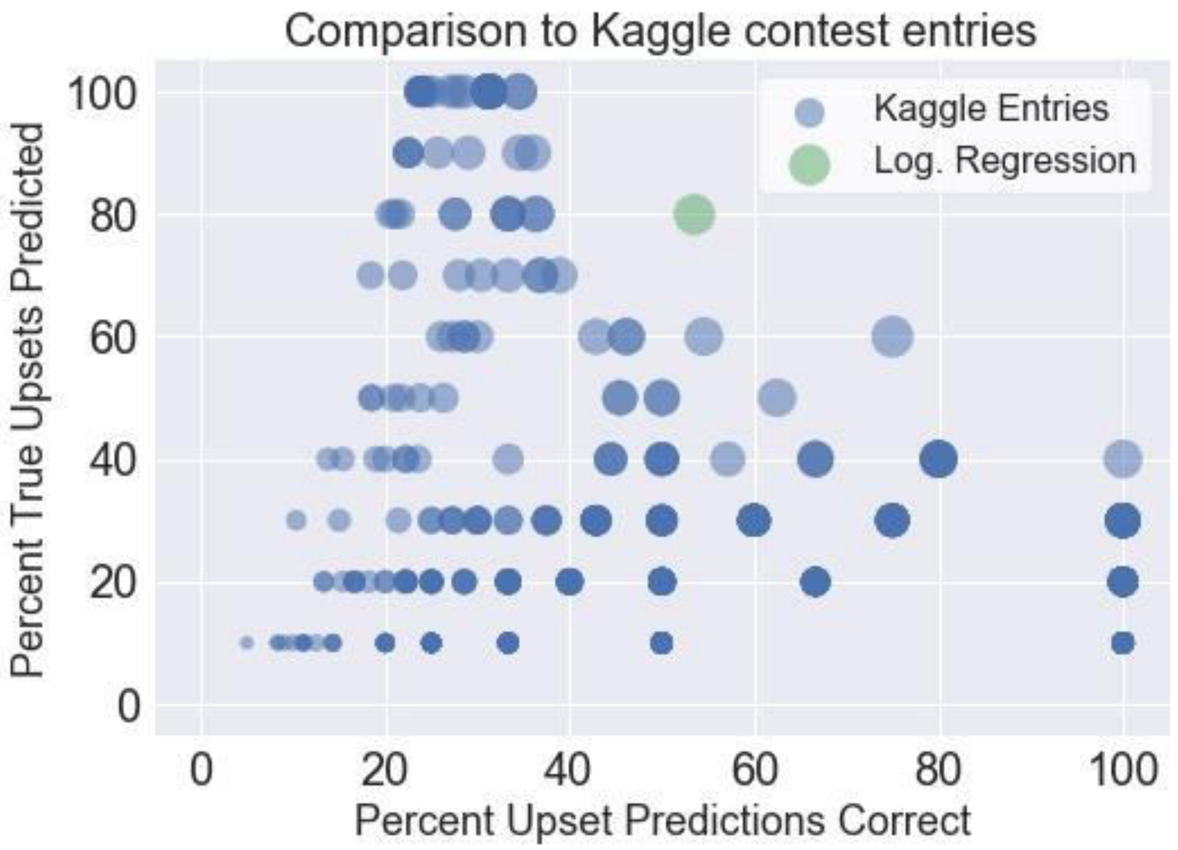


# Scoring the model vs. Kaggle submissions

A trade-off between predicting and few false positives (x-axis) and most true upsets (y-axis)

Model achieved good balance

In 1st percentile of Kaggle contest entries (one entry had higher *F1*)



# 21% return on wagers using predictions

## Scenario: Place $100 money line bet on each game

| | |
|---|---|
| 33 Correct Predictions | $1789 |
| 9 Incorrect Predictions | - $900 |
| Net Profit | $889 |

| | |
|---|---|
| Net Profit | $889 |
| Total Investment | ÷ $4200 |
| ROI | 21% |

# Client Recommendations

## Bracket Contest Players

**Pick Round 1 underdog winners**

79% accuracy rate in 2017

Differentiate scores from competitors

**Be skeptical of favorites predicted to be upset**

None made Final Four in 2017

## Game Wagers

**Weight bets to high-confidence picks**

Moderate-return underdogs

Small-return favorites

**Spread smaller bets across lower-confidence upset picks**

Account for most false positives

Pick games with larger returns