

# Predicting the 2016 NCAA Men's Basketball Tournament

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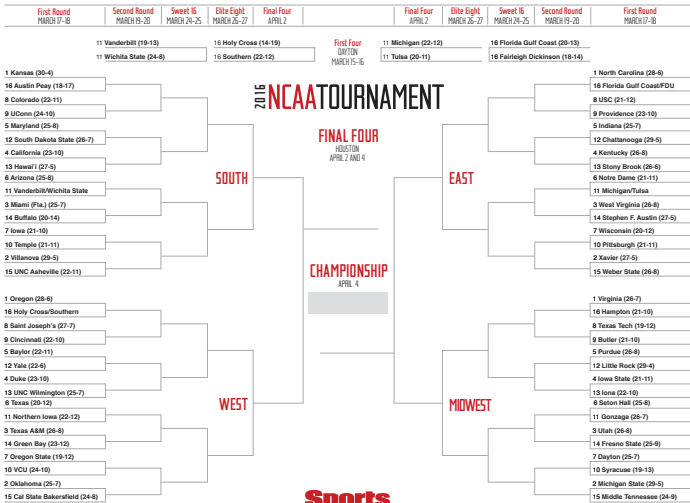
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# The Problem



NCAA is a registered trademark of the National Collegiate Athletic Association.

## March Machine Learning Mania 2016

1. Use provided data and other sources to create a predictive model
2. Estimate the probability that team  $i$  beats opponent  $j$  for all 2278 combinations of the 68 tournament teams in 2016
3. Get scored based on the actual results of the tournament

# The Data

- ▶ Subset of the original data
  - ▶ 2003/2004 season through 2015/2016 season
- ▶ Separate regular season and tournament data
- ▶ Traditional basketball statistics
  - ▶ Field goals made, field goals attempted, free throws made, free throws attempted, rebounds, etc.

# Related Work

- ▶ Purpose of Prediction
  - ▶ Betting odds, selection, performance, outcomes
- ▶ Data selection
  - ▶ Quality v.s. quantity, correlated statistics, regularization, contaminated data
- ▶ Model development and evaluation
  - ▶ Primarily supervised learning methods
  - ▶ Classification accuracy, predictive binomial deviance, AUC

# Our Approach

- ▶ For each tournament matchup, model the outcome of the game with the two teams' regular season information
- ▶ Two considerations for response:
  1. Win/Loss (1 or 0)
  2. Point Differential (team  $i$ 's score - opponent  $j$ 's score)

## Preliminary Variable Selection

| <b>Variable</b>         | Team $i$ | Opponent $j$ |
|-------------------------|----------|--------------|
| Seed                    | $w_1$    | $w_{16}$     |
| Pythagorean Expectation | $w_2$    | $w_9$        |
| Effective Field Goal %  | $w_3$    | $w_{10}$     |
| Points per Possesion    | $w_4$    | $w_{11}$     |
| Economy                 | $w_5$    | $w_{12}$     |
| Free Throw %            | $w_6$    | $w_{13}$     |
| Rating Percentage Index | $w_7$    | $w_{14}$     |
| Win %                   | $w_8$    | $w_{15}$     |



# Models Considered

1. Bayesian Linear Regression (BLR)
2. Logistic Regression (LR)
3. Bootstrap Linear Regression (BLS)
4. Random Forest (RF)
5. Generalized Boosted Regression (GBM)
6. Neural Network (NNET)

# Notation

Let

$$Y_{W_{ijk}} = \begin{cases} 1 & \text{if team } i \text{ beats opponent } j \\ 0 & \text{if opponent } j \text{ beats team } i \end{cases}$$

$\widehat{Y}_{W_{ijk}} = P(\widehat{Y}_{W_{ijk}} = 1)$  = predicted probability that team  $i$  beats opponent  $j$

$\mathbf{w}^T = (w_0, w_1, \dots, w_{16}) \leftarrow$  model parameters

$\mathbf{x}_{ijk} = k^{\text{th}}$  example of team  $i$  playing against opponent  $j$

$Y_{PD_{ijk}} = (\text{team } i\text{'s score} - \text{opponent } j\text{'s score})$  is called the *point differential*.

# Bayesian Linear Regression

## Prior Distributions [Cowles 2013]

$w_m \sim \text{Normal}(0, 10^6) \leftarrow$  Uninformative Prior

$$Y_{PD_{ijk}} | \mathbf{w}, \mathbf{x}_{ijk} \sim \text{Normal}(\mu_{Y_{PD_{ijk}}} = \mathbf{w}^T \mathbf{x}_{ijk}, \sigma_{Y_{PD_{ijk}}}^2)$$

## Predictive Distribution

The distribution for a new prediction was then obtained via R2openBUGS [Sturtz 2005].

$$f(\widehat{Y_{PD_{ijk}}} | \mathbf{x}_{ijk}) = \int_{\mathbf{w}} f(\widehat{Y_{PD_{ijk}}} | \mathbf{w}, \mathbf{x}_{ijk}) f(\mathbf{w} | \mathbf{Y}_{PD}) d\mathbf{w}$$

$$P(\widehat{Y_{W_{ijk}}} = 1) = P(\widehat{Y_{PD_{ijk}}} > 0 | \mathbf{x}_{ijk})$$

# Logistic Regression

Let

$$Y_{W_{ijk}} = \begin{cases} 1 & \text{if team } i \text{ beats opponent } j \\ 0 & \text{if opponent } j \text{ beats team } i \end{cases}$$

Then,

$$P(Y_{W_{ijk}} = 1) = \frac{1}{1 + e^{-\mathbf{w}^T \mathbf{x}_{ijk}}}$$

Methodology :

1. Model all possible subsets of predictors
2. Choose model with *lowest* AIC (Akaike's Information Criterion) [Ledolter 2006]
3. Estimate the probability of team  $i$  beating opponent  $j$

$$\widehat{Y}_{W_{ijk}} = P(\widehat{Y}_{W_{ijk}} = 1)$$

# Bootstrap Least-Squares Regression

Let

$$Y_{PD_{ijk}} = \text{team } i\text{'s score} - \text{opponent } j\text{'s score}$$

Then

$$Y_{PD_{ijk}} = \mathbf{w}^T \mathbf{x}_{ijk} = w_0 + w_1 x_{ijk1} + \dots + w_{16} x_{ijk16} + \epsilon_{ijk}$$

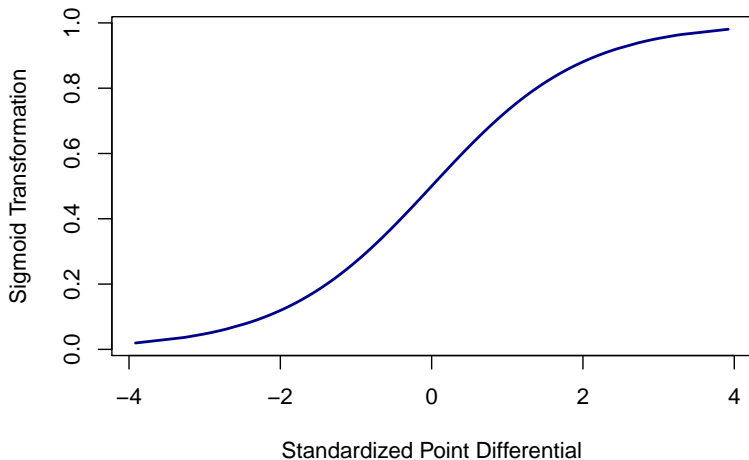
Methodology :

1. Find LS estimates for each of 100,000 bootstrap samples
2. Average LS estimates over all bootstrap models
3. Convert predicted point differentials to probabilities via the sigmoid function [Turner 2015]:

$$\widehat{Y}_{W_{ijk}} = P(\widehat{Y}_{W_{ijk}} = 1) = \frac{1}{1 + e^{-\widehat{Y}_{PD_{ijk}}}}$$

# Bootstrap Least-Squares Regression

## Point Differentials to Probabilities



# Random Forest

Let

$$Y_{W_{ijk}} = \begin{cases} 1 & \text{if team } i \text{ beats opponent } j \\ 0 & \text{if opponent } j \text{ beats team } i \end{cases}$$

Methodology :

- ▶ ensemble technique, refinement of bagged trees
- ▶ at each tree split, a random sample of  $m$  features is drawn and considered for splitting
- ▶  $m = \sqrt{p}$  where  $p$  is the number of features

Predicted class probability = mean predicted class probabilities of the trees or by votes

[Breiman 2001]

# Generalized Boosted Regression

Let

$$Y_{W_{ijk}} = \begin{cases} 1 & \text{if team } i \text{ beats opponent } j \\ 0 & \text{if opponent } j \text{ beats team } i \end{cases}$$

$$P(Y_{W_{ijk}} = 1) = \frac{1}{1 + e^{-\mathbf{w}^T \mathbf{x}_{ijk}}}$$

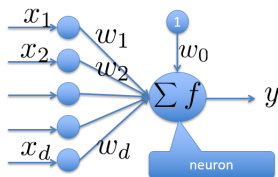
Methodology :

- ▶ ensemble of weak prediction models
- ▶ gradient descent algorithm
- ▶ at each stage  $1 < m < M$ , improve  $F_m(x)$  by fitting  $h(x)$  to the residual  $y - F_m(x)$
- ▶ add  $h(x)$  to the current model:  $F_{m+1}(x) = F_m(x) + h(x)$

[Ridgeway 2007]



# Neural Networks



$$P(Y_{W_{ijk}} = 1) = \frac{1}{1 + e^{-\mathbf{w}^T \mathbf{x}_{ijk}}}$$

## Methodology :

- ▶ stochastic gradient descent
- ▶ back propagation
- ▶ one hidden layer

[Yang 2016]

# Methods of Evaluation

1. Predictive Binomial Deviance [Kaggle 2016]

$$PBD = \frac{-1}{n} \sum_{i=1}^n Y_{W_{ijk}} \log(\widehat{Y}_{W_{ijk}}) + (1 - Y_{W_{ijk}}) \log(1 - \widehat{Y}_{W_{ijk}})$$

\*Scoring measure used in Kaggle competition

2. Percent of correct picks by match-up
3. ESPN Bracket Scoring [ESPN 2016]

| Round           | 1  | 2  | 3  | 4  | 5   | 6   |
|-----------------|----|----|----|----|-----|-----|
| Points per pick | 10 | 20 | 40 | 80 | 160 | 320 |

\*13.02 million brackets submitted this year

## Scores

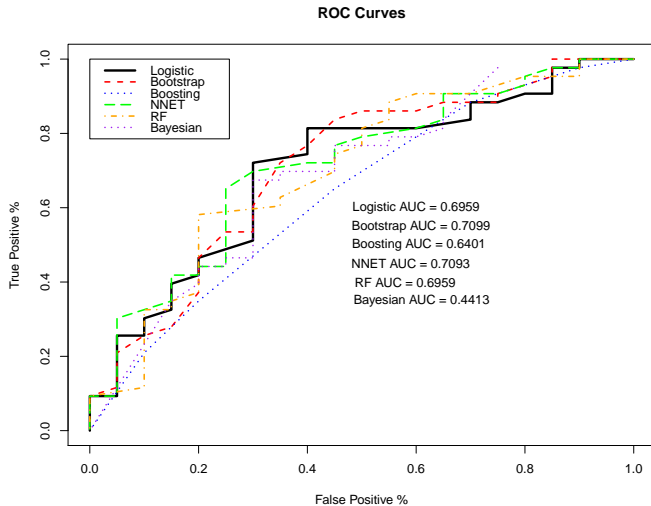
|           | BLR   | LR    | BLS   | RF    | GBM   | NNET  |
|-----------|-------|-------|-------|-------|-------|-------|
| PBD       | 1.682 | .5613 | .6084 | .5873 | .6770 | .5696 |
| Matchup % | 65.08 | 71.43 | 71.43 | 74.60 | 69.84 | 73.02 |
| ESPN      | 360   | 870   | 1380  | 1140  | 590   | 770   |

## Percentiles

|      | BLR | LR   | BLS  | RF   | GBM  | NNET |
|------|-----|------|------|------|------|------|
| PBD  | 1.4 | 80.2 | 44.1 | 57.7 | 30.8 | 74.3 |
| ESPN | 3.5 | 84.5 | 99.6 | 98.1 | 32.0 | 68.3 |

\*MCMC did not converge

# ROC curves and AUC



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