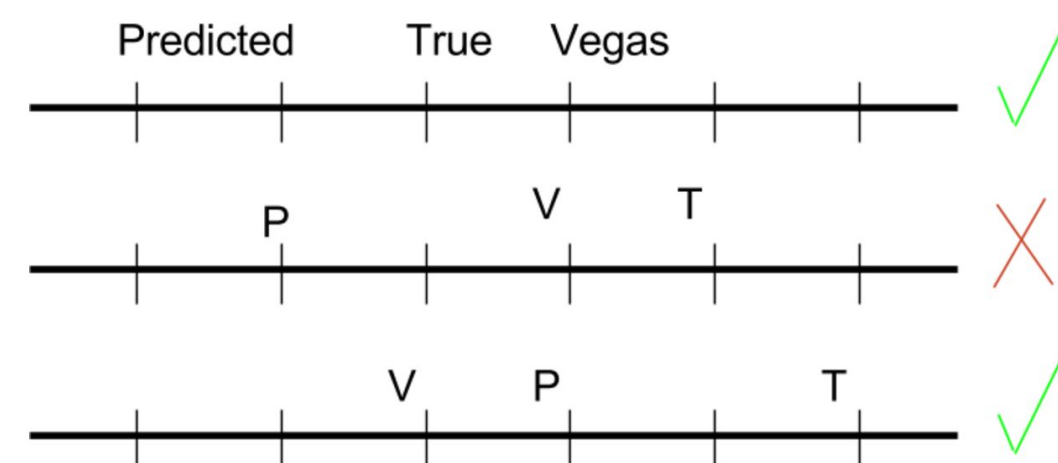


# Predicting Point Spread in NFL Games

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## Overview

Each year, \$1 billion is bet on NFL games. To place a bet, you can either make a line bet that simply selects the winning team or bet on a game's point spread, which is the difference in points between opposing teams. Our overall goal is to predict both **line** and **spread**.



When betting on spread, if your prediction is on the same side of Vegas' as the true spread is, you win.

## Data

Most of our data came from Pro Football Reference [1], a website that compiles statistics on the NFL. We also considered the previous season's ranking and ESPN's preseason "Power Rankings" [2] for each team on a separate sheet. An example of data for each game is shown below.

Week	homeTeam	awayTeam	startTime	vegasLine
1	San Francisco 49ers (10-6-0)	New York Giants (10-6-0)	8.38pm	San Francisco 49ers -4.0

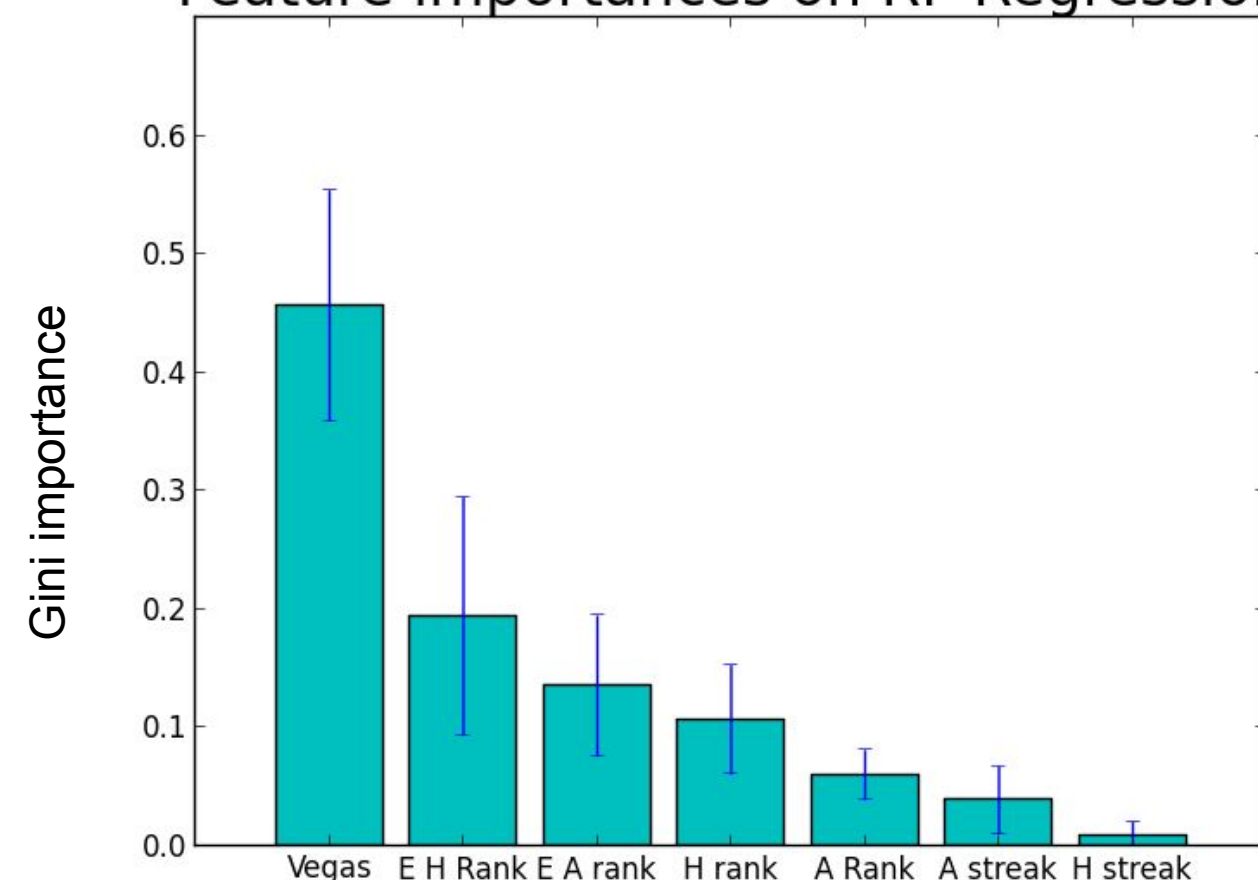
## Features

We made a few scripts to pull out each team's streak, and cleaned the rest of the data. The features we're using generally indicate which team will win, and by how much. Our features are:

- Each team's win streak
- Each team's NFL ranking from the previous season
- Each team's ESPN preseason "Power Ranking"
- The predicted Vegas spread

Interestingly, the feature that most increased our accuracy was ESPN rank. This would suggest that ESPN is better at predicting whether or not a team will win than the team's past performance (previous year's rankings) is.

Feature importances on RF Regression

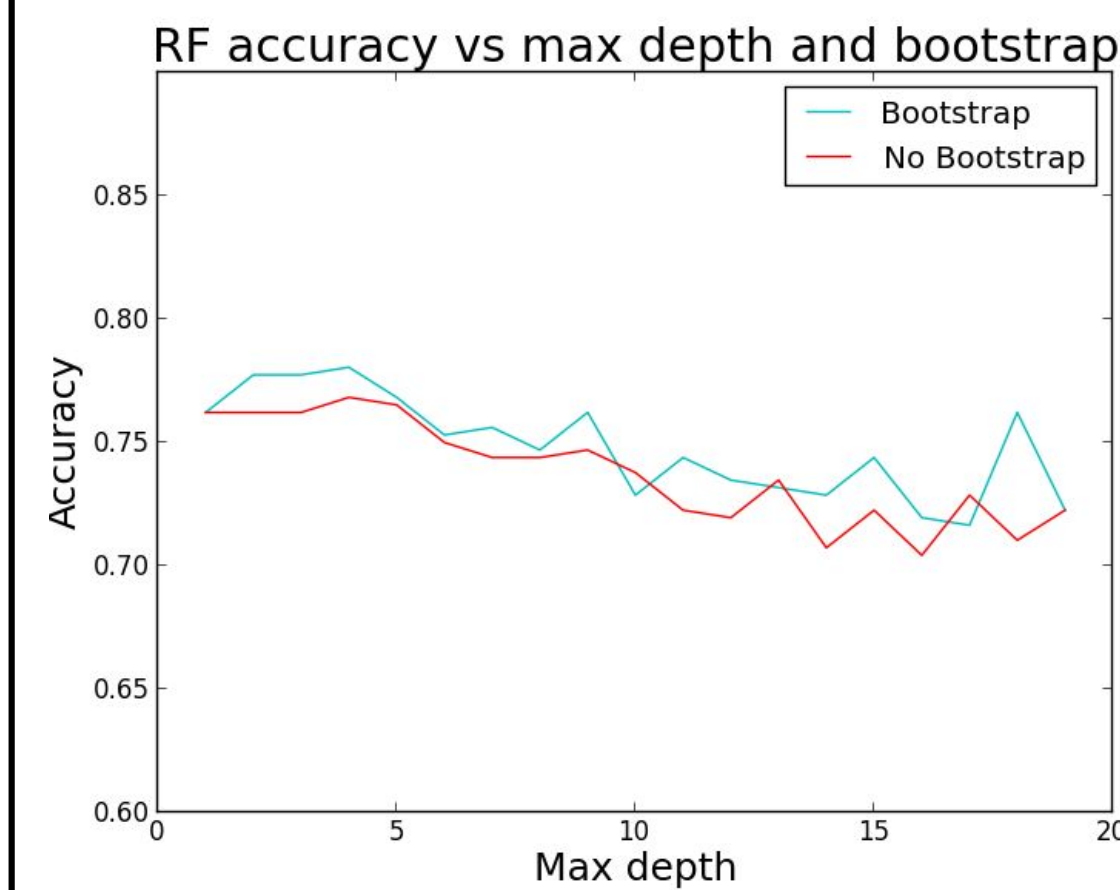


**Key**  
 Vegas: Vegas spread predictor  
 E H Rank: ESPN home team rank  
 E A Rank: ESPN away team rank  
 A Rank: Previous season away rank  
 H rank: Previous season home rank  
 A streak: Away team win streak  
 H streak: Home team win streak

## Models

We used each model as a classifier for line prediction and as a regressor for spread prediction. **Random Forest** fits a number of decision tree classifiers on various samples of the dataset and averages them to control overfitting. We adjusted the max depth of a tree to equal 5. We split each tree with gini impurity, below:

$$I_G(f) = \sum_{i=1}^J f_i(1 - f_i) = \sum_{i=1}^J (f_i - f_i^2) = \sum_{i=1}^J f_i - \sum_{i=1}^J f_i^2 = 1 - \sum_{i=1}^J f_i^2 = \sum_{i \neq k} f_i f_k$$



We selected max depth and the bootstrap boolean from the plot to the left, which shows maximum accuracy at 5 depth, with bootstrapping.

Other models include **meta-estimator bagging classifier**, **extra-trees**, **gradient boosting**, and **Ada boosting**. All of the methods are ensemble methods that help prevent overfitting. We made some adjustments to hyperparameters: max depth, num features, and num examples on a few models to limit the information used to train. Our classifier overfit more than our spread predictors, so we used more general parameters on the classifiers.

## Results

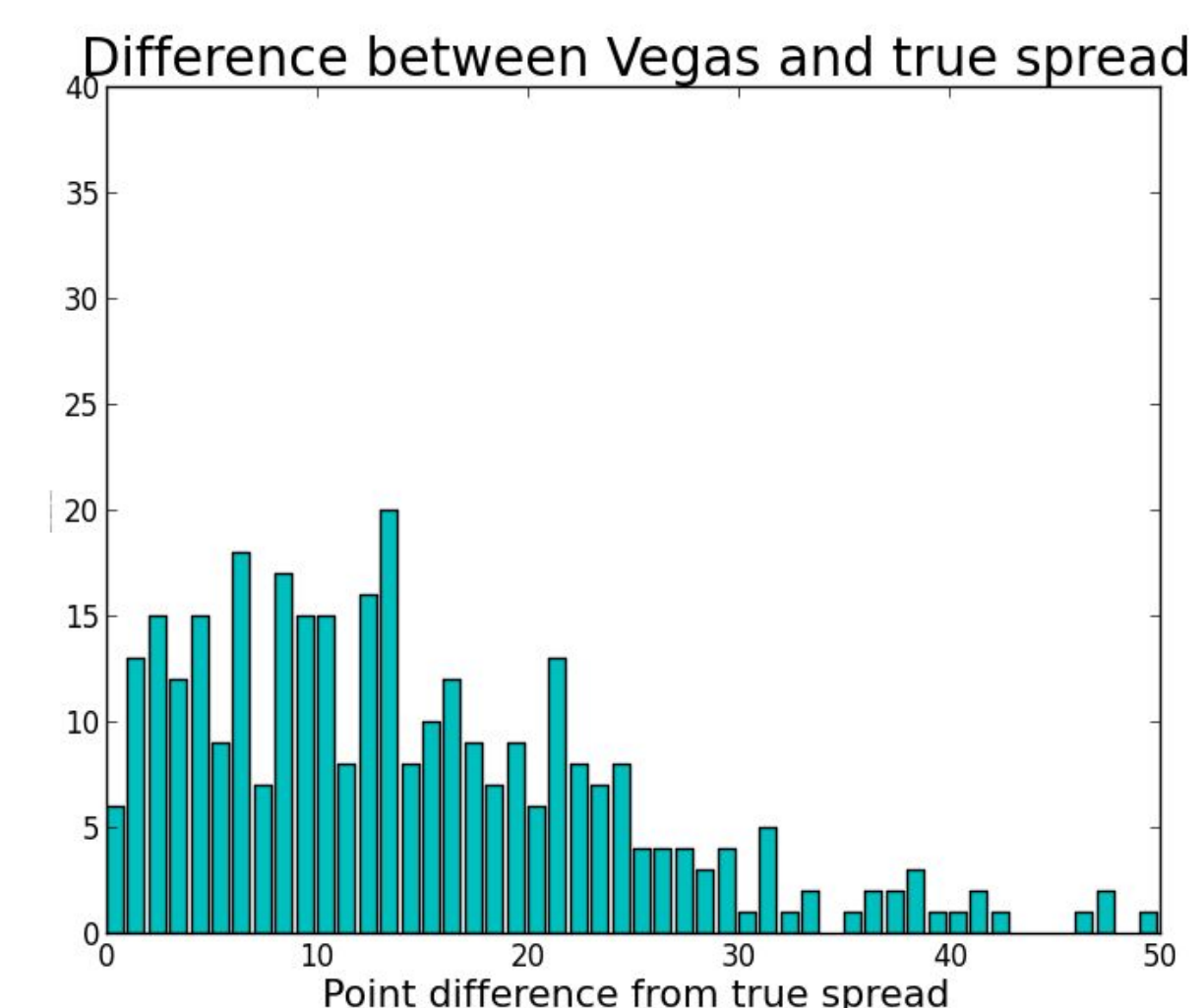
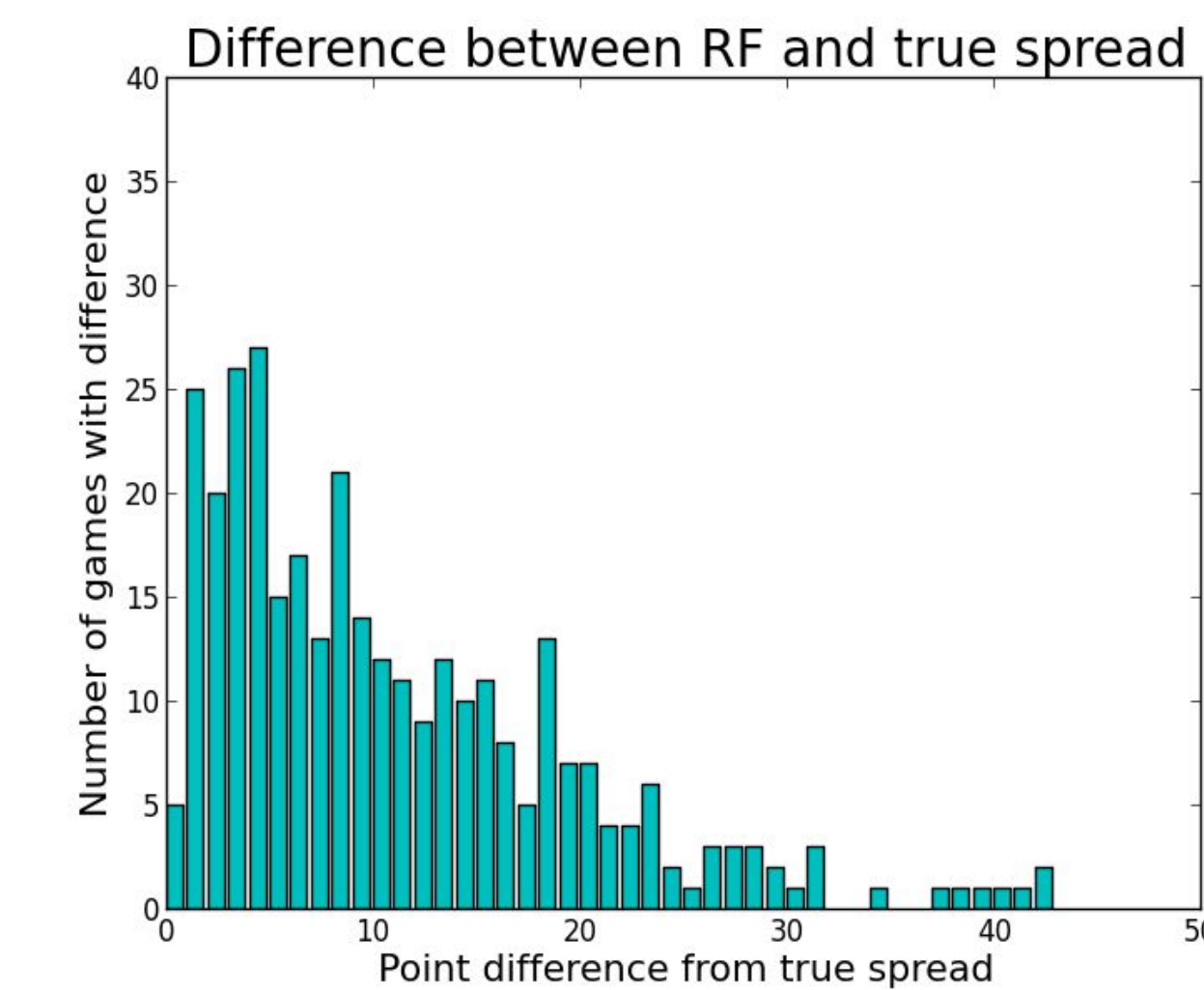
Model	Line train	Line test	Spread train	Spread test
Random forest	.8	.68	.8	.75
Extra-trees	.73	.7	.77	.76
Bagging	.8	.65	.78	.77
Gradient Boosting	.72	.72	.79	.78
Ada Boosting	.78	.68	.77	.74

We see the percentage of predictions that are correct for each model. Our best classifiers are **random forest** and **extra-trees**. Somewhat surprisingly, our spread predictors perform better than the classifiers. **Random forest** and **gradient boosting** were our best regressors. Our results are with train size = 655 and test size = 328.

## Discussion

Of all the other projects, papers, and experts that we've looked at who predict point spread or NFL game winner, we seem to be predicting among the best:

- **Nate Silver's ELO Rating** [3]: Perhaps one of the most reliable sources for the average sports bettor, his spread algorithm is surprisingly only winning Vegas 51% of the time, compared to our 78%.
- **ESPN/Sports Experts**: A 65-70% rate of correctly predicting game winner, which is about on par with our results.
- **Previous 229 Projects** [4]: Neither project used an ensemble method, and, as a result, neither of the two classifiers got above 69%.
- **Vegas**: Below are graphs of how far our predictions and Vegas predictions are from the true spread. We predict closer to the spread more often.



So, could we make money? Assuming that we perform at 78% accuracy, which is our best spread test result, and that we place bets with 1:1 odds, we're making a 26% profit. We probably can't make a living off of our algorithms, but we're much better than the average NFL bettor.

## Future Work

We weren't given an opportunity to dive into granular changes like roster or yardage. We're excited about the possibility of a model that updates a team's yards gained or points scored throughout a game, as well as injuries or personnel changes, to dynamically predict each team's percent chance of winning. This is still relevant to sports betting since betting is often open for the entire game – with the odds simply changing as the game progresses.

## References

- [1] Sports Reference LLC (2016). *Pro Football & NFL History* [Online]. Available: <http://www.pro-football-reference.com/years/>
- [2] ESPN's Power Panel (2010, September 8). *2010 NFL Power Rankings: Week 1* [Online]. Available: [http://www.espn.com/nfl/power Rankings/\\_year/2010/week/1](http://www.espn.com/nfl/power Rankings/_year/2010/week/1)
- [3] Silver, N (2014, September 14). *Introducing NFL Elo Ratings* [Online]. Available: <http://fivethirtyeight.com/datalab/introducing-nfl-elo-ratings/>
- [4] Shau, A., "Predicting outcomes of NFL Games," CS229: Machine Learning, Stanford, CA. December 16, 2011