MoneyBall Watson

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Goal

- Create a ML algorithm that would predict the wins and losses of all NBA teams during the regular season
- Provide insights for sports gambling/fantasy basketball

Data Acquisition

raw data: https://www.kaggle.com/nathanlauga/nba-games

- games.csv

(game level)

games_detail.csv (player level)



- players.csv
- ranking.csv
- teams.csv



Data Preprocessing

regular games

	regular garrie
•	15-16 seasor

	Game_id	Team_id	Player_id	Stats	
3	1	1	1	А	
	1	1	2	В	l
	1	2	1	С	
	1	2	2	D	

Game_id	Team_id	Stats	
1	1	A+B	
1	2	C+D	

Game_id	Home_team_id	Visitor_team_id	Home_features	Visitor_features
1	1	2	F(A+B)	F(C+D)

Feature Research

Offensive Efficiency	The number of points a team scores per 100 possessions
Defensive Efficiency	The number of points a team allows per 100 possessions
Strength	A simple measure of strength based on game-by-game using ELO Rating
Momentum	Running win rate of the past 5 games
Home Advantage	Percentage of home games won over percentage of total games won

Feature Engineering

home games won home_rate: for home team # all home games # away games won away_rate: for visitor team # all away games # home game won home_over_overall: for home team # all home games # all game won # all games # away game won away_over_overall: for home team # all away games # all game won # all games

Feature Engineering

games won in 5 previous games 5. win_avg5_home: for home team # games won in 5 previous games 6. win_avg5_away: for away team 5 PTS home 7. Offensive_efficiency_home: for home team Total possessions home PTS away for visitor team Offensive_efficiency_away: Total possessions away

Feature Engineering

9. Defensive_efficiency_home: ____

PTS away for home team

Total possessions home

10. Defensive_efficiency_away:

PTS home

for visitor team

Total_possessions_away

11. elo_home: r_i+1 = r_i + k * (S_home - E_home)

12. elo_away: $r_i+1 = r_i + k * (S_visitor - E_visitor)$

Here, S_team is a state variable: 1 if the team wins, 0 if the team loses. E_team represents the expected win probability of the team.

Exploratory Data Analysis

We picked five teams to represent teams of all levels:

- 1: best: Golden State Warriors (GSW)
- 2: good: LA Clippers (LAC)
- 3: mediocre: Houston Rockets (HOU)
- 4: bad: New Orleans Pelicans (NOP)
- 5: worst: LA Lakers (LAL)

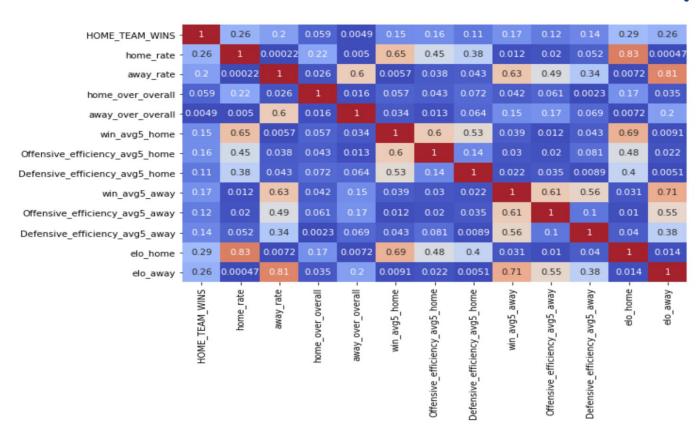
EDA - Correlation Heatmap

- 0.8

- 0.6

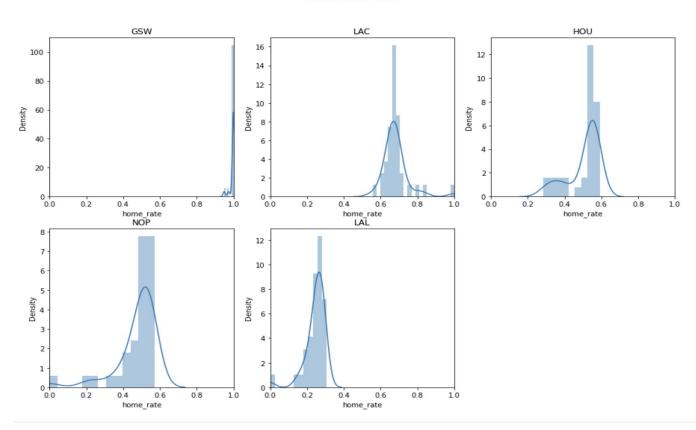
-0.4

- 0.2



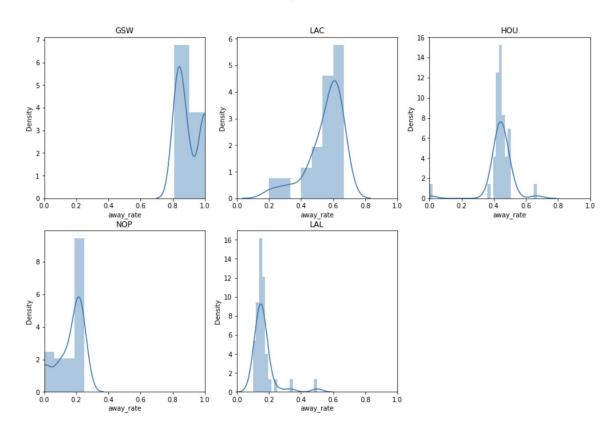
EDA - Distribution Plots (home_rate)

Home Win Rate



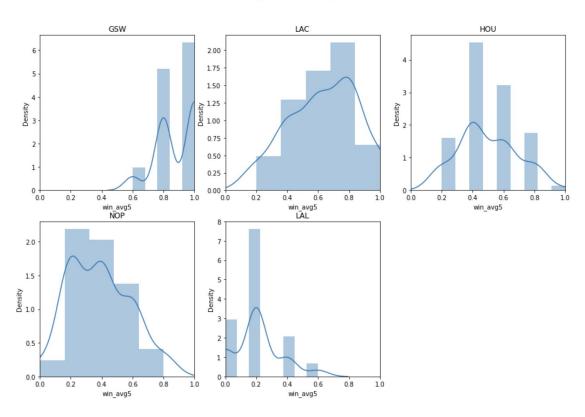
EDA - Distribution Plots (away_rate)

Away Win Rate



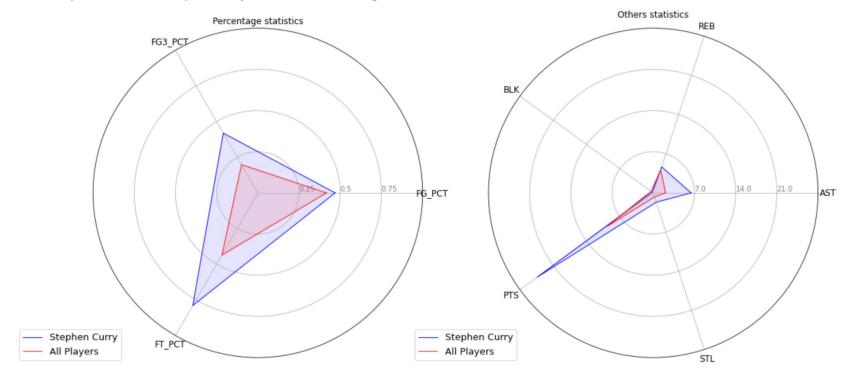
EDA - Distribution Plots (win_avg5)

Running win rate in 5 games

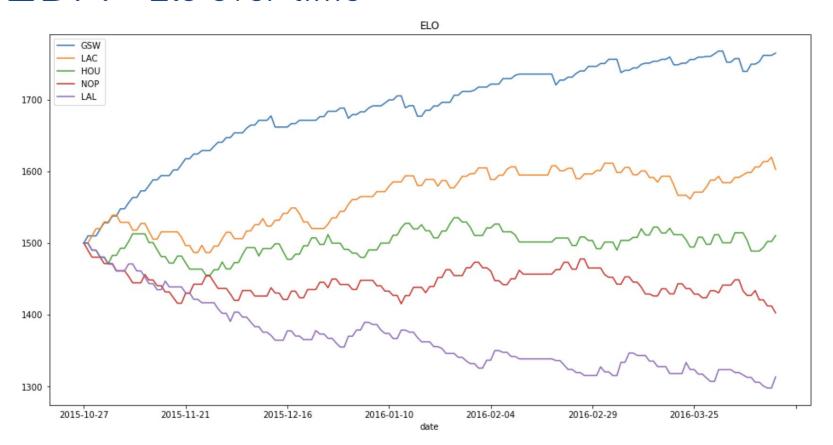


Player EDA - Stephen Curry vs. All Players avg

Stats comparison between Stephen Curry and the rest of the league

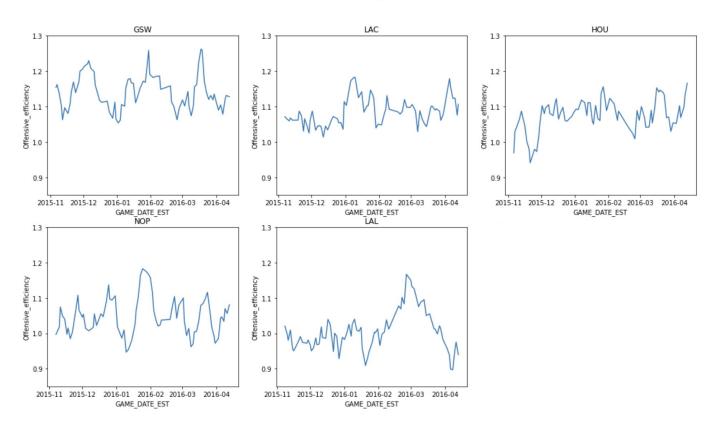


EDA - Elo over time



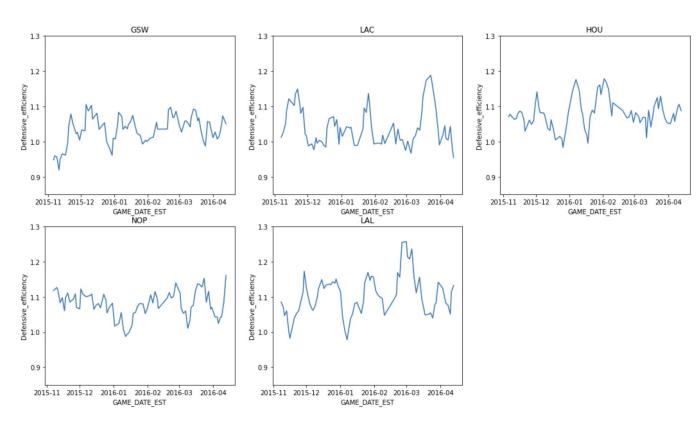
EDA - Offensive_efficiency over time

Offensive Efficiency over time



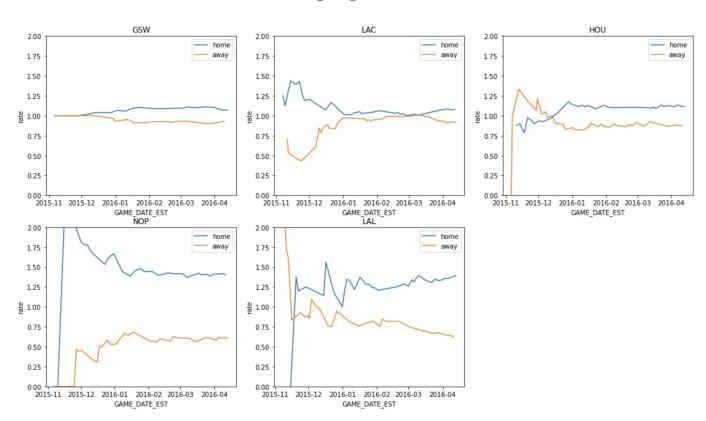
EDA - defensive_efficiency over time

Defensive Efficiency over time



EDA - home_away_rate over time

home away rate over time



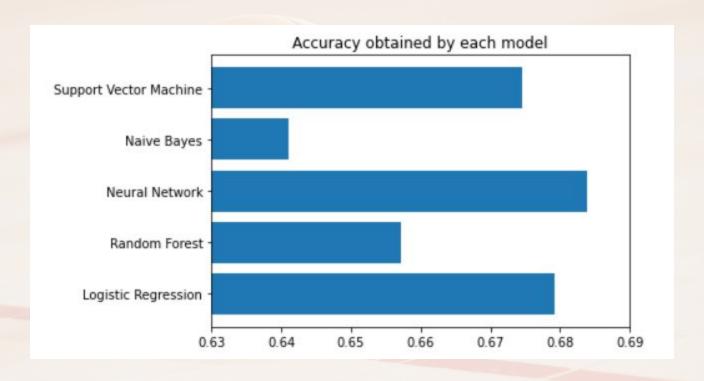
Modeling - Independent variables

- Offensive_efficiency_avg5_diff
- Defensive_efficiency_avg5_diff
- win_avg5_diff (momentum)
- elo_diff (strength)
- stad_diff (home_over_overall away_over_overall)

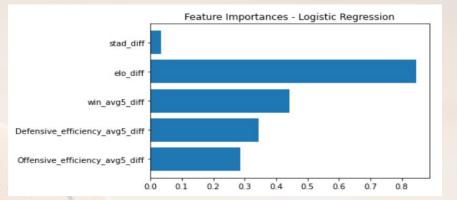
Modeling - Baseline: 50%

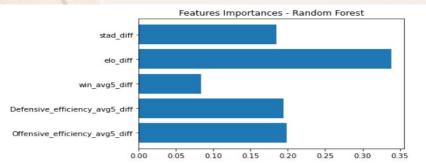
Modeling	K-Fold Cross Validation Accuracy	K-Fold Cross Validation Standard Deviation	Hyperparameter Tuning using GridSearchCV
Logistic Regression	67.58%	6.21%	67.93%
Random Forest	64.1%	5.80%	65.72%
Neural Network	68.04%	5.90%	68.39%
Naive Bayes	64.10%	8.12%	64.10%
Support Vector Machine	66.88%	5.67%	67.45%

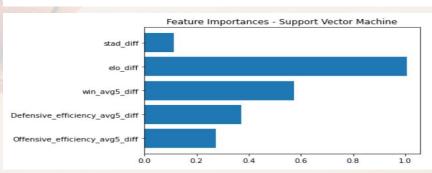
Modeling - Baseline: 50%



Modeling -Feature Importances







Conclusion

Results

- Improved accuracy from 50% to 69% (with highest accuracy recorded at 72%)
- Identified ELO rating and momentum as the most important factors

Further Applications & Improvement

- Incorporating data of dominant players & events (e.g. injuries, transactions)
- Compare differences between different NBA seasons to capture seasonal variation
- Modify ELO equation so number of games is taken into account when predicting games
- Implement a spread prediction model in order to use in real world gambling

