NBA HOME TEAM GAME OUTCOME CLASSIFICATION

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Metis Data Science and Engineering (flex program)

Module 4 – Classification

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Goal:

- Use classification models to predict whether the home team wins upcoming NBA games. home team wins = positive outcome = 1
 - 1. Assess the models and optimize best model for precision
 - 2. Interpret model most important features; can this model be used to turn a profit by wagering on the games?

Background and Motivation:

- Sports Betting: can potentially turn a profit by wagering on the outcomes of NBA games
- must consistently beat the odds that the oddsmakers lay
- insights gained would be beneficial to anyone interested in NBA, sports betting, making money

EVALUATION METRICS

1st -- Precision:

- only concerned when we actually place wagers
- False Positives = lose money
- True Positives = make money
- maximize precision = minimize FP and maximize TP

2nd -- Recall:

- must make enough wagers in a reasonable timeframe
 - weather variance of binomial distribution to reduce risk-of-ruin (losing everything)
 - bet sizes must be small enough relative to capital to make enough wagers

Soft Predictions:

- probabilities may be used as proxy for expected value (EV) calculations
- given the probability and payouts is the EV positive?
- · if positive bet on home team winning; else do not bet on the game

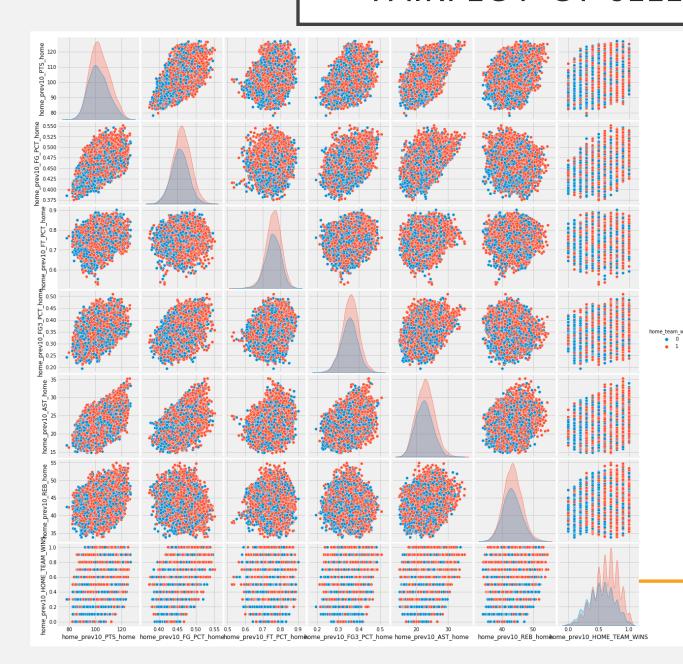
DATASET

- Raw data with historical game outcomes and statistics:
 https://www.kaggle.com/nathanlauga/nba-games?select=games.csv
- rolling previous 10 game averages were obtained for each game
- 24526 rows and 26 features (all quantitative)
- time period: Oct, 2003 Nov, 2021 (18.5 NBA seasons)
- Home team advantage
 - empirical probability of home team winning 59% of the time
 - not a big class imbalance

Tools used:

- Sklearn, Pandas, Matplotlib, Seaborn

PAIRPLOT OF SELECT FEATURES



Home team's previous 10
 home game average statistics
 not too promising as classification
 features

previous 10 game win-rate looks promising

separation of 0 vs I distributions

Classification Model Evaluation

Test Accuracies:

- Logistic Regression: **0.65**

- Random Forest: 0.63

- Grad Boosted Trees: 0.64

* empirical probability: 0.59

Precision:

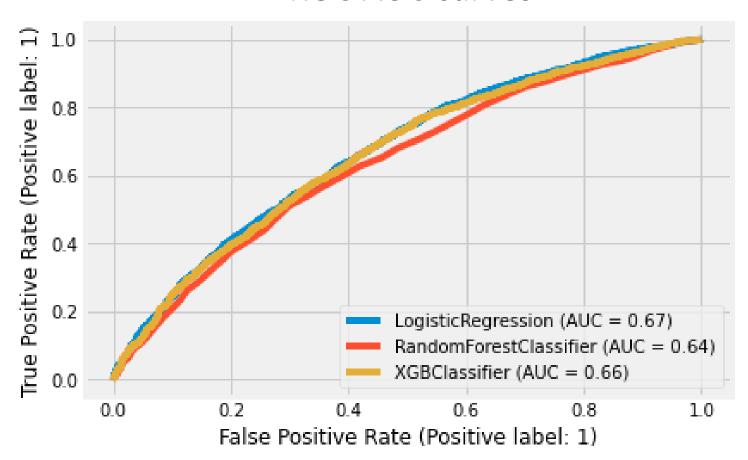
- Logistic Regression: 0.67

- Random Forest: 0.66

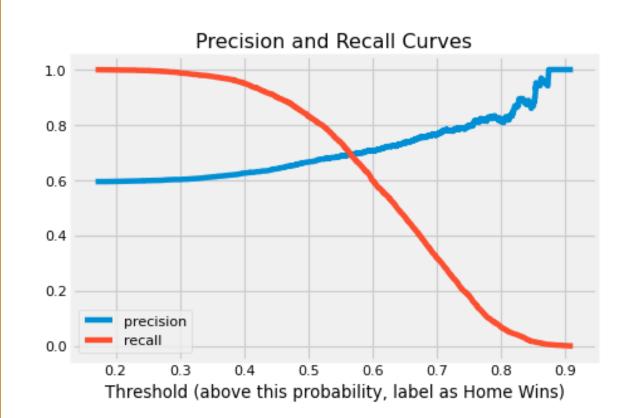
Grad Boosted Trees: 0.66

* 0.5 threshold

ROC AUC curves

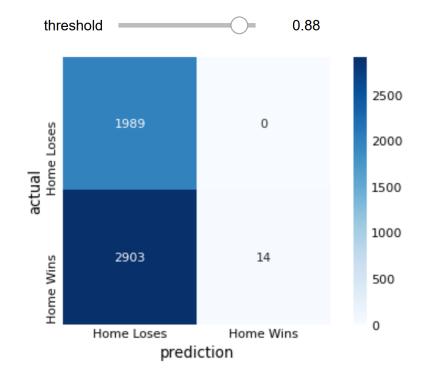


MAXIMIZING PRECISION FOR LOG-REG



higher threshold:
 higher precision but lower recall

Confusion Matrix (th = 0.88)



- 100% precision when th = 0.88
- only 14 games out of 24,000+
- need higher recall

Practical Application: wagering on NBA games

Breakeven Odds at 88% precision:

Expected Value = (win prob x (payout - wager)) - (lose prob x wager)

- let's say we wager \$100
- use soft probability threshold as proxy for real game outcome probabilities
- when EV = 0, we breakeven
- EV = $0 = 0.88 \times (payout wager) 0.12 \times 100
- (payout wager) = \$13.63 ← breakeven point: must be laid 0.136 to 1;-733.68 in sports betting terms
- For every \$100 wagered, we must be offered a profit > \$13.63 for our model to be profitable (positive EV, "beat the odds")

Practical Problem of Time - Low Recall:

- over 18.5 years, we found 14 games that had 88%+ chance of the home team winning
- to decrease the probability of going broke (tail risk) we must make enough wagers to endure variance
- in order to make many smaller wagers, we need more games to bet on (increase recall)

Conclusions and Future Projects

Conclusions:

- profitable scenarios exist for deploying our model successfully
- trying different ML techniques and tinkering with the hyperparameters led to similar performances
- need more features with better predictive power to increase F1 score
- previous 10-game win-rate is a good predictive feature

Future Projects:

- find more features: injury data, offensive and defensive rankings, player specific data
- obtain historic data for sports wagering odds
- calculate EV for each prediction and adjust threshold and bet sizes to find profitable strategies