Predicting NBA player improvement

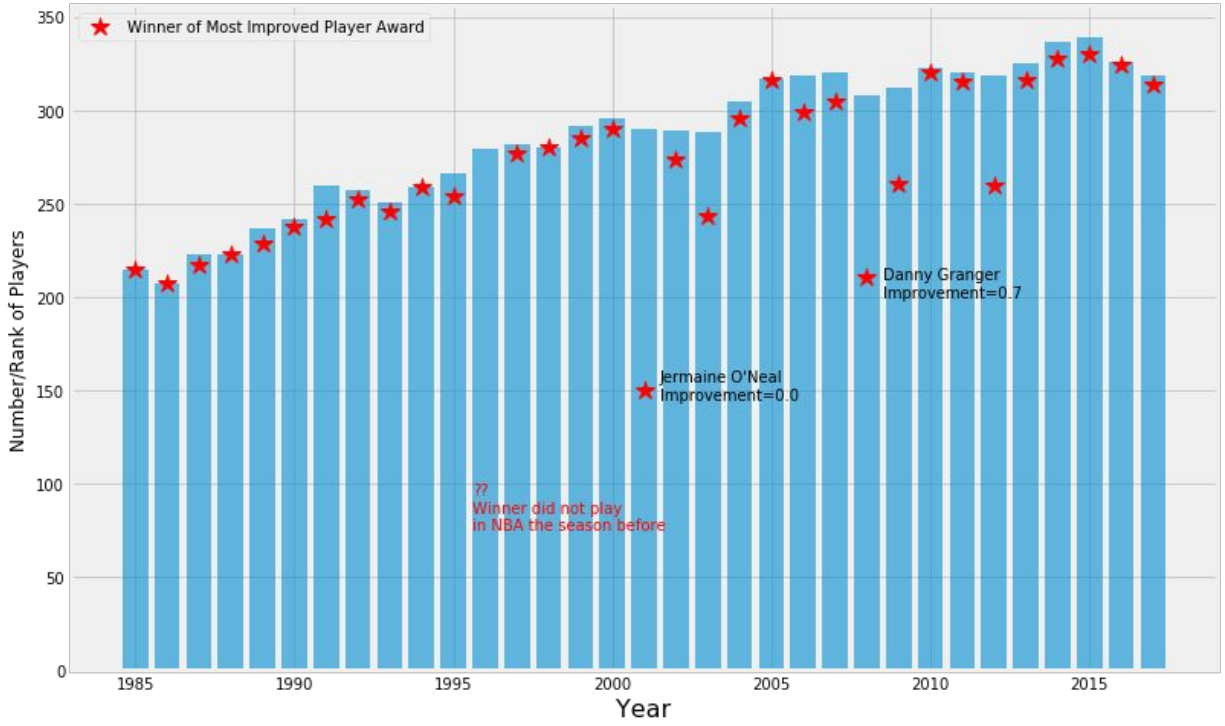
Predicting player improvement is valuable for NBA teams

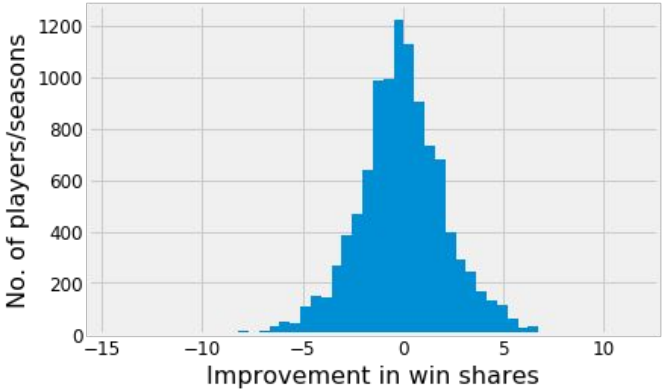
- Generally, players are valued by their past performances. Therefore, players who improve a lot bring both competitive and economic advantages to teams.
- Such value is recognized by NBA: Most Improved Player award.
- Predicting player improvement help team management.
  - Target players to acquire/release
  - Plan for performance changes of players already on the team
- Fans have interest as well (fantasy basketball)

Data acquisition and cleaning

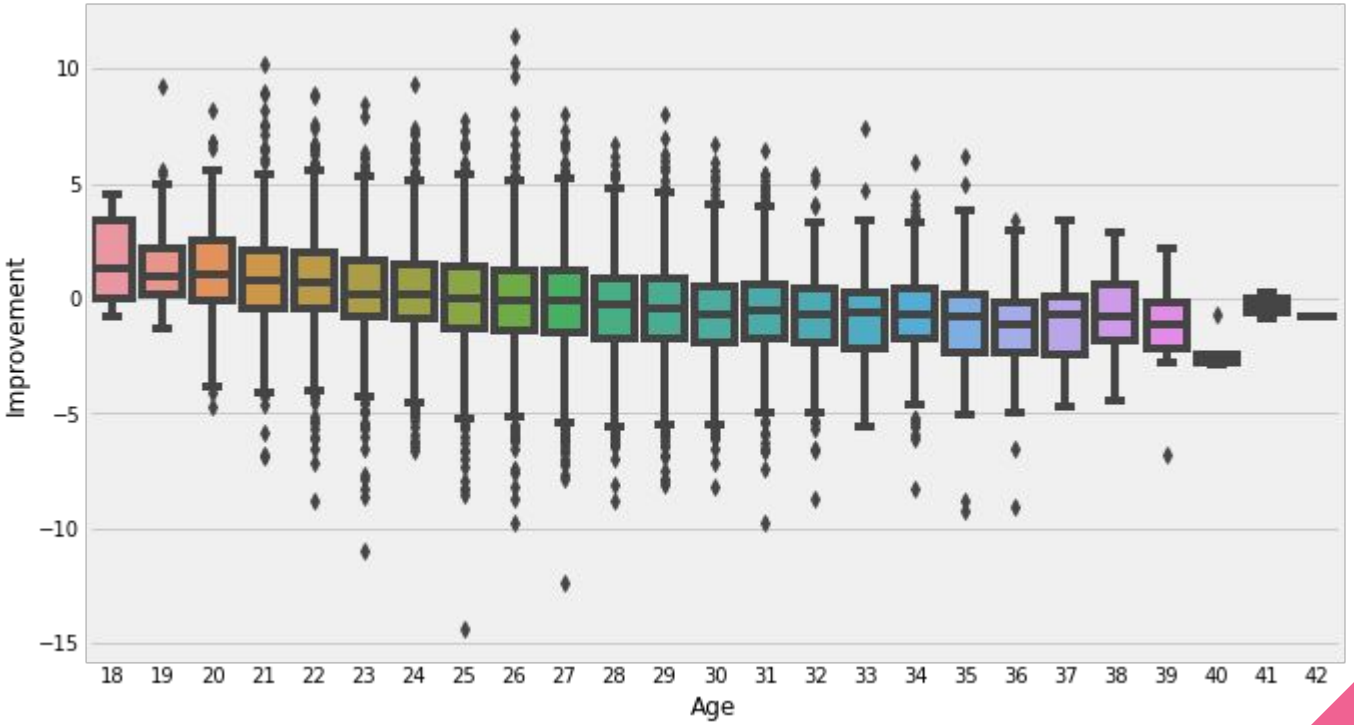
- Player age, team and performance data (1980-2017) from Kaggle dataset, 2018 data scraped from basketball-reference.com
- Player draft position data (1978-2015) from Kaggle dataset, 1965-1977, 2016-2017 data scraped from basketball-reference.com
- In total, 13,378 rows and 49 features in the raw dataset.
- Duplicate, highly similar or highly correlated features were dropped.
- Cleaned data contains 24 features.

Using ΔWS (win shares) as improvement measure



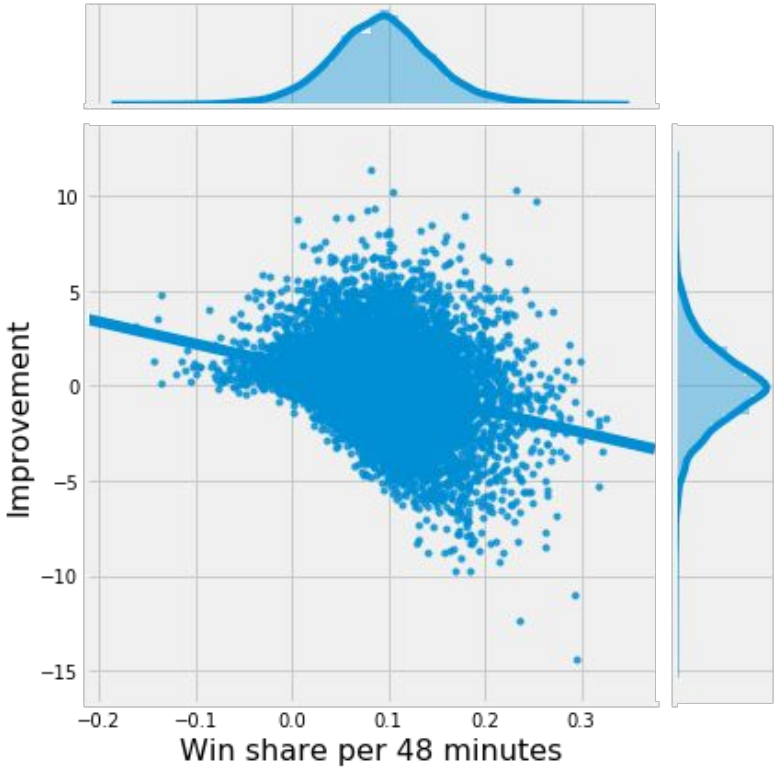


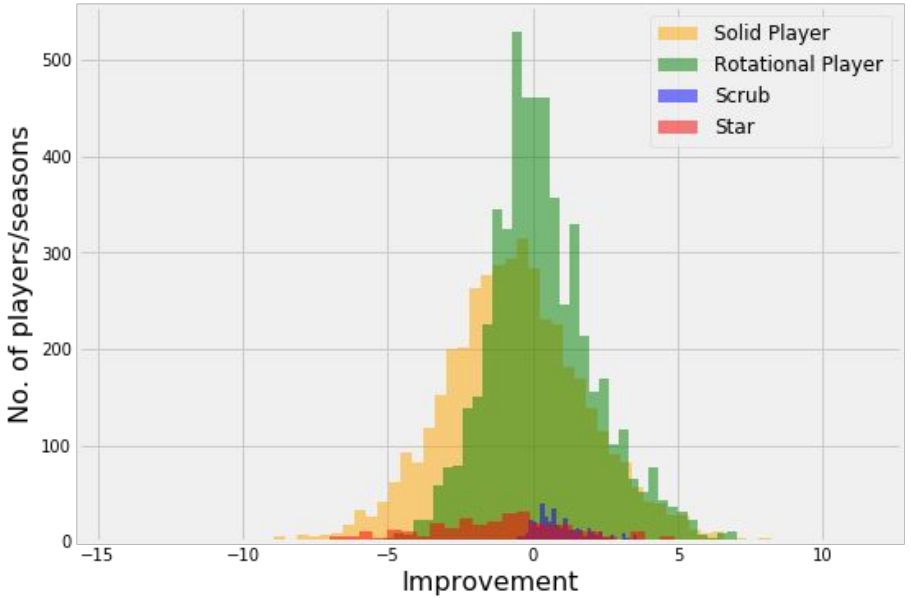
Young players improve, old players decline



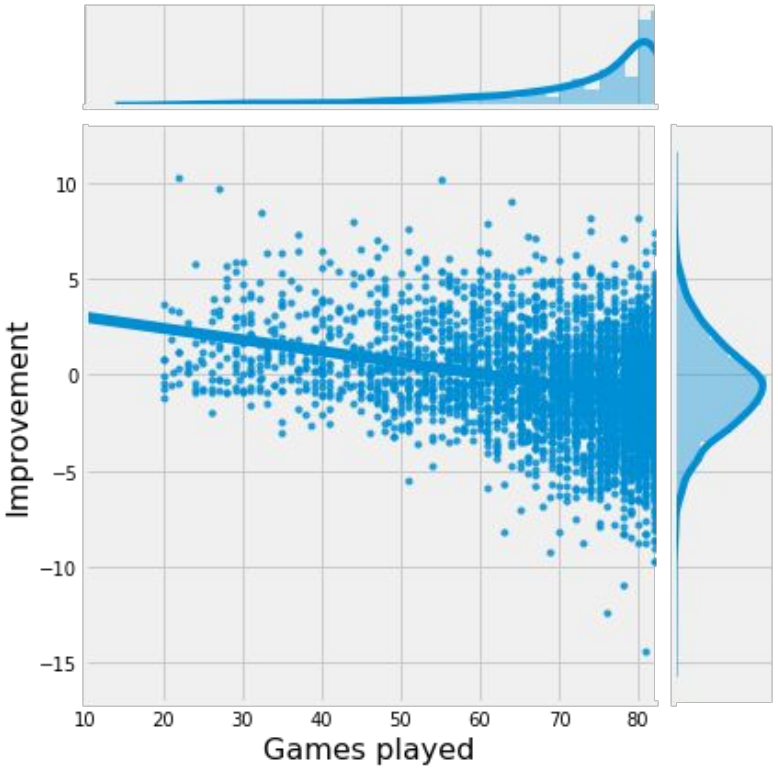
Improvements of different age groups(<25, 25-29, 30-34,>34) were significantly different from each other. ($p<0.001$)

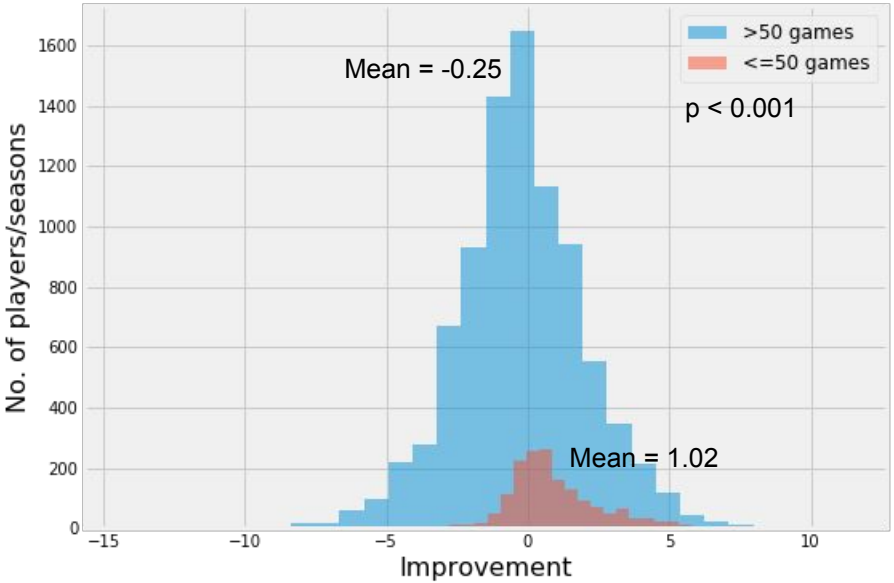
Worse players have more room for improvement



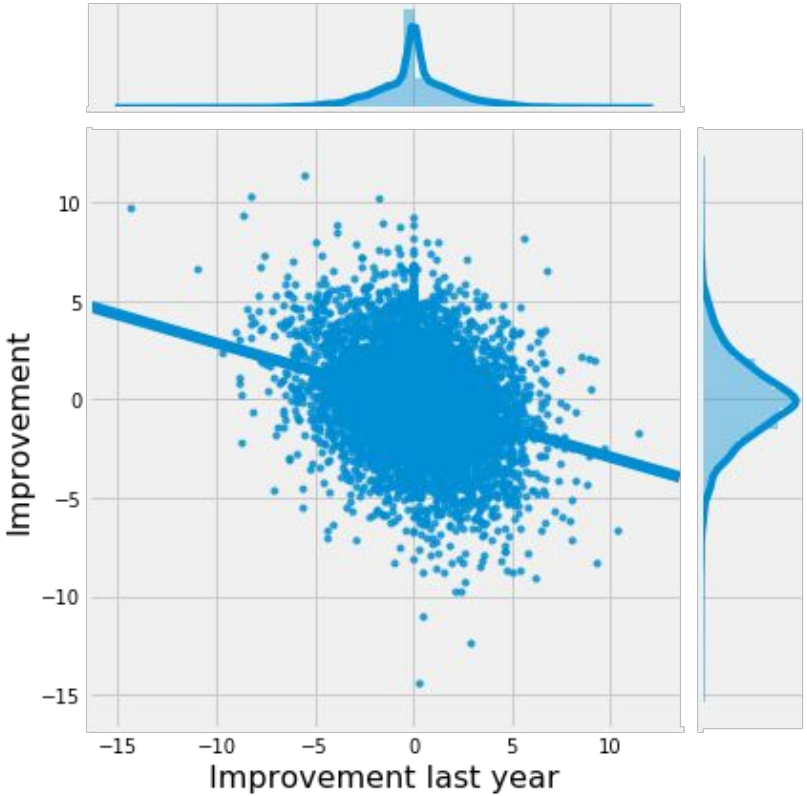


Players who missed more games are more likely to improve



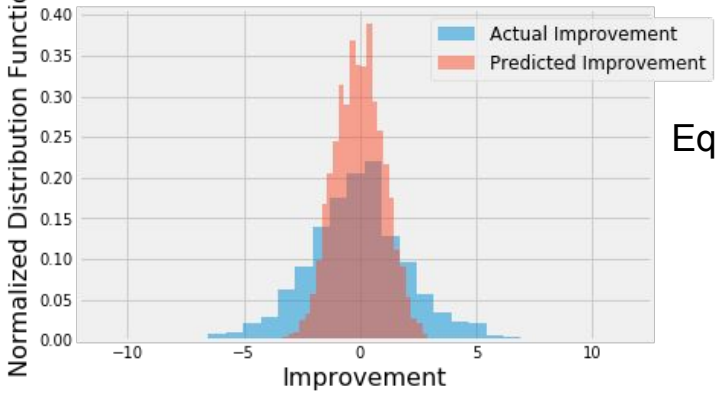


Players are more likely to “regress to the mean” than continously improve/decline

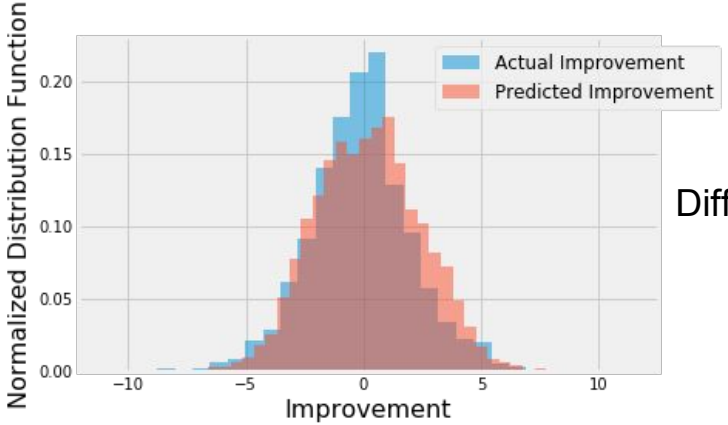


- Also examined other features and hypotheses, including:
  - Minutes played (slight negative correlation with improvement)
  - Player positions (no significant difference)
  - Player draft positions (no significant difference)
  - Team performance (very small negative correlation)

Regression models: dealing with unbalanced dataset



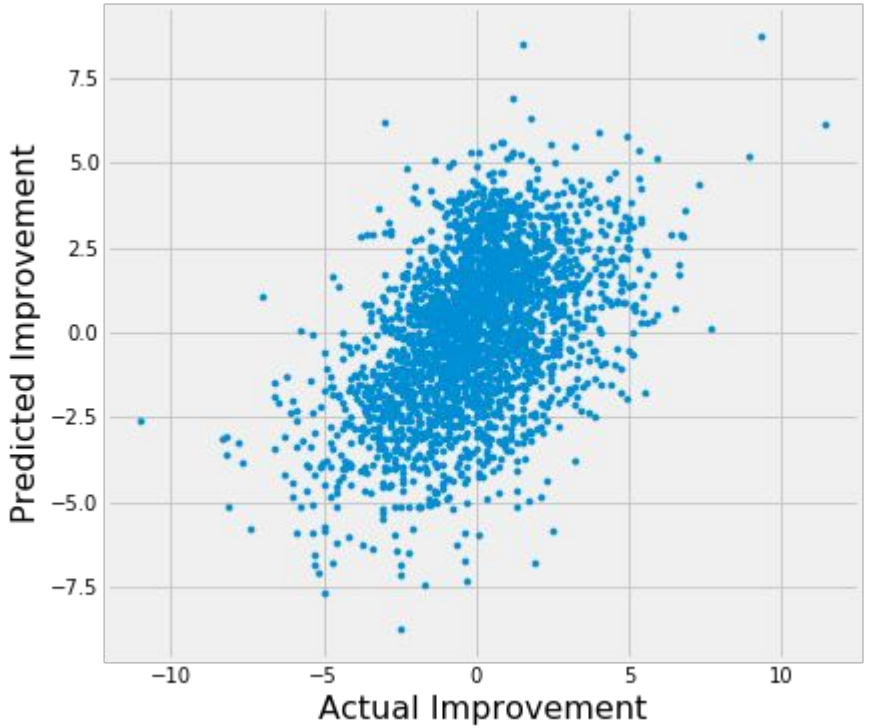
Equal weights



Different weights

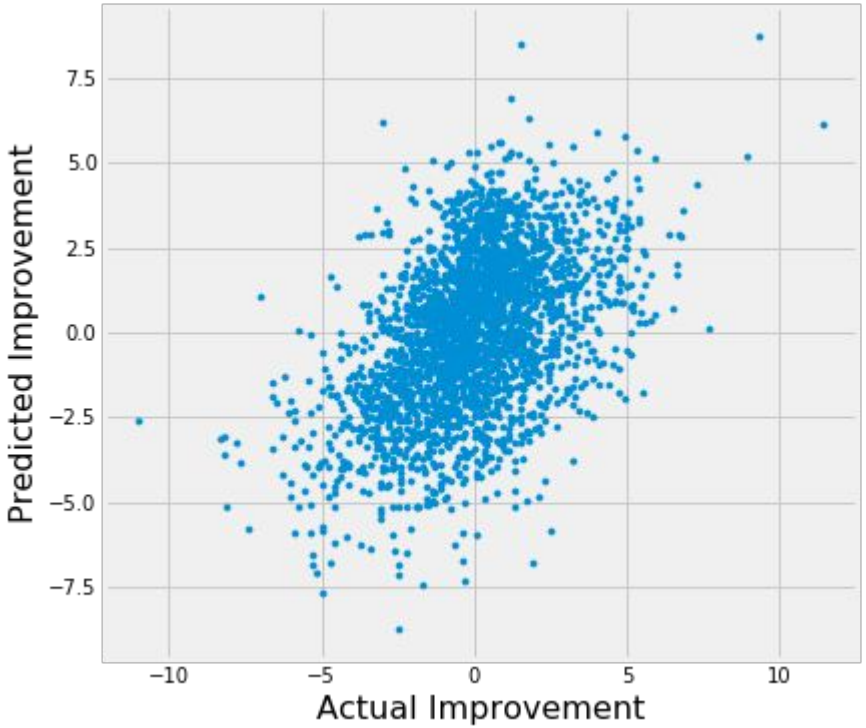
- Players with small changes are overrepresented.
- Unweighted model prioritize the error of those players.
- Resulting in narrower predicted range.
- Assigning more weights to underrepresented players help with this problem.

Regression models performance



- Weighted RMSE:
  - Benchmark (1 feature): 3.84
  - Linear regression: 2.98
  - SVM: 2.86
  - Random Forest: 2.93
  - Gradient Boost: 2.96

Classification models



- Log loss:
  - 0.603-0.613 between 5 models
- Accuracy:
  - 0.672-0.675 between 5 models
- SVM performed best among single algorithms, but the differences were small.

Conclusion and future directions

- Built useful models to predict whether and how much a player will improve.
- Accuracy of the models has room for improvement.
- Capture more of players' individual traits.
- Ideas include:
  - Physical data (speed, jump, etc.)
  - Financial data (contract year, amount of pay, etc.)
  - Team interaction data (strengths of players of the same position on the team)