Forecasting MLB Game Attendance

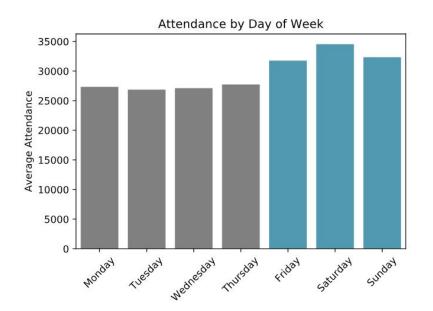
Rob Pagano

Predicting Attendance - Why it Matters

- Team marketing
- Local businesses
- Public Services

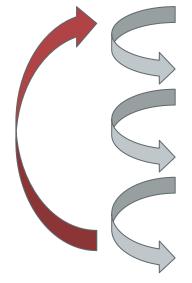


Approach



- What makes a team exciting
 - Baseball stats
 - Playoff contention
- What makes a specific game popular
 - Day of the week / Time of day
 - Opposing team
 - Promotions

Process



- 1. Scrape game data from 2014-2018
- 2. Clean data and transform features
- 3. Choose features for CV
- 4. Circle back to steps 1-3 until happy with model

Feature Editing

Original OLS

- Rank
- Games back
- Night or day
- Wins last 10
- Mean runs last 10
- Run differential

RMSE ≈ 9070.96

 $R^2 \approx 0.16$

Feature Editing

Original OLS

- Rank
- Games back
- Night or day
- Wins last 10
- Mean runs last 10
- Run differential

RMSE ≈ 9070.96

 $R^2 \approx 0.16$



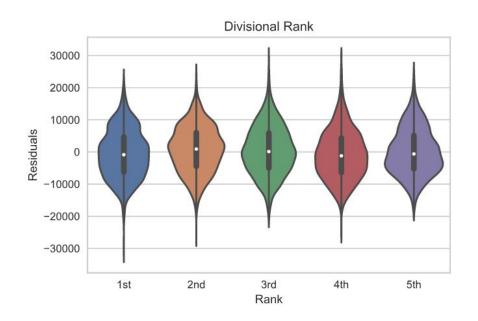
Lasso (Lamba ≈ 2.05, Standardized)

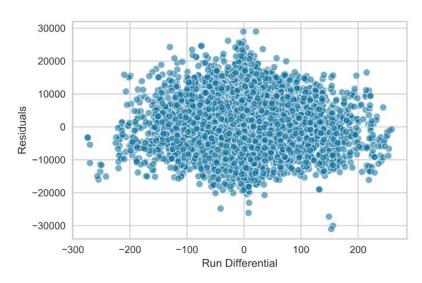
- Rank
- Games back
- Night or day
- Wins last 10
- Run differential
- Win differential
- Mean batter age
- # of current all-stars
- # of lifetime all-stars
- Team salary
- Day of week

RMSE ≈ 7434.25

 $R^2 \approx 0.44$

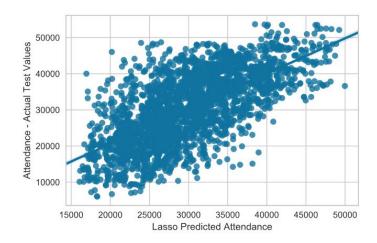
Checking Residuals

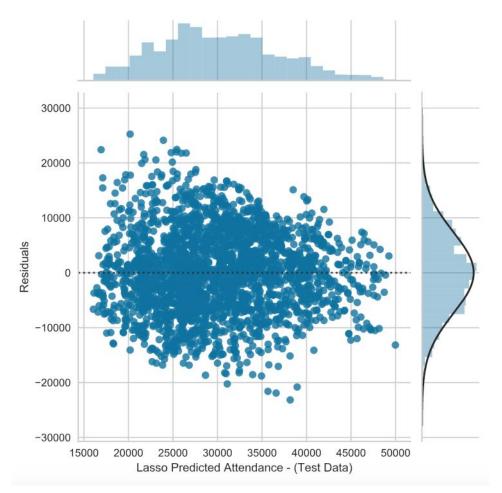




Outcome

- Lasso Model
 - RMSE ≈ 7124.2
 - \circ R² \approx 0.434





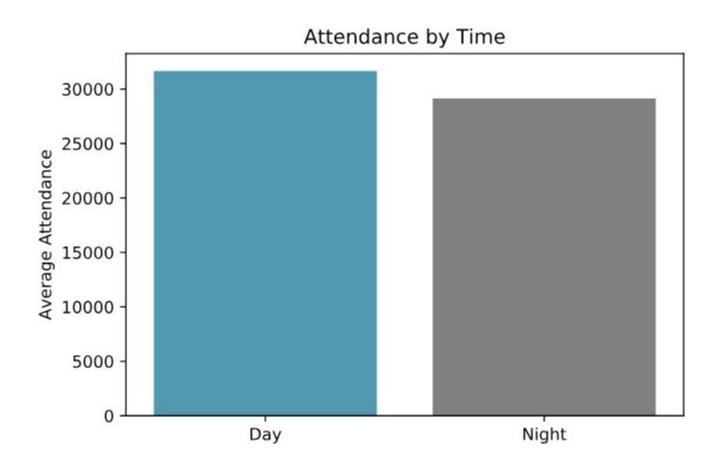
Future Work

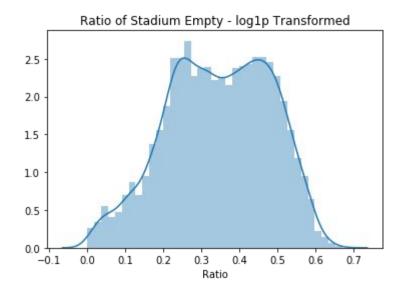


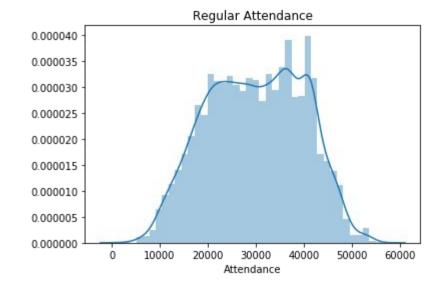
- Transforming Y variable
- Adding more features
 - Weather
 - Digging in further on opponent features
 - Other sports leagues

Questions?

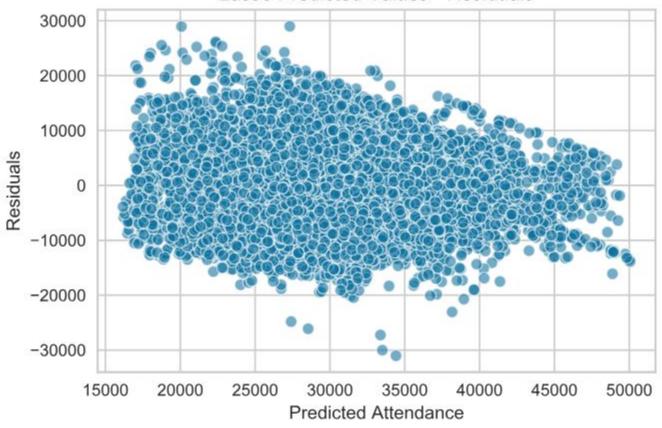
Appendix



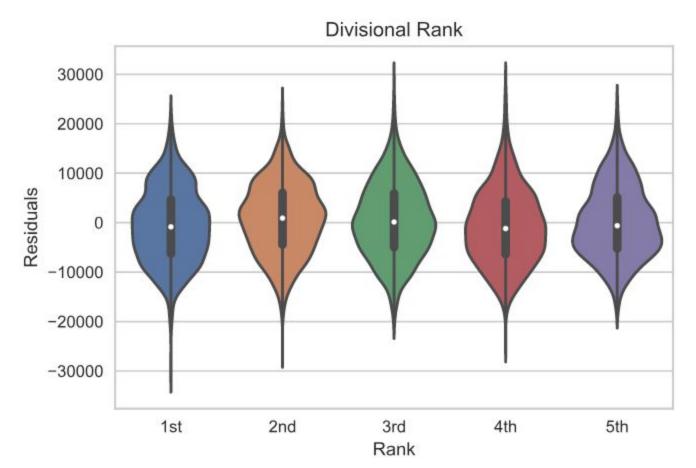




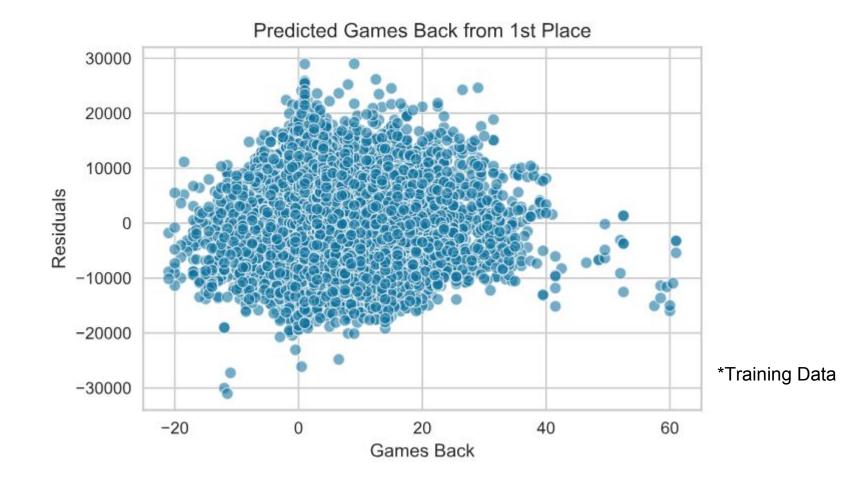
Lasso Predicted Values - Residuals

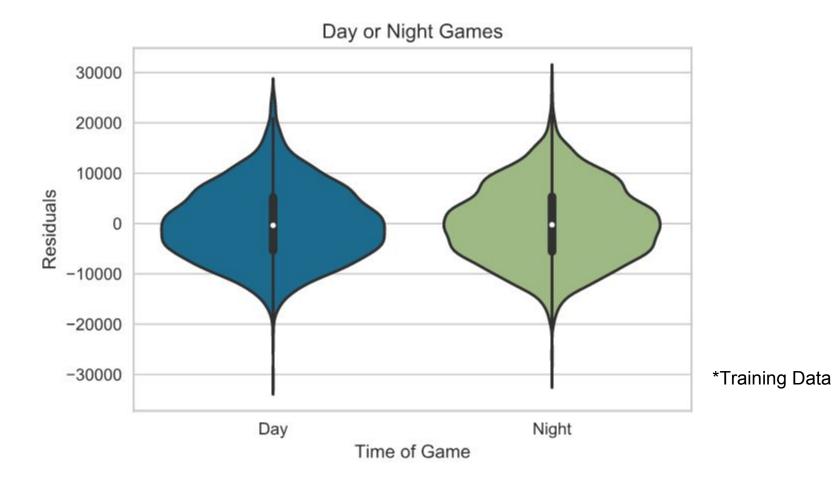


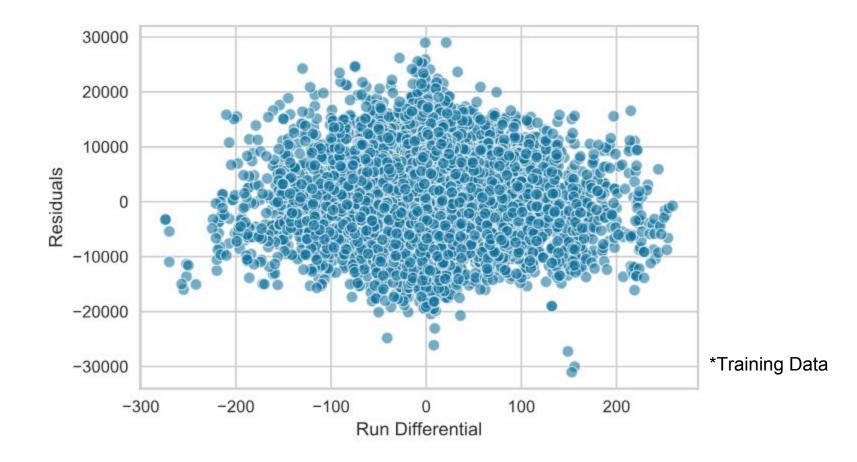
*Training Data

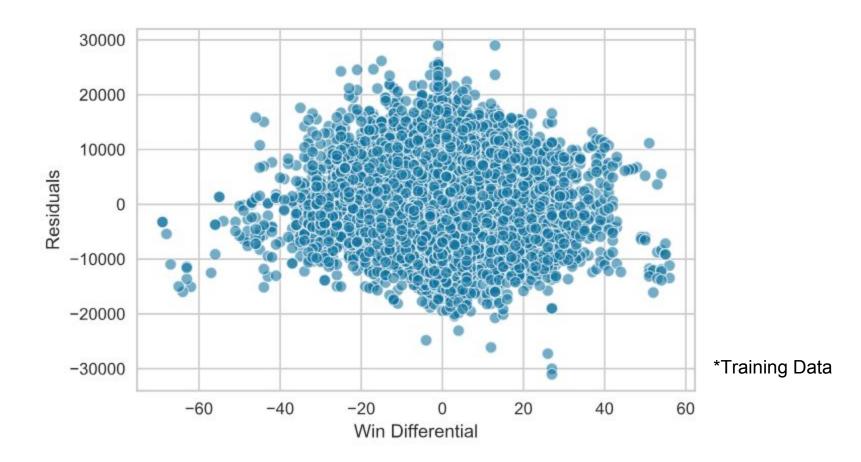


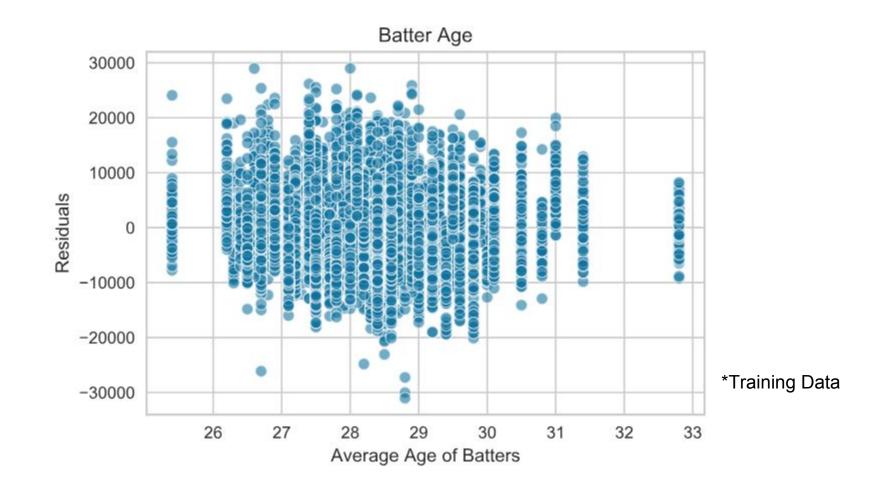
*Training Data



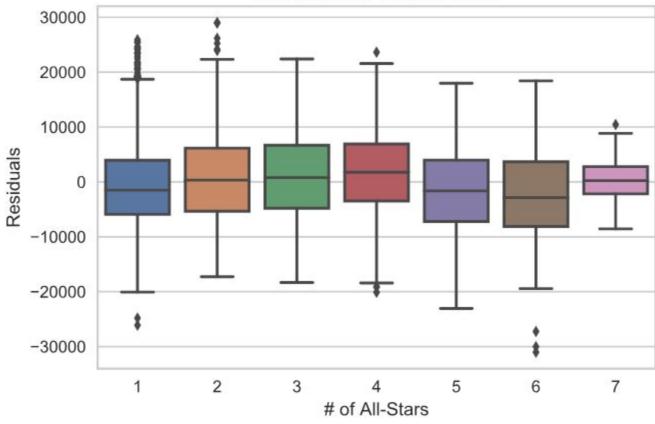




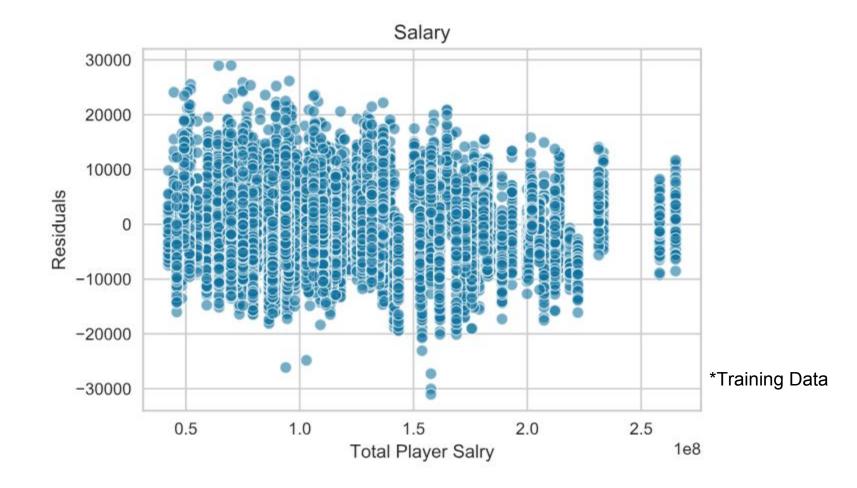




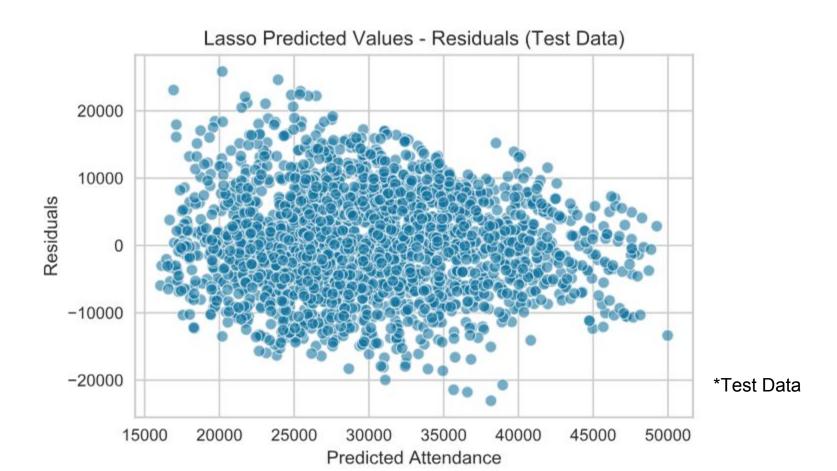
of Previous Year All-Stars



*Training Data







Opposing Team Features - Heat Map

