# Drivers of MLB Attendance: Is Winning Worth it?

An examination of the influence of various factors on Attendance in Major League Baseball

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# Who Cares: Why is MLB Attendance important?

- Interested Parties:
  - MLB Commissioner's Office
  - Front Offices of MLB Teams
- Emblematic of overall revenue and popularity of baseball
- Influences decisions around team construction and payroll as well as league rules, policies, and actions taken to grow the game

"If you go back and you look in a decade, those teams that win 54% of the time always wind up in the postseason. And they, more often than not, wind up in the World Series. So there's your bigger picture process. Nobody wants to hear the goal this year is, 'We're going to win 54% of the time.' Because sometimes 54% is -- one year, you're going to win 60%, another year you're going to win 50%. It's whatever it is. But over time, that type of mindset gets you there ... If what you're doing is focusing year-to-year on, 'what do we have to do to win the World Series this year?' You might be one of the teams that's laying in the mud and can't get up for another decade."

- Jerry Depoto: GM of the Seattle Mariners

# MLB Rule Changes, Industry Assumptions:

- Rule Changes in 2023 designed to improve run scoring and shorten games
  - Pitch Clock (adjusted again this year)
  - Limited pickoff attempts
  - Ban of the Shift
  - Other Recent Rule Changes include
- These rule changes suggest that MLB believes:
  - Strong offenses draw more fans than strong defenses
  - Shorter games bring in more fans
  - More action on the basepaths/runners on base draws more fans
- MLB has also expanded the playoffs twice in the last 10 years, allowing more teams who are not necessarily the best compete for a title

# Background Research:

- Factors that influence Major League and Minor League Baseball - 3241 Words | Research Paper Example (ivypanda.com)
  - Many factors have been shown to directly affect MLB game attendance, such as local household income levels, concession prices, and marketing of team rivalries
- Top Prospects and Minor League Baseball Attendance - Seth R. Gitter, Thomas A. Rhoads, 2011 (sagepub.com)
  - Prospects who have not yet played in the MLB can affect attendance
  - High quality minor league prospects tend to bring in lots of viewers from MiLB
- (PDF) Team Roster Turnover and Attendance in Major League Baseball. (researchgate.net)
  - Higher roster turnover correlates to lower attendances the following season
  - According to this study, a 1% increase in roster turnover can lead to a 0.4-0.7% decrease in attendance the following season for a given team

# Primary Questions and Project Goals

- Does offensive play have a greater impact on per game attendance than defensive play?
- Does it make sense for teams to aim for ‘just good enough’, or are there consistent marginal returns for more investment in players?
- How big of a role does local population play on game attendance?
- What factors beside population have the greatest impact on per game attendance?
- Can we predict a team’s season attendance given their in games statistical projections?
- How should MLB front offices spend in free agency if they want to increase attendance?

# Where We Sourced Our Data

- Out of game stats such as attendance and gametime are from Baseball Reference
- In-game and advanced stats are from Fangraphs
- Data on metro area populations came from MacroTrends
- 35 columns across 510 rows of clean data



# Our Data

| ...1 | Rk | Team | W | L | WL | R | RA | Rdiff | Home | Road | tYear | Attendance | Attend/G | BatAge | PAge |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 1 | Atlanta Braves | 104 | 58 | 0.642 | 5.8 | 4.4 | 1.4 | 52-29 | 52-29 | Atlanta Braves2023 | 3191505 | 39401 | 27.9 | 29.9 |
| 1 | 2 | Baltimore Orioles | 101 | 61 | 0.623 | 5.0 | 4.2 | 0.8 | 49-32 | 52-29 | Baltimore Orioles2023 | 1936798 | 23911 | 27.2 | 28.4 |
| 2 | 3 | Los Angeles Dodgers | 100 | 62 | 0.617 | 5.6 | 4.3 | 1.3 | 53-28 | 47-34 | Los Angeles Dodgers2023 | 3837079 | 47371 | 30.9 | 28.1 |
| 3 | 4 | Tampa Bay Rays | 99 | 63 | 0.611 | 5.3 | 4.1 | 1.2 | 53-28 | 46-35 | Tampa Bay Rays2023 | 1440301 | 17781 | 26.8 | 28.5 |
| 4 | 5 | Milwaukee Brewers | 92 | 70 | 0.568 | 4.5 | 4.0 | 0.5 | 49-32 | 43-38 | Milwaukee Brewers2023 | 2551347 | 31498 | 27.7 | 29.3 |
| 5 | 6 | Houston Astros | 90 | 72 | 0.556 | 5.1 | 4.3 | 0.8 | 39-42 | 51-30 | Houston Astros2023 | 3052347 | 37683 | 28.8 | 29.2 |
| 6 | 7 | Philadelphia Phillies | 90 | 72 | 0.556 | 4.9 | 4.4 | 0.5 | 49-32 | 41-40 | Philadelphia Phillies2023 | 3052605 | 37686 | 28.4 | 29.8 |
| 7 | 8 | Texas Rangers | 90 | 72 | 0.556 | 5.4 | 4.4 | 1.0 | 50-31 | 40-41 | Texas Rangers2023 | 2533044 | 31272 | 28.3 | 30.4 |
| 8 | 9 | Toronto Blue Jays | 89 | 73 | 0.549 | 4.6 | 4.1 | 0.5 | 43-38 | 46-35 | Toronto Blue Jays2023 | 3021904 | 37307 | 28.8 | 30.6 |
| 9 | 10 | Seattle Mariners | 88 | 74 | 0.543 | 4.7 | 4.1 | 0.6 | 45-36 | 43-38 | Seattle Mariners2023 | 2690418 | 33215 | 27.8 | 27.4 |
| 10 | 11 | Minnesota Twins | 87 | 75 | 0.537 | 4.8 | 4.1 | 0.7 | 47-34 | 40-41 | Minnesota Twins2023 | 1974124 | 24372 | 28.5 | 29.0 |
| 11 | 12 | Arizona Diamondbacks | 84 | 78 | 0.519 | 4.6 | 4.7 | -0.1 | 43-38 | 41-40 | Arizona Diamondbacks2023 | 1961182 | 24212 | 27.4 | 28.5 |
| 12 | 13 | Miami Marlins | 84 | 78 | 0.519 | 4.1 | 4.5 | -0.4 | 46-35 | 38-43 | Miami Marlins2023 | 1162819 | 14356 | 29.4 | 27.6 |
| 13 | 14 | Chicago Cubs | 83 | 79 | 0.512 | 5.1 | 4.5 | 0.6 | 45-36 | 38-43 | Chicago Cubs2023 | 2775149 | 34261 | 28.4 | 29.6 |
| 14 | 15 | San Diego Padres | 82 | 80 | 0.506 | 4.6 | 4.0 | 0.6 | 44-37 | 38-43 | San Diego Padres2023 | 3271554 | 40390 | 28.4 | 30.7 |
| 15 | 16 | Cincinnati Reds | 82 | 80 | 0.506 | 4.8 | 5.1 | -0.2 | 38-43 | 44-37 | Cincinnati Reds2023 | 2038302 | 25164 | 26.8 | 27.7 |
| 16 | 17 | New York Yankees | 82 | 80 | 0.506 | 4.2 | 4.3 | -0.2 | 42-39 | 40-41 | New York Yankees2023 | 3269016 | 40358 | 28.5 | 29.1 |
| 17 | 18 | San Francisco Giants | 79 | 83 | 0.488 | 4.2 | 4.4 | -0.3 | 45-36 | 34-47 | San Francisco Giants2023 | 2500153 | 30866 | 28.5 | 30.0 |
| 18 | 19 | Detroit Tigers | 78 | 84 | 0.481 | 4.1 | 4.6 | -0.5 | 37-44 | 41-40 | Detroit Tigers2023 | 1612876 | 19912 | 27.4 | 27.7 |
| 19 | 20 | Boston Red Sox | 78 | 84 | 0.481 | 4.8 | 4.8 | 0.0 | 39-42 | 39-42 | Boston Red Sox2023 | 2672130 | 32989 | 28.6 | 30.0 |
| 20 | 21 | Cleveland Guardians | 76 | 86 | 0.469 | 4.1 | 4.3 | -0.2 | 42-39 | 34-47 | Cleveland Guardians2023 | 1834068 | 22643 | 26.7 | 26.1 |
| 21 | 22 | Pittsburgh Pirates | 76 | 86 | 0.469 | 4.3 | 4.9 | -0.6 | 39-42 | 37-44 | Pittsburgh Pirates2023 | 1630624 | 20131 | 27.3 | 27.6 |
| 22 | 23 | New York Mets | 75 | 87 | 0.463 | 4.4 | 4.5 | -0.1 | 43-38 | 32-49 | New York Mets2023 | 2573555 | 31772 | 28.9 | 31.9 |
| 23 | 24 | Los Angeles Angels | 73 | 89 | 0.451 | 4.6 | 5.1 | -0.6 | 38-43 | 35-46 | Los Angeles Angels2023 | 2640575 | 32600 | 28.6 | 28.0 |
| 24 | 25 | St. Louis Cardinals | 71 | 91 | 0.438 | 4.4 | 5.1 | -0.7 | 35-46 | 36-45 | St. Louis Cardinals2023 | 3241091 | 40013 | 27.5 | 29.7 |

# Our Data

| #A-S | #a-tA-S | Est. Payroll | Time | Season | TeamAbb | TG | HR | RTotal | SB | K. | ISO | AVG | OBP | wOBA | wRC. | WAR | city.x | Population |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 8 | 16 | $194,197,500 | 02:42:00 | 2023 | ATL | 162 | 307 | 947 | 132 | 0.2062730 | 0.2251206 | 0.2756834 | 0.3439552 | 0.3593281 | 124.70284 | 40.3310896 | Atlanta | 6106000 |
| 4 | 10 | $82,758,114 | 02:47:00 | 2023 | BAL | 162 | 183 | 807 | 114 | 0.2237465 | 0.1663330 | 0.2545951 | 0.3207083 | 0.3204568 | 105.41290 | 24.0359798 | Baltimore | 2355000 |
| 5 | 12 | $227,091,667 | 02:43:00 | 2023 | LAD | 162 | 249 | 906 | 105 | 0.2145902 | 0.1973208 | 0.2574222 | 0.3402404 | 0.3411893 | 116.29866 | 32.3573717 | LosAngeles | 12534000 |
| 4 | 7 | $75,441,212 | 02:38:00 | 2023 | TBR | 162 | 230 | 860 | 160 | 0.2303699 | 0.1850844 | 0.2598439 | 0.3314388 | 0.3352108 | 117.93957 | 32.3094620 | Tampa | 2977000 |
| 2 | 11 | $138,288,760 | 02:40:00 | 2023 | MIL | 162 | 165 | 728 | 129 | 0.2320842 | 0.1455626 | 0.2395098 | 0.3192295 | 0.3086803 | 91.85584 | 18.1681236 | Milwaukee | 1455000 |
| 3 | 9 | $240,388,766 | 02:45:00 | 2023 | HOU | 162 | 222 | 827 | 107 | 0.1984647 | 0.1778337 | 0.2588468 | 0.3311928 | 0.3316407 | 111.80440 | 27.2326505 | Houston | 6707000 |
| 2 | 12 | $241,362,606 | 02:44:00 | 2023 | PHI | 162 | 220 | 796 | 141 | 0.2386016 | 0.1820971 | 0.2557300 | 0.3270877 | 0.3294203 | 105.48895 | 22.1396231 | Philadelphia | 5785000 |
| 6 | 11 | $248,537,867 | 02:40:00 | 2023 | TEX | 162 | 233 | 881 | 79 | 0.2245480 | 0.1896336 | 0.2627346 | 0.3371465 | 0.3396940 | 114.10619 | 32.3496756 | Arlington | 6574000 |
| 5 | 16 | $211,190,269 | 02:45:00 | 2023 | TOR | 162 | 188 | 746 | 99 | 0.2094855 | 0.1607335 | 0.2558432 | 0.3286657 | 0.3239747 | 106.97842 | 25.7162399 | Toronto | 6372000 |
| 3 | 9 | $128,155,663 | 02:43:00 | 2023 | SEA | 162 | 210 | 758 | 118 | 0.2585067 | 0.1703636 | 0.2421818 | 0.3213363 | 0.3192701 | 106.66413 | 25.4725303 | Seattle | 3519000 |
| 2 | 8 | $137,798,640 | 02:42:00 | 2023 | MIN | 162 | 233 | 778 | 86 | 0.2659592 | 0.1841866 | 0.2433959 | 0.3257612 | 0.3266612 | 108.74735 | 24.8086404 | Minneapolis | 2990000 |
| 4 | 8 | $115,247,571 | 02:43:00 | 2023 | ARI | 162 | 166 | 746 | 166 | 0.2036251 | 0.1582046 | 0.2500000 | 0.3216634 | 0.3169704 | 97.37705 | 20.4183641 | Phoenix | 4717000 |
| 2 | 15 | $114,351,500 | 02:38:00 | 2023 | MIA | 162 | 166 | 666 | 86 | 0.2129737 | 0.1458978 | 0.2588685 | 0.3163757 | 0.3121733 | 93.95988 | 11.1328793 | Miami | 6265000 |
| 3 | 10 | $162,918,250 | 02:43:00 | 2023 | CHC | 162 | 196 | 819 | 140 | 0.2236334 | 0.1666061 | 0.2541788 | 0.3298404 | 0.3257697 | 104.42706 | 24.1078056 | Chicago | 8937000 |
| 2 | 15 | $236,200,139 | 02:46:00 | 2023 | SDP | 162 | 205 | 752 | 137 | 0.2121359 | 0.1695982 | 0.2436586 | 0.3291633 | 0.3232177 | 107.04318 | 26.1657435 | SanDiego | 3319000 |
| 1 | 3 | $77,877,833 | 02:47:00 | 2023 | CIN | 162 | 198 | 783 | 190 | 0.2421308 | 0.1702128 | 0.2493181 | 0.3269106 | 0.3246395 | 97.62472 | 14.2907294 | Cincinnati | 1775000 |
| 2 | 12 | $259,417,008 | 02:42:00 | 2023 | NYY | 162 | 219 | 673 | 100 | 0.2389084 | 0.1705805 | 0.2267518 | 0.3037062 | 0.3044883 | 94.24732 | 14.9383197 | NewYork | 18937000 |
| 2 | 11 | $177,920,416 | 02:39:00 | 2023 | SFG | 162 | 174 | 674 | 57 | 0.2447908 | 0.1485588 | 0.2348485 | 0.3120474 | 0.3041781 | 92.85549 | 14.2172798 | SanFrancisco | 3328000 |
| 1 | 5 | $119,236,836 | 02:38:00 | 2023 | DET | 162 | 165 | 661 | 85 | 0.2422697 | 0.1456736 | 0.2358525 | 0.3048137 | 0.2998402 | 88.58722 | 10.9673681 | Detroit | 3521000 |
| 1 | 7 | $181,282,500 | 02:45:00 | 2023 | BOS | 162 | 182 | 772 | 112 | 0.2222222 | 0.1659475 | 0.2583603 | 0.3240169 | 0.3236913 | 99.21710 | 13.0694294 | Boston | 4344000 |
| 2 | 9 | $70,114,729 | 02:39:00 | 2023 | CLE | 162 | 124 | 662 | 151 | 0.1873360 | 0.1313260 | 0.2501360 | 0.3131678 | 0.3015157 | 92.29197 | 15.2214764 | Cleveland | 1764000 |
| 2 | 5 | $72,407,500 | 02:40:00 | 2023 | PIT | 162 | 159 | 692 | 117 | 0.2404336 | 0.1527932 | 0.2391787 | 0.3145308 | 0.3084180 | 90.35013 | 13.7190484 | Pittsburgh | 1702000 |
| 2 | 13 | $208,427,344 | 02:45:00 | 2023 | NYM | 162 | 215 | 717 | 118 | 0.2197820 | 0.1693082 | 0.2379265 | 0.3162606 | 0.3149904 | 100.77711 | 18.9046202 | NewYork | 18937000 |
| 3 | 13 | $218,537,055 | 02:44:00 | 2023 | LAA | 162 | 231 | 739 | 72 | 0.2480065 | 0.1809073 | 0.2452177 | 0.3168624 | 0.3199747 | 101.19558 | 15.8959003 | LosAngeles | 12534000 |

# The Models We Used

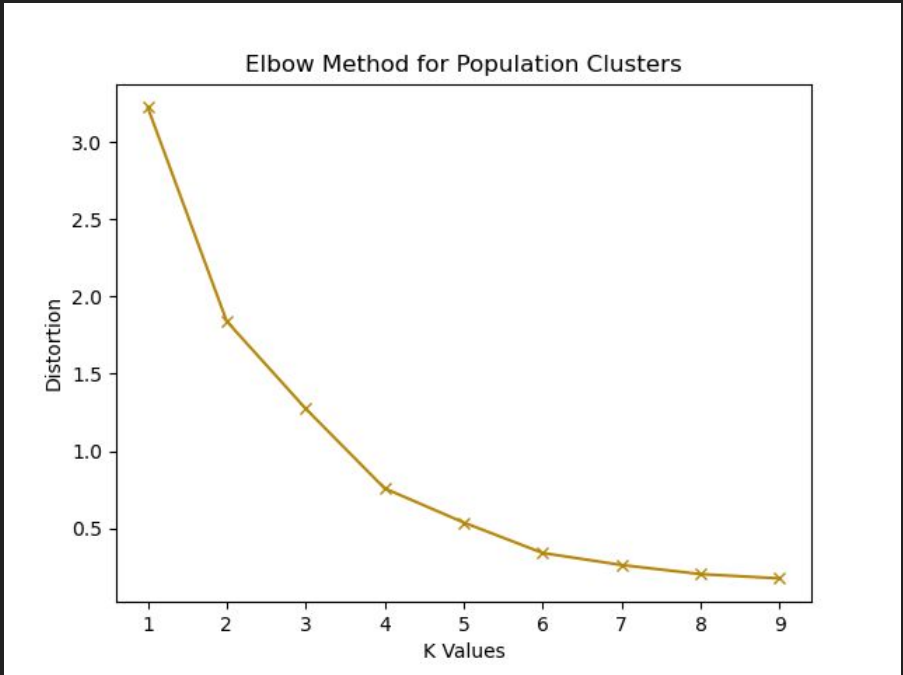
# Simple Linear Regression

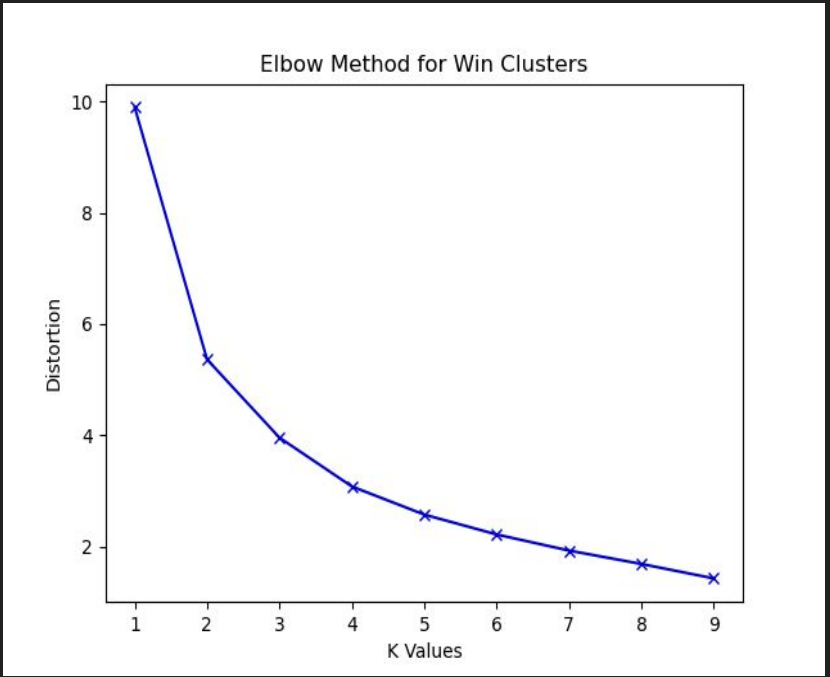
- We wanted to see if there might be an easier or simpler way to accomplish our goal
- Offensive Model
  - Used Runs Scored to predict Attendance - $R^2$ 0.11
  - After trying a combination of different variables, we eventually utilized On Base Percentage to predict Attendance - $R^2$ 0.23
- Defensive Model
  - Used Runs Against to predict Attendance - $R^2$ 0.08
- Could not get the results we wanted from these models, likely due to their simplicity, as well as the fact that the data was still relatively raw.

# K-Means Clustering

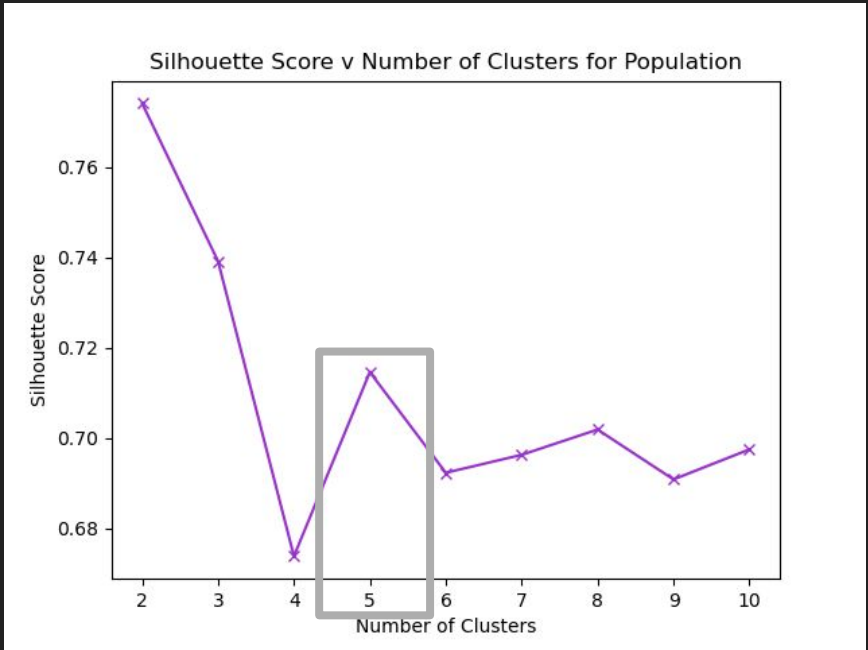
- We wanted to define thresholds for the population of metro areas around each MLB team's stadium and the contender status of individual teams based on wins to facilitate easier multiple linear regression
- Before we did that though, we needed to determine the appropriate number of clusters for each of these groups
- We used two methods to determine the appropriate number of clusters: the elbow method and silhouette scoring

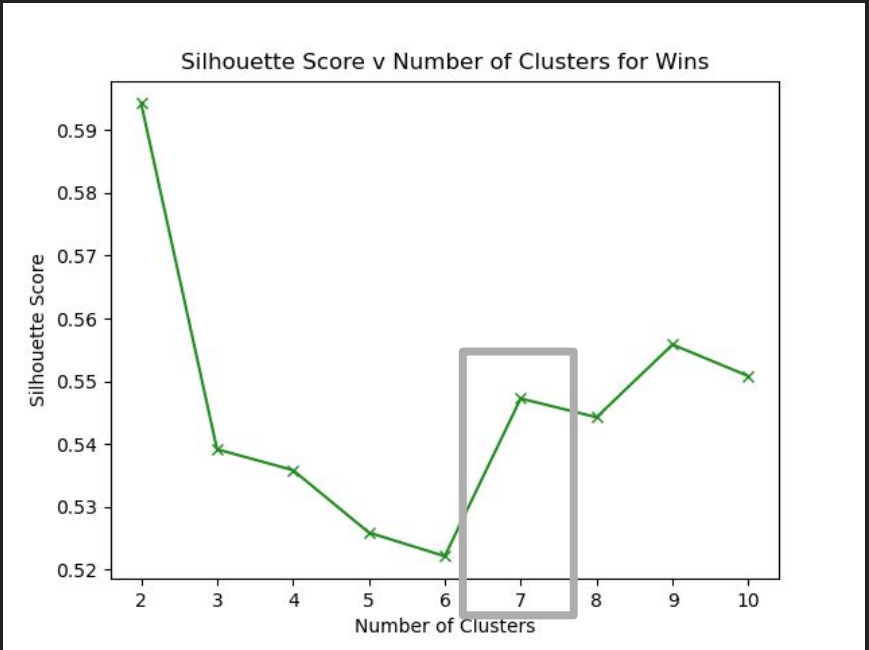
# K-Means Clustering: Elbow Method



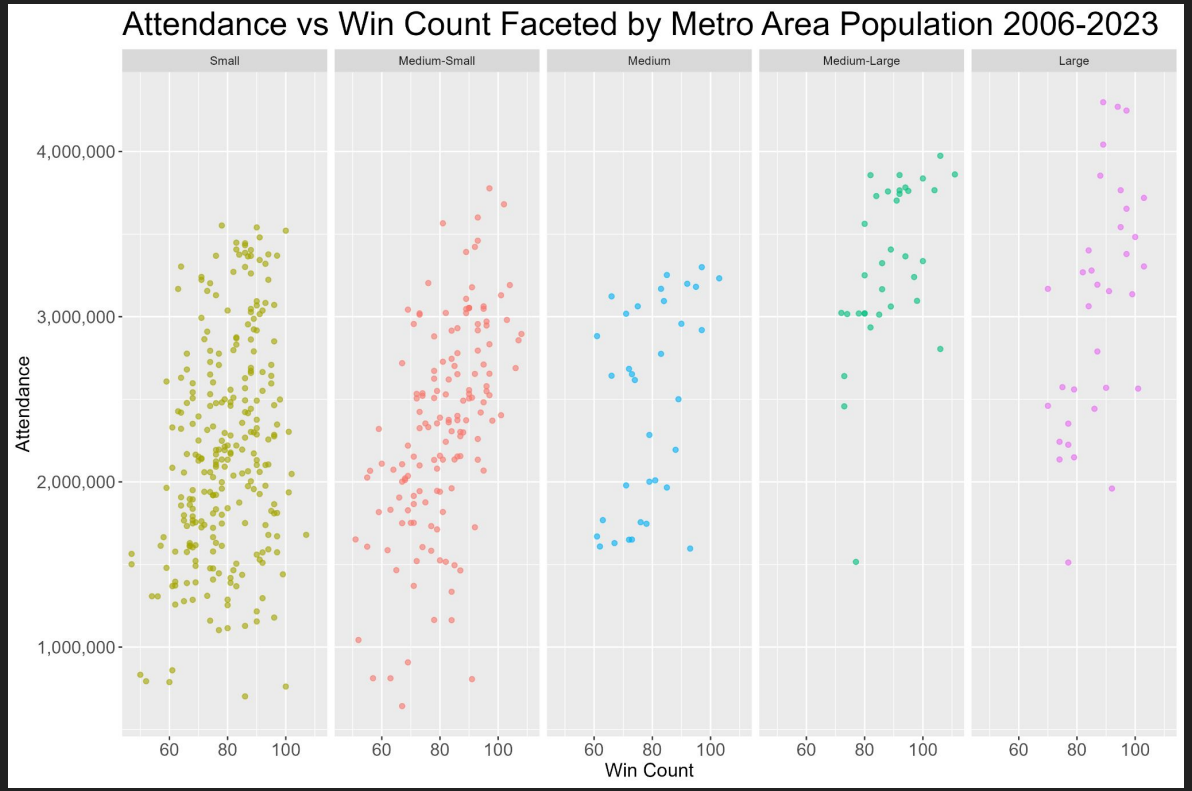
# K-Means Clustering: Silhouette Scores



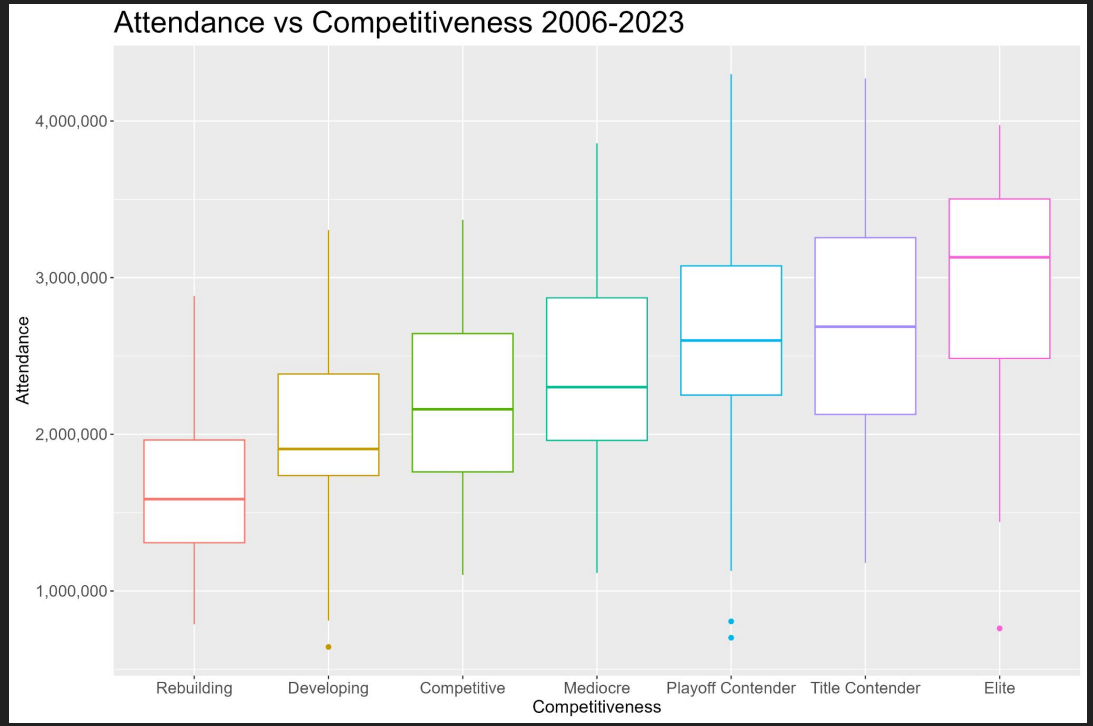
# K-Means Classification (Population Levels)

- This graph shows attendance vs win count faceted by population around stadiums

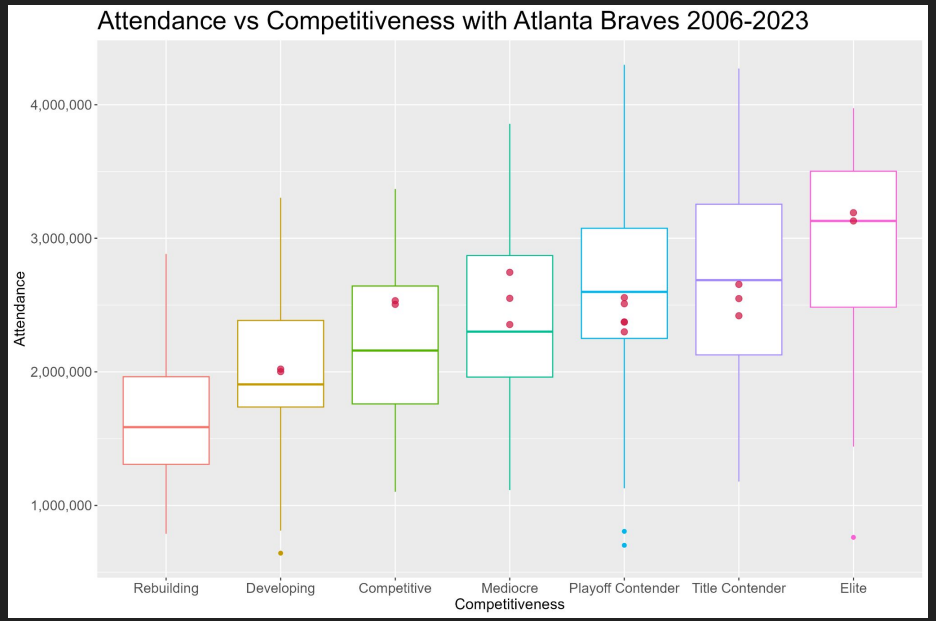


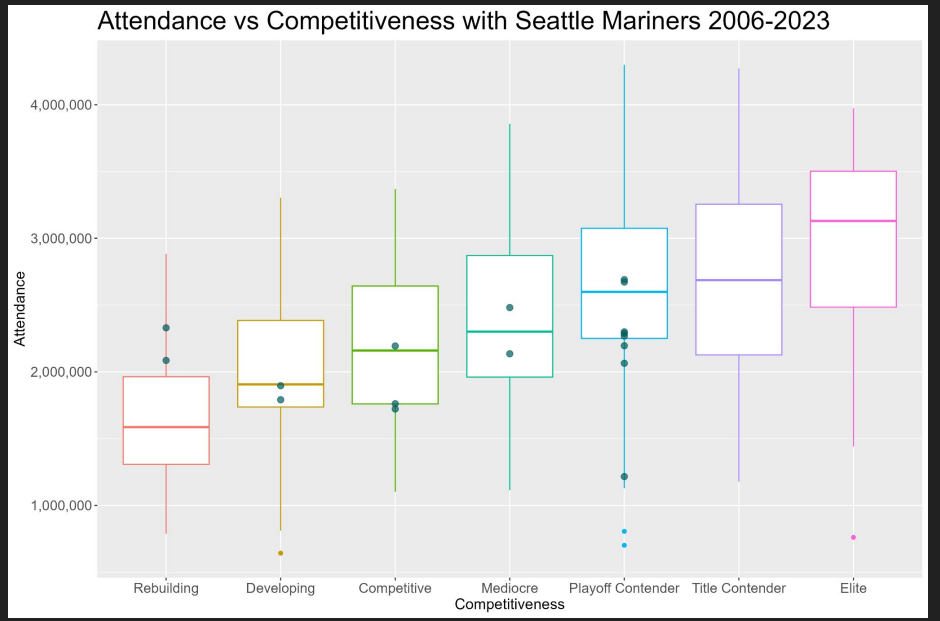
# Win Totals and Team Investment (Classified)

- This graph plots attendance vs team competitiveness
- For teams in the Playoff Contender and Title Contender, there is not a large difference between their medians, indicating that at the higher level, investing in team performance produces a small boost in attendance, unless you can push the team to the elite level



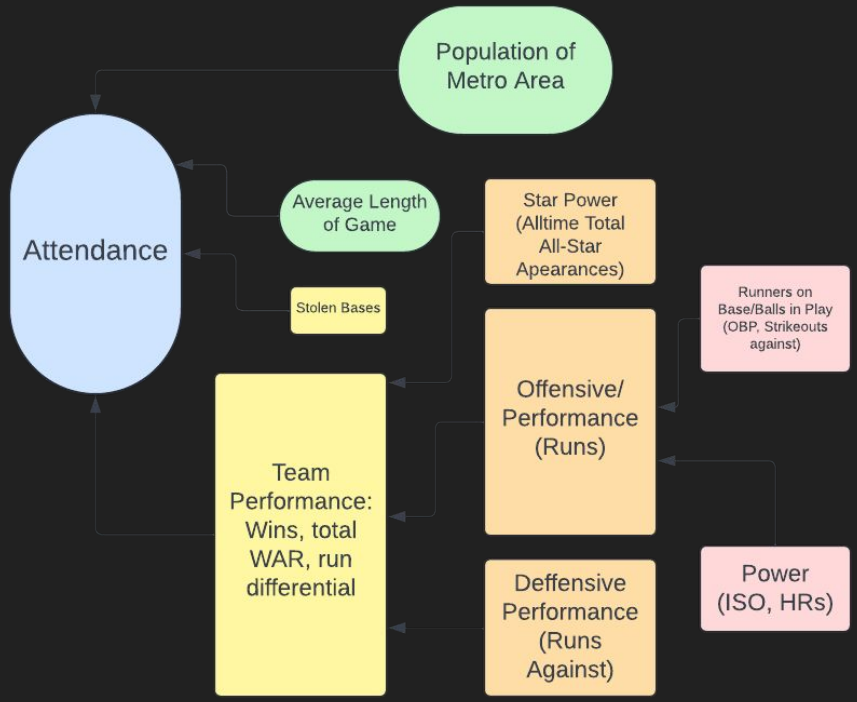
# Case Study: Atlanta Braves and Seattle Mariners



# Feature Selection for Regression Models

- Used a variety of methods to select appropriate features for model
  - Domain knowledge
  - Understanding of multicollinearity
  - Correlation Matrix
- The graphic on the right shows a visual representation of some of the issues caused by multicollinearity

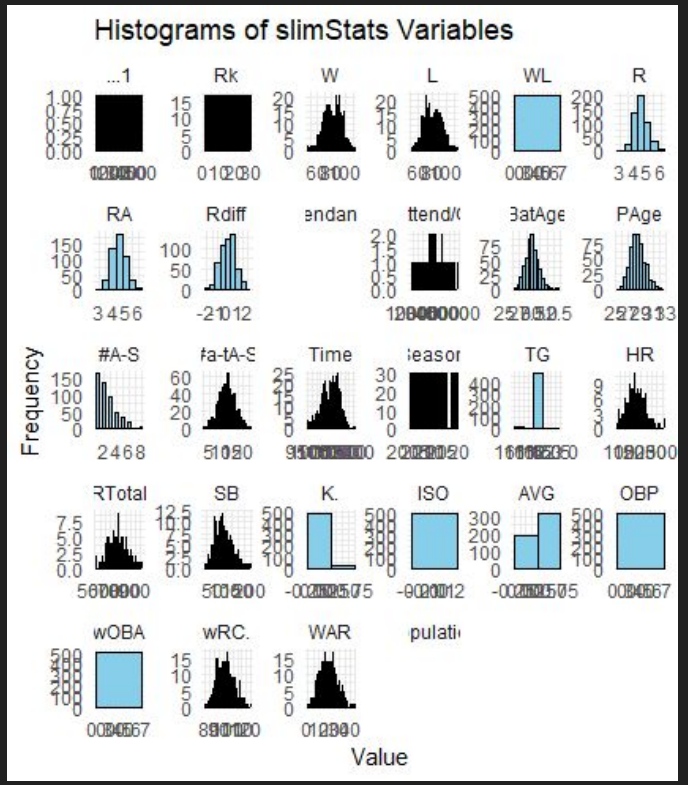


# Correlation Matrix

| | W | R | #a-tA-S | Rk | L | WL | RA | Rdiff | BatAge | PAge | #A-S | HR | RTotal | SB | K. | ISO | AVG | OBP | wOBA | wRC. | WAR | Population | Attendance |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **W** | 1.000000 | 0.598129 | 0.523908 | -0.972901 | -0.999743 | 0.999924 | -0.709319 | 0.939405 | NaN | NaN | 0.638213 | 0.411221 | 0.601933 | NaN | NaN | 0.443257 | NaN | 0.539844 | 0.574046 | 0.694340 | 0.787654 | NaN | 0.454468 |
| **R** | 0.598129 | 1.000000 | NaN | -0.579554 | -0.597639 | 0.597636 | NaN | 0.662475 | NaN | NaN | 0.464513 | 0.669415 | 0.997958 | NaN | NaN | 0.760924 | 0.656164 | 0.829521 | 0.913154 | 0.727238 | 0.677080 | NaN | NaN |
| **#a-tA-S** | 0.523908 | NaN | 1.000000 | -0.506384 | -0.524218 | 0.523954 | NaN | 0.537596 | 0.412276 | 0.404007 | 0.505135 | NaN | NaN | NaN | NaN | NaN | NaN | 0.427604 | 0.425478 | 0.436392 | 0.490762 | NaN | 0.529812 |
| **Rk** | -0.972901 | -0.579554 | -0.506384 | 1.000000 | 0.972866 | -0.972974 | 0.689855 | -0.910728 | NaN | NaN | -0.636945 | NaN | -0.582641 | NaN | NaN | -0.418073 | NaN | -0.525382 | -0.553458 | -0.669772 | -0.765465 | NaN | -0.444030 |
| **L** | -0.999743 | -0.597639 | -0.524218 | 0.972866 | 1.000000 | -0.999928 | 0.709620 | -0.939181 | NaN | NaN | -0.638587 | -0.410253 | -0.601045 | NaN | NaN | -0.442725 | NaN | -0.540106 | -0.573588 | -0.693690 | -0.788067 | NaN | -0.453437 |
| **WL** | 0.999924 | 0.597636 | 0.523954 | -0.972974 | -0.999928 | 1.000000 | -0.709821 | 0.939384 | NaN | NaN | 0.638518 | 0.410727 | 0.601256 | NaN | NaN | 0.442891 | NaN | 0.539700 | 0.573606 | 0.693871 | 0.787814 | NaN | 0.453718 |
| **RA** | -0.709319 | NaN | NaN | 0.689855 | 0.709620 | -0.709821 | 1.000000 | -0.728040 | NaN | NaN | -0.438417 | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | -0.499883 | NaN | NaN |
| **Rdiff** | 0.939405 | 0.662475 | 0.537596 | -0.910728 | -0.939181 | 0.939384 | -0.728040 | 1.000000 | NaN | NaN | 0.646474 | 0.435025 | 0.667417 | NaN | NaN | 0.478963 | NaN | 0.592012 | 0.626338 | 0.743122 | 0.836628 | NaN | 0.454272 |
| **BatAge** | NaN | NaN | 0.412276 | NaN | NaN | NaN | NaN | NaN | 1.000000 | NaN | NaN | NaN | NaN | NaN | -0.442867 | NaN | NaN | NaN | NaN | NaN | NaN | NaN | 0.481435 |
| **PAge** | NaN | NaN | 0.404007 | NaN | NaN | NaN | NaN | NaN | NaN | 1.000000 | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | 0.478674 |
| **#A-S** | 0.638213 | 0.464513 | 0.505135 | -0.636945 | -0.638587 | 0.638518 | -0.438417 | 0.646474 | NaN | NaN | 1.000000 | NaN | 0.464636 | NaN | NaN | NaN | NaN | 0.424077 | 0.468880 | 0.560244 | 0.615391 | NaN | 0.411121 |
| **HR** | 0.411221 | 0.669415 | NaN | NaN | -0.410253 | 0.410727 | NaN | 0.435025 | NaN | NaN | NaN | 1.000000 | 0.671364 | NaN | NaN | 0.964895 | NaN | NaN | 0.556925 | 0.557255 | 0.476682 | NaN | NaN |
| **RTotal** | 0.601933 | 0.997958 | NaN | -0.582641 | -0.601045 | 0.601256 | NaN | 0.667417 | NaN | NaN | 0.464636 | 0.671364 | 1.000000 | NaN | NaN | 0.762354 | 0.657474 | 0.831015 | 0.914340 | 0.729759 | 0.680214 | NaN | NaN |
| **SB** | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | 1.0 | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| **K.** | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | -0.442867 | NaN | NaN | NaN | NaN | NaN | 1.000000 | NaN | -0.695876 | -0.521348 | NaN | NaN | NaN | NaN | NaN |
| **ISO** | 0.443257 | 0.760924 | NaN | -0.418073 | -0.442725 | 0.442891 | NaN | 0.478963 | NaN | NaN | NaN | 0.964895 | 0.762354 | NaN | NaN | 1.000000 | NaN | 0.427667 | 0.663669 | 0.590253 | 0.534435 | NaN | NaN |
| **AVG** | NaN | 0.656164 | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | 0.657474 | NaN | -0.695876 | NaN | 1.000000 | 0.828894 | 0.793582 | 0.487247 | 0.450136 | NaN | NaN |
| **OBP** | 0.539844 | 0.829521 | 0.427604 | -0.525382 | -0.540106 | 0.539700 | NaN | 0.592012 | NaN | NaN | 0.424077 | NaN | 0.831015 | NaN | -0.521348 | 0.427667 | 0.828894 | 1.000000 | 0.927738 | 0.668301 | 0.654707 | NaN | 0.434960 |
| **wOBA** | 0.574046 | 0.913154 | 0.425478 | -0.553458 | -0.573588 | 0.573606 | NaN | 0.626338 | NaN | NaN | 0.468880 | 0.556925 | 0.914340 | NaN | NaN | 0.663669 | 0.793582 | 0.927738 | 1.000000 | 0.759195 | 0.703049 | NaN | 0.406616 |
| **wRC.** | 0.694340 | 0.727238 | 0.436392 | -0.669772 | -0.693690 | 0.693871 | NaN | 0.743122 | NaN | NaN | 0.560244 | 0.557255 | 0.729759 | NaN | NaN | 0.590253 | 0.487247 | 0.668301 | 0.759195 | 1.000000 | 0.859277 | NaN | NaN |
| **WAR** | 0.787654 | 0.677080 | 0.490762 | -0.765465 | -0.788067 | 0.787814 | -0.499883 | 0.836628 | NaN | NaN | 0.615391 | 0.476682 | 0.680214 | NaN | NaN | 0.534435 | 0.450136 | 0.654707 | 0.703049 | 0.859277 | 1.000000 | NaN | 0.419931 |
| **Population** | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | 1.000000 | 0.407611 |
| **Attendance** | 0.454468 | NaN | 0.529812 | -0.444030 | -0.453437 | 0.453718 | NaN | 0.454272 | 0.481435 | 0.478674 | 0.411121 | NaN | NaN | NaN | NaN | NaN | NaN | 0.434960 | 0.406616 | NaN | 0.419931 | 0.407611 | 1.000000 |

# Feature Scaling

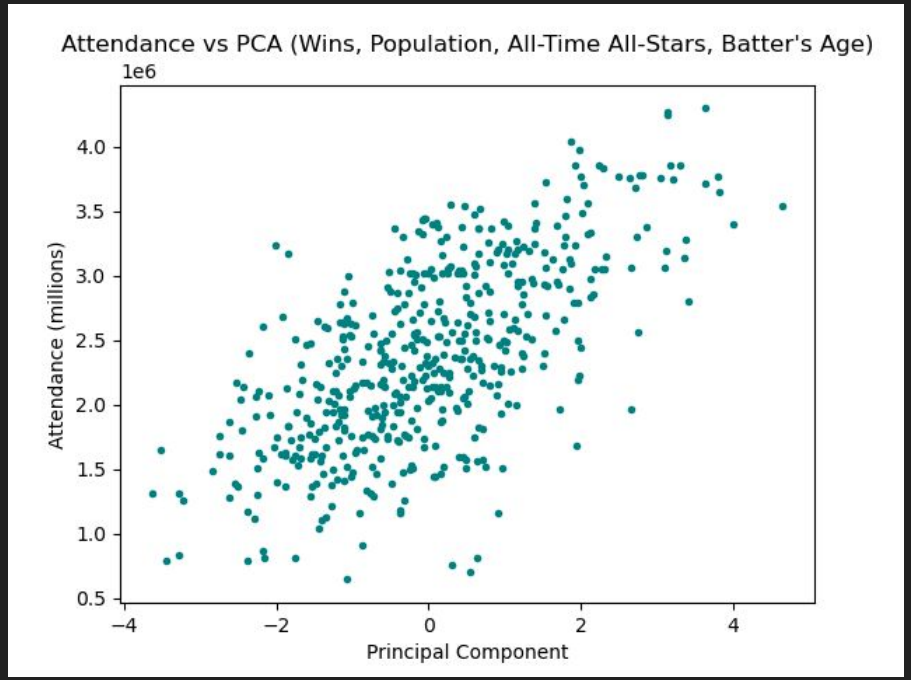
- In order to use some of our modeling techniques feature scaling was necessary to normalize the data
- Fortunately, the vast majority of our data was normally distributed
- This allowed for simple Z-score standardization of our data




* Example pre-processing EDA visualization, not intended to display results. Further visualizations showed normal distribution of metrics we used that are poorly visualized on this graphic

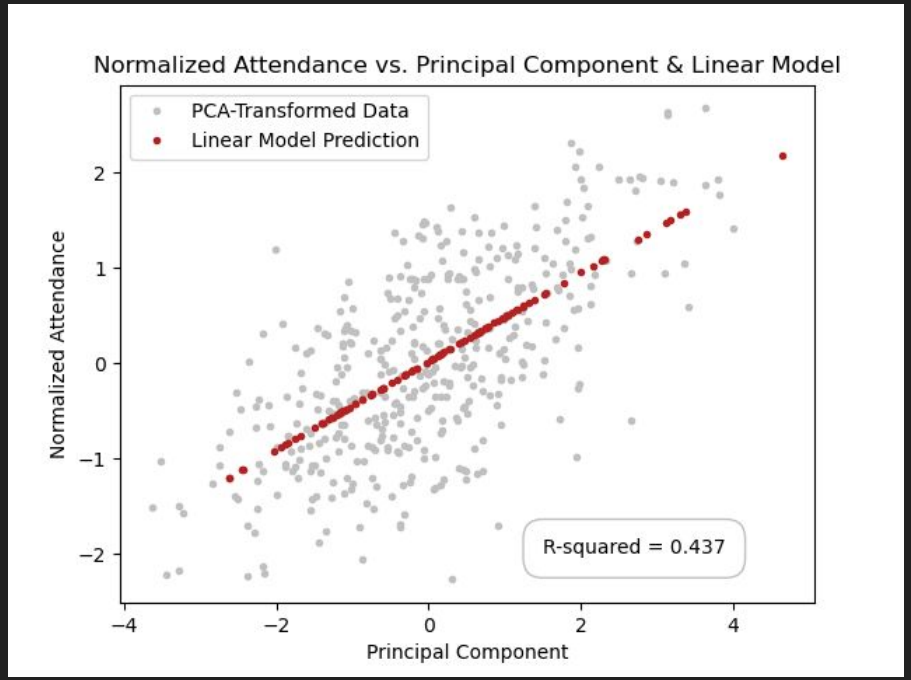
# Principal Component Analysis

- PCA is our method of choice for dimensionality reduction
- Using the correlation matrix, we determined the features that had the highest correlation with attendance
- The features we used for our PCA were population, wins, all-time All-Stars, and batter's age
- We decomposed these four features down into a single principal component, which we used to perform regression



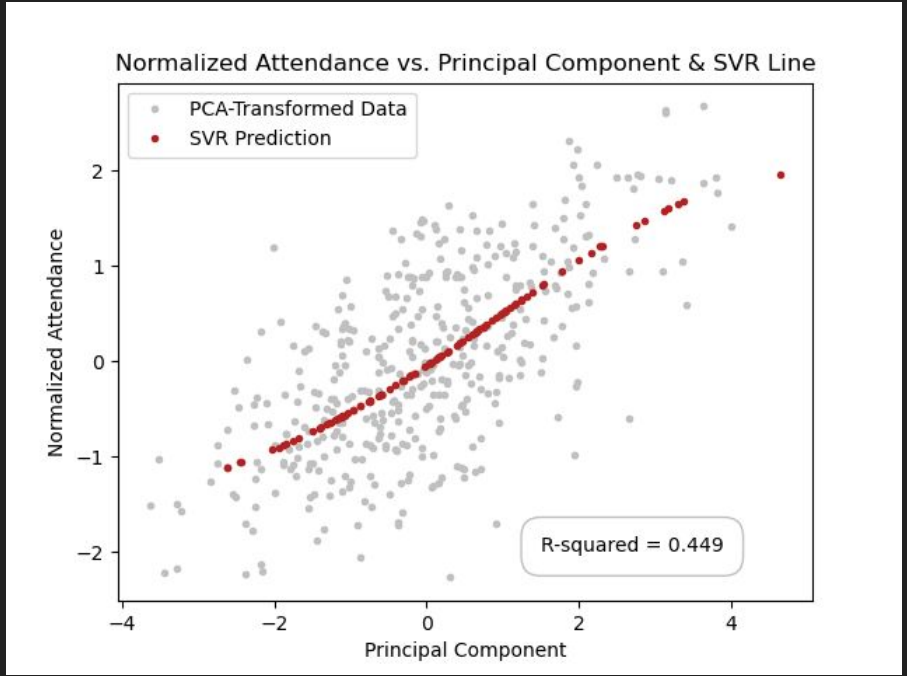
# PCA-Transformed Linear Regression

- Wanted to revisit linear regression with the PCA-transformed data
- Got much better results with normalized data, and a wider variety of features
- R-squared of 0.437, while still low, was better than the initial regression model



# Support Vector Regression

- Tried a handful of kernels, had best results with RBF
- Looped through combinations of C and gamma, eventually getting our highest accuracy with C=20 and gamma=0.04
- R-squared of 0.449 while less than ideal makes sense given the large amount of noise in attendance data



# Our Model of Choice

- The best model we built for predicting attendance was our Support Vector Regression model utilizing Principle Component data
- While the R-squared wasn’t as big as hoped, the model is still moderately strong, and outperformed the other regression models
- While the classification models with K-Means gave us some interesting observations, our SVR was by far most effective in predicting attendance
- Given the similar accuracies of our SVR and PCA-transformed linear regression models, the latter might be preferable if complexity/interpretability is a concern.

# Conclusions

- Clustering models show evidence that there is a plateau around the “54%” mark
  - Also, benefits teams hunting for expanded playoff starts
- Simple linear regression and the correlation matrix suggests that there is correlation from a number of rule change targets
  - Stolen bases
  - Balls in play (also affected attendance more than runs or power related statistics)
  - Game time
- Our final model shows that total number of all star appearances and  player age have a large impact on attendance suggesting that name recognition has a considerable effect on attendance that may be undervalued by MLB front offices

# Primary Questions and Project Goals Revisited

- Does offensive play have a greater impact on per game attendance than defensive play?
  - **Yes, but only marginally per our basic linear models**
- Does it make sense for teams to aim for ‘just good enough’, or are there consistent marginal returns for more investment in players?
  - **At the Playoff Contender and Title Contender levels, there is little difference in attendance. Attendance does increase at the elite level**
- How big of a role does local population play on game attendance?
  - **Population does have an effect on game attendance, though this feature is hard to gauge accurately**

# Primary Questions and Project Goals Revisited

- What factors beside population have the greatest impact on per game attendance?
  - **Per the correlation matrix and SVR, batter's age, wins, and all-time All-Stars have the greatest impact on attendance, indicating that name recognition is a factor in attendance**
- Can we predict a team's season attendance given their in games statistical projections?
  - **Our best model is SVR using a PCA decomposed from win count, batter's age, population and all-time All-Stars, which should allow us to predict somewhat accurately, though this can be improved with more non-collinear features**
- How should MLB front offices spend in free agency if they want to increase attendance?
  - **MLB front offices should invest in player's with higher name recognition as this seems to have the greatest effect on game attendance**

# Limitations of Our Data

- MLB attendance data is inherently noisy
  - There are only 30 teams and many teams have unique factors affecting their attendance that can be difficult to capture (stadium quality, team history, local interest in baseball). This also makes it difficult to account for outliers
  - Public interest in MLB goes has varied for a litany of reasons including things like negative press causing attendance dips after the steroid era, and the fallout of the pandemic
- There is no perfect way to capture the geographic and demographic influences on team fan bases and potential attendees
  - Some teams share geographic markets whereas others have entire regions to themselves
  - Some teams have more of a national audience and better branding than others
- Similarly there is no perfect way to capture access to ballparks and the influence of surrounding communities
  - Neighborhoods and access to stadiums are variable
  - Public transport and traffic can play a role in people attending games

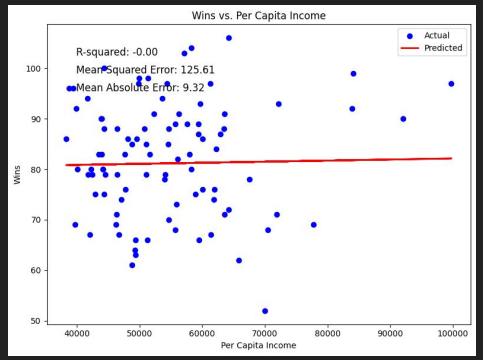
# Avenues for Future Research

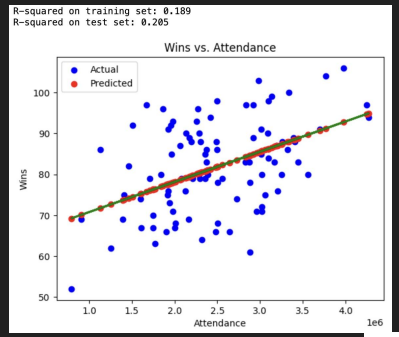
- To address many of the concerns with our data, many more advanced models could be implemented to more accurately account for the large variance in MLB attendances
  - Creating a complex model analyzing population and potential fans in surrounding regions that could account for larger issues
  - Finding more ways to adjust for league wide trends created by non baseball related influences
  - Creating a model to better address stadium quality and accessibility issues
- With the knowledge that established players appear to draw more fans, further research could be done on name recognition that could also incorporate roster turnover

# Extra Analysis

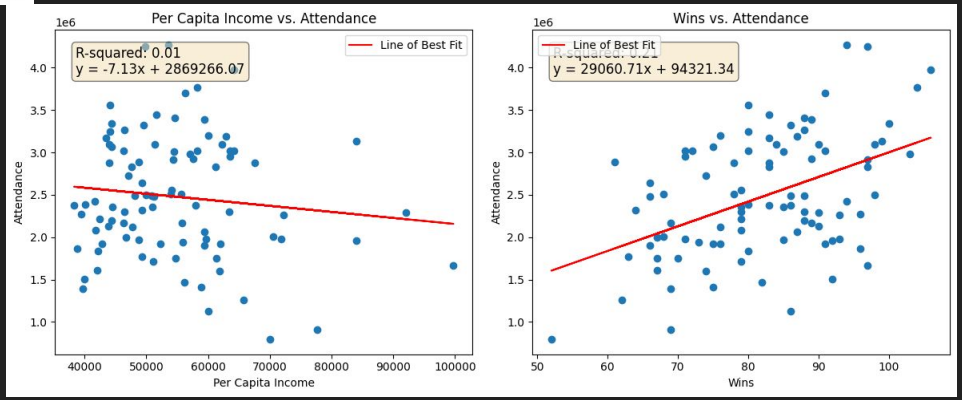
# Game Attendance, Per Capita Income, and Game Wins

- These graphs depict the relationship among variables such as per capita income, wins, and attendance. Below, the correlation matrix provides further details.



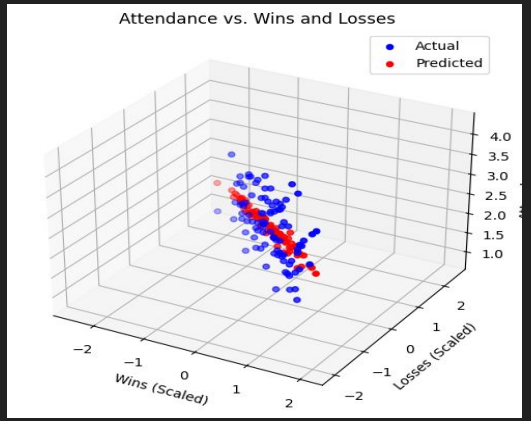

```
Correlation Matrix:
                  Per.Capita.Income         W  Attendance
Per.Capita.Income           1.000000  0.030943   -0.146347
W                           0.030943  1.000000    0.438560
Attendance                 -0.146347  0.438560    1.000000
```



# Attendance vs. Wins and Losses

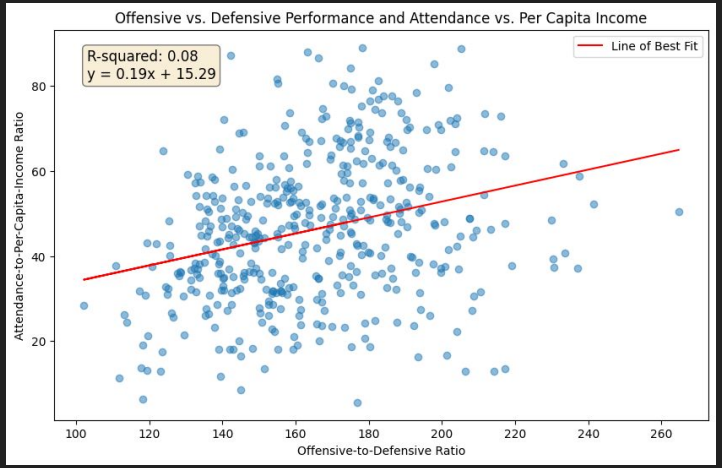
- This is a interesting thing to look at because of many factors. The R-squared 0.22 which show a moderate level of explanation.

```
R-squared: 0.22
Mean Squared Error: 399500473620.53
Cross-validation scores: [ 0.32729033 -0.26179479  0.22219672  0.058070
03  0.09173052]
Average cross-validation score: 0.09
```



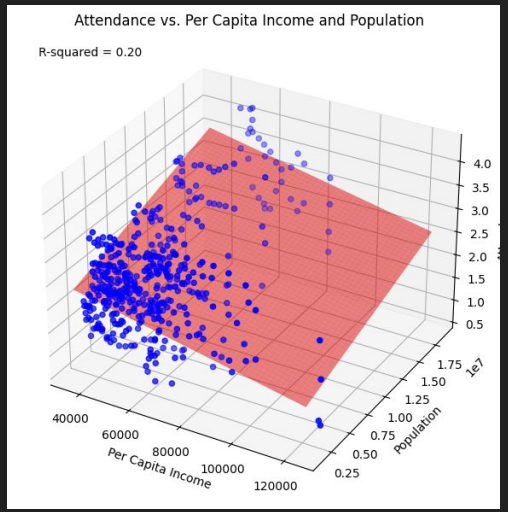
# Offensive-Defensive ratio divided by Attendance/Per Capita Income

- This is quite tentative, but with additional data, we could make into a more confident statement. There is a weak relation between these. The amount of data that is usable so if it was bigger it would be better.



# Attendance, Per Capita, and Population

- This observation is somewhat tentative, yet it displays a moderate level of explanatory capability. It's intriguing because it sheds light on our socioeconomic system and related aspects. Its R-Squared score of 0.20 which is a moderate level of explanatory power.



# Little Interesting Things I found…

- The R-squared for Per Capita Income vs. the Runs Scored is 0.00
- The R-squared for the Attendance Ratio vs Per Capita is 0.03

# Questions?