Final Executive Summary

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Our Research Question

Research Question: What are the most important and influential variables when trying to predict a Major League Baseball position players' first year arbitration salary?

Introduction and Important Baseline Information

To understand all the details of this study and to recognize what we are trying to predict, it is important to go over a few key concepts. The concepts include how MLB service time works, how the arbitration process works, and the definitions of the variables we will be using to predict arbitration salary.

Players receive Major League service time for each day spent on the 26-man Major League roster. Service time is used to determine when players are eligible for salary arbitration. Each Major League regular season consists of 187 days and each day spent on the active roster or injured list earns a player one day of service time. A player is deemed to have reached one year of Major League service upon accruing 172 days in a given year.

All players with between three and six years of Major League service time become eligible for salary arbitration. They can earn substantial raises relative to the Major League minimum salary. Also, Major League Baseball each year identifies the group of players that ended the prior season with between two and three years of Major League service. If a player has accumulated at least 86 days of Major League service in that season and designates in the top 22 percent, in terms of service team compared to the whole league, they will also be eligible for salary arbitration despite not having three years of service time. This was put in place to increase the likelihood of players receiving raises earlier in their playing careers.

It is completely possible for a team and a player to agree on a salary without ever having to deal with arbitration. But, if the club and player have not agreed on a salary by a deadline in mid-January, the club and player must exchange salary figures for the upcoming season. After the figures are exchanged, a hearing is scheduled in February. If no one-year or multi-year settlement can be reached by the hearing date, the case is brought before a panel of arbitrators. After hearing arguments from both sides, the panel selects either the salary figure of either the player or the club, not one in between, as the player's salary for the upcoming season. Now that service time and arbitration have been explained, it is important to know what each of the variables (baseball statistics) we will be looking at to predict salary. The following variables will be used in the model with the abbreviation and formula/definition listed next to it as well:

Batting Average (BA) = Hits / At Bats

On Base Percentage (OBP) = (Hits + Walks + Hit By Pitches) / Plate Appearances

Home Runs (HR) Includes over the fence and inside the park home runs

Runs Batted In (RBI)

Runs Scored (R)

Slugging Percentage (SLG)

= No. of Singles + (2 x (No. of Doubles)) + (3 x (No. of Triples)) + (4 x (No. of Home Runs)) / (At Bats)

On Base + Slugging Percentage (OPS) = OBP + SLG

Stolen Bases (SB)

Plate Appearances (PA)

Strikeout Percentage (K%, Kper in R) = Strikeouts / PA

Walk Percentage (BB%, BBper in R) = Walks / PA

Defensive Runs Saved (DRS) The number of runs above or below average the player was worth based on the number of plays made

Our data set consists of a collection of players from 2017-2021 who received first year salary arbitration. Their salaries were included in the data set and were compared to the previously mentioned variables.

Methodology

To identify what the most influential variables were, we used excel's data analysis toolpak for regression (since we are using multiple linear regression) and compared the adjusted R2and R values (for correlation and pos/neg relationship), and the p values for each variable compared to salary (which would allow us to determine if there is indeed a significant linear relationship between y (explanatory variable) and x (salary)). If the p-values were extremely low (e.g. 2.91674*10^(-6)) then we could conclude that there is a significant linear relationship between that variable and salary. If p-values were relatively high (over 0.05 (alpha)), then there would be a better chance that there is not enough evidence to prove that there is a sig. Linear relationship (NOTE: does not mean that there isn't, means that we don't have enough evidence to prove that outright).

So, after doing all that, we kept the variables with the highest correlation values and lowest p-values, as those go hand-in-hand.

Note: we used a 95% confidence level for these tests

Calculations, Graphs, Test Statistics, and Conclusions

```r
library(ggplot2)
```

```r
baseball = read.csv('DS Proposal - Sheet1.csv')
baseball
```

```
##                Player Salary First.Arbitration.Year    BA   OBP  HR RBI   R
## 1          Jose Abreu  10.83                   2017 0.299 0.360  91 308 235
## 2     George Springer   3.90                   2017 0.258 0.356  65 174 220
## 3     Cesar Hernandez   2.55                   2017 0.281 0.350   8  88 154
## 4     Tuffy Gosewisch   0.64                   2017 0.199 0.237   5  30  24
## 5      Derek Dietrich   1.70                   2017 0.251 0.338  31 106 140
## 6  Jackie Bradley Jr.   3.60                   2017 0.237 0.316  40 170 200
## 7          Sandy Leon   1.30                   2017 0.254 0.319   8  43  53
## 8        Caleb Joseph   0.70                   2017 0.213 0.271  20  77  67
```

```
## 9      Jake Marisnick   1.10                        2017 0.225 0.268  18  81 113
## 10        Jesus Sucre   0.63                        2017 0.209 0.246   2  20  18
## 11        Tim Beckham   0.89                        2017 0.238 0.288  14  54  50
## 12     Ehire Adrianza   0.60                        2017 0.220 0.292   3  26  27
## 13    Kevin Kiermaier   2.98                        2017 0.258 0.313  32 112 152
## 14        Kris Bryant  10.85                        2018 0.288 0.388  94 274 319
## 15      Maikel Franco   2.95                        2018 0.247 0.300  63 219 183
## 16           Ryan Rua   0.87                        2018 0.246 0.305  17  55  78
## 17    Addison Russell   3.20                        2018 0.240 0.312  46 192 179
## 18     Yolmer Sanchez   2.35                        2018 0.242 0.286  21 116 124
## 19        Matt Szczur   0.95                        2018 0.237 0.318  11  55  69
## 20       Devon Travis   1.45                        2018 0.292 0.331  24 109 114
## 21       Byron Buxton   1.75                        2019 0.237 0.292  38 145 185
## 22        Curt Casali   0.95                        2019 0.223 0.302  23  65  63
## 23      Brandon Drury   1.30                        2019 0.264 0.314  32 134 108
## 24      Austin Hedges   2.06                        2019 0.210 0.258  35 104  80
## 25   Travis Jankowski   1.17                        2019 0.242 0.319   8  42 117
## 26         Max Kepler   3.13                        2019 0.233 0.313  56 190 199
## 27       Nomar Mazara   3.30                        2019 0.258 0.320  60 242 184
## 28        Jose Peraza   2.78                        2019 0.282 0.319  22 121 163
## 29     Kevin Plawecki   1.14                        2019 0.218 0.308  14  75  68
## 30       Trevor Story   5.00                        2019 0.268 0.333  88 262 223
## 31      Blake Swihart   0.91                        2019 0.256 0.314   8  54  85
## 32        Trea Turner   3.73                        2019 0.289 0.346  44 159 236
## 33       Tony Wolters   0.96                        2019 0.226 0.322   6  73  76
## 34     Cody Bellinger  11.50                        2020 0.278 0.368 111 288 292
## 35      Johan Camargo   1.70                        2020 0.269 0.328  30 135 124
## 36         David Dahl   2.48                        2020 0.297 0.346  38 133 140
## 37       JaCoby Jones   1.58                        2020 0.211 0.276  25  75 110
## 38       Andrew Knapp   0.71                        2020 0.223 0.327   9  36  57
## 39     Hunter Renfroe   3.30                        2020 0.235 0.294  89 204 176
## 40   Daniel Robertson   1.03                        2020 0.231 0.340  16  72  91
## 41   Giovanny Urshela   2.48                        2020 0.269 0.313  29 113 119
## 42      J.P. Crawford   2.05                        2021 0.231 0.325  12  88 101
## 43         J.D. Davis   2.10                        2021 0.268 0.346  33  88 108
## 44      Clint Frazier   2.10                        2021 0.258 0.331  24  82  80
## 45       Carson Kelly   1.70                        2021 0.221 0.305  23  76  64
## 46 Isiah Kiner-Falefa   2.00                        2021 0.260 0.319   8  65  94
## 47  Anthony Santander   2.10                        2021 0.252 0.292  32  99  79
## 48      Austin Slater   1.15                        2021 0.258 0.346  14  67  74
## 49      Dominic Smith   2.55                        2021 0.258 0.317  35 104  93
## 50          Juan Soto   8.50                        2021 0.295 0.415  69 217 226
## 51    Jacob Stallings   1.30                        2021 0.262 0.327   9  41  44
## 52     Gleyber Torres   4.00                        2021 0.271 0.340  65 183 167
## 53   Daniel Vogelbach   1.40                        2021 0.206 0.332  40 107  98
## 54          Luke Voit   4.70                        2021 0.274 0.363  62 168 161
##      SLG   OPS  SB   PA  Kper BBper DRS
## 1  0.515 0.875   3 1985 0.200 0.069 -14
## 2  0.460 0.816  30 1540 0.260 0.115  12
## 3  0.361 0.711  37 1330 0.196 0.093 -17
## 4  0.286 0.522   2  416 0.185 0.043  -1
## 5  0.422 0.760   3 1117 0.218 0.071 -20
## 6  0.409 0.726  22 1421 0.256 0.092  34
## 7  0.362 0.681   0  518 0.243 0.077   8
```

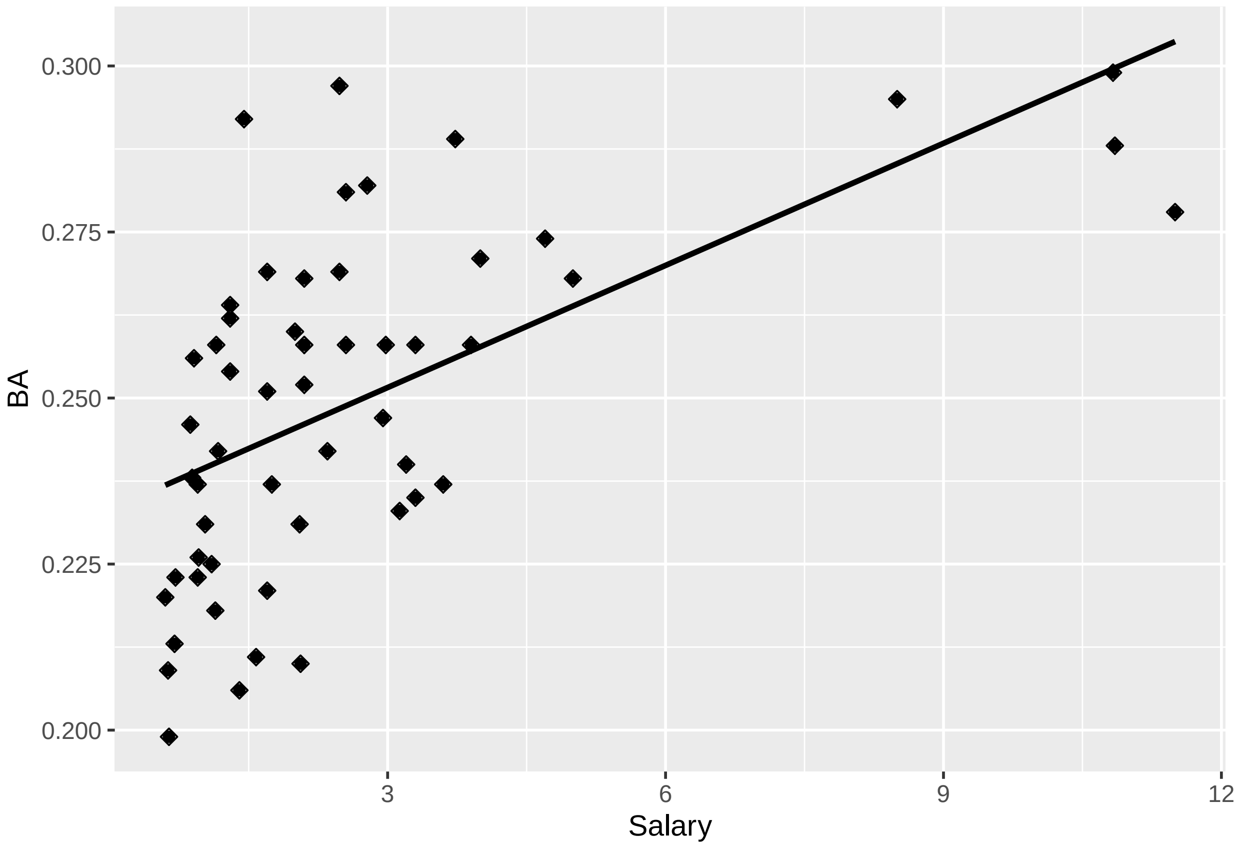
```
## 8  0.342 0.614   0  771 0.219 0.066  28
## 9  0.339 0.607  48 1038 0.272 0.046  53
## 10 0.276 0.522   0  264 0.167 0.038   4
## 11 0.431 0.720   5  446 0.305 0.061  -9
## 12 0.313 0.605   4  331 0.181 0.070  -1
## 13 0.425 0.738  44 1313 0.183 0.066  77
## 14 0.527 0.915  28 2014 0.239 0.123   3
## 15 0.426 0.726   2 1646 0.162 0.066 -18
## 16 0.388 0.693  12  608 0.293 0.066   1
## 17 0.408 0.719  11 1506 0.249 0.084  37
## 18 0.366 0.652  11 1221 0.212 0.051   9
## 19 0.368 0.686   4  583 0.187 0.098  -2
## 20 0.462 0.792  11  868 0.194 0.052  -3
## 21 0.414 0.706  60 1369 0.298 0.065  31
## 22 0.401 0.704   0  622 0.280 0.090   6
## 23 0.434 0.748   2 1124 0.206 0.061 -11
## 24 0.378 0.637   7  921 0.279 0.057  35
## 25 0.321 0.640  60  953 0.236 0.097  16
## 26 0.417 0.730  16 1633 0.187 0.098  28
## 27 0.425 0.746   3 1720 0.206 0.078 -22
## 28 0.381 0.700  70 1482 0.122 0.039 -15
## 29 0.330 0.638   1  804 0.218 0.095  15
## 30 0.530 0.862  42 1626 0.301 0.081  33
## 31 0.364 0.678  10  597 0.258 0.077 -17
## 32 0.456 0.803 124 1555 0.182 0.075   1
## 33 0.321 0.643   6  712 0.198 0.112  18
## 34 0.559 0.928  39 1841 0.220 0.124  38
## 35 0.438 0.765   2 1028 0.197 0.076   2
## 36 0.521 0.867  14  921 0.257 0.067 -12
## 37 0.369 0.645  26  982 0.319 0.061   9
## 38 0.336 0.663   2  579 0.314 0.126 -19
## 39 0.494 0.788  10 1450 0.281 0.072  27
## 40 0.352 0.692   5  831 0.252 0.116  -2
## 41 0.422 0.735   1  975 0.182 0.054  -8
## 42 0.359 0.683  14  853 0.212 0.111   7
## 43 0.448 0.795   4  863 0.234 0.096 -31
## 44 0.475 0.806   5  589 0.289 0.090  -9
## 45 0.396 0.701   0  625 0.205 0.099   3
## 46 0.351 0.670  18  846 0.169 0.066  12
## 47 0.467 0.759   2  709 0.198 0.049  11
## 48 0.388 0.735  16  648 0.276 0.102  -1
## 49 0.494 0.811   1  728 0.254 0.070 -12
## 50 0.557 0.972  23 1349 0.192 0.169 -11
## 51 0.372 0.699   1  425 0.224 0.085  21
## 52 0.493 0.834  12 1248 0.224 0.090 -15
## 53 0.409 0.741   0  840 0.266 0.154  -9
## 54 0.527 0.891   0 1029 0.262 0.109  -9
```

```r
summary(baseball)
```

```
##     Player              Salary       First.Arbitration.Year       BA
##  Length:54          Min.   : 0.600   Min.   :2017           Min.   :0.1990
##  Class :character   1st Qu.: 1.143   1st Qu.:2018           1st Qu.:0.2310
##  Mode  :character   Median : 2.025   Median :2019           Median :0.2515
```

```
##                      Mean   : 2.642   Mean   :2019           Mean   :0.2494
##                      3rd Qu.: 3.092   3rd Qu.:2020           3rd Qu.:0.2680
##                      Max.   :11.500   Max.   :2021           Max.   :0.2990
##       OBP                 HR              RBI               R
##  Min.   :0.2370   Min.   :  2.0   Min.   : 20.00   Min.   : 18.0
##  1st Qu.:0.3028   1st Qu.: 14.0   1st Qu.: 68.25   1st Qu.: 76.5
##  Median :0.3190   Median : 27.0   Median :104.00   Median :111.5
##  Mean   :0.3186   Mean   : 33.7   Mean   :118.81   Mean   :126.0
##  3rd Qu.:0.3367   3rd Qu.: 43.0   3rd Qu.:165.75   3rd Qu.:173.8
##  Max.   :0.4150   Max.   :111.0   Max.   :308.00   Max.   :319.0
##       SLG              OPS               SB                PA
##  Min.   :0.2760   Min.   :0.5220   Min.   :  0.00   Min.   : 264.0
##  1st Qu.:0.3625   1st Qu.:0.6787   1st Qu.:  2.00   1st Qu.: 663.2
##  Median :0.4090   Median :0.7230   Median :  6.50   Median : 937.0
##  Mean   :0.4127   Mean   :0.7314   Mean   : 16.17   Mean   :1026.2
##  3rd Qu.:0.4590   3rd Qu.:0.7910   3rd Qu.: 21.00   3rd Qu.:1364.0
##  Max.   :0.5590   Max.   :0.9720   Max.   :124.00   Max.   :2014.0
##       Kper            BBper              DRS
##  Min.   :0.1220   Min.   :0.03800   Min.   :-31.000
##  1st Qu.:0.1963   1st Qu.:0.06600   1st Qu.:-10.500
##  Median :0.2220   Median :0.07700   Median :  1.500
##  Mean   :0.2300   Mean   :0.08256   Mean   :  5.389
##  3rd Qu.:0.2615   3rd Qu.:0.09775   3rd Qu.: 15.750
##  Max.   :0.3190   Max.   :0.16900   Max.   : 77.000
```

```r
ggplot(data = baseball, aes(Salary, BA)) +
  geom_point(size=2, shape=23) +
           geom_smooth(method = "lm", se=FALSE, color="black", formula = y ~ x) +
           geom_point()
```



BA vs Salary

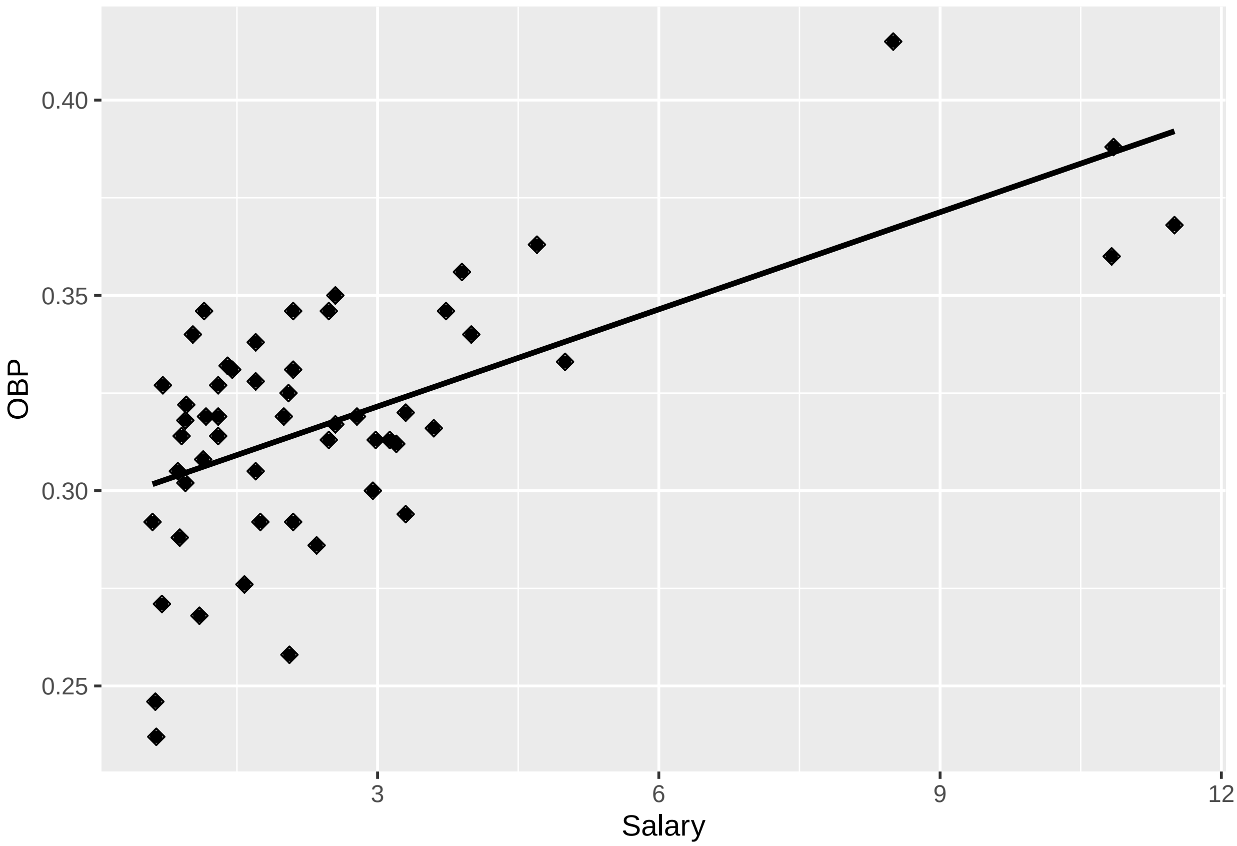
Equation for Line of Best Fit: y = 0.0061x + 0.233

Adjusted R-Squared:0.333 Interpretation: about one third of the salary values are explained by the observed values for batting average

R: 0.57706 Interpretation: between batting average and salary, there is a moderate positive relationship of .57706

p-value: 2.91674*10^(-6) Interpretation: We have more than enough evidence to conclude that there is a significant linear relationship between these two variables at any reasonable level of significance

```
ggplot(data = baseball, aes(Salary, OBP)) +
  geom_point(size=2, shape=23) +
            geom_smooth(method = "lm", se=FALSE, color="black", formula = y ~ x) +
            geom_point()
```



OBP Vs Salary

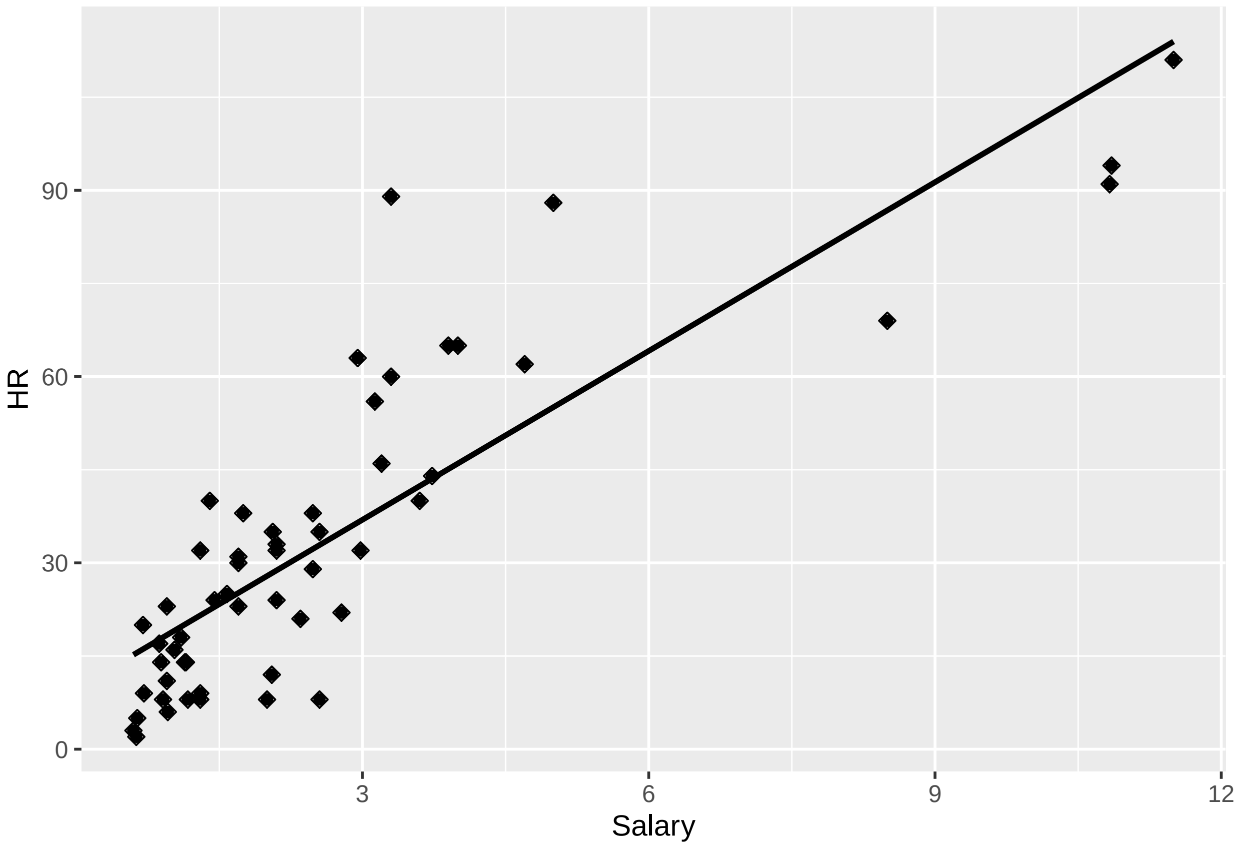
Equation for Line of Best Fit: y = 0.0085x + 0.2967

Adjusted R-Squared:0.3903 Interpretation: .3903 (39%) of the values for salary are explained by observed values for OBP

R: 0.6247 Interpretation: between OBP and salary, there is a moderate positive relationship of .6247

p-value: 2.65889*10^(-7) Inter: We have more than enough evidence to conclude that there is a significant linear relationship between these two variables at any reasonable level of significance

```
ggplot(data = baseball, aes(Salary, HR)) +
  geom_point(size=2, shape=23) +
            geom_smooth(method = "lm", se=FALSE, color="black", formula = y ~ x) +
            geom_point()
```



HR vs Salary

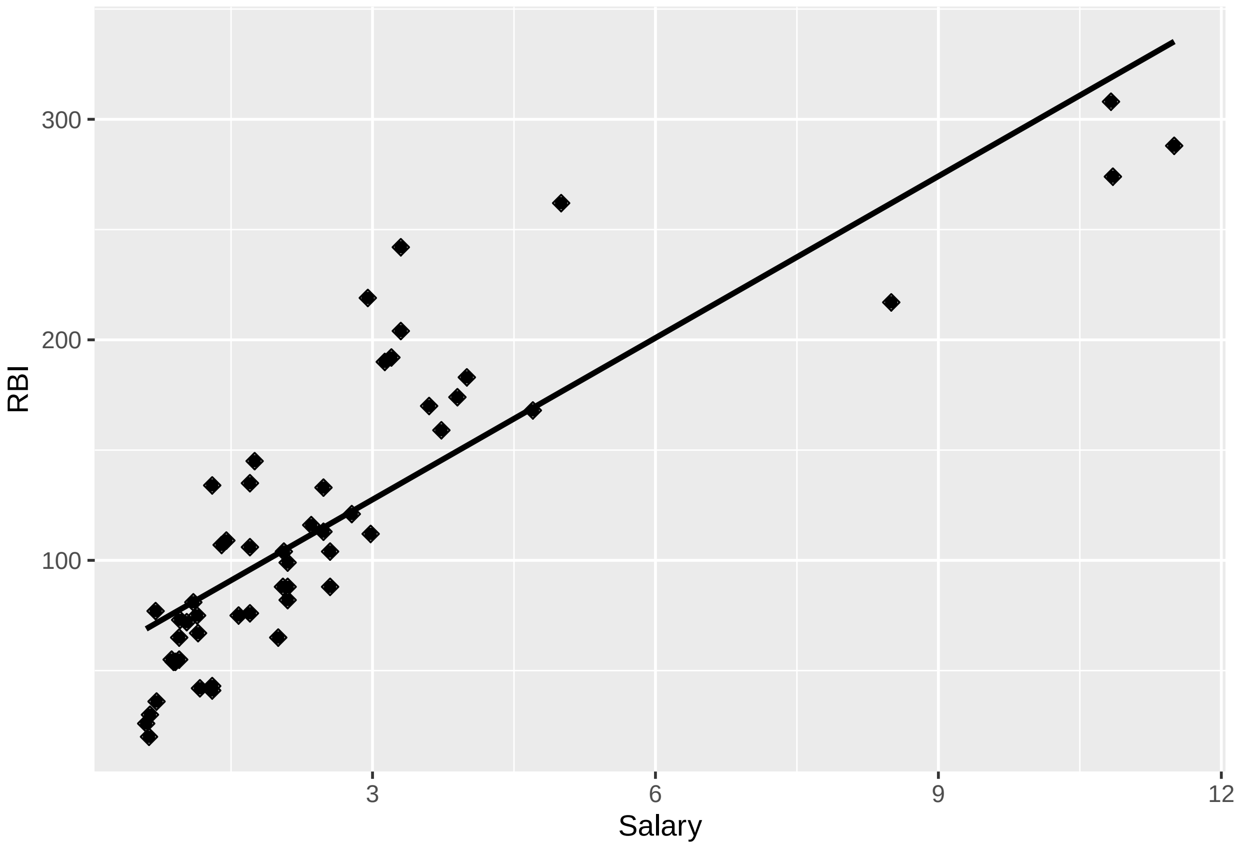
Equation for Line of Best Fit: y = 9.0603x + 9.7692

Adjusted R-Squared: 0.7151 Inter: about .7151 (71.5%) of the values for salary are explained by observed values for home runs

R: 0.8456 Inter: between HR and salary, there is a strong positive relationship of .8456

p-value: 5.1998*10^(-16) Inter: We have more than enough evidence to conclude that there is a significant linear relationship between these two variables at any reasonable level of significance

```
ggplot(data = baseball, aes(Salary, RBI)) +
  geom_point(size=2, shape=23) +
            geom_smooth(method = "lm", se=FALSE, color="black", formula = y ~ x) +
            geom_point()
```



RBI vs Salary

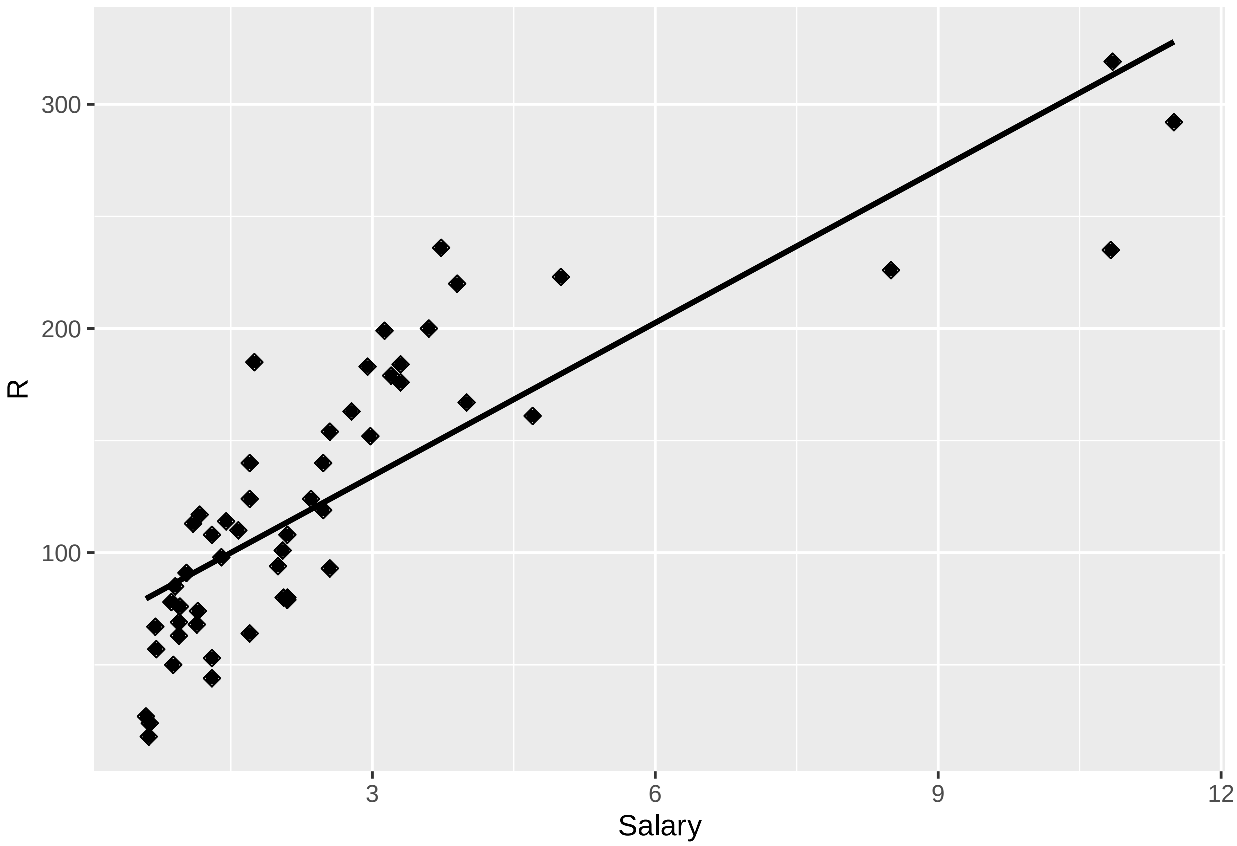
Equation for Line of Best Fit: y = 24.4347x + 54.2666

Adjusted R-Squared: 0.7174 Inter: about .7174 (71.7%) of values for salary are explained by observed values for RBI

R: 0.8470 Inter: between RBI and salary, there is a strong positive relationship of .8470

p-value: 4.19675*10^(-16) Inter: We have more than enough evidence to conclude that there is a significant linear relationship between these two variables at any reasonable level of significance

```
ggplot(data = baseball, aes(Salary, R)) +
  geom_point(size=2, shape=23) +
            geom_smooth(method = "lm", se=FALSE, color="black", formula = y ~ x) +
            geom_point()
```



R vs Salary

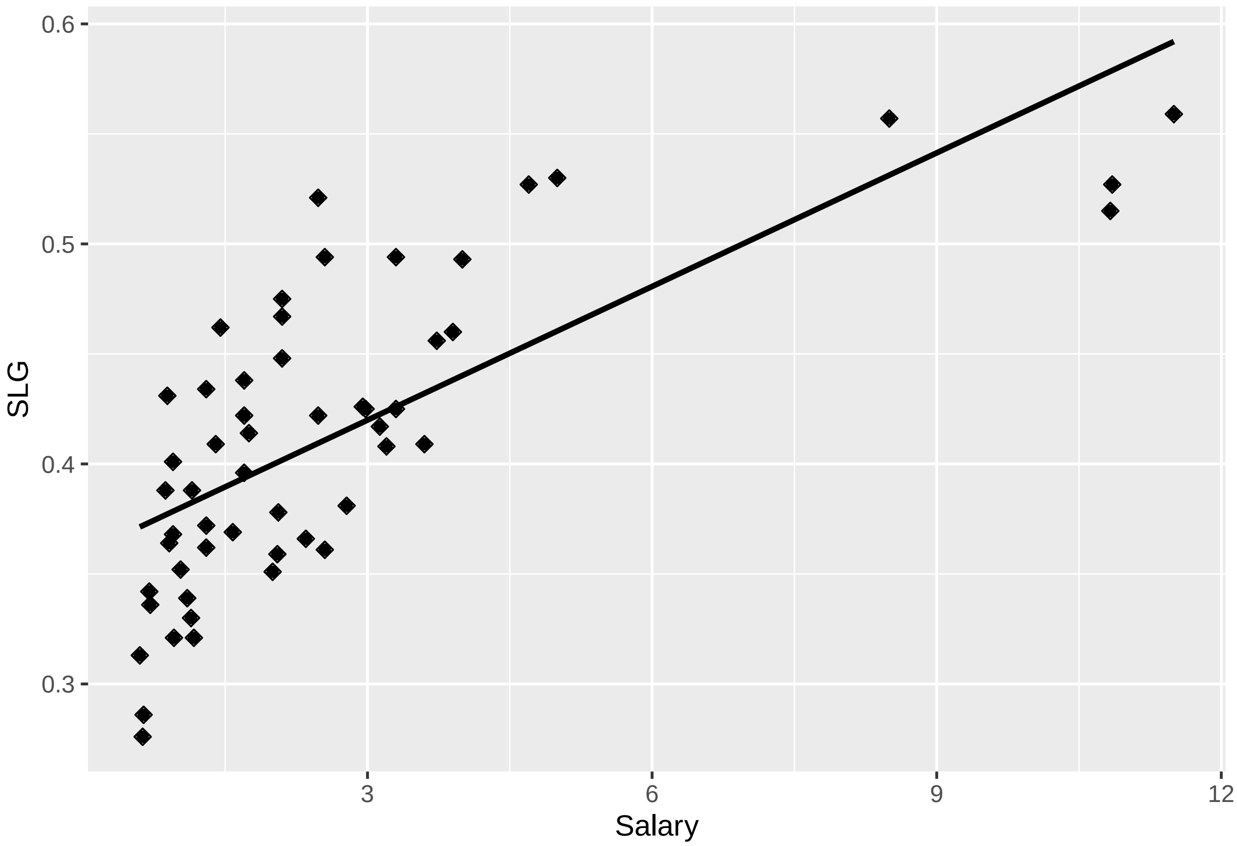
Equation for Line of Best Fit: y = 22.7884x + 65.8006

Adjusted R-Squared:0.6847 – about 68.5% of salary values are explained by observed values for runs

R: 0.8335 – between runs and salary, there is a strong positive relationship of .8335

p-value: 3.20004*10^(-15) – We have more than enough evidence to conclude that there is a significant linear relationship between these two variables at any reasonable level of significance

```
ggplot(data = baseball, aes(Salary, SLG)) +
  geom_point(size=2, shape=23) +
          geom_smooth(method = "lm", se=FALSE, color="black", formula = y ~ x) +
          geom_point()
```



SLG vs Salary

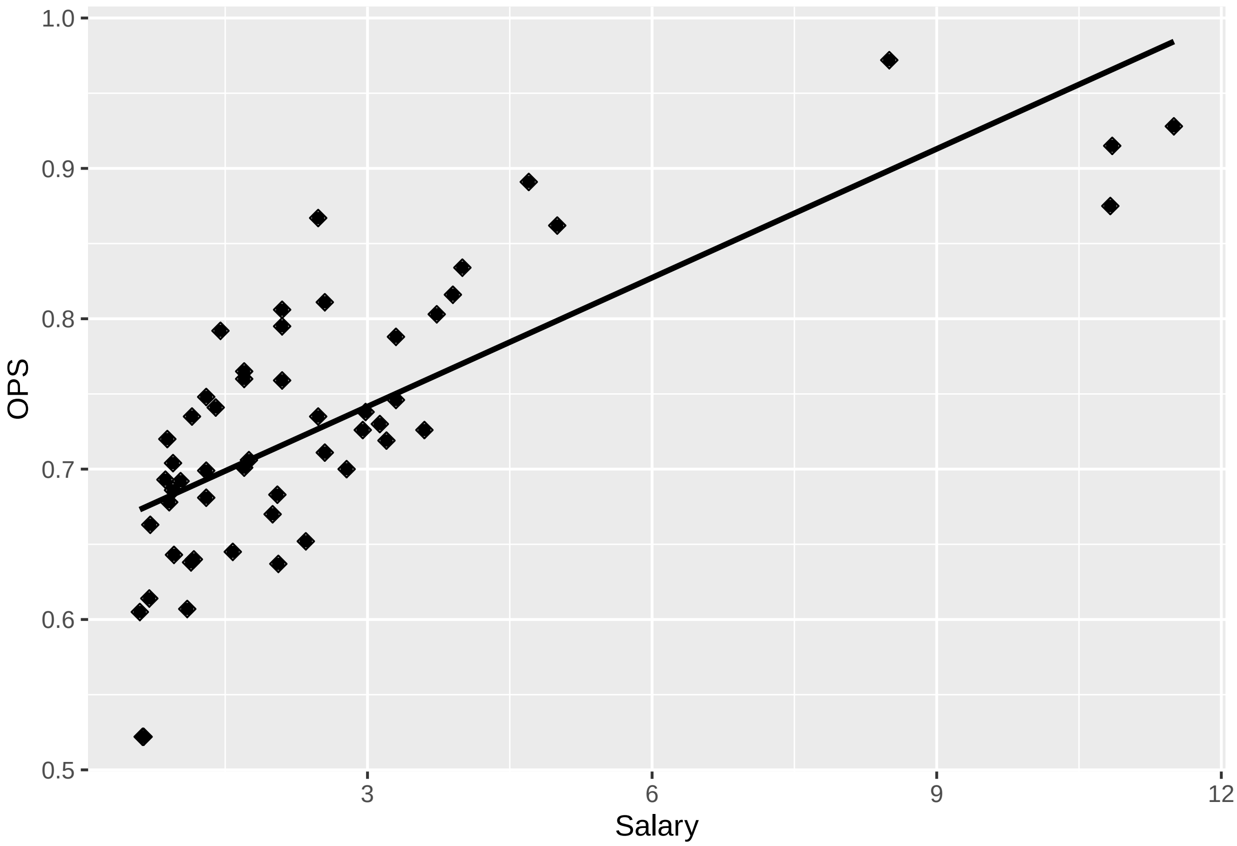
Equation for Line of Best Fit: y = 0.0202x + 0.3592

Adjusted R-Squared:0.5185 – about 51.9% of salary values are explained by observed values for SLG

R: 0.7201 – between slugging % and salary, there is a moderate to strong positive relationship of .7201

p-value: 5.07875*10^(-10) – We have more than enough evidence to conclude that there is a significant linear relationship between these two variables at any reasonable level of significance

```
ggplot(data = baseball, aes(Salary, OPS)) +
  geom_point(size=2, shape=23) +
            geom_smooth(method = "lm", se=FALSE, color="black", formula = y ~ x) +
            geom_point()
```



OPS vs Salary

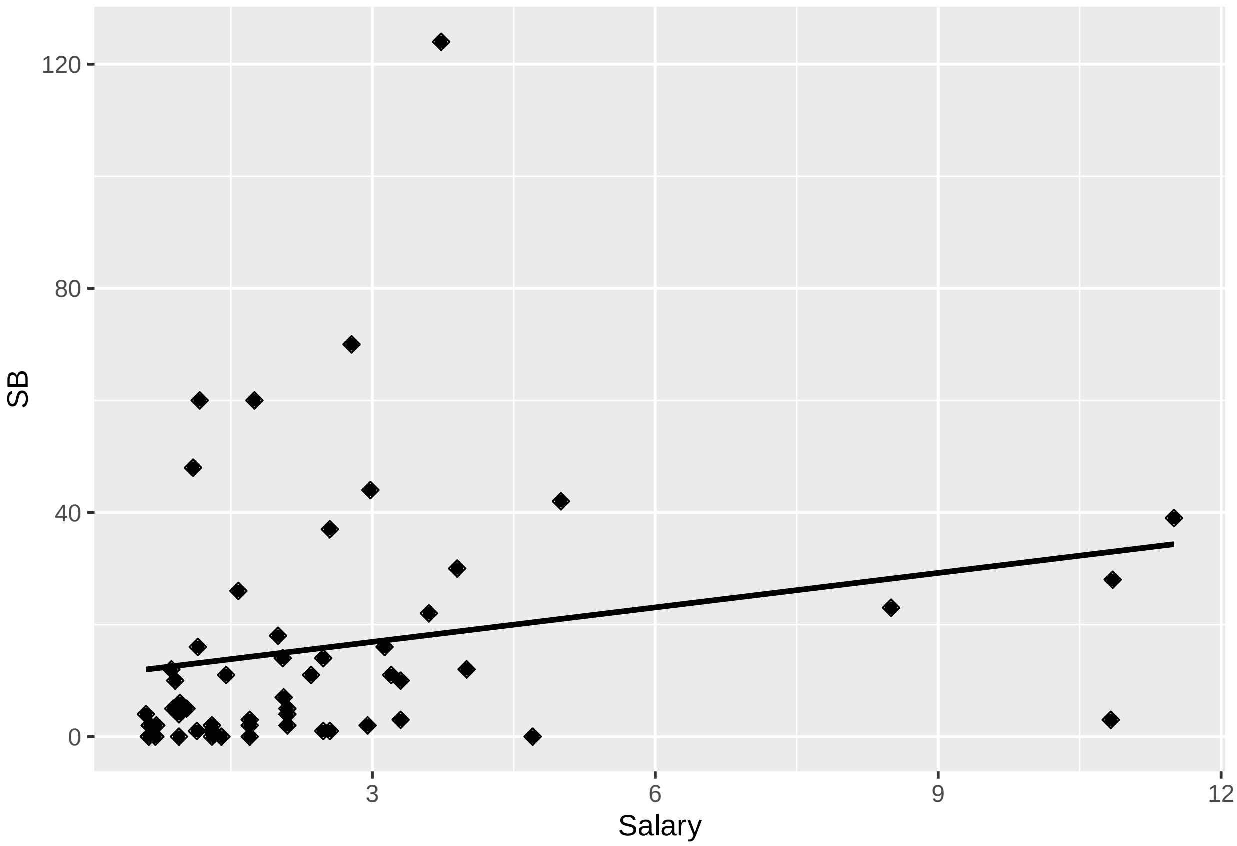
Equation for Line of Best Fit: y = 0.0286x + 0.656

Adjusted R-Squared:0.5644 – about 56.4% of salary values are explained by observed values for OPS

R: 0.7513 – between OPS and salary, there is a strong positive relationship of .7513

p-value: 3.61482*10^(-11) – We have more than enough evidence to conclude that there is a significant linear relationship between these two variables at any reasonable level of significance

```
ggplot(data = baseball, aes(Salary, SB)) +
  geom_point(size=2, shape=23) +
            geom_smooth(method = "lm", se=FALSE, color="black", formula = y ~ x) +
            geom_point()
```



SB vs Salary

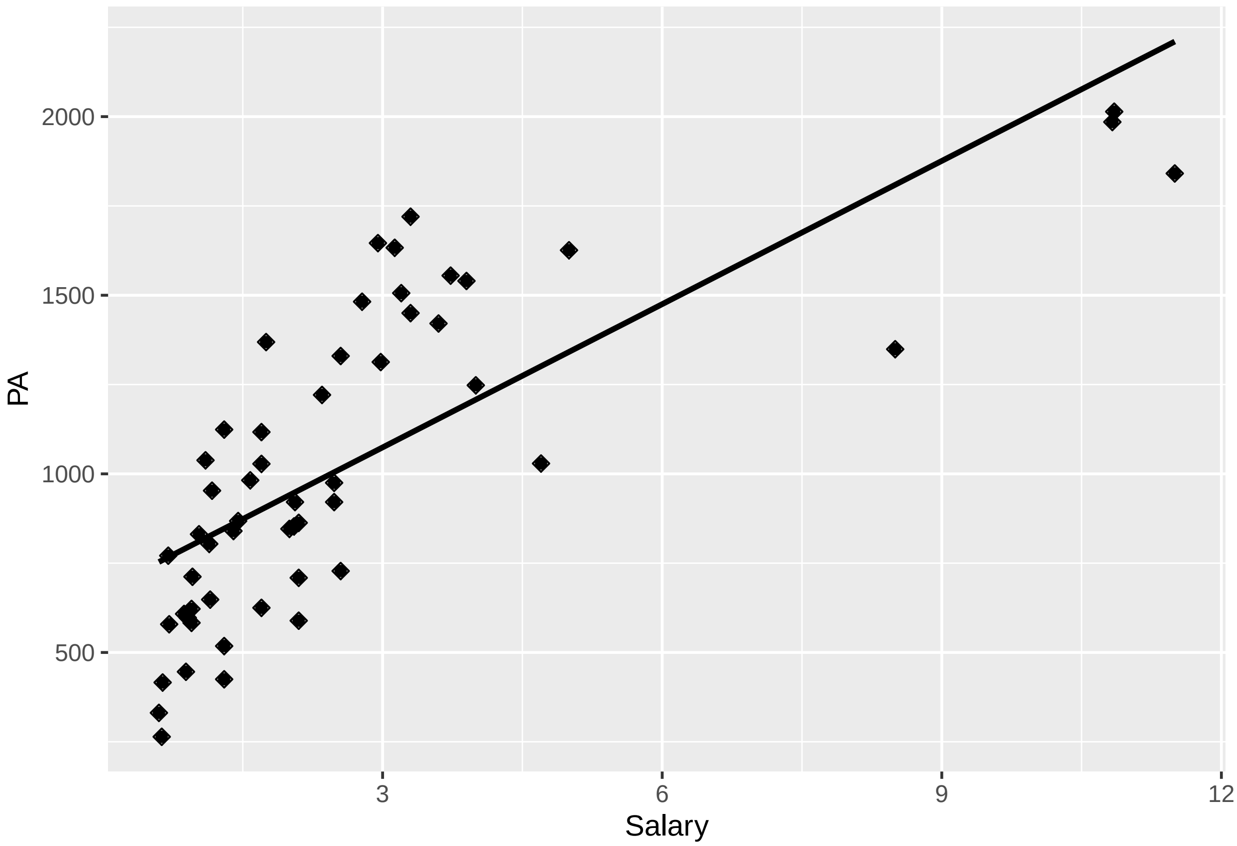
Equation for Line of Best Fit: 2.0513x + 10.7479

Adjusted R-Squared: 0.0311 – about 3.1% of salary values are explained by observed values for Stolen bases

R: 0.1764 – between SB and salary, there is a weak positive relationship of .1764

p-value: 0.106251966 – because the p-value is above our alpha of .05, we cannot conclude that there is a significant linear relationship between these variables

```
ggplot(data = baseball, aes(Salary, PA)) +
  geom_point(size=2, shape=23) +
            geom_smooth(method = "lm", se=FALSE, color="black", formula = y ~ x) +
            geom_point()
```



PA vs Salary

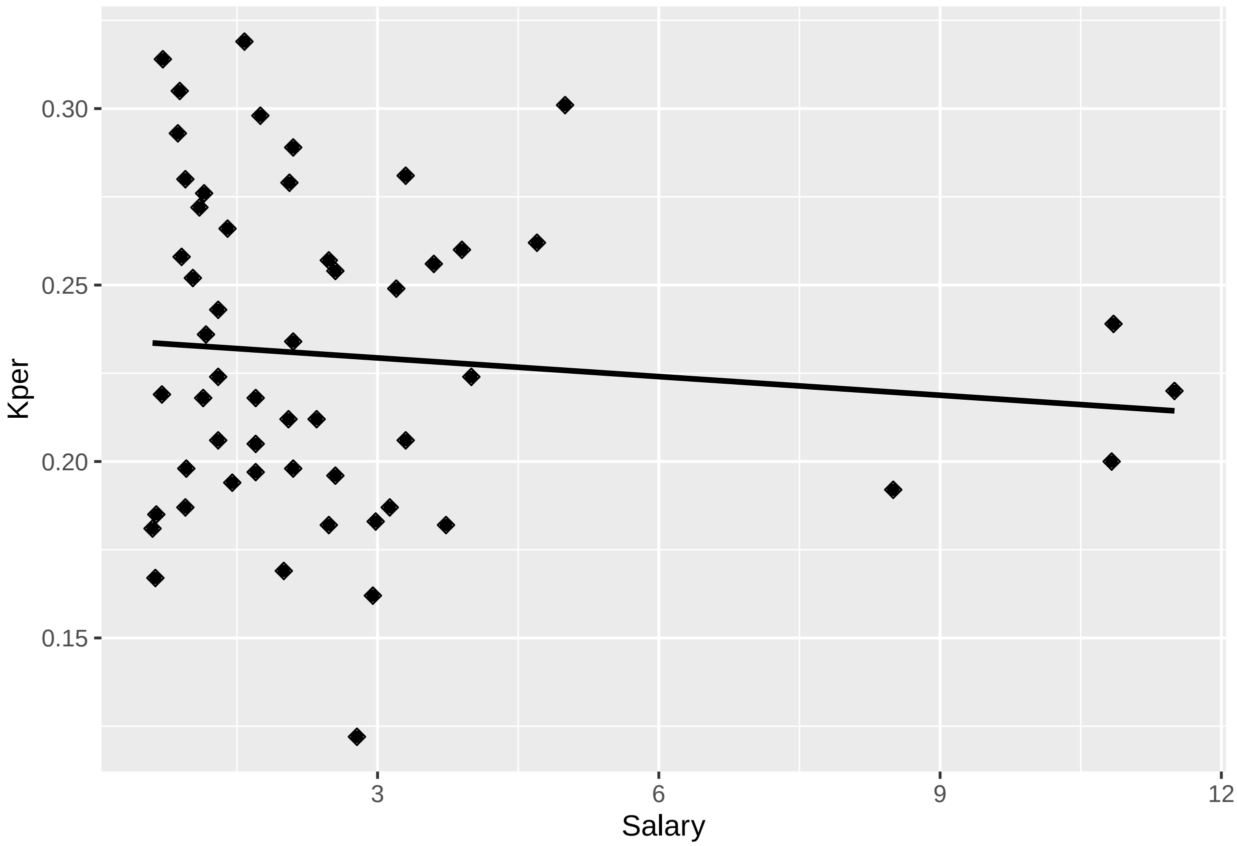
Equation for Line of Best Fit: y = 2.0513x + 10.7479

Adjusted R-Squared: 0.5558 – about 55.6% of salary values are explained by observed values for plate appearances

R: 0.7455 – between PA and salary, there is a moderate to strong positive relationship of .7455

p-value: 6.06771*10^(-11) – We have more than enough evidence to conclude that there is a significant linear relationship between these two variables at any reasonable level of significance

```
ggplot(data = baseball, aes(Salary, Kper)) +
  geom_point(size=2, shape=23) +
            geom_smooth(method = "lm", se=FALSE, color="black", formula = y ~ x) +
            geom_point()
```



Kper vs Salary

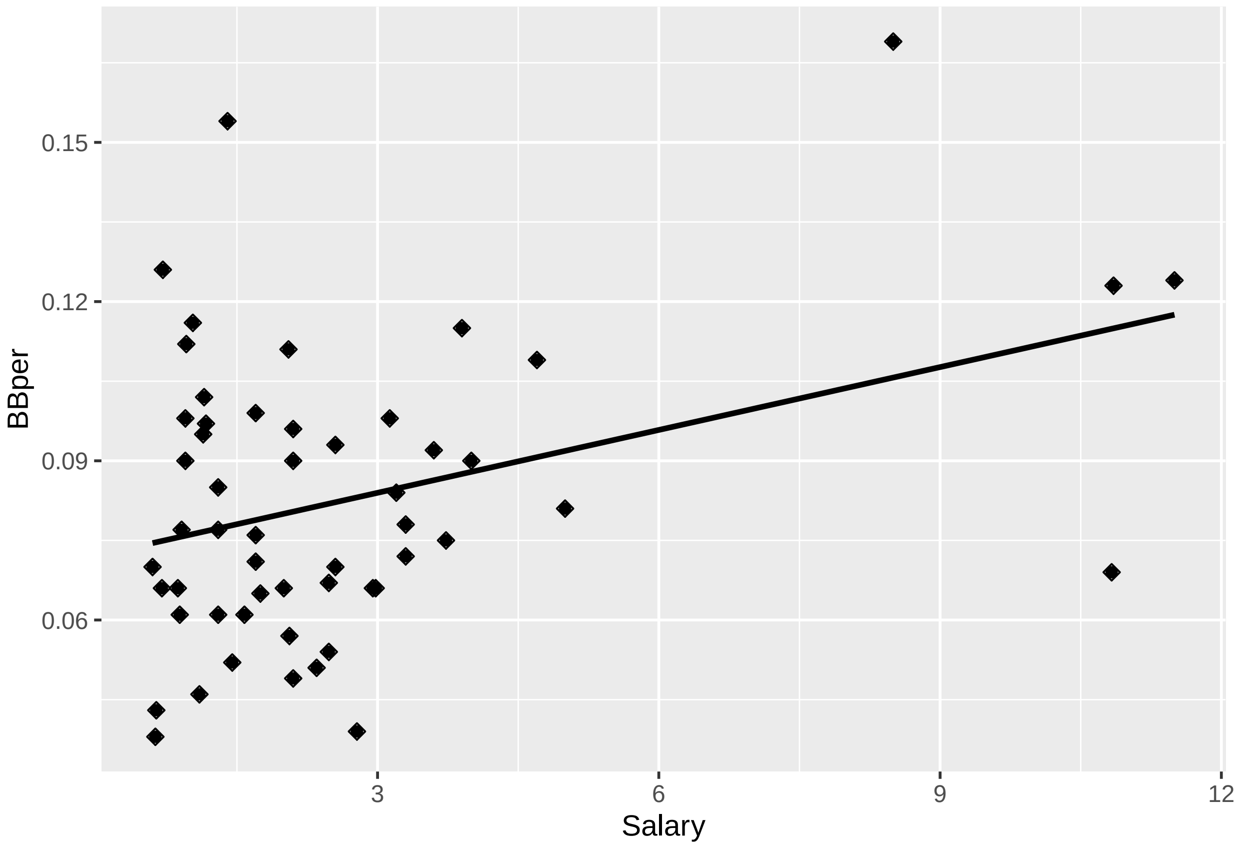
Equation for Line of Best Fit: y = -0.0018x + 0.2346

Adjusted R-Squared: -0.0094 – essentially none of the salary values are explained by the Kper (strikeouts per) variable

R: NA – because r^2 was negative, you cant find R (cant take sqrt of neg number)

p-value: 0.48084081 – because the p-value is well above our alpha of .05, we cannot conclude that there is a significant linear relationship between these two variables

```
ggplot(data = baseball, aes(Salary, BBper)) +
  geom_point(size=2, shape=23) +
            geom_smooth(method = "lm", se=FALSE, color="black", formula = y ~ x) +
            geom_point()
```



BBper vs Salary

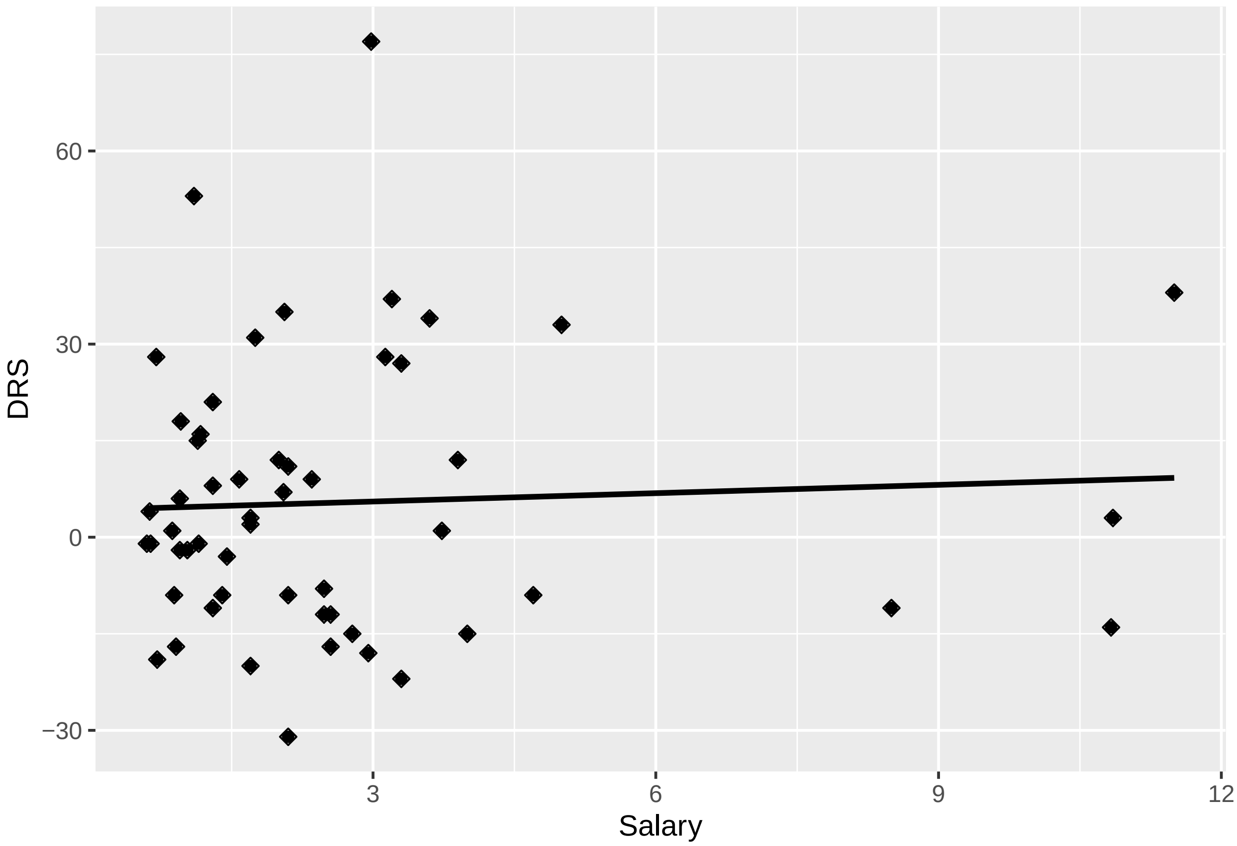
Equation for Line of Best Fit: y = 0.0039 + 0.0721

Adjusted R-Squared: 0.1113 – about 11.1% of salary values are explained by observed values for BBper (walks per)

R: 0.3336 – between BBper and salary, there is a weak positive relationship of .3336

p-value: 0.007878414 – We have more than enough evidence to conclude that there is a significant linear relationship between these two variables at any reasonable level of significance

```
ggplot(data = baseball, aes(Salary, DRS)) +
  geom_point(size=2, shape=23) +
            geom_smooth(method = "lm", se=FALSE, color="black", formula = y ~ x) +
            geom_point()
```



DRS vs Salary

Equation for Line of Best Fit: y = 4.321x + 4.2475

Adjusted R-Squared:-0.0166 – essentially none of the salary values are explained by the Kper (strikeouts per) variable

R: NA – because r^2 was negative, you cant find R (cant take sqrt of neg number)

p-value: 0.713261653 – because the p-value is well above our alpha of .05, we cannot conclude that there is a significant linear relationship between these two variables