Final_Project_Clean

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1. The statement of the problem

NBA players are on average the highest-paid athletes in the world, according to Statista.com. The NBA players get paid an average salary of around 7.5 million. The median salary is about 3.8 million. The highest salary in the NBA for the 2016-2017 season is about 25 million, including superstar LeBron James from Cleveland Cavaliers.

Oftentimes sports players would seem to have major contracts with really high annual salaries (some people would even think they should not get paid so much).

Since of one our group members is a super fan of the NBA, he believes that those basketball players are paid by their season total performance. However, other members in our group think otherwise.

Through this project, we want to find out whether the NBA players and their season total performance have a strong positive correlation.

For this project, we would use the 2016-2017 season total performance and actual salaries to create a prediction model. Then, we fit the 2017-2018 season total performance to the prediction model, see the difference between the salaries we expected during 2017-2018 season and the actual salaries in 2017-2018.

Purpose:

1. Discover which predictors variables are critical to the salaries of the NBA players
2. Use a multiple regression model to predict NBA players' salaries
3. Examine the difference between the predicted salaries and actual salaries

2. Data Section

Data source

Our season total performance and salary data sets were collected from Basketball Reference (https://www.basketball-reference.com/)

Processing the data

1. Data set:

Combines NBA player performance and salary data by using player ID and team. During the regular season, some of the players will change their team, so they have two different performances and salaries.

2. Data cleaning:

We combined three datasets (NBA player salaries summary 1985-2018, season performance for both 2016-2017 and 2017-2018) from Basketball Reference. We joined the data sets based on the playerID and their team names. Originally, the data set has a total of 34 variables, including 6 categorical variables, and 28 continuous variables.

In the first step of data cleaning, we removed 20 variables that seem to be either duplicated or are a combination of other variables. (i.e. trb = orb + drb). Later, we dropped the person who has the total performances as they transferred the teams during the season in order to focus on their performance.

3. Model Building Process

```r
NBA <- read_csv("NBA.csv")
```

```
## Rows: 418 Columns: 35
## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr  (6): player, player_id, trans_team, pos, tm, name
## dbl (29): rk, age, g, gs, mp, fg, fga, fg%, 3p, 3pa, 3p%, 2p, 2pa, 2p%, efg%...
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```r
head(NBA, 5)
```

```
## # A tibble: 5 x 35
##      rk player    player_id trans_team pos     age tm        g    gs    mp    fg
##   <dbl> <chr>     <chr>     <chr>      <chr> <dbl> <chr> <dbl> <dbl> <dbl> <dbl>
## 1     1 Alex Abr~ abrinal01 none       SG       23 OKC      68     6  1055   134
## 2     2 Quincy A~ acyqu01   trans      PF       26 DAL       6     0    48     5
## 3     2 Quincy A~ acyqu01   trans      PF       26 BRK      32     1   510    65
## 4     3 Steven A~ adamsst01 none       C        23 OKC      80    80  2389   374
## 5     4 Arron Af~ afflaar01 none       SG       31 SAC      61    45  1580   185
## # ... with 24 more variables: fga <dbl>, `fg%` <dbl>, `3p` <dbl>, `3pa` <dbl>,
## #   `3p%` <dbl>, `2p` <dbl>, `2pa` <dbl>, `2p%` <dbl>, `efg%` <dbl>, ft <dbl>,
## #   fta <dbl>, `ft%` <dbl>, orb <dbl>, drb <dbl>, trb <dbl>, ast <dbl>,
## #   stl <dbl>, blk <dbl>, tov <dbl>, pf <dbl>, pts <dbl>, name <chr>,
## #   `16_17_salary` <dbl>, `17_18salary` <dbl>
```

Data Set - salary with 14 predictors variables

The predictor variables include 2 categorical variables and 12 continuous variables.

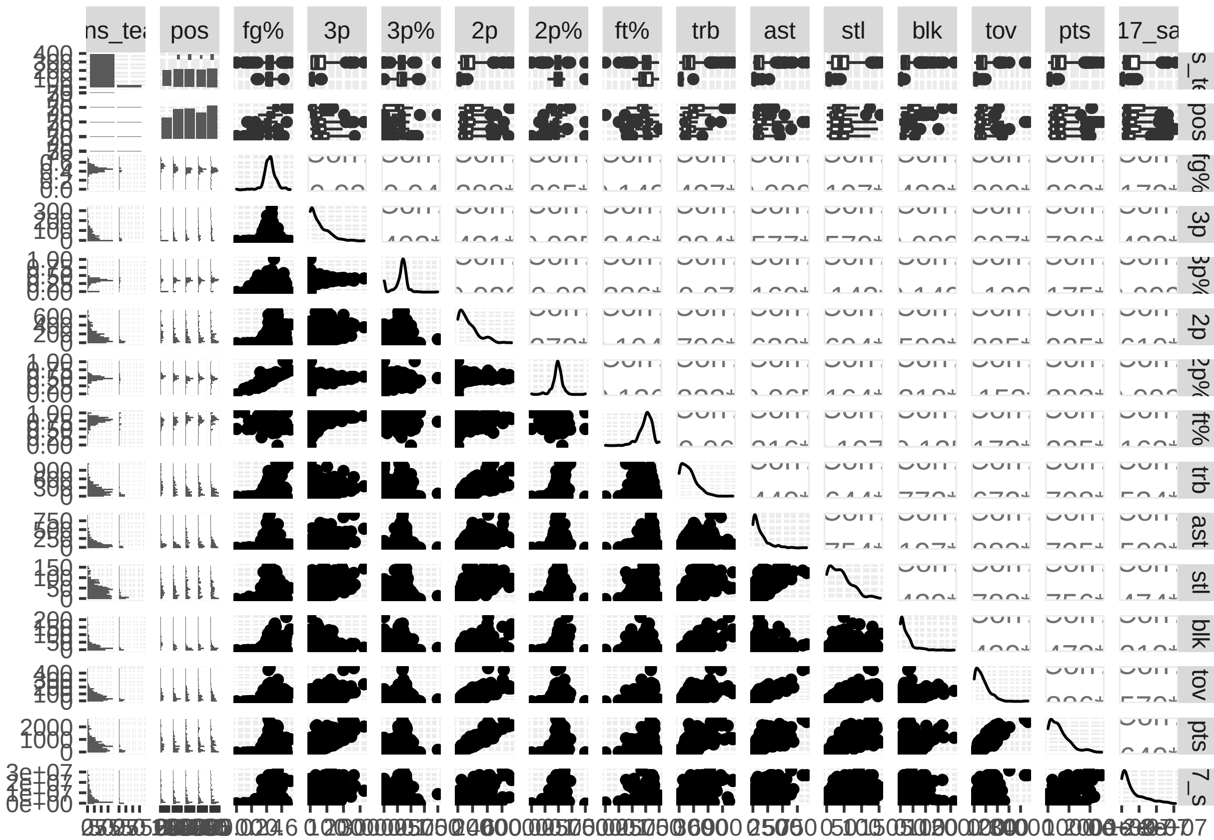
```r
original_data <- NBA %>%
  select(-rk, -player, -player_id, -`17_18salary`,
         -name, -tm, -`fg`, -`fga`, -`3pa`, -`2pa`, -ft, -fta, -g, -gs,
         -`efg%`, -mp, -orb, - drb, -pf, -age)

head(original_data, 5)
```

```
## # A tibble: 5 x 15
##   trans_team pos   `fg%`  `3p` `3p%`  `2p` `2p%` `ft%`   trb   ast   stl   blk
##   <chr>      <chr> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
## 1 none       SG    0.393    94 0.381    40 0.426 0.898    86    40    37     8
## 2 trans      PF    0.294     1 0.143     4 0.4   0.667     8     0     0     0
## 3 trans      PF    0.425    36 0.434    29 0.414 0.754   107    18    14    15
## 4 none       C     0.571     0 0       374 0.572 0.611   613    86    89    78
## 5 none       SG    0.44     62 0.411   123 0.457 0.892   125    78    21     6
## # ... with 3 more variables: tov <dbl>, pts <dbl>, `16_17_salary` <dbl>
```

Correlation Analysis

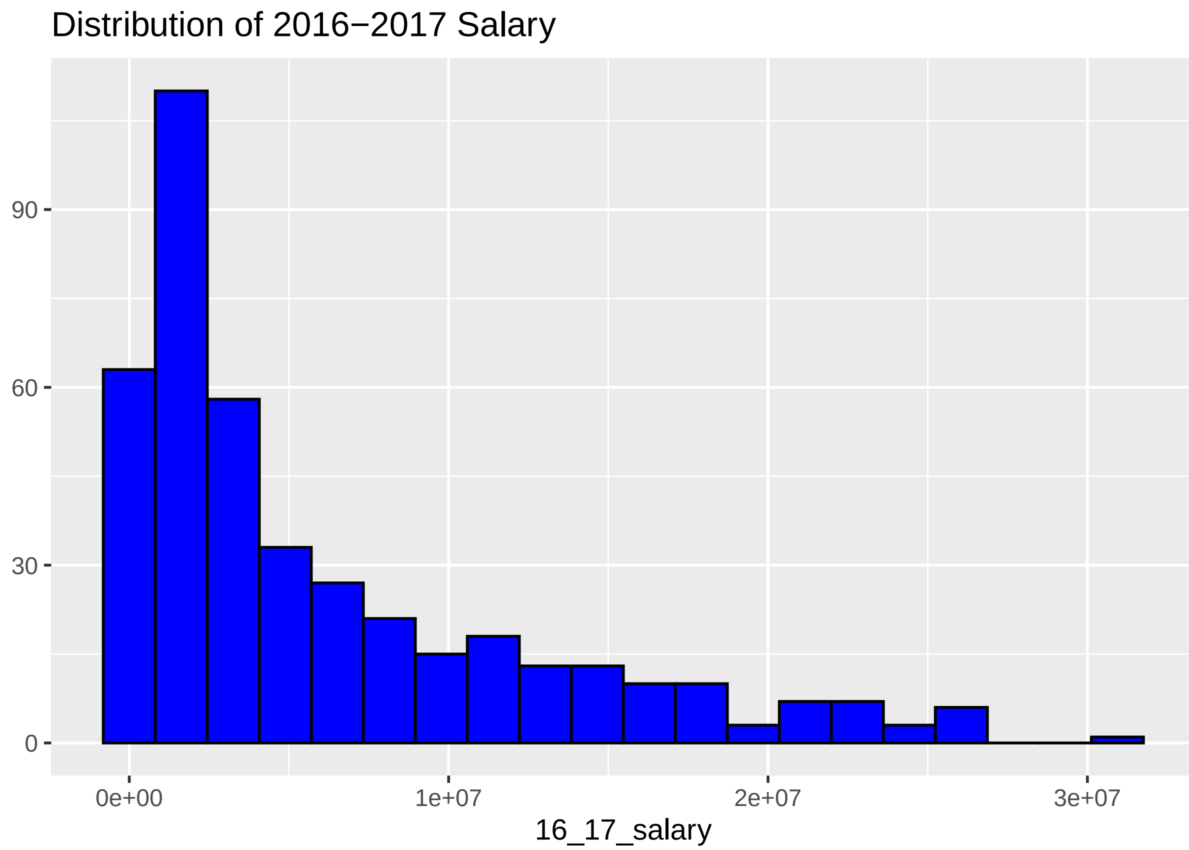
```r
original_data %>%
    ggpairs()
```



Based on the correlation plot, we can see the strongest linear relationship occurs between salary and points, although there could be a bit of a curvi-linear relationship. 3p, 2p, trb, ast, stl, tov have strong relationships as well.

Checking Y Predictable

```r
qplot(data = original_data, x = `16_17_salary`,
      geom = "histogram",
      main = "Distribution of 2016-2017 Salary",
      bins = 20, color = I("black"), fill = I("blue"))
```

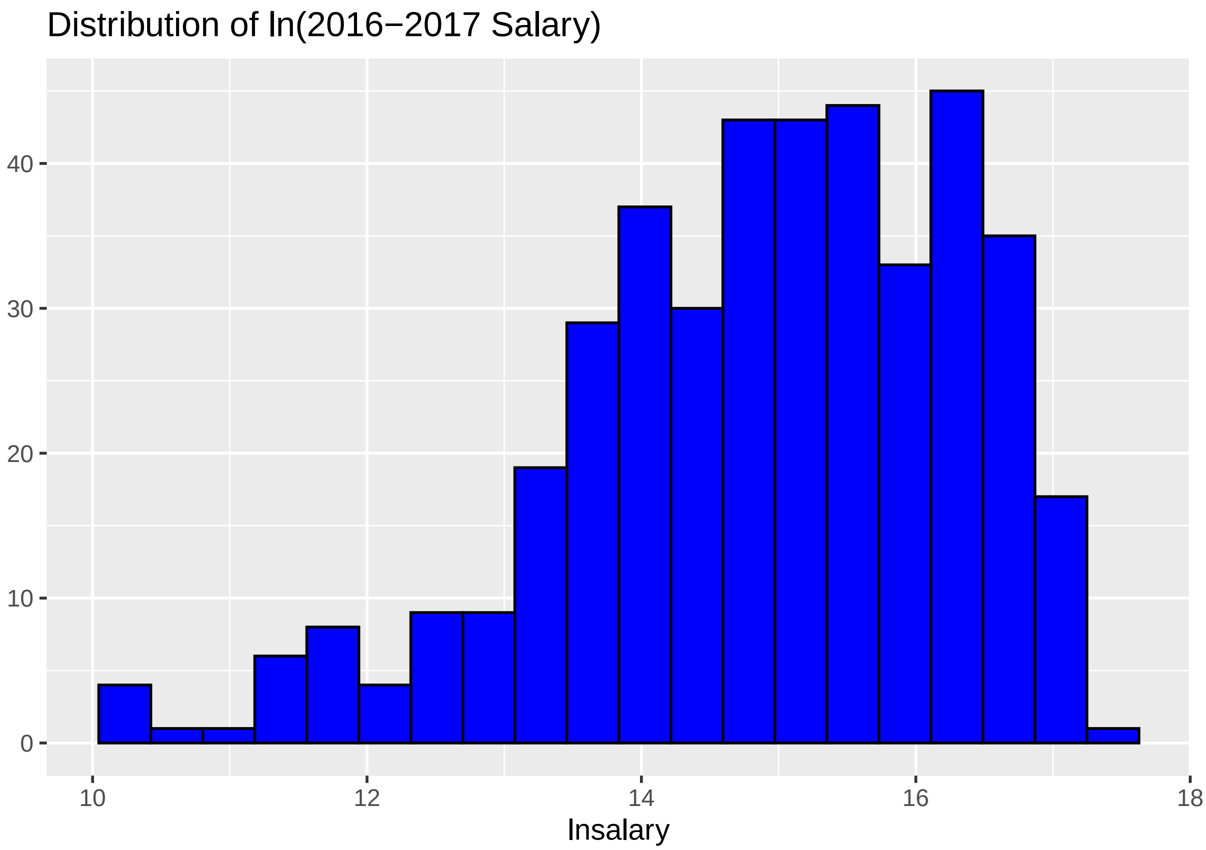


According to the histogram plot, we can see that the plot is right-skewed. To remedy the issue, we transformed the salary by taking logs.

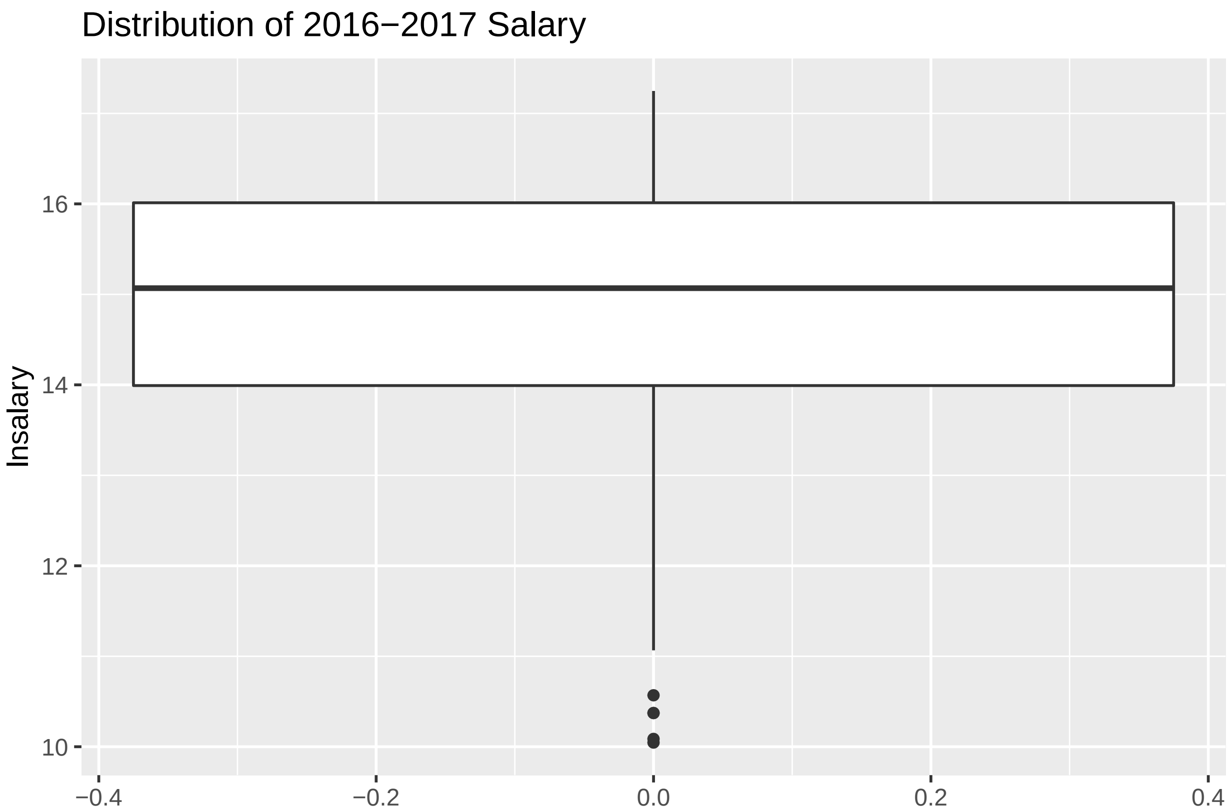
Log Salary for Better Prediction

```
original_data %>%
  mutate(lnsalary = log(`16_17_salary`)) ->
  original_data
```

```
qplot(data = original_data, x = lnsalary, geom = "histogram",
      bins = 20, color = I("black"), fill = I("blue"),
      main = "Distribution of ln(2016-2017 Salary)")
```




```
qplot(data = original_data, y = lnsalary, geom = "boxplot",
      main = "Distribution of 2016-2017 Salary")
```



Examining the histogram of log salary, we see possibly a very slight left skew, but it is closer to symmetric than without transform salary. According to the box plt, there are some of the outlines.

Original Model(only continuous variables)

```
original_data %>%
  select(-`16_17_salary`, -pos , -trans_team) ->
  new_og_data

og_model <- lm(lnsalary ~ ., data = new_og_data)

mult_og <- tidy(og_model)
mult_og
```

```
## # A tibble: 13 x 5
##    term        estimate std.error statistic  p.value
##    <chr>          <dbl>     <dbl>     <dbl>    <dbl>
##  1 (Intercept) 13.0      0.509      25.6    9.64e-87
##  2 `fg%`        6.46     1.50        4.29   2.19e- 5
##  3 `3p`         0.0111   0.00406     2.74   6.46e- 3
##  4 `3p%`       -0.0287   0.479      -0.0600 9.52e- 1
##  5 `2p`         0.00425  0.00292     1.46   1.46e- 1
##  6 `2p%`       -5.02     1.18       -4.24   2.79e- 5
##  7 `ft%`        0.400    0.504       0.793  4.28e- 1
##  8 trb          0.00241  0.000644    3.75   2.00e- 4
##  9 ast          0.00133  0.00105     1.27   2.03e- 1
## 10 stl          0.00191  0.00318     0.602  5.48e- 1
## 11 blk         -0.00397  0.00314    -1.27   2.07e- 1
```

```
## 12 tov          -0.00240  0.00309    -0.776  4.38e- 1
## 13 pts          -0.00109  0.00116    -0.940  3.48e- 1
```

- Fitted model: $ln(\widehat{salary})$ = 13.05 + 6.5 $\cdot fg$ + 0.01 $\cdot 3p$ - 0.028 $\cdot 3p$ + 0.004 $\cdot 2p$ - 5.02 $\cdot 2p$ + 0.39 $\cdot ft$ + 0.0024 $\cdot trb$ + 0.0013 $\cdot ast$ + 0.0019 $\cdot stl$

```
g_mult_og <- broom::glance(og_model)
g_mult_og
```

```
## # A tibble: 1 x 12
##   r.squared adj.r.squared sigma statistic  p.value    df logLik   AIC   BIC
##       <dbl>         <dbl> <dbl>     <dbl>    <dbl> <dbl>  <dbl> <dbl> <dbl>
## 1     0.427         0.410  1.10      25.1 5.40e-42    12  -627. 1283. 1339.
## # ... with 3 more variables: deviance <dbl>, df.residual <int>, nobs <int>
```

```
og_anova <- lb_anovat_lm(og_model, reg_collapse = TRUE)
og_anova
```

```
##       Source  Df       SS        MS        F            P
## 1 Regression  12 366.3515 30.529290 25.11287 5.396828e-42
## 2      Error 405 492.3517  1.215683       NA           NA
## 3      Total 417 858.7032  2.059240       NA           NA
```

```
vif(og_model)
```

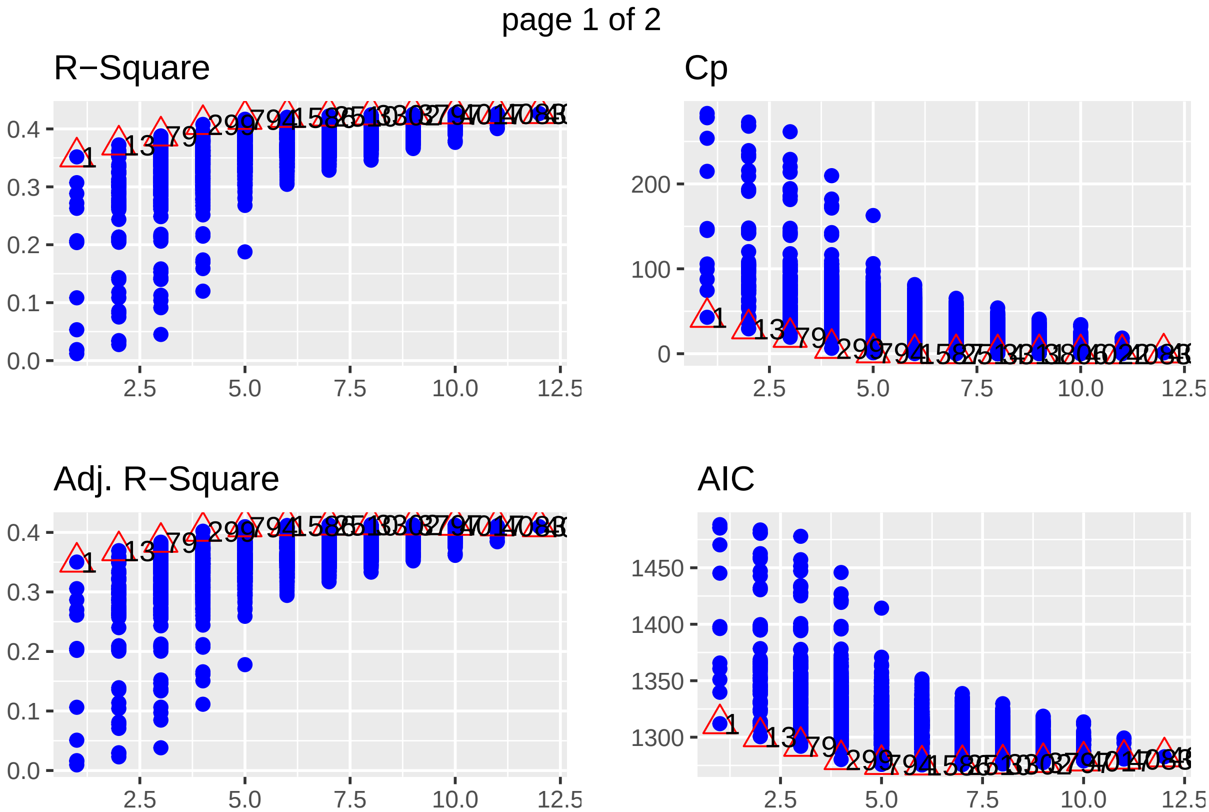
```
##      `fg%`       `3p`      `3p%`       `2p`      `2p%`      `ft%`        trb
##   5.212855  17.304773   1.377049  58.726716   4.390578   1.318019   5.222122
##        ast        stl        blk        tov        pts
##   6.799010   3.645980   2.771145  12.541091 107.912304
```

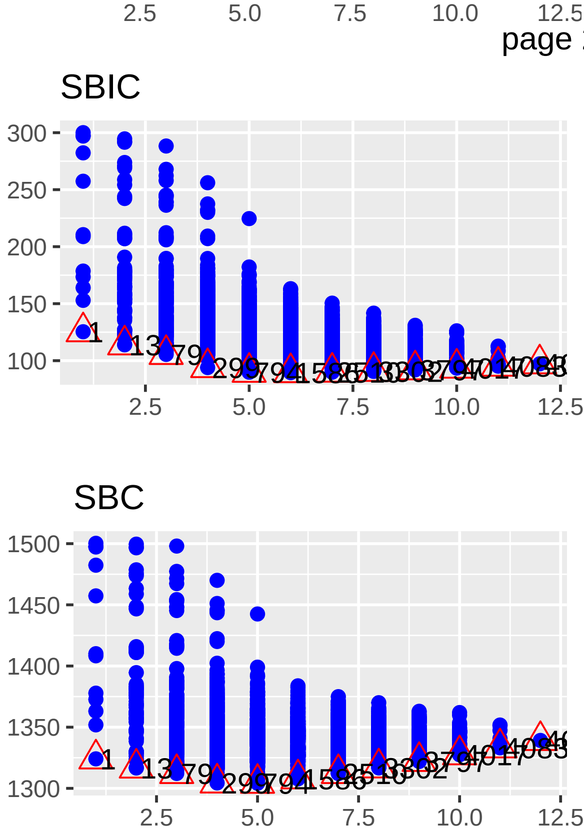
According to the VIF, it shows our original model isn't good enought to be our final model. Some of the varables are more than 5.

All Subset Models

```
all_subsets_model <- ols_step_all_possible(og_model)
```

```
plot(all_subsets_model)
```





- Based on the R^2_{adj} , Mallow's cp, and AIC criteria, we would choose the model that contains all 5 variables (Model 793). Model 793 has 5 variables, Cp = 6.09, AIC = 1275.92, $Rˆ2{adj} = 0.41.

Reduce Model based on All Subset Models Method

```
reduce <- NBA %>%
  mutate(lnsalary = log(`16_17_salary`)) %>%
  select(lnsalary,`fg%`,`3p`,`2p`,`2p%`,trb, pos, trans_team)
```

```
reducemodel <- lm(lnsalary ~`fg%` + `3p` + `2p`+`2p%`+ trb , data = new_og_data)

reduce_model_t <- tidy(reducemodel)
reduce_model_t
```

```
## # A tibble: 6 x 5
##   term        estimate std.error statistic   p.value
##   <chr>          <dbl>     <dbl>     <dbl>     <dbl>
## 1 (Intercept) 13.4      0.320        42.0  7.68e-151
## 2 `fg%`        6.31     1.46          4.32 1.92e-  5
## 3 `3p`         0.00857  0.00114       7.51 3.76e- 13
## 4 `2p`         0.00172  0.000687      2.50 1.29e-  2
## 5 `2p%`       -5.04     1.16         -4.34 1.76e-  5
## 6 trb          0.00183  0.000479      3.81 1.58e-  4
```

*Reduce model: $ln(\widehat{salary})$ = 13.441 + 6.308 $\cdot fg$ + 0.009 $\cdot 3p$ + 0.002 $\cdot 2p$ - 5.039 $\cdot 2p$ + 0.002 $\cdot trb$

```
reduce_model_g <- broom::glance(reducemodel)
reduce_model_g
```

```
## # A tibble: 1 x 12
##   r.squared adj.r.squared sigma statistic  p.value    df logLik   AIC   BIC
##       <dbl>         <dbl> <dbl>     <dbl>    <dbl> <dbl>  <dbl> <dbl> <dbl>
## 1     0.417         0.410  1.10      58.8 3.76e-46     5  -631. 1276. 1304.
## # ... with 3 more variables: deviance <dbl>, df.residual <int>, nobs <int>
```

```
reduce_model_a <- lb_anovat_lm(reducemodel)
reduce_model_a
```

```
##       Source  Df       SS        MS        F            P
## 1 Regression   5 357.7327 71.546533 58.84013 3.755897e-46
## 2      Error 412 500.9705  1.215948       NA           NA
## 3      Total 417 858.7032  2.059240       NA           NA
```

```
tidy(reducemodel, conf.int = "TRUE", conf.level = 0.98)
```

```
## # A tibble: 6 x 7
##   term        estimate std.error statistic   p.value  conf.low conf.high
##   <chr>          <dbl>     <dbl>     <dbl>     <dbl>     <dbl>     <dbl>
## 1 (Intercept) 13.4      0.320        42.0  7.68e-151 12.7       14.2
## 2 `fg%`        6.31     1.46          4.32 1.92e-  5  2.90       9.71
## 3 `3p`         0.00857  0.00114       7.51 3.76e- 13  0.00590    0.0112
## 4 `2p`         0.00172  0.000687      2.50 1.29e-  2  0.000112   0.00332
## 5 `2p%`       -5.04     1.16         -4.34 1.76e-  5 -7.75      -2.33
## 6 trb          0.00183  0.000479      3.81 1.58e-  4  0.000707   0.00294
```

```
vif(reducemodel)
```

```
##    `fg%`     `3p`     `2p`    `2p%`      trb
## 4.896551 1.364878 3.252252 4.211965 2.888815
```

According to the VIF, it shows our original model is good enough to be our final model, all of the variables are less than 5.

Adding Dummy Variables - lnsalary with 5 continuous predictors variables

We want to figure out will the position they play and transfer to different teams during the regular season influence their salaries?

Since some players had transferred teams during the season, we decided to create a dummy variable for transfer team or not (0=did not transfer, 1=transferred). We also created dummy variables for their positions to predict salary based on the position they played (c = center, pf = power forward, sf = small forward, pg = point guard, and sg = shooting guard; 0 = did not play in position, 1 = played in that position).

```
results <- dummy_cols(.data = reduce, select_columns = c("pos","trans_team"))

results %>%
  select(pos, pos_C, pos_PF, pos_PG, pos_SF, pos_SG, trans_team, trans_team_none,
         trans_team_trans) %>%
  head(6)
```

```
## # A tibble: 6 x 9
##   pos   pos_C pos_PF pos_PG pos_SF pos_SG trans_team trans_team_none
##   <chr> <int>  <int>  <int>  <int>  <int> <chr>                <int>
## 1 SG        0      0      0      0      1 none                     1
## 2 PF        0      1      0      0      0 trans                    0
## 3 PF        0      1      0      0      0 trans                    0
## 4 C         1      0      0      0      0 none                     1
## 5 SG        0      0      0      0      1 none                     1
## 6 C         1      0      0      0      0 none                     1
## # ... with 1 more variable: trans_team_trans <int>
```

```
newresult <- dummy_cols(.data = reduce, select_columns = c("pos","trans_team"),
                        remove_selected_columns = TRUE)

rename(.data = newresult, trans = trans_team_trans) -> newdummy

dummy_model <- lm(lnsalary ~ ., data = newdummy)
```

```
dumtidyout <- tidy(dummy_model)

dumglout <- glance(dummy_model)

dumtidyout
```

```
## # A tibble: 13 x 5
##    term            estimate std.error statistic    p.value
##    <chr>              <dbl>     <dbl>     <dbl>      <dbl>
##  1 (Intercept)     12.3      0.399        30.7   3.76e-108
##  2 `fg%`            6.36     1.50          4.24  2.72e-  5
##  3 `3p`             0.00867  0.00119       7.26  1.99e- 12
##  4 `2p`             0.00178  0.000696      2.56  1.07e-  2
##  5 `2p%`           -4.95     1.16         -4.26  2.56e-  5
##  6 trb              0.00132  0.000525      2.51  1.26e-  2
##  7 pos_C            0.274    0.226         1.21  2.27e-  1
##  8 pos_PF           0.451    0.173         2.60  9.56e-  3
##  9 pos_PG           0.313    0.157         1.99  4.71e-  2
## 10 pos_SF           0.516    0.168         3.07  2.27e-  3
## 11 pos_SG          NA       NA            NA    NA
```

```
## 12 trans_team_none  0.955    0.225         4.25  2.65e-  5
## 13 trans           NA       NA             NA    NA
```

```r
dumglout
```

```
## # A tibble: 1 x 12
##   r.squared adj.r.squared sigma statistic  p.value    df logLik   AIC   BIC
##       <dbl>         <dbl> <dbl>     <dbl>    <dbl> <dbl>  <dbl> <dbl> <dbl>
## 1     0.459         0.446  1.07      34.5 1.86e-48    10  -615. 1255. 1303.
## # ... with 3 more variables: deviance <dbl>, df.residual <int>, nobs <int>
```

```r
dummy_a <- lb_anovat_lm(dummy_model, reg_collapse = FALSE)
dummy_a
```

```
##             Source  Df          SS          MS           F            P
## 1            `fg%`   1  45.7115354  45.7115354  40.0336807 6.589589e-10
## 2             `3p`   1 181.4834296 181.4834296 158.9412740 5.413203e-31
## 3             `2p`   1  89.2304456  89.2304456  78.1470834 2.918848e-17
## 4            `2p%`   1  23.6276402  23.6276402  20.6928382 7.125296e-06
## 5              trb   1  17.6796146  17.6796146  15.4836201 9.784910e-05
## 6            pos_C   1   0.1990211   0.1990211   0.1743006 6.765379e-01
## 7           pos_PF   1   1.8985145   1.8985145   1.6626990 1.979716e-01
## 8           pos_PG   1   0.3603853   0.3603853   0.3156217 5.745600e-01
## 9           pos_SF   1  13.1593822  13.1593822  11.5248482 7.541662e-04
## 10 trans_team_none   1  20.6296784  20.6296784  18.0672548 2.646649e-05
## 11           Error 407 464.7235673   1.1418269          NA           NA
## 12           Total 417 858.7032143   2.0592403          NA           NA
```

- Reduce model: $\widehat{ln(salary)} = 12.277 + 6.357 \cdot fg + 0.009 \cdot 3p + 0.002 \cdot 2p$ -4.949 $\cdot 2p + 0.001 \cdot trb + 0.274 \cdot posC + 0.451 \cdot pos_P F + 0.313 \cdot posPG + 0.516 \cdot posSF + 0.955 \cdot transteamnone$

Comparing models

```r
dumglout #dummy models
```

```
## # A tibble: 1 x 12
##   r.squared adj.r.squared sigma statistic  p.value    df logLik   AIC   BIC
##       <dbl>         <dbl> <dbl>     <dbl>    <dbl> <dbl>  <dbl> <dbl> <dbl>
## 1     0.459         0.446  1.07      34.5 1.86e-48    10  -615. 1255. 1303.
## # ... with 3 more variables: deviance <dbl>, df.residual <int>, nobs <int>
```

```r
g_mult_og #full model wihtout dummy
```

```
## # A tibble: 1 x 12
##   r.squared adj.r.squared sigma statistic  p.value    df logLik   AIC   BIC
##       <dbl>         <dbl> <dbl>     <dbl>    <dbl> <dbl>  <dbl> <dbl> <dbl>
## 1     0.427         0.410  1.10      25.1 5.40e-42    12  -627. 1283. 1339.
## # ... with 3 more variables: deviance <dbl>, df.residual <int>, nobs <int>
```

```r
reduce_model_g # reduce model
```

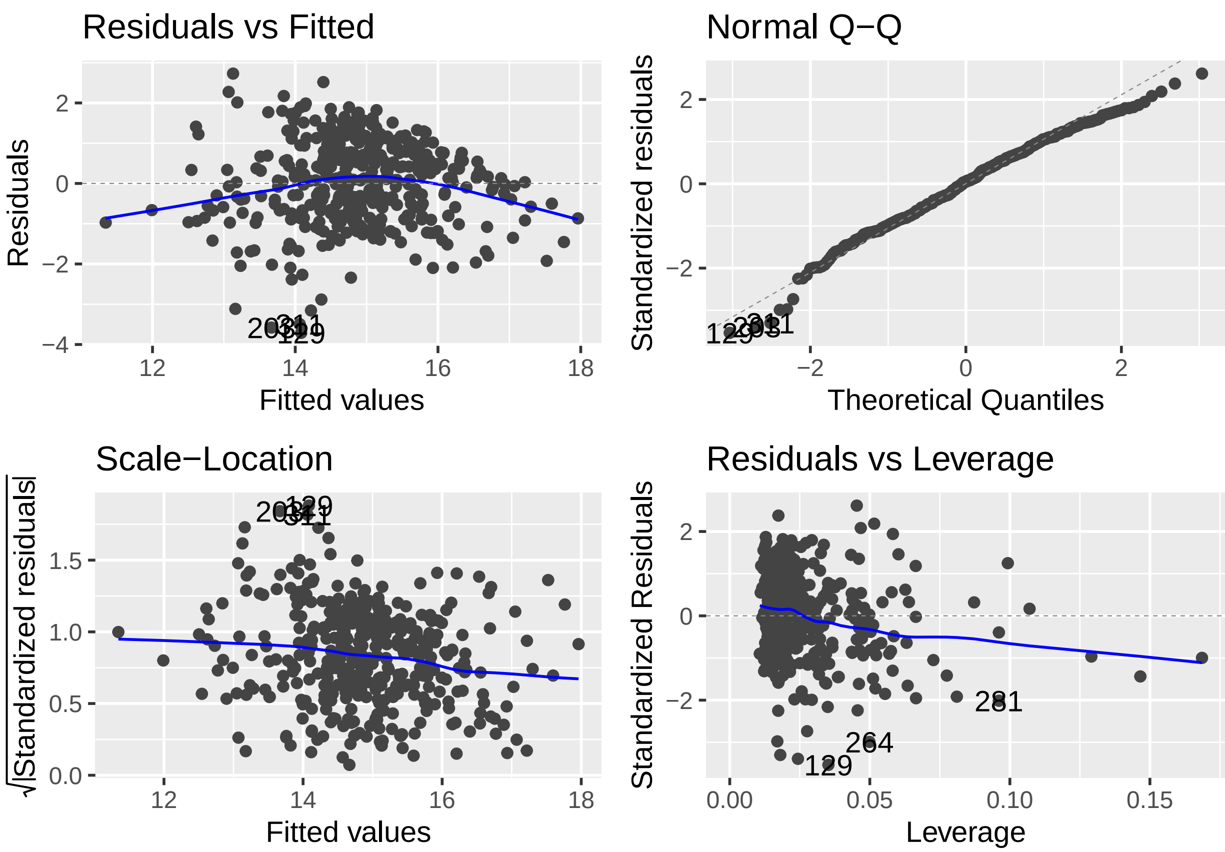
```
## # A tibble: 1 x 12
##   r.squared adj.r.squared sigma statistic  p.value    df logLik   AIC   BIC
##       <dbl>         <dbl> <dbl>     <dbl>    <dbl> <dbl>  <dbl> <dbl> <dbl>
## 1     0.417         0.410  1.10      58.8 3.76e-46     5  -631. 1276. 1304.
## # ... with 3 more variables: deviance <dbl>, df.residual <int>, nobs <int>
```

For the full model without dummy variables (12 variables) $R^2_{adj} = 0.4096448$ For the reduced model (5

variables) $R^2_{adj} = 0.4095163$
For the reduce model including dummy variables (10 variables) $R^2_{adj} = 0.4455106$
In terms of R^2_{adj}, the reduce model including dummy variables does a better job fitting the data as it has the higher R^2_{adj}

Model Testing

```
# Assumtion
autoplot(dummy_model)
```



Based on the fitted residual plot, it seems some multi-linear regression assumptions are violated.

```
# Residual normality test
shapiro.test(dummy_model$residuals)
```

```
##
##  Shapiro-Wilk normality test
##
## data:  dummy_model$residuals
## W = 0.98822, p-value = 0.00187
```

According to the Shapiro-Wilk normality test with a test statistic of 0.99 and an associated p-value = 0.00187, since the p-value is below 0.05 which indicates the NBA Dummy data significantly deviate from a normal distribution.

```
# Residual independence test
durbinWatsonTest(dummy_model)
```

```
##  lag Autocorrelation D-W Statistic p-value
```

```
##    1      0.09443852       1.80766   0.026
##  Alternative hypothesis: rho != 0
```

- H_0 = residual from the regression are not auto-correlated (autocorrelation coefficient, p=0)
- H_0: Alter = residuals from the regression are auto-correlated (AC, p > 0)

According to the Durbin-Watson test with a test statistic of 1.81 and an associated p-value = 0.024, since the test statistic fell into the range of 0 to 2, which indicates that that there is a positive autocorrelation.

```
# Residual variance homogeneity test
ncvTest(dummy_model)
```

```
## Non-constant Variance Score Test
## Variance formula: ~ fitted.values
## Chisquare = 16.55129, Df = 1, p = 4.7352e-05
```

According to the non-constant variance score test with a chisquare 16.5513 and an associated p-value = 0.000047, which indicates that there has a heteroskedasticity issue.

```
# Testing for Non-Constant Variance Residual by using Breusch-Pagan
library(lmtest)
```

```
## Loading required package: zoo
```

```
##
## Attaching package: 'zoo'
```

```
## The following objects are masked from 'package:base':
##
##     as.Date, as.Date.numeric
```

```
bptest(dummy_model)
```

```
##
##  studentized Breusch-Pagan test
##
## data:  dummy_model
## BP = 28.039, df = 10, p-value = 0.001779
```

Test: * $H_0 : \gamma_1 = 0$ * $H_1 : \gamma_1 \neq 0$

According to the Breusch-Pagan Test with a test statistic = 28.039 and an associated p-value = 0.0018, under the assumption that H_0 is true (variance of the disturbance terms is constant), it would be quite unlikely that we would observe a test statistic of our magnitude or larger.

Consequently, we can reject H_0 and conclude there is a sufficient statistical evidence to indicate that the variance is changing relative to the magnitude of lnsalary, which means we need to take further procedure to fix the issues.

As the results from several model testing, we can confirm there is some heteroskedascity issues with our residual and fitted value, as well as the residual normality.

Fixing Heteroskedasticity by Using WLS

Since the residual plot show that the error look like uneven distribution, it violates the assumption of homogeneity of variance. As the result, it has heterodasticity issue, so we solve this violation by using WLS.

```
refit <- lm(abs(residuals(dummy_model)) ~ fitted(dummy_model))
refit
```

```
##
```

```
## Call:
## lm(formula = abs(residuals(dummy_model)) ~ fitted(dummy_model))
##
## Coefficients:
##         (Intercept)  fitted(dummy_model)
##              2.5359              -0.1131
```

```
wts <- 1 / fitted(refit)^2
```

Final Model

Test: $H_0 : \beta_1 = \beta_2 = ... = \beta_{10} = 0$ $H_1 : \beta_i \neq 0$ for some $i = 1, 2, ...10$

```
lm_wls <- lm(lnsalary ~ ., data = newdummy, weights = wts)
tidy(lm_wls)
```

```
## # A tibble: 13 x 5
##    term             estimate std.error statistic   p.value
##    <chr>               <dbl>     <dbl>     <dbl>     <dbl>
##  1 (Intercept)     12.5      0.442       28.3    4.65e-98
##  2 `fg%`            5.73     1.60         3.58   3.89e- 4
##  3 `3p`             0.00743  0.00102      7.30   1.55e-12
##  4 `2p`             0.00168  0.000588     2.86   4.52e- 3
##  5 `2p%`           -4.65     1.29        -3.62   3.38e- 4
##  6 trb              0.00122  0.000445     2.74   6.44e- 3
##  7 pos_C            0.198    0.219        0.906  3.66e- 1
##  8 pos_PF           0.412    0.170        2.42   1.61e- 2
##  9 pos_PG           0.241    0.154        1.57   1.18e- 1
## 10 pos_SF           0.424    0.163        2.60   9.77e- 3
## 11 pos_SG          NA       NA           NA     NA
## 12 trans_team_none  1.03     0.266        3.88   1.21e- 4
## 13 trans           NA       NA           NA     NA
```

```
glance(lm_wls)
```

```
## # A tibble: 1 x 12
##   r.squared adj.r.squared sigma statistic  p.value    df logLik   AIC   BIC
##       <dbl>         <dbl> <dbl>     <dbl>    <dbl> <dbl>  <dbl> <dbl> <dbl>
## 1     0.450         0.437  1.24      33.3 4.20e-47    10  -606. 1236. 1284.
## # ... with 3 more variables: deviance <dbl>, df.residual <int>, nobs <int>
```

```
final_model_a <- lb_anovat_lm(lm_wls)
final_model_a
```

```
##       Source  Df        SS        MS       F            P
## 1 Regression  10  509.6673 50.966732 33.3337 4.198082e-47
## 2      Error 407  622.2970  1.528985      NA           NA
## 3      Total 417 1131.9643  2.714543      NA           NA
```

Test Statistic: * $F = \frac{MSR}{MSE} = 33.334$ * p-value < 0.00001

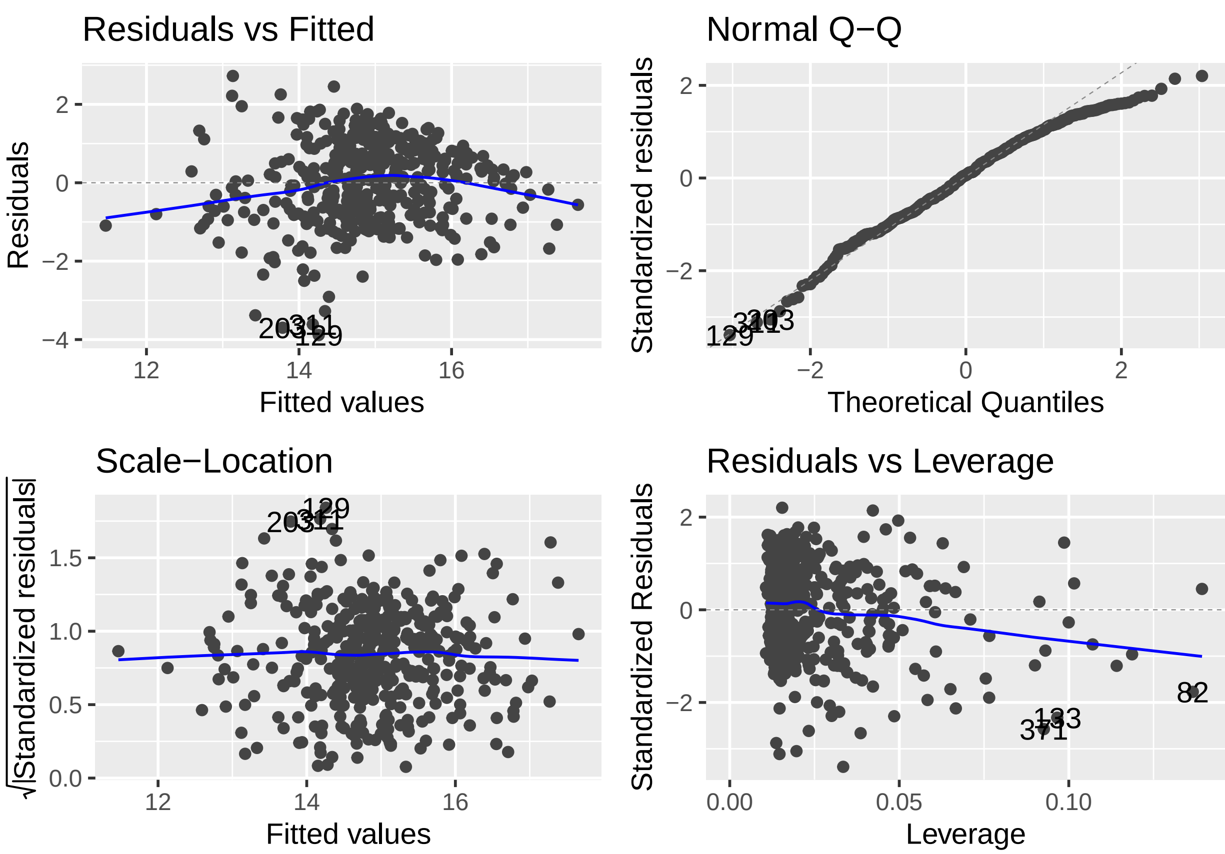
- Reduce model: $\widehat{ln(salary)} = 12.496 + 5.729 \cdot fg + 0.007 \cdot 3p + 0.002 \cdot 2p$ -4.648 $\cdot 2p + 0.001 \cdot trb + 0.198 \cdot posC + 0.412 \cdot posPF + 0.241 \cdot posPG + 0.424 \cdot posSF + 1.033 \cdot transteamnone$

For the final model $R^2_{adj} = 0.436743$.

Conclusion. Given the test statistic F = 33.334 and its corresponding p-value < 0.00001. If none of the predictor variables were useful in explaining the variation we see in log salary, it would be almost impossible to observe a test statistic of our magnitude or greater.

Consequently, we will reject and conclude that there is overwhelming statistical evidence to indicate that at least one the predictor variables is useful in explaining the variation in log salary.

```r
# Assumtion
autoplot(lm_wls)
```




```r
# Residual normality test
shapiro.test(lm_wls$residuals)
```

```
##
##  Shapiro-Wilk normality test
##
## data:  lm_wls$residuals
## W = 0.98346, p-value = 0.0001044
```

```r
# Residual independence test
durbinWatsonTest(lm_wls)
```

```
##  lag Autocorrelation D-W Statistic p-value
##    1      0.09488015       1.80693   0.044
##  Alternative hypothesis: rho != 0
```

```r
# Residual variance homogeneity test
ncvTest(lm_wls)
```

```
## Non-constant Variance Score Test
## Variance formula: ~ fitted.values
## Chisquare = 0.8191605, Df = 1, p = 0.36543
```

The model has followed all assumptions except residual normality test.

Evaluate Forecast Model

```
test <- read_csv("player17_18.csv")
```

```
## Rows: 605 Columns: 31
## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr  (5): Player, player_id, trans_team, Pos, Tm
## dbl (26): Age, G, GS, MP, FG, FGA, FG%, 3P, 3PA, 3P%, 2P, 2PA, 2P%, eFG%, FT...
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```
names(test)[1:31] <- tolower(names(test)[1:31])

test_result <- dummy_cols(.data = test,
                          select_columns = c("pos","trans_team"), remove_selected_columns = TRUE)
rename(.data = test_result, trans = trans_team_trans) -> test_dummy

# final reduce model
full_predict <- predict(lm_wls, newdata = test_dummy, interval = "confidence", level = 0.95)
```

```
## Warning in predict.lm(lm_wls, newdata = test_dummy, interval = "confidence", :
## prediction from a rank-deficient fit may be misleading
```

```
full_predict <- cbind(test_dummy, full_predict)

full_predict1 <- full_predict %>%
  left_join(NBA, by = c("player_id" = "player_id", "tm" = "tm")) %>%
  select(fit, `17_18salary`)

diff <- log(full_predict1$`17_18salary`)-full_predict1$fit

MAD <- mean(abs(diff),na.rm = TRUE)
MSE <- mean(diff^2,na.rm = TRUE)
```

We use a forecasting model to determine how well it does in producing accurate forecasts, not how well it fits the historical model. Measuring forecast accuracy, MAD=0.864, MSE=1.124.

From the result, both MAD and MSE are small and close to 0, actual values are very close to the predicted values. It means that the prediction model we done is working well.

4. Inferences Based on the Model

After we build the multiple regression model, we can predict NBA players' salaries. The model has followed all assumptions except residual normality test.

Furthermore, the difference between predicted and actual salaries is small, which means that our model is great for applying.

5. Further Directions

Since the data only offer the data that indicate players trans team during the regular season, isn't include off the season data that most of the palyers trans team time. For the further study, we recommend that add the resign the contrast or not, because the longer time interval model contrast effect maybe improve the results.

6. Group Work

Project Concept Contribution: Jack

Data collection: Adela

Data cleaning: Yuka

Model Building Process: Yuka, Adela

Analysis result: Yuka, Adela, Jack

PPT: Jack