Load, Clean, and Explore Data

Basketball Salaries Team

Load NBA 2K Data

Note: Primary dataset is directly downloaded from Kaggle. This video-game rankings dataset is scraped from http://mtdb.com/20

```r
library(stringr)
library(rvest)
library(tidyr)
if (!file.exists('../data/raw/nba2k/nba2k_16.csv')){ # only run if data is not already scraped
# constants
root <- 'data/raw/nba2k'
years <- c(16,17,18,19,20)
pages = c(84,68,72,68,46)
url_f <- 'http://mtdb.com/%d?page=%d&sortedBy=overall&sortOrder=Descending&'
for (i in 1:length(years)){
  year_df <- vector('list',12)
  names(year_df) <- c('name','position','ovr','out','ins','pla','ath','def','reb','xbox','ps4','pc')
  year <- years[i]
  page <- pages[i]
  for (page in 1:page){
    # load webpage
    url <- sprintf(url_f,year,page)
    webpage <- read_html(url)
    # load salary table
    player_tables <- html_nodes(webpage, css = 'table')
    player_df_page <- html_table(player_tables[[1]])#[-(1),]
    names(player_df_page) <- c('name','position','ovr','out','ins','pla','ath','def','reb','xbox','ps4','pc')
    year_df <- rbind(year_df,player_df_page)}
  write.csv(year_df,sprintf('%s/nba2k_%d.csv',root,year))
  cat(sprintf('%d nrows: %d\n',year,nrow(year_df)))}}
```

Clean Primary Dataset

```r
library("readxl")
df_primary <- read_excel('../data/raw/primary_dataset_raw.xlsx')
```

```
## Warning in read_fun(path = enc2native(normalizePath(path)), sheet_i = sheet, :
## Expecting numeric in D24626 / R24626C4: got 'z'
```

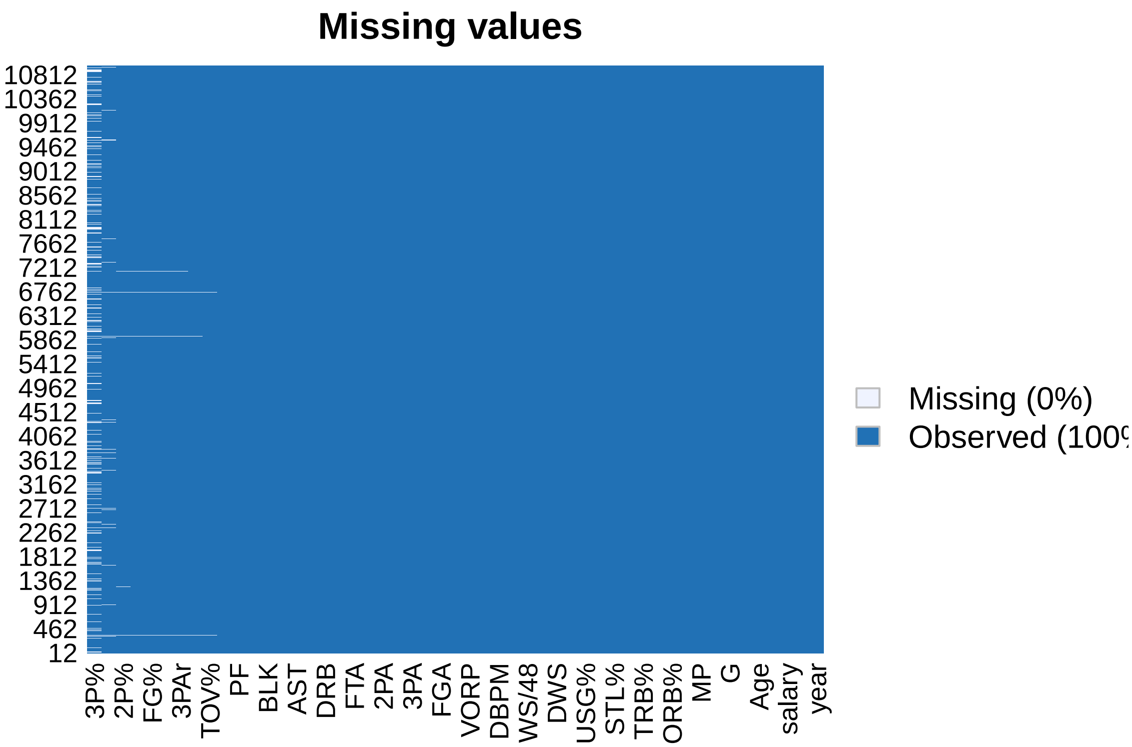
```r
df_primary <- df_primary[,!(names(df_primary)%in%c('#','blanl','blank2'))] # drop empty/non-stat columns
colnames(df_primary)[1:3] <- c('year','name_p','salary')
df_primary <- df_primary[!is.na(df_primary[['salary']]),] # drop rows with no salaryes

original_p <- df_primary
# Checking for missing values in primary dataset
library(Amelia)
missCounts <- sapply(df_primary,function(x) sum(is.na(x)))
missCounts
```

```
##   year name_p salary    Pos    Age     Tm      G     GS     MP    PER    TS%
##      0      0      0      0      0      0      0      0      0      0     24
##   3PAr    FTr   ORB%   DRB%   TRB%   AST%   STL%   BLK%   TOV%   USG%    OWS
##     30     30      0      0      0      0      0      0     19      0      0
##    DWS     WS  WS/48   OBPM   DBPM    BPM   VORP     FG    FGA    FG%     3P
```

```
##      0      0      0      0      0      0      0      0      0     30      0
##    3PA    3P%     2P    2PA    2P%   eFG%     FT    FTA    FT%    ORB    DRB
##      0   1562      0      0     40     30      0      0    233      0      0
##    TRB    AST    STL    BLK    TOV     PF    PTS
##      0      0      0      0      0      0      0
```

```
missmap(df_primary, main = "Missing values ")
```

```
## Warning: Unknown or uninitialised column: 'arguments'.

## Warning: Unknown or uninitialised column: 'arguments'.

## Warning: Unknown or uninitialised column: 'imputations'.
```




```
dev.copy(png,"../figures/Missing values/Missing_value_before_primary.png")
```

```
## png
##   3
```

```
dev.off()
```

```
## pdf
##   2
```

```
sum(missCounts)
```

```
## [1] 1998
```

```
nrow(df_primary)
```

```
## [1] 10977
```

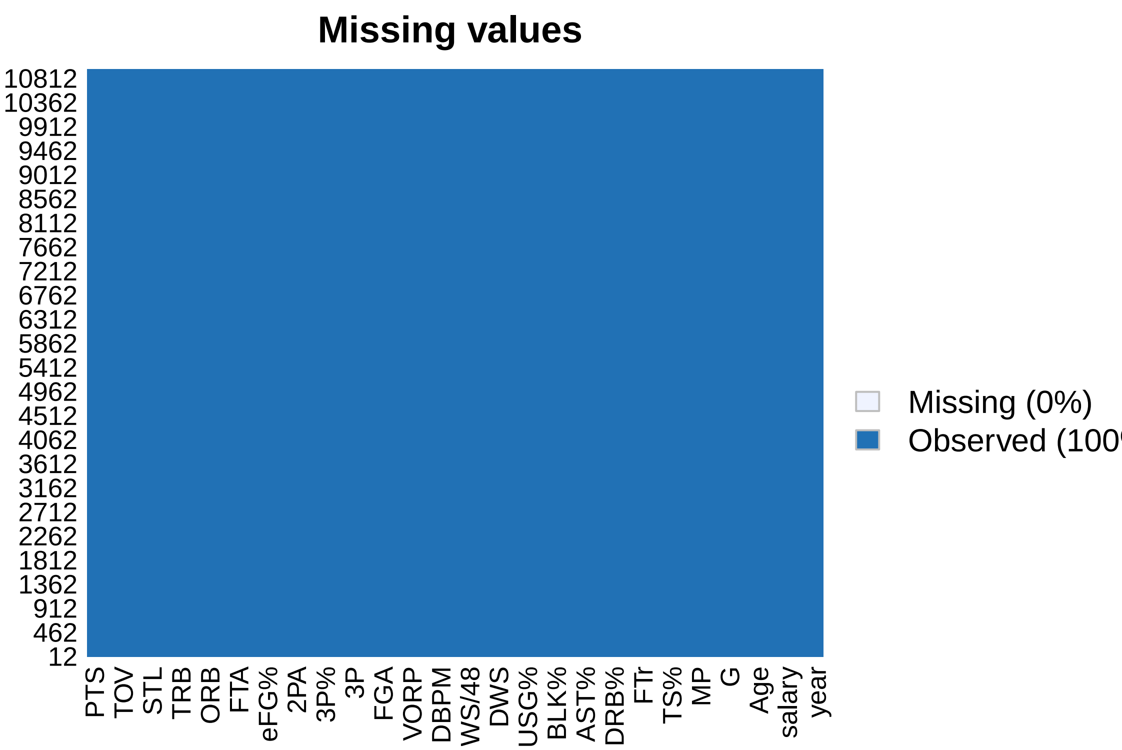
```
# Replacing the missng values with mean

df_primary$`3P%`[is.na(df_primary$`3P%`)] <- mean(df_primary$`3P%` , na.rm = T)
df_primary$`FT%`[is.na(df_primary$`FT%`)] <- mean(df_primary$`FT%` , na.rm = T)
df_primary$`TOV%`[is.na(df_primary$`TOV%`)] <- mean(df_primary$`TOV%` , na.rm = T)
df_primary$`FG%`[is.na(df_primary$`FG%`)] <- mean(df_primary$`FG%` , na.rm = T)
df_primary$`2P%`[is.na(df_primary$`2P%`)] <- mean(df_primary$`2P%` , na.rm = T)
df_primary$`eFG%`[is.na(df_primary$`eFG%`)] <- mean(df_primary$`eFG%` , na.rm = T)
df_primary$`TS%`[is.na(df_primary$`TS%`)] <- mean(df_primary$`TS%` , na.rm = T)
df_primary$`3PAr`[is.na(df_primary$`3PAr`)] <- mean(df_primary$`3PAr` , na.rm = T)
df_primary$`FTr`[is.na(df_primary$`FTr`)] <- mean(df_primary$`FTr` , na.rm = T)
```

```r
missCounts <- sapply(df_primary,function(x) sum(is.na(x)))
missCounts
```

```
##   year name_p salary    Pos    Age     Tm      G     GS     MP    PER    TS%
##      0      0      0      0      0      0      0      0      0      0      0
##   3PAr    FTr   ORB%   DRB%   TRB%   AST%   STL%   BLK%   TOV%   USG%    OWS
##      0      0      0      0      0      0      0      0      0      0      0
##    DWS     WS  WS/48   OBPM   DBPM    BPM   VORP     FG    FGA    FG%     3P
##      0      0      0      0      0      0      0      0      0      0      0
##    3PA    3P%     2P    2PA    2P%   eFG%     FT    FTA    FT%    ORB    DRB
##      0      0      0      0      0      0      0      0      0      0      0
##    TRB    AST    STL    BLK    TOV     PF    PTS
##      0      0      0      0      0      0      0
```

```r
missmap(df_primary, main = "Missing values ")
```

```
## Warning: Unknown or uninitialised column: 'arguments'.

## Warning: Unknown or uninitialised column: 'arguments'.

## Warning: Unknown or uninitialised column: 'imputations'.
```




```r
dev.copy(png,"../figures/Missing values/Missing_value_after_primary.png")
```

```
## png
##   3
```

```r
dev.off()
```

```
## pdf
##   2
```

```r
df_primary <- df_primary[df_primary$year%in%c(2016:2020),]    # take 2016-2017 player data
head(df_primary)
```

```
## # A tibble: 6 x 51
##    year name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##   <dbl> <chr>   <dbl> <chr> <dbl> <chr> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
## 1  2017 A.J. ~ 1.31e6 C        24 DAL      22     0   163   8.4 0.472  0.238
## 2  2016 Aaron~ 2.70e6 PG       31 CHI      69     0  1108  11.8 0.494  0.394
## 3  2017 Aaron~ 2.12e6 PG       32 IND      65     0   894   9.5 0.507  0.427
## 4  2016 Aaron~ 4.35e6 PF       20 ORL      78    37  1863  17   0.541  0.245
## 5  2017 Aaron~ 5.50e6 SF       21 ORL      80    72  2298  14.4 0.53   0.309
## 6  2016 Aaron~ 3.76e5 SG       21 CHO      21     0    93   4.3 0.371  0.526
```

```
## # ... with 39 more variables: FTr <dbl>, `ORB%` <dbl>, `DRB%` <dbl>,
## #   `TRB%` <dbl>, `AST%` <dbl>, `STL%` <dbl>, `BLK%` <dbl>, `TOV%` <dbl>,
## #   `USG%` <dbl>, OWS <dbl>, DWS <dbl>, WS <dbl>, `WS/48` <dbl>, OBPM <dbl>,
## #   DBPM <dbl>, BPM <dbl>, VORP <dbl>, FG <dbl>, 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>
```

```r
summary(df_primary)
```

```
##       year          name_p              salary            Pos
##  Min.   :2016   Length:965         Min.   :   11534   Length:965
##  1st Qu.:2016   Class :character   1st Qu.: 1551659   Class :character
##  Median :2017   Mode  :character   Median : 4000000   Mode  :character
##  Mean   :2017                      Mean   : 6789399
##  3rd Qu.:2017                      3rd Qu.:10500000
##  Max.   :2017                      Max.   :34682550
##       Age             Tm                  G               GS
##  Min.   :19.00   Length:965         Min.   : 1.00   Min.   : 0.00
##  1st Qu.:23.00   Class :character   1st Qu.:32.00   1st Qu.: 1.00
##  Median :26.00   Mode  :character   Median :61.00   Median :12.00
##  Mean   :26.48                      Mean   :53.41   Mean   :25.99
##  3rd Qu.:29.00                      3rd Qu.:75.00   3rd Qu.:52.00
##  Max.   :40.00                      Max.   :82.00   Max.   :82.00
##        MP            PER               TS%              3PAr
##  Min.   :   1   Min.   :-35.30   Min.   :0.0000   Min.   :0.0000
##  1st Qu.: 496   1st Qu.: 10.50   1st Qu.:0.5040   1st Qu.:0.1400
##  Median :1197   Median : 13.30   Median :0.5380   Median :0.3110
##  Mean   :1247   Mean   : 13.61   Mean   :0.5345   Mean   :0.3053
##  3rd Qu.:1954   3rd Qu.: 16.30   3rd Qu.:0.5710   3rd Qu.:0.4470
##  Max.   :3125   Max.   : 39.30   Max.   :1.0000   Max.   :1.0000
##       FTr              ORB%             DRB%            TRB%
##  Min.   :0.0000   Min.   : 0.000   Min.   : 0.00   Min.   : 0.000
##  1st Qu.:0.1680   1st Qu.: 1.900   1st Qu.:10.30   1st Qu.: 6.200
##  Median :0.2410   Median : 3.300   Median :14.00   Median : 8.800
##  Mean   :0.2695   Mean   : 4.868   Mean   :15.13   Mean   : 9.992
##  3rd Qu.:0.3380   3rd Qu.: 7.100   3rd Qu.:19.20   3rd Qu.:13.100
##  Max.   :2.0000   Max.   :27.300   Max.   :39.20   Max.   :30.300
##       AST%            STL%             BLK%             TOV%
##  Min.   : 0.00   Min.   : 0.000   Min.   : 0.000   Min.   : 0.00
##  1st Qu.: 7.00   1st Qu.: 1.100   1st Qu.: 0.500   1st Qu.: 9.90
##  Median :10.40   Median : 1.500   Median : 1.200   Median :12.50
##  Mean   :13.38   Mean   : 1.583   Mean   : 1.652   Mean   :12.88
##  3rd Qu.:17.80   3rd Qu.: 1.900   3rd Qu.: 2.300   3rd Qu.:15.20
##  Max.   :72.30   Max.   :11.100   Max.   :15.100   Max.   :43.60
##       USG%            OWS              DWS              WS
##  Min.   : 0.00   Min.   :-3.300   Min.   :0.000   Min.   :-2.10
##  1st Qu.:15.30   1st Qu.: 0.100   1st Qu.:0.400   1st Qu.: 0.50
##  Median :18.40   Median : 0.800   Median :1.000   Median : 1.80
##  Mean   :18.85   Mean   : 1.387   Mean   :1.272   Mean   : 2.66
##  3rd Qu.:21.80   3rd Qu.: 2.100   3rd Qu.:1.900   3rd Qu.: 3.80
##  Max.   :41.70   Max.   :13.800   Max.   :6.000   Max.   :17.90
##      WS/48               OBPM               DBPM              BPM
##  Min.   :-0.28300   Min.   :-17.3000   Min.   :-8.5000   Min.   :-24.100
##  1st Qu.: 0.05000   1st Qu.: -2.4000   1st Qu.:-1.5000   1st Qu.: -3.100
##  Median : 0.08700   Median : -0.9000   Median :-0.3000   Median : -1.200
##  Mean   : 0.08683   Mean   : -0.9566   Mean   :-0.2671   Mean   : -1.225
##  3rd Qu.: 0.12100   3rd Qu.:  0.4000   3rd Qu.: 1.0000   3rd Qu.:  0.700
##  Max.   : 0.63400   Max.   : 15.3000   Max.   :12.0000   Max.   : 15.600
##       VORP              FG               FGA              FG%
##  Min.   :-1.4000   Min.   :  0.0   Min.   :   0.0   Min.   :0.0000
##  1st Qu.:-0.1000   1st Qu.: 62.0   1st Qu.: 146.0   1st Qu.:0.4060
##  Median : 0.2000   Median :166.0   Median : 368.0   Median :0.4420
##  Mean   : 0.6493   Mean   :200.8   Mean   : 441.5   Mean   :0.4481
```

```
##  3rd Qu.: 1.0000   3rd Qu.:294.0   3rd Qu.: 644.0   3rd Qu.:0.4810
##  Max.   :12.4000   Max.   :824.0   Max.   :1941.0   Max.   :1.0000
##        3P              3PA              3P%              2P
##  Min.   :  0.00   Min.   :  0.0   Min.   :0.0000   Min.   :  0
##  1st Qu.:  3.00   1st Qu.: 12.0   1st Qu.:0.2711   1st Qu.: 43
##  Median : 30.00   Median : 92.0   Median :0.3330   Median :113
##  Mean   : 47.83   Mean   :133.8   Mean   :0.3042   Mean   :153
##  3rd Qu.: 77.00   3rd Qu.:215.0   3rd Qu.:0.3750   3rd Qu.:219
##  Max.   :402.00   Max.   :886.0   Max.   :1.0000   Max.   :730
##       2PA              2P%              eFG%              FT
##  Min.   :   0.0   Min.   :0.0000   Min.   :0.0000   Min.   :  0.00
##  1st Qu.:  93.0   1st Qu.:0.4480   1st Qu.:0.4680   1st Qu.: 23.00
##  Median : 235.0   Median :0.4830   Median :0.5010   Median : 59.00
##  Mean   : 307.8   Mean   :0.4875   Mean   :0.5006   Mean   : 92.23
##  3rd Qu.: 444.0   3rd Qu.:0.5290   3rd Qu.:0.5360   3rd Qu.:120.00
##  Max.   :1421.0   Max.   :1.0000   Max.   :1.0000   Max.   :746.00
##       FTA             FT%              ORB              DRB
##  Min.   :  0.0   Min.   :0.0000   Min.   :  0.00   Min.   :  0
##  1st Qu.: 33.0   1st Qu.:0.6910   1st Qu.: 13.00   1st Qu.: 62
##  Median : 78.0   Median :0.7640   Median : 33.00   Median :143
##  Mean   :120.3   Mean   :0.7463   Mean   : 52.69   Mean   :173
##  3rd Qu.:161.0   3rd Qu.:0.8310   3rd Qu.: 70.00   3rd Qu.:243
##  Max.   :881.0   Max.   :1.0000   Max.   :395.00   Max.   :817
##       TRB              AST              STL              BLK
##  Min.   :   0.0   Min.   :  0.0   Min.   :  0.00   Min.   :  0.00
##  1st Qu.:  79.0   1st Qu.: 30.0   1st Qu.: 14.00   1st Qu.:  5.00
##  Median : 178.0   Median : 74.0   Median : 33.00   Median : 15.00
##  Mean   : 225.7   Mean   :115.5   Mean   : 40.02   Mean   : 25.03
##  3rd Qu.: 307.0   3rd Qu.:151.0   3rd Qu.: 58.00   3rd Qu.: 33.00
##  Max.   :1198.0   Max.   :906.0   Max.   :169.00   Max.   :269.00
##       TOV               PF              PTS
##  Min.   :  0.00   Min.   :  0.0   Min.   :   0.0
##  1st Qu.: 25.00   1st Qu.: 47.0   1st Qu.: 166.0
##  Median : 57.00   Median :102.0   Median : 437.0
##  Mean   : 70.13   Mean   :103.4   Mean   : 541.8
##  3rd Qu.: 99.00   3rd Qu.:152.0   3rd Qu.: 780.0
##  Max.   :464.00   Max.   :278.0   Max.   :2558.0
```

Numeric / Factor Variables

```r
df_primary$Tm <- as.factor(df_primary$Tm) # TOT means they played for multiple teams
#    will be useful later when multiple records for a single player in a single year
df_primary$year <- as.factor(df_primary$year) # make year a factor variable
df_primary[df_primary$Pos=='PF-C',] # only 2 Power-Forwards / Centers
```

```
## # A tibble: 2 x 51
##   year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##   <fct> <chr>   <dbl> <chr> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
## 1 2016  Chann~ 7.81e6 PF-C     32 TOT      70    32  1200  12.9 0.586  0.677
## 2 2017  Joffr~ 1.52e6 PF-C     25 TOT      70     1   980  12.6 0.509  0.292
## # ... with 39 more variables: FTr <dbl>, `ORB%` <dbl>, `DRB%` <dbl>,
## #   `TRB%` <dbl>, `AST%` <dbl>, `STL%` <dbl>, `BLK%` <dbl>, `TOV%` <dbl>,
## #   `USG%` <dbl>, OWS <dbl>, DWS <dbl>, WS <dbl>, `WS/48` <dbl>, OBPM <dbl>,
## #   DBPM <dbl>, BPM <dbl>, VORP <dbl>, FG <dbl>, 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>
```

```r
# each player should only have 1 position
# both Channing Frye and Joffrey Lauvergne are classified as Forwards (PF)
# https://www.espn.com/nba/player/stats/_/id/2754/channing-frye
# https://www.espn.com/nba/player/stats/_/id/2959753/joffrey-lauvergne
df_primary$Pos <- gsub('PF-C','PF',df_primary$Pos)
```

```r
df_primary$Pos <- as.factor(df_primary$Pos) # make Pos a factor variable
table(df_primary$Pos)
```

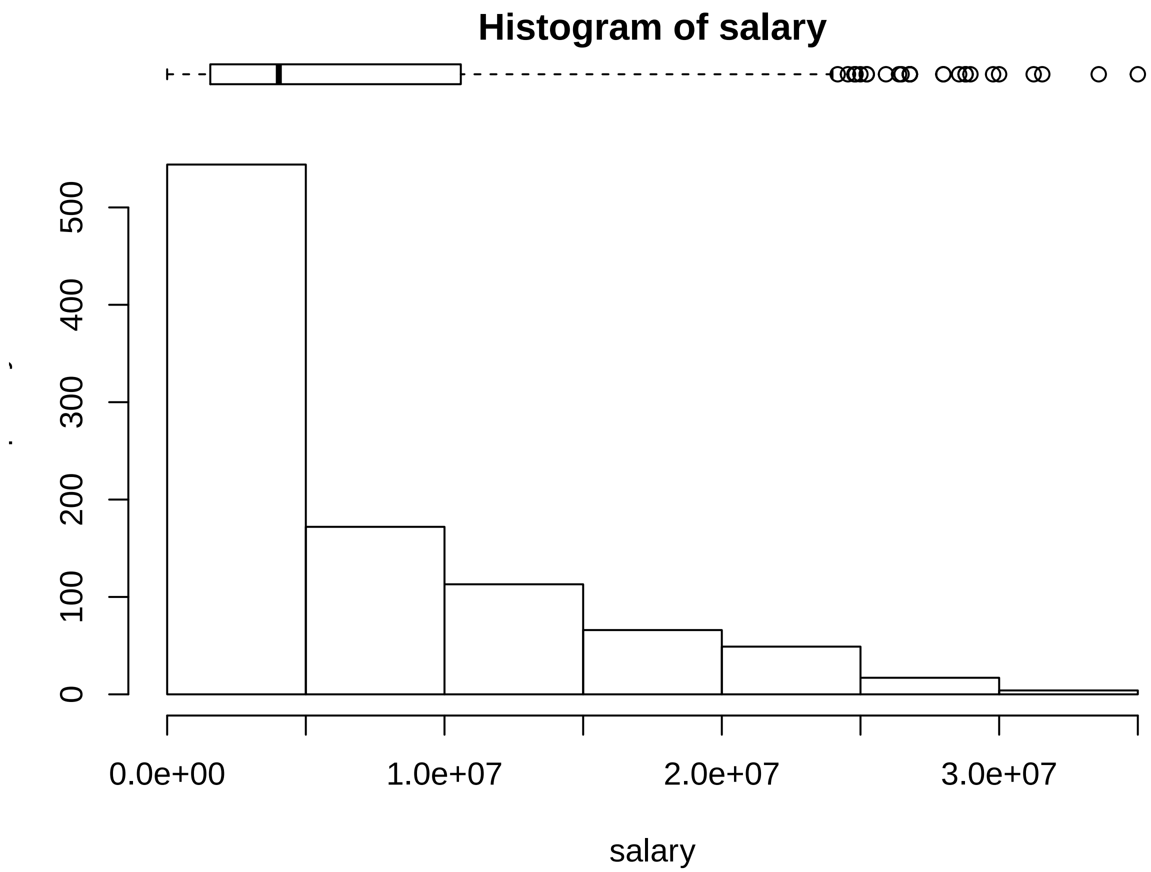
```
##
##   C  PF  PG  SF  SG
## 185 192 200 194 194
```

```r
str(df_primary)
```

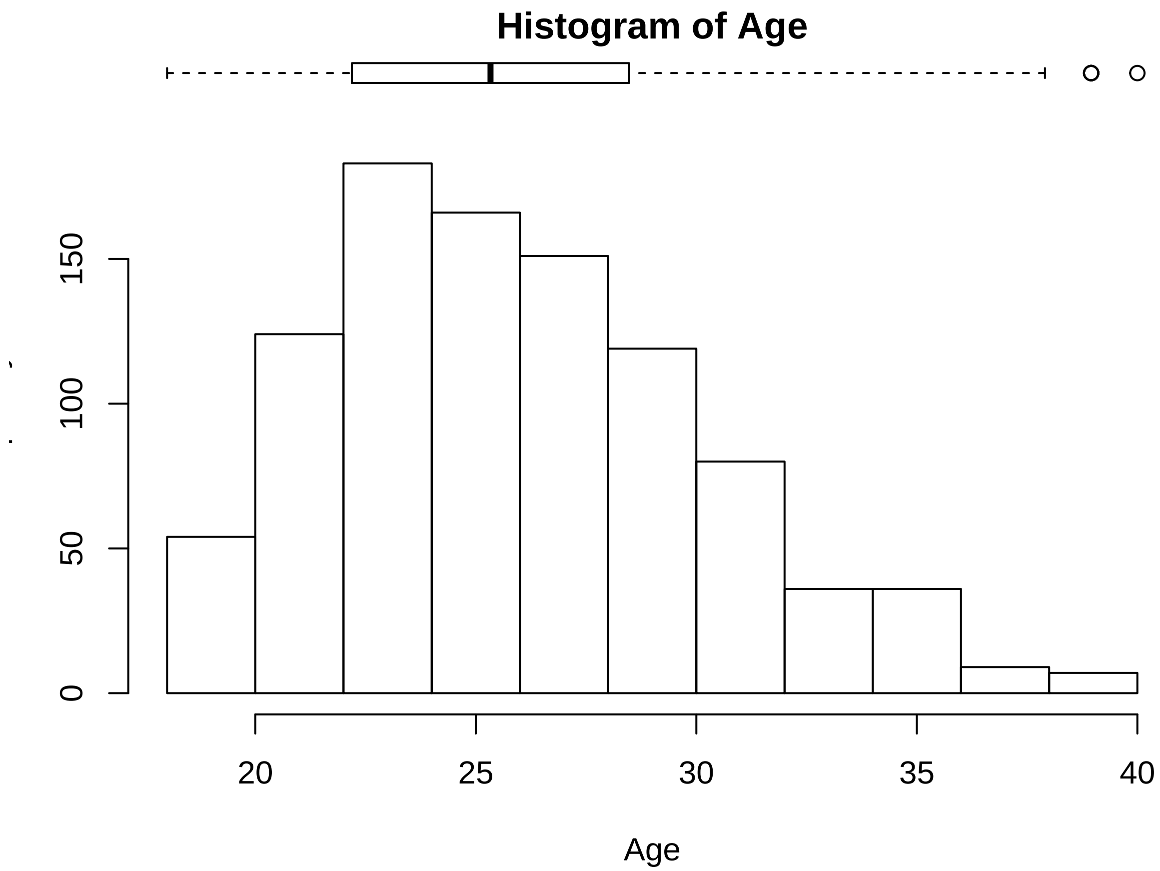
```
## Classes 'tbl_df', 'tbl' and 'data.frame':    965 obs. of  51 variables:
##  $ year  : Factor w/ 2 levels "2016","2017": 2 1 2 1 2 1 1 1 2 1 ...
##  $ name_p: chr  "A.J. Hammons" "Aaron Brooks" "Aaron Brooks" "Aaron Gordon" ...
##  $ salary: num  1312611 2700000 2116955 4351320 5504420 ...
##  $ Pos   : Factor w/ 5 levels "C","PF","PG",..: 1 3 3 2 4 5 2 1 1 1 ...
##  $ Age   : num  24 31 32 20 21 21 24 29 30 31 ...
##  $ Tm    : Factor w/ 31 levels "ATL","BOS","BRK",..: 7 4 12 22 22 5 18 1 2 5 ...
##  $ G     : num  22 69 65 78 80 21 52 82 68 47 ...
##  $ GS    : num  0 0 0 37 72 0 2 82 68 18 ...
##  $ MP    : num  163 1108 894 1863 2298 ...
##  $ PER   : num  8.4 11.8 9.5 17 14.4 4.3 5.6 19.4 17.7 18.2 ...
##  $ TS%   : num  0.472 0.494 0.507 0.541 0.53 0.371 0.422 0.565 0.553 0.507 ...
##  $ 3PAr  : num  0.238 0.394 0.427 0.245 0.309 0.526 0.221 0.244 0.302 0 ...
##  $ FTr   : num  0.476 0.136 0.133 0.333 0.251 0.632 0.179 0.123 0.169 0.22 ...
##  $ ORB%  : num  5.4 2 2.3 9 5.3 4.7 4.8 6.3 4.9 5.6 ...
##  $ DRB%  : num  20.9 7.5 6.3 21.3 14.1 13.1 21.5 18.2 18.6 24.6 ...
##  $ TRB%  : num  12.8 4.8 4.3 15.1 9.6 8.8 13.3 12.4 11.8 15 ...
##  $ AST%  : num  3.8 26 20.7 10.3 10.5 3 8.9 16.7 24.4 11.8 ...
##  $ STL%  : num  0.3 1.4 1.4 1.6 1.4 3.2 1.7 1.3 1.2 1.4 ...
##  $ BLK%  : num  7.2 0.7 0.9 2.4 1.4 0 1.8 3.6 3.3 3 ...
##  $ TOV%  : num  16.4 14.2 17.2 9 8.5 14.1 18.7 8.8 11.9 5.8 ...
##  $ USG%  : num  17.6 22.9 19.2 17.3 20.1 13.7 17.7 20.6 19.8 24.2 ...
##  $ OWS   : num  -0.2 0.2 -0.2 3.2 2 -0.2 -0.9 4.9 3.6 1 ...
##  $ DWS   : num  0.2 0.7 0.5 2.2 1.7 0.1 0.4 4.5 2.7 1.8 ...
##  $ WS    : num  0 0.9 0.3 5.4 3.7 0 -0.5 9.4 6.3 2.8 ...
##  $ WS/48 : num  -0.001 0.04 0.016 0.139 0.076 -0.014 -0.047 0.172 0.137 0.123 ...
##  $ OBPM  : num  -7.5 -0.5 -2.1 0.6 -0.2 -5.6 -5.9 1.5 1 -2.3 ...
##  $ DBPM  : num  1.9 -2.8 -2.6 1.2 -0.4 0.1 -0.2 2.6 2.1 1.2 ...
##  $ BPM   : num  -5.6 -3.3 -4.6 1.8 -0.7 -5.5 -6.1 4.1 3.1 -1.1 ...
##  $ VORP  : num  -0.1 -0.4 -0.6 1.8 0.8 -0.1 -0.5 4.1 2.8 0.2 ...
##  $ FG    : num  17 188 121 274 393 5 53 529 379 245 ...
##  $ FGA   : num  42 469 300 579 865 ...
##  $ FG%   : num  0.405 0.401 0.403 0.473 0.454 0.263 0.366 0.505 0.473 0.485 ...
##  $ 3P    : num  5 66 48 42 77 3 9 88 86 0 ...
##  $ 3PA   : num  10 185 128 142 267 10 32 256 242 0 ...
##  $ 3P%   : num  0.5 0.357 0.375 0.296 0.288 ...
##  $ 2P    : num  12 122 73 232 316 2 44 441 293 245 ...
##  $ 2PA   : num  32 284 172 437 598 9 113 792 559 505 ...
##  $ 2P%   : num  0.375 0.43 0.424 0.531 0.528 0.222 0.389 0.557 0.524 0.485 ...
##  $ eFG%  : num  0.464 0.471 0.483 0.509 0.499 0.342 0.397 0.547 0.527 0.485 ...
##  $ FT    : num  9 49 32 129 156 5 17 103 108 72 ...
##  $ FTA   : num  20 64 40 193 217 12 26 129 135 111 ...
##  $ FT%   : num  0.45 0.766 0.8 0.668 0.719 0.417 0.654 0.798 0.8 0.649 ...
##  $ ORB   : num  8 21 18 154 116 4 20 148 95 57 ...
##  $ DRB   : num  28 80 51 353 289 11 91 448 369 244 ...
##  $ TRB   : num  36 101 69 507 405 15 111 596 464 301 ...
##  $ AST   : num  4 180 125 128 150 2 29 263 337 70 ...
##  $ STL   : num  1 30 25 59 64 6 16 68 52 30 ...
##  $ BLK   : num  13 10 9 55 40 0 11 121 87 41 ...
##  $ TOV   : num  10 82 66 66 89 4 36 107 116 34 ...
##  $ PF    : num  21 132 93 153 172 10 77 163 138 117 ...
##  $ PTS   : num  48 491 322 719 1019 ...
```

Histogram Barcharts for Numeric Variables

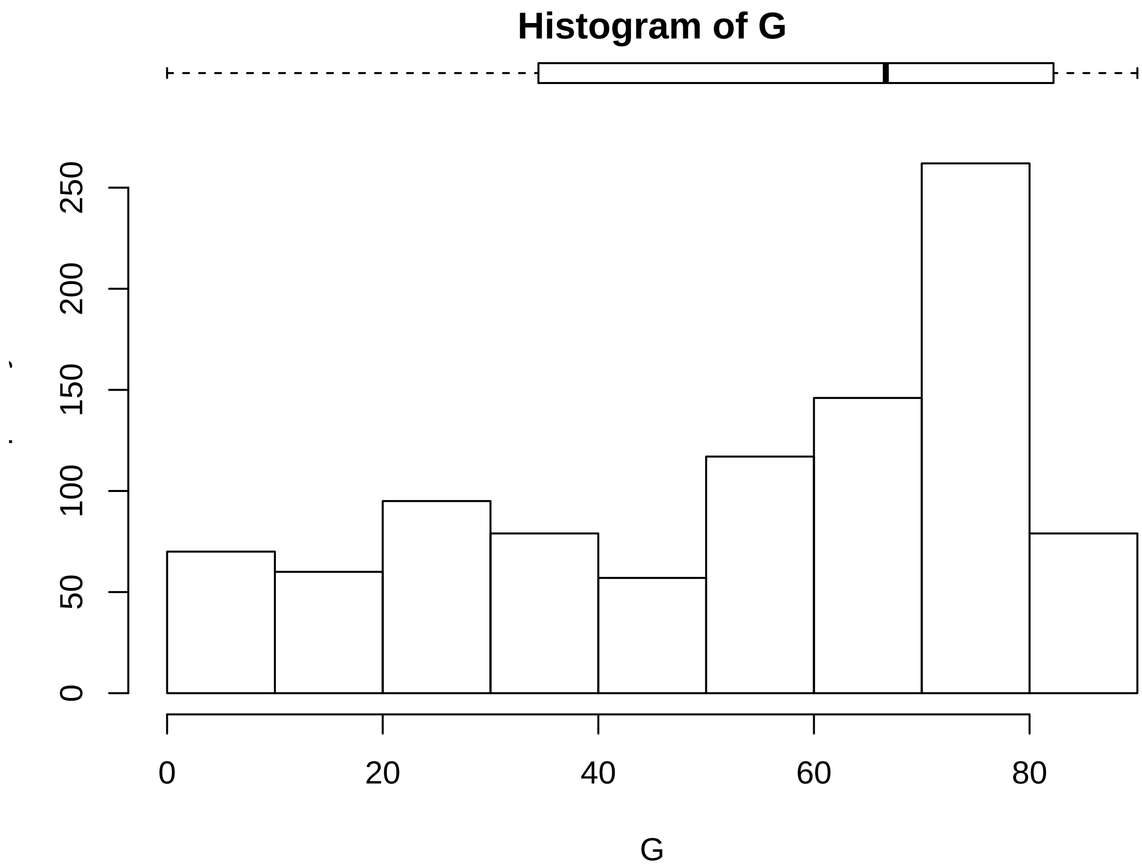
```r
df_p_numeric <- Filter(is.numeric,df_primary) # numeric variables
for (col in names(df_p_numeric)){
  data <- df_p_numeric[[col]]
  layout(mat = matrix(c(1,2),2,1, byrow=TRUE), height = c(1,8))
  par(mar=c(0, 3.1, 1.1, 2.1))
  boxplot(data , horizontal=TRUE , xaxt="n", frame=F, main=sprintf('Histogram of %s',col))
  par(mar=c(4, 3.1, 1.1, 2.1))
  hist(data,xlab=col,main='')
  # print top players in this category
  cat(sprintf('Top 10 Players by %s\n',col))
  df_top <- df_primary[order(df_primary[[col]],decreasing=T),]
  print(df_top[1:10,])}
```



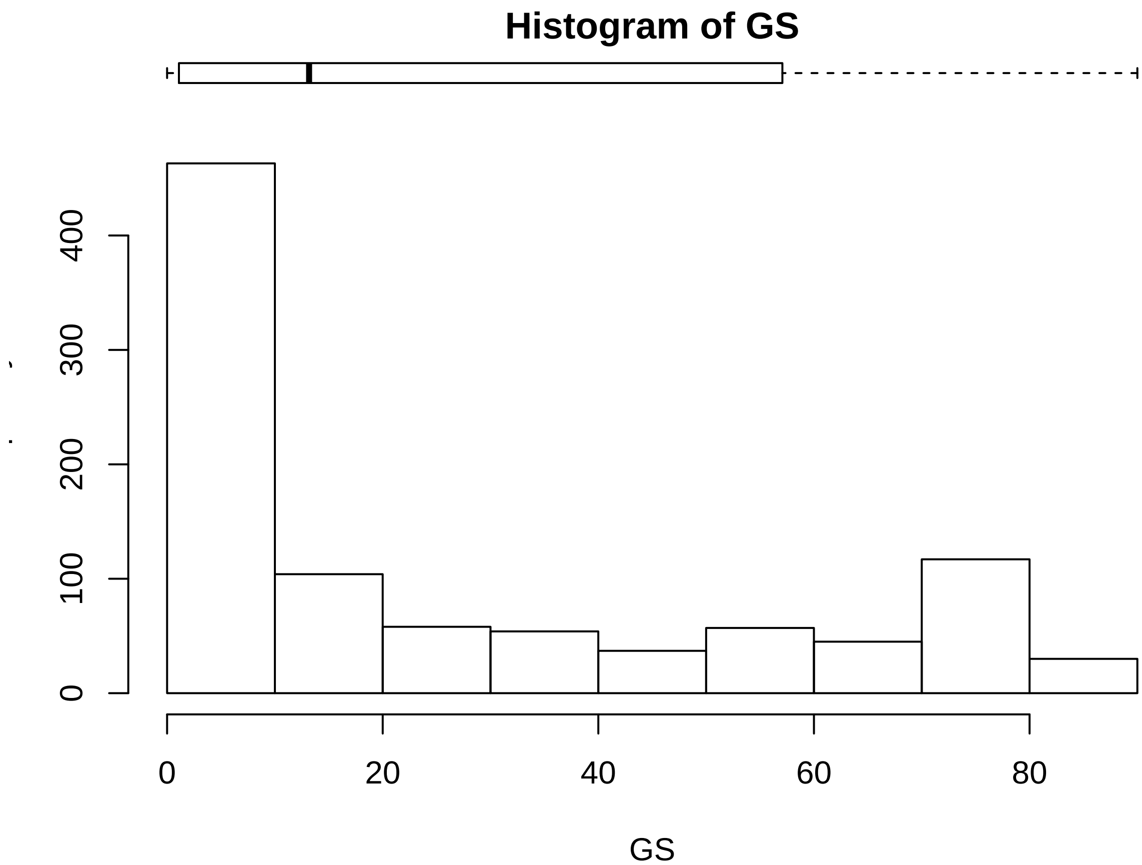

```
## Top 10 Players by salary
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2017  Steph~ 3.47e7 PG       28 GSW      79    79  2638  24.6 0.624  0.547
##  2 2017  LeBro~ 3.33e7 SF       32 CLE      74    74  2794  27   0.619  0.254
##  3 2017  Paul ~ 3.13e7 PF       31 ATL      69    67  2343  17.8 0.542  0.248
##  4 2016  LeBro~ 3.10e7 SF       31 CLE      76    76  2709  27.5 0.588  0.199
##  5 2017  Gordo~ 2.97e7 SF       26 UTA      73    73  2516  22.2 0.595  0.324
##  6 2017  Blake~ 2.95e7 PF       27 LAC      61    61  2076  22.7 0.569  0.116
##  7 2017  Kyle ~ 2.87e7 PG       30 TOR      60    60  2244  22.9 0.623  0.51
##  8 2017  Mike ~ 2.85e7 PG       29 MEM      69    68  2292  23.2 0.604  0.415
##  9 2017  Russe~ 2.85e7 PG       28 OKC      81    81  2802  30.6 0.554  0.3
## 10 2017  James~ 2.83e7 PG       27 HOU      81    81  2947  27.3 0.613  0.493
## # ... with 39 more variables: FTr <dbl>, `ORB%` <dbl>, `DRB%` <dbl>,
## #   `TRB%` <dbl>, `AST%` <dbl>, `STL%` <dbl>, `BLK%` <dbl>, `TOV%` <dbl>,
## #   `USG%` <dbl>, OWS <dbl>, DWS <dbl>, WS <dbl>, `WS/48` <dbl>, OBPM <dbl>,
## #   DBPM <dbl>, BPM <dbl>, VORP <dbl>, FG <dbl>, 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>
```



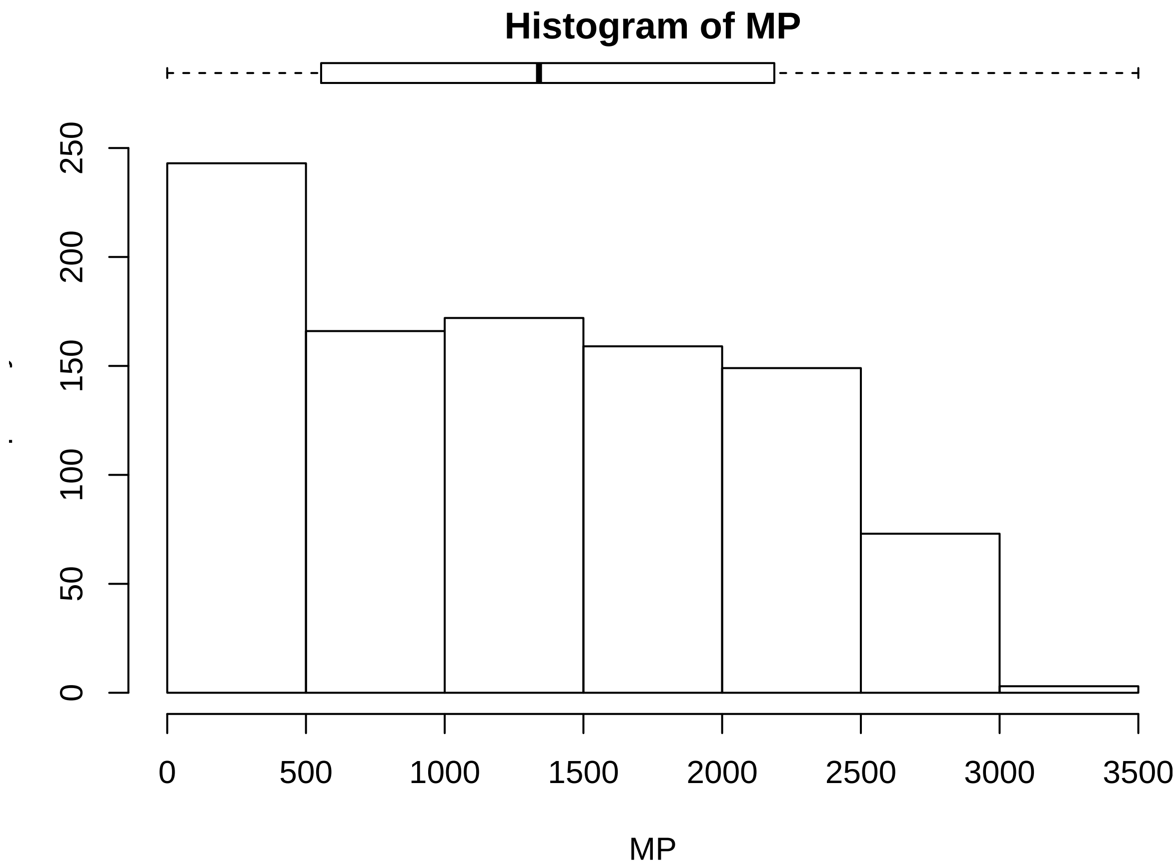

```
## Top 10 Players by Age
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2017  Vince~ 8.00e6 SF       40 MEM      73    15  1799  11.7 0.542  0.604
##  2 2017  Jason~ 2.33e6 SG       39 MIL      74     0  1365   9   0.6    0.704
##  3 2016  Kevin~ 8.00e6 PF       39 MIN      38    38   556  12.3 0.491  0.009
##  4 2017  Manu ~ 2.50e6 SG       39 SAS      69     0  1291  13.9 0.532  0.517
##  5 2017  Paul ~ 1.10e6 SF       39 LAC      25     7   277   5.7 0.535  0.614
##  6 2016  Tim D~ 1.88e6 C        39 SAS      61    60  1536  16.9 0.523  0.005
##  7 2016  Vince~ 4.26e6 SG       39 MEM      60     3  1005  12.7 0.52   0.493
##  8 2017  Dirk ~ 5.00e6 PF       38 DAL      54    54  1424  17   0.529  0.308
##  9 2016  Jason~ 1.55e6 SG       38 HOU      72     7  1258  10.2 0.54   0.694
## 10 2016  Manu ~ 1.40e7 SG       38 SAS      58     0  1134  17.8 0.573  0.411
## # ... with 39 more variables: FTr <dbl>, `ORB%` <dbl>, `DRB%` <dbl>,
## #   `TRB%` <dbl>, `AST%` <dbl>, `STL%` <dbl>, `BLK%` <dbl>, `TOV%` <dbl>,
## #   `USG%` <dbl>, OWS <dbl>, DWS <dbl>, WS <dbl>, `WS/48` <dbl>, OBPM <dbl>,
## #   DBPM <dbl>, BPM <dbl>, VORP <dbl>, FG <dbl>, 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>
```



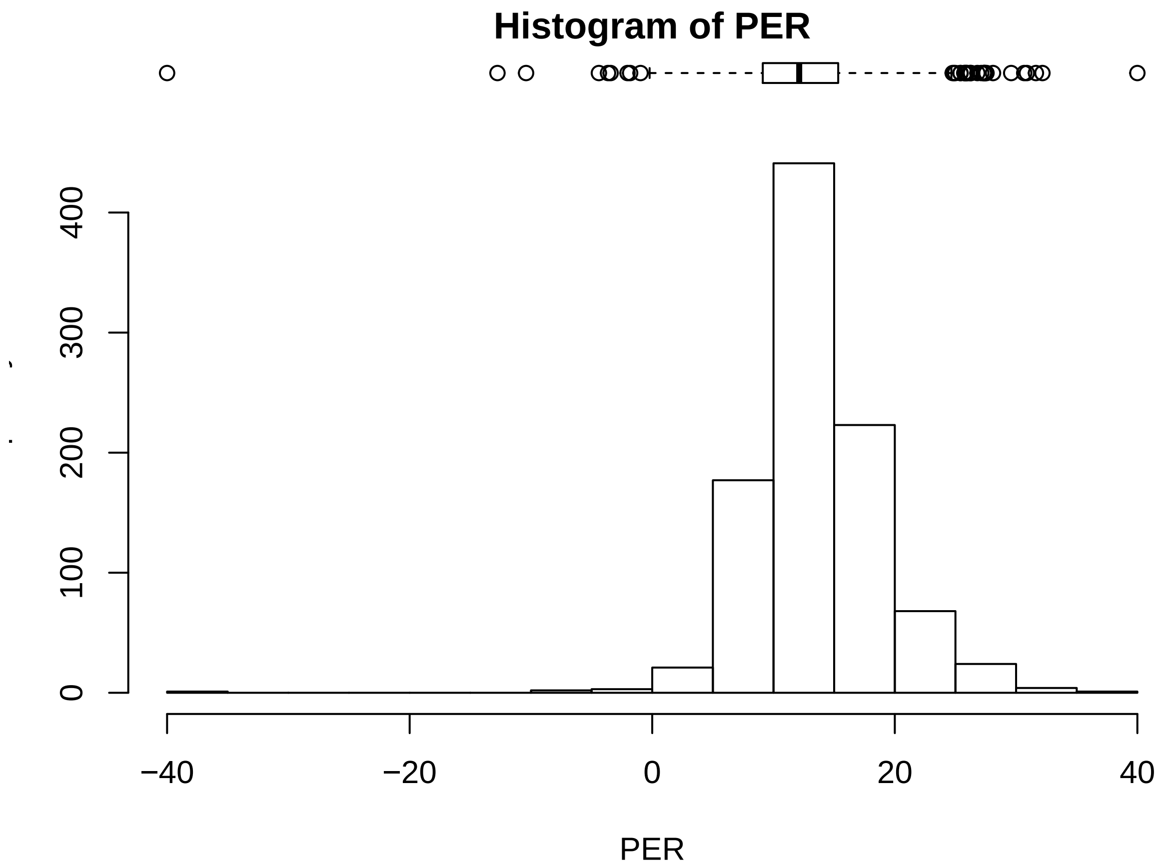

```
## Top 10 Players by G
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2016  Al Ho~ 2.65e7 C        29 ATL      82    82  2631  19.4 0.565  0.244
##  2 2016  Al-Fa~ 7.68e6 SF       25 POR      82    82  2341  12.7 0.533  0.485
##  3 2017  Andre~ 7.57e6 SF       21 MIN      82    82  3048  16.5 0.534  0.184
##  4 2016  Bisma~ 1.70e7 C        23 TOR      82    22  1808  14.9 0.586  0.003
##  5 2017  Buddy~ 3.68e6 SG       23 TOT      82    55  1888  11.8 0.54   0.493
##  6 2016  Corey~ 7.60e6 SF       29 HOU      82    12  1669   9.9 0.481  0.406
##  7 2017  Corey~ 7.58e6 SF       30 TOT      82    11  1281   9.1 0.491  0.339
##  8 2017  Elfri~ 3.33e6 PG       22 ORL      82    58  2412  17.2 0.52   0.16
##  9 2016  Enes ~ 1.71e7 C        23 OKC      82     1  1721  24   0.626  0.029
## 10 2017  Ersan~ 6.00e6 PF       29 TOT      82    52  2142  14.6 0.546  0.452
## # ... with 39 more variables: FTr <dbl>, `ORB%` <dbl>, `DRB%` <dbl>,
## #   `TRB%` <dbl>, `AST%` <dbl>, `STL%` <dbl>, `BLK%` <dbl>, `TOV%` <dbl>,
## #   `USG%` <dbl>, OWS <dbl>, DWS <dbl>, WS <dbl>, `WS/48` <dbl>, OBPM <dbl>,
## #   DBPM <dbl>, BPM <dbl>, VORP <dbl>, FG <dbl>, 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>
```



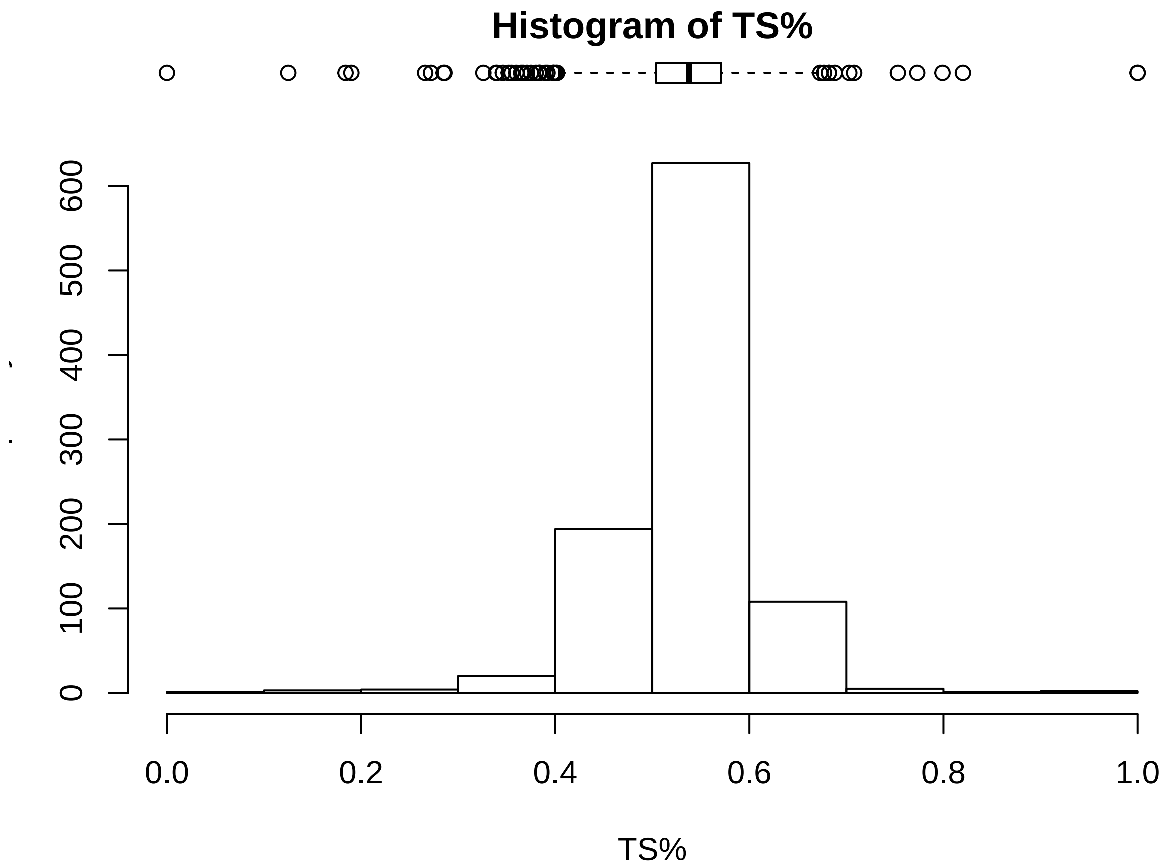

```
## Top 10 Players by GS
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2016  Al Ho~ 2.65e7 C        29 ATL      82    82  2631  19.4 0.565  0.244
##  2 2016  Al-Fa~ 7.68e6 SF       25 POR      82    82  2341  12.7 0.533  0.485
##  3 2017  Andre~ 7.57e6 SF       21 MIN      82    82  3048  16.5 0.534  0.184
##  4 2017  Gorgu~ 1.41e7 PF       27 MIN      82    82  2653  14.2 0.555  0.065
##  5 2016  James~ 2.65e7 SG       26 HOU      82    82  3125  25.3 0.598  0.406
##  6 2017  Jeff ~ 1.90e7 PG       28 IND      82    82  2657  19.2 0.574  0.277
##  7 2016  Karl-~ 5.96e6 C        20 MIN      82    82  2627  22.5 0.59   0.076
##  8 2017  Karl-~ 6.22e6 C        21 MIN      82    82  3030  26    0.618  0.186
##  9 2017  Marci~ 1.28e7 C        32 WAS      82    82  2556  15.5 0.593  0.003
## 10 2016  Mason~ 2.33e6 C        25 POR      82    82  2084  17.2 0.564  0.008
## # ... with 39 more variables: FTr <dbl>, `ORB%` <dbl>, `DRB%` <dbl>,
## #   `TRB%` <dbl>, `AST%` <dbl>, `STL%` <dbl>, `BLK%` <dbl>, `TOV%` <dbl>,
## #   `USG%` <dbl>, OWS <dbl>, DWS <dbl>, WS <dbl>, `WS/48` <dbl>, OBPM <dbl>,
## #   DBPM <dbl>, BPM <dbl>, VORP <dbl>, FG <dbl>, 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>
```



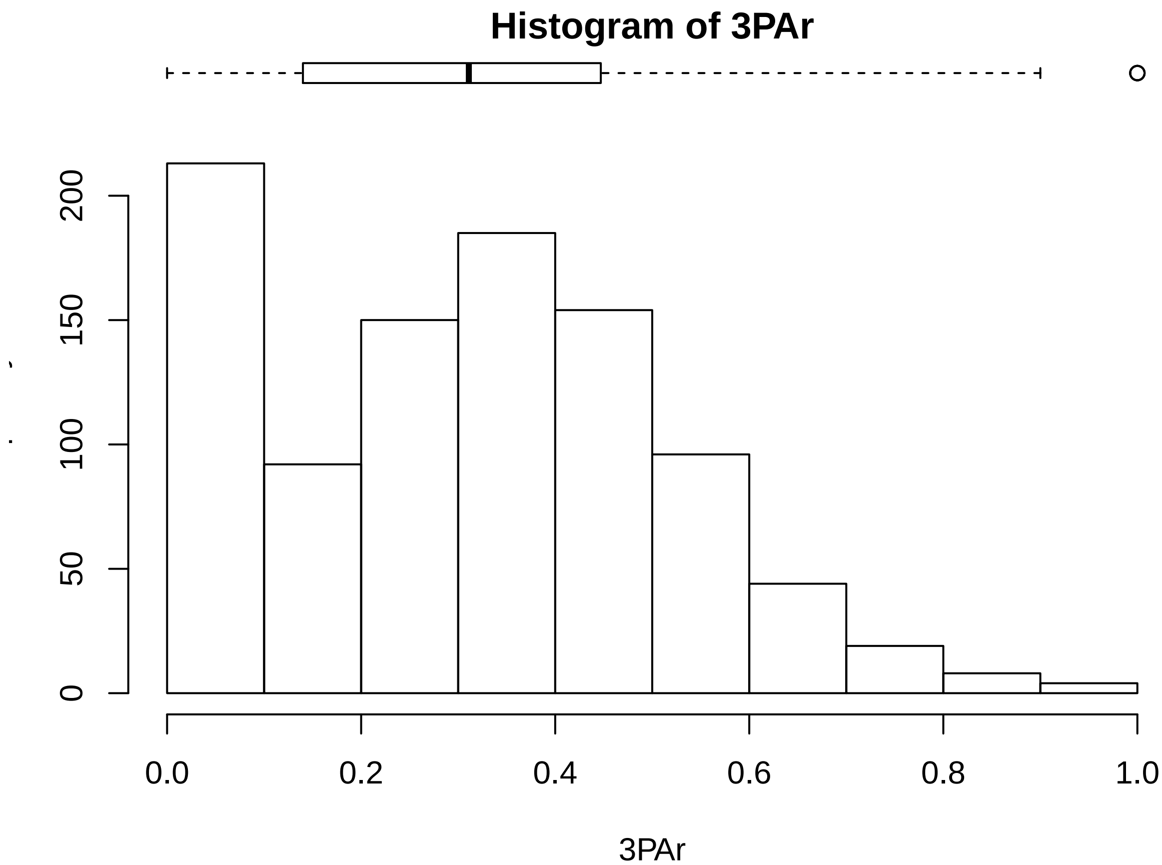

```
## Top 10 Players by MP
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2016  James~ 2.65e7 SG       26 HOU      82    82  3125  25.3 0.598  0.406
##  2 2017  Andre~ 7.57e6 SF       21 MIN      82    82  3048  16.5 0.534  0.184
##  3 2017  Karl-~ 6.22e6 C        21 MIN      82    82  3030  26   0.618  0.186
##  4 2017  James~ 2.83e7 PG       27 HOU      81    81  2947  27.3 0.613  0.493
##  5 2016  Gordo~ 1.61e7 SF       25 UTA      80    80  2893  18.3 0.559  0.341
##  6 2016  Kemba~ 1.20e7 PG       25 CHO      81    81  2885  20.8 0.554  0.368
##  7 2016  Trevo~ 7.81e6 SF       30 HOU      81    81  2859  12.9 0.551  0.581
##  8 2016  Marcu~ 4.62e6 SF       26 DET      80    80  2856  12.7 0.531  0.315
##  9 2016  Khris~ 1.52e7 SG       24 MIL      79    79  2852  16.8 0.56   0.316
## 10 2016  Kyle ~ 1.20e7 PG       29 TOR      77    77  2851  22.2 0.578  0.457
## # ... with 39 more variables: FTr <dbl>, `ORB%` <dbl>, `DRB%` <dbl>,
## #   `TRB%` <dbl>, `AST%` <dbl>, `STL%` <dbl>, `BLK%` <dbl>, `TOV%` <dbl>,
## #   `USG%` <dbl>, OWS <dbl>, DWS <dbl>, WS <dbl>, `WS/48` <dbl>, OBPM <dbl>,
## #   DBPM <dbl>, BPM <dbl>, VORP <dbl>, FG <dbl>, 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>
```



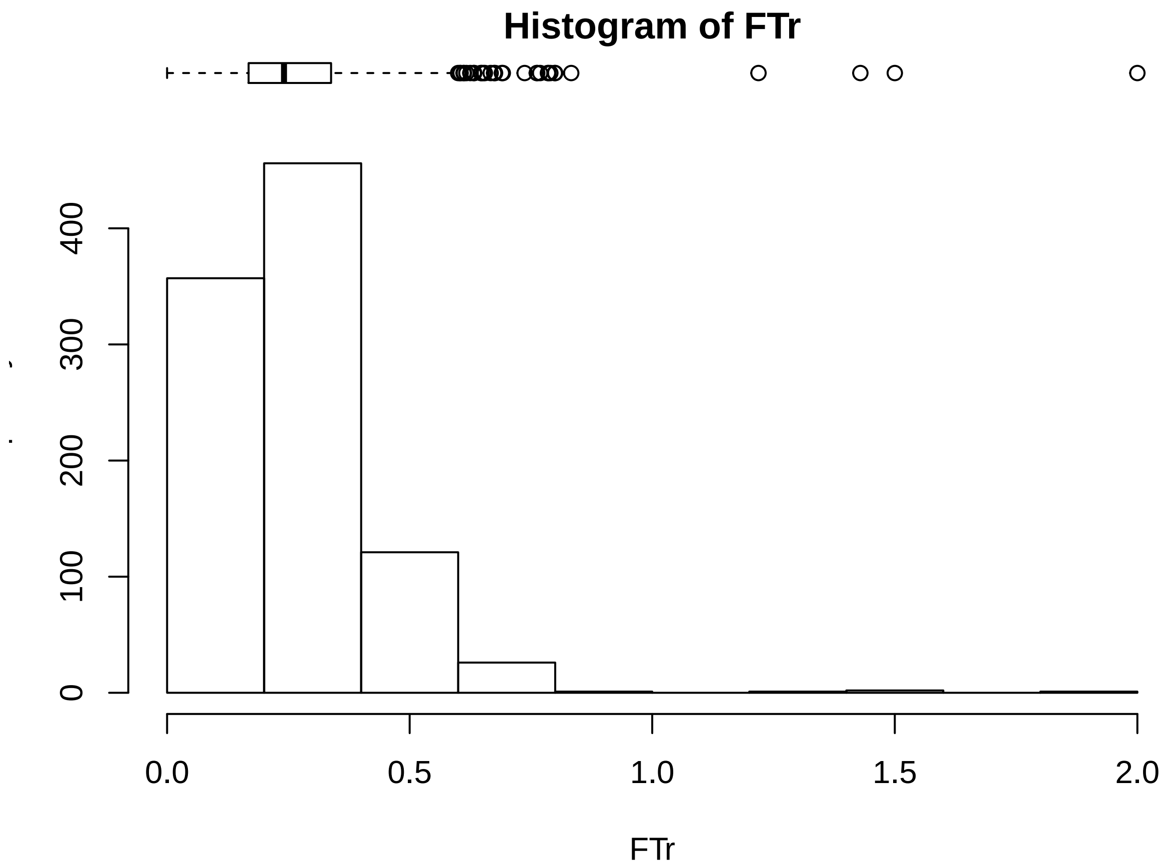

```
## Top 10 Players by PER
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2016  Brian~ 3.28e5 PG       23 MIA       1     0     3  39.3 1      0
##  2 2016  Rakee~ 1.05e6 PF       24 IND       1     0     6  32   1      0
##  3 2016  Steph~ 1.21e7 PG       27 GSW      79    79  2700  31.5 0.669  0.554
##  4 2017  Demet~ 9.29e4 PG       22 BOS       5     0    17  30.8 0.753  0.25
##  5 2017  Russe~ 2.85e7 PG       28 OKC      81    81  2802  30.6 0.554  0.3
##  6 2017  Boban~ 7.00e6 C        28 DET      35     0   293  29.6 0.606  0
##  7 2016  Kevin~ 2.65e7 SF       27 OKC      72    72  2578  28.2 0.634  0.348
##  8 2016  Boban~ 7.00e6 C        27 SAS      54     4   508  27.7 0.662  0
##  9 2017  Kevin~ 2.50e7 SF       28 GSW      62    62  2070  27.6 0.651  0.304
## 10 2016  Russe~ 2.65e7 PG       27 OKC      80    80  2750  27.6 0.554  0.236
## # ... with 39 more variables: FTr <dbl>, `ORB%` <dbl>, `DRB%` <dbl>,
## #   `TRB%` <dbl>, `AST%` <dbl>, `STL%` <dbl>, `BLK%` <dbl>, `TOV%` <dbl>,
## #   `USG%` <dbl>, OWS <dbl>, DWS <dbl>, WS <dbl>, `WS/48` <dbl>, OBPM <dbl>,
## #   DBPM <dbl>, BPM <dbl>, VORP <dbl>, FG <dbl>, 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>
```



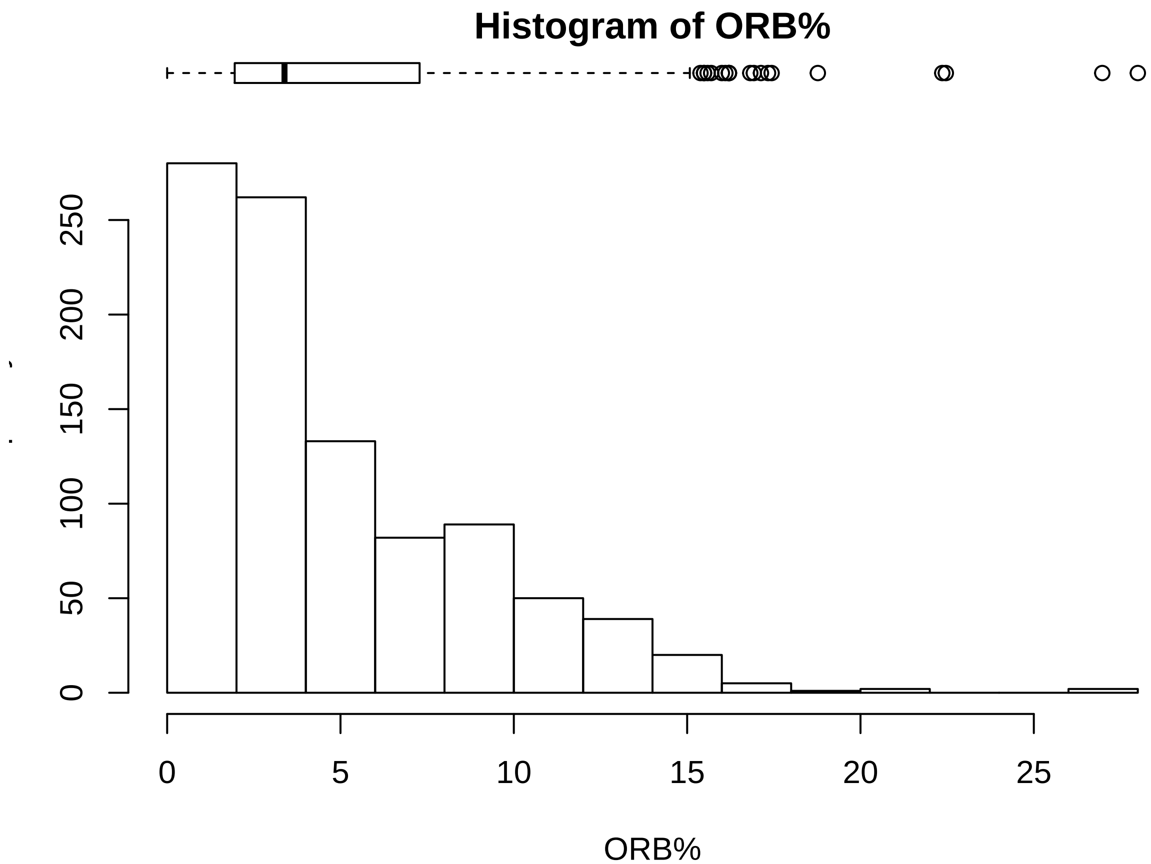

```
## Top 10 Players by TS%
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2016  Brian~ 3.28e5 PG       23 MIA       1     0     3  39.3 1      0
##  2 2016  Rakee~ 1.05e6 PF       24 IND       1     0     6  32   1      0
##  3 2017  Wayne~ 1.31e6 SG       22 NOP       3     3    47  10   0.82   0.875
##  4 2017  China~ 1.31e6 C        20 HOU       5     1    52  12.3 0.799  0
##  5 2017  Jarre~ 2.33e6 PG       33 NOP       2     0    33   7.7 0.773  0.333
##  6 2017  Demet~ 9.29e4 PG       22 BOS       5     0    17  30.8 0.753  0.25
##  7 2016  Steve~ 1.55e6 PF       32 OKC       7     0    24  20.8 0.708  0.75
##  8 2017  Tyson~ 1.30e7 C        34 PHO      47    46  1298  16.6 0.703  0
##  9 2017  Axel ~ 2.50e4 SF       24 NOP       2     0    41   8.6 0.688  0.375
## 10 2017  Lucas~ 2.95e6 C        24 TOR      57     6  1088  15.5 0.682  0.077
## # ... with 39 more variables: FTr <dbl>, `ORB%` <dbl>, `DRB%` <dbl>,
## #   `TRB%` <dbl>, `AST%` <dbl>, `STL%` <dbl>, `BLK%` <dbl>, `TOV%` <dbl>,
## #   `USG%` <dbl>, OWS <dbl>, DWS <dbl>, WS <dbl>, `WS/48` <dbl>, OBPM <dbl>,
## #   DBPM <dbl>, BPM <dbl>, VORP <dbl>, FG <dbl>, 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>
```



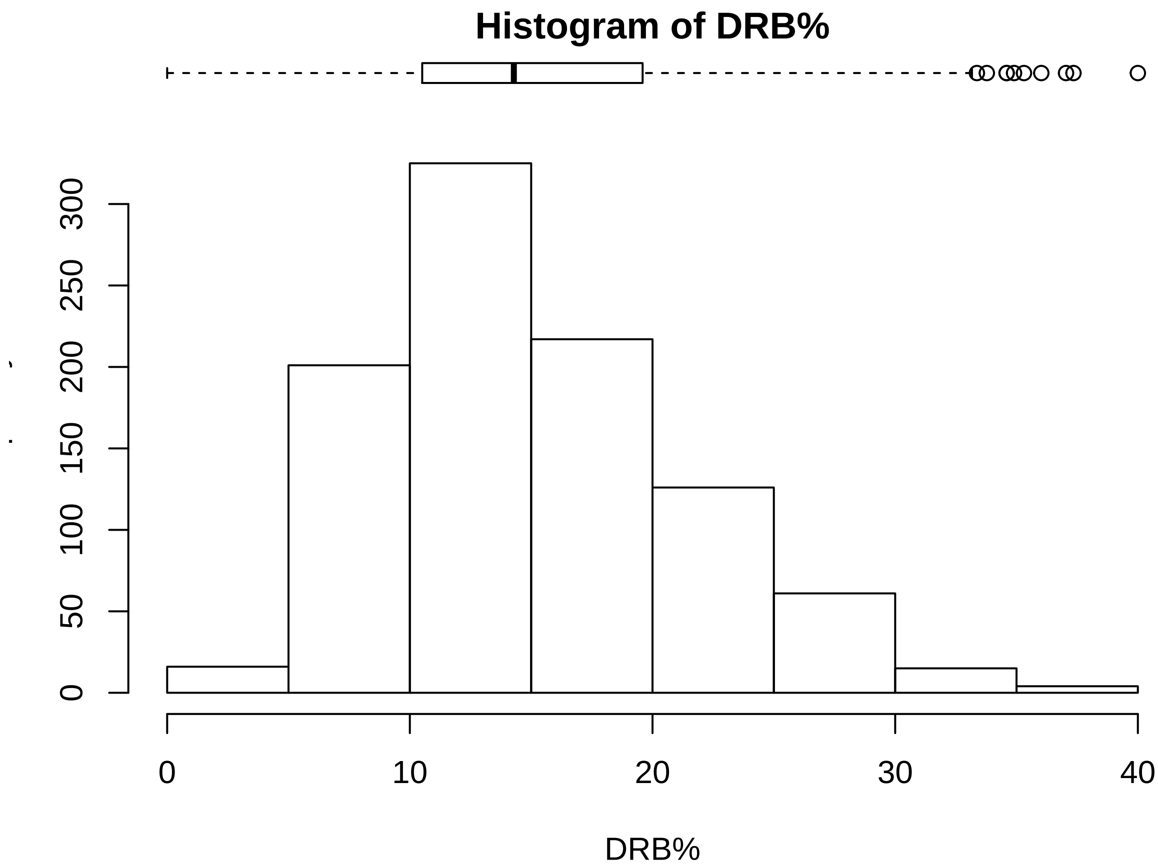

```
## Top 10 Players by 3PAr
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2017  Axel ~ 2.50e4 SF       24 MIL       2     0     6  -9.9 0       1
##  2 2017  Chris~ 1.47e6 PF       21 WAS       2     0     8   1.1 0.266   1
##  3 2016  Joe H~ 9.80e5 SG       24 CLE       5     0    15   3.4 0.375   1
##  4 2016  Steve~ 1.55e6 PF       32 MIL       3     0    20   6.7 0.543   1
##  5 2016  Justi~ 5.77e4 PF       26 DET       5     0    35   6.9 0.597   0.9
##  6 2017  Wayne~ 1.31e6 SG       22 NOP       3     3    47  10   0.82    0.875
##  7 2017  Jarel~ 1.72e4 SF       25 PHO       5     0    62   9.7 0.523   0.842
##  8 2016  Mike ~ 3.50e6 SF       35 DEN      47     2   373   6.5 0.508   0.839
##  9 2016  Steve~ 1.55e6 PF       32 TOT      10     0    44  14.4 0.651   0.833
## 10 2016  Antho~ 8.00e6 PF       30 DET      72     5  1341  10.2 0.543   0.819
## # ... with 39 more variables: FTr <dbl>, `ORB%` <dbl>, `DRB%` <dbl>,
## #   `TRB%` <dbl>, `AST%` <dbl>, `STL%` <dbl>, `BLK%` <dbl>, `TOV%` <dbl>,
## #   `USG%` <dbl>, OWS <dbl>, DWS <dbl>, WS <dbl>, `WS/48` <dbl>, OBPM <dbl>,
## #   DBPM <dbl>, BPM <dbl>, VORP <dbl>, FG <dbl>, 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>
```



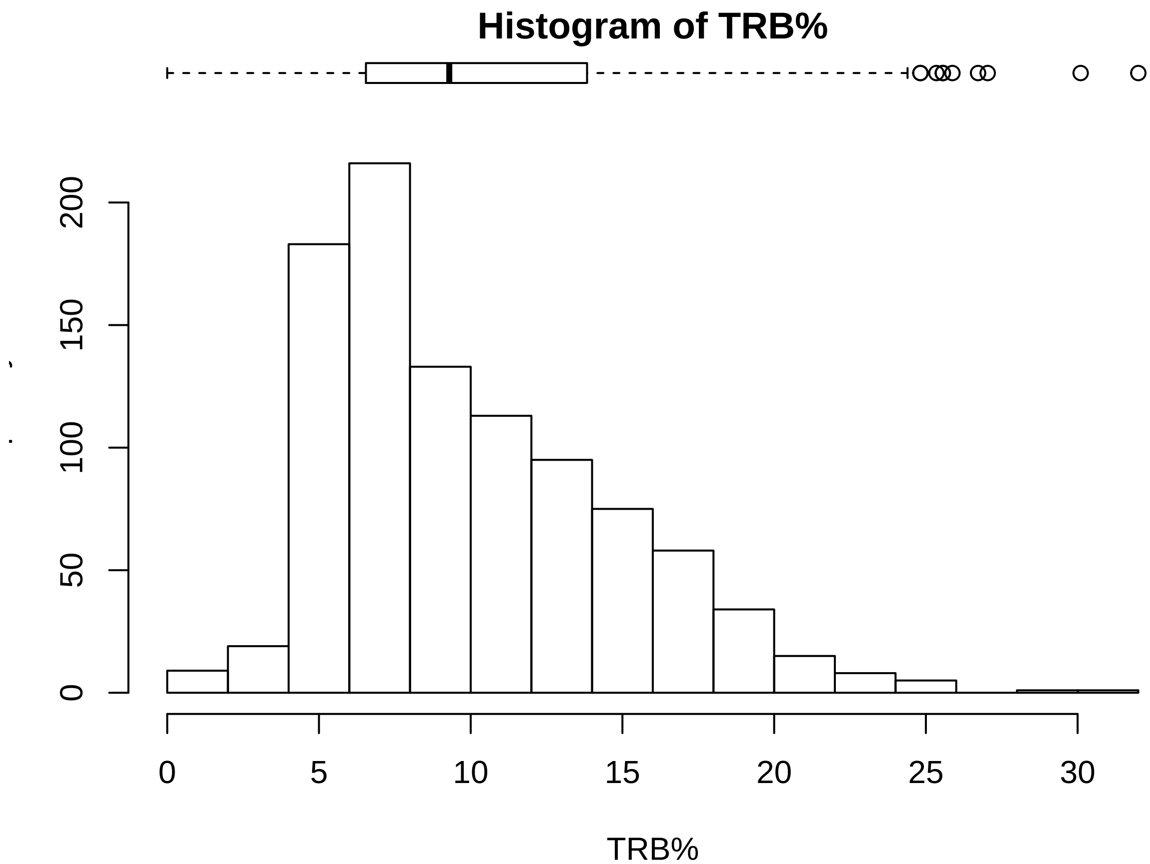

```
## Top 10 Players by FTr
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2017  Chris~ 1.47e6 PF       21 WAS       2     0     8   1.1 0.266  1
##  2 2017  Demet~ 9.29e4 PG       22 BOS       5     0    17  30.8 0.753  0.25
##  3 2017  Marcu~ 1.31e6 SG       22 ORL       5     0    48  10.2 0.614  0.286
##  4 2016  DeAnd~ 2.12e7 C        27 LAC      77    77  2598  20.6 0.628  0.002
##  5 2016  Jorda~ 1.47e6 SG       21 MEM       2     0    15  17.3 0.427  0.167
##  6 2016  Joel ~ 6.64e5 C        33 DET      19     0    96  14.1 0.666  0
##  7 2016  Rudy ~ 2.12e6 C        23 UTA      61    60  1932  17.5 0.582  0
##  8 2016  Dwigh~ 2.32e7 C        30 HOU      71    71  2280  18.9 0.604  0.01
##  9 2017  Ander~ 1.91e6 C        34 GSW      14     1    92   9.4 0.478  0
## 10 2016  Bisma~ 1.70e7 C        23 TOR      82    22  1808  14.9 0.586  0.003
## # ... with 39 more variables: FTr <dbl>, `ORB%` <dbl>, `DRB%` <dbl>,
## #   `TRB%` <dbl>, `AST%` <dbl>, `STL%` <dbl>, `BLK%` <dbl>, `TOV%` <dbl>,
## #   `USG%` <dbl>, OWS <dbl>, DWS <dbl>, WS <dbl>, `WS/48` <dbl>, OBPM <dbl>,
## #   DBPM <dbl>, BPM <dbl>, VORP <dbl>, FG <dbl>, 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>
```



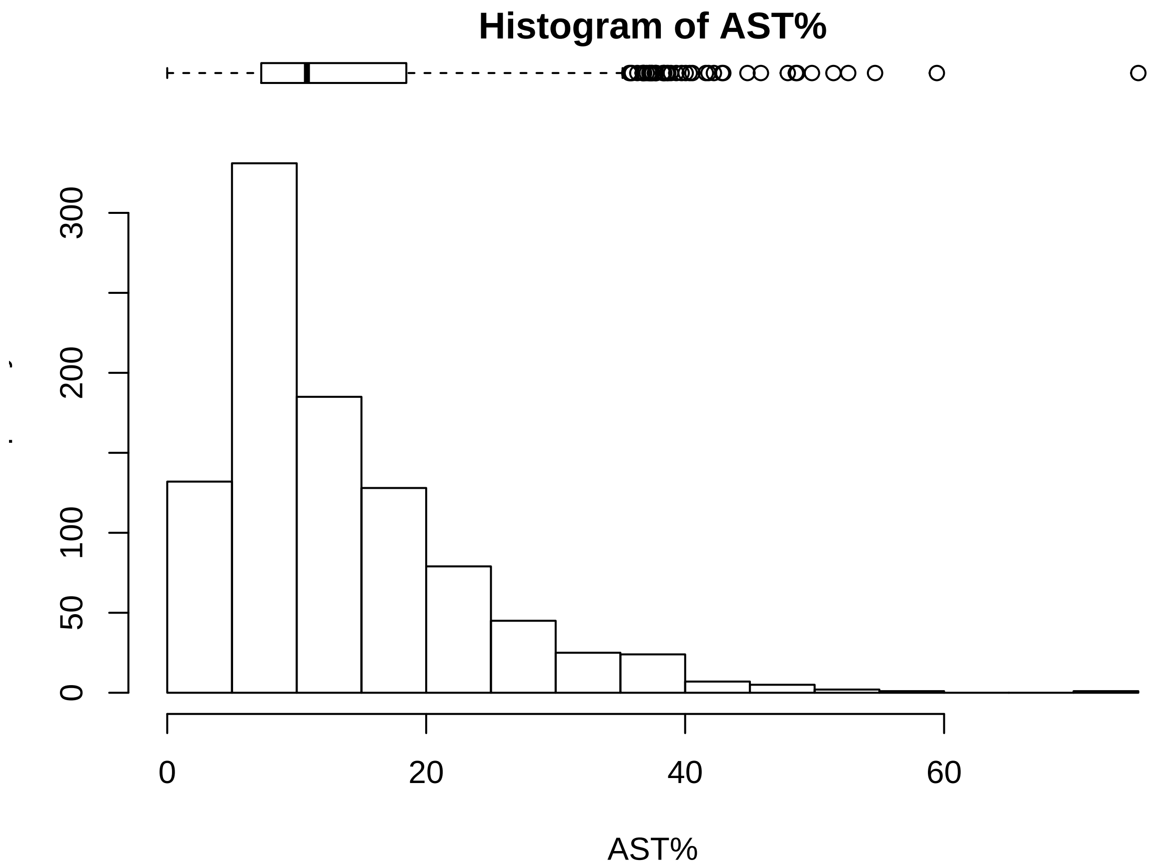

```
## Top 10 Players by ORB%
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2016  Jarne~ 1.50e5 C        22 MEM       2     0     4  13.6 0.515  0.191
##  2 2017  Larry~ 1.87e6 C        28 CLE       5     0    13   6.5 0.41   0
##  3 2016  Alan ~ 8.75e5 PF       23 PHO      10     0    68  21.1 0.481  0
##  4 2016  Kevon~ 1.18e6 PF       19 GSW       5     0    21  18.6 0.643  0.286
##  5 2016  Rakee~ 1.05e6 PF       24 IND       1     0     6  32   1      0
##  6 2017  Joaki~ 1.78e7 C        31 NYK      46    46  1015  15.2 0.493  0.005
##  7 2016  Boban~ 7.00e6 C        27 SAS      54     4   508  27.7 0.662  0
##  8 2016  Enes ~ 1.71e7 C        23 OKC      82     1  1721  24   0.626  0.029
##  9 2017  Boban~ 7.00e6 C        28 DET      35     0   293  29.6 0.606  0
## 10 2016  Thoma~ 1.05e6 PF       24 BRK      71     7   917  14.5 0.453  0.003
## # ... with 39 more variables: FTr <dbl>, `ORB%` <dbl>, `DRB%` <dbl>,
## #   `TRB%` <dbl>, `AST%` <dbl>, `STL%` <dbl>, `BLK%` <dbl>, `TOV%` <dbl>,
## #   `USG%` <dbl>, OWS <dbl>, DWS <dbl>, WS <dbl>, `WS/48` <dbl>, OBPM <dbl>,
## #   DBPM <dbl>, BPM <dbl>, VORP <dbl>, FG <dbl>, 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>
```



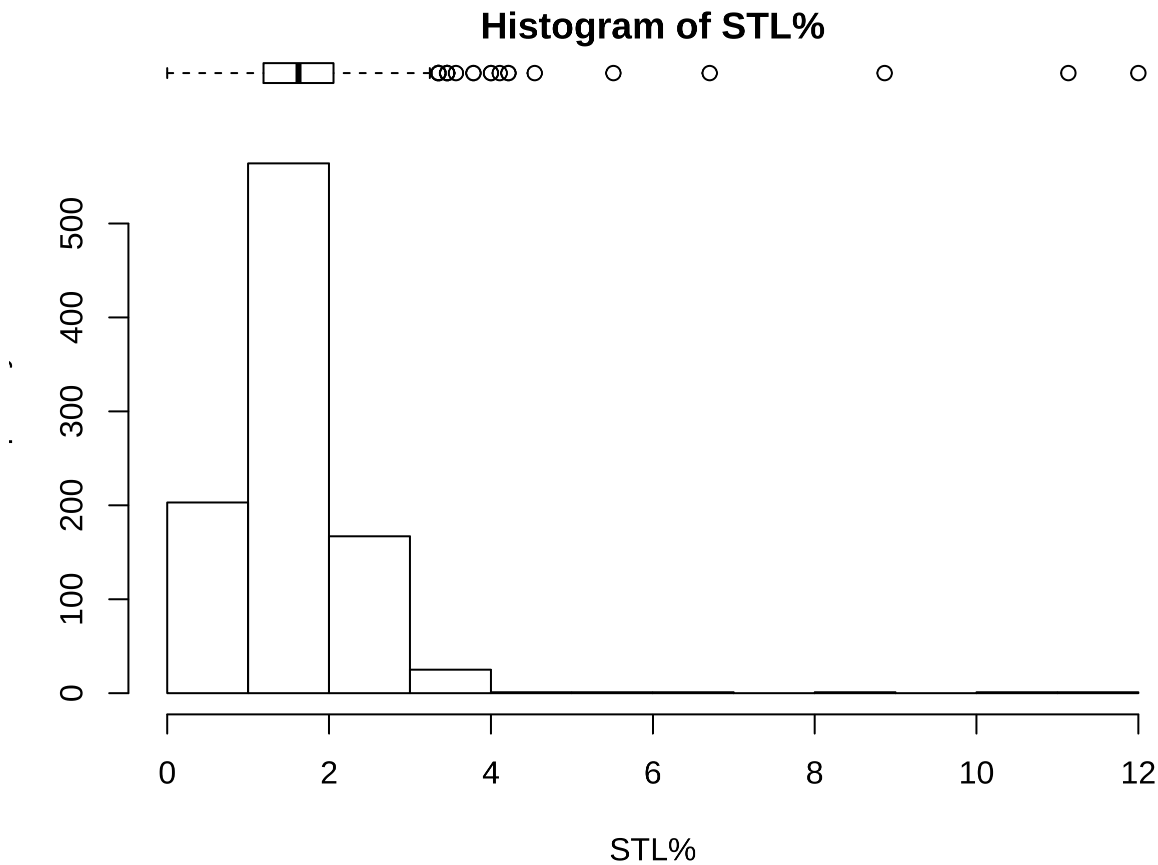

```
## Top 10 Players by DRB%
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2016  Alan ~ 8.75e5 PF       23 PHO      10     0    68  21.1 0.481  0
##  2 2016  Brian~ 3.28e5 PG       23 MIA       1     0     3  39.3 1      0
##  3 2017  Andre~ 2.38e7 C        23 DET      81    81  2409  20.9 0.518  0.008
##  4 2017  Hassa~ 2.38e7 C        27 MIA      77    77  2513  22.6 0.579  0
##  5 2017  DeAnd~ 2.26e7 C        28 LAC      81    81  2570  21.8 0.673  0.003
##  6 2016  Andre~ 2.21e7 C        22 DET      81    81  2666  21.2 0.499  0.006
##  7 2017  Andre~ 2.33e6 C        32 TOT      27    21   583   9.3 0.46   0.012
##  8 2017  Andre~ 2.33e6 C        32 DAL      26    21   582   9.4 0.46   0.012
##  9 2017  Tyson~ 1.30e7 C        34 PHO      47    46  1298  16.6 0.703  0
## 10 2016  DeAnd~ 2.12e7 C        27 LAC      77    77  2598  20.6 0.628  0.002
## # ... with 39 more variables: FTr <dbl>, `ORB%` <dbl>, `DRB%` <dbl>,
## #   `TRB%` <dbl>, `AST%` <dbl>, `STL%` <dbl>, `BLK%` <dbl>, `TOV%` <dbl>,
## #   `USG%` <dbl>, OWS <dbl>, DWS <dbl>, WS <dbl>, `WS/48` <dbl>, OBPM <dbl>,
## #   DBPM <dbl>, BPM <dbl>, VORP <dbl>, FG <dbl>, 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>
```



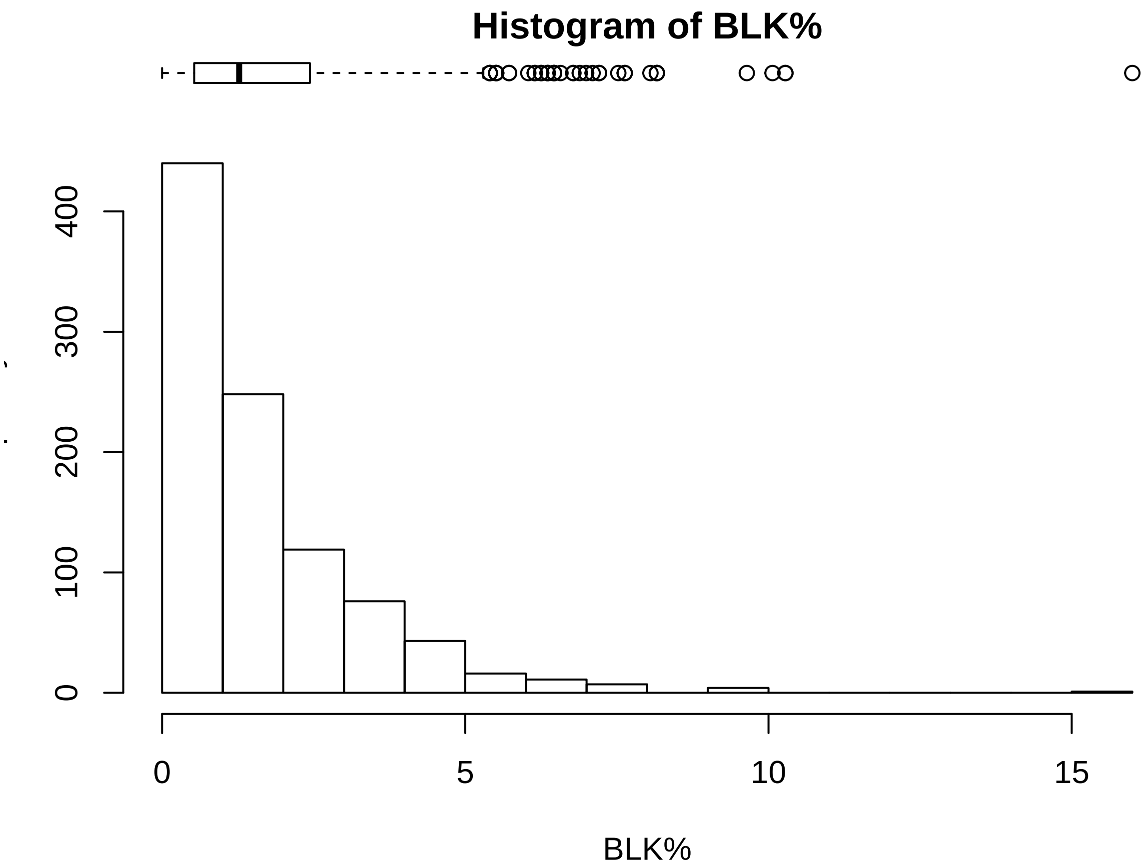

```
## Top 10 Players by TRB%
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2016  Alan ~ 8.75e5 PF       23 PHO      10     0    68  21.1 0.481  0
##  2 2016  Jarne~ 1.50e5 C        22 MEM       2     0     4  13.6 0.515  0.191
##  3 2016  Kevon~ 1.18e6 PF       19 GSW       5     0    21  18.6 0.643  0.286
##  4 2017  Andre~ 2.38e7 C        23 DET      81    81  2409  20.9 0.518  0.008
##  5 2016  Andre~ 2.21e7 C        22 DET      81    81  2666  21.2 0.499  0.006
##  6 2017  Boban~ 7.00e6 C        28 DET      35     0   293  29.6 0.606  0
##  7 2017  DeAnd~ 2.26e7 C        28 LAC      81    81  2570  21.8 0.673  0.003
##  8 2017  Hassa~ 2.38e7 C        27 MIA      77    77  2513  22.6 0.579  0
##  9 2017  Dwigh~ 2.35e7 C        31 ATL      74    74  2199  20.8 0.627  0.003
## 10 2016  Kris ~ 4.00e6 PF       30 PHO       4     3    74  13.5 0.367  0.278
## # ... with 39 more variables: FTr <dbl>, `ORB%` <dbl>, `DRB%` <dbl>,
## #   `TRB%` <dbl>, `AST%` <dbl>, `STL%` <dbl>, `BLK%` <dbl>, `TOV%` <dbl>,
## #   `USG%` <dbl>, OWS <dbl>, DWS <dbl>, WS <dbl>, `WS/48` <dbl>, OBPM <dbl>,
## #   DBPM <dbl>, BPM <dbl>, VORP <dbl>, FG <dbl>, 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>
```



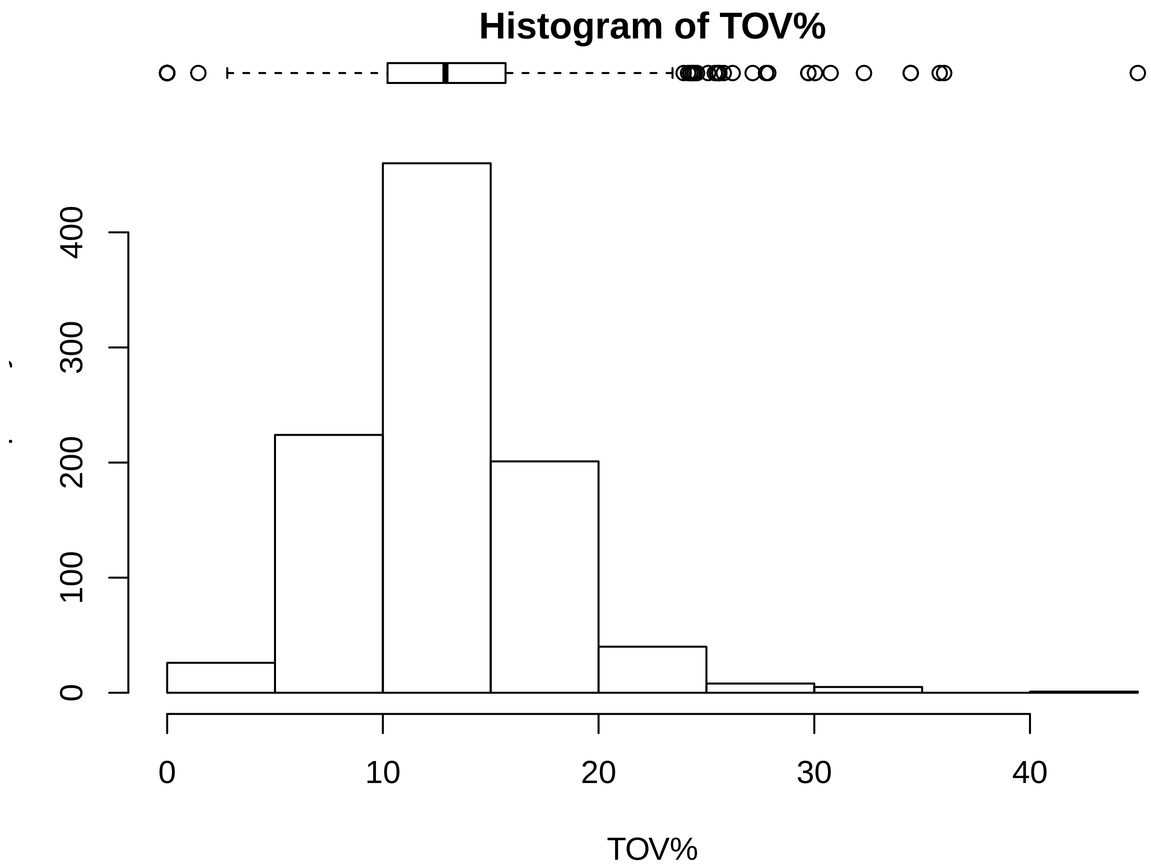

```
## Top 10 Players by AST%
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2016  Brian~ 3.28e5 PG       23 MIA       1     0     3  39.3 1      0
##  2 2017  Russe~ 2.85e7 PG       28 OKC      81    81  2802  30.6 0.554  0.3
##  3 2016  Chris~ 2.29e7 PG       30 LAC      74    74  2420  26.2 0.575  0.295
##  4 2017  James~ 2.83e7 PG       27 HOU      81    81  2947  27.3 0.613  0.493
##  5 2016  Russe~ 2.65e7 PG       27 OKC      80    80  2750  27.6 0.554  0.236
##  6 2016  Rajon~ 1.40e7 PG       29 SAC      72    72  2537  16.9 0.506  0.217
##  7 2017  John ~ 1.81e7 PG       26 WAS      78    78  2836  23.2 0.541  0.19
##  8 2017  Chris~ 2.46e7 PG       31 LAC      61    61  1921  26.2 0.614  0.385
##  9 2016  John ~ 1.70e7 PG       25 WAS      77    77  2784  19.8 0.51   0.243
## 10 2017  J.J. ~ 3.90e6 PG       32 DAL      35     6   771  17.2 0.521  0.431
## # ... with 39 more variables: FTr <dbl>, `ORB%` <dbl>, `DRB%` <dbl>,
## #   `TRB%` <dbl>, `AST%` <dbl>, `STL%` <dbl>, `BLK%` <dbl>, `TOV%` <dbl>,
## #   `USG%` <dbl>, OWS <dbl>, DWS <dbl>, WS <dbl>, `WS/48` <dbl>, OBPM <dbl>,
## #   DBPM <dbl>, BPM <dbl>, VORP <dbl>, FG <dbl>, 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>
```



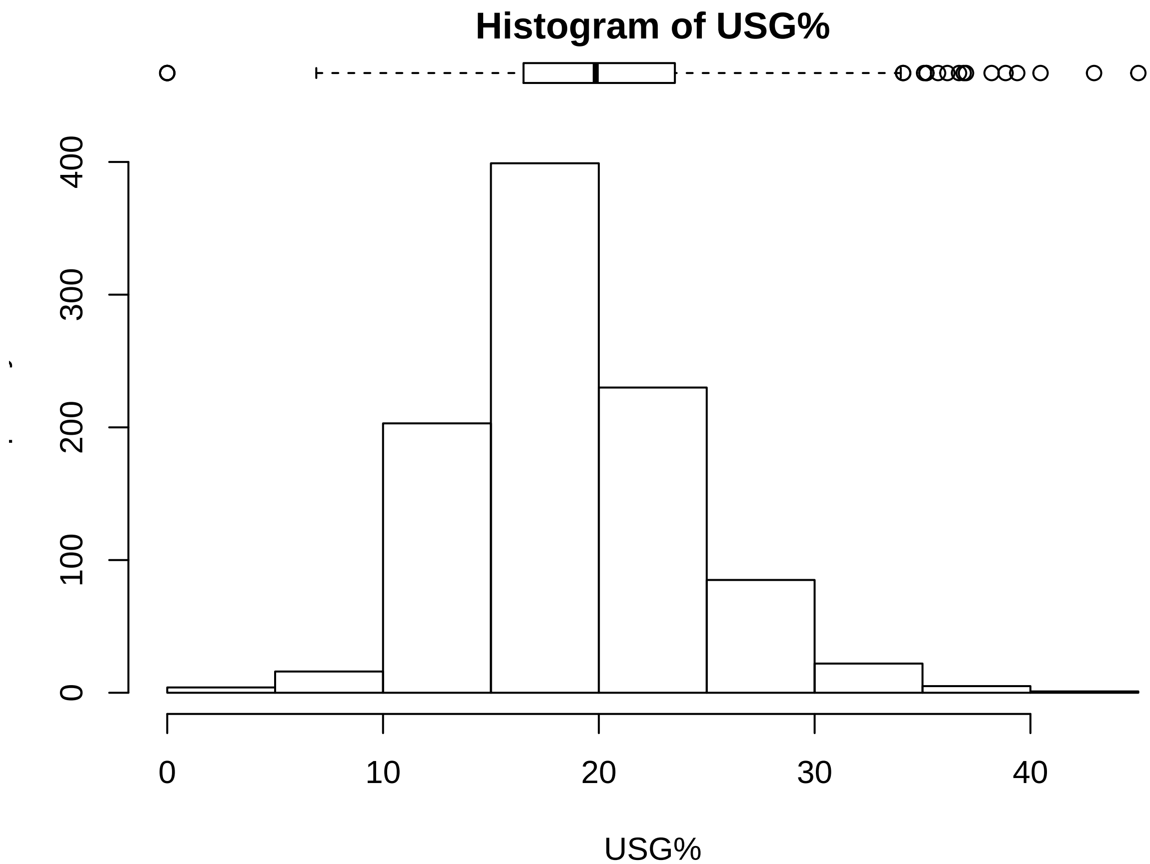

```
## Top 10 Players by STL%
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2017  Brice~ 1.33e6 PF       22 LAC       3     0     9  17.2 0.286  0
##  2 2016  Jorda~ 1.47e6 SG       21 MEM       2     0    15  17.3 0.427  0.167
##  3 2016  Sam D~ 1.72e6 SF       21 HOU       3     0     6  10.8 0.515  0.191
##  4 2017  Chris~ 1.47e6 PF       21 WAS       2     0     8   1.1 0.266  1
##  5 2016  James~ 2.90e6 SF       25 MEM      10     0    40  18.3 0.46   0.615
##  6 2017  DeAnd~ 1.58e6 SG       28 DAL       1     0    25  17.6 0.546  0.167
##  7 2016  Chris~ 1.19e6 PF       20 BRK      24     4   362  12.2 0.47   0.312
##  8 2017  Ronni~ 2.44e6 PG       33 PHO      14     0   134   5.9 0.272  0.708
##  9 2017  Larry~ 1.87e6 C        28 CLE       5     0    13   6.5 0.41   0
## 10 2016  Jarne~ 1.50e5 C        22 MIA       5     0    14  21.8 0.595  0
## # ... with 39 more variables: FTr <dbl>, `ORB%` <dbl>, `DRB%` <dbl>,
## #   `TRB%` <dbl>, `AST%` <dbl>, `STL%` <dbl>, `BLK%` <dbl>, `TOV%` <dbl>,
## #   `USG%` <dbl>, OWS <dbl>, DWS <dbl>, WS <dbl>, `WS/48` <dbl>, OBPM <dbl>,
## #   DBPM <dbl>, BPM <dbl>, VORP <dbl>, FG <dbl>, 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>
```



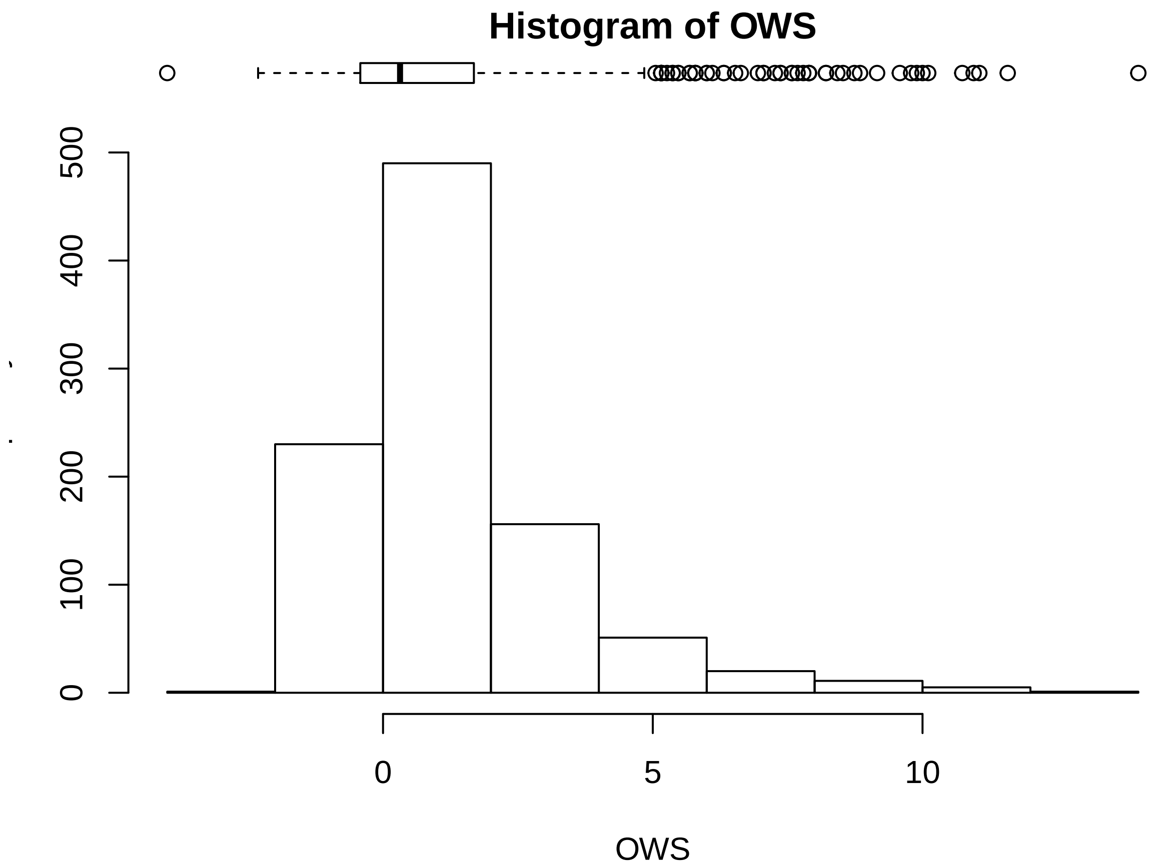

```
## Top 10 Players by BLK%
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2016  Jorda~ 1.22e6 PF       21 BOS      16     0    57  15.3 0.398  0
##  2 2016  Hassa~ 2.21e7 C        26 MIA      73    43  2125  25.7 0.629  0
##  3 2016  John ~ 1.25e7 C        25 MIL      57     1   960  18.6 0.580  0.003
##  4 2016  Joel ~ 6.64e5 C        33 DET      19     0    96  14.1 0.666  0
##  5 2017  Brice~ 1.33e6 PF       22 LAC       3     0     9  17.2 0.286  0
##  6 2017  Jeram~ 1.52e6 SF       22 PHI       2     0    41   3.3 0.39   0.118
##  7 2017  Joel ~ 6.10e6 C        22 PHI      31    31   786  24.1 0.584  0.228
##  8 2017  Josh ~ 1.47e6 PF       25 OKC       2     0    31  26.1 0.612  0.364
##  9 2016  Salah~ 8.75e5 C        29 DAL      34     6   397  16.8 0.636  0.013
## 10 2017  A.J. ~ 1.31e6 C        24 DAL      22     0   163   8.4 0.472  0.238
## # ... with 39 more variables: FTr <dbl>, `ORB%` <dbl>, `DRB%` <dbl>,
## #   `TRB%` <dbl>, `AST%` <dbl>, `STL%` <dbl>, `BLK%` <dbl>, `TOV%` <dbl>,
## #   `USG%` <dbl>, OWS <dbl>, DWS <dbl>, WS <dbl>, `WS/48` <dbl>, OBPM <dbl>,
## #   DBPM <dbl>, BPM <dbl>, VORP <dbl>, FG <dbl>, 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>
```



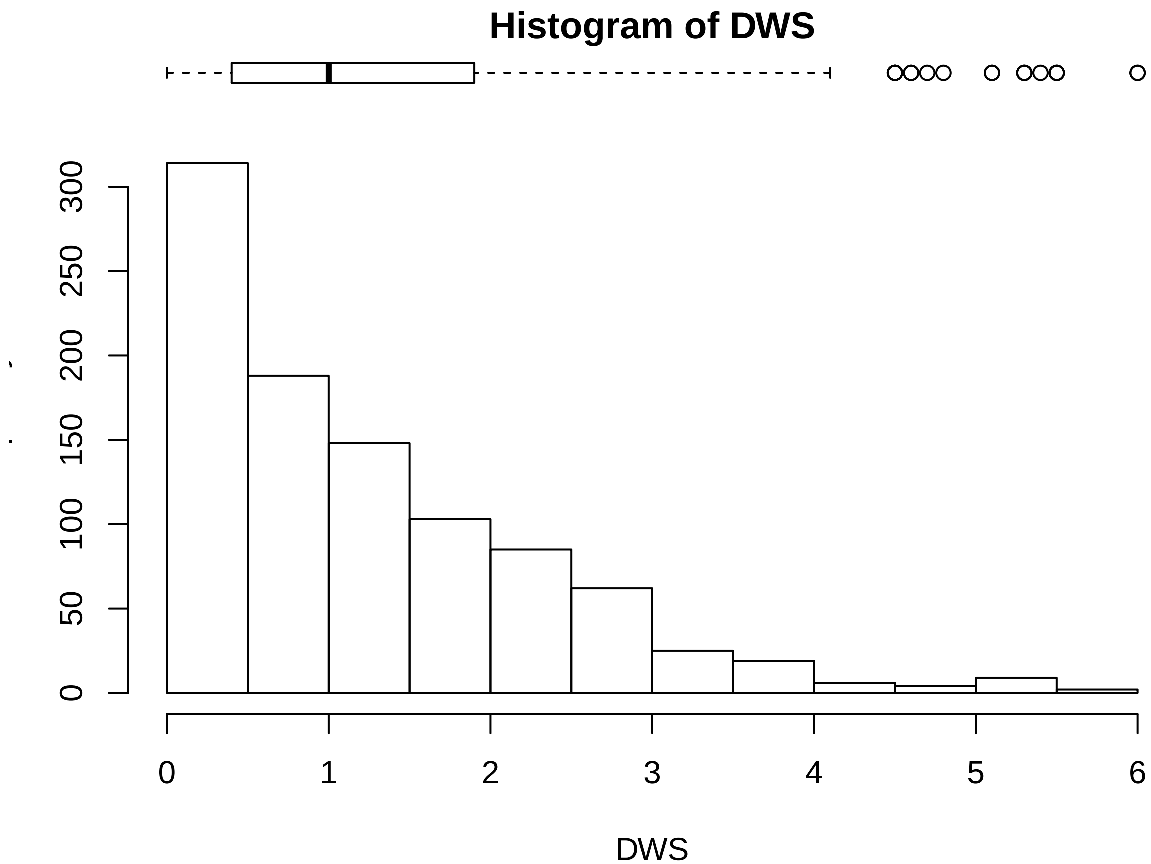

```
## Top 10 Players by TOV%
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2017  Jarre~ 2.33e6 PG       33 NOP       2     0    33   7.7 0.773  0.333
##  2 2016  Phil ~ 3.50e4 PG       24 PHO       9     0   113   8.6 0.422  0.217
##  3 2017  Chris~ 1.47e6 PF       21 WAS       2     0     8   1.1 0.266  1
##  4 2017  Andre~ 2.33e6 C        32 TOT      27    21   583   9.3 0.46   0.012
##  5 2017  Andre~ 2.33e6 C        32 DAL      26    21   582   9.4 0.46   0.012
##  6 2017  China~ 1.31e6 C        20 HOU       5     1    52  12.3 0.799  0
##  7 2017  Ander~ 1.91e6 C        34 GSW      14     1    92   9.4 0.478  0
##  8 2017  Larry~ 1.87e6 C        28 CLE       5     0    13   6.5 0.41   0
##  9 2016  Nick ~ 3.75e6 PF       35 OKC      59     4   699   7.7 0.498  0.018
## 10 2016  Tim F~ 2.09e6 PG       25 POR      35     1   272   4.7 0.383  0.283
## # ... with 39 more variables: FTr <dbl>, `ORB%` <dbl>, `DRB%` <dbl>,
## #   `TRB%` <dbl>, `AST%` <dbl>, `STL%` <dbl>, `BLK%` <dbl>, `TOV%` <dbl>,
## #   `USG%` <dbl>, OWS <dbl>, DWS <dbl>, WS <dbl>, `WS/48` <dbl>, OBPM <dbl>,
## #   DBPM <dbl>, BPM <dbl>, VORP <dbl>, FG <dbl>, 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>
```



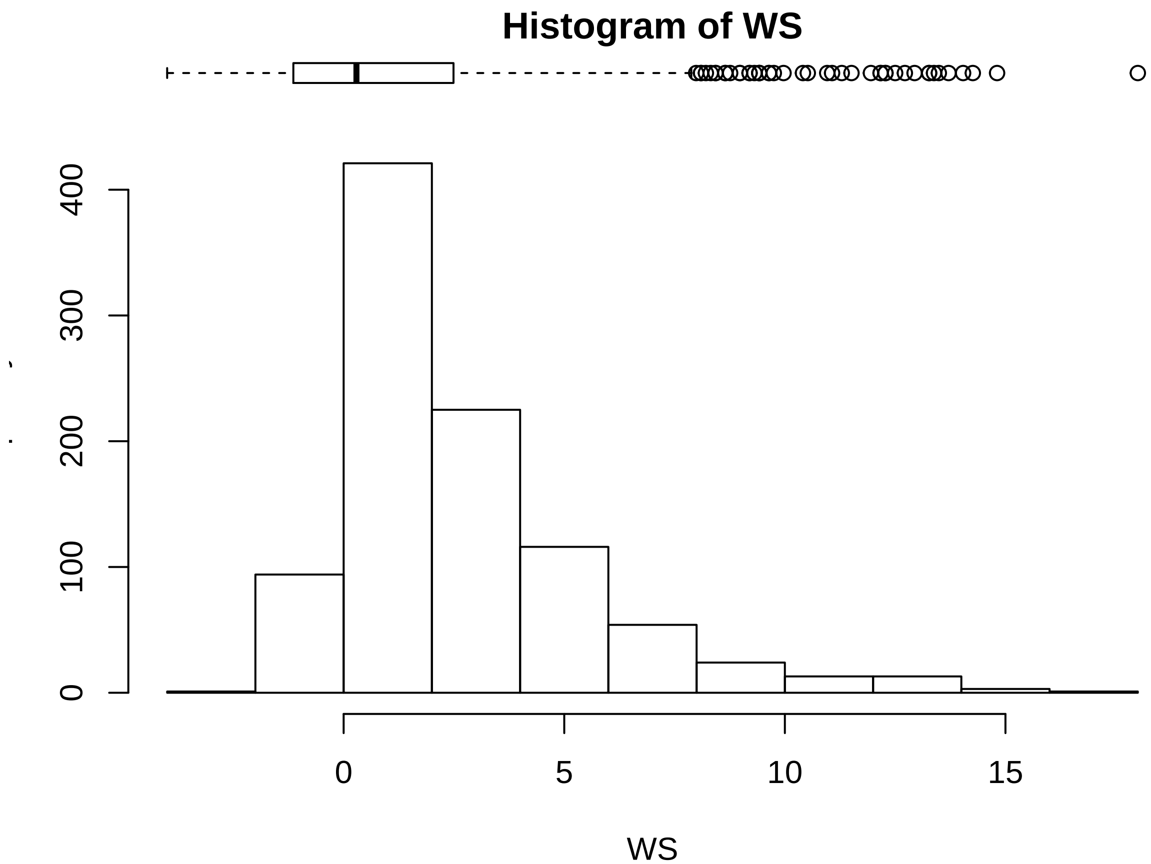

```
## Top 10 Players by USG%
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2017  Russe~ 2.85e7 PG       28 OKC      81    81  2802  30.6 0.554  0.3
##  2 2017  Brice~ 1.33e6 PF       22 LAC       3     0     9  17.2 0.286  0
##  3 2017  DeMar~ 1.81e7 C        26 SAC      55    55  1891  26.5 0.562  0.239
##  4 2017  DeMar~ 1.81e7 C        26 TOT      72    72  2465  25.7 0.562  0.254
##  5 2017  Joel ~ 6.10e6 C        22 PHI      31    31   786  24.1 0.584  0.228
##  6 2016  DeMar~ 1.70e7 C        25 SAC      65    65  2246  23.6 0.538  0.158
##  7 2017  DeMar~ 2.77e7 SG       27 TOR      74    74  2620  24   0.552  0.08
##  8 2017  James~ 2.83e7 PG       27 HOU      81    81  2947  27.3 0.613  0.493
##  9 2017  Isaia~ 6.26e6 PG       27 BOS      76    76  2569  26.5 0.625  0.439
## 10 2016  Tony ~ 2.50e4 PG       22 PHI       8     3   144   1.8 0.412  0.262
## # ... with 39 more variables: FTr <dbl>, `ORB%` <dbl>, `DRB%` <dbl>,
## #   `TRB%` <dbl>, `AST%` <dbl>, `STL%` <dbl>, `BLK%` <dbl>, `TOV%` <dbl>,
## #   `USG%` <dbl>, OWS <dbl>, DWS <dbl>, WS <dbl>, `WS/48` <dbl>, OBPM <dbl>,
## #   DBPM <dbl>, BPM <dbl>, VORP <dbl>, FG <dbl>, 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>
```



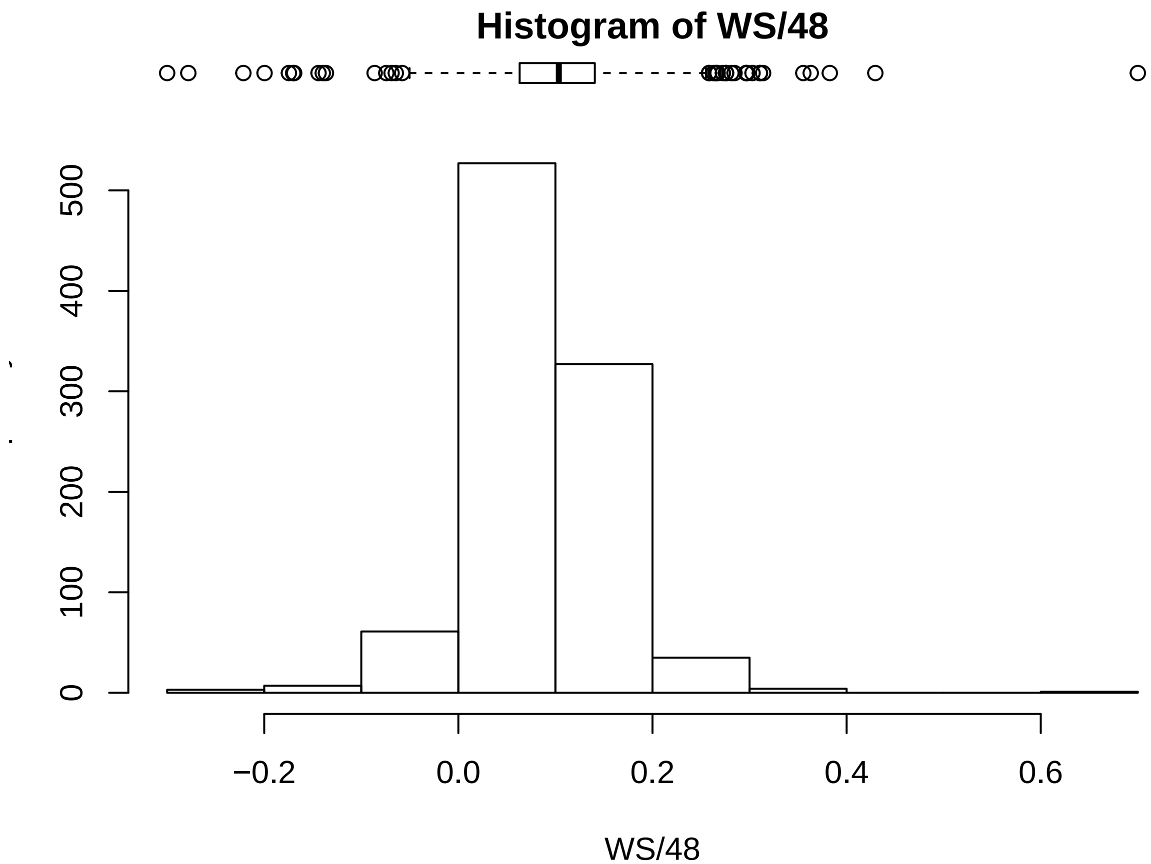

```
## Top 10 Players by OWS
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2016  Steph~ 1.21e7 PG       27 GSW      79    79  2700  31.5 0.669  0.554
##  2 2017  James~ 2.83e7 PG       27 HOU      81    81  2947  27.3 0.613  0.493
##  3 2016  Kevin~ 2.65e7 SF       27 OKC      72    72  2578  28.2 0.634  0.348
##  4 2017  Isaia~ 6.26e6 PG       27 BOS      76    76  2569  26.5 0.625  0.439
##  5 2016  James~ 2.65e7 SG       26 HOU      82    82  3125  25.3 0.598  0.406
##  6 2017  Jimmy~ 1.93e7 SF       27 CHI      76    75  2809  25.1 0.586  0.198
##  7 2016  Russe~ 2.65e7 PG       27 OKC      80    80  2750  27.6 0.554  0.236
##  8 2017  Karl-~ 6.22e6 C        21 MIN      82    82  3030  26   0.618  0.186
##  9 2017  LeBro~ 3.33e7 SF       32 CLE      74    74  2794  27   0.619  0.254
## 10 2016  LeBro~ 3.10e7 SF       31 CLE      76    76  2709  27.5 0.588  0.199
## # ... with 39 more variables: FTr <dbl>, `ORB%` <dbl>, `DRB%` <dbl>,
## #   `TRB%` <dbl>, `AST%` <dbl>, `STL%` <dbl>, `BLK%` <dbl>, `TOV%` <dbl>,
## #   `USG%` <dbl>, OWS <dbl>, DWS <dbl>, WS <dbl>, `WS/48` <dbl>, OBPM <dbl>,
## #   DBPM <dbl>, BPM <dbl>, VORP <dbl>, FG <dbl>, 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>
```



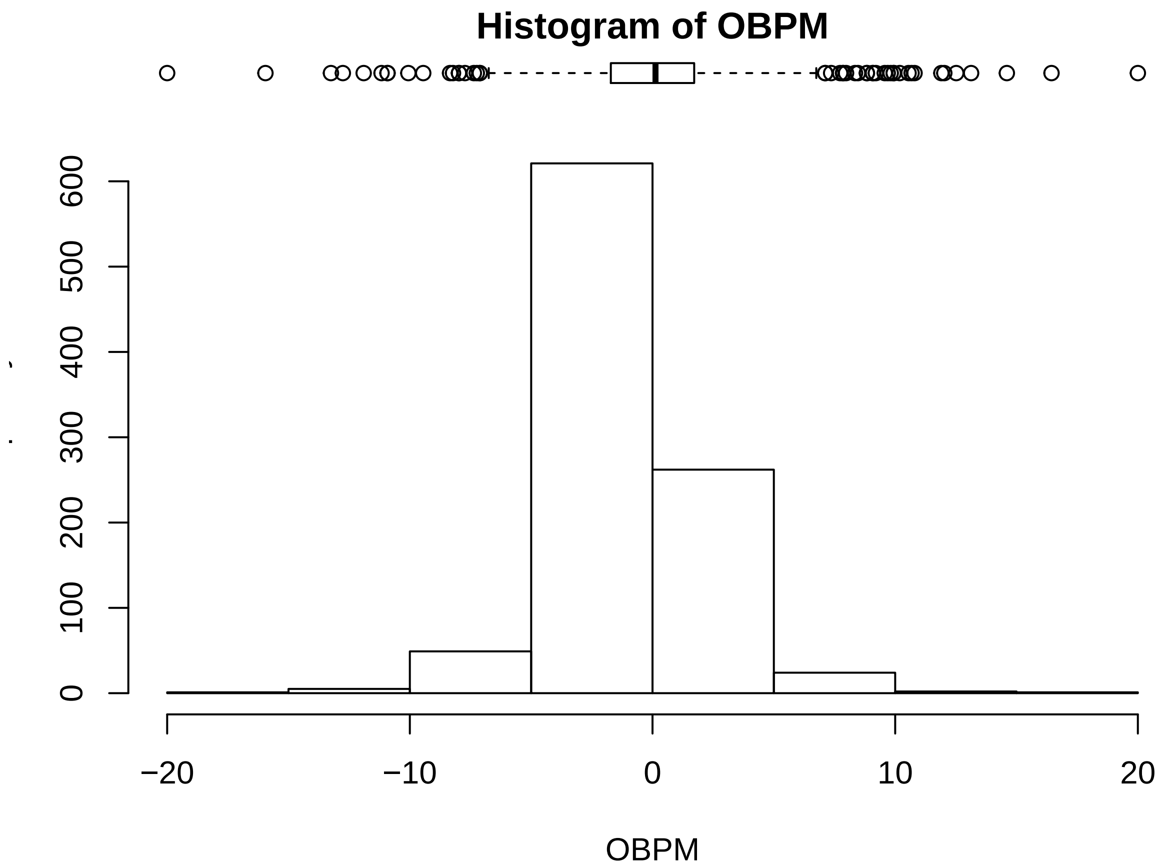

```
## Top 10 Players by DWS
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2016  Paul ~ 2.01e7 PF       30 ATL      81    81  2647  21.3 0.556  0.218
##  2 2017  Rudy ~ 2.20e7 C        24 UTA      81    81  2744  23.3 0.682  0.002
##  3 2016  Andre~ 2.21e7 C        22 DET      81    81  2666  21.2 0.499  0.006
##  4 2016  DeAnd~ 2.12e7 C        27 LAC      77    77  2598  20.6 0.628  0.002
##  5 2016  Kawhi~ 1.76e7 SF       24 SAS      72    72  2380  26   0.616  0.267
##  6 2017  Draym~ 1.64e7 PF       26 GSW      76    76  2471  16.5 0.522  0.405
##  7 2017  Andre~ 2.38e7 C        23 DET      81    81  2409  20.9 0.518  0.008
##  8 2016  Hassa~ 2.21e7 C        26 MIA      73    43  2125  25.7 0.629  0
##  9 2017  Hassa~ 2.38e7 C        27 MIA      77    77  2513  22.6 0.579  0
## 10 2017  Antho~ 2.38e7 C        23 NOP      75    75  2708  27.5 0.579  0.088
## # ... with 39 more variables: FTr <dbl>, `ORB%` <dbl>, `DRB%` <dbl>,
## #   `TRB%` <dbl>, `AST%` <dbl>, `STL%` <dbl>, `BLK%` <dbl>, `TOV%` <dbl>,
## #   `USG%` <dbl>, OWS <dbl>, DWS <dbl>, WS <dbl>, `WS/48` <dbl>, OBPM <dbl>,
## #   DBPM <dbl>, BPM <dbl>, VORP <dbl>, FG <dbl>, 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>
```



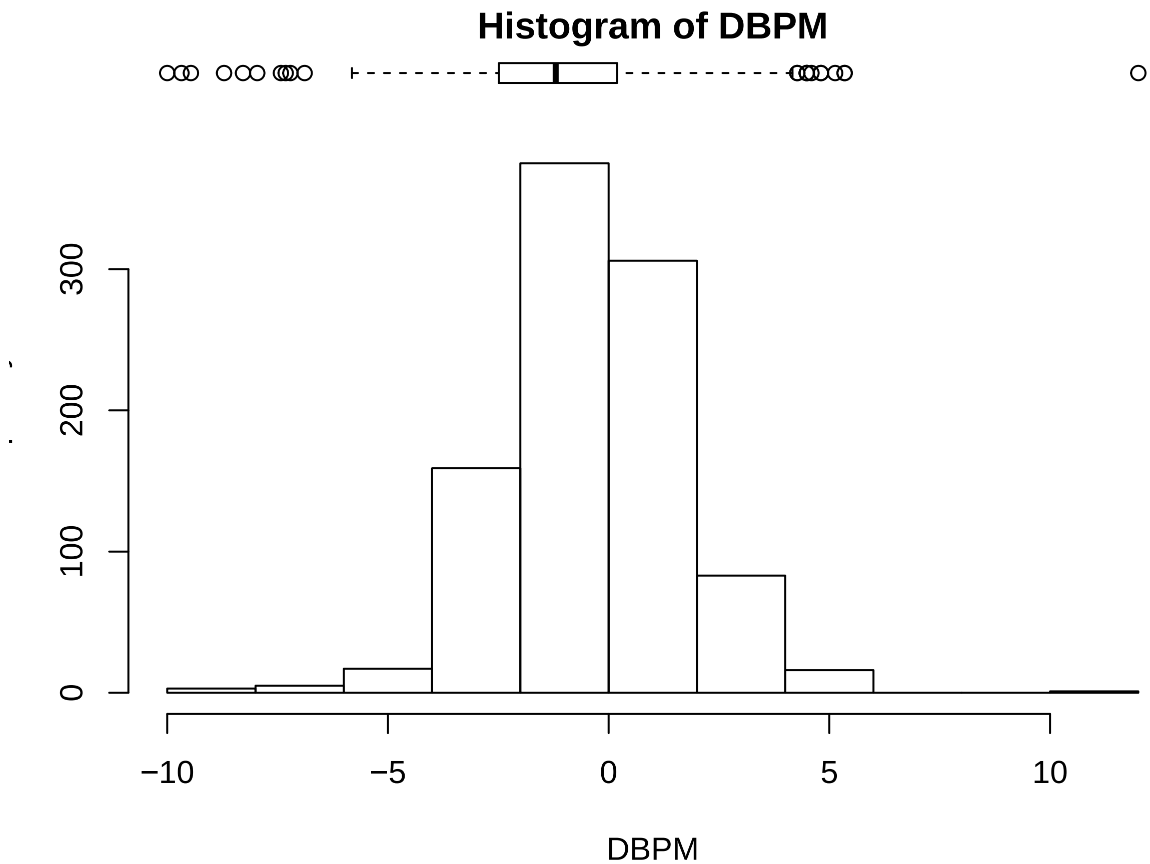

```
## Top 10 Players by WS
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2016  Steph~ 1.21e7 PG       27 GSW      79    79  2700  31.5 0.669  0.554
##  2 2017  James~ 2.83e7 PG       27 HOU      81    81  2947  27.3 0.613  0.493
##  3 2016  Kevin~ 2.65e7 SF       27 OKC      72    72  2578  28.2 0.634  0.348
##  4 2017  Rudy ~ 2.20e7 C        24 UTA      81    81  2744  23.3 0.682  0.002
##  5 2016  Russe~ 2.65e7 PG       27 OKC      80    80  2750  27.6 0.554  0.236
##  6 2017  Jimmy~ 1.93e7 SF       27 CHI      76    75  2809  25.1 0.586  0.198
##  7 2016  Kawhi~ 1.76e7 SF       24 SAS      72    72  2380  26   0.616  0.267
##  8 2017  Kawhi~ 1.89e7 SF       25 SAS      74    74  2474  27.5 0.611  0.294
##  9 2016  LeBro~ 3.10e7 SF       31 CLE      76    76  2709  27.5 0.588  0.199
## 10 2016  James~ 2.65e7 SG       26 HOU      82    82  3125  25.3 0.598  0.406
## # ... with 39 more variables: FTr <dbl>, `ORB%` <dbl>, `DRB%` <dbl>,
## #   `TRB%` <dbl>, `AST%` <dbl>, `STL%` <dbl>, `BLK%` <dbl>, `TOV%` <dbl>,
## #   `USG%` <dbl>, OWS <dbl>, DWS <dbl>, WS <dbl>, `WS/48` <dbl>, OBPM <dbl>,
## #   DBPM <dbl>, BPM <dbl>, VORP <dbl>, FG <dbl>, 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>
```



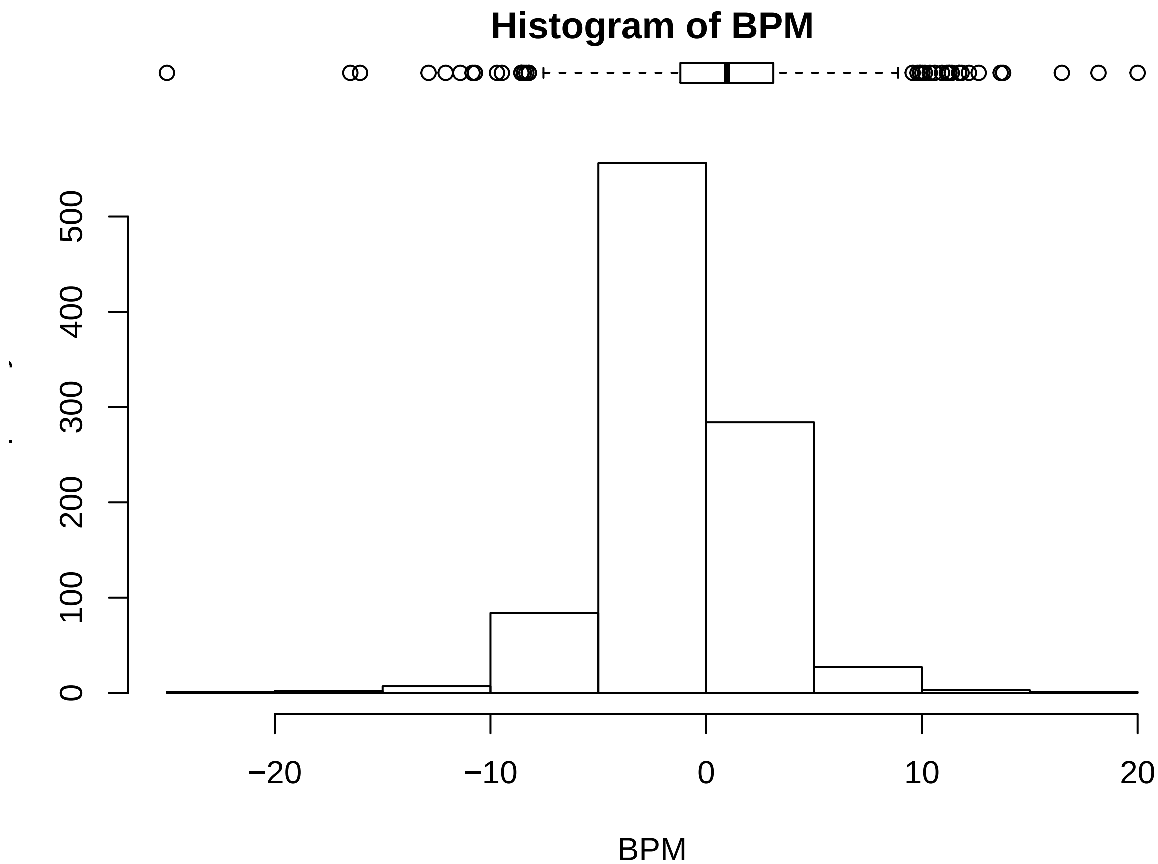

```
## Top 10 Players by WS/48
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2016  Brian~ 3.28e5 PG       23 MIA       1     0     3  39.3 1      0
##  2 2017  Demet~ 9.29e4 PG       22 BOS       5     0    17  30.8 0.753  0.25
##  3 2016  Rakee~ 1.05e6 PF       24 IND       1     0     6  32   1      0
##  4 2016  Boban~ 7.00e6 C        27 SAS      54     4   508  27.7 0.662  0
##  5 2016  Steph~ 1.21e7 PG       27 GSW      79    79  2700  31.5 0.669  0.554
##  6 2017  Boban~ 7.00e6 C        28 DET      35     0   293  29.6 0.606  0
##  7 2016  Kawhi~ 1.76e7 SF       24 SAS      72    72  2380  26   0.616  0.267
##  8 2017  Kevin~ 2.50e7 SF       28 GSW      62    62  2070  27.6 0.651  0.304
##  9 2016  Kevin~ 2.65e7 SF       27 OKC      72    72  2578  28.2 0.634  0.348
## 10 2017  Josh ~ 1.47e6 PF       25 OKC       2     0    31  26.1 0.612  0.364
## # ... with 39 more variables: FTr <dbl>, `ORB%` <dbl>, `DRB%` <dbl>,
## #   `TRB%` <dbl>, `AST%` <dbl>, `STL%` <dbl>, `BLK%` <dbl>, `TOV%` <dbl>,
## #   `USG%` <dbl>, OWS <dbl>, DWS <dbl>, WS <dbl>, `WS/48` <dbl>, OBPM <dbl>,
## #   DBPM <dbl>, BPM <dbl>, VORP <dbl>, FG <dbl>, 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>
```



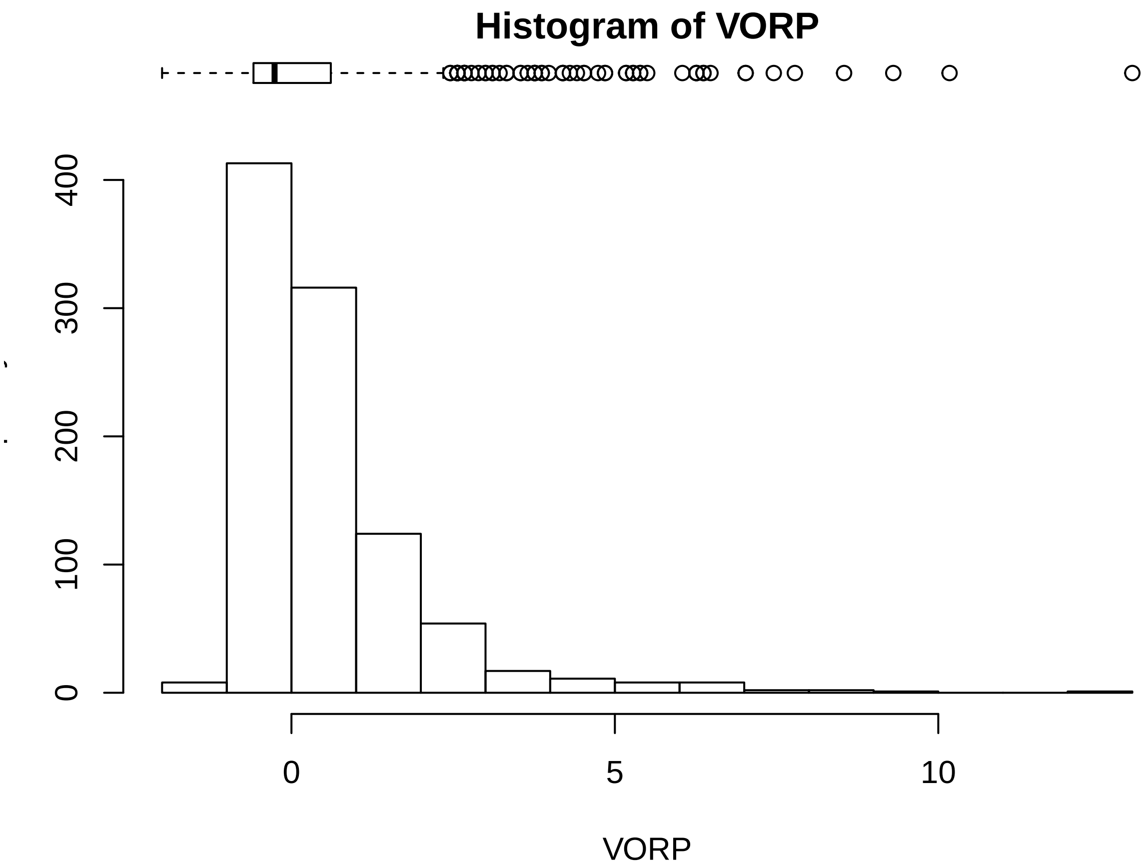

```
## Top 10 Players by OBPM
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2016  Brian~ 3.28e5 PG       23 MIA       1     0     3  39.3 1      0
##  2 2016  Steph~ 1.21e7 PG       27 GSW      79    79  2700  31.5 0.669  0.554
##  3 2017  Russe~ 2.85e7 PG       28 OKC      81    81  2802  30.6 0.554  0.3
##  4 2016  Rakee~ 1.05e6 PF       24 IND       1     0     6  32   1      0
##  5 2017  Demet~ 9.29e4 PG       22 BOS       5     0    17  30.8 0.753  0.25
##  6 2017  Isaia~ 6.26e6 PG       27 BOS      76    76  2569  26.5 0.625  0.439
##  7 2017  James~ 2.83e7 PG       27 HOU      81    81  2947  27.3 0.613  0.493
##  8 2017  Chris~ 2.46e7 PG       31 LAC      61    61  1921  26.2 0.614  0.385
##  9 2017  Steph~ 3.47e7 PG       28 GSW      79    79  2638  24.6 0.624  0.547
## 10 2016  Russe~ 2.65e7 PG       27 OKC      80    80  2750  27.6 0.554  0.236
## # ... with 39 more variables: FTr <dbl>, `ORB%` <dbl>, `DRB%` <dbl>,
## #   `TRB%` <dbl>, `AST%` <dbl>, `STL%` <dbl>, `BLK%` <dbl>, `TOV%` <dbl>,
## #   `USG%` <dbl>, OWS <dbl>, DWS <dbl>, WS <dbl>, `WS/48` <dbl>, OBPM <dbl>,
## #   DBPM <dbl>, BPM <dbl>, VORP <dbl>, FG <dbl>, 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>
```



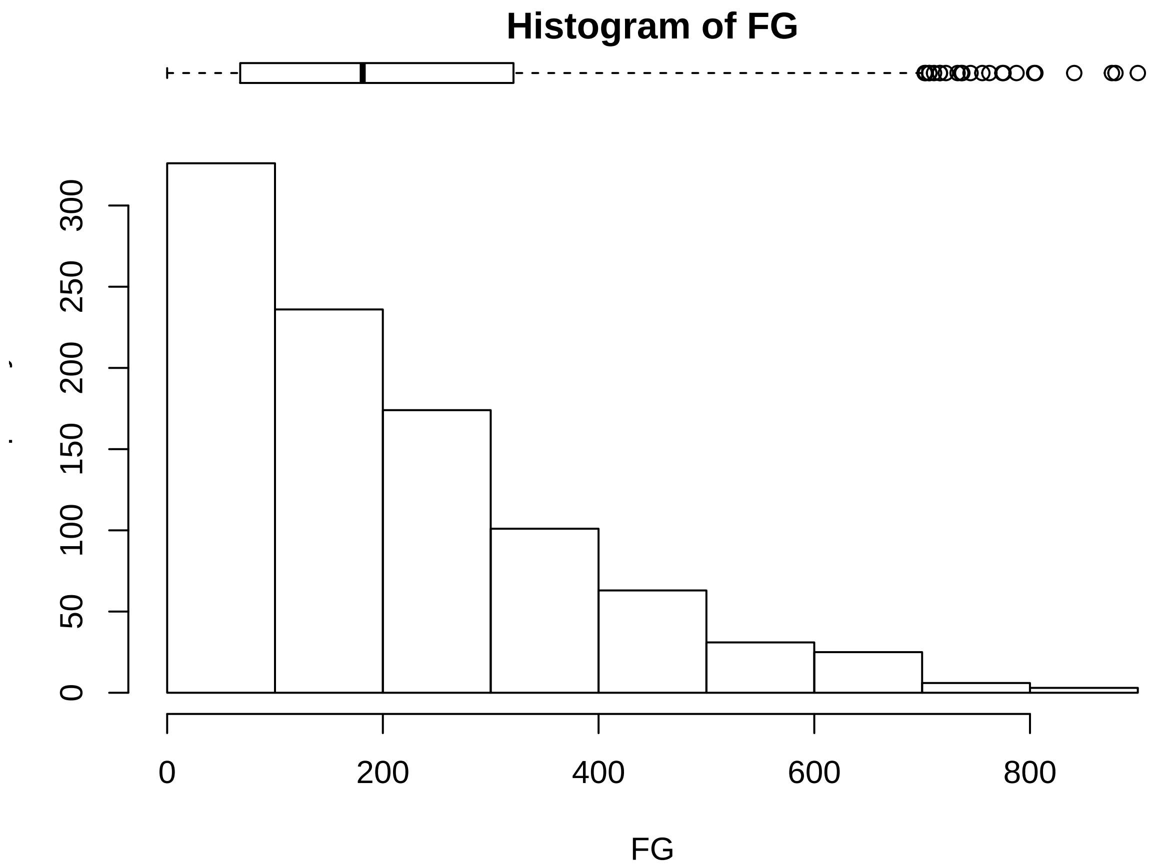

```
## Top 10 Players by DBPM
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2017  Brice~ 1.33e6 PF       22 LAC       3     0     9  17.2 0.286  0
##  2 2016  Cole ~ 7.64e6 C        27 LAC      60     5   800  21.3 0.626  0
##  3 2016  Sam D~ 1.72e6 SF       21 HOU       3     0     6  10.8 0.515  0.191
##  4 2017  Lucas~ 2.95e6 C        24 TOR      57     6  1088  15.5 0.682  0.077
##  5 2017  Andre~ 2.33e6 C        32 TOT      27    21   583   9.3 0.46   0.012
##  6 2017  Andre~ 2.33e6 C        32 DAL      26    21   582   9.4 0.46   0.012
##  7 2016  Andre~ 1.10e7 C        31 GSW      70    66  1451  15.9 0.623  0.004
##  8 2017  Draym~ 1.64e7 PF       26 GSW      76    76  2471  16.5 0.522  0.405
##  9 2016  Joel ~ 6.64e5 C        33 DET      19     0    96  14.1 0.666  0
## 10 2016  Tim D~ 1.88e6 C        39 SAS      61    60  1536  16.9 0.523  0.005
## # ... with 39 more variables: FTr <dbl>, `ORB%` <dbl>, `DRB%` <dbl>,
## #   `TRB%` <dbl>, `AST%` <dbl>, `STL%` <dbl>, `BLK%` <dbl>, `TOV%` <dbl>,
## #   `USG%` <dbl>, OWS <dbl>, DWS <dbl>, WS <dbl>, `WS/48` <dbl>, OBPM <dbl>,
## #   DBPM <dbl>, BPM <dbl>, VORP <dbl>, FG <dbl>, 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>
```



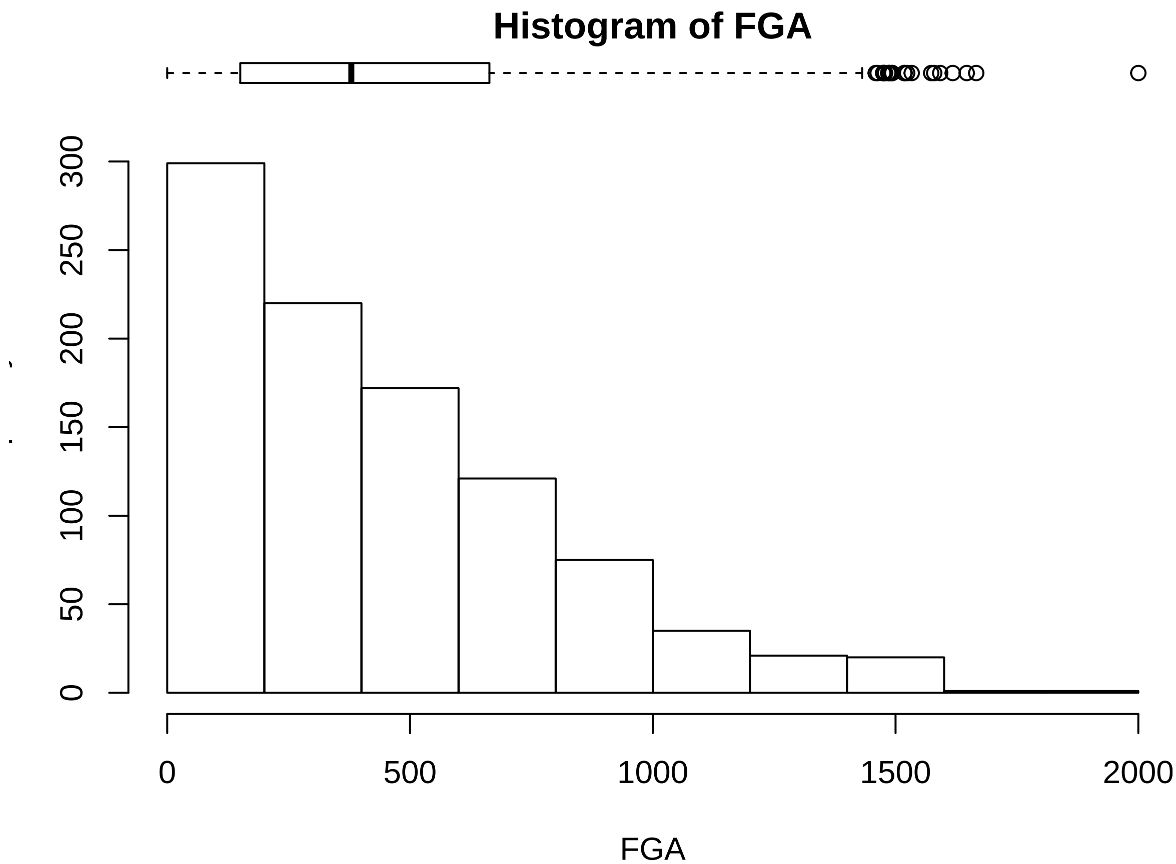

```
## Top 10 Players by BPM
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2017  Russe~ 2.85e7 PG       28 OKC      81    81  2802  30.6 0.554  0.3
##  2 2016  Brian~ 3.28e5 PG       23 MIA       1     0     3  39.3 1      0
##  3 2016  Steph~ 1.21e7 PG       27 GSW      79    79  2700  31.5 0.669  0.554
##  4 2017  James~ 2.83e7 PG       27 HOU      81    81  2947  27.3 0.613  0.493
##  5 2016  Russe~ 2.65e7 PG       27 OKC      80    80  2750  27.6 0.554  0.236
##  6 2016  LeBro~ 3.10e7 SF       31 CLE      76    76  2709  27.5 0.588  0.199
##  7 2017  Chris~ 2.46e7 PG       31 LAC      61    61  1921  26.2 0.614  0.385
##  8 2017  LeBro~ 3.33e7 SF       32 CLE      74    74  2794  27    0.619  0.254
##  9 2016  Kawhi~ 1.76e7 SF       24 SAS      72    72  2380  26    0.616  0.267
## 10 2017  Nikol~ 1.47e6 C        21 DEN      73    59  2038  26.4 0.64   0.163
## # ... with 39 more variables: FTr <dbl>, `ORB%` <dbl>, `DRB%` <dbl>,
## #   `TRB%` <dbl>, `AST%` <dbl>, `STL%` <dbl>, `BLK%` <dbl>, `TOV%` <dbl>,
## #   `USG%` <dbl>, OWS <dbl>, DWS <dbl>, WS <dbl>, `WS/48` <dbl>, OBPM <dbl>,
## #   DBPM <dbl>, BPM <dbl>, VORP <dbl>, FG <dbl>, 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>
```



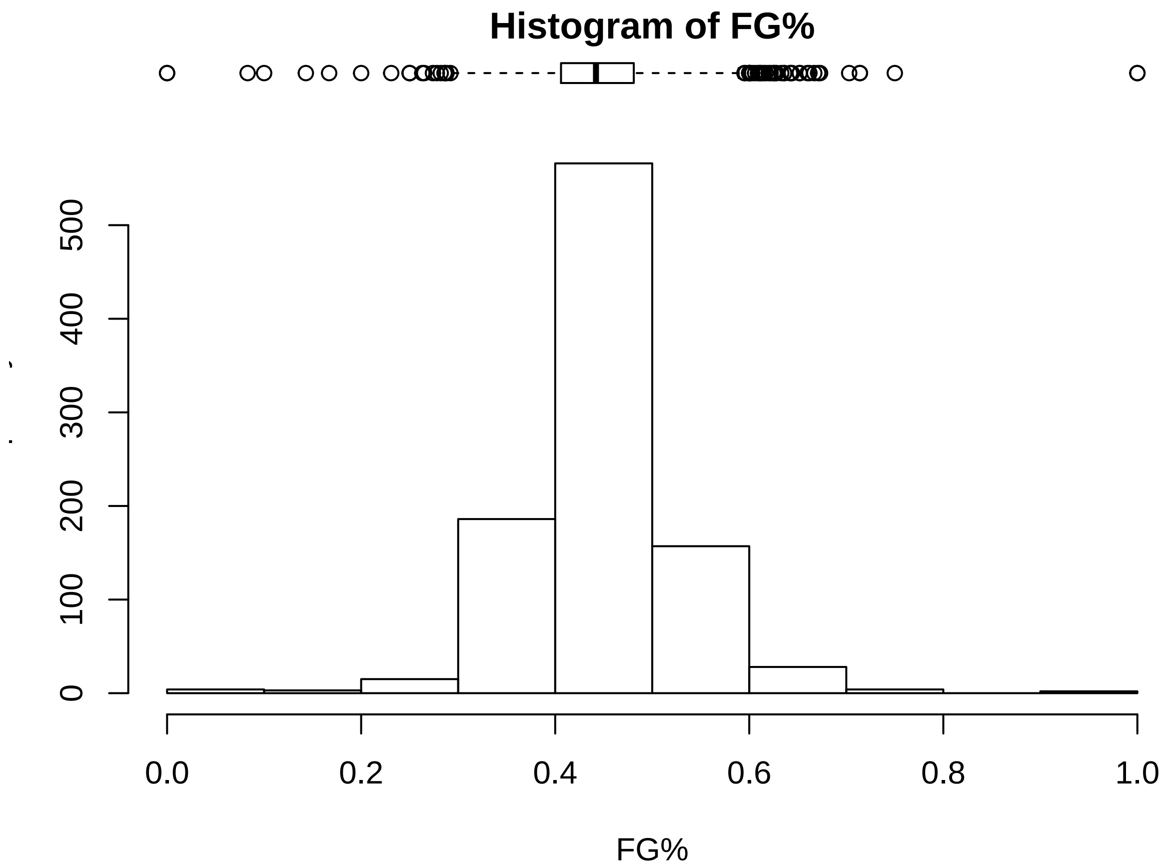

```
## Top 10 Players by VORP
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2017  Russe~ 2.85e7 PG       28 OKC      81    81  2802  30.6 0.554  0.3
##  2 2016  Steph~ 1.21e7 PG       27 GSW      79    79  2700  31.5 0.669  0.554
##  3 2017  James~ 2.83e7 PG       27 HOU      81    81  2947  27.3 0.613  0.493
##  4 2016  Russe~ 2.65e7 PG       27 OKC      80    80  2750  27.6 0.554  0.236
##  5 2016  LeBro~ 3.10e7 SF       31 CLE      76    76  2709  27.5 0.588  0.199
##  6 2017  LeBro~ 3.33e7 SF       32 CLE      74    74  2794  27    0.619  0.254
##  7 2017  Giann~ 2.25e7 SF       22 MIL      80    80  2845  26.1 0.599  0.143
##  8 2016  James~ 2.65e7 SG       26 HOU      82    82  3125  25.3 0.598  0.406
##  9 2016  Kevin~ 2.65e7 SF       27 OKC      72    72  2578  28.2 0.634  0.348
## 10 2017  Jimmy~ 1.93e7 SF       27 CHI      76    75  2809  25.1 0.586  0.198
## # ... with 39 more variables: FTr <dbl>, `ORB%` <dbl>, `DRB%` <dbl>,
## #   `TRB%` <dbl>, `AST%` <dbl>, `STL%` <dbl>, `BLK%` <dbl>, `TOV%` <dbl>,
## #   `USG%` <dbl>, OWS <dbl>, DWS <dbl>, WS <dbl>, `WS/48` <dbl>, OBPM <dbl>,
## #   DBPM <dbl>, BPM <dbl>, VORP <dbl>, FG <dbl>, 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>
```



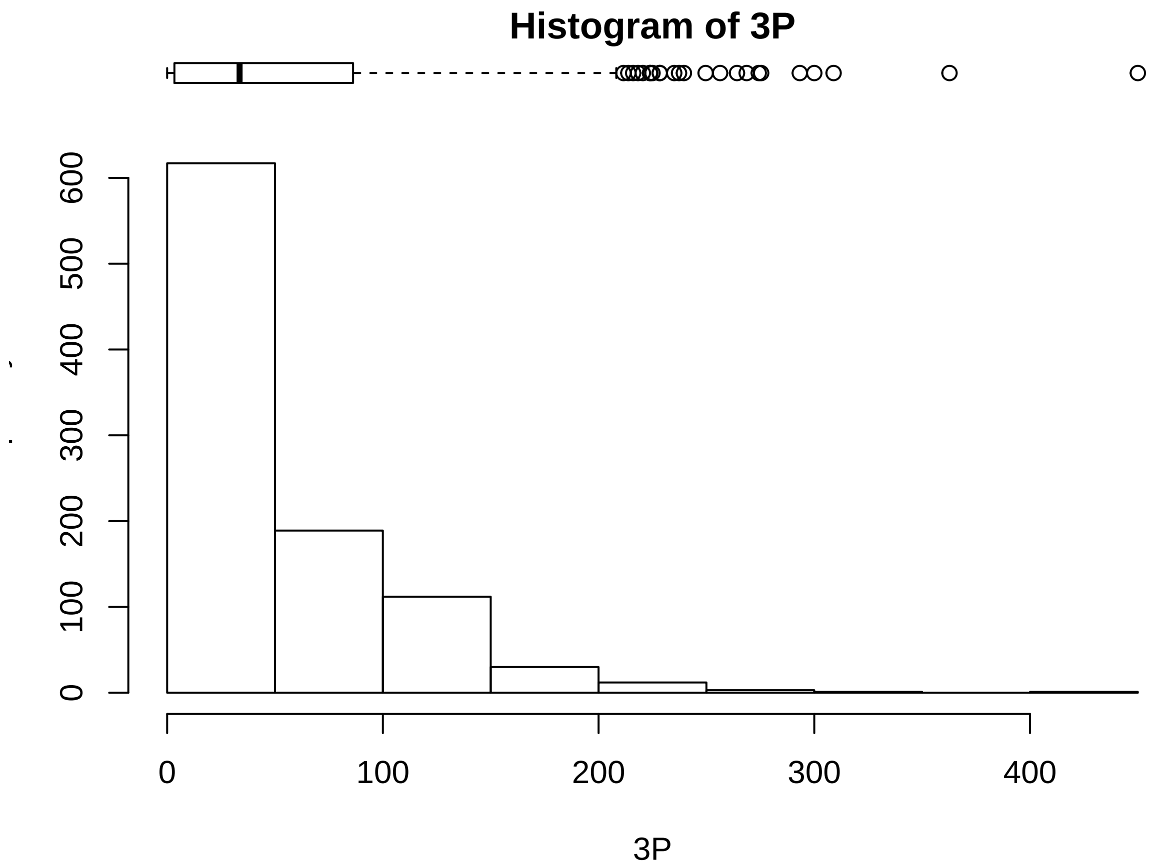

```
## Top 10 Players by FG
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2017  Russe~ 2.85e7 PG       28 OKC      81    81  2802  30.6 0.554  0.3
##  2 2016  Steph~ 1.21e7 PG       27 GSW      79    79  2700  31.5 0.669  0.554
##  3 2017  Karl-~ 6.22e6 C        21 MIN      82    82  3030  26   0.618  0.186
##  4 2017  Antho~ 2.38e7 C        23 NOP      75    75  2708  27.5 0.579  0.088
##  5 2016  LeBro~ 3.10e7 SF       31 CLE      76    76  2709  27.5 0.588  0.199
##  6 2017  LeBro~ 3.33e7 SF       32 CLE      74    74  2794  27   0.619  0.254
##  7 2017  DeMar~ 2.77e7 SG       27 TOR      74    74  2620  24   0.552  0.08
##  8 2016  James~ 2.65e7 SG       26 HOU      82    82  3125  25.3 0.598  0.406
##  9 2017  Andre~ 7.57e6 SF       21 MIN      82    82  3048  16.5 0.534  0.184
## 10 2016  Kevin~ 2.65e7 SF       27 OKC      72    72  2578  28.2 0.634  0.348
## # ... with 39 more variables: FTr <dbl>, `ORB%` <dbl>, `DRB%` <dbl>,
## #   `TRB%` <dbl>, `AST%` <dbl>, `STL%` <dbl>, `BLK%` <dbl>, `TOV%` <dbl>,
## #   `USG%` <dbl>, OWS <dbl>, DWS <dbl>, WS <dbl>, `WS/48` <dbl>, OBPM <dbl>,
## #   DBPM <dbl>, BPM <dbl>, VORP <dbl>, FG <dbl>, 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>
```



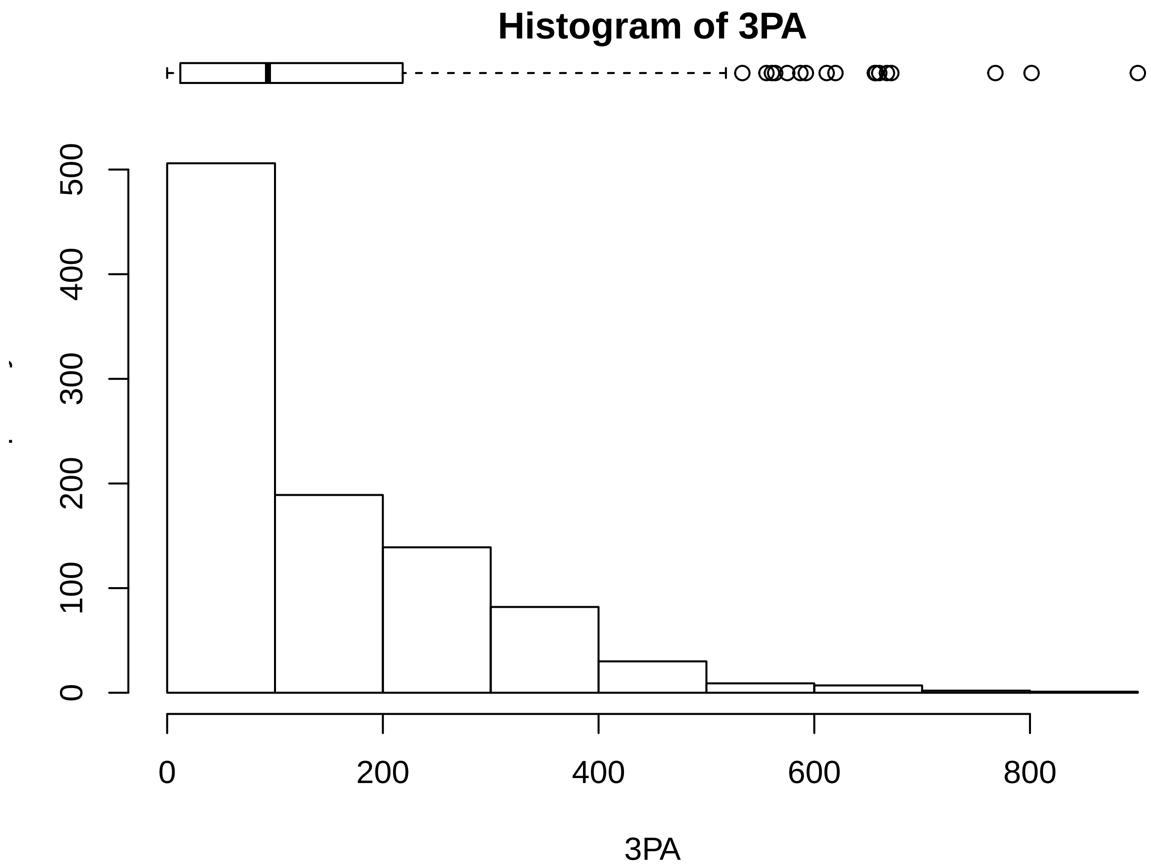

```
## Top 10 Players by FGA
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2017  Russe~ 2.85e7 PG       28 OKC      81    81  2802  30.6 0.554  0.3
##  2 2016  James~ 2.65e7 SG       26 HOU      82    82  3125  25.3 0.598  0.406
##  3 2016  Steph~ 1.21e7 PG       27 GSW      79    79  2700  31.5 0.669  0.554
##  4 2017  Andre~ 7.57e6 SF       21 MIN      82    82  3048  16.5 0.534  0.184
##  5 2017  DeMar~ 2.77e7 SG       27 TOR      74    74  2620  24   0.552  0.08
##  6 2017  James~ 2.83e7 PG       27 HOU      81    81  2947  27.3 0.613  0.493
##  7 2017  Antho~ 2.38e7 C        23 NOP      75    75  2708  27.5 0.579  0.088
##  8 2017  Damia~ 2.62e7 PG       26 POR      75    75  2694  24.1 0.586  0.388
##  9 2017  Karl-~ 6.22e6 C        21 MIN      82    82  3030  26   0.618  0.186
## 10 2016  Damia~ 2.43e7 PG       25 POR      75    75  2676  22.2 0.56   0.414
## # ... with 39 more variables: FTr <dbl>, `ORB%` <dbl>, `DRB%` <dbl>,
## #   `TRB%` <dbl>, `AST%` <dbl>, `STL%` <dbl>, `BLK%` <dbl>, `TOV%` <dbl>,
## #   `USG%` <dbl>, OWS <dbl>, DWS <dbl>, WS <dbl>, `WS/48` <dbl>, OBPM <dbl>,
## #   DBPM <dbl>, BPM <dbl>, VORP <dbl>, FG <dbl>, 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>
```



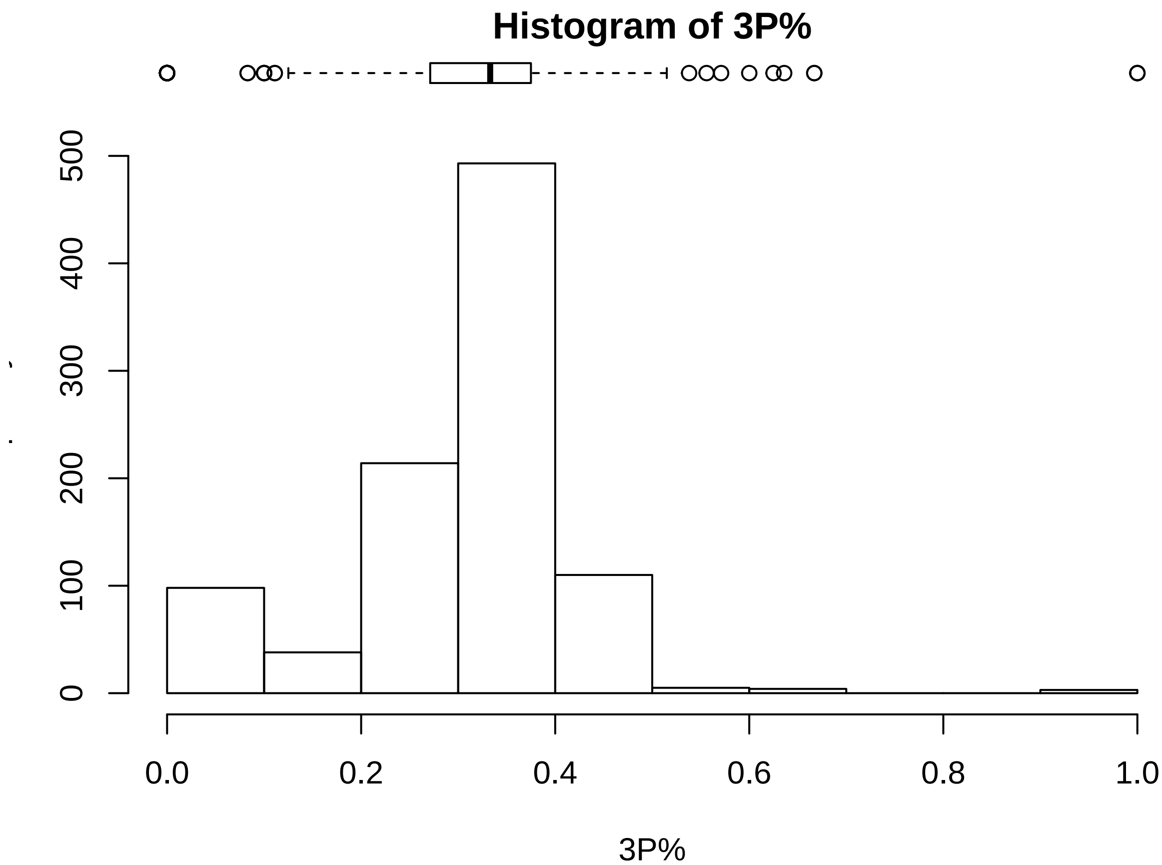

```
## Top 10 Players by FG%
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2016  Brian~ 3.28e5 PG       23 MIA       1     0     3  39.3 1      0
##  2 2016  Rakee~ 1.05e6 PF       24 IND       1     0     6  32   1      0
##  3 2017  Demet~ 9.29e4 PG       22 BOS       5     0    17  30.8 0.753  0.25
##  4 2017  China~ 1.31e6 C        20 HOU       5     1    52  12.3 0.799  0
##  5 2017  DeAnd~ 2.26e7 C        28 LAC      81    81  2570  21.8 0.673  0.003
##  6 2016  DeAnd~ 2.12e7 C        27 LAC      77    77  2598  20.6 0.628  0.002
##  7 2016  Brand~ 5.70e6 PF       28 MEM      12     2   212  18.3 0.663  0
##  8 2017  Tyson~ 1.30e7 C        34 PHO      47    46  1298  16.6 0.703  0
##  9 2017  Jarre~ 2.33e6 PG       33 NOP       2     0    33   7.7 0.773  0.333
## 10 2017  Rudy ~ 2.20e7 C        24 UTA      81    81  2744  23.3 0.682  0.002
## # ... with 39 more variables: FTr <dbl>, `ORB%` <dbl>, `DRB%` <dbl>,
## #   `TRB%` <dbl>, `AST%` <dbl>, `STL%` <dbl>, `BLK%` <dbl>, `TOV%` <dbl>,
## #   `USG%` <dbl>, OWS <dbl>, DWS <dbl>, WS <dbl>, `WS/48` <dbl>, OBPM <dbl>,
## #   DBPM <dbl>, BPM <dbl>, VORP <dbl>, FG <dbl>, 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>
```



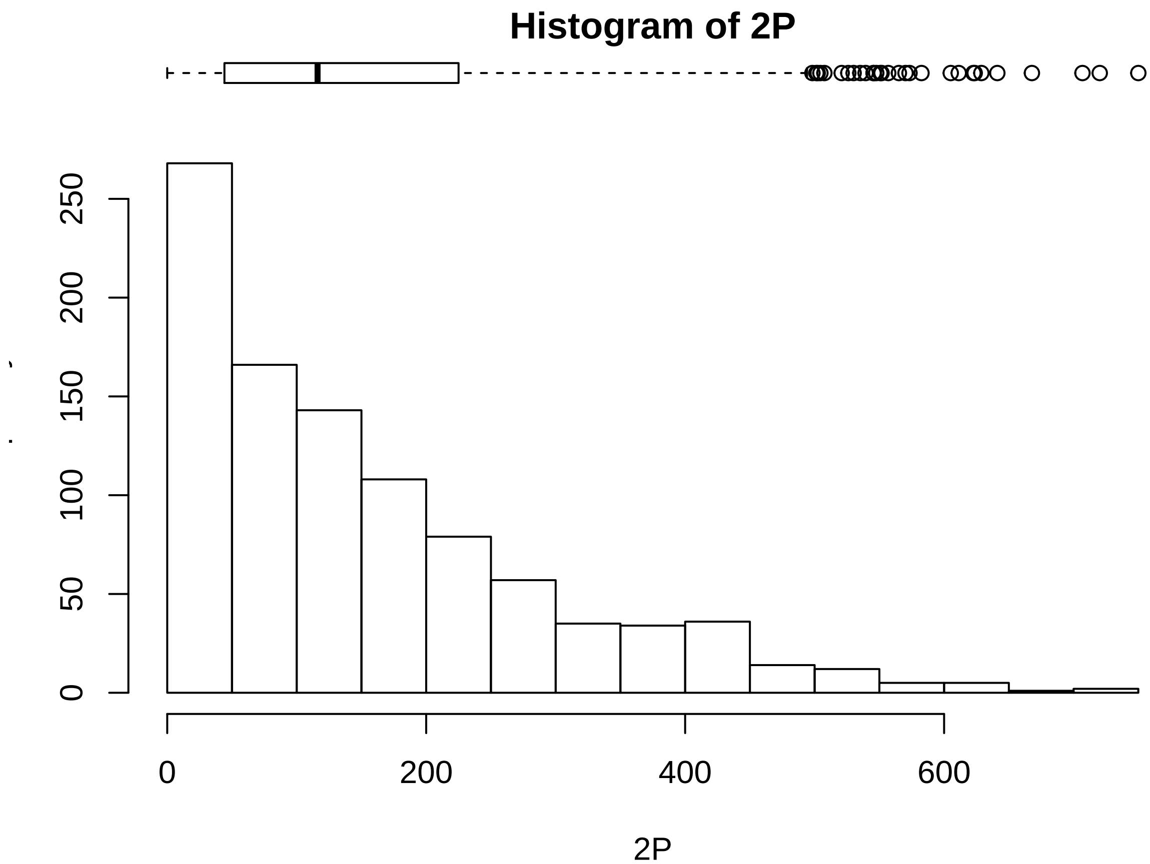

```
## Top 10 Players by 3P
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2016  Steph~ 1.21e7 PG       27 GSW      79    79  2700  31.5 0.669  0.554
##  2 2017  Steph~ 3.47e7 PG       28 GSW      79    79  2638  24.6 0.624  0.547
##  3 2016  Klay ~ 1.67e7 SG       25 GSW      80    80  2666  18.6 0.597  0.469
##  4 2017  Klay ~ 1.78e7 SG       26 GSW      78    78  2649  17.4 0.592  0.47
##  5 2017  James~ 2.83e7 PG       27 HOU      81    81  2947  27.3 0.613  0.493
##  6 2017  Eric ~ 1.29e7 SG       28 HOU      75    15  2323  13.1 0.557  0.651
##  7 2017  Isaia~ 6.26e6 PG       27 BOS      76    76  2569  26.5 0.625  0.439
##  8 2017  Kemba~ 1.20e7 PG       26 CHO      79    79  2739  21.3 0.569  0.415
##  9 2016  James~ 2.65e7 SG       26 HOU      82    82  3125  25.3 0.598  0.406
## 10 2016  Damia~ 2.43e7 PG       25 POR      75    75  2676  22.2 0.56   0.414
## # ... with 39 more variables: FTr <dbl>, `ORB%` <dbl>, `DRB%` <dbl>,
## #   `TRB%` <dbl>, `AST%` <dbl>, `STL%` <dbl>, `BLK%` <dbl>, `TOV%` <dbl>,
## #   `USG%` <dbl>, OWS <dbl>, DWS <dbl>, WS <dbl>, `WS/48` <dbl>, OBPM <dbl>,
## #   DBPM <dbl>, BPM <dbl>, VORP <dbl>, FG <dbl>, 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>
```



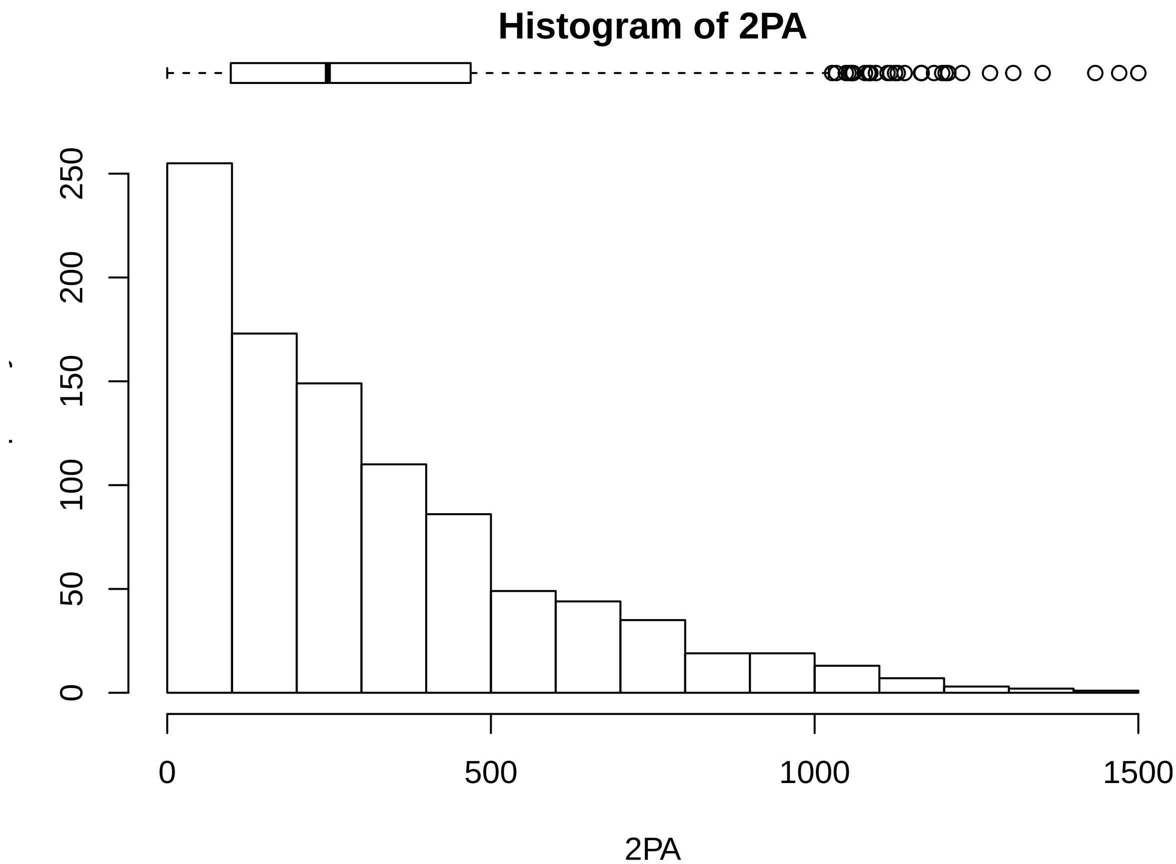

```
## Top 10 Players by 3PA
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2016  Steph~ 1.21e7 PG       27 GSW      79    79  2700  31.5 0.669  0.554
##  2 2017  Steph~ 3.47e7 PG       28 GSW      79    79  2638  24.6 0.624  0.547
##  3 2017  James~ 2.83e7 PG       27 HOU      81    81  2947  27.3 0.613  0.493
##  4 2017  Eric ~ 1.29e7 SG       28 HOU      75    15  2323  13.1 0.557  0.651
##  5 2016  James~ 2.65e7 SG       26 HOU      82    82  3125  25.3 0.598  0.406
##  6 2016  Klay ~ 1.67e7 SG       25 GSW      80    80  2666  18.6 0.597  0.469
##  7 2017  Klay ~ 1.78e7 SG       26 GSW      78    78  2649  17.4 0.592  0.47
##  8 2017  Isaia~ 6.26e6 PG       27 BOS      76    76  2569  26.5 0.625  0.439
##  9 2016  Damia~ 2.43e7 PG       25 POR      75    75  2676  22.2 0.56   0.414
## 10 2017  Kemba~ 1.20e7 PG       26 CHO      79    79  2739  21.3 0.569  0.415
## # ... with 39 more variables: FTr <dbl>, `ORB%` <dbl>, `DRB%` <dbl>,
## #   `TRB%` <dbl>, `AST%` <dbl>, `STL%` <dbl>, `BLK%` <dbl>, `TOV%` <dbl>,
## #   `USG%` <dbl>, OWS <dbl>, DWS <dbl>, WS <dbl>, `WS/48` <dbl>, OBPM <dbl>,
## #   DBPM <dbl>, BPM <dbl>, VORP <dbl>, FG <dbl>, 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>
```



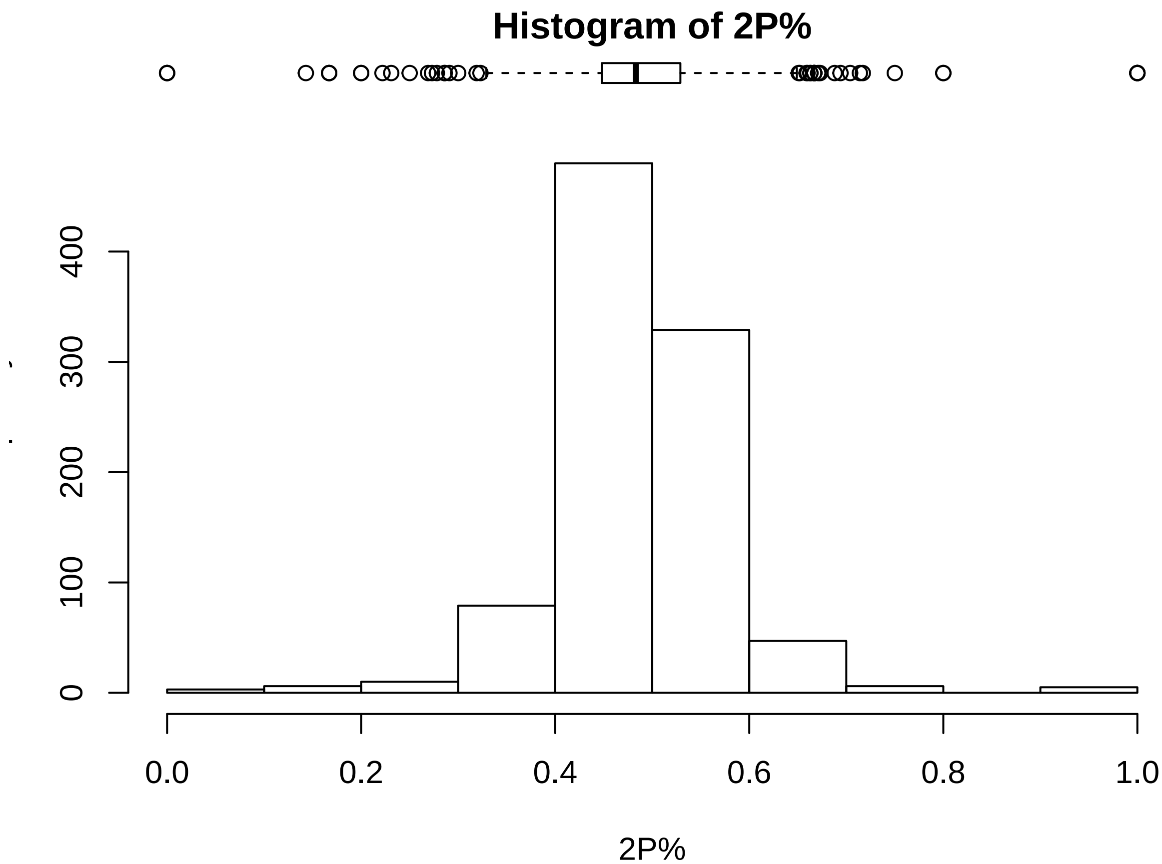

```
## Top 10 Players by 3P%
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2016  Andre~ 1.10e7 C        31 GSW      70    66  1451  15.9 0.623  0.004
##  2 2017  Demet~ 9.29e4 PG       22 BOS       5     0    17  30.8 0.753  0.25
##  3 2017  Taj G~ 1.40e7 PF       31 OKC      23    16   487  13.8 0.528  0.006
##  4 2016  Josh ~ 1.19e6 PF       24 OKC       5     0    55   6.7 0.509  0.5
##  5 2016  Marc ~ 2.12e7 C        31 MEM      52    52  1791  17.7 0.528  0.004
##  6 2016  Jorda~ 8.75e5 PG       24 CLE      15     1   113  14.2 0.537  0.212
##  7 2017  Lance~ 4.18e6 SG       26 IND       6     0   132  10.3 0.474  0.182
##  8 2017  Treve~ 1.31e6 SG       23 CHO      27     1   189  10.6 0.612  0.375
##  9 2017  Wayne~ 1.31e6 SG       22 NOP       3     3    47  10    0.82   0.875
## 10 2016  Steve~ 1.55e6 PF       32 OKC       7     0    24  20.8 0.708  0.75
## # ... with 39 more variables: FTr <dbl>, `ORB%` <dbl>, `DRB%` <dbl>,
## #   `TRB%` <dbl>, `AST%` <dbl>, `STL%` <dbl>, `BLK%` <dbl>, `TOV%` <dbl>,
## #   `USG%` <dbl>, OWS <dbl>, DWS <dbl>, WS <dbl>, `WS/48` <dbl>, OBPM <dbl>,
## #   DBPM <dbl>, BPM <dbl>, VORP <dbl>, FG <dbl>, 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>
```



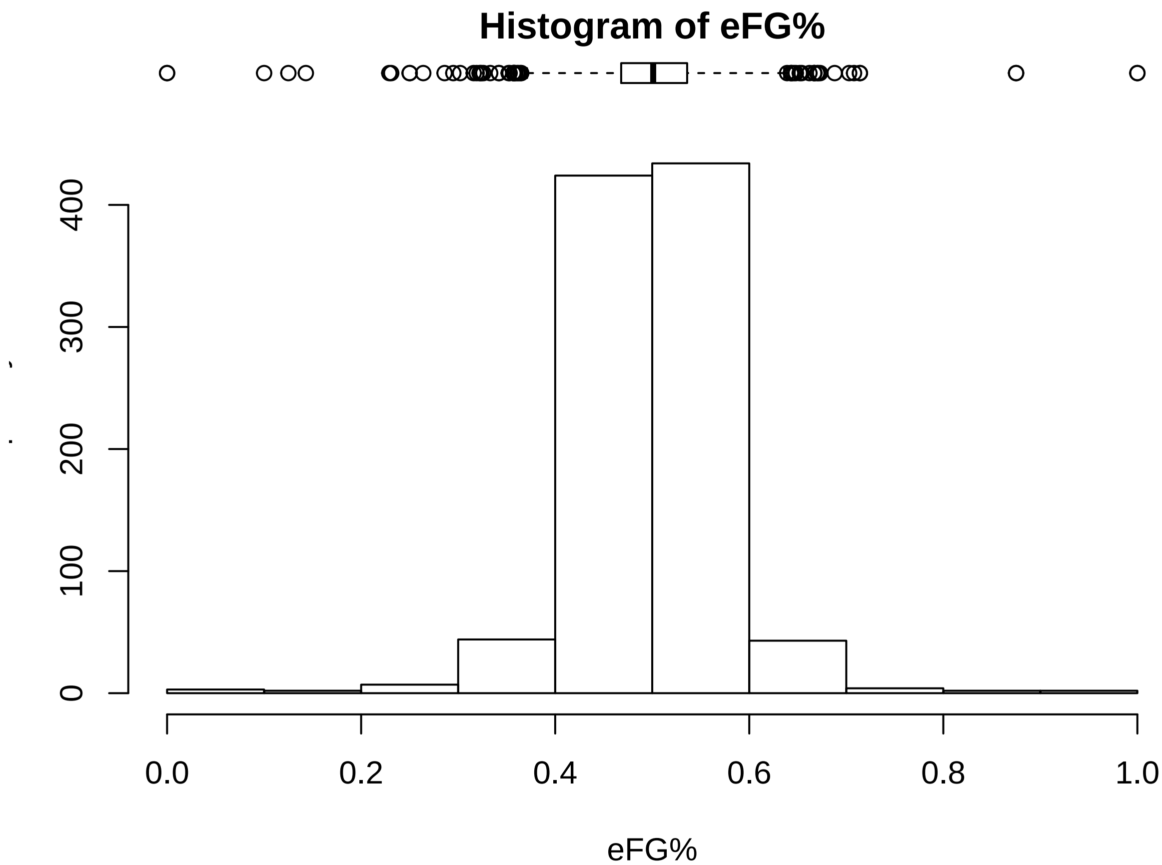

```
## Top 10 Players by 2P
## # A tibble: 10 x 51
##     year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##     <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##   1 2017  Antho~ 2.38e7 C        23 NOP      75    75  2708  27.5 0.579  0.088
##   2 2017  Karl-~ 6.22e6 C        21 MIN      82    82  3030  26   0.618  0.186
##   3 2017  DeMar~ 2.77e7 SG       27 TOR      74    74  2620  24   0.552  0.08
##   4 2016  LeBro~ 3.10e7 SF       31 CLE      76    76  2709  27.5 0.588  0.199
##   5 2017  Russe~ 2.85e7 PG       28 OKC      81    81  2802  30.6 0.554  0.3
##   6 2017  LeBro~ 3.33e7 SF       32 CLE      74    74  2794  27   0.619  0.254
##   7 2017  Giann~ 2.25e7 SF       22 MIL      80    80  2845  26.1 0.599  0.143
##   8 2017  Andre~ 7.57e6 SF       21 MIN      82    82  3048  16.5 0.534  0.184
##   9 2016  Karl-~ 5.96e6 C        20 MIN      82    82  2627  22.5 0.59   0.076
## 10 2016  Brook~ 2.12e7 C        27 BRK      73    73  2457  21.7 0.562  0.012
## # ... with 39 more variables: FTr <dbl>, `ORB%` <dbl>, `DRB%` <dbl>,
## #   `TRB%` <dbl>, `AST%` <dbl>, `STL%` <dbl>, `BLK%` <dbl>, `TOV%` <dbl>,
## #   `USG%` <dbl>, OWS <dbl>, DWS <dbl>, WS <dbl>, `WS/48` <dbl>, OBPM <dbl>,
## #   DBPM <dbl>, BPM <dbl>, VORP <dbl>, FG <dbl>, 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>
```



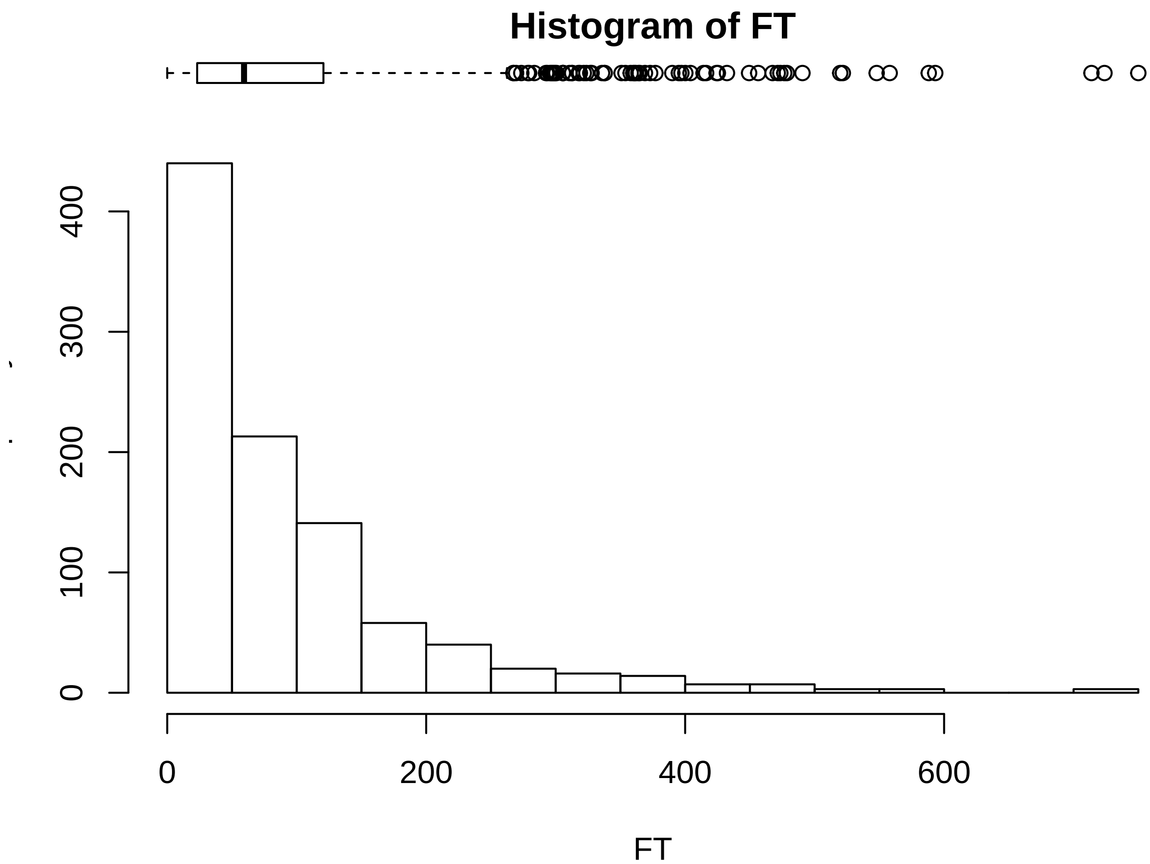

```
## Top 10 Players by 2PA
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2017  DeMar~ 2.77e7 SG       27 TOR      74    74  2620  24   0.552  0.08
##  2 2017  Antho~ 2.38e7 C        23 NOP      75    75  2708  27.5 0.579  0.088
##  3 2017  Russe~ 2.85e7 PG       28 OKC      81    81  2802  30.6 0.554  0.3
##  4 2017  Andre~ 7.57e6 SF       21 MIN      82    82  3048  16.5 0.534  0.184
##  5 2016  DeMar~ 2.65e7 SG       26 TOR      78    78  2804  21.5 0.55   0.101
##  6 2017  Karl-~ 6.22e6 C        21 MIN      82    82  3030  26   0.618  0.186
##  7 2017  John ~ 1.81e7 PG       26 WAS      78    78  2836  23.2 0.541  0.19
##  8 2016  Brook~ 2.12e7 C        27 BRK      73    73  2457  21.7 0.562  0.012
##  9 2016  Dwyan~ 2.32e7 SG       34 MIA      74    73  2258  20.3 0.517  0.037
## 10 2016  LeBro~ 3.10e7 SF       31 CLE      76    76  2709  27.5 0.588  0.199
## # ... with 39 more variables: FTr <dbl>, `ORB%` <dbl>, `DRB%` <dbl>,
## #   `TRB%` <dbl>, `AST%` <dbl>, `STL%` <dbl>, `BLK%` <dbl>, `TOV%` <dbl>,
## #   `USG%` <dbl>, OWS <dbl>, DWS <dbl>, WS <dbl>, `WS/48` <dbl>, OBPM <dbl>,
## #   DBPM <dbl>, BPM <dbl>, VORP <dbl>, FG <dbl>, 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>
```



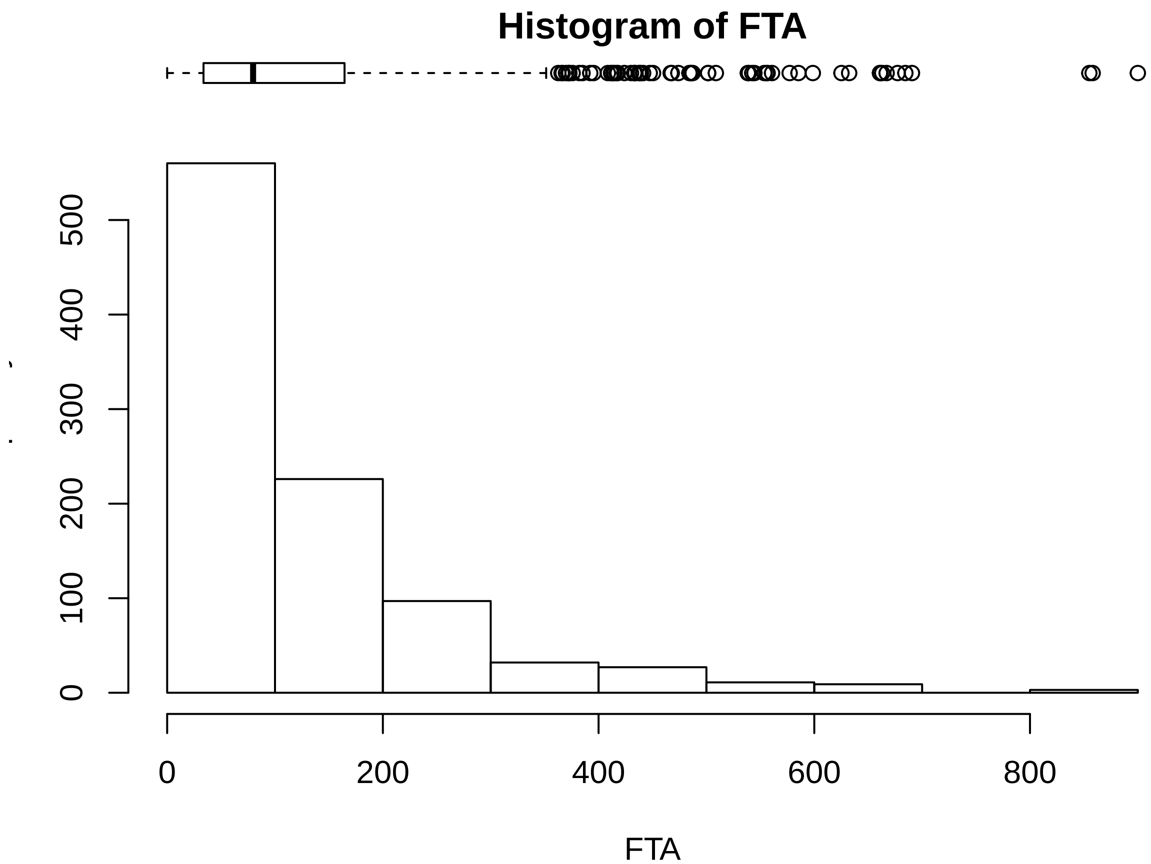

```
## Top 10 Players by 2P%
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2016  Brian~ 3.28e5 PG       23 MIA       1     0     3  39.3 1      0
##  2 2017  Jarre~ 2.33e6 PG       33 NOP       2     0    33   7.7 0.773  0.333
##  3 2016  Rakee~ 1.05e6 PF       24 IND       1     0     6  32   1      0
##  4 2016  Sean ~ 9.80e5 SG       26 DEN       8     0    82   8   0.551  0.81
##  5 2017  Wayne~ 1.31e6 SG       22 NOP       3     3    47  10   0.82   0.875
##  6 2017  Axel ~ 2.50e4 SF       24 TOT       4     0    47   6.2 0.611  0.444
##  7 2017  Axel ~ 2.50e4 SF       24 NOP       2     0    41   8.6 0.688  0.375
##  8 2017  Ersan~ 6.00e6 PF       29 OKC       3     0    62   6.9 0.469  0.75
##  9 2017  DeAnd~ 2.26e7 C        28 LAC      81    81  2570  21.8 0.673  0.003
## 10 2017  China~ 1.31e6 C        20 HOU       5     1    52  12.3 0.799  0
## # ... with 39 more variables: FTr <dbl>, `ORB%` <dbl>, `DRB%` <dbl>,
## #   `TRB%` <dbl>, `AST%` <dbl>, `STL%` <dbl>, `BLK%` <dbl>, `TOV%` <dbl>,
## #   `USG%` <dbl>, OWS <dbl>, DWS <dbl>, WS <dbl>, `WS/48` <dbl>, OBPM <dbl>,
## #   DBPM <dbl>, BPM <dbl>, VORP <dbl>, FG <dbl>, 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>
```



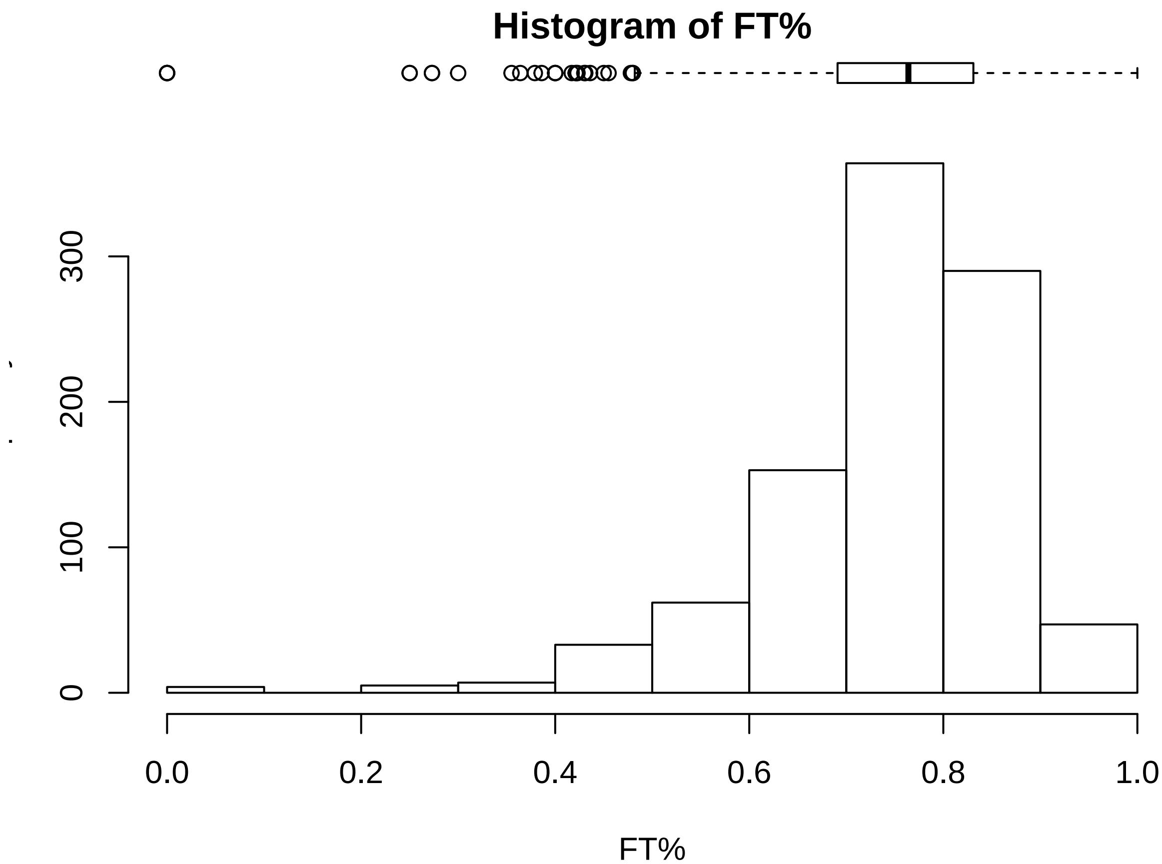

```
## Top 10 Players by eFG%
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2016  Brian~ 3.28e5 PG       23 MIA       1     0     3  39.3 1      0
##  2 2016  Rakee~ 1.05e6 PF       24 IND       1     0     6  32   1      0
##  3 2017  Demet~ 9.29e4 PG       22 BOS       5     0    17  30.8 0.753  0.25
##  4 2017  Wayne~ 1.31e6 SG       22 NOP       3     3    47  10   0.82   0.875
##  5 2017  China~ 1.31e6 C        20 HOU       5     1    52  12.3 0.799  0
##  6 2017  DeAnd~ 2.26e7 C        28 LAC      81    81  2570  21.8 0.673  0.003
##  7 2016  Steve~ 1.55e6 PF       32 OKC       7     0    24  20.8 0.708  0.75
##  8 2016  DeAnd~ 2.12e7 C        27 LAC      77    77  2598  20.6 0.628  0.002
##  9 2017  Axel ~ 2.50e4 SF       24 NOP       2     0    41   8.6 0.688  0.375
## 10 2016  Brand~ 5.70e6 PF       28 MEM      12     2   212  18.3 0.663  0
## # ... with 39 more variables: FTr <dbl>, `ORB%` <dbl>, `DRB%` <dbl>,
## #   `TRB%` <dbl>, `AST%` <dbl>, `STL%` <dbl>, `BLK%` <dbl>, `TOV%` <dbl>,
## #   `USG%` <dbl>, OWS <dbl>, DWS <dbl>, WS <dbl>, `WS/48` <dbl>, OBPM <dbl>,
## #   DBPM <dbl>, BPM <dbl>, VORP <dbl>, FG <dbl>, 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>
```



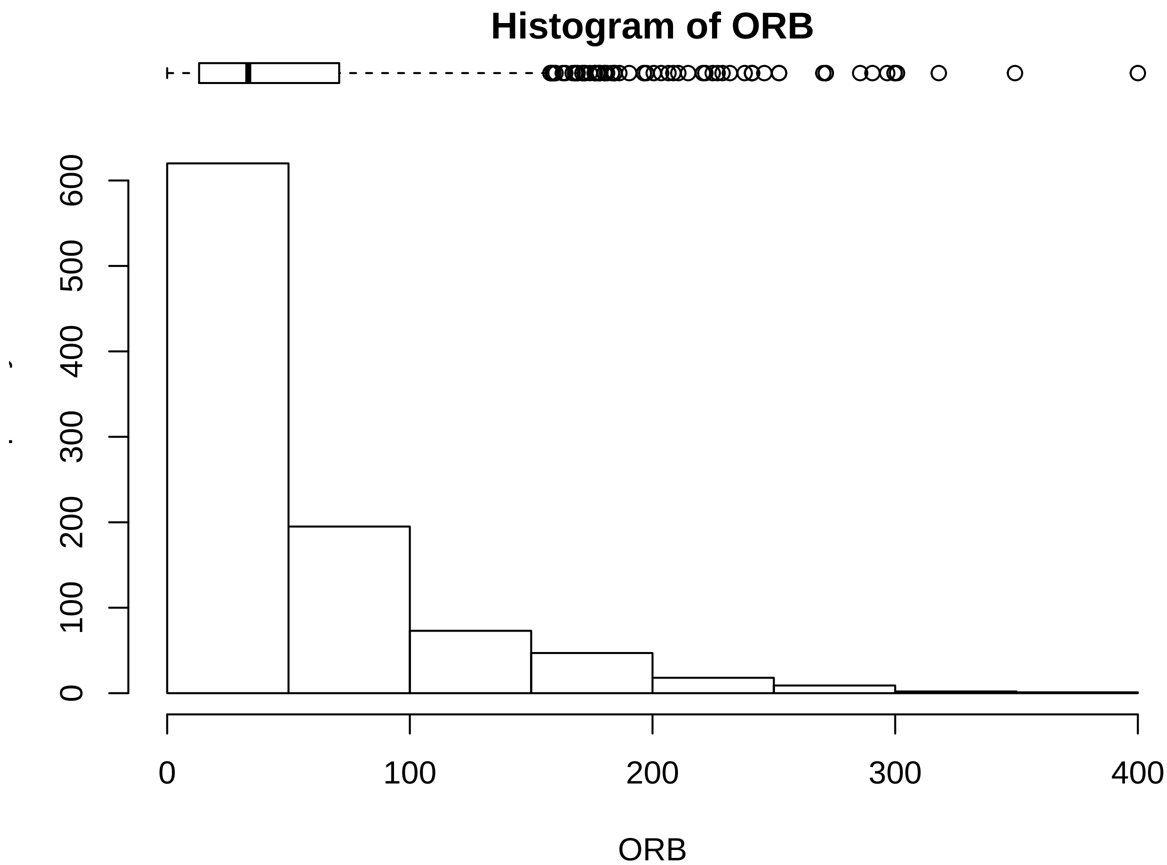

```
## Top 10 Players by FT
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2017  James~ 2.83e7 PG       27 HOU      81    81  2947  27.3 0.613  0.493
##  2 2016  James~ 2.65e7 SG       26 HOU      82    82  3125  25.3 0.598  0.406
##  3 2017  Russe~ 2.85e7 PG       28 OKC      81    81  2802  30.6 0.554  0.3
##  4 2017  Isaia~ 6.26e6 PG       27 BOS      76    76  2569  26.5 0.625  0.439
##  5 2017  Jimmy~ 1.93e7 SF       27 CHI      76    75  2809  25.1 0.586  0.198
##  6 2016  DeMar~ 2.65e7 SG       26 TOR      78    78  2804  21.5 0.55   0.101
##  7 2017  DeMar~ 2.77e7 SG       27 TOR      74    74  2620  24   0.552  0.08
##  8 2017  Antho~ 2.38e7 C        23 NOP      75    75  2708  27.5 0.579  0.088
##  9 2017  DeMar~ 1.81e7 C        26 TOT      72    72  2465  25.7 0.562  0.254
## 10 2017  Damia~ 2.62e7 PG       26 POR      75    75  2694  24.1 0.586  0.388
## # ... with 39 more variables: FTr <dbl>, `ORB%` <dbl>, `DRB%` <dbl>,
## #   `TRB%` <dbl>, `AST%` <dbl>, `STL%` <dbl>, `BLK%` <dbl>, `TOV%` <dbl>,
## #   `USG%` <dbl>, OWS <dbl>, DWS <dbl>, WS <dbl>, `WS/48` <dbl>, OBPM <dbl>,
## #   DBPM <dbl>, BPM <dbl>, VORP <dbl>, FG <dbl>, 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>
```



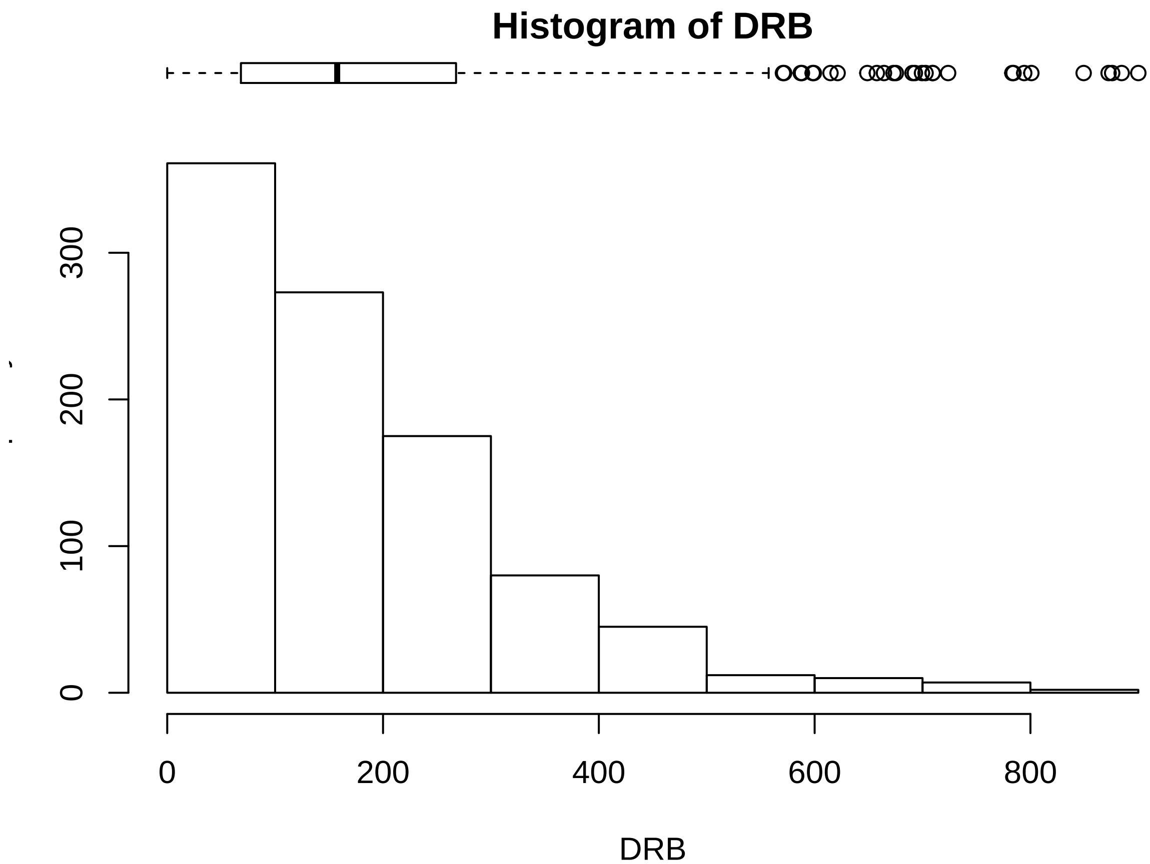

```
## Top 10 Players by FTA
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2017  James~ 2.83e7 PG       27 HOU      81    81  2947  27.3 0.613  0.493
##  2 2017  Russe~ 2.85e7 PG       28 OKC      81    81  2802  30.6 0.554  0.3
##  3 2016  James~ 2.65e7 SG       26 HOU      82    82  3125  25.3 0.598  0.406
##  4 2017  Jimmy~ 1.93e7 SF       27 CHI      76    75  2809  25.1 0.586  0.198
##  5 2017  DeMar~ 1.81e7 C        26 TOT      72    72  2465  25.7 0.562  0.254
##  6 2016  DeMar~ 1.70e7 C        25 SAC      65    65  2246  23.6 0.538  0.158
##  7 2016  DeMar~ 2.65e7 SG       26 TOR      78    78  2804  21.5 0.55   0.101
##  8 2017  Isaia~ 6.26e6 PG       27 BOS      76    76  2569  26.5 0.625  0.439
##  9 2017  Antho~ 2.38e7 C        23 NOP      75    75  2708  27.5 0.579  0.088
## 10 2017  DeMar~ 2.77e7 SG       27 TOR      74    74  2620  24   0.552  0.08
## # ... with 39 more variables: FTr <dbl>, `ORB%` <dbl>, `DRB%` <dbl>,
## #   `TRB%` <dbl>, `AST%` <dbl>, `STL%` <dbl>, `BLK%` <dbl>, `TOV%` <dbl>,
## #   `USG%` <dbl>, OWS <dbl>, DWS <dbl>, WS <dbl>, `WS/48` <dbl>, OBPM <dbl>,
## #   DBPM <dbl>, BPM <dbl>, VORP <dbl>, FG <dbl>, 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>
```



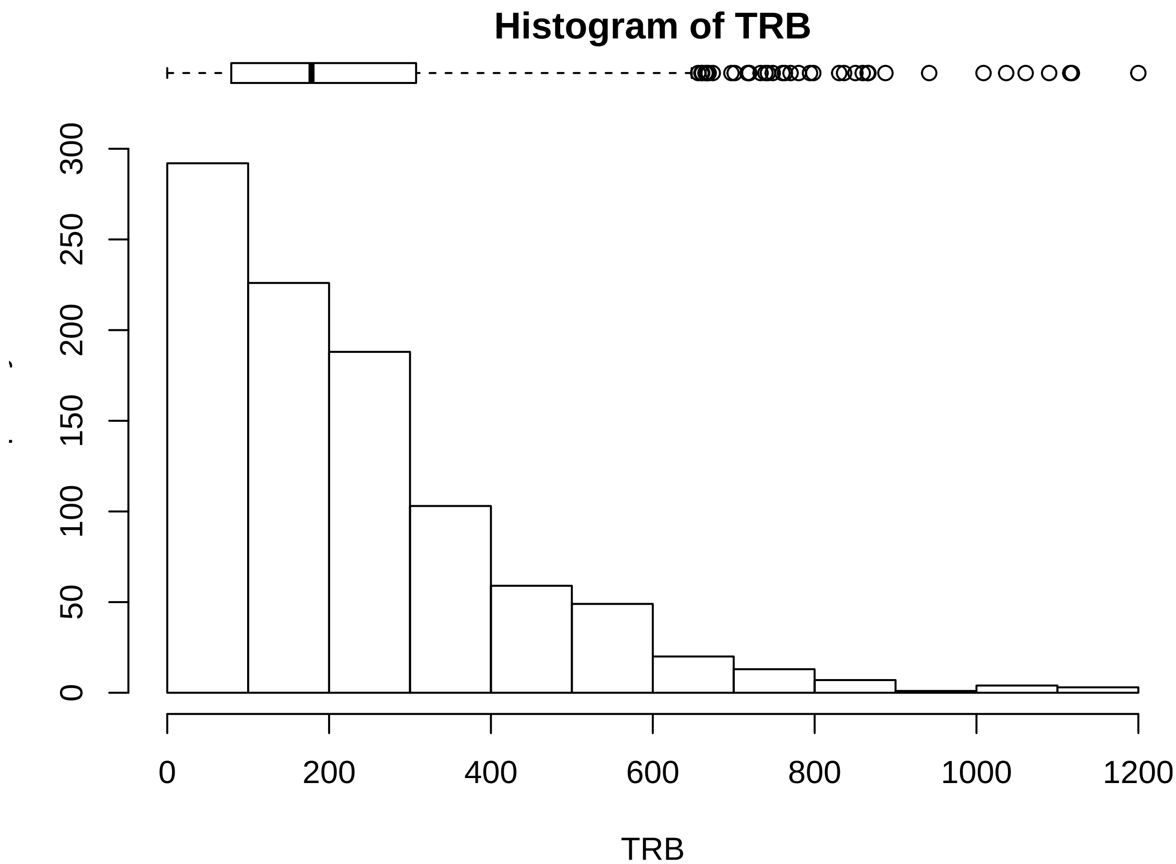

```
## Top 10 Players by FT%
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2017  Andre~ 2.84e6 PF       27 BRK      10     0   111   5   0.43   0.324
##  2 2016  Beno ~ 1.55e6 PG       33 MEM       8     0   120  12.6 0.497  0.239
##  3 2017  Bobby~ 1.52e6 PG       32 HOU      25     0   123  10.8 0.509  0.583
##  4 2017  Camer~ 2.20e6 PG       22 OKC      20     0   320   6.2 0.402  0.4
##  5 2017  Chass~ 1.31e6 PG       23 PHI       8     0    74  17.7 0.671  0.577
##  6 2017  China~ 1.31e6 C        20 HOU       5     1    52  12.3 0.799  0
##  7 2016  Damja~ 9.80e5 SF       29 MIN      33     0   277   5.5 0.572  0.806
##  8 2017  Diamo~ 1.31e6 C        19 LAC       7     0    24  -1.2 0.339  0
##  9 2017  Georg~ 1.00e5 PF       23 IND      23     0    93   0.1 0.285  0.333
## 10 2016  Jarel~ 1.75e5 SF       24 WAS      26     0   147  11   0.46   0.723
## # ... with 39 more variables: FTr <dbl>, `ORB%` <dbl>, `DRB%` <dbl>,
## #   `TRB%` <dbl>, `AST%` <dbl>, `STL%` <dbl>, `BLK%` <dbl>, `TOV%` <dbl>,
## #   `USG%` <dbl>, OWS <dbl>, DWS <dbl>, WS <dbl>, `WS/48` <dbl>, OBPM <dbl>,
## #   DBPM <dbl>, BPM <dbl>, VORP <dbl>, FG <dbl>, 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>
```



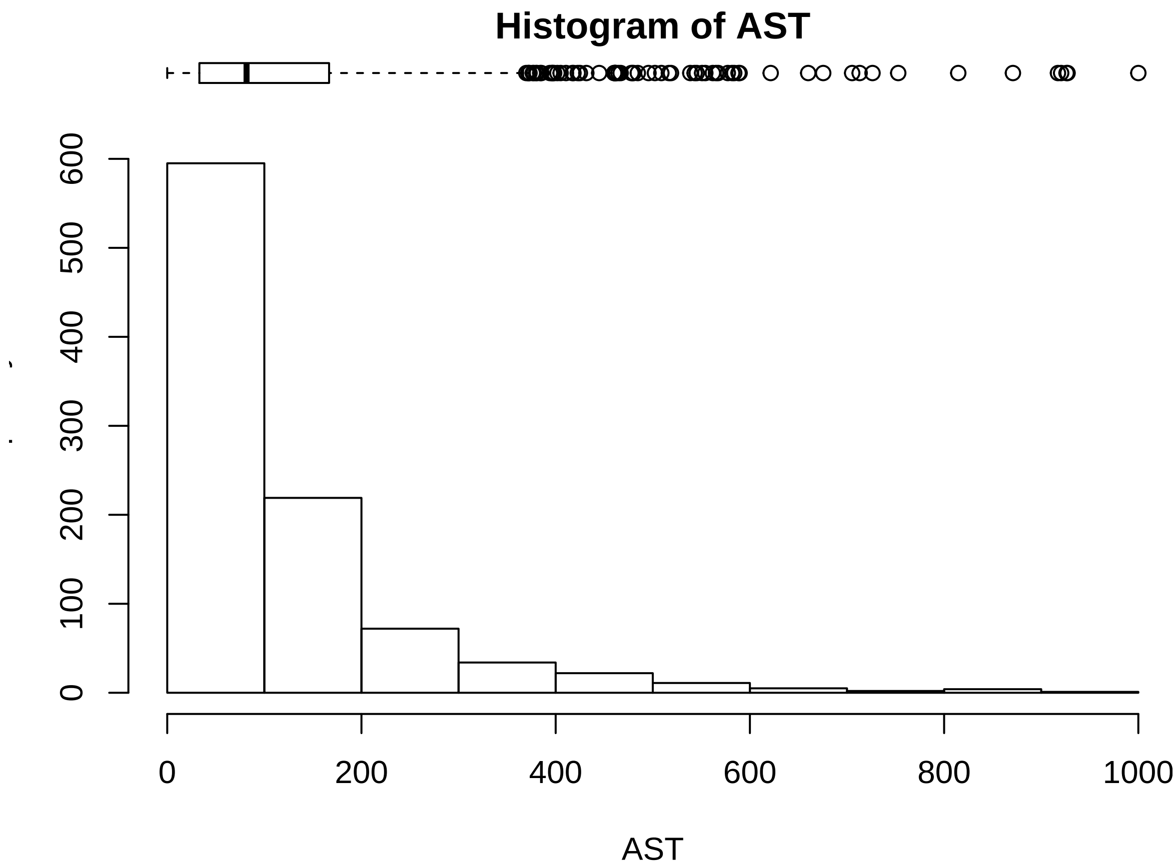

```
## Top 10 Players by ORB
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2016  Andre~ 2.21e7 C        22 DET      81    81  2666  21.2 0.499  0.006
##  2 2017  Andre~ 2.38e7 C        23 DET      81    81  2409  20.9 0.518  0.008
##  3 2017  Rudy ~ 2.20e7 C        24 UTA      81    81  2744  23.3 0.682  0.002
##  4 2017  DeAnd~ 2.26e7 C        28 LAC      81    81  2570  21.8 0.673  0.003
##  5 2017  Dwigh~ 2.35e7 C        31 ATL      74    74  2199  20.8 0.627  0.003
##  6 2017  Karl-~ 6.22e6 C        21 MIN      82    82  3030  26   0.618  0.186
##  7 2017  Hassa~ 2.38e7 C        27 MIA      77    77  2513  22.6 0.579  0
##  8 2017  Trist~ 1.64e7 C        25 CLE      78    78  2336  15.3 0.594  0.007
##  9 2017  Steve~ 2.25e7 C        23 OKC      80    80  2389  16.5 0.589  0.002
## 10 2016  Robin~ 1.32e7 C        27 NYK      82    82  2219  17.6 0.574  0.002
## # ... with 39 more variables: FTr <dbl>, `ORB%` <dbl>, `DRB%` <dbl>,
## #   `TRB%` <dbl>, `AST%` <dbl>, `STL%` <dbl>, `BLK%` <dbl>, `TOV%` <dbl>,
## #   `USG%` <dbl>, OWS <dbl>, DWS <dbl>, WS <dbl>, `WS/48` <dbl>, OBPM <dbl>,
## #   DBPM <dbl>, BPM <dbl>, VORP <dbl>, FG <dbl>, 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>
```



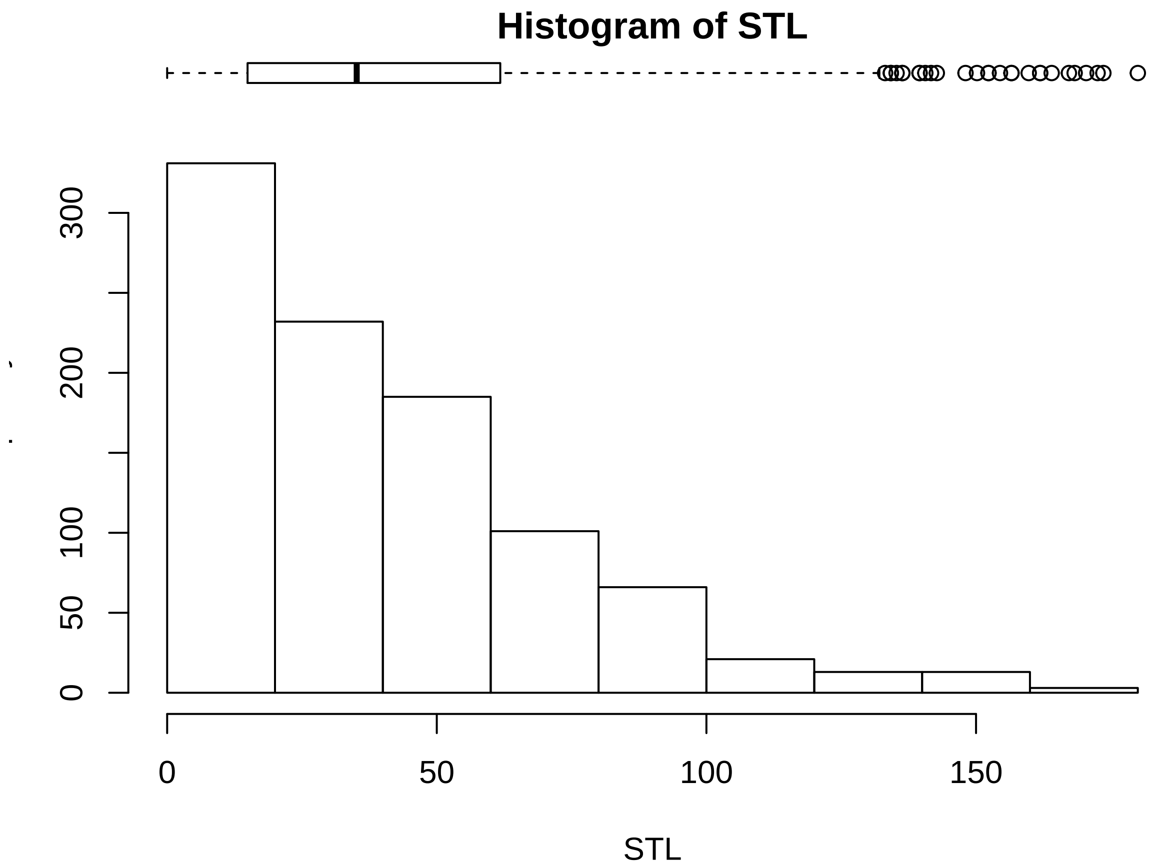

```
## Top 10 Players by DRB
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2017  DeAnd~ 2.26e7 C        28 LAC      81    81  2570  21.8 0.673  0.003
##  2 2016  Andre~ 2.21e7 C        22 DET      81    81  2666  21.2 0.499  0.006
##  3 2017  Hassa~ 2.38e7 C        27 MIA      77    77  2513  22.6 0.579  0
##  4 2016  DeAnd~ 2.12e7 C        27 LAC      77    77  2598  20.6 0.628  0.002
##  5 2017  Andre~ 2.38e7 C        23 DET      81    81  2409  20.9 0.518  0.008
##  6 2017  Russe~ 2.85e7 PG       28 OKC      81    81  2802  30.6 0.554  0.3
##  7 2017  Rudy ~ 2.20e7 C        24 UTA      81    81  2744  23.3 0.682  0.002
##  8 2017  Antho~ 2.38e7 C        23 NOP      75    75  2708  27.5 0.579  0.088
##  9 2017  Karl-~ 6.22e6 C        21 MIN      82    82  3030  26    0.618  0.186
## 10 2016  Juliu~ 3.27e6 PF       21 LAL      81    60  2286  13.9 0.482  0.043
## # ... with 39 more variables: FTr <dbl>, `ORB%` <dbl>, `DRB%` <dbl>,
## #   `TRB%` <dbl>, `AST%` <dbl>, `STL%` <dbl>, `BLK%` <dbl>, `TOV%` <dbl>,
## #   `USG%` <dbl>, OWS <dbl>, DWS <dbl>, WS <dbl>, `WS/48` <dbl>, OBPM <dbl>,
## #   DBPM <dbl>, BPM <dbl>, VORP <dbl>, FG <dbl>, 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>
```



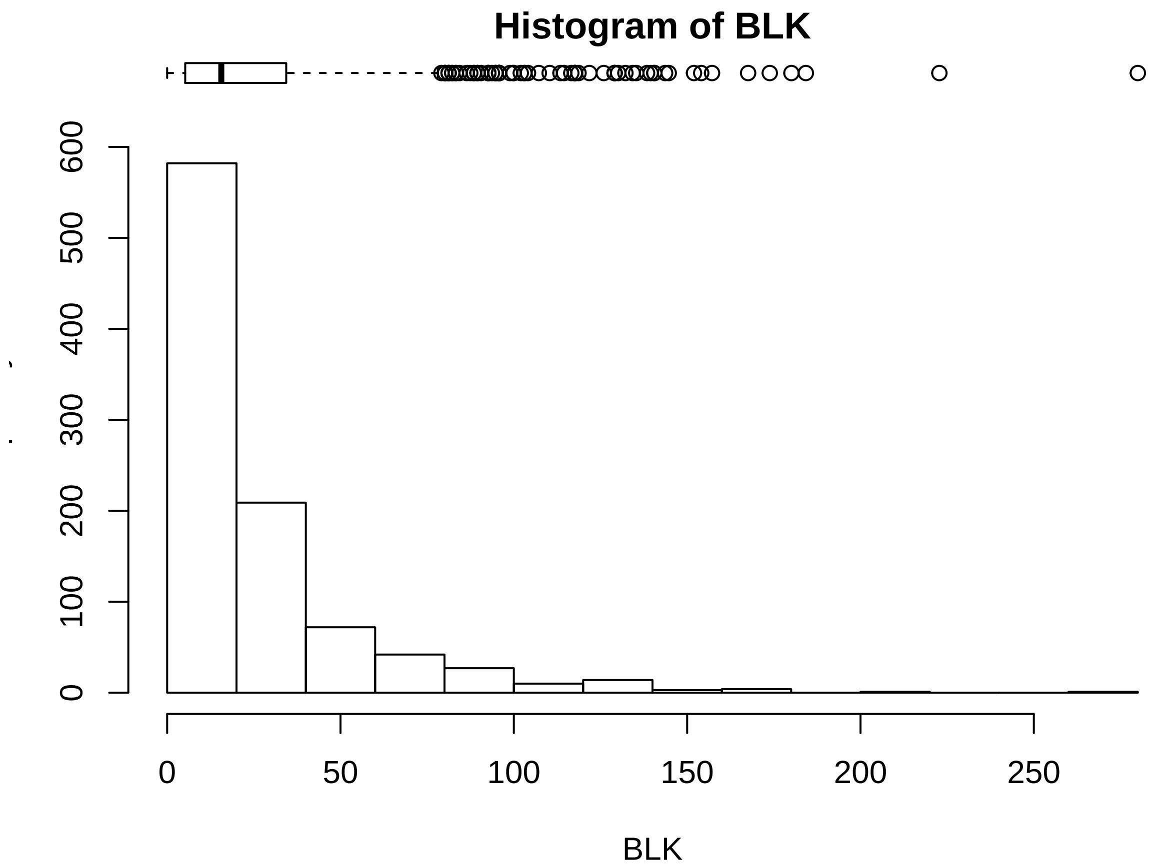

```
## Top 10 Players by TRB
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2016  Andre~ 2.21e7 C        22 DET      81    81  2666  21.2 0.499  0.006
##  2 2017  Andre~ 2.38e7 C        23 DET      81    81  2409  20.9 0.518  0.008
##  3 2017  DeAnd~ 2.26e7 C        28 LAC      81    81  2570  21.8 0.673  0.003
##  4 2017  Hassa~ 2.38e7 C        27 MIA      77    77  2513  22.6 0.579  0
##  5 2016  DeAnd~ 2.12e7 C        27 LAC      77    77  2598  20.6 0.628  0.002
##  6 2017  Rudy ~ 2.20e7 C        24 UTA      81    81  2744  23.3 0.682  0.002
##  7 2017  Karl-~ 6.22e6 C        21 MIN      82    82  3030  26   0.618  0.186
##  8 2017  Dwigh~ 2.35e7 C        31 ATL      74    74  2199  20.8 0.627  0.003
##  9 2017  Antho~ 2.38e7 C        23 NOP      75    75  2708  27.5 0.579  0.088
## 10 2016  Hassa~ 2.21e7 C        26 MIA      73    43  2125  25.7 0.629  0
## # ... with 39 more variables: FTr <dbl>, `ORB%` <dbl>, `DRB%` <dbl>,
## #   `TRB%` <dbl>, `AST%` <dbl>, `STL%` <dbl>, `BLK%` <dbl>, `TOV%` <dbl>,
## #   `USG%` <dbl>, OWS <dbl>, DWS <dbl>, WS <dbl>, `WS/48` <dbl>, OBPM <dbl>,
## #   DBPM <dbl>, BPM <dbl>, VORP <dbl>, FG <dbl>, 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>
```



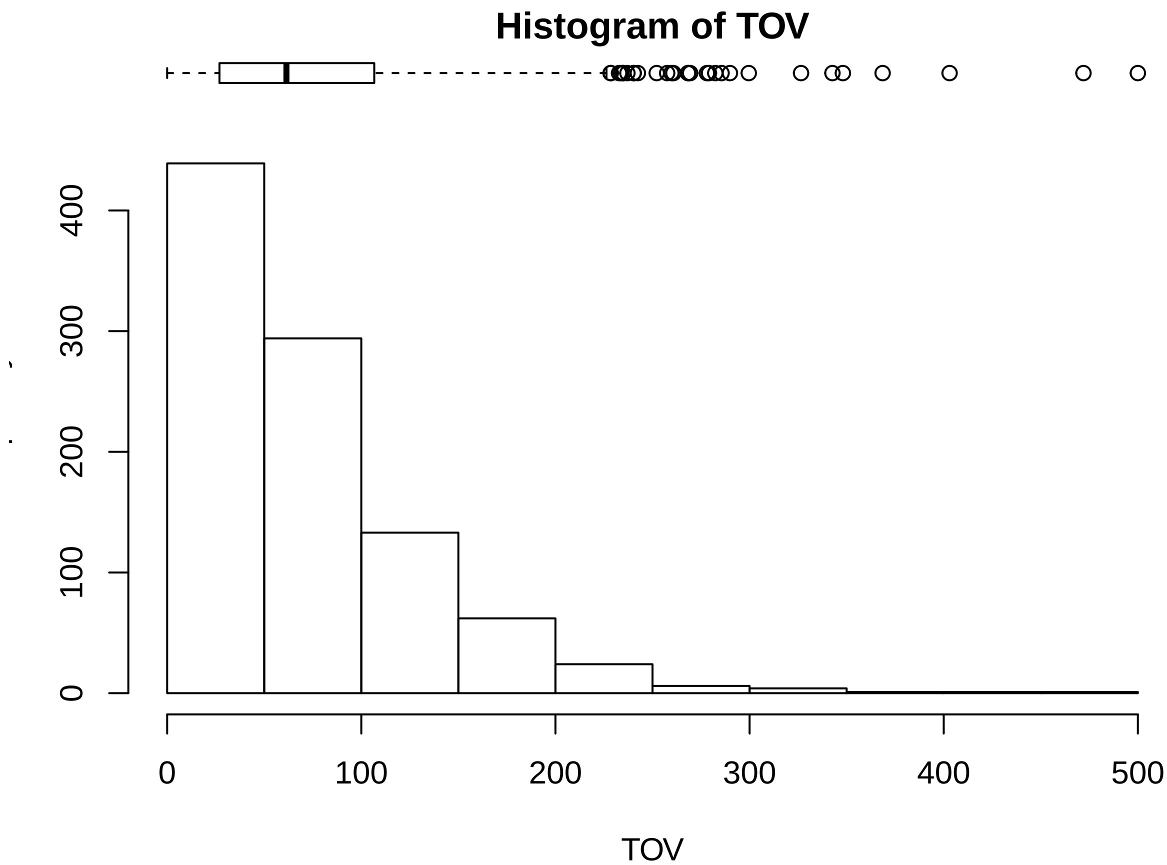

```
## Top 10 Players by AST
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2017  James~ 2.83e7 PG       27 HOU      81    81  2947  27.3 0.613  0.493
##  2 2017  Russe~ 2.85e7 PG       28 OKC      81    81  2802  30.6 0.554  0.3
##  3 2016  Rajon~ 1.40e7 PG       29 SAC      72    72  2537  16.9 0.506  0.217
##  4 2016  Russe~ 2.65e7 PG       27 OKC      80    80  2750  27.6 0.554  0.236
##  5 2017  John ~ 1.81e7 PG       26 WAS      78    78  2836  23.2 0.541  0.19
##  6 2016  John ~ 1.70e7 PG       25 WAS      77    77  2784  19.8 0.51   0.243
##  7 2016  Chris~ 2.29e7 PG       30 LAC      74    74  2420  26.2 0.575  0.295
##  8 2017  Ricky~ 1.43e7 PG       26 MIN      75    75  2469  16.8 0.539  0.302
##  9 2016  Ricky~ 1.36e7 PG       25 MIN      76    76  2323  17.6 0.529  0.324
## 10 2017  LeBro~ 3.33e7 SF       32 CLE      74    74  2794  27   0.619  0.254
## # ... with 39 more variables: FTr <dbl>, `ORB%` <dbl>, `DRB%` <dbl>,
## #   `TRB%` <dbl>, `AST%` <dbl>, `STL%` <dbl>, `BLK%` <dbl>, `TOV%` <dbl>,
## #   `USG%` <dbl>, OWS <dbl>, DWS <dbl>, WS <dbl>, `WS/48` <dbl>, OBPM <dbl>,
## #   DBPM <dbl>, BPM <dbl>, VORP <dbl>, FG <dbl>, 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>
```



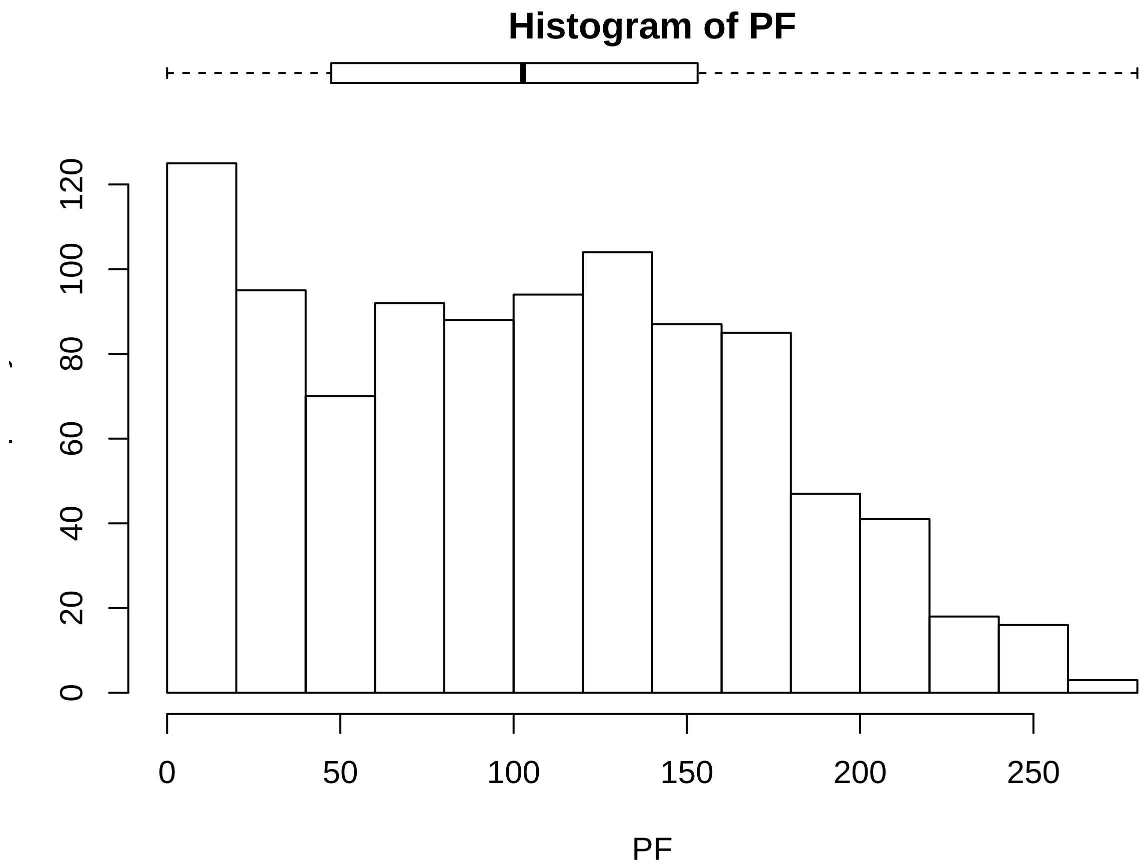

```
## Top 10 Players by STL
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2016  Steph~ 1.21e7 PG       27 GSW      79    79  2700  31.5 0.669  0.554
##  2 2016  Russe~ 2.65e7 PG       27 OKC      80    80  2750  27.6 0.554  0.236
##  3 2016  Ricky~ 1.36e7 PG       25 MIN      76    76  2323  17.6 0.529  0.324
##  4 2016  Trevo~ 7.81e6 SF       30 HOU      81    81  2859  12.9 0.551  0.581
##  5 2016  Kyle ~ 1.20e7 PG       29 TOR      77    77  2851  22.2 0.578  0.457
##  6 2017  John ~ 1.81e7 PG       26 WAS      78    78  2836  23.2 0.541  0.19
##  7 2017  Draym~ 1.64e7 PF       26 GSW      76    76  2471  16.5 0.522  0.405
##  8 2016  Chris~ 2.29e7 PG       30 LAC      74    74  2420  26.2 0.575  0.295
##  9 2016  Paul ~ 1.83e7 SF       25 IND      81    81  2819  20.9 0.557  0.391
## 10 2016  Monta~ 1.08e7 SG       30 IND      81    81  2734  13.7 0.504  0.276
## # ... with 39 more variables: FTr <dbl>, `ORB%` <dbl>, `DRB%` <dbl>,
## #   `TRB%` <dbl>, `AST%` <dbl>, `STL%` <dbl>, `BLK%` <dbl>, `TOV%` <dbl>,
## #   `USG%` <dbl>, OWS <dbl>, DWS <dbl>, WS <dbl>, `WS/48` <dbl>, OBPM <dbl>,
## #   DBPM <dbl>, BPM <dbl>, VORP <dbl>, FG <dbl>, 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>
```



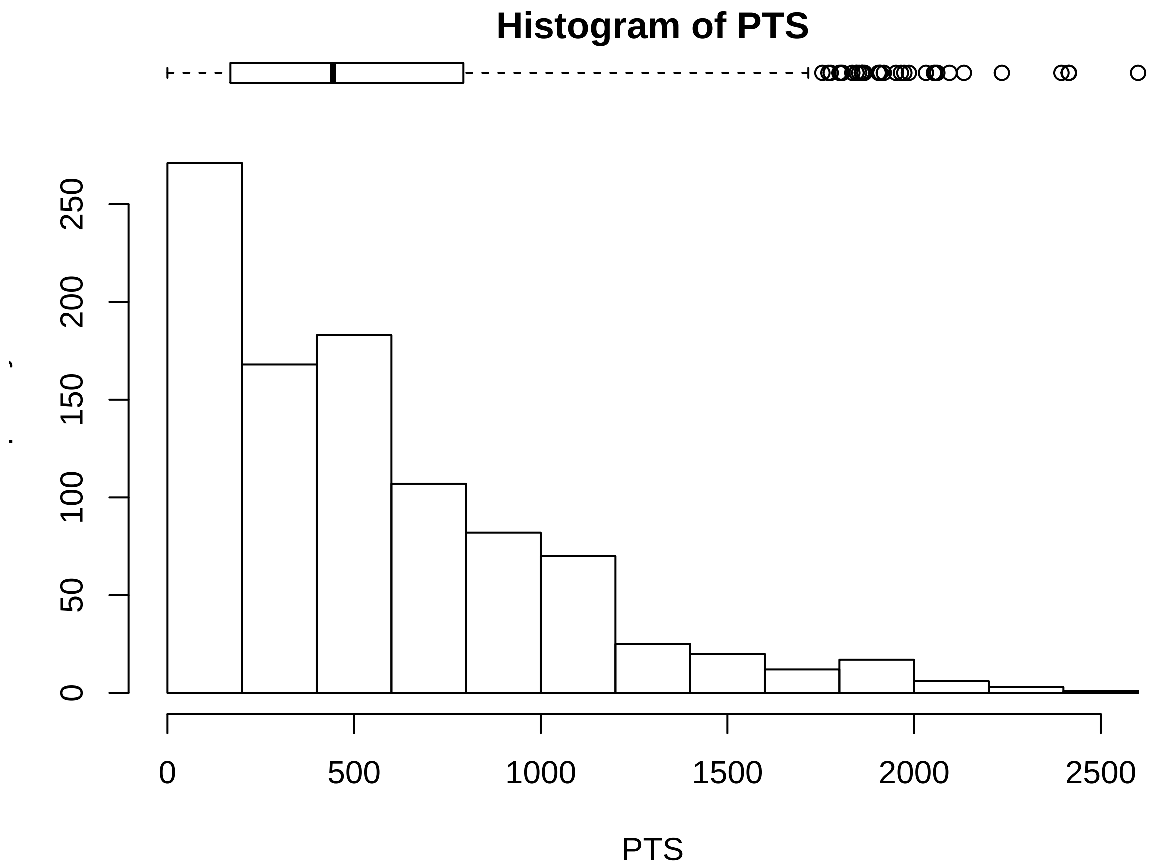

```
## Top 10 Players by BLK
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2016  Hassa~ 2.21e7 C        26 MIA      73    43  2125  25.7 0.629  0
##  2 2017  Rudy ~ 2.20e7 C        24 UTA      81    81  2744  23.3 0.682  0.002
##  3 2016  DeAnd~ 2.12e7 C        27 LAC      77    77  2598  20.6 0.628  0.002
##  4 2017  Myles~ 2.57e6 C        20 IND      81    81  2541  18.5 0.585  0.132
##  5 2017  Antho~ 2.38e7 C        23 NOP      75    75  2708  27.5 0.579  0.088
##  6 2017  Hassa~ 2.38e7 C        27 MIA      77    77  2513  22.6 0.579  0
##  7 2017  Giann~ 2.25e7 SF       22 MIL      80    80  2845  26.1 0.599  0.143
##  8 2016  Serge~ 1.23e7 PF       26 OKC      78    78  2500  13.9 0.533  0.212
##  9 2016  Pau G~ 1.55e7 C        35 CHI      72    72  2291  21.7 0.529  0.069
## 10 2016  Paul ~ 2.01e7 PF       30 ATL      81    81  2647  21.3 0.556  0.218
## # ... with 39 more variables: FTr <dbl>, `ORB%` <dbl>, `DRB%` <dbl>,
## #   `TRB%` <dbl>, `AST%` <dbl>, `STL%` <dbl>, `BLK%` <dbl>, `TOV%` <dbl>,
## #   `USG%` <dbl>, OWS <dbl>, DWS <dbl>, WS <dbl>, `WS/48` <dbl>, OBPM <dbl>,
## #   DBPM <dbl>, BPM <dbl>, VORP <dbl>, FG <dbl>, 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>
```




```
## Top 10 Players by TOV
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2017  James~ 2.83e7 PG       27 HOU      81    81  2947  27.3 0.613  0.493
##  2 2017  Russe~ 2.85e7 PG       28 OKC      81    81  2802  30.6 0.554  0.3
##  3 2016  James~ 2.65e7 SG       26 HOU      82    82  3125  25.3 0.598  0.406
##  4 2016  Russe~ 2.65e7 PG       27 OKC      80    80  2750  27.6 0.554  0.236
##  5 2017  John ~ 1.81e7 PG       26 WAS      78    78  2836  23.2 0.541  0.19
##  6 2016  John ~ 1.70e7 PG       25 WAS      77    77  2784  19.8 0.51   0.243
##  7 2017  LeBro~ 3.33e7 SF       32 CLE      74    74  2794  27   0.619  0.254
##  8 2016  Rajon~ 1.40e7 PG       29 SAC      72    72  2537  16.9 0.506  0.217
##  9 2017  DeMar~ 1.81e7 C        26 TOT      72    72  2465  25.7 0.562  0.254
## 10 2016  Paul ~ 1.83e7 SF       25 IND      81    81  2819  20.9 0.557  0.391
## # ... with 39 more variables: FTr <dbl>, `ORB%` <dbl>, `DRB%` <dbl>,
## #   `TRB%` <dbl>, `AST%` <dbl>, `STL%` <dbl>, `BLK%` <dbl>, `TOV%` <dbl>,
## #   `USG%` <dbl>, OWS <dbl>, DWS <dbl>, WS <dbl>, `WS/48` <dbl>, OBPM <dbl>,
## #   DBPM <dbl>, BPM <dbl>, VORP <dbl>, FG <dbl>, 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>
```



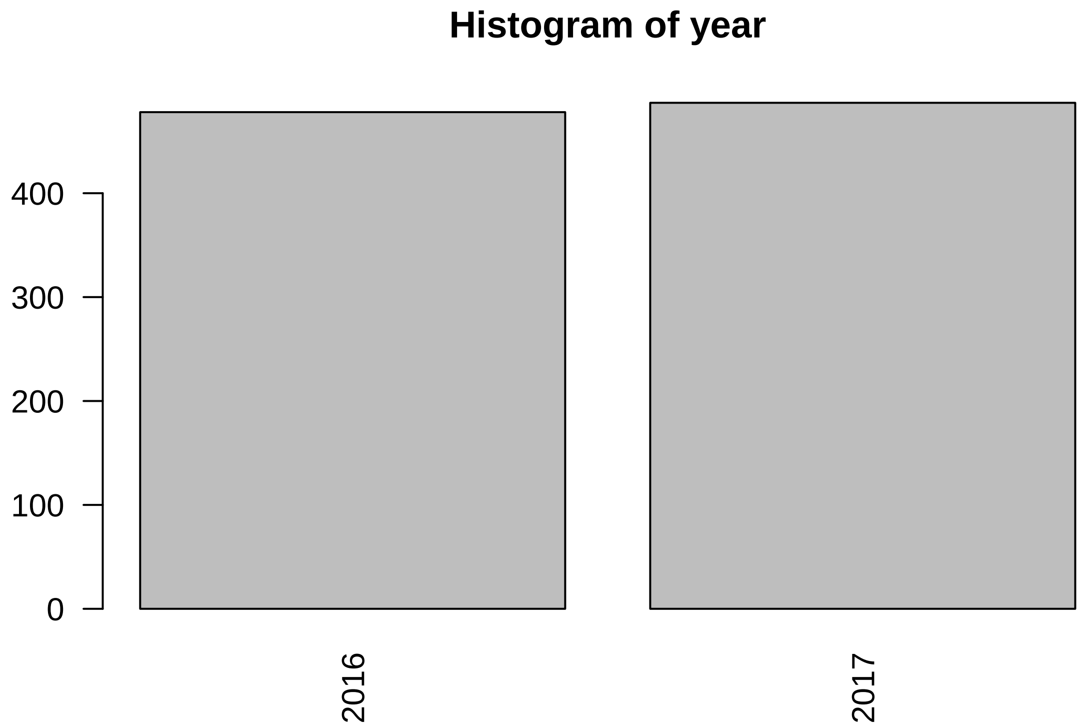

```
## Top 10 Players by PF
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2017  DeMar~ 1.81e7 C        26 TOT      72    72  2465  25.7 0.562  0.254
##  2 2017  Marqu~ 3.07e6 PF       19 PHO      82    75  1743  12.3 0.529  0.354
##  3 2017  Myles~ 2.57e6 C        20 IND      81    81  2541  18.5 0.585  0.132
##  4 2016  Giann~ 3.00e6 PG       21 MIL      80    79  2823  18.8 0.566  0.108
##  5 2017  Gorgu~ 1.41e7 PF       27 MIN      82    82  2653  14.2 0.555  0.065
##  6 2017  Marki~ 8.00e6 PF       27 WAS      76    76  2374  13.7 0.54   0.22
##  7 2016  Mason~ 2.33e6 C        25 POR      82    82  2084  17.2 0.564  0.008
##  8 2016  Roy H~ 5.00e6 C        29 LAL      81    81  1878  11.2 0.507  0.005
##  9 2017  JaMyc~ 8.53e6 PF       26 MEM      77    75  2101  13.5 0.601  0.290
## 10 2017  Juliu~ 4.15e6 PF       22 LAL      74    73  2132  16.3 0.543  0.082
## # ... with 39 more variables: FTr <dbl>, `ORB%` <dbl>, `DRB%` <dbl>,
## #   `TRB%` <dbl>, `AST%` <dbl>, `STL%` <dbl>, `BLK%` <dbl>, `TOV%` <dbl>,
## #   `USG%` <dbl>, OWS <dbl>, DWS <dbl>, WS <dbl>, `WS/48` <dbl>, OBPM <dbl>,
## #   DBPM <dbl>, BPM <dbl>, VORP <dbl>, FG <dbl>, 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>
```



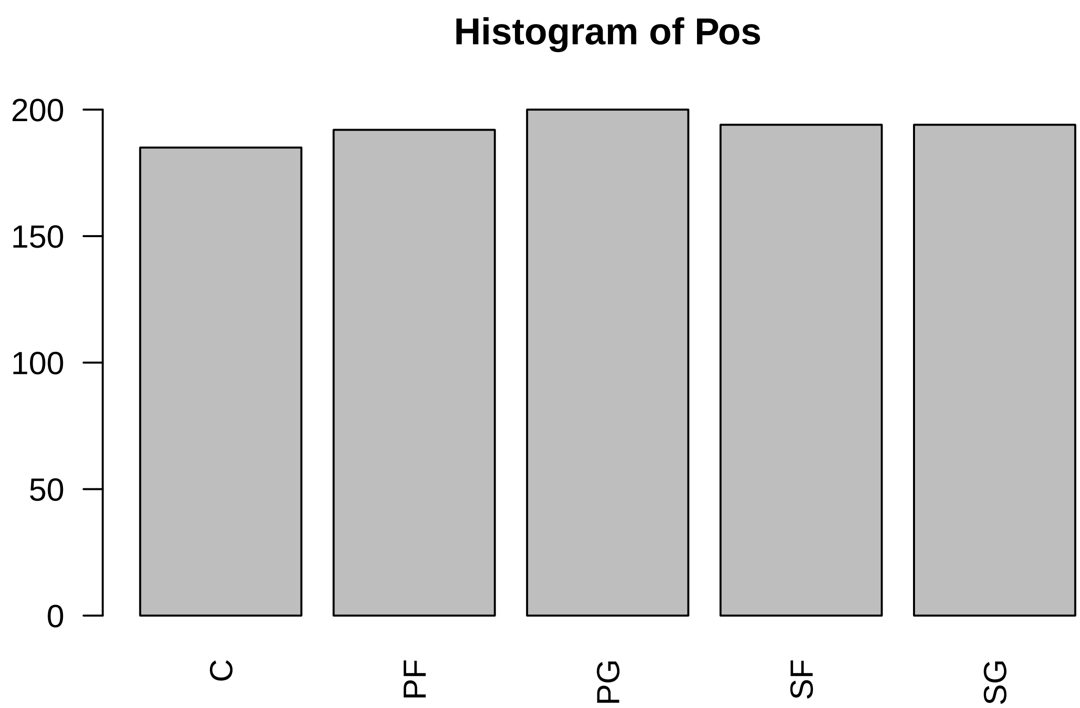

```
## Top 10 Players by PTS
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2017  Russe~ 2.85e7 PG       28 OKC      81    81  2802  30.6 0.554  0.3
##  2 2016  James~ 2.65e7 SG       26 HOU      82    82  3125  25.3 0.598  0.406
##  3 2016  Steph~ 1.21e7 PG       27 GSW      79    79  2700  31.5 0.669  0.554
##  4 2017  James~ 2.83e7 PG       27 HOU      81    81  2947  27.3 0.613  0.493
##  5 2017  Isaia~ 6.26e6 PG       27 BOS      76    76  2569  26.5 0.625  0.439
##  6 2017  Antho~ 2.38e7 C        23 NOP      75    75  2708  27.5 0.579  0.088
##  7 2017  Karl-~ 6.22e6 C        21 MIN      82    82  3030  26   0.618  0.186
##  8 2016  Kevin~ 2.65e7 SF       27 OKC      72    72  2578  28.2 0.634  0.348
##  9 2017  Damia~ 2.62e7 PG       26 POR      75    75  2694  24.1 0.586  0.388
## 10 2017  DeMar~ 2.77e7 SG       27 TOR      74    74  2620  24   0.552  0.08
## # ... with 39 more variables: FTr <dbl>, `ORB%` <dbl>, `DRB%` <dbl>,
## #   `TRB%` <dbl>, `AST%` <dbl>, `STL%` <dbl>, `BLK%` <dbl>, `TOV%` <dbl>,
## #   `USG%` <dbl>, OWS <dbl>, DWS <dbl>, WS <dbl>, `WS/48` <dbl>, OBPM <dbl>,
## #   DBPM <dbl>, BPM <dbl>, VORP <dbl>, FG <dbl>, 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>
```

Histograms for Categorical Variables

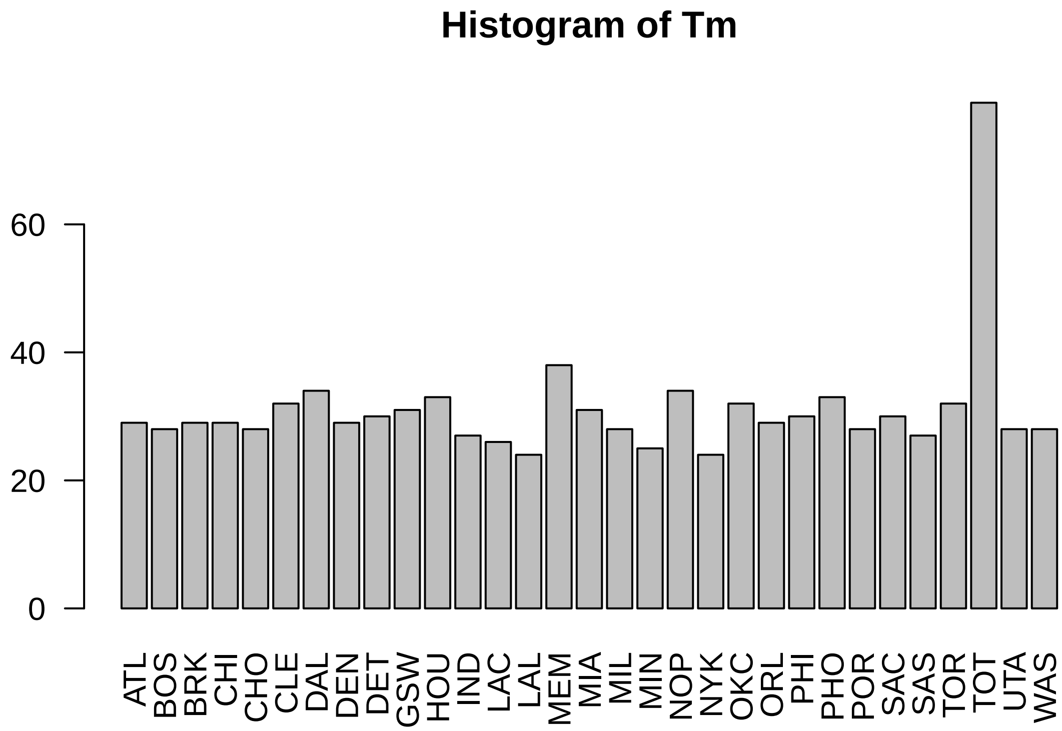
```
categorical_vars <- c('year','Pos','Tm')
for (col in categorical_vars){
  data <- df_primary[[col]]
  barplot(table(data),main=sprintf('Histogram of %s',col),las=2)
  print('\n')}
```


Histogram of year
0
100
200
300
400
2016
2017

```
## [1] "\n"
```


Histogram of Pos
0
50
100
150
200
C
PF
PG
SF
SG

```
## [1] "\n"
```



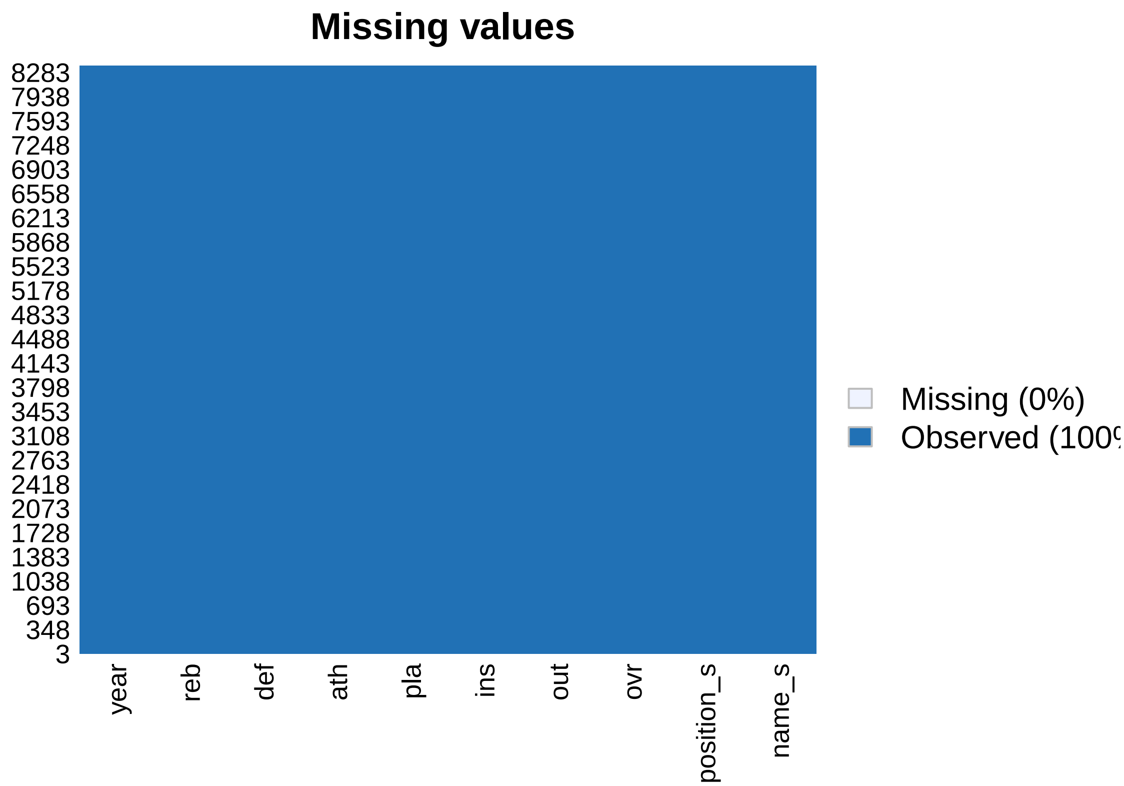

```
## [1] "\n"
```

Pool Together and Clean NBA 2K Data (Secondary Dataset)

```
secondary_attriutes <- c('name_s','position_s','ovr','out','ins','pla','ath','def','reb')
df_secondary <- vector('list',9)
names(df_secondary) <- secondary_attriutes
path_f = '../data/raw/nba2k/nba2k_%d.csv'
for (year in c(16:20)){
  df_year <- read.csv(sprintf(path_f,year))
  headers <- names(df_year)
  names(df_year) <- c('drop1',headers[1:length(headers)-1])
  df_year <- df_year[,c('name','position','ovr','out','ins','pla','ath','def','reb')]
  names(df_year) <- secondary_attriutes
  df_year[,'year'] <- 2000+year
  df_secondary <- rbind(df_secondary,df_year)}
original_s <- df_secondary
# Checking for missing values in primary dataset
missCounts <- sapply(df_secondary,function(x) sum(is.na(x)))
missCounts
```

```
##     name_s position_s        ovr        out        ins        pla        ath
##          0          0          0          0          0          0          0
##        def        reb       year
##          0          0          0
```

```
library(Amelia)
missmap(df_secondary, main = "Missing values ")
```




```
dev.copy(png,"../figures/Missing values/Missing_value_secondary.png")
```

```
## png
##   3
```

```
dev.off()
```

```
## pdf
##   2
```

```
df_secondary <- df_secondary[df_secondary$year%in%c(2016,2017),]   # take 2016-2017 2K ratings data
head(df_secondary)
```

```
##                     name_s position_s ovr out ins pla ath def reb year
## 1      '96 Michael Jordan         SG  99  95  88  91  93  92  75 2016
## 2         '15 Kobe Bryant         SG  99  97  79  95  84  88  65 2016
## 3           Stephen Curry         PG  99  98  66  98  89  78  54 2016
## 4            LeBron James         SF  99  94  89  91  92  91  91 2016
## 5 '71 Kareem Adbul-Jabbar          C  99  75  93  56  89  86  98 2016
## 6            Kyrie Irving         PG  98  98  70  95  91  74  49 2016
```

```
summary(df_secondary)
```

```
##                 name_s       position_s       ovr              out
##  Jimmy Butler     :  10   PG     :812   Min.   :40.00   Min.   :25.0
##  Kyrie Irving     :  10   SF     :782   1st Qu.:71.00   1st Qu.:62.0
##  Russell Westbrook:  10   SG     :749   Median :78.00   Median :73.0
##  Damian Lillard   :   9   PF     :710   Mean   :78.89   Mean   :71.3
##  Demar Derozan    :   9   C      :708   3rd Qu.:86.00   3rd Qu.:82.0
##  James Harden     :   9   C/PF   :  0   Max.   :99.00   Max.   :99.0
##  (Other)          :3704   (Other):  0
##       ins             pla             ath             def
##  Min.   :25.00   Min.   :25.00   Min.   :25.00   Min.   :25.00
##  1st Qu.:58.00   1st Qu.:48.00   1st Qu.:68.00   1st Qu.:58.00
##  Median :64.00   Median :61.00   Median :74.00   Median :65.00
##  Mean   :65.43   Mean   :62.04   Mean   :73.68   Mean   :66.28
##  3rd Qu.:72.00   3rd Qu.:76.00   3rd Qu.:80.00   3rd Qu.:73.00
##  Max.   :98.00   Max.   :99.00   Max.   :98.00   Max.   :98.00
##
##       reb             year
##  Min.   :25.00   Min.   :2016
```

```
##  1st Qu.:43.00   1st Qu.:2016
##  Median :57.00   Median :2016
##  Mean   :59.62   Mean   :2016
##  3rd Qu.:75.00   3rd Qu.:2017
##  Max.   :99.00   Max.   :2017
##
```

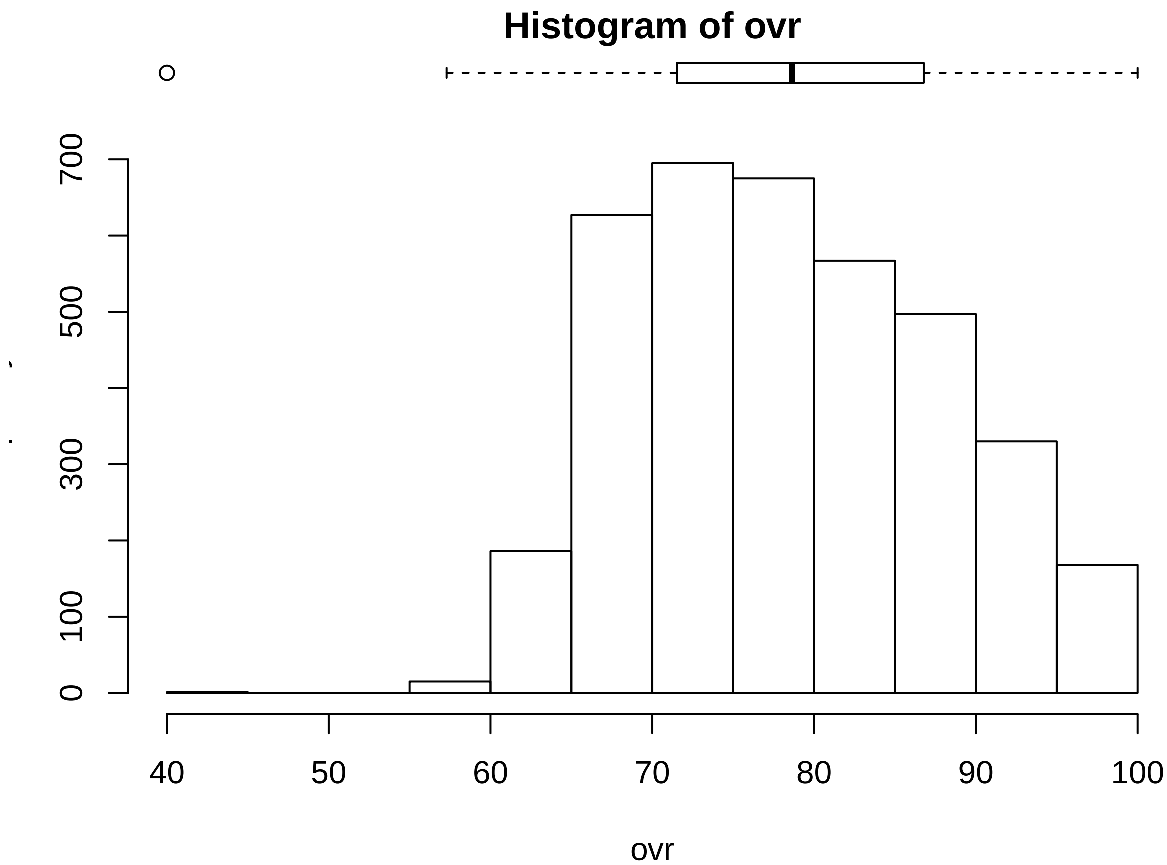
Numeric / Factor Variables

```
df_secondary$name_s <- as.character(df_secondary$name_s)
df_secondary$year <- as.factor(df_secondary$year) # make year a factor variable
df_secondary$position_s <- factor(df_secondary$position_s) # make position a factor variable
str(df_secondary)
```

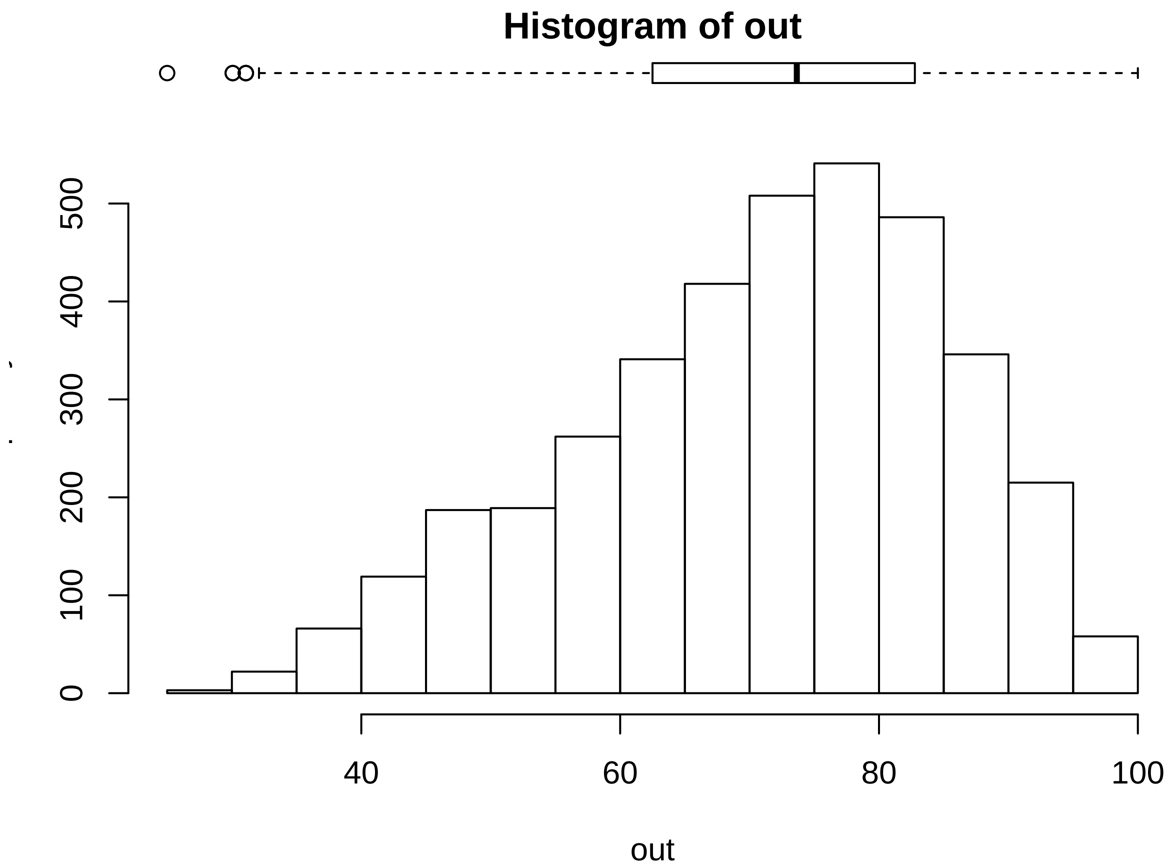
```
## 'data.frame':    3761 obs. of  10 variables:
##  $ name_s    : chr  "'96 Michael Jordan" "'15 Kobe Bryant" "Stephen Curry" "LeBron James" ...
##  $ position_s: Factor w/ 5 levels "C","PF","PG",..: 5 5 3 4 1 3 3 5 2 5 ...
##  $ ovr       : int  99 99 99 99 99 98 98 98 98 98 ...
##  $ out       : int  95 97 98 94 75 98 92 90 84 96 ...
##  $ ins       : int  88 79 66 89 93 70 78 82 89 81 ...
##  $ pla       : int  91 95 98 91 56 95 98 93 76 81 ...
##  $ ath       : int  93 84 89 92 89 91 90 92 81 88 ...
##  $ def       : int  92 88 78 91 86 74 84 83 87 83 ...
##  $ reb       : int  75 65 54 91 98 49 88 76 98 60 ...
##  $ year      : Factor w/ 2 levels "2016","2017": 1 1 1 1 1 1 1 1 1 1 ...
```

Histogram Barcharts for Numeric Variables

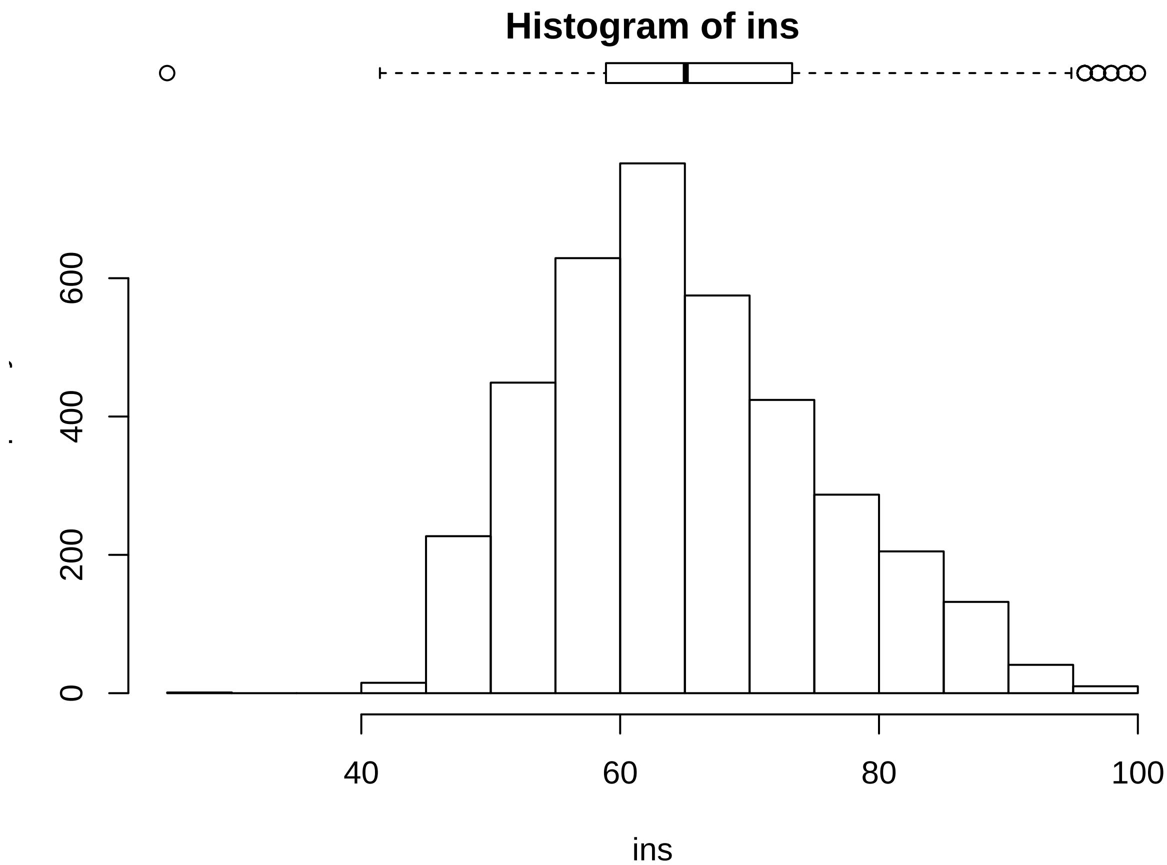
```
df_s_numeric <- Filter(is.numeric,df_secondary) # numeric variables
for (col in names(df_s_numeric)){
  data <- df_s_numeric[[col]]
  layout(mat = matrix(c(1,2),2,1, byrow=TRUE), height = c(1,8))
  par(mar=c(0, 3.1, 1.1, 2.1))
  boxplot(data , horizontal=TRUE , xaxt="n", frame=F, main=sprintf('Histogram of %s',col))
  par(mar=c(4, 3.1, 1.1, 2.1))
  hist(data,xlab=col,main='')
  # print top players in this category
  cat(sprintf('Top 10 Players by %s\n',col))
  df_top <- df_secondary[order(df_secondary[[col]],decreasing=T),]
  print(df_top[1:10,])}
```



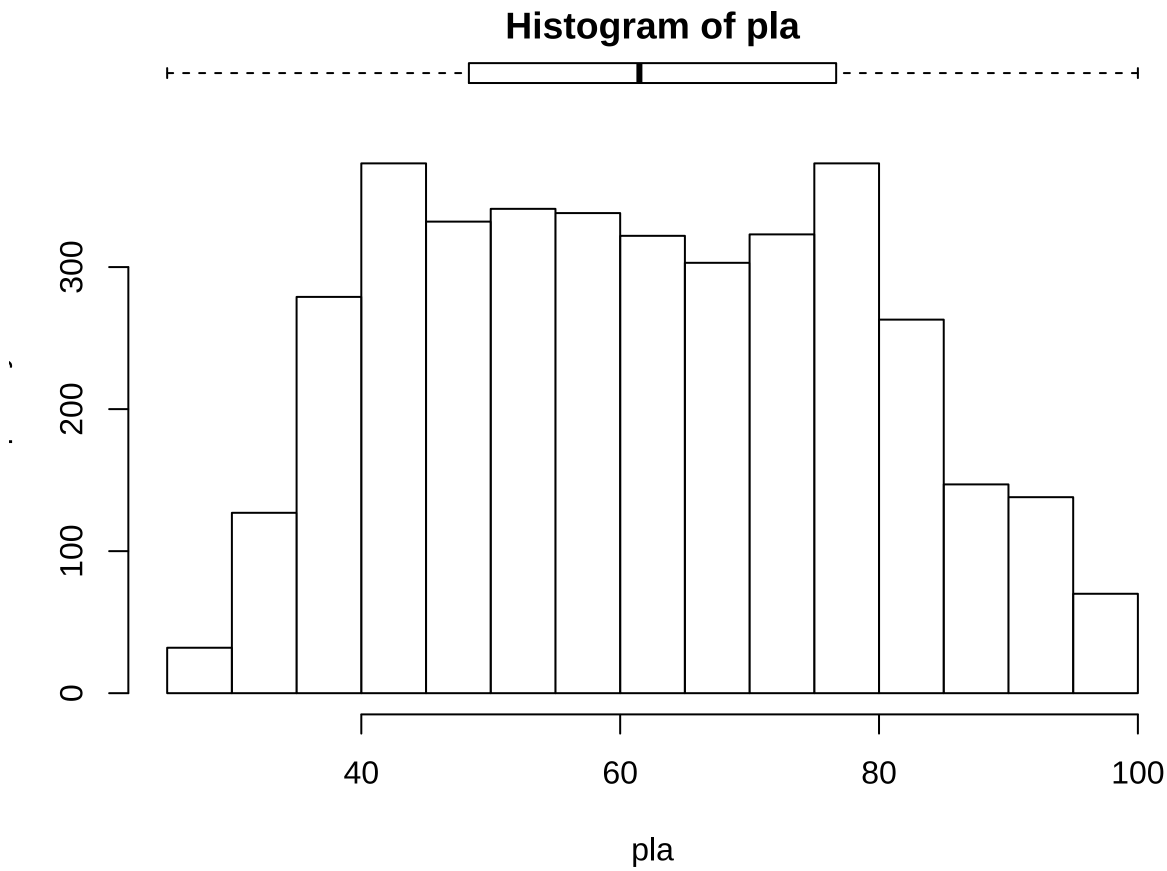

```
## Top 10 Players by ovr
##                        name_s position_s ovr out ins pla ath def reb year
## 1         '96 Michael Jordan         SG  99  95  88  91  93  92  75 2016
## 2            '15 Kobe Bryant         SG  99  97  79  95  84  88  65 2016
## 3              Stephen Curry         PG  99  98  66  98  89  78  54 2016
## 4               LeBron James         SF  99  94  89  91  92  91  91 2016
## 5    '71 Kareem Adbul-Jabbar          C  99  75  93  56  89  86  98 2016
## 2082             Kobe Bryant         SG  99  98  93  91  94  91  74 2017
## 2083        Wilt Chamberlain          C  99  65  95  68  89  88  98 2017
## 2084              Jerry West         PG  99  97  68  94  90  85  65 2017
## 2085             Kobe Bryant         SG  99  97  82  82  89  83  60 2017
## 2086          Michael Jordan         SG  99  94  85  86  91  91  66 2017
```



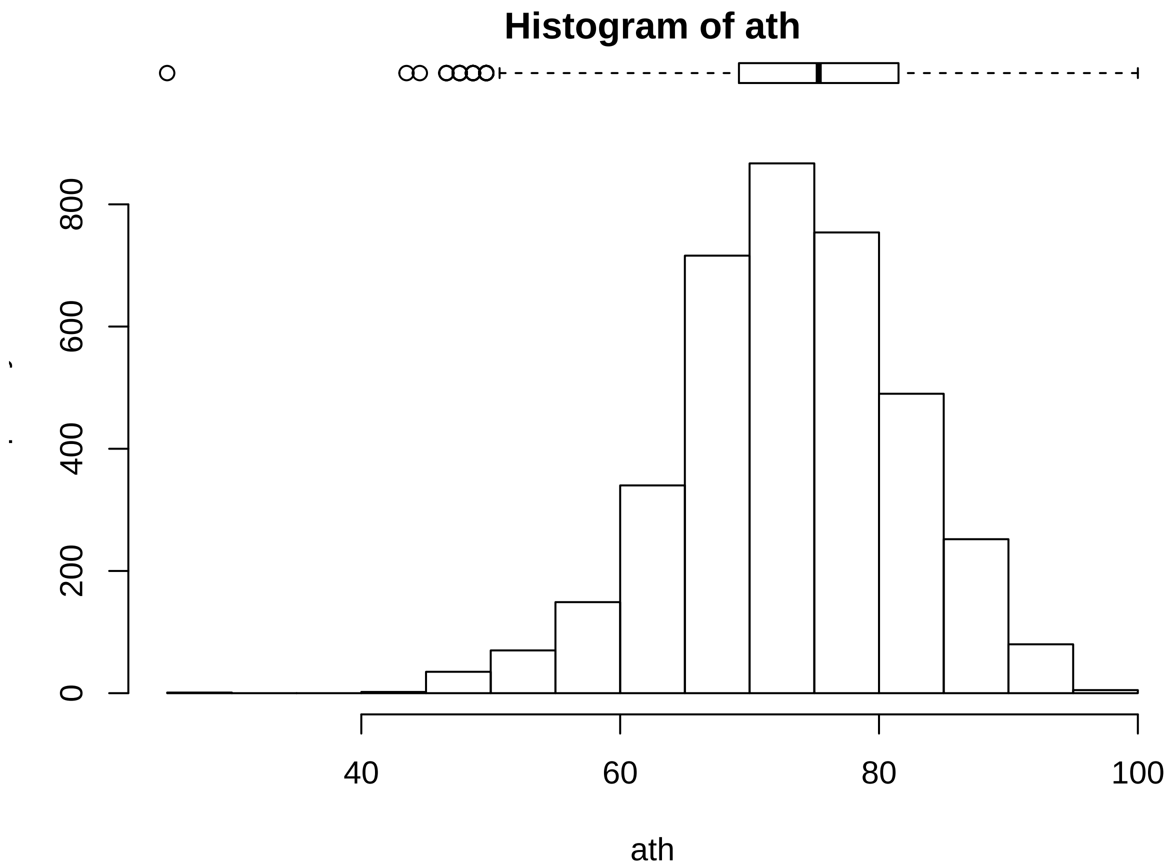

```
## Top 10 Players by out
##                 name_s position_s ovr out ins pla ath def reb year
## 2098    Stephen Curry         PG  98  99  70  98  92  86  78 2017
## 3       Stephen Curry         PG  99  98  66  98  89  78  54 2016
## 6        Kyrie Irving         PG  98  98  70  95  91  74  49 2016
## 17   Kyrie Irving TBT         PG  97  98  67  94  86  74  49 2016
## 35      Klay Thompson         SG  97  98  77  79  89  86  49 2016
## 2082      Kobe Bryant         SG  99  98  93  91  94  91  74 2017
## 2100     Kevin Durant         SF  98  98  88  85  84  91  82 2017
## 2105     James Harden         SG  98  98  85  98  91  80  88 2017
## 2143    Isaiah Thomas         PG  97  98  62  97  92  71  54 2017
## 2146    Klay Thompson         SG  97  98  81  84  88  93  55 2017
```



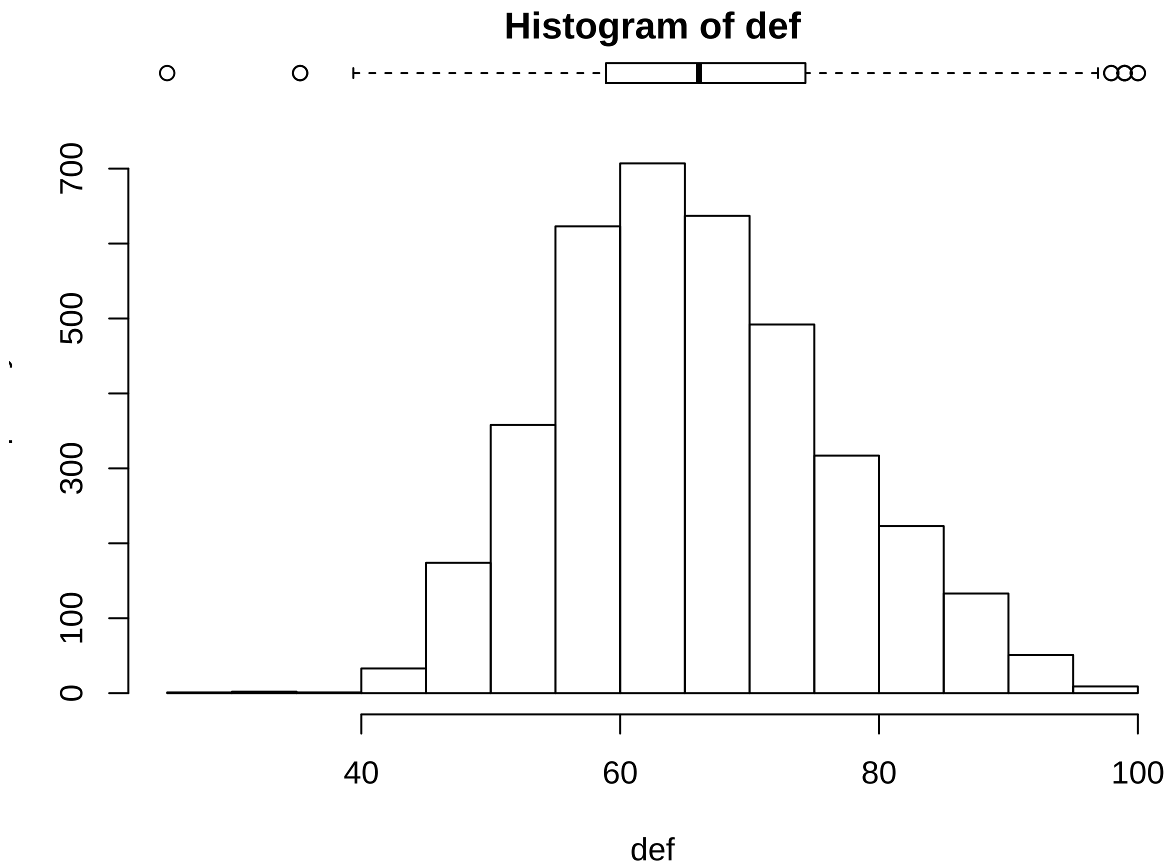

```
## Top 10 Players by ins
##                   name_s position_s ovr out ins pla ath def reb year
## 2091     Charles Barkley         PF  99  95  98  89  95  97  98 2017
## 2106 Kareem Adbul-Jabbar          C  98  83  98  85  90  95  98 2017
## 2107         Karl Malone         PF  98  88  98  80  96  94  98 2017
## 2110       Anthony Davis         PF  98  87  97  65  91  94  97 2017
## 2135       Kevin Garnett         PF  97  86  97  80  93  94  98 2017
## 2227   Amar'e Stoudemire         PF  95  82  97  63  88  82  94 2017
## 2096      Michael Jordan         SG  99  97  96  95  96  95  80 2017
## 2103        Bill Russell          C  98  57  96  79  92  97  99 2017
## 2205          Wes Unseld          C  95  78  96  89  90  94  98 2017
## 2213          Shawn Kemp         PF  95  83  96  63  92  85  95 2017
```



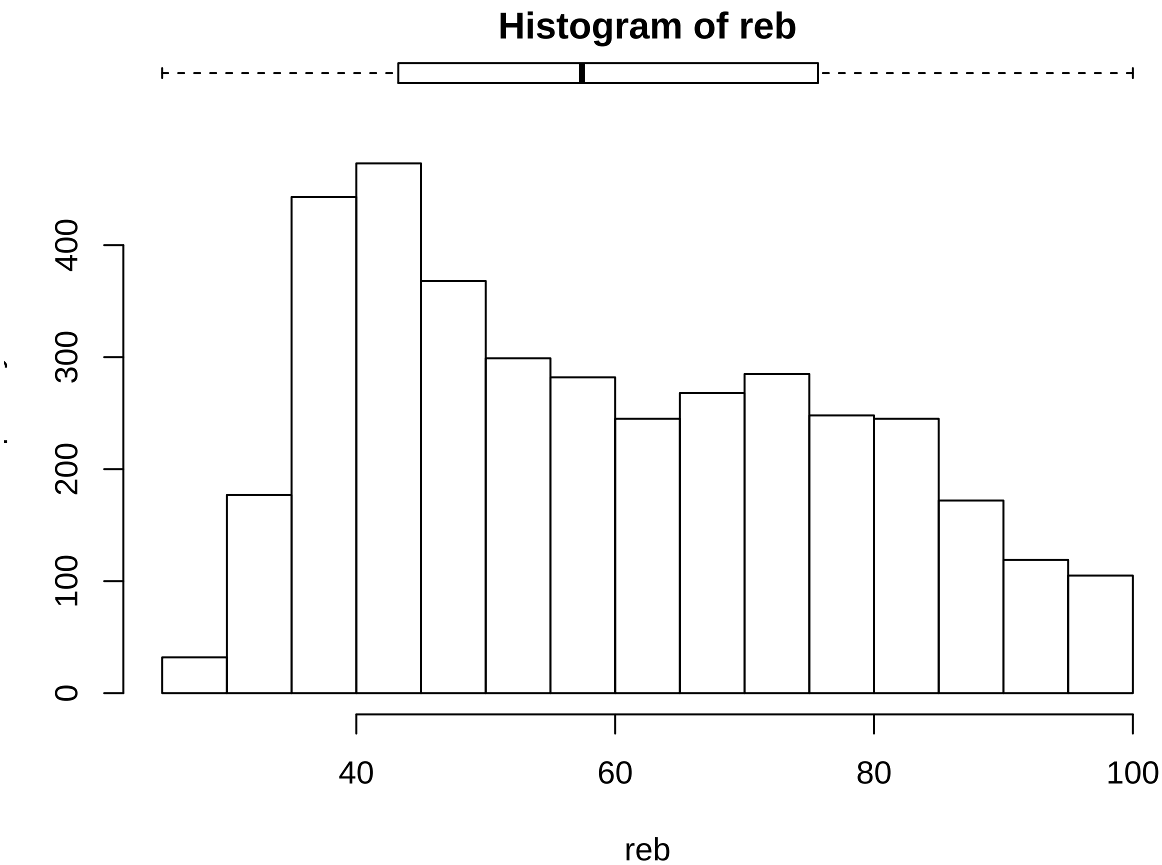

```
## Top 10 Players by pla
##                  name_s position_s ovr out ins pla ath def reb year
## 2101       Magic Johnson         PG  98  95  90  99  96  95  89 2017
## 2115       John Stockton         PG  98  97  70  99  92  90  51 2017
## 3          Stephen Curry         PG  99  98  66  98  89  78  54 2016
## 7    '62 Oscar Robertson         PG  98  92  78  98  90  84  88 2016
## 14     '90 John Stockton         PG  97  93  64  98  86  86  38 2016
## 61         '57 Bob Cousy         PG  96  92  65  98  83  82  59 2016
## 72        '07 Steve Nash         PG  96  95  61  98  85  75  42 2016
## 79      '85 Isiah Thomas         PG  95  87  65  98  90  82  52 2016
## 94        '02 Jason Kidd         PG  95  86  64  98  83  85  75 2016
## 2090        Isiah Thomas         PG  99  94  69  98  90  83  40 2017
```




```
## Top 10 Players by ath
##                 name_s position_s ovr out ins pla ath def reb year
## 2097 Russell Westbrook         PG  99  97  83  98  98  91  97 2017
## 2099      Lebron James         SF  98  94  94  95  97  92  74 2017
## 2096    Michael Jordan         SG  99  97  96  95  96  95  80 2017
## 2101     Magic Johnson         PG  98  95  90  99  96  95  89 2017
## 2107       Karl Malone         PF  98  88  98  80  96  94  98 2017
## 2091   Charles Barkley         PF  99  95  98  89  95  97  98 2017
## 2108     Allen Iverson         SG  98  96  71  97  95  84  53 2017
## 2112 Russell Westbrook         PG  98  96  76  97  95  86  93 2017
## 2148  Chauncey Billups         PG  96  97  64  97  95  90  43 2017
## 2200         Bob Cousy         PG  95  97  70  98  95  83  75 2017
```



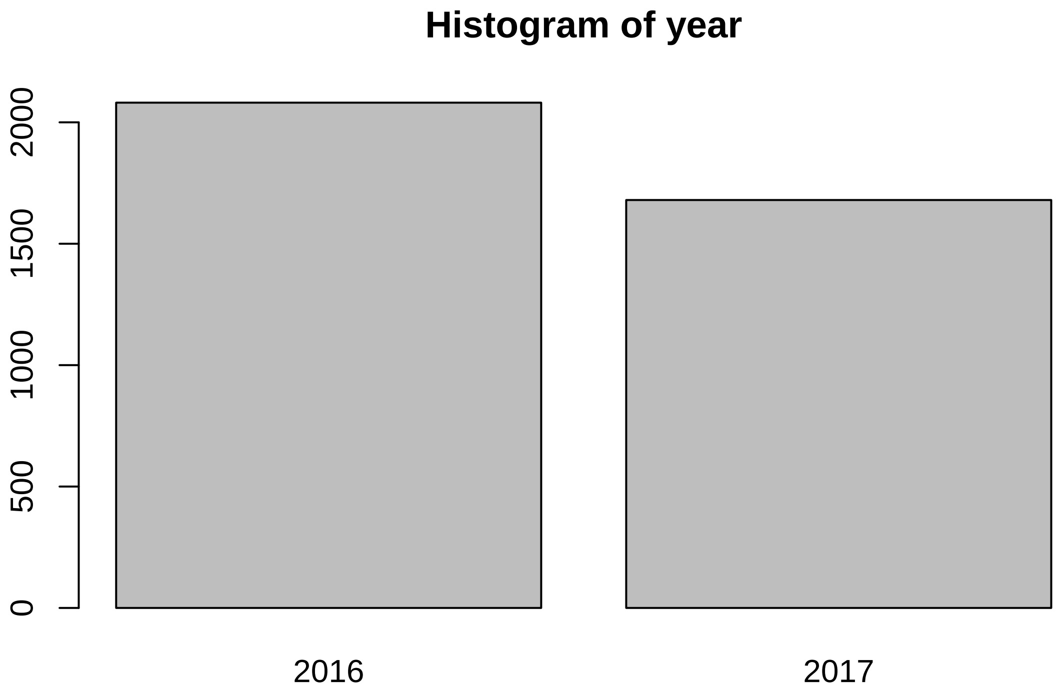

```
## Top 10 Players by def
##                name_s position_s ovr out ins pla ath def reb year
## 2109    Dennis Rodman         PF  98  77  88  61  92  98  99 2017
## 2233   Draymond Green         PF  95  90  86  94  91  98  92 2017
## 2091  Charles Barkley         PF  99  95  98  89  95  97  98 2017
## 2103     Bill Russell          C  98  57  96  79  92  97  99 2017
## 2111  Hakeem Olajuwon          C  98  82  94  74  84  97  98 2017
## 2195      Ben Wallace          C  95  46  85  52  89  97  97 2017
## 2321 Dave Debusschere         PF  92  90  90  82  85  97  96 2017
## 2102 Shaquille O'Neal          C  98  55  95  75  90  96  99 2017
## 2104       Larry Bird         SF  98  96  88  92  89  96  94 2017
## 2087       Tim Duncan         PF  99  74  95  73  87  95  98 2017
```




```
## Top 10 Players by reb
##                        name_s position_s ovr out ins pla ath def reb year
## 2102        Shaquille O'Neal          C  98  55  95  75  90  96  99 2017
## 2103            Bill Russell          C  98  57  96  79  92  97  99 2017
## 2109           Dennis Rodman         PF  98  77  88  61  92  98  99 2017
## 2345           Dennis Rodman         PF  92  59  74  49  85  87  99 2017
## 2598           Dennis Rodman         PF  88  54  68  49  80  85  99 2017
## 5    '71 Kareem Adbul-Jabbar          C  99  75  93  56  89  86  98 2016
## 9              '03 Tim Duncan        PF  98  84  89  76  81  87  98 2016
## 18           '60 Bill Russell          C  97  58  88  73  90  93  98 2016
## 21           '62 Bill Russell          C  97  57  89  73  88  92  98 2016
## 24              Anthony Davis        PF  97  91  89  64  87  87  98 2016
```

Histograms for Categorical Variables

```
categorical_vars <- c('year','position_s')
for (col in categorical_vars){
  data <- df_secondary[[col]]
  barplot(table(data),main=sprintf('Histogram of %s',col))
  print('\n')}
```




```
## [1] "\n"
```


```
## [1] "\n"
```

Merge Primary and Secondary Datasets

Name Cleaning

```
library(stringdist)
library(reshape)
library(stringr)
sub_n_diff_score <- function(ppl,n){
    str_dist <- melt(stringdistmatrix(a=ppl, b=ppl, method = 'lv', useNames = 'strings'))
    str_dist_1_to_n <- str_dist[str_dist$value<=n & str_dist$value>0,]
    return (str_dist_1_to_n[order(str_dist_1_to_n$value),])}
clean_names <- function(names){
  names <- tolower(names)
  names <- str_squish(names)
  names <- gsub('\\.','',names)
```

```r
  names <- gsub('-',' ',names)
  return (names)}
df_primary$name <- clean_names(df_primary[['name_p']]) # clean primary dataset names
df_secondary$name <- clean_names(df_secondary[['name_s']])# clean secondary dataset
df_primary$name <- iconv(df_primary$name,to='ASCII//TRANSLIT') # convert to ascii
df_secondary$name <- iconv(df_secondary$name,to='ASCII//TRANSLIT') # convert to asii
df_secondary <- df_secondary[!grepl("\\d",df_secondary$name),]
#    remove players with numbers in name as this signifies a legendary player
df_secondary <- df_secondary[!grepl("dynamic",df_secondary$name),]
#    remove dynamic versions of players
replace_names <- list(
  `isiah thomas` = 'isaiah thomas',
  `jonathan simmons` = 'jonathon simmons',
  `lance stepheson` = 'lance stephenson',
  `luke babbit` = 'luke babbitt',
  `patrick beverly` = 'patrick beverley',
  `willis reed` = 'willie reed',
  `kiki vanderweghe` = 'kiki vandeweghe',
  `mychael thompson` = 'mychal thompson',
  `drayamond green` = 'draymond green',
  `louis amundson` = 'lou amundson',
  `louis williams` = 'lou williams')
for (n in names(replace_names)){
  df_primary$name <- gsub(n,replace_names[[n]],df_primary$name)
  df_secondary$name <- gsub(n,replace_names[[n]],df_secondary$name)
}
all_names <- unique(c(df_primary$name,df_secondary$name))
sub_n_diff_score(unique(all_names),2)
```

```
##                         X1                 X2 value
## 162412         zoran dragic       goran dragic     1
## 299490         luke babbitt      luke babbittt     1
## 609192         goran dragic       zoran dragic     1
## 1009318       luke babbittt       luke babbitt     1
## 7438          ryan anderson      alan anderson     2
## 8954         alvin williams      alan williams     2
## 90435           damon jones       damian jones     2
## 104165           david wear         david west     2
## 133476       dryamond green     draymond green     2
## 161685       flynn robinson     glenn robinson     2
## 179137           josh smith          ish smith     2
## 217008          brian grant       jerian grant     2
## 247409            ish smith         josh smith     2
## 295807          mo williams       lou williams     2
## 311210        darius morris      marcus morris     2
## 319499       alvin williams    marvin williams     2
## 337975         lou williams        mo williams     2
## 375741         paul pressey       phil pressey     2
## 404018        alan anderson      ryan anderson     2
## 478902         willie green        willie reed     2
## 487381           joe bryant        kobe bryant     2
## 524082          willie reed       willie green     2
## 586816         darius miles      darius miller     2
## 608993          drew gooden        drew gordon     2
## 652349           david west         david wear     2
## 667630        marcus morris      darius morris     2
## 686256       charles oakley    charles barkley     2
## 749680        ervin johnson      kevin johnson     2
## 805879  shareef abdur rahim shareef adbur rahim     2
## 819208       draymond green     dryamond green     2
## 849908      charles barkley     charles oakley     2
## 878167  shareef adbur rahim shareef abdur rahim     2
## 879749         phil pressey       paul pressey     2
```

```
## 888581       glenn robinson      flynn robinson     2
## 905084        darius miller        darius miles     2
## 917574        alan williams      alvin williams     2
## 917883      marvin williams      alvin williams     2
## 936876         jerian grant         brian grant     2
## 959516        kevin johnson       ervin johnson     2
## 965285          kobe bryant          joe bryant     2
## 972441          drew gordon         drew gooden     2
## 994035         damian jones         damon jones     2
```

Joining Datasets

```r
# if multiple versions of a player, take the one with the max overall
df_secondary_max <- aggregate(df_secondary['ovr'],df_secondary[c('name','year')],max)
df_secondary_max <- merge(df_secondary_max,df_secondary,by=c('name','year','ovr'),all=F)
df_secondary_max_2 <- aggregate(df_secondary_max['out'],df_secondary_max[c('name','year')],max)
df_full_s <- merge(df_secondary_max,df_secondary_max_2,by=c('name','year','out'),all=F)
# only take totals from players who changed teams mid-year
df_p_tot <- df_primary[df_primary$Tm=='TOT',]
traded_player_years <- interaction(df_primary[,c('year','name')]) %in%
                       interaction(df_p_tot[,c('year','name')])
df_p_wo_tot <- df_primary[!traded_player_years,]
df_full_p <- rbind(df_p_wo_tot,df_p_tot)
# join datasets
df_full <- merge(df_full_p,df_full_s,by=c('name','year'),all=F)
df_full <- df_full[order(df_full$name,df_full$year),]
df_full <- unique(df_full)
head(df_full[,1:5])
```

```
##             name year        name_p  salary Pos
## 1  aaron brooks 2016  Aaron Brooks 2700000  PG
## 2  aaron brooks 2017  Aaron Brooks 2116955  PG
## 3  aaron gordon 2016  Aaron Gordon 4351320  PF
## 4  aaron gordon 2017  Aaron Gordon 5504420  SF
## 5 adreian payne 2016 Adreian Payne 2022240  PF
## 6    aj hammons 2017  A.J. Hammons 1312611   C
```

```r
# joined datasets checks
max(table(df_full$name)) # should be 2 (2016,2017)
```

```
## [1] 2
```

```r
nrow(df_full)
```

```
## [1] 733
```

Clean Up Joined Data

```r
drop_cols <- c('name_p','name_s','position_s')
df_final <- df_full[,!(names(df_full)%in%drop_cols)]
names(df_final)[names(df_final)=='position_p'] <- 'position'
s_columns <- c('ovr','out','ins','pla','ath','def','reb')
df_p_final <- df_final[,!(names(df_final)%in%s_columns)] # final primary dataset
df_s_final <- df_final[,c('name',s_columns)] # final secondary dataset
summary(df_final)
```

```
##      name              year         salary           Pos           Age
##  Length:733         2016:369   Min.   :   11534   C :157   Min.   :19.00
##  Class :character   2017:364   1st Qu.: 2116955   PF:147   1st Qu.:23.00
##  Mode  :character              Median : 5200000   PG:138   Median :26.00
##                                Mean   : 7837816   SF:142   Mean   :26.55
##                                3rd Qu.:12016854   SG:149   3rd Qu.:29.00
##                                Max.   :34682550            Max.   :40.00
```

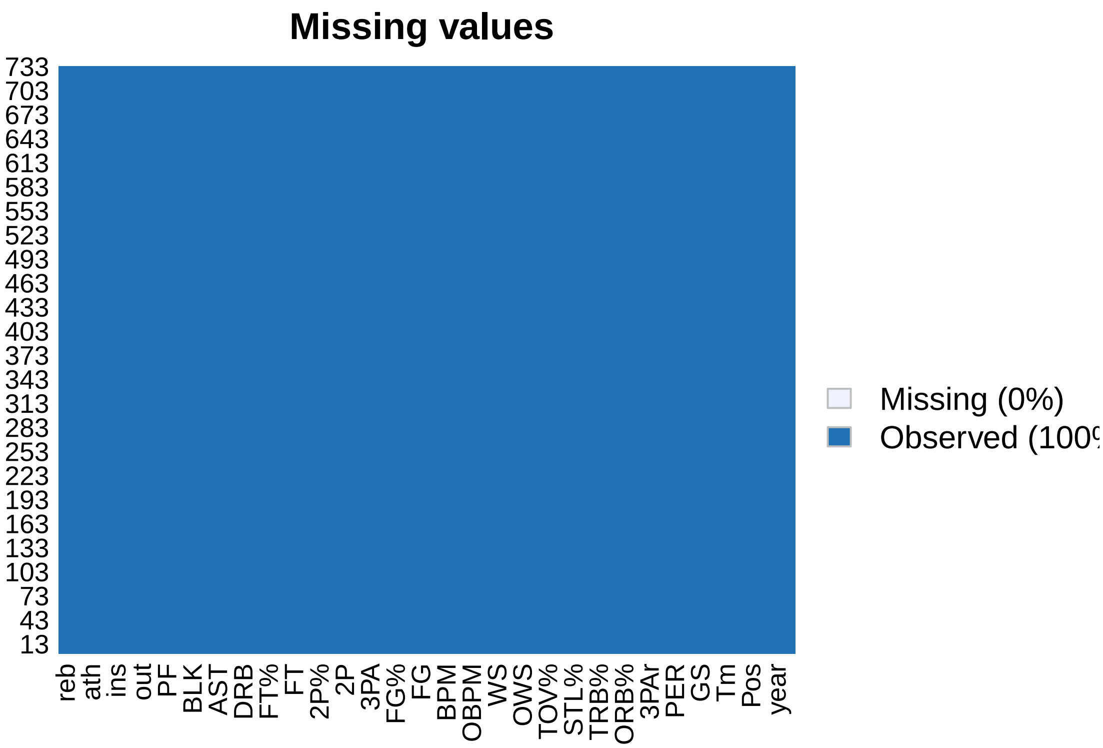
```
##
##        Tm            G              GS              MP           PER
##  TOT    : 70   Min.   : 1.00   Min.   : 0.00   Min.   :   6   Min.   :-7.70
##  GSW    : 27   1st Qu.:52.00   1st Qu.: 3.00   1st Qu.: 846   1st Qu.:10.90
##  TOR    : 27   Median :68.00   Median :20.00   Median :1508   Median :13.70
##  PHO    : 25   Mean   :61.17   Mean   :31.68   Mean   :1475   Mean   :14.17
##  UTA    : 25   3rd Qu.:77.00   3rd Qu.:63.00   3rd Qu.:2119   3rd Qu.:16.90
##  DET    : 24   Max.   :82.00   Max.   :82.00   Max.   :3125   Max.   :32.00
##  (Other):535
##       TS%             3PAr            FTr              ORB%
##  Min.   :0.1250   Min.   :0.000   Min.   :0.0000   Min.   : 0.000
##  1st Qu.:0.5090   1st Qu.:0.106   1st Qu.:0.1790   1st Qu.: 2.000
##  Median :0.5410   Median :0.305   Median :0.2480   Median : 3.600
##  Mean   :0.5389   Mean   :0.293   Mean   :0.2724   Mean   : 5.073
##  3rd Qu.:0.5720   3rd Qu.:0.442   3rd Qu.:0.3400   3rd Qu.: 7.500
##  Max.   :1.0000   Max.   :0.900   Max.   :1.2190   Max.   :21.800
##
##       DRB%            TRB%           AST%           STL%             BLK%
##  Min.   : 0.00   Min.   : 0.0   Min.   : 0.0   Min.   : 0.000   Min.   :0.000
##  1st Qu.:10.50   1st Qu.: 6.3   1st Qu.: 7.2   1st Qu.: 1.100   1st Qu.:0.600
##  Median :14.60   Median : 9.3   Median :10.3   Median : 1.500   Median :1.200
##  Mean   :15.53   Mean   :10.3   Mean   :13.4   Mean   : 1.586   Mean   :1.737
##  3rd Qu.:19.60   3rd Qu.:13.3   3rd Qu.:17.7   3rd Qu.: 1.900   3rd Qu.:2.500
##  Max.   :36.30   Max.   :25.6   Max.   :57.3   Max.   :11.100   Max.   :9.700
##
##       TOV%            USG%            OWS              DWS
##  Min.   : 0.00   Min.   : 0.00   Min.   :-3.300   Min.   :0.000
##  1st Qu.:10.00   1st Qu.:15.40   1st Qu.: 0.200   1st Qu.:0.700
##  Median :12.50   Median :18.50   Median : 1.100   Median :1.300
##  Mean   :12.77   Mean   :19.18   Mean   : 1.722   Mean   :1.522
##  3rd Qu.:15.10   3rd Qu.:22.20   3rd Qu.: 2.500   3rd Qu.:2.200
##  Max.   :43.60   Max.   :41.70   Max.   :13.800   Max.   :6.000
##
##        WS             WS/48               OBPM              DBPM
##  Min.   :-2.100   Min.   :-0.28300   Min.   :-17.3000   Min.   :-8.20000
##  1st Qu.: 1.100   1st Qu.: 0.05600   1st Qu.: -2.1000   1st Qu.:-1.30000
##  Median : 2.500   Median : 0.09100   Median : -0.7000   Median :-0.10000
##  Mean   : 3.243   Mean   : 0.09283   Mean   : -0.6689   Mean   :-0.08868
##  3rd Qu.: 4.500   3rd Qu.: 0.12700   3rd Qu.:  0.5000   3rd Qu.: 1.10000
##  Max.   :17.900   Max.   : 0.34300   Max.   : 12.4000   Max.   :12.00000
##
##       BPM               VORP              FG             FGA
##  Min.   :-24.1000   Min.   :-1.4000   Min.   :  0.0   Min.   :   0.0
##  1st Qu.: -2.7000   1st Qu.:-0.1000   1st Qu.:116.0   1st Qu.: 256.0
##  Median : -0.7000   Median : 0.4000   Median :208.0   Median : 462.0
##  Mean   : -0.7569   Mean   : 0.8359   Mean   :240.3   Mean   : 526.3
##  3rd Qu.:  1.0000   3rd Qu.: 1.3000   3rd Qu.:338.0   3rd Qu.: 731.0
##  Max.   : 15.6000   Max.   :12.4000   Max.   :824.0   Max.   :1941.0
##
##       FG%              3P              3PA             3P%
##  Min.   :0.0830   Min.   :  0.00   Min.   :  0.0   Min.   :0.0000
##  1st Qu.:0.4110   1st Qu.:  4.00   1st Qu.: 16.0   1st Qu.:0.2711
##  Median :0.4450   Median : 42.00   Median :120.0   Median :0.3330
##  Mean   :0.4533   Mean   : 56.32   Mean   :157.1   Mean   :0.3034
##  3rd Qu.:0.4880   3rd Qu.: 91.00   3rd Qu.:256.0   3rd Qu.:0.3730
##  Max.   :1.0000   Max.   :402.00   Max.   :886.0   Max.   :1.0000
##
##        2P            2PA              2P%              eFG%
##  Min.   :  0   Min.   :   0.0   Min.   :0.0000   Min.   :0.1000
##  1st Qu.: 75   1st Qu.: 157.0   1st Qu.:0.4530   1st Qu.:0.4730
##  Median :153   Median : 308.0   Median :0.4850   Median :0.5060
##  Mean   :184   Mean   : 369.2   Mean   :0.4889   Mean   :0.5043
##  3rd Qu.:258   3rd Qu.: 513.0   3rd Qu.:0.5310   3rd Qu.:0.5370
##  Max.   :730   Max.   :1421.0   Max.   :1.0000   Max.   :1.0000
```

```
##
##        FT              FTA             FT%              ORB
##  Min.   :  0.0   Min.   :  0.0   Min.   :0.0000   Min.   :  0.00
##  1st Qu.: 38.0   1st Qu.: 51.0   1st Qu.:0.7000   1st Qu.: 21.00
##  Median : 80.0   Median :110.0   Median :0.7690   Median : 44.00
##  Mean   :111.6   Mean   :145.3   Mean   :0.7518   Mean   : 63.34
##  3rd Qu.:145.0   3rd Qu.:194.0   3rd Qu.:0.8310   3rd Qu.: 86.00
##  Max.   :746.0   Max.   :881.0   Max.   :1.0000   Max.   :395.00
##
##       DRB              TRB               AST              STL
##  Min.   :  0.0   Min.   :   0.0   Min.   :  0.0   Min.   :  0.00
##  1st Qu.:103.0   1st Qu.: 128.0   1st Qu.: 47.0   1st Qu.: 22.00
##  Median :180.0   Median : 229.0   Median : 97.0   Median : 42.00
##  Mean   :206.8   Mean   : 270.1   Mean   :137.2   Mean   : 47.39
##  3rd Qu.:279.0   3rd Qu.: 365.0   3rd Qu.:176.0   3rd Qu.: 66.00
##  Max.   :817.0   Max.   :1198.0   Max.   :906.0   Max.   :169.00
##
##       BLK               TOV                PF              PTS
##  Min.   :  0.00   Min.   :  0.00   Min.   :  0.0   Min.   :   0.0
##  1st Qu.:  9.00   1st Qu.: 39.00   1st Qu.: 79.0   1st Qu.: 307.0
##  Median : 20.00   Median : 69.00   Median :125.0   Median : 544.0
##  Mean   : 30.21   Mean   : 83.28   Mean   :121.6   Mean   : 648.6
##  3rd Qu.: 39.00   3rd Qu.:114.00   3rd Qu.:165.0   3rd Qu.: 898.0
##  Max.   :269.00   Max.   :464.00   Max.   :278.0   Max.   :2558.0
##
##       out             ovr             ins              pla              ath
##  Min.   :30.00   Min.   :61.0   Min.   :44.00   Min.   :28.00   Min.   :49.00
##  1st Qu.:61.00   1st Qu.:71.0   1st Qu.:58.00   1st Qu.:47.00   1st Qu.:68.00
##  Median :72.00   Median :76.0   Median :64.00   Median :59.00   Median :73.00
##  Mean   :71.19   Mean   :78.5   Mean   :65.35   Mean   :61.27   Mean   :73.49
##  3rd Qu.:83.00   3rd Qu.:85.0   3rd Qu.:71.00   3rd Qu.:76.00   3rd Qu.:79.00
##  Max.   :99.00   Max.   :99.0   Max.   :97.00   Max.   :98.00   Max.   :98.00
##
##       def             reb
##  Min.   :43.00   Min.   :27.00
##  1st Qu.:58.00   1st Qu.:44.00
##  Median :64.00   Median :59.00
##  Mean   :65.49   Mean   :60.86
##  3rd Qu.:72.00   3rd Qu.:74.00
##  Max.   :98.00   Max.   :98.00
##
```

```r
missCounts <- sapply(df_final,function(x) sum(is.na(x)))
missCounts
```

```
##    name   year salary    Pos    Age     Tm      G     GS     MP    PER    TS%
##       0      0      0      0      0      0      0      0      0      0      0
##    3PAr    FTr   ORB%   DRB%   TRB%   AST%   STL%   BLK%   TOV%   USG%    OWS
##       0      0      0      0      0      0      0      0      0      0      0
##     DWS     WS  WS/48   OBPM   DBPM    BPM   VORP     FG    FGA    FG%     3P
##       0      0      0      0      0      0      0      0      0      0      0
##     3PA    3P%     2P    2PA    2P%   eFG%     FT    FTA    FT%    ORB    DRB
##       0      0      0      0      0      0      0      0      0      0      0
##     TRB    AST    STL    BLK    TOV     PF    PTS    out    ovr    ins    pla
##       0      0      0      0      0      0      0      0      0      0      0
##     ath    def    reb
##       0      0      0
```

```r
library(Amelia)
missmap(df_final, main = "Missing values ")
```




```r
# Output final complete, primary, and seconday datasets
write.csv(df_final,'../data/pooled/complete.csv',row.names=F)
write.csv(df_p_final,'../data/pooled/primary.csv',row.names=F)
write.csv(df_s_final,'../data/pooled/secondary.csv',row.names=F)
# preview datasets
head(df_p_final)
```

```
##             name year  salary Pos Age  Tm  G GS   MP  PER   TS%  3PAr   FTr ORB%
## 1  aaron brooks 2016 2700000  PG  31 CHI 69  0 1108 11.8 0.494 0.394 0.136  2.0
## 2  aaron brooks 2017 2116955  PG  32 IND 65  0  894  9.5 0.507 0.427 0.133  2.3
## 3  aaron gordon 2016 4351320  PF  20 ORL 78 37 1863 17.0 0.541 0.245 0.333  9.0
## 4  aaron gordon 2017 5504420  SF  21 ORL 80 72 2298 14.4 0.530 0.309 0.251  5.3
## 5 adreian payne 2016 2022240  PF  24 MIN 52  2  486  5.6 0.422 0.221 0.179  4.8
## 6    aj hammons 2017 1312611   C  24 DAL 22  0  163  8.4 0.472 0.238 0.476  5.4
##   DRB% TRB% AST% STL% BLK% TOV% USG%  OWS DWS   WS  WS/48 OBPM DBPM  BPM VORP
## 1  7.5  4.8 26.0  1.4  0.7 14.2 22.9  0.2 0.7  0.9  0.040 -0.5 -2.8 -3.3 -0.4
## 2  6.3  4.3 20.7  1.4  0.9 17.2 19.2 -0.2 0.5  0.3  0.016 -2.1 -2.6 -4.6 -0.6
## 3 21.3 15.1 10.3  1.6  2.4  9.0 17.3  3.2 2.2  5.4  0.139  0.6  1.2  1.8  1.8
## 4 14.1  9.6 10.5  1.4  1.4  8.5 20.1  2.0 1.7  3.7  0.076 -0.2 -0.4 -0.7  0.8
## 5 21.5 13.3  8.9  1.7  1.8 18.7 17.7 -0.9 0.4 -0.5 -0.047 -5.9 -0.2 -6.1 -0.5
## 6 20.9 12.8  3.8  0.3  7.2 16.4 17.6 -0.2 0.2  0.0 -0.001 -7.5  1.9 -5.6 -0.1
##    FG FGA   FG% 3P 3PA   3P%  2P 2PA   2P%  eFG%  FT FTA   FT% ORB DRB TRB AST
## 1 188 469 0.401 66 185 0.357 122 284 0.430 0.471  49  64 0.766  21  80 101 180
## 2 121 300 0.403 48 128 0.375  73 172 0.424 0.483  32  40 0.800  18  51  69 125
## 3 274 579 0.473 42 142 0.296 232 437 0.531 0.509 129 193 0.668 154 353 507 128
## 4 393 865 0.454 77 267 0.288 316 598 0.528 0.499 156 217 0.719 116 289 405 150
## 5  53 145 0.366  9  32 0.281  44 113 0.389 0.397  17  26 0.654  20  91 111  29
## 6  17  42 0.405  5  10 0.500  12  32 0.375 0.464   9  20 0.450   8  28  36   4
##   STL BLK TOV  PF  PTS
## 1  30  10  82 132  491
## 2  25   9  66  93  322
## 3  59  55  66 153  719
## 4  64  40  89 172 1019
## 5  16  11  36  77  132
## 6   1  13  10  21   48
```

```r
head(df_s_final)
```

```
##             name ovr out ins pla ath def reb
## 1  aaron brooks  75  79  52  74  77  52  36
## 2  aaron brooks  85  87  51  81  82  57  37
```

```
## 3  aaron gordon  90  87  91  69  86  69  87
## 4  aaron gordon  92  86  91  49  86  75  94
## 5 adreian payne  69  56  65  43  66  64  68
## 6    aj hammons  66  47  64  40  58  57  71
```

```
head(df_final)
```

```
##            name year  salary Pos Age  Tm  G GS   MP  PER   TS%  3PAr   FTr ORB%
## 1  aaron brooks 2016 2700000  PG  31 CHI 69  0 1108 11.8 0.494 0.394 0.136  2.0
## 2  aaron brooks 2017 2116955  PG  32 IND 65  0  894  9.5 0.507 0.427 0.133  2.3
## 3  aaron gordon 2016 4351320  PF  20 ORL 78 37 1863 17.0 0.541 0.245 0.333  9.0
## 4  aaron gordon 2017 5504420  SF  21 ORL 80 72 2298 14.4 0.530 0.309 0.251  5.3
## 5 adreian payne 2016 2022240  PF  24 MIN 52  2  486  5.6 0.422 0.221 0.179  4.8
## 6    aj hammons 2017 1312611   C  24 DAL 22  0  163  8.4 0.472 0.238 0.476  5.4
##   DRB% TRB% AST% STL% BLK% TOV% USG%  OWS DWS   WS  WS/48 OBPM DBPM  BPM VORP
## 1  7.5  4.8 26.0  1.4  0.7 14.2 22.9  0.2 0.7  0.9  0.040 -0.5 -2.8 -3.3 -0.4
## 2  6.3  4.3 20.7  1.4  0.9 17.2 19.2 -0.2 0.5  0.3  0.016 -2.1 -2.6 -4.6 -0.6
## 3 21.3 15.1 10.3  1.6  2.4  9.0 17.3  3.2 2.2  5.4  0.139  0.6  1.2  1.8  1.8
## 4 14.1  9.6 10.5  1.4  1.4  8.5 20.1  2.0 1.7  3.7  0.076 -0.2 -0.4 -0.7  0.8
## 5 21.5 13.3  8.9  1.7  1.8 18.7 17.7 -0.9 0.4 -0.5 -0.047 -5.9 -0.2 -6.1 -0.5
## 6 20.9 12.8  3.8  0.3  7.2 16.4 17.6 -0.2 0.2  0.0 -0.001 -7.5  1.9 -5.6 -0.1
##    FG FGA   FG% 3P 3PA   3P%  2P 2PA   2P%  eFG%  FT FTA   FT% ORB DRB TRB AST
## 1 188 469 0.401 66 185 0.357 122 284 0.430 0.471  49  64 0.766  21  80 101 180
## 2 121 300 0.403 48 128 0.375  73 172 0.424 0.483  32  40 0.800  18  51  69 125
## 3 274 579 0.473 42 142 0.296 232 437 0.531 0.509 129 193 0.668 154 353 507 128
## 4 393 865 0.454 77 267 0.288 316 598 0.528 0.499 156 217 0.719 116 289 405 150
## 5  53 145 0.366  9  32 0.281  44 113 0.389 0.397  17  26 0.654  20  91 111  29
## 6  17  42 0.405  5  10 0.500  12  32 0.375 0.464   9  20 0.450   8  28  36   4
##   STL BLK TOV  PF  PTS out ovr ins pla ath def reb
## 1  30  10  82 132  491  79  75  52  74  77  52  36
## 2  25   9  66  93  322  87  85  51  81  82  57  37
## 3  59  55  66 153  719  87  90  91  69  86  69  87
## 4  64  40  89 172 1019  86  92  91  49  86  75  94
## 5  16  11  36  77  132  56  69  65  43  66  64  68
## 6   1  13  10  21   48  47  66  64  40  58  57  71
```

Explore Data

Summarize Datasets

```
# primary dataset
str(df_p_final)
```

```
## 'data.frame':    733 obs. of  51 variables:
##  $ name  : chr  "aaron brooks" "aaron brooks" "aaron gordon" "aaron gordon" ...
##  $ year  : Factor w/ 2 levels "2016","2017": 1 2 1 2 1 2 1 2 1 2 ...
##  $ salary: num  2700000 2116955 4351320 5504420 2022240 ...
##  $ Pos   : Factor w/ 5 levels "C","PF","PG",..: 3 3 2 4 2 1 4 4 1 1 ...
##  $ Age   : num  31 32 20 21 24 24 25 26 29 30 ...
##  $ Tm    : Factor w/ 31 levels "ATL","BOS","BRK",..: 4 12 22 22 18 7 25 25 1 2 ...
##  $ G     : num  69 65 78 80 52 22 82 61 82 68 ...
##  $ GS    : num  0 0 37 72 2 0 82 25 82 68 ...
##  $ MP    : num  1108 894 1863 2298 486 ...
##  $ PER   : num  11.8 9.5 17 14.4 5.6 8.4 12.7 11.3 19.4 17.7 ...
##  $ TS%   : num  0.494 0.507 0.541 0.53 0.422 0.472 0.533 0.506 0.565 0.553 ...
##  $ 3PAr  : num  0.394 0.427 0.245 0.309 0.221 0.238 0.485 0.455 0.244 0.302 ...
##  $ FTr   : num  0.136 0.133 0.333 0.251 0.179 0.476 0.217 0.292 0.123 0.169 ...
##  $ ORB%  : num  2 2.3 9 5.3 4.8 5.4 4.5 4.8 6.3 4.9 ...
##  $ DRB%  : num  7.5 6.3 21.3 14.1 21.5 20.9 18.6 23.5 18.2 18.6 ...
##  $ TRB%  : num  4.8 4.3 15.1 9.6 13.3 12.8 11.5 14.1 12.4 11.8 ...
##  $ AST%  : num  26 20.7 10.3 10.5 8.9 3.8 8.8 7.9 16.7 24.4 ...
##  $ STL%  : num  1.4 1.4 1.6 1.4 1.7 0.3 1.5 1.7 1.3 1.2 ...
```

```
##  $ BLK%  : num  0.7 0.9 2.4 1.4 1.8 7.2 1.8 2 3.6 3.3 ...
##  $ TOV%  : num  14.2 17.2 9 8.5 18.7 16.4 13.2 15.2 8.8 11.9 ...
##  $ USG%  : num  22.9 19.2 17.3 20.1 17.7 17.6 16.9 15.4 20.6 19.8 ...
##  $ OWS   : num  0.2 -0.2 3.2 2 -0.9 -0.2 1.7 -0.1 4.9 3.6 ...
##  $ DWS   : num  0.7 0.5 2.2 1.7 0.4 0.2 2.3 2 4.5 2.7 ...
##  $ WS    : num  0.9 0.3 5.4 3.7 -0.5 0 4 1.9 9.4 6.3 ...
##  $ WS/48 : num  0.04 0.016 0.139 0.076 -0.047 -0.001 0.082 0.051 0.172 0.137 ...
##  $ OBPM  : num  -0.5 -2.1 0.6 -0.2 -5.9 -7.5 -0.4 -2.3 1.5 1 ...
##  $ DBPM  : num  -2.8 -2.6 1.2 -0.4 -0.2 1.9 0.7 1.2 2.6 2.1 ...
##  $ BPM   : num  -3.3 -4.6 1.8 -0.7 -6.1 -5.6 0.2 -1.1 4.1 3.1 ...
##  $ VORP  : num  -0.4 -0.6 1.8 0.8 -0.5 -0.1 1.3 0.4 4.1 2.8 ...
##  $ FG    : num  188 121 274 393 53 17 299 183 529 379 ...
##  $ FGA   : num  469 300 579 865 145 ...
##  $ FG%   : num  0.401 0.403 0.473 0.454 0.366 0.405 0.416 0.393 0.505 0.473 ...
##  $ 3P    : num  66 48 42 77 9 5 126 70 88 86 ...
##  $ 3PA   : num  185 128 142 267 32 10 349 212 256 242 ...
##  $ 3P%   : num  0.357 0.375 0.296 0.288 0.281 0.5 0.361 0.33 0.344 0.355 ...
##  $ 2P    : num  122 73 232 316 44 12 173 113 441 293 ...
##  $ 2PA   : num  284 172 437 598 113 32 370 254 792 559 ...
##  $ 2P%   : num  0.43 0.424 0.531 0.528 0.389 0.375 0.468 0.445 0.557 0.524 ...
##  $ eFG%  : num  0.471 0.483 0.509 0.499 0.397 0.464 0.503 0.468 0.547 0.527 ...
##  $ FT    : num  49 32 129 156 17 9 115 96 103 108 ...
##  $ FTA   : num  64 40 193 217 26 20 156 136 129 135 ...
##  $ FT%   : num  0.766 0.8 0.668 0.719 0.654 0.45 0.737 0.706 0.798 0.8 ...
##  $ ORB   : num  21 18 154 116 20 8 98 77 148 95 ...
##  $ DRB   : num  80 51 353 289 91 28 401 374 448 369 ...
##  $ TRB   : num  101 69 507 405 111 36 499 451 596 464 ...
##  $ AST   : num  180 125 128 150 29 4 138 99 263 337 ...
##  $ STL   : num  30 25 59 64 16 1 72 60 68 52 ...
##  $ BLK   : num  10 9 55 40 11 13 53 44 121 87 ...
##  $ TOV   : num  82 66 66 89 36 10 120 94 107 116 ...
##  $ PF    : num  132 93 153 172 77 21 171 102 163 138 ...
##  $ PTS   : num  491 322 719 1019 132 ...
```

```
# secondary dataset
str(df_s_final)
```

```
## 'data.frame':    733 obs. of  8 variables:
##  $ name: chr  "aaron brooks" "aaron brooks" "aaron gordon" "aaron gordon" ...
##  $ ovr : int  75 85 90 92 69 66 91 83 83 91 ...
##  $ out : int  79 87 87 86 56 47 90 75 81 80 ...
##  $ ins : int  52 51 91 91 65 64 77 72 76 82 ...
##  $ pla : int  74 81 69 49 43 40 60 59 58 82 ...
##  $ ath : int  77 82 86 86 66 58 81 75 75 77 ...
##  $ def : int  52 57 69 75 64 57 76 66 70 80 ...
##  $ reb : int  36 37 87 94 68 71 94 65 73 87 ...
```

Complete Dataset Histograms

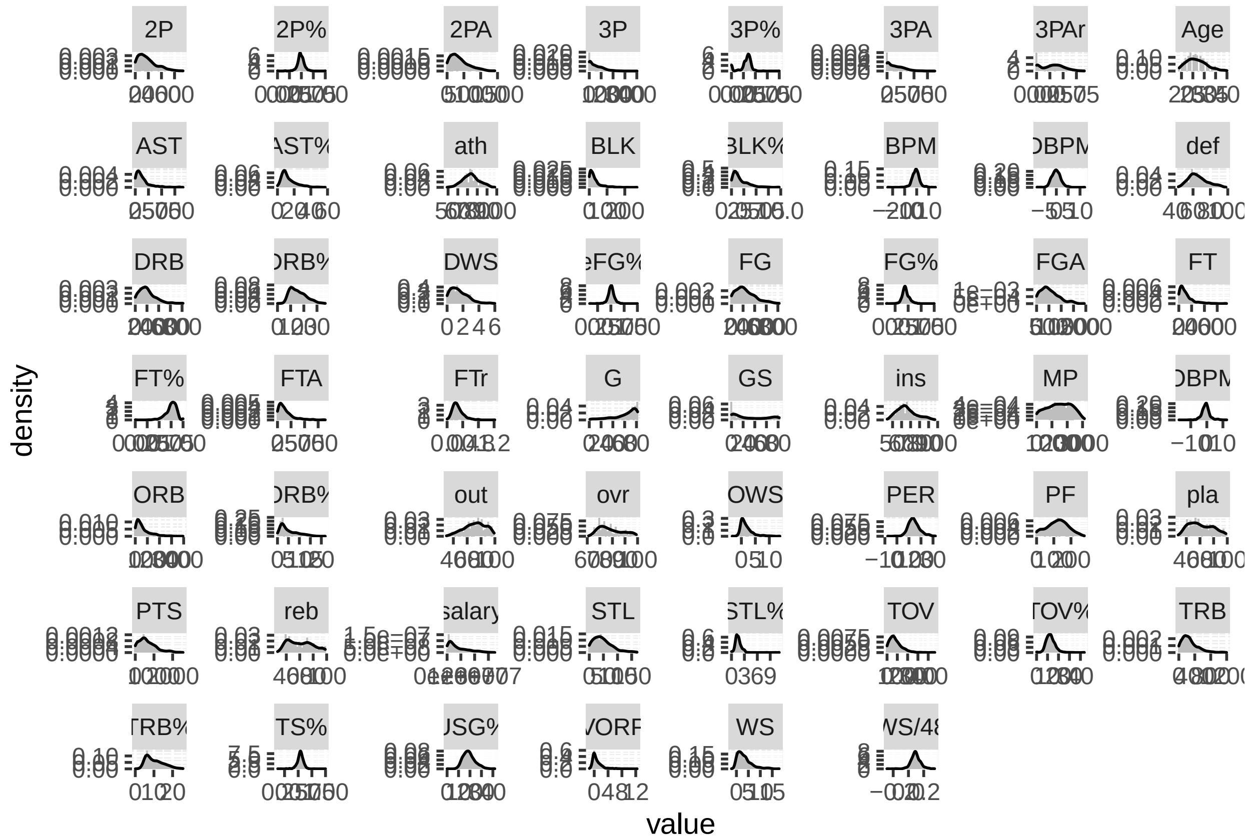
```
library(purrr)
```

```
##
## Attaching package: 'purrr'

## The following object is masked from 'package:rvest':
##
##     pluck
```

```
library(tidyr)
library(ggplot2)
df_final %>%
  keep(is.numeric) %>%
  gather() %>%
  ggplot(aes(value)) +
```

```r
    facet_wrap(~ key, scales = "free") +
    geom_histogram(aes(y=..density..), fill = "grey") +
    geom_density()
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

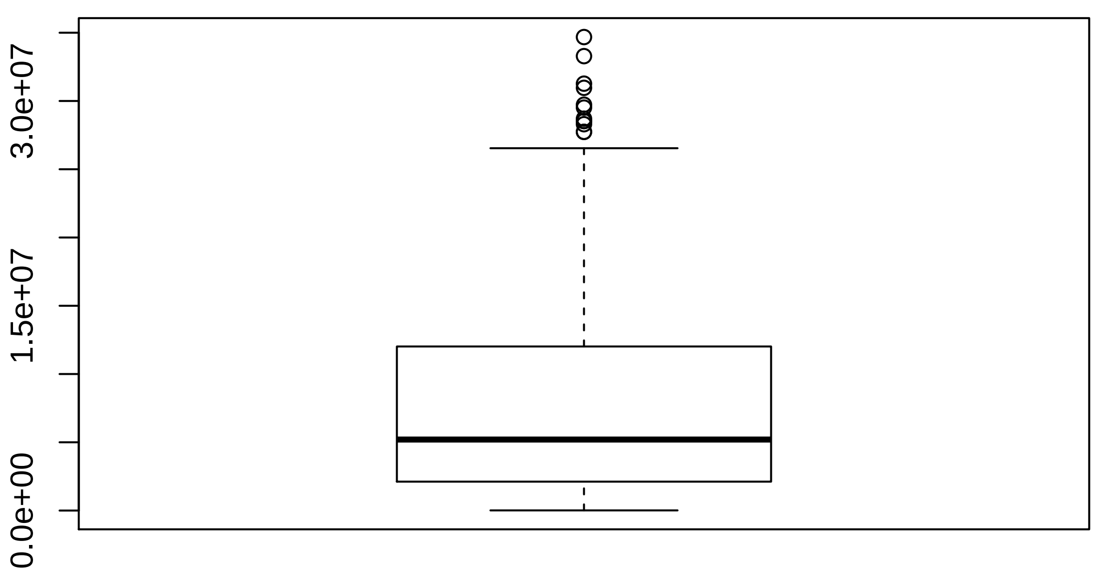



```r
ggsave("../figures/hist_complete_vars.png", width=15, height=13)
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

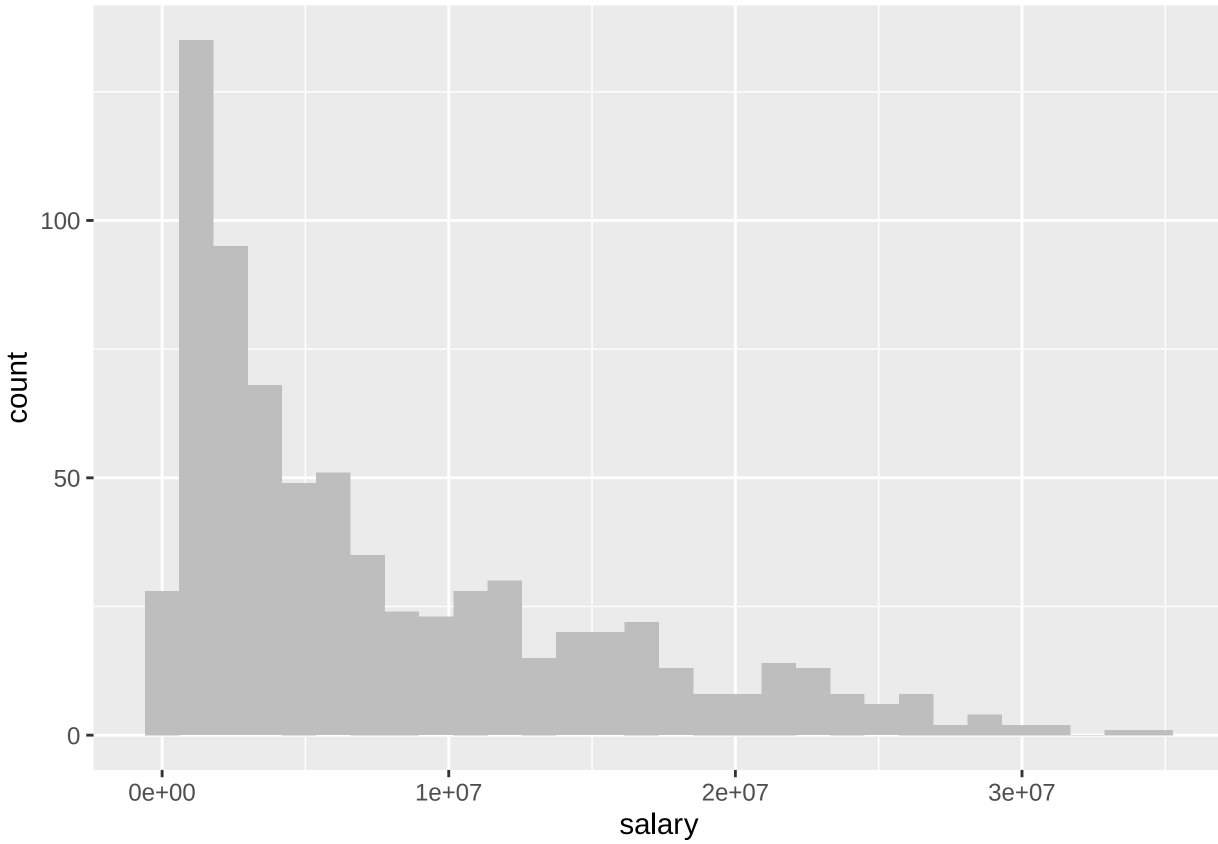
Salary variable

```r
library(ggplot2)
boxplot(df_final$salary)
```

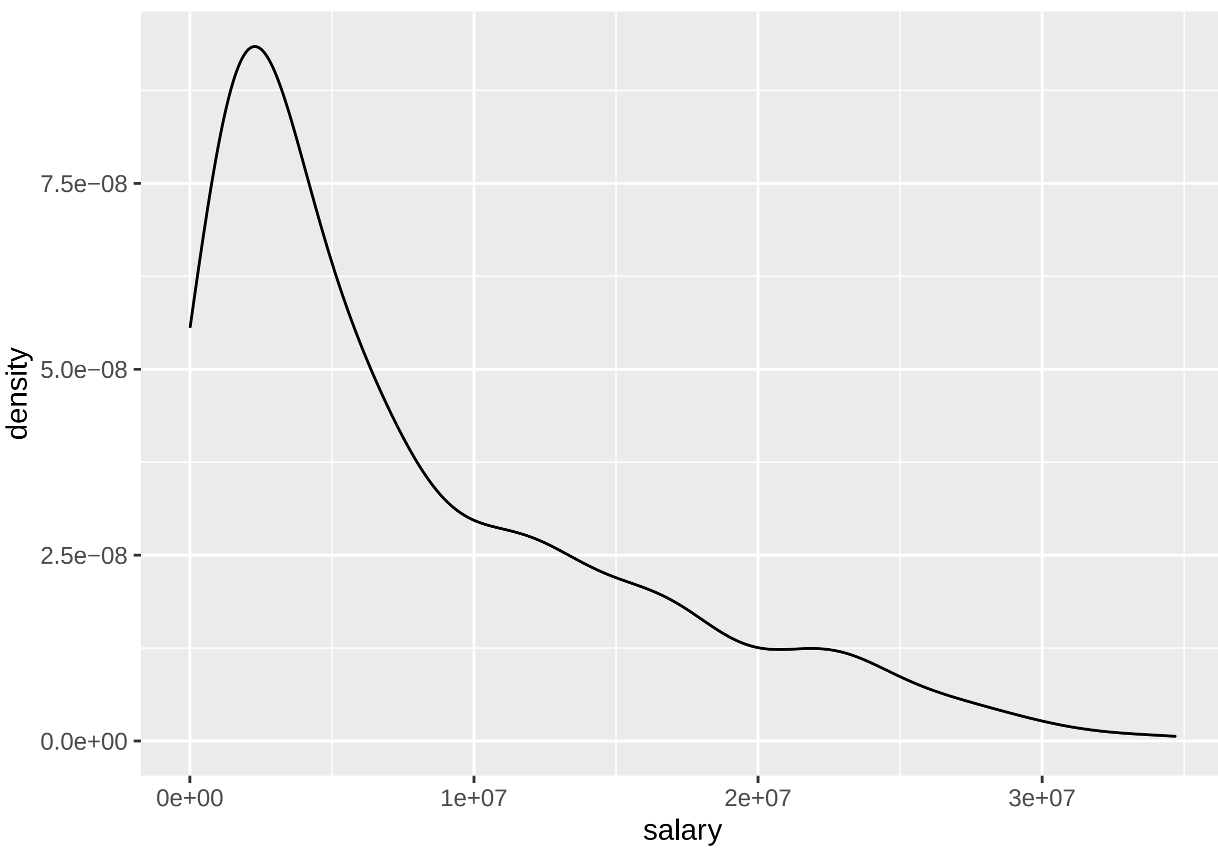



```r
ggplot(df_final, aes(x = salary)) + geom_histogram(fill = "grey")
```

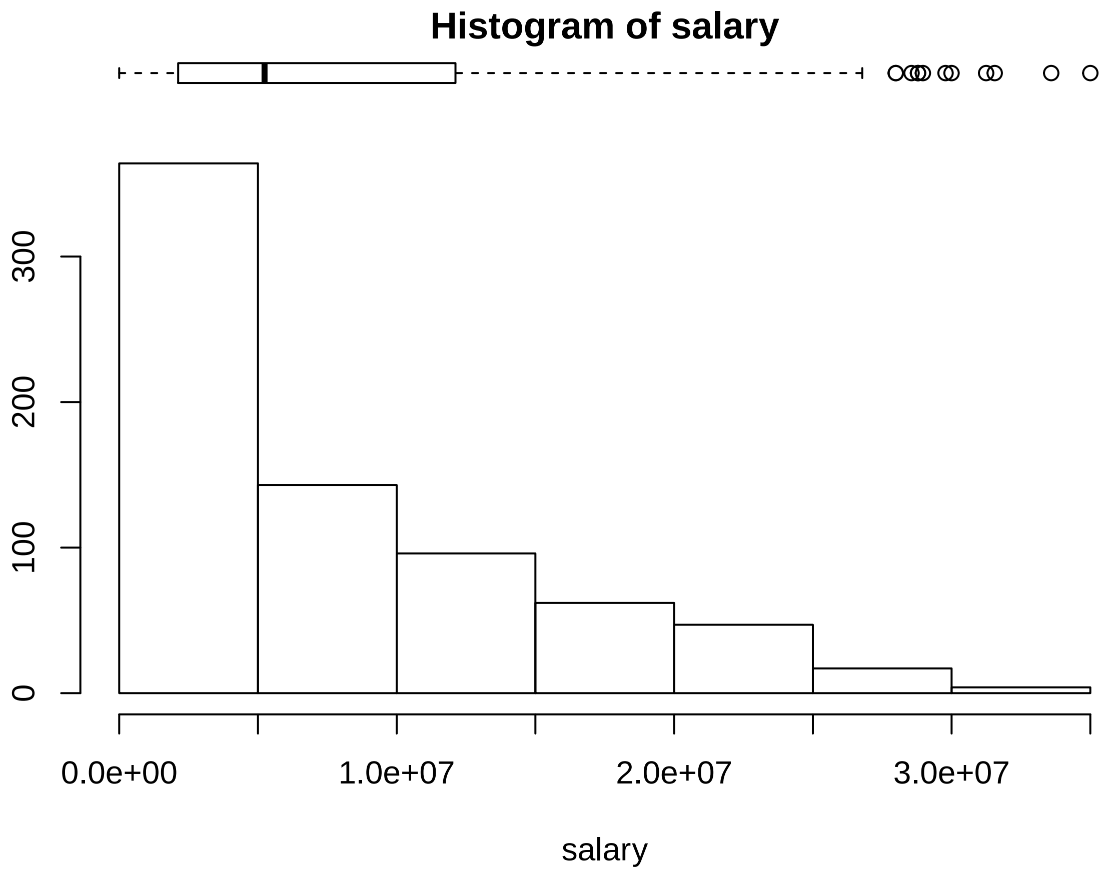
```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```




```
ggplot(df_final, aes(x = salary)) + geom_density()
```




```
layout(mat = matrix(c(1,2),2,1, byrow=TRUE), height = c(1,8))
par(mar=c(0, 3.1, 1.1, 2.1))
boxplot(df_final$salary , horizontal=TRUE , xaxt="n", frame=F, main=sprintf('Histogram of salary'))
par(mar=c(4, 3.1, 1.1, 2.1))
hist(df_final$salary,main='', xlab = "salary", ylab = "count")
```



salary stats

```r
mean(df_p_final$salary)
```

```
## [1] 7837816
```

```r
median(df_p_final$salary)
```

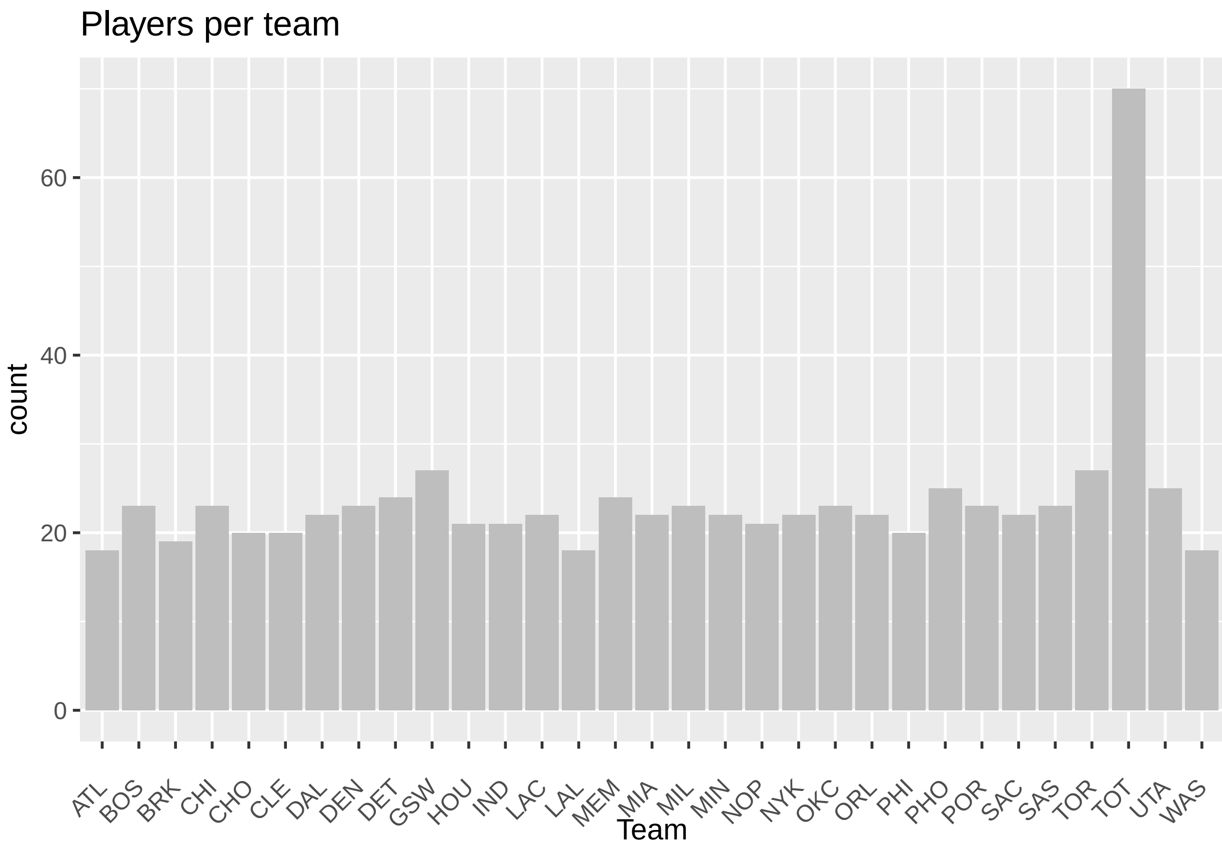
```
## [1] 5200000
```

```r
getmode <- function(v) {
   uniqv <- unique(v)
   uniqv[which.max(tabulate(match(v, uniqv)))]
}
result <- getmode(df_p_final$salary)
print(result)
```

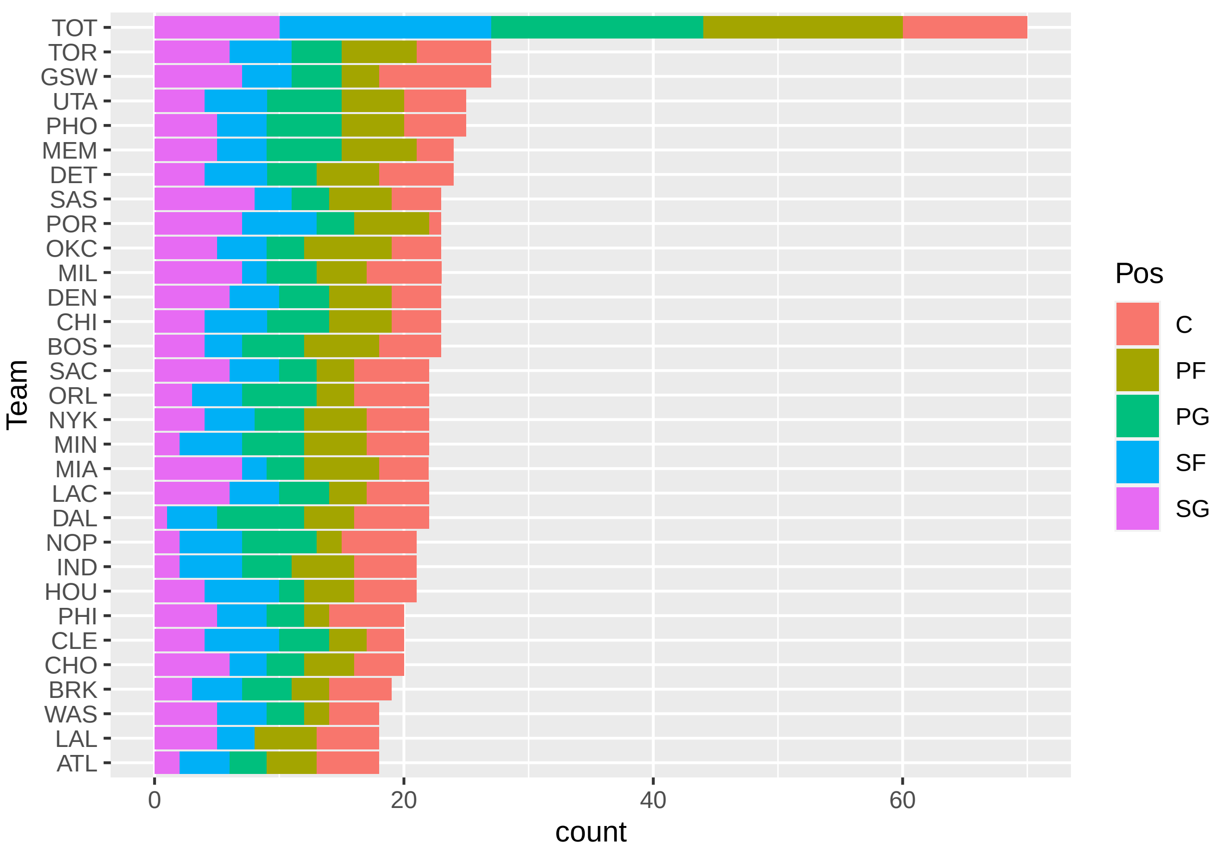
```
## [1] 1312611
```

Bar Chart of Player by Team from Complete Dataset

```r
library(ggplot2)
ggplot(df_final, aes(x = Tm)) +
  geom_bar(fill = "grey") +
  labs(x = "Team", title = "Players per team") +
  theme(axis.text.x=element_text(angle=45,hjust=1,vjust=0.5))
```




```
ggsave("../figures/bar_complete_player_per_team.png", width=10, height=7)

ggplot(df_final, aes(x=reorder(Tm,Tm,FUN = length), fill = Pos)) + geom_bar() + xlab("Team") + coord_flip()
```

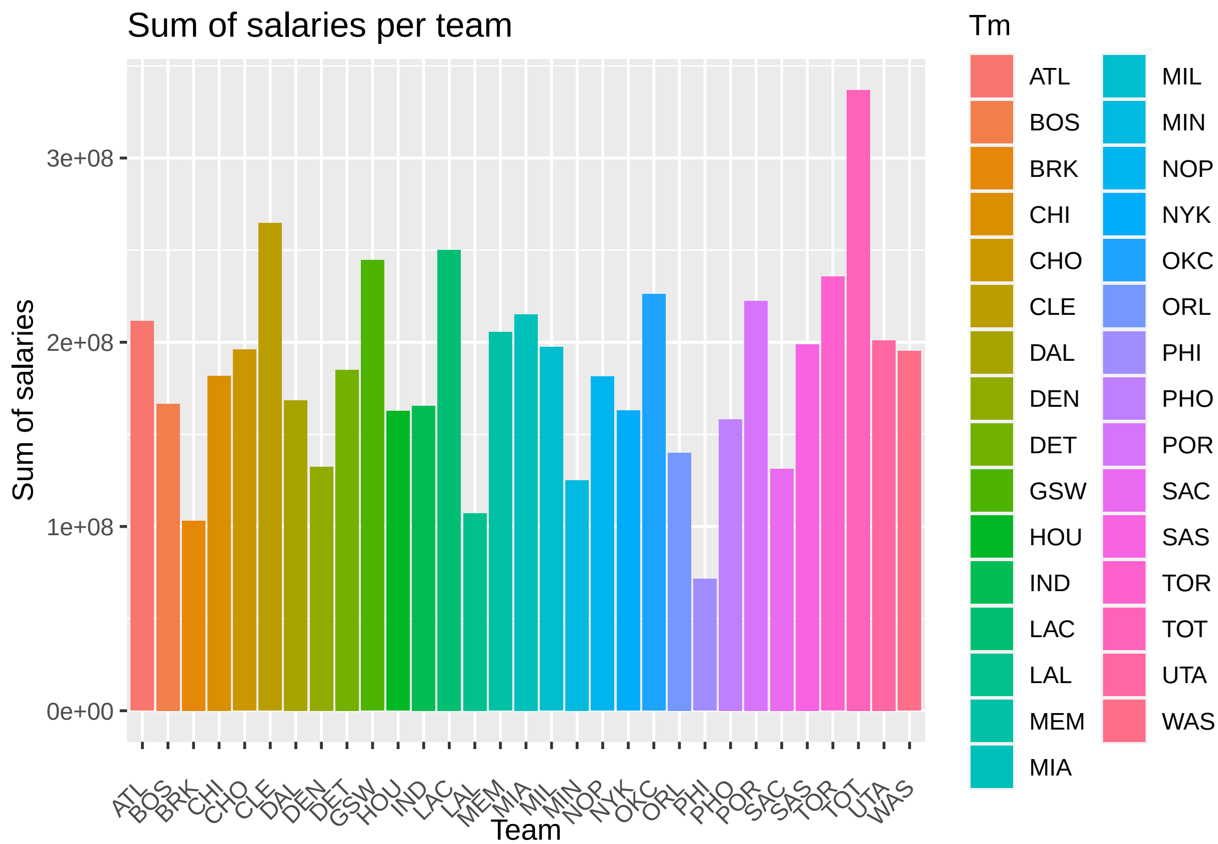


Sum of Salaries per Team for Complete Dataset

```
library(ggplot2)
ggplot(df_final,aes(x = Tm, y = salary, fill = Tm)) + stat_summary(fun.y =  "sum", geom = "bar") +
```

```
    labs(
        x = "Team",
        y = "Sum of salaries",
        title = paste("Sum of salaries per team")) +
    theme(axis.text.x=element_text(angle=45,hjust=1,vjust=0.5))
```

```
## Warning: `fun.y` is deprecated. Use `fun` instead.
```

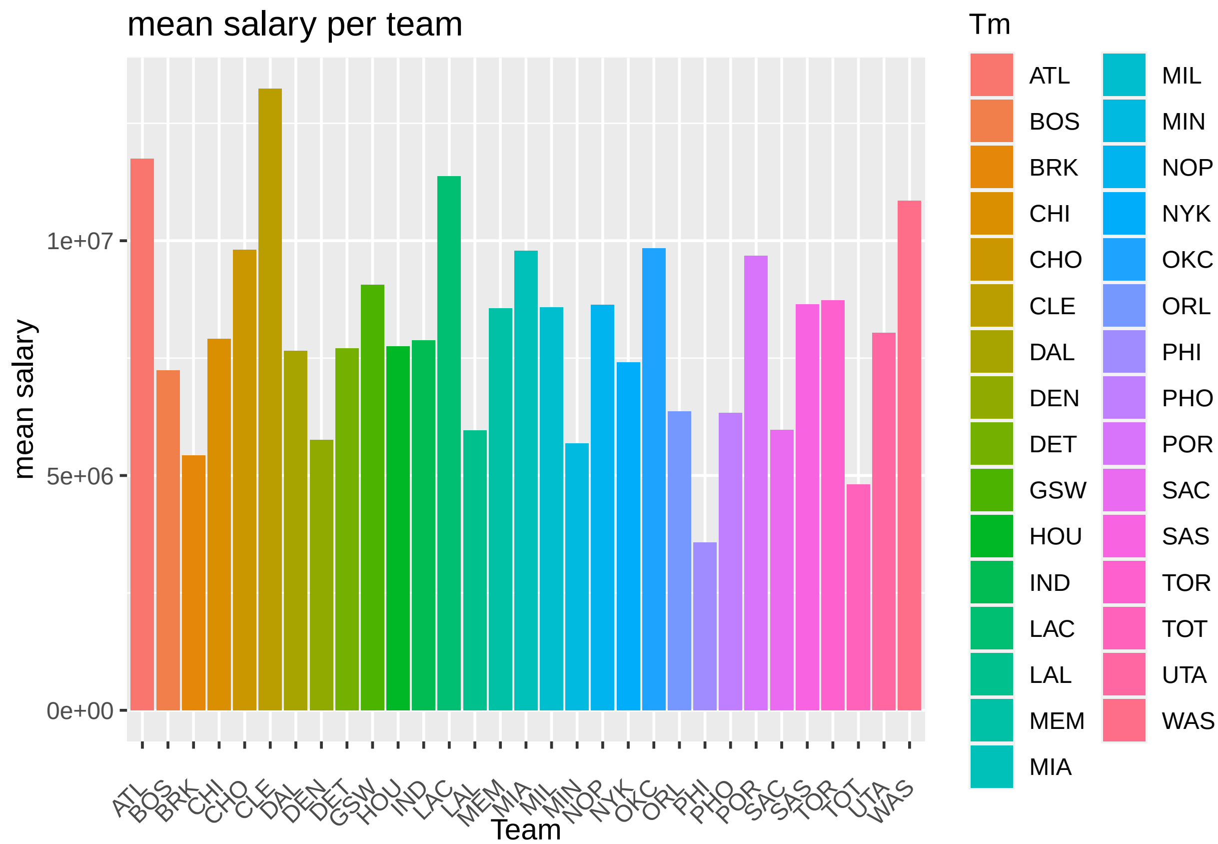



```
ggsave("../figures/bar_complete_sum_salaries_per_team.png", width=10, height=7)
```

Mean Salaries per Team for Complete Dataset

```
library(ggplot2)
ggplot(df_final,aes(x = Tm, y = salary, fill = Tm)) + stat_summary(fun.y =  "mean", geom = "bar") +
    labs(
        x = "Team",
        y = "mean salary",
        title = paste(
            "mean salary per team")) +
    theme(axis.text.x=element_text(angle=45,hjust=1,vjust=0.5))
```

```
## Warning: `fun.y` is deprecated. Use `fun` instead.
```



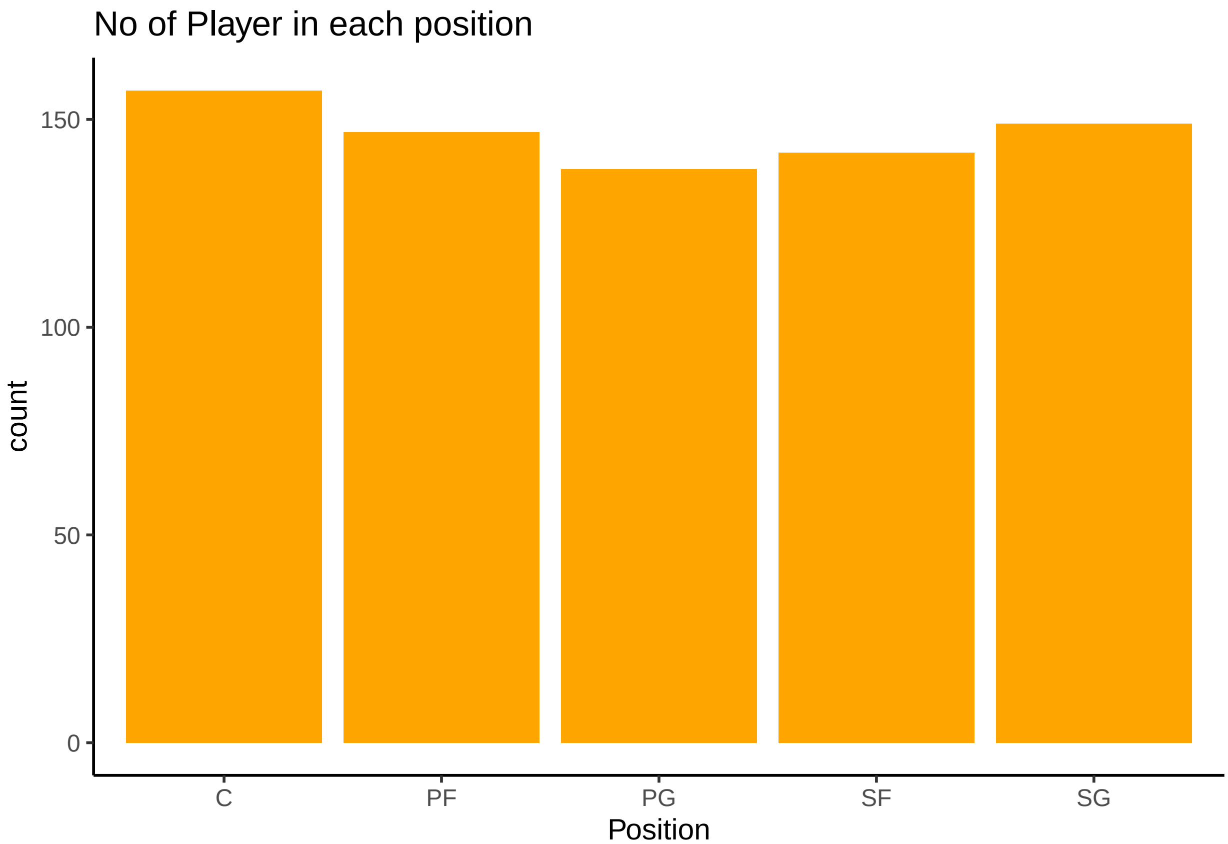

```r
ggsave("../figures/bar_complete_mean_salaries_per_team.png", width=10, height=7)
```

Players in each position

```r
nrow(df_p_final)
```

```
## [1] 733
```

```r
library(ggplot2)
ggplot(df_p_final, aes(x = Pos)) +
  geom_bar(fill = "orange") +
  labs(x = "Position", title = "No of Player in each position") +
  theme_classic()
```




```
ggsave("../figures/bar_complete_player_Position.png", width=10, height=7)
```

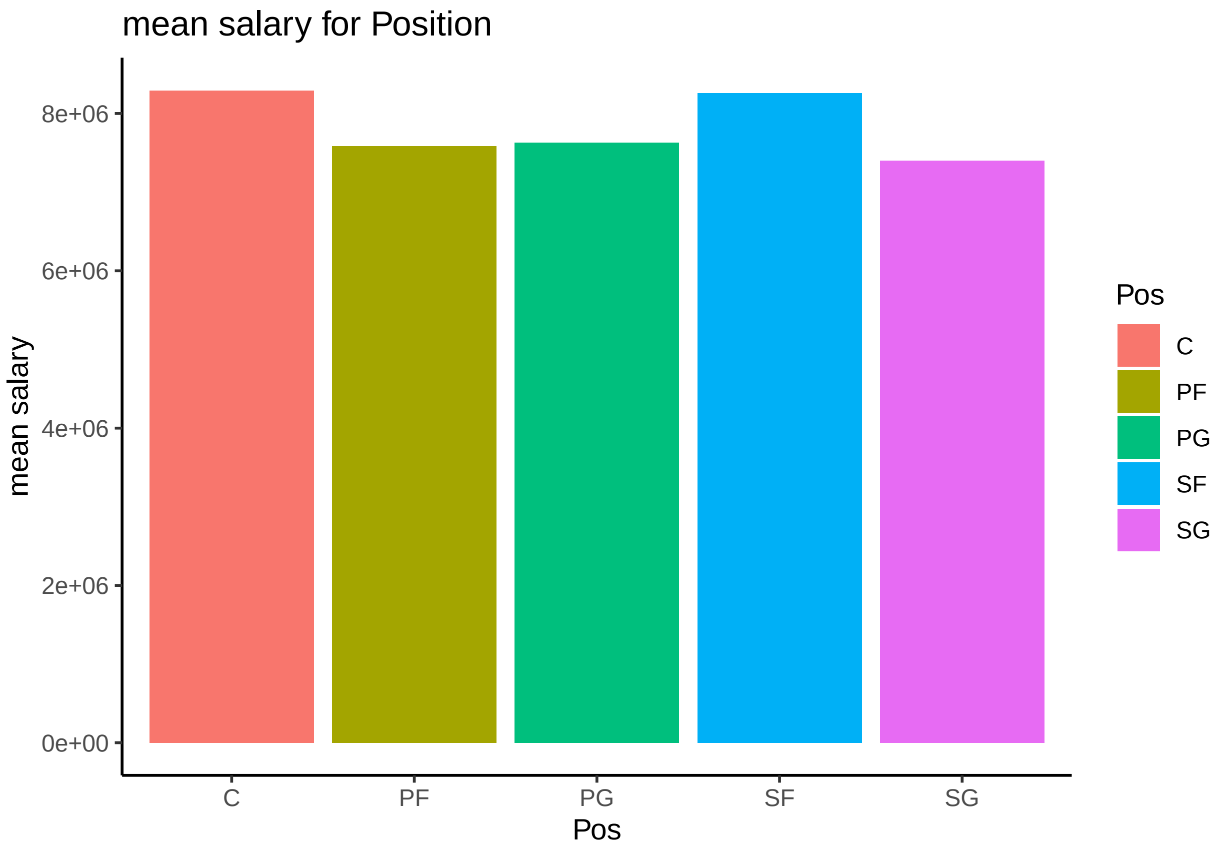
Mean salaries for each position

```
library(ggplot2)
library(tidyr)
library(dplyr)
```

```
##
## Attaching package: 'dplyr'

## The following object is masked from 'package:reshape':
##
##     rename

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```
ggplot(df_final,aes(x = Pos, y = salary, fill = Pos)) + stat_summary(fun.y =  "mean", geom = "bar") +
    labs(
        x = "Pos",
        y = "mean salary",
        title = paste(
            "mean salary for Position")) +
    theme_classic()
```

```
## Warning: `fun.y` is deprecated. Use `fun` instead.
```




```r
ggsave("../figures/bar_complete_mean_salaries_for_Position.png", width=10, height=7)
```

Correlation Matrix for complete dataset

```r
corr_matrix_c <- cor(Filter(is.numeric,df_final[2:ncol(df_final)]),method = "pearson")
correlation_salary_c <- sort(corr_matrix_c[,'salary'],decreasing = TRUE)
correlation_salary_c
```

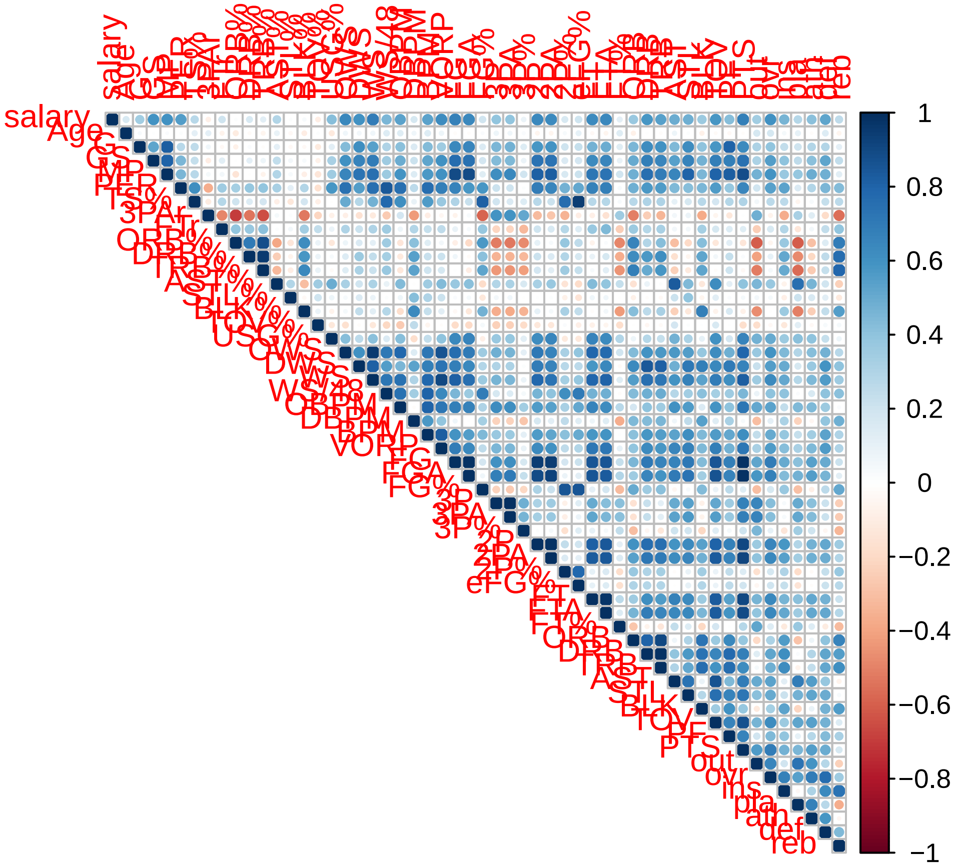
```
##      salary          WS         PTS          FG         FGA          2P
##  1.00000000  0.69654545  0.68147201  0.67871374  0.64964867  0.64945688
##         FTA         OWS          FT         2PA        VORP          MP
##  0.64822250  0.64762530  0.63630269  0.63534810  0.62400574  0.60387680
##         ovr         DWS          GS         TOV         DRB         PER
##  0.60386589  0.60093014  0.59461775  0.58439384  0.58130461  0.55068657
##         TRB         BPM        OBPM         def         AST         STL
##  0.54195071  0.53967876  0.53657917  0.52198890  0.49574308  0.48956302
##         ins       WS/48        USG%          PF         ath          3P
##  0.46613871  0.45295278  0.42790513  0.42275773  0.41069301  0.39214372
##         3PA         ORB         BLK           G         out        AST%
##  0.39058935  0.37213223  0.36870041  0.34675456  0.34594270  0.29653627
##         pla         TS%         reb        eFG%         FTr         FG%
##  0.28565474  0.27181444  0.25525211  0.20570361  0.20202229  0.19929701
##        DBPM         Age        DRB%         2P%        TRB%         FT%
##  0.17061810  0.16977681  0.16761161  0.16597870  0.12064951  0.11487058
##         3P%        BLK%        STL%        ORB%        3PAr        TOV%
##  0.08619947  0.03554661  0.01677941  0.01510555 -0.08755677 -0.09488064
```

Correlation Plot for complete dataset

```r
library(corrplot)
```

```
## corrplot 0.84 loaded
```

```r
corrplot(corr_matrix_c,type = "upper")
```

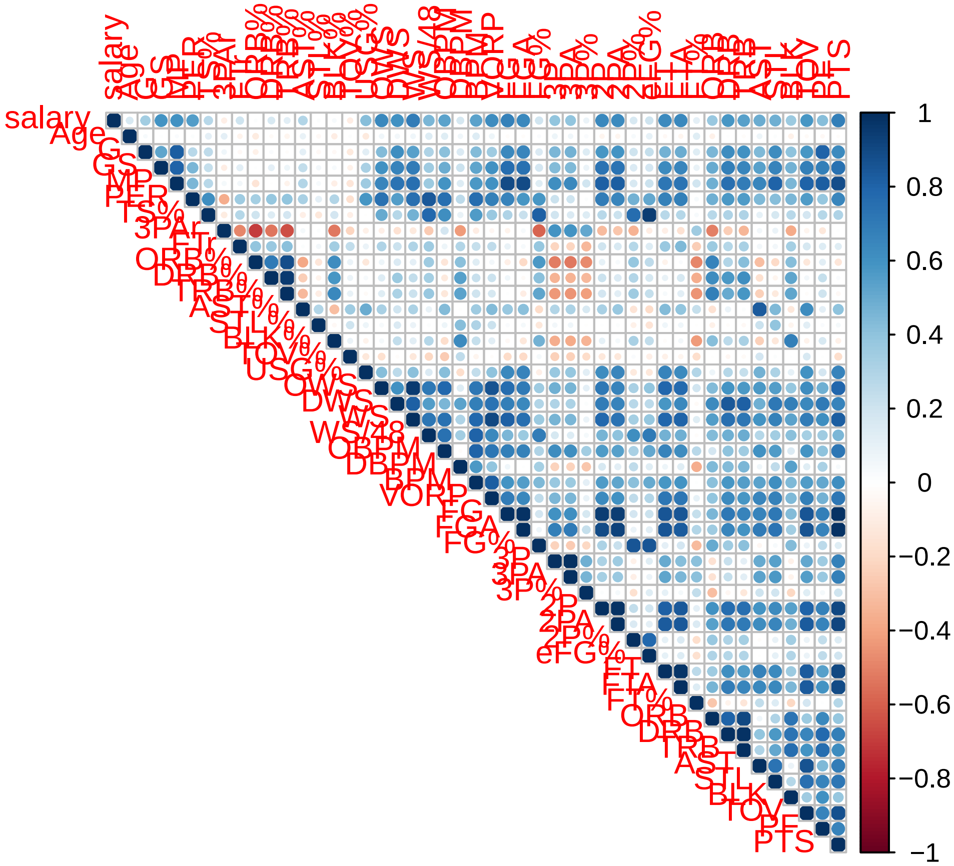


Correlation plot for Primary dataset

```r
corr_matrix_p <- cor(Filter(is.numeric,df_p_final[2:ncol(df_p_final)]),method = "pearson")
correlation_salary_p <- sort(corr_matrix_p[,'salary'],decreasing = TRUE)
correlation_salary_p
```

```
##      salary          WS         PTS          FG         FGA          2P
##  1.00000000  0.69654545  0.68147201  0.67871374  0.64964867  0.64945688
##         FTA         OWS          FT         2PA        VORP          MP
##  0.64822250  0.64762530  0.63630269  0.63534810  0.62400574  0.60387680
##         DWS          GS         TOV         DRB         PER         TRB
##  0.60093014  0.59461775  0.58439384  0.58130461  0.55068657  0.54195071
##         BPM        OBPM         AST         STL       WS/48        USG%
##  0.53967876  0.53657917  0.49574308  0.48956302  0.45295278  0.42790513
##          PF          3P         3PA         ORB         BLK           G
##  0.42275773  0.39214372  0.39058935  0.37213223  0.36870041  0.34675456
##        AST%         TS%        eFG%         FTr         FG%        DBPM
##  0.29653627  0.27181444  0.20570361  0.20202229  0.19929701  0.17061810
##         Age        DRB%         2P%        TRB%         FT%         3P%
##  0.16977681  0.16761161  0.16597870  0.12064951  0.11487058  0.08619947
##        BLK%        STL%        ORB%        3PAr        TOV%
##  0.03554661  0.01677941  0.01510555 -0.08755677 -0.09488064
```

```r
library(corrplot)
corrplot(corr_matrix_p,type = "upper")
```



Save correlation plots.

```
# complete dataset
png(file = "../figures/Correlation_plot_c.png")
corrplot(corr_matrix_c,type = "upper")
# primary dataset
png(file = "../figures/Correlation_plot_p.png")
corrplot(corr_matrix_p,type = "upper")
dev.off()
```

```
## pdf
##   2
```

Salary vs all other variable scatterplots

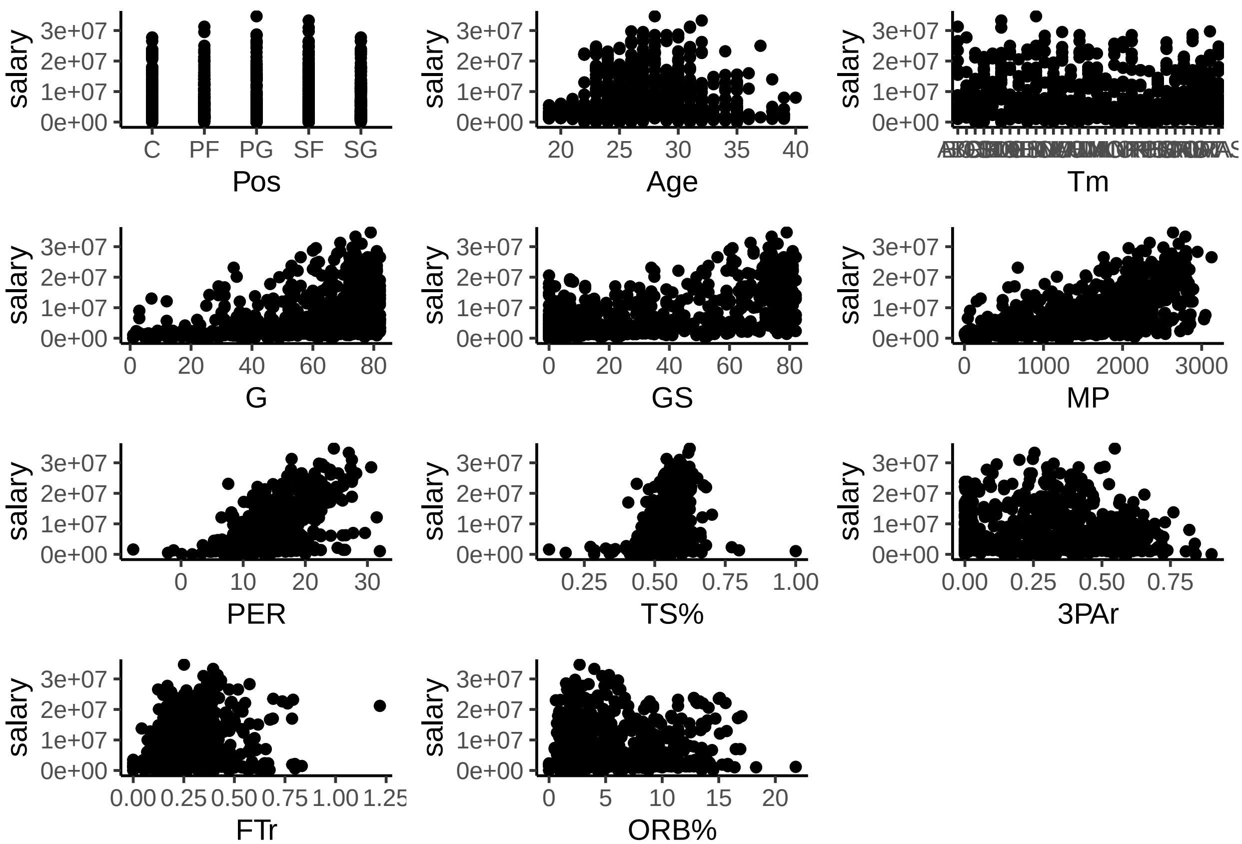
```
plot = function(variable){
  print(variable)
  ggplot(df_final,aes(x = df_final[,variable], y = salary)) + geom_point() + theme_classic() + labs(x=variable)}

library(gridExtra)
```

```
##
## Attaching package: 'gridExtra'

## The following object is masked from 'package:dplyr':
##
##     combine
```

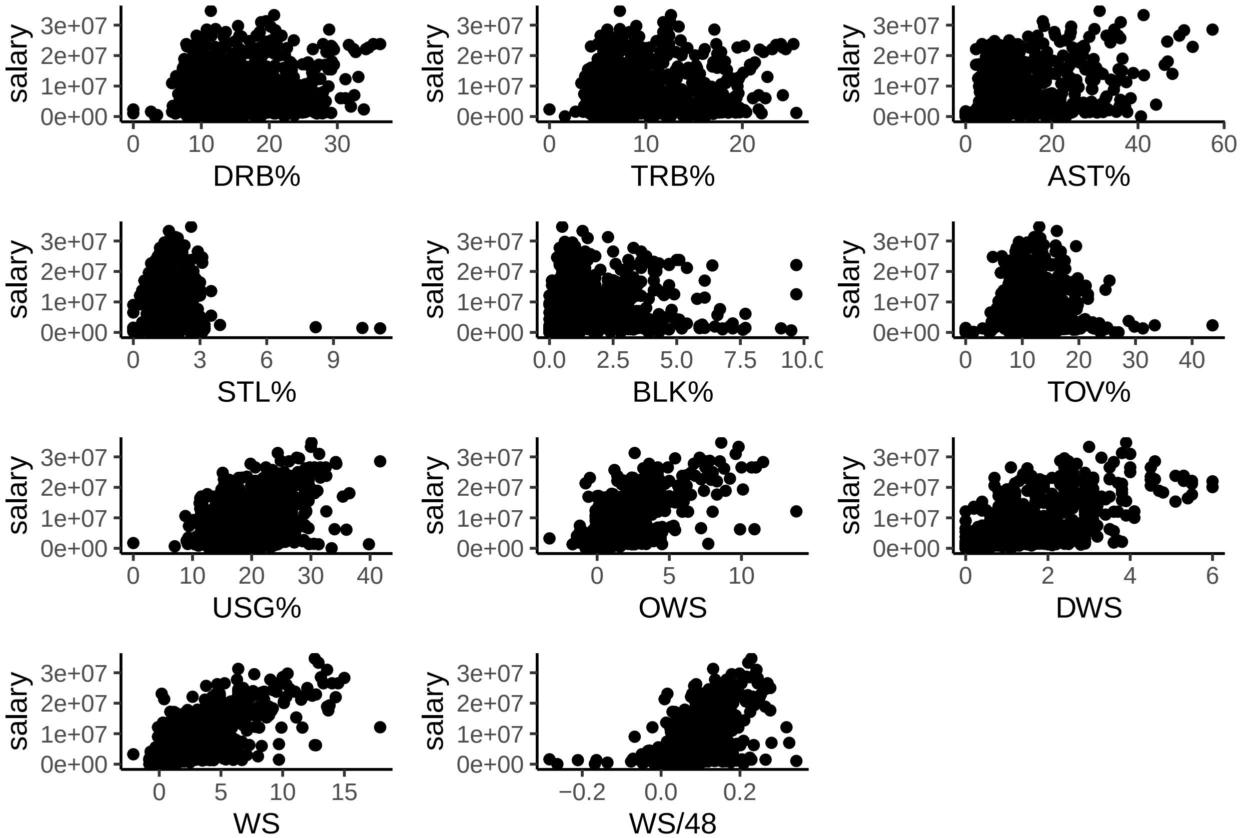
```
p = list()
p <- NULL
val <- 0
d <- df_final[,4:ncol(df_final)]
for(j in 1:5){
  for(i in 1:11){
```

```r
    name = names(d[i+val])
    p[[i]] = plot(as.character(name))}
  val = i+val
  do.call(grid.arrange,p)
  p <- NULL}
```

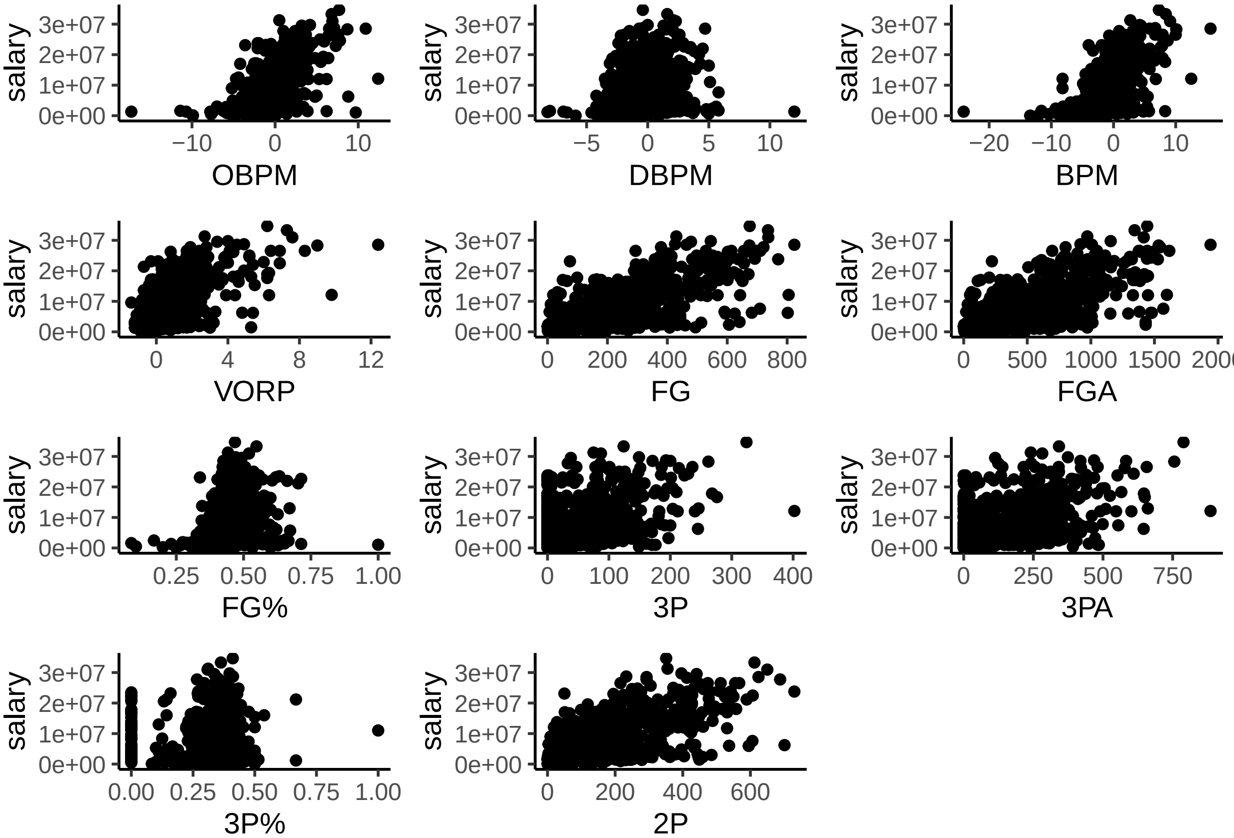
```
## [1] "Pos"
## [1] "Age"
## [1] "Tm"
## [1] "G"
## [1] "GS"
## [1] "MP"
## [1] "PER"
## [1] "TS%"
## [1] "3PAr"
## [1] "FTr"
## [1] "ORB%"
```



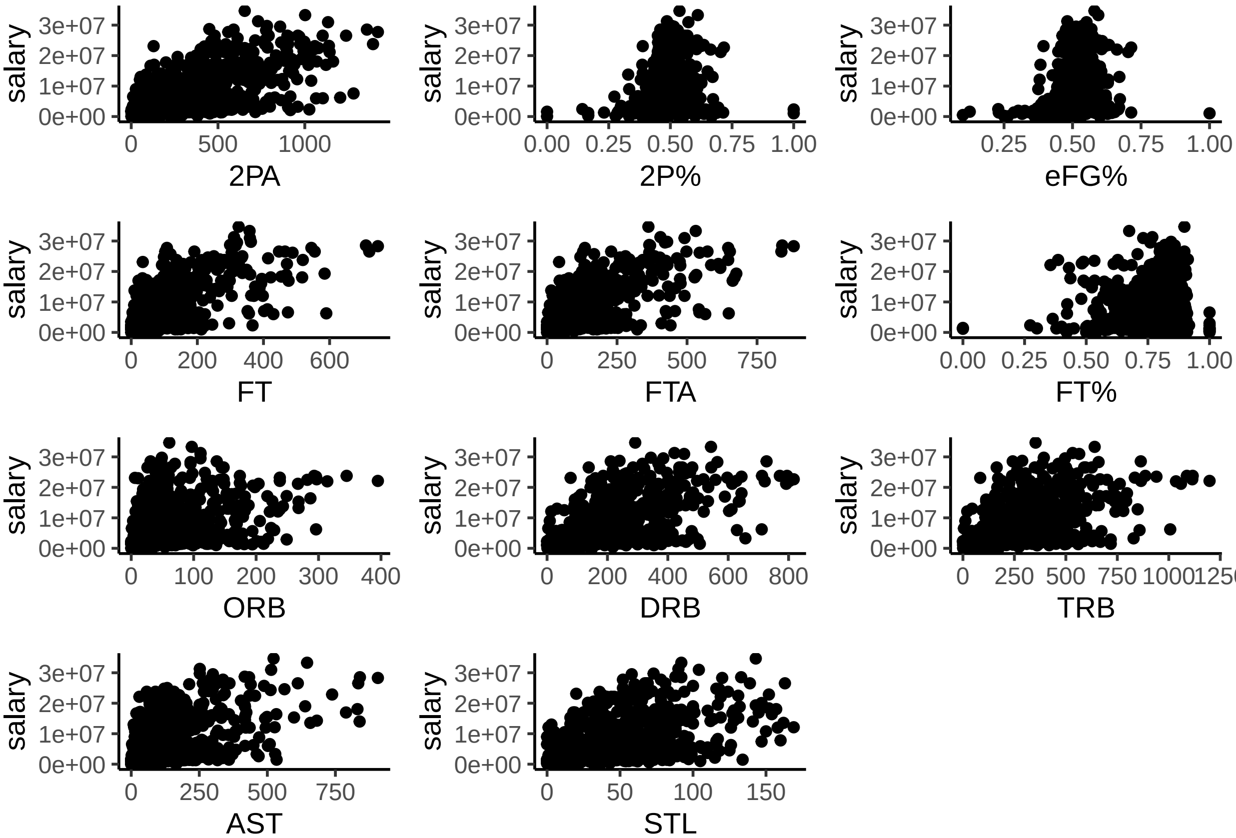

```
## [1] "DRB%"
## [1] "TRB%"
## [1] "AST%"
## [1] "STL%"
## [1] "BLK%"
## [1] "TOV%"
## [1] "USG%"
## [1] "OWS"
## [1] "DWS"
## [1] "WS"
## [1] "WS/48"
```



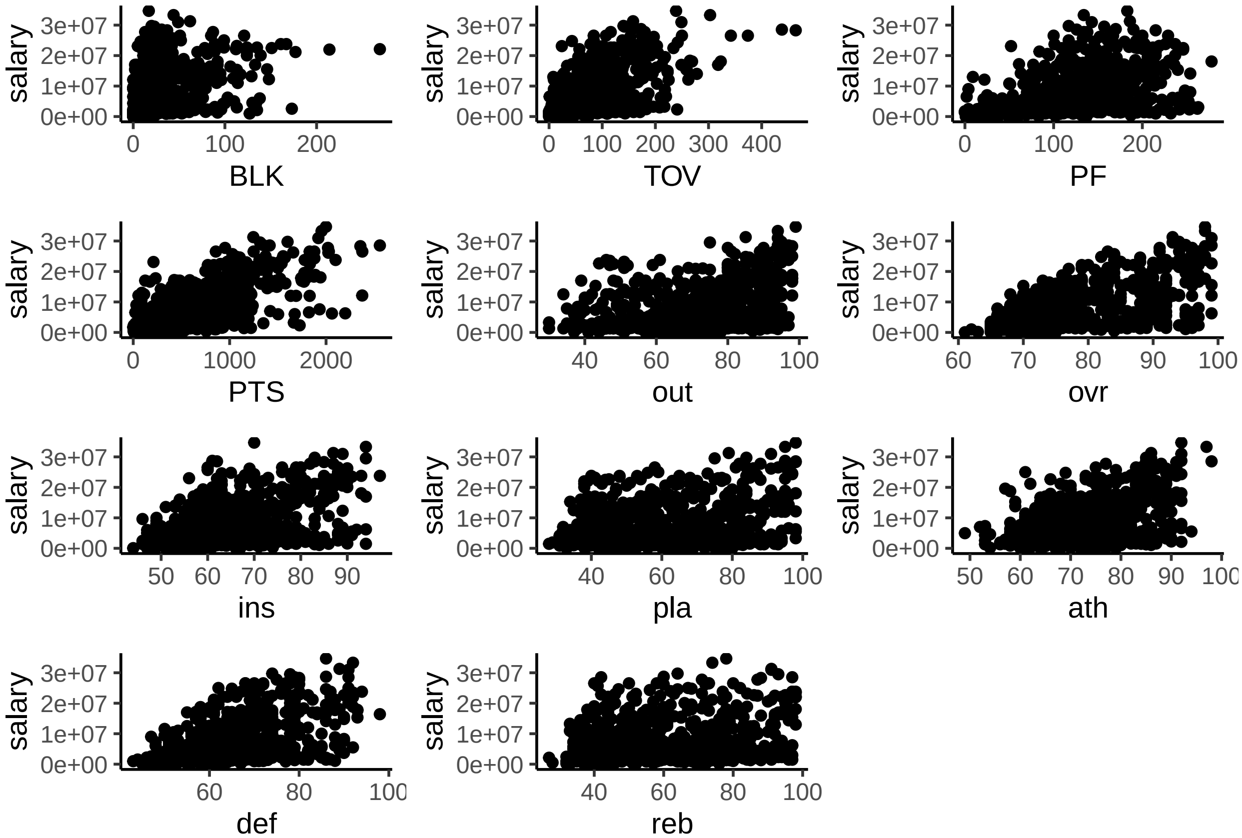

```
## [1] "OBPM"
## [1] "DBPM"
## [1] "BPM"
## [1] "VORP"
## [1] "FG"
## [1] "FGA"
## [1] "FG%"
## [1] "3P"
## [1] "3PA"
## [1] "3P%"
## [1] "2P"
```




```
## [1] "2PA"
## [1] "2P%"
## [1] "eFG%"
## [1] "FT"
## [1] "FTA"
## [1] "FT%"
## [1] "ORB"
## [1] "DRB"
## [1] "TRB"
## [1] "AST"
## [1] "STL"
```




```
## [1] "BLK"
## [1] "TOV"
## [1] "PF"
## [1] "PTS"
## [1] "out"
## [1] "ovr"
## [1] "ins"
## [1] "pla"
## [1] "ath"
## [1] "def"
## [1] "reb"
```



selecting relevant variables

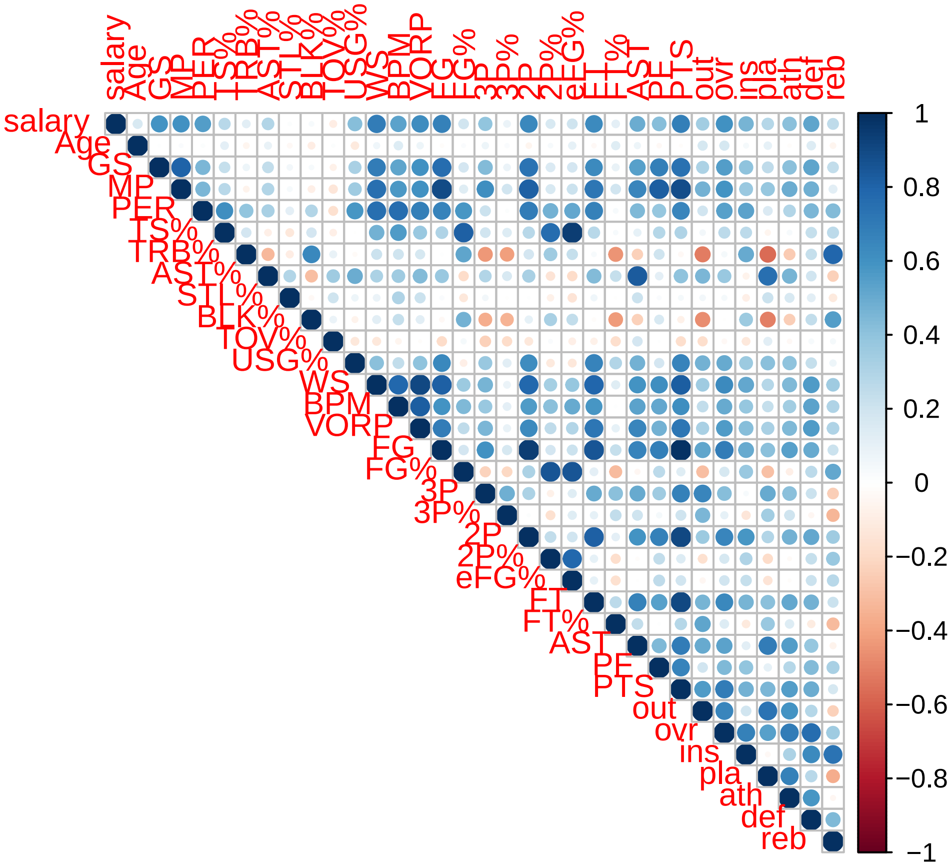
```
rel_p <- c("name","year","salary","Pos","Age","Tm","GS","MP","PER","TS%","TRB%","AST%","STL%","BLK%","TOV%","USG%"

rel_c <- c("name","year","salary","Pos","Age","Tm","GS","MP","PER","TS%","TRB%","AST%","STL%","BLK%","TOV%","USG%"


df_p_final_relevant <- df_p_final[names(df_p_final) %in% rel_p]
head(df_p_final_relevant)
```

```
##             name year  salary Pos Age  Tm GS   MP  PER   TS% TRB% AST% STL% BLK%
## 1  aaron brooks 2016 2700000  PG  31 CHI  0 1108 11.8 0.494  4.8 26.0  1.4  0.7
## 2  aaron brooks 2017 2116955  PG  32 IND  0  894  9.5 0.507  4.3 20.7  1.4  0.9
## 3  aaron gordon 2016 4351320  PF  20 ORL 37 1863 17.0 0.541 15.1 10.3  1.6  2.4
## 4  aaron gordon 2017 5504420  SF  21 ORL 72 2298 14.4 0.530  9.6 10.5  1.4  1.4
## 5 adreian payne 2016 2022240  PF  24 MIN  2  486  5.6 0.422 13.3  8.9  1.7  1.8
## 6    aj hammons 2017 1312611   C  24 DAL  0  163  8.4 0.472 12.8  3.8  0.3  7.2
##   TOV% USG%   WS  BPM VORP  FG   FG% 3P   3P%  2P   2P%  eFG%  FT   FT% AST  PF
## 1 14.2 22.9  0.9 -3.3 -0.4 188 0.401 66 0.357 122 0.430 0.471  49 0.766 180 132
## 2 17.2 19.2  0.3 -4.6 -0.6 121 0.403 48 0.375  73 0.424 0.483  32 0.800 125  93
## 3  9.0 17.3  5.4  1.8  1.8 274 0.473 42 0.296 232 0.531 0.509 129 0.668 128 153
## 4  8.5 20.1  3.7 -0.7  0.8 393 0.454 77 0.288 316 0.528 0.499 156 0.719 150 172
## 5 18.7 17.7 -0.5 -6.1 -0.5  53 0.366  9 0.281  44 0.389 0.397  17 0.654  29  77
## 6 16.4 17.6  0.0 -5.6 -0.1  17 0.405  5 0.500  12 0.375 0.464   9 0.450   4  21
##    PTS
## 1  491
## 2  322
## 3  719
## 4 1019
## 5  132
## 6   48
```

```
df_final_relevant <- df_final[names(df_final) %in% rel_c]
```

correlation plot of relevant variables

```
library(corrplot)
# primary dataset
corr_matrix_p_relevant <- cor(Filter(is.numeric,df_p_final_relevant[2:ncol(df_p_final_relevant)]),method = "pearso
correlation_salary_p_relevant <- sort(df_p_final_relevant[,'salary'],decreasing = TRUE)

# complete dataset
corr_matrix_c_relevant <- cor(Filter(is.numeric,df_final_relevant[2:ncol(df_final_relevant)]),method = "pearson")
correlation_salary_c_relevant <- sort(df_final_relevant[,'salary'],decreasing = TRUE)


corrplot(corr_matrix_c_relevant,type = "upper")
```



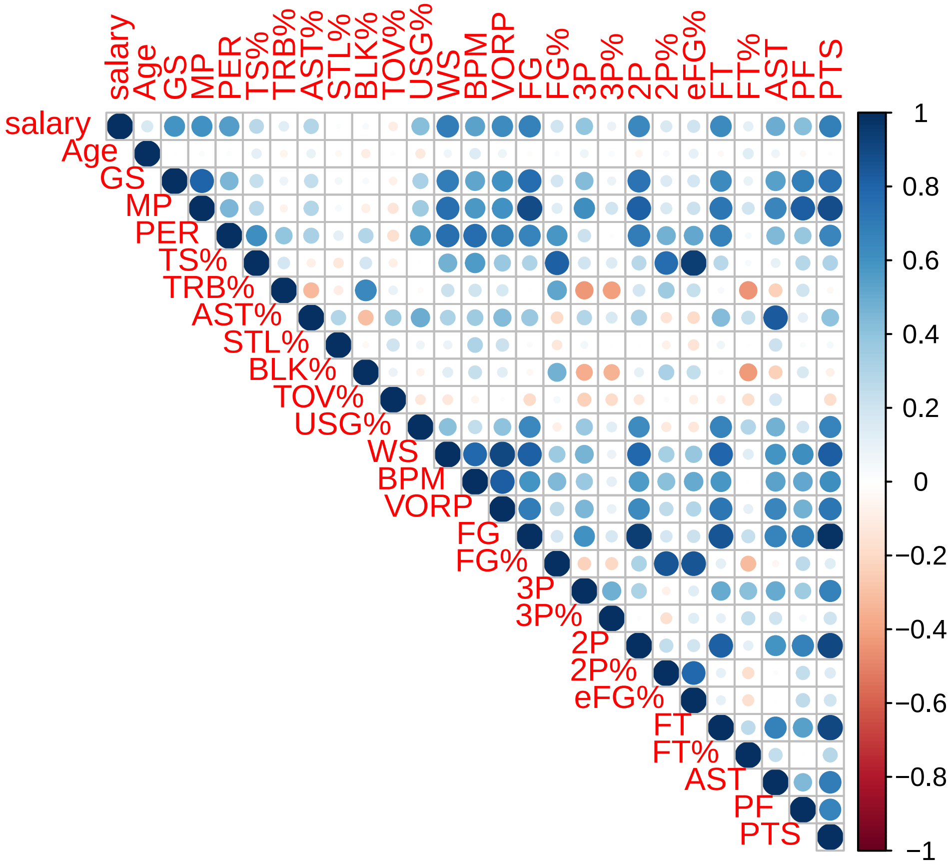

```
dev.copy(png,"../figures/Correlation_plot_c_relevant.png")
```

```
## png
##   4
```

```
dev.off()
```

```
## pdf
##   2
```

```
# primary dataset
corrplot(corr_matrix_p_relevant,type = "upper")
```




```r
dev.copy(png,"../figures/Correlation_plot_p_relevant.png")
```

```
## png
##   4
```

```r
dev.off()
```

```
## pdf
##   2
```

Detecting outliers

```r
df_cook <- df_final_relevant[which(sapply(df_final_relevant,is.numeric))]
mod <- lm(salary ~ ., data = df_cook )
cooksd <- cooks.distance(mod)

# All outliers
influential <- as.numeric(names(cooksd)[(cooksd > 9*mean(cooksd, na.rm=T))])  # influential row numbers
influential <- na.omit(influential)
df_final_relevant[influential, names(df_final_relevant) %in% c("name","year","salary","Pos","Age","Tm","GS","MP","
```

```
##                    name year   salary Pos Age  Tm GS   MP AST%   WS   FG%
## 260       isaiah thomas 2017  6261395  PG  27 BOS 76 2569 32.6 12.6 0.463
## 294        jarrett jack 2017  2328652  PG  33 NOP  0   33 20.3  0.0 0.667
## 384 karl anthony towns 2017  6216840   C  21 MIN 82 3030 13.2 12.7 0.542
## 530      nikola mirotic 2016  5782450  PF  24 CHI 38 1646  9.4  3.9 0.407
## 616          sam dekker 2017  1794600  SF  22 HOU  2 1419  7.7  3.1 0.473
## 641       stephen curry 2017 34682550  PG  28 GSW 79 2638 31.1 12.6 0.468
## 642  stephen zimmerman 2017  1312611   C  20 ORL  0  108  5.3  0.0 0.323
##           3P%   2P%   FT%  PF  PTS
## 260 0.3790000 0.528 0.909 167 2199
## 294 0.0000000 1.000 1.000   4    6
## 384 0.3670000 0.582 0.832 241 2061
## 530 0.3900000 0.430 0.807 151  777
## 616 0.3210000 0.591 0.559  83  504
## 641 0.4110000 0.537 0.898 183 1999
```

```
## 642 0.2711419 0.323 0.600  17   23
```

Plot Cook's Distance

```
plot(cooksd, pch="*", cex=2, main="Outliers")  # plot cook's distance
abline(h = 8*mean(cooksd, na.rm=T), col="red")
# add cutoff line. Those observations that have a cook's distance greater than 8
# times the mean may be classified as influential.
text(x=1:length(cooksd)+1, y=cooksd, labels=ifelse(cooksd>8*mean(cooksd, na.rm=T),names(cooksd),""), col="red")  #
dev.copy(png,"../figures/Missing values/outliers.png")
dev.off()
```

Variable Selection

Split Train-Test

```
library(caret)
set.seed(7)
```

Primary Dataset

```
train_rows <- createDataPartition(y=df_p_final[,'salary'], list=FALSE, p=.8)
p_train_df <- df_p_final[train_rows,]
p_test_df <- df_p_final[-train_rows,]
stopifnot(nrow(p_train_df) + nrow(p_test_df) == nrow(df_p_final))
nrow(p_train_df)
```

```
## [1] 588
```

```
nrow(p_test_df)
```

```
## [1] 145
```

```
names(p_train_df)
```

```
##  [1] "name"   "year"   "salary" "Pos"    "Age"    "Tm"     "G"      "GS"
##  [9] "MP"     "PER"    "TS%"    "3PAr"   "FTr"    "ORB%"   "DRB%"   "TRB%"
## [17] "AST%"   "STL%"   "BLK%"   "TOV%"   "USG%"   "OWS"    "DWS"    "WS"
## [25] "WS/48"  "OBPM"   "DBPM"   "BPM"    "VORP"   "FG"     "FGA"    "FG%"
## [33] "3P"     "3PA"    "3P%"    "2P"     "2PA"    "2P%"    "eFG%"   "FT"
## [41] "FTA"    "FT%"    "ORB"    "DRB"    "TRB"    "AST"    "STL"    "BLK"
## [49] "TOV"    "PF"     "PTS"
```

```
head(p_train_df)
```

```
##             name year  salary Pos Age  Tm  G GS   MP  PER   TS%  3PAr   FTr ORB%
## 1  aaron brooks 2016 2700000  PG  31 CHI 69  0 1108 11.8 0.494 0.394 0.136  2.0
## 2  aaron brooks 2017 2116955  PG  32 IND 65  0  894  9.5 0.507 0.427 0.133  2.3
## 3  aaron gordon 2016 4351320  PF  20 ORL 78 37 1863 17.0 0.541 0.245 0.333  9.0
## 4  aaron gordon 2017 5504420  SF  21 ORL 80 72 2298 14.4 0.530 0.309 0.251  5.3
## 5 adreian payne 2016 2022240  PF  24 MIN 52  2  486  5.6 0.422 0.221 0.179  4.8
## 6    aj hammons 2017 1312611   C  24 DAL 22  0  163  8.4 0.472 0.238 0.476  5.4
##   DRB% TRB% AST% STL% BLK% TOV% USG%  OWS DWS   WS  WS/48 OBPM DBPM  BPM VORP
## 1  7.5  4.8 26.0  1.4  0.7 14.2 22.9  0.2 0.7  0.9  0.040 -0.5 -2.8 -3.3 -0.4
## 2  6.3  4.3 20.7  1.4  0.9 17.2 19.2 -0.2 0.5  0.3  0.016 -2.1 -2.6 -4.6 -0.6
## 3 21.3 15.1 10.3  1.6  2.4  9.0 17.3  3.2 2.2  5.4  0.139  0.6  1.2  1.8  1.8
## 4 14.1  9.6 10.5  1.4  1.4  8.5 20.1  2.0 1.7  3.7  0.076 -0.2 -0.4 -0.7  0.8
## 5 21.5 13.3  8.9  1.7  1.8 18.7 17.7 -0.9 0.4 -0.5 -0.047 -5.9 -0.2 -6.1 -0.5
## 6 20.9 12.8  3.8  0.3  7.2 16.4 17.6 -0.2 0.2  0.0 -0.001 -7.5  1.9 -5.6 -0.1
##    FG FGA   FG% 3P 3PA   3P%  2P 2PA   2P%  eFG%  FT FTA   FT% ORB DRB TRB AST
```

```
## 1 188 469 0.401 66 185 0.357 122 284 0.430 0.471  49  64 0.766  21  80 101 180
## 2 121 300 0.403 48 128 0.375  73 172 0.424 0.483  32  40 0.800  18  51  69 125
## 3 274 579 0.473 42 142 0.296 232 437 0.531 0.509 129 193 0.668 154 353 507 128
## 4 393 865 0.454 77 267 0.288 316 598 0.528 0.499 156 217 0.719 116 289 405 150
## 5  53 145 0.366  9  32 0.281  44 113 0.389 0.397  17  26 0.654  20  91 111  29
## 6  17  42 0.405  5  10 0.500  12  32 0.375 0.464   9  20 0.450   8  28  36   4
##   STL BLK TOV  PF  PTS
## 1  30  10  82 132  491
## 2  25   9  66  93  322
## 3  59  55  66 153  719
## 4  64  40  89 172 1019
## 5  16  11  36  77  132
## 6   1  13  10  21   48
```

```r
write.csv(p_train_df,'../data/train_test/primary/train.csv',row.names=F)
write.csv(p_test_df,'../data/train_test/primary/test.csv',row.names=F)

train_rows_relevant <- createDataPartition(y=df_p_final_relevant[,'salary'], list=FALSE, p=.8)
p_train_relevant_df <- df_p_final_relevant[train_rows,]
p_test_relevant_df <- df_p_final_relevant[-train_rows,]
stopifnot(nrow(p_train_relevant_df) + nrow(p_test_relevant_df) == nrow(df_p_final_relevant))
head(p_train_relevant_df)
```

```
##            name year  salary Pos Age  Tm GS   MP  PER   TS% TRB% AST% STL% BLK%
## 1  aaron brooks 2016 2700000  PG  31 CHI  0 1108 11.8 0.494  4.8 26.0  1.4  0.7
## 2  aaron brooks 2017 2116955  PG  32 IND  0  894  9.5 0.507  4.3 20.7  1.4  0.9
## 3  aaron gordon 2016 4351320  PF  20 ORL 37 1863 17.0 0.541 15.1 10.3  1.6  2.4
## 4  aaron gordon 2017 5504420  SF  21 ORL 72 2298 14.4 0.530  9.6 10.5  1.4  1.4
## 5 adreian payne 2016 2022240  PF  24 MIN  2  486  5.6 0.422 13.3  8.9  1.7  1.8
## 6    aj hammons 2017 1312611   C  24 DAL  0  163  8.4 0.472 12.8  3.8  0.3  7.2
##   TOV% USG%   WS  BPM VORP  FG   FG% 3P   3P%  2P   2P%  eFG%  FT   FT% AST  PF
## 1 14.2 22.9  0.9 -3.3 -0.4 188 0.401 66 0.357 122 0.430 0.471  49 0.766 180 132
## 2 17.2 19.2  0.3 -4.6 -0.6 121 0.403 48 0.375  73 0.424 0.483  32 0.800 125  93
## 3  9.0 17.3  5.4  1.8  1.8 274 0.473 42 0.296 232 0.531 0.509 129 0.668 128 153
## 4  8.5 20.1  3.7 -0.7  0.8 393 0.454 77 0.288 316 0.528 0.499 156 0.719 150 172
## 5 18.7 17.7 -0.5 -6.1 -0.5  53 0.366  9 0.281  44 0.389 0.397  17 0.654  29  77
## 6 16.4 17.6  0.0 -5.6 -0.1  17 0.405  5 0.500  12 0.375 0.464   9 0.450   4  21
##    PTS
## 1  491
## 2  322
## 3  719
## 4 1019
## 5  132
## 6   48
```

```r
head(p_test_relevant_df)
```

```
##                name year   salary Pos Age  Tm GS   MP  PER   TS% TRB% AST% STL%
## 7  al farouq aminu 2016  7680965  SF  25 POR 82 2341 12.7 0.533 11.5  8.8  1.5
## 13   alan anderson 2016  1315448  SG  33 WAS  0  192  9.2 0.495  7.9 10.3  1.0
## 24      alonzo gee 2016  1400000  SF  28 NOP 38 1632  8.4 0.572  8.3  6.2  1.9
## 29  andre drummond 2016 22116750   C  22 DET 81 2666 21.2 0.499 24.5  4.4  2.3
## 32  andre iguodala 2017 14814815  SF  33 GSW  0 1998 14.4 0.624  8.3 16.7  1.8
## 45   anthony davis 2016 22116750   C  22 NOP 61 2164 25.0 0.559 16.1 10.0  1.8
##    BLK% TOV% USG%  WS  BPM VORP  FG   FG%  3P   3P%  2P   2P%  eFG%  FT   FT%
## 7   1.8 13.2 16.9 4.0  0.2  1.3 299 0.416 126 0.361 173 0.468 0.503 115 0.737
## 13  0.4  3.0 15.4 0.3 -2.8  0.0  21 0.356  12 0.324   9 0.409 0.458  11 0.733
## 24  0.7 16.2  9.2 1.9 -0.8  0.5 132 0.518  17 0.283 115 0.590 0.551  44 0.667
## 29  3.2 10.5 24.1 7.4 -0.5  1.0 552 0.521   2 0.333 550 0.522 0.522 208 0.355
## 32  1.5 11.2 11.2 6.9  3.0  2.5 219 0.528  64 0.362 155 0.651 0.605  72 0.706
## 45  4.7  8.4 29.6 7.2  2.2  2.3 560 0.493  35 0.324 525 0.511 0.508 326 0.758
##    AST  PF  PTS
## 7  138 171  839
## 13  14  25   65
## 24  72 169  325
```

```
## 29  67 245 1314
## 32 262  97  574
## 45 116 148 1481
```

```
write.csv(p_train_relevant_df,'../data/train_test/primary/train_relevant.csv',row.names=F)
write.csv(p_test_relevant_df,'../data/train_test/primary/test_relevant.csv',row.names=F)
```

Complete Dataset

```
library(caret)
set.seed(7)
train_rows <- createDataPartition(y=df_final[,'salary'], list=FALSE, p=.8)
c_train_df <- df_final[train_rows,]
c_test_df <- df_final[-train_rows,]
stopifnot(nrow(c_train_df) + nrow(c_test_df) == nrow(df_final))
nrow(c_train_df)
```

```
## [1] 588
```

```
nrow(c_test_df)
```

```
## [1] 145
```

```
names(c_train_df)
```

```
##  [1] "name"   "year"   "salary" "Pos"    "Age"    "Tm"     "G"      "GS"
##  [9] "MP"     "PER"    "TS%"    "3PAr"   "FTr"    "ORB%"   "DRB%"   "TRB%"
## [17] "AST%"   "STL%"   "BLK%"   "TOV%"   "USG%"   "OWS"    "DWS"    "WS"
## [25] "WS/48"  "OBPM"   "DBPM"   "BPM"    "VORP"   "FG"     "FGA"    "FG%"
## [33] "3P"     "3PA"    "3P%"    "2P"     "2PA"    "2P%"    "eFG%"   "FT"
## [41] "FTA"    "FT%"    "ORB"    "DRB"    "TRB"    "AST"    "STL"    "BLK"
## [49] "TOV"    "PF"     "PTS"    "out"    "ovr"    "ins"    "pla"    "ath"
## [57] "def"    "reb"
```

```
head(c_train_df)
```

```
##             name year  salary Pos Age  Tm  G GS   MP  PER   TS%  3PAr   FTr ORB%
## 1  aaron brooks 2016 2700000  PG  31 CHI 69  0 1108 11.8 0.494 0.394 0.136  2.0
## 2  aaron brooks 2017 2116955  PG  32 IND 65  0  894  9.5 0.507 0.427 0.133  2.3
## 3  aaron gordon 2016 4351320  PF  20 ORL 78 37 1863 17.0 0.541 0.245 0.333  9.0
## 4  aaron gordon 2017 5504420  SF  21 ORL 80 72 2298 14.4 0.530 0.309 0.251  5.3
## 5 adreian payne 2016 2022240  PF  24 MIN 52  2  486  5.6 0.422 0.221 0.179  4.8
## 6    aj hammons 2017 1312611   C  24 DAL 22  0  163  8.4 0.472 0.238 0.476  5.4
##   DRB% TRB% AST% STL% BLK% TOV% USG%  OWS DWS   WS  WS/48 OBPM DBPM  BPM VORP
## 1  7.5  4.8 26.0  1.4  0.7 14.2 22.9  0.2 0.7  0.9  0.040 -0.5 -2.8 -3.3 -0.4
## 2  6.3  4.3 20.7  1.4  0.9 17.2 19.2 -0.2 0.5  0.3  0.016 -2.1 -2.6 -4.6 -0.6
## 3 21.3 15.1 10.3  1.6  2.4  9.0 17.3  3.2 2.2  5.4  0.139  0.6  1.2  1.8  1.8
## 4 14.1  9.6 10.5  1.4  1.4  8.5 20.1  2.0 1.7  3.7  0.076 -0.2 -0.4 -0.7  0.8
## 5 21.5 13.3  8.9  1.7  1.8 18.7 17.7 -0.9 0.4 -0.5 -0.047 -5.9 -0.2 -6.1 -0.5
## 6 20.9 12.8  3.8  0.3  7.2 16.4 17.6 -0.2 0.2  0.0 -0.001 -7.5  1.9 -5.6 -0.1
##    FG FGA   FG% 3P 3PA   3P%  2P 2PA   2P%  eFG%  FT FTA   FT% ORB DRB TRB AST
## 1 188 469 0.401 66 185 0.357 122 284 0.430 0.471  49  64 0.766  21  80 101 180
## 2 121 300 0.403 48 128 0.375  73 172 0.424 0.483  32  40 0.800  18  51  69 125
## 3 274 579 0.473 42 142 0.296 232 437 0.531 0.509 129 193 0.668 154 353 507 128
## 4 393 865 0.454 77 267 0.288 316 598 0.528 0.499 156 217 0.719 116 289 405 150
## 5  53 145 0.366  9  32 0.281  44 113 0.389 0.397  17  26 0.654  20  91 111  29
## 6  17  42 0.405  5  10 0.500  12  32 0.375 0.464   9  20 0.450   8  28  36   4
##   STL BLK TOV  PF  PTS out ovr ins pla ath def reb
## 1  30  10  82 132  491  79  75  52  74  77  52  36
## 2  25   9  66  93  322  87  85  51  81  82  57  37
## 3  59  55  66 153  719  87  90  91  69  86  69  87
## 4  64  40  89 172 1019  86  92  91  49  86  75  94
## 5  16  11  36  77  132  56  69  65  43  66  64  68
## 6   1  13  10  21   48  47  66  64  40  58  57  71
```

```r
write.csv(c_train_df,'../data/train_test/complete/train.csv',row.names=F)
write.csv(c_test_df,'../data/train_test/complete/test.csv',row.names=F)

train_rows_relevant <- createDataPartition(y=df_final_relevant[,'salary'], list=FALSE, p=.8)
c_train_relevant_df <- df_final_relevant[train_rows,]
c_test_relevant_df <- df_final_relevant[-train_rows,]
stopifnot(nrow(c_train_relevant_df) + nrow(c_test_relevant_df) == nrow(df_final_relevant))
head(c_train_relevant_df)
```

```
##            name year  salary Pos Age  Tm GS   MP  PER   TS% TRB% AST% STL% BLK%
## 1  aaron brooks 2016 2700000  PG  31 CHI  0 1108 11.8 0.494  4.8 26.0  1.4  0.7
## 2  aaron brooks 2017 2116955  PG  32 IND  0  894  9.5 0.507  4.3 20.7  1.4  0.9
## 3  aaron gordon 2016 4351320  PF  20 ORL 37 1863 17.0 0.541 15.1 10.3  1.6  2.4
## 4  aaron gordon 2017 5504420  SF  21 ORL 72 2298 14.4 0.530  9.6 10.5  1.4  1.4
## 5 adreian payne 2016 2022240  PF  24 MIN  2  486  5.6 0.422 13.3  8.9  1.7  1.8
## 6    aj hammons 2017 1312611   C  24 DAL  0  163  8.4 0.472 12.8  3.8  0.3  7.2
##   TOV% USG%   WS  BPM VORP  FG   FG% 3P   3P%  2P   2P%  eFG%  FT   FT% AST  PF
## 1 14.2 22.9  0.9 -3.3 -0.4 188 0.401 66 0.357 122 0.430 0.471  49 0.766 180 132
## 2 17.2 19.2  0.3 -4.6 -0.6 121 0.403 48 0.375  73 0.424 0.483  32 0.800 125  93
## 3  9.0 17.3  5.4  1.8  1.8 274 0.473 42 0.296 232 0.531 0.509 129 0.668 128 153
## 4  8.5 20.1  3.7 -0.7  0.8 393 0.454 77 0.288 316 0.528 0.499 156 0.719 150 172
## 5 18.7 17.7 -0.5 -6.1 -0.5  53 0.366  9 0.281  44 0.389 0.397  17 0.654  29  77
## 6 16.4 17.6  0.0 -5.6 -0.1  17 0.405  5 0.500  12 0.375 0.464   9 0.450   4  21
##    PTS out ovr ins pla ath def reb
## 1  491  79  75  52  74  77  52  36
## 2  322  87  85  51  81  82  57  37
## 3  719  87  90  91  69  86  69  87
## 4 1019  86  92  91  49  86  75  94
## 5  132  56  69  65  43  66  64  68
## 6   48  47  66  64  40  58  57  71
```

```r
head(c_test_relevant_df)
```

```
##                name year   salary Pos Age  Tm GS   MP  PER   TS% TRB% AST% STL%
## 7   al farouq aminu 2016  7680965  SF  25 POR 82 2341 12.7 0.533 11.5  8.8  1.5
## 13    alan anderson 2016  1315448  SG  33 WAS  0  192  9.2 0.495  7.9 10.3  1.0
## 24       alonzo gee 2016  1400000  SF  28 NOP 38 1632  8.4 0.572  8.3  6.2  1.9
## 29   andre drummond 2016 22116750   C  22 DET 81 2666 21.2 0.499 24.5  4.4  2.3
## 32   andre iguodala 2017 14814815  SF  33 GSW  0 1998 14.4 0.624  8.3 16.7  1.8
## 45    anthony davis 2016 22116750   C  22 NOP 61 2164 25.0 0.559 16.1 10.0  1.8
##    BLK% TOV% USG%  WS  BPM VORP  FG   FG%  3P   3P%  2P   2P%  eFG%  FT   FT%
## 7   1.8 13.2 16.9 4.0  0.2  1.3 299 0.416 126 0.361 173 0.468 0.503 115 0.737
## 13  0.4  3.0 15.4 0.3 -2.8  0.0  21 0.356  12 0.324   9 0.409 0.458  11 0.733
## 24  0.7 16.2  9.2 1.9 -0.8  0.5 132 0.518  17 0.283 115 0.590 0.551  44 0.667
## 29  3.2 10.5 24.1 7.4 -0.5  1.0 552 0.521   2 0.333 550 0.522 0.522 208 0.355
## 32  1.5 11.2 11.2 6.9  3.0  2.5 219 0.528  64 0.362 155 0.651 0.605  72 0.706
## 45  4.7  8.4 29.6 7.2  2.2  2.3 560 0.493  35 0.324 525 0.511 0.508 326 0.758
##    AST  PF  PTS out ovr ins pla ath def reb
## 7  138 171  839  90  91  77  60  81  76  94
## 13  14  25   65  73  69  57  49  71  60  42
## 24  72 169  325  65  70  61  50  76  63  46
## 29  67 245 1314  47  86  81  42  77  73  97
## 32 262  97  574  81  91  79  89  87  90  45
## 45 116 148 1481  91  97  89  64  87  87  98
```

```r
write.csv(c_train_relevant_df,'../data/train_test/complete/train_relevant.csv',row.names=F)
write.csv(c_test_relevant_df,'../data/train_test/complete/test_relevant.csv',row.names=F)
```

Helper Functions

```r
get_salary_formula <- function(x_vars){
  return(as.formula(sprintf('salary ~ `%s`',paste(x_vars,collapse='` + `'))))}
```

Primary Dataset Variable Selection Using Automated F-Test-Based Backward Selection

```r
library(rms)
p_x_vars <- names(p_train_relevant_df)[!(names(p_train_relevant_df))%in%c('salary','name','2P','PTS')]
# 2P, 2PA, PTS, and TRB were causing singularity in predictor matrix, so they were dropped
p_formula <- get_salary_formula(p_x_vars)
p_formula
```

```
## salary ~ year + Pos + Age + Tm + GS + MP + PER + `TS%` + `TRB%` +
##     `AST%` + `STL%` + `BLK%` + `TOV%` + `USG%` + WS + BPM + VORP +
##     FG + `FG%` + `3P` + `3P%` + `2P%` + `eFG%` + FT + `FT%` +
##     AST + PF
## <environment: 0x557f642f8db8>
```

```r
p_selection_model <- ols(p_formula, data = p_train_relevant_df)
p_selection_model
```

```
## Linear Regression Model
##
##  ols(formula = p_formula, data = p_train_relevant_df)
##
##                      Model Likelihood     Discrimination
##                         Ratio Test           Indexes
##  Obs            588    LR chi2    611.37    R2       0.646
##  sigma4596847.8837    d.f.            59    R2 adj   0.607
##  d.f.           528    Pr(> chi2) 0.0000    g  6402520.583
##
##  Residuals
##
##        Min        1Q    Median        3Q       Max
##  -13700680  -2839583   -118251   2432935  16150653
##
##
##            Coef          S.E.          t     Pr(>|t|)
##  Intercept   1553909.3793  5487540.3109  0.28 0.7772
##  year=2017   1396393.5240   410654.1299  3.40 0.0007
##  Pos=PF      -202092.5519   747694.9011 -0.27 0.7870
##  Pos=PG     -3292889.8860  1274714.2015 -2.58 0.0101
##  Pos=SF      -787449.7161   996472.5655 -0.79 0.4297
##  Pos=SG     -1667019.3745  1109742.2133 -1.50 0.1337
##  Age          228455.3982    52049.9531  4.39 <0.0001
##  Tm=BOS     -2785931.6466  1728002.0114 -1.61 0.1075
##  Tm=BRK     -3486926.0974  1861094.6892 -1.87 0.0615
##  Tm=CHI     -3432180.3405  1701529.4924 -2.02 0.0442
##  Tm=CHO     -2296047.1673  1755368.1972 -1.31 0.1914
##  Tm=CLE      -269514.0025  1773216.8239 -0.15 0.8793
##  Tm=DAL     -3544609.1832  1823155.7160 -1.94 0.0524
##  Tm=DEN     -5724530.8187  1803188.8342 -3.17 0.0016
##  Tm=DET     -3034455.8277  1759690.2742 -1.72 0.0852
##  Tm=GSW     -3038617.9359  1723530.0875 -1.76 0.0785
##  Tm=HOU     -4310794.4377  1787829.5830 -2.41 0.0162
##  Tm=IND     -2861199.3161  1773768.9052 -1.61 0.1073
##  Tm=LAC     -1112210.6476  1714078.2922 -0.65 0.5167
##  Tm=LAL     -2619114.2524  1901871.7607 -1.38 0.1691
##  Tm=MEM     -1198674.8873  1713918.4356 -0.70 0.4846
##  Tm=MIA     -2265976.3922  1824684.7594 -1.24 0.2148
##  Tm=MIL     -1506577.8752  1830047.4931 -0.82 0.4107
##  Tm=MIN     -4413367.8770  1758662.1429 -2.51 0.0124
##  Tm=NOP      -543968.6628  1809940.5978 -0.30 0.7639
##  Tm=NYK     -3869428.0379  1739634.9390 -2.22 0.0266
##  Tm=OKC     -1536298.1613  1773700.4062 -0.87 0.3868
##  Tm=ORL     -2344680.9015  1764761.8299 -1.33 0.1846
##  Tm=PHI     -4180411.0786  1834550.6960 -2.28 0.0231
##  Tm=PHO     -1962454.0170  1729161.0671 -1.13 0.2569
```

```
##   Tm=POR      -901135.7685  1786072.3010 -0.50 0.6141
##   Tm=SAC     -2519878.2277  1820260.8287 -1.38 0.1668
##   Tm=SAS     -4502772.1861  1765011.7078 -2.55 0.0110
##   Tm=TOR     -1706921.1054  1664347.5002 -1.03 0.3056
##   Tm=TOT     -4009263.3457  1517228.0922 -2.64 0.0085
##   Tm=UTA     -2913684.6345  1710244.0288 -1.70 0.0890
##   Tm=WAS      -824536.3771  1833293.5143 -0.45 0.6531
##   GS           39308.3338    11806.9938  3.33 0.0009
##   MP            2064.9760     1229.7283  1.68 0.0937
##   PER         126764.2182   244045.7934  0.52 0.6037
##   TS%       -24140528.8730 19763737.5697 -1.22 0.2225
##   TRB%        -29773.9229   127930.1738 -0.23 0.8161
##   AST%         68316.3597    96508.0542  0.71 0.4793
##   STL%       -360976.0005   376028.1501 -0.96 0.3375
##   BLK%       -265298.4560   224013.2607 -1.18 0.2368
##   TOV%        143716.7979    95378.5587  1.51 0.1325
##   USG%        159027.7466   127640.1549  1.25 0.2134
##   WS         1302637.7917   335318.9879  3.88 0.0001
##   BPM         199060.6721   230806.7374  0.86 0.3888
##   VORP       -805540.9322   546414.6389 -1.47 0.1410
##   FG           -4424.3274     6111.8509 -0.72 0.4695
##   FG%       18670714.2339 12580853.5108  1.48 0.1384
##   3P           15955.3209     8166.2767  1.95 0.0513
##   3P%        1279080.8965  2175294.4764  0.59 0.5568
##   2P%       -4892750.5433  5316650.5216 -0.92 0.3579
##   eFG%       -474083.8835 17197941.6970 -0.03 0.9780
##   FT            6098.7192     5459.5719  1.12 0.2645
##   FT%        -823725.5012  2683898.3634 -0.31 0.7590
##   AST          -1619.3377     5027.6268 -0.32 0.7475
##   PF          -27671.9031     7966.2727 -3.47 0.0006
##
```

```r
p_seleced <- fastbw(p_selection_model, rule = "p", sls = 0.1)
p_seleced
```

```
##
##   Deleted Chi-Sq d.f. P      Residual d.f. P      AIC    R2
##   eFG%    0.00   1    0.9780  0.00     1   0.9780  -2.00 0.646
##   TRB%    0.05   1    0.8156  0.06     2   0.9728  -3.94 0.646
##   FT%     0.10   1    0.7513  0.16     3   0.9844  -5.84 0.646
##   AST     0.10   1    0.7495  0.26     4   0.9924  -7.74 0.646
##   PER     0.20   1    0.6539  0.46     5   0.9936  -9.54 0.646
##   3P%     0.41   1    0.5241  0.86     6   0.9902 -11.14 0.646
##   FG      0.52   1    0.4716  1.38     7   0.9861 -12.62 0.646
##   STL%    0.89   1    0.3466  2.27     8   0.9717 -13.73 0.645
##   BLK%    0.72   1    0.3967  2.99     9   0.9648 -15.01 0.644
##   BPM     1.31   1    0.2532  4.29    10   0.9332 -15.71 0.644
##   TOV%    1.27   1    0.2590  5.57    11   0.9007 -16.43 0.643
##   2P%     1.59   1    0.2073  7.16    12   0.8471 -16.84 0.642
##   MP      2.10   1    0.1469  9.26    13   0.7530 -16.74 0.640
##   USG%    1.89   1    0.1697 11.15    14   0.6746 -16.85 0.639
##
## Approximate Estimates after Deleting Factors
##
##                  Coef    S.E.    Wald Z         P
## Intercept     456240 2758634  0.165386 8.686e-01
## year=2017    1148156  388402  2.956106 3.115e-03
## Pos=PF        -11982  655951 -0.018267 9.854e-01
## Pos=PG      -3909901 1005868 -3.887090 1.015e-04
## Pos=SF       -822935  748241 -1.099826 2.714e-01
## Pos=SG      -1676955  835061 -2.008182 4.462e-02
## Age           223020   49448  4.510194 6.477e-06
## Tm=BOS      -2740006 1714345 -1.598281 1.100e-01
## Tm=BRK      -3114659 1832586 -1.699598 8.921e-02
```

```
## Tm=CHI      -2969940 1676308 -1.771715 7.644e-02
## Tm=CHO      -2055523 1730507 -1.187816 2.349e-01
## Tm=CLE         10815 1752056  0.006173 9.951e-01
## Tm=DAL      -3271557 1805859 -1.811635 7.004e-02
## Tm=DEN      -5341317 1777449 -3.005047 2.655e-03
## Tm=DET      -2467550 1711062 -1.442116 1.493e-01
## Tm=GSW      -2802620 1675123 -1.673083 9.431e-02
## Tm=HOU      -4610332 1756599 -2.624579 8.676e-03
## Tm=IND      -2574200 1749950 -1.471014 1.413e-01
## Tm=LAC       -908521 1698406 -0.534925 5.927e-01
## Tm=LAL      -2580728 1845602 -1.398312 1.620e-01
## Tm=MEM       -904715 1684780 -0.536993 5.913e-01
## Tm=MIA      -1866583 1799064 -1.037530 2.995e-01
## Tm=MIL      -1400747 1806075 -0.775575 4.380e-01
## Tm=MIN      -4619876 1719838 -2.686228 7.226e-03
## Tm=NOP       -539496 1775019 -0.303938 7.612e-01
## Tm=NYK      -3342984 1707081 -1.958305 5.019e-02
## Tm=OKC      -1310920 1721128 -0.761664 4.463e-01
## Tm=ORL      -2180258 1736059 -1.255867 2.092e-01
## Tm=PHI      -3635593 1799022 -2.020872 4.329e-02
## Tm=PHO      -1899465 1688962 -1.124635 2.607e-01
## Tm=POR       -629952 1749315 -0.360114 7.188e-01
## Tm=SAC      -2618708 1804384 -1.451302 1.467e-01
## Tm=SAS      -3666757 1711710 -2.142160 3.218e-02
## Tm=TOR      -1246616 1637512 -0.761286 4.465e-01
## Tm=TOT      -3752179 1493017 -2.513153 1.197e-02
## Tm=UTA      -2085085 1669685 -1.248789 2.117e-01
## Tm=WAS       -706936 1816507 -0.389173 6.971e-01
## GS             47059   10642  4.422134 9.773e-06
## TS%        -20082937 8093218 -2.481453 1.308e-02
## AST%          176331   39929  4.416133 1.005e-05
## WS           1422260  243711  5.835842 5.352e-09
## VORP        -1079988  374926 -2.880538 3.970e-03
## FG%         17131465 7566993  2.263973 2.358e-02
## 3P             22732    6296  3.610792 3.053e-04
## FT             11611    3549  3.271312 1.070e-03
## PF            -19874    4847 -4.100289 4.126e-05
##
## Factors in Final Model
##
##  [1] year Pos  Age  Tm   GS   TS%  AST% WS   VORP FG%  3P   FT   PF
```

Checking for Multicollinearity Among Optimal Subset of Primary Variables.

```r
p_subset_formula <- get_salary_formula(p_seleced[['names.kept']])
p_subset_formula
```

```
## salary ~ year + Pos + Age + Tm + GS + `TS%` + `AST%` + WS + VORP +
##     `FG%` + `3P` + FT + PF
## <environment: 0x557f687ee8c8>
```

```r
p_subset_lm <- lm(p_subset_formula , data=p_train_relevant_df)
summary(p_subset_lm)
```

```
##
## Call:
## lm(formula = p_subset_formula, data = p_train_relevant_df)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -14236239  -2846907   -194149   2554876  15549671
##
## Coefficients:
```

```
##                Estimate Std. Error t value Pr(>|t|)    
## (Intercept)     456240    2751361   0.166 0.868358    
## year2017       1148156     387378   2.964 0.003171 ** 
## PosPF           -11982     654222  -0.018 0.985394    
## PosPG         -3909901    1003216  -3.897 0.000109 ***
## PosSF          -822935     746268  -1.103 0.270632    
## PosSG         -1676955     832860  -2.013 0.044557 *  
## Age             223020      49318   4.522 7.53e-06 ***
## TmBOS         -2740006    1709825  -1.603 0.109626    
## TmBRK         -3114659    1827754  -1.704 0.088937 .  
## TmCHI         -2969940    1671888  -1.776 0.076228 .  
## TmCHO         -2055523    1725944  -1.191 0.234192    
## TmCLE            10815    1747437   0.006 0.995064    
## TmDAL         -3271557    1801097  -1.816 0.069858 .  
## TmDEN         -5341317    1772762  -3.013 0.002708 ** 
## TmDET         -2467550    1706550  -1.446 0.148775    
## TmGSW         -2802620    1670706  -1.678 0.094020 .  
## TmHOU         -4610332    1751967  -2.632 0.008743 ** 
## TmIND         -2574200    1745336  -1.475 0.140819    
## TmLAC          -908520    1693928  -0.536 0.591944    
## TmLAL         -2580728    1840736  -1.402 0.161485    
## TmMEM          -904715    1680338  -0.538 0.590513    
## TmMIA         -1866583    1794321  -1.040 0.298677    
## TmMIL         -1400746    1801313  -0.778 0.437129    
## TmMIN         -4619876    1715303  -2.693 0.007293 ** 
## TmNOP          -539496    1770339  -0.305 0.760680    
## TmNYK         -3342984    1702580  -1.963 0.050101 .  
## TmOKC         -1310920    1716590  -0.764 0.445392    
## TmORL         -2180258    1731481  -1.259 0.208505    
## TmPHI         -3635593    1794279  -2.026 0.043232 *  
## TmPHO         -1899465    1684509  -1.128 0.259985    
## TmPOR          -629952    1744703  -0.361 0.718191    
## TmSAC         -2618708    1799627  -1.455 0.146210    
## TmSAS         -3666757    1707197  -2.148 0.032170 *  
## TmTOR         -1246616    1633195  -0.763 0.445617    
## TmTOT         -3752179    1489080  -2.520 0.012029 *  
## TmUTA         -2085085    1665283  -1.252 0.211077    
## TmWAS          -706936    1811718  -0.390 0.696541    
## GS               47059      10614   4.434 1.12e-05 ***
## `TS%`        -20082937    8071879  -2.488 0.013145 *  
## `AST%`          176331      39824   4.428 1.15e-05 ***
## WS             1422260     243069   5.851 8.45e-09 ***
## VORP          -1079988     373937  -2.888 0.004030 ** 
## `FG%`         17131465    7547042   2.270 0.023602 *  
## `3P`             22732       6279   3.620 0.000322 ***
## FT               11612       3540   3.280 0.001105 ** 
## PF              -19874       4834  -4.111 4.55e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 
## Residual standard error: 4585000 on 542 degrees of freedom
## Multiple R-squared:  0.639,  Adjusted R-squared:  0.609 
## F-statistic: 21.32 on 45 and 542 DF,  p-value: < 2.2e-16
```

```r
sort(vif(p_subset_lm),decreasing=T) # All variables have low VIF values. So no multicollinearity.
```

```
##        WS     `FG%`      VORP     `TS%`     TmTOT     PosPG        FT    `AST%` 
## 14.914773  9.299794  8.728394  7.144946  5.086995  4.190961  4.167082  3.650485 
##      `3P`     PosSG     TmTOR        GS     TmPHO     TmGSW     TmUTA     TmMEM 
##  3.456991  3.092757  3.037526  2.863495  2.858784  2.812127  2.793899  2.720141 
##     TmCHI     TmSAS     TmLAC     TmOKC     TmMIN     TmBOS     TmDET     TmNYK 
##  2.692851  2.678805  2.637327  2.577475  2.573613  2.557200  2.547414  2.535575 
##     TmPOR        PF     PosSF     TmORL     TmCHO     TmHOU     TmCLE     TmIND 
##  2.526887  2.499607  2.498992  2.488734  2.472843  2.410641  2.398189  2.392428 
```

```
##      TmPHI      TmDEN      TmNOP      TmMIL      TmDAL      TmSAC      TmMIA      TmLAL
##  2.383919  2.327086  2.320728  2.256420  2.255879  2.252197  2.238935  2.203021
##      TmBRK      TmWAS      PosPF        Age   year2017
##  2.172056  2.134109  1.908324  1.280955  1.049395
```

```
p_vars_final <- p_seleced[['names.kept']]
```

Complete Dataset Variable Selection Using Automated F-Test-Based Backward Selection

```
library(rms)

c_x_vars <- names(c_train_relevant_df)[!(names(c_train_relevant_df)%in%c('salary','name','2P','PTS'))]
# 2P, 2PA, PTS, and TRB were causing singularity in predictor matrix, so they were dropped
c_formula <- get_salary_formula(c_x_vars)
c_formula
```

```
## salary ~ year + Pos + Age + Tm + GS + MP + PER + `TS%` + `TRB%` +
##     `AST%` + `STL%` + `BLK%` + `TOV%` + `USG%` + WS + BPM + VORP +
##     FG + `FG%` + `3P` + `3P%` + `2P%` + `eFG%` + FT + `FT%` +
##     AST + PF + out + ovr + ins + pla + ath + def + reb
## <environment: 0x557f691eff08>
```

```
c_selection_model <- ols(c_formula, data = c_train_relevant_df)
c_selection_model
```

```
## Linear Regression Model
##
##  ols(formula = c_formula, data = c_train_relevant_df)
##
##                      Model Likelihood     Discrimination
##                         Ratio Test           Indexes
##  Obs            588    LR chi2    628.30    R2       0.656
##  sigma4561484.3734    d.f.           66    R2 adj   0.613
##  d.f.           521    Pr(> chi2) 0.0000    g  6461689.853
##
##  Residuals
##
##        Min        1Q    Median        3Q       Max
##  -14615864  -2715524    -58045   2320543  15483115
##
##
##            Coef          S.E.          t     Pr(>|t|)
##  Intercept  -4450716.0365  5998793.1509 -0.74 0.4585
##  year=2017    760705.4915   482461.2858  1.58 0.1155
##  Pos=PF        74539.8571   803155.8480  0.09 0.9261
##  Pos=PG     -3836878.9447  1555010.3953 -2.47 0.0139
##  Pos=SF     -1258327.9963  1109153.8535 -1.13 0.2571
##  Pos=SG     -2229161.2986  1315989.1726 -1.69 0.0909
##  Age          183833.9201    56612.2582  3.25 0.0012
##  Tm=BOS     -2628991.6776  1720351.8481 -1.53 0.1271
##  Tm=BRK     -2736554.4384  1862720.9863 -1.47 0.1424
##  Tm=CHI     -2995521.2555  1697962.6680 -1.76 0.0783
##  Tm=CHO     -1761601.5566  1751683.2846 -1.01 0.3150
##  Tm=CLE      -301085.0774  1768353.6568 -0.17 0.8649
##  Tm=DAL     -2936783.5564  1820380.4139 -1.61 0.1073
##  Tm=DEN     -5271247.2217  1796587.4649 -2.93 0.0035
##  Tm=DET     -2311494.8222  1766632.9505 -1.31 0.1913
##  Tm=GSW     -2929811.2390  1717307.2321 -1.71 0.0886
##  Tm=HOU     -4103929.8613  1780682.0268 -2.30 0.0216
##  Tm=IND     -2489194.9946  1770797.7073 -1.41 0.1604
##  Tm=LAC     -1202650.9418  1709070.2142 -0.70 0.4819
##  Tm=LAL     -2177721.0384  1905133.9114 -1.14 0.2535
##  Tm=MEM     -1037106.6453  1720323.5834 -0.60 0.5469
##  Tm=MIA     -2126510.1423  1820100.3235 -1.17 0.2432
```

```
##   Tm=MIL      -1214985.2485  1828326.4484 -0.66 0.5066
##   Tm=MIN      -4001352.1516  1758474.2533 -2.28 0.0233
##   Tm=NOP         21140.4371  1811950.0683  0.01 0.9907
##   Tm=NYK      -3336784.6326  1736758.5335 -1.92 0.0552
##   Tm=OKC      -1352270.0393  1767269.8076 -0.77 0.4445
##   Tm=ORL      -1799749.2956  1760933.0656 -1.02 0.3072
##   Tm=PHI      -3793899.7880  1826979.5079 -2.08 0.0383
##   Tm=PHO      -1577555.2151  1722415.0409 -0.92 0.3601
##   Tm=POR       -640419.9138  1786764.8593 -0.36 0.7202
##   Tm=SAC      -2169962.3157  1814299.0247 -1.20 0.2322
##   Tm=SAS      -4275397.2442  1772555.1440 -2.41 0.0162
##   Tm=TOR      -1719009.1870  1654753.7609 -1.04 0.2994
##   Tm=TOT      -3792944.0219  1512534.5163 -2.51 0.0125
##   Tm=UTA      -2664225.0325  1712794.5186 -1.56 0.1204
##   Tm=WAS       -374397.8758  1833690.3460 -0.20 0.8383
##   GS            31816.7256     12027.0596  2.65 0.0084
##   MP             1629.4118      1229.3833  1.33 0.1856
##   PER           71614.5033    245458.5622  0.29 0.7706
##   TS%       -17583139.1749 19803751.3763 -0.89 0.3750
##   TRB%         -26736.1539    135755.2647 -0.20 0.8439
##   AST%          48530.1029     98264.9450  0.49 0.6216
##   STL%        -431443.8808    374067.2963 -1.15 0.2493
##   BLK%        -352613.5122    227975.4926 -1.55 0.1225
##   TOV%         128179.6970     95344.5002  1.34 0.1794
##   USG%         182409.1965    130260.4636  1.40 0.1620
##   WS          1321244.6707    340113.5798  3.88 0.0001
##   BPM          260554.8234    232173.0172  1.12 0.2623
##   VORP        -868072.4082    561452.2193 -1.55 0.1227
##   FG            -3206.8276      6231.9083 -0.51 0.6071
##   FG%         8165411.8125 13699749.6412  0.60 0.5514
##   3P            13659.9759      8398.4451  1.63 0.1045
##   3P%         2152269.0839  2204548.1926  0.98 0.3294
##   2P%        -2560480.5425  5425189.0482 -0.47 0.6372
##   eFG%         926144.8007 17351129.5191  0.05 0.9575
##   FT             3901.0355      5466.8639  0.71 0.4758
##   FT%         1017445.9093  2729863.9001  0.37 0.7095
##   AST            -522.4391      5047.8340 -0.10 0.9176
##   PF           -26497.9175      7919.0612 -3.35 0.0009
##   out          -83202.4401     39290.7595 -2.12 0.0347
##   ovr          154156.9747     88178.6903  1.75 0.0810
##   ins           -6198.2512     47693.1011 -0.13 0.8966
##   pla            -784.7456     31215.2598 -0.03 0.9800
##   ath           12953.2418     50208.8708  0.26 0.7965
##   def           41452.8120     38423.5914  1.08 0.2812
##   reb          -40896.7907     26705.1724 -1.53 0.1263
##
```

```r
c_seleced <- fastbw(c_selection_model, rule = "p", sls = 0.1)
c_seleced
```

```
##
##   Deleted Chi-Sq d.f. P      Residual d.f. P      AIC    R2
##   pla      0.00   1   0.9799  0.00     1   0.9799  -2.00 0.656
##   eFG%     0.00   1   0.9573  0.00     2   0.9983  -4.00 0.656
##   AST      0.01   1   0.9182  0.01     3   0.9996  -5.99 0.656
##   ins      0.02   1   0.9000  0.03     4   0.9999  -7.97 0.656
##   TRB%     0.04   1   0.8493  0.07     5   0.9999  -9.93 0.656
##   PER      0.05   1   0.8302  0.11     6   1.0000 -11.89 0.656
##   ath      0.05   1   0.8170  0.17     7   1.0000 -13.83 0.656
##   FT%      0.16   1   0.6873  0.33     8   1.0000 -15.67 0.656
##   FG       0.17   1   0.6808  0.50     9   1.0000 -17.50 0.656
##   2P%      0.20   1   0.6520  0.70    10   1.0000 -19.30 0.656
##   FG%      0.07   1   0.7869  0.77    11   1.0000 -21.23 0.656
##   FT       0.54   1   0.4619  1.31    12   0.9999 -22.69 0.656
```

```
##  AST%      0.90   1   0.3429  2.21    13   0.9996 -23.79 0.655
##  3P%       1.11   1   0.2920  3.32    14   0.9983 -24.68 0.654
##  def       1.23   1   0.2676  4.55    15   0.9953 -25.45 0.653
##  year      2.25   1   0.1334  6.81    16   0.9768 -25.19 0.652
##  VORP      2.06   1   0.1513  8.86    17   0.9444 -25.14 0.651
##  STL%      2.43   1   0.1194 11.29    18   0.8816 -24.71 0.649
##  TS%       1.82   1   0.1767 13.11    19   0.8326 -24.89 0.648
##  BPM       1.21   1   0.2715 14.32    20   0.8137 -25.68 0.647
##  BLK%      1.51   1   0.2195 15.83    21   0.7790 -26.17 0.646
##  TOV%      3.20   1   0.0737 19.03    22   0.6435 -24.97 0.644
##  Pos       7.05   4   0.1331 26.08    26   0.4585 -25.92 0.639
##  reb       0.17   1   0.6817 26.25    27   0.5047 -27.75 0.639
##  Tm       40.84  30   0.0895 67.09    57   0.1694 -46.91 0.612
##  3P        3.79   1   0.0516 70.88    58   0.1193 -45.12 0.610
##
## Approximate Estimates after Deleting Factors
##
##                Coef      S.E. Wald Z         P
## Intercept -15775543 2146247.3 -7.350 1.977e-13
## Age          238362   46224.8  5.157 2.515e-07
## GS            29122   11158.4  2.610 9.057e-03
## MP             2578     668.5  3.857 1.150e-04
## USG%         206060   45994.2  4.480 7.460e-06
## WS           985550  109877.2  8.970 0.000e+00
## PF           -27716    6030.8 -4.596 4.313e-06
## out          -78216   19627.0 -3.985 6.745e-05
## ovr          184278   33719.4  5.465 4.628e-08
##
## Factors in Final Model
##
## [1] Age  GS   MP   USG% WS   PF   out  ovr
```

Checking for Multicollinearity Among Optimal Subset of Complete Variables.

```
c_subset_formula <- get_salary_formula(c_seleced[['names.kept']])
c_subset_formula
```

```
## salary ~ Age + GS + MP + `USG%` + WS + PF + out + ovr
## <environment: 0x557f62632bc8>
```

```
c_subset_lm <- lm(c_subset_formula , data=c_train_relevant_df)
summary(c_subset_lm)
```

```
##
## Call:
## lm(formula = c_subset_formula, data = c_train_relevant_df)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -15368141  -2923935   -261742   2216792  17647516
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept) -1.578e+07  2.170e+06  -7.270 1.17e-12 ***
## Age          2.384e+05  4.674e+04   5.100 4.61e-07 ***
## GS           2.912e+04  1.128e+04   2.581 0.010087 *
## MP           2.578e+03  6.759e+02   3.814 0.000151 ***
## `USG%`       2.061e+05  4.650e+04   4.431 1.12e-05 ***
## WS           9.856e+05  1.111e+05   8.871  < 2e-16 ***
## PF          -2.772e+04  6.098e+03  -4.545 6.68e-06 ***
## out         -7.822e+04  1.984e+04  -3.941 9.09e-05 ***
## ovr          1.843e+05  3.409e+04   5.405 9.47e-08 ***
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4612000 on 579 degrees of freedom
## Multiple R-squared:  0.6098, Adjusted R-squared:  0.6044
## F-statistic: 113.1 on 8 and 579 DF,  p-value: < 2.2e-16
```

```r
sort(vif(c_subset_lm),decreasing=T) # All variables have low VIF values. So no multicollinearity.
```

```
##       MP       PF       GS       WS      ovr      out   `USG%`      Age
## 7.984500 3.929993 3.197309 3.078852 2.832498 2.563631 1.613312 1.136827
```

```r
c_seleced[['names.kept']] <- c_seleced[['names.kept']][!(c_seleced[['names.kept']]%in%c("FGA"))]
c_subset_formula <- get_salary_formula(c_seleced[['names.kept']])
c_subset_formula
```

```
## salary ~ Age + GS + MP + `USG%` + WS + PF + out + ovr
## <environment: 0x557f600fde18>
```

```r
c_subset_lm <- lm(c_subset_formula , data=c_train_relevant_df)
summary(c_subset_lm)
```

```
##
## Call:
## lm(formula = c_subset_formula, data = c_train_relevant_df)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -15368141  -2923935   -261742   2216792  17647516
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept) -1.578e+07  2.170e+06  -7.270 1.17e-12 ***
## Age          2.384e+05  4.674e+04   5.100 4.61e-07 ***
## GS           2.912e+04  1.128e+04   2.581 0.010087 *
## MP           2.578e+03  6.759e+02   3.814 0.000151 ***
## `USG%`       2.061e+05  4.650e+04   4.431 1.12e-05 ***
## WS           9.856e+05  1.111e+05   8.871  < 2e-16 ***
## PF          -2.772e+04  6.098e+03  -4.545 6.68e-06 ***
## out         -7.822e+04  1.984e+04  -3.941 9.09e-05 ***
## ovr          1.843e+05  3.409e+04   5.405 9.47e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4612000 on 579 degrees of freedom
## Multiple R-squared:  0.6098, Adjusted R-squared:  0.6044
## F-statistic: 113.1 on 8 and 579 DF,  p-value: < 2.2e-16
```

```r
sort(vif(c_subset_lm),decreasing=T)
```

```
##       MP       PF       GS       WS      ovr      out   `USG%`      Age
## 7.984500 3.929993 3.197309 3.078852 2.832498 2.563631 1.613312 1.136827
```

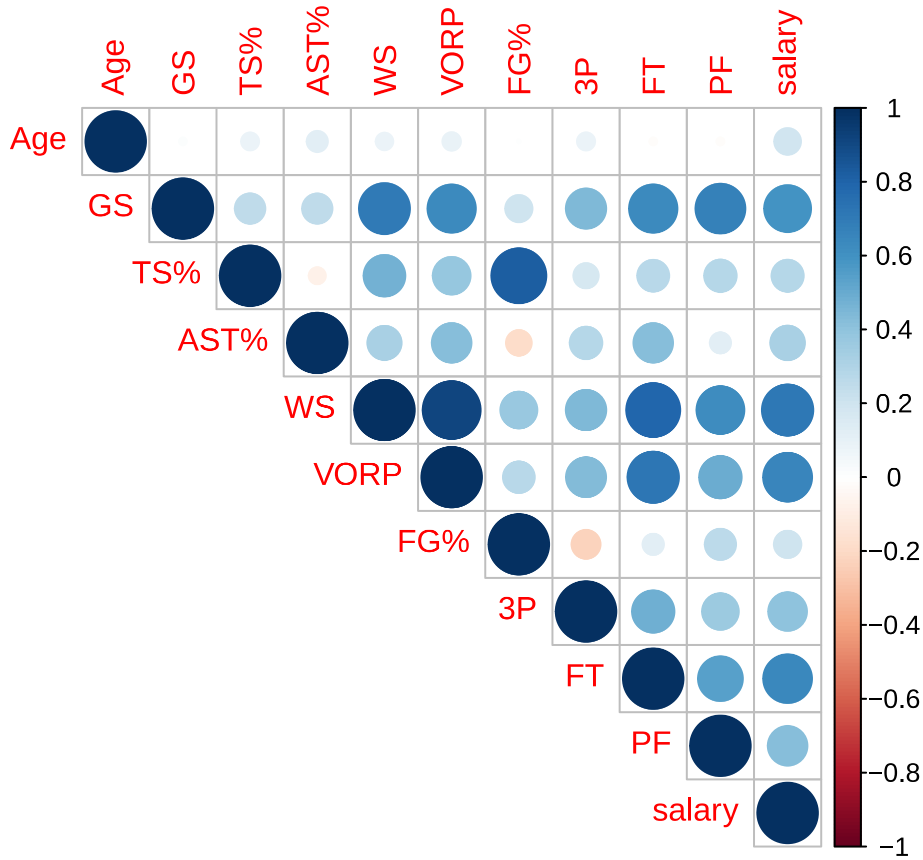
```r
c_vars_final <- c_seleced[['names.kept']]

pred <- predict(c_subset_lm, c_test_relevant_df)
SST8 <- sum((c_test_relevant_df$salary - mean(c_test_relevant_df$salary))^2)
SSR8 <- sum((pred - mean(c_test_relevant_df$salary))^2)
Rsqm8<-SSR8/SST8
Rsqm8
```

```
## [1] 0.6111508
```

Correlation plots for relevant variables for complete and primary dataset

```r
v <- c(p_vars_final,"salary")
corr_matrix_c <- cor(Filter(is.numeric,p_train_df[v]),method = "pearson")
```

```r
library(corrplot)
corrplot(corr_matrix_c,type = "upper")
```




```r
dev.copy(png,"../figures/Correlation_selected_variables_primary.png")
```

```
## png
##   4
```

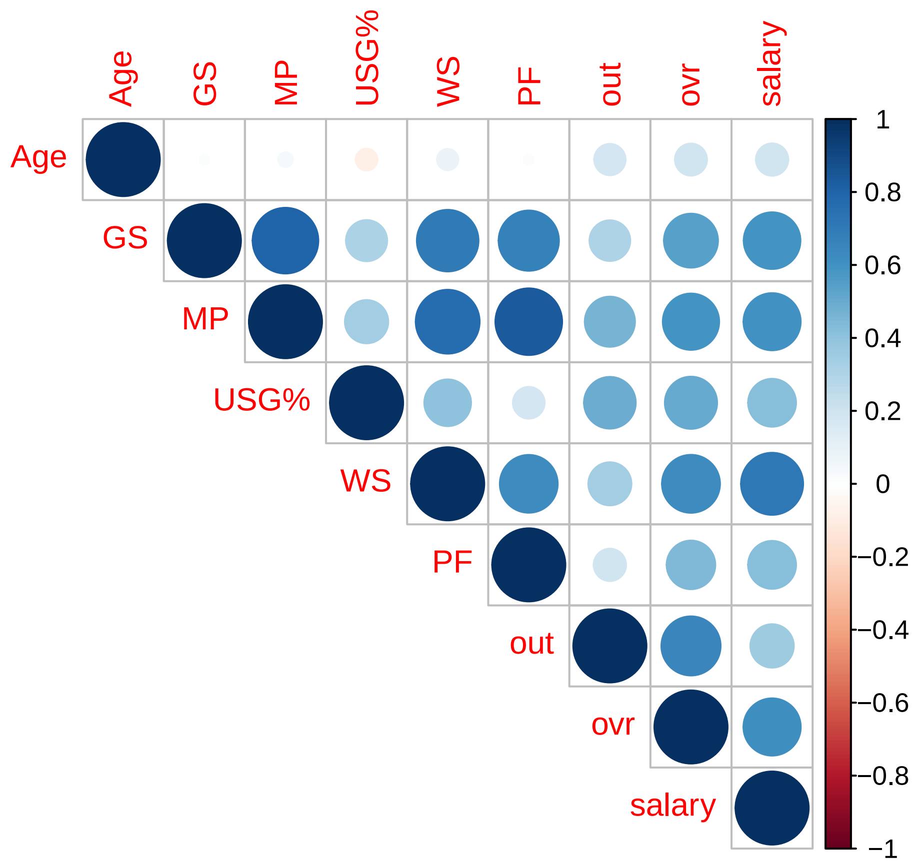
```r
dev.off()
```

```
## pdf
##   2
```

```r
v <- c(c_vars_final,"salary")
corr_matrix_c <- cor(Filter(is.numeric,c_train_df[v]),method = "pearson")
correlation_salary_c <- sort(corr_matrix_c[,'salary'],decreasing = TRUE)
correlation_salary_c
```

```
##    salary        WS       ovr        MP        GS        PF      USG%       out
## 1.0000000 0.7191658 0.6118097 0.6094748 0.5994794 0.4286004 0.4278609 0.3512832
##       Age
## 0.1951513
```

```r
library(corrplot)
corrplot(corr_matrix_c,type = "upper")
```




```
dev.copy(png,"../figures/Correlation_selected_variables_complete.png")
```

```
## png
##   4
```

```
dev.off()
```

```
## pdf
##   2
```

Subset Primary and Complete Dataframes to Include Only Name, Salary, and Selected Variables

```
p_vars_subset <- c('name','salary',p_vars_final)
df_p_subset_final <- df_p_final[,p_vars_subset]

c_vars_subset <- c('name','salary',c_vars_final)
df_c_subset_final <- df_final[,c_vars_subset]

train_rows_relevant <- createDataPartition(y=df_p_subset_final[,'salary'], list=FALSE, p=.8)
p_train_selected_df <- df_p_subset_final[train_rows,]
p_test_selected_df <- df_p_subset_final[-train_rows,]
stopifnot(nrow(p_train_selected_df) + nrow(p_test_selected_df) == nrow(df_p_subset_final))
head(p_train_selected_df)
```

```
##             name  salary year Pos Age  Tm GS   TS% AST%   WS VORP   FG% 3P  FT
## 1  aaron brooks 2700000 2016  PG  31 CHI  0 0.494 26.0  0.9 -0.4 0.401 66  49
## 2  aaron brooks 2116955 2017  PG  32 IND  0 0.507 20.7  0.3 -0.6 0.403 48  32
## 3  aaron gordon 4351320 2016  PF  20 ORL 37 0.541 10.3  5.4  1.8 0.473 42 129
## 4  aaron gordon 5504420 2017  SF  21 ORL 72 0.530 10.5  3.7  0.8 0.454 77 156
## 5 adreian payne 2022240 2016  PF  24 MIN  2 0.422  8.9 -0.5 -0.5 0.366  9  17
## 6    aj hammons 1312611 2017   C  24 DAL  0 0.472  3.8  0.0 -0.1 0.405  5   9
##    PF
## 1 132
## 2  93
## 3 153
## 4 172
```

```
## 5  77
## 6  21
```

```r
head(p_test_selected_df)
```

```
##                name   salary year Pos Age  Tm GS   TS% AST%  WS VORP   FG%  3P
## 7  al farouq aminu  7680965 2016  SF  25 POR 82 0.533  8.8 4.0  1.3 0.416 126
## 13   alan anderson  1315448 2016  SG  33 WAS  0 0.495 10.3 0.3  0.0 0.356  12
## 24      alonzo gee  1400000 2016  SF  28 NOP 38 0.572  6.2 1.9  0.5 0.518  17
## 29  andre drummond 22116750 2016   C  22 DET 81 0.499  4.4 7.4  1.0 0.521   2
## 32  andre iguodala 14814815 2017  SF  33 GSW  0 0.624 16.7 6.9  2.5 0.528  64
## 45   anthony davis 22116750 2016   C  22 NOP 61 0.559 10.0 7.2  2.3 0.493  35
##     FT  PF
## 7  115 171
## 13  11  25
## 24  44 169
## 29 208 245
## 32  72  97
## 45 326 148
```

```r
write.csv(p_train_selected_df,'../data/train_test/primary/train_selected.csv',row.names=F)
write.csv(p_test_selected_df,'../data/train_test/primary/test_selected.csv',row.names=F)

train_rows_relevant <- createDataPartition(y=df_c_subset_final[,'salary'], list=FALSE, p=.8)
c_train_selected_df <- df_c_subset_final[train_rows,]
c_test_selected_df <- df_c_subset_final[-train_rows,]
stopifnot(nrow(c_train_selected_df) + nrow(c_test_selected_df) == nrow(df_c_subset_final))
head(c_train_selected_df)
```

```
##             name  salary Age GS   MP USG%   WS  PF out ovr
## 1  aaron brooks 2700000  31  0 1108 22.9  0.9 132  79  75
## 2  aaron brooks 2116955  32  0  894 19.2  0.3  93  87  85
## 3  aaron gordon 4351320  20 37 1863 17.3  5.4 153  87  90
## 4  aaron gordon 5504420  21 72 2298 20.1  3.7 172  86  92
## 5 adreian payne 2022240  24  2  486 17.7 -0.5  77  56  69
## 6    aj hammons 1312611  24  0  163 17.6  0.0  21  47  66
```

```r
head(c_test_selected_df)
```

```
##                name   salary Age GS   MP USG%  WS  PF out ovr
## 7  al farouq aminu  7680965  25 82 2341 16.9 4.0 171  90  91
## 13   alan anderson  1315448  33  0  192 15.4 0.3  25  73  69
## 24      alonzo gee  1400000  28 38 1632  9.2 1.9 169  65  70
## 29  andre drummond 22116750  22 81 2666 24.1 7.4 245  47  86
## 32  andre iguodala 14814815  33  0 1998 11.2 6.9  97  81  91
## 45   anthony davis 22116750  22 61 2164 29.6 7.2 148  91  97
```

```r
write.csv(c_train_selected_df,'../data/train_test/complete/train_selected.csv',row.names=F)
write.csv(c_test_selected_df,'../data/train_test/complete/test_selected.csv',row.names=F)
```