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

```
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

```
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'
```

```
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
df_primary[is.na(df_primary)] <- 0
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.:0.1360
##  Median :1197   Median : 13.30   Median :0.5380   Median :0.3110
##  Mean   :1247   Mean   : 13.61   Mean   :0.5324   Mean   :0.3045
##  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.:0.1670   1st Qu.: 1.900   1st Qu.:10.30   1st Qu.: 6.200
##  Median :0.2400   Median : 3.300   Median :14.00   Median : 8.800
##  Mean   :0.2682   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   :12.82
##  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.:0.4050
##  Median : 0.2000   Median :166.0   Median : 368.0   Median :0.4410
```

```
##  Mean   : 0.6493   Mean   :200.8   Mean   : 441.5   Mean   :0.4463
##  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.:0.2450   1st Qu.: 43
##  Median : 30.00   Median : 92.0   Median :0.3330   Median :113
##  Mean   : 47.83   Mean   :133.8   Mean   :0.2846   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.:0.4460   1st Qu.:0.4670   1st Qu.: 23.00
##  Median : 235.0   Median :0.4830   Median :0.5010   Median : 59.00
##  Mean   : 307.8   Mean   :0.4837   Mean   :0.4986   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.:0.6740   1st Qu.: 13.00   1st Qu.: 62
##  Median : 78.0   Median :0.7640   Median : 33.00   Median :143
##  Mean   :120.3   Mean   :0.7305   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
```

```r
df_primary$Pos <- gsub('PF-C','PF',df_primary$Pos)
df_primary$Pos <- as.factor(df_primary$Pos) # make Pos a factor variable
table(df_primary$Pos)
```

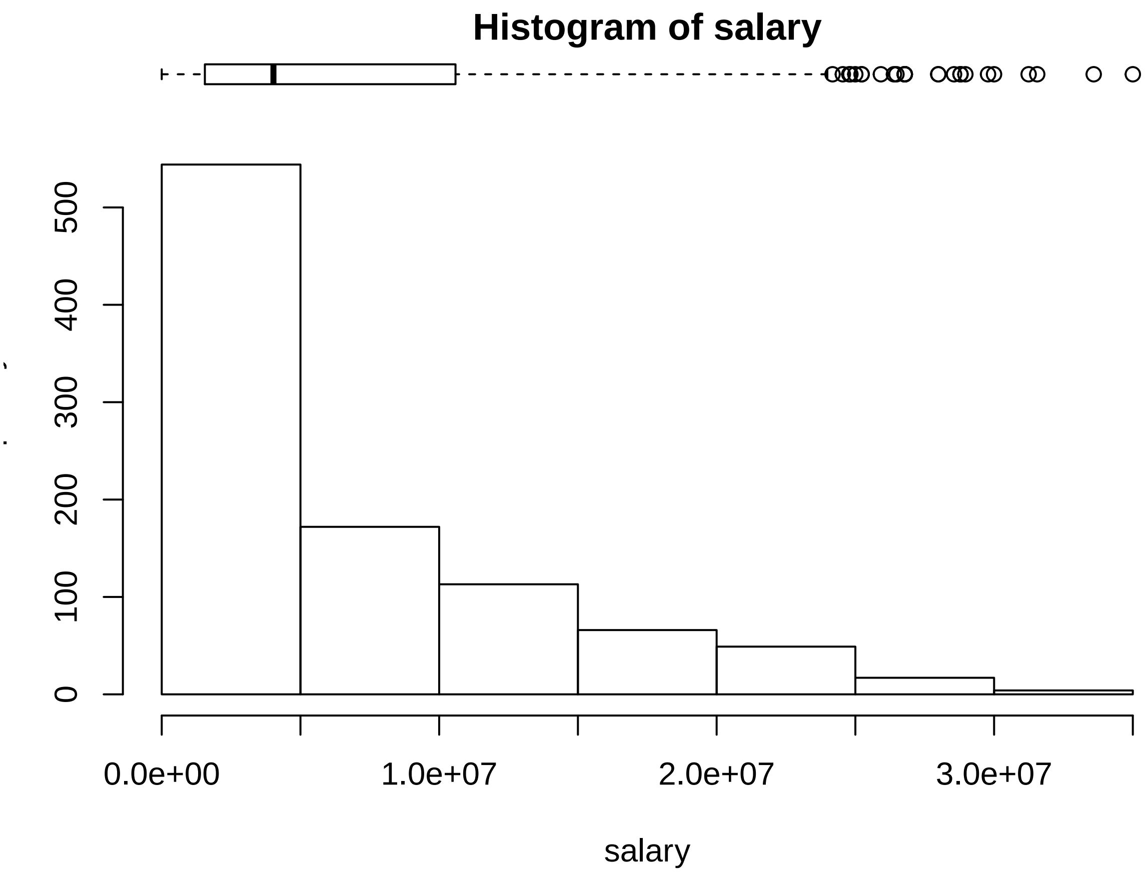
```
##
##   C  PF  PG  SF  SG
## 185 192 200 194 194
```

```r
str(df_primary)
```

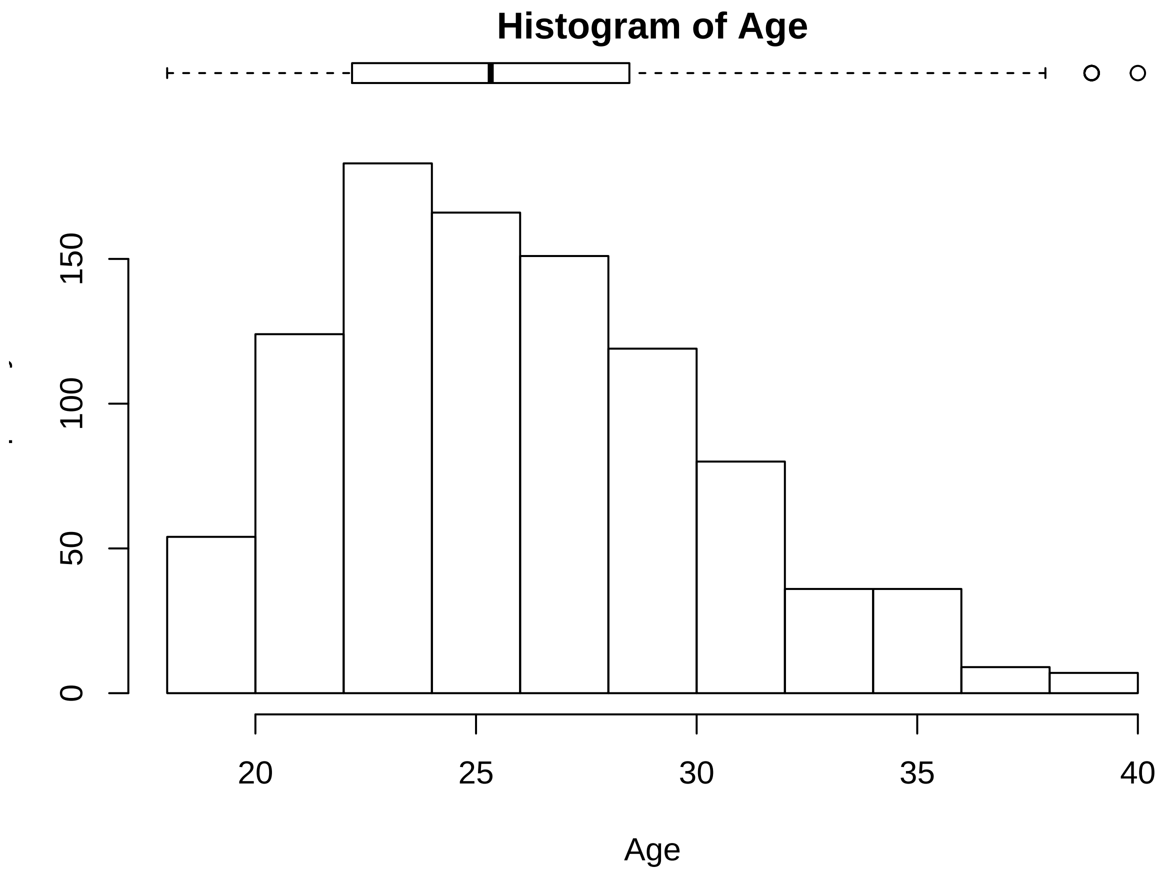
```
## Classes 'tbl_df', 'tbl' and 'data.frame':    965 obs. of  51 variables:
##  $ year  : Factor w/ 2 levels "2016","2017": 2 1 2 1 2 1 1 1 2 1 ...
##  $ name_p: chr  "A.J. Hammons" "Aaron Brooks" "Aaron Brooks" "Aaron Gordon" ...
##  $ salary: num  1312611 2700000 2116955 4351320 5504420 ...
##  $ 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 0.3 0.281 0.344 0.355 0 ...
##  $ 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

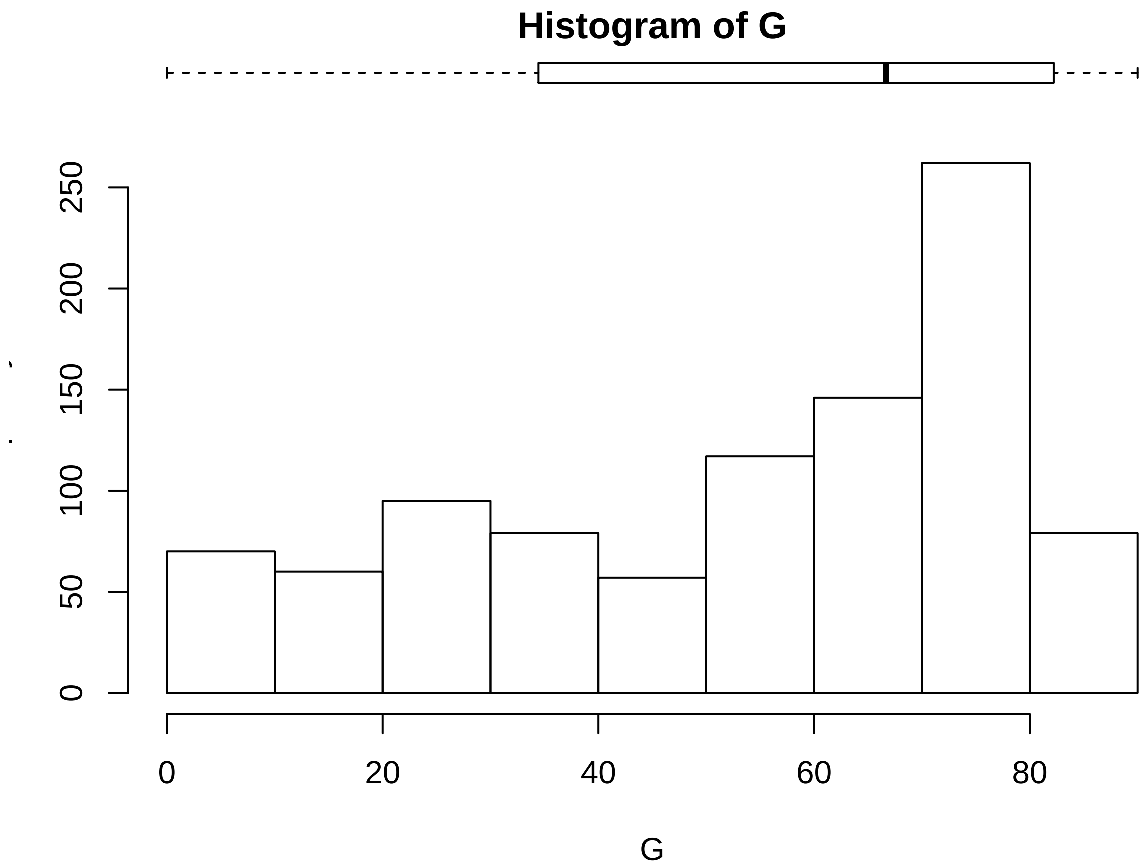
```r
df_p_numeric <- Filter(is.numeric,df_primary) # numeric variables
for (col in names(df_p_numeric)){
  data <- df_p_numeric[[col]]
  layout(mat = matrix(c(1,2),2,1, byrow=TRUE), height = c(1,8))
  par(mar=c(0, 3.1, 1.1, 2.1))
  boxplot(data , horizontal=TRUE , xaxt="n", frame=F, main=sprintf('Histogram 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,])}
```



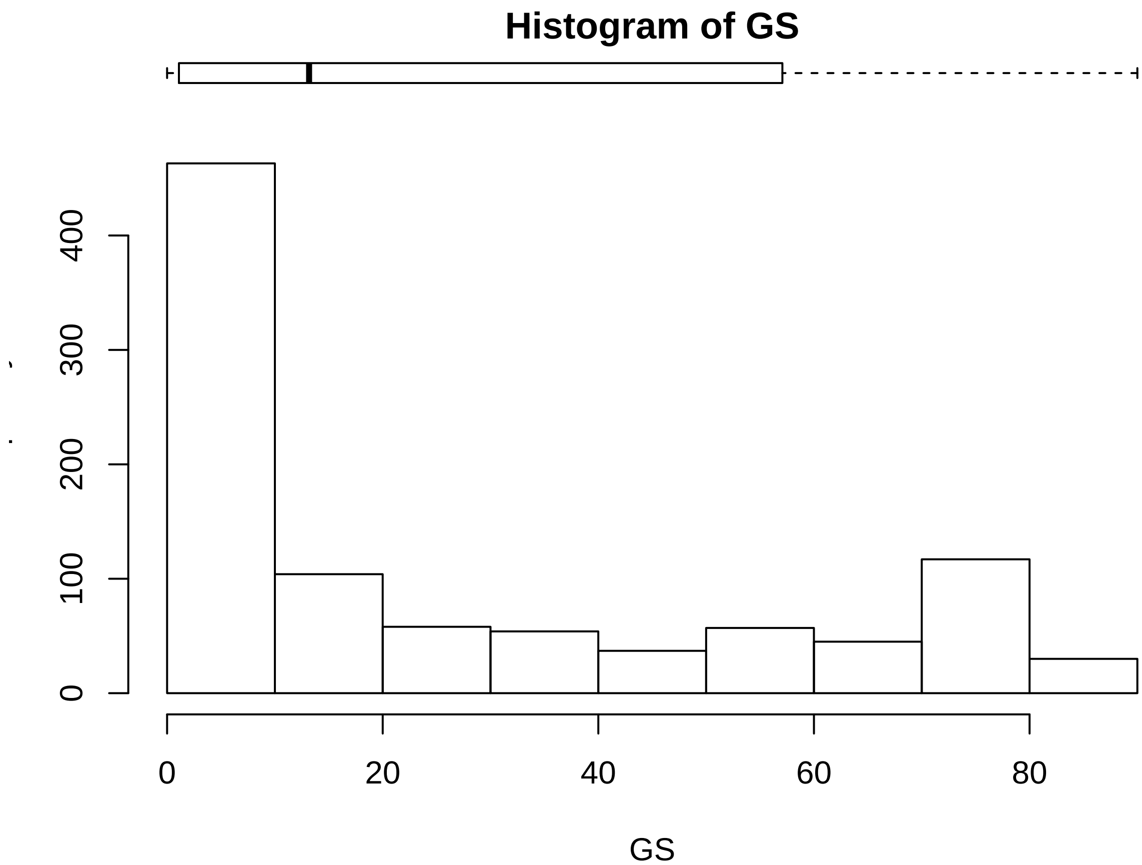

```
## Top 10 Players by salary
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2017  Steph~ 3.47e7 PG       28 GSW      79    79  2638  24.6 0.624  0.547
##  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>
```



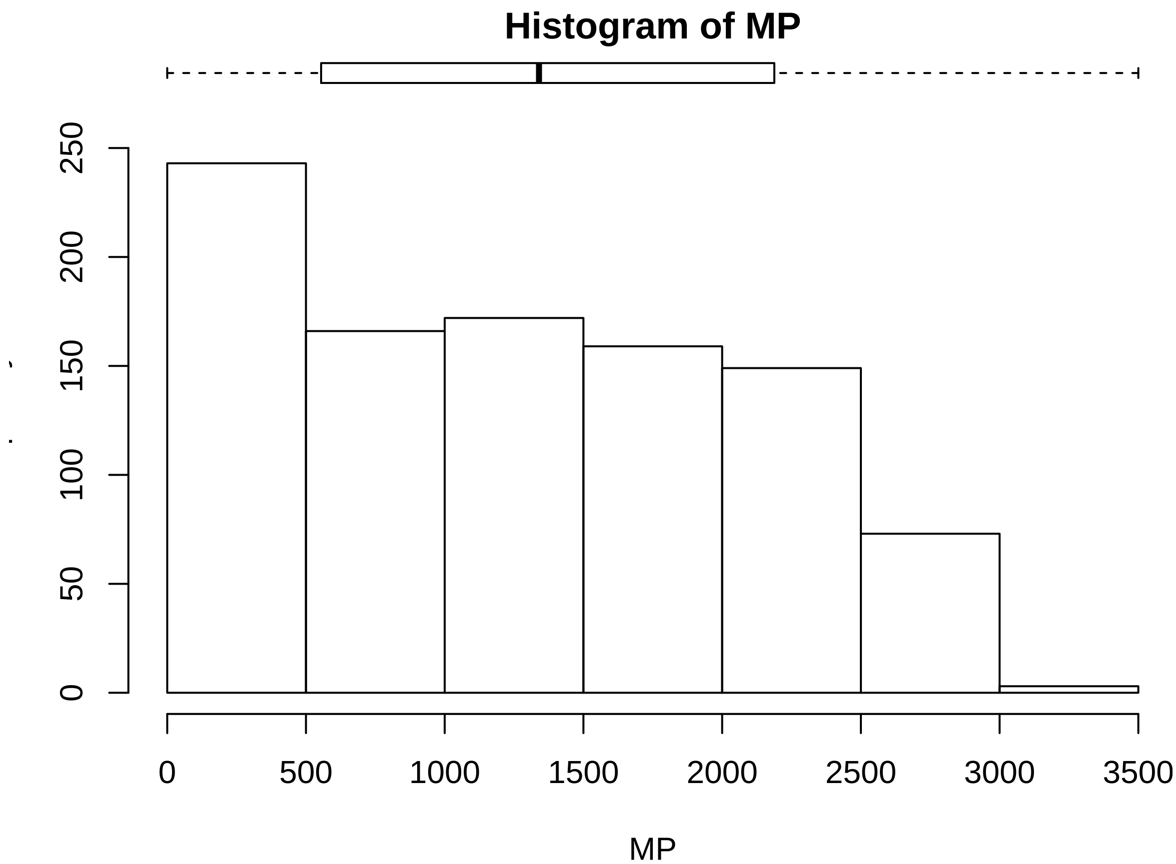

```
## Top 10 Players by Age
## # A tibble: 10 x 51
##     year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2017  Vince~ 8.00e6 SF       40 MEM      73    15  1799  11.7 0.542  0.604
##  2 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>
```



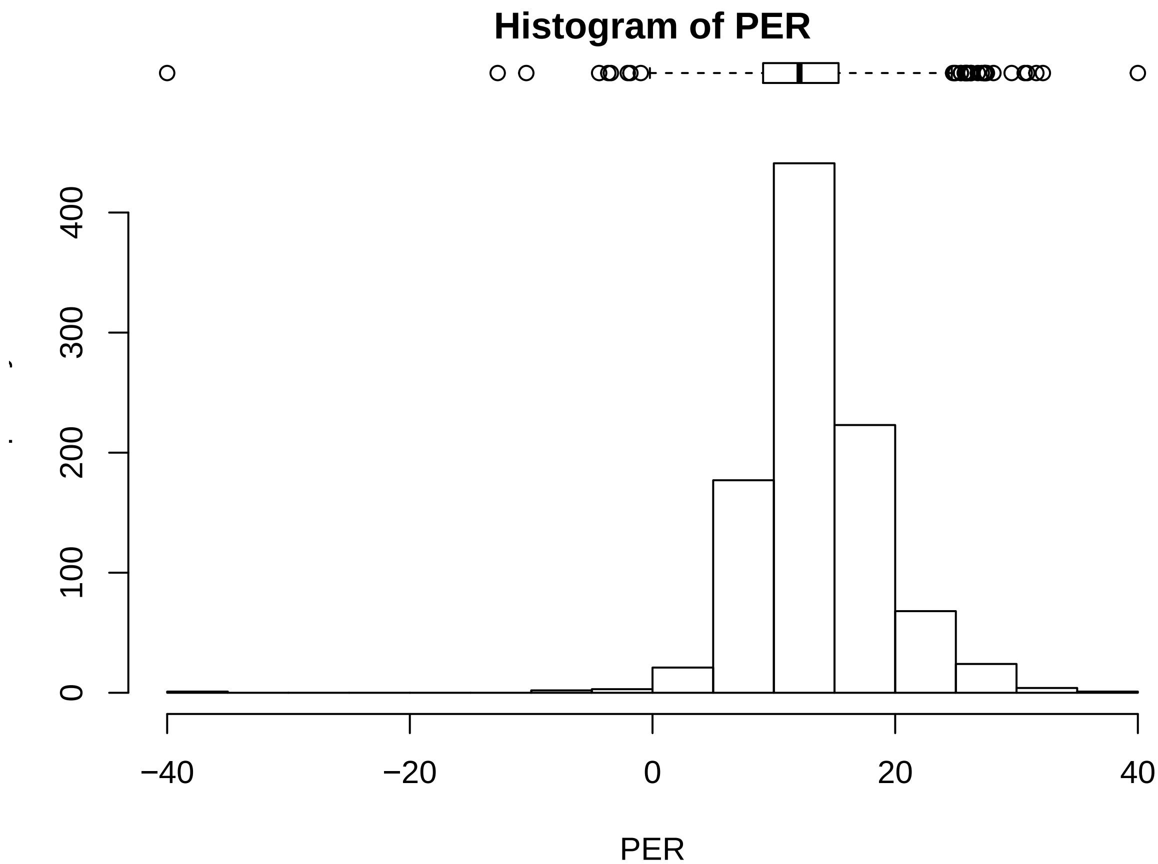

```
## Top 10 Players by G
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2016  Al Ho~ 2.65e7 C        29 ATL      82    82  2631  19.4 0.565  0.244
##  2 2016  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>
```



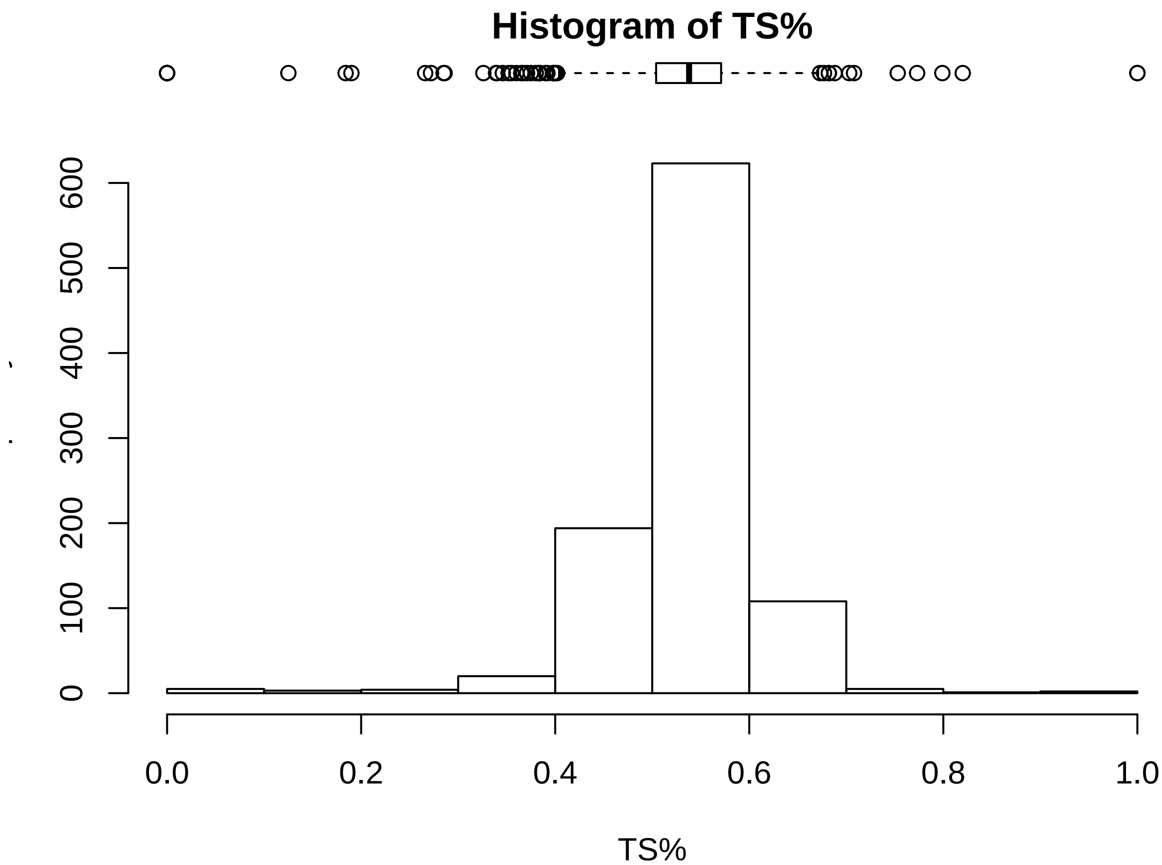

```
## Top 10 Players by GS
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2016  Al Ho~ 2.65e7 C        29 ATL      82    82  2631  19.4 0.565  0.244
##  2 2016  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>
```



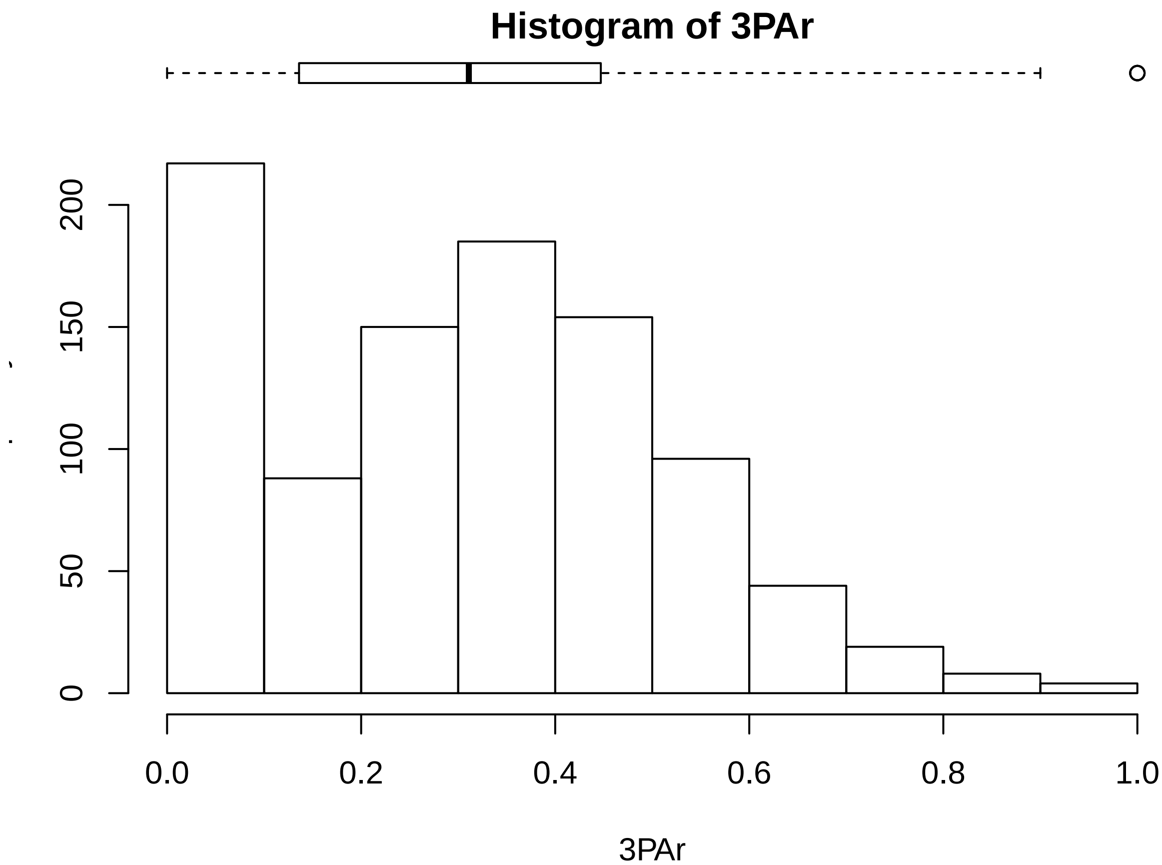

```
## Top 10 Players by MP
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2016  James~ 2.65e7 SG       26 HOU      82    82  3125  25.3 0.598  0.406
##  2 2017  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>
```



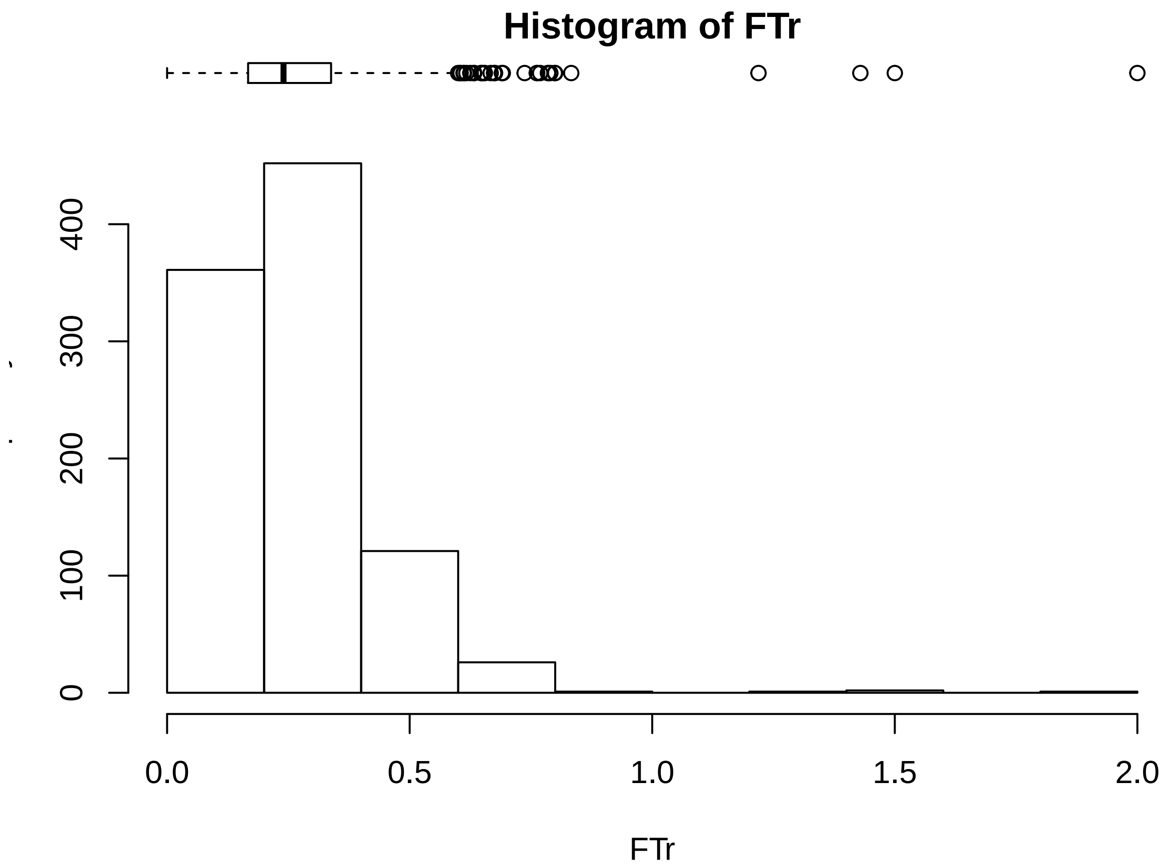

```
## Top 10 Players by PER
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2016  Brian~ 3.28e5 PG       23 MIA       1     0     3  39.3 1      0
##  2 2016  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>
```



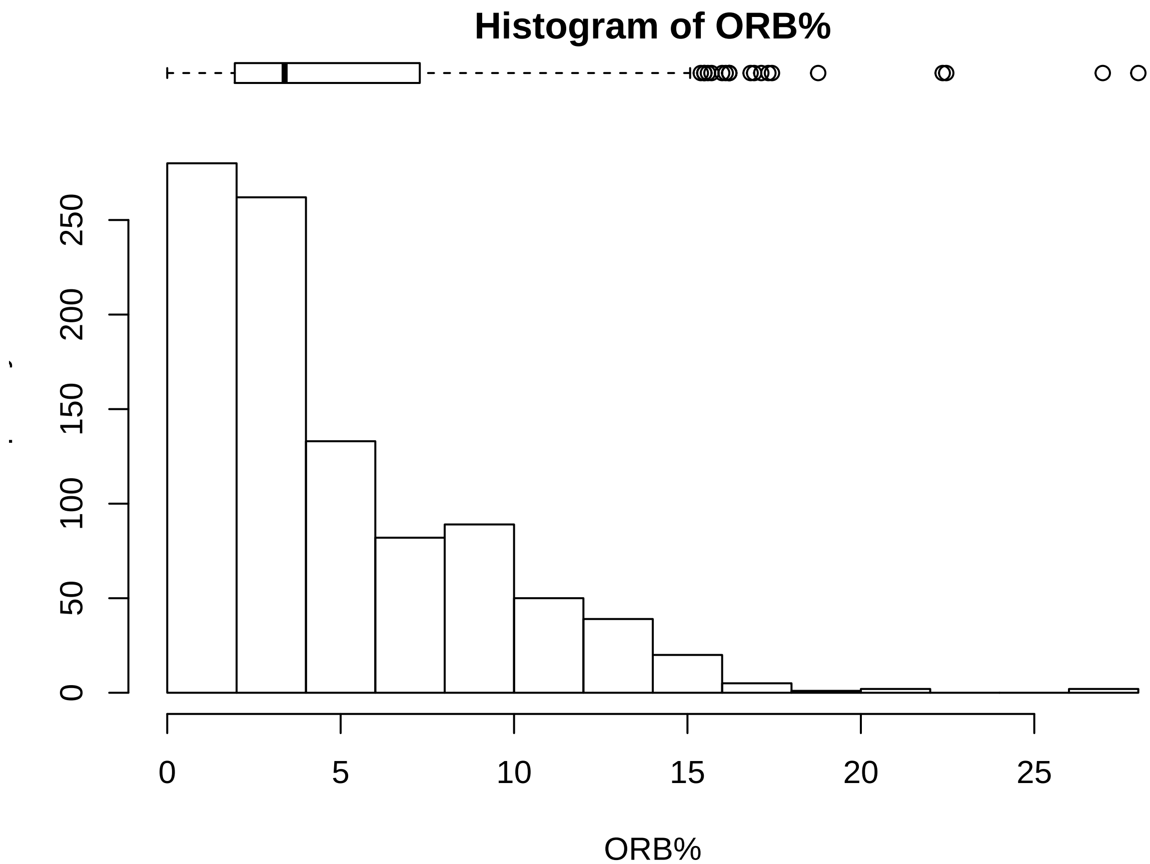

```
## Top 10 Players by TS%
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2016  Brian~ 3.28e5 PG       23 MIA       1     0     3  39.3 1      0
##  2 2016  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>
```



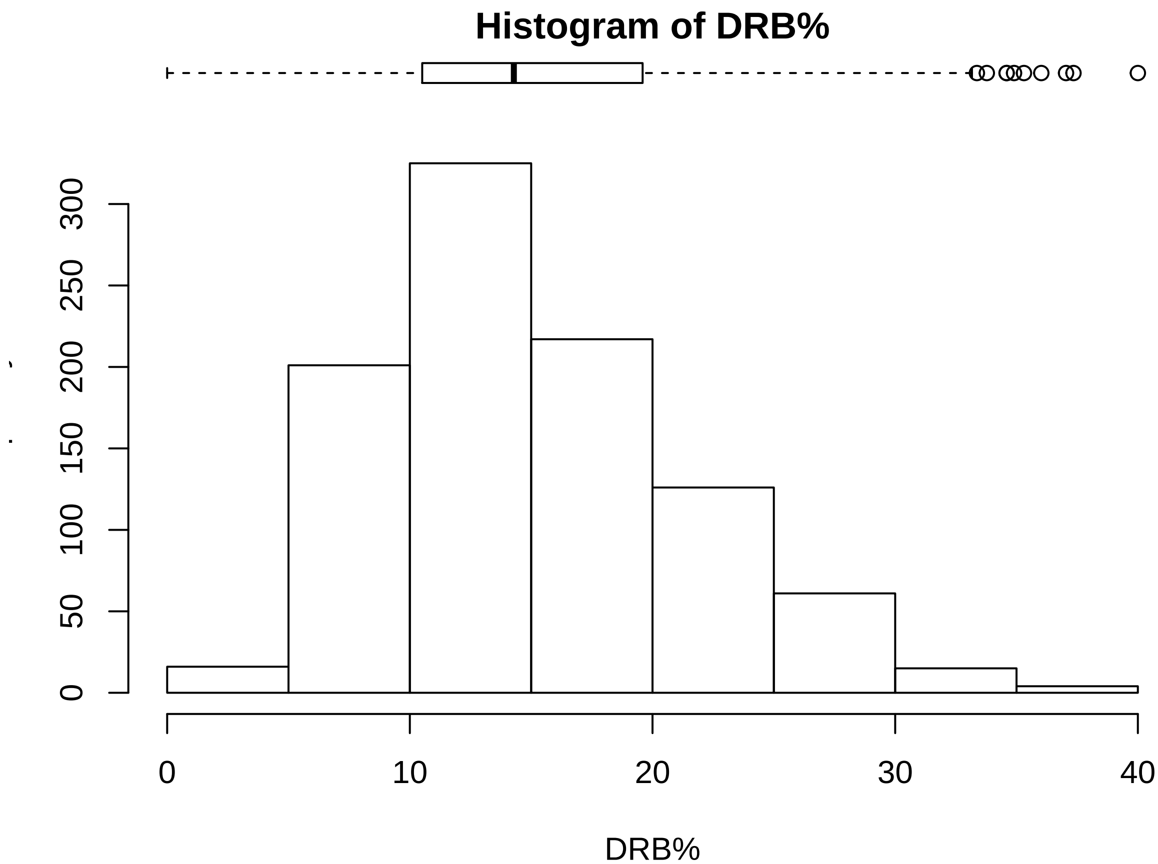

```
## Top 10 Players by 3PAr
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2017  Axel ~ 2.50e4 SF       24 MIL       2     0     6  -9.9 0       1
##  2 2017  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>
```



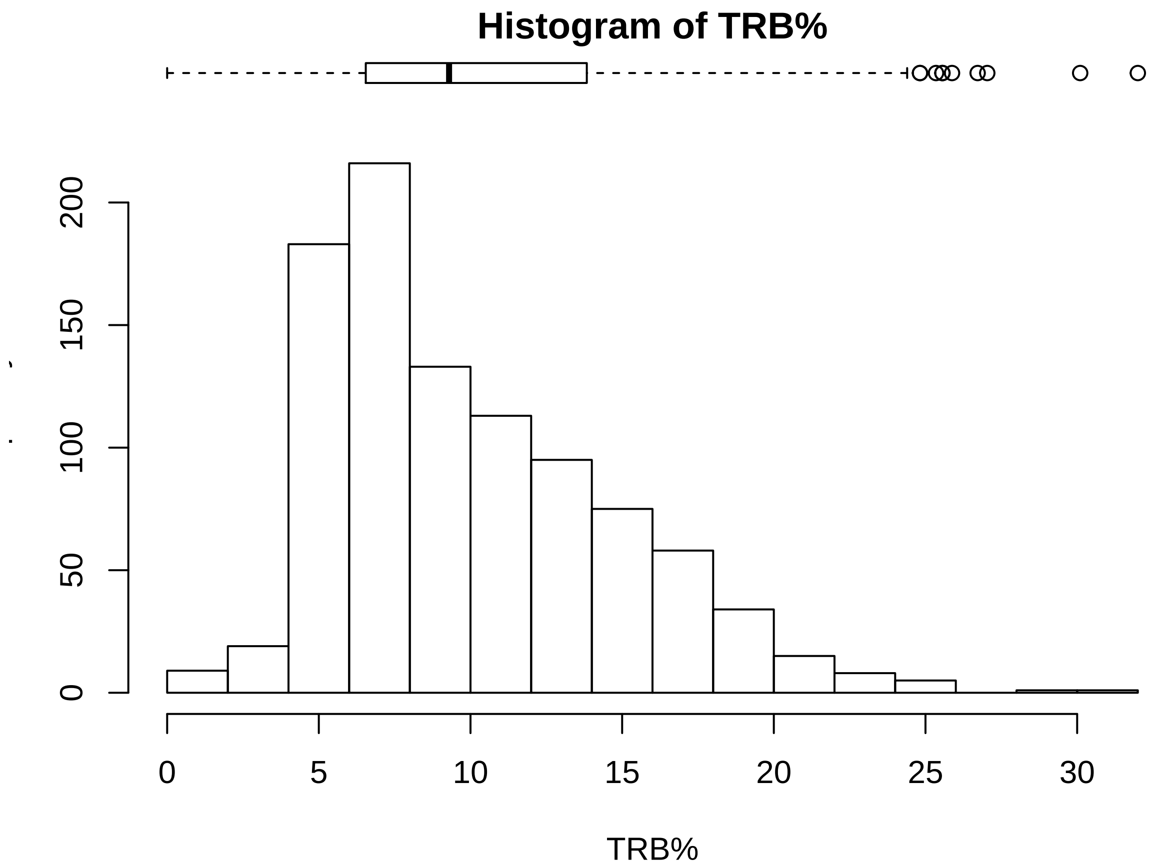

```
## Top 10 Players by FTr
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2017  Chris~ 1.47e6 PF       21 WAS       2     0     8   1.1 0.266  1
##  2 2017  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>
```



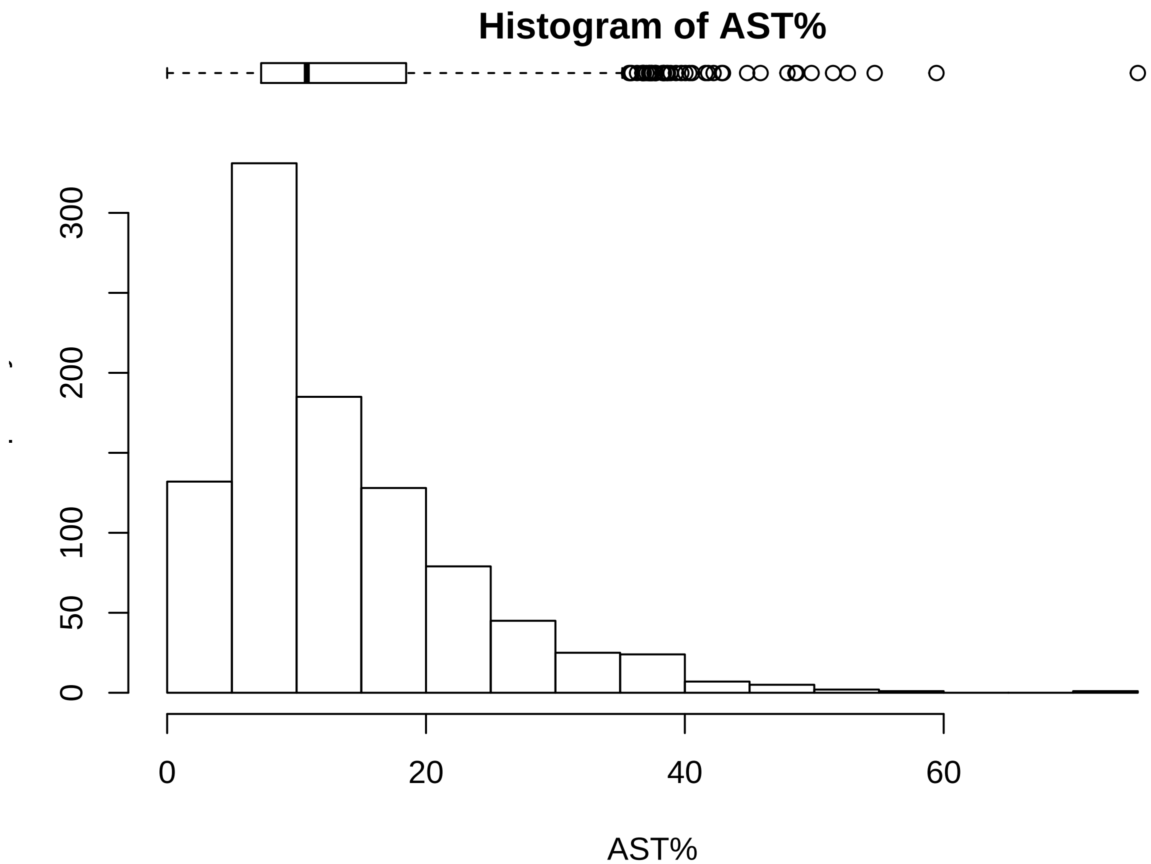

```
## Top 10 Players by ORB%
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2016  Jarne~ 1.50e5 C        22 MEM       2     0     4  13.6 0      0
##  2 2017  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>
```



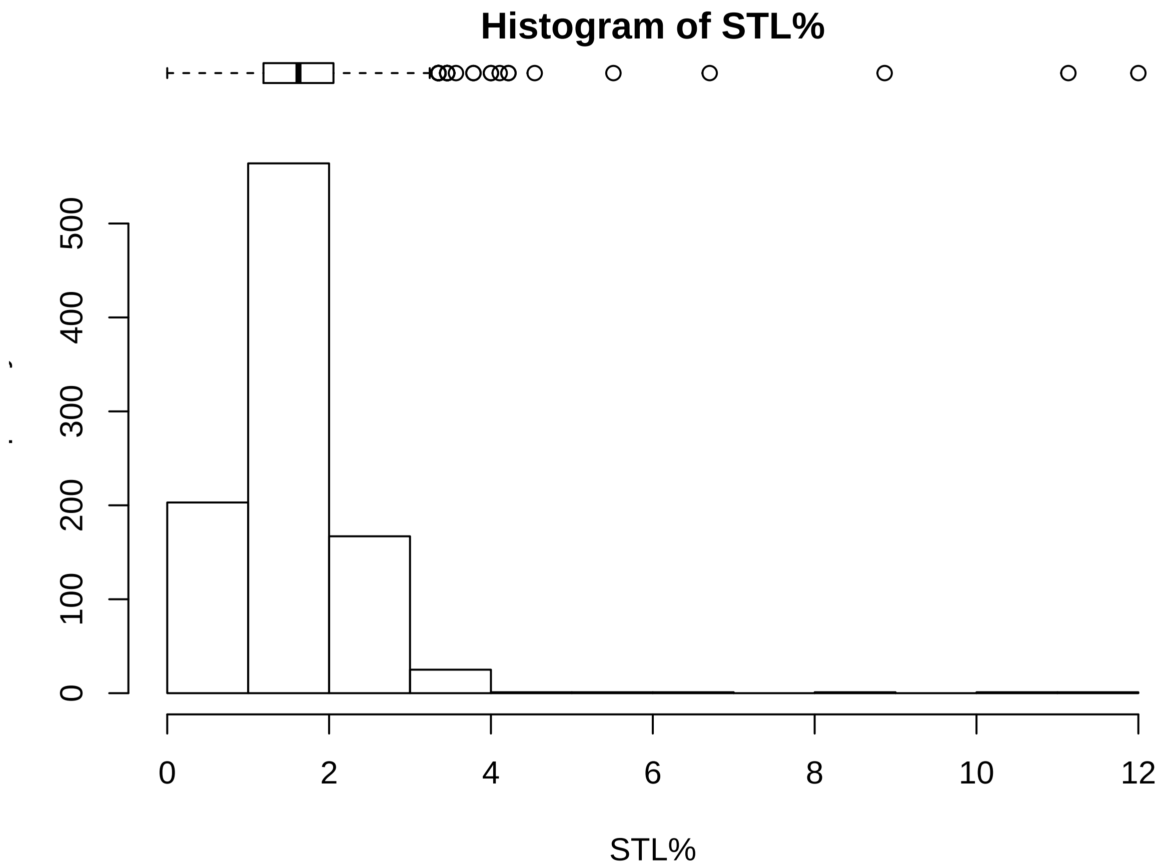

```
## Top 10 Players by DRB%
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2016  Alan ~ 8.75e5 PF       23 PHO      10     0    68  21.1 0.481  0
##  2 2016  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>
```



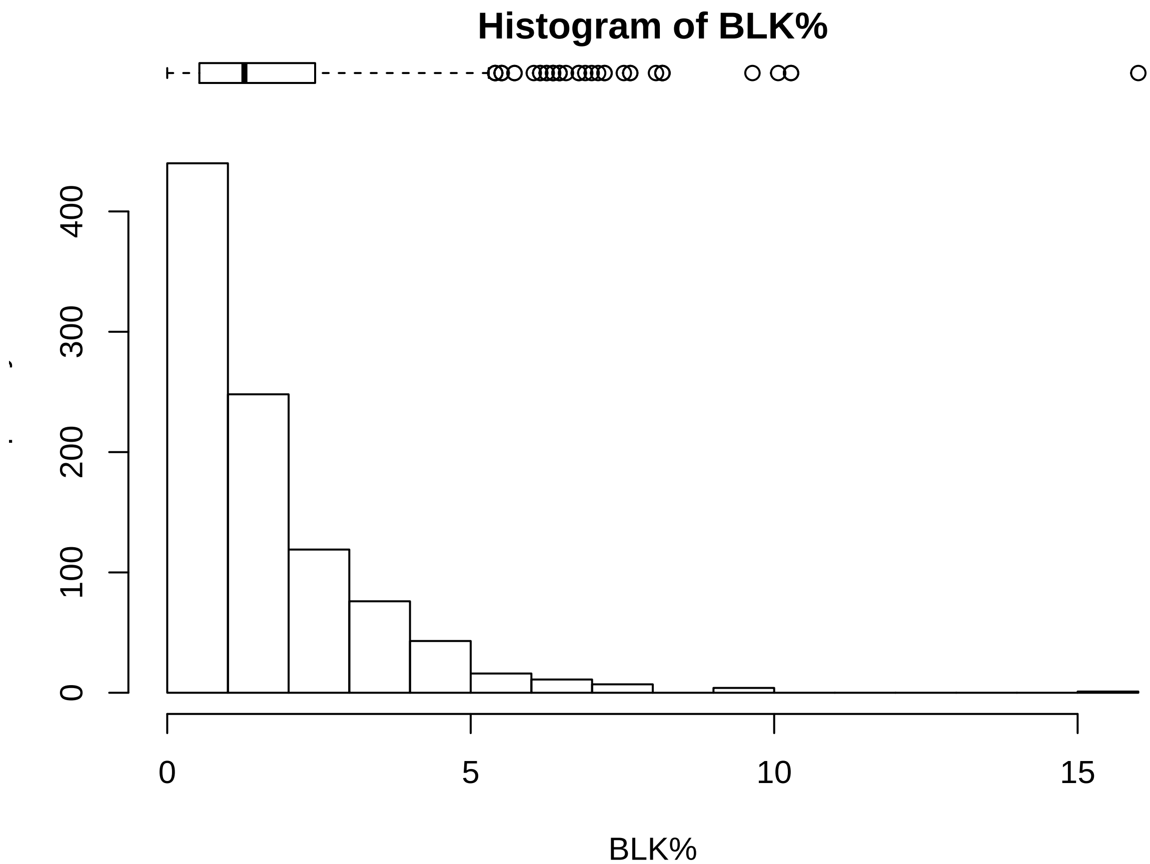

```
## Top 10 Players by TRB%
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2016  Alan ~ 8.75e5 PF       23 PHO      10     0    68  21.1 0.481  0
##  2 2016  Jarne~ 1.50e5 C        22 MEM       2     0     4  13.6 0      0
##  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>
```



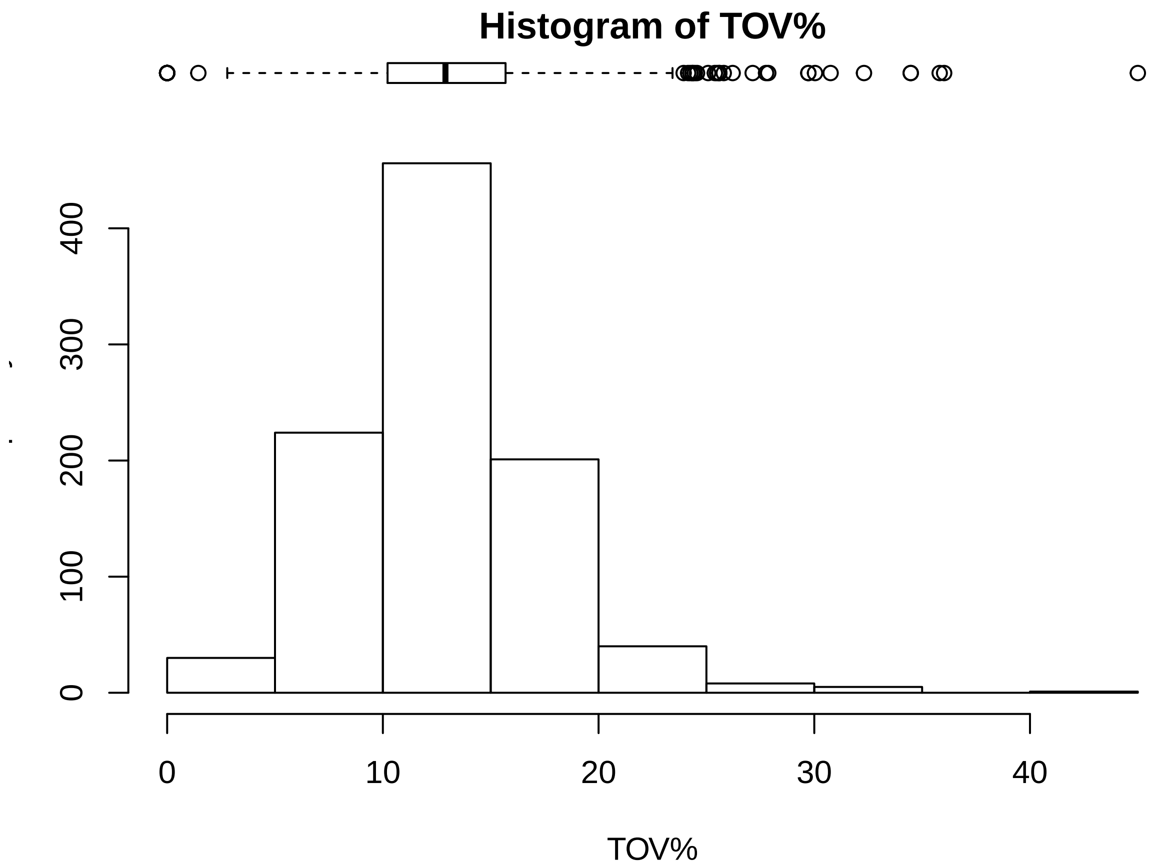

```
## Top 10 Players by AST%
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2016  Brian~ 3.28e5 PG       23 MIA       1     0     3  39.3 1      0
##  2 2017  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>
```



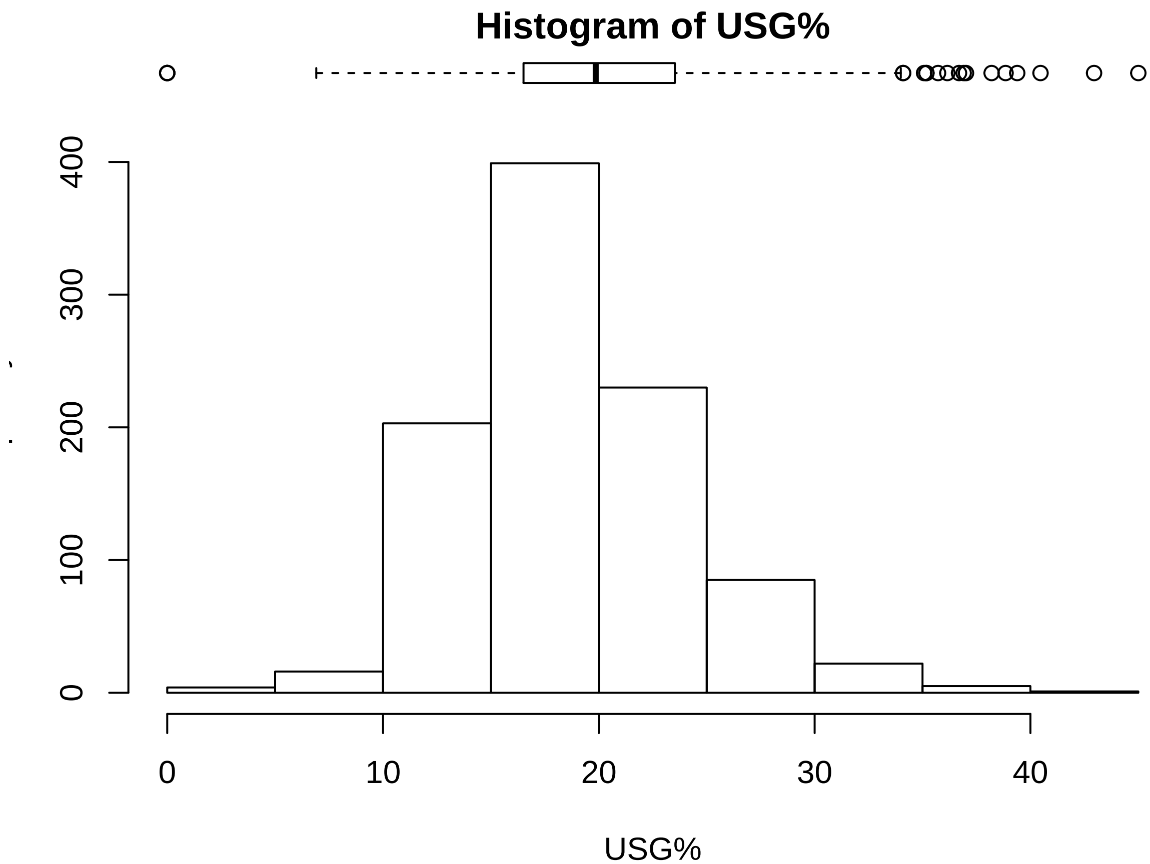

```
## Top 10 Players by STL%
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2017  Brice~ 1.33e6 PF       22 LAC       3     0     9  17.2 0.286  0
##  2 2016  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      0
##  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>
```



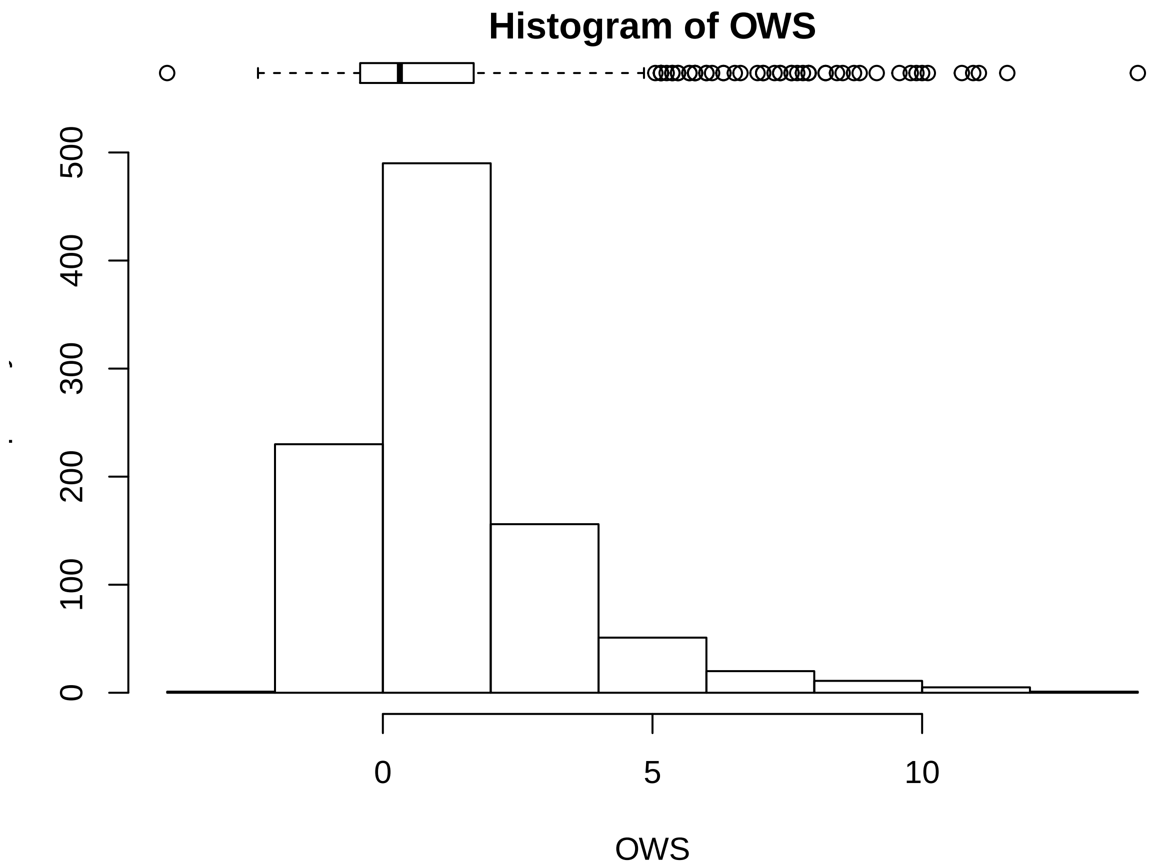

```
## Top 10 Players by BLK%
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2016  Jorda~ 1.22e6 PF       21 BOS      16     0    57  15.3 0.398  0
##  2 2016  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>
```



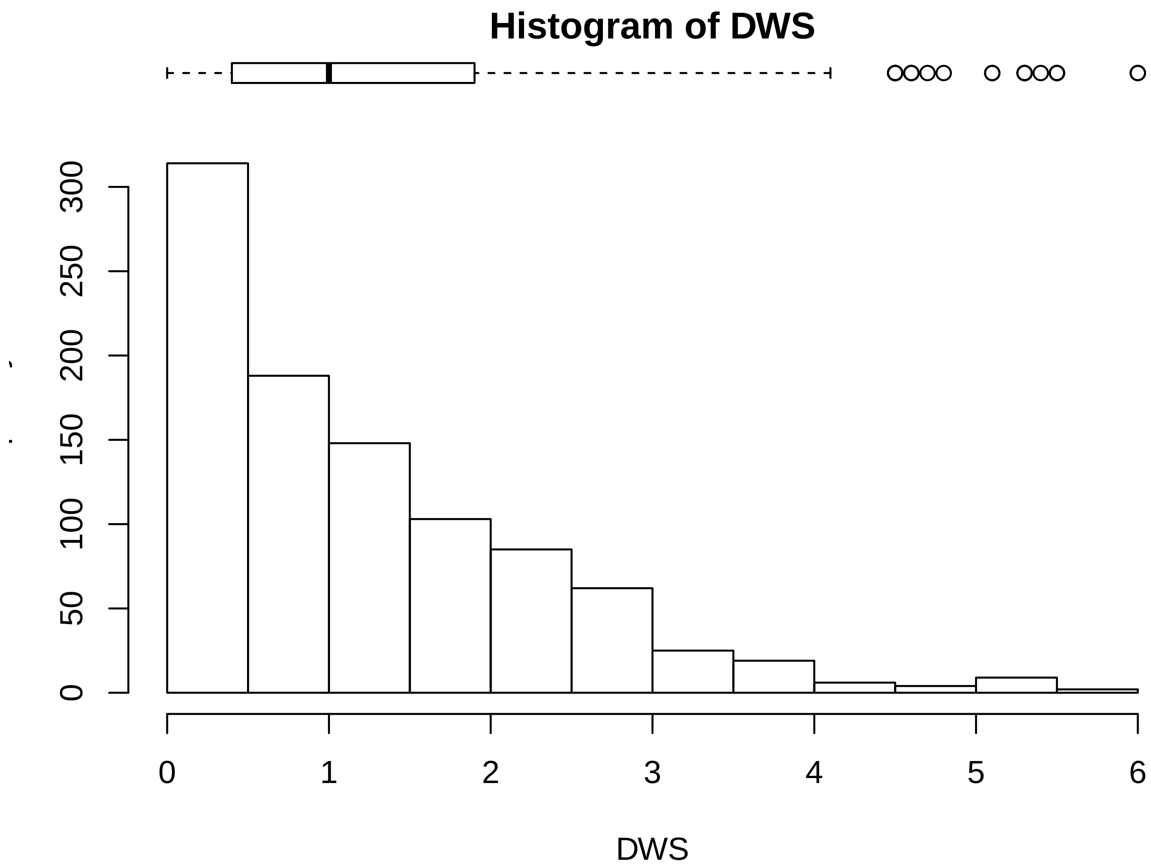

```
## Top 10 Players by TOV%
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2017  Jarre~ 2.33e6 PG       33 NOP       2     0    33   7.7 0.773  0.333
##  2 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>
```



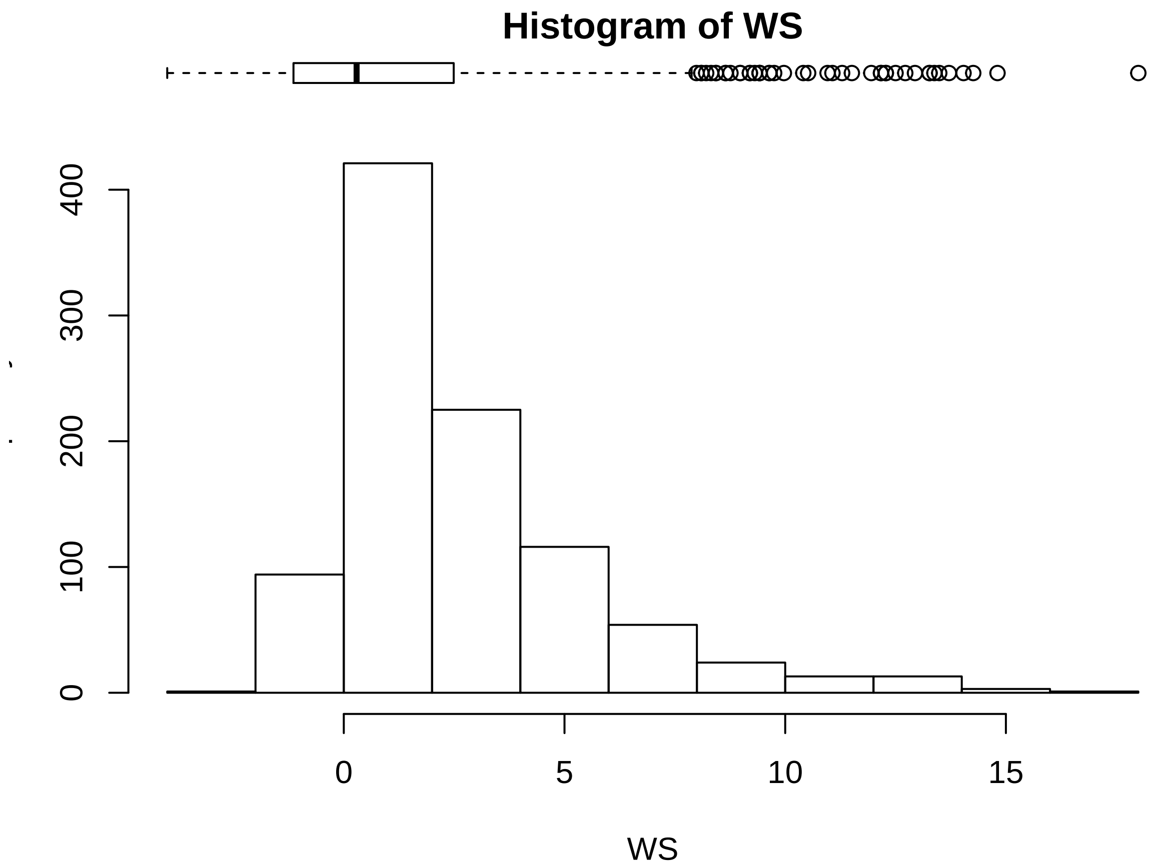

```
## Top 10 Players by USG%
## # A tibble: 10 x 51
##     year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2017  Russe~ 2.85e7 PG       28 OKC      81    81  2802  30.6 0.554  0.3
##  2 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>
```



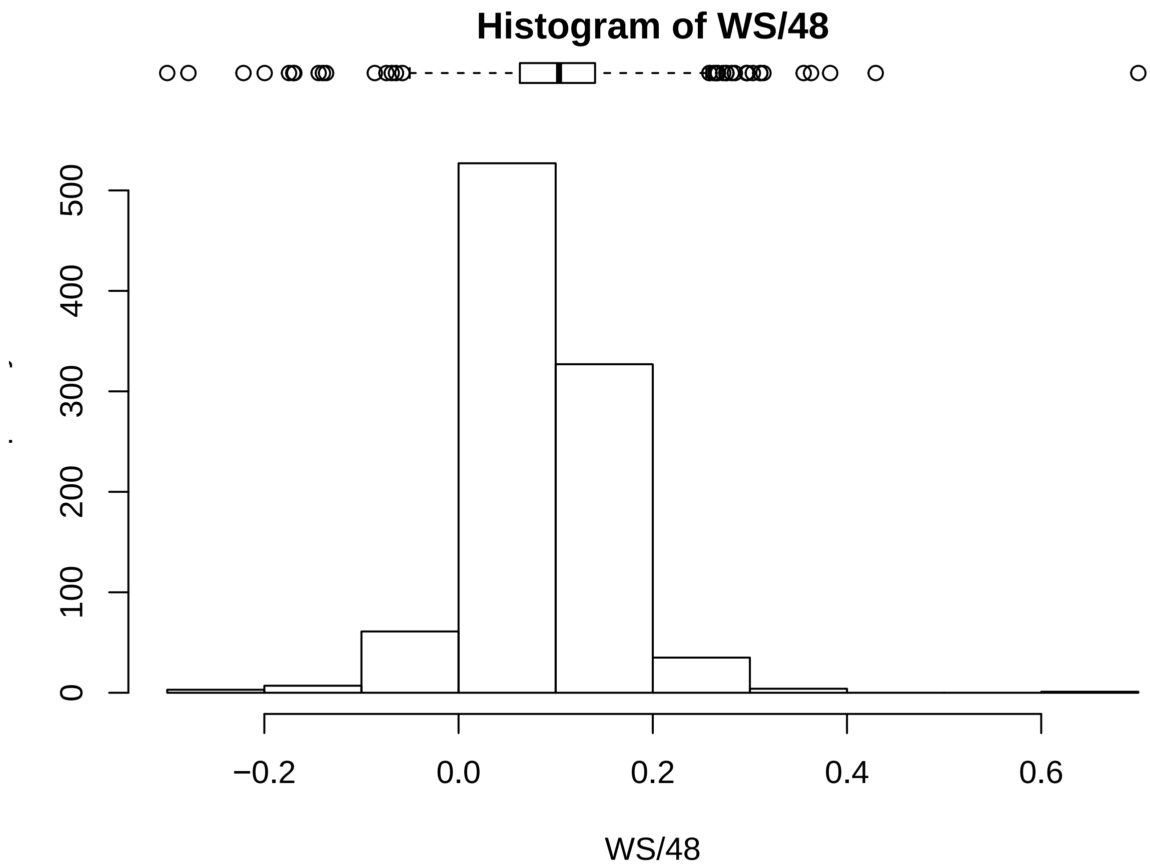

```
## Top 10 Players by OWS
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2016  Steph~ 1.21e7 PG       27 GSW      79    79  2700  31.5 0.669  0.554
##  2 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>
```



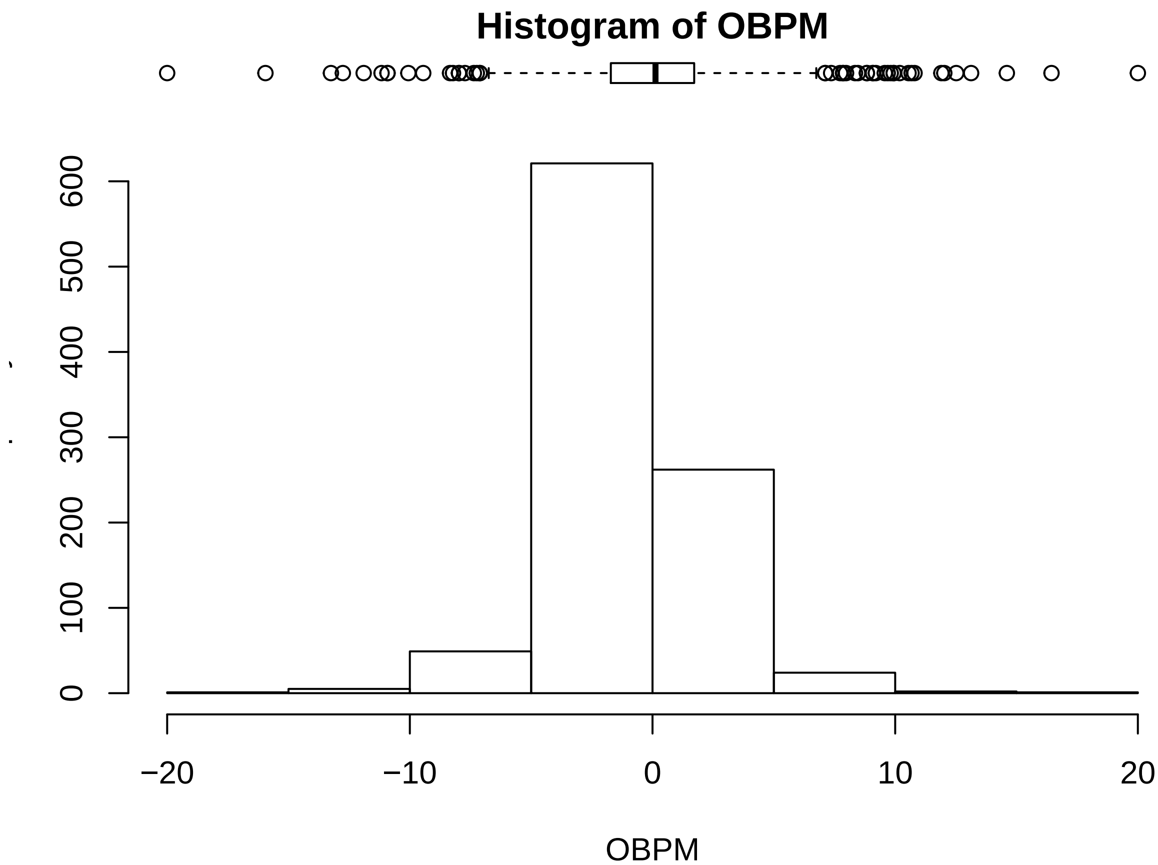

```
## Top 10 Players by DWS
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2016  Paul ~ 2.01e7 PF       30 ATL      81    81  2647  21.3 0.556  0.218
##  2 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>
```



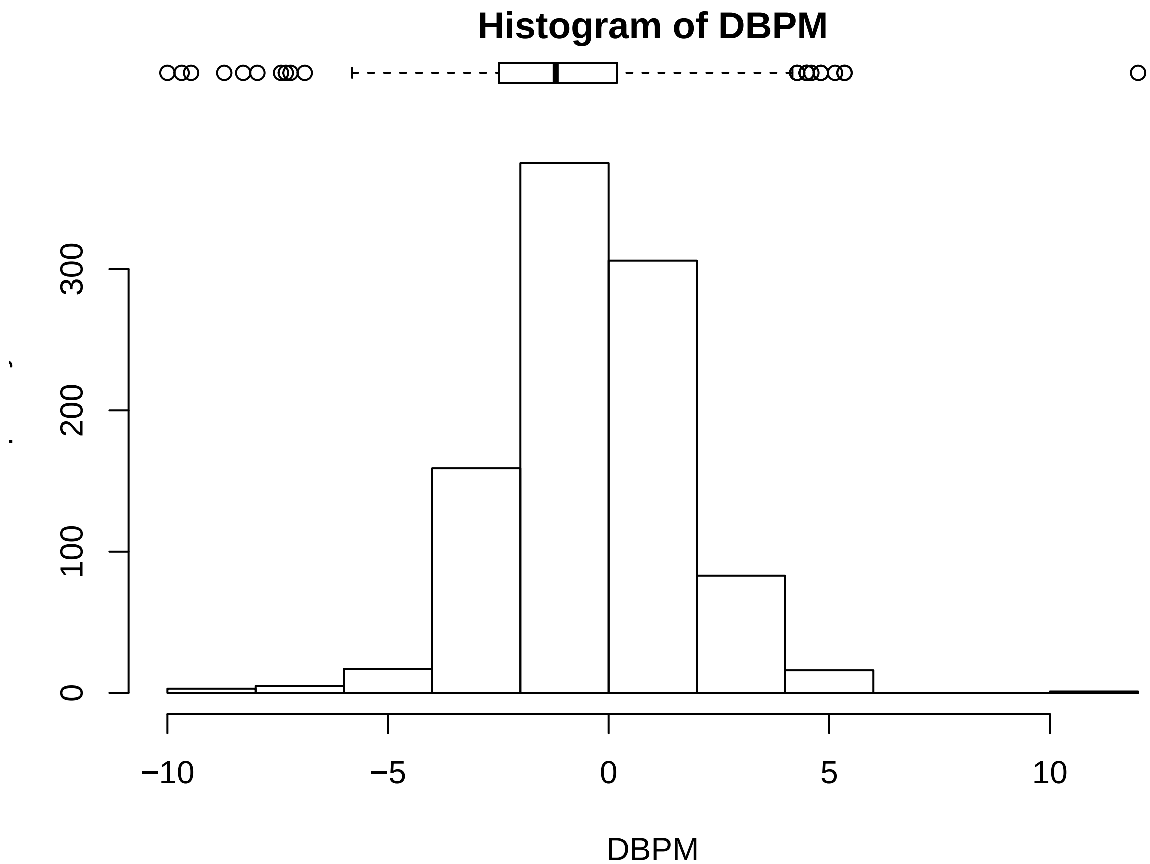

```
## Top 10 Players by WS
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2016  Steph~ 1.21e7 PG       27 GSW      79    79  2700  31.5 0.669  0.554
##  2 2017  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>
```



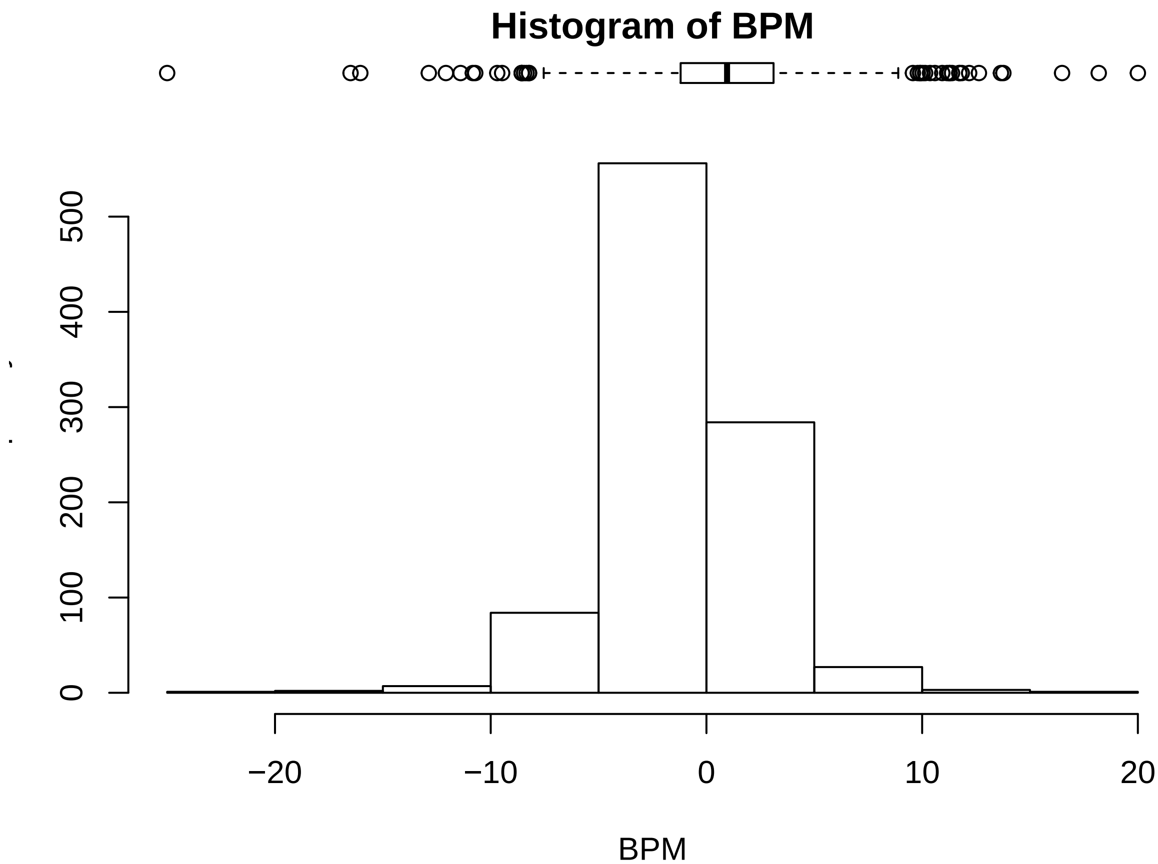

```
## Top 10 Players by WS/48
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2016  Brian~ 3.28e5 PG       23 MIA       1     0     3  39.3 1      0
##  2 2017  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>
```



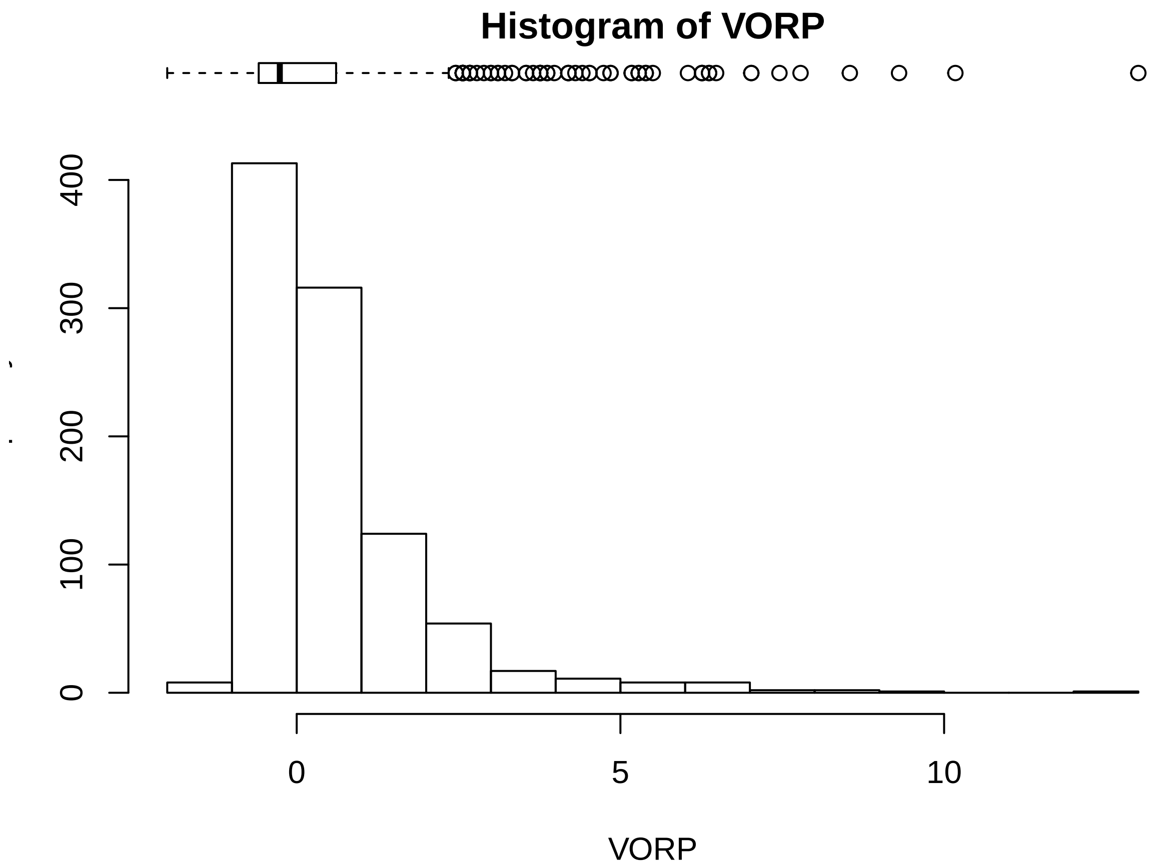

```
## Top 10 Players by OBPM
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2016  Brian~ 3.28e5 PG       23 MIA       1     0     3  39.3 1      0
##  2 2016  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>
```



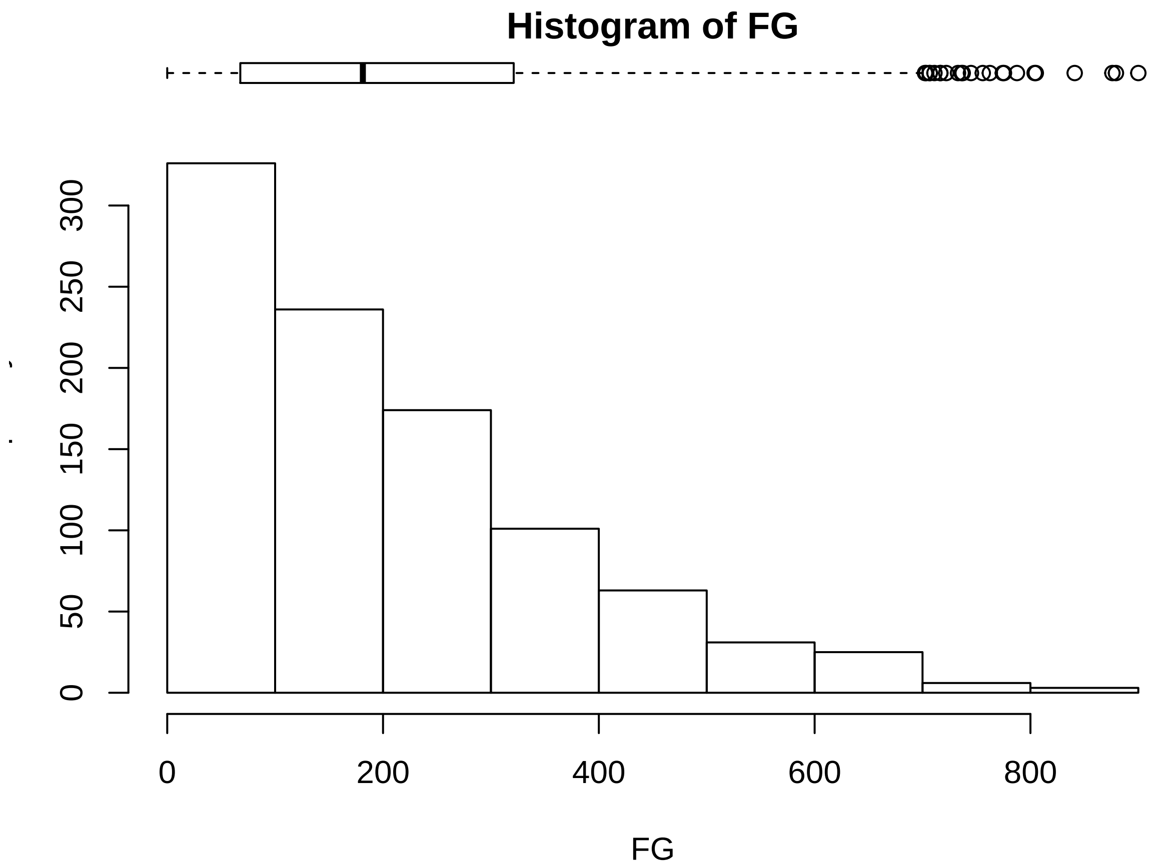

```
## Top 10 Players by DBPM
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2017  Brice~ 1.33e6 PF       22 LAC       3     0     9  17.2 0.286  0
##  2 2016  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      0
##  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>
```



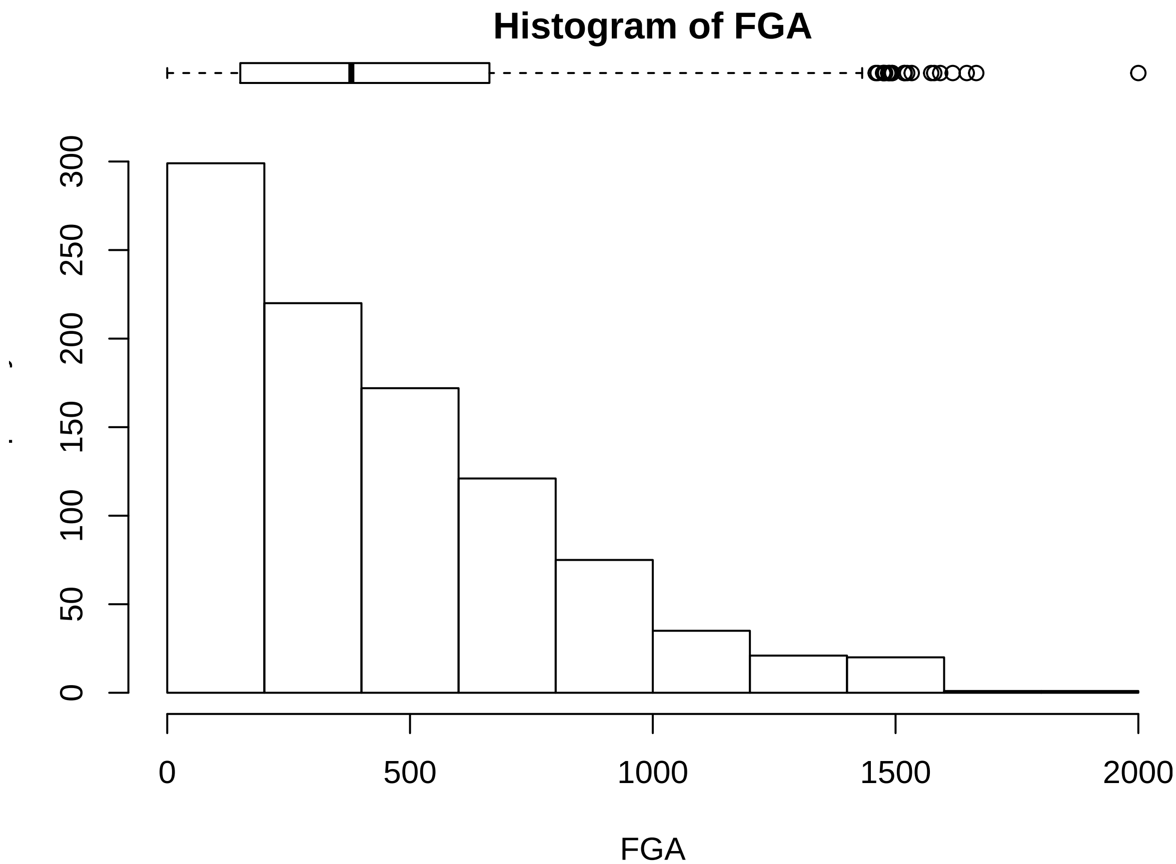

```
## Top 10 Players by BPM
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2017  Russe~ 2.85e7 PG       28 OKC      81    81  2802  30.6 0.554  0.3
##  2 2016  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>
```



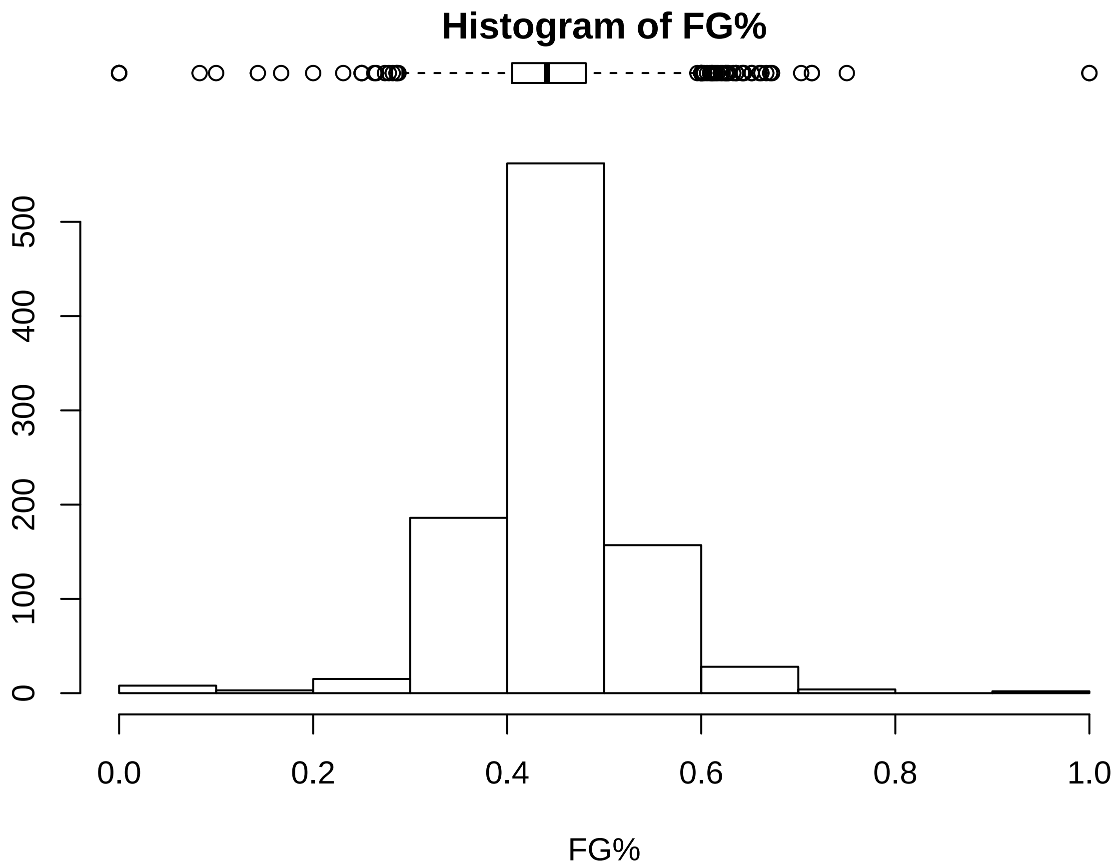

```
## Top 10 Players by VORP
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2017  Russe~ 2.85e7 PG       28 OKC      81    81  2802  30.6 0.554  0.3
##  2 2016  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>
```



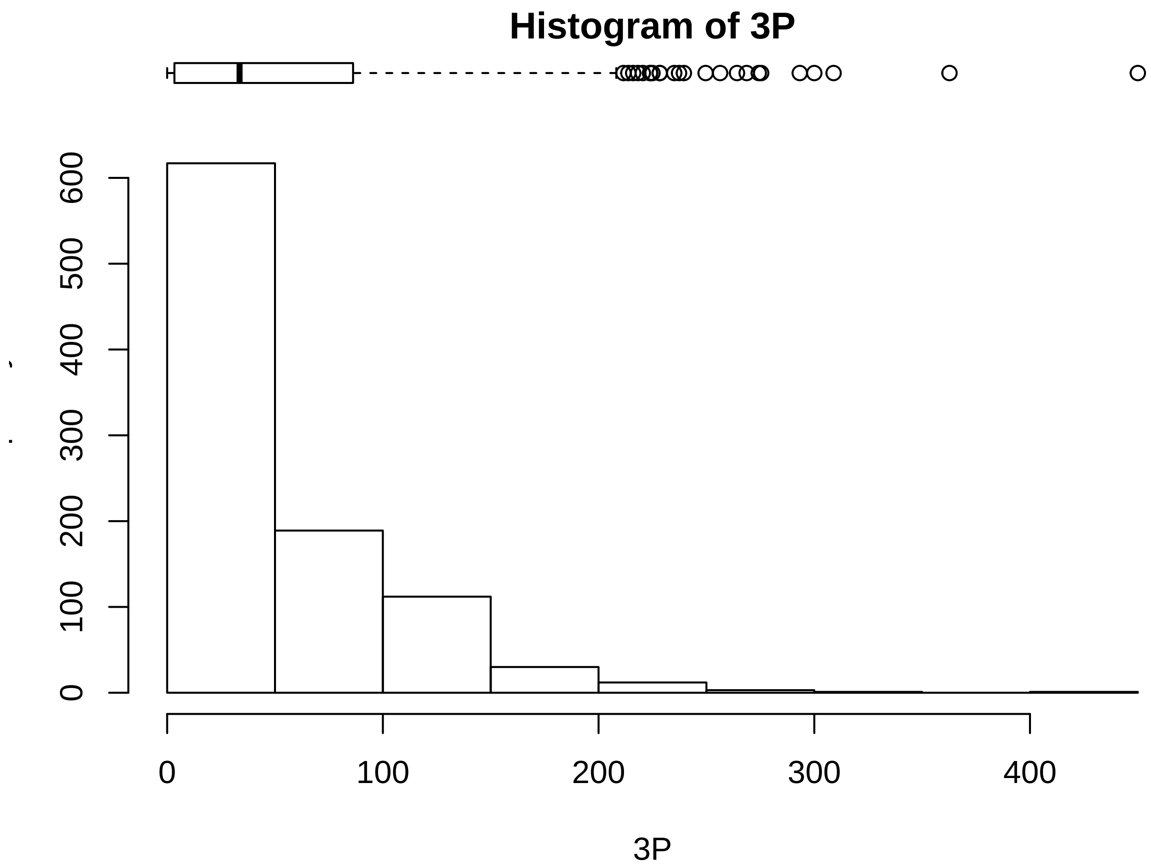

```
## Top 10 Players by FG
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2017  Russe~ 2.85e7 PG       28 OKC      81    81  2802  30.6 0.554  0.3
##  2 2016  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>
```



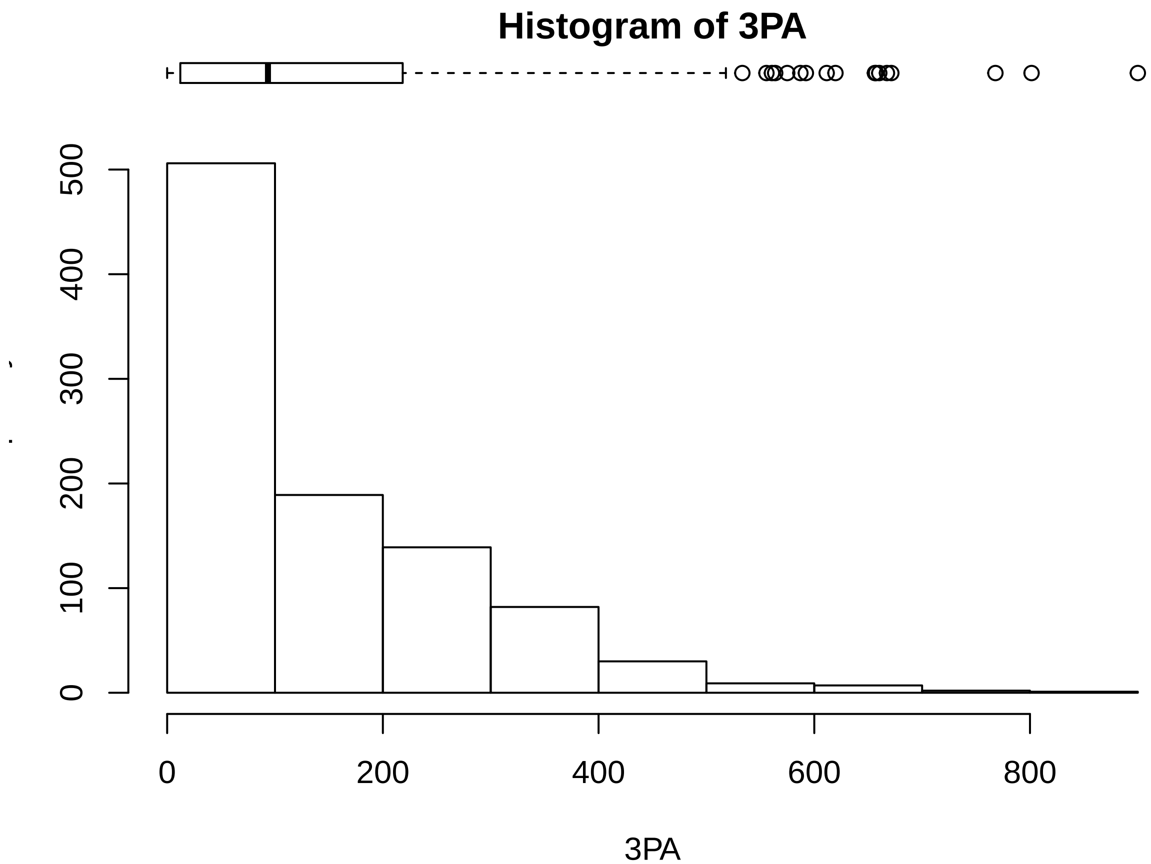

```
## Top 10 Players by FGA
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2017  Russe~ 2.85e7 PG       28 OKC      81    81  2802  30.6 0.554  0.3
##  2 2016  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>
```



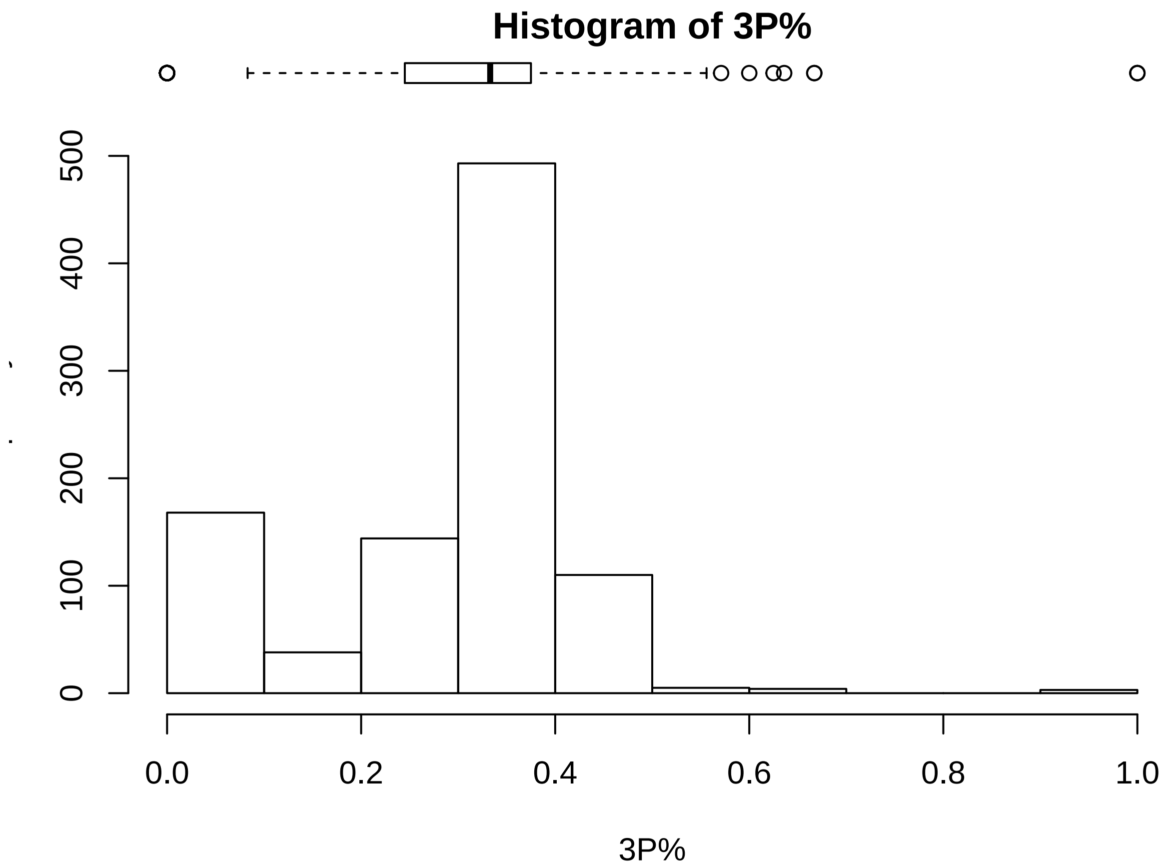

```
## Top 10 Players by FG%
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2016  Brian~ 3.28e5 PG       23 MIA       1     0     3  39.3 1      0
##  2 2016  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>
```



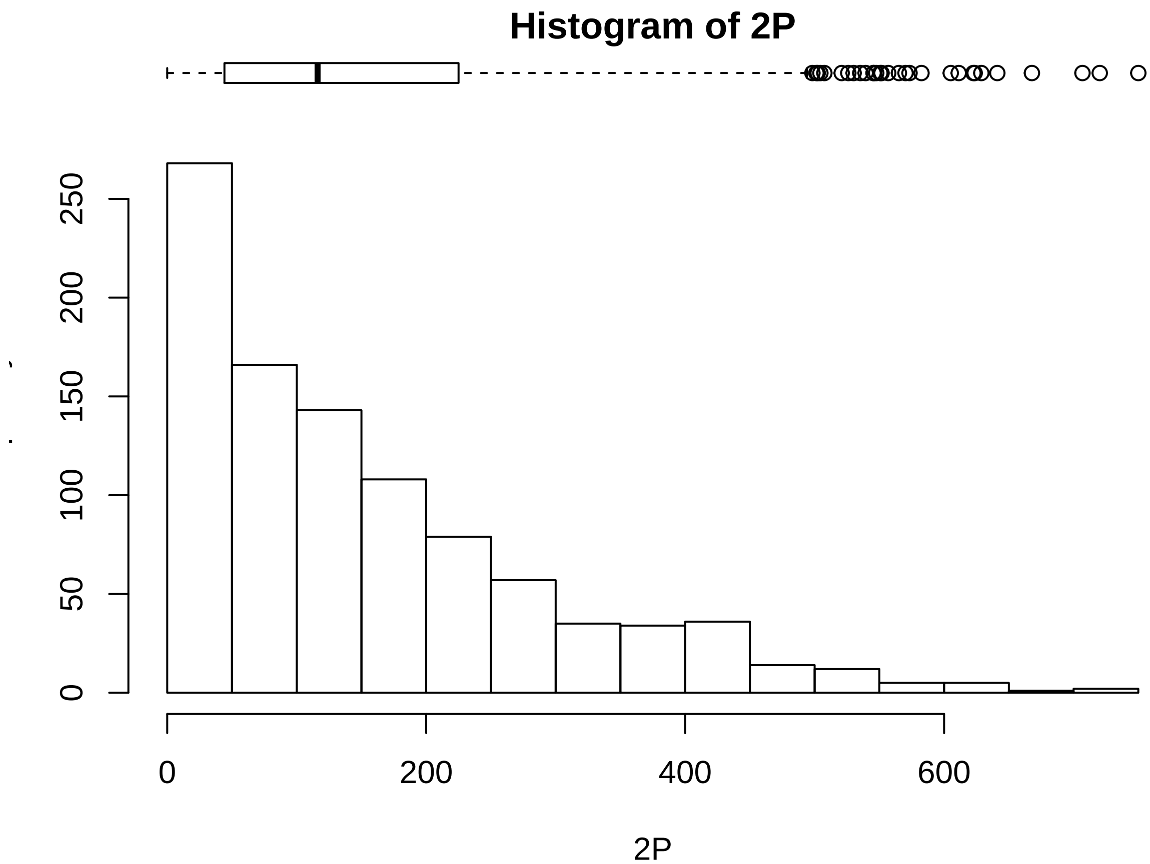

```
## Top 10 Players by 3P
## # A tibble: 10 x 51
##     year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##     <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2016  Steph~ 1.21e7 PG       27 GSW      79    79  2700  31.5 0.669  0.554
##  2 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>
```



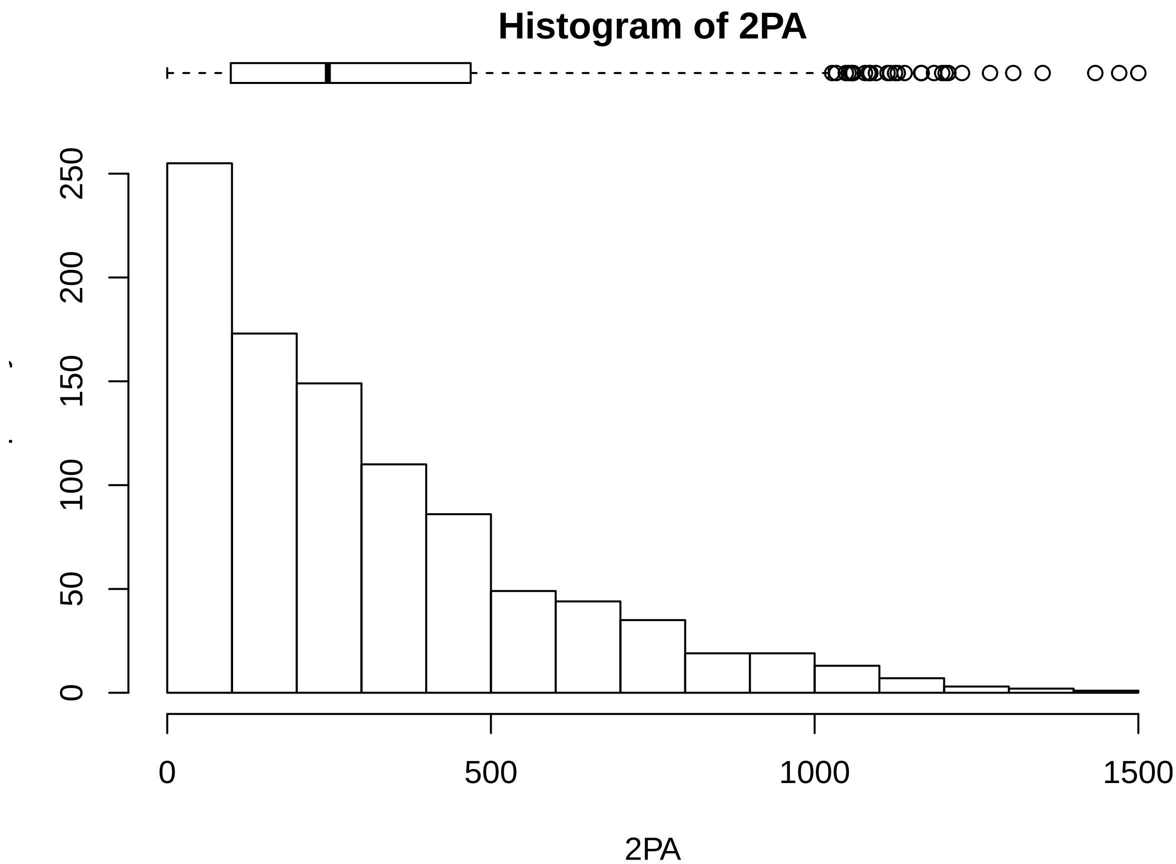

```
## Top 10 Players by 3PA
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2016  Steph~ 1.21e7 PG       27 GSW      79    79  2700  31.5 0.669  0.554
##  2 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>
```



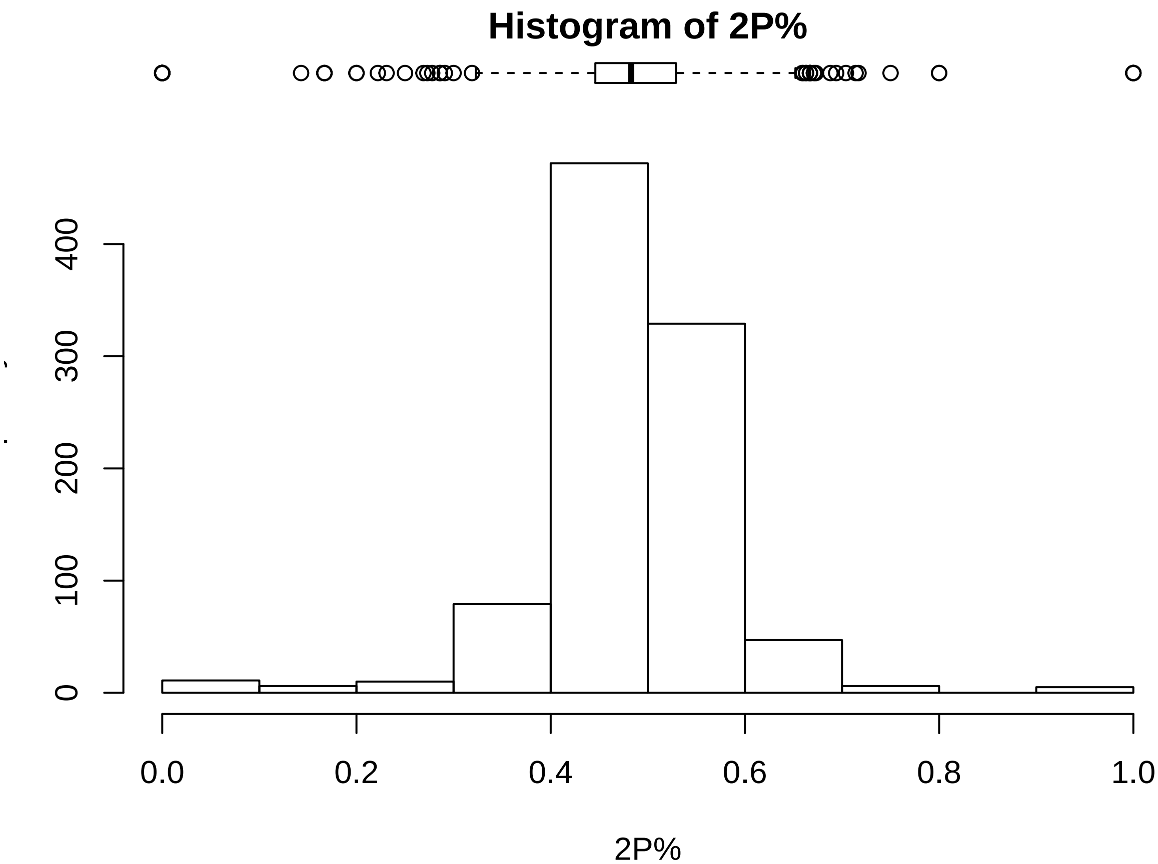

```
## Top 10 Players by 3P%
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2016  Andre~ 1.10e7 C        31 GSW      70    66  1451  15.9 0.623  0.004
##  2 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>
```



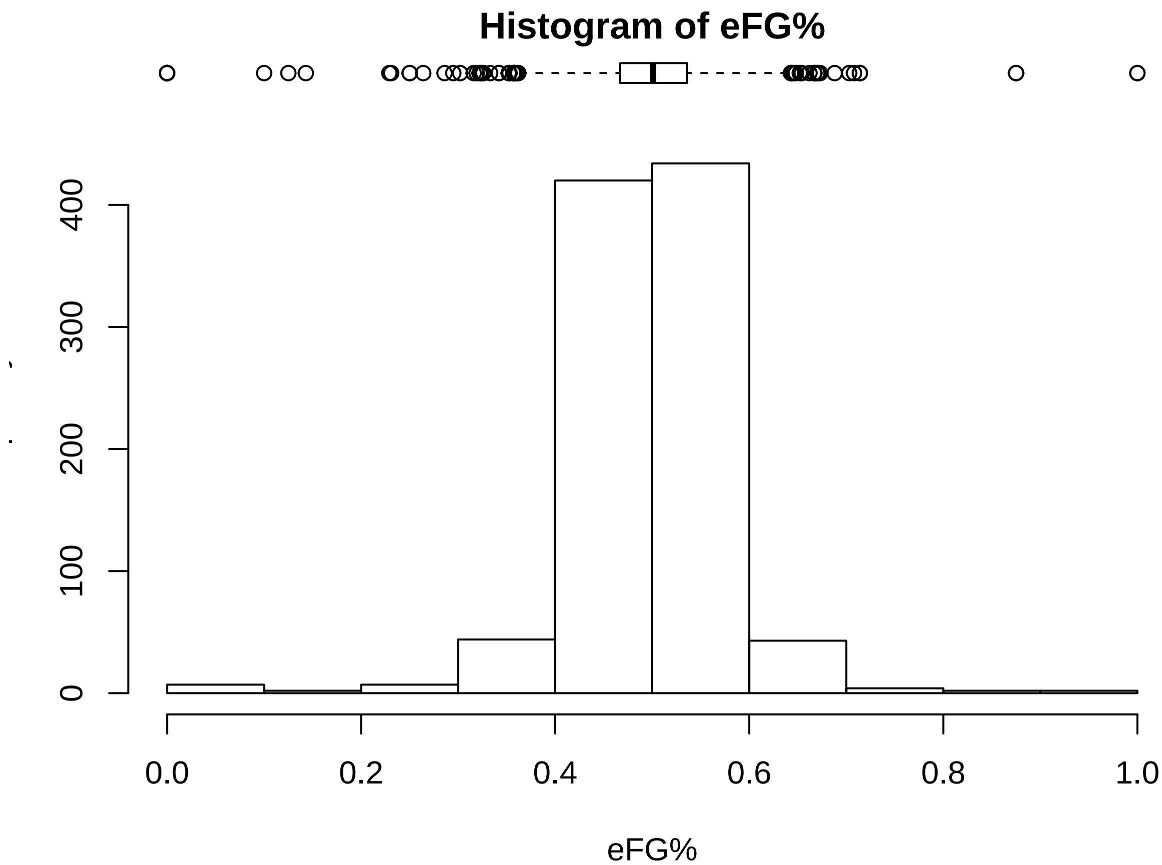

```
## Top 10 Players by 2P
## # A tibble: 10 x 51
##     year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##     <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2017  Antho~ 2.38e7 C        23 NOP      75    75  2708  27.5 0.579  0.088
##  2 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>
```



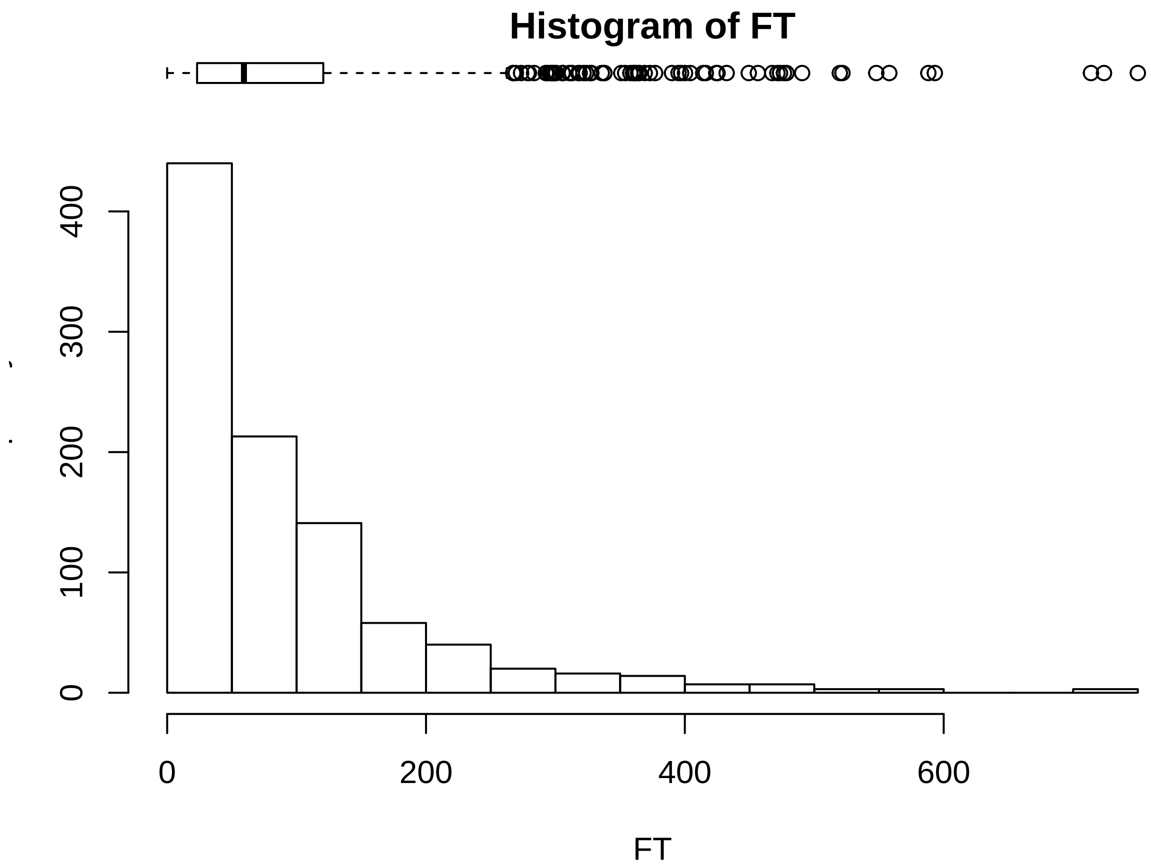

```
## Top 10 Players by 2PA
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2017  DeMar~ 2.77e7 SG       27 TOR      74    74  2620  24   0.552  0.08
##  2 2017  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>
```



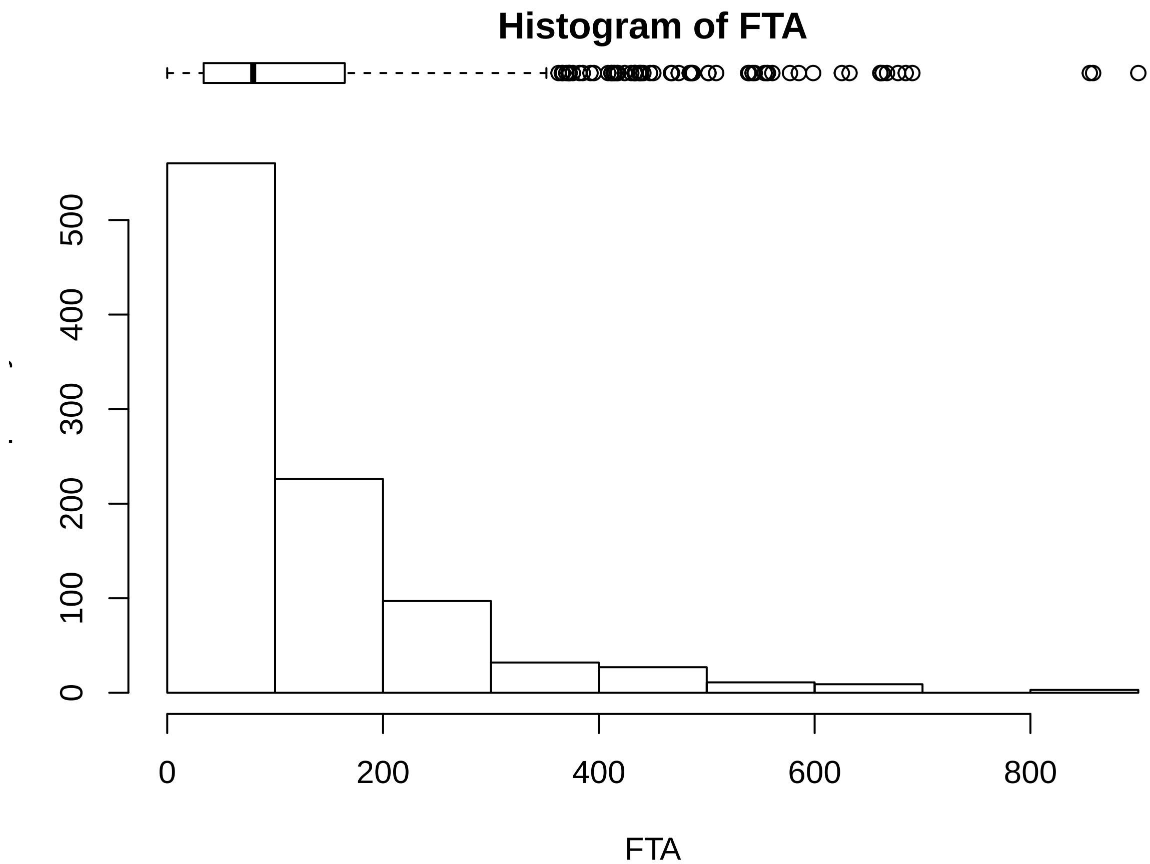

```
## Top 10 Players by 2P%
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2016  Brian~ 3.28e5 PG       23 MIA       1     0     3  39.3 1      0
##  2 2017  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>
```



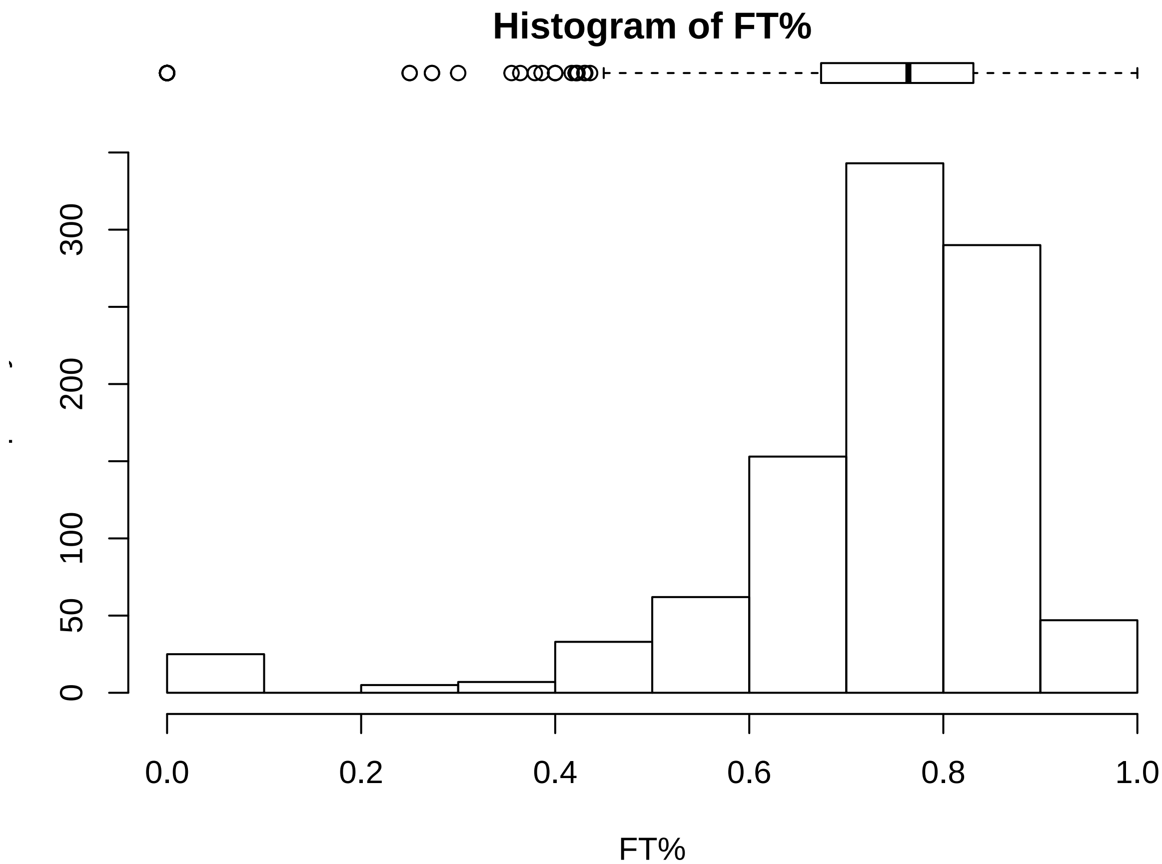

```
## Top 10 Players by eFG%
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2016  Brian~ 3.28e5 PG       23 MIA       1     0     3  39.3 1      0
##  2 2016  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>
```



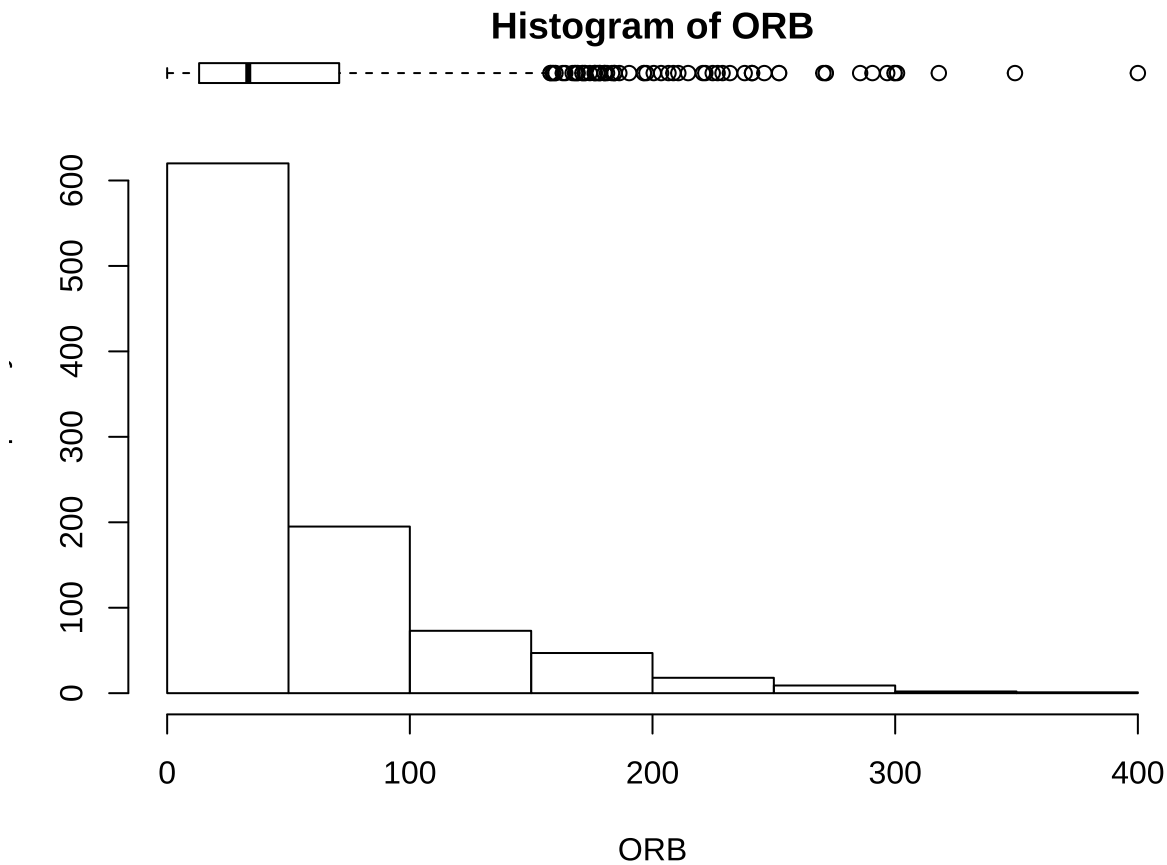

```
## Top 10 Players by FT
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2017  James~ 2.83e7 PG       27 HOU      81    81  2947  27.3 0.613  0.493
##  2 2016  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>
```



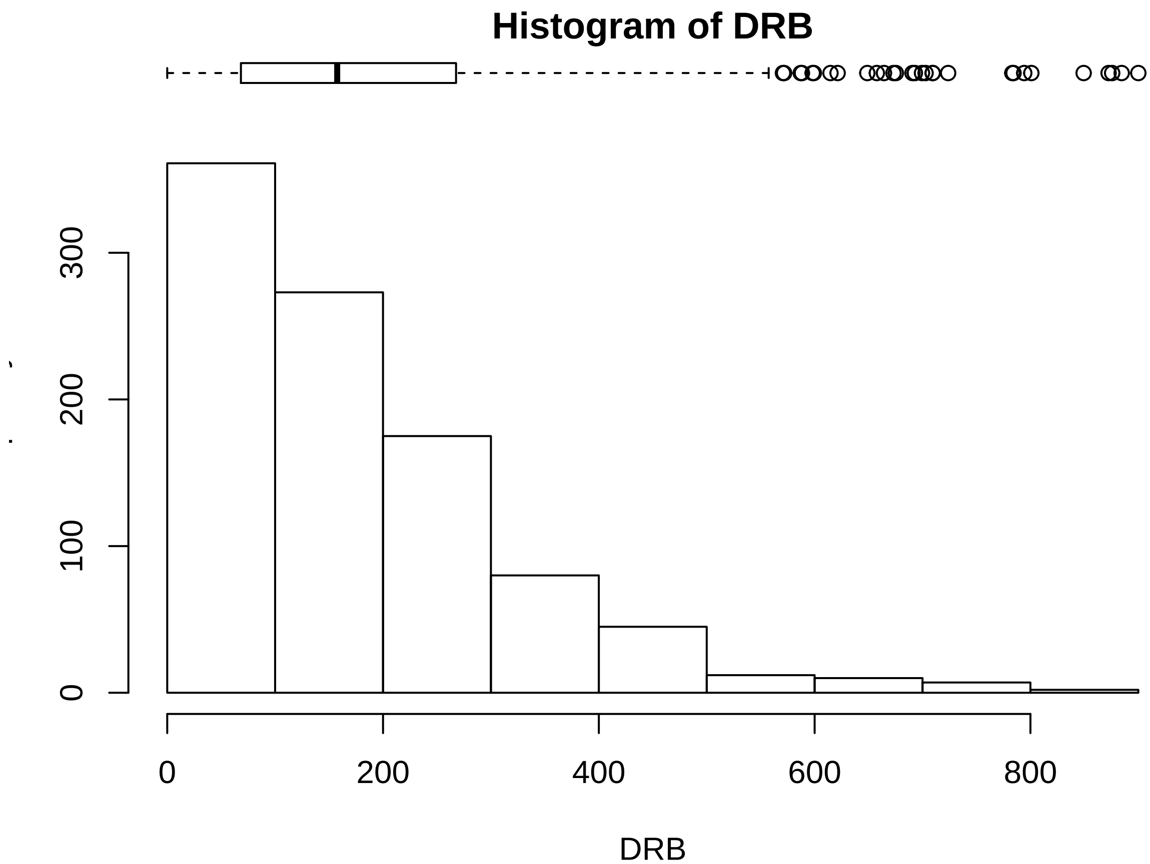

```
## Top 10 Players by FTA
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2017  James~ 2.83e7 PG       27 HOU      81    81  2947  27.3 0.613  0.493
##  2 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>
```



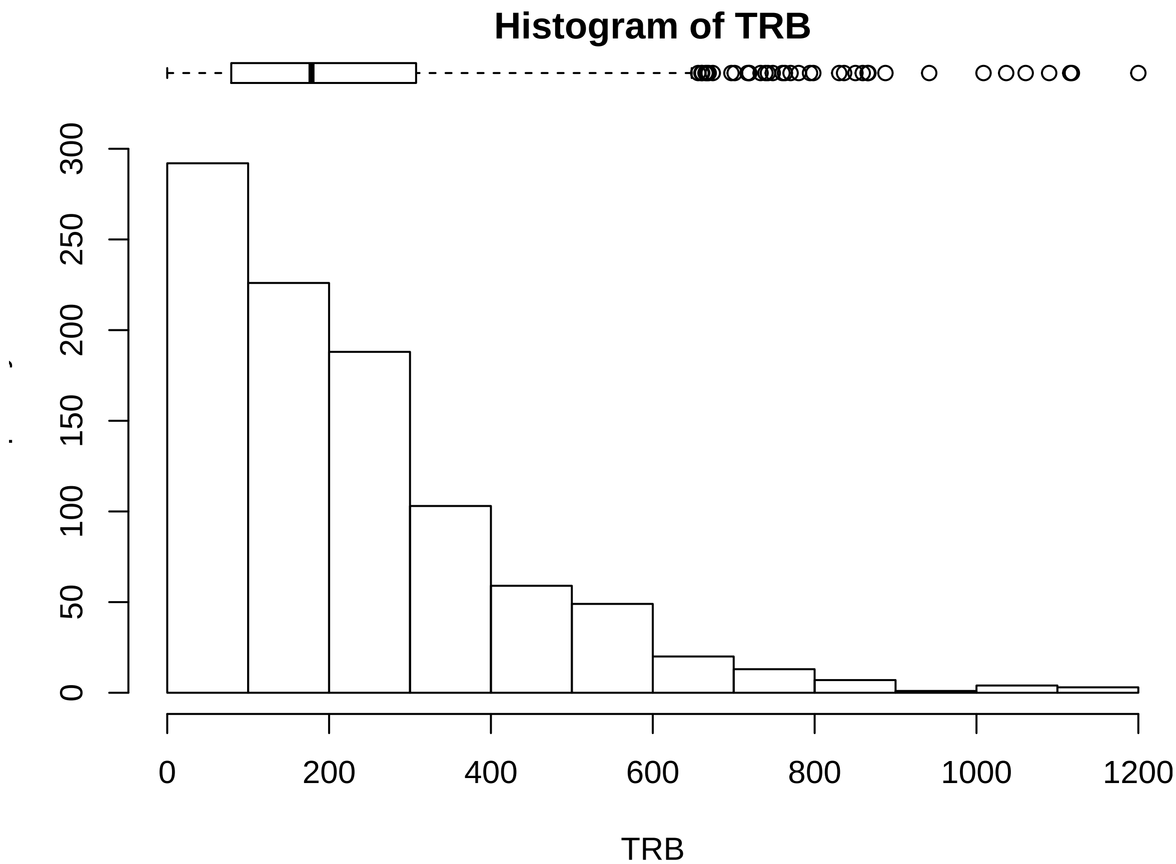

```
## Top 10 Players by FT%
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2017  Andre~ 2.84e6 PF       27 BRK      10     0   111   5   0.43   0.324
##  2 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>
```



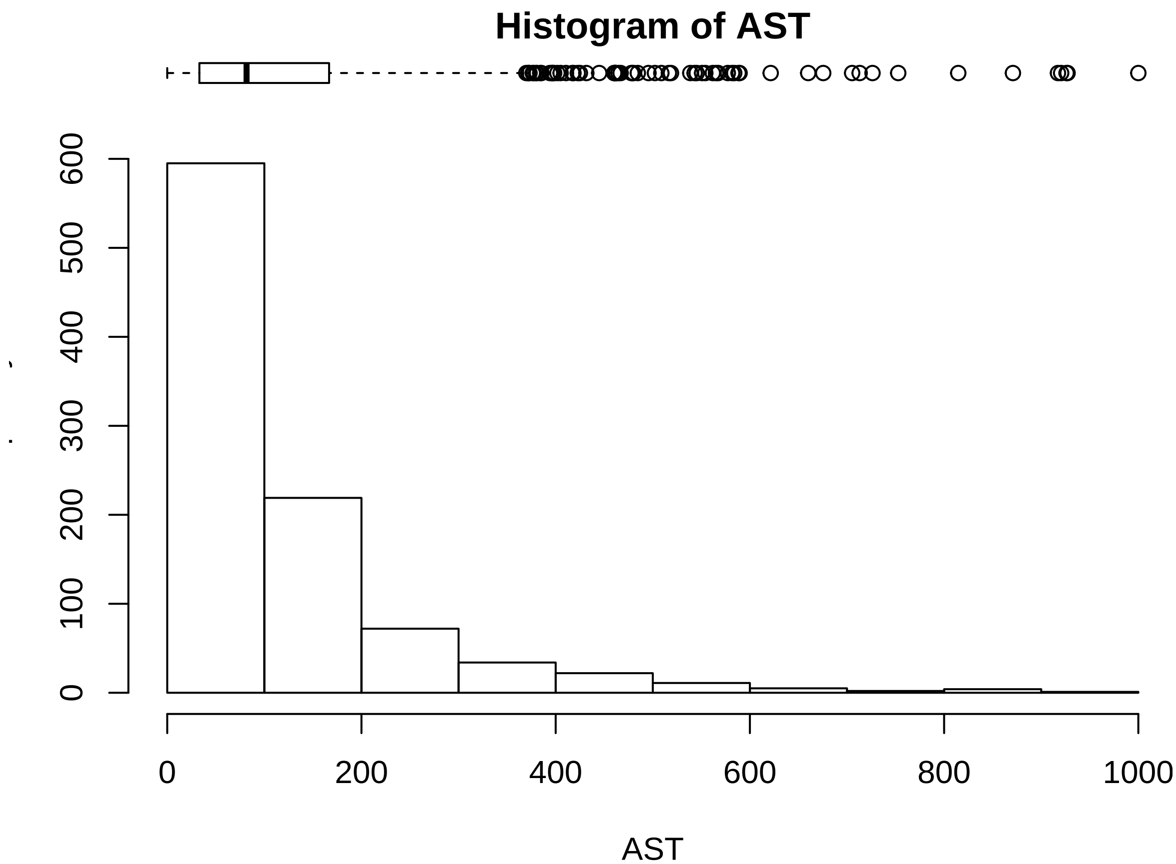

```
## Top 10 Players by ORB
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2016  Andre~ 2.21e7 C        22 DET      81    81  2666  21.2 0.499  0.006
##  2 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>
```



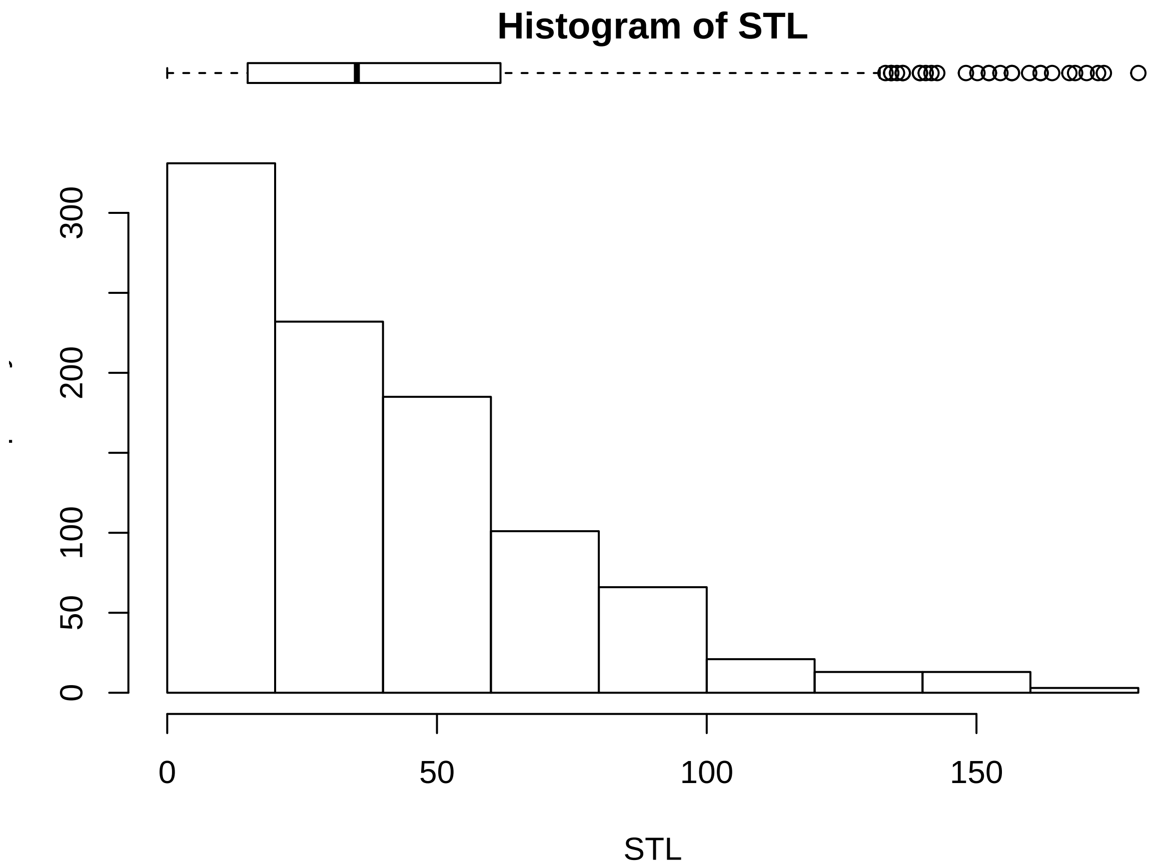

```
## Top 10 Players by DRB
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2017  DeAnd~ 2.26e7 C        28 LAC      81    81  2570  21.8 0.673  0.003
##  2 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>
```



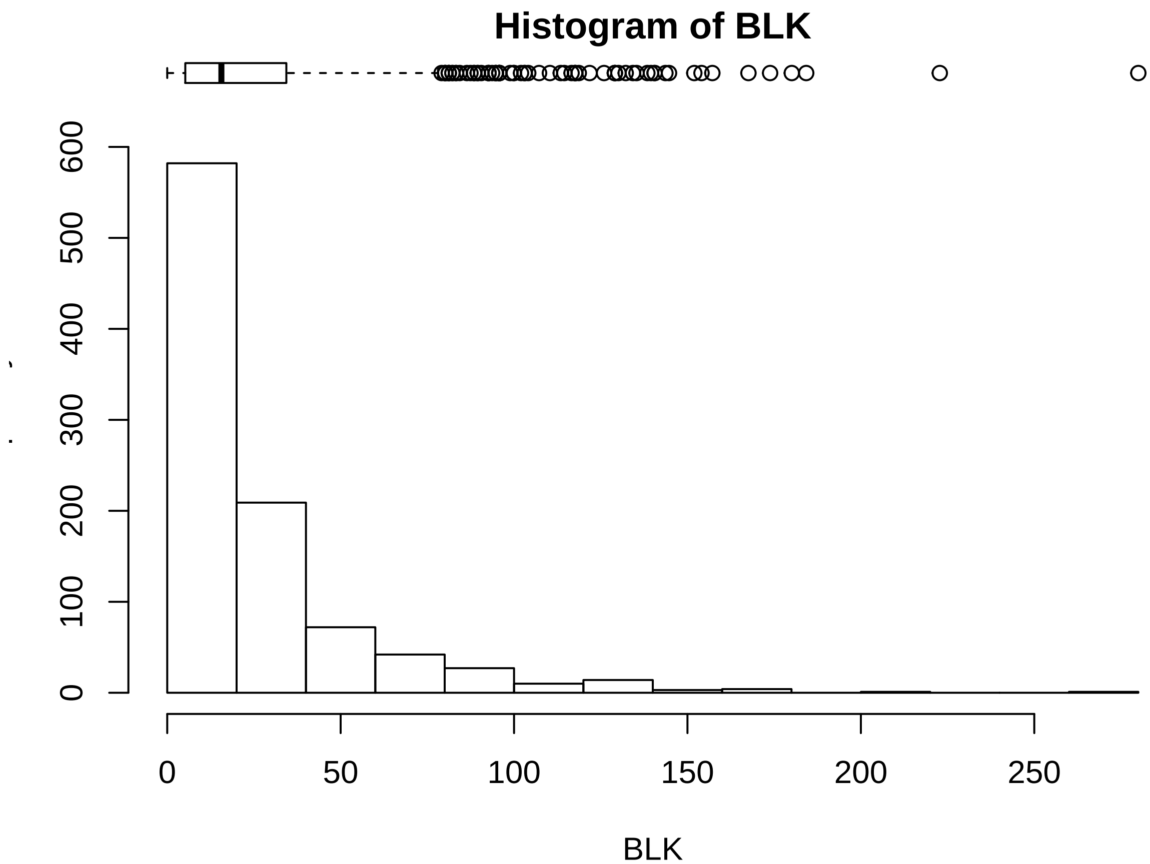

```
## Top 10 Players by TRB
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2016  Andre~ 2.21e7 C        22 DET      81    81  2666  21.2 0.499  0.006
##  2 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>
```



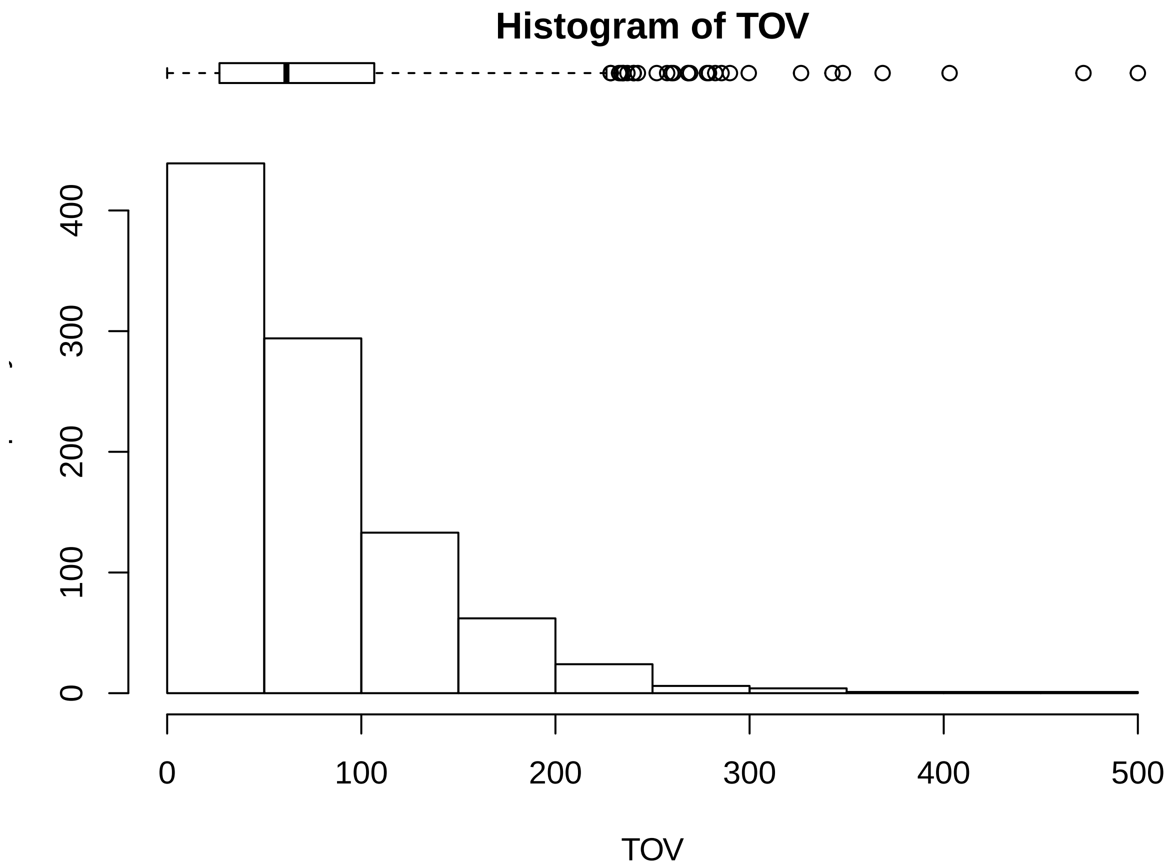

```
## Top 10 Players by AST
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2017  James~ 2.83e7 PG       27 HOU      81    81  2947  27.3 0.613  0.493
##  2 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>
```



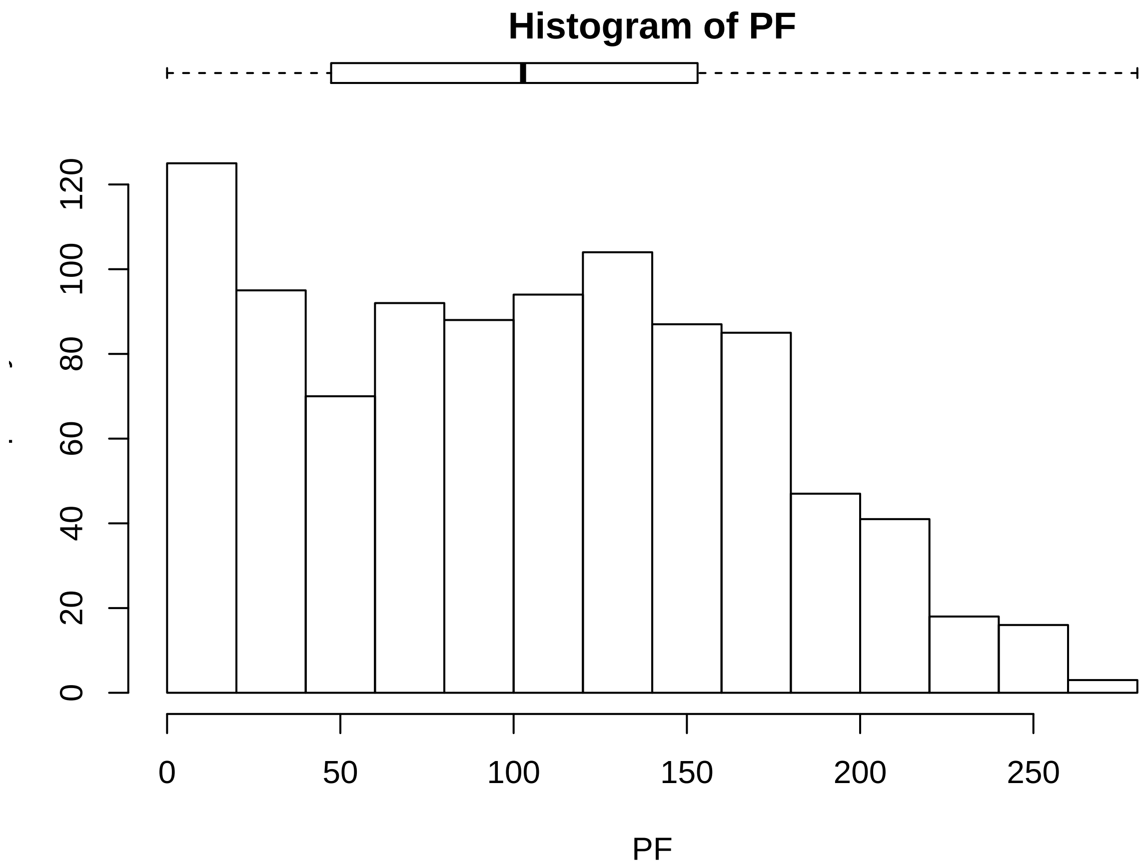

```
## Top 10 Players by STL
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2016  Steph~ 1.21e7 PG       27 GSW      79    79  2700  31.5 0.669  0.554
##  2 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>
```



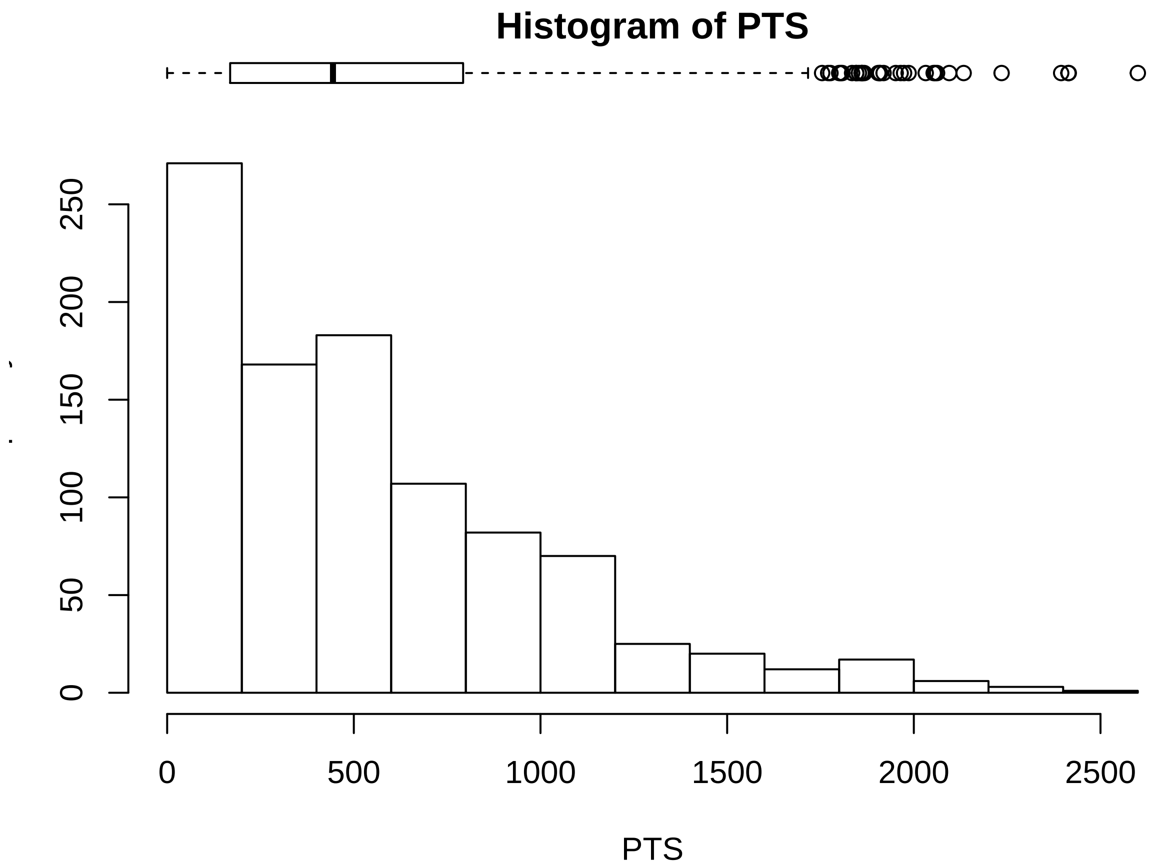

```
## Top 10 Players by BLK
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2016  Hassa~ 2.21e7 C        26 MIA      73    43  2125  25.7 0.629  0
##  2 2017  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>
```



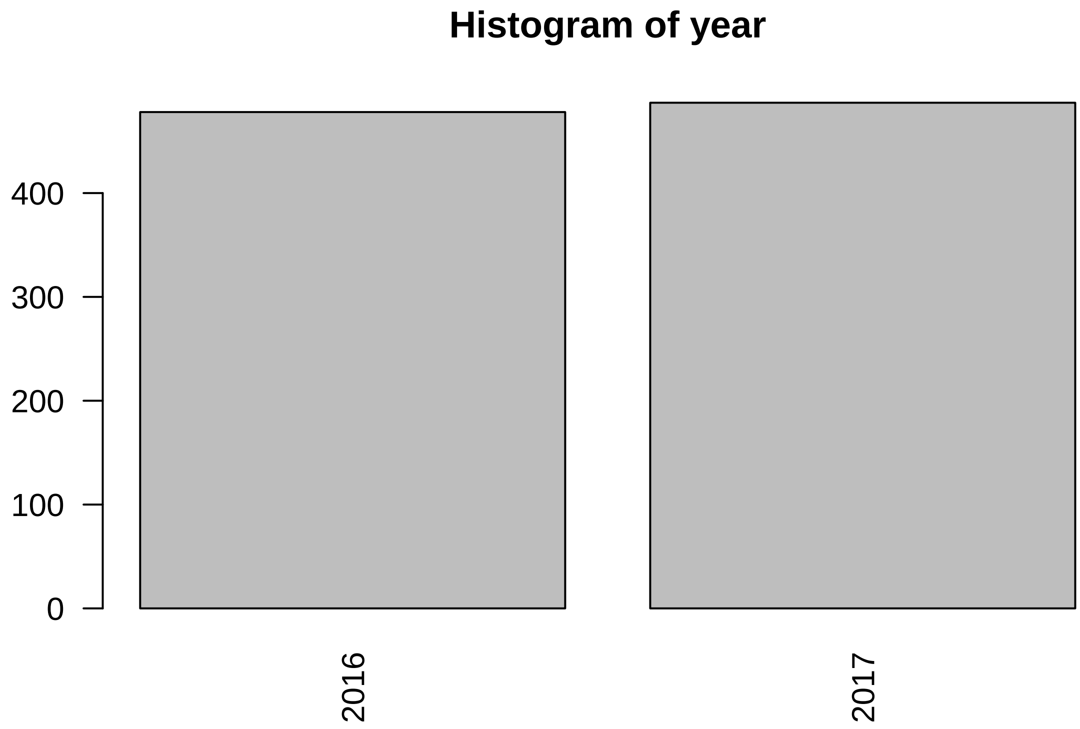

```
## Top 10 Players by PF
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2017  DeMar~ 1.81e7 C        26 TOT      72    72  2465  25.7 0.562  0.254
##  2 2017  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>
```



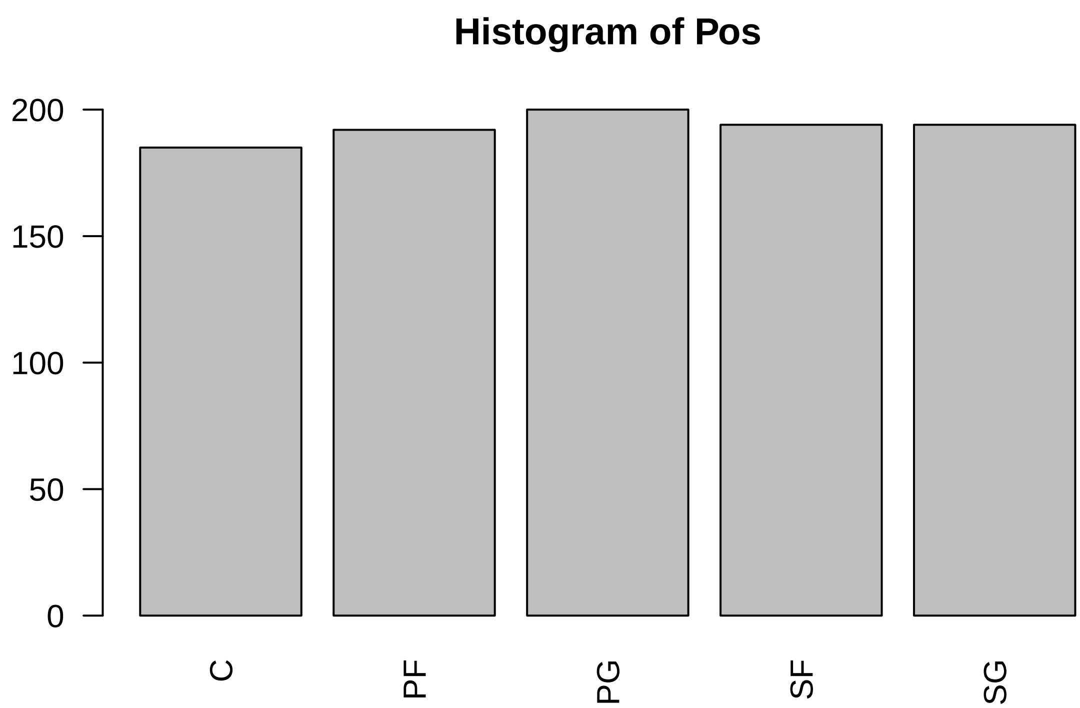

```
## Top 10 Players by PTS
## # A tibble: 10 x 51
##    year  name_p salary Pos     Age Tm        G    GS    MP   PER `TS%` `3PAr`
##    <fct> <chr>   <dbl> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
##  1 2017  Russe~ 2.85e7 PG       28 OKC      81    81  2802  30.6 0.554  0.3
##  2 2016  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

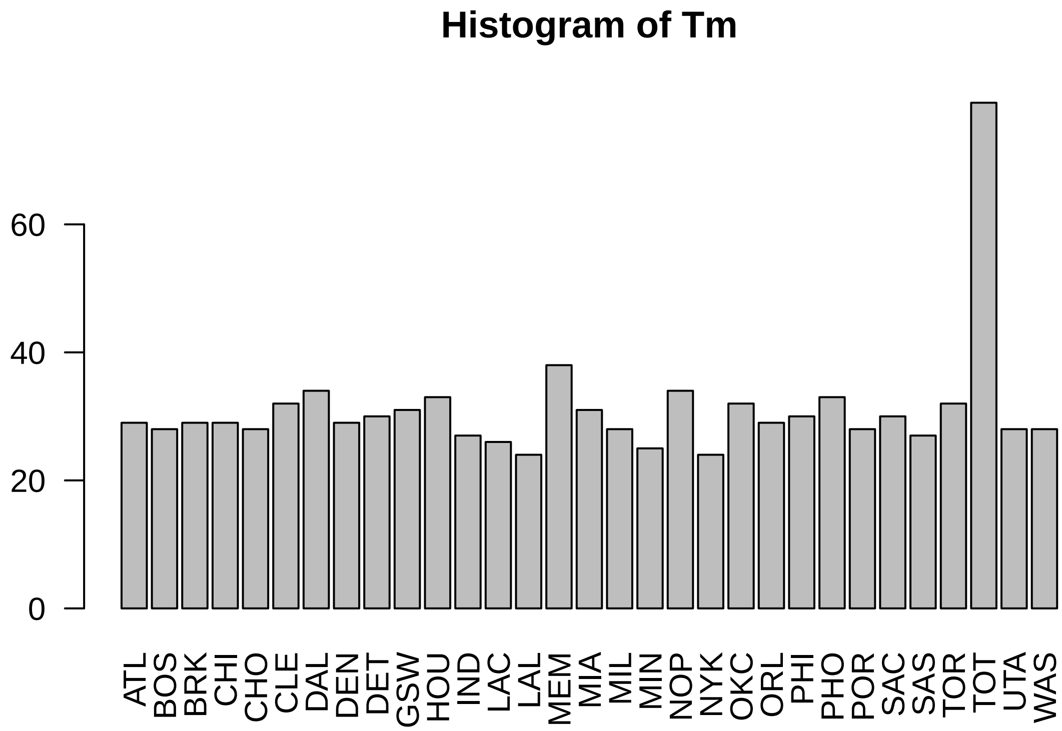
```
categorical_vars <- c('year','Pos','Tm')
for (col in categorical_vars){
  data <- df_primary[[col]]
  barplot(table(data),main=sprintf('Histogram of %s',col),las=2)
  print('\n')}
```


Histogram of year
400
300
200
100
0
2016
2017

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


Histogram of Pos
200
150
100
50
0
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)}
df_secondary[is.na(df_secondary)] <- 0
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
##
```

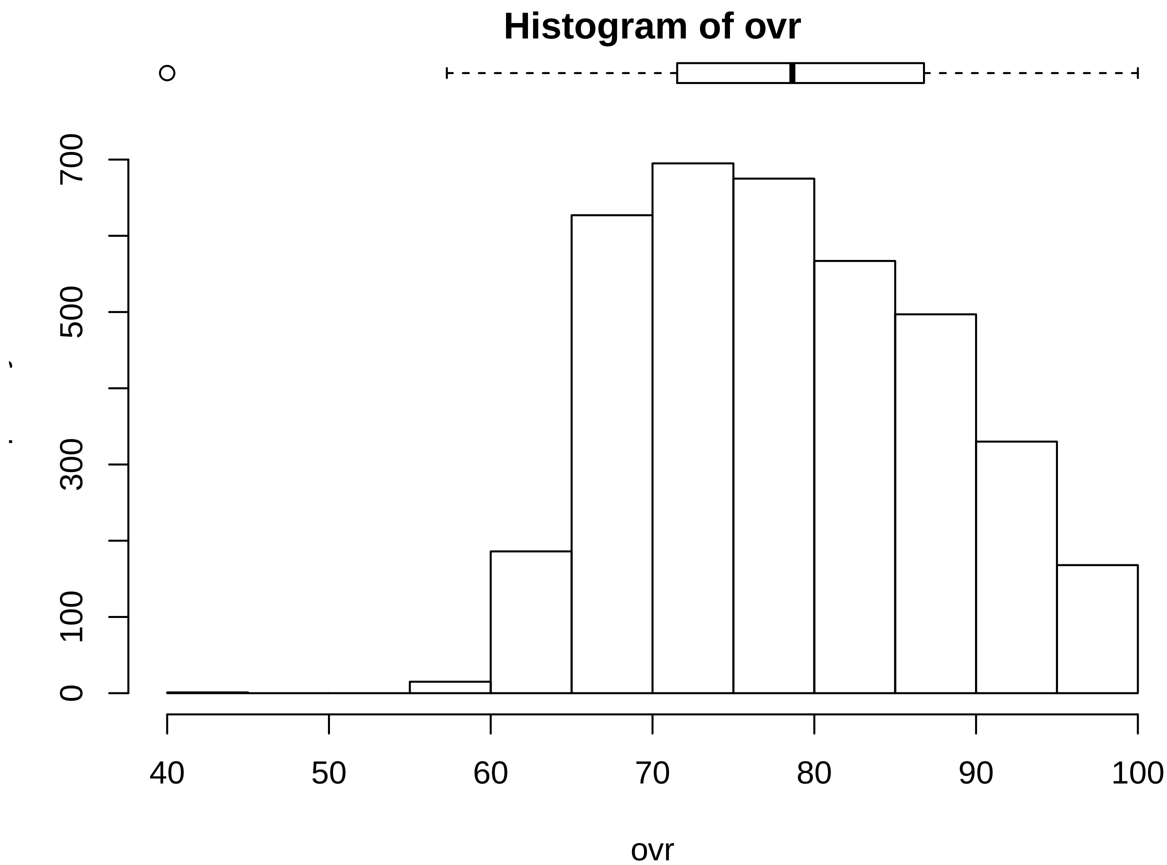
Numeric / Factor Variables

```
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)
```

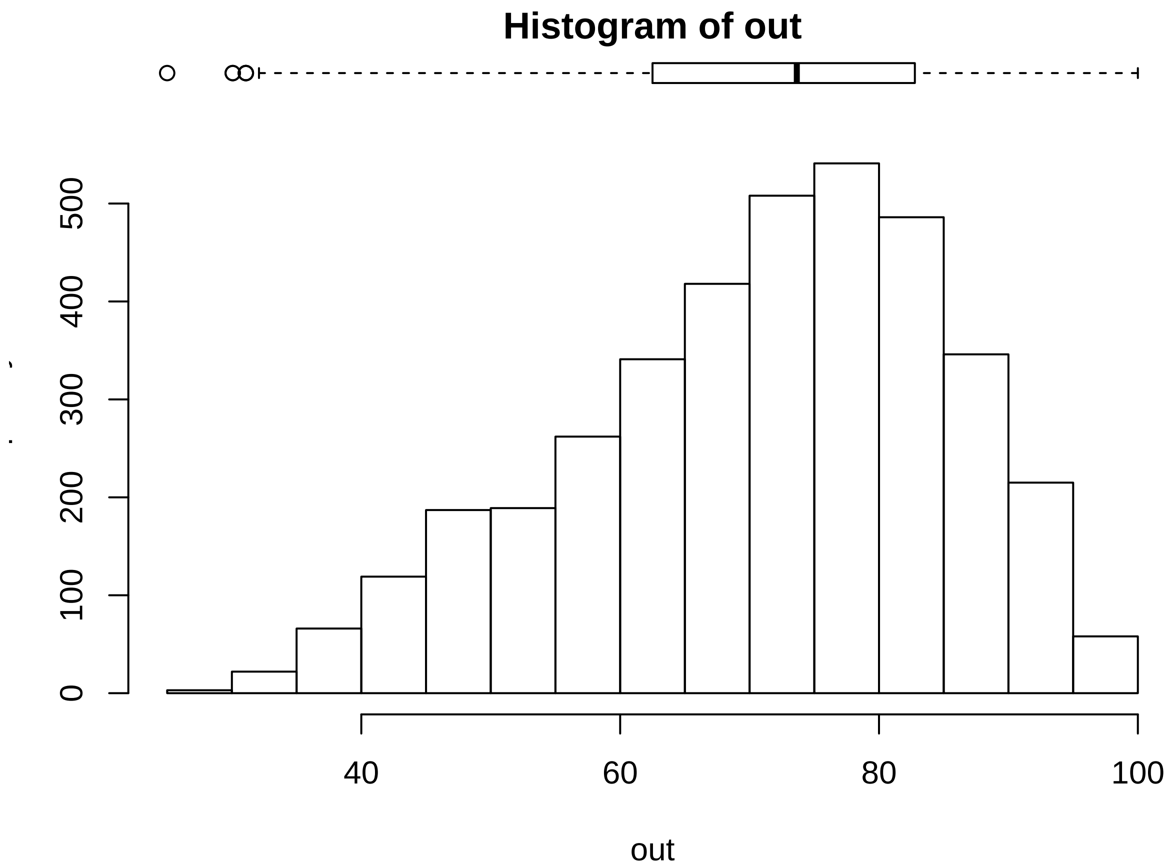
```
## 'data.frame':    3761 obs. of  10 variables:
##  $ name_s    : chr  "'96 Michael Jordan" "'15 Kobe Bryant" "Stephen Curry" "LeBron James" ...
##  $ position_s: Factor w/ 5 levels "C","PF","PG",..: 5 5 3 4 1 3 3 5 2 5 ...
##  $ ovr       : int  99 99 99 99 99 98 98 98 98 98 ...
##  $ out       : 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

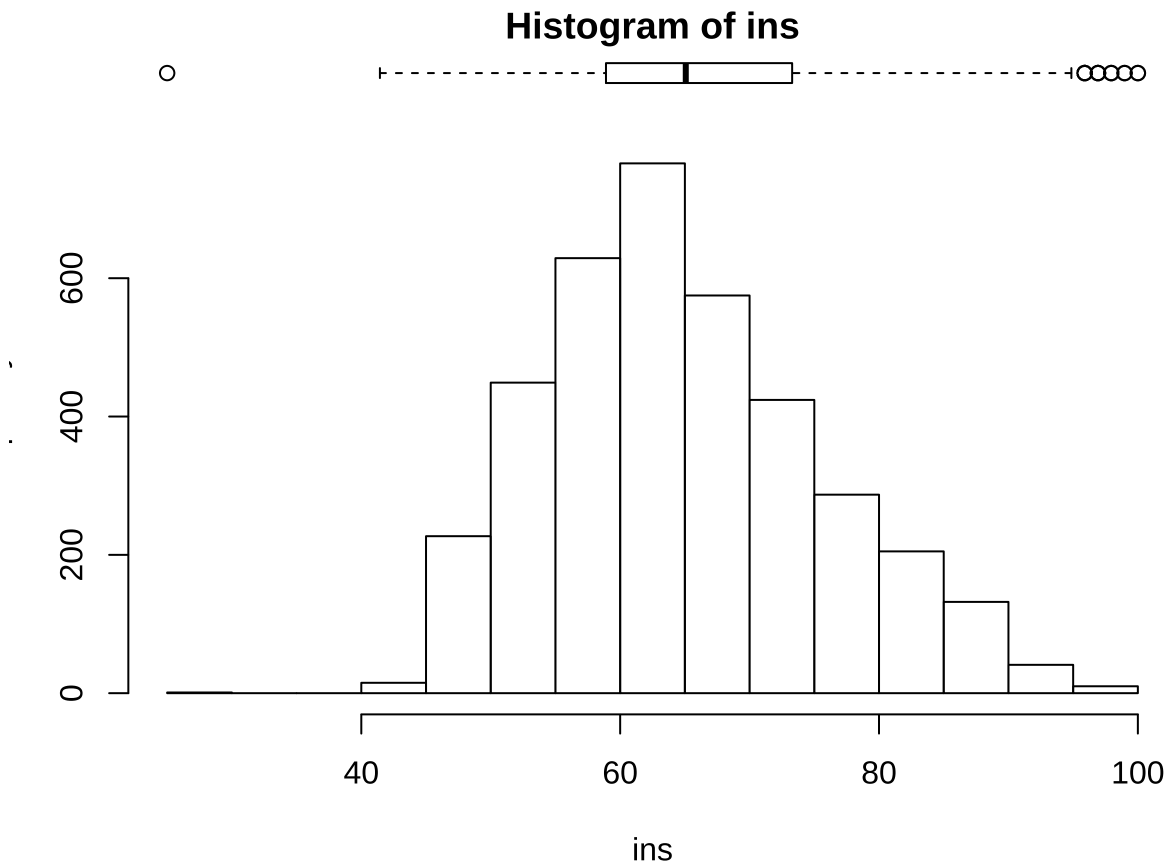
```
df_s_numeric <- Filter(is.numeric,df_secondary) # numeric variables
for (col in names(df_s_numeric)){
  data <- df_s_numeric[[col]]
  layout(mat = matrix(c(1,2),2,1, byrow=TRUE), height = c(1,8))
  par(mar=c(0, 3.1, 1.1, 2.1))
  boxplot(data , horizontal=TRUE , xaxt="n", frame=F, main=sprintf('Histogram 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,])}
```



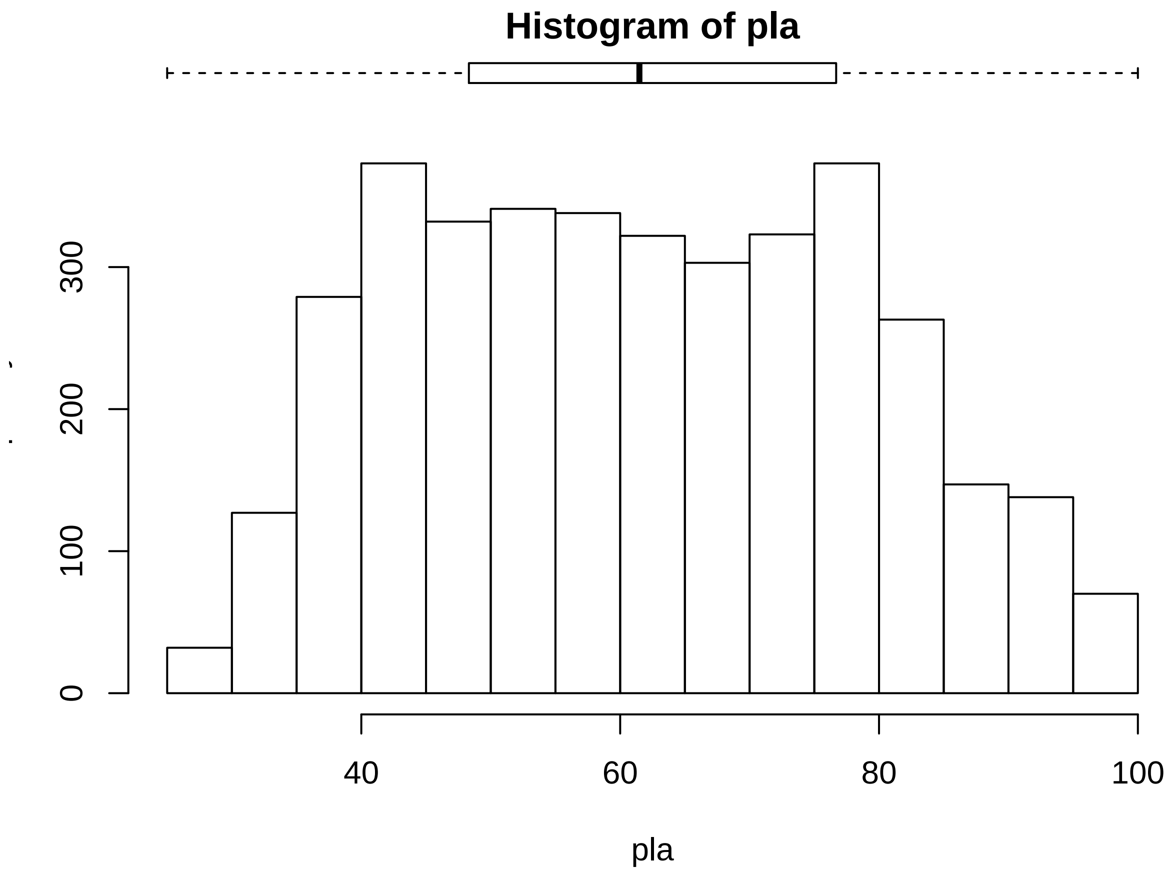

```
## Top 10 Players by ovr
##                        name_s position_s ovr out ins pla ath def reb year
## 1          '96 Michael Jordan         SG  99  95  88  91  93  92  75 2016
## 2             '15 Kobe Bryant         SG  99  97  79  95  84  88  65 2016
## 3               Stephen Curry         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
```



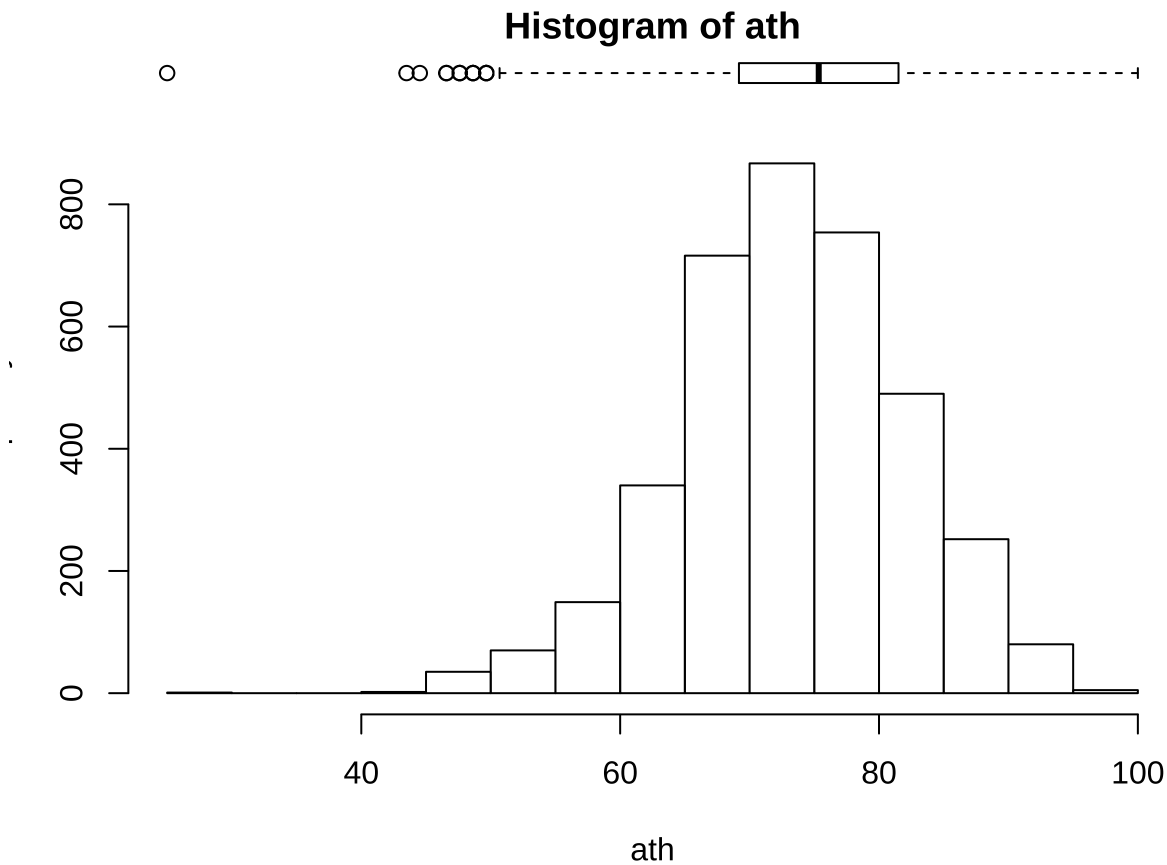

```
## Top 10 Players by out
##                 name_s position_s ovr out ins pla ath def reb year
## 2098    Stephen Curry         PG  98  99  70  98  92  86  78 2017
## 3       Stephen Curry         PG  99  98  66  98  89  78  54 2016
## 6        Kyrie Irving         PG  98  98  70  95  91  74  49 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
```



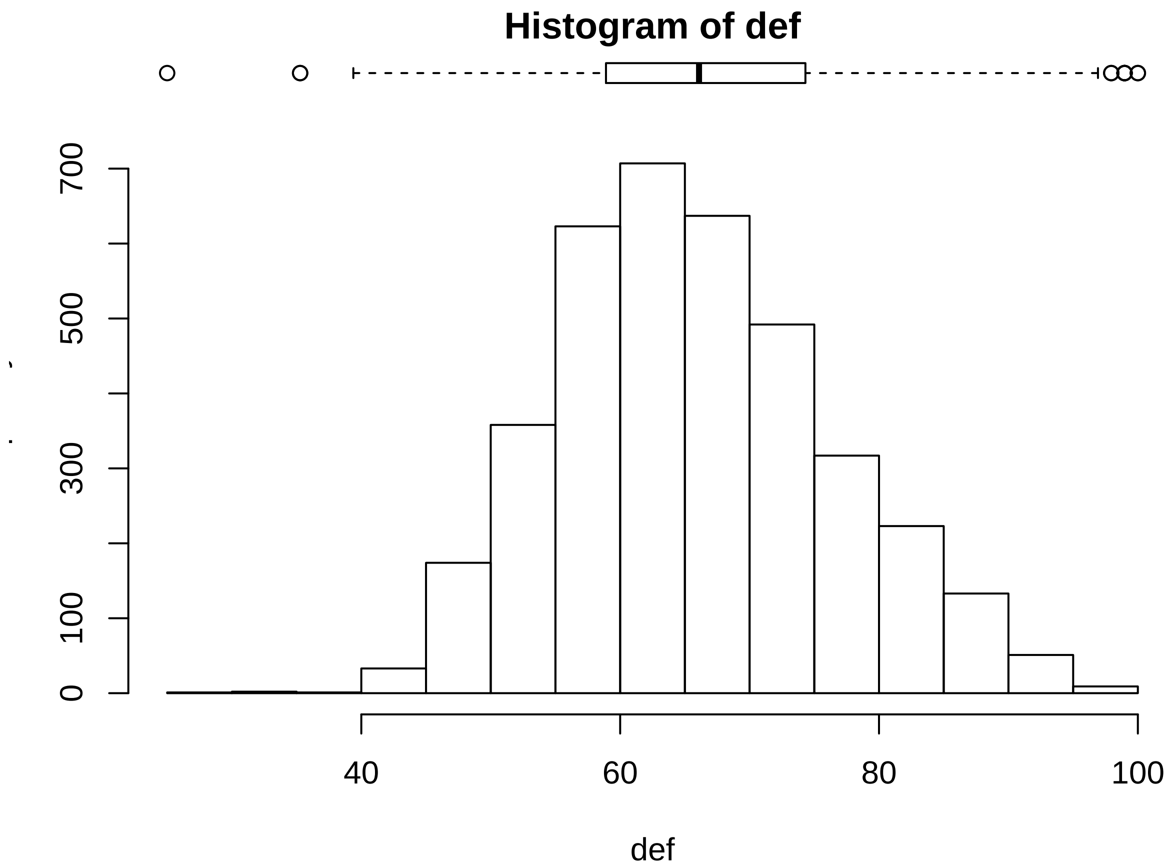

```
## Top 10 Players by ins
##                  name_s position_s ovr out ins pla ath def reb year
## 2091     Charles Barkley         PF  99  95  98  89  95  97  98 2017
## 2106 Kareem Adbul-Jabbar          C  98  83  98  85  90  95  98 2017
## 2107          Karl Malone         PF  98  88  98  80  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
```



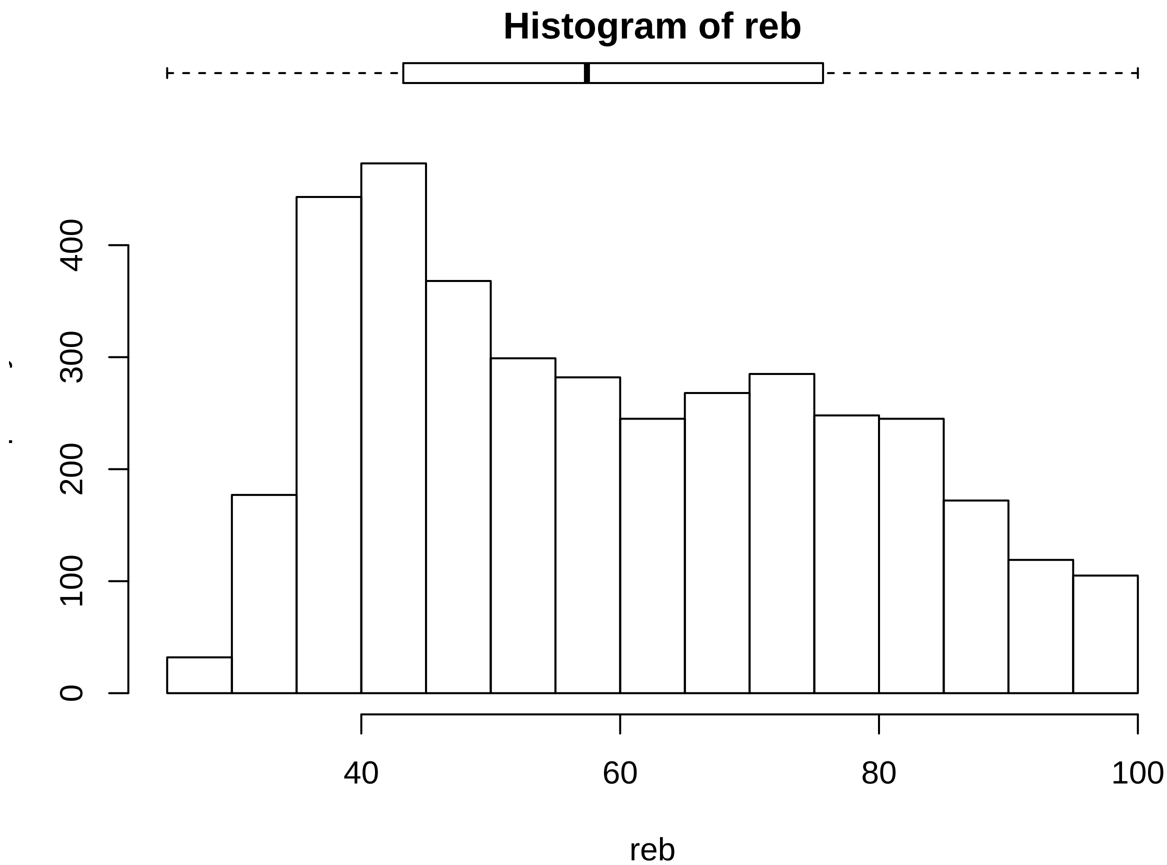

```
## Top 10 Players by pla
##                    name_s position_s ovr out ins pla ath def reb year
## 2101       Magic Johnson         PG  98  95  90  99  96  95  89 2017
## 2115       John Stockton         PG  98  97  70  99  92  90  51 2017
## 3          Stephen Curry         PG  99  98  66  98  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
```



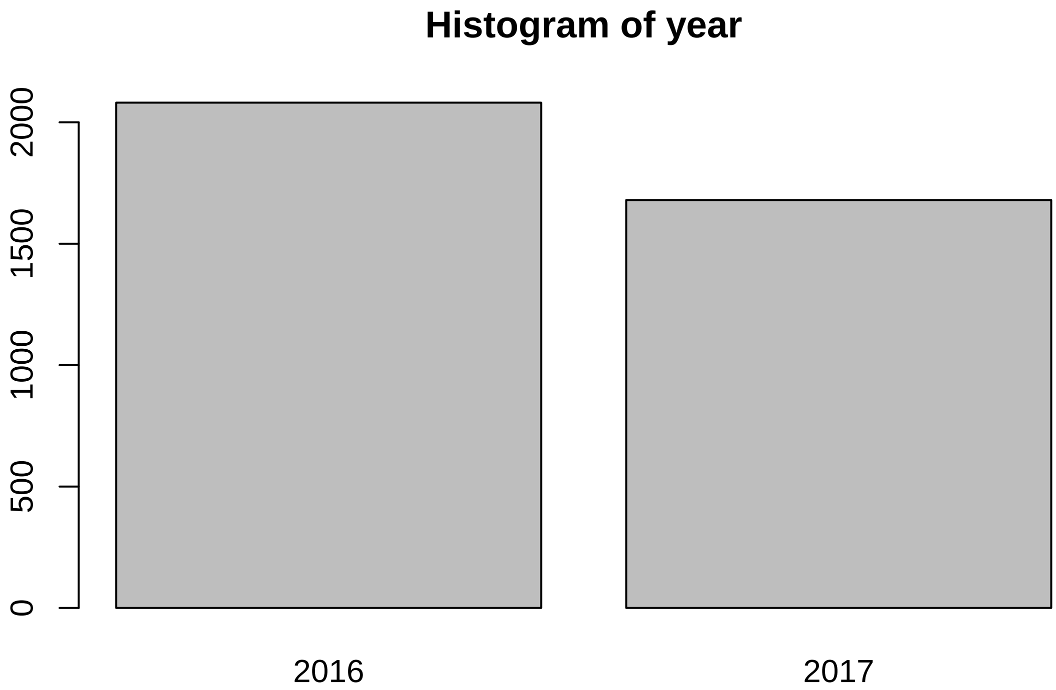

```
## Top 10 Players by def
##                 name_s position_s ovr out ins pla ath def reb year
## 2109    Dennis Rodman         PF  98  77  88  61  92  98  99 2017
## 2233   Draymond Green         PF  95  90  86  94  91  98  92 2017
## 2091  Charles Barkley         PF  99  95  98  89  95  97  98 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

```r
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 babbitt` = 'luke babbit',
  `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
## 162251        zoran dragic        goran dragic     1
## 608586        goran dragic        zoran dragic     1
## 7431         ryan anderson       alan anderson     2
## 8946        alvin williams       alan williams     2
## 90346          damon jones        damian jones     2
## 104062          david wear          david west     2
## 133344      dryamond green      draymond green     2
## 161525      flynn robinson      glenn robinson     2
## 178959          josh smith           ish smith     2
## 216793         brian grant        jerian grant     2
## 247163           ish smith          josh smith     2
## 295513         mo williams        lou williams     2
## 310901       darius morris       marcus morris     2
## 319182      alvin williams     marvin williams     2
## 337639        lou williams         mo williams     2
## 375368        paul pressey        phil pressey     2
## 403616       alan anderson       ryan anderson     2
## 478426        willie green         willie reed     2
## 486897          joe bryant         kobe bryant     2
## 523561         willie reed        willie green     2
## 586233        darius miles       darius miller     2
## 608388         drew gooden         drew gordon     2
## 651700          david west          david wear     2
## 666966       marcus morris       darius morris     2
## 685574      charles oakley     charles barkley     2
## 748935       ervin johnson       kevin johnson     2
## 805078 shareef abdur rahim shareef adbur rahim     2
## 818393      draymond green      dryamond green     2
## 849063     charles barkley      charles oakley     2
## 877294 shareef adbur rahim shareef abdur rahim     2
## 878874        phil pressey        paul pressey     2
## 887697      glenn robinson      flynn robinson     2
```

```
## 904184       darius miller       darius miles     2
## 916661       alan williams      alvin williams     2
## 916970     marvin williams      alvin williams     2
## 935944        jerian grant         brian grant     2
## 958562       kevin johnson       ervin johnson     2
## 964325         kobe bryant          joe bryant     2
## 971474         drew gordon         drew gooden     2
## 993046        damian jones         damon jones     2
```

Joining Datasets

```
# 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
```

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

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

```
nrow(df_full)
```

```
## [1] 734
```

Clean Up Joined Data

```
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:734         2016:369   Min.   :   11534   C :157   Min.   :19.00
##  Class :character   2017:365   1st Qu.: 2113599   PF:147   1st Qu.:23.00
##  Mode  :character              Median : 5196000   PG:138   Median :26.00
##                                Mean   : 7829827   SF:143   Mean   :26.55
##                                3rd Qu.:12012640   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.: 848   1st Qu.:10.90
##  TOR    : 27   Median :68.00   Median :20.50   Median :1506   Median :13.70
##  PHO    : 25   Mean   :61.18   Mean   :31.72   Mean   :1474   Mean   :14.17
##  UTA    : 25   3rd Qu.:77.00   3rd Qu.:62.75   3rd Qu.:2118   3rd Qu.:16.90
##  DET    : 24   Max.   :82.00   Max.   :82.00   Max.   :3125   Max.   :32.00
##  (Other):536
##       TS%              3PAr             FTr              ORB%
##  Min.   :0.0000   Min.   :0.0000   Min.   :0.0000   Min.   : 0.000
##  1st Qu.:0.5090   1st Qu.:0.1060   1st Qu.:0.1760   1st Qu.: 2.000
##  Median :0.5415   Median :0.3050   Median :0.2480   Median : 3.600
##  Mean   :0.5382   Mean   :0.2933   Mean   :0.2717   Mean   : 5.068
##  3rd Qu.:0.5720   3rd Qu.:0.4427   3rd Qu.:0.3397   3rd Qu.: 7.500
##  Max.   :1.0000   Max.   :0.9000   Max.   :1.2190   Max.   :21.800
##
##       DRB%            TRB%            AST%             STL%
##  Min.   : 0.00   Min.   : 0.0   Min.   : 0.000   Min.   : 0.000
##  1st Qu.:10.53   1st Qu.: 6.3   1st Qu.: 7.125   1st Qu.: 1.100
##  Median :14.60   Median : 9.3   Median :10.300   Median : 1.500
##  Mean   :15.53   Mean   :10.3   Mean   :13.386   Mean   : 1.586
##  3rd Qu.:19.57   3rd Qu.:13.3   3rd Qu.:17.650   3rd Qu.: 1.900
##  Max.   :36.30   Max.   :25.6   Max.   :57.300   Max.   :11.100
##
##       BLK%            TOV%            USG%            OWS
##  Min.   :0.000   Min.   : 0.00   Min.   : 0.00   Min.   :-3.30
##  1st Qu.:0.600   1st Qu.:10.00   1st Qu.:15.40   1st Qu.: 0.20
##  Median :1.200   Median :12.50   Median :18.50   Median : 1.10
##  Mean   :1.736   Mean   :12.74   Mean   :19.18   Mean   : 1.72
##  3rd Qu.:2.500   3rd Qu.:15.10   3rd Qu.:22.18   3rd Qu.: 2.50
##  Max.   :9.700   Max.   :43.60   Max.   :41.70   Max.   :13.80
##
##       DWS              WS              WS/48              OBPM
##  Min.   :0.000   Min.   :-2.100   Min.   :-0.28300   Min.   :-17.3000
##  1st Qu.:0.700   1st Qu.: 1.100   1st Qu.: 0.05600   1st Qu.: -2.1000
##  Median :1.300   Median : 2.500   Median : 0.09100   Median : -0.7000
##  Mean   :1.521   Mean   : 3.241   Mean   : 0.09281   Mean   : -0.6693
##  3rd Qu.:2.200   3rd Qu.: 4.475   3rd Qu.: 0.12700   3rd Qu.:  0.5000
##  Max.   :6.000   Max.   :17.900   Max.   : 0.34300   Max.   : 12.4000
##
##       DBPM                BPM                VORP               FG
##  Min.   :-8.20000   Min.   :-24.1000   Min.   :-1.4000   Min.   :  0.0
##  1st Qu.:-1.30000   1st Qu.: -2.6750   1st Qu.:-0.1000   1st Qu.:114.5
##  Median :-0.10000   Median : -0.7000   Median : 0.4000   Median :208.0
##  Mean   :-0.08965   Mean   : -0.7583   Mean   : 0.8349   Mean   :240.2
##  3rd Qu.: 1.10000   3rd Qu.:  1.0000   3rd Qu.: 1.3000   3rd Qu.:338.0
##  Max.   :12.00000   Max.   : 15.6000   Max.   :12.4000   Max.   :824.0
##
##       FGA              FG%               3P               3PA
##  Min.   :   0.0   Min.   :0.0000   Min.   :  0.00   Min.   :  0.00
##  1st Qu.: 256.8   1st Qu.:0.4110   1st Qu.:  4.00   1st Qu.: 16.25
##  Median : 459.0   Median :0.4450   Median : 42.50   Median :120.00
##  Mean   : 526.0   Mean   :0.4527   Mean   : 56.36   Mean   :157.22
##  3rd Qu.: 730.8   3rd Qu.:0.4880   3rd Qu.: 90.75   3rd Qu.:256.00
##  Max.   :1941.0   Max.   :1.0000   Max.   :402.00   Max.   :886.00
##
##       3P%               2P               2PA               2P%
##  Min.   :0.0000   Min.   :  0.00   Min.   :   0.0   Min.   :0.0000
##  1st Qu.:0.2500   1st Qu.: 74.25   1st Qu.: 157.0   1st Qu.:0.4522
##  Median :0.3330   Median :153.00   Median : 308.0   Median :0.4850
##  Mean   :0.2847   Mean   :183.82   Mean   : 368.8   Mean   :0.4881
##  3rd Qu.:0.3738   3rd Qu.:258.00   3rd Qu.: 513.0   3rd Qu.:0.5308
##  Max.   :1.0000   Max.   :730.00   Max.   :1421.0   Max.   :1.0000
##
```

```
##       eFG%              FT              FTA              FT%
##  Min.   :0.0000   Min.   :  0.0   Min.   :  0.0   Min.   :0.0000
##  1st Qu.:0.4730   1st Qu.: 38.0   1st Qu.: 51.0   1st Qu.:0.6943
##  Median :0.5060   Median : 79.5   Median :109.5   Median :0.7685
##  Mean   :0.5038   Mean   :111.4   Mean   :145.1   Mean   :0.7438
##  3rd Qu.:0.5370   3rd Qu.:145.0   3rd Qu.:194.0   3rd Qu.:0.8310
##  Max.   :1.0000   Max.   :746.0   Max.   :881.0   Max.   :1.0000
##
##       ORB              DRB              TRB               AST
##  Min.   :  0.00   Min.   :  0.0   Min.   :   0.0   Min.   :  0.0
##  1st Qu.: 21.00   1st Qu.:103.0   1st Qu.: 128.0   1st Qu.: 47.0
##  Median : 44.00   Median :180.0   Median : 229.0   Median : 97.0
##  Mean   : 63.27   Mean   :206.7   Mean   : 269.9   Mean   :137.1
##  3rd Qu.: 86.00   3rd Qu.:278.2   3rd Qu.: 364.2   3rd Qu.:176.0
##  Max.   :395.00   Max.   :817.0   Max.   :1198.0   Max.   :906.0
##
##       STL              BLK               TOV              PF
##  Min.   :  0.00   Min.   :  0.00   Min.   :  0.0   Min.   :  0.0
##  1st Qu.: 22.00   1st Qu.:  9.00   1st Qu.: 39.0   1st Qu.: 79.0
##  Median : 42.00   Median : 20.00   Median : 69.0   Median :125.0
##  Mean   : 47.36   Mean   : 30.19   Mean   : 83.2   Mean   :121.6
##  3rd Qu.: 65.75   3rd Qu.: 39.00   3rd Qu.:113.8   3rd Qu.:165.0
##  Max.   :169.00   Max.   :269.00   Max.   :464.0   Max.   :278.0
##
##       PTS              out              ovr              ins
##  Min.   :   0.0   Min.   :30.00   Min.   :61.00   Min.   :44.00
##  1st Qu.: 307.0   1st Qu.:61.00   1st Qu.:71.00   1st Qu.:58.00
##  Median : 543.5   Median :72.00   Median :76.00   Median :64.00
##  Mean   : 648.1   Mean   :71.18   Mean   :78.48   Mean   :65.33
##  3rd Qu.: 897.0   3rd Qu.:82.75   3rd Qu.:85.00   3rd Qu.:71.00
##  Max.   :2558.0   Max.   :99.00   Max.   :99.00   Max.   :97.00
##
##       pla              ath              def              reb
##  Min.   :28.00   Min.   :49.00   Min.   :43.00   Min.   :27.00
##  1st Qu.:47.00   1st Qu.:68.00   1st Qu.:58.00   1st Qu.:44.00
##  Median :59.00   Median :73.00   Median :64.00   Median :59.00
##  Mean   :61.25   Mean   :73.47   Mean   :65.47   Mean   :60.85
##  3rd Qu.:75.75   3rd Qu.:79.00   3rd Qu.:72.00   3rd Qu.:74.00
##  Max.   :98.00   Max.   :98.00   Max.   :98.00   Max.   :98.00
##
```

```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
```

```r
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

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

```
## 'data.frame':    734 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 ...
```

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

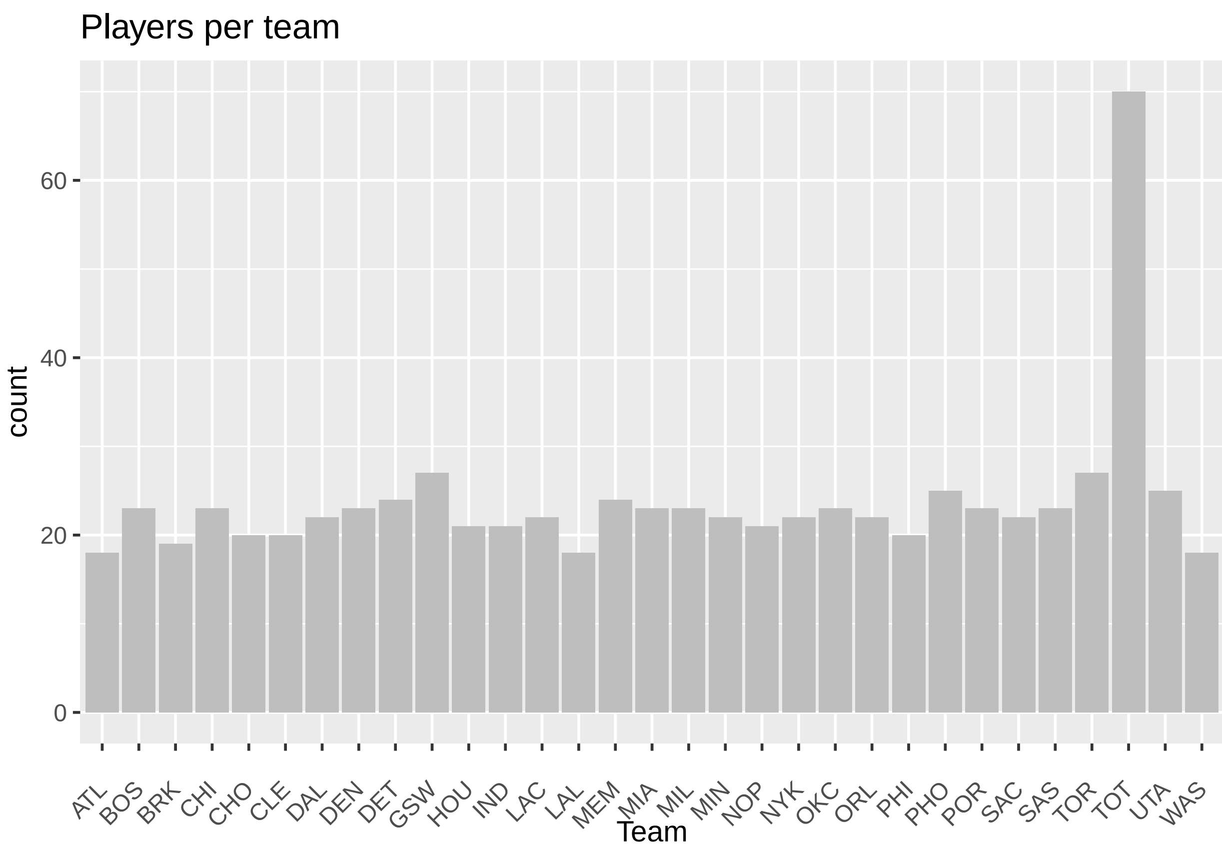
```
## 'data.frame':    734 obs. of  8 variables:
##  $ name: chr  "aaron brooks" "aaron brooks" "aaron gordon" "aaron gordon" ...
##  $ ovr : int  75 85 90 92 69 66 91 83 83 91 ...
##  $ out : int  79 87 87 86 56 47 90 75 81 80 ...
##  $ ins : int  52 51 91 91 65 64 77 72 76 82 ...
##  $ pla : int  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)
library(tidyr)
library(ggplot2)
df_final %>%
  keep(is.numeric) %>%
  gather() %>%
  ggplot(aes(value)) +
      facet_wrap(~ key, scales = "free") +
      geom_histogram(aes(y=..density..), fill = "grey") +
      geom_density()
ggsave("figures/hist_complete_vars.png", width=15, height=13)
```

Bar Chart of Player by Team from Complete Dataset

```
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))
```

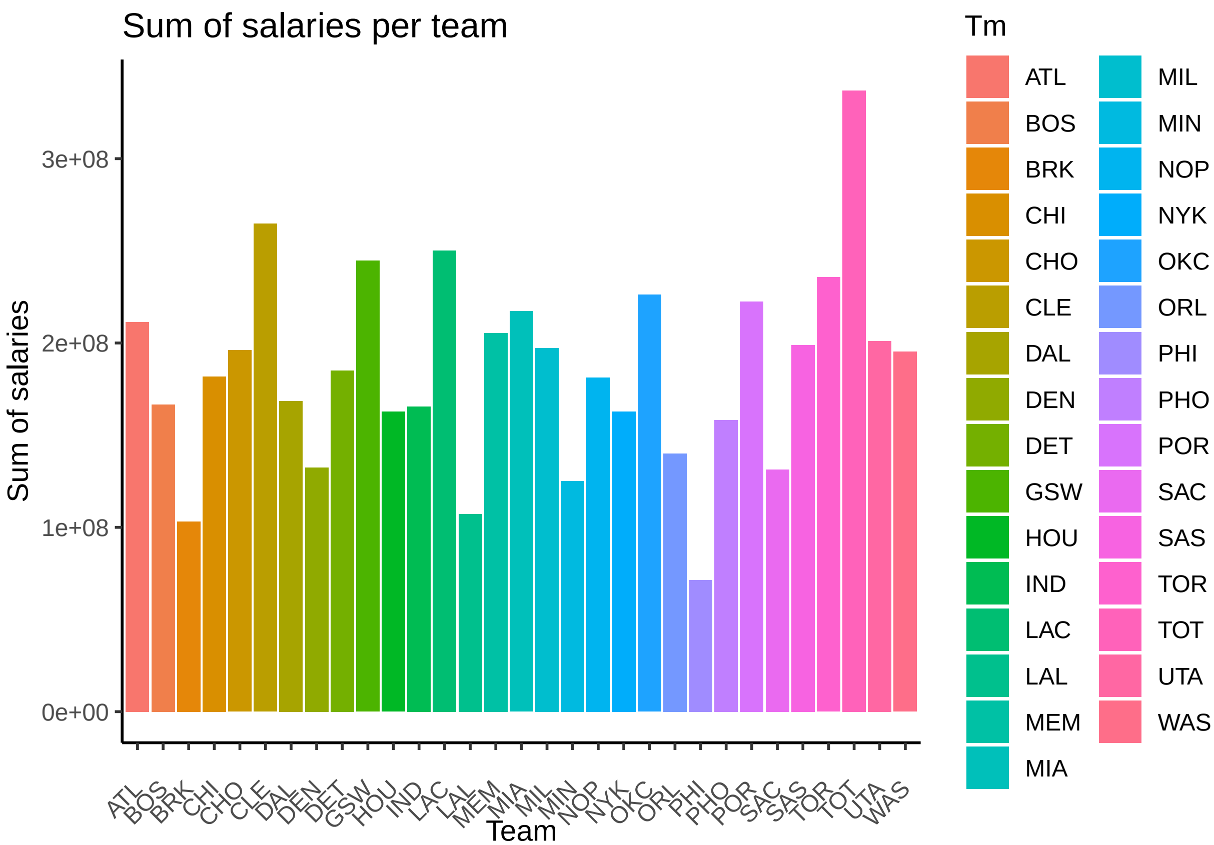



```
ggsave("figures/bar_complete_player_per_team.png", width=10, height=7)
```

Sum of Salaries per Team for Complete Dataset

```
library(ggplot2)
library(tidyr)
library(dplyr)
df_final %>%
  group_by(Tm) %>%
  summarise(sum_salary = sum(salary)) %>%
  ggplot(aes(x = Tm, y = sum_salary, fill = Tm)) +
```

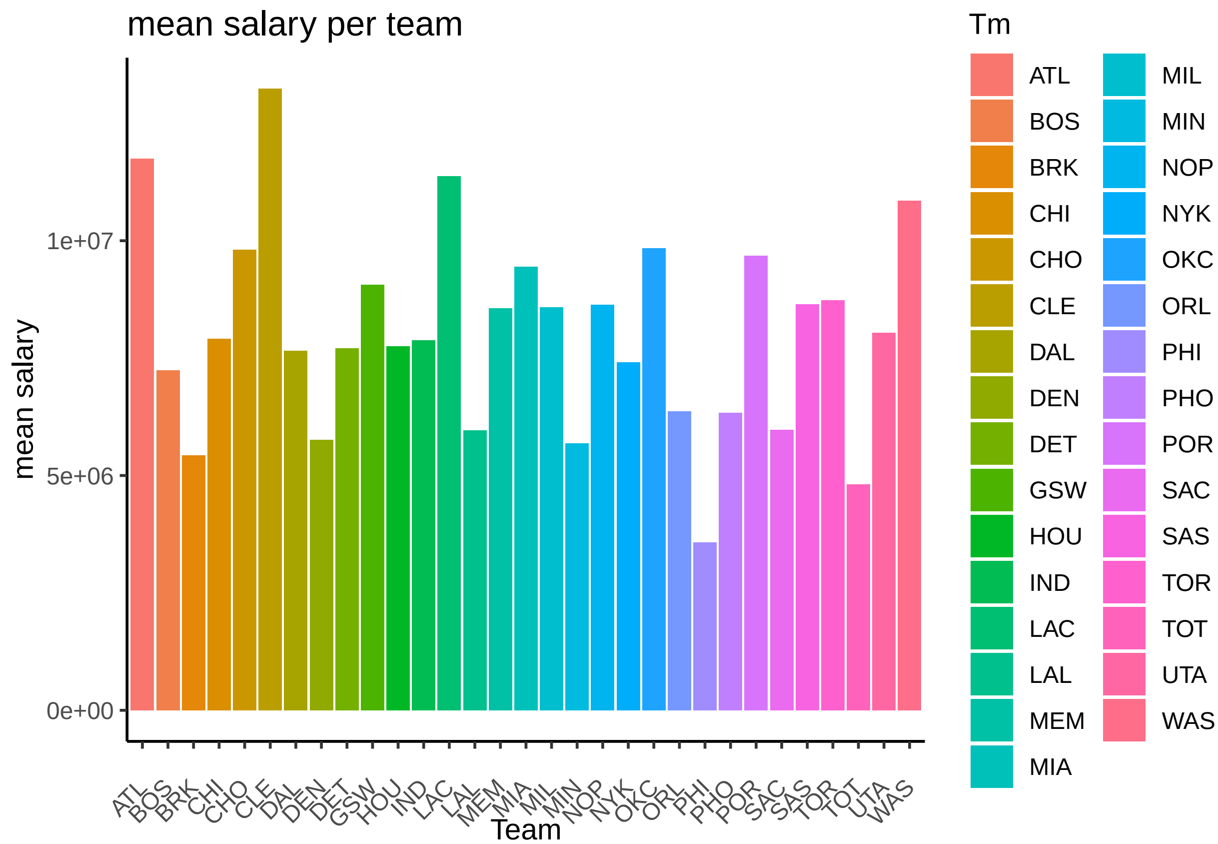
```
    geom_bar(stat = "identity") +
    theme_classic() +
    labs(
        x = "Team",
        y = "Sum of salaries",
        title = paste("Sum of salaries per team")) +
    theme(axis.text.x=element_text(angle=45,hjust=1,vjust=0.5))
```




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

Mean Salaries per Team for Complete Dataset

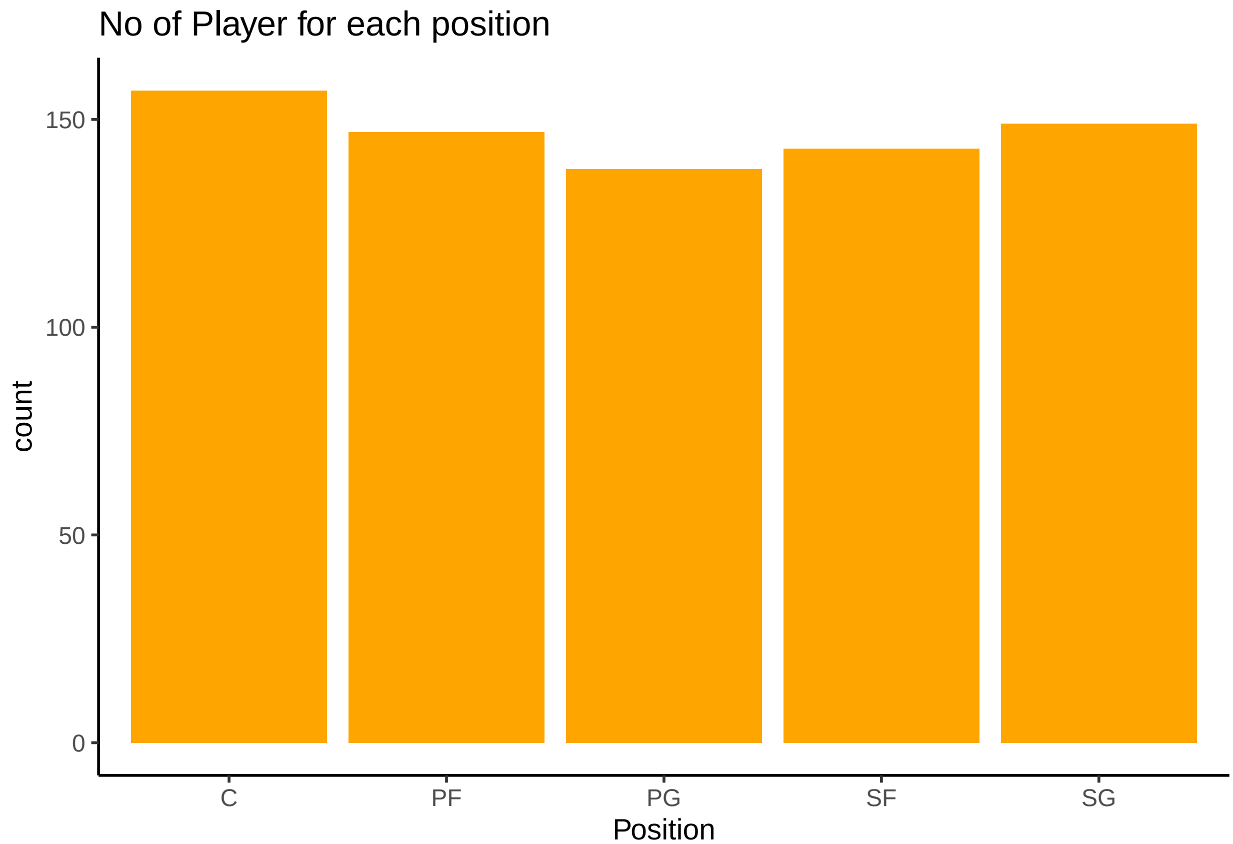
```
library(ggplot2)
library(tidyr)
library(dplyr)
df_final %>%
  group_by(Tm) %>%
  summarise(mean_salary = mean(salary)) %>%
  ggplot(aes(x = Tm, y = mean_salary, fill = Tm)) +
    geom_bar(stat = "identity") +
    theme_classic() +
    labs(
        x = "Team",
        y = "mean salary",
        title = paste(
            "mean salary per team")) +
    theme(axis.text.x=element_text(angle=45,hjust=1,vjust=0.5))
```




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

Players in each position

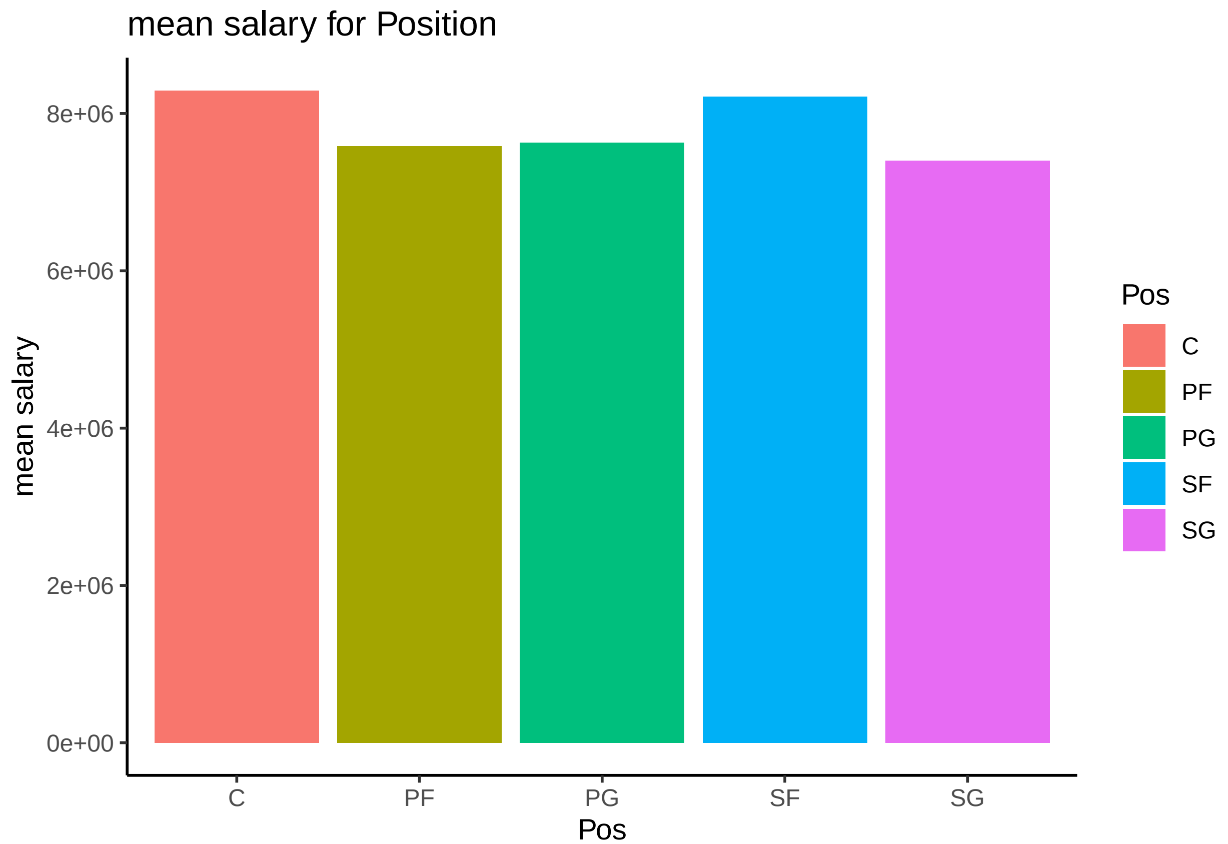
```r
library(ggplot2)
ggplot(df_final, aes(x = Pos)) +
  geom_bar(fill = "orange") +
  labs(x = "Position", title = "No of Player for each position") +
  theme_classic()
```




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

Mean salaries for each position

```r
library(ggplot2)
library(tidyr)
library(dplyr)
df_final %>%
  group_by(Pos) %>%
  summarise(mean_salary = mean(salary)) %>%
  ggplot(aes(x = Pos, y = mean_salary, fill = Pos)) +
    geom_bar(stat = "identity") +
    theme_classic() +
    labs(
        x = "Pos",
        y = "mean salary",
        title = paste(
            "mean salary for Position"))
```




```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
```

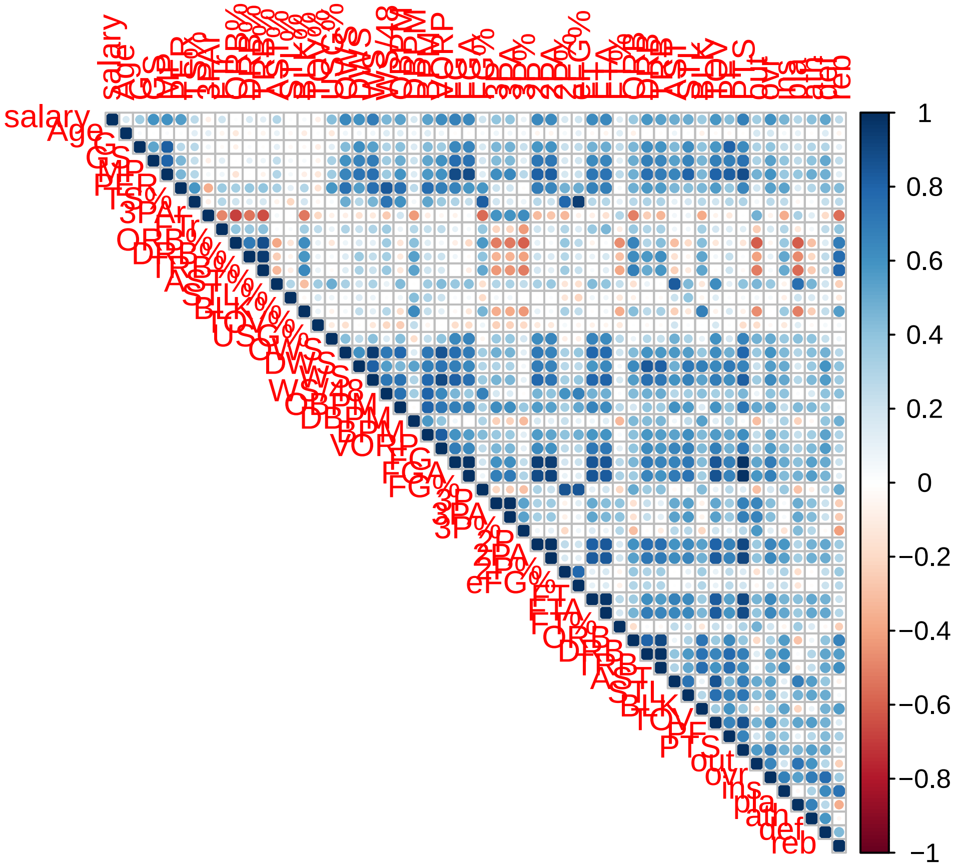
```
##      salary          WS         PTS          FG         FGA          2P
##  1.00000000  0.69665645  0.68170454  0.67897723  0.64990139  0.64984231
##         FTA         OWS          FT         2PA        VORP         ovr
##  0.64858045  0.64772438  0.63666066  0.63574577  0.62415826  0.60432440
##          MP         DWS          GS         TOV         DRB         PER
##  0.60407111  0.60108603  0.59325726  0.58481090  0.58151748  0.55121387
##         TRB         BPM        OBPM         def         AST         STL
##  0.54226307  0.53975078  0.53647127  0.52260324  0.49614270  0.49000118
##         ins       WS/48        USG%          PF         ath          3P
##  0.46685385  0.45292509  0.42859771  0.42263528  0.41158151  0.39131386
##         3PA         ORB         BLK         out           G        AST%
##  0.39000035  0.37269808  0.36909524  0.34625196  0.34620759  0.29725170
##         pla         TS%         reb         FTr        eFG%         FG%
##  0.28611363  0.26743221  0.25553148  0.20526496  0.20501001  0.20170219
##        DBPM         2P%         Age        DRB%         FT%        TRB%
##  0.17092923  0.16971591  0.16958607  0.16788419  0.14395542  0.12124045
##         3P%        BLK%        STL%        ORB%        3PAr        TOV%
##  0.09261836  0.03617047  0.01753918  0.01613656 -0.08847379 -0.08924334
```

Correlation Plot for complete dataset

```r
library(corrplot)
```

```
## corrplot 0.84 loaded
```

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

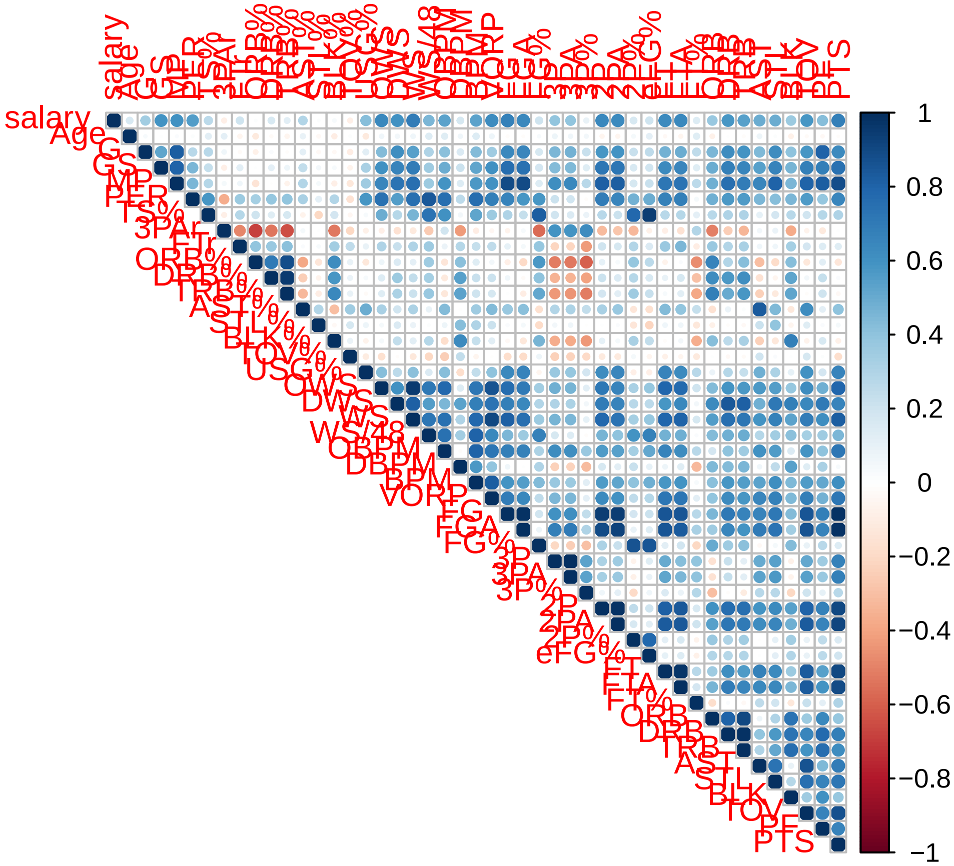


Correlation plot for Primary dataset

```
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  0.69665645  0.68170454  0.67897723  0.64990139  0.64984231
##         FTA         OWS          FT         2PA        VORP          MP
##  0.64858045  0.64772438  0.63666066  0.63574577  0.62415826  0.60407111
##         DWS          GS         TOV         DRB         PER         TRB
##  0.60108603  0.59325726  0.58481090  0.58151748  0.55121387  0.54226307
##         BPM        OBPM         AST         STL       WS/48        USG%
##  0.53975078  0.53647127  0.49614270  0.49000118  0.45292509  0.42859771
##          PF          3P         3PA         ORB         BLK           G
##  0.42263528  0.39131386  0.39000035  0.37269808  0.36909524  0.34620759
##        AST%         TS%         FTr        eFG%         FG%        DBPM
##  0.29725170  0.26743221  0.20526496  0.20501001  0.20170219  0.17092923
##         2P%         Age        DRB%         FT%        TRB%         3P%
##  0.16971591  0.16958607  0.16788419  0.14395542  0.12124045  0.09261836
##        BLK%        STL%        ORB%        3PAr        TOV%
##  0.03617047  0.01753918  0.01613656 -0.08847379 -0.08924334
```

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



Save correlation plots.

```r
# 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
```

Detecting Outliers

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


library(gridExtra)
```

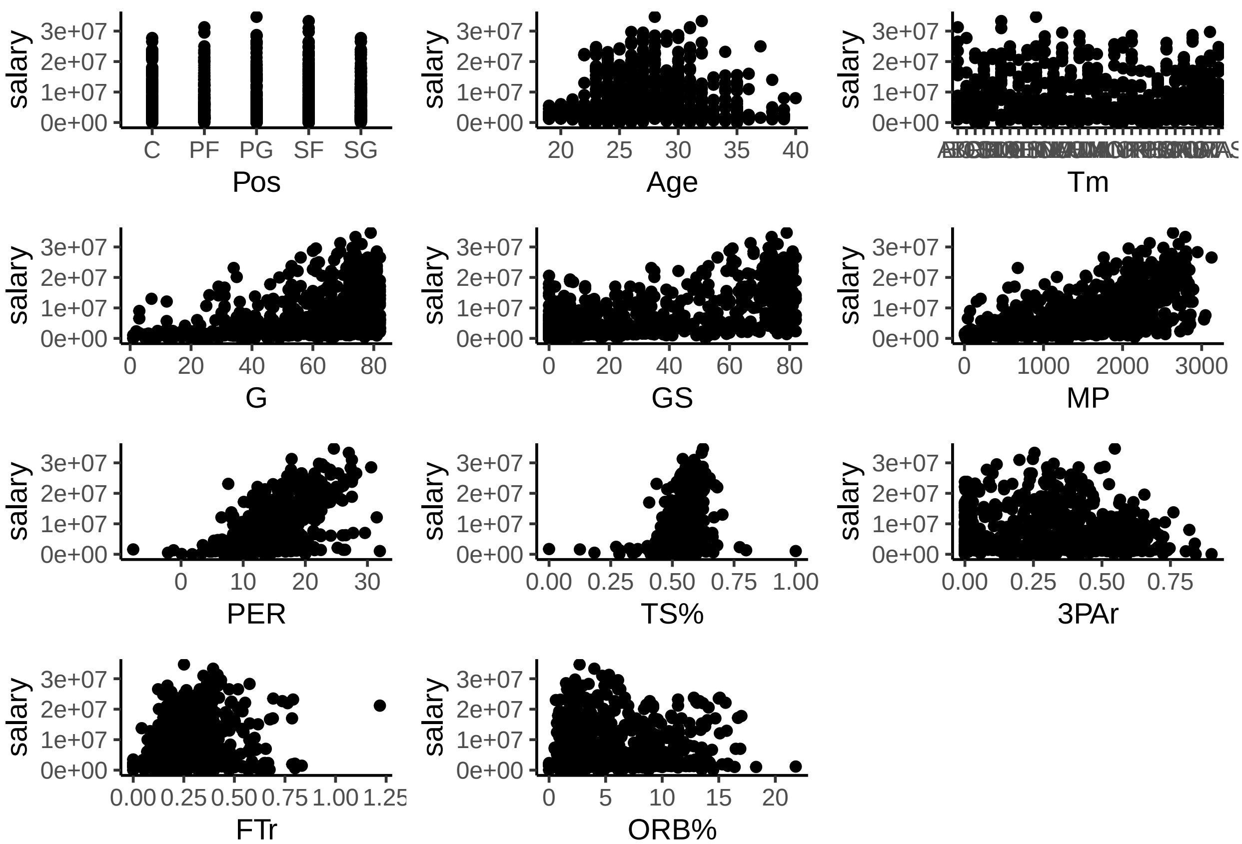
```
##
## Attaching package: 'gridExtra'

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

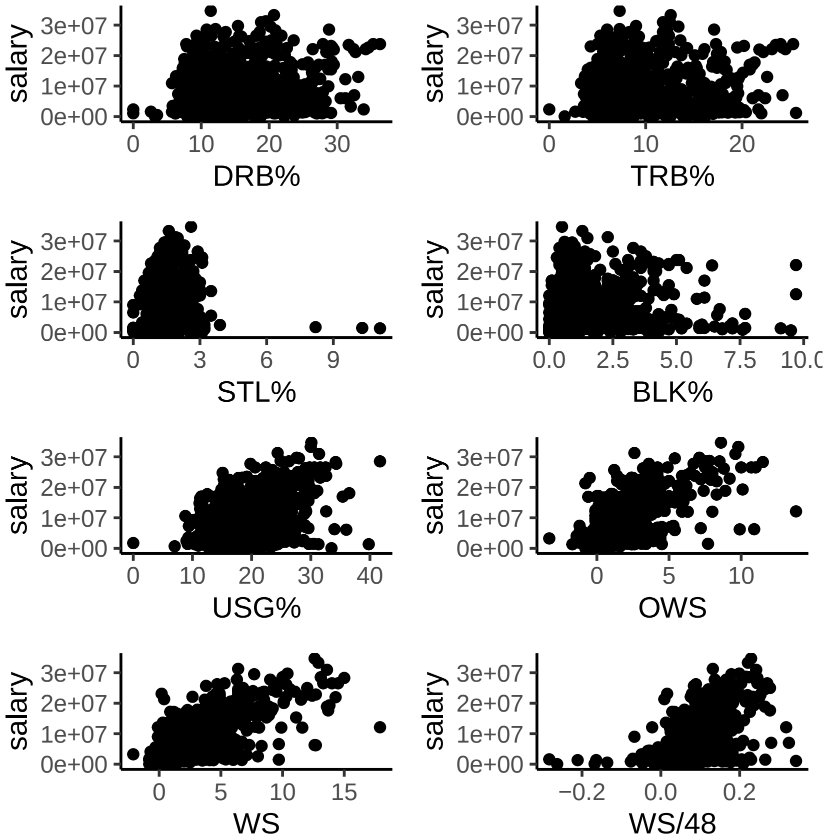
```r
p = list()
p <- NULL
val <- 0
```

```
d <- df_final[,4:ncol(df_final)]
for(j in 1:5)
{
  for(i in 1:11) {
  name = names(d[i+val])
  p[[i]] = plot(as.character(name))
  }
  val = i+val
do.call(grid.arrange,p)
p <- NULL
}
```

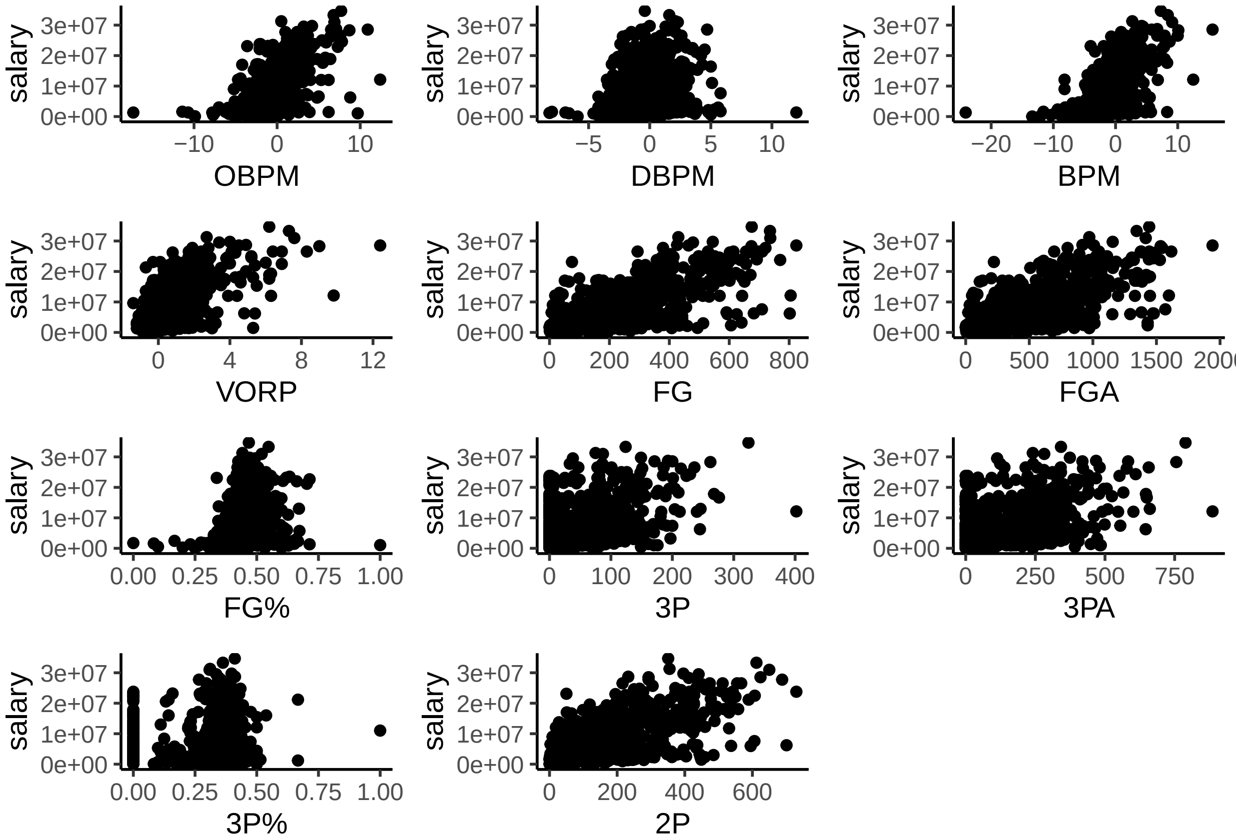
```
## [1] "Pos"
## [1] "Age"
## [1] "Tm"
## [1] "G"
## [1] "GS"
## [1] "MP"
## [1] "PER"
## [1] "TS%"
## [1] "3PAr"
## [1] "FTr"
## [1] "ORB%"
```



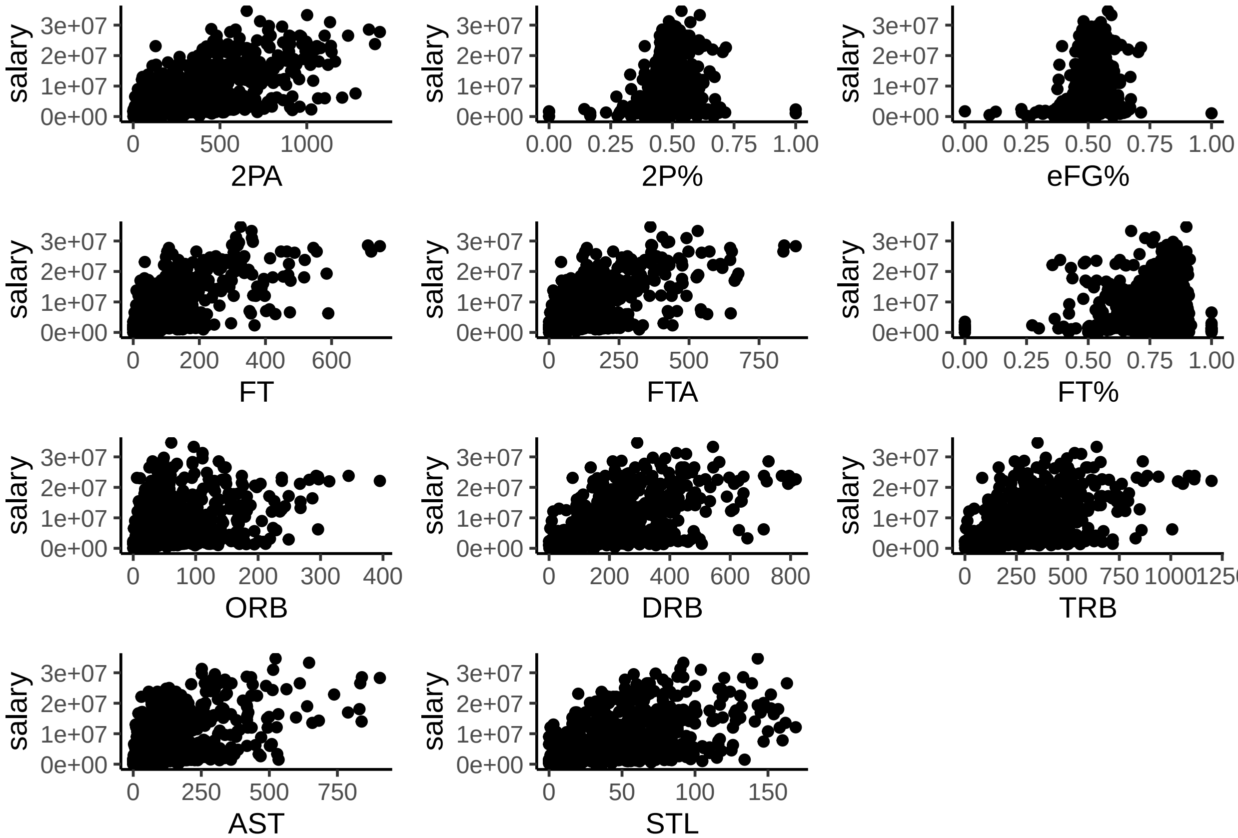

```
## [1] "DRB%"
## [1] "TRB%"
## [1] "AST%"
## [1] "STL%"
## [1] "BLK%"
## [1] "TOV%"
## [1] "USG%"
## [1] "OWS"
## [1] "DWS"
## [1] "WS"
## [1] "WS/48"
```



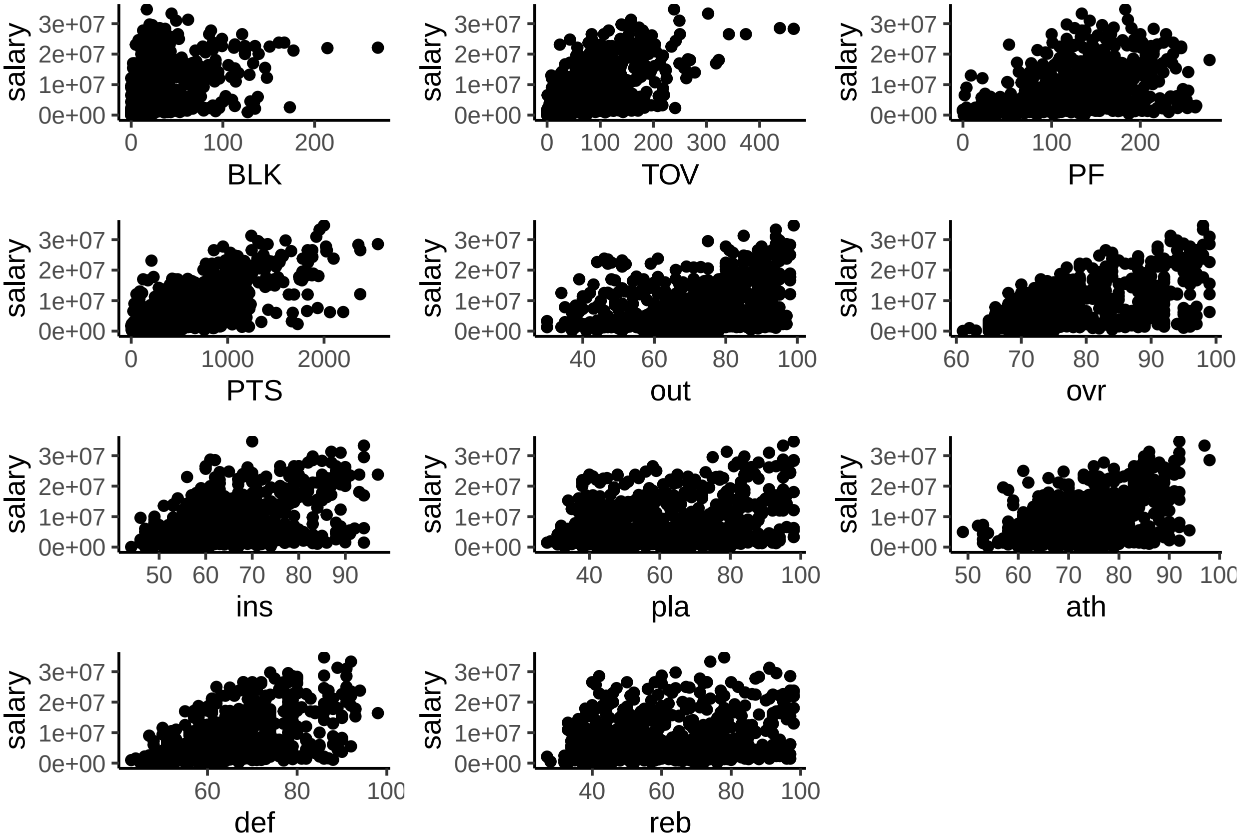

```
## [1] "OBPM"
## [1] "DBPM"
## [1] "BPM"
## [1] "VORP"
## [1] "FG"
## [1] "FGA"
## [1] "FG%"
## [1] "3P"
## [1] "3PA"
## [1] "3P%"
## [1] "2P"
```




```
## [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"
```



VARIABLE SELECTION

Helper Functions

```
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

```
library(rms)
```

```
## Loading required package: Hmisc

## Loading required package: lattice

## Loading required package: survival

## Loading required package: Formula

##
## Attaching package: 'Hmisc'

## The following objects are masked from 'package:dplyr':
##
##     src, summarize

## The following object is masked from 'package:rvest':
##
##     html

## The following objects are masked from 'package:base':
##
##     format.pval, units

## Loading required package: SparseM
```

```
##
## Attaching package: 'SparseM'

## The following object is masked from 'package:base':
##
##     backsolve
```

```
p_x_vars <- names(df_p_final)[!(names(df_p_final))%in%c('salary','name','2P','2PA','PTS','TRB')]
# 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 + G + GS + MP + PER + `TS%` +
##     `3PAr` + FTr + `ORB%` + `DRB%` + `TRB%` + `AST%` + `STL%` +
##     `BLK%` + `TOV%` + `USG%` + OWS + DWS + WS + `WS/48` + OBPM +
##     DBPM + BPM + VORP + FG + FGA + `FG%` + `3P` + `3PA` + `3P%` +
##     `2P%` + `eFG%` + FT + FTA + `FT%` + ORB + DRB + AST + STL +
##     BLK + TOV + PF
## <environment: 0x55a7ceb691a0>
```

```
p_selection_model <- ols(p_formula, data = df_p_final)
p_selection_model
```

```
## Linear Regression Model
##
##  ols(formula = p_formula, data = df_p_final)
##
##                     Model Likelihood     Discrimination
##                        Ratio Test           Indexes
##  Obs           734    LR chi2    771.48    R2       0.650
##  sigma4554312.9448    d.f.           77    R2 adj   0.609
##  d.f.          656    Pr(> chi2) 0.0000    g  6422499.821
##
##  Residuals
##
##        Min        1Q    Median        3Q       Max
##  -14921310  -2699391   -225890   2596986  14905073
##
##
##              Coef          S.E.          t     Pr(>|t|)
##  Intercept   9214166.5550  5544796.3006  1.66 0.0970
##  year=2017   1446953.2357   464566.5387  3.11 0.0019
##  Pos=PF      -419863.3840   680204.5900 -0.62 0.5373
##  Pos=PG     -4142194.2617  1141749.4202 -3.63 0.0003
##  Pos=SF      -929354.8944   913025.4517 -1.02 0.3091
##  Pos=SG     -2319108.4079   995521.8816 -2.33 0.0201
##  Age         214746.8625    46356.5201  4.63 <0.0001
##  Tm=BOS     -1755692.1070  1530900.6289 -1.15 0.2519
##  Tm=BRK     -1672476.4192  1826108.1461 -0.92 0.3601
##  Tm=CHI     -1435775.3454  1599108.0198 -0.90 0.3696
##  Tm=CHO     -1121286.8171  1626374.7318 -0.69 0.4908
##  Tm=CLE      2011951.4170  1657897.6039  1.21 0.2254
##  Tm=DAL      -452096.9019  1665070.3130 -0.27 0.7861
##  Tm=DEN     -2285430.0846  1795602.7183 -1.27 0.2035
##  Tm=DET     -1329591.8752  1675441.1485 -0.79 0.4277
##  Tm=GSW     -1115910.2109  1553594.3395 -0.72 0.4728
##  Tm=HOU     -1705158.6310  1739505.9995 -0.98 0.3273
##  Tm=IND     -1977666.2135  1585568.1044 -1.25 0.2127
##  Tm=LAC      966243.9607  1595703.0275  0.61 0.5450
##  Tm=LAL      -399415.1886  2044572.1263 -0.20 0.8452
##  Tm=MEM      512292.1746  1693690.2585  0.30 0.7624
##  Tm=MIA     -1302523.1923  1567836.0016 -0.83 0.4064
##  Tm=MIL      522625.3410  1723741.5914  0.30 0.7618
##  Tm=MIN     -2153395.7770  1875319.7471 -1.15 0.2513
##  Tm=NOP      732905.5603  1734514.9265  0.42 0.6728
##  Tm=NYK     -1374276.3665  1756556.8104 -0.78 0.4343
```

```
##   Tm=OKC      1053757.3280  1670618.6121  0.63 0.5284
##   Tm=ORL      -807923.6520  1708700.6813 -0.47 0.6365
##   Tm=PHI     -3530252.2850  1767380.0526 -2.00 0.0462
##   Tm=PHO        38231.7585  1826307.9806  0.02 0.9833
##   Tm=POR      2336575.3834  1750402.3841  1.33 0.1824
##   Tm=SAC     -1229779.8996  1741639.8592 -0.71 0.4804
##   Tm=SAS     -2719268.7329  1584189.3239 -1.72 0.0865
##   Tm=TOR       272743.0838  1661348.2487  0.16 0.8696
##   Tm=TOT     -2001328.9485  1423648.2302 -1.41 0.1603
##   Tm=UTA     -1306977.2553  1558770.6600 -0.84 0.4021
##   Tm=WAS       805652.6230  1682466.2477  0.48 0.6322
##   G            -85878.9727    22558.5550 -3.81 0.0002
##   GS            21880.4935    11615.8265  1.88 0.0601
##   MP             2565.8600     1772.3533  1.45 0.1482
##   PER          -20969.8371   432167.2140 -0.05 0.9613
##   TS%        -6669563.4611 21665362.9662 -0.31 0.7583
##   3PAr       -9208140.9546  6583976.8260 -1.40 0.1624
##   FTr         -864832.0012  2966216.2684 -0.29 0.7707
##   ORB%         -13935.3085   983455.7931 -0.01 0.9887
##   DRB%          96905.9868   952108.9228  0.10 0.9190
##   TRB%        -127898.5705  1925475.0388 -0.07 0.9471
##   AST%          22358.3863    87919.7488  0.25 0.7993
##   STL%        -318597.4194   549093.9678 -0.58 0.5620
##   BLK%        -125003.0175   446685.1093 -0.28 0.7797
##   TOV%         162938.3018    93647.8751  1.74 0.0823
##   USG%          63188.3455   191214.7960  0.33 0.7412
##   OWS         3802326.4106  3685604.0741  1.03 0.3026
##   DWS         5753339.0399  3706359.0546  1.55 0.1211
##   WS         -2766186.6134  3665208.6031 -0.75 0.4507
##   WS/48     -13514187.4727 23306267.6705 -0.58 0.5622
##   OBPM       -3349707.6554  3739313.3692 -0.90 0.3707
##   DBPM       -4411997.3281  3702135.0896 -1.19 0.2338
##   BPM         4395848.8350  3705300.2579  1.19 0.2359
##   VORP       -1466784.7748   578669.7910 -2.53 0.0115
##   FG             5321.2958    29759.5462  0.18 0.8581
##   FGA           -1427.3974    14748.7000 -0.10 0.9229
##   FG%       -19482411.5673 37525528.8747 -0.52 0.6038
##   3P           -27458.0568    38356.6988 -0.72 0.4743
##   3PA           16857.2778    15702.1863  1.07 0.2834
##   3P%        -1458432.2260  2062109.4362 -0.71 0.4797
##   2P%        -2848969.5726  6705704.4713 -0.42 0.6711
##   eFG%       14601808.7383 36443979.8601  0.40 0.6888
##   FT           -31094.2371    24687.5980 -1.26 0.2083
##   FTA           28981.2745    15243.1741  1.90 0.0577
##   FT%         1239694.3273  2270353.8892  0.55 0.5852
##   ORB           -9758.0069    13596.9216 -0.72 0.4732
##   DRB             471.5758     6390.2429  0.07 0.9412
##   AST            4909.9933     9000.0989  0.55 0.5856
##   STL          -20833.1875    18431.4023 -1.13 0.2588
##   BLK           10471.4317    18122.7556  0.58 0.5636
##   TOV           -9249.0388    22702.3733 -0.41 0.6838
##   PF           -22655.3333     9017.1945 -2.51 0.0122
##
```

```
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
##   ORB%    0.00   1    0.9887 0.00     1    0.9887 -2.00 0.650
##   PER     0.00   1    0.9604 0.00     2    0.9987 -4.00 0.650
##   DRB     0.01   1    0.9428 0.01     3    0.9998 -5.99 0.650
##   FGA     0.01   1    0.9278 0.02     4    1.0000 -7.98 0.650
##   AST%    0.06   1    0.8010 0.08     5    0.9999 -9.92 0.650
```

```
##  TS%     0.10   1    0.7542  0.18     6   0.9999 -11.82 0.650
##  eFG%    0.07   1    0.7896  0.25     7   0.9999 -13.75 0.650
##  BLK%    0.10   1    0.7517  0.35     8   1.0000 -15.65 0.650
##  FG      0.16   1    0.6933  0.50     9   1.0000 -17.50 0.650
##  TOV     0.13   1    0.7199  0.63    10   1.0000 -19.37 0.650
##  FT%     0.17   1    0.6811  0.80    11   1.0000 -21.20 0.650
##  BLK     0.24   1    0.6272  1.04    12   1.0000 -22.96 0.650
##  FTr     0.42   1    0.5165  1.46    13   1.0000 -24.54 0.650
##  3P%     0.39   1    0.5339  1.85    14   0.9999 -26.15 0.649
##  2P%     0.44   1    0.5091  2.28    15   0.9999 -27.72 0.649
##  WS      0.60   1    0.4402  2.88    16   0.9999 -29.12 0.649
##  OBPM    0.67   1    0.4114  3.55    17   0.9998 -30.45 0.649
##  3P      0.57   1    0.4496  4.12    18   0.9997 -31.88 0.648
##  ORB     0.50   1    0.4804  4.62    19   0.9997 -33.38 0.648
##  USG%    0.71   1    0.3990  5.33    20   0.9995 -34.67 0.648
##  STL%    0.57   1    0.4492  5.91    21   0.9995 -36.09 0.647
##  AST     2.68   1    0.1014  8.59    22   0.9952 -35.41 0.646
##  GS      3.18   1    0.0744 11.77    23   0.9738 -34.23 0.644
##  3PA     3.68   1    0.0551 15.45    24   0.9068 -32.55 0.642
##  FT      2.19   1    0.1388 17.64    25   0.8572 -32.36 0.641
##  TRB%    3.54   1    0.0600 21.18    26   0.7326 -30.82 0.639
##  DRB%    0.84   1    0.3588 22.02    27   0.7363 -31.98 0.639
##  VORP    5.25   1    0.0219 27.28    28   0.5033 -28.72 0.636
##  OWS     1.82   1    0.1768 29.10    29   0.4598 -28.90 0.635
##  WS/48   1.90   1    0.1676 31.00    30   0.4152 -29.00 0.634
##  FTA     7.36   1    0.0067 38.37    31   0.1701 -23.63 0.630
##
## Approximate Estimates after Deleting Factors
##
##                Coef      S.E.    Wald Z         P
## Intercept  11368576 2727851.6  4.167593 3.078e-05
## year=2017   1666466  345793.0  4.819259 1.441e-06
## Pos=PF      -734026  603754.2 -1.215770 2.241e-01
## Pos=PG     -3600195  816386.1 -4.409917 1.034e-05
## Pos=SF     -1084503  743912.2 -1.457838 1.449e-01
## Pos=SG     -2215167  806338.7 -2.747192 6.011e-03
## Age          205814   43171.4  4.767363 1.867e-06
## Tm=BOS     -1480253 1463348.8 -1.011552 3.118e-01
## Tm=BRK     -1661045 1578683.2 -1.052171 2.927e-01
## Tm=CHI     -1808958 1462290.5 -1.237071 2.161e-01
## Tm=CHO     -1126049 1502063.7 -0.749668 4.535e-01
## Tm=CLE      2243122 1517714.6  1.477961 1.394e-01
## Tm=DAL      -268113 1494602.6 -0.179387 8.576e-01
## Tm=DEN     -2191865 1538554.2 -1.424626 1.543e-01
## Tm=DET     -1498243 1452736.7 -1.031325 3.024e-01
## Tm=GSW     -1076531 1409553.6 -0.763739 4.450e-01
## Tm=HOU      -849539 1534211.5 -0.553730 5.798e-01
## Tm=IND     -2325625 1490515.5 -1.560282 1.187e-01
## Tm=LAC      2107487 1474254.0  1.429528 1.529e-01
## Tm=LAL      -123513 1655380.4 -0.074613 9.405e-01
## Tm=MEM        86986 1480249.0  0.058764 9.531e-01
## Tm=MIA     -1252501 1460806.8 -0.857403 3.912e-01
## Tm=MIL       600669 1498849.8  0.400753 6.886e-01
## Tm=MIN     -2103225 1568247.4 -1.341131 1.799e-01
## Tm=NOP       800044 1522970.8  0.525318 5.994e-01
## Tm=NYK     -1464675 1521011.3 -0.962961 3.356e-01
## Tm=OKC       797103 1470721.8  0.541981 5.878e-01
## Tm=ORL      -674383 1506074.6 -0.447776 6.543e-01
## Tm=PHI     -2929741 1560719.2 -1.877174 6.049e-02
## Tm=PHO       -52994 1524861.2 -0.034754 9.723e-01
## Tm=POR      2480883 1518392.5  1.633888 1.023e-01
## Tm=SAC      -974468 1535754.8 -0.634521 5.257e-01
## Tm=SAS     -3174467 1476189.9 -2.150446 3.152e-02
## Tm=TOR         4237 1431884.8  0.002959 9.976e-01
```

```
## Tm=TOT     -1863692 1261176.0 -1.477741 1.395e-01
## Tm=UTA     -1507688 1429298.9 -1.054844 2.915e-01
## Tm=WAS      1044388 1560997.7  0.669051 5.035e-01
## G           -103906   17813.9 -5.832870 5.448e-09
## MP             6512     701.8  9.279091 0.000e+00
## 3PAr       -8430336 1415510.9 -5.955684 2.590e-09
## TOV%         183538   50384.3  3.642767 2.697e-04
## DWS         3025582  403476.0  7.498790 6.439e-14
## DBPM       -1567736  185014.1 -8.473603 0.000e+00
## BPM         1029230  117101.2  8.789239 0.000e+00
## FG%       -20767380 3845676.5 -5.400189 6.657e-08
## STL          -42860   11479.1 -3.733711 1.887e-04
## PF           -26674    6769.4 -3.940413 8.134e-05
##
## Factors in Final Model
##
##  [1] year Pos  Age  Tm   G    MP   3PAr TOV% DWS  DBPM BPM  FG%  STL  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 + G + MP + `3PAr` + `TOV%` + DWS +
##     DBPM + BPM + `FG%` + STL + PF
## <environment: 0x55a7c6290a78>
```

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

```
##
## Call:
## lm(formula = p_subset_formula, data = df_p_final)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -13774314  -2907843   -191667   2718447  16789754
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  1.137e+07  2.742e+06   4.145 3.82e-05 ***
## year2017     1.666e+06  3.476e+05   4.794 2.01e-06 ***
## PosPF       -7.340e+05  6.070e+05  -1.209 0.226963
## PosPG       -3.600e+06  8.208e+05  -4.386 1.33e-05 ***
## PosSF       -1.085e+06  7.479e+05  -1.450 0.147492
## PosSG       -2.215e+06  8.107e+05  -2.733 0.006446 **
## Age          2.058e+05  4.340e+04   4.742 2.57e-06 ***
## TmBOS       -1.480e+06  1.471e+06  -1.006 0.314688
## TmBRK       -1.661e+06  1.587e+06  -1.047 0.295665
## TmCHI       -1.809e+06  1.470e+06  -1.230 0.218935
## TmCHO       -1.126e+06  1.510e+06  -0.746 0.456116
## TmCLE        2.243e+06  1.526e+06   1.470 0.141993
## TmDAL       -2.681e+05  1.503e+06  -0.178 0.858436
## TmDEN       -2.192e+06  1.547e+06  -1.417 0.156923
## TmDET       -1.498e+06  1.461e+06  -1.026 0.305329
## TmGSW       -1.077e+06  1.417e+06  -0.760 0.447709
## TmHOU       -8.495e+05  1.542e+06  -0.551 0.581961
## TmIND       -2.326e+06  1.498e+06  -1.552 0.121127
## TmLAC        2.107e+06  1.482e+06   1.422 0.155503
## TmLAL       -1.235e+05  1.664e+06  -0.074 0.940860
## TmMEM        8.699e+04  1.488e+06   0.058 0.953406
## TmMIA       -1.253e+06  1.469e+06  -0.853 0.394045
## TmMIL        6.007e+05  1.507e+06   0.399 0.690296
```

```
## TmMIN       -2.103e+06  1.577e+06  -1.334 0.182648
## TmNOP        8.000e+05  1.531e+06   0.523 0.601475
## TmNYK       -1.465e+06  1.529e+06  -0.958 0.338482
## TmOKC        7.971e+05  1.479e+06   0.539 0.589995
## TmORL       -6.744e+05  1.514e+06  -0.445 0.656176
## TmPHI       -2.930e+06  1.569e+06  -1.867 0.062301 .
## TmPHO       -5.299e+04  1.533e+06  -0.035 0.972434
## TmPOR        2.481e+06  1.527e+06   1.625 0.104580
## TmSAC       -9.745e+05  1.544e+06  -0.631 0.528156
## TmSAS       -3.174e+06  1.484e+06  -2.139 0.032787 *
## TmTOR        4.237e+03  1.440e+06   0.003 0.997652
## TmTOT       -1.864e+06  1.268e+06  -1.470 0.142052
## TmUTA       -1.508e+06  1.437e+06  -1.049 0.294440
## TmWAS        1.044e+06  1.569e+06   0.665 0.505959
## G           -1.039e+05  1.791e+04  -5.802 1.00e-08 ***
## MP           6.512e+03  7.056e+02   9.230  < 2e-16 ***
## `3PAr`      -8.430e+06  1.423e+06  -5.924 4.97e-09 ***
## `TOV%`       1.835e+05  5.065e+04   3.623 0.000312 ***
## DWS          3.026e+06  4.056e+05   7.459 2.64e-13 ***
## DBPM        -1.568e+06  1.860e+05  -8.429  < 2e-16 ***
## BPM          1.029e+06  1.177e+05   8.742  < 2e-16 ***
## `FG%`       -2.077e+07  3.866e+06  -5.371 1.07e-07 ***
## STL         -4.286e+04  1.154e+04  -3.714 0.000221 ***
## PF          -2.667e+04  6.806e+03  -3.919 9.76e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4579000 on 687 degrees of freedom
## Multiple R-squared:   0.63,  Adjusted R-squared:  0.6052
## F-statistic: 25.43 on 46 and 687 DF,  p-value: < 2.2e-16
```

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

```
##        MP       DWS        PF       STL       BPM     TmTOT         G      DBPM
## 10.699640  7.253925  6.003790  5.286187  5.265620  4.855967  4.658775  4.551077
##     PosSG     PosPG     `FG%`     PosSF    `3PAr`     TmPHO     TmTOR     TmDEN
##  3.722505  3.600599  3.090799  3.072027  3.035783  2.707105  2.570736  2.542619
##     TmMIN     TmGSW     TmPOR     TmMEM     TmSAC     TmMIL     TmNYK     TmUTA
##  2.530405  2.491177  2.476417  2.452434  2.426636  2.413081  2.380267  2.378431
##     TmDET     TmSAS     TmORL     TmOKC     TmLAL     TmHOU     TmBOS     TmDAL
##  2.362118  2.340670  2.333747  2.323361  2.319740  2.314928  2.300124  2.298330
##     TmCHI     TmMIA     TmPHI     TmNOP     TmLAC     TmBRK     TmIND     TmCLE
##  2.296799  2.292140  2.284736  2.281131  2.236174  2.223862  2.184943  2.160561
##     TmCHO     PosPF     TmWAS    `TOV%`       Age  year2017
##  2.116231  2.066017  2.062758  1.690431  1.229562  1.057815
```

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

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

```
library(rms)
c_x_vars <- names(df_final)[!(names(df_final)%in%c('salary','name','2P','2PA','PTS','TRB'))]
# 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 + G + GS + MP + PER + `TS%` +
##     `3PAr` + FTr + `ORB%` + `DRB%` + `TRB%` + `AST%` + `STL%` +
##     `BLK%` + `TOV%` + `USG%` + OWS + DWS + WS + `WS/48` + OBPM +
##     DBPM + BPM + VORP + FG + FGA + `FG%` + `3P` + `3PA` + `3P%` +
##     `2P%` + `eFG%` + FT + FTA + `FT%` + ORB + DRB + AST + STL +
##     BLK + TOV + PF + out + ovr + ins + pla + ath + def + reb
## <environment: 0x55a7c66fd470>
```

```r
c_selection_model <- ols(c_formula, data = df_final)
c_selection_model
```

```
## Linear Regression Model
##
##  ols(formula = c_formula, data = df_final)
##
##                       Model Likelihood     Discrimination
##                          Ratio Test           Indexes
##  Obs            734    LR chi2    784.09    R2       0.656
##  sigma4539655.3086    d.f.            84    R2 adj   0.612
##  d.f.           649    Pr(> chi2) 0.0000    g  6444818.561
##
##  Residuals
##
##        Min        1Q    Median        3Q       Max
##  -16194213  -2558542   -107917   2485207  14679029
##
##
##            Coef           S.E.          t     Pr(>|t|)
##  Intercept   5069879.8497  6057385.9045  0.84 0.4029
##  year=2017   1026799.6630   537415.8908  1.91 0.0565
##  Pos=PF      -213699.9327   719393.8901 -0.30 0.7665
##  Pos=PG     -4530000.1865  1375907.7253 -3.29 0.0010
##  Pos=SF     -1246715.1812   999443.4478 -1.25 0.2127
##  Pos=SG     -2628516.2955  1170261.5843 -2.25 0.0250
##  Age          180118.7983    50586.3694  3.56 0.0004
##  Tm=BOS     -1910782.5143  1531454.8079 -1.25 0.2126
##  Tm=BRK     -1027333.4462  1836543.0295 -0.56 0.5761
##  Tm=CHI     -1235154.2953  1600571.2118 -0.77 0.4406
##  Tm=CHO      -806715.1214  1626793.9177 -0.50 0.6201
##  Tm=CLE      1810376.1242  1662862.9070  1.09 0.2767
##  Tm=DAL      -213499.3871  1662666.2103 -0.13 0.8979
##  Tm=DEN     -2028846.3612  1799714.1896 -1.13 0.2600
##  Tm=DET      -967487.2096  1680411.3219 -0.58 0.5650
##  Tm=GSW     -1286489.9973  1561334.9816 -0.82 0.4103
##  Tm=HOU     -1700951.4787  1738177.4563 -0.98 0.3282
##  Tm=IND     -1710858.8654  1588124.1583 -1.08 0.2818
##  Tm=LAC       882690.7239  1592572.0266  0.55 0.5796
##  Tm=LAL      -236822.0964  2042542.9447 -0.12 0.9077
##  Tm=MEM       539004.4487  1704502.4187  0.32 0.7519
##  Tm=MIA     -1148356.1482  1566535.6889 -0.73 0.4638
##  Tm=MIL       807317.2762  1736914.8761  0.46 0.6422
##  Tm=MIN     -1797604.5336  1884855.1503 -0.95 0.3406
##  Tm=NOP       969831.5406  1734862.6445  0.56 0.5763
##  Tm=NYK     -1194019.2090  1762895.0678 -0.68 0.4985
##  Tm=OKC      1040172.6929  1674304.6286  0.62 0.5346
##  Tm=ORL      -429140.9323  1708364.4490 -0.25 0.8017
##  Tm=PHI     -3092421.7525  1769717.6303 -1.75 0.0810
##  Tm=PHO       338524.2954  1828707.3826  0.19 0.8532
##  Tm=POR      2466807.4132  1752140.0259  1.41 0.1596
##  Tm=SAC      -948962.4587  1744399.9545 -0.54 0.5866
##  Tm=SAS     -2775949.5750  1593231.6903 -1.74 0.0819
##  Tm=TOR       231609.2909  1664445.9920  0.14 0.8894
##  Tm=TOT     -1881972.5803  1423107.3755 -1.32 0.1865
##  Tm=UTA     -1363039.6807  1559125.1493 -0.87 0.3823
##  Tm=WAS      1089527.4447  1683625.8370  0.65 0.5178
##  G            -75883.1333    22855.8379 -3.32 0.0010
##  GS            20244.9840    11717.5256  1.73 0.0845
##  MP             2128.0078     1795.7054  1.19 0.2364
##  PER          -21337.9181   432048.8045 -0.05 0.9606
##  TS%         1614363.8063 21889647.7330  0.07 0.9412
##  3PAr       -8710974.9721  6574253.9610 -1.33 0.1856
```

```
## FTr         -1751621.8308  2995131.4794 -0.58 0.5589
## ORB%           93447.0686   985377.2109  0.09 0.9245
## DRB%          144385.7456   952758.9161  0.15 0.8796
## TRB%         -300388.0615  1927609.0706 -0.16 0.8762
## AST%            9230.9182    89334.7433  0.10 0.9177
## STL%         -295561.7893   552323.8476 -0.54 0.5927
## BLK%         -254371.4054   452379.7970 -0.56 0.5741
## TOV%          168439.9776    94724.2638  1.78 0.0758
## USG%           98834.2503   192779.1510  0.51 0.6083
## OWS          3726467.4784  3697059.0193  1.01 0.3139
## DWS          5425708.1459  3707651.9702  1.46 0.1438
## WS          -2635473.5557  3669699.5315 -0.72 0.4729
## WS/48       -8402747.4398 23359333.8287 -0.36 0.7192
## OBPM        -3207274.0621  3733338.3518 -0.86 0.3906
## DBPM        -4030858.2537  3699995.5729 -1.09 0.2764
## BPM          4079645.8399  3700140.0605  1.10 0.2706
## VORP        -1330323.9000   589958.2154 -2.25 0.0245
## FG              2515.6487    30121.5891  0.08 0.9335
## FGA              375.5791    14884.0044  0.03 0.9799
## FG%        -25561757.2251 37765742.3383 -0.68 0.4987
## 3P            -35049.0329    38850.1281 -0.90 0.3673
## 3PA            18880.1008    15817.1429  1.19 0.2331
## 3P%          -824870.5240  2122420.2492 -0.39 0.6977
## 2P%         -2356650.3731  6794461.5338 -0.35 0.7288
## eFG%        12420433.1872 36498836.7788  0.34 0.7337
## FT            -30536.8475    24891.4453 -1.23 0.2203
## FTA            26552.1472    15332.8802  1.73 0.0838
## FT%          1326996.2442  2266847.9637  0.59 0.5585
## ORB           -11686.6123    13698.9782 -0.85 0.3939
## DRB             3919.5191     6521.5827  0.60 0.5480
## AST             5525.7960     9171.0101  0.60 0.5470
## STL           -29141.3105    18660.1985 -1.56 0.1189
## BLK             7554.9460    18352.7056  0.41 0.6807
## TOV           -10045.4418    23113.9737 -0.43 0.6640
## PF            -21759.1628     9011.0403 -2.41 0.0160
## out           -66470.5101    36533.9396 -1.82 0.0693
## ovr           103934.6911    81796.4626  1.27 0.2043
## ins             4894.2371    44068.3014  0.11 0.9116
## pla             -374.5551    28163.8693 -0.01 0.9894
## ath             -788.0691    44103.6760 -0.02 0.9857
## def            44044.5138    35411.9386  1.24 0.2140
## reb           -43928.0359    24579.9507 -1.79 0.0744
##
```

```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    0.9894  0.00     1   0.9894  -2.00 0.656
## ath     0.00   1    0.9842  0.00     2   0.9997  -4.00 0.656
## FGA     0.00   1    0.9787  0.00     3   1.0000  -6.00 0.656
## PER     0.00   1    0.9531  0.00     4   1.0000  -8.00 0.656
## TS%     0.01   1    0.9424  0.01     5   1.0000  -9.99 0.656
## AST%    0.01   1    0.9265  0.02     6   1.0000 -11.98 0.656
## ORB%    0.01   1    0.9221  0.03     7   1.0000 -13.97 0.656
## ins     0.01   1    0.9197  0.04     8   1.0000 -15.96 0.656
## DRB%    0.08   1    0.7748  0.12     9   1.0000 -17.88 0.656
## 2P%     0.09   1    0.7626  0.21    10   1.0000 -19.79 0.656
## 3P%     0.14   1    0.7068  0.35    11   1.0000 -21.65 0.656
## TRB%    0.16   1    0.6934  0.51    12   1.0000 -23.49 0.656
## BLK     0.28   1    0.5956  0.79    13   1.0000 -25.21 0.656
## STL%    0.27   1    0.6022  1.06    14   1.0000 -26.94 0.656
## BLK%    0.24   1    0.6270  1.30    15   1.0000 -28.70 0.656
```

```
##  USG%    0.25   1    0.6199  1.54    16   1.0000 -30.46 0.656
##  TOV     0.37   1    0.5426  1.91    17   1.0000 -32.09 0.655
##  FTr     0.35   1    0.5553  2.26    18   1.0000 -33.74 0.655
##  OBPM    0.54   1    0.4623  2.80    19   1.0000 -35.20 0.655
##  WS      0.60   1    0.4368  3.41    20   1.0000 -36.59 0.655
##  eFG%    0.93   1    0.3352  4.34    21   1.0000 -37.66 0.654
##  3P      0.62   1    0.4323  4.95    22   0.9999 -39.05 0.654
##  FG      0.96   1    0.3260  5.92    23   0.9999 -40.08 0.653
##  FT%     0.92   1    0.3365  6.84    24   0.9998 -41.16 0.653
##  AST     1.35   1    0.2454  8.19    25   0.9994 -41.81 0.652
##  3PA     0.80   1    0.3718  8.99    26   0.9992 -43.01 0.652
##  def     1.30   1    0.2550 10.28    27   0.9985 -43.72 0.651
##  DRB     1.50   1    0.2202 11.79    28   0.9969 -44.21 0.650
##  reb     2.45   1    0.1177 14.23    29   0.9901 -43.77 0.649
##  GS      2.41   1    0.1203 16.65    30   0.9766 -43.35 0.648
##  FT      2.62   1    0.1053 19.27    31   0.9502 -42.73 0.646
##  FTA     2.53   1    0.1116 21.80    32   0.9126 -42.20 0.645
##  VORP    5.69   1    0.0170 27.49    33   0.7377 -38.51 0.642
##  WS/48   2.96   1    0.0854 30.45    34   0.6422 -37.55 0.640
##  OWS     4.36   1    0.0367 34.82    35   0.4770 -35.18 0.638
##  ORB     3.60   1    0.0577 38.42    36   0.3605 -33.58 0.636
##  out     5.31   1    0.0212 43.73    37   0.2072 -30.27 0.633
##
## Approximate Estimates after Deleting Factors
##
##                Coef      S.E.    Wald Z         P
## Intercept   5896725 3504215.6  1.682752 9.242e-02
## year=2017   1343200  368589.3  3.644166 2.683e-04
## Pos=PF      -619750  603579.1 -1.026791 3.045e-01
## Pos=PG     -3484554  815098.4 -4.275009 1.911e-05
## Pos=SF     -1058211  741594.1 -1.426941 1.536e-01
## Pos=SG     -2244312  803829.8 -2.792023 5.238e-03
## Age          184012   43924.5  4.189272 2.799e-05
## Tm=BOS     -1612686 1459619.9 -1.104867 2.692e-01
## Tm=BRK     -1619365 1573692.4 -1.029023 3.035e-01
## Tm=CHI     -1698077 1458272.4 -1.164444 2.442e-01
## Tm=CHO      -963081 1498676.2 -0.642621 5.205e-01
## Tm=CLE      2014658 1515642.6  1.329243 1.838e-01
## Tm=DAL      -272497 1489793.4 -0.182909 8.549e-01
## Tm=DEN     -2077768 1534295.0 -1.354217 1.757e-01
## Tm=DET     -1128787 1455732.3 -0.775408 4.381e-01
## Tm=GSW     -1231953 1406419.3 -0.875950 3.811e-01
## Tm=HOU      -921033 1529546.5 -0.602161 5.471e-01
## Tm=IND     -2243262 1486090.9 -1.509506 1.312e-01
## Tm=LAC      1929302 1471271.2  1.311316 1.898e-01
## Tm=LAL      -200703 1650347.3 -0.121612 9.032e-01
## Tm=MEM         7518 1475834.1  0.005094 9.959e-01
## Tm=MIA     -1150693 1456686.0 -0.789939 4.296e-01
## Tm=MIL       512355 1494451.8  0.342838 7.317e-01
## Tm=MIN     -2095279 1563203.5 -1.340375 1.801e-01
## Tm=NOP       885845 1518464.9  0.583382 5.596e-01
## Tm=NYK     -1276740 1518015.8 -0.841058 4.003e-01
## Tm=OKC       806826 1465993.7  0.550361 5.821e-01
## Tm=ORL      -638599 1501297.0 -0.425365 6.706e-01
## Tm=PHI     -2930377 1555696.2 -1.883643 5.961e-02
## Tm=PHO       -69435 1519968.0 -0.045682 9.636e-01
## Tm=POR      2375810 1514100.8  1.569123 1.166e-01
## Tm=SAC      -834386 1531857.8 -0.544689 5.860e-01
## Tm=SAS     -3172968 1471439.1 -2.156371 3.105e-02
## Tm=TOR        58125 1427442.5  0.040720 9.675e-01
## Tm=TOT     -1857670 1257119.4 -1.477719 1.395e-01
## Tm=UTA     -1322482 1426662.0 -0.926976 3.539e-01
## Tm=WAS      1247451 1558134.6  0.800605 4.234e-01
## G            -97610   17937.8 -5.441588 5.281e-08
```

```
## MP              6109     718.2  8.505608 0.000e+00
## 3PAr        -7476606 1462612.3 -5.111817 3.191e-07
## TOV%          165806   50730.4  3.268380 1.082e-03
## DWS          2773984  414821.8  6.687170 2.275e-11
## DBPM        -1404939  195794.0 -7.175601 7.199e-13
## BPM           936082  122639.7  7.632782 2.298e-14
## FG%        -18924506 3904922.1 -4.846321 1.258e-06
## STL           -39837   11507.1 -3.461954 5.363e-04
## PF            -25940    6754.1 -3.840600 1.227e-04
## ovr            70843   28618.4  2.475425 1.331e-02
##
## Factors in Final Model
##
##  [1] year Pos  Age  Tm   G    MP   3PAr TOV% DWS  DBPM BPM  FG%  STL  PF   ovr
```

Checking for Multicollinearity Among Optimal Subset of Complete Variables.

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

```
## salary ~ year + Pos + Age + Tm + G + MP + `3PAr` + `TOV%` + DWS +
##     DBPM + BPM + `FG%` + STL + PF + ovr
## <environment: 0x55a7c6a5d4c0>
```

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

```
##
## Call:
## lm(formula = c_subset_formula, data = df_final)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -13829069  -2864315   -174920   2678634  15997459
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  5.897e+06  3.521e+06   1.675 0.094478 .
## year2017     1.343e+06  3.704e+05   3.626 0.000309 ***
## PosPF       -6.197e+05  6.065e+05  -1.022 0.307241
## PosPG       -3.485e+06  8.191e+05  -4.254 2.39e-05 ***
## PosSF       -1.058e+06  7.452e+05  -1.420 0.156065
## PosSG       -2.244e+06  8.078e+05  -2.778 0.005612 **
## Age          1.840e+05  4.414e+04   4.169 3.45e-05 ***
## TmBOS       -1.613e+06  1.467e+06  -1.099 0.271942
## TmBRK       -1.619e+06  1.581e+06  -1.024 0.306192
## TmCHI       -1.698e+06  1.465e+06  -1.159 0.246952
## TmCHO       -9.631e+05  1.506e+06  -0.639 0.522717
## TmCLE        2.015e+06  1.523e+06   1.323 0.186353
## TmDAL       -2.725e+05  1.497e+06  -0.182 0.855622
## TmDEN       -2.078e+06  1.542e+06  -1.348 0.178226
## TmDET       -1.129e+06  1.463e+06  -0.772 0.440599
## TmGSW       -1.232e+06  1.413e+06  -0.872 0.383687
## TmHOU       -9.210e+05  1.537e+06  -0.599 0.549219
## TmIND       -2.243e+06  1.493e+06  -1.502 0.133518
## TmLAC        1.929e+06  1.478e+06   1.305 0.192355
## TmLAL       -2.007e+05  1.658e+06  -0.121 0.903711
## TmMEM        7.518e+03  1.483e+06   0.005 0.995957
## TmMIA       -1.151e+06  1.464e+06  -0.786 0.432086
## TmMIL        5.124e+05  1.502e+06   0.341 0.733081
## TmMIN       -2.095e+06  1.571e+06  -1.334 0.182697
## TmNOP        8.858e+05  1.526e+06   0.581 0.561741
## TmNYK       -1.277e+06  1.525e+06  -0.837 0.402906
```

```
## TmOKC        8.068e+05  1.473e+06   0.548 0.584090
## TmORL       -6.386e+05  1.509e+06  -0.423 0.672215
## TmPHI       -2.930e+06  1.563e+06  -1.874 0.061291 .
## TmPHO       -6.943e+04  1.527e+06  -0.045 0.963755
## TmPOR        2.376e+06  1.522e+06   1.561 0.118872
## TmSAC       -8.344e+05  1.539e+06  -0.542 0.587970
## TmSAS       -3.173e+06  1.479e+06  -2.146 0.032234 *
## TmTOR        5.813e+04  1.434e+06   0.041 0.967689
## TmTOT       -1.858e+06  1.263e+06  -1.471 0.141879
## TmUTA       -1.322e+06  1.434e+06  -0.922 0.356613
## TmWAS        1.247e+06  1.566e+06   0.797 0.425898
## G           -9.761e+04  1.803e+04  -5.415 8.48e-08 ***
## MP           6.109e+03  7.218e+02   8.464  < 2e-16 ***
## `3PAr`      -7.477e+06  1.470e+06  -5.087 4.70e-07 ***
## `TOV%`       1.658e+05  5.098e+04   3.252 0.001200 **
## DWS          2.774e+06  4.169e+05   6.655 5.81e-11 ***
## DBPM        -1.405e+06  1.968e+05  -7.141 2.37e-12 ***
## BPM          9.361e+05  1.232e+05   7.596 1.01e-13 ***
## `FG%`       -1.892e+07  3.924e+06  -4.823 1.75e-06 ***
## STL         -3.984e+04  1.156e+04  -3.445 0.000606 ***
## PF          -2.594e+04  6.787e+03  -3.822 0.000144 ***
## ovr          7.084e+04  2.876e+04   2.463 0.014008 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4562000 on 686 degrees of freedom
## Multiple R-squared:  0.6332, Adjusted R-squared:  0.6081
## F-statistic:  25.2 on 47 and 686 DF,  p-value: < 2.2e-16
```

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

```
##        MP       DWS        PF       BPM       STL      DBPM     TmTOT         G
## 11.279200  7.717215  6.015393  5.812854  5.346383  5.129833  4.855985  4.754360
##     PosSG     PosPG    `3PAr`     `FG%`     PosSF     TmPHO     TmTOR     TmDEN
##  3.723304  3.612465  3.262140  3.207377  3.072658  2.707156  2.571335  2.544916
##       ovr     TmMIN     TmGSW     TmPOR     TmMEM     TmSAC     TmMIL     TmDET
##  2.538978  2.530416  2.496152  2.478364  2.453595  2.429952  2.414457  2.387211
##     TmNYK     TmUTA     TmSAS     TmORL     TmOKC     TmLAL     TmHOU     TmBOS
##  2.386236  2.384990  2.340670  2.333964  2.323378  2.320569  2.315754  2.303219
##     TmCHI     TmDAL     TmMIA     TmPHI     TmNOP     TmLAC     TmBRK     TmIND
##  2.298968  2.298333  2.293969  2.284736  2.282320  2.241539  2.224116  2.186038
##     TmCLE     TmCHO     PosPF     TmWAS    `TOV%`       Age  year2017
##  2.168603  2.120323  2.078174  2.068491  1.724820  1.281067  1.209658
```

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

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]
```

Split Train-Test

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

Primary Dataset

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

```
## [1] 590
```

```r
nrow(p_test_df)
```

```
## [1] 144
```

```r
names(p_train_df)
```

```
##  [1] "name"   "salary" "year"   "Pos"    "Age"    "Tm"     "G"      "MP"
##  [9] "3PAr"   "TOV%"   "DWS"    "DBPM"   "BPM"    "FG%"    "STL"    "PF"
```

```r
head(p_train_df)
```

```
##             name  salary year Pos Age  Tm  G   MP  3PAr TOV% DWS DBPM  BPM   FG%
## 1  aaron brooks 2700000 2016  PG  31 CHI 69 1108 0.394 14.2 0.7 -2.8 -3.3 0.401
## 2  aaron brooks 2116955 2017  PG  32 IND 65  894 0.427 17.2 0.5 -2.6 -4.6 0.403
## 3  aaron gordon 4351320 2016  PF  20 ORL 78 1863 0.245  9.0 2.2  1.2  1.8 0.473
## 4  aaron gordon 5504420 2017  SF  21 ORL 80 2298 0.309  8.5 1.7 -0.4 -0.7 0.454
## 5 adreian payne 2022240 2016  PF  24 MIN 52  486 0.221 18.7 0.4 -0.2 -6.1 0.366
## 6    aj hammons 1312611 2017   C  24 DAL 22  163 0.238 16.4 0.2  1.9 -5.6 0.405
##   STL  PF
## 1  30 132
## 2  25  93
## 3  59 153
## 4  64 172
## 5  16  77
## 6   1  21
```

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

Complete Dataset

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

```
## [1] 590
```

```r
nrow(c_test_df)
```

```
## [1] 144
```

```r
names(c_train_df)
```

```
##  [1] "name"   "salary" "year"   "Pos"    "Age"    "Tm"     "G"      "MP"
##  [9] "3PAr"   "TOV%"   "DWS"    "DBPM"   "BPM"    "FG%"    "STL"    "PF"
## [17] "ovr"
```

```r
head(c_train_df)
```

```
##             name  salary year Pos Age  Tm  G   MP  3PAr TOV% DWS DBPM  BPM   FG%
## 1  aaron brooks 2700000 2016  PG  31 CHI 69 1108 0.394 14.2 0.7 -2.8 -3.3 0.401
## 2  aaron brooks 2116955 2017  PG  32 IND 65  894 0.427 17.2 0.5 -2.6 -4.6 0.403
## 3  aaron gordon 4351320 2016  PF  20 ORL 78 1863 0.245  9.0 2.2  1.2  1.8 0.473
```

```
## 4  aaron gordon 5504420 2017  SF  21 ORL 80 2298 0.309  8.5 1.7 -0.4 -0.7 0.454
## 5 adreian payne 2022240 2016  PF  24 MIN 52  486 0.221 18.7 0.4 -0.2 -6.1 0.366
## 6    aj hammons 1312611 2017   C  24 DAL 22  163 0.238 16.4 0.2  1.9 -5.6 0.405
##   STL  PF ovr
## 1  30 132  75
## 2  25  93  85
## 3  59 153  90
## 4  64 172  92
## 5  16  77  69
## 6   1  21  66
```

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