Reproducible Data Analysis Project

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1. Introduction

Every team owner wish to have top players only. But, its also a business and we need to "purcahse!" only value for money players for maximum utilization of money. The report finds top 5 value for money players with the help of linear regression analysis.

The top 5 players are:

```
##   POSITION             PLAYER SALARYmillions
## 1       PG   D'Angelo Russell           7.01
## 2       SG       Devin Booker           3.31
## 3       SF     Brandon Ingram           5.75
## 4       PF       John Collins           2.29
## 5        C Karl-Anthony Towns           7.83
## 6                       TOTAL          26.19
```

a) Description of scenario

Chicago Bulls is a Basketball team which participates in the NBA (National Basketball Association) seasons. General manager of Chicago Bulls has approached me, i.e. the author of this project; to find 5 best players for 5 positions, one player for each position for the next NBA season 2019-20.

b) Background information

It is better to get some idea of the basketball game. Normally, a team has 5 players and these players are assigned to 5 positions. The basketball positions are assigned a number as under:

1. Point Guard [PG]
2. Shooting Guard [SG]
3. Small Forward [SF]
4. Power Forward [PF]
5. Center [C]

c) Aim of project

The aim of this project is to find out the 5 best players, one for each position for Chicago Bulls for the next session 2019-20. It may be noted that we are not going to just pick the top 5 players. We need to consider the budget and need to develop a model which identifies the undervalued players.

d) Justification and importance

The budget of Chicago Bulls for player contracts next season is $118 million. If this project is able to provide an accurate prediction of the 5 player who are value for money, then the Chicago Bulls will be able to get good players in reasonable amount. Besides that the recommendation and selection of the players shall be free from bias as it shall be data based. Linear regression shall help in finding the undervalued players. We need to find the players with the ability to score high points but getting a lower to moderate salary. Thus, at first we shall develop a model to predict the players ability to score points and thereafter compare this with players salary and select the value for money players of different positions with help of this framework. As stated earlier that the top players are very costly, hence it makes sense to develop a metric to value players based on that metric to their relative contribution to score points. The confidence interval limits are positive. i.e. it is not that one limit is negative and one limit is positive.

2. Reading and cleaning the raw data

Date Description

The data set consists of 5 csv files. The data description is can be seen by clicking below link: https://github.com/Sreekardeshamoni/Assessment-4/blob/main/Data%20Description.pdf

Loading tidyverse library and reading the data

The csv files are saved in data frames tibbles of readr package.

```
library(tidyverse)
```

```
## Warning: replacing previous import 'lifecycle::last_warnings' by
## 'rlang::last_warnings' when loading 'pillar'

## Warning: replacing previous import 'lifecycle::last_warnings' by
## 'rlang::last_warnings' when loading 'tibble'

## Warning: replacing previous import 'lifecycle::last_warnings' by
## 'rlang::last_warnings' when loading 'hms'

## -- Attaching packages --------------------------------------- tidyverse 1.3.1 --

## v ggplot2 3.3.5     v purrr   0.3.4
## v tibble  3.1.2     v dplyr   1.0.6
## v tidyr   1.1.3     v stringr 1.4.0
## v readr   2.1.2     v forcats 0.5.1

## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
```

```
library(broom)
player_stat = read_csv("data/raw/2018-19_nba_player-statistics.csv")
```

```
## Rows: 708 Columns: 29
```

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

```
player_salary = read_csv("data/raw/2018-19_nba_player-salaries.csv")
```

```
## Rows: 576 Columns: 3-- Column specification --------------------------------------------------------
## Delimiter: ","
## chr (1): player_name
## dbl (2): player_id, salary
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```
team_payroll = read_csv("data/raw/2019-20_nba_team-payroll.csv")
```

```
## Rows: 30 Columns: 3-- Column specification --------------------------------------------------------
## Delimiter: ","
## chr (2): team, salary
## dbl (1): team_id
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```
team_stat_1 = read_csv("data/raw/2018-19_nba_team-statistics_1.csv")
```

```
## New names:
## * `` -> ...23
## * `` -> ...24
## * `` -> ...25
## Rows: 30 Columns: 25-- Column specification --------------------------------------------------------
## Delimiter: ","
## chr  (1): Team
## dbl (21): Rk, Age, W, L, PW, PL, MOV, SOS, SRS, ORtg, DRtg, NRtg, Pace, FTr,...
## lgl  (3): ...23, ...24, ...25
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```
team_stat_2 = read_csv("data/raw/2018-19_nba_team-statistics_2.csv")
```

```
## Rows: 30 Columns: 25-- Column specification --------------------------------------------------------
## Delimiter: ","
## chr  (1): Team
## dbl (24): Rk, G, MP, FG, FGA, FG%, 3P, 3PA, 3P%, 2P, 2PA, 2P%, FT, FTA, FT%,...
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

Now, its time to have a look at data structure.

```r
str(player_stat)
```

```
## spec_tbl_df [708 x 29] (S3: spec_tbl_df/tbl_df/tbl/data.frame)
##  $ player_name: chr [1:708] "Alex Abrines" "Quincy Acy" "Jaylen Adams" "Steven Adams" ...
##  $ Pos        : chr [1:708] "SG" "PF" "PG" "C" ...
##  $ Age        : num [1:708] 25 28 22 25 21 21 25 33 21 23 ...
##  $ Tm         : chr [1:708] "OKC" "PHO" "ATL" "OKC" ...
##  $ G          : num [1:708] 31 10 34 80 82 19 7 81 10 38 ...
##  $ GS         : num [1:708] 2 0 1 80 28 3 0 81 1 2 ...
##  $ MP         : num [1:708] 588 123 428 2669 1913 ...
##  $ FG         : num [1:708] 56 4 38 481 280 11 3 684 13 67 ...
##  $ FGA        : num [1:708] 157 18 110 809 486 ...
##  $ FG%        : num [1:708] 0.357 0.222 0.345 0.595 0.576 0.306 0.3 0.519 0.333 0.376 ...
##  $ 3P         : num [1:708] 41 2 25 0 3 6 0 10 3 32 ...
##  $ 3PA        : num [1:708] 127 15 74 2 15 23 4 42 12 99 ...
##  $ 3P%        : num [1:708] 0.323 0.133 0.338 0 0.2 0.261 0 0.238 0.25 0.323 ...
##  $ 2P         : num [1:708] 15 2 13 481 277 5 3 674 10 35 ...
##  $ 2PA        : num [1:708] 30 3 36 807 471 ...
##  $ 2P%        : num [1:708] 0.5 0.667 0.361 0.596 0.588 0.385 0.5 0.528 0.37 0.443 ...
##  $ eFG%       : num [1:708] 0.487 0.278 0.459 0.595 0.579 0.389 0.3 0.522 0.372 0.466 ...
##  $ FT         : num [1:708] 12 7 7 146 166 4 1 349 8 45 ...
##  $ FTA        : num [1:708] 13 10 9 292 226 4 2 412 12 60 ...
##  $ FT%        : num [1:708] 0.923 0.7 0.778 0.5 0.735 1 0.5 0.847 0.667 0.75 ...
##  $ ORB        : num [1:708] 5 3 11 391 165 3 1 251 11 3 ...
##  $ DRB        : num [1:708] 43 22 49 369 432 16 3 493 15 20 ...
##  $ TRB        : num [1:708] 48 25 60 760 597 19 4 744 26 23 ...
##  $ AST        : num [1:708] 20 8 65 124 184 5 6 194 13 25 ...
##  $ STL        : num [1:708] 17 1 14 117 71 1 2 43 1 6 ...
##  $ BLK        : num [1:708] 6 4 5 76 65 4 0 107 0 6 ...
##  $ TOV        : num [1:708] 14 4 28 135 121 6 2 144 8 33 ...
##  $ PF         : num [1:708] 53 24 45 204 203 13 4 179 7 47 ...
##  $ PTS        : num [1:708] 165 17 108 1108 729 ...
##  - attr(*, "spec")=
##   .. cols(
##   ..   player_name = col_character(),
##   ..   Pos = col_character(),
##   ..   Age = col_double(),
##   ..   Tm = col_character(),
##   ..   G = col_double(),
##   ..   GS = col_double(),
##   ..   MP = col_double(),
##   ..   FG = col_double(),
##   ..   FGA = col_double(),
##   ..   `FG%` = col_double(),
##   ..   `3P` = col_double(),
##   ..   `3PA` = col_double(),
##   ..   `3P%` = col_double(),
##   ..   `2P` = col_double(),
##   ..   `2PA` = col_double(),
##   ..   `2P%` = col_double(),
##   ..   `eFG%` = col_double(),
##   ..   FT = col_double(),
##   ..   FTA = col_double(),
```

```
##   ..   `FT%` = col_double(),
##   ..   ORB = col_double(),
##   ..   DRB = col_double(),
##   ..   TRB = col_double(),
##   ..   AST = col_double(),
##   ..   STL = col_double(),
##   ..   BLK = col_double(),
##   ..   TOV = col_double(),
##   ..   PF = col_double(),
##   ..   PTS = col_double()
##   .. )
##  - attr(*, "problems")=<externalptr>
```

```
str(player_salary)
```

```
## spec_tbl_df [576 x 3] (S3: spec_tbl_df/tbl_df/tbl/data.frame)
##  $ player_id  : num [1:576] 1 2 3 4 5 6 7 8 9 10 ...
##  $ player_name: chr [1:576] "Alex Abrines" "Quincy Acy" "Steven Adams" "Jaylen Adams" ...
##  $ salary     : num [1:576] 3667645 213948 24157304 236854 2955840 ...
##  - attr(*, "spec")=
##   .. cols(
##   ..   player_id = col_double(),
##   ..   player_name = col_character(),
##   ..   salary = col_double()
##   .. )
##  - attr(*, "problems")=<externalptr>
```

```
str(team_payroll)
```

```
## spec_tbl_df [30 x 3] (S3: spec_tbl_df/tbl_df/tbl/data.frame)
##  $ team_id: num [1:30] 1 2 3 4 5 6 7 8 9 10 ...
##  $ team   : chr [1:30] "Miami" "Golden State" "Oklahoma City" "Toronto" ...
##  $ salary : chr [1:30] "$153,171,497" "$146,291,276" "$144,916,427" "$137,793,831" ...
##  - attr(*, "spec")=
##   .. cols(
##   ..   team_id = col_double(),
##   ..   team = col_character(),
##   ..   salary = col_character()
##   .. )
##  - attr(*, "problems")=<externalptr>
```

```
str(team_stat_1)
```

```
## spec_tbl_df [30 x 25] (S3: spec_tbl_df/tbl_df/tbl/data.frame)
##  $ Rk    : num [1:30] 1 2 3 4 5 6 7 8 9 10 ...
##  $ Team  : chr [1:30] "Milwaukee Bucks" "Golden State Warriors" "Toronto Raptors" "Utah Jazz" ...
##  $ Age   : num [1:30] 26.9 28.4 27.3 27.3 29.2 26.2 24.9 25.7 25.7 27 ...
##  $ W     : num [1:30] 60 57 58 50 53 53 54 49 49 48 ...
##  $ L     : num [1:30] 22 25 24 32 29 29 28 33 33 34 ...
##  $ PW    : num [1:30] 61 56 56 54 53 51 51 52 50 50 ...
##  $ PL    : num [1:30] 21 26 26 28 29 31 31 30 32 32 ...
##  $ MOV   : num [1:30] 8.87 6.46 6.09 5.26 4.77 4.2 3.95 4.44 3.4 3.33 ...
```

```
## $ SOS   : num [1:30] -0.82 -0.04 -0.6 0.03 0.19 0.24 0.24 -0.54 0.15 -0.57 ...
## $ SRS   : num [1:30] 8.04 6.42 5.49 5.28 4.96 4.43 4.19 3.9 3.56 2.76 ...
## $ ORtg  : num [1:30] 114 116 113 111 116 ...
## $ DRtg  : num [1:30] 105 110 107 106 111 ...
## $ NRtg  : num [1:30] 8.6 6.4 6 5.2 4.8 4.2 4.1 4.4 3.3 3.4 ...
## $ Pace  : num [1:30] 103.3 100.9 100.2 100.3 97.9 ...
## $ FTr   : num [1:30] 0.255 0.227 0.247 0.295 0.279 0.258 0.232 0.215 0.266 0.242 ...
## $ 3PAr  : num [1:30] 0.419 0.384 0.379 0.394 0.519 0.339 0.348 0.381 0.347 0.292 ...
## $ TS%   : num [1:30] 0.583 0.596 0.579 0.572 0.581 0.568 0.558 0.567 0.545 0.561 ...
## $ eFG%  : num [1:30] 0.55 0.565 0.543 0.538 0.542 0.528 0.527 0.534 0.514 0.53 ...
## $ TOV%  : num [1:30] 12 12.6 12.4 13.4 12 12.1 11.9 11.5 11.7 12.4 ...
## $ ORB%  : num [1:30] 20.8 22.5 21.9 22.9 22.8 26.6 26.6 21.6 26 21.9 ...
## $ FT/FGA: num [1:30] 0.197 0.182 0.198 0.217 0.221 0.21 0.175 0.173 0.19 0.182 ...
## $ DRB%  : num [1:30] 80.3 77.1 77.1 80.3 74.4 77.9 78 77 78.2 76.2 ...
## $ ...23 : logi [1:30] NA NA NA NA NA NA ...
## $ ...24 : logi [1:30] NA NA NA NA NA NA ...
## $ ...25 : logi [1:30] NA NA NA NA NA NA ...
## - attr(*, "spec")=
##  .. cols(
##  ..   Rk = col_double(),
##  ..   Team = col_character(),
##  ..   Age = col_double(),
##  ..   W = col_double(),
##  ..   L = col_double(),
##  ..   PW = col_double(),
##  ..   PL = col_double(),
##  ..   MOV = col_double(),
##  ..   SOS = col_double(),
##  ..   SRS = col_double(),
##  ..   ORtg = col_double(),
##  ..   DRtg = col_double(),
##  ..   NRtg = col_double(),
##  ..   Pace = col_double(),
##  ..   FTr = col_double(),
##  ..   `3PAr` = col_double(),
##  ..   `TS%` = col_double(),
##  ..   `eFG%` = col_double(),
##  ..   `TOV%` = col_double(),
##  ..   `ORB%` = col_double(),
##  ..   `FT/FGA` = col_double(),
##  ..   `DRB%` = col_double(),
##  ..   ...23 = col_logical(),
##  ..   ...24 = col_logical(),
##  ..   ...25 = col_logical()
##  .. )
## - attr(*, "problems")=<externalptr>
```

```
str(team_stat_2)
```

```
## spec_tbl_df [30 x 25] (S3: spec_tbl_df/tbl_df/tbl/data.frame)
## $ Rk  : num [1:30] 1 2 3 4 5 6 7 8 9 10 ...
## $ Team: chr [1:30] "Milwaukee Bucks" "Golden State Warriors" "New Orleans Pelicans" "Philadelphia 7
## $ G   : num [1:30] 82 82 82 82 82 82 82 82 82 82 ...
## $ MP  : num [1:30] 19780 19805 19755 19805 19830 ...
```

```
##  $ FG  : num [1:30] 3555 3612 3581 3407 3384 ...
##  $ FGA : num [1:30] 7471 7361 7563 7233 7178 ...
##  $ FG% : num [1:30] 0.476 0.491 0.473 0.471 0.471 0.467 0.454 0.474 0.464 0.468 ...
##  $ 3P  : num [1:30] 1105 1087 842 889 821 ...
##  $ 3PA : num [1:30] 3134 2824 2449 2474 2118 ...
##  $ 3P% : num [1:30] 0.353 0.385 0.344 0.359 0.388 0.359 0.348 0.366 0.378 0.341 ...
##  $ 2P  : num [1:30] 2450 2525 2739 2518 2563 ...
##  $ 2PA : num [1:30] 4337 4537 5114 4759 5060 ...
##  $ 2P% : num [1:30] 0.565 0.557 0.536 0.529 0.507 0.523 0.51 0.539 0.504 0.543 ...
##  $ FT  : num [1:30] 1471 1339 1462 1742 1853 ...
##  $ FTA : num [1:30] 1904 1672 1921 2258 2340 ...
##  $ FT% : num [1:30] 0.773 0.801 0.761 0.771 0.792 0.814 0.713 0.804 0.726 0.768 ...
##  $ ORB : num [1:30] 762 797 909 892 796 ...
##  $ DRB : num [1:30] 3316 2990 2969 3025 2936 ...
##  $ TRB : num [1:30] 4078 3787 3878 3917 3732 ...
##  $ AST : num [1:30] 2136 2413 2216 2207 1970 ...
##  $ STL : num [1:30] 615 625 610 606 561 546 766 680 679 683 ...
##  $ BLK : num [1:30] 486 525 441 432 385 413 425 437 363 379 ...
##  $ TOV : num [1:30] 1137 1169 1215 1223 1193 ...
##  $ PF  : num [1:30] 1608 1757 1732 1745 1913 ...
##  $ PTS : num [1:30] 9686 9650 9466 9445 9442 ...
##  - attr(*, "spec")=
##   .. cols(
##   ..   Rk = col_double(),
##   ..   Team = col_character(),
##   ..   G = col_double(),
##   ..   MP = col_double(),
##   ..   FG = col_double(),
##   ..   FGA = col_double(),
##   ..   `FG%` = col_double(),
##   ..   `3P` = col_double(),
##   ..   `3PA` = col_double(),
##   ..   `3P%` = col_double(),
##   ..   `2P` = col_double(),
##   ..   `2PA` = col_double(),
##   ..   `2P%` = col_double(),
##   ..   FT = col_double(),
##   ..   FTA = col_double(),
##   ..   `FT%` = col_double(),
##   ..   ORB = col_double(),
##   ..   DRB = col_double(),
##   ..   TRB = col_double(),
##   ..   AST = col_double(),
##   ..   STL = col_double(),
##   ..   BLK = col_double(),
##   ..   TOV = col_double(),
##   ..   PF = col_double(),
##   ..   PTS = col_double()
##   .. )
##  - attr(*, "problems")=<externalptr>
```

R can manage the "illegal" variable names by surrounding the variable name by ", however, as a best practice it makes sense to rename the variables.

```r
player_stat <-rename(player_stat,
                    FGp = `FG%`,
                    x3P = `3P`,
                    x3PA = `3PA`,
                    x3Pp = `3P%`,
                    x2P = `2P`,
                    x2PA = `2PA`,
                    x2Pp = `2P%`,
                    eFGp = `eFG%`,
                    FTp = `FT%`)

team_stat_1 <-rename(team_stat_1,
                           x3PAr = `3PAr`,
                           TSp = `TS%`,
                           eFGp = `eFG%`,
                           TOVp = `TOV%`,
                           ORBp = `ORB%`,
                           FTpFGA = `FT/FGA`,
                           DRBp = `DRB%`)

team_stat_2 <-rename(team_stat_2,
                           FGp = `FG%`,
                           x3P = `3P`,
                           x3PA = `3PA`,
                           x3Pp = `3P%`,
                           x2P = `2P`,
                           x2PA = `2PA`,
                           x2Pp = `2P%`,
                           FTp = `FT%`)
```

3. Exploratory analysis

Checking missing values player__stat

At first need to check the missing values.

```r
sum(is.na(player_stat))
```

```
## [1] 117
```

```r
which(is.na(player_stat), arr.ind = TRUE)
```

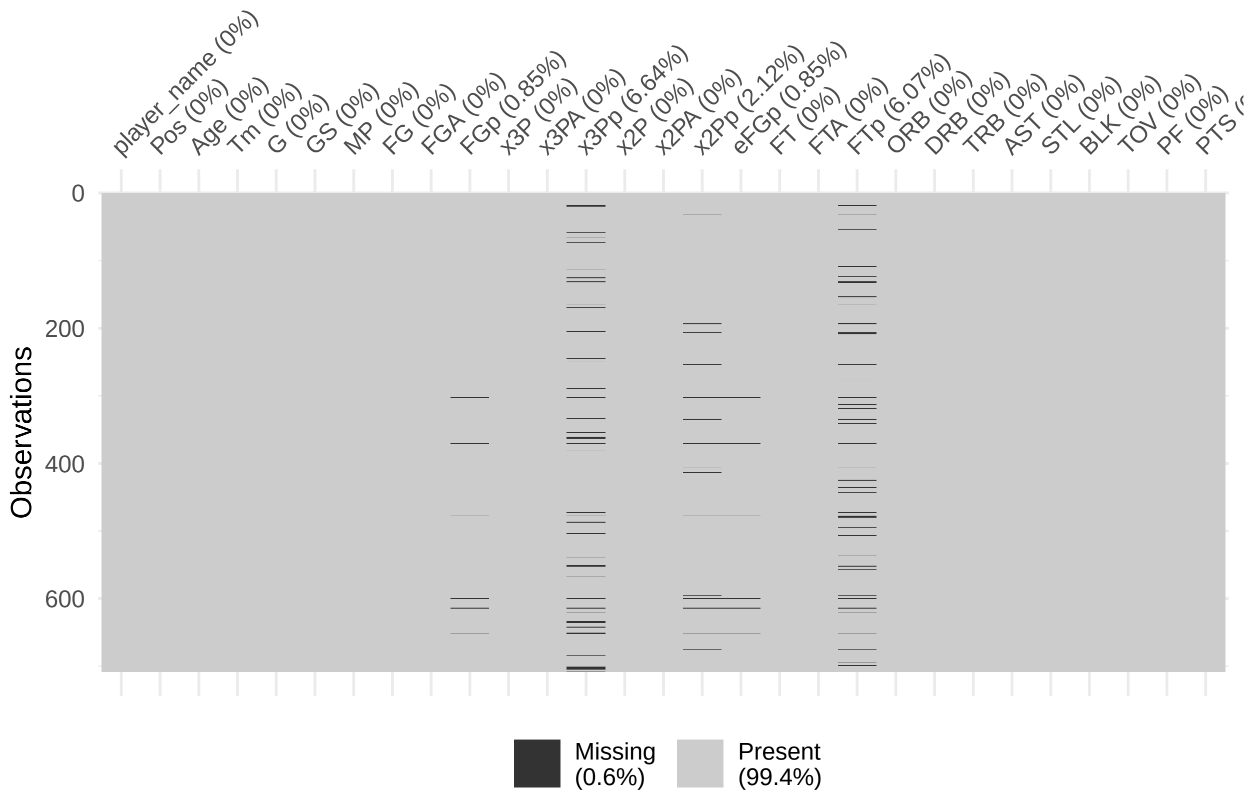
```
##        row col
##   [1,] 303  10
##   [2,] 371  10
##   [3,] 478  10
##   [4,] 600  10
##   [5,] 614  10
##   [6,] 652  10
##   [7,]  19  13
##   [8,]  21  13
```

```
##   [9,]  59  13
##  [10,]  66  13
##  [11,]  74  13
##  [12,] 113  13
##  [13,] 126  13
##  [14,] 132  13
##  [15,] 165  13
##  [16,] 170  13
##  [17,] 205  13
##  [18,] 245  13
##  [19,] 249  13
##  [20,] 290  13
##  [21,] 303  13
##  [22,] 305  13
##  [23,] 311  13
##  [24,] 334  13
##  [25,] 355  13
##  [26,] 361  13
##  [27,] 362  13
##  [28,] 363  13
##  [29,] 371  13
##  [30,] 382  13
##  [31,] 473  13
##  [32,] 478  13
##  [33,] 487  13
##  [34,] 504  13
##  [35,] 540  13
##  [36,] 551  13
##  [37,] 552  13
##  [38,] 568  13
##  [39,] 600  13
##  [40,] 614  13
##  [41,] 621  13
##  [42,] 634  13
##  [43,] 635  13
##  [44,] 636  13
##  [45,] 642  13
##  [46,] 651  13
##  [47,] 652  13
##  [48,] 684  13
##  [49,] 701  13
##  [50,] 702  13
##  [51,] 703  13
##  [52,] 704  13
##  [53,] 708  13
##  [54,]  32  16
##  [55,] 194  16
##  [56,] 207  16
##  [57,] 254  16
##  [58,] 303  16
##  [59,] 335  16
##  [60,] 371  16
##  [61,] 407  16
##  [62,] 414  16
```

```
##  [63,] 478  16
##  [64,] 595  16
##  [65,] 600  16
##  [66,] 614  16
##  [67,] 652  16
##  [68,] 675  16
##  [69,] 303  17
##  [70,] 371  17
##  [71,] 478  17
##  [72,] 600  17
##  [73,] 614  17
##  [74,] 652  17
##  [75,]  19  20
##  [76,]  32  20
##  [77,]  55  20
##  [78,] 109  20
##  [79,] 124  20
##  [80,] 132  20
##  [81,] 133  20
##  [82,] 154  20
##  [83,] 165  20
##  [84,] 193  20
##  [85,] 194  20
##  [86,] 207  20
##  [87,] 208  20
##  [88,] 209  20
##  [89,] 254  20
##  [90,] 277  20
##  [91,] 303  20
##  [92,] 313  20
##  [93,] 319  20
##  [94,] 335  20
##  [95,] 341  20
##  [96,] 371  20
##  [97,] 407  20
##  [98,] 425  20
##  [99,] 436  20
## [100,] 443  20
## [101,] 473  20
## [102,] 478  20
## [103,] 479  20
## [104,] 480  20
## [105,] 495  20
## [106,] 507  20
## [107,] 537  20
## [108,] 552  20
## [109,] 557  20
## [110,] 595  20
## [111,] 600  20
## [112,] 614  20
## [113,] 621  20
## [114,] 652  20
## [115,] 675  20
## [116,] 695  20
```

```
## [117,] 699  20
```

```r
naniar::vis_miss(player_stat)
```

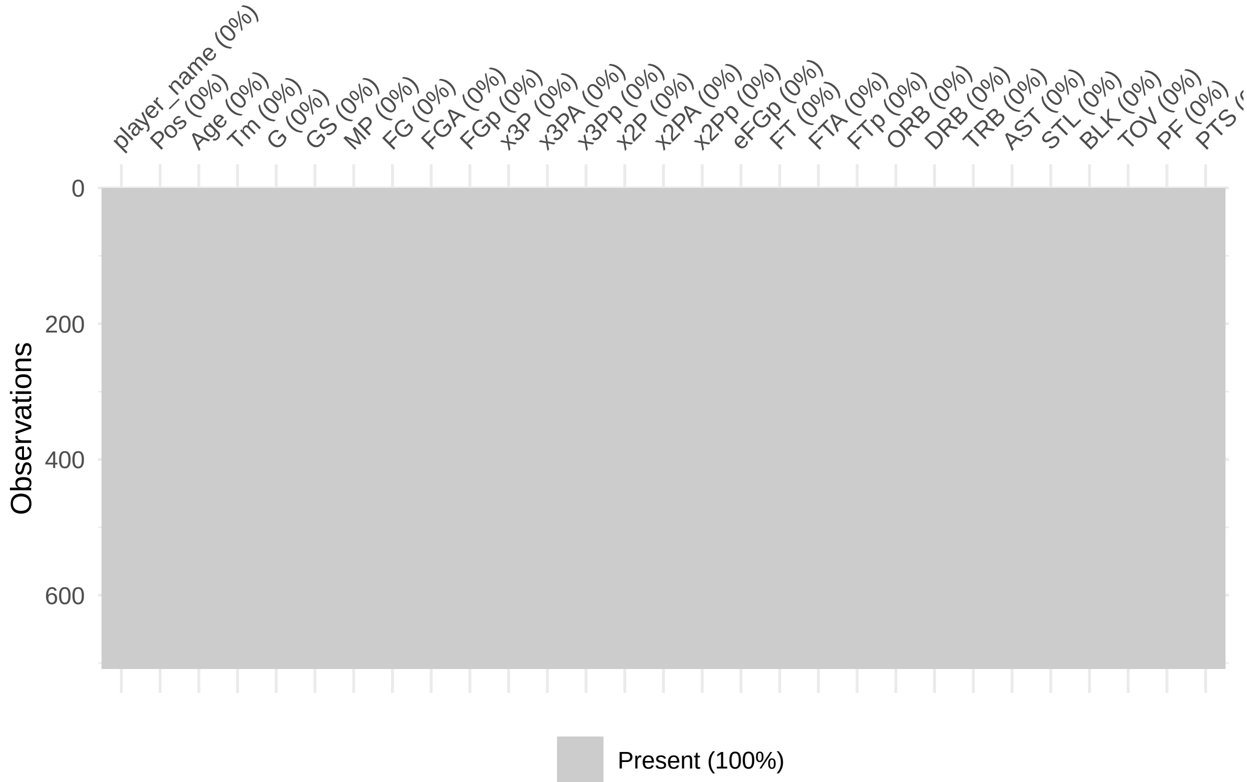


There are missing values for FGp, x3Pp, x2Pp, eFGp, and FTp. These are calculated field in the raw data itself, and where the denominator and/or numerator is zero, these fields becomes NA. However, it is understood that these are values where field goal, 2 Pointer and 3 Pointer was not done by the player. Hence, it is a good idea to replace these values by 0%.

```r
player_stat <- replace_na(player_stat, list(FGp = 0,x3Pp = 0,x2Pp = 0, eFGp = 0, FTp = 0))
sum(is.na(player_stat))
```

```
## [1] 0
```

```r
naniar::vis_miss(player_stat)
```



If we check the player_name variable, we find that a total of 86 players have played for more than 1 team in the season. mydf1 = df1 %>% group_by(player_name) %>% summarise(num_of_teams =n()) %>% filter(num_of_teams>1)

Checking missing values player_salary

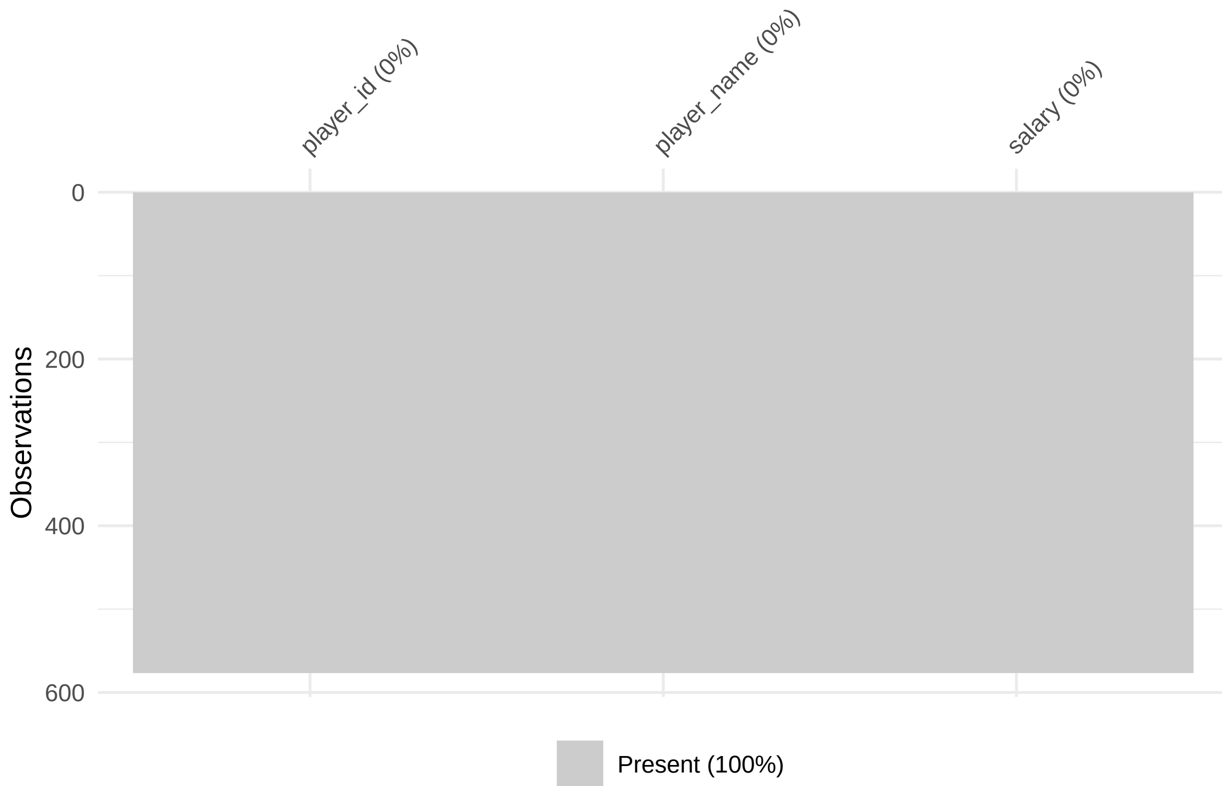
```
sum(is.na(player_salary))
```

```
## [1] 0
```

```
which(is.na(player_salary), arr.ind = TRUE)
```

```
##      row col
```

```
naniar::vis_miss(player_salary)
```



Checking missing values team_payroll

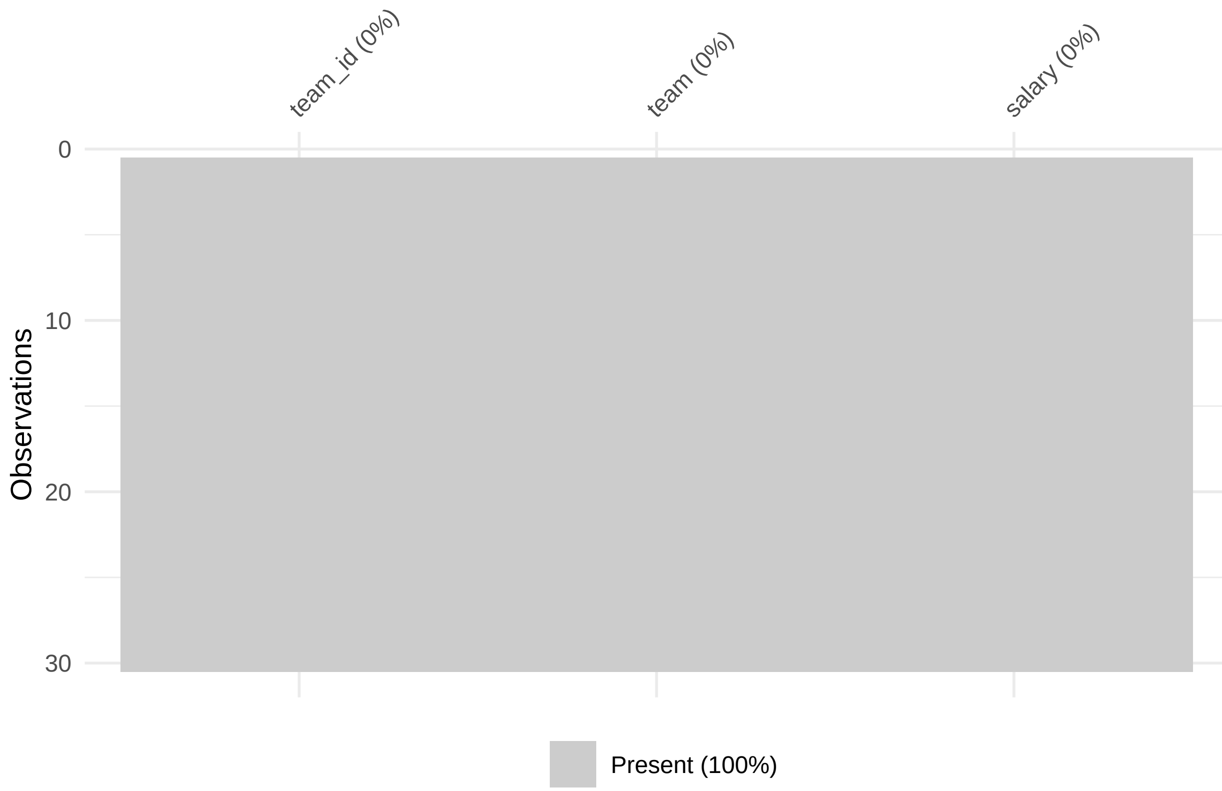
```
sum(is.na(team_payroll))
```

```
## [1] 0
```

```
which(is.na(team_payroll), arr.ind = TRUE)
```

```
##      row col
```

```
naniar::vis_miss(team_payroll)
```



Checking missing values team_stat_1

```
sum(is.na(team_stat_1))
```

```
## [1] 90
```

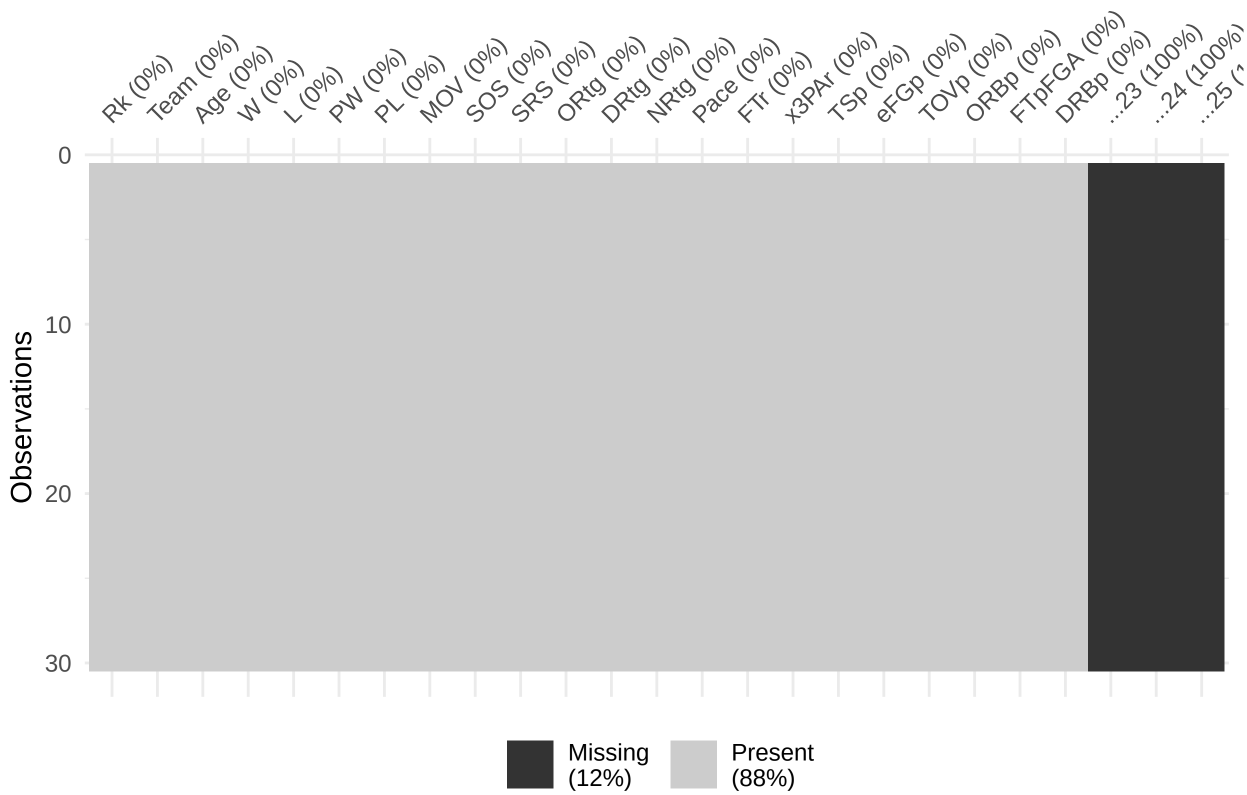
```
which(is.na(team_stat_1), arr.ind = TRUE)
```

```
##       row col
##  [1,]   1  23
##  [2,]   2  23
##  [3,]   3  23
##  [4,]   4  23
##  [5,]   5  23
##  [6,]   6  23
##  [7,]   7  23
##  [8,]   8  23
##  [9,]   9  23
## [10,]  10  23
## [11,]  11  23
## [12,]  12  23
## [13,]  13  23
## [14,]  14  23
```

```
## [15,]   15   23
## [16,]   16   23
## [17,]   17   23
## [18,]   18   23
## [19,]   19   23
## [20,]   20   23
## [21,]   21   23
## [22,]   22   23
## [23,]   23   23
## [24,]   24   23
## [25,]   25   23
## [26,]   26   23
## [27,]   27   23
## [28,]   28   23
## [29,]   29   23
## [30,]   30   23
## [31,]    1   24
## [32,]    2   24
## [33,]    3   24
## [34,]    4   24
## [35,]    5   24
## [36,]    6   24
## [37,]    7   24
## [38,]    8   24
## [39,]    9   24
## [40,]   10   24
## [41,]   11   24
## [42,]   12   24
## [43,]   13   24
## [44,]   14   24
## [45,]   15   24
## [46,]   16   24
## [47,]   17   24
## [48,]   18   24
## [49,]   19   24
## [50,]   20   24
## [51,]   21   24
## [52,]   22   24
## [53,]   23   24
## [54,]   24   24
## [55,]   25   24
## [56,]   26   24
## [57,]   27   24
## [58,]   28   24
## [59,]   29   24
## [60,]   30   24
## [61,]    1   25
## [62,]    2   25
## [63,]    3   25
## [64,]    4   25
## [65,]    5   25
## [66,]    6   25
## [67,]    7   25
## [68,]    8   25
```

```
## [69,]   9  25
## [70,]  10  25
## [71,]  11  25
## [72,]  12  25
## [73,]  13  25
## [74,]  14  25
## [75,]  15  25
## [76,]  16  25
## [77,]  17  25
## [78,]  18  25
## [79,]  19  25
## [80,]  20  25
## [81,]  21  25
## [82,]  22  25
## [83,]  23  25
## [84,]  24  25
## [85,]  25  25
## [86,]  26  25
## [87,]  27  25
## [88,]  28  25
## [89,]  29  25
## [90,]  30  25
```

```
naniar::vis_miss(team_stat_1)
```



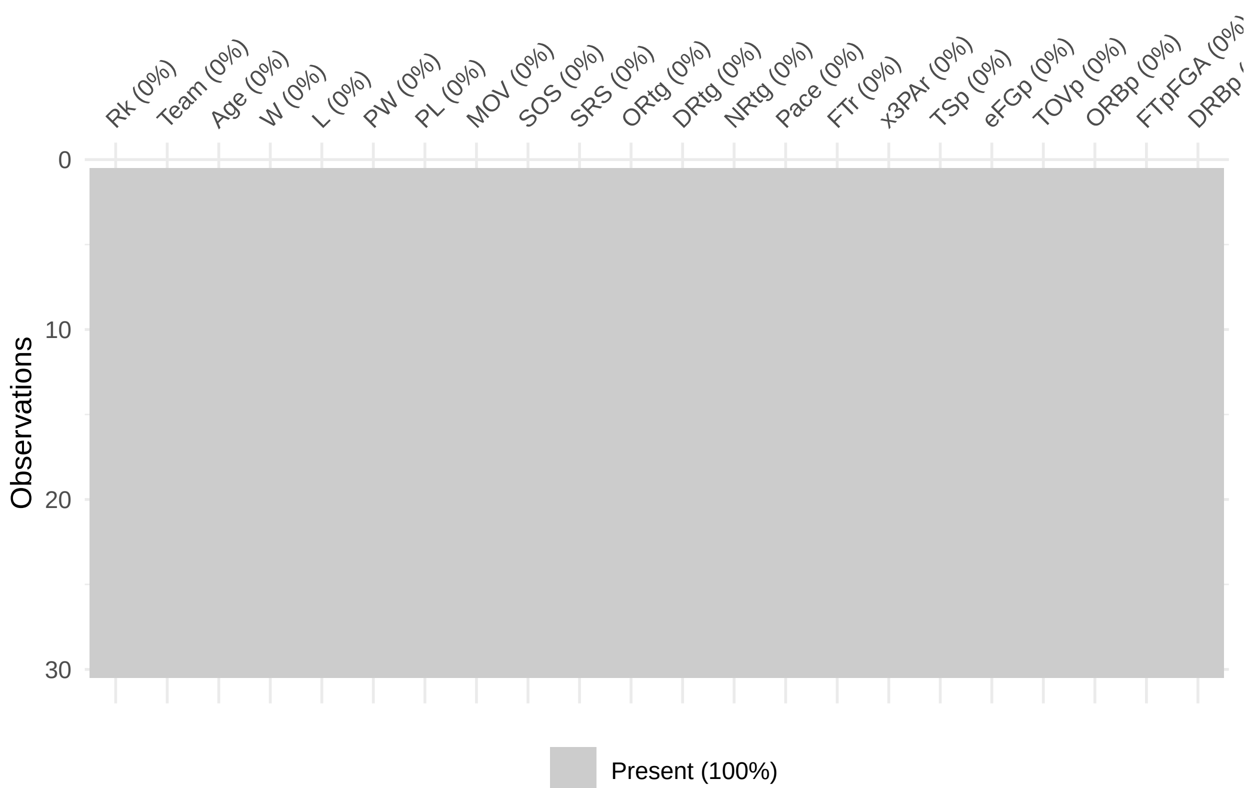
team_stat_1 has last 3 columns ...23, ...24, ...25 and these appears to be bogus columns and there is need to deleted these columns. The tidy team_stat_1 shall be as under:

```
team_stat_1 = select(team_stat_1,-c(...23:...25))
team_stat_1
```

```
## # A tibble: 30 x 22
##       Rk Team    Age     W     L    PW    PL   MOV   SOS   SRS  ORtg  DRtg  NRtg
##    <dbl> <chr> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
##  1     1 Milw~  26.9    60    22    61    21  8.87 -0.82  8.04  114.  105.   8.6
##  2     2 Gold~  28.4    57    25    56    26  6.46 -0.04  6.42  116.  110.   6.4
##  3     3 Toro~  27.3    58    24    56    26  6.09 -0.6   5.49  113.  107.   6
##  4     4 Utah~  27.3    50    32    54    28  5.26  0.03  5.28  111.  106.   5.2
##  5     5 Hous~  29.2    53    29    53    29  4.77  0.19  4.96  116.  111.   4.8
##  6     6 Port~  26.2    53    29    51    31  4.2   0.24  4.43  115.  110.   4.2
##  7     7 Denv~  24.9    54    28    51    31  3.95  0.24  4.19  113   109.   4.1
##  8     8 Bost~  25.7    49    33    52    30  4.44 -0.54  3.9   112.  108.   4.4
##  9     9 Okla~  25.7    49    33    50    32  3.4   0.15  3.56  110.  107    3.3
## 10    10 Indi~  27      48    34    50    32  3.33 -0.57  2.76  110.  106.   3.4
## # ... with 20 more rows, and 9 more variables: Pace <dbl>, FTr <dbl>,
## #   x3PAr <dbl>, TSp <dbl>, eFGp <dbl>, TOVp <dbl>, ORBp <dbl>, FTpFGA <dbl>,
## #   DRBp <dbl>
```

Now, the bogus columns are gone. This can be crossed checked:

```
naniar::vis_miss(team_stat_1)
```



Checking missing values team_stat_2

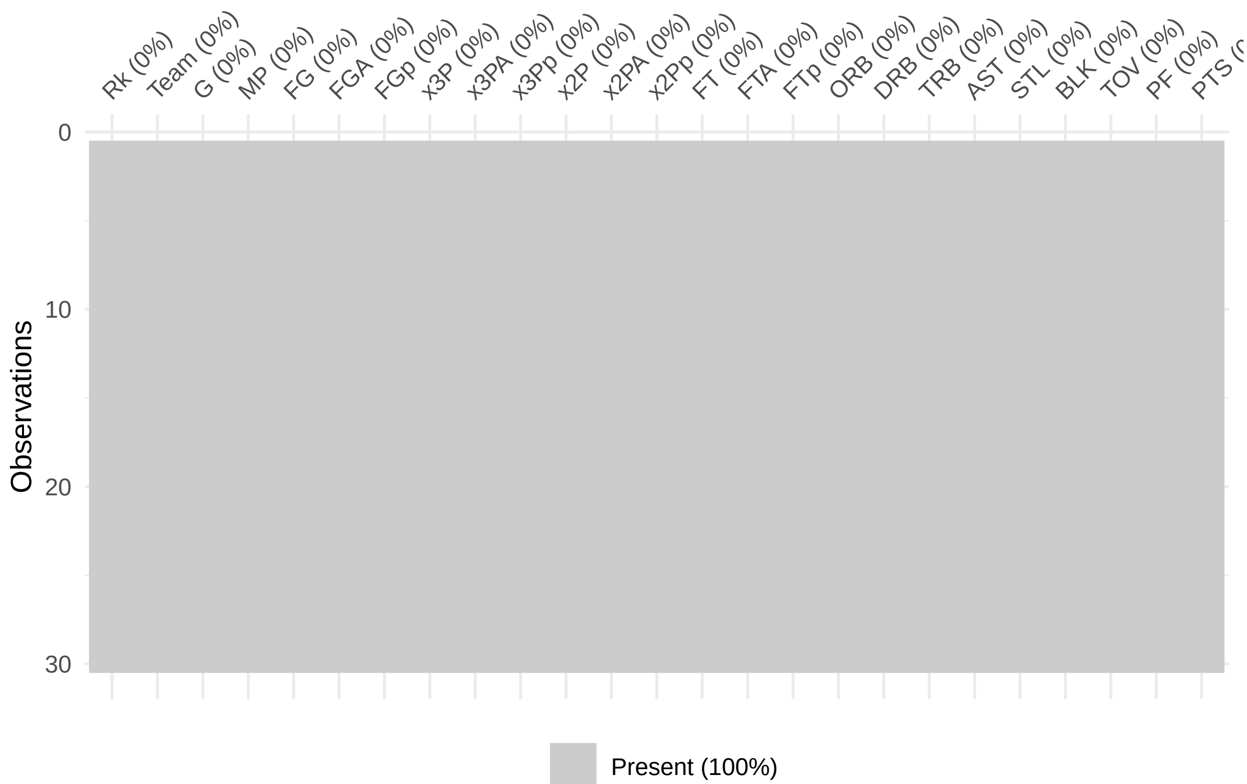
```
sum(is.na(team_stat_2))
```

```
## [1] 0
```

```
which(is.na(team_stat_2), arr.ind = TRUE)
```

```
##      row col
```

```
naniar::vis_miss(team_stat_2)
```



We can combine team_stat_1 and team_stat_2.

```
team_stat <- left_join(x = team_stat_1[-1], y = team_stat_2[-1], by = "Team") #don't need cols 1 of Ran
```

Other aspects

Interesting fact is that there are 30 teams, but in the player statistics table, there are 31 teams.We find that extra team is TOT which represents the total of all the instances matrices,where a player played from 2 or more teams in the season. We need the total of performance done by such players for the teams they were playing. This can be get with row where team name is "TOT". Thus, fur such players,we can keep only the row having "TOT" as team.

```r
player_stat <- player_stat %>% group_by(player_name) %>% add_tally() %>% filter(n==1 | n>1 & Tm == "TOT
```

Earlier, the player_stat has 730 rows, however, it has 530 rows.But one more issue is remaining.We find that there are a number of players who have played at different positions. However, we need to consider only a single position for these players. The best approach is to select the position for which the player has played most of the games. Luckily, we find that the raw data file, has already done this in some way. For example.. We just need to extract the characters before -, in the Pos column.

```r
player_stat <- player_stat %>% separate(col = Pos, into = "Pos")
```

```
## Warning: Expected 1 pieces. Additional pieces discarded in 8 rows [33, 84, 101,
## 288, 324, 330, 448, 455].
```

Also, some of the players have played a lower number of games. In fact, there are 20 players who have played only 1 game. We need to create a sort of cutoff and minimum 10 games cutoff is a reasonable cut off.

```r
player_stat <- player_stat %>% filter(G>=10)
```

There are 576 players in players salary table, however, there are only 530 unique players in the player statistics table. It means that some of the players did not played in NBA or the data for them is not available in player statistics. However, this fact is considered unimportant for the given project analysis. We can combine player_salary and player_stat

```r
player_stat <- inner_join(x = player_stat, y = player_salary, by = "player_name")
```

4. Data modelling and results

Valuing Players

Now, we will create a metric to value the players based upon certain factors/variables. This metric can be called exp_PTS_per_game. We shall then identify the undervalue players with the help of this metric. For this, we need to find some key metrics for our analysis. Some of the metrics to be used are below: FG Field Goals TRB Total Rebounds
AST Assists STL Steals BLK Blocks TOV Turnovers

However, as number of games played by players are different, it makes sense to normalize these metrics per game.

```r
normalised_team_stat <- team_stat %>% mutate(
  PTS_per_game = PTS / G,
  FG_per_game = FG / G,
  TRB_per_game = TRB / G,
  AST_per_game = AST / G,
  STL_per_game = STL / G,
  BLK_per_game = BLK / G,
  TOV_per_game = TOV / G)
```

Now, we create a multiple regression model for exp_PTS_per_game.

```
fit <- lm(PTS_per_game ~
  FG_per_game + TRB_per_game  + AST_per_game  + STL_per_game  + BLK_per_game  + TOV_per_game, data = no
tidy(fit, conf.int = TRUE)
```

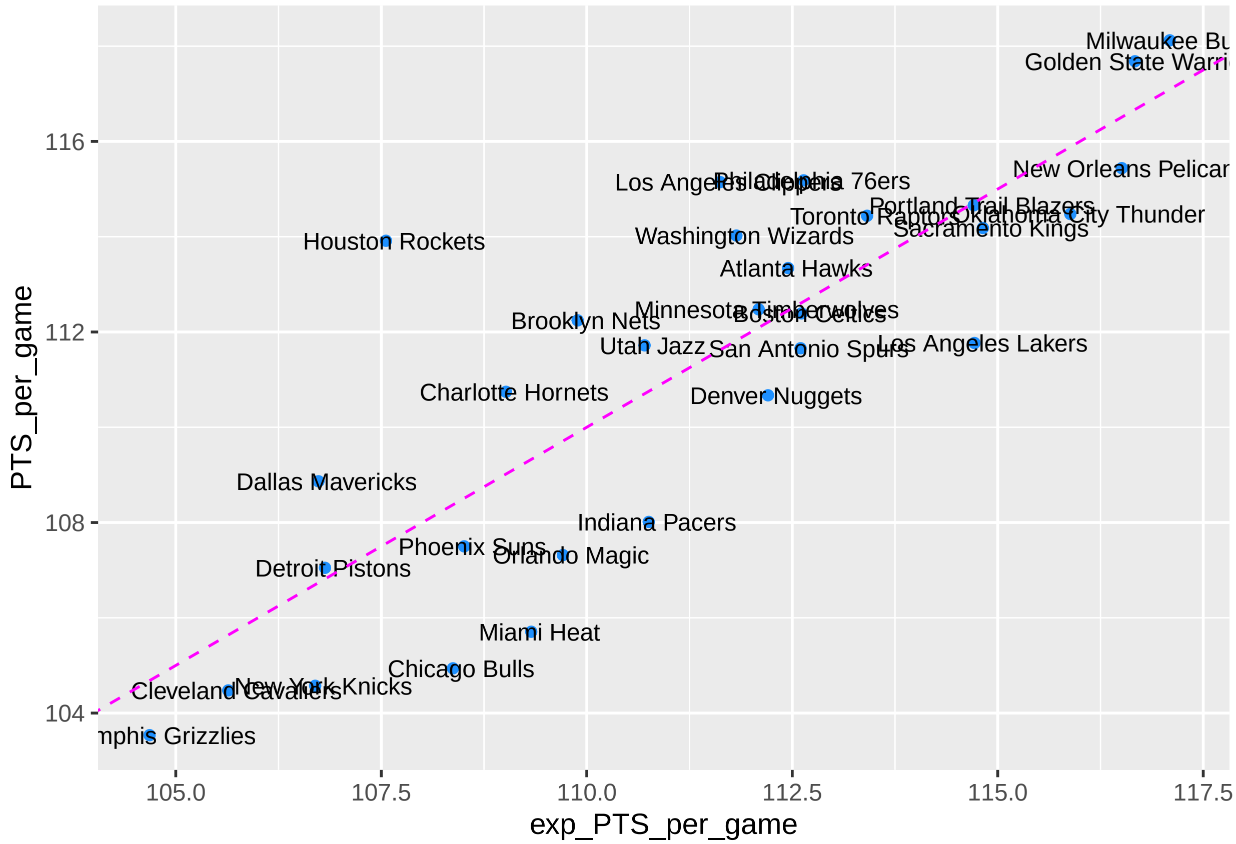
```
## # A tibble: 7 x 7
##   term         estimate std.error statistic  p.value conf.low conf.high
##   <chr>           <dbl>     <dbl>     <dbl>    <dbl>    <dbl>     <dbl>
## 1 (Intercept)    18.0      15.2        1.19  0.247     -13.4      49.4
## 2 FG_per_game     1.89      0.493      3.84  0.000844    0.872     2.91
## 3 TRB_per_game    0.340     0.324      1.05  0.304      -0.329     1.01
## 4 AST_per_game   -0.251     0.369     -0.680 0.503      -1.01      0.512
## 5 STL_per_game    0.195     0.707      0.276 0.785      -1.27      1.66
## 6 BLK_per_game    0.474     0.850      0.558 0.582      -1.28      2.23
## 7 TOV_per_game    0.172     0.500      0.344 0.734      -0.862     1.21
```

Model Testing

```
normalised_team_stat <- mutate(normalised_team_stat,exp_PTS_per_game=predict(fit,newdata=normalised_tea
```

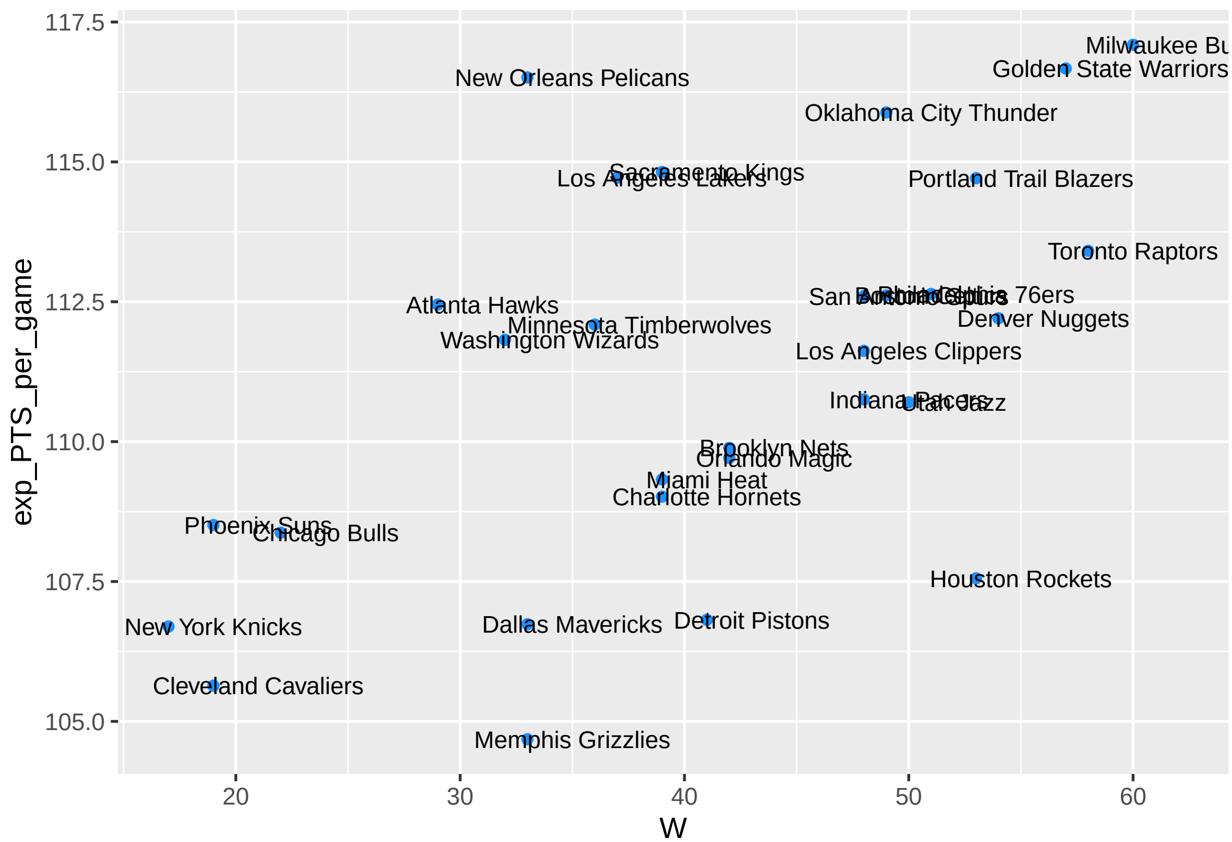
graph

```
ggplot(normalised_team_stat, aes(exp_PTS_per_game, PTS_per_game, label = Team)) +
geom_point(colour = "dodgerblue") +
geom_text(nudge_x = 0.1, cex = 3) +
geom_abline(linetype = "dashed", colour = "magenta")
```



graph

```
ggplot(normalised_team_stat, aes(x = W, y = exp_PTS_per_game, label = Team)) +
geom_point(colour = "dodgerblue") +
geom_text(nudge_x = 2, cex = 3)
```



Player Metric

At first we normalize the player_stat

```
normalised_player_stat <- player_stat %>% mutate(
  PTS_per_game = PTS / G,
  FG_per_game = FG / G,
  TRB_per_game = TRB / G,
  AST_per_game = AST / G,
  STL_per_game = STL / G,
  BLK_per_game = BLK / G,
  TOV_per_game = TOV / G)
str(normalised_player_stat)
```

```
## grouped_df [454 x 39] (S3: grouped_df/tbl_df/tbl/data.frame)
##  $ player_name : chr [1:454] "Alex Abrines" "Quincy Acy" "Jaylen Adams" "Steven Adams" ...
##  $ Pos         : chr [1:454] "SG" "PF" "PG" "C" ...
##  $ Age         : num [1:454] 25 28 22 25 21 21 33 21 23 20 ...
##  $ Tm          : chr [1:454] "OKC" "PHO" "ATL" "OKC" ...
##  $ G           : num [1:454] 31 10 34 80 82 19 81 10 38 80 ...
##  $ GS          : num [1:454] 2 0 1 80 28 3 81 1 2 80 ...
##  $ MP          : num [1:454] 588 123 428 2669 1913 ...
##  $ FG          : num [1:454] 56 4 38 481 280 11 684 13 67 335 ...
##  $ FGA         : num [1:454] 157 18 110 809 486 ...
##  $ FGp         : num [1:454] 0.357 0.222 0.345 0.595 0.576 0.306 0.519 0.333 0.376 0.59 ...
```

```
## $ x3P        : num [1:454] 41 2 25 0 3 6 10 3 32 6 ...
## $ x3PA       : num [1:454] 127 15 74 2 15 23 42 12 99 45 ...
## $ x3Pp       : num [1:454] 0.323 0.133 0.338 0 0.2 0.261 0.238 0.25 0.323 0.133 ...
## $ x2P        : num [1:454] 15 2 13 481 277 5 674 10 35 329 ...
## $ x2PA       : num [1:454] 30 3 36 807 471 ...
## $ x2Pp       : num [1:454] 0.5 0.667 0.361 0.596 0.588 0.385 0.528 0.37 0.443 0.629 ...
## $ eFGp       : num [1:454] 0.487 0.278 0.459 0.595 0.579 0.389 0.522 0.372 0.466 0.595 ...
## $ FT         : num [1:454] 12 7 7 146 166 4 349 8 45 197 ...
## $ FTA        : num [1:454] 13 10 9 292 226 4 412 12 60 278 ...
## $ FTp        : num [1:454] 0.923 0.7 0.778 0.5 0.735 1 0.847 0.667 0.75 0.709 ...
## $ ORB        : num [1:454] 5 3 11 391 165 3 251 11 3 191 ...
## $ DRB        : num [1:454] 43 22 49 369 432 16 493 15 20 481 ...
## $ TRB        : num [1:454] 48 25 60 760 597 19 744 26 23 672 ...
## $ AST        : num [1:454] 20 8 65 124 184 5 194 13 25 110 ...
## $ STL        : num [1:454] 17 1 14 117 71 1 43 1 6 43 ...
## $ BLK        : num [1:454] 6 4 5 76 65 4 107 0 6 120 ...
## $ TOV        : num [1:454] 14 4 28 135 121 6 144 8 33 103 ...
## $ PF         : num [1:454] 53 24 45 204 203 13 179 7 47 184 ...
## $ PTS        : num [1:454] 165 17 108 1108 729 ...
## $ n          : int [1:454] 1 1 1 1 1 1 1 1 1 1 ...
## $ player_id  : num [1:454] 1 2 4 3 5 6 10 11 12 13 ...
## $ salary     : num [1:454] 3667645 213948 236854 24157304 2955840 ...
## $ PTS_per_game: num [1:454] 5.32 1.7 3.18 13.85 8.89 ...
## $ FG_per_game : num [1:454] 1.81 0.4 1.12 6.01 3.41 ...
## $ TRB_per_game: num [1:454] 1.55 2.5 1.76 9.5 7.28 ...
## $ AST_per_game: num [1:454] 0.645 0.8 1.912 1.55 2.244 ...
## $ STL_per_game: num [1:454] 0.548 0.1 0.412 1.462 0.866 ...
## $ BLK_per_game: num [1:454] 0.194 0.4 0.147 0.95 0.793 ...
## $ TOV_per_game: num [1:454] 0.452 0.4 0.824 1.688 1.476 ...
## - attr(*, "groups")= tibble [454 x 2] (S3: tbl_df/tbl/data.frame)
##  ..$ player_name: chr [1:454] "Aaron Gordon" "Aaron Holiday" "Abdel Nader" "Al Horford" ...
##  ..$ .rows      : list<int> [1:454]
##  .. ..$ : int 169
##  .. ..$ : int 202
##  .. ..$ : int 317
##  .. ..$ : int 208
##  .. ..$ : int 12
##  .. ..$ : int 76
##  .. ..$ : int 1
##  .. ..$ : int 89
##  .. ..$ : int 262
##  .. ..$ : int 355
##  .. ..$ : int 292
##  .. ..$ : int 229
##  .. ..$ : int 107
##  .. ..$ : int 412
##  .. ..$ : int 226
##  .. ..$ : int 230
##  .. ..$ : int 132
##  .. ..$ : int 213
##  .. ..$ : int 53
##  .. ..$ : int 189
##  .. ..$ : int 437
##  .. ..$ : int 386
```

```
##    .. ..$ : int 454
##    .. ..$ : int 115
##    .. ..$ : int 409
##    .. ..$ : int 48
##    .. ..$ : int 34
##    .. ..$ : int 363
##    .. ..$ : int 58
##    .. ..$ : int 5
##    .. ..$ : int 293
##    .. ..$ : int 384
##    .. ..$ : int 46
##    .. ..$ : int 180
##    .. ..$ : int 281
##    .. ..$ : int 352
##    .. ..$ : int 51
##    .. ..$ : int 52
##    .. ..$ : int 429
##    .. ..$ : int 36
##    .. ..$ : int 168
##    .. ..$ : int 215
##    .. ..$ : int 247
##    .. ..$ : int 375
##    .. ..$ : int 271
##    .. ..$ : int 67
##    .. ..$ : int 79
##    .. ..$ : int 151
##    .. ..$ : int 199
##    .. ..$ : int 396
##    .. ..$ : int 345
##    .. ..$ : int 266
##    .. ..$ : int 17
##    .. ..$ : int 337
##    .. ..$ : int 211
##    .. ..$ : int 342
##    .. ..$ : int 156
##    .. ..$ : int 357
##    .. ..$ : int 123
##    .. ..$ : int 297
##    .. ..$ : int 57
##    .. ..$ : int 344
##    .. ..$ : int 446
##    .. ..$ : int 287
##    .. ..$ : int 299
##    .. ..$ : int 438
##    .. ..$ : int 83
##    .. ..$ : int 451
##    .. ..$ : int 380
##    .. ..$ : int 59
##    .. ..$ : int 241
##    .. ..$ : int 260
##    .. ..$ : int 147
##    .. ..$ : int 373
##    .. ..$ : int 42
##    .. ..$ : int 236
```

```
##    .. ..$ : int 267
##    .. ..$ : int 261
##    .. ..$ : int 130
##    .. ..$ : int 181
##    .. ..$ : int 402
##    .. ..$ : int 158
##    .. ..$ : int 175
##    .. ..$ : int 111
##    .. ..$ : int 143
##    .. ..$ : int 209
##    .. ..$ : int 453
##    .. ..$ : int 300
##    .. ..$ : int 101
##    .. ..$ : int 328
##    .. ..$ : int 43
##    .. ..$ : int 360
##    .. ..$ : int 153
##    .. ..$ : int 296
##    .. ..$ : int 22
##    .. ..$ : int 240
##    .. ..$ : int 447
##    .. ..$ : int 121
##    .. ..$ : int 105
##    .. .. [list output truncated]
##    .. ..@ ptype: int(0)
##    ..- attr(*, ".drop")= logi TRUE
```

Next, step is to calculate player specific expected points.

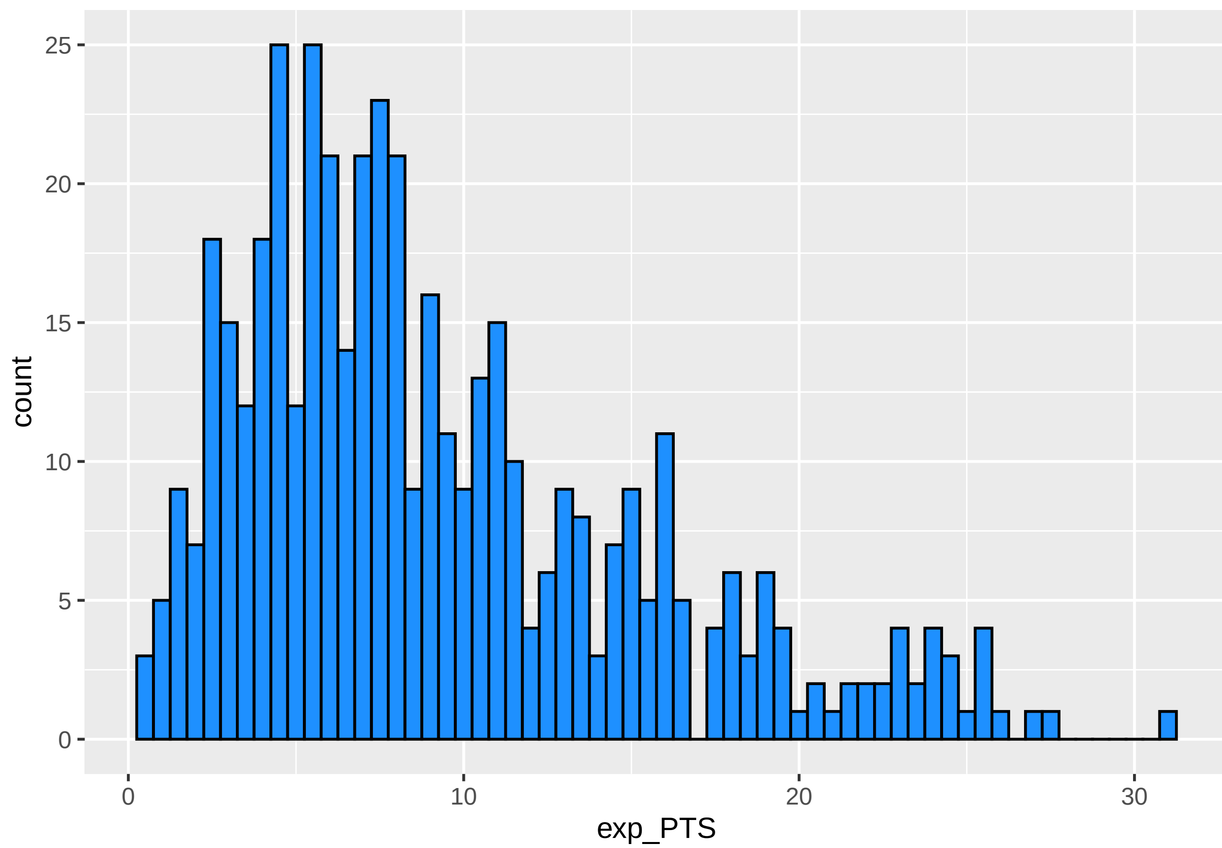
```
fit <- lm(PTS_per_game ~
  FG_per_game + TRB_per_game  + AST_per_game  + STL_per_game  + BLK_per_game  + TOV_per_game, data = no
tidy(fit, conf.int = TRUE)
```

```
## # A tibble: 7 x 7
##   term         estimate std.error statistic   p.value conf.low conf.high
##   <chr>           <dbl>     <dbl>     <dbl>     <dbl>    <dbl>     <dbl>
## 1 (Intercept)  -0.00688    0.0805   -0.0855 9.32e-  1  -0.165     0.151
## 2 FG_per_game   2.69       0.0371   72.5    2.55e-249   2.62      2.77
## 3 TRB_per_game -0.123      0.0269   -4.57   6.43e-  6  -0.176    -0.0700
## 4 AST_per_game -0.139      0.0489   -2.85   4.63e-  3  -0.235    -0.0430
## 5 STL_per_game  0.250      0.143     1.75   8.05e-  2  -0.0305    0.531
## 6 BLK_per_game -0.309      0.133    -2.33   2.01e-  2  -0.570    -0.0487
## 7 TOV_per_game  0.684      0.139     4.90   1.31e-  6   0.410     0.957
```

```
normalised_player_stat <- normalised_player_stat%>% ungroup() %>% mutate(exp_PTS = predict(fit,newdata =
```

histogram

```
normalised_player_stat %>%
ggplot(aes(x = exp_PTS)) +
geom_histogram(binwidth = 0.5, colour = "black", fill = "dodgerblue")
```



5. Player recommendations

Value for money player for Point Guard Position

```
player_PG <- normalised_player_stat %>% select(player_name, Pos, salary, exp_PTS) %>% filter(Pos == "PG
arrange(desc(exp_PTS), salary) %>%
top_n(10)
```

```
## Selecting by exp_PTS
```

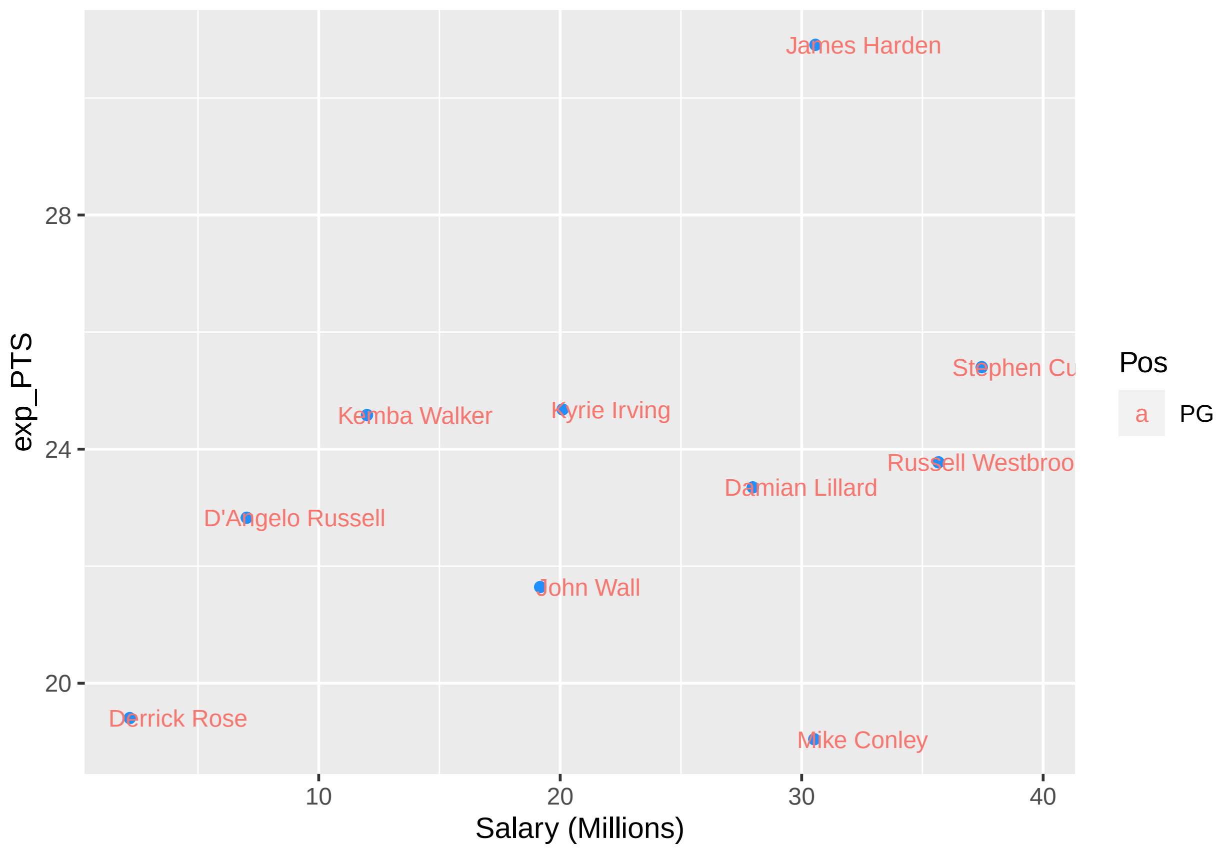
```
player_PG
```

```
## # A tibble: 10 x 4
##    player_name       Pos      salary exp_PTS
##    <chr>             <chr>     <dbl>   <dbl>
##  1 James Harden      PG     30570000    30.9
##  2 Stephen Curry     PG     37457154    25.4
##  3 Kyrie Irving      PG     20099189    24.7
##  4 Kemba Walker      PG     12000000    24.6
##  5 Russell Westbrook PG     35665000    23.8
##  6 Damian Lillard    PG     27977689    23.3
##  7 D'Angelo Russell  PG      7019698    22.8
##  8 John Wall         PG     19169800    21.6
```

Figure 1: D'Angelo Russell

```
##  9 Derrick Rose      PG     2176260    19.4
## 10 Mike Conley       PG    30521115    19.0
```

```
player_PG %>% ggplot(aes(x = salary/1000000, y = exp_PTS, label = player_name, color = Pos)) +
geom_point(colour = "dodgerblue") +
geom_text(nudge_x = 2, cex = 3) +
xlab("Salary (Millions)")
```



We can see that D'Angelo Russell has exp_PTS of 22.8 at just 7.01 millions. So, he is our player for point guard position.

Value for money player for Shooting Guard Position

```
player_SG <- normalised_player_stat %>% select(player_name, Pos, salary, exp_PTS) %>% filter(Pos == "SG
arrange(desc(exp_PTS), salary) %>%
top_n(10)
```

```
## Selecting by exp_PTS
```

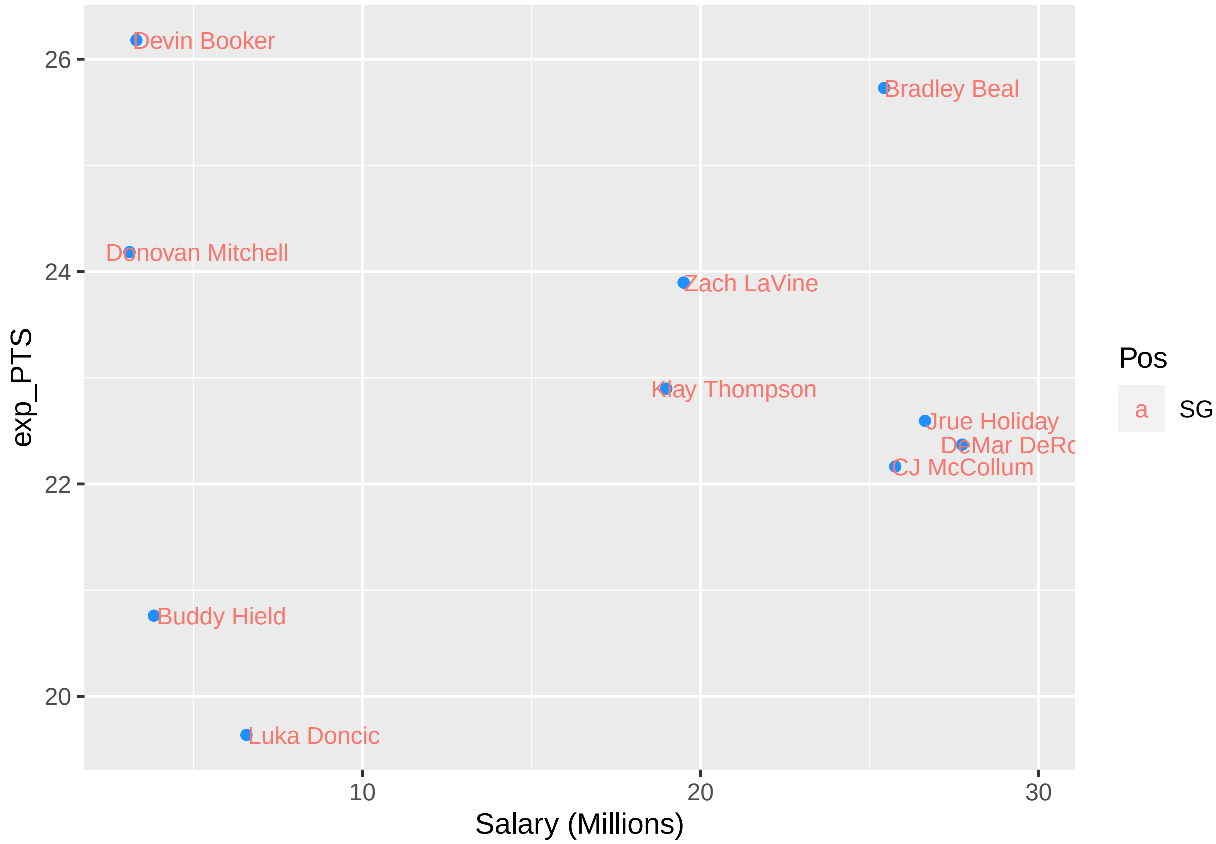
```
player_SG
```

```
## # A tibble: 10 x 4
##    player_name      Pos      salary exp_PTS
##    <chr>            <chr>     <dbl>   <dbl>
##  1 Devin Booker     SG      3314365    26.2
##  2 Bradley Beal     SG     25434262    25.7
##  3 Donovan Mitchell SG      3111480    24.2
##  4 Zach LaVine      SG     19500000    23.9
##  5 Klay Thompson    SG     18988725    22.9
##  6 Jrue Holiday     SG     26641111    22.6
##  7 DeMar DeRozan    SG     27739975    22.4
```

Figure 2: Devin Booker

```
## 8 CJ McCollum      SG    25759766    22.2
## 9 Buddy Hield      SG     3833760    20.8
## 10 Luka Doncic     SG     6569040    19.6
```

```
player_SG %>% ggplot(aes(x = salary/1000000, y = exp_PTS, label = player_name, color = Pos)) +
geom_point(colour = "dodgerblue") +
geom_text(nudge_x = 2, cex = 3) +
xlab("Salary (Millions)")
```



We can see that Devin Booker has exp_PTS of 26.2 just at 3.31 millions. So, he is our player for shooting guard position.

Value for money player for Small Forward Position

```
player_SF <- normalised_player_stat %>% select(player_name, Pos, salary, exp_PTS) %>% filter(Pos == "SF
arrange(desc(exp_PTS), salary) %>%
top_n(10)
```

```
## Selecting by exp_PTS
```

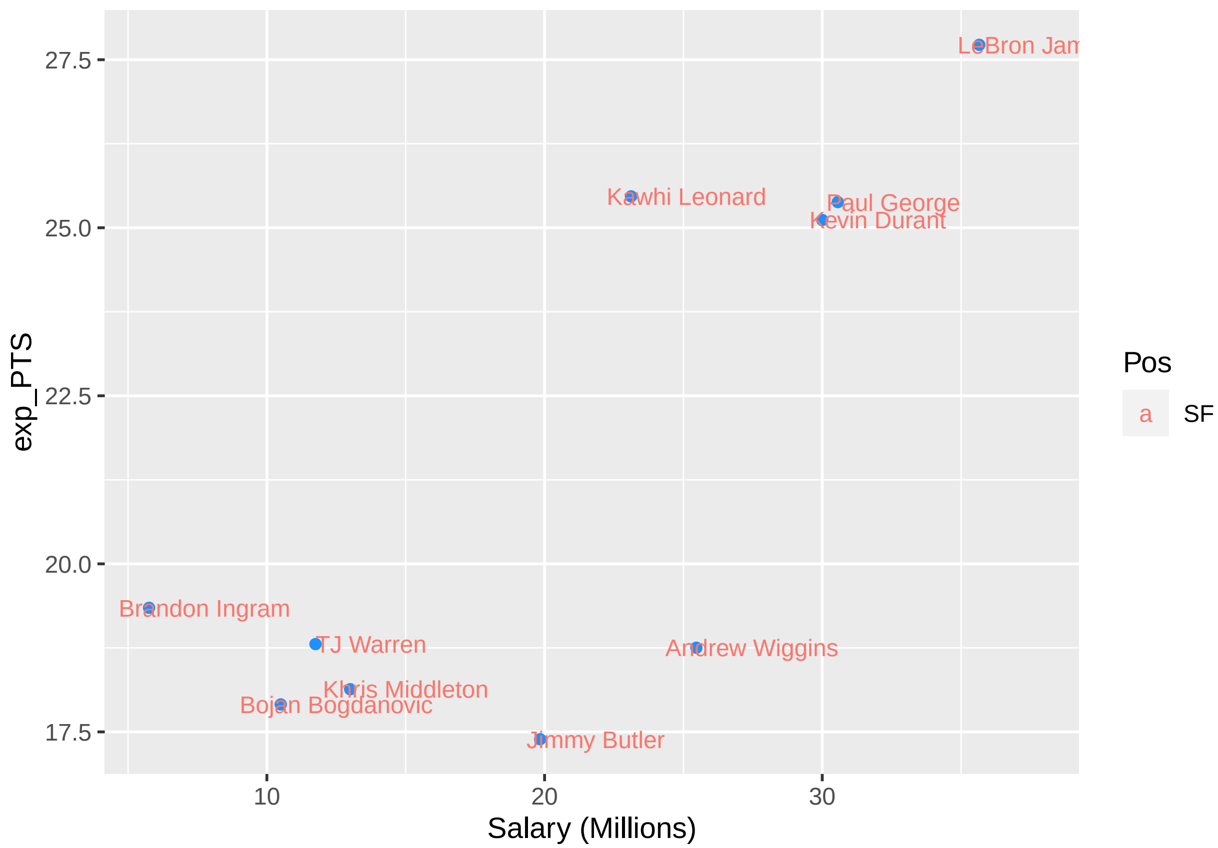
```
player_SF
```

```
## # A tibble: 10 x 4
##    player_name      Pos      salary exp_PTS
##    <chr>            <chr>     <dbl>   <dbl>
##  1 LeBron James     SF     35654150    27.7
##  2 Kawhi Leonard    SF     23114066    25.5
##  3 Paul George      SF     30560700    25.4
##  4 Kevin Durant     SF     30000000    25.1
##  5 Brandon Ingram   SF      5757120    19.3
##  6 TJ Warren        SF     11750000    18.8
##  7 Andrew Wiggins   SF     25467250    18.8
```

Figure 3: Brandon Ingram

```
##  8 Khris Middleton   SF     13000000     18.1
##  9 Bojan Bogdanovic  SF     10500000     17.9
## 10 Jimmy Butler      SF     19841627     17.4
```

```
player_SF %>% ggplot(aes(x = salary/1000000, y = exp_PTS, label = player_name, color = Pos)) +
geom_point(colour = "dodgerblue") +
geom_text(nudge_x = 2, cex = 3) +
xlab("Salary (Millions)")
```



We can see that Brandon Ingram has exp_PTS of 19.3 just at 5.75 millions. So, he is our player for small forward position.

Value for money player for Power Forward Position

```
player_PF <- normalised_player_stat %>% select(player_name, Pos, salary, exp_PTS) %>% filter(Pos == "PF
arrange(desc(exp_PTS), salary) %>%
top_n(10)
```

```
## Selecting by exp_PTS
```

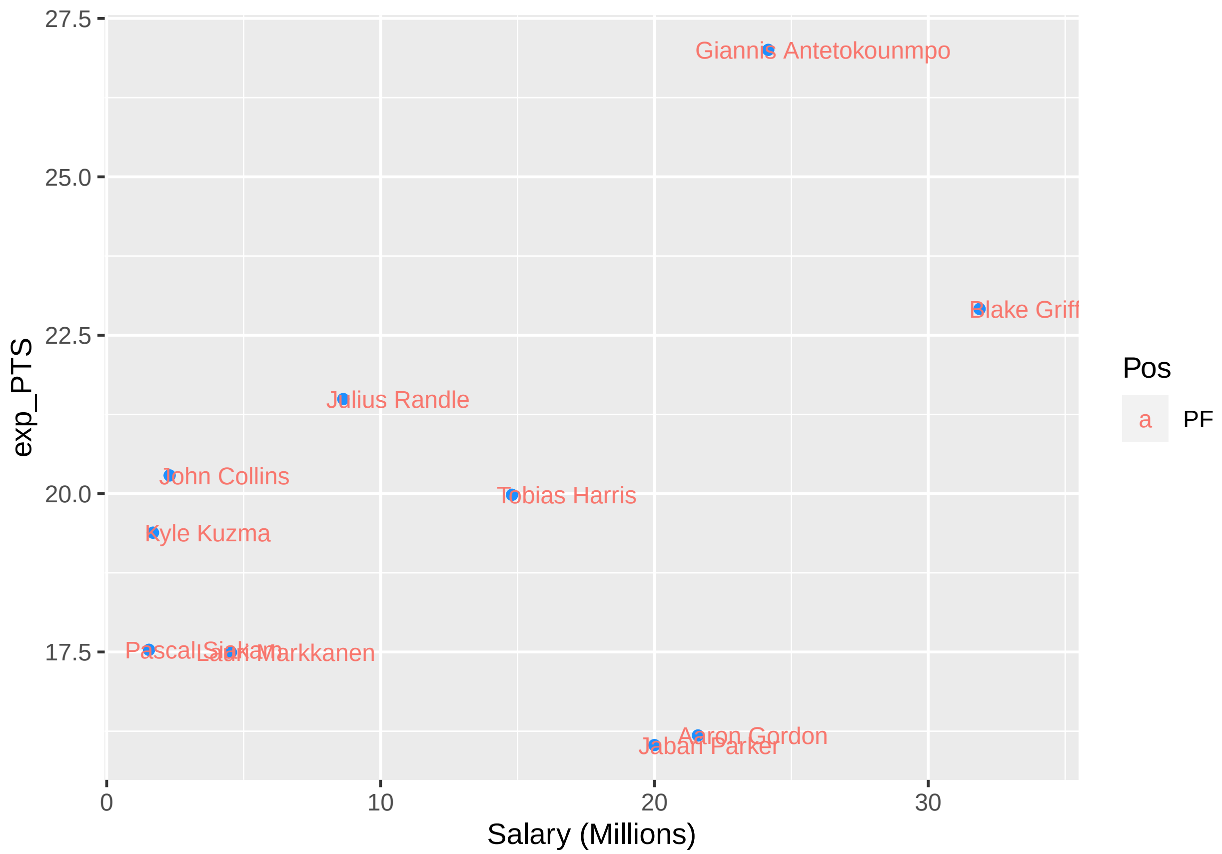
```
player_PF
```

```
## # A tibble: 10 x 4
##    player_name           Pos      salary exp_PTS
##    <chr>                 <chr>     <dbl>   <dbl>
##  1 Giannis Antetokounmpo PF     24157304    27.0
##  2 Blake Griffin         PF     31873932    22.9
##  3 Julius Randle         PF      8641000    21.5
##  4 John Collins          PF      2299080    20.3
##  5 Tobias Harris         PF     14800000    20.0
##  6 Kyle Kuzma            PF      1689840    19.4
##  7 Pascal Siakam         PF      1544951    17.5
```

Figure 4: John Collins

```
##  8 Lauri Markkanen       PF      4536120     17.5
##  9 Aaron Gordon          PF     21590909     16.2
## 10 Jabari Parker         PF     20000000     16.0
```

```
player_PF %>% ggplot(aes(x = salary/1000000, y = exp_PTS, label = player_name, color = Pos)) +
geom_point(colour = "dodgerblue") +
geom_text(nudge_x = 2, cex = 3) +
xlab("Salary (Millions)")
```



We can see that John Collins has exp_PTS of 20.3 at just 2.29 millions. So, he is our player for power forward position.

Value for money player for Center Position

```
player_C <- normalised_player_stat %>% select(player_name, Pos, salary, exp_PTS) %>% filter(Pos == "C")%
arrange(desc(exp_PTS), salary) %>%
top_n(10)
```

```
## Selecting by exp_PTS
```

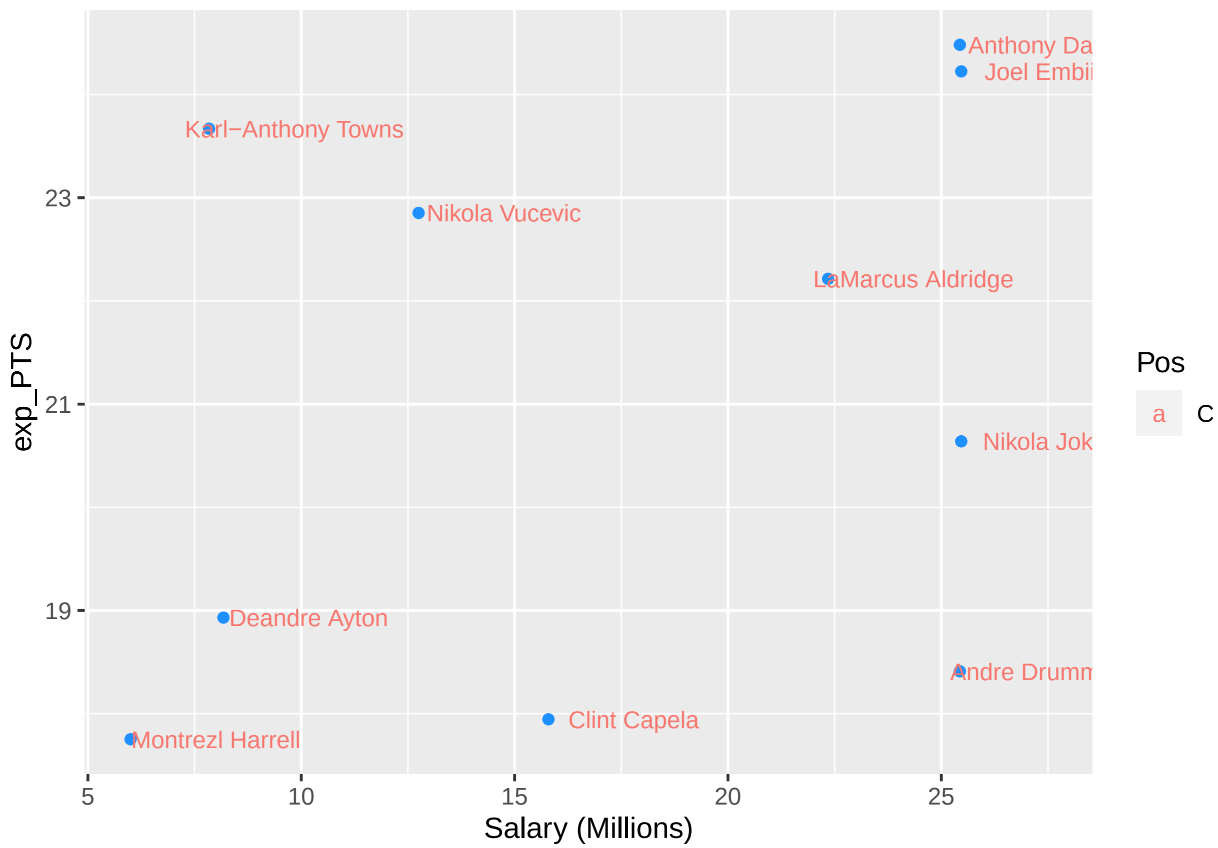
```
player_C
```

```
## # A tibble: 10 x 4
##    player_name         Pos      salary exp_PTS
##    <chr>               <chr>     <dbl>   <dbl>
##  1 Anthony Davis       C      25434263    24.5
##  2 Joel Embiid         C      25467250    24.2
##  3 Karl-Anthony Towns  C       7839435    23.7
##  4 Nikola Vucevic      C      12750000    22.9
##  5 LaMarcus Aldridge   C      22347015    22.2
##  6 Nikola Jokic        C      25467250    20.6
##  7 Deandre Ayton       C       8175840    18.9
```

Figure 5: Karl-Anthony Towns

```
##  8 Andre Drummond     C      25434262    18.4
##  9 Clint Capela       C      15793104    17.9
## 10 Montrezl Harrell   C       6000000    17.8
```

```
player_C %>% ggplot(aes(x = salary/1000000, y = exp_PTS, label = player_name, color = Pos)) +
geom_point(colour = "dodgerblue") +
geom_text(nudge_x = 2, cex = 3) +
xlab("Salary (Millions)")
```



We can see that Karl-Anthony Towns has exp_PTS of 23.7 at just 7.83 millions. So, he is our player for center position.

6. Summary

```
final_players<-data.frame(POSITION=c('PG','SG','SF','PF','C',""),PLAYER=c('D'Angelo Russell','Devin Bool
             SALARYmillions=c(7.01,3.31,5.75,2.29,7.83,26.19))
final_players
```

```
##   POSITION             PLAYER SALARYmillions
## 1       PG   D'Angelo Russell           7.01
## 2       SG       Devin Booker           3.31
## 3       SF     Brandon Ingram           5.75
## 4       PF       John Collins           2.29
## 5        C Karl-Anthony Towns           7.83
## 6                       TOTAL          26.19
```

We are able to find top 5 value for money players in just 26.19 millions. We are left with ample money to make remaining team.

7. Reference List

1. https://www.espn.in/nba/

2. https://www.rstudio.com/wp-content/uploads/2015/02/rmarkdown-cheatsheet.pdf
3. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3661887/
4. https://www.researchgate.net/publication/233682287_Performance_indicators_that_distinguish_winning_and_losing_teams_in_basketball
5. https://www.nba.com/players