NBA players' ability analysis

678 midterm project by Shicheng Wang

11/1/2019

1.Abstract

This is a statistical analysis report about NBA situation. The aim of this report is to develop series of methods to measure the comprehensive strengthes of players in NBA union and trying to figure out how each kind of player's abilities could influence his shooting results in the small ball era. Additionally, the project has also analyzed the strategies and preferences of players. Specifically, EDA(Exploratory Data Analysis) and modeling are involved in this report. Overall, readers will get the general idea about how various elements influence players' shooting result.

2.Introduction

2.1 Background

As NBA steps into a commercialize stage for almost 80 years, it have become a mature business alliance through decades' development, which has always been regarded as a focus and attracting bunches of capitals overseas. It is acknowledged that the players' performances is straightly related to the ratings and could determine the future of a team and related industries, making it is meaningful to conduct a depth analysis for these players' shooting ability.

More importantly, NBA has experienced a huge change since 2014-2015 season. It could be attributed to the rise of three-point shooters leading by Curry and Tompson. Along with Golden State Warriors win the NBA championship finally, it has initiated a new stage for NBA. That is to say, NBA has completed the transformation from old times (Tactical arrangement dominated by tall players inside the three-point line) to small ball era (Dominated by the three points shots outside the line). Hence, player's scoring choice would change since then.

2.2 Data sources

There are overall three datasets included in the report. For the EDA part, I will use NBA League Averages(season) which contains averages statistics of all players in NBA in each year to get the general idea of players' condition in the whole association throughout 70 years. This dataset is collected in Basketball Reference. Besides, I also use NBA Season Data(player) for EDA part to analyze players' performance throughout 70 years, and this dataset is collected in Pro Basketball Statistics. The main dataset(da) i used to further analyze is NBA Shot Logs during 2014-2015 season, this dataset detailly record each player's performance at each time period in each game, and this is collected in Kaggle, while they are originally scraped from NBA's REST API. The following are websites of each dataset.

- NBA League Averages - Totals: link
- NBA Season Data: link
- NBA Shot Logs during 2014-2015 season: link

2.3 Research question

For the former part of EDA in this project, I would analyze how players' characteristics and how average skill level could change throughout 70 years based on the relavant database. Main research question of this project is to analyze how each players' series of charactistics could influence the actural shooting ability in each single game.

3.Methodology

3.1 Data process

- Data access Importing three datasets.

```
team <- read.csv("/Applications/BU/BU/678 Applied Statistical Modeling/MA678 midterm project/678 midterm
player <- read.csv("/Applications/BU/BU/678 Applied Statistical Modeling/MA678 midterm project/678 midte
data <- read.csv("/Applications/BU/BU/678 Applied Statistical Modeling/MA678 midterm project/678 midterm
```

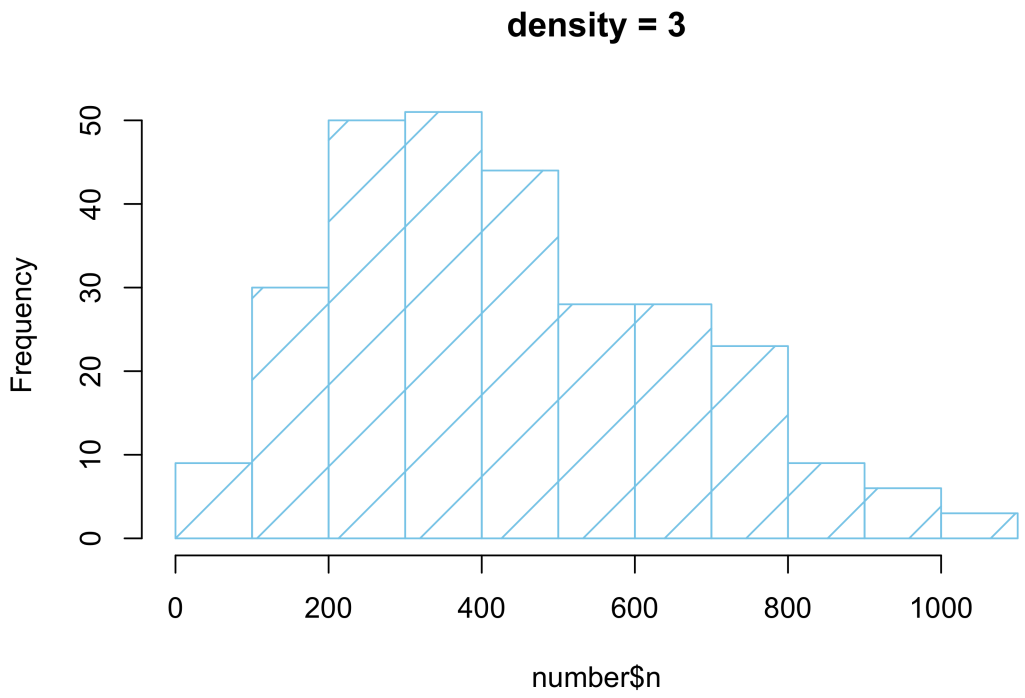
- Data organize

For the season average dataset, clear the NA data in the beginning. Because the row are arranged from big to small, so i reverse the data order by year, then select the columns which are going to be analyzed in EDA part. In order to be easily understood, i rename the variables' name.

For NBA players dataset, drop out players whose data are incompelete. Then i get all players' dataset from 1980 to 2017. This dataset is used for analyzing player's preference and ability of shooting.

For the main dataset, the data cleaning procession shows as below:
* Step1: cleaning

```
### players data amount
hist(number$n, density = 3, col = "skyblue", main  = "density = 3")
```



Firstly, clearing the NA value, then calculate how many rows does each player have, and draw a barplot based on each player's data amount. Notice that several players have less than 200 rows which could hinder modeling procession, so i drop these players.

- Step2: adjustment

```
### select useful column
data <- dplyr::select(data,-n)
da <- data[,c(1,4,5,6,7,8,10:15,18)]

### rename variables' names
library(reshape)
da <- plyr::rename(da,c(player_name="name",LOCATION="location",W="winlose",FINAL_MARGIN="margin",SHOT_NU

### adjust variables
da$location=as.numeric(da$location)-1   # 1 for home, 0 for away
da$winlose=as.numeric(da$winlose)-1     # 1 for win, 0 for lose
da$result=2-as.numeric(da$result)       # 1 for made, 0 for miss
da$type=as.numeric(da$type)
```

After organizing the dataset well, I select specific information and rename the variable name. Additionally, i adjust variables' value which could be beneficial for later analysis.

- Data overview The head of shot log.

Table 1: Overview of shot log

name	location	winlose	margin	shotnumber	period	shotclock	dribble	touch	range	type	result	c
aaron brooks	1	1	5	10	3	20.7	4	3.9	24.8	3	0	
aaron brooks	1	1	5	11	4	9.3	17	13.5	7.8	2	1	

name	location	winlose	margin	shotnumber	period	shotclock	dribble	touch	range	type	result	c
aaron brooks	1	1	5	12	4	6.6	4	3.4	4.1	2	0	
aaron brooks	1	1	5	13	4	3.9	0	1.1	22.3	3	1	
aaron brooks	1	1	5	14	4	14.9	6	5.1	7.4	2	0	
aaron brooks	1	1	5	1	1	10.1	20	13.8	0.5	2	0	

Type variables's categories and overview.

Var1	Freq
A	58405
H	58369

Var1	Freq
1	31307
2	28390
3	30024
4	26068
5	797
6	149
7	39

Var1	Freq
2	87071
3	29703

Var1	Freq
made	53382
missed	63392

3.2 Variables interpretation

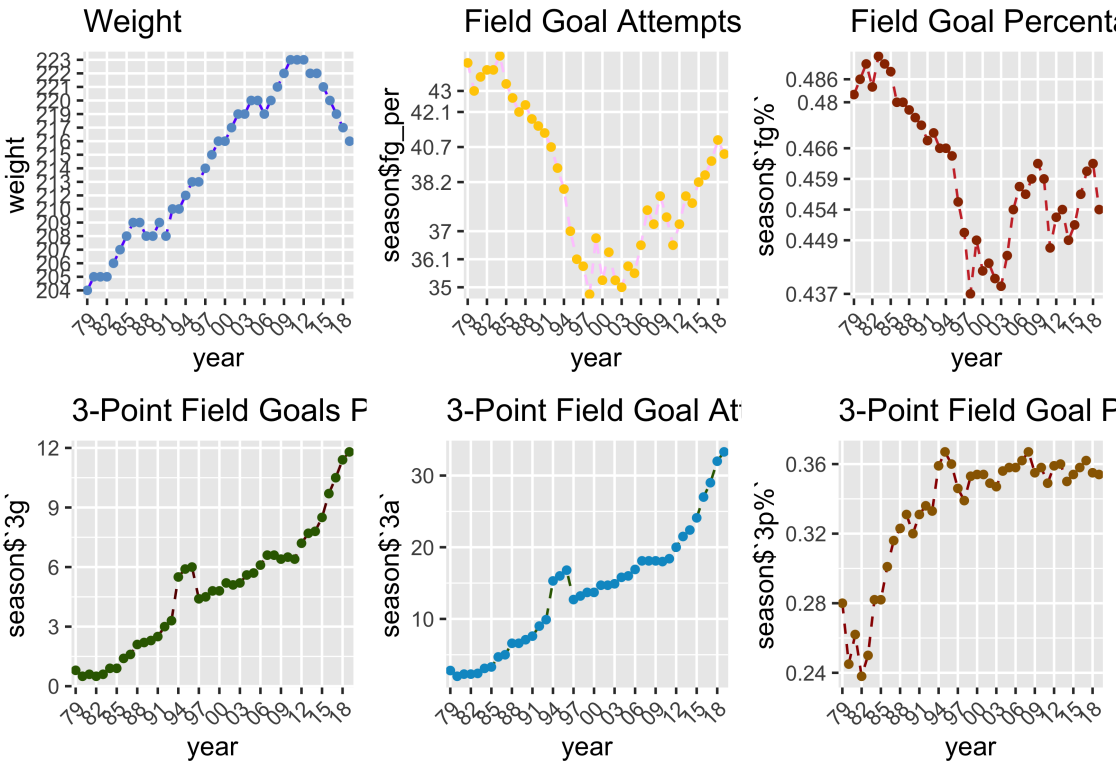
- The main data i use is named 'da', the following table shows variables interpretations that are included in the cleaned dataset.

Variable Name	Interpretation
name	player's name
location	game home or away
winlose	game win or lose
margin	game final margin
shotnumber	play's shooting number
period	player's shoot in which game period
shotclock	the rest attacking time when shooting
dribble	player's dribble times before shooting
touch	player's touching times before shooting
range	shooting distance from the board

Variable Name	Interpretation
type	2 points shoot or 3 points shoot
defence	the defence player's distance from shooting player
result	goal or miss

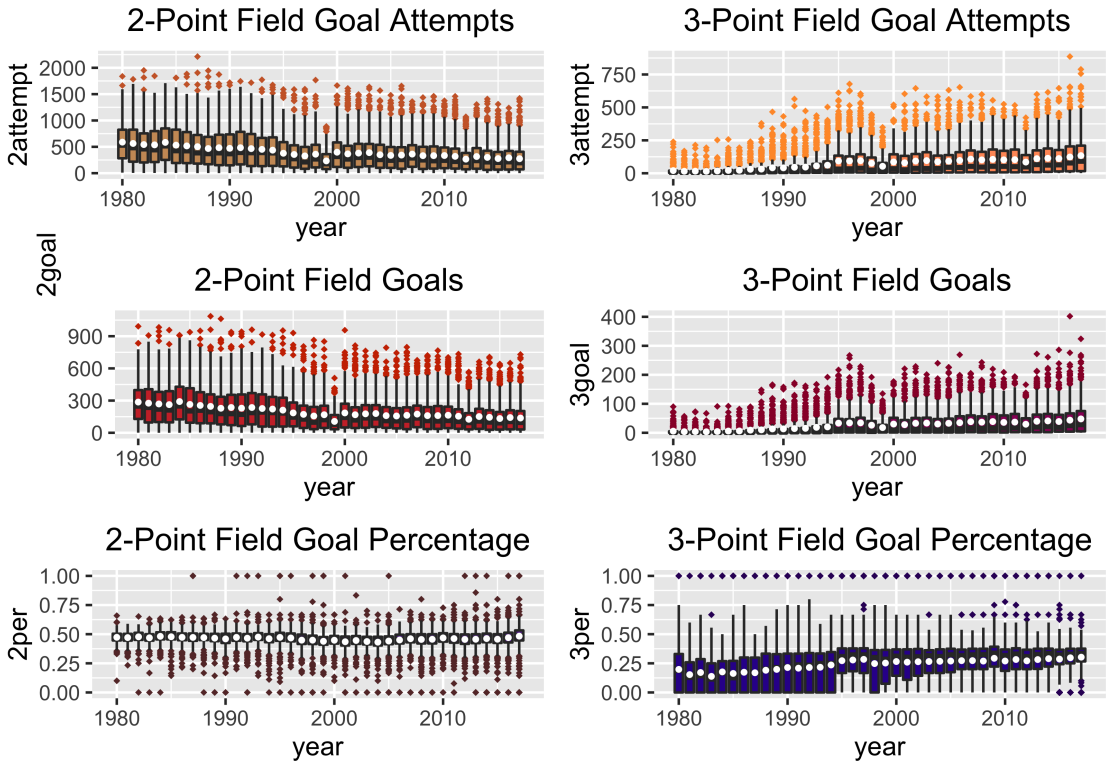
4.EDA visualization

4.1 Player's shooting average overyear



For the weight aspect, we could see the weight requirement is incresing, while there is an obvious decrease in 2012, it can be ascribed to the fact that the center position has been dominated the whole union until 2012 and then comes the small ball era, which relies more on light and flexible players to shooting 3-point shots.
For the field goal condition, we could see it vibrate overyears and one characteristic is that the big drop 1990-2000, this is because players would like to concentrate more on defencing than offencing.
For 3-point field goals, there exists steady increase in recent 30 years and the growth rate increases since 2012 due to the small ball era.

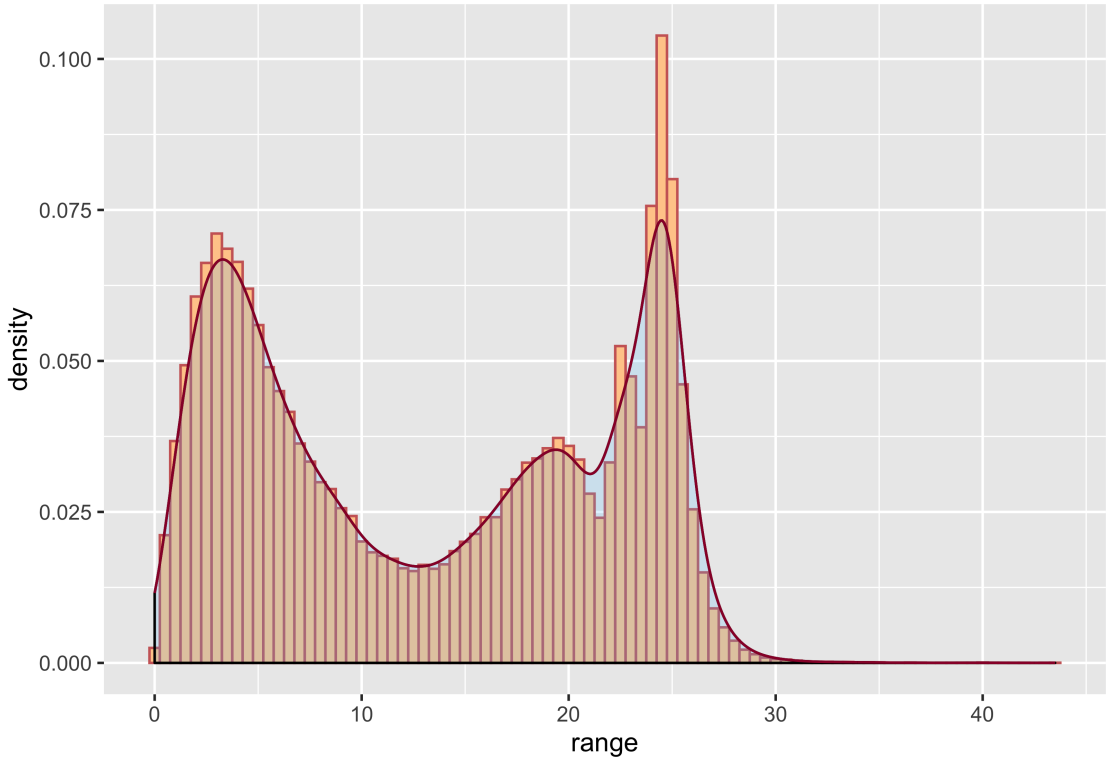
4.2 Distribution of players' 2-point and 3-point ability overyear



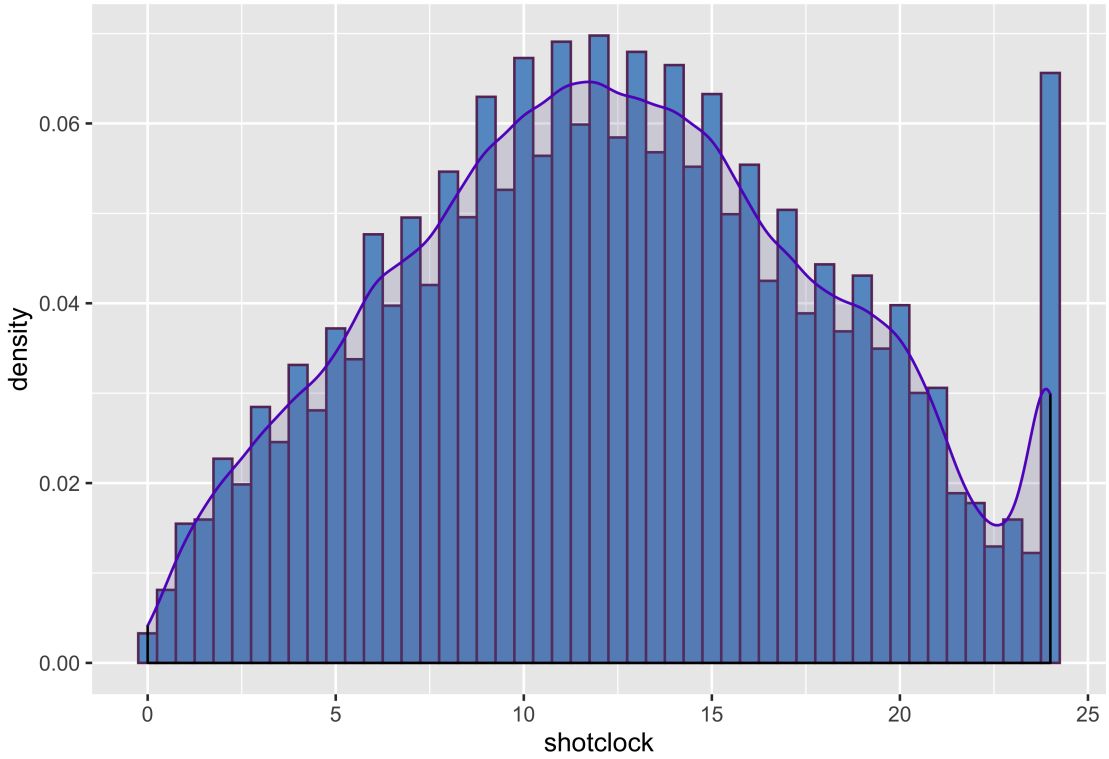
Of all the players in the NBA from 1980 to 2017, their shooting trends are obvious. In the comparasion between 2-point field goals and 3-point field goal, 2-point field goal attempts/goals have been decreasing while 3-point field goal attempts/goals have been increasing. In the meantime, the 2-point field goal percentage keep developing steady, while the 3-point shooting quality increases to an upper level.

4.3 Shooting preference 2014-2015 season.

- shoot type preference: It is well acknowledged that 2014-2015 season could be regarded as the beginning of the small ball era,



From the first plot we could see player's main scoring distance distribute located in 0-5 meters and 22-25 meters area which indicates players nowadays prefer layup, dunk or throw 3-point balls during the game

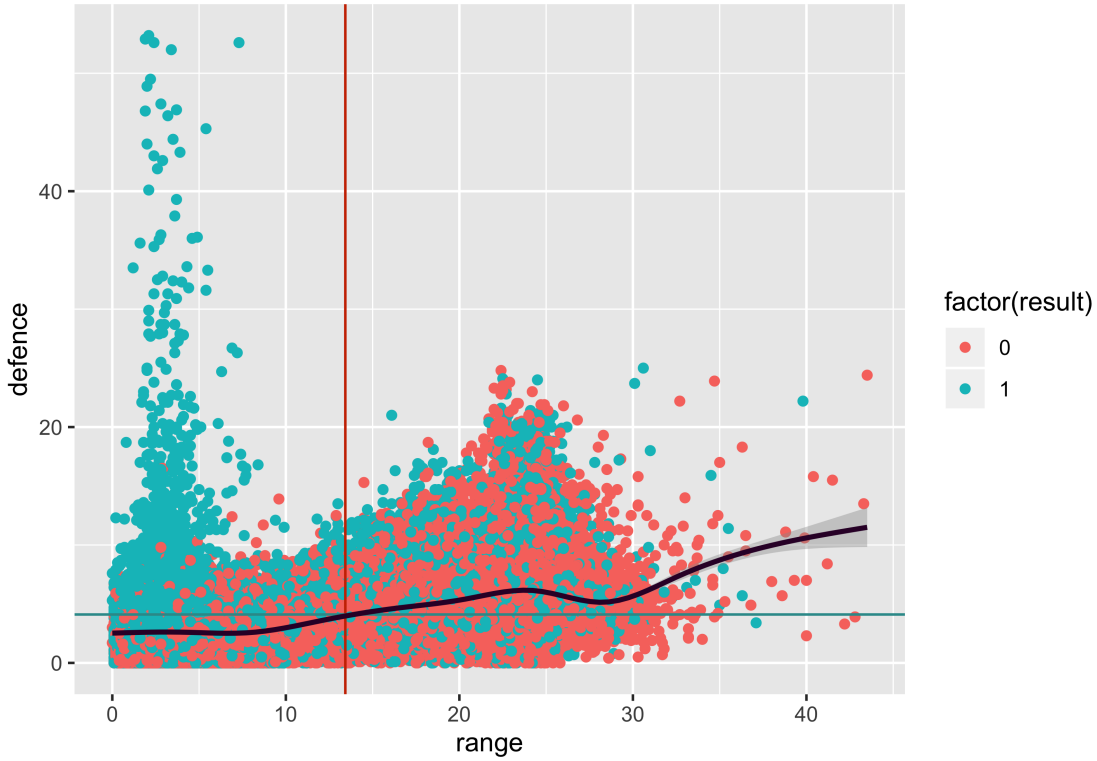


From the second plot, we could see majority of players prefer more organized attacks, that is to say they are

not willing to hurry up shoots or shot until the last second.

4.4 How variables influence player's shoot result.

```
## Warning: Ignoring unknown parameters: type
```

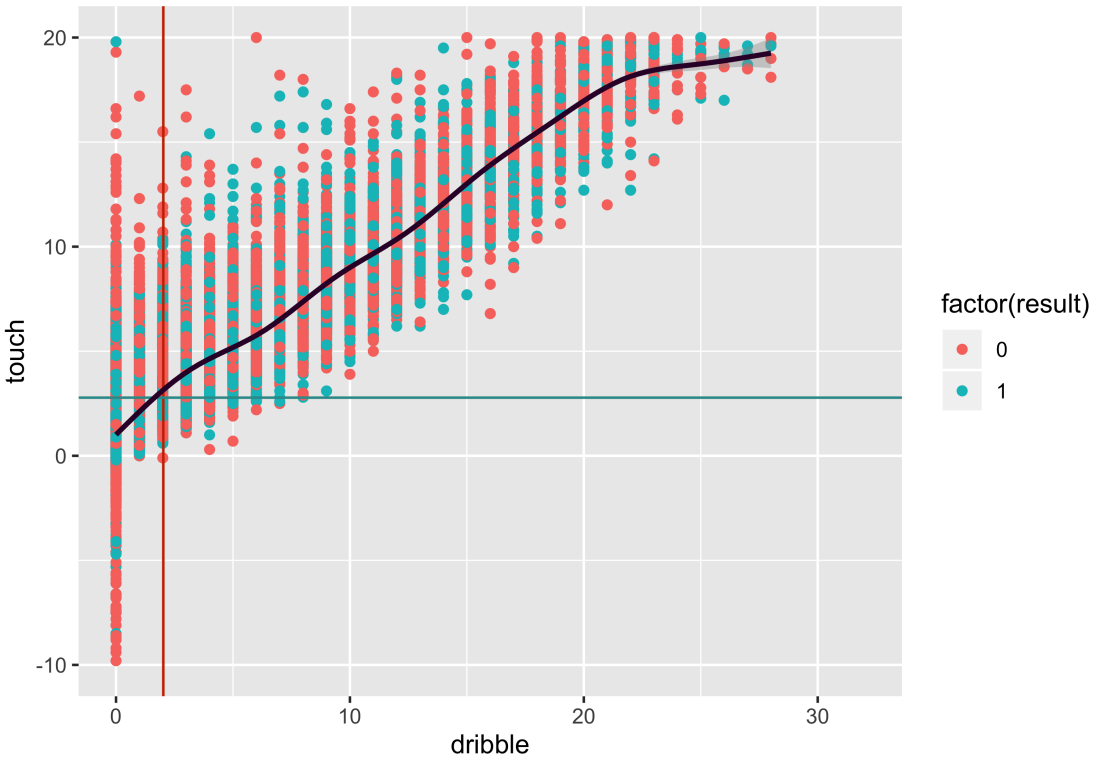


In this plot we can discover the relationships between defence and range categorized by result. It turn out that players could make more shots in 0-9 meters and 25 meters around range. As the range rise, the defence range could correspondlingly rise because defender believes it is difficult to make a shot at far range.

```
## Warning: Ignoring unknown parameters: type
```

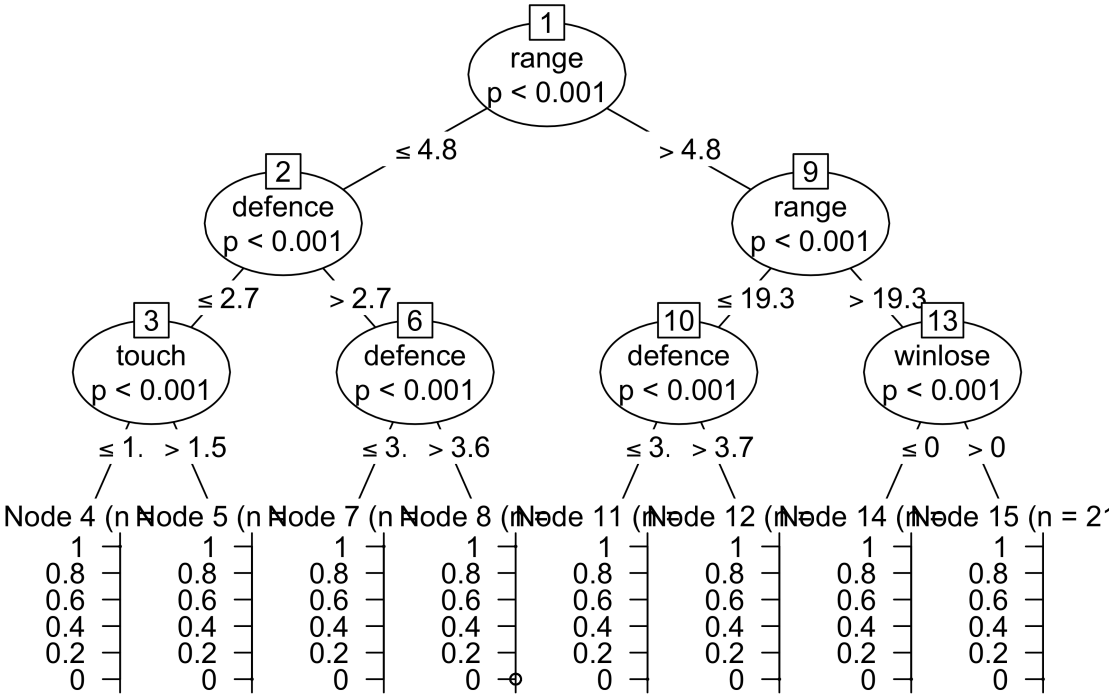
```
## Warning: Removed 194 rows containing non-finite values (stat_smooth).
```

```
## Warning: Removed 194 rows containing missing values (geom_point).
```



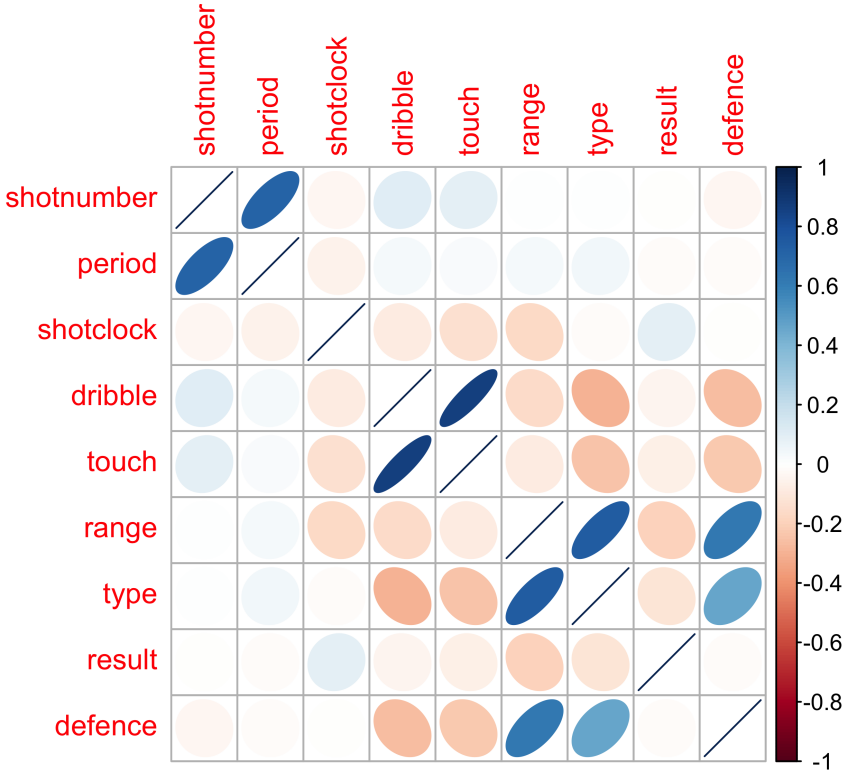
As we can see, if a players dribble more, they would exert more touching time. While, in this plot we could not see an obvious difference that more dirbbles and touch time could bring to higher hit rate.

4.5 C-tree analysis



From the C-tree, we could see the decisive relationship between variables, the shooting range large influence the other variables.

4.6 Corelation Test



Corelation plot shows there exists obvious relationships ammong touch, dribbles, distance, range, shotclock, type, and shooting result.

After i have done EDA, I believe the players shooting preference has changed so much in recent years that i decide to analyze how their shooting results are influenced by other factor.
Based on NBA shot log dataset, I pick some of variables to build the model.

5.Model analysis

5.1 General linear model

- Building model
  The first model i use is general linear model, cause output of the model is bineary distribution, I use the glm function to build model. Model shows below:

```
model_1<-glm(result~location+shotclock+shotnumber+period+dribble+touch+range+defence+type+as.factor(nam
display(model_1)
```

```
## glm(formula = result ~ location + shotclock + shotnumber + period +
##     dribble + touch + range + defence + type + as.factor(name),
##     family = binomial, data = da)
##                                     coef.est coef.se
## (Intercept)                          0.01     0.11
## location                             0.04     0.01
## shotclock                            0.01     0.00
## shotnumber                           0.00     0.00
## period                               0.00     0.01
## dribble                              0.02     0.01
```

```
## touch                                -0.06     0.01
## range                                -0.07     0.00
## defence                               0.11     0.00
## type                                  0.11     0.02
## as.factor(name)al farouq aminu       -0.35     0.16
## as.factor(name)al horford             0.18     0.12
## as.factor(name)al jefferson          -0.01     0.12
## as.factor(name)alan anderson          0.04     0.15
## as.factor(name)alex len              -0.13     0.15
## as.factor(name)alexis ajinca          0.22     0.17
## as.factor(name)amare stoudemire       0.11     0.15
## as.factor(name)amir johnson           0.11     0.14
## as.factor(name)andre drummond        -0.31     0.12
## as.factor(name)andre iguodala         0.00     0.15
## as.factor(name)andrew bogut          -0.12     0.16
## as.factor(name)andrew wiggins        -0.11     0.12
## as.factor(name)anthony bennett       -0.29     0.16
## as.factor(name)anthony davis          0.21     0.12
## as.factor(name)anthony morrow         0.10     0.14
## as.factor(name)aron baynes           -0.04     0.16
## as.factor(name)arron afflalo          0.07     0.12
## as.factor(name)avery bradley          0.05     0.12
## as.factor(name)ben gordon             0.17     0.16
## as.factor(name)ben mclemore           0.00     0.13
## as.factor(name)beno urdih             0.25     0.15
## as.factor(name)blake griffin          0.03     0.12
## as.factor(name)bojan bogdanovic      -0.21     0.15
## as.factor(name)boris diaw            -0.19     0.14
## as.factor(name)bradley beal          -0.12     0.13
## as.factor(name)brandon bass          -0.06     0.13
## as.factor(name)brandon jennings      -0.10     0.13
## as.factor(name)brandon knight         0.01     0.12
## as.factor(name)brian roberts          0.04     0.14
## as.factor(name)brook lopez           -0.05     0.12
## as.factor(name)carl landry           -0.02     0.15
## as.factor(name)carlos boozer          0.03     0.13
## as.factor(name)carmelo anthony        0.11     0.12
## as.factor(name)caron butler          -0.05     0.16
## as.factor(name)chandler parsons      -0.05     0.12
## as.factor(name)channing frye          0.01     0.14
## as.factor(name)charlie villanueva    -0.05     0.16
## as.factor(name)chris bosh             0.13     0.12
## as.factor(name)chris copeland        -0.24     0.16
## as.factor(name)chris kaman           -0.11     0.14
## as.factor(name)chris paul             0.35     0.12
## as.factor(name)cj miles              -0.05     0.13
## as.factor(name)cj watson              0.08     0.15
## as.factor(name)cody zeller           -0.26     0.14
## as.factor(name)cory joseph            0.14     0.15
## as.factor(name)courtney lee           0.14     0.13
## as.factor(name)damian lillard         0.10     0.11
## as.factor(name)danilo gallinai       -0.06     0.15
## as.factor(name)danny green           -0.01     0.13
## as.factor(name)dante cunningham      -0.03     0.16
```

```
## as.factor(name)dante exum              -0.36     0.16
## as.factor(name)darrell arthur          -0.15     0.15
## as.factor(name)darren collison          0.20     0.13
## as.factor(name)david west               0.08     0.13
## as.factor(name)deandre jordan           0.43     0.15
## as.factor(name)demarcus cousins        -0.18     0.12
## as.factor(name)demarre carroll         -0.04     0.13
## as.factor(name)dennis schroder         -0.11     0.14
## as.factor(name)deron williams          -0.11     0.13
## as.factor(name)derrick favors           0.09     0.12
## as.factor(name)derrick rose            -0.08     0.12
## as.factor(name)derrick williams        -0.17     0.15
## as.factor(name)devin harris            -0.14     0.14
## as.factor(name)dirk nowtizski           0.19     0.12
## as.factor(name)dj augustin             -0.08     0.13
## as.factor(name)donald sloan             0.06     0.15
## as.factor(name)donatas motiejunas      -0.07     0.13
## as.factor(name)draymond green          -0.19     0.13
## as.factor(name)dwayne wade              0.13     0.12
## as.factor(name)dwight howard            0.09     0.15
## as.factor(name)ed davis                 0.18     0.15
## as.factor(name)elfrid payton           -0.41     0.13
## as.factor(name)enes kanter             -0.15     0.12
## as.factor(name)eric bledsoe            -0.05     0.12
## as.factor(name)evan fournier           -0.11     0.13
## as.factor(name)evan turner             -0.21     0.13
## as.factor(name)gary neal               -0.05     0.14
## as.factor(name)gerald green             0.04     0.12
## as.factor(name)gerald henderson         0.00     0.13
## as.factor(name)giannis antetokounmpo   -0.05     0.13
## as.factor(name)goran dragic             0.06     0.12
## as.factor(name)gordon hayward           0.02     0.12
## as.factor(name)gorgui dieng            -0.13     0.14
## as.factor(name)greg monroe             -0.22     0.12
## as.factor(name)greivis vasquez         -0.05     0.13
## as.factor(name)harrison barnes         -0.04     0.13
## as.factor(name)henry sims              -0.12     0.14
## as.factor(name)hollis thompson         -0.14     0.15
## as.factor(name)isaiah thomas           -0.04     0.13
## as.factor(name)jamal crawford           0.15     0.12
## as.factor(name)james harden             0.15     0.11
## as.factor(name)james johnson            0.36     0.15
## as.factor(name)jared dudley             0.17     0.14
## as.factor(name)jared sullinger         -0.10     0.12
## as.factor(name)jarrett jack             0.11     0.13
## as.factor(name)jason smith             -0.01     0.14
## as.factor(name)jason terry              0.11     0.15
## as.factor(name)jason thompson          -0.26     0.15
## as.factor(name)jeff green              -0.11     0.12
## as.factor(name)jeff teague             -0.05     0.12
## as.factor(name)jerami grant            -0.46     0.17
## as.factor(name)jeremy lamb              0.06     0.17
## as.factor(name)jeremy lin               0.02     0.13
## as.factor(name)jerryd bayless           0.01     0.14
```

```
## as.factor(name)jimmy butler             0.00     0.12
## as.factor(name)jj hickson               -0.33     0.15
## as.factor(name)jj redick                 0.19     0.12
## as.factor(name)joakim noah              -0.49     0.14
## as.factor(name)joe johnson               0.11     0.12
## as.factor(name)john henson               0.05     0.16
## as.factor(name)john wall                 0.07     0.12
## as.factor(name)jon ingles               -0.07     0.17
## as.factor(name)jon leuer                -0.25     0.16
## as.factor(name)jonas jerebko            -0.02     0.16
## as.factor(name)jonas valanciunas         0.04     0.13
## as.factor(name)jordan hill              -0.07     0.13
## as.factor(name)jose calderon             0.11     0.15
## as.factor(name)jose juan barea          -0.08     0.14
## as.factor(name)jrue holiday              0.00     0.13
## as.factor(name)jusuf nurkic             -0.44     0.15
## as.factor(name)kawhi leonard            -0.03     0.13
## as.factor(name)kelly olynyk             -0.01     0.15
## as.factor(name)kemba walker             -0.06     0.12
## as.factor(name)kenneth faried           -0.25     0.13
## as.factor(name)kentavious caldwell-pope -0.10     0.12
## as.factor(name)kevin garnett            -0.02     0.15
## as.factor(name)kevin love               -0.10     0.12
## as.factor(name)kevin seraphin            0.04     0.14
## as.factor(name)khris middleton           0.10     0.13
## as.factor(name)kirk hinrich             -0.25     0.15
## as.factor(name)kj mcdaniels             -0.36     0.14
## as.factor(name)klay thompson             0.18     0.11
## as.factor(name)kobe bryant               0.04     0.12
## as.factor(name)kosta koufos             -0.21     0.16
## as.factor(name)kris humphries           -0.14     0.14
## as.factor(name)kyle korver               0.43     0.13
## as.factor(name)kyle lowry                0.06     0.12
## as.factor(name)kyle oquinn               0.08     0.17
## as.factor(name)kyle singler             -0.17     0.14
## as.factor(name)kyrie irving              0.19     0.11
## as.factor(name)lamarcus aldridge         0.00     0.11
## as.factor(name)lance stephenson         -0.35     0.14
## as.factor(name)lavoy allen              -0.15     0.16
## as.factor(name)leandro barbosa          -0.05     0.16
## as.factor(name)lebron james              0.28     0.11
## as.factor(name)lou williams              0.16     0.12
## as.factor(name)luc mbah a moute         -0.26     0.13
## as.factor(name)luis scola               -0.10     0.13
## as.factor(name)luol deng                 0.05     0.13
## as.factor(name)manu ginobili            -0.12     0.14
## as.factor(name)marc gasol                0.05     0.12
## as.factor(name)marcin gortat             0.00     0.13
## as.factor(name)marco belinelli           0.01     0.15
## as.factor(name)marcus morris             0.07     0.13
## as.factor(name)marcus smart             -0.15     0.16
## as.factor(name)marcus thornton          -0.03     0.15
## as.factor(name)mario chalmers           -0.21     0.13
## as.factor(name)markieff morris          -0.01     0.12
```

```
## as.factor(name)marreese speights        -0.03     0.13
## as.factor(name)marvin williams           0.02     0.15
## as.factor(name)mason plumlee             0.03     0.14
## as.factor(name)matt barnes              -0.06     0.13
## as.factor(name)matthew dellavedova      -0.35     0.18
## as.factor(name)michael carter-williams  -0.27     0.12
## as.factor(name)michael kidd-gilchrist   -0.14     0.14
## as.factor(name)mike conley               0.02     0.12
## as.factor(name)mike scott               -0.11     0.14
## as.factor(name)mirza teletovic          -0.15     0.15
## as.factor(name)mnta ellis                0.05     0.11
## as.factor(name)mo williams               0.28     0.13
## as.factor(name)nene hilario              0.03     0.13
## as.factor(name)nerles noel              -0.43     0.13
## as.factor(name)nick collison            -0.42     0.17
## as.factor(name)nick young                0.08     0.14
## as.factor(name)nicolas batum            -0.22     0.14
## as.factor(name)nikola mirotic           -0.19     0.15
## as.factor(name)nikola vucevic            0.08     0.12
## as.factor(name)norris cole              -0.21     0.14
## as.factor(name)oj mayo                  -0.07     0.13
## as.factor(name)omer asik                -0.40     0.15
## as.factor(name)omri casspi              -0.23     0.16
## as.factor(name)otto porter               0.01     0.16
## as.factor(name)patrick beverley         -0.23     0.14
## as.factor(name)patrick patterson        -0.03     0.14
## as.factor(name)pau gasol                 0.00     0.12
## as.factor(name)paul millsap             -0.12     0.12
## as.factor(name)paul pierce               0.11     0.13
## as.factor(name)pero antic               -0.34     0.18
## as.factor(name)pj tucker                -0.08     0.14
## as.factor(name)quincy acy               -0.07     0.16
## as.factor(name)ramon sessions           -0.57     0.17
## as.factor(name)rasual butler             0.15     0.14
## as.factor(name)ray mccallum             -0.15     0.17
## as.factor(name)reggie jackson           -0.03     0.12
## as.factor(name)richard jefferson        -0.06     0.17
## as.factor(name)robert covington         -0.13     0.13
## as.factor(name)robert sacre             -0.37     0.17
## as.factor(name)rodney stuckey           -0.02     0.13
## as.factor(name)roy hibbert              -0.15     0.13
## as.factor(name)rudy gay                  0.03     0.12
## as.factor(name)rudy gobert               0.11     0.16
## as.factor(name)russell westbrook        -0.02     0.11
## as.factor(name)ryan anderson            -0.07     0.12
## as.factor(name)serge ibaka               0.04     0.12
## as.factor(name)shabazz muhammad         -0.09     0.14
## as.factor(name)shane larkin             -0.13     0.16
## as.factor(name)shaun livingston          0.15     0.16
## as.factor(name)shawn marion             -0.36     0.17
## as.factor(name)shawne williams          -0.02     0.16
## as.factor(name)solomon hill             -0.33     0.13
## as.factor(name)spencer hawes            -0.23     0.15
## as.factor(name)stephen curry             0.32     0.11
```

```
## as.factor(name)steve adams              -0.08     0.15
## as.factor(name)steve blake               0.05     0.17
## as.factor(name)taj gibson               -0.21     0.14
## as.factor(name)terrence ross            -0.01     0.13
## as.factor(name)thaddeus young           -0.13     0.12
## as.factor(name)tim duncan               -0.08     0.12
## as.factor(name)time hardaway jr         -0.06     0.13
## as.factor(name)timofey mozgov           -0.09     0.14
## as.factor(name)tobias harris            -0.04     0.12
## as.factor(name)tony allen               -0.33     0.14
## as.factor(name)tony parker               0.05     0.13
## as.factor(name)tony snell                0.06     0.17
## as.factor(name)trevor ariza             -0.27     0.12
## as.factor(name)trevor booker            -0.07     0.15
## as.factor(name)trey burke               -0.10     0.12
## as.factor(name)tristan thompson         -0.14     0.14
## as.factor(name)ty lawson                 0.02     0.12
## as.factor(name)tyler zeller             -0.04     0.14
## as.factor(name)tyreke evans             -0.21     0.12
## as.factor(name)tyson chandler            0.32     0.15
## as.factor(name)victor oladipo           -0.08     0.12
## as.factor(name)vince carter             -0.22     0.16
## as.factor(name)wayne ellington           0.18     0.14
## as.factor(name)wesley johnson            0.01     0.14
## as.factor(name)wesley matthews           0.17     0.12
## as.factor(name)wilson chandler          -0.12     0.12
## as.factor(name)zach lavine              -0.02     0.14
## as.factor(name)zach randolph            -0.07     0.12
## as.factor(name)zaza pachulia            -0.39     0.14
## ---
##   n = 116774, k = 251
##   residual deviance = 154100.6, null deviance = 161024.0 (difference = 6923.4)
```

There are 242 players in my dataset, each player has their own constructed function.

- Interpretation
  In this model, the majority of the coefficient are significant. Choose my favorite player called Damian Lillard, his predicting function shows below:

$$logit(result) = 0.01 + 0.04location + 0.01shotclock + 0.02dribble - 0.06touch - 0.07range + 0.11defence + 0.11type + 0.1(player)$$

In this model, the majority of the coefficient are significant. But the according to the binned residual plot, there exists an obvious pattern, and the outliers are pretty large, hence this model needs improvement.

Intercept: The log odds of shooting percetage of a player is 0.01 when he is playing away with no touch/dribble and no shoot intentation.

The coefficient of location: Gaming home would has 0.04 log odds of shooting percentage more than gaming away for players with all other variables the same.

The coefficient of type: Shooting 3-point field goal would has 0.11 log odds of shooting percentage more than shooting 2-point field goal with all other variables the same

The coefficient of shotclock: With every 1 level increase in shotclock level, the expected log odds of shooting percentage for specific player would increase by 0.04 unit with all other variables the same.

The coefficient of dribble: With every 1 level increase in dribble level, the expected log odds of shooting percentage for specific player would increase by 0.02 unit with all other variables the same.

The coefficient of touch: With every 1 level increase in touch level, the expected log odds of shooting percentage for specific player would decrease by 0.06 unit with all other variables the same.

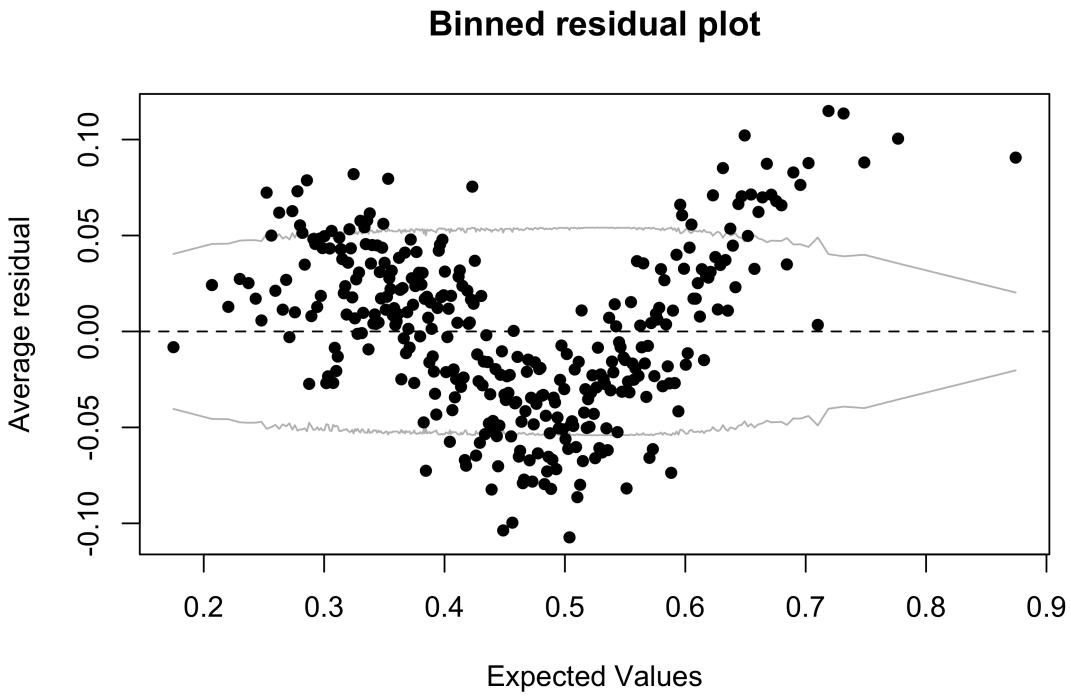
The coefficient of range: With every 1 level increase in range level, the expected log odds of shooting percentage for specific player would decrease by 0.07 unit with all other variables the same.

The coefficient of defence: With every 1 level increase in defence level, the expected log odds of shooting percentage for specific player would increase by 0.11 unit with all other variables the same.

The coefficient of player: With each player, his log odds of shooting percentage would corespond with their own coefficient in the model summary.

- Model check

```
binnedplot(predict(model_1,type="response"), residuals(model_1,type="response"))
```



In this model, the majority of the coefficient are significant. But the according to the binned residual plot, there exists an obvious pattern(like a character V). What's more the outliers are pretty large, showing that this model does not fit very well. Hence this model needs improvement.

5.2 Bayesian generlized linear model

The second model i construct is bayesian generlized linear model with proper transformation and interaction, model shows below:

```
model_2<-rstanarm::stan_glm(result ~          shotnumber+I(shotclock^2)+period+dribble+touch+touch*dribbl
                            family=binomial(),da,cores = 4)
summary(model_2)
```

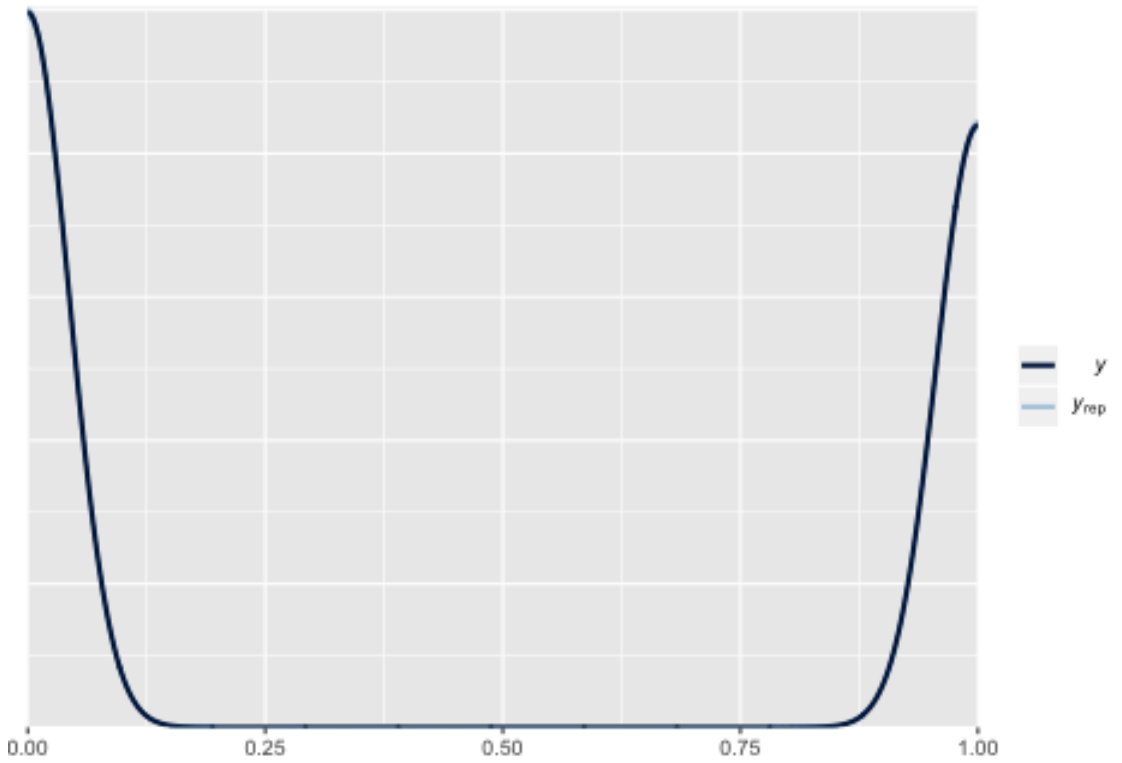
```
##
```

```
## Model Info:
##  function:     stan_glm
##  family:       binomial [logit]
##  formula:      result ~ shotnumber + I(shotclock^2) + period + dribble + touch +
##     touch * dribble + type * range + I(range^2) + I(defence^2)
##  algorithm:    sampling
##  sample:       4000 (posterior sample size)
##  priors:       see help('prior_summary')
##  observations: 116774
##  predictors:   12
##
## Estimates:
##                  mean   sd   10%   50%   90%
## (Intercept)    -2.7    0.4 -3.3  -2.7  -2.1
## shotnumber      0.0    0.0  0.0   0.0   0.0
## I(shotclock^2)  0.0    0.0  0.0   0.0   0.0
## period          0.0    0.0  0.0   0.0   0.0
## dribble         0.0    0.0  0.0   0.0   0.0
## touch          -0.1    0.0 -0.1  -0.1  -0.1
## type            1.7    0.2  1.4   1.7   2.0
## range           0.0    0.0  0.0   0.0   0.1
## I(range^2)      0.0    0.0  0.0   0.0   0.0
## I(defence^2)    0.0    0.0  0.0   0.0   0.0
## dribble:touch   0.0    0.0  0.0   0.0   0.0
## type:range     -0.1    0.0 -0.1  -0.1  -0.1
##
## Fit Diagnostics:
##            mean   sd   10%   50%   90%
## mean_PPD 0.5    0.0  0.5   0.5   0.5
##
## The mean_ppd is the sample average posterior predictive distribution of the outcome variable (for de
##
## MCMC diagnostics
##                mcse Rhat n_eff
## (Intercept)    0.0  1.0  1263
## shotnumber     0.0  1.0  3929
## I(shotclock^2) 0.0  1.0  5854
## period         0.0  1.0  3936
## dribble        0.0  1.0  2362
## touch          0.0  1.0  2950
## type           0.0  1.0  1253
## range          0.0  1.0  1315
## I(range^2)     0.0  1.0  2224
## I(defence^2)   0.0  1.0  4677
## dribble:touch  0.0  1.0  3088
## type:range     0.0  1.0  1222
## mean_PPD       0.0  1.0  4139
## log-posterior  0.1  1.0  1797
##
## For each parameter, mcse is Monte Carlo standard error, n_eff is a crude measure of effective sample
```

Using the binomial family for bayesian general linear model and do the MCMC diagnostics. From the summary, we can see the sample's mean/standard devation and the standard error. The next step to examine this model is to see the simulate y-output of this model

- Model check

```
rstanarm::pp_check(model_2)
```



The simulation result show the output of my model is quite corespond with the binomial observation which is 0 or 1, indicating the model fits quite well.
According to the EDA part and the formoer models, I found that there could exist interaction among variables. Moreover, different players could leads to different shooting range and defending strategies. So the next following model i will introduce is mutilevel model.

5.3 Mutilevel model

random intercept

```
### m1
m1<-glmer(result~location+shotnumber+period+shotclock+dribble+touch+type+range+defence+
            dribble*touch+type*range+(1|name), data=da,family = binomial(),REML = T)
```

First model i apply is mutilevel level with random intercept. In this model, different player would has different intercept.

```
### summary
summary(m1)
```

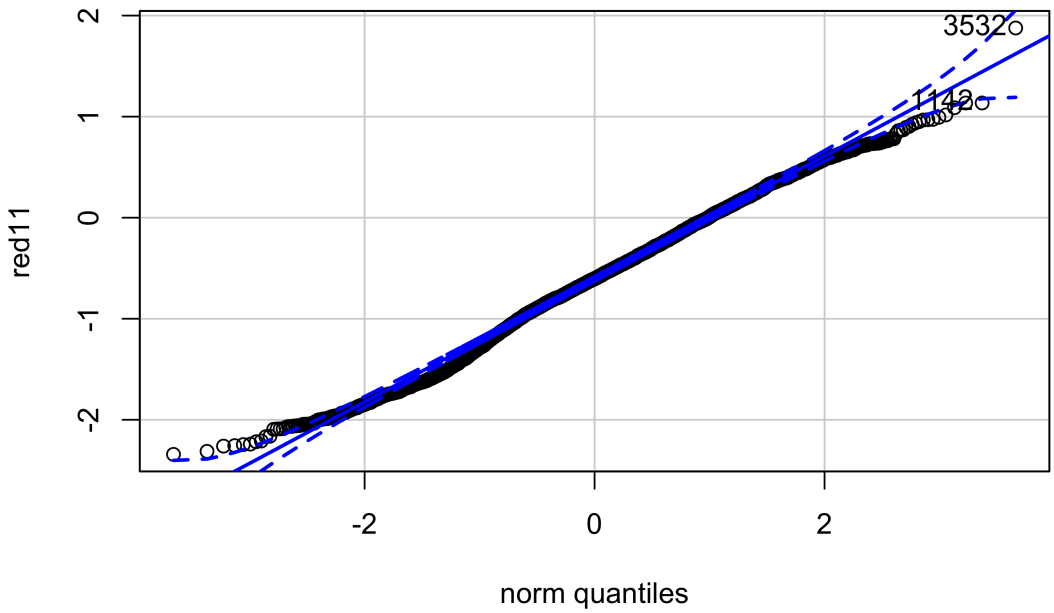
```
## Generalized linear mixed model fit by maximum likelihood (Laplace
##   Approximation) [glmerMod]
##  Family: binomial  ( logit )
## Formula: result ~ location + shotnumber + period + shotclock + dribble +
##     touch + type + range + defence + dribble * touch + type *
##     range + (1 | name)
##    Data: da
```

```
##
##      AIC      BIC   logLik deviance df.resid
## 154521.8 154647.4 -77247.9 154495.8   116761
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -16.7085  -0.8768  -0.6401   0.9885   2.6931
##
## Random effects:
##  Groups Name        Variance Std.Dev.
##  name   (Intercept) 0.01638  0.128
## Number of obs: 116774, groups:  name, 242
##
## Fixed effects:
##                 Estimate Std. Error z value Pr(>|z|)
## (Intercept)    0.7480432  0.4121106   1.815  0.06950 .
## location       0.0349269  0.0121303   2.879  0.00399 **
## shotnumber     0.0009547  0.0020350   0.469  0.63898
## period        -0.0093570  0.0078908  -1.186  0.23569
## shotclock      0.0144802  0.0011300  12.814  < 2e-16 ***
## dribble       -0.0089126  0.0061154  -1.457  0.14500
## touch         -0.0657122  0.0057935 -11.342  < 2e-16 ***
## type          -0.2668588  0.2048571  -1.303  0.19269
## range         -0.0938429  0.0170915  -5.491 4.01e-08 ***
## defence        0.1040335  0.0029685  35.045  < 2e-16 ***
## dribble:touch  0.0031906  0.0003346   9.536  < 2e-16 ***
## type:range     0.0140771  0.0084323   1.669  0.09503 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) locatn shtnmb period shtclc dribbl touch  type   range
## location    -0.012
## shotnumber  -0.012  0.006
## period      -0.017 -0.007 -0.732
## shotclock   -0.057 -0.006 -0.008  0.039
## dribble     -0.014  0.005  0.012 -0.023 -0.130
## touch       -0.055 -0.003 -0.016  0.025  0.173 -0.657
## type        -0.997 -0.002  0.016 -0.009  0.013  0.020  0.030
## range       -0.987 -0.002  0.019 -0.007  0.042  0.007  0.023  0.987
## defence      0.066  0.001 -0.003  0.015 -0.114  0.048  0.053 -0.078 -0.110
## dribble:tch  0.052  0.000 -0.035  0.013  0.045 -0.584 -0.131 -0.039 -0.022
## type:range   0.993  0.002 -0.017  0.007 -0.025 -0.008 -0.024 -0.994 -0.997
##             defenc drbbl:
## location
## shotnumber
## period
## shotclock
## dribble
## touch
## type
## range
## defence
## dribble:tch -0.090
```

```
## type:range   0.078  0.024
## convergence code: 0
## Model failed to converge with max|grad| = 0.0249899 (tol = 0.001, component 1)
## Model is nearly unidentifiable: very large eigenvalue
##  - Rescale variables?
## Model is nearly unidentifiable: large eigenvalue ratio
##  - Rescale variables?
```

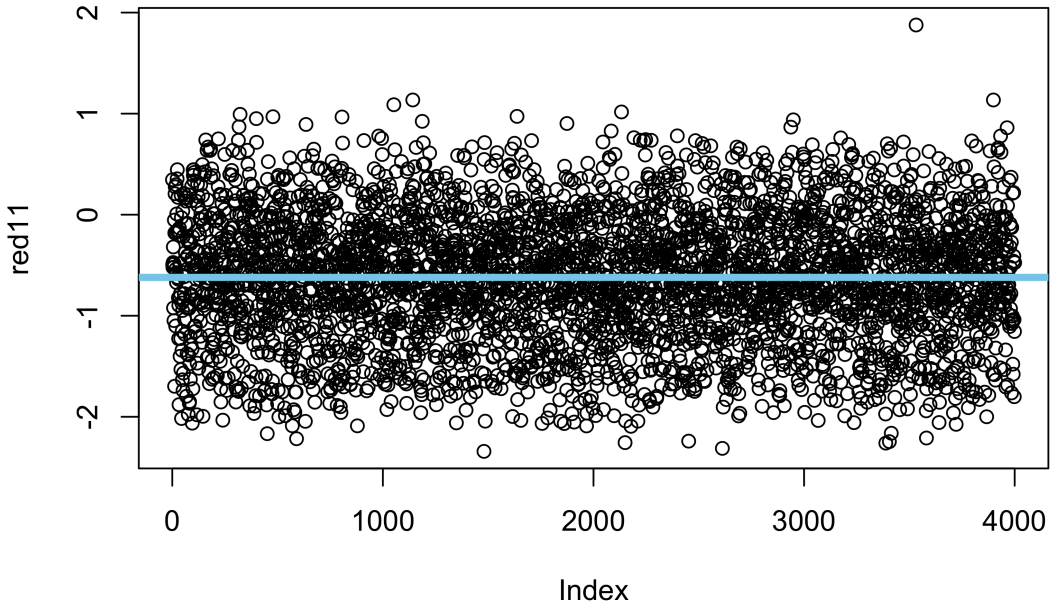
I set players name as pooling principle, so i get nearly 250 groups. From summary of m1 we can see the most coefficients's p-value are quite small and they are significant, indicting the varibales could influence player's shooting result, there might exist mix effect in this model. From the result, we can see the variance is 0.01638, the random effect exists among different players. The AIC and BIC are 154521.8 and 154647.4. Additionally, there exists corelationships between these variables.

```
### check
pred1 = predict(m1,type = "link")
red1 = as.numeric(as.character(pred1))-da$result
com1 = data.frame(obs = da$result,pre = pred1) %>% pivot_longer(cols = 1:2,names_to = "type",values_to =
red11 = sample(red1,4000)
### check visualization
car::qqPlot(red11)
```




```
## [1] 3532 1142
```

```
plot(red11)+abline(h=mean(red11),lwd=4,col="skyblue")
```




```
## integer(0)
```

The residual plot shows the residuals are randomly distributed but mean value also below 0 which could be regarded as a flaw.

random slope

```
### m2
m2<-glmer(result~location+shotnumber+shotclock+dribble+touch+type+range+defence+
          dribble*touch+type*range+(touch-1|name),
          data=da,family = binomial(),REML = T)
```

Second model i apply is mutilevel level with random slope. In this model, different player would has different range slope.

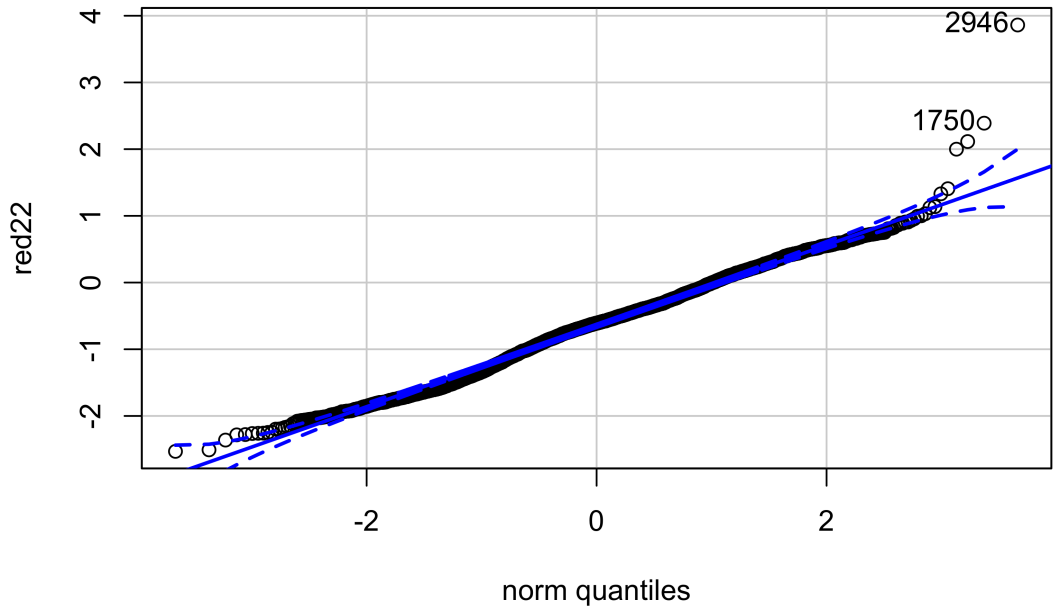
```
### summary
summary(m2)
```

```
## Generalized linear mixed model fit by maximum likelihood (Laplace
##   Approximation) [glmerMod]
##  Family: binomial  ( logit )
## Formula: result ~ location + shotnumber + shotclock + dribble + touch +
##     type + range + defence + dribble * touch + type * range +
##     (touch - 1 | name)
##    Data: da
##
##      AIC      BIC   logLik deviance df.resid
## 154590.2 154706.2 -77283.1 154566.2   116762
##
## Scaled residuals:
```

```
##     Min      1Q  Median      3Q     Max
## -2.6535 -0.8747 -0.6445  0.9870  2.6971
##
## Random effects:
##  Groups Name  Variance Std.Dev.
##  name   touch 0.00105  0.03241
## Number of obs: 116774, groups:  name, 242
##
## Fixed effects:
##                 Estimate Std. Error z value Pr(>|z|)
## (Intercept)    0.6854744  0.3993713   1.716  0.08609 .
## location       0.0343534  0.0121129   2.836  0.00457 **
## shotnumber     0.0004964  0.0013514   0.367  0.71339
## shotclock      0.0145781  0.0011270  12.935  < 2e-16 ***
## dribble       -0.0077733  0.0061910  -1.256  0.20927
## touch         -0.0695342  0.0063356 -10.975  < 2e-16 ***
## type          -0.2440369  0.1986120  -1.229  0.21918
## range         -0.0909796  0.0165782  -5.488 4.07e-08 ***
## defence        0.1024842  0.0029366  34.899  < 2e-16 ***
## dribble:touch  0.0025804  0.0003419   7.548 4.43e-14 ***
## type:range     0.0131100  0.0081801   1.603  0.10901
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) locatn shtnmb shtclc dribbl touch  type   range  defenc
## location    -0.013
## shotnumber  -0.045  0.001
## shotclock   -0.055 -0.006  0.026
## dribble     -0.010  0.005 -0.011 -0.113
## touch       -0.055 -0.002  0.027  0.154 -0.614
## type        -0.998 -0.002  0.022  0.012  0.015  0.031
## range       -0.988 -0.001  0.025  0.041  0.005  0.025  0.986
## defence      0.064  0.000  0.022 -0.108  0.060  0.045 -0.076 -0.110
## dribble:tch  0.044  0.001  0.001  0.074 -0.506 -0.105 -0.036 -0.019 -0.094
## type:range   0.993  0.001 -0.025 -0.024 -0.006 -0.026 -0.994 -0.997  0.078
##             drbbl:
## location
## shotnumber
## shotclock
## dribble
## touch
## type
## range
## defence
## dribble:tch
## type:range   0.024
## convergence code: 0
## Model failed to converge with max|grad| = 0.254732 (tol = 0.001, component 1)
## Model is nearly unidentifiable: very large eigenvalue
##  - Rescale variables?
## Model is nearly unidentifiable: large eigenvalue ratio
##  - Rescale variables?
```

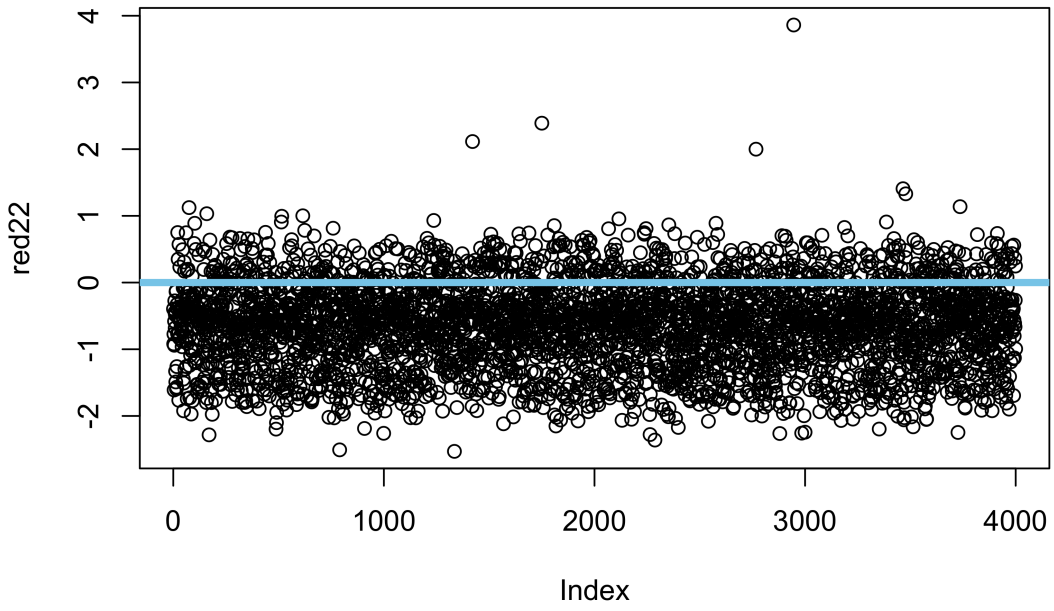
This time, two interaction variables are introduced in the model and i define a random slope mutilevel model. The slope of the range could vary from players.From model2 we can see the most coefficients's p-value are quite small and they are significant, the AIC and BIC are 154590.2 and 154706.2. We could see the range preference could be different because some players(like Lilard) prefer to shoot long distance ball. Additionally, random effect exist between players and shooting range.

```
### check
pred2 = predict(m2,type = "link")
red2 = as.numeric(as.character(pred2))-da$result
com2 = data.frame(obs = da$result,pre = pred1) %>% pivot_longer(cols = 1:2,names_to = "type",values_to =
red22 = sample(red2,4000)
### check visualization
car::qqPlot(red22)
```




```
## [1] 2946 1750
```

```
plot(red22)+abline(h=0,lwd=4,col="skyblue")
```




```
## integer(0)
```

The residual plot shows the residuals are randomly distributed but mean value below 0. The qq-plot indicate the residual do not has more information. The model fits well in this way.

random slope and random intercept

```
### m3
m3<-glmer(result~location+shotnumber+shotclock+dribble+touch+type+range+defence+
          dribble*touch+type*range+(1+range|name),
          data=da,family = binomial(),REML = T)
```

Last model i apply is mutilevel level with random intercept and slope. In this model, different player would has different intercept and different range slope.

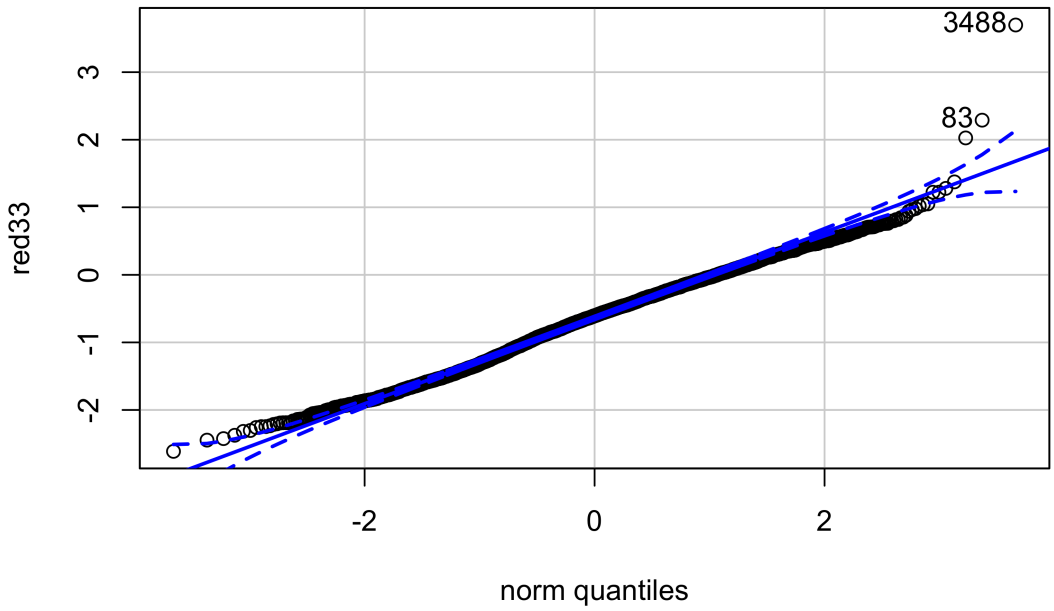
```
### summary
summary(m3)
```

```
## Generalized linear mixed model fit by maximum likelihood (Laplace
##   Approximation) [glmerMod]
##  Family: binomial  ( logit )
## Formula: result ~ location + shotnumber + shotclock + dribble + touch +
##     type + range + defence + dribble * touch + type * range +
##     (1 + range | name)
##    Data: da
##
##      AIC      BIC   logLik deviance df.resid
## 154428.4 154563.7 -77200.2 154400.4   116760
##
## Scaled residuals:
```

```
##      Min       1Q   Median       3Q      Max
## -14.5112  -0.8753  -0.6369   0.9905   2.7188
##
## Random effects:
##  Groups Name        Variance  Std.Dev. Corr
##  name   (Intercept) 0.0344049 0.18549
##         range       0.0001873 0.01369  -0.78
## Number of obs: 116774, groups:  name, 242
##
## Fixed effects:
##                 Estimate Std. Error z value Pr(>|z|)
## (Intercept)    0.4016785  0.4090876   0.982  0.32615
## location       0.0344213  0.0121496   2.833  0.00461 **
## shotnumber    -0.0008310  0.0013920  -0.597  0.55050
## shotclock      0.0139196  0.0011371  12.241  < 2e-16 ***
## dribble       -0.0068525  0.0061468  -1.115  0.26493
## touch         -0.0650106  0.0058092 -11.191  < 2e-16 ***
## type          -0.1081019  0.2033960  -0.531  0.59508
## range         -0.0773900  0.0170390  -4.542 5.57e-06 ***
## defence        0.1091225  0.0030583  35.681  < 2e-16 ***
## dribble:touch  0.0030564  0.0003357   9.103  < 2e-16 ***
## type:range     0.0054606  0.0084045   0.650  0.51587
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) locatn shtnmb shtclc dribbl touch  type   range  defenc
## location    -0.011
## shotnumber  -0.033  0.001
## shotclock   -0.048 -0.006  0.033
## dribble     -0.017  0.006 -0.001 -0.125
## touch       -0.052 -0.003  0.004  0.169 -0.654
## type        -0.997 -0.003  0.010  0.005  0.022  0.027
## range       -0.986 -0.003  0.018  0.032  0.010  0.020  0.984
## defence      0.046  0.000  0.008 -0.126  0.044  0.054 -0.057 -0.084
## dribble:tch  0.052  0.000 -0.042  0.044 -0.586 -0.132 -0.039 -0.021 -0.089
## type:range   0.992  0.003 -0.014 -0.014 -0.010 -0.022 -0.993 -0.996  0.050
##             drbbl:
## location
## shotnumber
## shotclock
## dribble
## touch
## type
## range
## defence
## dribble:tch
## type:range   0.023
## convergence code: 0
## Model failed to converge with max|grad| = 0.0725334 (tol = 0.001, component 1)
## Model is nearly unidentifiable: very large eigenvalue
##  - Rescale variables?
## Model is nearly unidentifiable: large eigenvalue ratio
##  - Rescale variables?
```

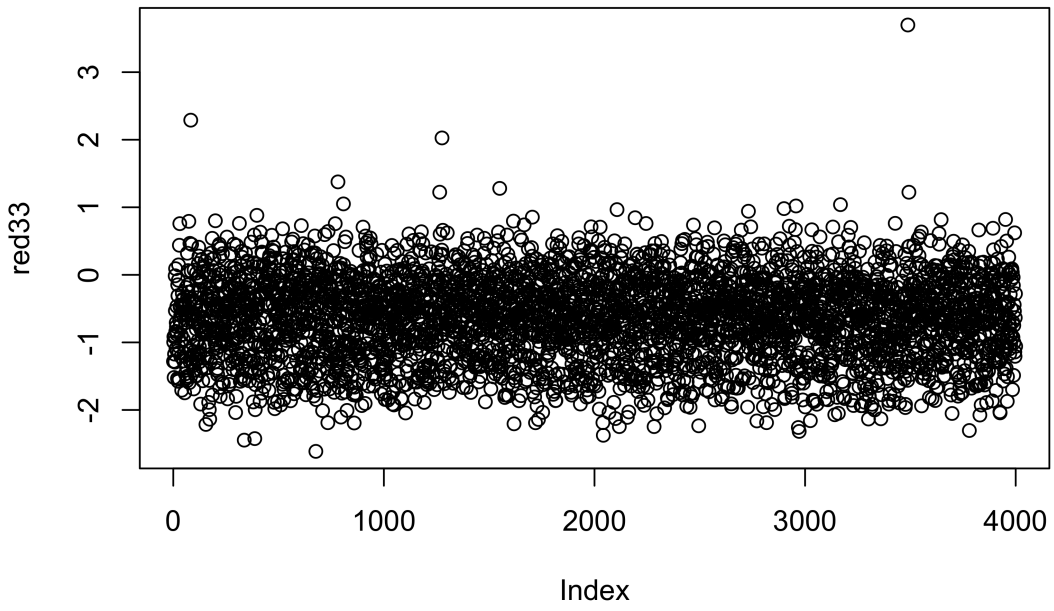
From model3 we can see the most coefficients's p-value are quite small and they are significant. I set players name as pooling principle,and the slope of range varys form different players, the intercept could vary for different players. We could see the range preference could be different because some players(like Lilard) prefer to shoot long distance ball. Additionally, there exists corelationships between these variables.

```
### check
pred3 = predict(m3,type = "link")
red3 = as.numeric(as.character(pred3))-da$result
com3 = data.frame(obs = da$result,pre = pred1) %>% pivot_longer(cols = 1:2,names_to = "type",values_to =
red33 = sample(red3,4000)
### check visualization
car::qqPlot(red33)
```




```
## [1] 3488   83
```

```
plot(red33)
```



The qq-plot and residual plot shows the residuals are randomly normal distributed, while the mean of residual turn to be -1 which henders model's effectiveness.

5.4 Model evaluation and selection

```
anova(m2,m3,m1)
```

```
## Data: da
## Models:
## m2: result ~ location + shotnumber + shotclock + dribble + touch +
## m2:     type + range + defence + dribble * touch + type * range +
## m2:     (touch - 1 | name)
## m1: result ~ location + shotnumber + period + shotclock + dribble +
## m1:     touch + type + range + defence + dribble * touch + type *
## m1:     range + (1 | name)
## m3: result ~ location + shotnumber + shotclock + dribble + touch +
## m3:     type + range + defence + dribble * touch + type * range +
## m3:     (1 + range | name)
##    Df    AIC    BIC logLik deviance  Chisq Chi Df Pr(>Chisq)
## m2 12 154590 154706 -77283   154566
## m1 13 154522 154647 -77248   154496 70.422      1  < 2.2e-16 ***
## m3 14 154428 154564 -77200   154400 95.385      1  < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

From the anova test we can see the difference between three model are slight. Nonetheless, according to AIC and BIC, the model3 is quite small so we can regard this as a better model. Hence, model 3 has more perfect performance in predicting shooting result.

6.Result and discussion

6.1 Result

- The analysis i present in this report does good to predict a player's shooting performance during the game. From the glm model we could see a player could be influenced by various elements, such as shooting distance, defending distance, touch time, dribble number, and the like. After we pooling the players issue, we could see there exists slightly relationship between players and shooting distance/touch time/dribbles number.

6.2 Limitation

- We all know the internal relations, mood, and other potential factors might impact the shooting result, these factors are differ from places and difficult to track.

- Regular season is quite different with the off season. Some team probably play less agressive in regular season because the risk of losing a single game is low. But when it comes to the play offs, all teams would spare no effort to chasing the championship, so some strategies might change.

6.3 Improvement

- The defensive strength could vary from teams, some teams has many tall players(LA Lakers), so teams are consist of low players(Portland Trail Blazers). Some information about opponents could largely improve the analysis quality.

- Players are easily to get injured during games and might absent several games if injured. They need time to go back to former condition after recovery. If more information could be collected, the analysis would be more accurate.

- NBA has the trading market machanism before a new season start, so each team's player could vary through years, how to organize each player's data needs to think again.

6.4 Future direction

- Some other method could be added into this analysis such as statistical learning to make this analysis more strengthful. Additionally, this analysis could be used into sports field(not limited to NBA), NFL, FIFA, hockey, and the like.

7.Reference website

- https://www.kaggle.com/

- http://www.stat-nba.com/

- https://www.basketball-reference.com/

- https://www.hupu.com/

- https://blog.csdn.net/

8.Appendix

shooting period preference