# 关于 NBA 球员正负值的讨论

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### 简介

RPM, 即 NBA 球员的正负值,表示该球员在场上时球队净胜分的情况,是衡量球员综合表现得一个指标。本次作业选取 17 年 NBA 所有球员的数据,分析 RPM 与球员出场时间以及球员薪酬的关系。首先读入数据:

```
#extract from
#https://www.kaqqle.com/dhamlett/nba-player-rpm-prediction-defense-vs-offense
nba<- nba %>% select(-1)
head(nba)
## # A tibble: 6 x 38
                        Rk PLAYER POSITION
##
                                                                                          AGE
                                                                                                                                  FG
                                                                                                                                                  FGA `FG%`
                                                                                                                                                                                    `3P` `3PA` `3P%`
##
                <dbl> <chr> <chr>
                                                                                    <dbl> <dbl <dbl >dbl <dbl <dbl >dbl <dbl <
                           1 Russe~ PG
                                                                                                                                                                                                                                               7.7
## 1
                                                                                                         34.6 10.2 24
                                                                                                                                                              0.425
                                                                                                                                                                                       2.5
                                                                                                                                                                                                         7.2 0.343
## 2
                           2 James~ PG
                                                                                                         36.4
                                                                                                                               8.3 18.9 0.44
                                                                                                                                                                                       3.2
                                                                                                                                                                                                          9.3 0.347
                                                                                                                                                                                                                                               5.1
                                                                                             27
## 3
                           3 Isaia~ PG
                                                                                             27 33.8
                                                                                                                                               19.4 0.463
                                                                                                                                                                                       3.2
                                                                                                                                                                                                          8.5 0.379
                                                                                                                                                                                                                                               5.8
## 4
                           4 Antho~ C
                                                                                             23
                                                                                                         36.1
                                                                                                                           10.3 20.3 0.505
                                                                                                                                                                                       0.5
                                                                                                                                                                                                          1.8 0.299
                                                                                                                                                                                                                                               9.7
                           6 DeMar~ C
## 5
                                                                                             26 34.2
                                                                                                                               9
                                                                                                                                               19.9 0.452
                                                                                                                                                                                       1.8
                                                                                                                                                                                                                                               7.2
                                                                                                                                                                                                          5
                                                                                                                                                                                                                      0.361
                           7 Damia~ PG
                                                                                                                               8.8 19.8 0.444
                                                                                                                                                                                       2.9
                                                                                                                                                                                                          7.7 0.37
## 6
                                                                                             26 35.9
               ... with 26 more variables: `2PA` <dbl>, `2P%` <dbl>, `eFG%` <dbl>, FT <dbl>,
                     FTA <dbl>, `FT%` <dbl>, ORB <dbl>, DRB <dbl>, TRB <dbl>, AST <dbl>,
## #
## #
                     STL <dbl>, BLK <dbl>, TOV <dbl>, PF <dbl>, POINTS <dbl>, TEAM <chr>,
## #
                     GP <dbl>, MPG <dbl>, ORPM <dbl>, DRPM <dbl>, RPM <dbl>, WINS RPM <dbl>,
                     PIE <dbl>, PACE <dbl>, W <dbl>, SALARY_MILLIONS <dbl>
## #
```

nba <- read csv("~/github/Rcourse 1/project/nba 2017 nba players with salary.csv")

其次检查数据完整情况,其中 na 类型只出现在两项命中率数据上,说明所有数据都完整,只是某些球员整个赛季没有三分和罚球,因此对应命中率为 na。

<pre>rowSums(apply(nba,1,is.na))</pre>					
##	Rk	PLAYER	POSITION	AGE	MP
##	0	0	0	0	0
##	FG	FGA	FG%	3P	3PA
##	0	0	0	0	0
##	3P%	2P	2PA	2P%	eFG%
##	22	0	0	0	0
##	FT	FTA	FT%	ORB	DRB
##	0	0	5	0	0
##	TRB	AST	STL	BLK	TOV
##	0	0	0	0	0
##	PF	POINTS	TEAM	GP	MPG
##	0	0	0	0	0
##	ORPM	DRPM	RPM	WINS_RPM	PIE
##	0	0	0	0	0
##	PACE	W	SALARY_MILLIONS		

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## RPM 与出场时间

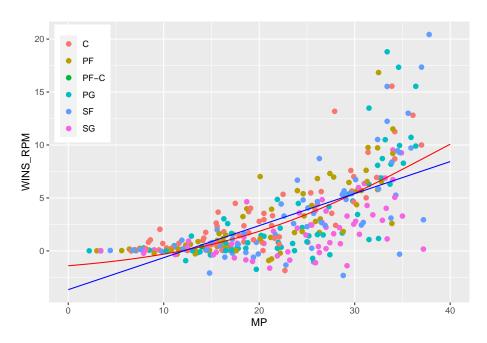
0

```
temp1 <- min(nba$WINS_RPM)
nba<-nba %>% mutate(RPM1 = WINS_RPM-temp1)
temp2 <-max(nba$RPM1)
nba$RPM1 <-nba$RPM1/temp2
L1<- glm(RPM1~MP,family = binomial(),data = nba)
summary(L1)</pre>
```

##

```
## Call:
## glm(formula = RPM1 ~ MP, family = binomial(), data = nba)
## Deviance Residuals:
       Min
                   1Q
                      Median
                                      ЗQ
                                               Max
## -0.87674 -0.13350
                      0.01699 0.13202
                                           1.17947
##
## Coefficients:
##
              Estimate Std. Error z value Pr(>|z|)
## (Intercept) -3.16779
                          0.44091 -7.185 6.74e-13 ***
## MP
               0.08368
                          0.01691 4.949 7.47e-07 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##
       Null deviance: 52.462 on 341 degrees of freedom
## Residual deviance: 24.469 on 340 degrees of freedom
## AIC: 208.11
##
## Number of Fisher Scoring iterations: 5
L2<- lm(WINS_RPM~MP,data = nba)
summary(L2)
##
## Call:
## lm(formula = WINS_RPM ~ MP, data = nba)
##
## Residuals:
##
       Min
               1Q Median
                                3Q
                                      Max
## -7.4157 -1.5305 -0.0712 1.3673 12.6630
##
## Coefficients:
```

```
##
                Estimate Std. Error t value Pr(>|t|)
## (Intercept) -3.6593
                              0.4053 -9.028 <2e-16 ***
## MP
                  0.3023
                              0.0174 17.373 <2e-16 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.829 on 340 degrees of freedom
## Multiple R-squared: 0.4702, Adjusted R-squared: 0.4687
## F-statistic: 301.8 on 1 and 340 DF, p-value: < 2.2e-16
k < -0:40
Y \leftarrow \exp(\operatorname{coef}(L1)[1] + \operatorname{coef}(L1)[2]*k)/(1+\exp(\operatorname{coef}(L1)[1] + \operatorname{coef}(L1)[2]*k))
Y<- Y*temp2 + temp1
Y2 \leftarrow coef(L2)[1] + coef(L2)[2]*k
ggplot()+
  geom_point(aes(x = nba$MP,y = nba$WINS_RPM,col = nba$POSITION),size = 2) +
  geom_line(aes(x = k,y = Y),col = "red")+
  geom_line(aes(x = k,y = Y2),col = "blue")+
  theme(legend.position = c(0.08,0.78),legend.title = element_blank())+
  labs(x = "MP",y = 'WINS_RPM')
```



从结果来看,出场时间与 RPM 有着明显的正相关关系,这也与实际情况相符,球队往往希望表现更好的球员多打一会。另外,还可以发现,在拥有较高 RPM 的球员中,SG 位置似乎很少,说明可能现在球队更喜欢将 PG或 SF 作为球队核心。下面的图也将说明这一关系 (因为 PF-C 分类太少,就将其去除)。

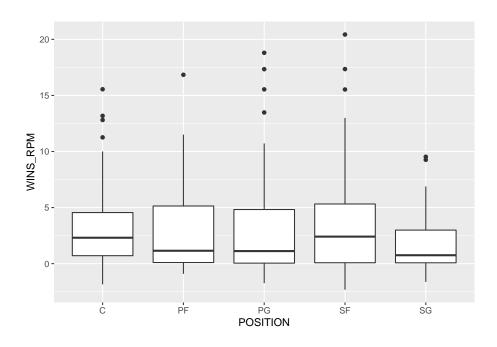
#### table(nba\$POSITION)

```
##
```

```
## C PF PF-C PG SF SG
## 67 70 2 70 65 68
```

```
nba %>% filter(POSITION != 'PF-C') %>% ggplot(aes(x = POSITION,y = WINS_RPM))+
geom_boxplot()+labs(x = "POSITION",y = 'WINS_RPM')
```

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# RPM 与薪酬

```
L3<- lm(WINS_RPM~SALARY_MILLIONS,data = nba)
summary(L3)
##
## Call:
## lm(formula = WINS_RPM ~ SALARY_MILLIONS, data = nba)
##
## Residuals:
       Min
                1Q Median
##
                                3Q
                                        Max
## -8.0102 -1.6998 -0.6954 1.2745 14.3838
##
## Coefficients:
##
                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)
                    0.47149
                               0.26362
                                          1.789
                                                  0.0746 .
## SALARY_MILLIONS 0.32770
                               0.02697 12.150
                                                  <2e-16 ***
```

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```
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.245 on 340 degrees of freedom
## Multiple R-squared: 0.3028, Adjusted R-squared: 0.3007
## F-statistic: 147.6 on 1 and 340 DF, p-value: < 2.2e-16

k<-0:32
Y <- coef(L3)[1] + coef(L3)[2]*k
ggplot()+
geom_point(aes(x = nba$SALARY_MILLIONS,y = nba$WINS_RPM,col = nba$POSITION))+
geom_line(aes(x = k,y = Y))+
theme(legend.title = element_blank())+
labs(x = "SALARY_MILLIONS",y = 'WINS_RPM')</pre>
```

可见 RPM 与薪酬基本上也保持正相关,但是不如出场时间拟合的那么好。结合实际情况,有些低薪球员为了在将来获得高薪合同奋力表现自己,而有些球员拿到高额报酬后就开始"放松养生",表现糟糕。尽管实际情况可能更加复杂,但是从 17 年的数据来看,确实有许多球员在 RPM 这一项指标上表现的与他的薪水不符。

SALARY\_MILLIONS

30

WINS\_RPM

0