

Post01-Meiyong Huang

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Abstract

This post involves analyzing data of top 5 professional sports in the U.S. in the 2016-2017 season. Data includes the revenue, average salary, highest salary. The purpose of this post is to study the different salary of 5 professional sports, and mainly identify the factors that are most likely to contribute to NBA player salaries. And to identify the performance variables i.e. scoring, assists, fouls, and other variables that significantly contributed to determine a NBA player's salary. Additionally, this post also indentifies some question whether NBA plyers are overpaid or underpaid.

keywords: Professional Sports, National Basketball Assiciation, Player Salaries, Player Performances



Abstract

This post involves analyzing data of top 5 professional sports in the U.S. in the 2016-2017 season. Data includes the revenue, average salary, highest salary. The purpose of this post is to study the different salary of 5 professional sports, and mainly identify the factors that are most likely to contribute to NBA player salaries. The objective of this post is to explain the salaries of the National Basketball Association(NBA) players. This post is to provide analytics for professional basketball teams and it includes determining the factors resulting in high or low salaries to the player. In other words, it is to identify the performance variables i.e. scoring, assists, fouls, and other variables that significantly contributed to determine a NBA player's salary.

Keywords: Professional Sports, National Basketball Assiciation, Player Salaries, Player Performances

Introduction

In the 2016-2017 National Basketball Association(NBA) season, LeBron James earned the highest salary \$30.96 million. The average salary of an NBA player for the 2016-2017 season was \$6.2 million which was higher than the average salary of a National Football League(NFL), National Hockey League(NHL), Major League Baseball(MLB), or Major League Soccer(MLS). What's more, 34.2% of NBA players have a salary higher than the NBA player average salary. Standard economic reasoning suggest that a NBA player's salary will be set to approximately equal his expected contribution to the team's revenues over the season and that is what we called "marginal revenue product." From a fan's perspective, a player's contributions mostly relate to the team's win-rate: can this athlete help win the team more games and eventually secure a championship title.

Getting the data: The data is gathered from different places: NBA.com States, Basketball Reference, github.

Cleaning: As it turns out, a lot of the columns of data needed to be removed.

Modeling: Most of the model used their stats as an input, and salary as output. Therefore, throughout this post, I frequently refer to the term of different cost driver, which is an independent variable that drives or affects the dependent variable of salary. Basically, I gathered data and put salary on the y-axis by using different terms of x-axis variables. The different cost drivers I chose for testing are including total points scored, rebounds, assists, games played, height, point per game, and efficiency. The output is scaled from the min to max contract price for 2016-2017 season.

Shortcomings: It is important to note that this only analyzes stats based on past year performance, which is very isolated. It doesn't take into account team strength, and potential (though many models take wins into account).

```
library(dplyr)
```

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

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

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

```
library(ggplot2)
```

```
dat2<-read.csv("~/stat133/stat133-hws-fall17/stat133/stat133-hws-fall17/hw03/data/nba2017-stats.csv")
write.csv(dat2,
          file="/Users/liminhuang/stat133-hws-fall17/post01/nba2017-ststa.csv", row.names=FALSE)
```

```
dat3<- read.csv("~/stat133/stat133-hws-fall17/stat133/stat133-hws-fall17/hw03/data/nba2017-roster.csv")
write.csv(dat3,
          file = "/Users/liminhuang/stat133-hws-fall17/post01/nba2017-roster.csv", row.names = FALSE)
```

```
##Top 5 professional sports leagues in U.S. by Revenue in 2016(by billion)
rev_nfl=13
rev_mlb=9.5
rev_nba=4.8
rev_nhl=3.7
rev_mls=0.6
value<-c(13,9.5,4.8,3.7,0.6)
sports<-c("NFL", "MLB", "NBA", "NHL", "MLS")
png(file="barchart_sports_revenue.png")

barplot(value,names.arg= sports, xlab= "Sports", ylab="revenue", col="orange",main="Top 5 professional sports leagues in U.S. by Revenue (in 2016 by billion)")
dev.off()
```

```
## quartz_off_screen
##           2
```

From the revenue barplot, NFL has the highest revenue in 2016 followed by MLB(\$9.5 billion), NBA(\$4.8 billion), NHL(\$3.7 billion), and MLS(\$0.6 billion). According to ESP, the major reason of NFL has a highest revenue is its sponsorship revenue. NFL received \$1.25 billion (9.6% of its total revenue) in 2016 season. Another major money maker for the NFL is its \$1 billion per season (four-year \$4 billion partnership) with DirecTV.

```
##major U.S. sports leagues
##collecting the data from the reference
avg_nba=6.2
highest_nba=30.96 ##LeBron James

avg_mlb=4.4
highest_mlb=32 ##Clayton Kershaw

avg_nhl=2.9
highest_nhl=14 ##Anze Kopitar

avg_nfl=2.1
highest_nfl=31.25 ##Drew Brees

avg_mls=0.3
highest_mls=7.2 ##Kaka
##create the data for the bar chart
H<- c(6.2,4.4,2.9,2.1,0.3)
sports<-c("NBA", "MLB", "NHL", "NFL", "MLS")
png(file="barchart_sports_avg_salary.png")

barplot(H,names.arg= sports, xlab= "Sports", ylab="Avg_salary(million)", col="blue",main="Avg_salary of 5 most popular sports")
dev.off()
```

```
## quartz_off_screen
##
2
```

According to “The average player salary and highest-paid in NBA,MLB,NHL,NFL and MLS,” the average salary of an NBA player for the 2016-2017 season is \$6.2 million which is tops across all sports, followed by MLB(\$4.4 million), NHL(\$2.9 million), NFL(\$2.1 million), and MLS(\$0.3 million). Although NFL has a higher revenue than NBA, NFL’s average salary is lower than NBA’s average salary. One of the reasons is that NBA players get a slightly bigger slice of league revenue than do NFL players. NBA players get roughly half of all league revenue before expense. Secondly, the major reason is that NFL has a bigger roster size than NBA. Even NFL players get twice as much money as NBA players, NFL has almost four times as many athletes as NBA. For example, there are 32 NFL teams with 53 roster spots each, total has 1696 NFL players at any given moment. Meanwhile, NBA has 30 teams with 15 roster spots each, making only around 450 NBA players.

```
##avg_salary and highest salary in 5 different sports
colors<- c("blue", "green")
sports<-c("NBA", "MLB", "NHL", "NFL", "MLS")
salary<-c("avg_salary", "highest_salary")
##create the matrix of the values
values<- matrix(c(6.2,4.4,2.9,2.1,0.3,31,32,14,31.25,7.2),nrow = 2,ncol = 5, byrow = TRUE)

png(file="barchart_avg_salary_and_highest_salary.png")

barplot(values,main = "avg salary and highest salary in 5 different sports", names.arg= sports, xlab = "sports", ylab = "salary", col = colors)
legend("topright",salary, cex = 1,fill = colors)
dev.off()
```

```
## quartz_off_screen
##
2
```

The “avg salary and highest salary in 5 different sports” shows the average salary and highest salary break down among the major U.S. sports leagues based on the 2016 data. As we can see, MLB player Clayton Kershaw has the highest salary \$32 million, followed by NFL player Drew Brees with \$31.25 million, NBA players LeBron James with \$31 million, NHL player Anze Kopitar with \$14 million, and MLS player Kaka with \$7.2 million.

```
##average salary group by player
salary_player<-dat3[, c('salary','player')]
salary_player
```

##	salary	player
## 1	650000	A.J. Hammons
## 2	2700000	Aaron Brooks
## 3	4351320	Aaron Gordon
## 4	2022240	Adreian Payne
## 5	26540100	Al Horford
## 6	10230179	Al Jefferson
## 7	7680965	Al-Farouq Aminu
## 8	1315448	Alan Anderson
## 9	874636	Alan Williams
## 10	10154495	Alec Burks
## 11	5994764	Alex Abrines
## 12	4823621	Alex Len
## 13	31969	Alex Poythress
## 14	4600000	Alexis Ajinca
## 15	18500000	Allen Crabbe
## 16	12000000	Amir Johnson
## 17	22116750	Andre Drummond
## 18	11131368	Andre Iguodala
## 19	2183072	Andre Roberson
## 20	945000	Andrew Harrison
## 21	6088993	Andrew Nicholson
## 22	6006600	Andrew Wiggins
## 23	22116750	Anthony Davis
## 24	3488000	Anthony Morrow
## 25	8000000	Anthony Tolliver
## 26	119494	Archie Goodwin
## 27	6500000	Aron Baynes
## 28	12500000	Arron Afflalo
## 29	11000000	Austin Rivers
## 30	8269663	Avery Bradley
## 31	20580	Axel Toupane
## 32	4008882	Ben McLemore
## 33	1551659	Beno Udrih
## 34	17000000	Bismack Biyombo
## 35	20140838	Blake Griffin
## 36	7000000	Boban Marjanovic
## 37	680534	Bobby Brown
## 38	1453680	Bobby Portis
## 39	3730653	Bojan Bogdanovic
## 40	7000000	Boris Diaw
## 41	22116750	Bradley Beal
## 42	5700000	Brandan Wright

## 43	1551659	Brandon Bass
## 44	5281680	Brandon Ingram
## 45	1200000	Brandon Jennings
## 46	12606250	Brandon Knight
## 47	3500000	Brandon Rush
## 48	1050961	Brian Roberts
## 49	102898	Briante Weber
## 50	1273920	Brice Johnson
## 51	21165675	Brook Lopez
## 52	1589640	Bruno Caboclo
## 53	543471	Bryn Forbes
## 54	3517200	Buddy Hield
## 55	3219579	C.J. McCollum
## 56	4583450	C.J. Miles
## 57	5000000	C.J. Watson
## 58	2112480	Cameron Payne
## 59	1562280	Caris LeVert
## 60	24559380	Carmelo Anthony
## 61	22116750	Chandler Parsons
## 62	7806971	Channing Frye
## 63	143860	Chasson Randle
## 64	543471	Cheick Diallo
## 65	543471	Chinanu Onuaku
## 66	1191480	Chris McCullough
## 67	22868828	Chris Paul
## 68	874636	Christian Wood
## 69	1296240	Clint Capela
## 70	5318313	Cody Zeller
## 71	7643979	Cole Aldrich
## 72	7600000	Corey Brewer
## 73	7330000	Cory Joseph
## 74	11242000	Courtney Lee
## 75	874636	Cristiano Felicio
## 76	7250000	D.J. Augustin
## 77	5332800	D'Angelo Russell
## 78	18255	Dahntay Jones
## 79	1171560	Damian Jones
## 80	24328425	Damian Lillard
## 81	980431	Damjan Rudez
## 82	543471	Daniel Ochefu
## 83	15050000	Danilo Gallinari
## 84	10000000	Danny Green
## 85	2978250	Dante Cunningham
## 86	3940320	Dante Exum
## 87	2318280	Dario Saric
## 88	8070175	Darrell Arthur
## 89	5229454	Darren Collison
## 90	874060	Darrun Hilliard
## 91	1551659	David Lee
## 92	73528	David Nwaba
## 93	1551659	David West
## 94	543471	Davis Bertans
## 95	21165675	DeAndre Jordan
## 96	1015696	DeAndre Liggins
## 97	1499760	DeAndre' Bembry
## 98	1180080	Dejounte Murray
## 99	1577280	Delon Wright
## 100	26540100	DeMar DeRozan
## 101	16957900	DeMarcus Cousins
## 102	14200000	DeMarre Carroll
## 103	1450000	Demetrius Jackson
## 104	2708582	Dennis Schroder
## 105	2092200	Denzel Valentine
## 106	259626	Deron Williams
## 107	11050000	Derrick Favors
## 108	543471	Derrick Jones
## 109	21323250	Derrick Rose
## 110	268029	Derrick Williams
## 111	2223600	Devin Booker
## 112	4228000	Devin Harris
## 113	2898000	Dewayne Dedmon
## 114	1369229	Deyonta Davis
## 115	543471	Diamond Stone
## 116	2898000	Dion Waiters
## 117	25000000	Dirk Nowitzki
## 118	2440200	Domantas Sabonis
## 119	576724	Donatas Motiejunas
## 120	543471	Dorian Finney-Smith
## 121	2483040	Doug McDermott
## 122	4276320	Dragan Bender
## 123	15330435	Draymond Green
## 124	23180275	Dwight Howard
## 125	8375000	Dwight Powell
## 126	23200000	Dwyane Wade
## 127	8081363	E'Twaun Moore

## 128	6666667	Ed Davis
## 129	5145	Edy Tavares
## 130	2613600	Elfrid Payton
## 131	23069	Elijah Millsap
## 132	3241800	Emmanuel Mudiay
## 133	17145838	Enes Kanter
## 134	14000000	Eric Bledsoe
## 135	12385364	Eric Gordon
## 136	8400000	Ersan Ilyasova
## 137	17000000	Evan Fournier
## 138	16393443	Evan Turner
## 139	2730000	Frank Kaminsky
## 140	543471	Fred VanVleet
## 141	8000000	Garrett Temple
## 142	1655880	Gary Harris
## 143	8000000	George Hill
## 144	650000	Georges Niang
## 145	2202240	Georgios Papagiannis
## 146	1410598	Gerald Green
## 147	9000000	Gerald Henderson
## 148	2995421	Giannis Antetokounmpo
## 149	15890000	Goran Dragic
## 150	16073140	Gordon Hayward
## 151	2348783	Gorgui Dieng
## 152	17100000	Greg Monroe
## 153	22116750	Harrison Barnes
## 154	22116750	Hassan Whiteside
## 155	1704120	Henry Ellenson
## 156	1015696	Ian Clark
## 157	15944154	Ian Mahinmi
## 158	9700000	Iman Shumpert
## 159	1015696	Isaiah Canaan
## 160	255000	Isaiah Taylor
## 161	6587132	Isaiah Thomas
## 162	1074145	Isaiah Whitehead
## 163	6000000	Ish Smith
## 164	1034956	Ivica Zubac
## 165	4096950	J.J. Barea
## 166	7377500	J.J. Redick
## 167	12800000	J.R. Smith
## 168	5374320	Jabari Parker
## 169	6286408	Jae Crowder
## 170	4788840	Jahlil Okafor
## 171	600000	Jake Layman
## 172	2703960	Jakob Poeltl
## 173	13253012	Jamal Crawford
## 174	3210840	Jamal Murray
## 175	4540525	Jameer Nelson
## 176	2898000	James Ennis
## 177	26540100	James Harden
## 178	4000000	James Johnson
## 179	1551659	James Jones
## 180	980431	James Michael McAdoo
## 181	1825200	James Young
## 182	980431	JaMychal Green
## 183	10470000	Jared Dudley
## 184	1286160	Jarell Martin
## 185	63938	Jarrold Uthoff
## 186	5000000	Jason Smith
## 187	1551659	Jason Terry
## 188	1403611	JaVale McGee
## 189	4743000	Jaylen Brown
## 190	15000000	Jeff Green
## 191	8800000	Jeff Teague
## 192	1015696	Jeff Withey
## 193	980431	Jerami Grant
## 194	6511628	Jeremy Lamb
## 195	11483254	Jeremy Lin
## 196	1643040	Jerian Grant
## 197	9424084	Jerryd Bayless
## 198	17552209	Jimmy Butler
## 199	17000000	Joakim Noah
## 200	6540000	Jodie Meeks
## 201	980431	Joe Harris
## 202	2250000	Joe Ingles
## 203	11000000	Joe Johnson
## 204	1052342	Joe Young
## 205	165952	Joel Anthony
## 206	600000	Joel Bolomboy
## 207	4826160	Joel Embiid
## 208	1709720	Joffrey Lauvergne
## 209	12517606	John Henson
## 210	16957900	John Wall
## 211	161483	Johnny O'Bryant
## 212	10991957	Jon Leuer
## 213	6000000	Jonas Valanciunas

## 213	5000000	Jonas Jerebko
## 214	14382022	Jonas Valanciunas
## 215	874636	Jonathon Simmons
## 216	12500000	Jordan Clarkson
## 217	173094	Jordan Crawford
## 218	3911380	Jordan Hill
## 219	1223653	Jordan Mickey
## 220	392478	Jose Calderon
## 221	1191480	Josh Huestis
## 222	5782450	Josh McRoberts
## 223	874636	Josh Richardson
## 224	11286518	Jrue Holiday
## 225	1987440	Juan Hernangomez
## 226	3267120	Julius Randle
## 227	1514160	Justin Anderson
## 228	3000000	Justin Hamilton
## 229	1015696	Justin Holiday
## 230	2593440	Justise Winslow
## 231	1921320	Jusuf Nurkic
## 232	3333333	K.J. McDaniels
## 233	5960160	Karl-Anthony Towns
## 234	17638063	Kawhi Leonard
## 235	543471	Kay Felder
## 236	3094014	Kelly Olynyk
## 237	12000000	Kemba Walker
## 238	12078652	Kenneth Faried
## 239	15730338	Kent Bazemore
## 240	3678319	Kentavious Caldwell-Pope
## 241	26540100	Kevin Durant
## 242	21165675	Kevin Love
## 243	1800000	Kevin Seraphin
## 244	1182840	Kevon Looney
## 245	15200000	Khris Middleton
## 246	16663575	Klay Thompson
## 247	8046500	Kosta Koufos
## 248	3872520	Kris Dunn
## 249	4000000	Kris Humphries
## 250	4317720	Kristaps Porzingis
## 251	1192080	Kyle Anderson
## 252	5239437	Kyle Korver
## 253	12000000	Kyle Lowry
## 254	3900000	Kyle O'Quinn
## 255	4837500	Kyle Singler
## 256	543471	Kyle Wiltjer
## 257	17638063	Kyrie Irving
## 258	20575005	LaMarcus Aldridge
## 259	4000000	Lance Stephenson
## 260	6191000	Lance Thomas
## 261	5200000	Langston Galloway
## 262	1207680	Larry Nance Jr.
## 263	4000000	Lavoy Allen
## 264	4000000	Leandro Barbosa
## 265	30963450	LeBron James
## 266	7000000	Lou Williams
## 267	2203000	Luc Mbah a Moute
## 268	1921320	Lucas Nogueira
## 269	1227000	Luke Babbitt
## 270	18000000	Luol Deng
## 271	1439880	Malachi Richardson
## 272	925000	Malcolm Brogdon
## 273	2500000	Malcolm Delaney
## 274	1627320	Malik Beasley
## 275	14000000	Manu Ginobili
## 276	21165675	Marc Gasol
## 277	12000000	Marcin Gortat
## 278	6333333	Marco Belinelli
## 279	31969	Marcus Georges-Hunt
## 280	4625000	Marcus Morris
## 281	3578880	Marcus Smart
## 282	3909840	Mario Hezonja
## 283	7400000	Markieff Morris
## 284	2941440	Marquese Chriss
## 285	1403611	Marreese Speights
## 286	543471	Marshall Plumlee
## 287	12250000	Marvin Williams
## 288	2328530	Mason Plumlee
## 289	383351	Matt Barnes
## 290	9607500	Matthew Dellavedova
## 291	8988764	Maurice Harkless
## 292	543471	Maurice Ndour
## 293	1551659	Metta World Peace
## 294	9213484	Meyers Leonard
## 295	1403611	Michael Beasley
## 296	3183526	Michael Carter-Williams
## 297	650000	Michael Gbinije
## 298	13000000	Michael Kidd-Gilchrist

##	299	26540100	Mike Conley
##	300	4837500	Mike Dunleavy
##	301	3500000	Mike Miller
##	302	1015696	Mike Muscala
##	303	12500000	Miles Plumlee
##	304	2898000	Mindaugas Kuzminskas
##	305	10500000	Mirza Teletovic
##	306	10770000	Monta Ellis
##	307	1000000	Montrezl Harrell
##	308	2463840	Myles Turner
##	309	3800000	Nemanja Bjelica
##	310	4384490	Nerlens Noel
##	311	3750000	Nick Collison
##	312	5443918	Nick Young
##	313	20869566	Nicolas Batum
##	314	543471	Nicolas Brussino
##	315	2993040	Nik Stauskas
##	316	1358500	Nikola Jokic
##	317	5782450	Nikola Mirotic
##	318	11750000	Nikola Vucevic
##	319	2751360	Noah Vonleh
##	320	874636	Norman Powell
##	321	247991	Norris Cole
##	322	210995	Okaro White
##	323	9904494	Omer Asik
##	324	138414	Omri Casspi
##	325	5893981	Otto Porter
##	326	5300000	P.J. Tucker
##	327	1196040	Pascal Siakam
##	328	874636	Pat Connaughton
##	329	31969	Patricio Garino
##	330	6000000	Patrick Beverley
##	331	543471	Patrick McCaw
##	332	6050000	Patrick Patterson
##	333	3578948	Patty Mills
##	334	15500000	Pau Gasol
##	335	18314532	Paul George
##	336	20072033	Paul Millsap
##	337	3500000	Paul Pierce
##	338	750000	Paul Zipser
##	339	1790902	Quincy Acy
##	340	63938	Quinn Cook
##	341	14000000	Rajon Rondo
##	342	1052342	Rakeem Christmas
##	343	6000000	Ramon Sessions
##	344	2500000	Randy Foye
##	345	1811040	Rashad Vaughn
##	346	937800	Raul Neto
##	347	1551659	Raymond Felton
##	348	2255644	Reggie Bullock
##	349	14956522	Reggie Jackson
##	350	2500000	Richard Jefferson
##	351	1025831	Richaun Holmes
##	352	13550000	Ricky Rubio
##	353	1015696	Robert Covington
##	354	13219250	Robin Lopez
##	355	1406520	Rodney Hood
##	356	543471	Rodney McGruder
##	357	543471	Ron Baker
##	358	1395600	Rondae Hollis-Jefferson
##	359	282595	Ronnie Price
##	360	5000000	Roy Hibbert
##	361	13333333	Rudy Gay
##	362	2121288	Rudy Gobert
##	363	26540100	Russell Westbrook
##	364	18735364	Ryan Anderson
##	365	418228	Ryan Kelly
##	366	874636	Salah Mejri
##	367	1720560	Sam Dekker
##	368	1410598	Sasha Vujacic
##	369	980431	Sean Kilpatrick
##	370	543471	Semaj Christon
##	371	12250000	Serge Ibaka
##	372	8000000	Sergio Rodriguez
##	373	2898000	Seth Curry
##	374	3046299	Shabazz Muhammad
##	375	1350120	Shabazz Napier
##	376	5782450	Shaun Livingston
##	377	89513	Shawn Long
##	378	543471	Sheldon McClellan
##	379	2433334	Shelvin Mack
##	380	1188840	Skal Labissiere
##	381	11241218	Solomon Hill
##	382	726672	Spencer Dinwiddie
##	383	6348759	Spencer Hawes

```
## 384 2969880 Stanley Johnson
## 385 12112359 Stephen Curry
## 386 950000 Stephen Zimmerman
## 387 3140517 Steven Adams
## 388 874636 T.J. McConnell
## 389 2128920 T.J. Warren
## 390 8950000 Taj Gibson
## 391 6191000 Tarik Black
## 392 10000000 Terrence Ross
## 393 1906440 Terry Rozier
## 394 3850000 Thabo Sefolosha
## 395 14153652 Thaddeus Young
## 396 1050961 Thomas Robinson
## 397 2568600 Thon Maker
## 398 8550000 Tiago Splitter
## 399 2090000 Tim Frazier
## 400 2281605 Tim Hardaway
## 401 543471 Tim Quarterman
## 402 16000000 Timofey Mozgov
## 403 1326960 Timothe Luwawu-Cabarrot
## 404 17200000 Tobias Harris
## 405 2870813 Tomas Satoransky
## 406 5505618 Tony Allen
## 407 14445313 Tony Parker
## 408 2368327 Tony Snell
## 409 543471 Treveon Graham
## 410 7806971 Trevor Ariza
## 411 9250000 Trevor Booker
## 412 3386598 Trey Burke
## 413 2340600 Trey Lyles
## 414 15330435 Tristan Thompson
## 415 3332940 Troy Daniels
## 416 150000 Troy Williams
## 417 1315448 Ty Lawson
## 418 1733880 Tyler Ennis
## 419 5628000 Tyler Johnson
## 420 918369 Tyler Ulis
## 421 8000000 Tyler Zeller
## 422 10661286 Tyreke Evans
## 423 12415000 Tyson Chandler
## 424 1339680 Tyus Jones
## 425 4000000 Udonis Haslem
## 426 6552960 Victor Oladipo
## 427 4264057 Vince Carter
## 428 1793760 Wade Baldwin
## 429 6000000 Wayne Ellington
## 430 83119 Wayne Selden
## 431 5628000 Wesley Johnson
## 432 17100000 Wesley Matthews
## 433 3533333 Will Barton
## 434 3551160 Willie Cauley-Stein
## 435 1015696 Willie Reed
## 436 1375000 Willy Hernangomez
## 437 11200000 Wilson Chandler
## 438 207798 Yogi Ferrell
## 439 2240880 Zach LaVine
## 440 10361445 Zach Randolph
## 441 2898000 Zaza Pachulia
```

```
mean(dat3$salary)
```

```
## [1] 6187014
```

```
##The average salary of an NBA player for the 2016-2017 season was $6.19million.
```

```
##Pie Chart with Percentages
##Creat data for the graph
nrow(dat3[dat3$player,])
```

```
## [1] 441
```

```
mean(dat3$salary)
```

```
## [1] 6187014
```

```
dat1<-arrange(dat3,desc(salary))##441
```

```
salary1<-dat1[dat1$salary>=20000000,]
nrow(salary1) ##28
```



```
## [1] 28
```

```
salary2<-dat1[dat1$salary<20000000 &  
              dat1$salary>=15000000,]  
nrow(salary2) ##29
```

```
## [1] 29
```

```
salary3<-dat1[dat1$salary<15000000 &  
              dat1$salary>=10000000,]  
nrow(salary3) ##49
```

```
## [1] 49
```

```
salary4<-dat1[dat1$salary<10000000 &  
              dat1$salary>=5000000,]  
nrow(salary4) ##75
```

```
## NULL
```

```
salary5<-dat1[dat1$salary<5000000 &  
              dat1$salary>=1000000,]  
nrow(salary5) ##179
```

```
## [1] 179
```

```
salary6<-dat1[dat1$salary<1000000,]  
nrow(salary6) ##81
```

```
## [1] 81
```

```
x<- c(28,29,49,75,179,81)  
labels<-c("salary1","salary2","salary3","salary4","salary5","salary6")  
piepercent<-round(100*x/sum(x),1)  
  
##give the chart file a name  
png(file="pie chart of salary.png")  
  
##plot the chart  
pie(x,labels=piepercent,main="Pie Chart of Salary",  
    col = rainbow(length(x)))  
legend("topright",c("salary1","salary2",  
                    "salary3","salary4","salary5","salary6"),  
       cex = 1, fill =rainbow(length(x)))  
  
##save the file  
dev.off()
```

```
## quartz_off_screen  
##                2
```

First of all, as we saw in the results, the average salary of an NBA player for the 2016-2017 season was \$6,187,014 (around \$6.2 million.) (Around 40.6%) Most of the NBA players earned between \$1 million and \$5 million during 2016 to 2017 season. 81.6% of the NBA players earned more than \$1 million in 2016-2017 season.

What's more, from the pie chart of salary, 28 (6.3%) of NBA players earned higher than \$20 million during the 2016-2017 season.

```
above_avg_salary<- dat1[dat1$salary>=6187014,]  
below_avg_salary<- dat1[dat1$salary<6187014,]  
nrow(above_avg_salary) ##151
```

```
## [1] 151
```

```
nrow(below_avg_salary) ##290
```

```
## [1] 290
```

```
x<-c(151,290)
labels<-c("above_avg_salary", "below_avg_salary")
piepercent<-round(100*x/sum(x),1)
png(file = "pie chart of avg_salary.png")
pie(x,labels=piepercent,main="Pie Chart of avg_Salary",
    col = rainbow(length(x)))
legend("topright",c("above_avg_salary", "below_avg_salary"),
    cex = 1, fill =rainbow(length(x)))
dev.off()
```

```
## quartz_off_screen
##                2
```

```
head(salary,1)
```

```
## [1] "avg_salary"
```

From the pie chart of the avg_salary, there was 65.8% of NBA players have a salary below the average salary and only 34.2% of NBA players have a salary higher than the average salary. However, in the 2016-2017, the highest salary was Cleveland Cavaliers's LeBron James who made \$31 million.

```
##Performance of players
##scatterplot_1
mutate(dat3,dat)
```

```
## Error in mutate_impl(.data, dots): Binding not found: dat.
```

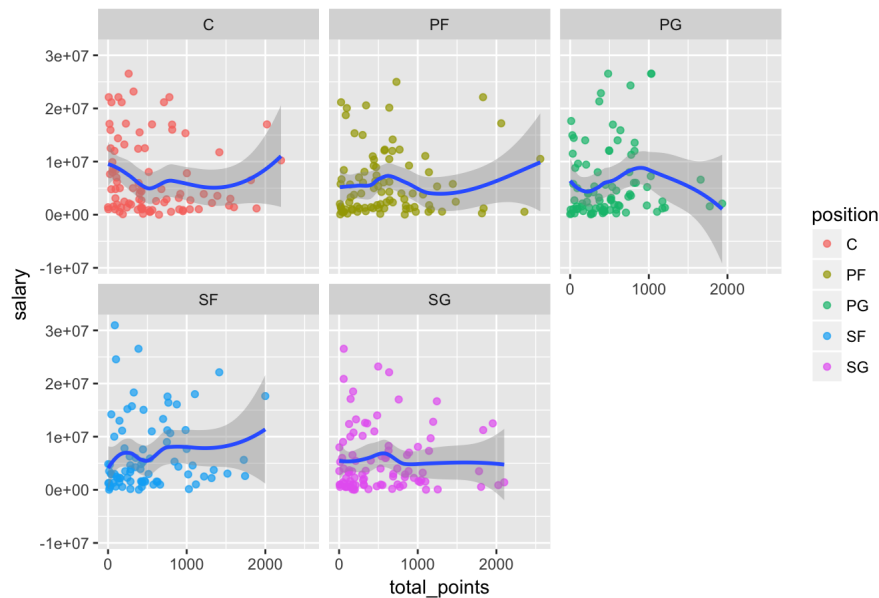
```
ggplot(data=dat3,aes(x=points, y=salary))+
  geom_point(aes(color= position), alpha=0.7)+
  ggtitle("points vs salary")
```

```
## Don't know how to automatically pick scale for object of type function. Defaulting to continuous.
```

```
## Error in (function (..., row.names = NULL, check.rows = FALSE, check.names = TRUE, : arguments imply differing number of rows: 441, 0
```

```
total_points=3*dat2$points3_made+2*dat2$points2_made+dat2$points1_made
dat3<-mutate(dat3,total_points)
ggplot(data = dat3,
    aes(x = total_points, y = salary)) +
  geom_point(aes(color= position),alpha=0.7) +
  facet_wrap(~ position)+
  geom_smooth(method = loess)+
  ggtitle("points vs salary in different positions")
```

points vs salary in different positions



Here is a general plot of how different total points affect the salary in different positions. The relationship between the total points and salary is not very strong but we can see that the higher points player make, the higher salary they are tending to get.

```
data1<-data.frame(dat2)
missed_fg=dat2$field_goals_atts-dat2$field_goals_made
missed_ft=dat2$points1_atts-dat2$points1_made
total_points=3*dat2$points3_made+2*dat2$points2_made+dat2$points1_made
rebounds=dat2$off_rebounds+dat2$def_rebounds
assist=dat2$assists
steals=dat2$steals
blocks=dat2$blocks
turnovers=dat2$turnovers
fouls=dat2$fouls
efficiency=total_points+rebounds+assist+steals+blocks-missed_fg-
  missed_ft-turnovers
min_per_game=dat2$minutes/dat2$games_played
position=dat3$position
pts_per_game=total_points/dat2$games_played

data2<-mutate(dat3,missed_fg,missed_ft,total_points,rebounds,assist,steals,blocks,turnovers,fouls,efficiency,min_p
er_game,pts_per_game,salary, position)
```

```
c_avg_salary<- filter(data2,position=="C")
mean(c_avg_salary$salary) ##6987682
```

```
## [1] 6987682
```

```
pf_avg_salary<-filter(data2,position=="PF")
mean(pf_avg_salary$salary) ##5890363
```

```
## [1] 5890363
```

```
pg_avg_salary<- filter(data2,position=="PG")
mean(pg_avg_salary$salary) ##6069029
```

```
## [1] 6069029
```

```
sf_avg_salary<- filter(data2,position=="SF")
mean(sf_avg_salary$salary) ##6513374
```

```
## [1] 6513374
```

```
sg_avg_salary<- filter(data2,position=="SG")
mean(sg_avg_salary$salary) ##5535260
```

```
## [1] 5535260
```

```
value<-c(6987682,5890363,6069029,6513374,5535260)
positions<-c("C-position","PF-position","PG-position","SF-position","SG-position")
png(file="barchart_position_salary.png")

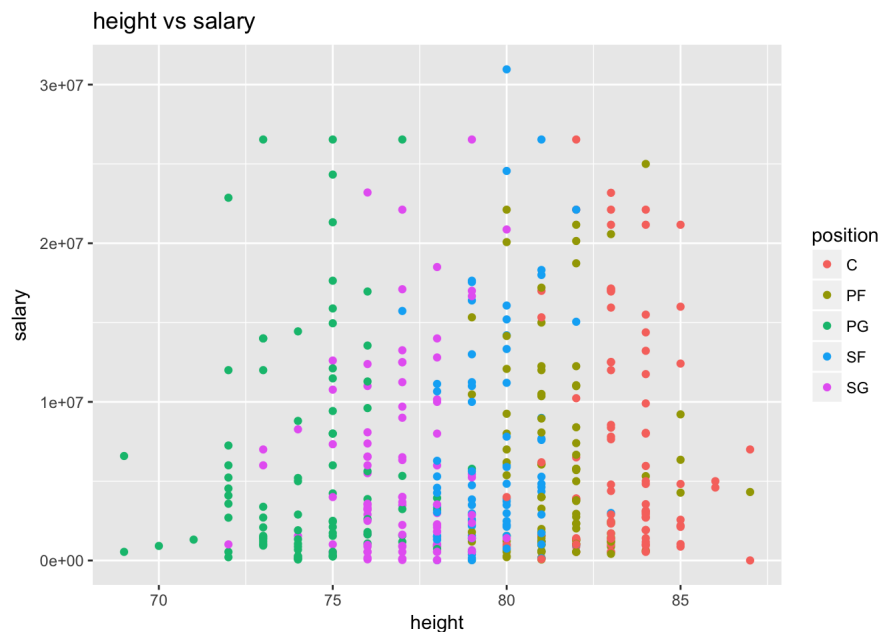
barplot(value,names.arg= positions, xlab= "position", ylab="avg_salary", col="orange",main="positions vs salary of
NBA player")
dev.off()
```

```
## quartz_off_screen
## 2
```

Among 441 NBA player, C position players have a higher average salary of \$7.0 million. And SG position players have a lowest average salary \$5.5 million which is \$1.5 millions lower than C position player.

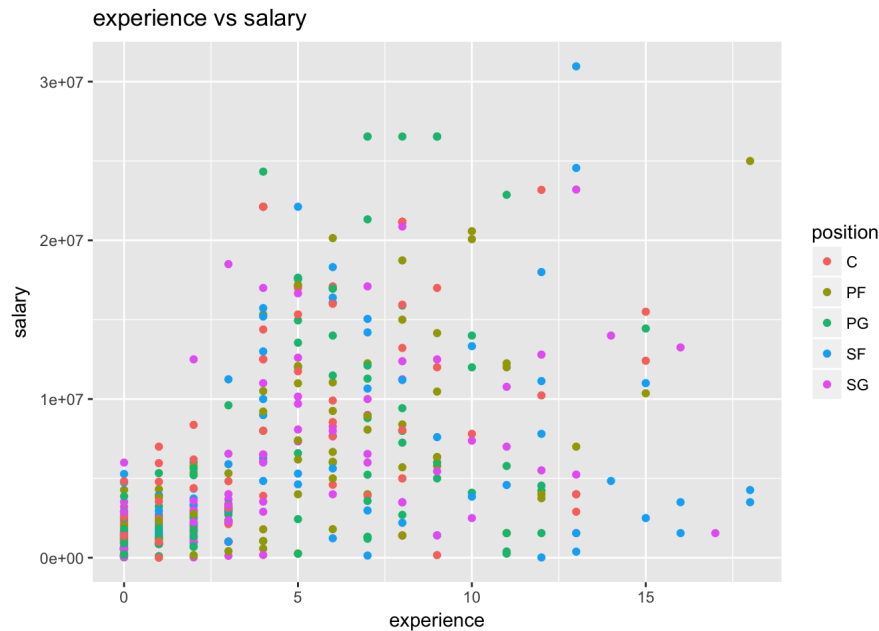
It shows us that the salary does not has a strong relationship with positions. But C position players tend to have a higher average salary

```
height=dat3$height
ggplot(data=data2,aes(x=height, y=salary))+
  geom_point(aes(color= position))+
  ggtitle("height vs salary")
```



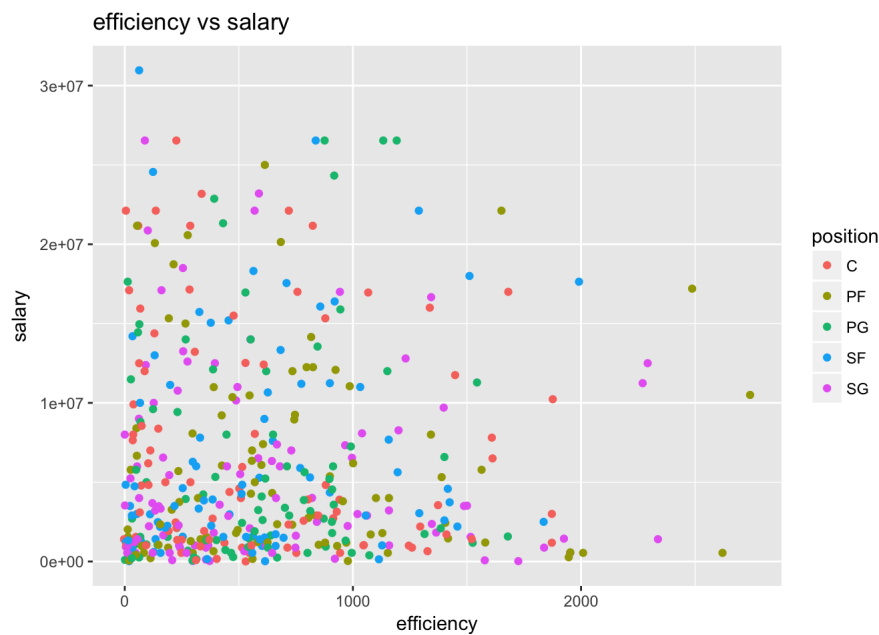
There appears to be a weak positive correlation between the players height vs salary. However, it shows us that C position players tend to have a higher height between 82 to 88, followed by PF position player (between 80 to 85), SF position player (between 78 to 82), SG position player (between 75 to 78), and PG position player (between 68 to 77).

```
experience=dat3$experience
ggplot(data=data2,aes(x=experience, y=salary))+
  geom_point(aes(color= position))+
  ggtitle("experience vs salary")
```



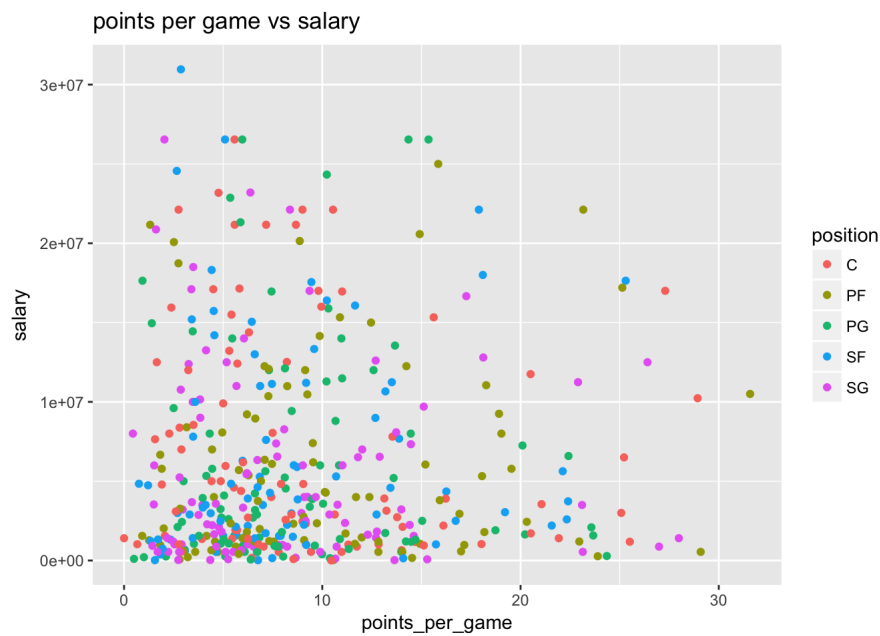
There appears to be a positive correlation between the players experience vs salary. Players with higher experience tend to have a higher salary.

```
efficiency= data2$efficiency
ggplot(data=data2,aes(x=efficiency, y=salary))+
  geom_point(aes(color= position))+
  ggtitle("efficiency vs salary")
```



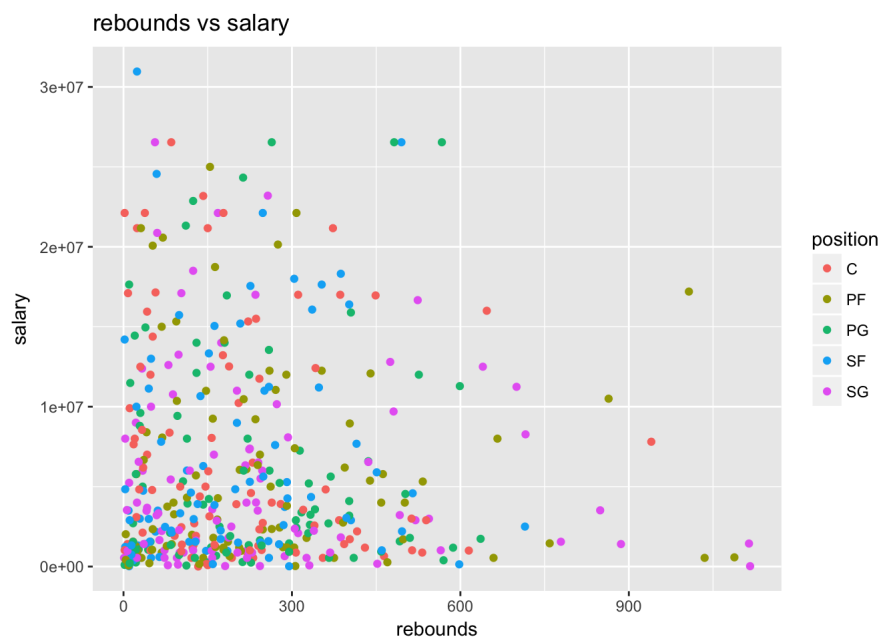
It shows a weak correlation between efficiency and salary. However, the higher efficiency, the higher salary NBA players are tending to have.

```
points_per_game=data2$pts_per_game
ggplot(data=data2,aes(x=points_per_game, y=salary))+
  geom_point(aes(color= position))+
  ggtitle("points per game vs salary")
```



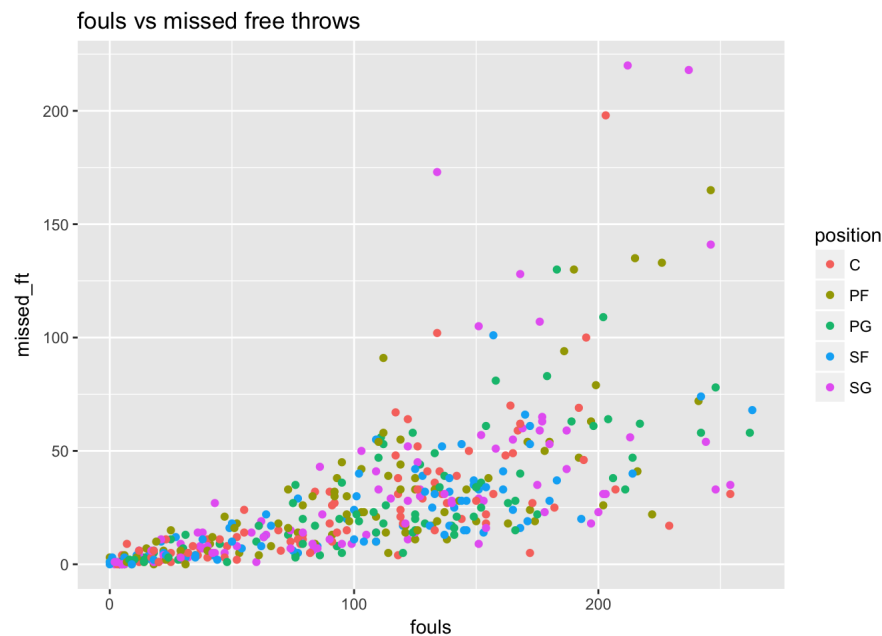
It shows a weak correlation between fouls and salary.

```
rebounds=data2$rebounds
ggplot(data=data2,aes(x=rebounds, y=salary))+
  geom_point(aes(color= position))+
  ggtitle("rebounds vs salary")
```



It shows a weak correlation between fouls and salary.

```
fouls=data2$fouls
missed_ft=data2$missed_ft
ggplot(data=data2,aes(x=fouls, y=missed_ft))+
  geom_point(aes(color= position))+
  ggtitle("fouls vs missed free throws")
```



Players who fouls a lot tend to have a higher rate of missed free throws.

```
gp=data2$games_played
ggplot(data=data2,aes(x=gp, y=salary))+
  geom_point(aes(color=position))+
  ggtitle("games played vs salary")
```

```
## Error: Aesthetics must be either length 1 or the same as the data (441): colour, x, y
```

It shows a not strong relationship between game played and salary. Players have a higher game_played rate, tend to have a higher salary. But it is weak.

Conclusions

The purpose for this study was to study between NBA players' average salary and other professional sports' average salary. And identify the variables that were most likely to contribute to NBA player salaries. I found that game played and height were the two main contributors to NBA player salary. Moreover, rebounds, assists, and personal fouls were statistically significant. Players who has a lower rebound rate tend to have a higher salary. Additionally, in the case of fouls, players who fouls a lot, tend to have a higher missed free throws.

However, points scored, assists, rebounds, and games player can not determine with absolute certainly an NBA player's salary based on this statistic analysis. What's more, I was able to learn that a player's salary is not solely based on the measurable performance stats. There are some immeasurable factors such as popularity, exposure, loyalty, and leadership which determined a player's value as well.


Based on this research, I believed that nba player's salary is determined by both personal characteristics and on-court performance. For further research, I will like to study about if signing a new contract have any incentive or effect on the player's performance which makes the player be overpaid or underpaid in the year of signing the contract? And which kind of contracts and what kind of players tend to be overpaid? In order to do that, I will introduce the on-court performance, personal characteristics and salary. Then I will build and find a connection

between them and run two regressions to analyze the determinants of salary and overpayment in the year of signing a new contract.

<<<<<<< HEAD

Conclusions

NBA players have the highest average salary among those top 5 popular professional sports. The purpose for this study was to study between NBA players' average salary and other professional sports' average salary. And identify the variables that were most likely to contribute to NBA player salaries. I found that game played and height were the two main contributors to NBA player salary. Moreover, rebounds, assists, and personal fouls were statistically significant. In regards to assists, teams may be focusing on a player's ability to contribute to scoring. In regards to rebounds, the value of a player can be enhanced if the player is able to either prevent the opponent from another scoring chance by grabbing defensive rebounds and conversely, providing additional scoring chances for his team by grabbing offensive rebounds. However, players who has a lower rebound rate tend to have a higher salary. Additionally, in the case of fouls, players who fouls a lot, tend to have a higher missed free throws. On the other hand, a player who does not accumulate fouls is definitely an asset to his team.



2b0786952a0b1fca6fc5d467978798aa0467d2b1 ##Reference: 1,NBA2017-players.csv. Retrieved from <https://github.com/ucb-stat133/stat133-fall-2017/raw/master/data/nba2017-players.csv>

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