Course 3 - Superstars in Music, Sports, and Entertainment

UCLA - Econ 19 - Fall 2018

François Geerolf

Contents

Introduction

Rosen [1981] writes:

> Performers of first rank comprise a limited handful out of these small totals and have very large incomes. There are also known to be substantial differences in income between them and those in the second rank, even though most consumers would have difficulty detecting more than minor differences in a "blind" hearing.

What Sherwin Rosen says is that there are very few differences in talents at the very top.

> The elusive quality of "box office appeal," the ability to attract an audience and generate a large volume of transactions, is the issue that must be confronted. Recognition that one's personal market scale is important, in the theory of income distribution has a long history, but the idea has not been developed very extensively in the literature.
>
> Rest assured that prospective impresarios will receive no guidance here on what makes for box office appeal, sometimes said to involve a combination of talent and charisma in uncertain proportions. In the formal model all that is taken for granted and represented by a single factor rather than by two, an index q labeled talent or quality.
>
> Albert Rees is a good introduction to the size distribution of income. The selectivity effects of differential talent and comparative advantage on the skew in income distributions are spelled out in my 1978 article, also see the references there. Melvin Reder's survey touches some of the issues raised here.
>
> Of course social scientists and statisticians have had a long standing fascination with rank-size relationships, as perusal of the many entries in the Encyclopedia of the Social Sciences will attest.

1 Statistical Distributions for Superstars

We use the methods we saw in course 2 and plot the log rank on the y axis against the log of the outcome of interest (revenues, number of views, number of sales, etc.) We show that many of these distributions associated to superstar phenomena display a Pareto-like behavior in the tail: this means that there are very many observations which deviate substantially from the mean, and that earnings and success accrue disproportionately to the very top.

1.1 Most-downloaded songs in the United Kingdom

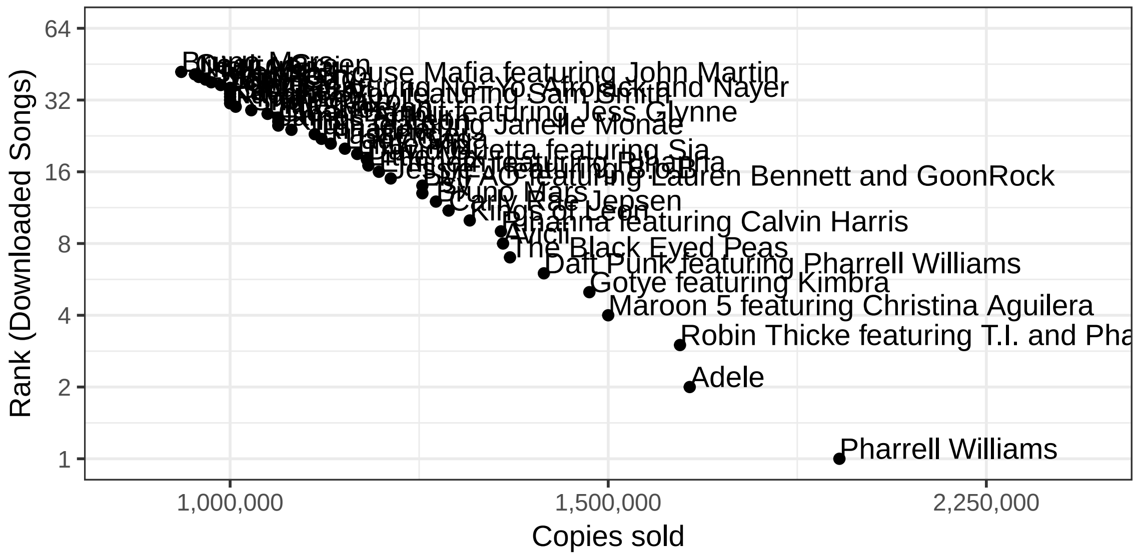
The data comes from the following Wikipedia entry: List of most-downloaded songs in the United Kingdom.

```
data <- "https://en.wikipedia.org/wiki/List_of_most-downloaded_songs_in_the_United_Kingdom" %>%
  read_html %>%
  html_table(header = TRUE, fill = TRUE)
```

```
data[[2]][, c(1, 2, 3, 7)] %>%
  as.tibble %>%
  head(10) %>%
  kable(align = "c")
```

No.	Artist	Song	Copies sold[a]
1	Pharrell Williams	"Happy"	1,922,000[3]
2	Adele	"Someone Like You"	1,637,000+[4]
3	Robin Thicke featuring T.I. and Pharrell Williams	"Blurred Lines"	1,620,000+
4	Maroon 5 featuring Christina Aguilera	"Moves Like Jagger"	1,500,000+
5	Gotye featuring Kimbra	"Somebody That I Used to Know"	1,470,000+
6	Daft Punk featuring Pharrell Williams	"Get Lucky"	1,400,000+
7	The Black Eyed Peas	"I Gotta Feeling"	1,350,000+
8	Avicii	"Wake Me Up"	1,340,000+
9	Rihanna featuring Calvin Harris	"We Found Love"	1,337,000+
10	Kings of Leon	"Sex on Fire"	1,293,000+

```
data[[2]][, c(1, 2, 3, 7)] %>%
  as.tibble %>%
  select("Artist", value = "Copies sold[a]") %>%
  mutate(value = value %>% substr(1, 9) %>% gsub(",", "", .) %>% as.numeric) %>%
  arrange(-value) %>%
  mutate(rank = 1:n()) %>%
  ggplot(aes(x = value, y = rank)) + geom_point() + theme_bw() +
  geom_text(aes(label = Artist), hjust = 0, vjust = 0) +
  scale_y_log10(breaks = 2^(seq(0, 10, 1)),
                limits = c(1, 64)) +
  scale_x_log10(breaks = c(1000000, 1500000, 2250000),
                limits = c(900000, 2500000),
                labels = comma) +
  ylab("Rank (Downloaded Songs)") + xlab("Copies sold")
```



1.2 Most-streamed songs on Spotify

The data comes from the following Wikipedia entry: List of most-streamed songs on Spotify.

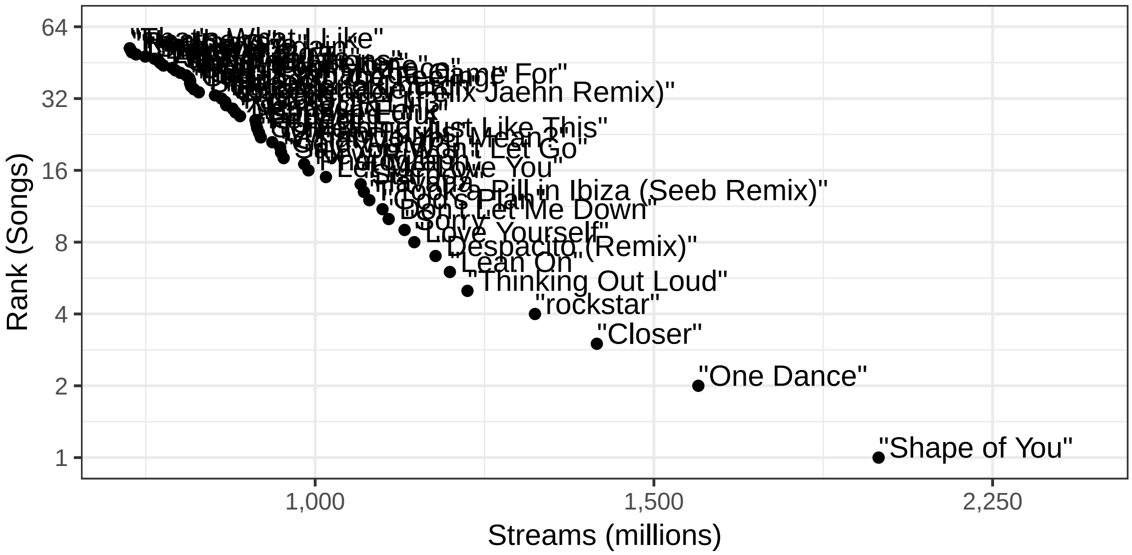
```
data <- "https://en.wikipedia.org/wiki/List_of_most-streamed_songs_on_Spotify" %>%
  read_html %>%
  html_table(header = TRUE, fill = TRUE)
```

```
data[[1]][, c(1, 2, 5, 6)] %>%
  rename(song = "Song name", value = "Streams(millions)", date = "Date published") %>%
  as.tibble %>%
  head(10) %>%
  kable(align = "c")
```

Rank	song	value	date
1.	“Shape of You”	1,963	6 January, 2017
2.	“One Dance”	1,582	5 April, 2016
3.	“Closer”	1,401	29 July, 2016
4.	“rockstar”	1,301	15 September, 2017
5.	“Thinking Out Loud”	1,200	21 June, 2014
6.	“Lean On”	1,175	2 March, 2015
7.	“Despacito (Remix)”	1,155	17 April, 2017
8.	“Love Yourself”	1,126	9 November, 2015
9.	“Sorry”	1,113	23 October, 2015
10.	“Don’t Let Me Down”	1,092	5 February, 2016

```
data[[1]] %>%
  as.tibble %>%
  select(song = "Song name", value = "Streams(millions)") %>%
  mutate(value = value %>% substr(1, 9) %>% gsub(",", "", .) %>% as.numeric) %>%
  arrange(-value) %>%
  mutate(rank = 1:n()) %>%
  ggplot(aes(x = value, y = rank, label = song)) + geom_point() + theme_bw() +
  geom_text(aes(label = song), hjust = 0, vjust = 0) +
```

```r
  scale_y_log10(breaks = 2^(seq(0, 10, 1)),
                limits = c(1, 64)) +
  scale_x_log10(breaks = c(1000, 1500, 2250),
                limits = c(800, 2500),
                labels = comma) +
  ylab("Rank (Songs)") + xlab("Streams (millions)")
```



1.3 Most-viewed YouTube videos

The data comes from the following Wikipedia entry: List of most-viewed YouTube videos.

```r
data <- "https://en.wikipedia.org/wiki/List_of_most-viewed_YouTube_videos" %>%
  read_html %>%
  html_table(header = TRUE, fill = TRUE)
```

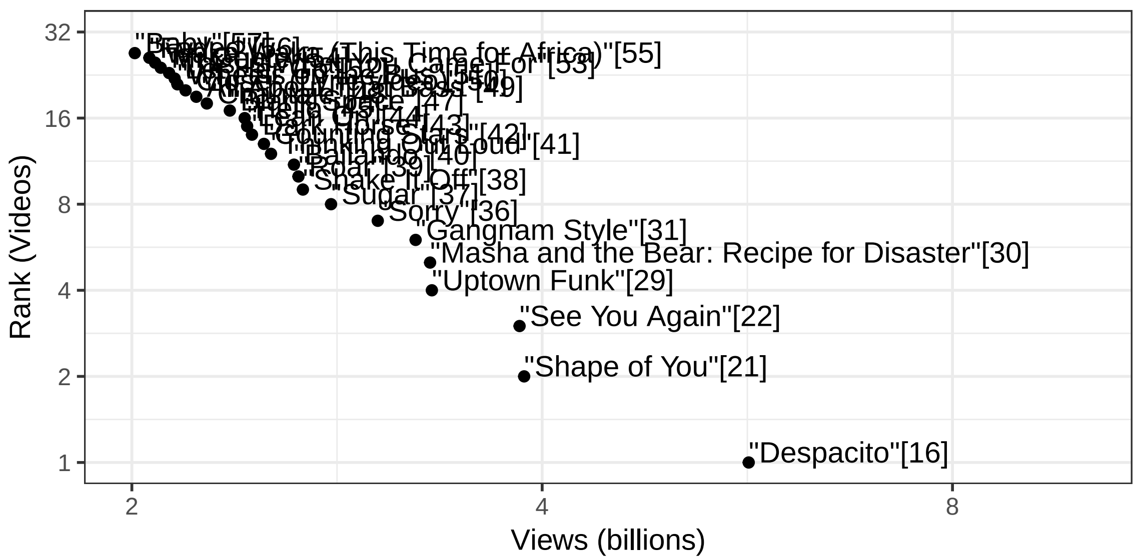
We then display the first rows of the data:

```r
data[[1]][, c(1, 2, 4)] %>%
  as.tibble %>%
  rename(video = "Video name", value = "Views (billions)") %>%
  head(10) %>%
  kable(align = "c")
```

#	video	value
1.	“Despacito”[16]	5.67
2.	“Shape of You”[21]	3.88
3.	“See You Again”[22]	3.85
4.	“Uptown Funk”[29]	3.32
5.	“Masha and the Bear: Recipe for Disaster”[30]	3.31
6.	“Gangnam Style”[31]	3.23
7.	“Sorry”[36]	3.03
8.	“Sugar”[37]	2.80
9.	“Shake It Off”[38]	2.67
10.	“Roar”[39]	2.65

The first 100 top Youtube videos have been seen a couple **billion** times:
- Luis Fonsi - Despacito ft. Daddy Yankee: 5.7 Billion
- Ed Sheeran - Shape of You: 3.88 Billion
- Wiz Khalifa - See You Again ft. Charlie Puth: 3.84 Billion
- etc.

```
data[[1]][, c(1, 2, 4)] %>%
  as.tibble %>%
  select(video = "Video name", value = "Views (billions)") %>%
  mutate(value = value %>% substr(1, 9) %>% gsub(",", "", .) %>% as.numeric) %>%
  arrange(-value) %>%
  mutate(rank = 1:n()) %>%
  ggplot(aes(x = value, y = rank)) + geom_point() + theme_bw() +
  geom_text(aes(label = video), hjust = 0, vjust = 0) +
  scale_y_log10(breaks = 2^(seq(0, 10, 1)),
                limits = c(1, 32)) +
  scale_x_log10(breaks = c(2, 4, 8),
                limits = c(2, 10),
                labels = comma) +
  ylab("Rank (Videos)") + xlab("Views (billions)")
```



1.4 Highest paid American television stars

The data comes from the following Wikipedia entry: List of highest paid American television stars.

Network primetime salaries per episode

```
data <- "https://en.wikipedia.org/wiki/List_of_highest_paid_American_television_stars" %>%
  read_html %>%
  html_table(header = TRUE, fill = TRUE)
```

We then display the first rows of the data:

```
data[[1]][, c(1, 2, 3, 4)] %>%
  as.tibble %>%
  head(10) %>%
  kable(align = "c")
```

Name	Program	Role	Salary
Peter Dinklage	Game of Thrones	Tyrion Lannister	£2,000,000[a]
Nikolaj Coster-Waldau	Game of Thrones	Jaime Lannister	£2,000,000[a]
Lena Headey	Game of Thrones	Cersei Lannister	£2,000,000[a]
Emilia Clarke	Game of Thrones	Daenerys Targaryen	£2,000,000[a]
Kit Harington	Game of Thrones	Jon Snow	£2,000,000[a]
Charlie Sheen	Two and a Half Men	Charlie Harper	$1.8 million
Ray Romano	Everybody Loves Raymond	Raymond Barone	$1.7 million
Kelsey Grammer	Frasier	Frasier Crane	$1.6 million
Tim Allen	Home Improvement	Tim Taylor	$1.25 million
James Gandolfini	The Sopranos	Tony Soprano	$1 million

1.5 Highest grossing concert tours

The data comes from the following Wikipedia entry: List of highest-grossing concert tours. We first input the data from the Wikipedia page, using the `rvest` package to extract tables from the html source code:

```
data <- "https://en.wikipedia.org/wiki/List_of_highest-grossing_concert_tours" %>%
  read_html %>%
  html_table(header = TRUE, fill = TRUE)
```

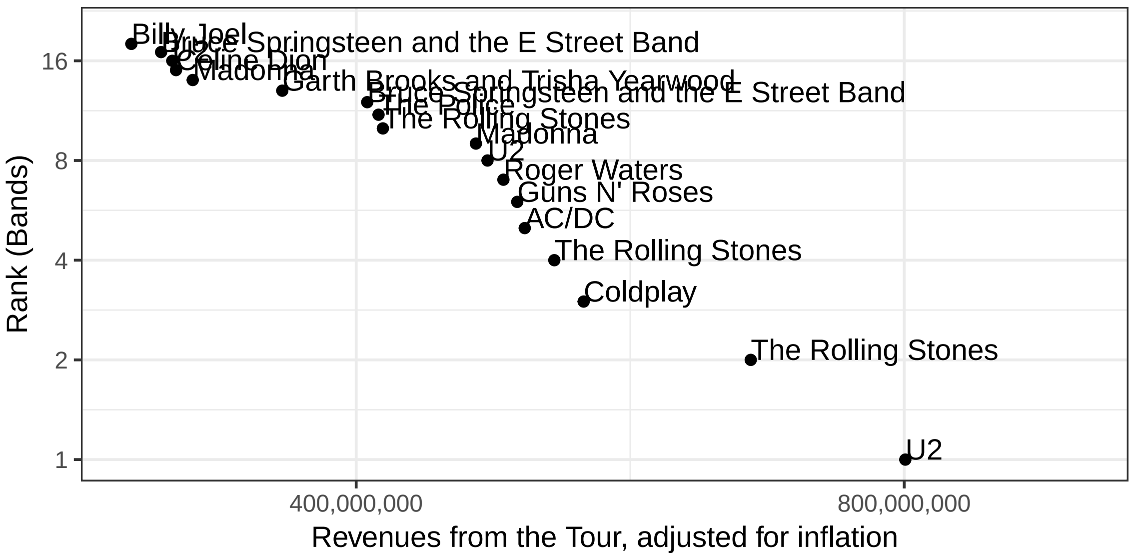
We then display the first rows of the data:

```
data[[1]][, c(1, 2, 3, 4)] %>%
  rename(`Gross Infl Adj` = "Gross adjusted for inflation(2018 $)") %>%
  as.tibble %>%
  head(10) %>%
  kable(align = "c")
```

Rank	Actual gross	Gross Infl Adj	Artist
1	$736,421,584	$801,130,818	U2
2	$558,255,524	$658,868,741	The Rolling Stones
3	$523,033,675	$533,331,898	Coldplay
4	$480,900,000	$490,368,636	Guns N' Roses
5	$458,673,798	$481,869,587	Roger Waters
6	$441,121,000	$495,041,025	AC/DC
7	$408,000,000	$465,399,721	Madonna
8	$389,047,636	$472,277,371	U2
9	$364,300,000	$364,300,000	Garth Brooks and Trisha Yearwood
10	$362,000,000	$411,460,278	The Police

```
data[[1]][, c(1, 2, 3, 4)] %>%
  as.tibble %>%
  rename(gross = "Gross adjusted for inflation(2018 $)") %>%
  mutate(gross = gross %>% substr(2, 13) %>% gsub(",", "", .) %>% as.numeric) %>%
  arrange(-gross) %>%
  mutate(rank = 1:n()) %>%
  ggplot(aes(x = gross, y = rank, label = Artist)) + geom_point() + theme_bw() +
  geom_text(aes(label = Artist), hjust = 0, vjust = 0) +
  scale_y_log10(breaks = 2^(seq(0, 10, 1))) +
  scale_x_log10(breaks = 10^8*c(2, 4, 8),
                limits= c(3*10^8, 10^9),
```

```
                     labels = comma) +
  ylab("Rank (Bands)") + xlab("Revenues from the Tour, adjusted for inflation")
```



1.6 Highest paid film actors

The data comes from the following Wikipedia entry: List of highest paid film actors. We first input the data from the Wikipedia page, using the `rvest` package to extract tables from the html source code:

```
data <- "https://en.wikipedia.org/wiki/List_of_highest_paid_film_actors" %>%
  read_html %>%
  html_table(header = TRUE, fill = TRUE)
```

We then display the first rows of the data:

```
data[[1]] %>%
  select(-Ref) %>%
  as.tibble %>%
  head(15) %>%
  kable(align = "c")
```

Actor	Film	Year	Salary	Total income
Keanu Reeves	The Matrix ReloadedThe Matrix Revolutions	2003	$30,000,000	$156,000,000
Bruce Willis	The Sixth Sense	1999	$14,000,000	$100,000,000
Tom Cruise	Mission: Impossible 2	2000		$100,000,000
Tom Cruise	War of the Worlds	2005		$100,000,000
Will Smith	Men in Black 3	2012		$100,000,000
Robert Downey, Jr.	Iron Man 3	2013		$75,000,000
Sandra Bullock	Gravity	2013	$20,000,000	$70,000,000+
Tom Hanks	Forrest Gump	1994		$70,000,000
Tom Cruise	Mission: Impossible	1996		$70,000,000
Harrison Ford	Indiana Jones and the Kingdom of the Crystal Skull	2008		$65,000,000
Jack Nicholson	Batman	1989	$6,000,000	$60,000,000
Leonardo DiCaprio	Inception	2010		$59,000,000
Robert Downey, Jr.	Captain America: Civil War	2014	$40,000,000	$40,000,000+
Robert Downey, Jr.	Avengers: Age of Ultron	2014		$40,000,000

Actor	Film	Year	Salary	Total income
Johnny Depp	Pirates of the Caribbean: On Stranger Tides	2011	$35,000,000	$55,000,000

1.7 Largest sports contracts

The data comes from the following Wikipedia entry: List of largest sports contracts.

```
data <- "https://en.wikipedia.org/wiki/List_of_largest_sports_contracts" %>%
  read_html %>%
  html_table(header = TRUE, fill = TRUE)
```

We then display the first rows of the data:

```
data[[1]] %>%
  select(Player, Sport, length = "Length of contract" , value = "Contract value (USD)") %>%
  as.tibble %>%
  head(10) %>%
  kable(align = "c")
```

Player	Sport	length	value
Canelo Álvarez	Boxing	5 years (2018–2023)	$365,000,000
Giancarlo Stanton	Baseball	13 years (2014–2027)	$325,000,000
Alex Rodriguez1R	Baseball	10 years (2008–2017)	$275,000,000
Alex Rodriguez2R	Baseball	10 years (2001–2010)	$252,000,000
Miguel Cabrera	Baseball	8 years (2016–2023)	$247,000,000
Robinson Cano	Baseball	10 years (2014–2023)	$240,000,000
Albert Pujols	Baseball	10 years (2012–2021)	$240,000,000
James Harden	Basketball	6 years (2017–2023)	$228,000,000
Joey Votto	Baseball	10 years (2014–2024)	$225,000,000
David Price	Baseball	7 years (2016–2022)	$217,000,000

2 Other examples

2.1 Billionaires from Forbes

Preparing the data from the Forbes Website.

```
page <- readLines("https://www.forbes.com/sites/chasewithorn/2015/03/02/forbes-billionaires-full-list-o

forbes.top.wealth <- cbind(grep("B</p>", page, value = TRUE),
                           grep("<p><strong>", page, value = TRUE),
                           grep("<p>Source of wealth:", page, value = TRUE)) %>%
  as.data.frame %>%
  select(billionaire = V2, wealth = V1, source = V3) %>%
  mutate_all(paste) %>%
  mutate(source = source %>%
           gsub("<p>Source of wealth: ", "", .) %>%
           gsub("</p>", "", .) %>%
           gsub("&amp;amp;", "&", .),
         wealth = wealth %>%
           gsub("<p>Net Worth: ", "", .) %>%
```

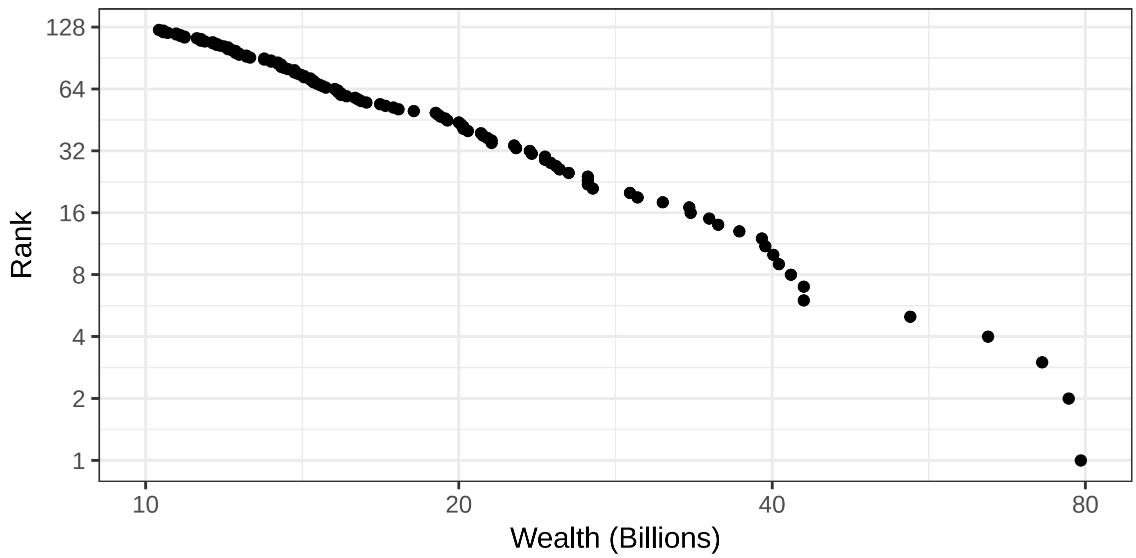
```
           gsub("</p>", "", .) %>%
           gsub(" B", "", .) %>%
           substr(., 2, nchar(.)) %>%
           as.numeric,
         billionaire = billionaire %>%
           gsub("<p><strong>", "", .) %>%
           gsub("</strong></p>", "", .) %>%
           gsub("&amp;amp;", "&", .))
```

The first 25 billionaires are:

```
forbes.top.wealth %>%
  rename(Bilionaire = billionaire) %>%
  as.tibble %>%
  head(25) %>%
  kable(align = "c")
```

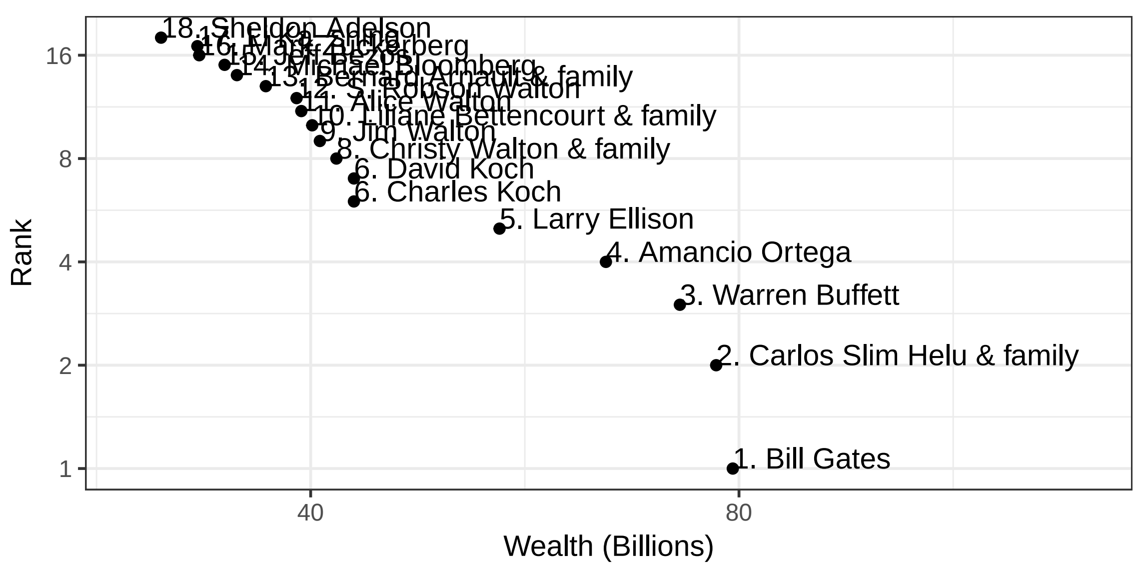
Bilionaire	wealth	source
1. Bill Gates	79.2	Microsoft
2. Carlos Slim Helu & family	77.1	telecom
3. Warren Buffett	72.7	Berkshire Hathaway
4. Amancio Ortega	64.5	Zara
5. Larry Ellison	54.3	Oracle
6. Charles Koch	42.9	diversified
6. David Koch	42.9	diversified
8. Christy Walton & family	41.7	Wal-Mart
9. Jim Walton	40.6	Wal-Mart
10. Liliane Bettencourt & family	40.1	L'Oreal
11. Alice Walton	39.4	Wal-Mart
12. S. Robson Walton	39.1	Wal-Mart
13. Bernard Arnault & family	37.2	LVMH
14. Michael Bloomberg	35.5	Bloomberg LP
15. Jeff Bezos	34.8	Amazon.com
16. Mark Zuckerberg	33.4	Facebook
17. Li Ka-shing	33.3	diversified
18. Sheldon Adelson	31.4	casinos
19. Larry Page	29.7	Google
20. Sergey Brin	29.2	Google
21. Georg Schaeffler	26.9	ball bearings
22. Forrest Mars Jr	26.6	candy
22. Jacqueline Mars	26.6	candy
22. John Mars	26.6	candy
25. David Thomson & family	25.5	media

```
forbes.top.wealth %>%
  rename(name = billionaire) %>%
  filter(wealth >= 10) %>%
  mutate(rank = 1:n()) %>%
  ggplot(aes(x = wealth, y = rank, label = name)) + geom_point() + theme_bw() +
  scale_y_log10(breaks = 2^(seq(0, 14, 1))) +
  scale_x_log10(breaks = c(10, 20, 40, 80),
                limits= c(10, 80)) +
  ylab("Rank") + xlab("Wealth (Billions)")
```



The Pareto distribution does not work very well for the very top (Bill Gates is not rich enough!)

```
forbes.top.wealth %>%
  rename(name = billionaire) %>%
  filter(wealth >= 30) %>%
  mutate(rank = 1:n()) %>%
  ggplot(aes(x = wealth, y = rank, label = name)) + geom_point() + theme_bw() +
  geom_text(aes(label = name), hjust = 0, vjust = 0) +
  scale_y_log10(breaks = 2^(seq(0, 14, 1))) +
  scale_x_log10(breaks = c(10, 20, 40, 80, 160),
                limits = c(30, 140)) +
  ylab("Rank") + xlab("Wealth (Billions)")
```



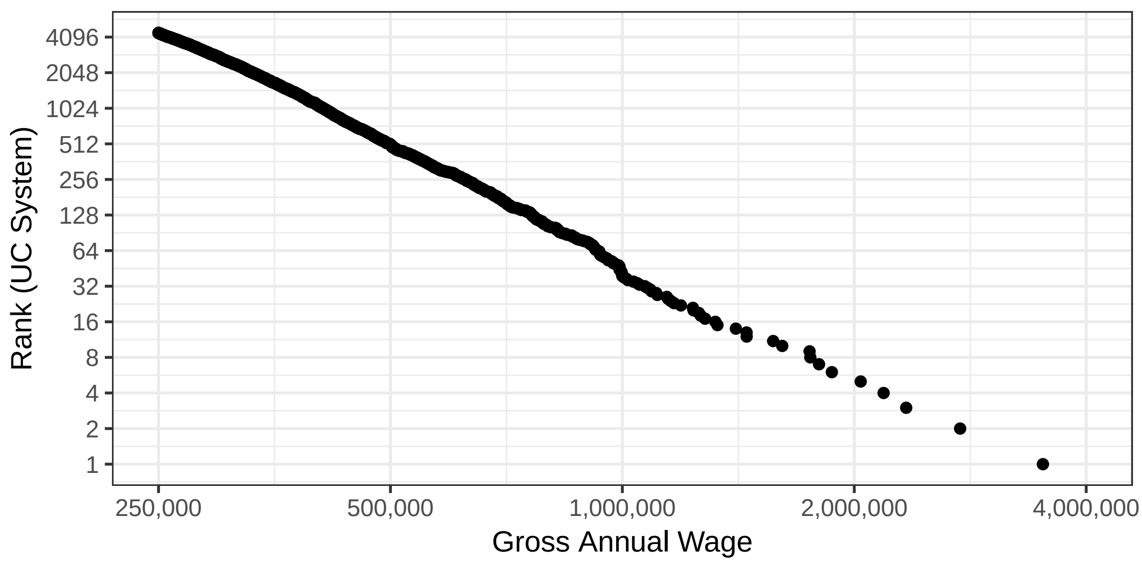
2.2 Salaries at the University of California (UC)

The salaries at the University of California are public and available at this website: https://ucannualwage.ucop.edu/wage/

```
ucop.2015 <- read.csv("https://raw.githubusercontent.com/raleighlittles/UC-Employee-Salaries/master/UCO
  # use clean_names() from janitor package
  clean_names() %>%
  mutate_all(. %>% paste %>% gsub("'", "", .)) %>%
  mutate_at(vars(ends_with("pay")), funs(as.numeric)) %>%
  arrange(-x_gross_pay) %>%
  mutate(rank = 1:n())
```

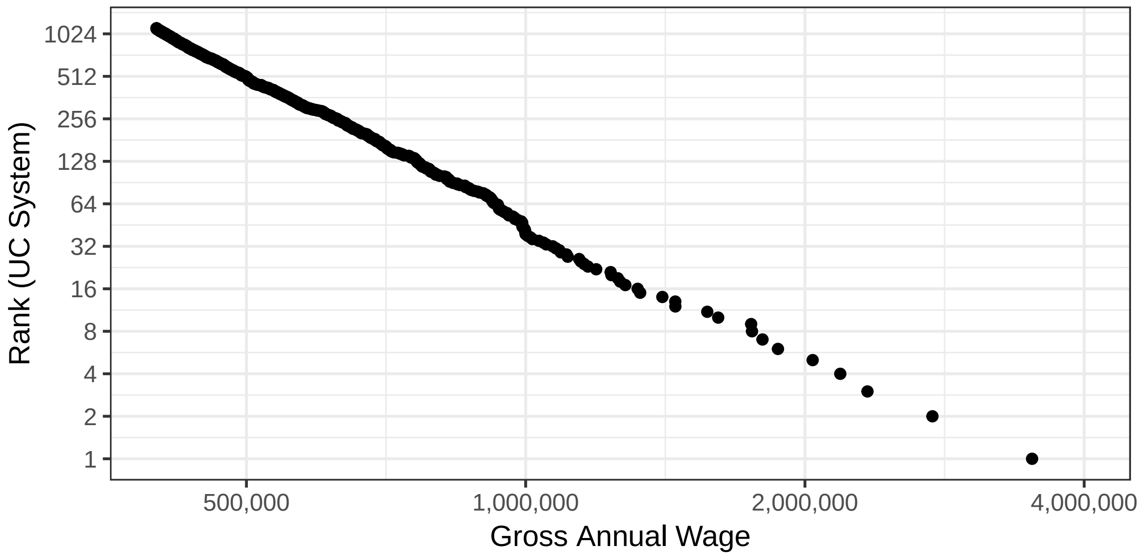
The distribution in the tail at the University of California is really well approximated by a Pareto distribution. Below is the plot of wages higher than $250K.

```
ucop.2015 %>%
  rename(gross = x_gross_pay, name = x_last_name) %>%
  filter(gross >= 250000) %>%
  ggplot(aes(x = gross, y = rank, label = name)) + geom_point() + theme_bw() +
  scale_y_log10(breaks = 2^(seq(0, 14, 1))) +
  scale_x_log10(breaks = c(250000, 500000, 1000000, 2000000, 4000000),
                limits= c(250000, 4000000),
                labels = comma) +
  ylab("Rank (UC System)") + xlab("Gross Annual Wage")
```



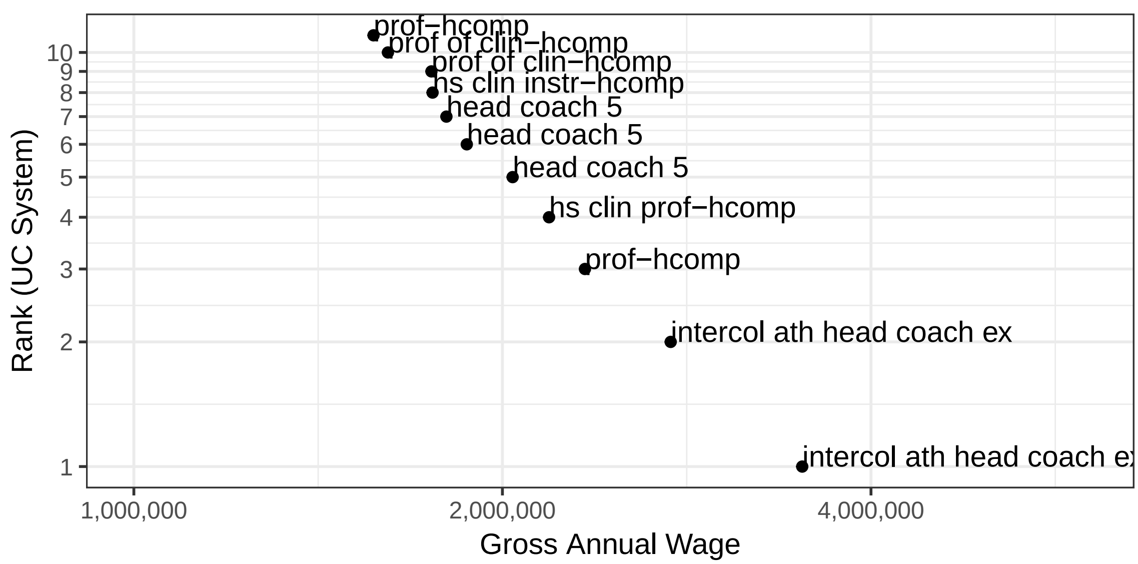
The distribution in the tail at the University of California is really well approximated by a Pareto distribution. Below is the plot of wages higher than $400K.

```
ucop.2015 %>%
  rename(gross = x_gross_pay, name = x_last_name) %>%
  filter(gross >= 400000) %>%
  ggplot(aes(x = gross, y = rank, label = name)) + geom_point() + theme_bw() +
  scale_y_log10(breaks = 2^(seq(0, 10, 1))) +
  scale_x_log10(breaks = c(500000, 1000000, 2000000, 4000000),
                limits= c(400000, 4000000),
                labels = comma) +
  ylab("Rank (UC System)") + xlab("Gross Annual Wage")
```



Below is a zoom on the distribution of wages higher than 1.5 million annual. You can see that the highest paid superstars on campus are the Head Coaches, and superstar physicians. Again, it is striking that these distributions are very well approximated by a Pareto distribution.

```
ucop.2015 %>%
  rename(gross = x_gross_pay, name = x_title) %>%
  mutate(name = tolower(name)) %>%
  filter(gross >= 1500000) %>%
  ggplot(aes(x = gross, y = rank, label = name)) + geom_point() + theme_bw() +
  geom_text(aes(label = name), hjust = 0, vjust = 0) +
  scale_y_log10(breaks = seq(1, 10, 1)) +
  scale_x_log10(breaks = c(1000000, 2000000, 4000000),
                limits= c(1000000, 6000000),
                labels = comma) +
  ylab("Rank (UC System)") + xlab("Gross Annual Wage")
```



2.3 Market for Executive Officers in large firms

Again, from Sherwin Rosen:

> Such considerations are important for understanding the market for executive officers in large firms. Unusually good information on executive compensation is available from public proxy statements circulated to stockholders by requirement of the Securities and Exchange Commission. Examination of these statements is instructive. They reveal Superstar-scale rewards that are highly concentrated among the top half-dozen executives in these firms. More detailed study indicates that the top incomes vary systematically with the size of the organization. Large firms pay executives more than smaller firms do. Even the occasional, well-publicized dollar-a-year man falls in line once stock options, pensions, and other forms of deferred compensation are properly accounted. The value to the organization of good top-level decisions and avoidance of bad decisions is abundantly clear once the nature of control of resources on such a vast scale is considered.
>
> Common use of the term Officer for corporate executives Suggests certain parallels with the military. A good or bad decision by a platoon leader does not have much effect on the overall fortunes of war, but the same cannot be said of decisions made by the chief strategists. The value of extra talent is much larger at the top of the organizational hierarchy than at the bottom because those decisions percolate through the enterprise, and they have much further to travel in a larger enterprise than in a smaller one.

References

Sherwin Rosen. The Economics of Superstars. *The American Economic Review*, 71(5):845–858, 1981. ISSN 0002-8282. URL http://www.jstor.org/stable/1803469.