Course 3 - Superstars in Music, Sports, and Entertainment

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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 Pareto Distributions

1.1 Highest grossing concert tours

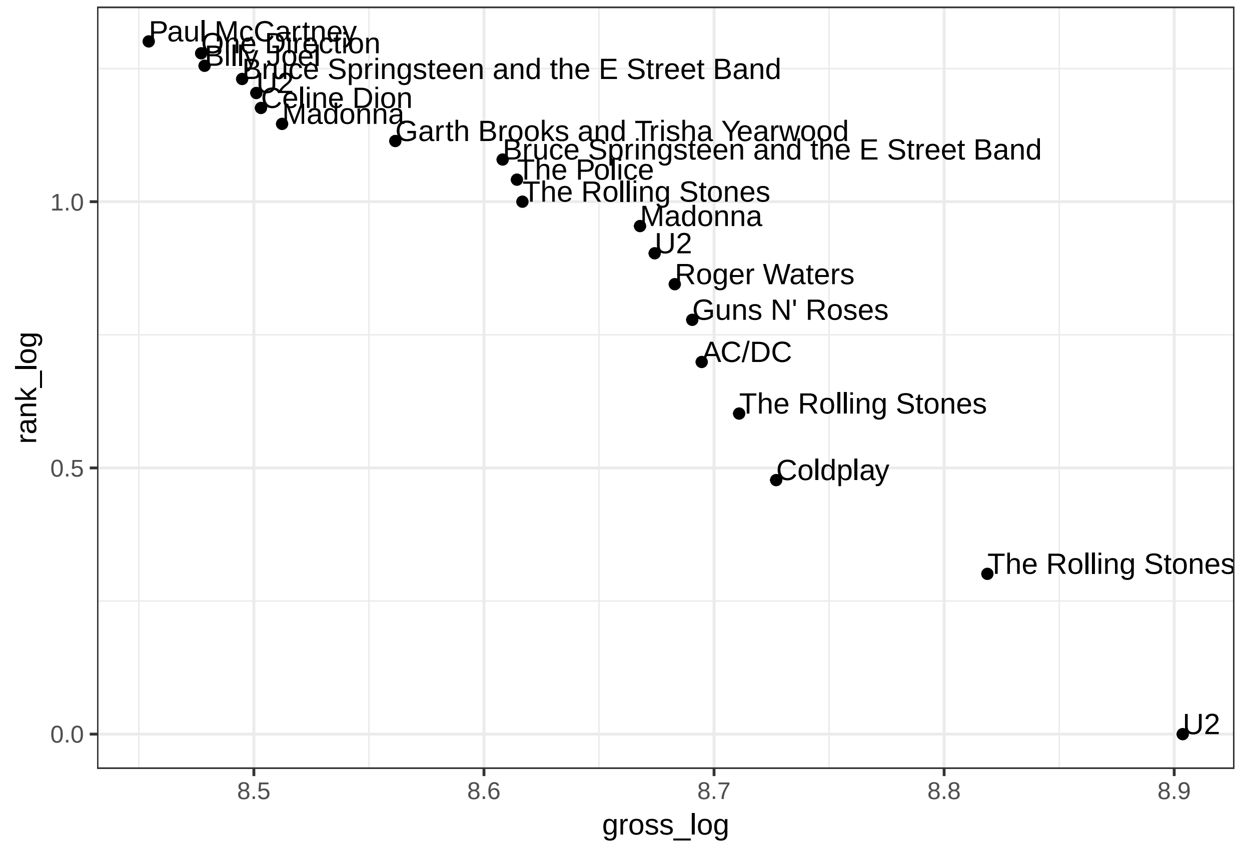
The data comes from the following Wikipedia entry: List of highest-grossing concert tours.

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

data[[1]][, c(1, 2, 3, 4)] %>%
  as.tibble
```

```
## # A tibble: 20 x 4
##     Rank `Actual gross` `Gross adjusted for inflat~ Artist
##    <int> <chr>          <chr>                       <chr>
##  1     1 $736,421,584   $801,130,818                U2
##  2     2 $558,255,524   $658,868,741                The Rolling Stones
##  3     3 $523,033,675   $533,331,898                Coldplay
##  4     4 $480,900,000   $490,368,636                Guns N' Roses
##  5     5 $458,673,798   $481,869,587                Roger Waters
##  6     6 $441,121,000   $495,041,025                AC/DC
##  7     7 $408,000,000   $465,399,721                Madonna
##  8     8 $389,047,636   $472,277,371                U2
##  9     9 $364,300,000   $364,300,000                Garth Brooks and Tris~
## 10    10 $362,000,000   $411,460,278                The Police
## 11    11 $355,600,000   $405,627,796                Bruce Springsteen and~
## 12    12 $320,000,000   $513,928,805                The Rolling Stones
## 13    13 $316,990,940   $316,990,940                U2
## 14    14 $311,000,000   $413,729,016                The Rolling Stones
## 15    15 $306,500,000   $312,534,803                Bruce Springsteen and~
## 16    16 $305,158,363   $325,284,041                Madonna
## 17    17 $301,000,000   $301,000,000                Billy Joel
## 18    18 $290,178,452   $299,967,998                One Direction
## 19    19 $279,200,000   $318,479,417                Celine Dion
## 20    20 $275,700,000   $284,640,994                Paul McCartney
```

```
data[[1]][, c(1, 2, 3, 4)] %>%
  as.tibble %>%
  select(gross = "Gross adjusted for inflation(2018 $)", "Artist") %>%
  mutate(gross = gross %>% substr(2, 13) %>% gsub(",", "", .) %>% as.numeric) %>%
  arrange(-gross) %>%
  mutate(rank = 1:n()) %>%
  mutate(rank_log = log10(rank),
         gross_log =log10(gross)) %>%
  ggplot(aes(x = gross_log, y = rank_log, label = Artist)) + geom_point() + theme_bw() +
  geom_text(aes(label = Artist), hjust = 0, vjust = 0)
```



1.2 Most-downloaded songs in the United Kingdom

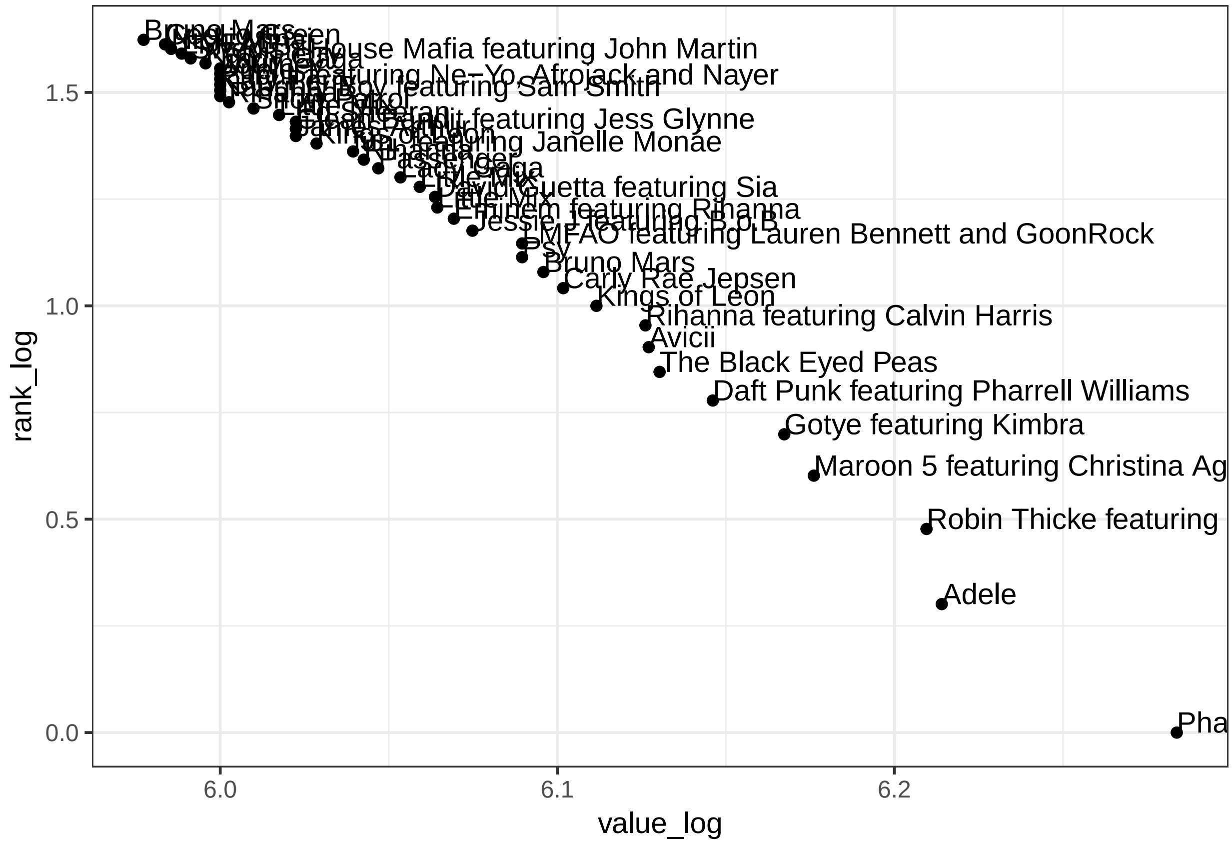
The data comes from the following Wikipedia entry: List of most-downloaded songs in the United Kingdom.

```
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
```

```
## # A tibble: 42 x 4
##      No. Artist                       Song                `Copies sold[a]`
##    <int> <chr>                        <chr>               <chr>
##  1     1 Pharrell Williams            "\"Happy\""         1,922,000[3]
##  2     2 Adele                        "\"Someone Like Yo~ 1,637,000+[4]
##  3     3 Robin Thicke featuring T.I.~ "\"Blurred Lines\"" 1,620,000+
##  4     4 Maroon 5 featuring Christin~ "\"Moves Like Jagg~ 1,500,000+
##  5     5 Gotye featuring Kimbra       "\"Somebody That I~ 1,470,000+
##  6     6 Daft Punk featuring Pharrel~ "\"Get Lucky\""     1,400,000+
##  7     7 The Black Eyed Peas          "\"I Gotta Feeling~ 1,350,000+
##  8     8 Avicii                       "\"Wake Me Up\""    1,340,000+
##  9     9 Rihanna featuring Calvin Ha~ "\"We Found Love\"" 1,337,000+
## 10    10 Kings of Leon                "\"Sex on Fire\""   1,293,000+
## # ... with 32 more rows
```

```
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()) %>%
  mutate(rank_log = log10(rank),
         value_log =log10(value)) %>%
  ggplot(aes(x = value_log, y = rank_log, label = Artist)) + geom_point() + theme_bw() +
  geom_text(aes(label = Artist), hjust = 0, vjust = 0)
```



1.3 Most-streamed songs on Spotify

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

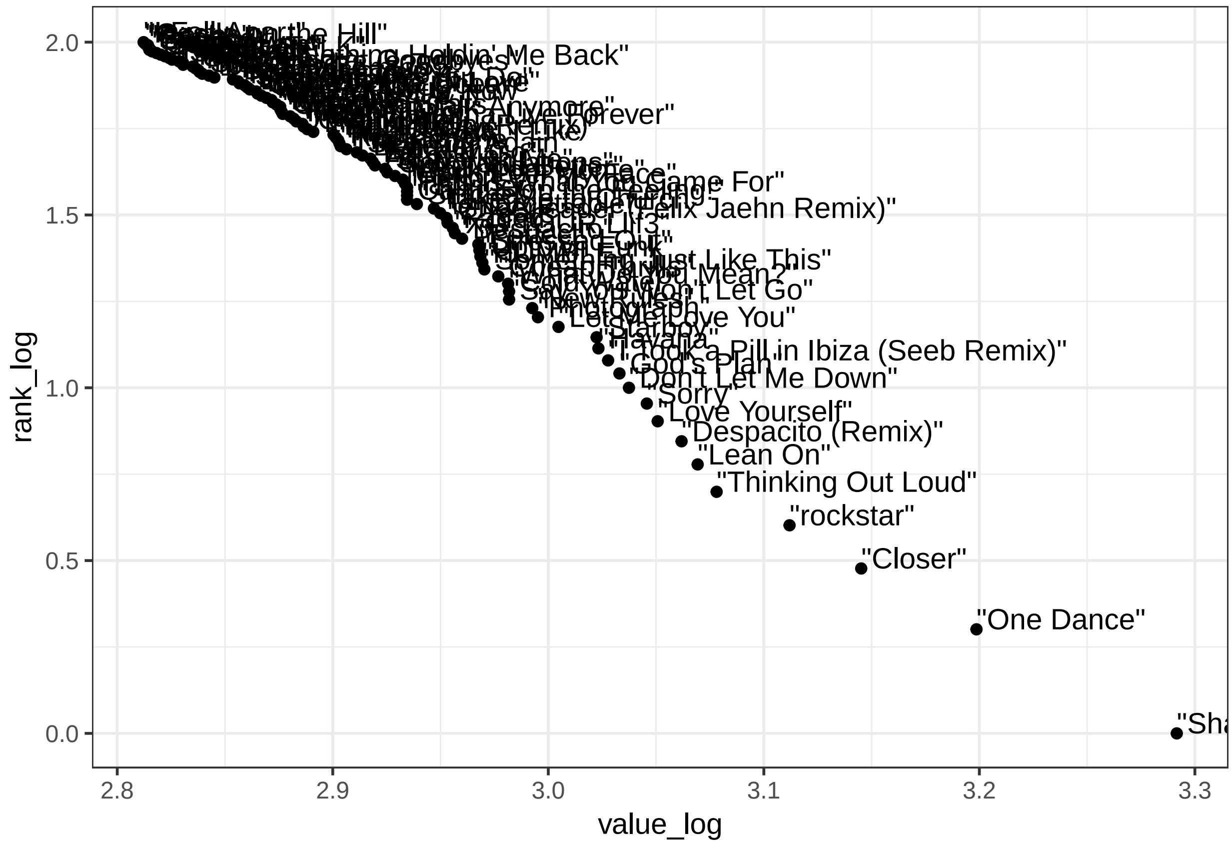
```
data <- "https://en.wikipedia.org/wiki/List_of_most-streamed_songs_on_Spotify" %>%
  read_html %>%
  html_table(header = TRUE, fill = TRUE)

data[[1]][, c(1, 2, 5, 6)] %>%
  as.tibble
```

```
## # A tibble: 101 x 4
##    Rank  `Song name`            `Streams(millions)` `Date published`
##    <chr> <chr>                  <chr>               <chr>
##  1 1.    "\"Shape of You\""     1,957               6 January, 2017
```

```
##   2 2.    "\"One Dance\""         1,580               5 April, 2016
##   3 3.    "\"Closer\""            1,397               29 July, 2016
##   4 4.    "\"rockstar\""          1,294               15 September, 2017
##   5 5.    "\"Thinking Out Loud\"" 1,197               21 June, 2014
##   6 6.    "\"Lean On\""           1,173               2 March, 2015
##   7 7.    "\"Despacito (Remix)\"" 1,153               17 April, 2017
##   8 8.    "\"Love Yourself\""     1,124               9 November, 2015
##   9 9.    "\"Sorry\""             1,111               23 October, 2015
##  10 10.   "\"Don't Let Me Down\"" 1,090               5 February, 2016
## # ... with 91 more rows
```

```
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()) %>%
  mutate(rank_log = log10(rank),
         value_log =log10(value)) %>%
  ggplot(aes(x = value_log, y = rank_log, label = song)) + geom_point() + theme_bw() +
  geom_text(aes(label = song), hjust = 0, vjust = 0)
```



1.4 Most-viewed YouTube videos

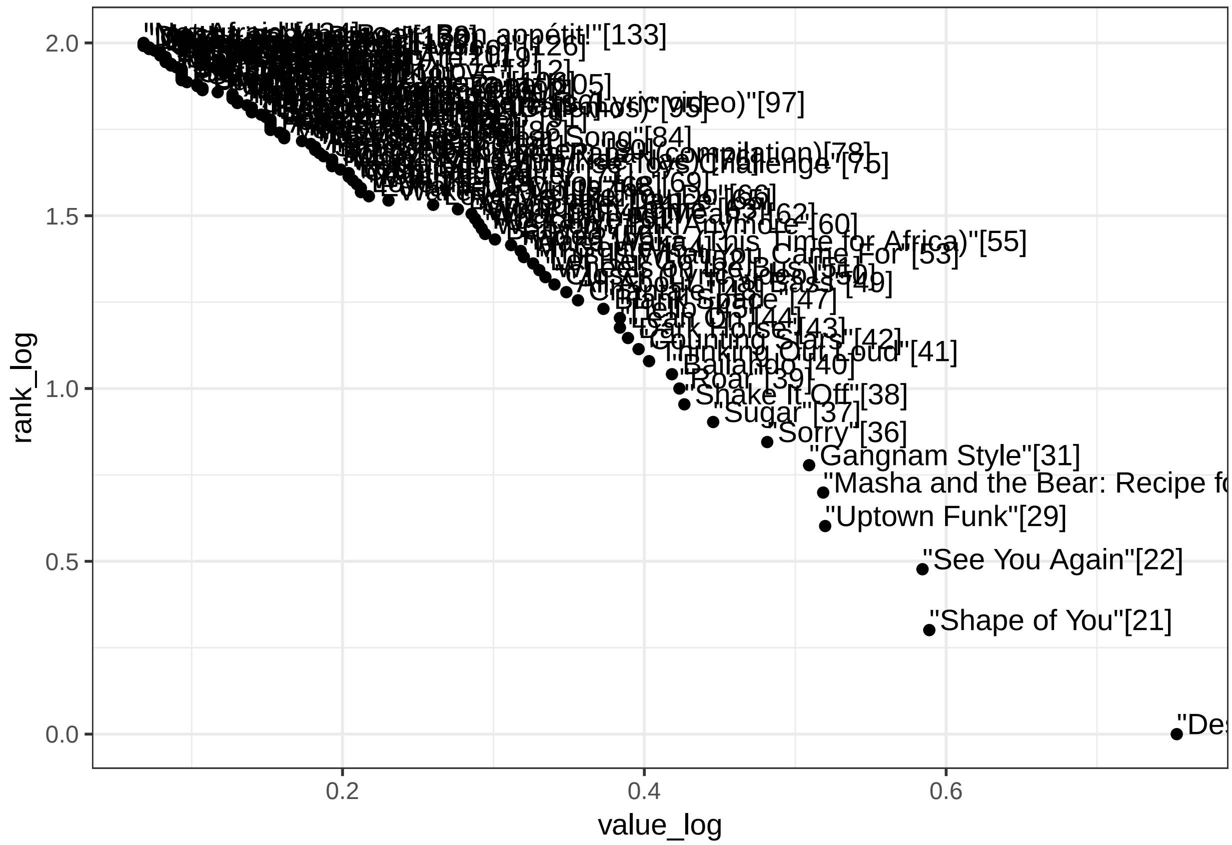
The data comes from the following Wikipedia entry: List of most-viewed YouTube videos.

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

data[[1]][, c(1, 2, 4)] %>%
  as.tibble
```

```
## # A tibble: 101 x 3
##    `#`   `Video name`                                 `Views (billions~
##    <chr> <chr>                                        <chr>
##  1 1.    "\"Despacito\"[16]"                          5.66
##  2 2.    "\"Shape of You\"[21]"                       3.88
##  3 3.    "\"See You Again\"[22]"                      3.84
##  4 4.    "\"Uptown Funk\"[29]"                        3.31
##  5 5.    "\"Masha and the Bear: Recipe for Disaster\"[3~ 3.30
##  6 6.    "\"Gangnam Style\"[31]"                      3.23
##  7 7.    "\"Sorry\"[36]"                              3.03
##  8 8.    "\"Sugar\"[37]"                              2.79
##  9 9.    "\"Shake It Off\"[38]"                       2.67
## 10 10.   "\"Roar\"[39]"                               2.65
## # ... with 91 more rows
```

```
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()) %>%
  mutate(rank_log = log10(rank),
         value_log =log10(value)) %>%
  ggplot(aes(x = value_log, y = rank_log, label = video)) + geom_point() + theme_bw() +
  geom_text(aes(label = video), hjust = 0, vjust = 0)
```



2 Other examples

2.1 Salaries at the University of California (UC)

https://raw.githubusercontent.com/raleighlittles/UC-Employee-Salaries/master/UCOP%20Database_2017.txt

These salaries are public

```
ucop.2015 <- read.csv("https://raw.githubusercontent.com/raleighlittles/UC-Employee-Salaries/master/UCOP
```

2.2 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.

2.3 Ed Sheeran's advice

On Charlie Rose:

https://www.youtube.com/watch?v=DIJs8091ipY

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.