

will-v-denzel raw

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12/10/2020

```
library(stringr)
library(rvest)

## Loading required package: xml2

grabFilmInfoFromFilmsPage = function(page)
{
  # 50 elements
  # # title = id = rank = year = rating = minutes = genre = votes = metascore = desc = millions

  movies = page %>%
    html_nodes(".mode-detail");

  pagecount = length(movies);

  result = data.frame(
    matrix(ncol = 11,nrow = pagecount) );
  # a matrix-type form with lots of NA values ...

  colnames(result) = c("rank", "title", "ttid", "year", "rated", "minutes", "genre", "ratings", "metaa", "desc", "millions");

  for(i in 1:pagecount)
  {
    movie = movies[i];

    rank = movie %>%
      html_node(".list-item-index") %>%
      html_text() %>%
      as.numeric();
    result$rank[i] = rank;

    title = movie %>%
      html_node(".list-item-header a") %>%
      html_text();
    result$title[i] = title;

    ttid = movie %>%
      html_node(".list-item-header a") %>%
      html_attr("href");

    temp = strsplit(ttid,"/",fixed=T);
```

```

ttid = temp[[1]][3];
result$ttid[i] = ttid;

year = movie %>%
  html_node(".lister-item-year") %>%
  html_text();
year = cleanupYear(year);
result$year[i] = year;

rated = movie %>%
  html_node(".certificate") %>%
  html_text();
result$rated[i] = rated;

minutes = movie %>%
  html_node(".runtime") %>%
  html_text();
minutes = cleanupMinutes(minutes);
result$minutes[i] = minutes;

genre = movie %>%
  html_node(".genre") %>%
  html_text();
genre = str_trim(genre);
result$genre[i] = genre;

ratings = movie %>%
  html_node("div .rating-list") %>%
  html_attr("title");
  temp = strsplit(ratings, "/", fixed=T);
  temp = gsub("Users rated this", "", temp[[1]][1], fixed=T);
  temp = str_trim(temp);
ratings = as.numeric(temp);
result$ratings[i] = ratings;

metacritic = movie %>%
  html_node(".ratings-metascore span") %>%
  html_text();
metacritic = as.numeric(str_trim(metacritic));
result$metacritic[i] = metacritic;

info = movie %>%
  html_nodes(".lister-item-content p span") %>%
  html_text();

votes = as.numeric(gsub(",", "", info[8], fixed=T));
result$votes[i] = votes;

millions = cleanupMillions(info[11]);
result$millions[i] = millions;
}

result;

```

```

}

cleanupMillions = function(millions)
{
  millions = gsub('$','',millions, fixed=T);
  millions = gsub('M','',millions, fixed=T);

  millions = as.numeric(millions);
  millions;
}

cleanupMinutes = function(minutes)
{
  minutes = gsub('min','',minutes, fixed=T);

  minutes = as.numeric(minutes);
  minutes;
}

cleanupYear = function(year)
{
  year = gsub('(',' ',year, fixed=T);
  year = gsub(')',' ',year, fixed=T);
  year = gsub('I','',year, fixed=T);
  year = as.numeric(year);
  year;
}

grabNameFromFilmsPage = function(page)
{
  name = page %>%
    html_node(".header") %>%
    html_text();

  name = gsub("Most Rated Feature Films With","",name,fixed=T);
  name = str_trim(name);

  name;
}

grabFilmCountFromFilmsPage = function(page)
{
  totalcount = page %>%
    html_nodes(".desc") %>%
    html_text();

  temp = strsplit(totalcount,"of",fixed=T);
  temp2 = strsplit(temp[[1]][2],"titles", fixed=T);

  totalcount = str_trim(temp2[[1]][1]);
  totalcount = as.numeric(totalcount);
}

```

```

    temp2 = strsplit(temp[[1]][1], "to", fixed=T);

    pagecount = str_trim(temp2[[1]][2]);
    pagecount = as.numeric(pagecount);

    result = list();

    result$totalcount = totalcount;
    result$pagecount = pagecount;

    result;
}

grabFilmsForPerson = function(nmid)
{
  url = paste("https://www.imdb.com/filmosearch/?explore=title_type&role=", nmid, "&ref_=filmo_ref_typ&");

  page1 = read_html(url);
  result = list();
  ## useful for other data purposes
  result$nmid = nmid;

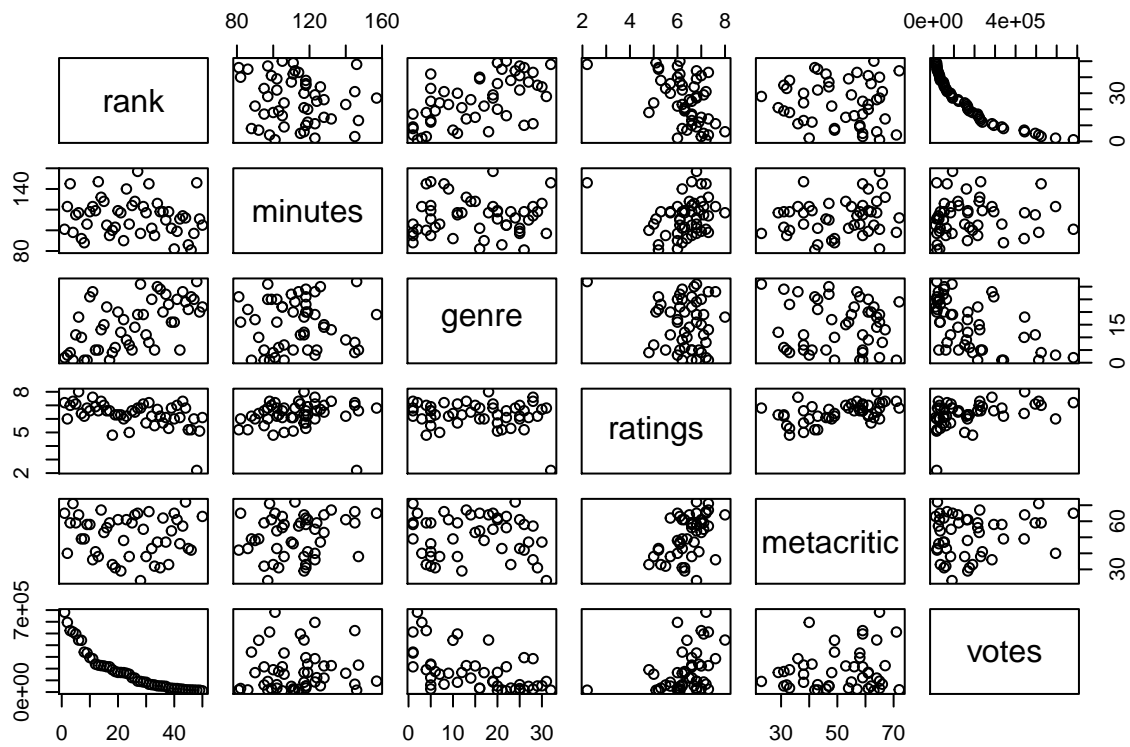
  ## name of person
  result$name = grabNameFromFilmsPage(page1);
  result$countfilms = grabFilmCountFromFilmsPage(page1);

  result$movies.50 = grabFilmInfoFromFilmsPage(page1);

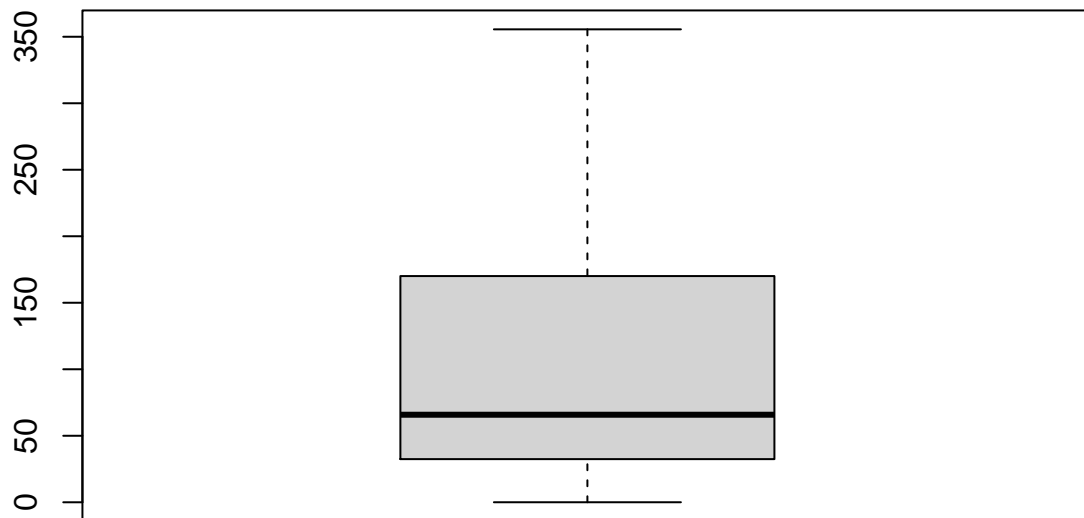
  result;
}

nmid = "nm0000226";
will = grabFilmsForPerson(nmid);
plot(will$movies.50[, c(1, 6, 7:10)]);

```



```
boxplot(will$movies.50$millions);
```



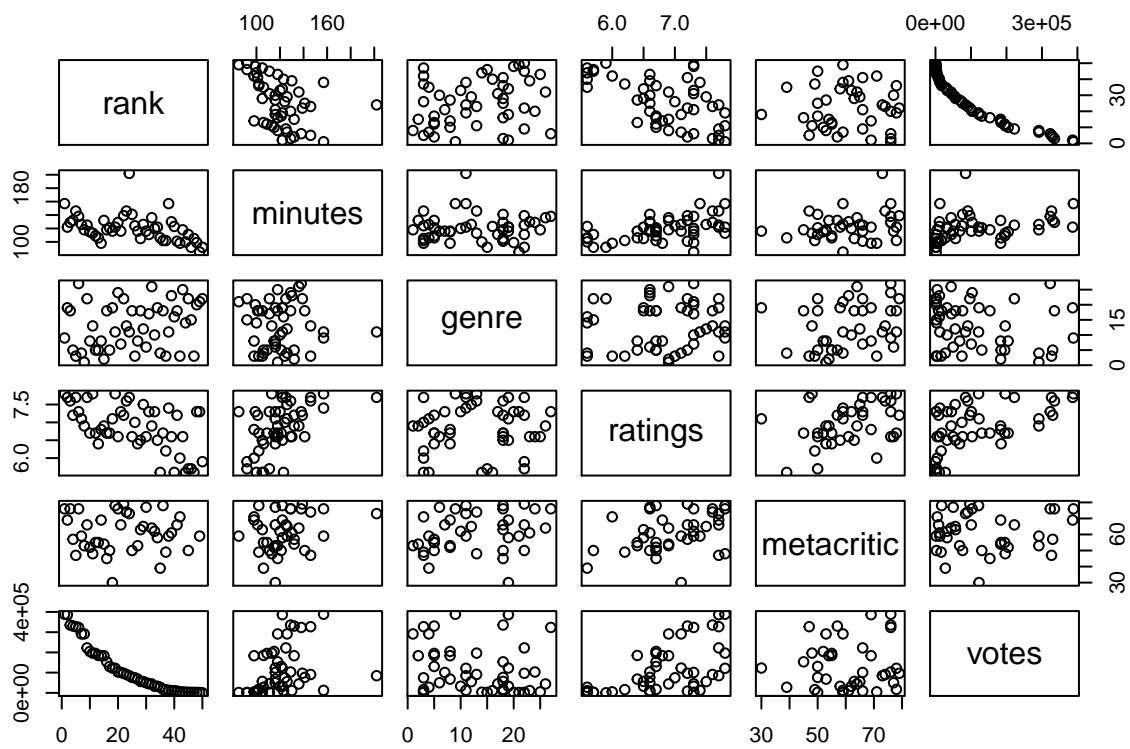
```
widx = which.max(will$movies.50$millions);
will$movies.50[widx,];
```

```
##   rank  title      ttid year rated minutes      genre ratings
## 15   15 Aladdin tt6139732 2019   PG    128 Adventure, Family, Fantasy      7
##   metacritic votes millions
## 15          53 222928    355.56
```

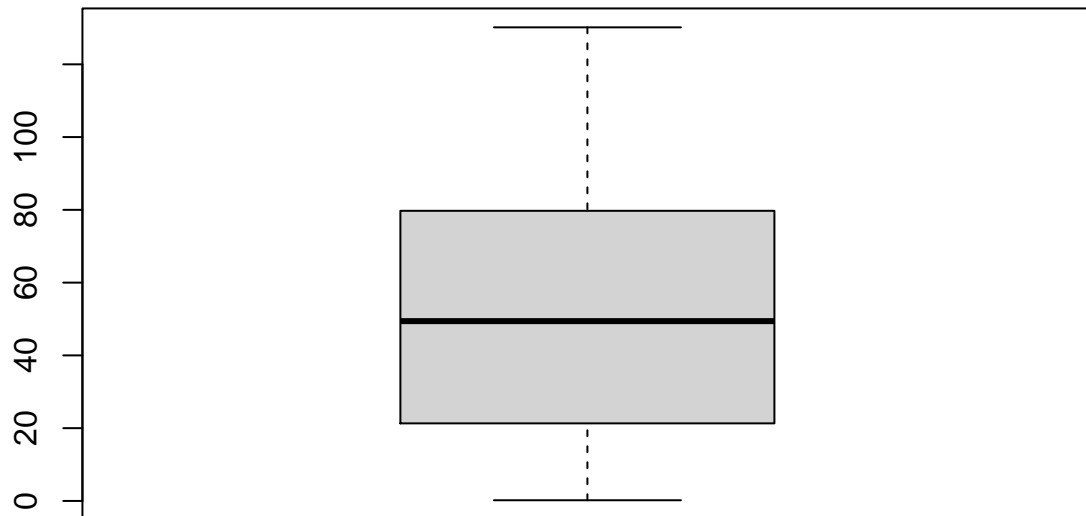
```
summary(will$movies.50$year); # bad boys for life ... did data change?
```

```
##   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   1993   2001   2006     2007   2014     2020
```

```
nmid = "nm0000243";
denzel = grabFilmsForPerson(nmid);
plot(denzel$movies.50[,c(1,6,7:10)]);
```



```
boxplot(denzel$movies.50$millions);
```



```

didx = which.max(denzel$movies.50$millions);
denzel$movies.50[didx,];

```

```

##   rank      title      ttid year rated minutes      genre
## 1     1 American Gangster tt0765429 2007     R     157 Biography, Crime, Drama
## ratings metacritic votes millions
## 1      7.8          76 388731   130.16

```

```

summary(denzel$movies.50$year);

```

```

##   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   1981   1993   1999     2000   2008     2018

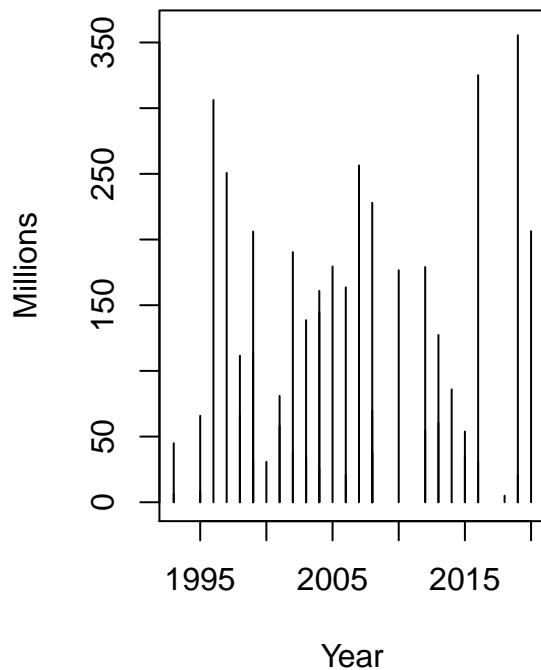
```

```

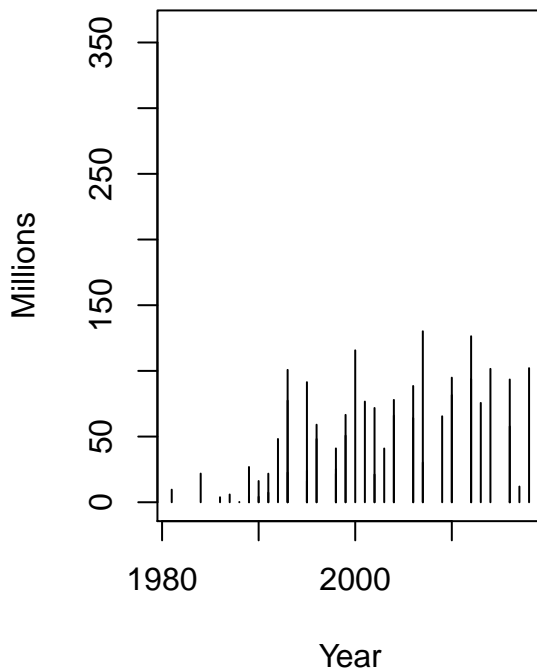
par(mfrow=c(1,2));
plot(will$movies.50$year,will$movies.50$millions, main="Smith Box Office", xlab="Year",ylim=c(0,360),
plot(denzel$movies.50$year,denzel$movies.50$millions, main="Denzel Box Office", xlab="Year",ylim=c(0,100))

```


Smith Box Office



Denzel Box Office



```
summary(will$movies.50$millions)
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.   NA's
##      0.02  32.42   65.81  103.42  170.08  355.56     3
```

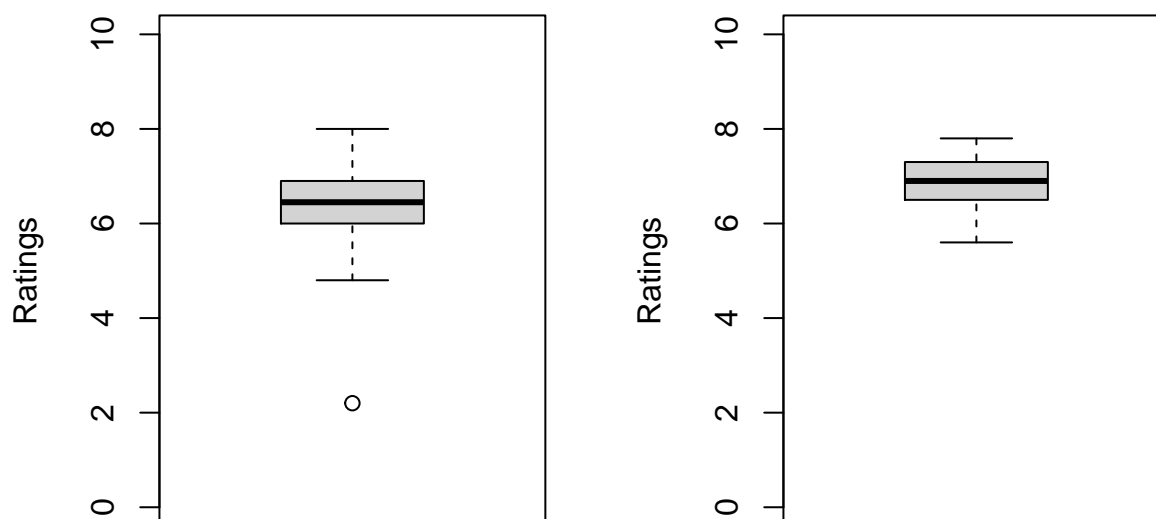
```
summary(denzel$movies.50$millions)
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.   NA's
##      0.19  21.43   49.42   52.12   78.82  130.16     2
```

*# In the dollars department, there is no contest. Will Smith's movies have higher lows,
higher highs, a higher average, and higher quartiles. Unequivocally, Will Smith's movies
are a bigger success at the box office than Denzel Washington's.*

```
par(mfrow=c(1,2));
boxplot(will$movies.50$ratings, main=will$name, ylim=c(0,10), ylab="Ratings" )
boxplot(denzel$movies.50$ratings, main=denzel$name, ylim=c(0,10), ylab="Ratings")
```

Sort by Number of Votes – Will Snt by Number of Votes – Denzel Was



```
summary(will$movies.50$ratings)
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  2.200   6.000   6.450   6.326   6.875   8.000
```

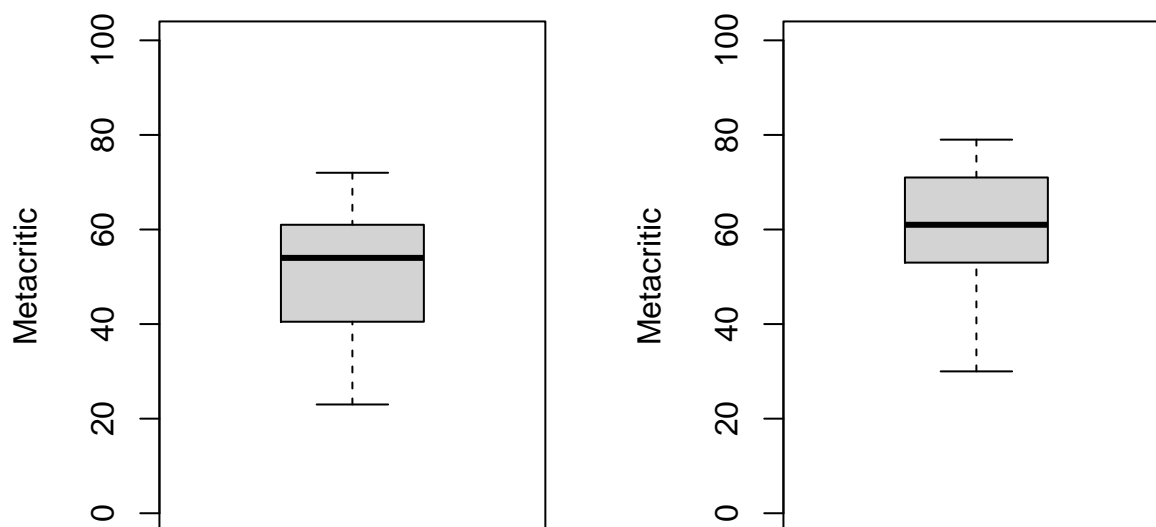
```
summary(denzel$movies.50$ratings)
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  5.600   6.525   6.900   6.852   7.300   7.800
```

*# Viewer ratings tell a different story than box office earnings. While Denzel's highest
rated movies are unable to crack a rating of 8/10 like Will Smith's highest rated movie,
his average movie rating, quartile ratings, and lowest rating are all higher. On average,
viewers enjoy Denzel Washington's movies more than Will Smith's.*

```
par(mfrow=c(1,2));
boxplot(will$movies.50$metacritic, main=will$name, ylim=c(0,100), ylab="Metacritic" )
boxplot(denzel$movies.50$metacritic, main=denzel$name, ylim=c(0,100), ylab="Metacritic")
```

Sort by Number of Votes – Will Snt by Number of Votes – Denzel Was



```
par(mfrow=c(1,1))
summary(will$movies.50$metacritic)
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.     NA's
##  23.00  40.50   54.00   50.87  61.00   72.00         3
```

```
summary(denzel$movies.50$metacritic)
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.     NA's
##  30.00  53.00   61.00   61.15  71.00   79.00         9
```

In general, critics seem to agree with the viewers. Their average rating of Denzel Washington's movies are higher, as well as the minimum and maximum ratings. There is a large area underneath the average in Will Smith's boxplot, indicating that his worse movies greatly outnumber his good movies, and thus bring down his metacritic average.

```
library(devtools);
```

```
## Loading required package: usethis
```

```
library(humanVerseWSU);
```

```
path.github = "https://raw.githubusercontent.com/MonteShaffer/humanVerseWSU/master/";
```

```
include.me = paste0(path.github, "misc/functions-nlp.R");
```

```
source_url( include.me );
```

```
## SHA-1 hash of file is 704afa69d52215d315cb5f59cdc020b0bbfd0b13
```

```

## Warning: package 'tm' was built under R version 4.0.3
## Loading required package: NLP
## Warning: package 'NLP' was built under R version 4.0.3
## Warning: package 'SentimentAnalysis' was built under R version 4.0.3
##
## Attaching package: 'SentimentAnalysis'
## The following object is masked from 'package:base':
##
##      write

include.me = paste0(path.github, "misc/functions-nlp-str.R");
source_url( include.me );

## SHA-1 hash of file is 6bdb234fa84eea995969dc29d6ff2a78f3982131
include.me = paste0(path.github, "misc/functions-nlp-stack.R");
source_url( include.me );

## SHA-1 hash of file is 034efbce0405954198545f8798e119b77a4809c9
include.me = paste0(path.github, "misc/functions-nlp-pos.R");
source_url( include.me );

## SHA-1 hash of file is d8c8cf01c8ead1b6d4228891aa52bac77084a6e7
## Warning: package 'openNLP' was built under R version 4.0.3
include.me = paste0(path.github, "humanVerseWSU/R/functions-encryption.R");
source_url( include.me );

## SHA-1 hash of file is da71dde620bed33db055778b752eefb476f7bf6b
path.to.nascent = "C:/Users/Alexander Nevsky/Dropbox/WSU-419/Fall 2020/__student_access__/unit_02_confir";

folder.nlp = "nlp/";
path.to.nlp = paste0(path.to.nascent, folder.nlp);

##### UPDATES TO dataframe subset function #####
# inflation adjustments for NA ... and improvements on subsetting
include.me = paste0(path.github, "humanVerseWSU/R/functions-dataframe.R");
source_url( include.me );

## SHA-1 hash of file is 1149cbf3e865f692b50d4d1983e6364dc56ce62d
include.me = paste0(path.github, "humanVerseWSU/R/functions-inflation.R");
source_url( include.me );

## SHA-1 hash of file is b6d29327e3fe030ca132b135f4a89b6fc6a61a66
library(imdb);
imdb::loadDataIMDB();
names(imdb.data);

## [1] "all.movies.creatives"      "all.movies.companies"
## [3] "all.movies.actors.characters" "all.actors.rank"
## [5] "all.actors.movies"        "all.actors.info"

```

```
## [7] "moviecount.byyear"      "actors"
## [9] "glue"                    "headliners"
## [11] "movies"                  "movies.df"
```

```
humanVerseWSU::loadInflationData();
will.search = IMDB.searchPersonName("Will* Smith*");

will.search;
```

```
##          nmid          name          roles  born.when
## 226   nm0000226   Will Smith Music Department,Actor,Producer 1968-9-25
## 41738 nm0810342   William Smith Actor,Stunts,Miscellaneous Crew 1933-3-24
## 41739 nm0810349   William Smith          Actor          <NA>
## 41744 nm0810461 William Smithers          Actor 1927-7-10
## 58036 nm2405238   Willow Smith          Soundtrack,Actress,Writer 2000-10-31
##
##          born.where died.when died.where starmeter.rank
## 226   Philadelphia, Pennsylvania, USA          <NA>          <NA>          500
## 41738          Columbia, Missouri, USA          <NA>          <NA>          5000
## 41739          <NA>          <NA>          <NA>          NA
## 41744          Richmond, Virginia, USA          <NA>          <NA>          NA
## 58036          Los Angeles, California, USA          <NA>          <NA>          NA
##
##          starmeter.delta
## 226          67
## 41738          1386
## 41739          -191098
## 41744          627
## 58036          -1525
##
## 226   Willard Carroll "Will" Smith, Jr. (born September 25, 1968) is an American actor, comedian, p
## 41738 William Smith is probably best known for his portrayal as "Falconetti" in Rich Man, Poor Man (
## 41739
## 41744 Although character actor William (or Bill) Smithers is not recognizable perhaps by name, the f
## 58036
```

```
will.nmid = will.search$nmid[1];
will.nmid = "nm0000226";
will.movies = IMDB.getMoviesForPerson(will.nmid);
will.movies;
```

```
##          ttid          nmid rank year          title
## 39   tt0480249 nm0000226    1 2007          I Am Legend
## 65   tt1386697 nm0000226    2 2016          Suicide Squad
## 6    tt0116629 nm0000226    3 1996          Independence Day
## 7    tt0119654 nm0000226    4 1997          Men in Black
## 26   tt0343818 nm0000226    5 2004          I, Robot
## 35   tt0454921 nm0000226    6 2006          The Pursuit of Happyness
## 34   tt0448157 nm0000226    7 2008          Hancock
## 12   tt0120912 nm0000226    8 2002          Men in Black II
## 66   tt1409024 nm0000226    9 2012          Men in Black 3
## 31   tt0386588 nm0000226   10 2005          Hitch
## 41   tt0814314 nm0000226   11 2008          Seven Pounds
## 4    tt0112442 nm0000226   12 1995          Bad Boys
## 17   tt0172156 nm0000226   13 2003          Bad Boys II
## 8    tt0120660 nm0000226   14 1998          Enemy of the State
## 104  tt6139732 nm0000226   15 2019          Aladdin
```

## 13	tt0145660	nm0000226	16	1999	Austin Powers: The Spy Who Shagged Me
## 90	tt2381941	nm0000226	17	2015	Focus
## 80	tt1815862	nm0000226	18	2013	After Earth
## 74	tt1596350	nm0000226	19	2012	This Means War
## 57	tt1229340	nm0000226	20	2013	Anchorman 2: The Legend Continues
## 100	tt5519340	nm0000226	21	2017	Bright
## 23	tt0307453	nm0000226	22	2004	Shark Tale
## 54	tt1155076	nm0000226	23	2010	The Karate Kid
## 11	tt0120891	nm0000226	24	1999	Wild Wild West
## 10	tt0120783	nm0000226	25	1998	The Parent Trap
## 70	tt1502397	nm0000226	26	2020	Bad Boys For Life
## 19	tt0248667	nm0000226	27	2001	Ali
## 97	tt4682786	nm0000226	28	2016	Collateral Beauty
## 93	tt3322364	nm0000226	29	2015	Concussion
## 47	tt1025100	nm0000226	30	2019	Gemini Man
## 5	tt0114558	nm0000226	31	1995	Strange Days
## 22	tt0300051	nm0000226	32	2004	Jersey Girl
## 21	tt0284490	nm0000226	33	2002	Showtime
## 14	tt0146984	nm0000226	34	2000	The Legend of Bagger Vance
## 83	tt1837709	nm0000226	35	2014	Winter's Tale
## 25	tt0338466	nm0000226	36	2003	Stuck on You
## 44	tt0947802	nm0000226	37	2008	Lakeview Terrace
## 82	tt1823664	nm0000226	38	2014	Annie
## 20	tt0268397	nm0000226	39	2001	Jimmy Neutron: Boy Genius
## 50	tt1082886	nm0000226	40	2008	The Wackness
## 101	tt5814534	nm0000226	41	2019	Spies in Disguise
## 94	tt3721964	nm0000226	42	2018	Gringo
## 33	tt0416212	nm0000226	43	2008	The Secret Life of Bees
## 3	tt0108149	nm0000226	44	1993	Six Degrees of Separation
## 24	tt0328099	nm0000226	45	2003	Malibu's Most Wanted
## 15	tt0167427	nm0000226	46	1999	Superstar
## 37	tt0466839	nm0000226	47	2007	I Could Never Be Your Woman
## 2	tt0107478	nm0000226	48	1993	Made in America
## 106	tt7255568	nm0000226	49	2019	Student of the Year 2
## 38	tt0466856	nm0000226	50	2006	ATL
## 30	tt0384504	nm0000226	51	2004	Saving Face
## 108	tt7440432	nm0000226	52	2018	Quincy
## 1	tt0105810	nm0000226	53	1992	Where the Day Takes You
## 29	tt0380277	nm0000226	54	2004	The Cookout
## 53	tt1109477	nm0000226	55	2008	The Human Contract
## 64	tt1383607	nm0000226	56	2008	Ramadan Mabrouk Abul-Alamein Hamouda
## 46	tt1015971	nm0000226	57	2009	The Boys: The Sherman Brothers' Story
## 95	tt4209900	nm0000226	58	2015	Fresh Dressed
## 16	tt0169376	nm0000226	59	1998	Welcome to Hollywood
## 9	tt0120707	nm0000226	60	1998	Ride
## 51	tt10883124	nm0000226	61	2019	Dads
## 58	tt1230214	nm0000226	62	2009	Stuntmen
## 28	tt0379487	nm0000226	63	2004	The Seat Filler
## 89	tt2350432	nm0000226	64	2012	Free Angela and All Political Prisoners
## 103	tt5903926	nm0000226	65	2018	Sprinter
## 67	tt1409772	nm0000226	66	2010	A Man's Story
## 27	tt0375663	nm0000226	67	2003	A Closer Walk
## 73	tt1584918	nm0000226	68	2014	Murder101
## 86	tt2074488	nm0000226	69	2005	Will Smith: Live in Concert

## 99	tt5230508	nm0000226	70	2005	AMV Hell 3: The Motion Picture
## 32	tt0414587	nm0000226	71	2005	There's a God on the Mic
## 18	tt0205314	nm0000226	72	1998	Pesel Ha'Zahav
## 71	tt1546668	nm0000226	73	2007	The 100 Best Black Movies (Ever)
## 102	tt5839150	nm0000226	74	2009	The Muhammad Ali Story
## 98	tt4919268	nm0000226	75	NA	Bad Boys 4
## 76	tt1674782	nm0000226	76	NA	The Karate Kid 2
## 111	tt9620288	nm0000226	77	2021	King Richard
## 105	tt6598238	nm0000226	78	2020	Life in a Year
## 110	tt7820302	nm0000226	79	NA	Bright 2
## 52	tt11012318	nm0000226	80	NA	The Council
## 62	tt12915962	nm0000226	81	NA	Planes, Trains & Automobiles
## 69	tt1498780	nm0000226	82	NA	Hancock 2
## 60	tt12530246	nm0000226	83	NA	Emancipation
## 72	tt1578276	nm0000226	84	NA	Uptown Saturday Night
## 91	tt2776710	nm0000226	85	NA	Brilliance
## 55	tt1181790	nm0000226	86	NA	The Billionaire's Vinegar
## 96	tt4463004	nm0000226	87	NA	Bounty
## 61	tt12608018	nm0000226	88	NA	Bounce
## 107	tt7331400	nm0000226	89	NA	1921
## 78	tt1692497	nm0000226	90	NA	The Redemption of Cain
## 40	tt0812268	nm0000226	91	NA	The Last Pharaoh
## 49	tt10344550	nm0000226	92	NA	Untitled Solvan Naim Project
## 68	tt1470831	nm0000226	93	NA	The City That Sailed
## 63	tt1368421	nm0000226	94	NA	Angelology
## 92	tt2846190	nm0000226	95	NA	La escribana de uraba
## 42	tt0911023	nm0000226	96	NA	My Wife Hates Your Wife
## 36	tt0464265	nm0000226	97	NA	Time Share
## 75	tt1609486	nm0000226	98	NA	Harold and the Purple Crayon
## 81	tt1817789	nm0000226	99	NA	Wheeler Dealers
## 77	tt1691439	nm0000226	100	NA	Untitled Dr. S. Allen Counter Project
## 85	tt1879098	nm0000226	101	NA	What Would Kenny Do?
## 88	tt2246761	nm0000226	102	NA	Interpol
## 59	tt1235550	nm0000226	103	NA	Welcome to the Sticks
## 79	tt1714201	nm0000226	104	NA	Monster Witness Relocation Program
## 43	tt0942916	nm0000226	105	NA	Sisters of Mercy
## 48	tt1028582	nm0000226	106	NA	Newton's Law
## 45	tt0979959	nm0000226	107	NA	Cooked
## 109	tt7737796	nm0000226	108	NA	The Prospect
## 56	tt1206884	nm0000226	109	NA	The Long Run
## 87	tt2168954	nm0000226	110	NA	Ghost Graduation
## 84	tt1852816	nm0000226	111	NA	Joe
##		genre	rated	minutes	ratings metacritic votes
## 39	Action, Adventure, Drama	PG-13	101	7.2	65 675160
## 65	Action, Adventure, Fantasy	PG-13	123	6.0	40 588064
## 6	Action, Adventure, Sci-Fi	PG-13	145	7.0	59 520592
## 7	Action, Adventure, Comedy	PG-13	98	7.3	71 507597
## 26	Action, Drama, Sci-Fi	PG-13	115	7.1	59 491474
## 35	Biography, Drama	PG-13	117	8.0	64 438121
## 34	Action, Fantasy	PG-13	92	6.4	49 437887
## 12	Action, Adventure, Comedy	PG-13	88	6.2	49 337458
## 66	Action, Adventure, Comedy	PG-13	106	6.8	58 329948
## 31	Comedy, Romance	PG-13	118	6.6	58 291991
## 41	Drama	PG-13	123	7.6	36 282568

## 4	Action, Comedy, Crime	R	119	6.9	41	235766
## 17	Action, Comedy, Crime	R	147	6.6	38	228329
## 8	Action, Thriller	R	132	7.3	67	224019
## 104	Adventure, Family, Fantasy	PG	128	7.0	53	216257
## 13	Action, Adventure, Comedy	PG-13	95	6.6	59	214064
## 90	Comedy, Crime, Drama	R	105	6.6	56	212789
## 80	Action, Adventure, Sci-Fi	PG-13	100	4.8	33	189337
## 74	Action, Comedy, Romance	PG-13	103	6.3	31	174205
## 57	Comedy	PG-13	119	6.3	61	165909
## 100	Action, Fantasy, Thriller	TV-MA	117	6.3	29	164913
## 23	Animation, Adventure, Comedy	PG	90	6.0	48	164132
## 54	Action, Drama, Family	PG	140	6.2	61	158842
## 11	Action, Comedy, Sci-Fi	PG-13	106	5.0	38	151132
## 10	Adventure, Comedy, Drama	PG	128	6.5	64	117780
## 70	Action, Comedy, Crime	R	124	6.6	59	112826
## 19	Biography, Drama, Sport	R	157	6.8	65	92508
## 97	Drama, Romance	PG-13	97	6.8	23	89138
## 93	Biography, Drama, Sport	PG-13	123	7.1	55	84750
## 47	Action, Drama, Sci-Fi	PG-13	117	5.7	38	76145
## 5	Action, Crime, Drama	R	145	7.2	66	66102
## 22	Comedy, Drama, Romance	PG-13	102	6.2	43	62700
## 21	Action, Comedy, Crime	PG-13	95	5.5	32	59984
## 14	Drama, Fantasy, Sport	PG-13	126	6.7	47	52831
## 83	Drama, Fantasy, Mystery	PG-13	118	6.2	31	51469
## 25	Comedy	PG-13	118	5.7	62	50682
## 44	Crime, Drama, Thriller	PG-13	110	6.1	47	48231
## 82	Comedy, Drama, Family	PG	118	5.3	33	33448
## 20	Animation, Action, Adventure	G	82	6.0	65	30195
## 50	Comedy, Drama, Romance	R	99	7.0	61	29701
## 101	Animation, Action, Adventure	PG	102	6.8	54	28764
## 94	Action, Comedy, Crime	R	111	6.1	46	25794
## 33	Drama	PG-13	114	7.3	57	23962
## 3	Comedy, Drama, Mystery	R	112	6.8	72	19473
## 24	Comedy, Crime	PG-13	86	5.2	43	18356
## 15	Comedy, Romance	PG-13	81	5.2	42	17781
## 37	Comedy, Drama, Romance	PG-13	97	6.0	NA	16855
## 2	Comedy	PG-13	111	5.1	NA	15447
## 106	Drama, Romance, Sport	Not Rated	146	2.3	NA	15200
## 38	Comedy, Crime, Drama	PG-13	105	6.1	63	10580
## 30	Comedy, Drama, Romance	R	91	7.4	65	10016
## 108	Documentary, Biography	TV-MA	124	7.6	60	3359
## 1	Crime, Drama, Thriller	R	105	6.6	NA	3112
## 29	Comedy	PG-13	97	3.7	15	2741
## 53	Drama	R	103	5.1	NA	1970
## 64	Comedy, Family	<NA>	105	6.4	NA	NA
## 46	Documentary	PG	101	7.8	78	853
## 95	Documentary, History, Music	Not Rated	90	6.6	69	840
## 16	Comedy	R	89	4.9	NA	715
## 9	Comedy	R	90	4.6	NA	683
## 51	Documentary, Comedy, Family	TV-14	87	6.3	59	668
## 58	Comedy	R	90	5.1	NA	627
## 28	Comedy, Romance	PG-13	90	5.5	NA	607
## 89	Documentary	Not Rated	102	6.9	73	565
## 103	Drama, Sport	<NA>	114	6.1	NA	NA

## 67	Documentary	Not Rated	98	6.2	49	126
## 27	Documentary	<NA>	NA	8.6	NA	NA
## 73	Thriller	PG-13	90	4.4	NA	41
## 86	Documentary, Music	Not Rated	52	5.7	NA	34
## 99	Comedy	<NA>	68	7.5	NA	NA
## 32	Documentary	<NA>	NA	5.6	NA	NA
## 18	Documentary	<NA>	55	5.2	NA	NA
## 71	Documentary	<NA>	NA	5.0	NA	NA
## 102	Documentary	<NA>	52	5.7	NA	NA
## 98	Action, Adventure, Comedy	<NA>	NA	NA	NA	NA
## 76	Action, Drama	<NA>	NA	NA	NA	NA
## 111	Drama	<NA>	NA	NA	NA	NA
## 105	Drama, Romance	PG-13	NA	NA	NA	NA
## 110	Action, Adventure, Crime	<NA>	NA	NA	NA	NA
## 52	Biography	<NA>	NA	NA	NA	NA
## 62	Comedy	<NA>	NA	NA	NA	NA
## 69	Action, Fantasy	<NA>	NA	NA	NA	NA
## 60	Action, Thriller	<NA>	NA	NA	NA	NA
## 72	Comedy	<NA>	NA	NA	NA	NA
## 91	Sci-Fi, Thriller	<NA>	NA	NA	NA	NA
## 55	Drama	<NA>	NA	NA	NA	NA
## 96	Action	<NA>	NA	NA	NA	NA
## 61	Drama	<NA>	NA	NA	NA	NA
## 107	Drama	<NA>	NA	NA	NA	NA
## 78	Drama	<NA>	NA	NA	NA	NA
## 40	Drama	<NA>	NA	NA	NA	NA
## 49	Musical	<NA>	NA	NA	NA	NA
## 68	Drama, Fantasy	<NA>	NA	NA	NA	NA
## 63	Drama	<NA>	NA	NA	NA	NA
## 92	Drama	<NA>	NA	NA	NA	NA
## 42	Comedy	<NA>	NA	NA	NA	NA
## 36	Comedy	<NA>	NA	NA	NA	NA
## 75	Animation	<NA>	NA	NA	NA	NA
## 81	Drama	<NA>	NA	NA	NA	NA
## 77	Drama	<NA>	NA	NA	NA	NA
## 85	Comedy	<NA>	NA	NA	NA	NA
## 88	Comedy	<NA>	NA	NA	NA	NA
## 59	Comedy	<NA>	NA	NA	NA	NA
## 79	Sci-Fi	<NA>	NA	NA	NA	NA
## 43	Comedy, Drama, Romance	<NA>	NA	NA	NA	NA
## 48	Adventure, Comedy, Family	<NA>	NA	NA	NA	NA
## 45	Drama	<NA>	NA	NA	NA	NA
## 109	<NA>	<NA>	NA	NA	NA	NA
## 56	Drama	<NA>	NA	NA	NA	NA
## 87	Comedy, Fantasy	<NA>	NA	NA	NA	NA
## 84	Drama	<NA>	NA	NA	NA	NA
##	millions					
## 39	256.39					
## 65	325.10					
## 6	306.17					
## 7	250.69					
## 26	144.80					
## 35	163.57					
## 34	227.95					

## 12	190.42
## 66	179.02
## 31	179.50
## 41	69.95
## 4	65.81
## 17	138.61
## 8	111.55
## 104	355.56
## 13	206.04
## 90	53.86
## 80	60.52
## 74	54.76
## 57	127.35
## 100	NA
## 23	160.86
## 54	176.59
## 11	113.81
## 10	66.31
## 70	204.42
## 19	58.20
## 97	31.02
## 93	34.54
## 47	20.55
## 5	7.92
## 22	25.27
## 21	38.08
## 14	30.70
## 83	0.02
## 25	33.83
## 44	39.26
## 82	85.91
## 20	80.94
## 50	2.08
## 101	NA
## 94	4.97
## 33	37.77
## 3	6.41
## 24	34.31
## 15	30.63
## 37	NA
## 2	44.94
## 106	0.78
## 38	21.16
## 30	1.19
## 108	NA
## 1	0.39
## 29	11.54
## 53	NA
## 64	NA
## 46	0.05
## 95	NA
## 16	NA
## 9	5.48
## 51	NA

## 58	NA
## 28	NA
## 89	NA
## 103	NA
## 67	NA
## 27	NA
## 73	NA
## 86	NA
## 99	NA
## 32	NA
## 18	NA
## 71	NA
## 102	NA
## 98	NA
## 76	NA
## 111	NA
## 105	NA
## 110	NA
## 52	NA
## 62	NA
## 69	NA
## 60	NA
## 72	NA
## 91	NA
## 55	NA
## 96	NA
## 61	NA
## 107	NA
## 78	NA
## 40	NA
## 49	NA
## 68	NA
## 63	NA
## 92	NA
## 42	NA
## 36	NA
## 75	NA
## 81	NA
## 77	NA
## 85	NA
## 88	NA
## 59	NA
## 79	NA
## 43	NA
## 48	NA
## 45	NA
## 109	NA
## 56	NA
## 87	NA
## 84	NA
##	
## 39	
## 65	
## 6	

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64
46

It's the summer of 1994, and the streets of New York are pulsing

A group of teenagers

Their music is unforgettable

95 Fresh Dressed chron
 ## 16
 ## 9
 ## 51 Director Bryce Dallas Howard teams up with her father, <a href="/n
 ## 58
 ## 28
 ## 89
 ## 103
 ## 67
 ## 27 This document
 ## 73
 ## 86 Will Smith: L
 ## 99 An enormousl
 ## 32
 ## 18
 ## 71
 ## 102
 ## 98
 ## 76
 ## 111
 ## 105
 ## 110
 ## 52
 ## 62
 ## 69
 ## 60
 ## 72
 ## 91
 ## 55
 ## 96
 ## 61
 ## 107 Green
 ## 78
 ## 40
 ## 49
 ## 68
 ## 63 When God crea
 ## 92
 ## 42
 ## 36
 ## 75
 ## 81
 ## 77
 ## 85
 ## 88
 ## 59
 ## 79
 ## 43
 ## 48
 ## 45
 ## 109
 ## 56
 ## 87
 ## 84

```
will.movies = standardizeDollarsInDataFrame(will.movies, 2000, "millions", "year", "millions2000");
will.movies = sortDataFrameByNumericColumns(will.movies, "millions2000", "DESC");
will.movies$rank.money = 1:nrow(will.movies);
will.rank = subsetDataFrame(imdb.data$all.movies.actors.characters, "nmid", "==", will.nmid);
will.rank;
```

##	ttid	actor.rank	nmid	
##	349353	tt0105810	6	nm0000226
##	353669	tt0107478	3	nm0000226
##	355578	tt0108149	2	nm0000226
##	365501	tt0112442	11	nm0000226
##	376889	tt0116629	1	nm0000226
##	387158	tt0119654	2	nm0000226
##	391606	tt0120660	1	nm0000226
##	393444	tt0120891	1	nm0000226
##	393576	tt0120912	2	nm0000226
##	413566	tt0146984	1	nm0000226
##	434016	tt0172156	2	nm0000226
##	460734	tt0205314	11	nm0000226
##	486656	tt0248667	1	nm0000226
##	521274	tt0307453	1	nm0000226
##	540127	tt0343818	1	nm0000226
##	562065	tt0386588	1	nm0000226
##	586225	tt0448157	1	nm0000226
##	588916	tt0454921	1	nm0000226
##	599482	tt0480249	1	nm0000226
##	613408	tt0814314	1	nm0000226
##	633149	tt1025100	1	nm0000226
##	680397	tt1386697	1	nm0000226
##	682251	tt1409024	1	nm0000226
##	689408	tt1502397	1	nm0000226
##	693711	tt1546668	9	nm0000226
##	715818	tt1815862	2	nm0000226
##	750095	tt2381941	1	nm0000226
##	778362	tt3322364	1	nm0000226
##	809470	tt4682786	1	nm0000226
##	825451	tt5519340	1	nm0000226
##	831014	tt5814534	6	nm0000226
##	837383	tt6139732	1	nm0000226
##	859453	tt7820302	1	nm0000226
##	876732	tt9620288	1	nm0000226
##	642982	tt10883124	13	nm0000226
##				character
##	349353			Manny
##	353669			Tea Cake Walters
##	355578			Paul
##	365501			Mike Lowrey
##	376889			Capt. Steven Hiller
##	387158			Jay
##	391606			Robert Clayton Dean
##	393444			James West
##	393576			Jay
##	413566			Bagger Vance
##	434016			Detective Mike Lowrey

```

## 460734                                     Self
## 486656 Cassius Clay /                     Muhammad Ali
## 521274                                     Oscar      (voice)
## 540127                                     Del Spooner
## 562065                                     Hitch
## 586225                                     John Hancock
## 588916                                     Chris Gardner
## 599482                                     Robert Neville
## 613408                                     Ben
## 633149      Henry Brogan /                 Junior
## 680397                                     Deadshot
## 682251                                     Agent J
## 689408                                     Mike
## 693711                                     Self
## 715818                                     Cypher Raige
## 750095                                     Nicky
## 778362                                     Dr. Bennet Omalu
## 809470                                     Howard
## 825451                                     Daryl Ward
## 831014      Lance                         (voice)
## 837383      Genie /                       Mariner
## 859453                                     Daryl Ward
## 876732                                     Richard Williams
## 642982                                     Self

will.n = nrow(will.movies);
will.ttids = will.movies$ttid;
length( intersect(will.ttids, imdb.data$movies$popular50$ttid) );

## [1] 19

mean(will.rank$actor.rank)

## [1] 2.628571

```