

# 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", "meta

  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;

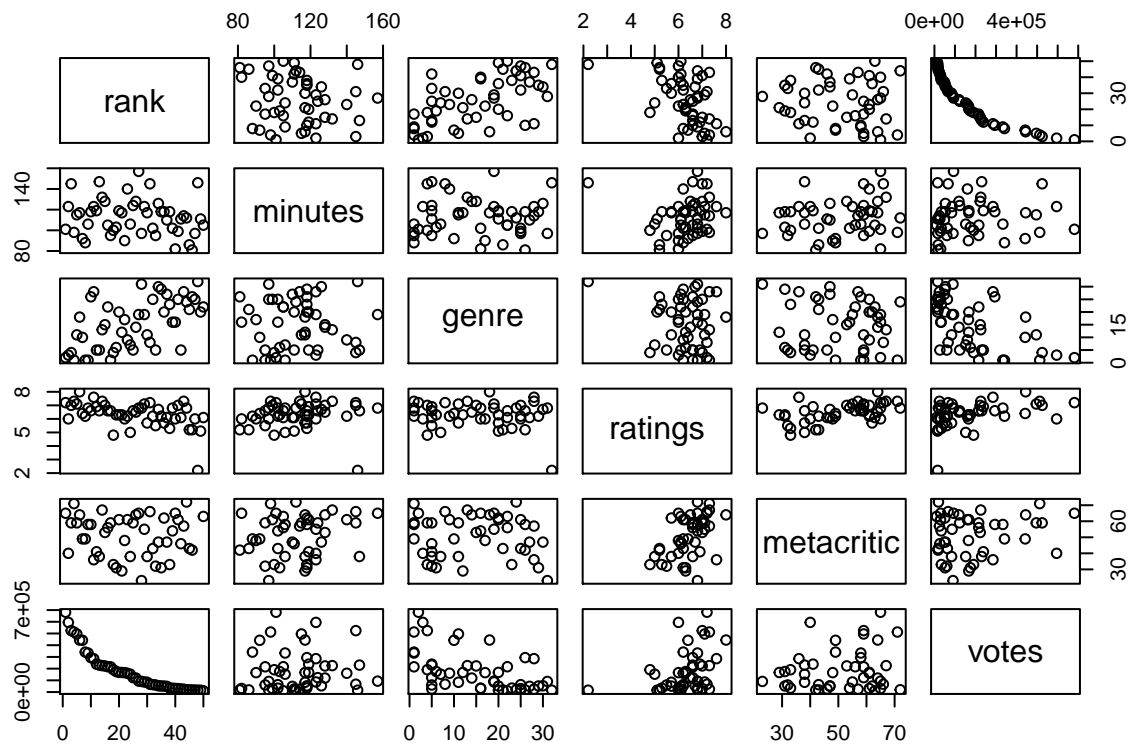
    ## name of person
    result$name = grabNameFromFilmsPage(page1);
    result$countfilms = grabFilmCountFromFilmsPage(page1);

    result$movies.50 = grabFilmInfoFromFilmsPage(page1);

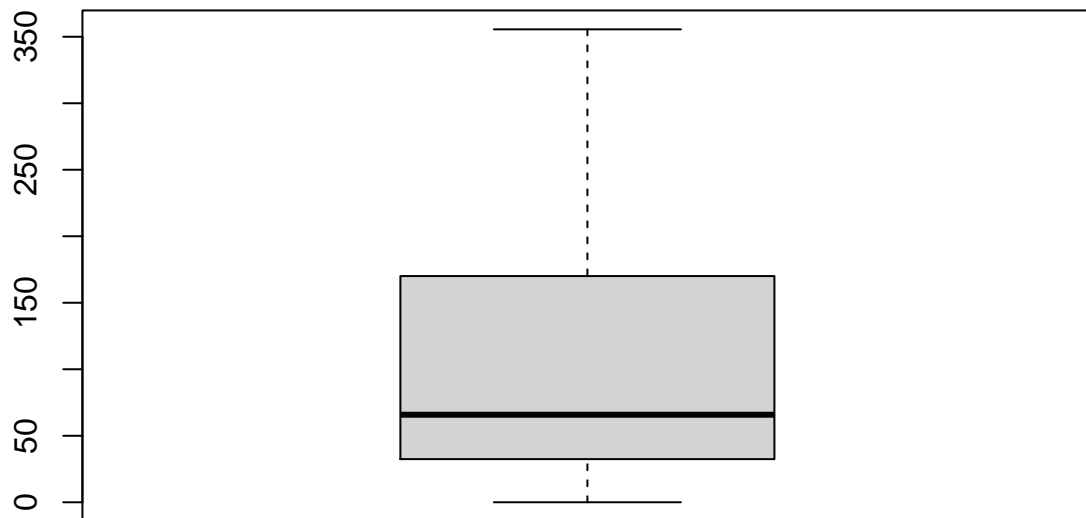
    result;
}

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

```



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



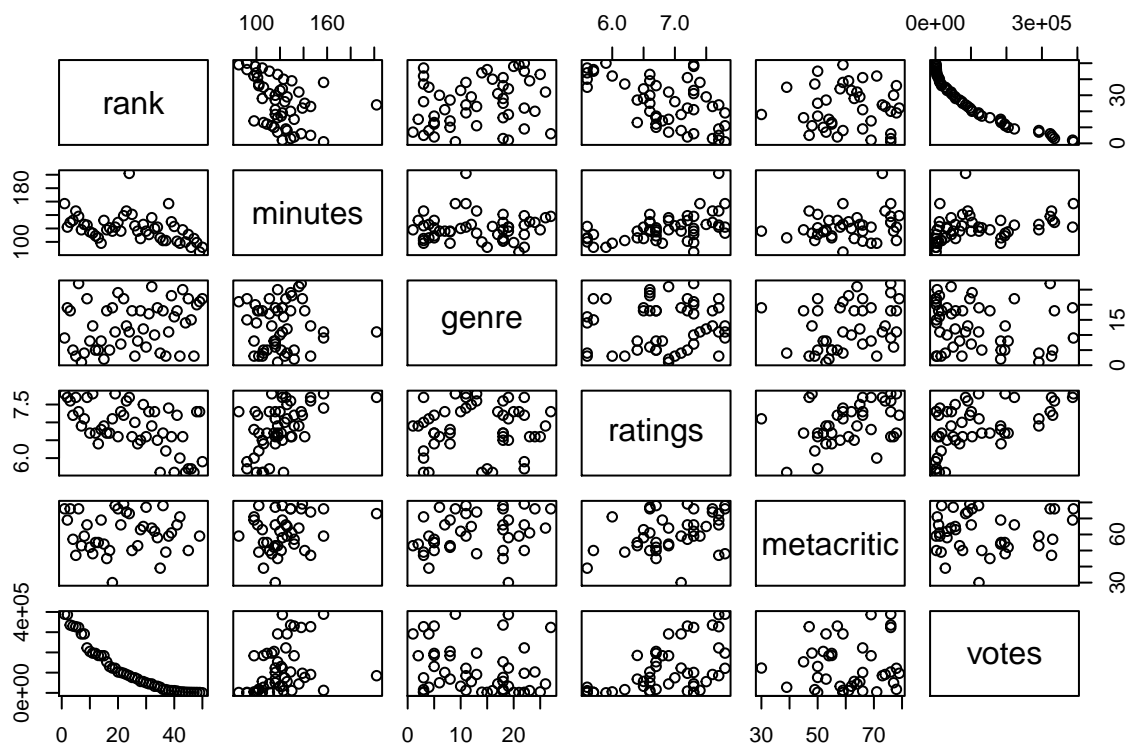
```
widx = which.max(will$movies.50$millions);
will$movies.50[widx,];
```

```
##   rank  title      ttid year rated minutes      genre ratings
## 15   15 Aladdin tt6139732 2019   PG    128 Adventure, Family, Fantasy      7
##   metacritic votes millions
## 15          53 223044    355.56
```

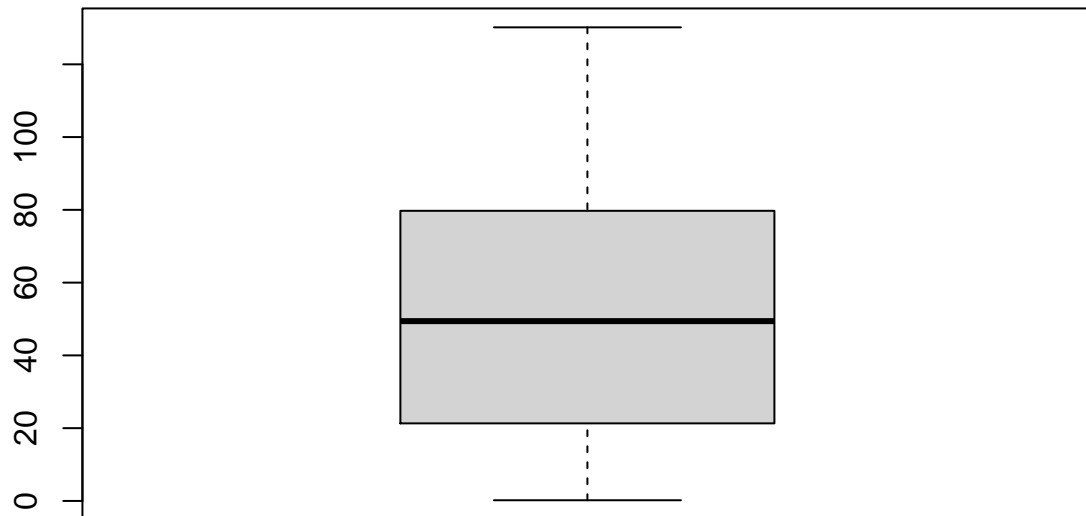
```
summary(will$movies.50$year); # bad boys for life ... did data change?
```

```
##   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 388822   130.16

```

```

summary(denzel$movies.50$year);

```

```

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

```

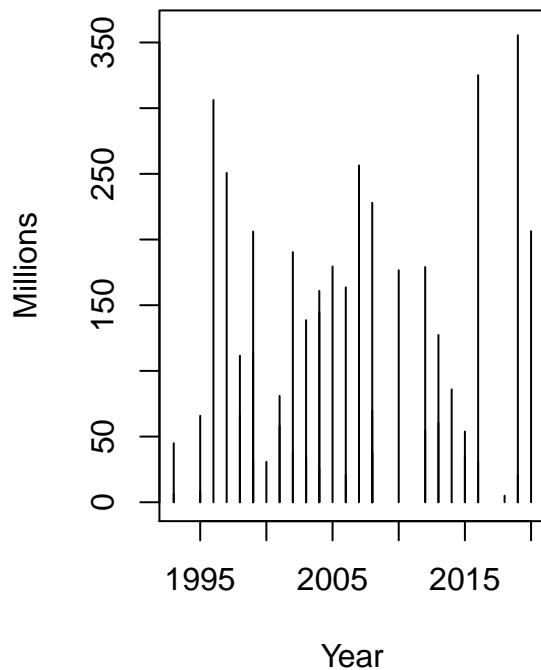
```

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))

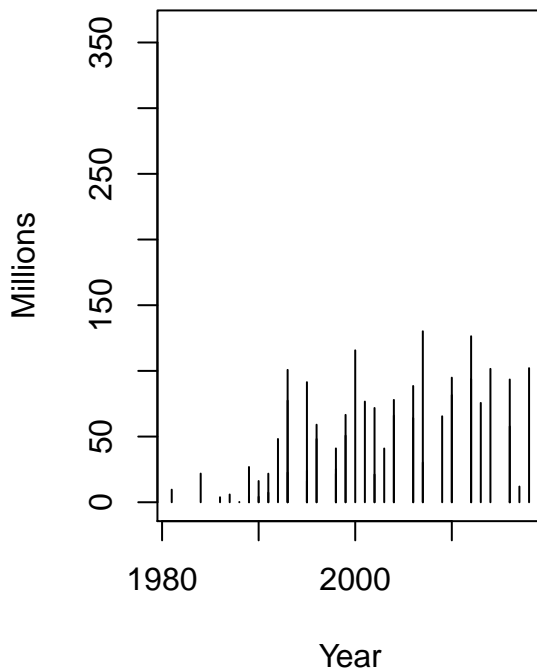
```



### 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
```

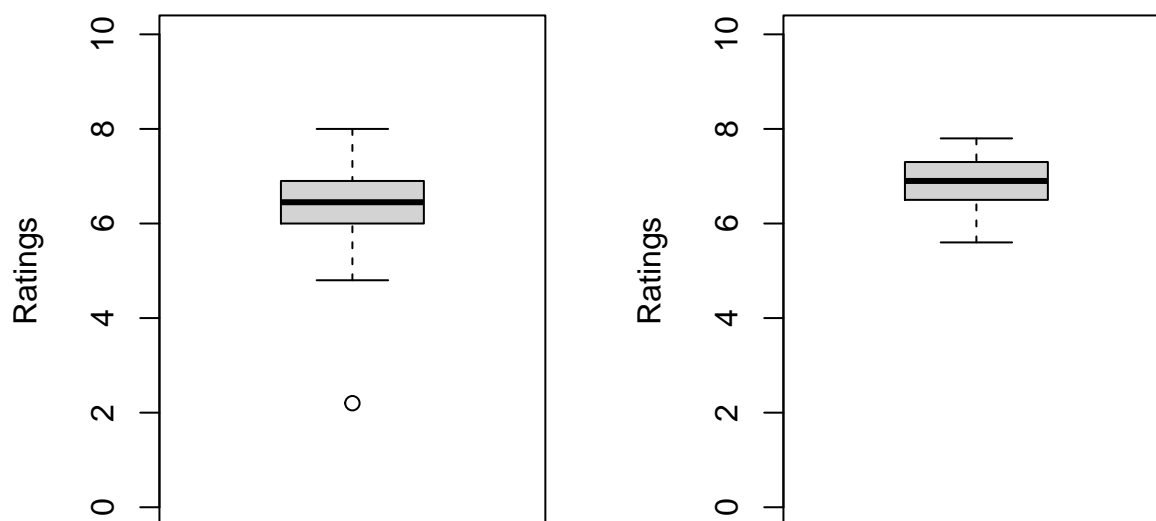
```
summary(denzel$movies.50$millions)
```

```
##      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
```

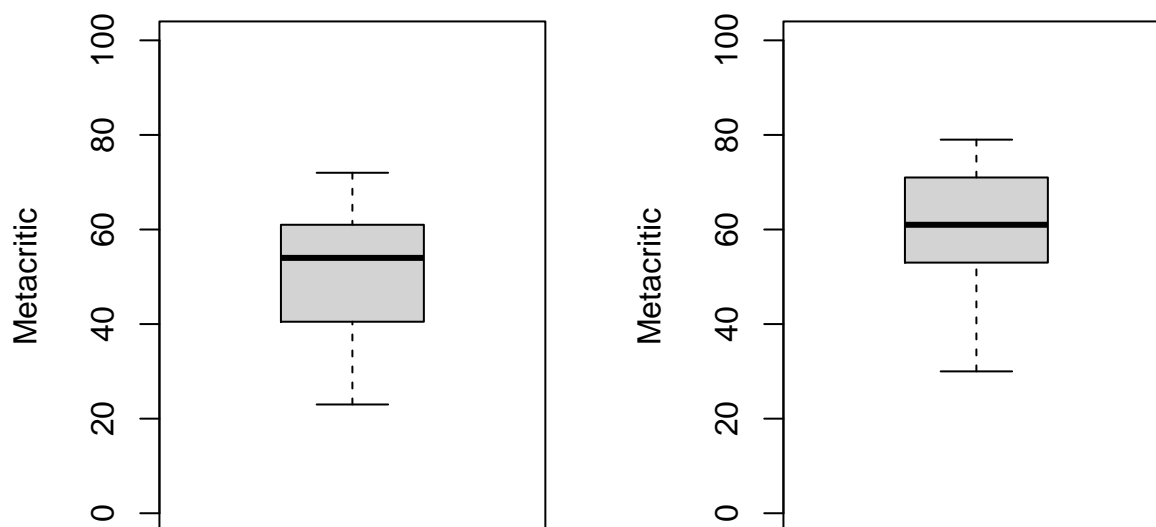
```
summary(denzel$movies.50$ratings)
```

```
##      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 Smith Data
```

```
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 Baggar 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  
## 7  
## 26  
## 35  
## 34  
## 12  
## 66  
## 31  
## 41  
## 4  
## 17  
## 8  
## 104  
## 13  
## 90  
## 80  
## 74  
## 57  
## 100  
## 23  
## 54  
## 11  
## 10  
## 70  
## 19  
## 97  
## 93  
## 47  
## 5  
## 22  
## 21  
## 14  
## 83  
## 25  
## 44  
## 82  
## 20  
## 50  
## 101  
## 94  
## 33  
## 3  
## 24  
## 15  
## 37  
## 2  
## 106  
## 38  
## 30  
## 108  
## 1  
## 29  
## 53

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

A group of tee

## 64  
 ## 46 Their music is unforg  
 ## 95 Fresh Dressed chron  
 ## 16  
 ## 9  
 ## 51 Director <a href="/name/nm0397171">Bryce Dallas Howard</a> teams up with her father, <a href="/n  
 ## 58  
 ## 28  
 ## 89  
 ## 103  
 ## 67  
 ## 27 This document  
 ## 73  
 ## 86 Will Smith: L  
 ## 99 An enormously  
 ## 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
```

```
# Denzel Washington Data
```

```
denzel.search = IMDB.searchPersonName("Denzel* Washington*");
```

```
denzel.search;
```

```
##      nmid      name      roles  born.when
## 243 nm0000243 Denzel Washington Actor,Producer,Director 1954-12-28
##      born.where died.when died.where starmeter.rank
## 243 Mount Vernon, New York, USA      <NA>      <NA>      500
##      starmeter.delta
## 243      -64
##
```

```
## 243 Denzel Hayes Washington, Jr. was born on December 28, 1954 in Mount Vernon, New York. He is the r
```

```
denzel.nmid = denzel.search$nmid[1];
```

```
#denzel.nmid = "nm0000226";
```

```
denzel.movies = IMDB.getMoviesForPerson(denzel.nmid);
```

```
denzel.movies;
```

```
##      ttid      nmid rank year      title
```

## 41	tt0765429	nm0000243	1	2007	American Gangster
## 27	tt0139654	nm0000243	2	2001	Training Day
## 38	tt0454848	nm0000243	3	2006	Inside Man
## 39	tt0455944	nm0000243	4	2014	The Equalizer
## 34	tt0328107	nm0000243	5	2004	Man on Fire
## 55	tt1907668	nm0000243	6	2012	Flight
## 37	tt0453467	nm0000243	7	2006	Deja Vu
## 45	tt1037705	nm0000243	8	2010	The Book of Eli
## 15	tt0107818	nm0000243	9	1993	Philadelphia
## 52	tt1599348	nm0000243	10	2012	Safe House
## 31	tt0210945	nm0000243	11	2000	Remember the Titans
## 49	tt1272878	nm0000243	12	2013	2 Guns
## 47	tt1111422	nm0000243	13	2009	The Taking of Pelham 123
## 40	tt0477080	nm0000243	14	2010	Unstoppable
## 56	tt2404435	nm0000243	15	2016	The Magnificent Seven
## 28	tt0145681	nm0000243	16	1999	The Bone Collector
## 58	tt3766354	nm0000243	17	2018	The Equalizer 2
## 32	tt0251160	nm0000243	18	2002	John Q
## 6	tt0097441	nm0000243	19	1989	Glory
## 35	tt0368008	nm0000243	20	2004	The Manchurian Candidate
## 17	tt0112740	nm0000243	21	1995	Crimson Tide
## 57	tt2671706	nm0000243	22	2016	Fences
## 30	tt0174856	nm0000243	23	1999	The Hurricane
## 12	tt0104797	nm0000243	24	1992	Malcolm X
## 14	tt0107798	nm0000243	25	1993	The Pelican Brief
## 24	tt0119099	nm0000243	26	1998	Fallen
## 26	tt0133952	nm0000243	27	1998	The Siege
## 33	tt0313443	nm0000243	28	2003	Out of Time
## 36	tt0427309	nm0000243	29	2007	The Great Debaters
## 21	tt0115956	nm0000243	30	1996	Courage Under Fire
## 13	tt0107616	nm0000243	31	1993	Much Ado About Nothing
## 25	tt0124718	nm0000243	32	1998	He Got Game
## 29	tt0168786	nm0000243	33	2002	Antwone Fisher
## 60	tt6000478	nm0000243	34	2017	Roman J. Israel, Esq.
## 20	tt0114857	nm0000243	35	1995	Virtuosity
## 18	tt0112857	nm0000243	36	1995	Devil in a Blue Dress
## 11	tt0102789	nm0000243	37	1991	Ricochet
## 4	tt0092804	nm0000243	38	1987	Cry Freedom
## 9	tt0100168	nm0000243	39	1990	Mo' Better Blues
## 22	tt0117372	nm0000243	40	1996	The Preacher's Wife
## 2	tt0088146	nm0000243	41	1984	A Soldier's Story
## 7	tt0097880	nm0000243	42	1989	The Mighty Quinn
## 10	tt0102456	nm0000243	43	1991	Mississippi Masala
## 8	tt0099750	nm0000243	44	1990	Heart Condition
## 3	tt0091786	nm0000243	45	1986	Power
## 1	tt0082138	nm0000243	46	1981	Carbon Copy
## 5	tt0097373	nm0000243	47	1988	For Queen & Country
## 59	tt4283892	nm0000243	48	2016	Chasing Trane: The John Coltrane Documentary
## 53	tt1698652	nm0000243	49	2014	Champs
## 23	tt0118783	nm0000243	50	1997	A Brother's Kiss
## 16	tt0109390	nm0000243	51	1994	A Century of Cinema
## 19	tt0113254	nm0000243	52	1995	Hank Aaron: Chasing the Dream
## 54	tt1801048	nm0000243	53	2010	The Start of Dreams
## 51	tt1546668	nm0000243	54	2007	The 100 Best Black Movies (Ever)



## 46	tt10514222	nm0000243	55	2020	Ma Rainey's Black Bottom
## 43	tt10016180	nm0000243	56	2021	The Little Things
## 44	tt10095582	nm0000243	57	2021	Macbeth
## 50	tt12747748	nm0000243	58	NA	Leave the World Behind
## 42	tt0995854	nm0000243	59	NA	Journal for Jordan
## 48	tt11394338	nm0000243	60	2020	Giving Voice
## 61	tt6426462	nm0000243	61	2017	The 40 Year Journey of Marvin L. Winans
##		genre	rated	minutes	ratings metacritic votes
## 41		Biography, Crime, Drama	R	157	7.8 76 383980
## 27		Crime, Drama, Thriller	R	122	7.7 69 382022
## 38		Crime, Drama, Mystery	R	129	7.6 76 332729
## 39		Action, Crime, Thriller	R	132	7.2 57 326110
## 34		Action, Crime, Drama	R	146	7.7 47 324172
## 55		Drama, Thriller	R	138	7.3 76 320297
## 37		Action, Crime, Sci-Fi	PG-13	126	7.0 59 288953
## 45		Action, Adventure, Drama	R	118	6.9 53 288652
## 15		Drama	PG-13	125	7.7 66 219940
## 52		Action, Thriller	R	115	6.7 52 202460
## 31		Biography, Drama, Sport	PG	113	7.8 48 194611
## 49		Action, Comedy, Thriller	R	109	6.7 55 192981
## 47		Action, Crime, Thriller	R	106	6.4 55 183374
## 40		Action, Thriller	PG-13	98	6.8 69 182082
## 56		Action, Adventure, Western	PG-13	132	6.9 54 181889
## 28		Crime, Drama, Mystery	R	118	6.7 45 151721
## 58		Action, Crime, Thriller	R	121	6.7 50 126514
## 32		Crime, Drama, Thriller	PG-13	116	7.1 30 121459
## 6		Biography, Drama, History	R	122	7.8 78 119801
## 35		Drama, Mystery, Sci-Fi	R	129	6.6 76 102245
## 17		Action, Drama, Thriller	R	116	7.3 66 99414
## 57		Drama	PG-13	139	7.2 79 95482
## 30		Biography, Drama, Sport	R	146	7.6 74 90216
## 12		Biography, Drama, History	PG-13	202	7.7 73 83628
## 14		Crime, Drama, Mystery	PG-13	141	6.6 50 75635
## 24		Action, Crime, Drama	R	124	7.0 NA 73486
## 26		Action, Thriller	R	116	6.4 53 67467
## 33		Crime, Drama, Mystery	PG-13	105	6.5 63 56106
## 36		Biography, Drama, Romance	PG-13	126	7.5 65 55273
## 21		Action, Drama, Mystery	R	116	6.6 77 49485
## 13		Comedy, Drama, Romance	PG-13	111	7.3 NA 44429
## 25		Drama, Sport	R	136	6.9 64 43683
## 29		Biography, Drama	PG-13	120	7.3 62 32370
## 60		Crime, Drama, Thriller	PG-13	122	6.5 58 31127
## 20		Action, Crime, Sci-Fi	R	106	5.6 39 27492
## 18		Crime, Drama, Mystery	R	102	6.7 78 17130
## 11		Action, Crime, Drama	R	102	6.2 49 15777
## 4		Biography, Drama, History	PG	157	7.4 59 12231
## 9		Drama, Music, Romance	R	130	6.6 61 10929
## 22		Comedy, Drama, Fantasy	PG	123	5.6 NA 10748
## 2		Crime, Drama, Mystery	PG	101	7.2 66 8628
## 7		Action, Crime, Drama	R	98	6.0 71 4964
## 10		Drama, Romance	R	118	6.6 NA 4671
## 8		Comedy, Crime, Drama	R	100	5.6 NA 3208
## 3		Drama	R	111	5.7 50 2663
## 1		Comedy, Drama	PG	92	5.7 NA 2484

## 5	Action, Crime, Drama	R	105	5.6	NA	2170
## 59	Documentary, Biography, Music	Not Rated	99	7.3	NA	1964
## 53	Documentary, Biography, Sport	Not Rated	85	7.3	59	1843
## 23	Drama	R	92	6.0	NA	330
## 16	Documentary	<NA>	72	5.2	NA	NA
## 19	Documentary, Biography, Sport	<NA>	120	6.7	NA	NA
## 54	Documentary, Biography, Drama	<NA>	82	8.5	NA	NA
## 51	Documentary	<NA>	NA	5.0	NA	NA
## 46	Drama, Music	R	NA	NA	NA	NA
## 43	Thriller	R	NA	NA	NA	NA
## 44	Drama	<NA>	NA	NA	NA	NA
## 50	Drama	<NA>	NA	NA	NA	NA
## 42	Comedy, Drama	<NA>	NA	NA	NA	NA
## 48	Documentary	PG-13	87	NA	NA	NA
## 61	Documentary	<NA>	60	NA	NA	NA
##	millions					
## 41	130.16					
## 27	76.63					
## 38	88.51					
## 39	101.53					
## 34	77.91					
## 55	93.77					
## 37	64.04					
## 45	94.84					
## 15	77.32					
## 52	126.37					
## 31	115.65					
## 49	75.61					
## 47	65.45					
## 40	81.56					
## 56	93.43					
## 28	66.52					
## 58	102.08					
## 32	71.76					
## 6	26.83					
## 35	65.96					
## 17	91.40					
## 57	57.64					
## 30	50.67					
## 12	48.17					
## 14	100.77					
## 24	25.19					
## 26	40.98					
## 33	40.91					
## 36	30.23					
## 21	59.03					
## 13	22.55					
## 25	21.55					
## 29	21.08					
## 60	11.96					
## 20	24.05					
## 18	16.03					
## 11	21.76					
## 4	5.90					

## 9 16.15  
 ## 22 48.10  
 ## 2 21.82  
 ## 7 4.56  
 ## 10 7.31  
 ## 8 4.13  
 ## 3 3.80  
 ## 1 9.57  
 ## 5 0.19  
 ## 59 0.41  
 ## 53 NA  
 ## 23 NA  
 ## 16 NA  
 ## 19 NA  
 ## 54 NA  
 ## 51 NA  
 ## 46 NA  
 ## 43 NA  
 ## 44 NA  
 ## 50 NA  
 ## 42 NA  
 ## 48 NA  
 ## 61 NA  
 ##  
 ## 41  
 ## 27  
 ## 38  
 ## 39  
 ## 34  
 ## 55  
 ## 37  
 ## 45  
 ## 15  
 ## 52  
 ## 31  
 ## 49  
 ## 47  
 ## 40  
 ## 56  
 ## 28  
 ## 58  
 ## 32  
 ## 6  
 ## 35  
 ## 17  
 ## 57  
 ## 30  
 ## 12  
 ## 14  
 ## 24  
 ## 26  
 ## 33  
 ## 36  
 ## 21

A man believes he has put his myster

After a ferry is bombed in L

Armed men hijack a New York City s

Bio

A drama based on the true story of Me

```

## 13
## 25
## 29 Antwone Fisher
## 60
## 20
## 18
## 11
## 4
## 9
## 22
## 2
## 7 When police officer Xavier Quinn's childhood is
## 10 An Indian family is expelled from Uganda when Idi Amin takes power. They move to Mississippi and
## 8
## 3
## 1
## 5
## 59
## 53
## 23 Two brothers, Lex and younger Mick, are living in Harlem. Mick is a policeman, and Lex, who spe
## 16
## 19
## 54
## 51
## 46 Chicago, 1927. A recording session. Tensions rise
## 43
## 44
## 50
## 42
## 48
## 61 The 40 Year Journey of Marvin L. Wianans catalogs the life of one of the most recognized names in
denzel.movies = standardizeDollarsInDataFrame(denzel.movies, 2000, "millions", "year", "millions2000");
denzel.movies = sortDataFrameByNumericColumns(denzel.movies, "millions2000", "DESC");
denzel.movies$rank.money = 1:nrow(denzel.movies);
denzel.rank = subsetDataFrame(imdb.data$all.movies.actors.characters, "nmid", "==", denzel.nmid);
denzel.rank;

##          ttid actor.rank      nmid      character
## 278760 tt0082138         5 nm0000243      Roger Porter
## 296252 tt0088146         9 nm0000243 Private First Class Peterson
## 306935 tt0091786         5 nm0000243      Arnold Billings
## 309732 tt0092804        13 nm0000243      Steve Biko
## 324011 tt0097373         1 nm0000243      Reuben James
## 324284 tt0097441         2 nm0000243      Pvt. Trip
## 325715 tt0097880         1 nm0000243      Xavier Quinn
## 332498 tt0100168         1 nm0000243      Bleek Gilliam
## 340585 tt0102789         1 nm0000243      Nick Styles
## 346203 tt0104797         1 nm0000243      Malcolm X
## 354113 tt0107616        12 nm0000243      Don Pedro
## 354692 tt0107798         2 nm0000243      Gray Grantham
## 354752 tt0107818         2 nm0000243      Joe Miller
## 366574 tt0112740         1 nm0000243      Hunter
## 366964 tt0112857         1 nm0000243      Easy Rawlins
## 372622 tt0114857         1 nm0000243      Lt. Parker Barnes

```

## 374560	tt0115956	1 nm0000243	Nat Serling
## 384676	tt0119099	1 nm0000243	John Hobbes
## 396478	tt0124718	1 nm0000243	Jake Shuttlesworth
## 403408	tt0133952	1 nm0000243	Anthony Hubbard
## 408069	tt0139654	1 nm0000243	Alonzo
## 431245	tt0168786	4 nm0000243	Dr. Jerome Davenport
## 435974	tt0174856	1 nm0000243	Rubin Carter
## 464508	tt0210945	1 nm0000243	Coach Herman Boone
## 488282	tt0251160	2 nm0000243	John Quincy Archibald
## 533381	tt0328107	1 nm0000243	John W. Creasy
## 552091	tt0368008	9 nm0000243	Ben Marco
## 577663	tt0427309	1 nm0000243	Melvin B. Tolson
## 588322	tt0453467	1 nm0000243	Doug Carlin
## 588758	tt0454848	1 nm0000243	Detective Keith Frazier
## 589536	tt0455944	1 nm0000243	Robert McCall
## 598037	tt0477080	1 nm0000243	Frank
## 607371	tt0765429	1 nm0000243	Frank Lucas
## 635597	tt1037705	1 nm0000243	Eli
## 646167	tt1111422	1 nm0000243	Walter Garber
## 669913	tt1272878	1 nm0000243	Bobby
## 693712	tt1546668	10 nm0000243	Self
## 698461	tt1599348	1 nm0000243	Tobin Frost
## 721822	tt1907668	2 nm0000243	Whip Whitaker
## 752221	tt2404435	1 nm0000243	Chisolm
## 760468	tt2671706	1 nm0000243	Troy Maxson
## 790837	tt3766354	1 nm0000243	Robert McCall
## 834463	tt6000478	1 nm0000243	Roman J. Israel, Esq.
## 629718	tt10016180	1 nm0000243	
## 630739	tt10095582	1 nm0000243	Lord Macbeth
## 650815	tt11394338	9 nm0000243	Self

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

```
## [1] 19
```

```
mean(denzel.rank$actor.rank)
```

```
## [1] 2.565217
```