Data Analysis of Movie Recommender Project

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- Download Data
- Read in data
  - ratings data
  - movies data
  - user data
- Exploration
  - Check for unique users
  - Check for unique movies
  - Dist of ratings
  - Ratings per users
  - Ratings per movie
  - Dist of Genres

```
# Load necessary libraries
library(dplyr)
library(ggplot2)
library(recommenderlab)
library(DT)
library(data.table)
library(reshape2)
```

Download Data

```
myurl = "https://raw.githubusercontent.com/Vivek2696/movie-recommender/main/data/"
```

Check the readme file to understand the format of the other three files. You can also download them from the original site: https://grouplens.org/datasets/movielens/ (https://grouplens.org/datasets/movielens/).

Read in data

ratings data

```r
# use colClasses = 'NULL' to skip columns
ratings = read.csv(paste0(myurl, 'ratings.dat?raw=true'),
                   sep = ':',
                   colClasses = c('integer', 'NULL'),
                   header = FALSE)
colnames(ratings) = c('UserID', 'MovieID', 'Rating', 'Timestamp')
head(ratings)
```

	UserID <int>	MovieID <int>	Rating <int>	Timestamp <int>
1	1	1193	5	978300760
2	1	661	3	978302109
3	1	914	3	978301968
4	1	3408	4	978300275
5	1	2355	5	978824291
6	1	1197	3	978302268

6 rows

movies data

```r
movies = readLines(paste0(myurl, 'movies.dat?raw=true'))
movies = strsplit(movies, split = "::", fixed = TRUE, useBytes = TRUE)
movies = matrix(unlist(movies), ncol = 3, byrow = TRUE)
movies = data.frame(movies, stringsAsFactors = FALSE)
colnames(movies) = c('MovieID', 'Title', 'Genres')
movies$MovieID = as.integer(movies$MovieID)

# convert accented characters
movies$Title[73]
```

```
## [1] "Mis\xe9rables, Les (1995)"
```

```r
movies$Title = iconv(movies$Title, "latin1", "UTF-8")
movies$Title[73]
```

```
## [1] "Misérables, Les (1995)"
```

```r
# extract year
movies$Year = as.numeric(unlist(
  lapply(movies$Title, function(x) substr(x, nchar(x)-4, nchar(x)-1))))
```

```
head(movies)
```

	Movi... <int>	Title <chr>	Genres <chr>	Y... <dbl>
1	1	Toy Story (1995)	Animation|Children's|Comedy	1995
2	2	Jumanji (1995)	Adventure|Children's|Fantasy	1995
3	3	Grumpier Old Men (1995)	Comedy|Romance	1995
4	4	Waiting to Exhale (1995)	Comedy|Drama	1995
5	5	Father of the Bride Part II (1995)	Comedy	1995
6	6	Heat (1995)	Action|Crime|Thriller	1995

6 rows

user data

```
users = read.csv(paste0(myurl, 'users.dat?raw=true'),
                 sep = ':', header = FALSE)
users = users[, -c(2,4,6,8)] # skip columns
colnames(users) = c('UserID', 'Gender', 'Age', 'Occupation', 'Zip-code')

head(users)
```

	UserID <int>	Gender <chr>	Age <int>	Occupation <int>	Zip-code <chr>
1	1	F	1	10	48067
2	2	M	56	16	70072
3	3	M	25	15	55117
4	4	M	45	7	02460
5	5	M	25	20	55455
6	6	F	50	9	55117

6 rows

For users, Gender is denoted by “M” for male and “F” for female, Age is chosen from the following ranges:

```
*  1:  "Under 18"
* 18:  "18-24"
* 25:  "25-34"
* 35:  "35-44"
* 45:  "45-49"
* 50:  "50-55"
* 56:  "56+"
```

and Occupation is chosen from the following choices:

```
*  0:  "other" or not specified
*  1:  "academic/educator"
*  2:  "artist"
*  3:  "clerical/admin"
*  4:  "college/grad student"
*  5:  "customer service"
*  6:  "doctor/health care"
*  7:  "executive/managerial"
*  8:  "farmer"
*  9:  "homemaker"
* 10:  "K-12 student"
* 11:  "lawyer"
* 12:  "programmer"
* 13:  "retired"
* 14:  "sales/marketing"
* 15:  "scientist"
* 16:  "self-employed"
* 17:  "technician/engineer"
* 18:  "tradesman/craftsman"
* 19:  "unemployed"
* 20:  "writer"
```

Exploration

Check for unique users

```
dim(users)
```

```
## [1] 6040    5
```

```
length(unique(ratings$UserID))
```

```
## [1] 6040
```

Check for unique movies

```
dim(movies)
```

```
## [1] 3883    4
```

```
length(unique(ratings$MovieID))
```

```
## [1] 3706
```

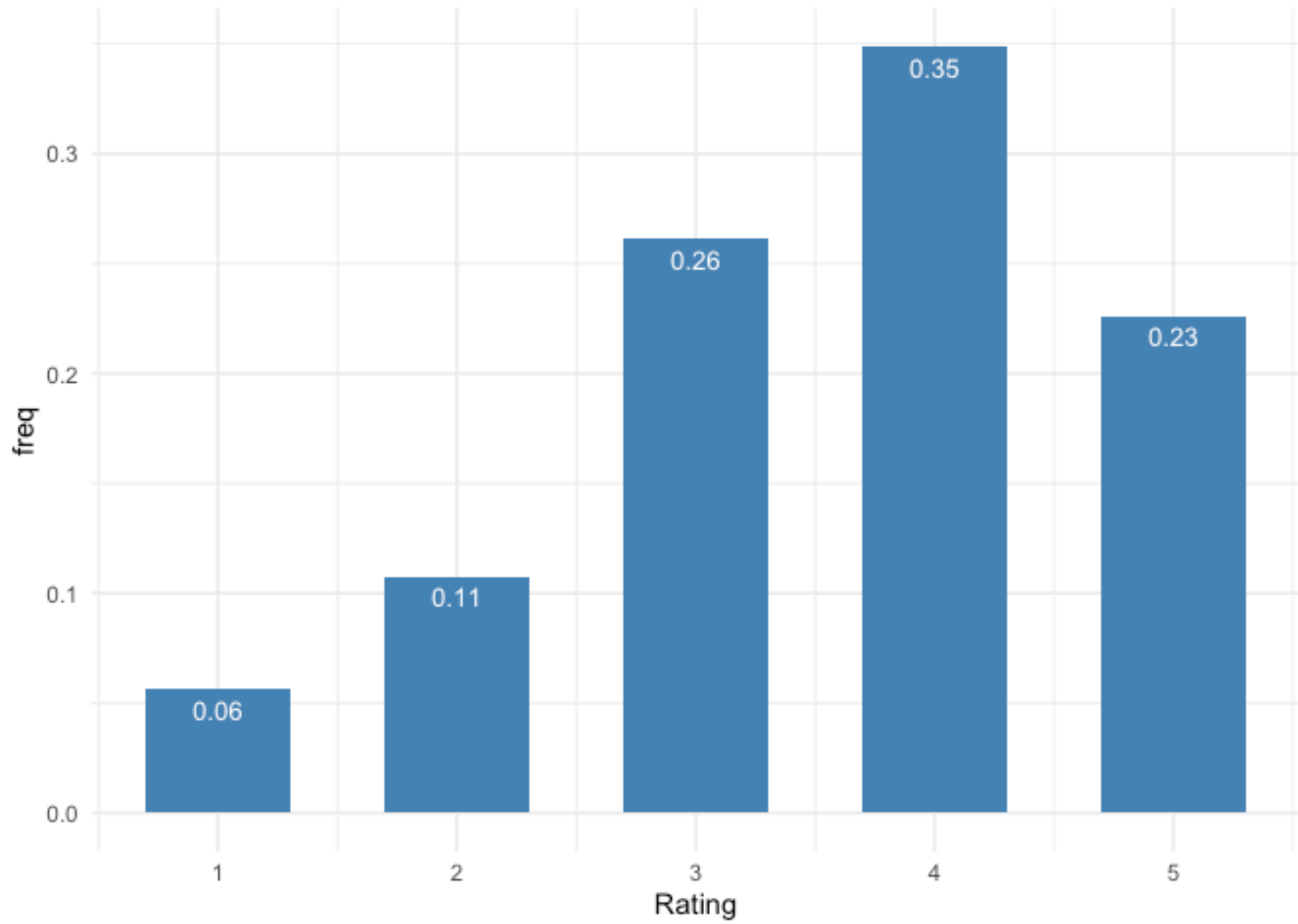
```
movies_not_rated = movies %>%
  filter(!(MovieID %in% ratings$MovieID))
dim(movies_not_rated)
```

```
## [1] 177   4
```

Dist of ratings

Most of the ratings are in the 3-5 range.

```
tmp = data.frame(Rating = 1:5,
                 freq = as.vector(table(ratings$Rating)/nrow(ratings)))
ggplot(data = tmp, aes(x = Rating, y = freq)) +
  geom_bar(stat="identity", fill = 'steelblue', width = 0.6) +
  geom_text(aes(label=round(freq, dig=2)),
                vjust=1.6, color="white", size=3.5) +
  theme_minimal()
```



Ratings per users

```
tmp = ratings %>%
  group_by(UserID) %>%
  summarize(ratings_per_user = n())
summary(tmp$ratings_per_user)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    20.0    44.0    96.0   165.6   208.0  2314.0
```

```
stem(tmp$ratings_per_user)
```

```
##
##   The decimal point is 2 digit(s) to the right of the |
##
##    0 | 2222222222222222222222222222222222222222222222222222222222222222222+2922
##    1 | 0000000000000000000000000000000000000000000000000000000000000000000+1323
##    2 | 0000000000000000000000000000000000000000000000000000000000000000000+560
##    3 | 0000000000000000000000000000000000000000000000000000000000000011111+293
##    4 | 0000000000000000000000000000000000000000111111111111111111111111111+138
##    5 | 0000000000000001111111111111111111111112222222222222233333333333333+61
##    6 | 0000000111111111111222222222233333333333334444444555556666777777777+2
##    7 | 00000000111111222222233333333333444444555566666677777788888999999
##    8 | 000011222222233333344444455555566667777777888899999
##    9 | 00112223344456666667789
##   10 | 0001112222224558
##   11 | 245678
##   12 | 1222234466789
##   13 | 024
##   14 |
##   15 | 22
##   16 | 0
##   17 | 4
##   18 | 5
##   19 |
##   20 |
##   21 |
##   22 |
##   23 | 1
```

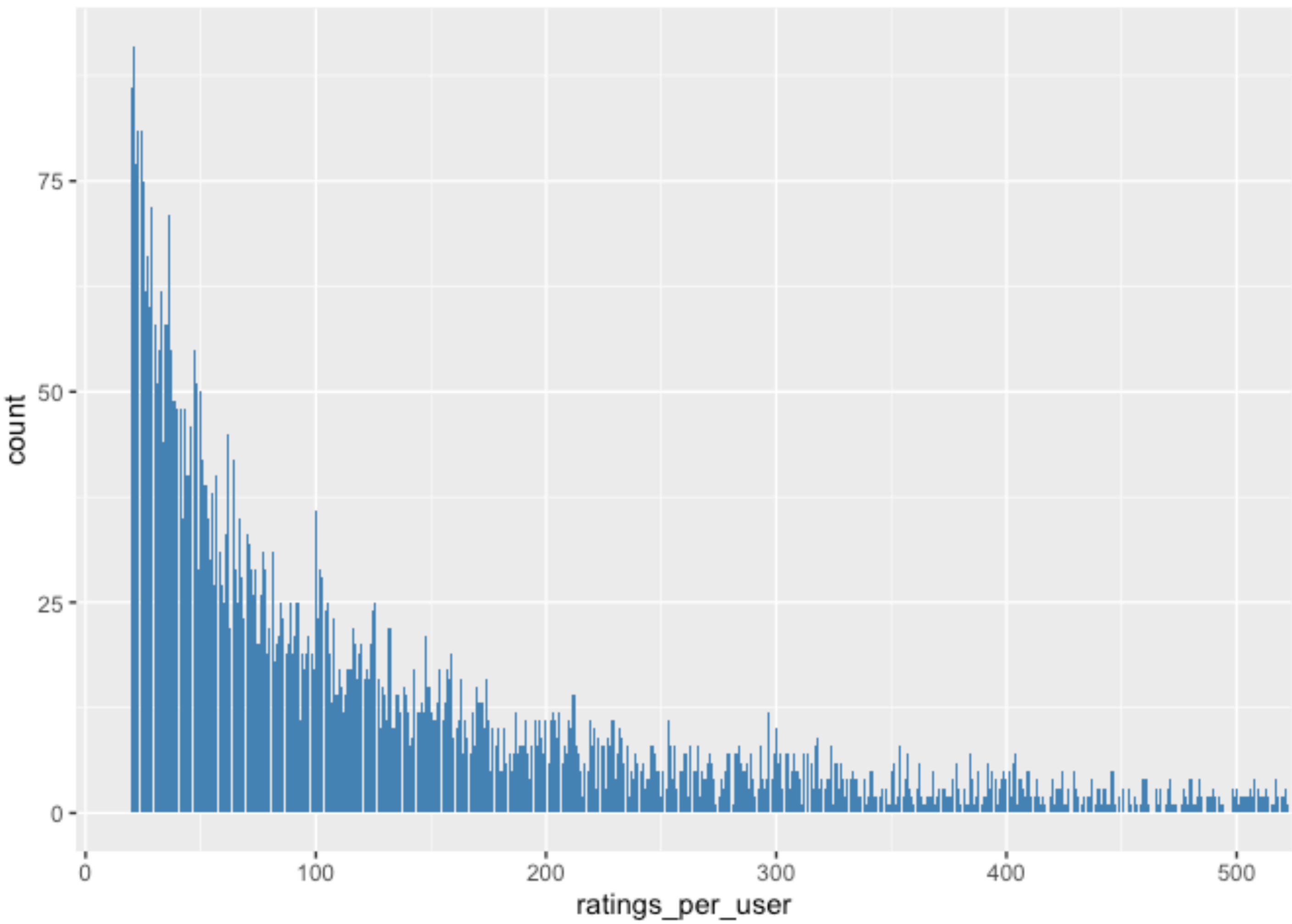
```
sum(tmp$ratings_per_user > 500)
```

```
## [1] 396
```

```
sort(tmp$ratings_per_user[tmp$ratings_per_user>1300])
```

```
## [1] 1302 1323 1344 1518 1521 1595 1743 1850 2314
```

```
tmp %>%
  ggplot(aes(ratings_per_user)) +
  geom_bar(fill = "steelblue") + coord_cartesian(c(20, 500))
```



Combining users and tmp, you could further explore how ratings_per_user depends on Gender, Age, and Occupation of users.

```
tmp = tmp %>% full_join(users, by = 'UserID')
```

Ratings per movie

There are 31 movies that have received more than 2000 ratings. The most popular movie is “American Beauty (1999)”, followed by the “Star Wars” series. Throughout, popular means receiving many ratings; a popular movie may not be a highly-rated movie.

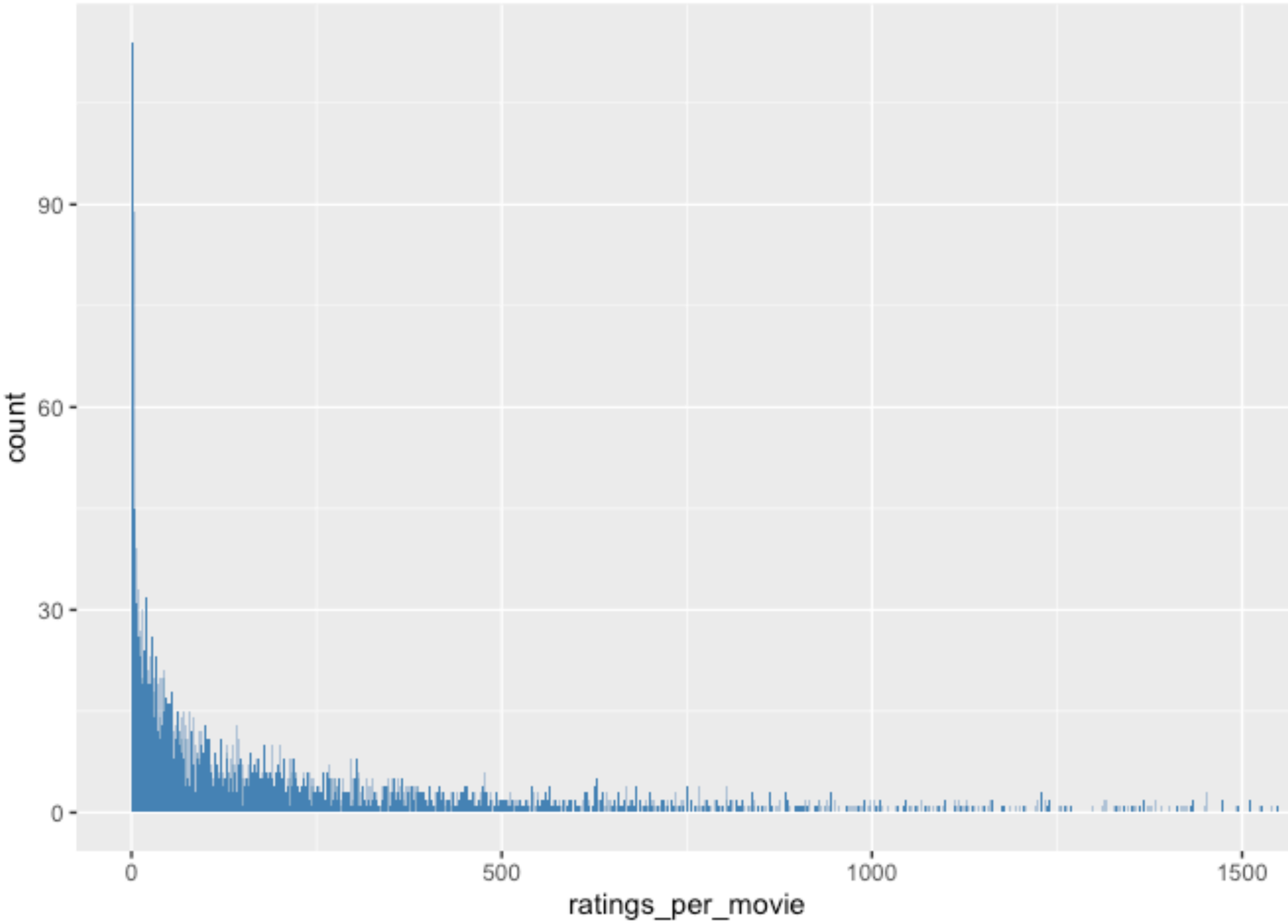
```
tmp = ratings %>%
  group_by(MovieID) %>%
  summarize(ratings_per_movie = n(), ave_ratings = mean(Rating)) %>%
  inner_join(movies, by = 'MovieID')
summary(tmp$ratings_per_movie)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##     1.0    33.0   123.5   269.9   350.0  3428.0
```

```r
tmp %>%
  filter(ratings_per_movie > 2000) %>%
  arrange(desc = ratings_per_movie) %>%
  select(c("Title", "ratings_per_movie")) %>%
  print(n = 31)
```

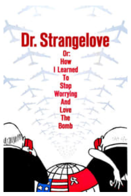
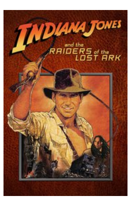
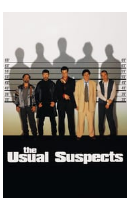
```
## # A tibble: 31 × 2
##    Title                                                  ratings_per_movie
##    <chr>                                                              <int>
##  1 Alien (1979)                                                        2024
##  2 Toy Story (1995)                                                    2077
##  3 Terminator, The (1984)                                              2098
##  4 Pulp Fiction (1994)                                                 2171
##  5 Ghostbusters (1984)                                                 2181
##  6 Forrest Gump (1994)                                                 2194
##  7 Godfather, The (1972)                                               2223
##  8 Shawshank Redemption, The (1994)                                    2227
##  9 Being John Malkovich (1999)                                         2241
## 10 Star Wars: Episode I - The Phantom Menace (1999)                    2250
## 11 E.T. the Extra-Terrestrial (1982)                                   2269
## 12 Groundhog Day (1993)                                                2278
## 13 L.A. Confidential (1997)                                            2288
## 14 Schindler's List (1993)                                             2304
## 15 Princess Bride, The (1987)                                          2318
## 16 Shakespeare in Love (1998)                                          2369
## 17 Braveheart (1995)                                                   2443
## 18 Sixth Sense, The (1999)                                             2459
## 19 Fargo (1996)                                                        2513
## 20 Raiders of the Lost Ark (1981)                                      2514
## 21 Men in Black (1997)                                                 2538
## 22 Silence of the Lambs, The (1991)                                    2578
## 23 Back to the Future (1985)                                           2583
## 24 Matrix, The (1999)                                                  2590
## 25 Terminator 2: Judgment Day (1991)                                   2649
## 26 Saving Private Ryan (1998)                                          2653
## 27 Jurassic Park (1993)                                                2672
## 28 Star Wars: Episode VI - Return of the Jedi (1983)                   2883
## 29 Star Wars: Episode V - The Empire Strikes Back (1980)               2990
## 30 Star Wars: Episode IV - A New Hope (1977)                           2991
## 31 American Beauty (1999)                                              3428
```

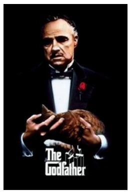
```r
tmp %>% ggplot(aes(ratings_per_movie)) +
  geom_bar(fill = "steelblue", width = 1) + coord_cartesian(c(1,1500))
```



The top ten highly-rated (based on their average ratings) among all movies that have received at least 1000 ratings.

```
small_image_url = "https://github.com/Vivek2696/movie-recommender/blob/main/data/Movi
eImages/"
ratings %>%
  group_by(MovieID) %>%
  summarize(ratings_per_movie = n(),
            ave_ratings = round(mean(Rating), dig=3)) %>%
  inner_join(movies, by = 'MovieID') %>%
  filter(ratings_per_movie > 1000) %>%
  top_n(10, ave_ratings) %>%
  mutate(Image = paste0('<img src="',
                        small_image_url,
                        MovieID,
                        '.jpg?raw=true"></img>')) %>%
  select('Image', 'Title', 'ave_ratings') %>%
  arrange(desc(-ave_ratings)) %>%
  datatable(class = "nowrap hover row-border",
            escape = FALSE,
            options = list(dom = 't',
                           scrollX = TRUE, autoWidth = TRUE))
```

	Image	Title	ave_rati
1		Sixth Sense, The (1999)	
2		Casablanca (1942)	
3		Dr. Strangelove or: How I Learned to Stop Worrying and Love the Bomb (1963)	
4		Star Wars: Episode IV - A New Hope (1977)	
5		Rear Window (1954)	
6		Raiders of the Lost Ark (1981)	
7		Schindler's List (1993)	
8		Usual Suspects, The (1995)	

9		Godfather, The (1972)
10		Shawshank Redemption, The (1994)

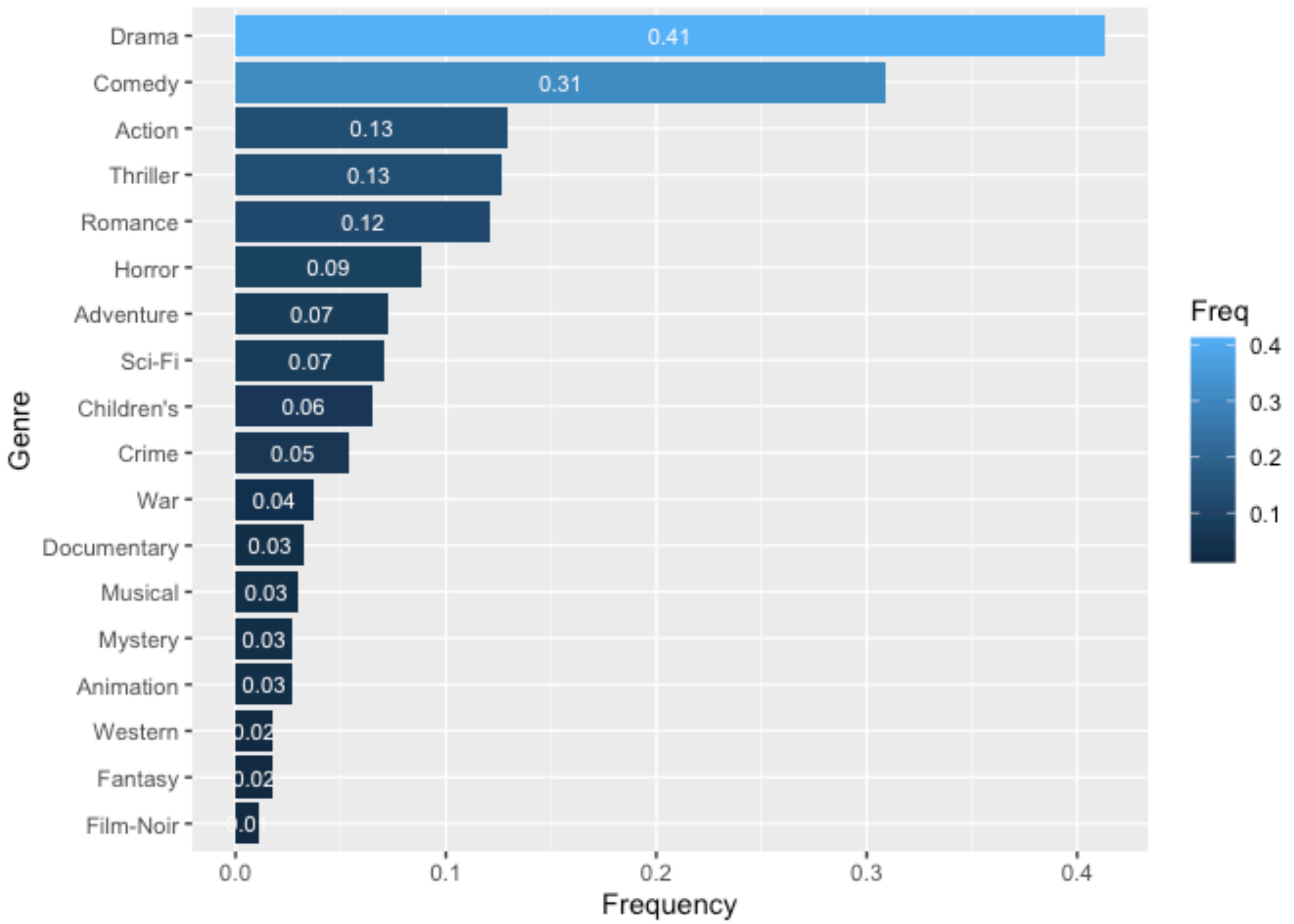
Dist of Genres

First cretae a bibary indicator for the 18 genres for each movie.

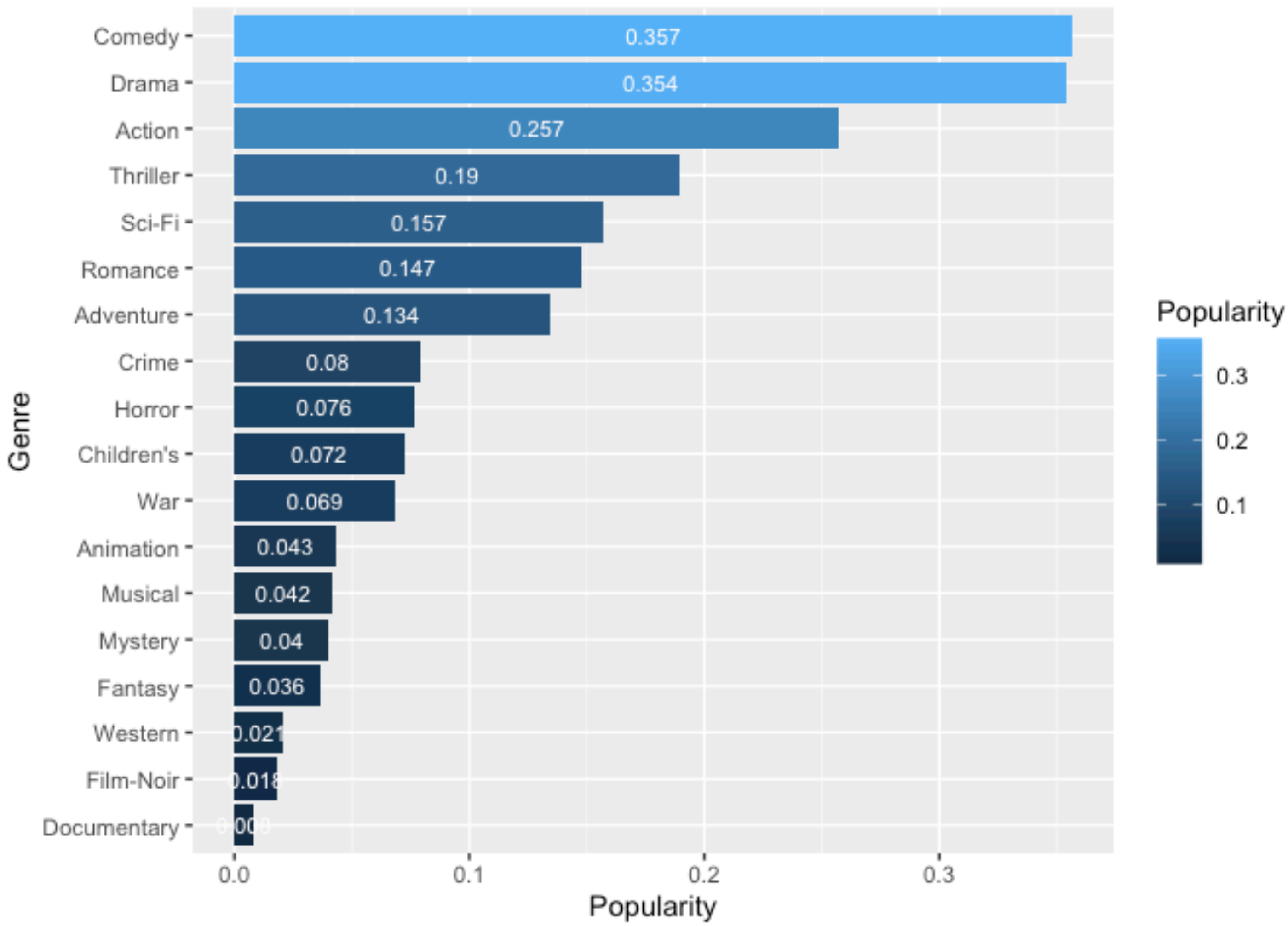
```
genres = as.data.frame(movies$Genres, stringsAsFactors=FALSE)
tmp = as.data.frame(tstrsplit(genres[,1], '[|]',
                              type.convert=TRUE),
                    stringsAsFactors=FALSE)
genre_list = c("Action", "Adventure", "Animation",
               "Children's", "Comedy", "Crime",
               "Documentary", "Drama", "Fantasy",
               "Film-Noir", "Horror", "Musical",
               "Mystery", "Romance", "Sci-Fi",
               "Thriller", "War", "Western")
m = length(genre_list)
genre_matrix = matrix(0, nrow(movies), length(genre_list))
for(i in 1:nrow(tmp)){
  genre_matrix[i,genre_list %in% tmp[i,]]=1
}
colnames(genre_matrix) = genre_list
remove("tmp", "genres")
```

Then we can output historograms of the 18 genres baesd on movies or based on ratings.

```
data.frame(Genres = genre_list,
                 Freq = as.vector(colMeans(genre_matrix))) %>%
  ggplot(aes(reorder(Genres, Freq), Freq, fill = Freq)) +
  geom_bar(stat = "identity") +
    geom_text(aes(label = round(Freq, dig=2)),
            position = position_stack(vjust = 0.5),
            color="white", size=3) +
  coord_flip() +
  scale_colour_brewer(palette="Set1") +
  labs(y = 'Frequency', x = 'Genre')
```




```
tmp = ratings %>%
  left_join(data.frame(MovieID = movies$MovieID, genre_matrix),
            by = "MovieID") %>%
  select(-c("UserID", "MovieID", "Rating", "Timestamp"))
data.frame(Genres = genre_list,
                 Popularity = as.vector(colMeans(tmp))) %>%
  ggplot(aes(reorder(Genres, Popularity), Popularity, fill = Popularity)) +
  geom_bar(stat = "identity") +
  geom_text(aes(label = round(Popularity, dig=3)),
            position = position_stack(vjust = 0.5),
            color="white", size=3) +
  coord_flip() +
  labs(y = 'Popularity', x = 'Genre')
```



About half of the movies belong to only one genre; about one-third are categorized into two genres; a few are categorized into more than four genres. The movie "The Transformers" (1986) are categorized into six genres: Action, Animation, Children's, Sci-Fi, Thriller, and War.

```
tmp = rowSums(genre_matrix)
summary(tmp)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    1.00    1.00    1.00    1.65    2.00    6.00
```

```
movies[which(tmp==6), ]
```

	Movi...	Title	Genres
	<int>	<chr>	<chr>
1188	1205	Transformers: The Movie, The (1986)	Action|Animation|Children's|Sci-Fi|Thriller|

1 row | 1-4 of 5 columns

```
movies[which(tmp==5), ]
```

	MovieID	Title
	<int>	<chr>
70	70	From Dusk Till Dawn (1996)
256	258	Kid in King Arthur's Court, A (1995)
555	558	Pagemaster, The (1994)
607	610	Heavy Metal (1981)
668	673	Space Jam (1996)
1179	1196	Star Wars: Episode V - The Empire Strikes Back (1980)
1193	1210	Star Wars: Episode VI - Return of the Jedi (1983)
1198	1215	Army of Darkness (1993)
1245	1264	Diva (1981)
1527	1566	Hercules (1997)

1-10 of 14 rows | 1-3 of 5 columns Previous **1** 2 Next

For illustration purpose only, let’s assume movies contains all the movies available to users from 1919 to 2000. Then we can compute the cumulative percentages of the 18 genres over year from 1919 to 2000 and store them in the 81-by-19 matrix tmp. For example, till 2000, users can access about 7.8% Action, 4.4% Adventure, 25% Drama, etc. A graphical display of such CDF over 10 generes are displayed below.

```r
# range(movies$Year) % 1919 to 2000
tmp = data.frame(Year = movies$Year, genre_matrix) %>%
  group_by(Year) %>%
  summarise_all(sum)
tmp[,-1] = apply(tmp[, -1], 2, cumsum)
tmp[,-1] = tmp[,-1]/sum(tmp[nrow(tmp), -1])
print(round(tmp[nrow(tmp),-1], dig=3))
```

```
## # A tibble: 1 × 18
##   Action Adventure Animation Children.s Comedy Crime Documentary Drama Fantasy
##    <dbl>     <dbl>     <dbl>      <dbl>  <dbl> <dbl>       <dbl> <dbl>   <dbl>
## 1  0.078     0.044     0.016      0.039  0.187 0.033        0.02  0.25   0.011
## # ℹ 9 more variables: Film.Noir <dbl>, Horror <dbl>, Musical <dbl>,
## #   Mystery <dbl>, Romance <dbl>, Sci.Fi <dbl>, Thriller <dbl>, War <dbl>,
## #   Western <dbl>
```

```
tmp = reshape2::melt(tmp, id.vars="Year")
tmp %>%
  ggplot(aes(Year, value, group = variable)) +
  geom_area(aes(fill = variable)) +
  geom_line(aes(group = variable), position = "stack")
```