Top 1000 Movies According to IMDB Users

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```
library(knitr)
library(ggplot2)
library(fitdistrplus)
```

```
## Loading required package: MASS

## Loading required package: survival

## Loading required package: npsurv

## Loading required package: lsei
```

Finding The Data

```
#DATA LOADER
#A function that takes in an empty vector and reads in the html files that
contain data on the top 1000 movies on IMDB. It then combines them into one
character vector and outputs that vector, 'movies'
#v = empty vector
html_loader=function(v){
  imdb50=readLines("imdb50.html")
  imdb100=readLines("imdb100.html")
  imdb150=readLines("imdb150.html")
  imdb200=readLines("imdb200.html")
  imdb250=readLines("imdb250.html")
  imdb300=readLines("imdb300.html")
  imdb350=readLines("imdb350.html")
  imdb400=readLines("imdb400.html")
  imdb450=readLines("imdb450.html")
  imdb500=readLines("imdb500.html")
  imdb550=readLines("imdb550.html")
  imdb600=readLines("imdb600.html")
  imdb650=readLines("imdb650.html")
  imdb700=readLines("imdb700.html")
  imdb750=readLines("imdb750.html")
  imdb800=readLines("imdb800.html")
  imdb850=readLines("imdb850.html")
  imdb900=readLines("imdb900.html")
  imdb950=readLines("imdb950.html")
  imdb1000=readLines("imdb1000.html")


movies=c(imdb50,imdb100,imdb150,imdb200,imdb250,imdb300,imdb350,imdb400,imdb4
50,imdb500,imdb550,imdb600,imdb650,imdb700,imdb750,imdb800,imdb850,imdb900,im
db950,imdb1000)
```

```r
  return(movies)
}

#TITLE FINDER
#A Function that takes in a character string and searches for a pattern that 
contains the movie title. It then 'gets rid' of any unnecessary symbols 
and/or punctuations that don't pertain to the movie and outputs a vector that 
contains the movie titles, 'titles'.
#char.v = character string
title.finder=function(char.v){

  title.pattern=">\\s+<img\\s+alt.*"
  start.pat="([0-9]|[A-Z])"
  stop.pat="\"$"

  title.junk=regmatches(char.v,regexpr(title.pattern,char.v))
  titles=substr(title.junk,start = regexpr(start.pat,title.junk),stop = 
regexpr(stop.pat,title.junk)-1)
  titles=titles[titles!=""]
  return(titles)
}

#GENRE FINDER
#A funtion that takes in a character string and searches for a pattern that 
contains the movies' genre(s). It then 'gets rid' of any unnecessary symbols 
and/or punctuations that don't pertain to the movie genre(s) and outputs a 
vector that contains the movie genres, 'genre'.
#char.v = character string
genre.finder=function(char.v){

  genre.pattern="[A-Z].*\\s+</span>"
  start.pat="[A-Z]"
  stop.pat="[a-z]\\s+</span>"

  genre.junk=regmatches(char.v,regexpr(genre.pattern,char.v))
  genre=substr(genre.junk,start = regexpr(start.pat,genre.junk),stop = 
regexpr(stop.pat,genre.junk))

  return(genre)
}

#ACTOR FINDER
#A funtion that takes in a character string and searches for the location of 
the top 4 actors/actresses. It then 'gets rid' of any unnecessary symbols 
and/or punctuations that don't pertain to their names and outputs a vector 
that contains the top 4 paid actors and actresses from each movie, 'actor'.
#char.v = character string
actor.finder=function(char.v){
  actors.pattern="Stars:"
  stars.loc=grep(actors.pattern,char.v)

  a1.loc=stars.loc+2
  a2.loc=stars.loc+4
  a3.loc=stars.loc+6
  a4.loc=stars.loc+8

  a1=char.v[a1.loc]
  a2=char.v[a2.loc]
  a3=char.v[a3.loc]
  a4=char.v[a4.loc]

  stop.pat="</a>"

  a1=substr(a1,start = 2,stop = regexpr(stop.pat,a1)-1)
  a2=substr(a2,start = 2,stop = regexpr(stop.pat,a2)-1)
  a3=substr(a3,start = 2,stop = regexpr(stop.pat,a3)-1)
  a4=substr(a4,start = 2,stop = regexpr(stop.pat,a4)-1)

  actor=paste(a1,a2,a3,a4,sep = ", ")

  return(actor)
}

#REVENUE FINDER
#A funtion that takes in a character string and searches for the location of
the gross US revenue of a movie. It then 'gets rid' of any unnecessary
symbols and/or punctuations that don't pertain to the gross US revenue and
outputs a vector that contains the the gross US revenue for each movie,
'rev'. If gross US revenue isn't listed, gross revenue becomes NA.
#char.v = character string
rev.finder=function(char.v){

  rev.pat="Votes:"
  rev.loc=grep(rev.pat,char.v)
  rev.loc=rev.loc+3
  rev=char.v[rev.loc]
  rev=substr(rev,start = regexpr("\\$[0-9]",rev)+1,stop = regexpr("M",rev)-1)
  rev=as.numeric(rev)
  return(rev)
}

#RELEASE DATE FINDER
#A funtion that takes in a character string and searches for the location of
the year when the movie was released. It then gets rid of any unnecessary
symbols and/or punctuations and outputs a vector that contains the year in
which the movie was released, 'date'.
#char.v = character string
year.finder=function(char.v){
  date.pat="lister-item-year.*[0-9]{4}"
  date.junk=regmatches(char.v,regexpr(date.pat,char.v))
  date=substr(date.junk,start = regexpr("[0-9]",date.junk),stop =
length(date.junk))
  date=as.numeric(date)

  return(date)
}

#RATING/VOTES FINDER
#A funtion that takes in a character string and searches for the location of
the rating/voting statistics. It then isolates the average rating into 1
variable, 'rates', and the total number of votes, 'votes', into another
variable. Then it gets rid of any unnecessary symbols and/or punctuations and
outputs a list of 2 vectors that contain the average rating by IMDB users
`$rating` and the total number of votes `$votes`.
#char.v = character string
vote.finder=function(char.v){

  vote.pat="Users rated.*votes"
  vote.junk=regmatches(char.v,regexpr(vote.pat,char.v))

  rate=substr(vote.junk,start = regexpr("[0-9]",vote.junk),stop =
regexpr("[0-9]/[0-9]{2}",vote.junk))
  rate=as.numeric(rate)

  votes=substr(vote.junk,start = regexpr("\\([0-9]",vote.junk)+1,stop =
regexpr("\\svotes",vote.junk))
  votes=gsub("(\\,)+","",votes)
  votes=as.numeric(votes)

 return(list(rating=rate,votes=votes))
}

#INFO FINDER
#A function that takes in a character string and searches for the rating,
total votes, title, year released, genre, top 4 paid actors, and gross US
revenue for a list of movies and outputs a chart of the previously stated
categories.
#v = character string
info.finder=function(v){

  Rating=vote.finder(v)$rating
  Total_Votes=vote.finder(v)$votes
  Title=title.finder(v)
  Year=year.finder(v)
  Genre=genre.finder(v)
  Actors=actor.finder(v)
  Revenue=rev.finder(v)
movie.chart=cbind.data.frame(Rating,Total_Votes,Title,Year,Genre,Actors,Reven
ue)

  movie.chart$Title=as.character(movie.chart$Title)
  movie.chart$Genre=as.character(movie.chart$Genre)
  movie.chart$Actors=as.character(movie.chart$Actors)

  return(movie.chart)
}

#Reads in the movie text for the top 1000 movies and puts the relevant
information into a dataframe called 'movies'
movie.text=0
movie.text=html_loader(movie.text)
movies=info.finder(movie.text)

#Checks that data aligns properly by printing the first 5 and last 5 movies
kable(movies[1:5,],caption = "Movies #1-5")
```

Movies #1-5

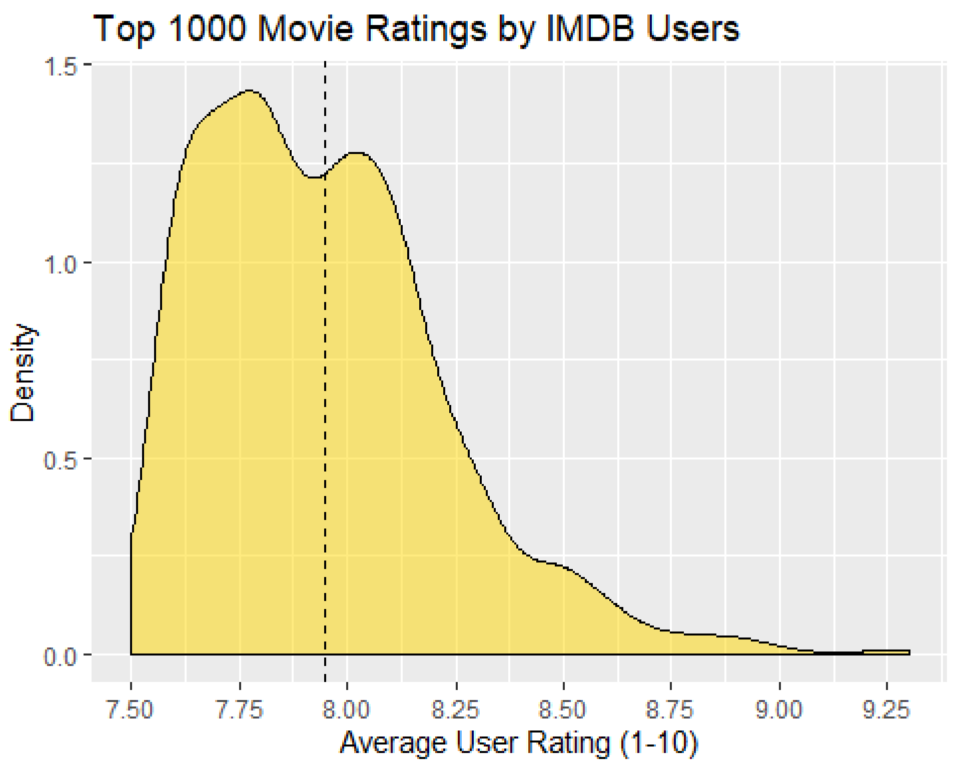
Rating	Total_Votes	Title	Year	Genre	Actors	Revenue
9.3	2061970	The Shawshank Redemption	1994	Drama	Tim Robbins, Morgan Freeman, Bob Gunton, William Sadler	28.34
9.2	1414562	The Godfather	1972	Crime, Drama	Marlon Brando, Al Pacino, James Caan, Diane Keaton	134.97
9.0	2028211	The Dark Knight	2008	Action, Crime, Drama	Christian Bale, Heath Ledger, Aaron Eckhart, Michael Caine	534.86
9.0	981305	The Godfather: Part II	1974	Crime, Drama	Al Pacino, Robert De Niro, Robert Duvall, Diane Keaton	57.30
8.9	1468152	The Lord of the Rings: The Return of the King	2003	Adventure, Drama, Fantasy	Elijah Wood, Viggo Mortensen, Ian McKellen, Orlando Bloom	377.85

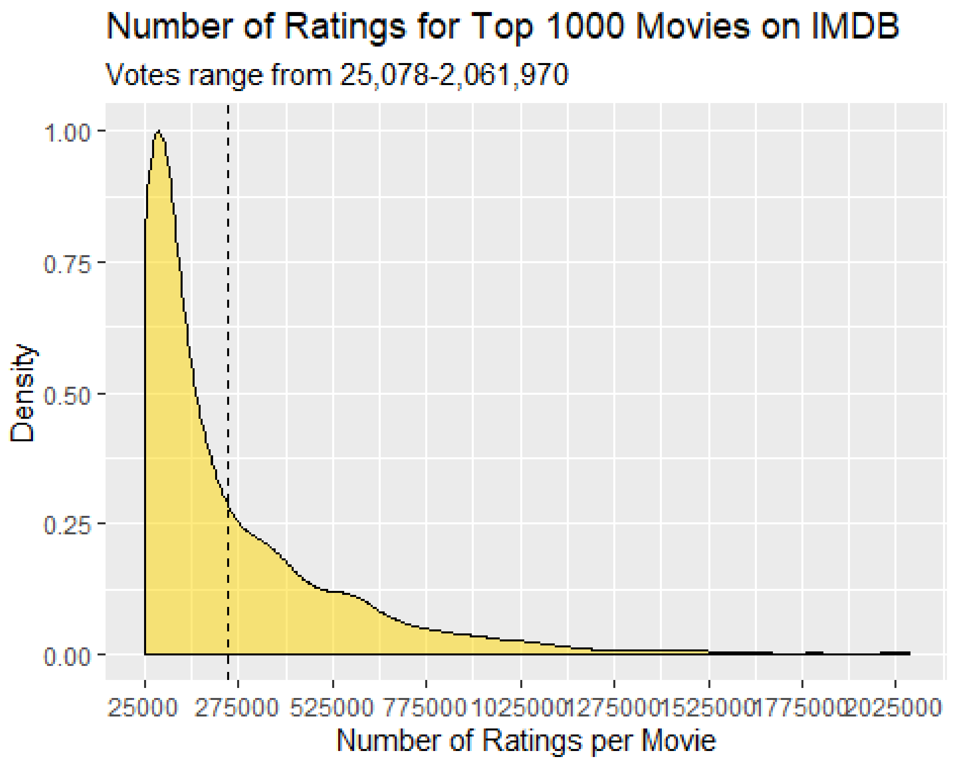
```
kable(movies[996:1000,],caption = "Movies #996-1000")
```

Movies #996-1000

	Rating	Total_Votes	Title	Year	Genre	Actors	Revenue
996	7.5	332546	Collateral	2004	Crime, Drama, Thriller	Tom Cruise, Jamie Foxx, Jada Pinkett Smith, Mark Ruffalo	101.01
997	7.5	395231	Ice Age	2002	Animation, Adventure, Comedy	Denis Leary, John Leguizamo, Ray Romano, Goran Visnjic	176.39
998	7.5	367291	Gangs of New York	2002	Crime, Drama	Leonardo DiCaprio, Cameron Diaz, Daniel Day-Lewis, Jim Broadbent	77.81
999	7.5	309201	Batman	1989	Action, Adventure	Michael Keaton, Jack Nicholson, Kim Basinger, Robert Wuhl	251.19
1000	7.5	142584	The Fly	1986	Drama, Horror, Sci-Fi	Jeff Goldblum, Geena Davis, John Getz, Joy Boushel	40.46

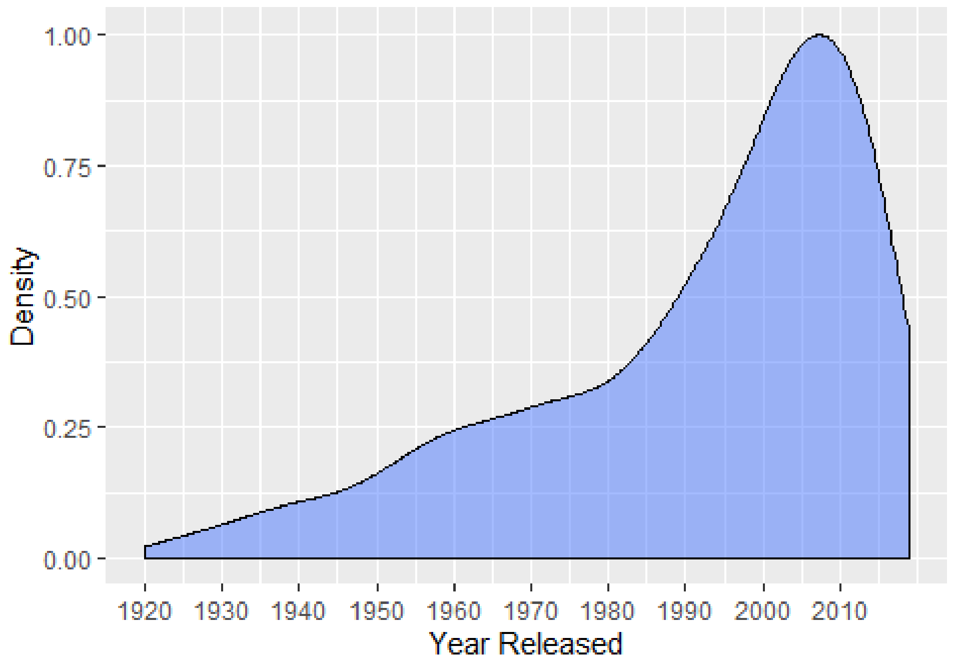
Probability Distributions for Numerical Data





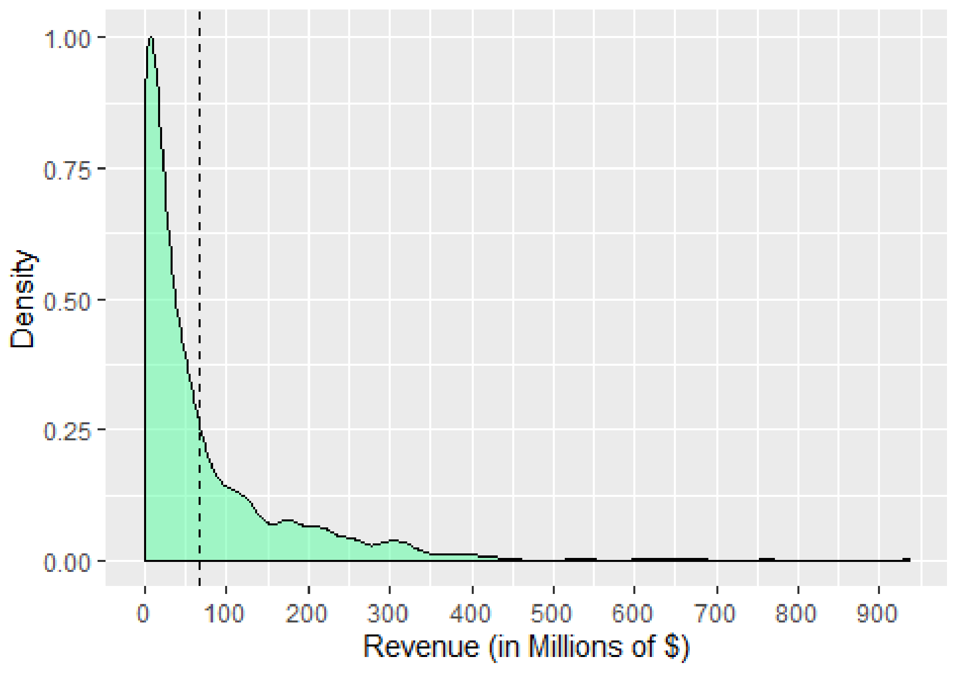
Top 1000 Movies' Release Date

1920-2019



Gross US Revenue of Top 1000 Movies

Movies at $0 made less than $10,000 in US Revenue

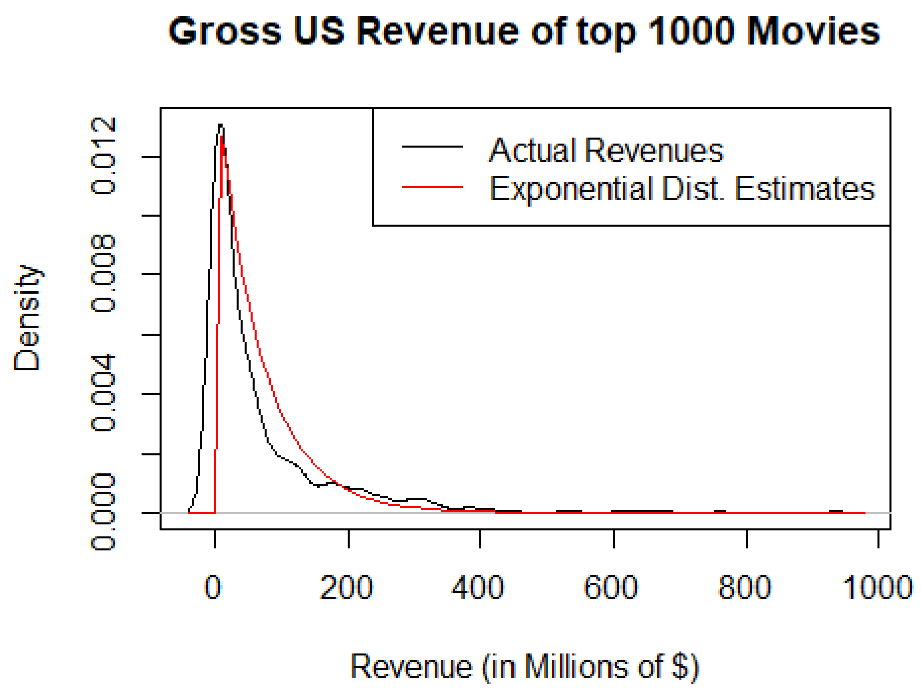


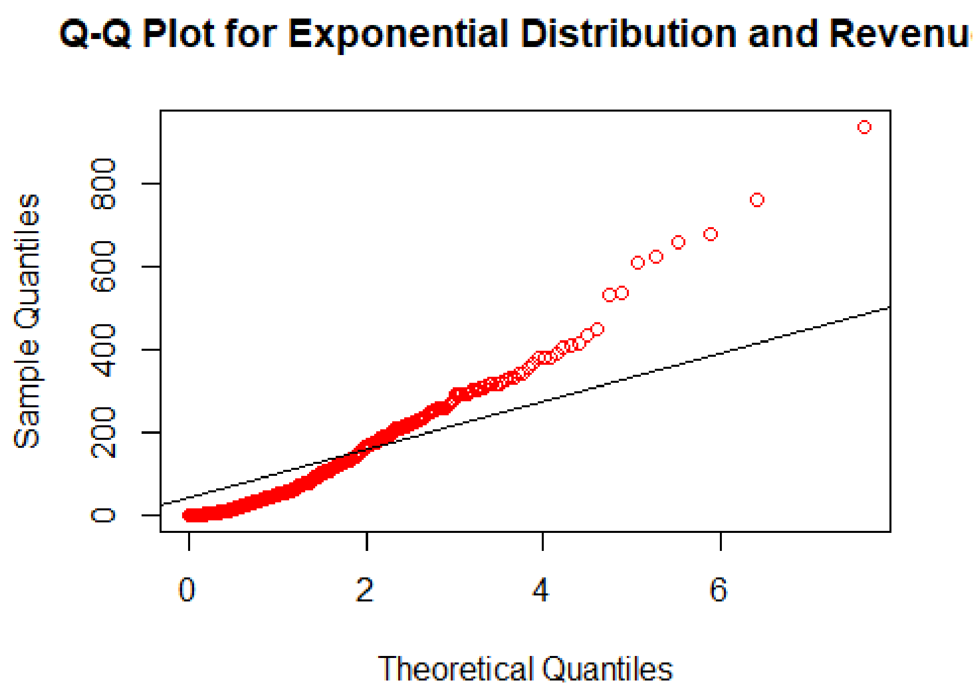
Distribution Fitting to Numerical Data

Revenue

When fitting the exponential and log-normal distribution to the revenue data, I opted to omit the movies that didn't have a gross US revenue reported. If I were to insert values in place of the NA values, it would have skewed my distributions with parameters that truly didn't reflect the data set. When I was fitting the log-normal distribution to the revenue data, I had to omit values that were equal to 0, because log(0) is undefined and if I were to input a small decimal equal to about 0, 0.000001 for example, the log of my small decimal value would result in large negative numbers and potentially skew my parameter estimates.

-Exponential Distribution

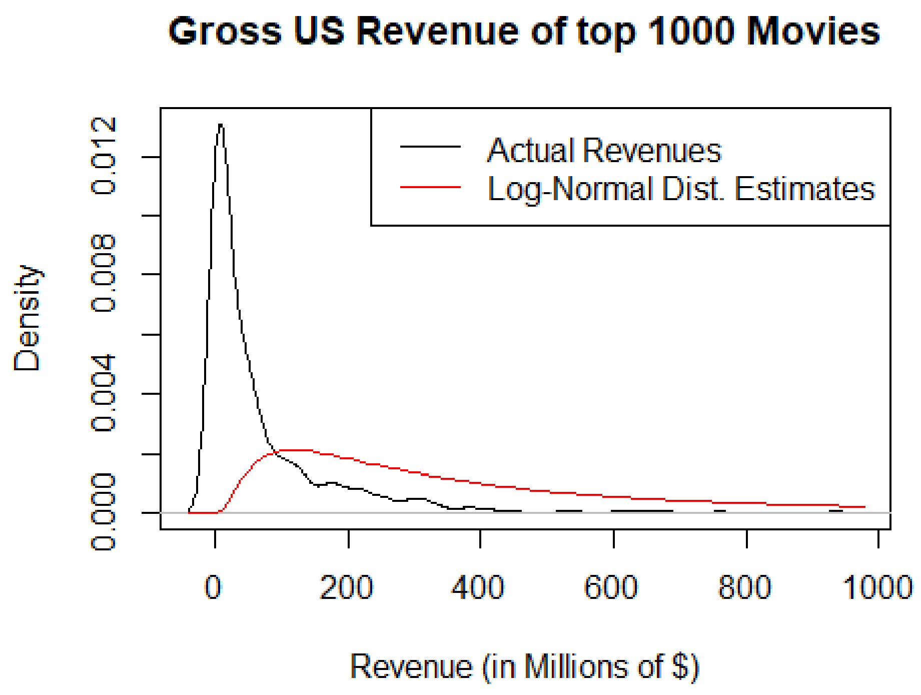


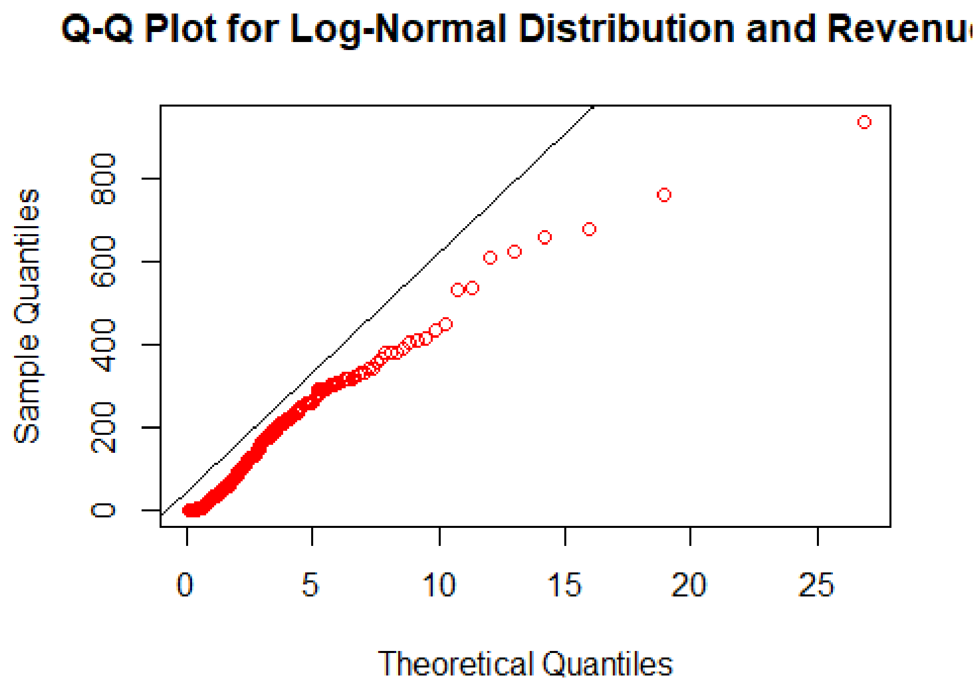


```
##
##  One-sample Kolmogorov-Smirnov test
```

```
##
## data:  movies$Revenue
## D = 0.21355, p-value < 2.2e-16
## alternative hypothesis: two-sided
```

-Log-Normal Distribution





```
## 
##  One-sample Kolmogorov-Smirnov test
```

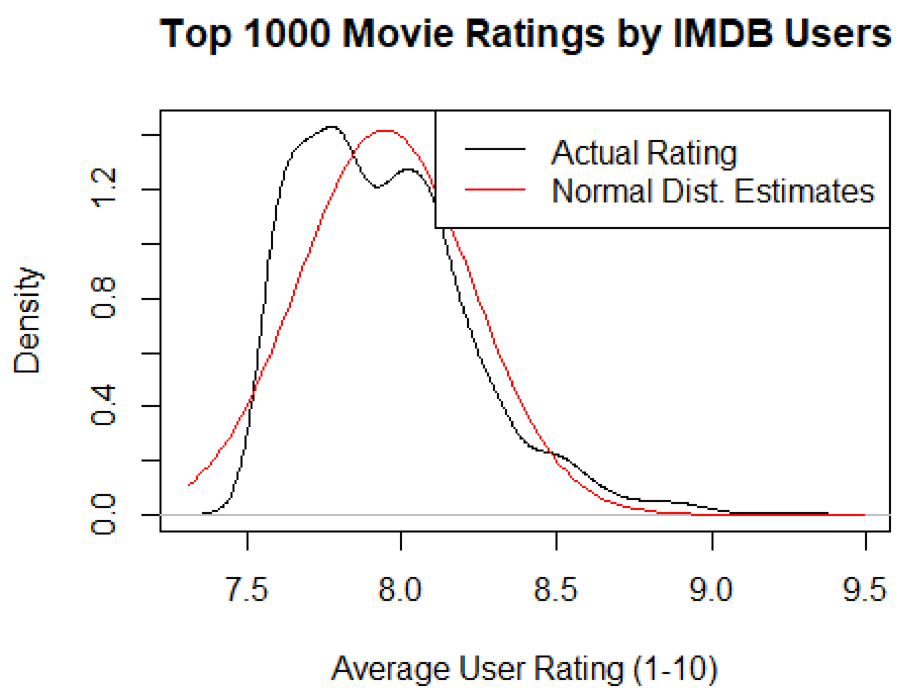
```
##
## data:  revs.gr8r.0
## D = 0.15567, p-value < 2.2e-16
## alternative hypothesis: two-sided
```

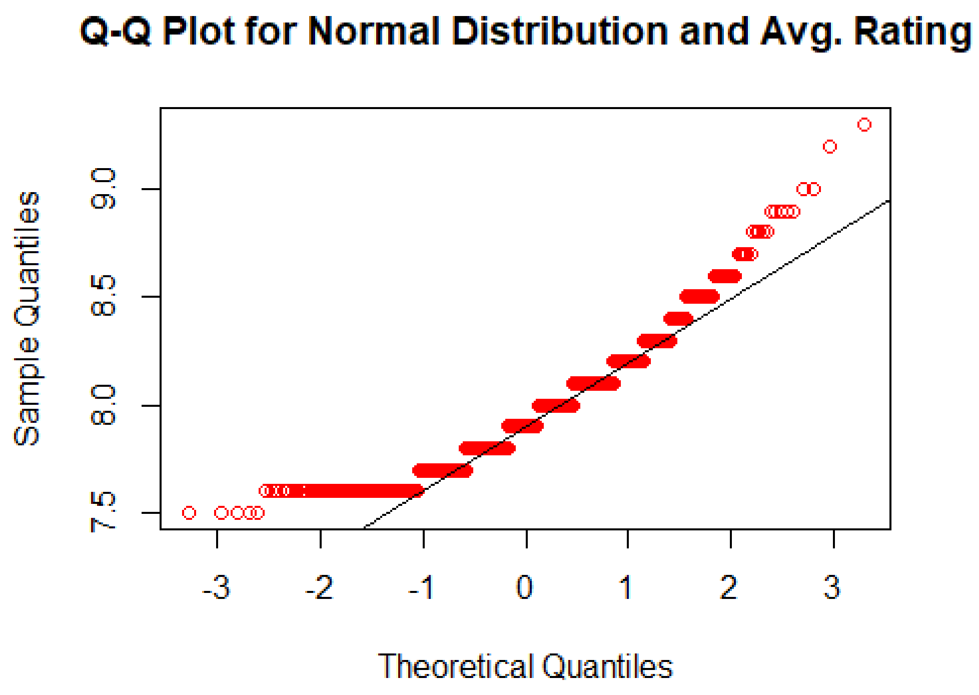
Distribution Fitted to Revenue	Parameters	Estimated Values
Exponential	λ	0.01474
Log-Normal	$\hat{\mu}$	5.74328
	$\hat{\sigma}^2$	0.96797

After fitting an exponential distribution and log-normal distribution to the revenue data, I ran a few tests to determine their good-ness of fit relative to the data. By creating a density plot of the revenue data and overlaying both distributions, I was able to see what distributions appeared to 'fit' the data. Through this test, it appeared that the exponential distribution best fit the revenue data, but to be sure I conducted two more tests. My next test was to create a Q-Q Plot for both distributions. For the exponential distribution, the plotted points fall closely around the identity line, but don't fall on the line enough for us to say the exponential distribution fits our revenue data, especially as our Revenue increases. When looking at the Q-Q Plot for the log-normal distribution, we don't have any points falling on our identity line, making the log-normal distribution a poor fit for the revenue data. My final test for the exponential and log-normal distributions was a Kolmogorov-Smirnov Test. Both tests resulted in p-values close to 0, therefore making both distributions 'appear' to fit better than the actually do. Finally, from these three tests, I've concluded that our exponential distribution best fits our revenue data.

Average User Rating

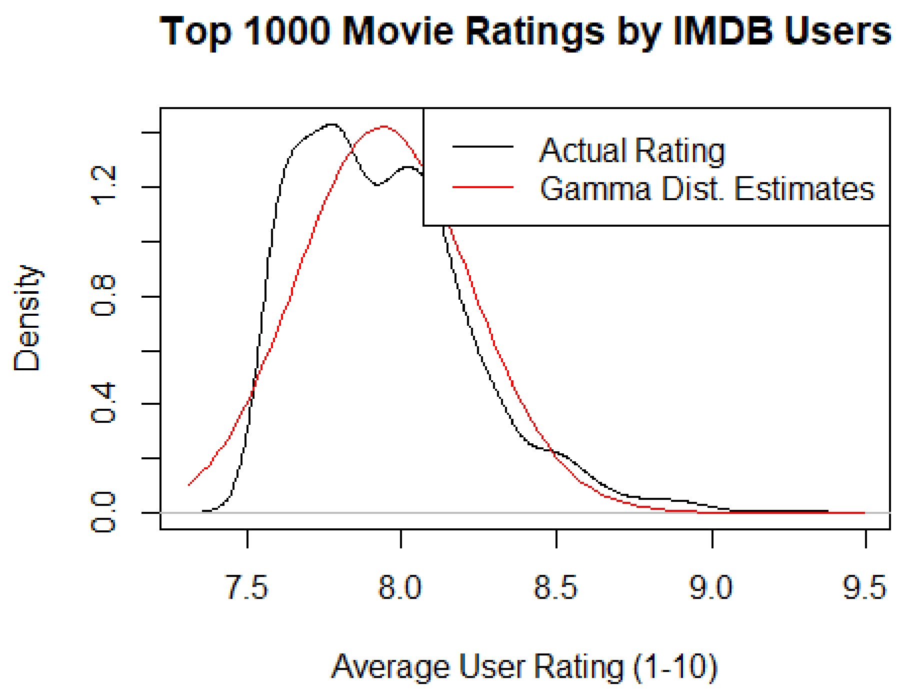
-Gaussian (Normal) Distribution

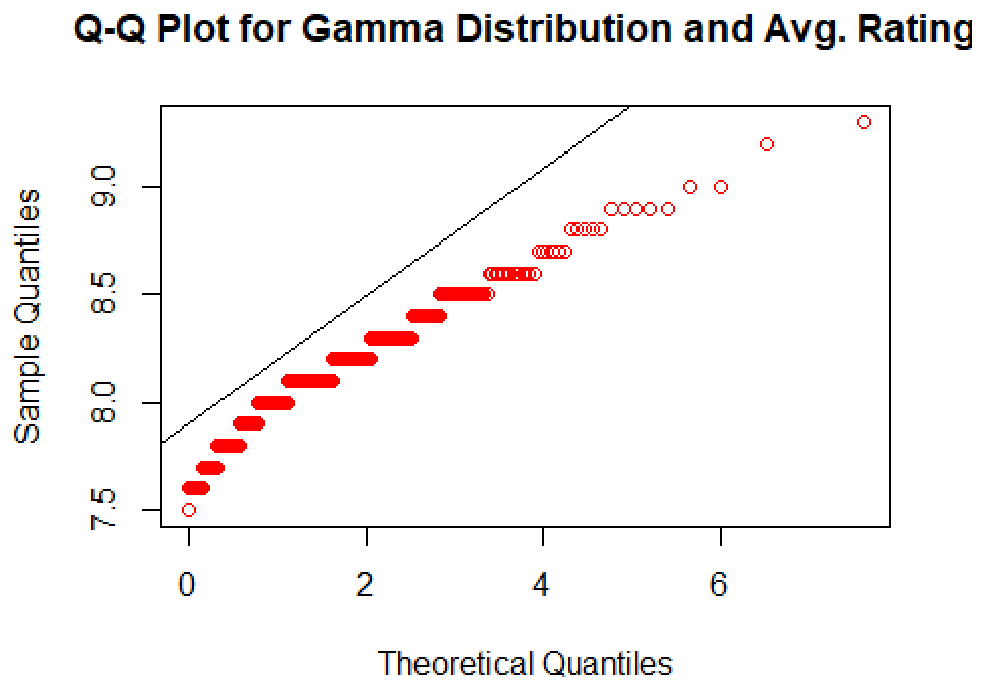




```
##
##  One-sample Kolmogorov-Smirnov test
##
## data:  movies$Rating
## D = 0.13325, p-value = 7.772e-16
## alternative hypothesis: two-sided
```

-Gamma Distribution





```
##
##  One-sample Kolmogorov-Smirnov test
```

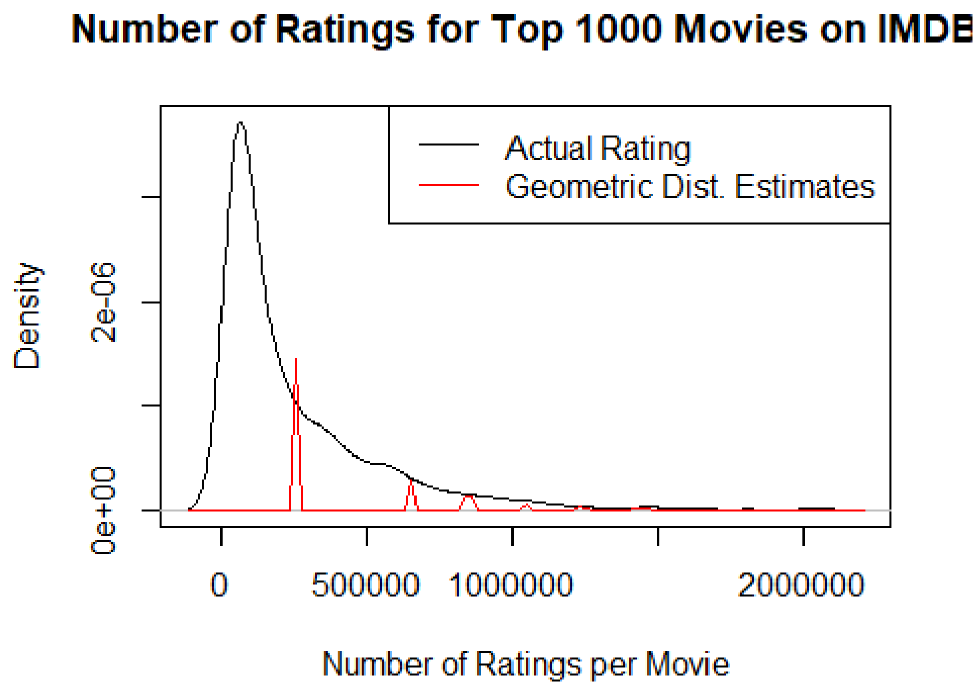
```
##
## data:  movies$Rating
## D = 1, p-value < 2.2e-16
## alternative hypothesis: two-sided
```

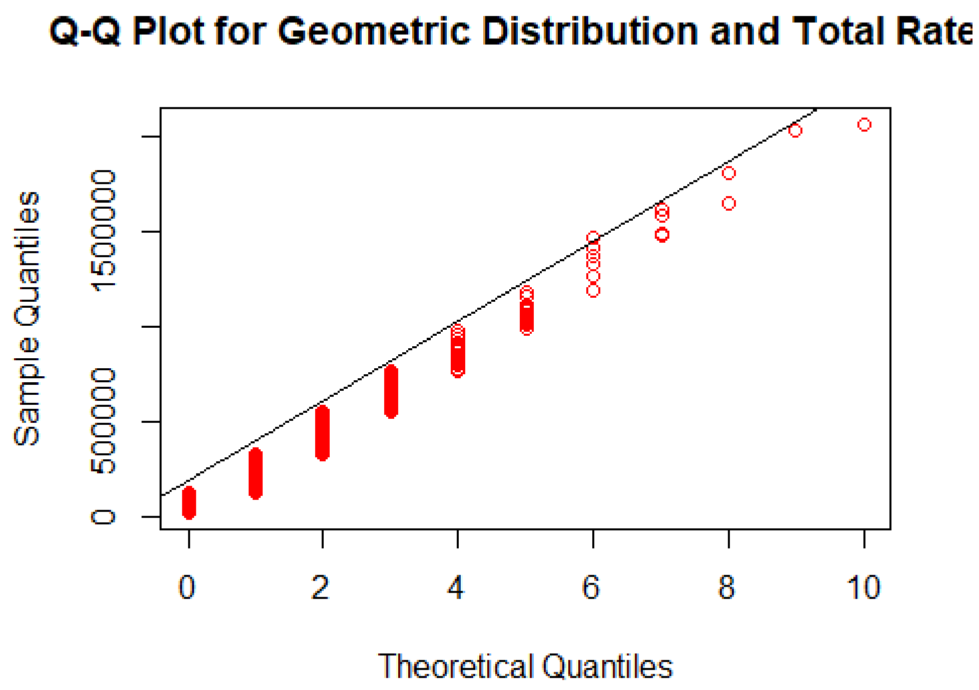
Distribution Fitted to Average User Rating	Parameters	Estimated Values
Gaussian	$\hat{\mu}$	7.9457
	$\hat{\sigma}^2$	0.0787
Gamma	a(shape)	802.2107
	s(scale)	0.0099

When I fit a normal and gamma distribution to the average user rating data, I found that there wasn't significant evidence that either distribution fit better than the other or that either distribution fit the data well. When I overlayed my distributions with the average user rating density plot, I found that both distributions had a similar shape, relative to eachother, and that they both 'fit' the sample data in an 'ok' way. Comparing their Q-Q Plots, neither distributions had plotted points that fell mostly on the identity line and both showed signs of skewness. After running a KS test, both tests yield a p-value close to 0, making both distributions 'appear' to be a good fit. Based on these three tests, I've concluded that there wasn't enough evidence to prove that either distribution is a good fit for the average user rating data.

Number of Votes

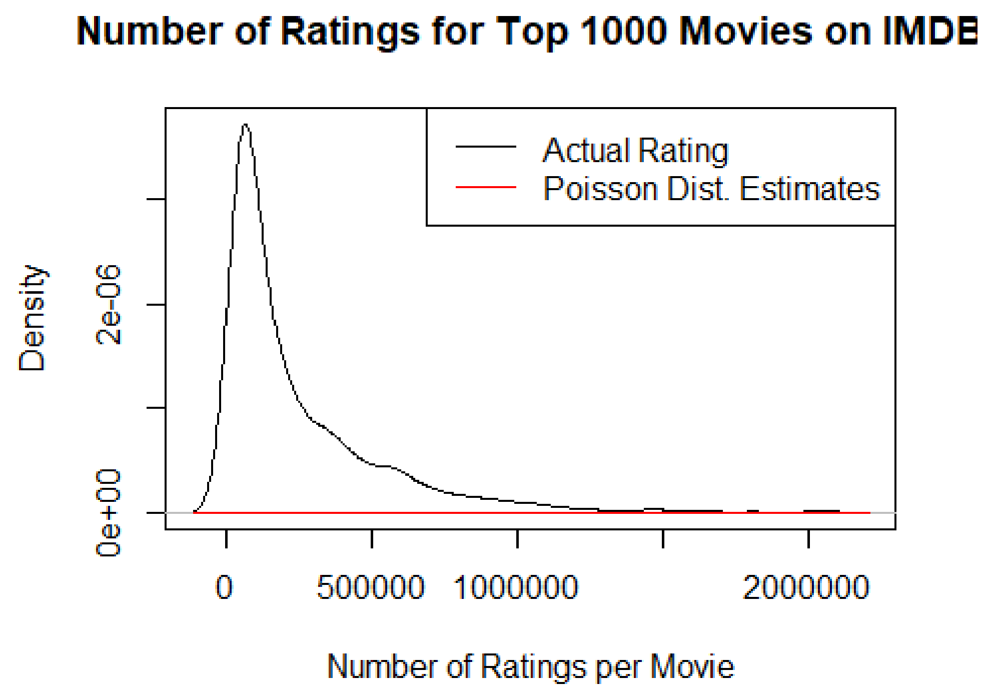
-Geometric Distribution

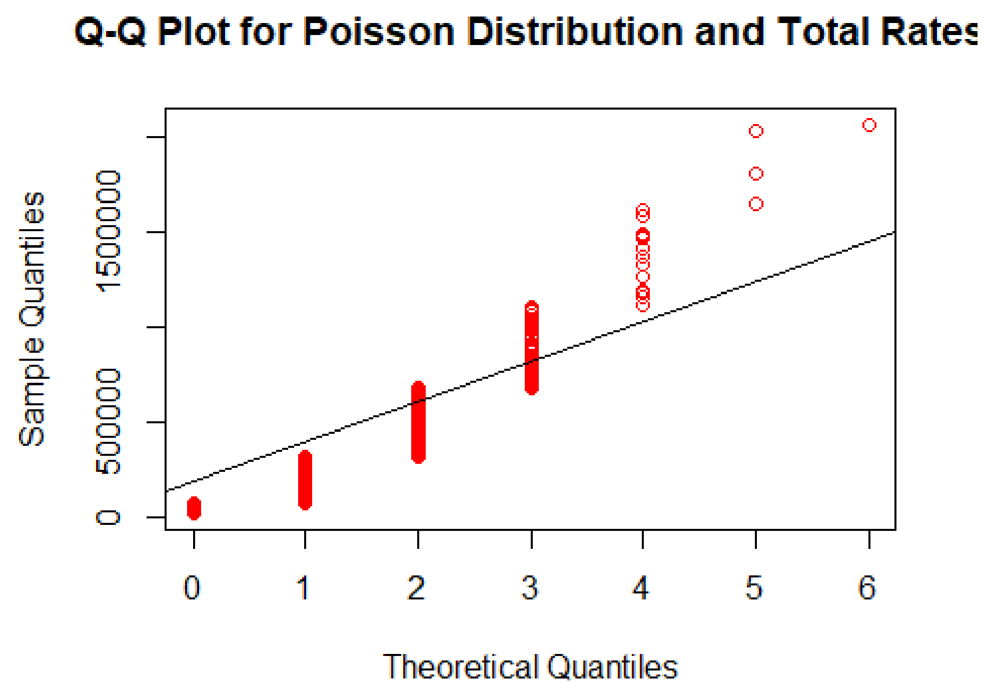




```
##
##  One-sample Kolmogorov-Smirnov test
##
## data:  movies$Total_Votes
## D = 0.10778, p-value = 1.626e-10
## alternative hypothesis: two-sided
```

-Poisson Distribution





Distribution Fitted to Total Ratings per Movie	Parameters	Estimated Values

Geometric	p	4.06095e-06
Poisson	λ	246247.424

Finally, I fit a geometric and poisson distribution to the total number of votes per movie data set. While testing the geometric distribution with a Q-Q Plot, it appeared that the geometric distribution was not a good fit, as seen above. I also found that when I plotted the number of ratings density plot over my estimated geometric distribution, they were lacking in similar shape. Therefore it did not seem plausible to conclude that the geometric distribution was a good fit for this data set. Meanwhile, the KS test said otherwise, but due to the shape of both density plots side by side I concluded that the the geometric distribution did not fit 'well' for this data set. In my attempt to fit a poisson distribution to the total number of votes data, I plotted the density of my distribution with the actual data, and found that my distribution resulted in a line that did not resemble the actual density plot at all. Then by making a Q-Q Plot of the data I was also able to confirm that the poisson distribution was also not a good fit for the total number of ratings data.

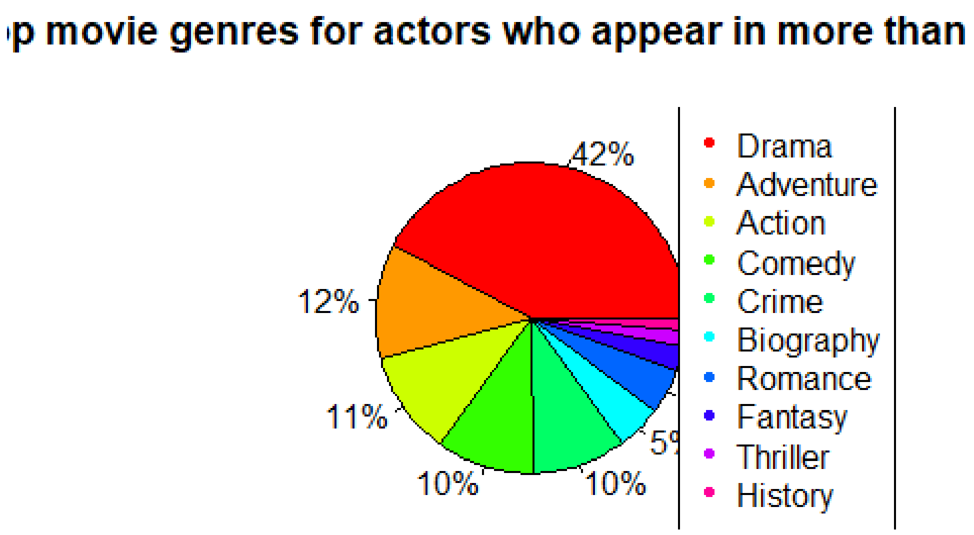
Good Acting or Good Movie Genre?

Under the "Stars" heading for each movie, IMDB lists the top 4 highest billed actors for each movie. Shown in the table below is a list of the top 5 actors who are one of the highest billed actors of a movie, in more than 5 of IMDB's 'Top 1000 Movies' list. The final column in the table, `Top2Genres`, consists of the two genres that the actor would most likely appear in, if that movie made this top 1000 list. For example, of the 16 'Top 1000 Movies' that Robert De Niro has starred in, if we were to draw one of them at random, they would most likely be listed as either a Drama and/or Crime movie.

```
kable(top.actor[1:5,])
```

Actors	NumberOfMovies	Top2Genres
Robert De Niro	16	Drama, Crime
Brad Pitt	13	Drama, Crime
Tom Hanks	13	Drama, Adventure
Al Pacino	12	Drama, Crime
Clint Eastwood	12	Western, Drama

But, how does an actor appear as one of the highest billed actors in multiple movies from the 'Top 1000 Movies' list? Could it have something to do with their acting ability, or could it be the type of movie they chose to act in, that makes this movie a success. I decided to explore this hypothesis with the same data set. I started off by locating every actor who appeared in five or more movies on IMDB's 'Top 1000 Movies' list. I then took all 86 'top actors' and found the genre(s) of the movies they appeared in. Shown below is a pie chart of the top movie genres that an actor would appear in, if they were to appear in more than 5 movies on this list.



From this, I was able to find that the majority of these 'top actors,' have acted in a Drama movie. What I found to be most significant about this pie chart was the second most frequent movie genre, that these 86 'top actors' may act in, was an Adventure movie. However, it's more than three times smaller than the percentage of actors who have acted in Drama Movies. Raising the question, are these considered the 'top actors' due to they're great at acting ability, or because they seem to land roles in a popular movie genre.