Predicting IMBD Scores

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STA 9750 Final Project

Hypothesis

Introduction

Many factors make a movie successful and profitable. Some of the factors include user reviews, budget of the movie, actor's and director's popularity. We will find out which factor has the most impact on a movie's success and profitability.

We have the IMDB 5000 movie dataset (https://www.kaggle.com/suchitgupta60/IMDB-data), which has 28 variables, 5043 movies across 100 years in 66 countries. There are many variables in the dataset such as Director, Actors, Duration, Gross, Budget, Genres, Facebook Likes, etc.

We will be using some of the modeling techniques with associated visualizations to identify the most important variables that impact the success and ratings of the movie along with their profitability.

Data Exploration

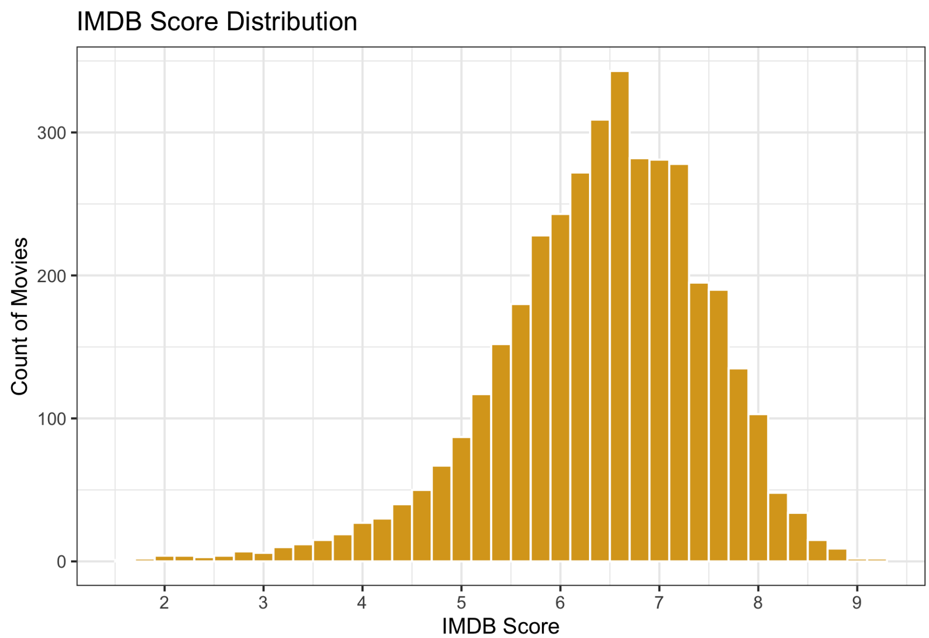
After cleaning the data, we are now left with 26 variables and 3806 rows. Some features like aspect ratio, imdb movie link and color as they reduced the quality of the data.

Movies rated above 7.5 are considered to be highly recommended. Majority of the movies are rated 7.6 with only a handful rated above 9 as per the distribution shown below. The highest rating received by one movie is 9.3.

IMDB offers a scoring scale that allows users to rate films on a scale of one to ten. It indicates that submitted scores are filtered and weighted in various ways in order to produce a weighted mean that is displayed for each movie.

Majority of the movies are between the range of 6.5 to 7.7 which is considered as an average IMDB score. The histogram closely fits a normal distribution.

However, there are only a handful of phenomenal movies which are rated above 8.



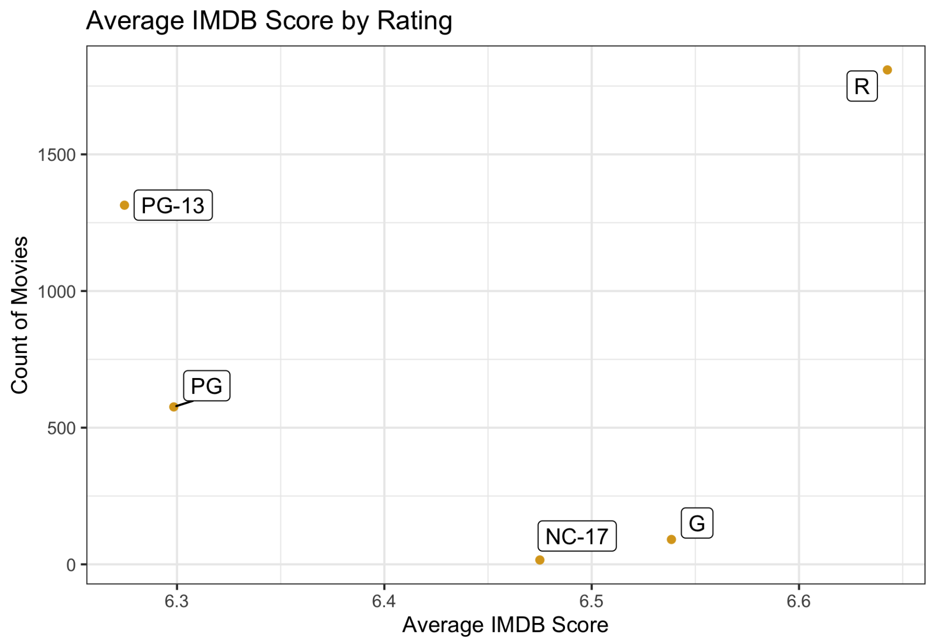
The table below is sorted by imdb score greater than 7.5 and arranged in descending order. IMDB score of 7.6 has the majority of the movies. As the IMDB score increases above 8.8, the movies drop to less than 5. Only .21% of the movies are rated above 8.8 which is represented in the histogram above as well.

```
## # A tibble: 17 x 2
## # Groups:   imdb_score [17]
##    imdb_score     n
##         <dbl> <int>
##  1        7.6   100
##  2        7.7    90
##  3        7.8    83
##  4        8      55
##  5        7.9    52
##  6        8.1    48
##  7        8.2    24
##  8        8.3    24
##  9        8.5    19
## 10        8.4    15
## 11        8.6     8
## 12        8.7     7
## 13        8.8     5
## 14        8.9     4
## 15        9       2
## 16        9.2     1
## 17        9.3     1
```

Impact of content rating on IMDB score

The average IMDB score is 6.46which is considered a poor IMDB score. Content rating R has the highest count of 1809 which may be the reason it has the highest IMDB rating compared to others. However, PG-13 has the second highest count of 1314 movies with an average IMDB score of less than 6.3. As per this distribution, content rating does not show a strong impact on the IMDB score.

```
## `summarise()` ungrouping output (override with `.groups` argument)
```

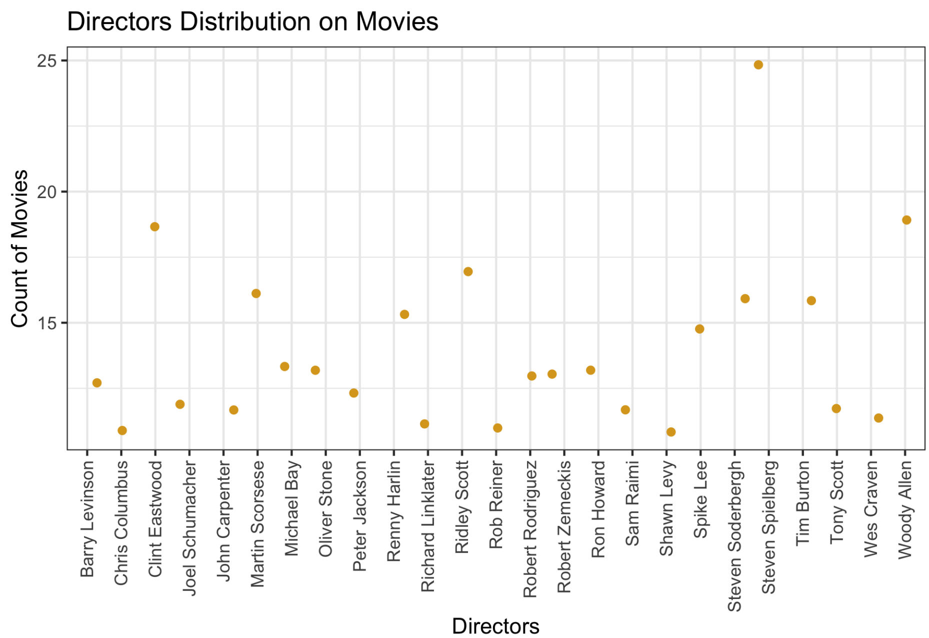


Understanding the distribution of directors and their effect on IMDB score

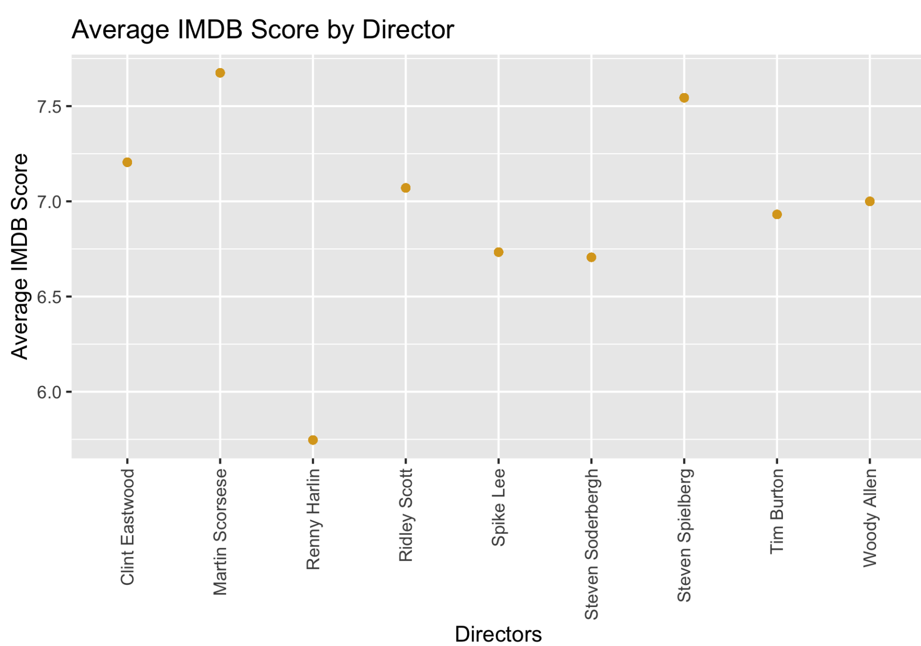
Directors have been grouped by the number of movies directed. The data has been filtered to only show directors with movies directed above 10 and below 50 to remove any anomalies in the data. Directors with more movies could have a higher fan following, credibility and success rate possibly leading to a higher IMDB score.

According to the below distribution, even after filtering, the number of movies for most of the directors are between 10 to 15, few are in the range of 15 to 20 and rest two are outliers. This indicates that in this time frame, the most naturalistic production of movies by the directors are between 10 to 15 range. The rational can be budget, resources or time constraints.

```
## `summarise()` ungrouping output (override with `.groups` argument)
```



Only a handful of directors have over 15 movies directed in this data set. Steven Spielberg is the only director to have ~ 24 movies directed. The chart below shows the average IMDB score for directors with 15 or more directed movies. The IMDB score is above 5.5 for directors with more than 15 movies. Most directors have received a higher IMDB score that shows the number of movies directed has a slight impact on the IMDB score.

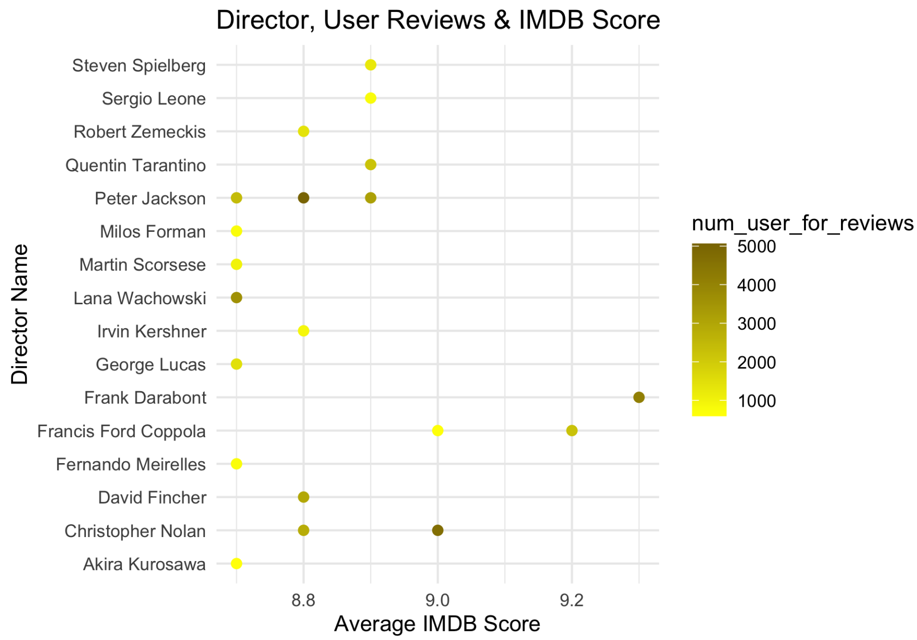


Top 20 movies by IMDB score

The below scatter plot shows the top 20 movies that have received the highest IMDB scores. Most directors have more than one movie rated above 7.5 which is considered to be a good score. These movies have recieved higher user reivews compared to other movies in the dataset. The minimum user reviews are 1000 for these top 20 movies which is significantly higher than the median of 205 user reviews.

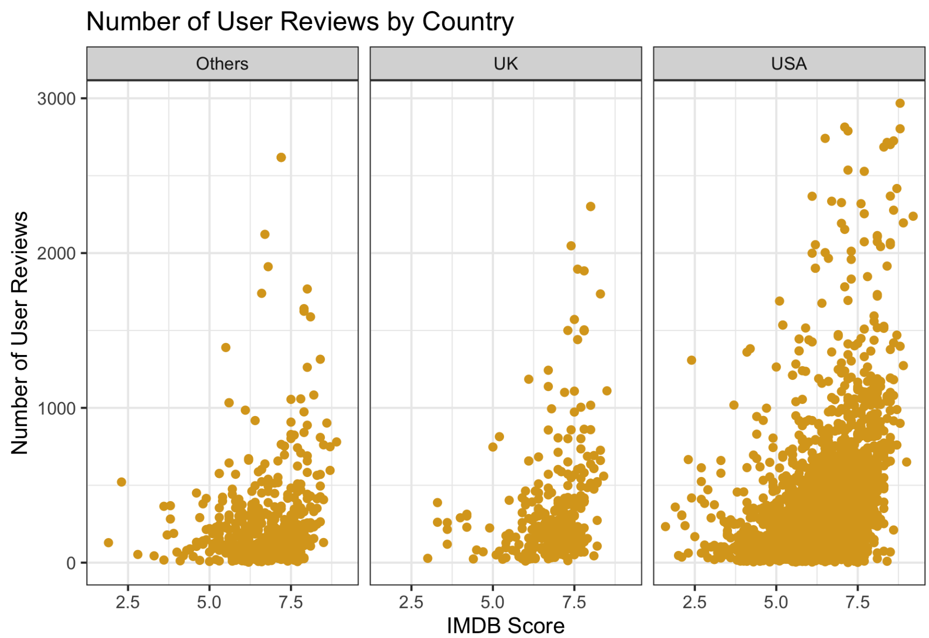
1, 105, 205, 330.08, 392.75, 5060

```
## `summarise()` regrouping output by 'director_name' (override with `.groups` argument)
```



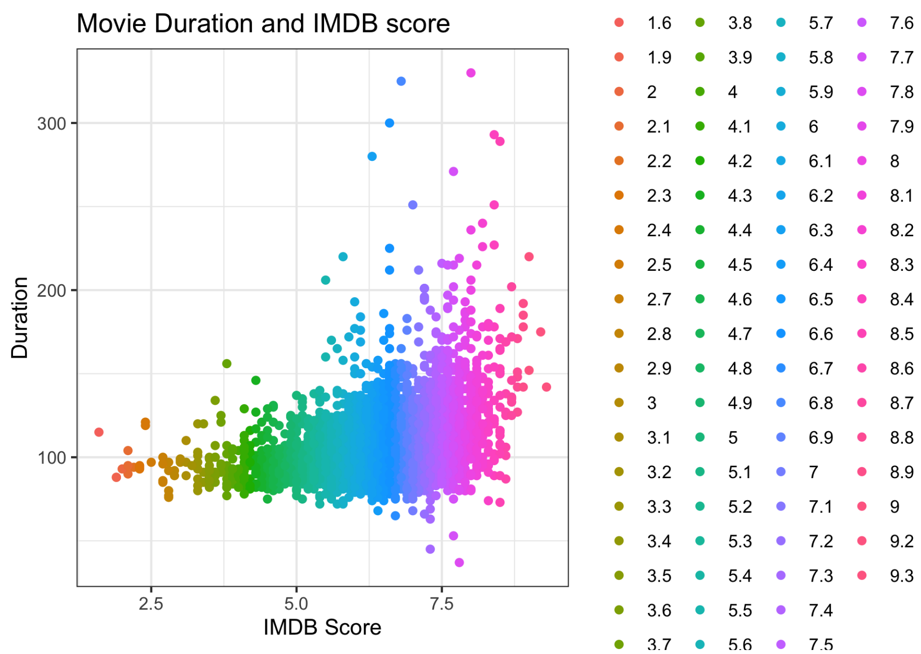
Impact of country on the IMDB score

All countries other than U.S and U.K were grouped as others while cleaning the data as they were significantly lower than these top two countries. As per the below scatter plot, highest number of movies reviewed are from the U.S followed by the U.K. Higher IMDB ratings are seen in the U.S with the most number of user reviews. We can see the pattern of higher scores and higher user reviews repeat in the blow plot as well.



Movie durations impact on the IMDB score

The below scatter plot shows a linear relationship between IMDB score and duration. As the duration increases the IMDB score also increases. Most movies with a score higher 7.5 have a longer duration.

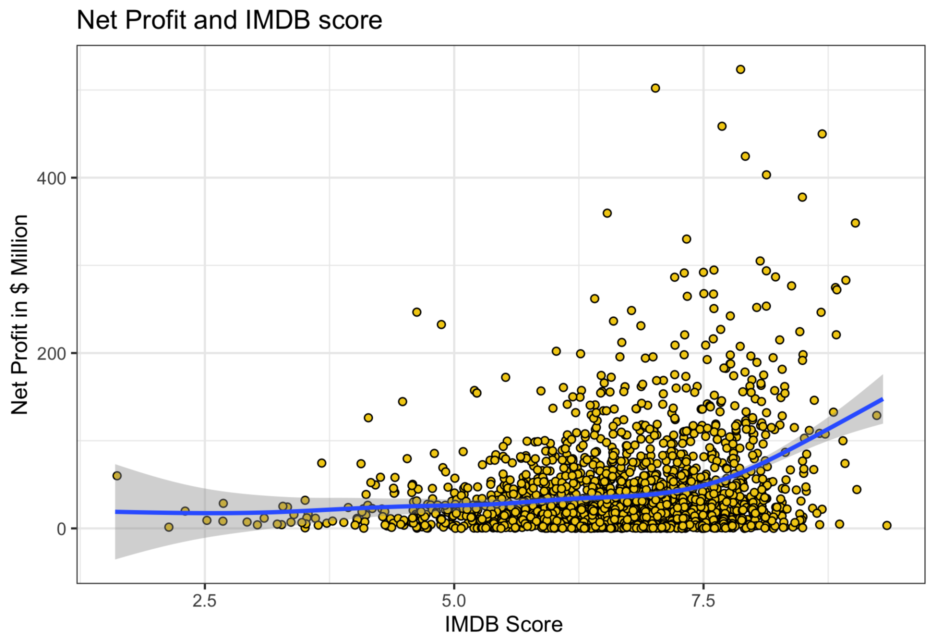


Impact of net profit on IMDB score.

Movies with a net profit over 200 million have a higher IMDB rating. The trend below shows higher net profits translates to a higher rating. It could be assumed that the viewership for movies with higher net profits was higher and thus, received a higher movie rating.

The movies with higher IMDB score should generate higher net profit. But this is not always true. There are many movies that have very good IMDB score but did not generate much profit. So, IMDB score cannot be a sole factor to consider the net profit.

```
## `geom_smooth()` using method = 'gam' and formula 'y ~ s(x, bs = "cs")'
```



Modeling techniques to identify the most important variables that impact IMDB ratings of the movie

Dividing the data set into two with 80% of the data as training dataset and the rest 20% for testing.

Linear Model

The linear model below shows that the number of voted users, number of critic reviews and duration has the most impact on the IMDB score. The R-squared of 0.28 is extremely low which suggests the relationship between these variables is not linear.

This low R-squared value indicates that IMDB score is not explaining much in the variation of the dependent variables such as duration, num_voted_users, num_critic_for_reviews or movie_facebook_likes. Regardless of the variable significance, this is letting us know that the identified independent variable, even though significant, is not accounting for much of the mean of the dependent variable.

```
##
## Call:
## lm(formula = imdb_score ~ duration + num_voted_users + num_critic_for_reviews +
##     movie_facebook_likes, data = IMDB_train)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -4.813 -0.504  0.096  0.644  2.547
##
## Coefficients:
##                         Estimate Std. Error t value Pr(>|t|)
```

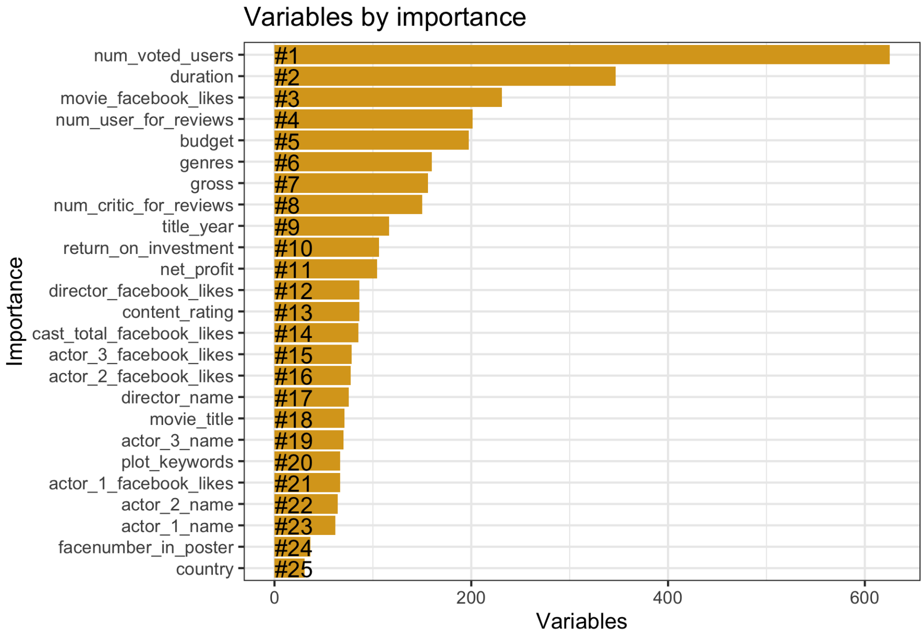
```
## (Intercept)           4.91e+00   8.48e-02   57.86   <2e-16 ***
## duration              1.04e-02   7.73e-04   13.51   <2e-16 ***
## num_voted_users       2.49e-06   1.49e-07   16.80   <2e-16 ***
## num_critic_for_reviews 6.42e-04   2.01e-04    3.19   0.0014 **
## movie_facebook_likes   1.06e-06   1.18e-06    0.90   0.3673
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.91 on 3039 degrees of freedom
## Multiple R-squared:  0.275,  Adjusted R-squared:  0.274
## F-statistic:  288 on 4 and 3039 DF,  p-value: <2e-16
```

```
## [1] 0.85
```

Random Forest to determine the variable that has the most impact on the IMDB score

We will be creating a random forest to identify the most important variables on the training data. Random forest will include all the variables from the dataset. Variables by importance are plotted below which show us the number of voted user have the most impact on the IMDB score.

```
##      |      Out-of-bag   |
## Tree |      MSE  %Var(y) |
##   50 |    0.536    47.50 |
##  100 |   0.5168    45.80 |
##  150 |   0.5075    44.97 |
##  200 |   0.5062    44.86 |
##  250 |   0.5055    44.80 |
##  300 |   0.5054    44.79 |
##  350 |   0.5042    44.69 |
##  400 |   0.5037    44.64 |
##  450 |   0.5039    44.65 |
##  500 |   0.5036    44.62 |
```



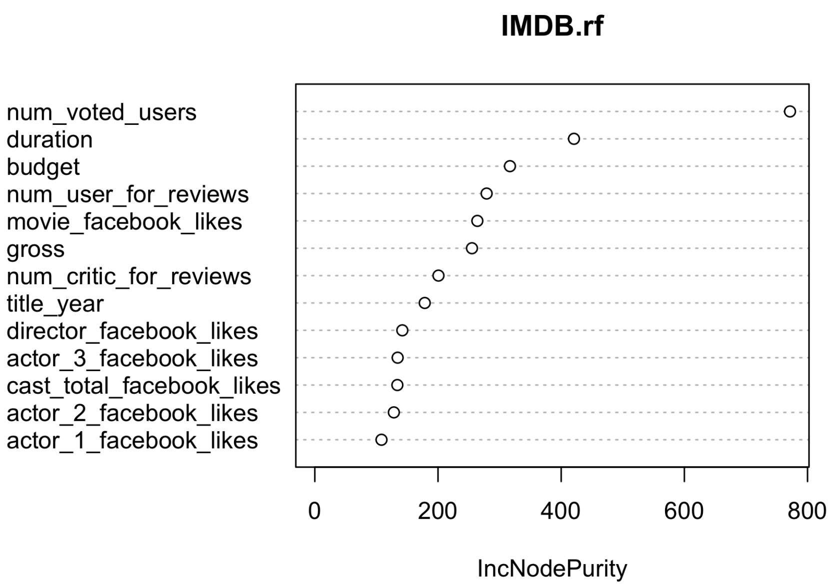
The root mean squared error for the above random forest is 0.68 making it an average model.

Random Forest with select variables to reduce the mean squared error

The mean squared error of the model below is `mean((predict.IMDB.rf - IMDB_test$imdb_score)^2)` which is lower than the previous model `mean((predicted.rf - IMDB_test$imdb_score)^2)`. This model only uses some of the most important variables which could be the reason for a lower root mean sqaured error.

```
## [1] 0.65
```

```
## [1] 0.42
```



We can see that the most important variable is the number of voted users. The reason is quite obvious because the rating only generates when people vote or give reviews for the movies. There are a good number of people who vote for their favorite movies which is used to calculate the IMDB score. Second most important factor is the duration of the movies. This is quite interesting because this is not something which is easily guessed. However, the logical rationale behind this could be that the long hours movies are generally high budgeted ones with popular star cast. Therefore, the quality of the movies with longer duration are usually better. The next factor is the facebook likes. Even though this factor is a difficult predictor to assume, we can say that people likes something on facebook when they truly enjoy something. So, they might have a tendency to provide good IMDB rating as well.

The importance of next three variables, budget, genres and number of user reviews, is very close. A high budgeted movie will typically have a tendency to get high IMDB scores because they are usually created with with a lot of hype and promotion. Genres also have an impact because some genres are more attractive to users than others. Typically, action and thriller movies are preferred to many viewers. For obvious reasons, number of user reviews are important. These users directly rate the movies on the IMDB website. So, certainly this will be one of the most important factors.

Conclusion

Random Forest took into consideration all the variables from the dataset to understand their impact on the IMDB score. Number of voted users is the most important variable for a high IMDB score. Followed by duration and facebook likes received by the audience. It is surprising to see, actors and directors names were among the least impactful factors as one would think directors and actors bring in publicity leading to a higher viewership.