# Prediction of Netflix Movie Rating


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Springboard

**Thanks to springboard mentor:**
**Yadunath Gupta**

# About Netflix

Netflix is a subscription-based online streaming service that offers streaming of films and television series.

It started in 1997 in USA and now makes its service available in most of the countries in the world.

# Netflix recommendation system

Netflix is well known for its efficient recommendation engines providing users choice of movies/shows. The engines work behind the scene and based on:

- Content-based filtering algorithm
- Collaborative filtering algorithm
- Hybrid of both

# Problem statement

In Netflix's recommendation system, user's rating plays an important role. Here, I'll build a predictive model to predict movie rating (user review).

To carry out this

- Different predictive models will be developed to predict movies' rating.
- The best one will be selected based on the R2 score (co-efficient of determination)

  i.e how close the actual ratings are to the predicted values.

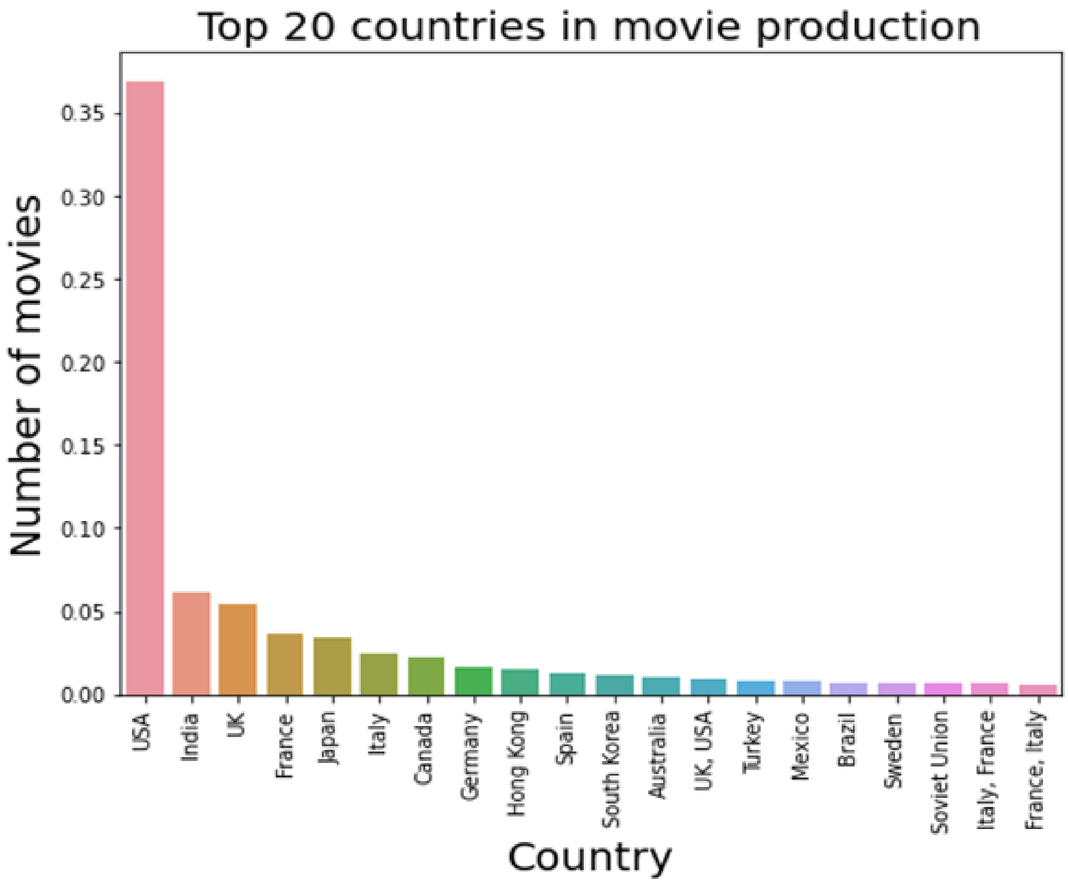
# Data

Data has been collected from

- Kaggle
- IMDB

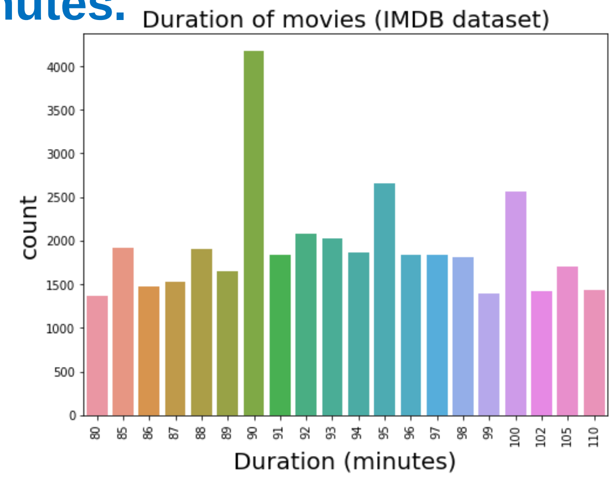
# Key findings from Exploratory Data Analysis

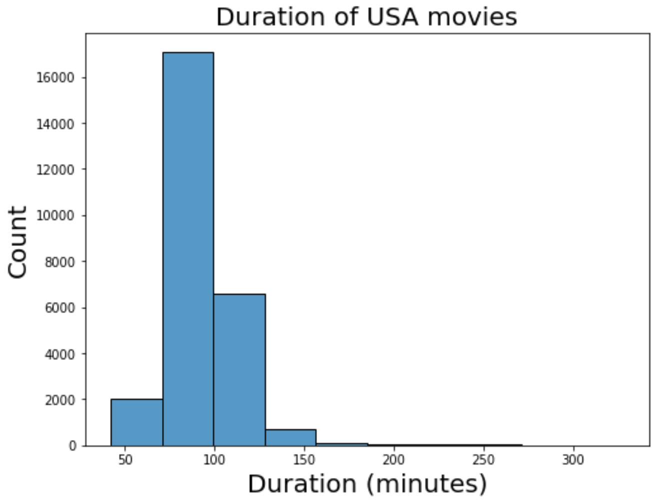
**USA ranked Number One in movie production, while India ranked Second followed by United Kingdom in Third place.**

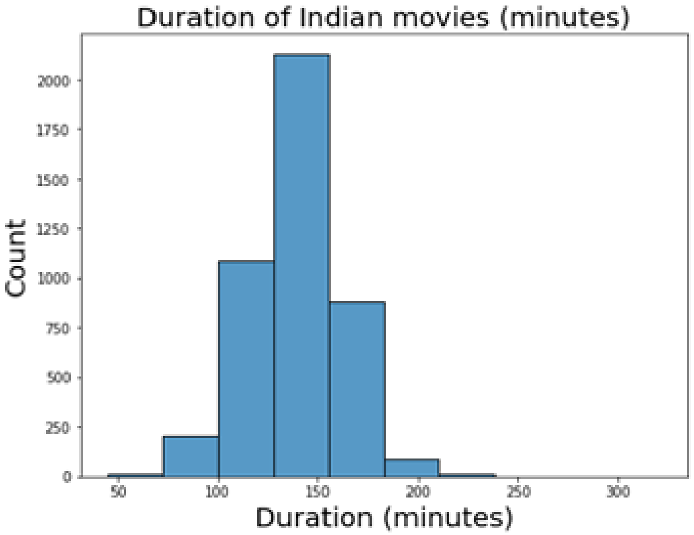


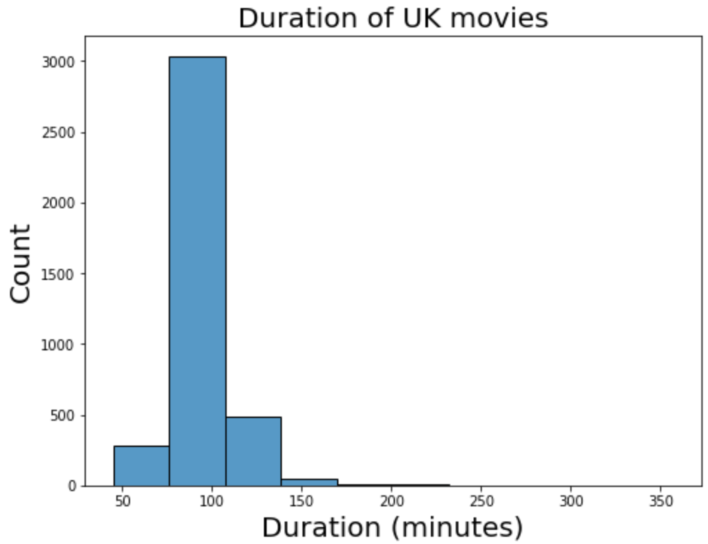
# Key findings from Exploratory Data Analysis (continued):

- **Most of the movies are of duration (approximately) 90 mins. However, it varies in different countries. In USA and UK, movies are mostly of 90-100 minutes, whereas in India, movies are mostly of 120-150 minutes.**



# Key findings from Exploratory Data Analysis (continued):

- **These are three top movie production companies:**

  **1. Metro-Goldwyn-Mayer**
  **2. Warner Bros.**
  **3. Columbia Pictures**

  **Top movie production company of USA: Metro-Goldwyn-May**
  **Top movie production company of India: NH Studioz**
  **Top movie production company of UK: The Rank Organisation**

# Feature Engineering

**Two new datasets were formed out of Kaggle and IMDB dataset before feature engineering:**

- **Movies found only in IMDB dataset (not in Kaggle) were used for predictive model building.**
- **Movies common to both were used for testing the model.**

**Feature engineering was carried out as follows:**

- **Dummie variables were created out of categorical variables: genre, language, actors, directors, production company.**
- **Genre, language have <300 unique values, so dummie values for all these features were created.**
- **Actors, directors, production company have >300 unique values. Out of them, for top 200 unique values, dummie values were obtained.**
- **Standard scaling was carried out on duration time, votes, reviews from users columns.**
- **Outliers are filled with 95$^{th}$ percentile of the values of respective column.**

# Model development

**Different Regression models were developed to predict the movies rating:**

- **Simple Linear Regression**
- **Lasso Regression**
- **Ridge Regression**
- **Random Forest Regressor**
- **Gradient Boosting Regressor**

# Models’ performance

- **The Simple Linear regression model performance was poor, however it improved significantly when regularization was applied. Among Lasso and Ridge, the later performed best.**

- **To have better performance, ensemble model Random Forest Regressor was developed. It improved the model performance as compared to Linear regression.**

- **To achieve much higher performance, ensemble model Gradient Boosting Regressor was also developed. This model had the best performance among all the models.**

# Principal Component Analysis application

**To improve the models' performance, PCA (Principal Component Analysis) was applied and models were trained again.**

**Though it improved Linear Regression's performance and run time, it didn't help both ensemble models.**

# Best model

**Gradient Boosting Regressor was the best among all the predictive models.**

| Model | r2_score |
|---|---|
| Linear Regression | 0.40 |
| Lasso Regression | 0.33 |
| Ridge Regression | 0.42 |
| Random Forest Regressor | 0.44 |
| Gradient Boosting Regressor | 0.51 |

# Gradient Boosting Regressor details

| Model | No. of Features | Hyperparameters | r2_score |
|---|---|---|---|
| Gradient Boosting Regressor | 300 | Learning rate: 0.1<br>n_estimators: 700<br>max_depth: 7 | 0.51 |

# Model for future Use

**Among all the predictive models, as Gradient Boosting Regressor was the best with R2 score 0.51, it was saved for deployment.**

# Future Recommendation

**The model's performance can be improved further with Inclusion of more movie features: music quality, picture quality, chorography quality, actors' ranking, users' age, etc. Hence data on these should be included in future model building.**

# Thank You