Streaming Platform Analysis

Group 6

CHEN, Taoyue 1155141543
LAU, Ho Cheung 1155157540
LI, Yuji 1155157174
POON, Yin Ki
ZHAO, Shengchun 1155157253

Problem Statement

★ How to choose a streaming platform?

★ Should audiences pay for newly released movie ？

Introduction of the Dataset

Two sets of dataset

Part 1 & 3

16 thousand movie records and their features

Part 2

movie records and their release date on the corresponding platform

Approach to the Problem

Part 1	Expository data analysis of our movie data to navigate platform-based characteristics of movies
Part 2	Forecasting the number of new movies available on each platform(Hulu, Disney, Netflix)
Part 3	Modelling the relationship between features of a movie and its IMDb rating

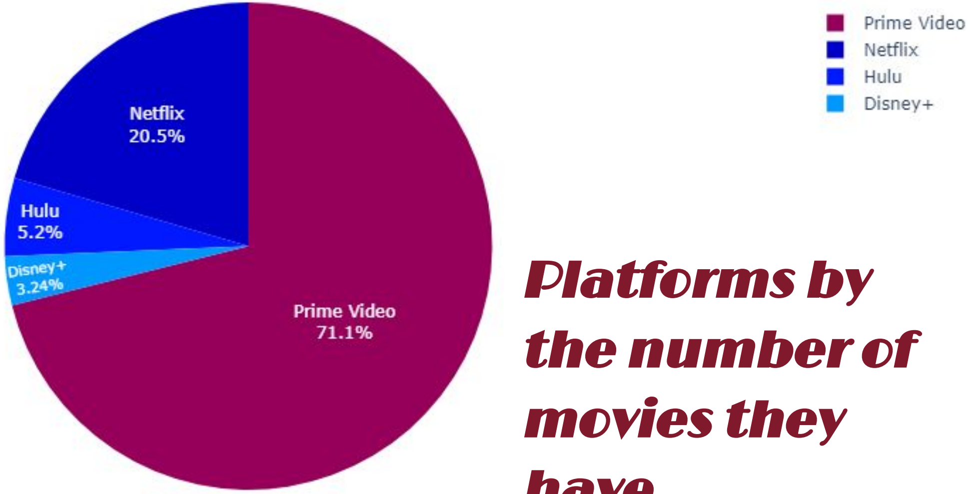
01

Expository Data Analysis result

Analysis result in case 25

Movie Count Of Different Platforms

01

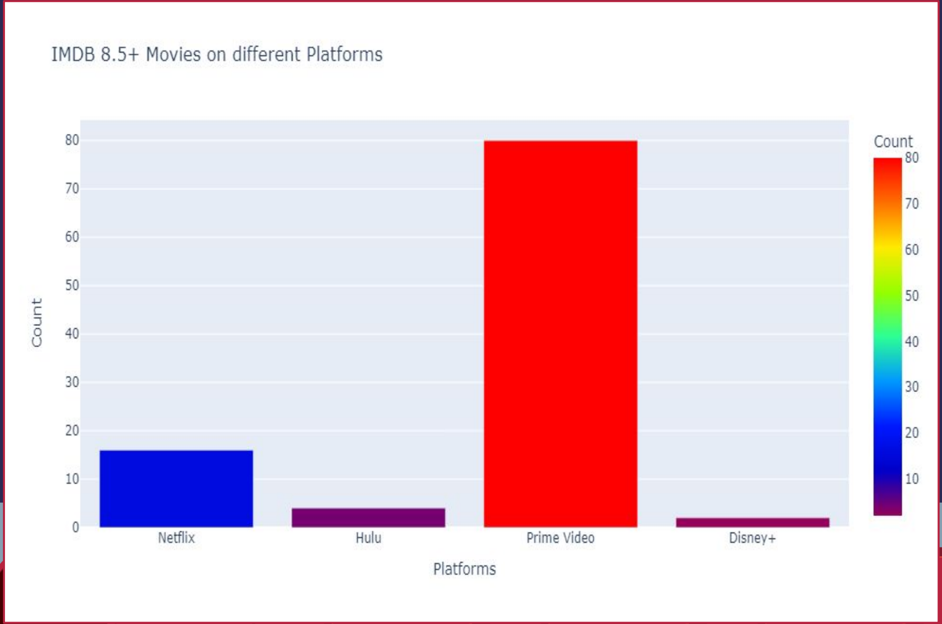


Platforms by the number of movies they have

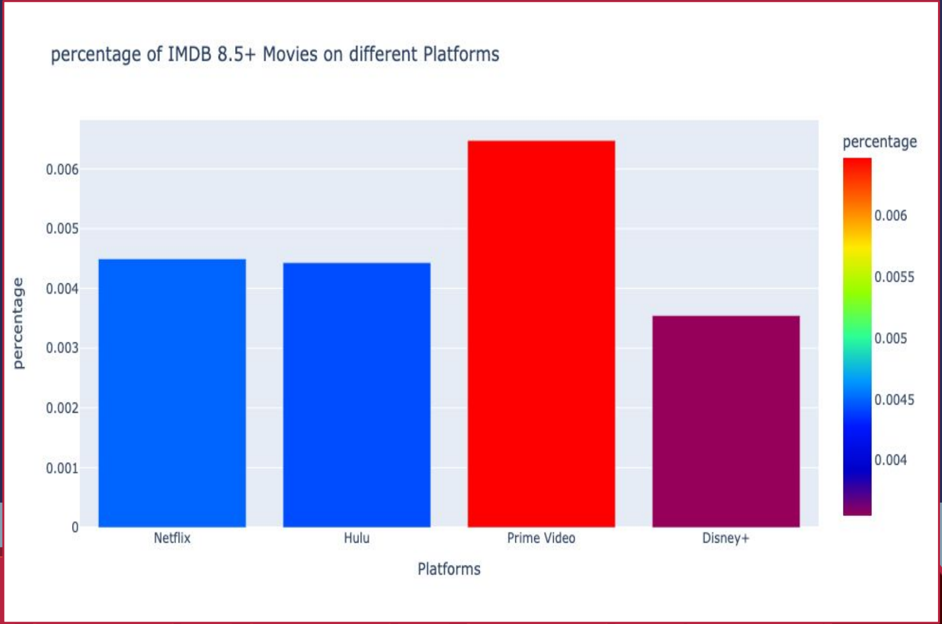
Analysis result in case 25

02 *Platforms by the number and percentage of high-quality(IMDb 8.5+) movie*

By quantity:

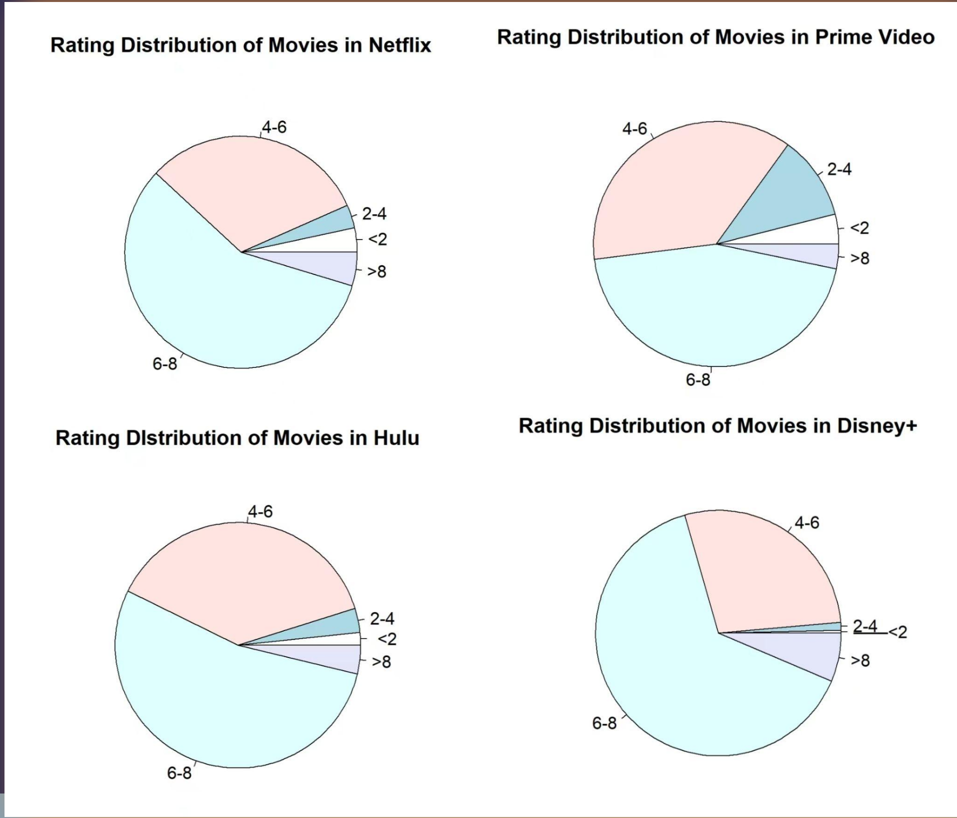


By percentage:

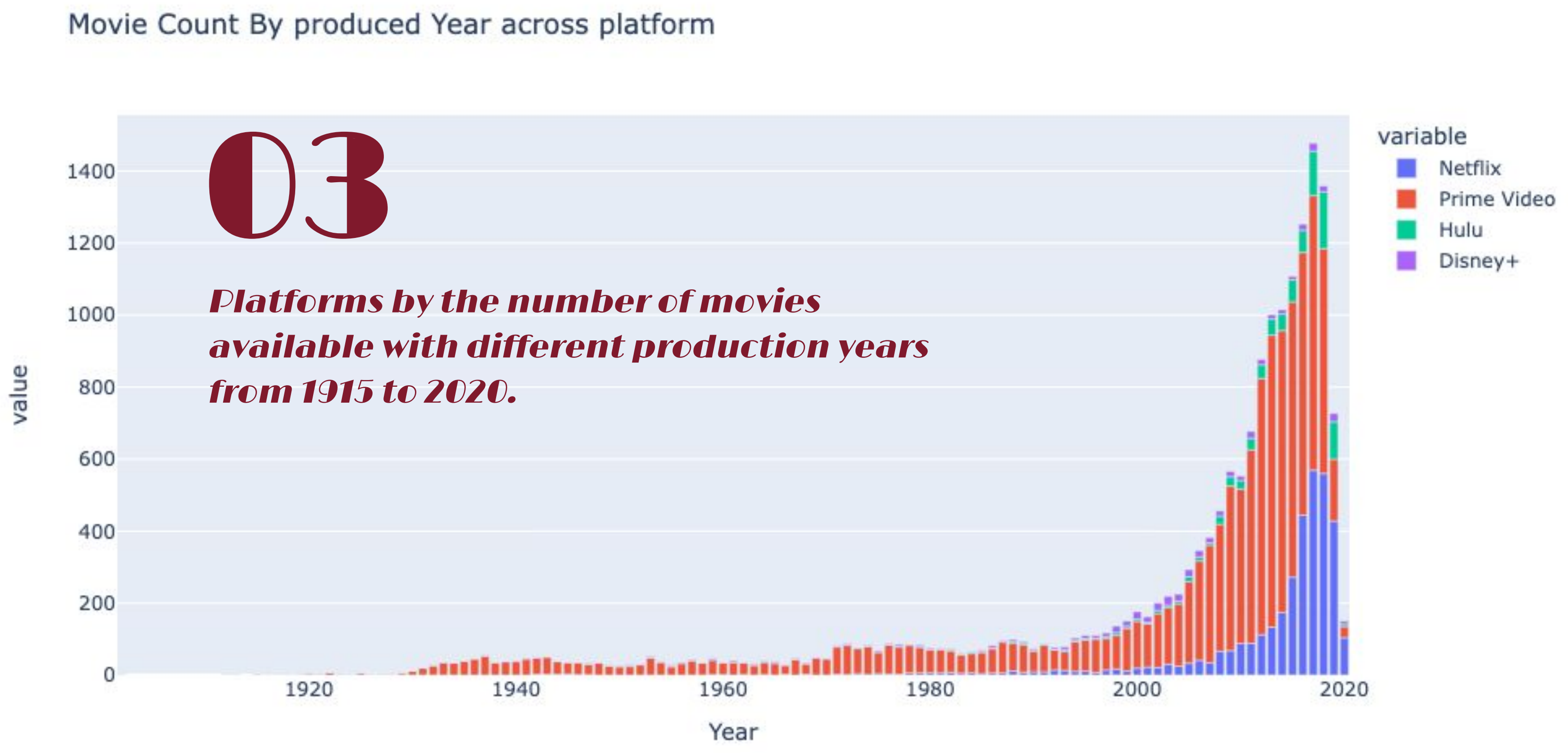


02

Platforms by the number and percentage of high-quality(IMDb 8.5+) movie



Extended Analysis of case 25

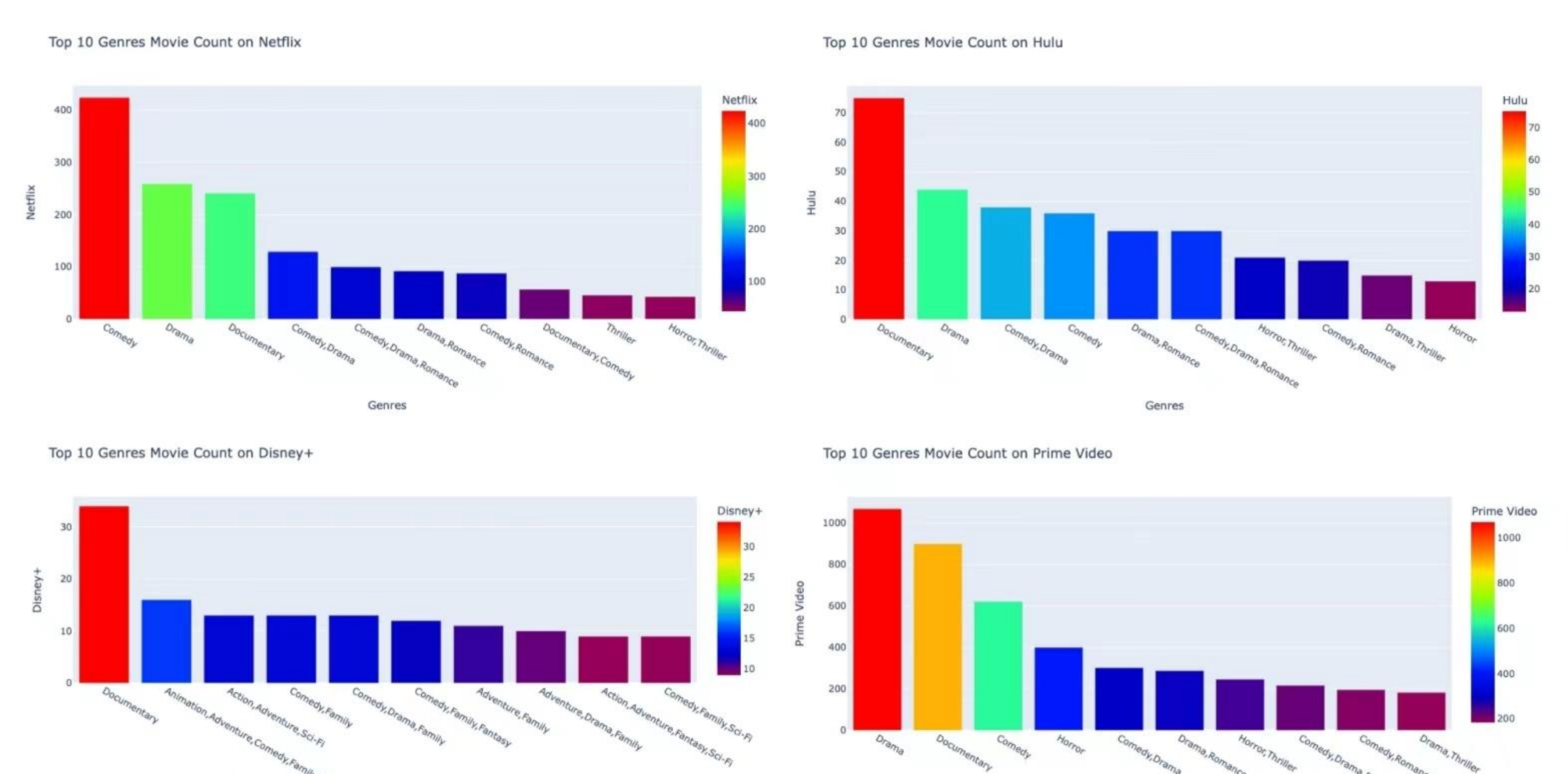


03

Platforms by the number of movies available with different production years from 1915 to 2020.

Extended Analysis of case 25

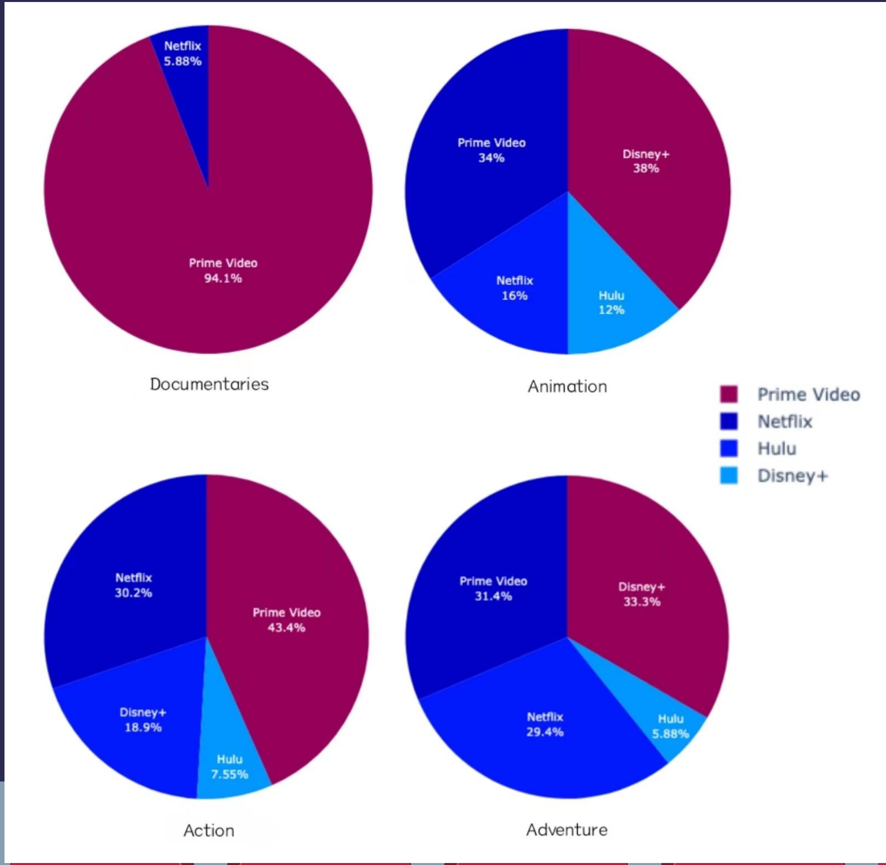
04 *Platforms by their top ten genres of movies*



Extended Analysis of case 25

05

Platforms shares of top 50 movies in Genre Documentaries, Action, Animation, and Adventure



Extended Analysis of case 25

90%

Netflix

95%

Prime Video

94%

Disney+

71%

Hulu

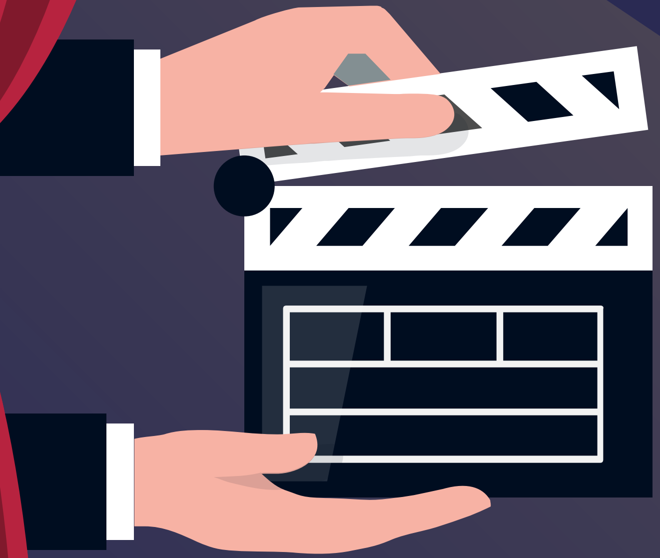
Limitation ?

Completeness

or

representability

of our dataset



02

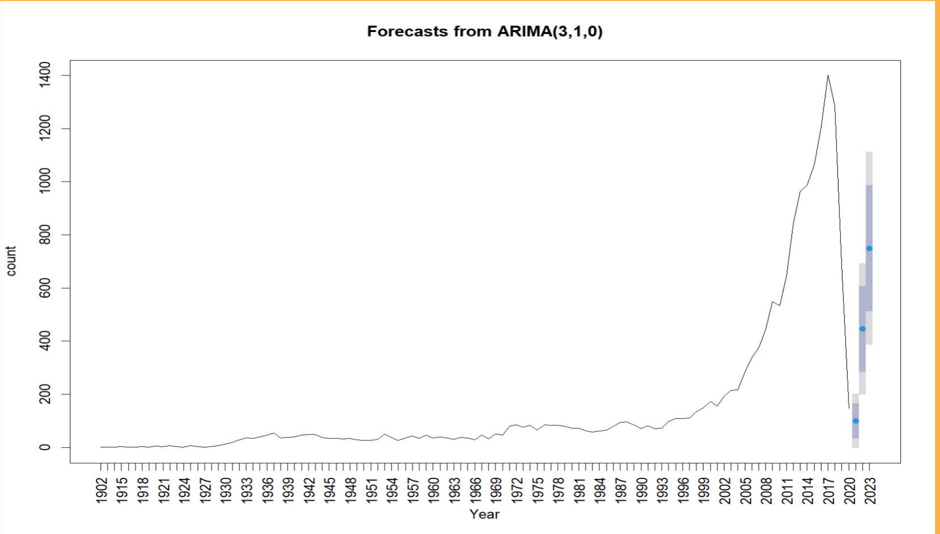
Forecasting the number of new movies in 2023

Which platforms will have more new contents?

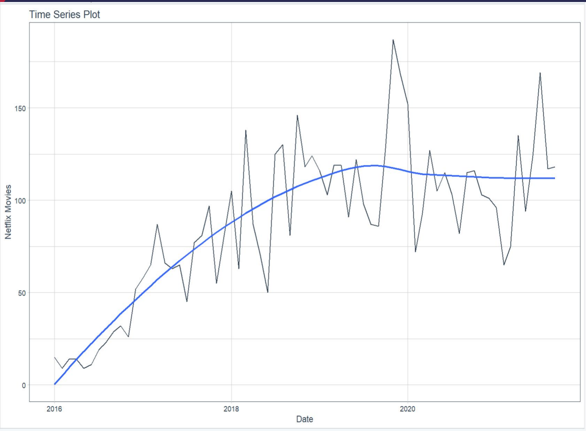
Overall Movie Market Forecasting

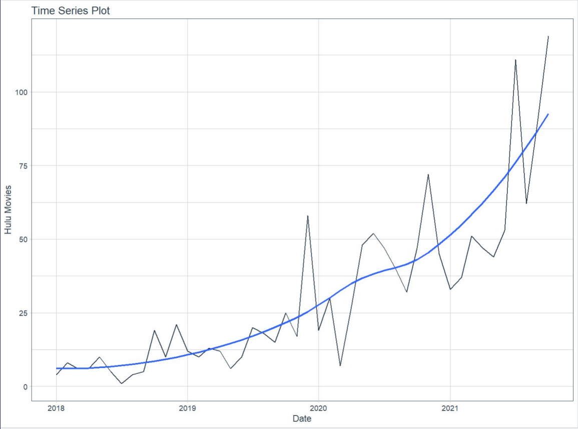
Rapidly developed around 2002

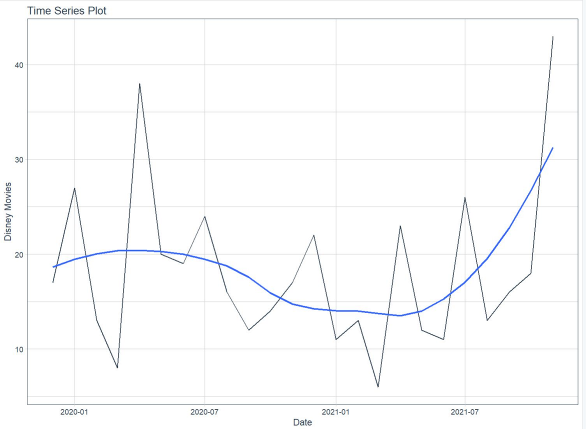
Reached the peak around 2017



Data Visualization





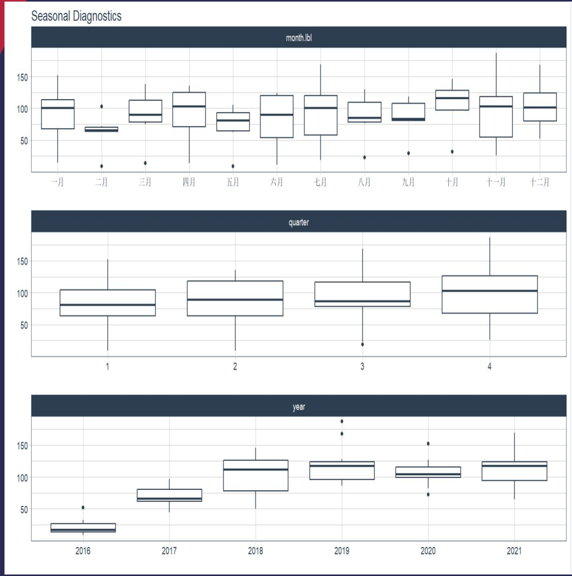


Netflix

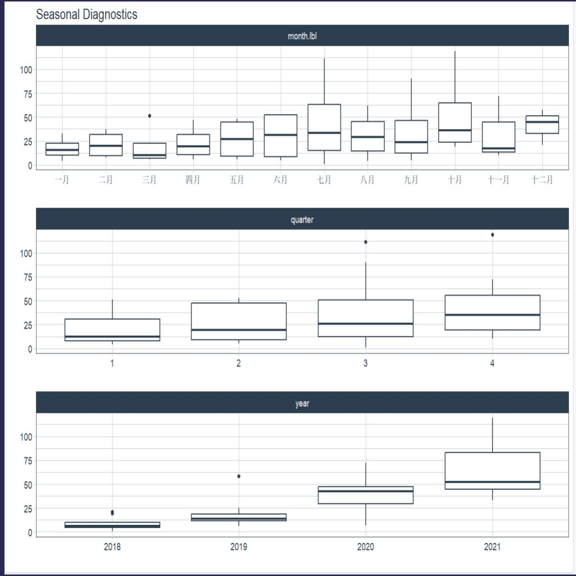
Hulu

Disney

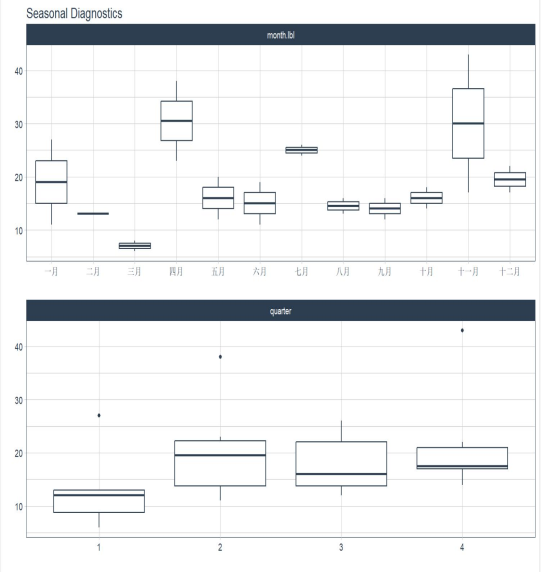
Seasonality Testing



Netflix



Hulu



Disney

Forecasting The Number Of New Movies Will Be Released On Different Streaming Platforms

NETFLIX

Netflix

Disney

Disney

hulu

Hulu

Model We Used

1, Auto-ARIMA Model

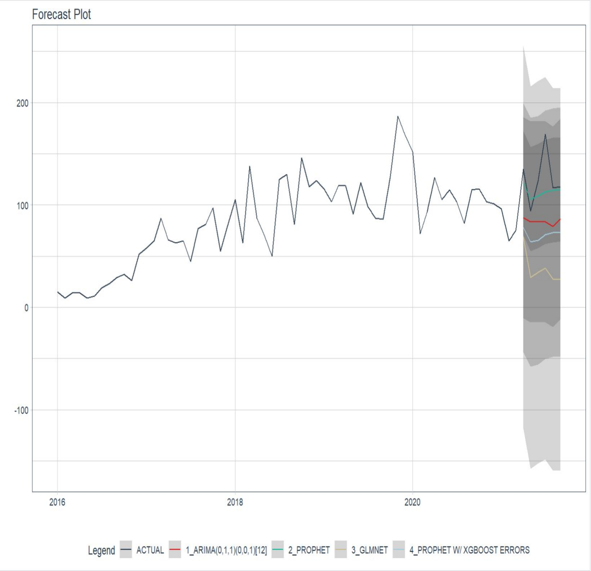
2, Prophet Model

3, Elastic Net (GLMNET)

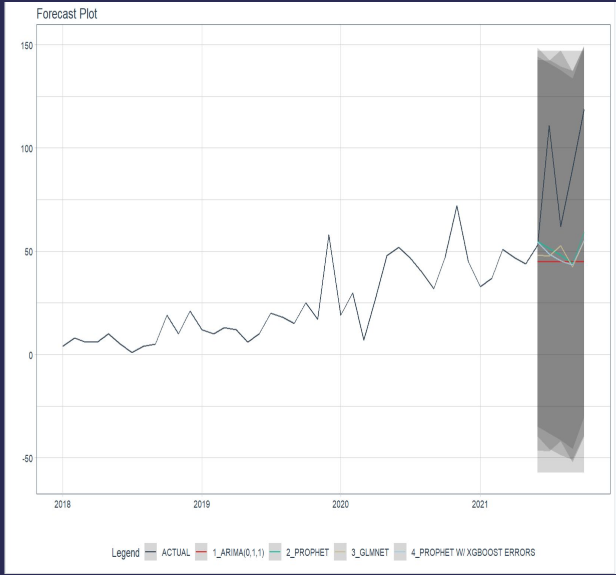
4, Hybrid ML Model

(combine Prophet and XGBoost)

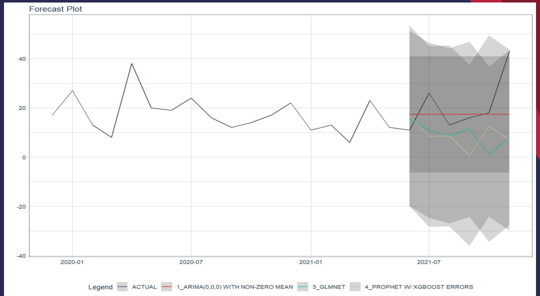
Validation

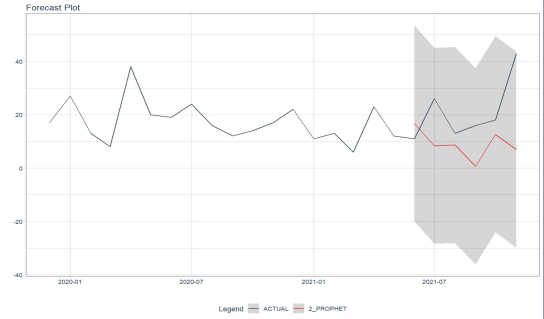


Netflix



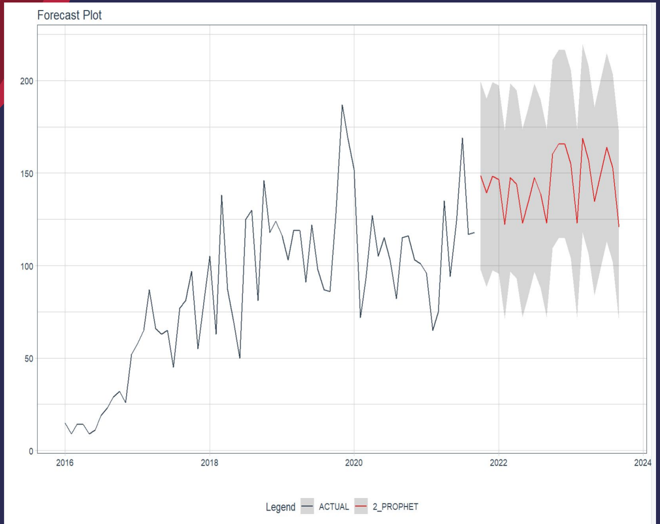
Hulu



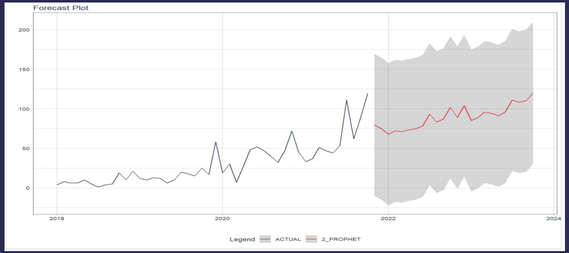


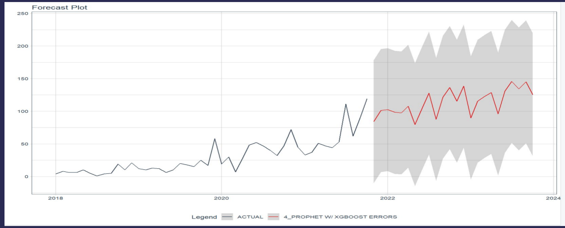
Disney

Forecasting For Each Platforms

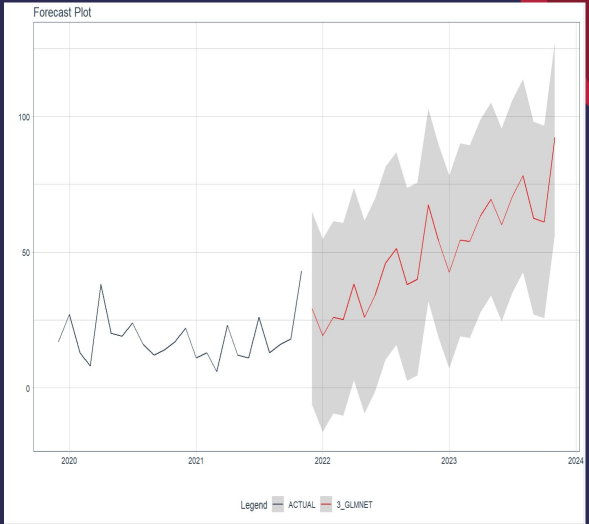


Netflix





Hulu



Disney

Platform recommendation

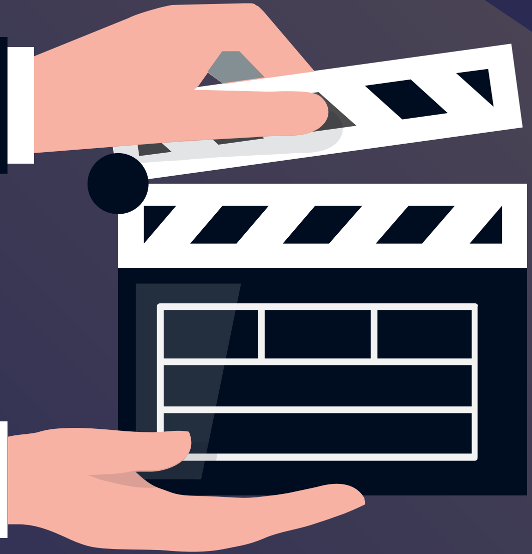
★ Netflix

Limitations

1, Not add other variables to the model

2, Some uncontrollable societal factors may have an influence to the forecasting result

3, Hard to verify the completeness of the dataset



03

Model Development

How could we choose movies
on streaming platform ?

Which Movie is worth watching ?

- ★ The IMDb score can be used as a movie viewing guide.
- ★ But what about newly released movies that don't have rating?

We need to know what features of the movies affect the IMDb score.

Data Preprocessing

Standardization

Model requirements

Data cleaning

Remove & Fill the N/A

Dummy variables

For qualitative variables

The problems with OLS model

★ Over-fitting

train_R2	test_R2
0.360868406	-2.785E+13
train_RMSE	test_RMSE
1.0719	7133974.488
train_MAE	test_MAE
0.8314	184777.7621

Ridge regression model

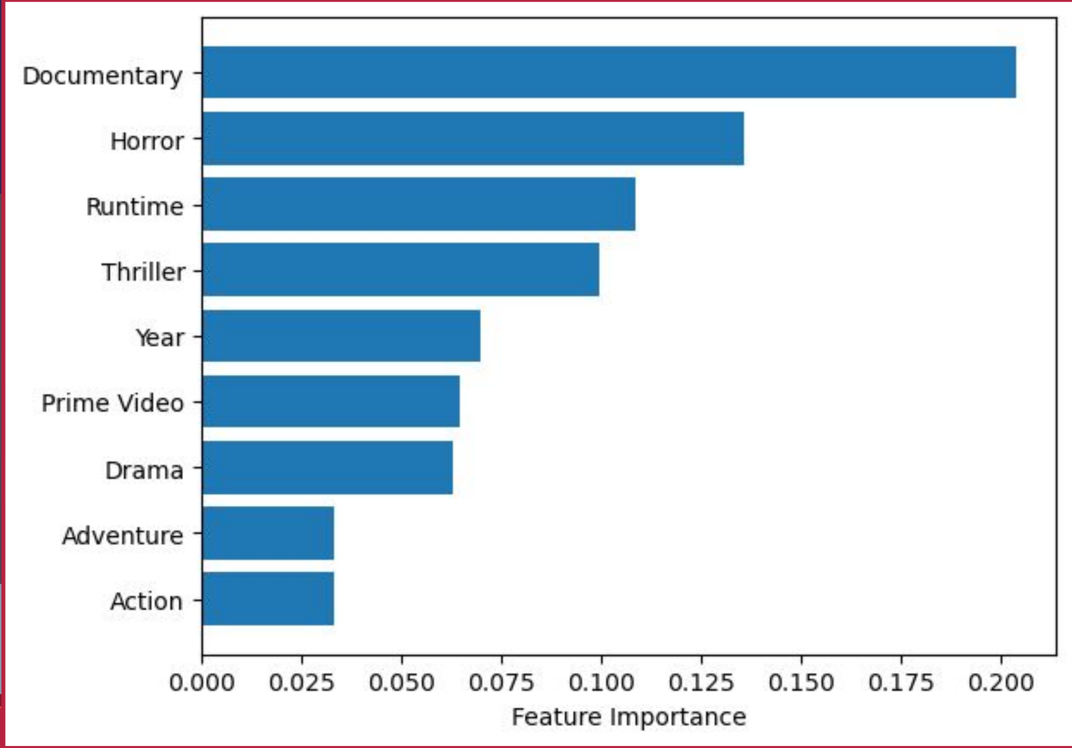
Ridge vs. OLS

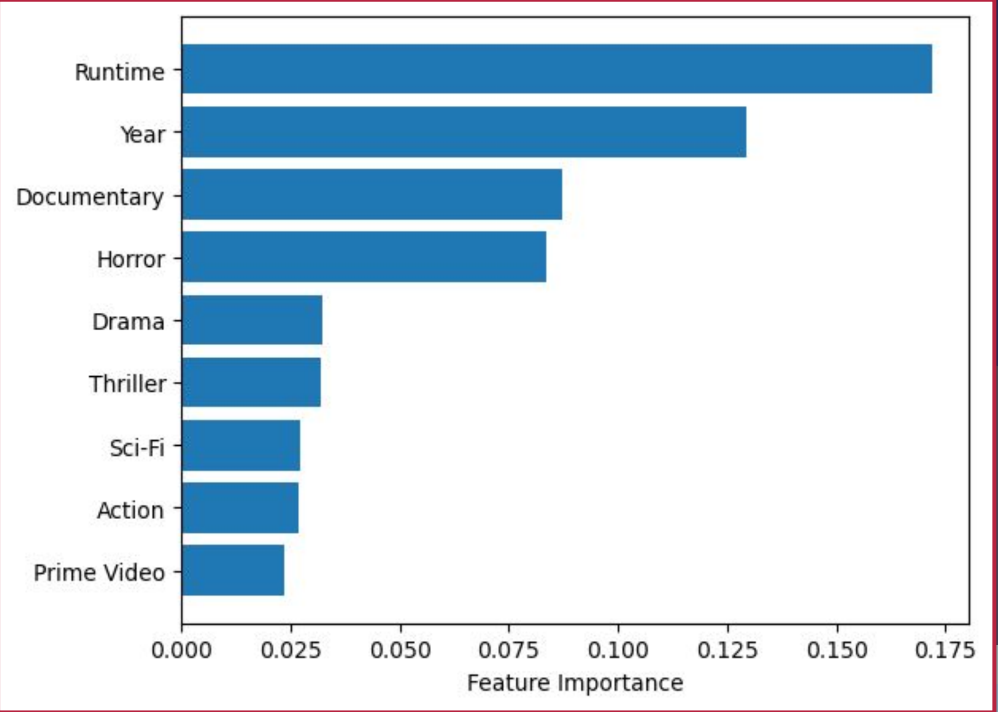
R2	train_R2	test_R2
Ridge	0.3528	0.3638
OLS	0.3609	-2.785E+13
RMSE	train_RMSE	test_RMSE
Ridge	1.0787	1.0782
OLS	1.0719	7133974.488
MAE	train_MAE	test_MAE
Ridge	0.8402	0.8374
OLS	0.8314	184777.7621

Decision tree

What features contribute the most to movie ratings ?

R2	train_R2	test_R2
Decision Tree	0.4066	0.3358
RMSE	train_RMSE	test_RMSE
Decision Tree	1.0328	1.1017
MAE	train_MAE	test_MAE
Decision Tree	0.7983	0.851





Random forest

R2	train_R2	test_R2
Decision Tree	0.4066	0.3358
Random Forest	0.7731	0.437335321
RMSE	train_RMSE	test_RMSE
Decision Tree	1.0328	1.1017
Random Forest	0.6387	1.014
MAE	train_MAE	test_MAE
Decision Tree	0.7983	0.851
Random Forest	0.4739	0.7779

Model results

	train_RMSE	test_RMSE	train_MAE	test_MAE
OLS	1.0719	7133974.4877	0.8314	184777.7621
Lasso	1.0798	1.0790	0.8410	0.8382
Ridge	1.0787	1.0782	0.8402	0.8374
SVR	1.0808	1.0819	0.8270	0.8356
Decision Tree	1.0328	1.1017	0.7983	0.8510
Random Forest	0.6387	1.0140	0.4739	0.7779
Ada boost	0.4191	1.0557	0.2571	0.8023
Gradient boost	0.4295	1.2204	0.3311	0.9405

Limitations and application

- Our weakness lies in need for other essential information about the movies.
- The model can be used as a helpful guide for audience to decide on whether to buy a movie online without previous reviews.

Summary

- ★ Exploratory data analysis for each platform
- ★ Time series and machine learning approaches to forecast the number of new movies in 2023
- ★ Model the relationship between movie features and IMDb ratings with regression and tree-based models


Thank
You!