# **Netflix Rating Recommendation Analysis**

**Chia Wei Tu 300289967**

**Introduction and discovery**

* Background

Netflix canceled user film review system and use artificial intelligence algorithms to recommend movies in these years. For getting more viewers, Netflix try to obtain viewer’s flavor of movie and recommend more feature of movie which match with user’s taste. Also, use the most popular result for increasing Netflix’s movie variety.

* Problem

Does the rating score really indicate how well Netflix system feel the recommended content fits the specific user? Does the recommendation score really help user find their love shows and movies?

* Developing initial hypotheses

If the Netflix rating recommendation is higher than scores 80, The result is yes (highly recommend).

If the Netflix rating recommendation is lower than scores 80, The result is No (not recommend).

**Data Preparation**

The Dataset is form Data World  <https://data.world/chasewillden/netflix-shows>

The dataset is about Netflix each title (movie name)'s rating information, including the rating category for different ages(rating), the description of rating, the release year, user rating size (only more than 80 sizes can be record on the user score standard) and the rating score.

* Original Dataset:

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Description automatically generated

- Compute length of rating level and add to a new column

- Examine the categorical columns in the netflix rating to 5 ages level - **Preschool, child, Juvenile, Teenager, Adult**

- Categorize columns in the user\_rating\_score, if user\_rating\_score >=80, highly recommend=yes, otherwise=No

Create dummy to transformation variables

Table

Description automatically generated

**Model Planning and Implementation**

*#!pip install yellowbrick*

*# import yellowbrick library*

*from yellowbrick.cluster import KElbowVisualizer*

The original data have overlapping the same ages but different TV rating names, it can be categorized to 5 different age levels. And the user rating score is from the lowest score 55 to highest score 99 excluding the 0 (unrated movie). So, I planned to divide the score to two results-Not Recommend and Highly Recommend. Over 80 are yes for recommend, others are no for recommend. For the Not Recommend and Highly Recommend target, it can change it to the binary category.

Base on the data transform, I create two series of machine learning pipeline. One is for the clustering analysis which can find the related group in different rating.

The clustering can be analyzed into more detail in each rating group. For example, the teenager can be divided by 7 classes (k=7). So, this can observe the relationship between each specific user’s reaction and in different flavor of movies (like release year).

Second is for Logistic regression and classifications algorithms to make predictions for the recommend result. Logistic regression is mostly used to solve binary classification.

After through the classification pipeline model, it can use the best model to predict the release year, different user group or rating description whether will have a good effect on the result of recommendation.

I use list to store every machine learning models and best parameter. And then zip all the list into for loop to use GridSearchCV finding the optimal parameter and pipeline predicting the X test and then append to the result list.

**Results Interpretation and Implications**

**Clustering Analysis**

Chart, scatter chart

Description automatically generated

The plot shows that 7 clusters display by child and release year. It is good for Netflix to analyze different release years of movie to the user that in the same child program rated.

Chart, scatter chart

Description automatically generated

The plot shows that 7 clusters display by teenager and rating length. There has a specific length of rating description have fit more teenager. Netflix’s program rated description is good for determine the result of recommendation.

**Multiple Regression and Classification Analysis**

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The accuracy of the data in classification report is 84% which is a nice percentage of correct predictions for the test data in random forest model. The model shows there are 78% accuracy of positive predictions for yes of highly recommend and 98% positives that were correctly identified for yes of highly recommend.

It is a nice result of Netflix rating recommendation; it really can help specific users finding their favorite shows or movie depend on the recommendation system. Most of users will give thumbs up for the movie depend on its release year, the description or the programs rated.

Text, table

Description automatically generated

The best model score is Random Forest Classifier which is 82% and have the lowest RMSE. I use Grid Search CV to find the optimal parameter which the max depths set to 8 and the n estimators set to 10.

Chart, treemap chart

Description automatically generated

There are almost 90 cases was positive and predicted positive. It is good for getting higher correct predictions.

There are 26 and 2 cases of false positive and false negative. Compare to the true positive, it seems has avoid some intolerable mistakes.

I think it should have more data in Netflix dataset, the user will keep growing up and change their interest of movie quickly. The more updated dataset is needed. But at the same time, the old data should be deleted and replaced by new data.

Using clustering and classification algorithms method can answer the question “Does the recommendation score really help user find their love shows and movies?” The Netflix recommendation system can compute the algorithm that the user’s favorite movie such like some people like to watch old school style and some people like to watch cartoon films.

What is more, the question “Does the rating score really indicate how well Netflix system feel the recommended content fits the specific user?” I think it really can help different ages people finding what they are able to watch depend on their program rated category.

**Out-of-sample Predictions**

Import a new sample csv file ‘X\_New\_Sample.csv’ to a final model

There have 5 samples to be predict in the model.

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Description automatically generated

After Scaling and transform the sample data then perform predictions using new sample data

Graphical user interface, text, application, email

Description automatically generated

The result is 4 out of 5 in highly recommend. It is quite high of result in this model.

It means Netflix have make a nice classification in different category, each age or release years. It makes the rating score more reliable for the recommendation.

**Concluding Remarks**

As the number of people subscribing and watching Netflix grew, the task became a big data project. Netflix rating recommendation system can help viewers by choosing among numerous options available to them through the streaming service. It also can filter the program rated group and remove unnecessary information from the data stream before it reaches to them.

Moreover, through the highly recommendation system, it can increase the viewer’s trust of selecting the films from recommendation which they like a lot and then giving a nice feedback.

If Netflix rating recommendation system obtain more updated and enough size of data, it seems to be a ideally cycle between user and business strategy.