

Capstone Project NETFLIX MOVIES & TV SHOWS CLUSTERING

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ABSTRACT

- The goal was to predict clusters similar content by matching text-based features.
- Exploratory Data Analysis is done on the dataset to get the insights from the data but first null values handled. Also, some hypothesis testing also performed from the insights from EDA. After that description column is our target variable has to be feature engineered where NLP operations such as removing symbols, stop words, punctuations, tokenizing performed on it and after that vectorized by using TFIDF. After that all left was to find the clusters and fitted our models by knowing number of clusters and further the model is evaluated using the metrics.



PROBLEM STATEMENT

- This dataset consists of tv shows and movies available on Netflix as of 2019. The dataset is collected from Flixable which is a third-party Netflix search engine.
- In 2018, they released an interesting report which shows that the number of TV shows on Netflix has nearly tripled since 2010. The streaming service's number of movies has decreased by more than 2,000 titles since 2010, while its number of TV shows has nearly tripled. It will be interesting to explore what all other insights can be obtained from the same dataset.

So, the goal is to predict clusters by similar content by matching text-based features whichever case is the description column which is a small plot summary of the contents.



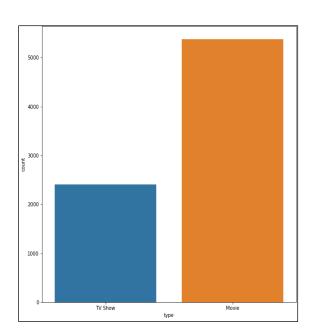
HANDLING NULL VALUES

- We will need to replace blank countries with the mode (most common) country. It would be better to keep director because it can be fascinating to look at a specific filmmaker's movie. As a result, we substitute the null values with the word 'unknown' for further analysis.
- There are very few null entries in the date_added fields thus we delete them.

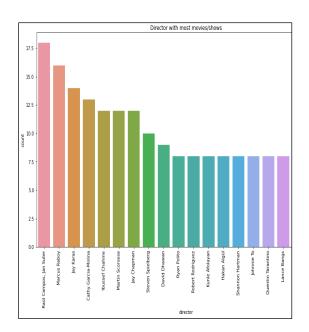
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- There are very few null entries in the date_added fields thus we delete them.
- Duplicate values dose not contribute anything to accuracy of results.
- Our dataset dose not contains any duplicate values.



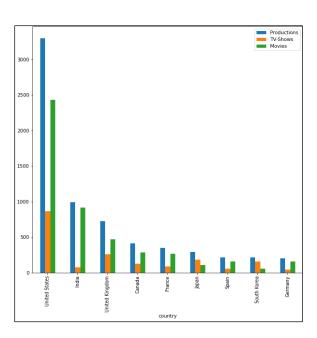
Exploratory Data Analysis



The above figure is count plot of movie and tv shows and the from the visualization we can draw the conclusion that almost 70% of datapoints belong to movie, rest 30% to TV show.

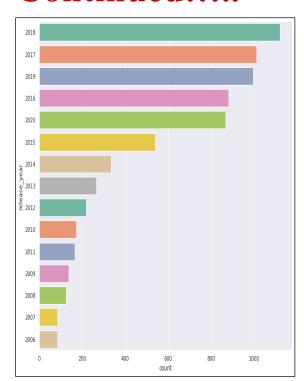


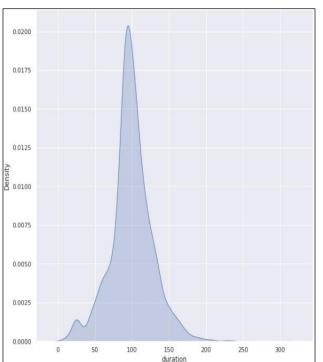
The above figure is a bar plot of count vs director which tells about director with the greatest number of movies or tv shows. The visualization depicts that Raul Campos, Jan Suter are the director with most tv shows or movies followed by Marcus Rabov.

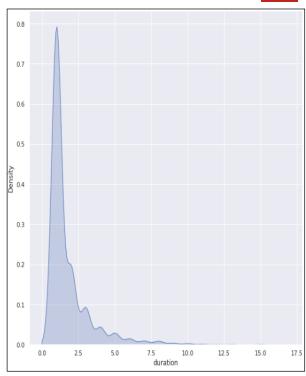


The top countries with Tv shows and movies along with production is plotted and the from visualization it is clear that United States tops the chart followed by India and Germany has the least TV shows and movies with a smaller number of productions.







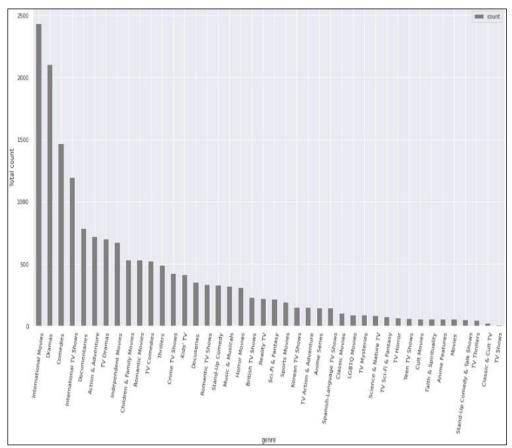


From the count plot it is clear that year 2018 is the year with the greatest number of movies and TV shows with an approximate count value of 1400 and the least movies and TV shows in the year 2006.

The below plot is a density plot for duration of movies and from the plot it is clear that most of the content is about 70 to 120 minutes duration for movies.

The below plot is a density plot for duration of show for no of seasons and from the plot it is clear that most of the shows are 1 to 2 seasons long.





From the above count plot for genre distribution, it is pretty evident that 'international movies' is the genre with highest count followed by 'Dramas' and the least is tv shows.



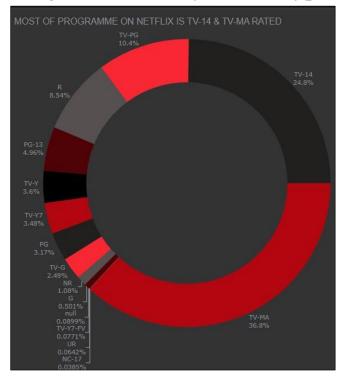
From the word cloud for movies most words like life, family popped up.

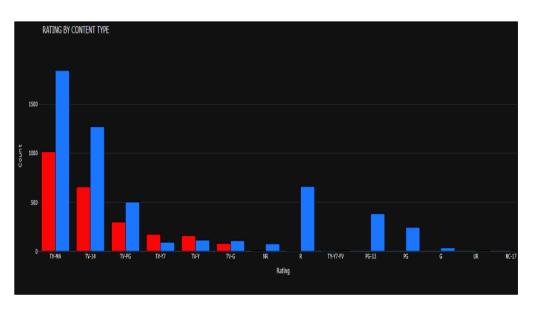


From the word cloud for shows most words like 'life', 'world', 'new', 'adventure', 'friend', 'family' popped up.

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• Rating distribution by content type

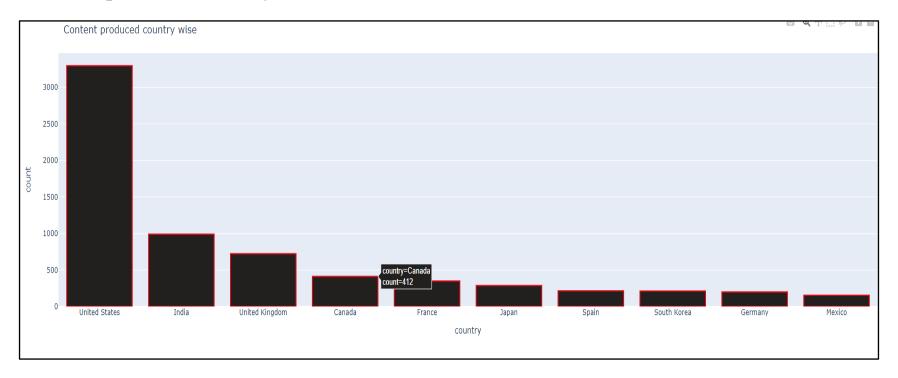




• From the pie chart it is clear that most of the programs on Netflix are TV-14 and TV-MA rated we can say that more content with mature content is available on Netflix.



• Content produced country wise



• From the above figure united states is the country that has produced the most content.



• Genre distribution by content type

| Count | | |
|--|--------------------------|-------|
| Dramas 2106 Comedies 1471 International TV Shows 1199 Documentaries 786 Action & Adventure 721 TV Dramas 704 Independent Movies 673 Children & Family Movies 532 Romantic Movies 531 TV Comedies 525 Thrillers 491 Crime TV Shows 427 Kids' TV 414 Docuseries 353 Romantic TV Shows 333 Stand-Up Comedy 329 Music & Musicals 321 | | count |
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| Crime TV Shows 427 Kids' TV 414 Docuseries 353 Romantic TV Shows 333 Stand-Up Comedy 329 Music & Musicals 321 | TV Comedies | 525 |
| Kids' TV 414 Docuseries 353 Romantic TV Shows 333 Stand-Up Comedy 329 Music & Musicals 321 | Thrillers | 491 |
| Docuseries 353 Romantic TV Shows 333 Stand-Up Comedy 329 Music & Musicals 321 | Crime TV Shows | 427 |
| Romantic TV Shows 333 Stand-Up Comedy 329 Music & Musicals 321 | Kids' TV | 414 |
| Stand-Up Comedy 329 Music & Musicals 321 | Docuseries | 353 |
| Music & Musicals 321 | Romantic TV Shows | 333 |
| | Stand-Up Comedy | 329 |
| | Music & Musicals | 321 |
| Horror Movies 312 | Horror Movies | 312 |

| British TV Shows | 232 |
|------------------------------|-----|
| Reality TV | 222 |
| Sci-Fi & Fantasy | 218 |
| Sports Movies | 196 |
| Korean TV Shows | 150 |
| TV Action & Adventure | 150 |
| Anime Series | 148 |
| Spanish-Language TV Shows | 147 |
| Classic Movies | 103 |
| LGBTQ Movies | 90 |
| TV Mysteries | 90 |
| Science & Nature TV | 85 |
| TV Sci-Fi & Fantasy | 76 |
| TV Horror | 69 |
| Teen TV Shows | 60 |
| Cult Movies | 59 |
| Faith & Spirituality | |
| Anime Features | |
| Movies | 56 |
| Stand-Up Comedy & Talk Shows | |
| TV Thrillers | 50 |
| Classic & Cult TV | |
| TV Shows | 12 |

• From the above table we can see genre of international movie is the most available content.

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• Top 20 Countries with more number of productions

| | country | Productions | TV-Shows | Movies |
|----|----------------|-------------|----------|--------|
| 0 | United States | 3297 | 866 | 2431 |
| 1 | India | 990 | 75 | 915 |
| 2 | United Kingdom | 723 | 256 | 467 |
| 3 | Canada | 412 | 126 | 286 |
| 4 | France | 349 | 84 | 265 |
| 5 | Japan | 287 | 184 | 103 |
| 6 | Spain | 215 | 57 | 158 |
| 7 | South Korea | 212 | 157 | 55 |
| 8 | Germany | 199 | 42 | 157 |
| 9 | Mexico | 154 | 53 | 101 |
| 10 | China | 147 | 45 | 102 |
| 11 | Australia | 144 | 60 | 84 |
| 12 | Egypt | 110 | 13 | 97 |
| 13 | Turkey | 108 | 28 | 80 |
| 14 | Hong Kong | 102 | 5 | 97 |
| 15 | Italy | 90 | 23 | 67 |
| 16 | Brazil | 88 | 29 | 59 |
| 17 | Belgium | 85 | 11 | 74 |
| 18 | Taiwan | 85 | 70 | 15 |
| 19 | Argentina | 82 | 18 | 64 |



Data preprocessing

Removing punctuation:

Punctuation has no meaning in clustering, so removing punctuation helps to get rid of useless bits of data or noise.

Removing stop words:

Stop-words are basically a collection of commonly used words in any language, not just English. If we remove words that are very commonly used in a given language, we can focus on important words instead.



Clusters Model Implementation

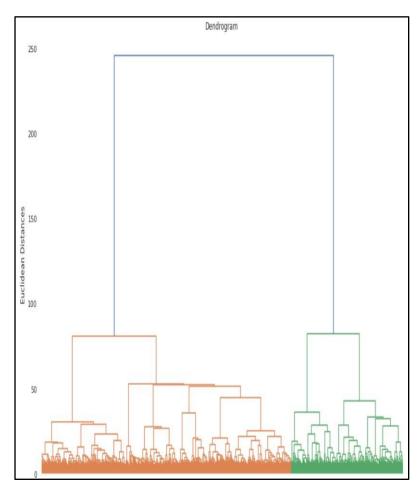
Agglomerative Clustering:

It is a type of hierarchical clustering algorithm. It is an unsupervised machine learning technique that divides the population into several clusters such that data points in the same cluster are more similar and data points in different clusters are dissimilar. Points in the same cluster are closer to each other.

Dendrogram

It is a type of tree diagram showing hierarchical clustering — relationships between similar sets of data. They are frequently used in biology to show clustering between genes or samples, but they can represent any type of grouped data.

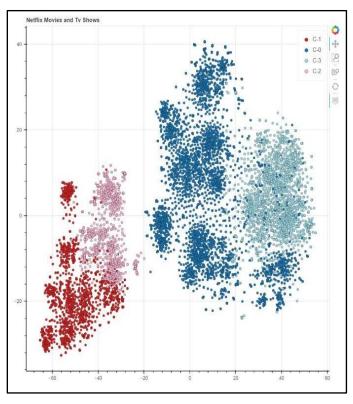




From the Figure we got after using the hierarchical clustering, we concluded that the best value for the number of clusters based on the Euclidian distances in the given figure was 4.

Using this value we tried to cluster the given dataset and got the results accordingly.





Cluster groups for movies or TV shows

• The above figure consists of different cluster groups for Movies and Tv shows over different parts of globe.

Conclusion



- 1. Exploratory Data Analysis was done for all the attributes to study the deep insights from the Given Dataset.
- 2. Univariate & multivariate analysis.
- 3. Visualized Data, inferred insights
- 4. Analysed various trends in Countries and the corresponding analysis was visualized to get a clear picture of the analysis.
- 5.TV Shows or Movies? Of course over the period of time the trend has been moving towards Netflix series instead of Movies. We tried to analyze this with graphical representation as well on yearly basis.
- 6. We used TFIDF Vectorizer and Sigmoid Kernel in order to recommend movies based on the similarities in the Textual Attributes.
- 7.Identified 4 distinct clusters and used Interactive Visualizations to dive deeper into the clustered data.



Thank you