

# **Capstone Project - 4**

# **Netflix Movies and TV Shows Clustering**

Submitted by

**Shaloy Elshan Lewis** 

Data science trainee, Almabetter



# **Agenda**

- Problem Statement
- Data Summary
- Data Cleaning
- Exploratory Data Analysis (EDA)
- Feature Engineering
- Dimensionality Reduction
- Clustering
- Word cloud on Clusters
- Content Based Recommender System
- Challenges Faced
- Conclusions





#### **Abstract**

- Netflix is a popular streaming service and production firm.
- According to Statista, Netflix had approximately 220.67 million paid subscribers worldwide as of the second quarter of 2022.
- It is crucial that they effectively cluster the shows that are hosted on their platform in order to enhance the user experience for its subscribers.





#### **Problem Statement**

- The goal of this project is to cluster the shows on Netflix such that the shows within a cluster are similar to each other and the shows in different clusters are dissimilar to each other.
- These clusters may be later leveraged to offer the consumers personalized show recommendations based on their interests.
- The dataset contains 7787 records, and
   11 attributes





## **Data Summary**

- Show ID
- Type Movie / TV show
- **Title** Show title
- Director Name of the director
- Cast Name of the cast
- Country Production country
- Date added
- Release year
- Rating Show age rating
- **Duration** Minutes / seasons
- Listed in Genre
- Description





# **Data Cleaning**

- Handling missing values:
  - Director (2389), cast (718), and country (507) –
     replace with 'Unknown'
  - o Date added (10) **dropped**.
  - Rating (7) **mode** imputation.
- Only primary genre and country were selected to simplify the EDA
- The dataset contained separate age ratings for movies and TV shows, and were replaced with values of: 'Adults', 'Teens', 'Young Adults', 'Older Kids', 'Kids'

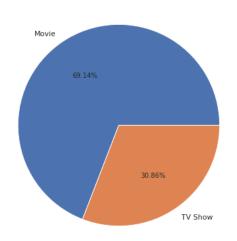


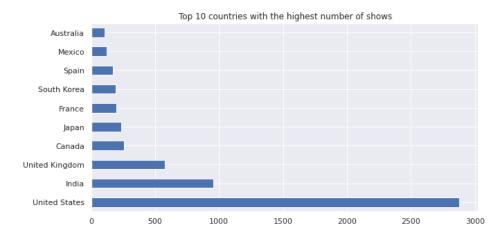


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# **Exploratory Data Analysis (EDA)**

- **69.14%** of the shows on Netflix are movies, and **30.86%** TV shows.
- The top 3 countries together account for about 56% of all movies and TV shows in the dataset.
- This value increases to about
   78% for top ten countries.

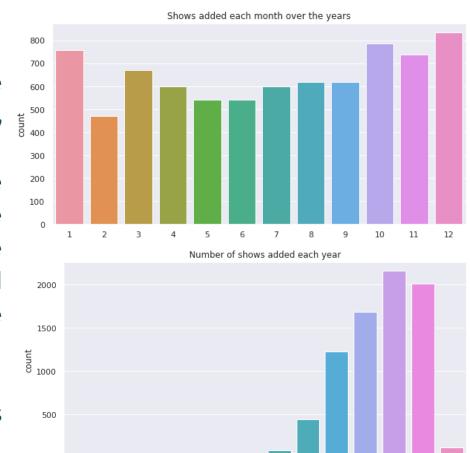






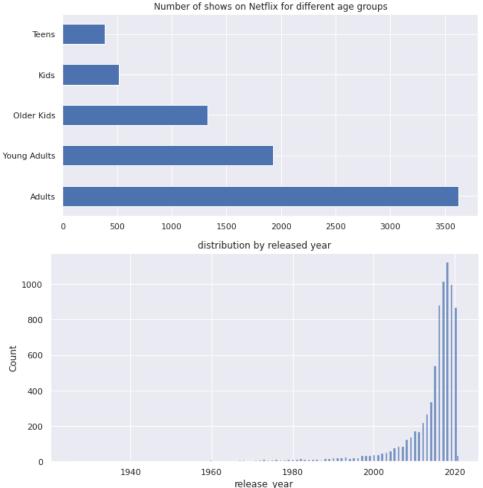
2016 2017 2018 2019 2020

- More shows are added in the months of October, November,
   December, and January.
- There is a decrease in the number of shows added in the year 2020, which might be attributed to the Covid-induced lockdowns, which halted the creation of shows.
- There are very few shows added in the year **2021**, since the data is available only up to 16<sup>th</sup> January.



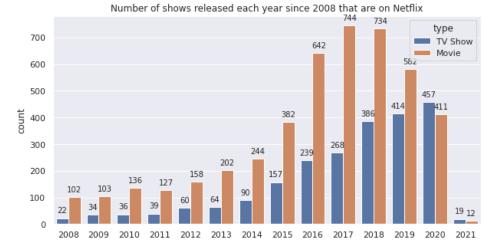


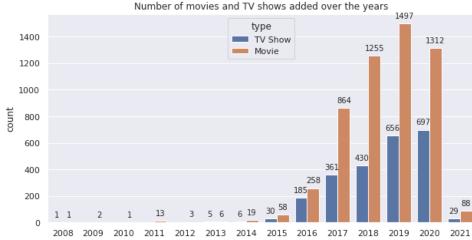
- The majority of the shows on Netflix are catered to the needs of adult and young adult population.
- Netflix has greater number of new movies / TV shows than the old ones.



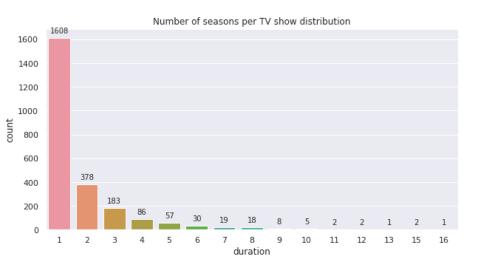


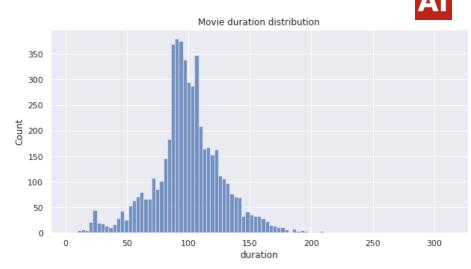
- Though there was a decrease in the number of movies added in 2020, this pattern did not exist in the number of TV shows added in the same year.
- This might signal that Netflix is increasingly concentrating on introducing more TV series to its platform rather than movies.

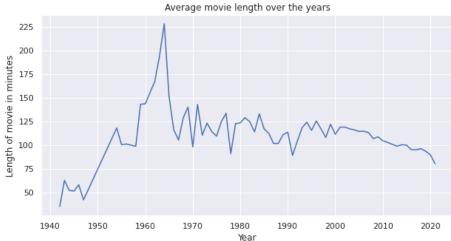




- The length of movies in the are almost **normally distributed**.
- Majority of the TV shows are still in the 1<sup>st</sup> season.

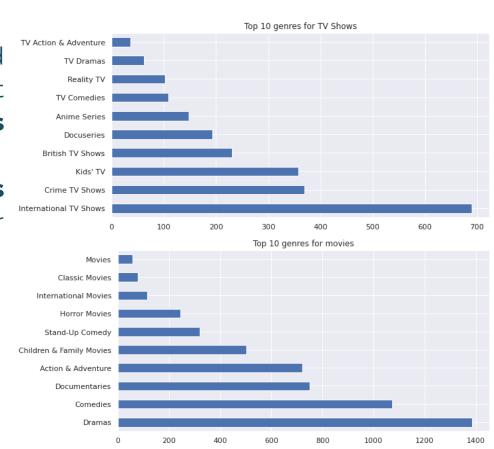






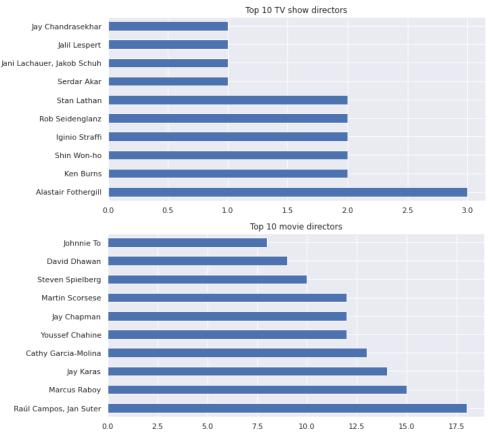


- Dramas, comedies, and documentaries are the most popular genre for the movies on Netflix.
- International, crime, and kids are the most popular genre for TV shows on Netflix.





- Raul Campos and Jan Suter have directed 18 movies, higher than anyone yet.
- Alastair Fothergill has directed three TV shows, higher than anyone yet.
- Only six directors have directed more than one television show.





# **Feature Engineering**

- Clusters are built based on the attributes: Director, Cast, Country, Listed in (genres), and Description
- Steps involved in data pre-processing:
  - Removing non-ascii characters
  - Removing stop words and converting to lowercase
  - Removing punctuation marks
  - Lemmatization, tokenization and text vectorization
  - Dimensionality reduction using PCA



# Feature Engineering (Contd.)

• **TFIDF** (Term Frequency Inverse Document Frequency) vectorizer was used to vectorize the corpus.

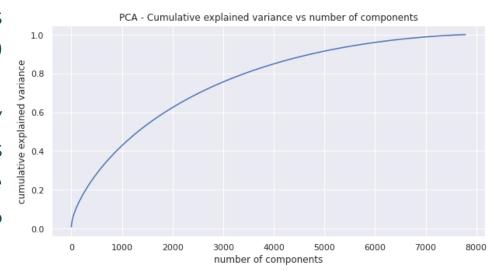
$$TF = \frac{\text{Number of times term t appears in a document}}{\text{Total number of terms in the document}}$$
 
$$IDF = \log_e \left( \frac{\text{Total number of documents}}{\text{Number of documents with term t in it}} \right)$$
 
$$TFIDF = TF \times IDF$$

Maximum number of features were taken as 20000.



# **Dimensionality Reduction**

- 100% of the variance in data is explained by about ~7500 components.
- To reduce dimensionality, only the top 4000 components were taken, which will still be able to capture more than 80% of variance in the data.



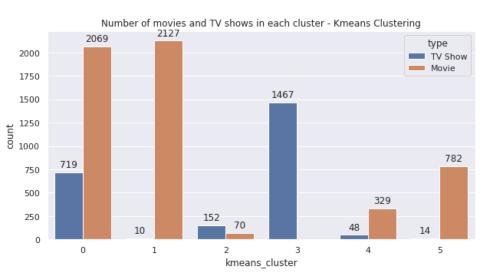


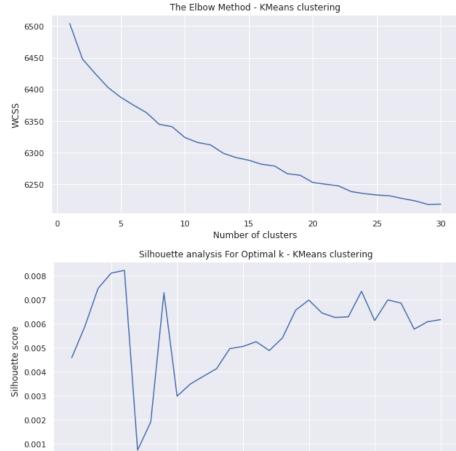
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# **K Means Clustering**

- Distortion: 6374.78
- Silhouette score: 0.0082
- Number of clusters: 6





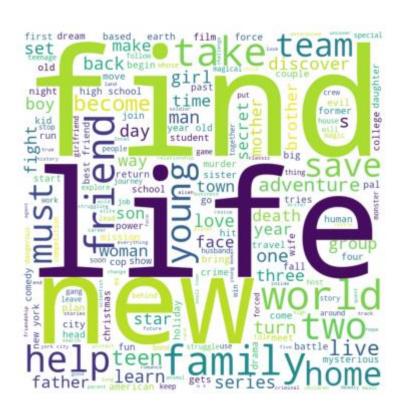
Values of K

5

10



#### **Word Clouds: K Means Clusters**



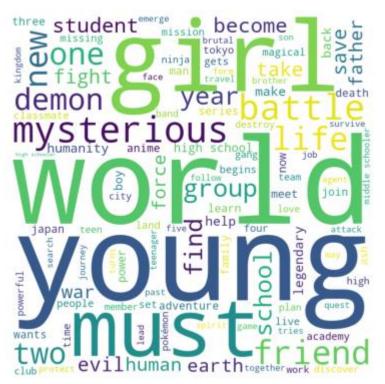


K Means Cluster - 0

K Means Cluster - 1



## Word Clouds: K Means Clusters (Contd.)

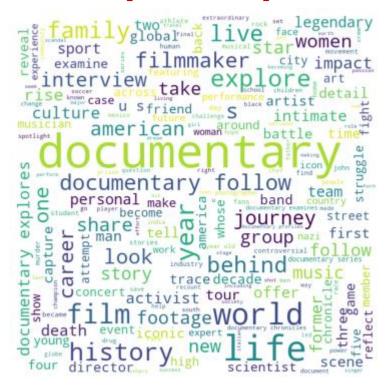






# Word Clouds: K Means Clusters (Contd.)

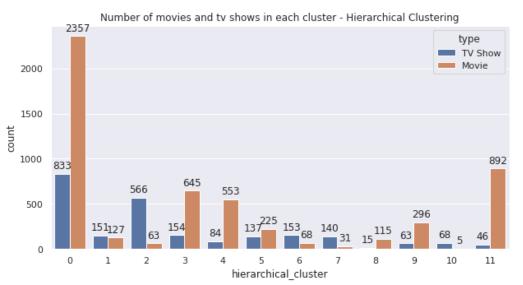


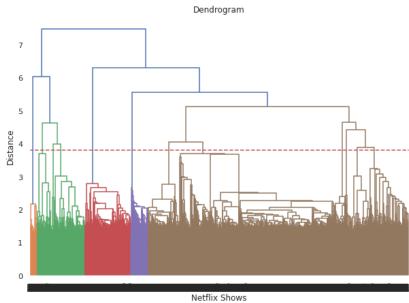




# **Hierarchical Clustering**

- Agglomerative clustering.
- Distance: Euclidean
- Linkage: Ward
- Number of clusters: 12





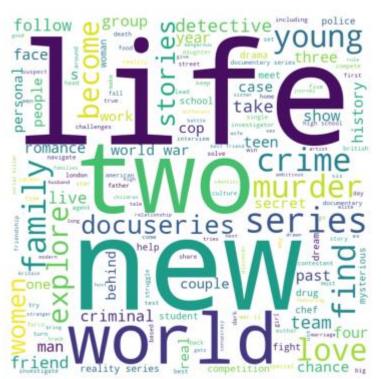


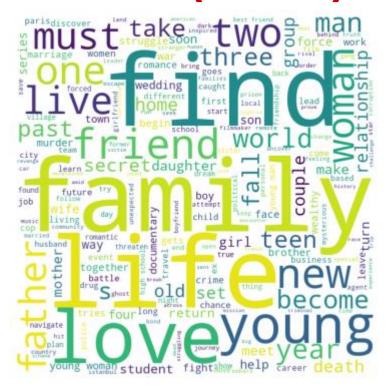
#### **Word Clouds: Hierarchical Clusters**



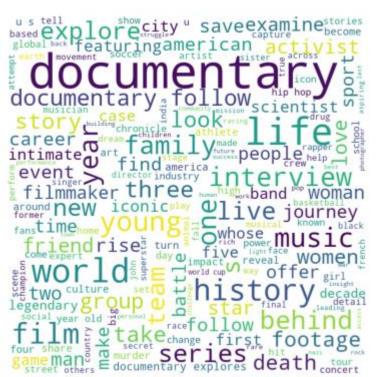






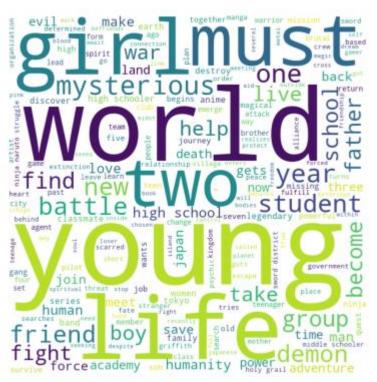






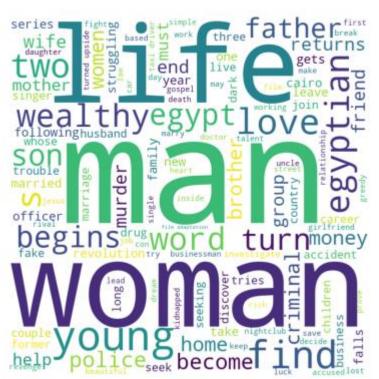








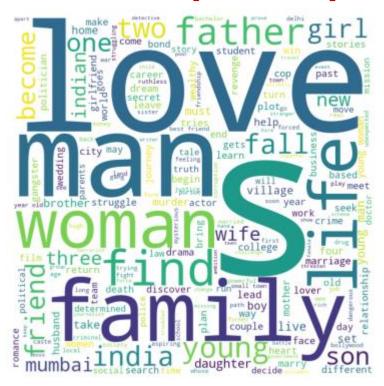














# **Content Based Recommender System**

- We can build a simple content based recommender system based on the similarity of the shows.
- If a person has watched a show on Netflix, the recommender system must be able to recommend a list of similar shows that s/he likes.
- To get the similarity score of the shows, we can use cosine similarity
- The Cosine Similarity score of two vectors increases as the angle between them decreases.

$$\cos \theta = \frac{A \cdot B}{|A| \cdot |B|}$$



# Content Based Recommender System (Contd.)

 10 recommendations for the show "A Man Called God" and "Stranger Things"

```
If you liked 'A Man Called God', you may also enjoy:

['Mr. Sunshine',
  'One Spring Night',
  'Rugal',
  'The King: Eternal Monarch',
  'My Mister',
  'My Little Baby',
  'Reply 1994',
  'Extracurricular',
  'My Secret Romance',
  'Chef & My Fridge']
```

```
If you liked 'Stranger Things', you may also enjoy:

['Beyond Stranger Things',
   'Prank Encounters',
   'The Umbrella Academy',
   'Haunted',
   'Scream',
   'Warrior Nun',
   'Nightflyers',
   'Zombie Dumb',
   'Kiss Me First',
   'The Vampire Diaries']
```



# Content Based Recommender System (Contd.)

• 10 recommendations for the show "Peaky Blinders" and "Lucifer"

```
If you liked 'Peaky Blinders', you may also enjoy:

['Kiss Me First',
    'Happy Valley',
    'London Spy',
    'The Frankenstein Chronicles',
    'Paranoid',
    'Get Even',
    'Giri / Haji',
    'My Hotter Half',
    'The Murder Detectives',
    'I AM A KILLER: RELEASED']
```

```
If you liked 'Lucifer', you may also enjoy:

['Rica, Famosa, Latina',
   'Get Shorty',
   'The Good Cop',
   'Jack Taylor',
   'Better Call Saul',
   'Dramaworld',
   'Father Brown',
   "Marvel's Iron Fist",
   'Young Wallander',
   'No Good Nick']
```



# **Challenges Faced**

- Deciding the attributes on which we can build the clusters
- Feature engineering deciding on the features to be dropped/kept/transformed
- Choosing the best visualization to show the trends clearly in the EDA phase
- Deciding on ways to handle the missing values
- Deciding on the attributes to be considered for clustering the dataset
- High computation time





#### **Conclusions**

- In this project, we worked on a **text clustering problem** wherein we had to cluster the Netflix shows such that the shows within a cluster are similar to each other and the shows in different clusters are dissimilar to each other.
- The dataset contained about 7787 records, and 11 attributes.
- We began by dealing with the dataset's missing values and doing exploratory data analysis (EDA).
- It was found that Netflix hosts more movies than TV shows on its platform, and the total number of shows added on Netflix is growing exponentially. Also, majority of the shows were produced in the United States, and the majority of the shows on Netflix were created for adults and young adults age group.



# **Conclusions (Contd.)**

- It was decided to cluster the data based on the attributes: director, cast, country, genre, and description. The values in these attributes were pre-processed, tokenized and then vectorized using TFIDF vectorizer.
- Through TFIDF Vectorization, we created a total of 20000 attributes.
- We used Principal Component Analysis (PCA) to handle the curse of dimensionality. 4000 components were able to capture more than 80% of variance, and hence, the number of components were restricted to 4000.
- We first built clusters using the k-means clustering algorithm, and the optimal number of clusters came out to be 6. This was obtained through the elbow method and Silhouette score analysis.



# **Conclusions (Contd.)**

- Hierarchical clustering model was built using the Agglomerative clustering algorithm, and the optimal number of clusters came out to be 12. This was obtained after visualizing the dendrogram.
- A content-based recommender system was built using the Cosine Similarity score. This recommender system will make 10 recommendations to the user based on the type of show they watch.



# Thank You!