Streaming Content Dashboard

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ABSTRACT

As we all know in today's world data analysis and visualization is becoming important thing because of the way the human brain processes information, using charts or graphs to visualize large amounts of complex data is easier than poring over spreadsheets or reports. Data visualization is a quick, easy way to convey concepts in a universal manner – and you can experiment with different scenarios by making slight adjustments. Now a days people do not want to waste any time on viewing bad shows and they first look at the ratings and later they decide what to see. According to this situation we designed our project to make streaming content dashboard which will enable us to visualize all the famous shows in every aspect we can understand in a clear way. We also clustered the combined data from Netflix, Hulu, Disney Plus and Amazon Prime using K-Means and created a recommendation system to find similar movies to what the viewer has watched.

KEYWORD

Netflix, Hulu, Disney Plus, Amazon Prime, recommendation system, text clustering, data visualization and analytics, OTT Content and k-means algorithms

1. INTRODUCTION

Recommender Systems (RSs) are characterized by the capability of filtering large information spaces and selecting the items that are likely to be more interesting and attractive to a user.

OTT Platforms are the biggest users of recommendation systems. So, in this Project we aim to visualize the content library of top OTT Platforms like Netflix, Disney Plus, Hulu and Amazon Prime. While doing this we will also discover correlations and recurring patterns in the dataset with interesting inferences.

Finally, we will see how the recommendation engine works to deliver similar content as quickly as possible.

2. About The Dataset

For this project we will use 4 datasets containing of listings of all the movies and tv shows

available on Netflix, Hulu, Disney Plus and Amazon Prime, along with details such as - cast, directors, ratings, release year, duration, etc. In total there are approximately 22k observations. It is obtained from Kaggle Open-Source Dataset Library (Source).

2.1 Feature components for analysis & visualization

For this visualization and analysis, we use feature attributes from the dataset, namely,

- Type
- Title
- Director
- Cast
- Country
- Date Added
- Release Year
- Rating
- Duration
- Listed In
- Description

Each individual dataset contains all the following attributes. During the project we will combine all 4 datasets into one and then we will append a column denoting the OTT platform.

3. Design and flow of models

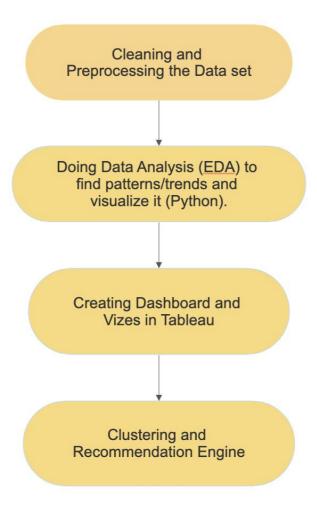


Fig.1 design and flow of model

For the Visualization we have used the following modules and analysis parameters:

3.1 Module 1: data cleaning and dataset analysis

After Importing the data set, we need to clean it and analyze what data we were able to collect. After this we can easily plan which parameters to visualize.

3.2 Module 2: Doing Data Analysis (EDA) to find patterns/trends and visualize it (Python).

The attributes from the obtained data set are compared with each other to find correlations and dependencies and then these are visualized using different types of graphs. We can use these graphs to visualize common trends in the dataset.

3.3 Module 3: Creating Dashboard and Vizes in Tableau

We then use Tableau to further Visualize the Dataset and create interactive Dashboards. We found Tableau to be an incredibly versatile and powerful tool for this purpose.

3.4 Module 4: Clustering and Recommendation Engine

We will use K-Means clustering to cluster similar data. We then append the cluster id generated to the combined dataset to facilitate the recommendation engine

K-means

K-means algorithm is an iterative algorithm that tries to partition the dataset into K pre-defined distinct non-overlapping subgroups (clusters) where each data point belongs to only one group. It tries to make the intra-cluster data points as similar as possible while also keeping the clusters as different (far) as possible.

The way kmeans algorithm works is as follows:

- 1. Specify number of clusters *K*.
- 2. Initialize centroids by first shuffling the dataset and then randomly selecting *K* data points for the centroids without replacement.
- 3. Keep iterating until there is no change to the centroids.
- 4. Compute the sum of the squared distance between data points and all centroids.
- 5. Assign each data point to the closest cluster (centroid).

Compute the centroids for the clusters by taking the average of the alldata points that belong to each cluster.

The objective function is:

$$J = \sum_{i=1}^{m} \sum_{k=1}^{K} w_{ik} ||x^{i} - \mu_{k}||^{2}$$

Recommendation Engine

The recommendation Engine takes a Movie or Show Title as an input. It then finds the cluster id of that entry. It uses the cluster id to reduce the search space.

Now it runs a text similarity check between the description of entered show or movie to find similar content from that cluster.

Thus, using K-Means and Text Similarity, it achieves fast and accurate results.

4. IMPLEMENTATION

4.1 First we import modules and datasets.

Importing all the libraries and modules

First import the libraries to better analyze the data set. Here matplotlib and plotly are used for visualization and word cloud.

```
[ ] import pandas as pd
          import numpy as np
          import plotly.express as px
          import plotly.graph objects as go
          import matplotlib.pyplot as plt
          import seaborn as sns
          import plotly.io as pio
          from plotly.offline import iplot
          from plotly.subplots import make subplots
          from wordcloud import WordCloud, STOPWORDS
          import random
         import re
                                                                                                                                Add text cell

    In the following codes

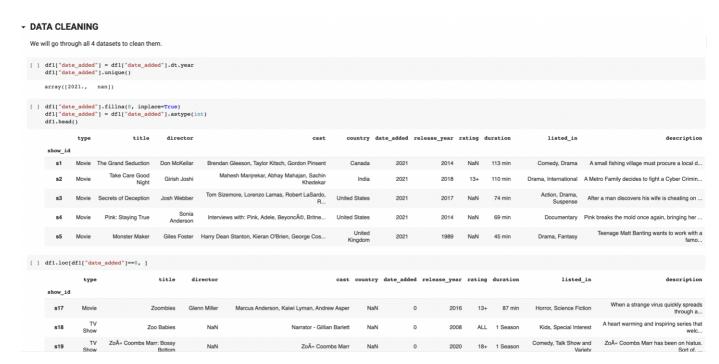
    df1- Amazon Prime Dataset
    df2- Hulu Dataset
    df3 - Disney Plus Dataset
    df4 - Netflix Dataset
                                                                                                     + Code — + Text
         df1 = pd.read_csv("amazon_prime_titles.csv", delimiter=",", encoding="latin-1", parse_dates=["date_added"], index_col=["show_id"])
df2 = pd.read_csv("hulu_titles.csv", delimiter=",", encoding="latin-1", parse_dates=["date_added"], index_col=["show_id"])
df3 = pd.read_csv("disney_plus_titles.csv", delimiter=",", encoding="latin-1", parse_dates=["date_added"], index_col=["show_id"])
          df4 = pd.read_csv("netflix_titles.csv", delimiter=",", encoding="latin-1", parse_dates=["date_added"], index_col=["show_id"])
```

4.2 Dataset Analysis



Here we can see the size and attributes of the dataset. All data is in correct form except cast in df2 (Hulu) which is in float64 format. We will resolve that in pre processing

4.3 Data Cleaning and Preprocessing



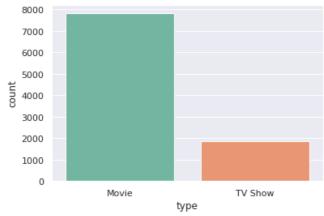
Here we transform the date_added and date_released fields to extract years from it. We also check for and remove Null values. We do the same for all dataset.

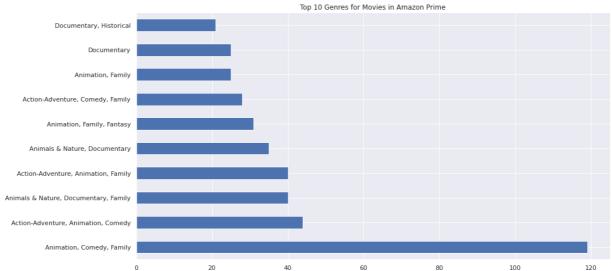
```
[ ] dfl.info()
    <class 'pandas.core.frame.DataFrame'>
    Index: 9668 entries, s1 to s9668
Data columns (total 11 columns):
        Column
                       Non-Null Count Dtype
                        9668 non-null
         title
                        9668 non-null
                                        object
     2 director
                       7586 non-null
                                        object
                       8435 non-null
                                        object
         cast
         country
                        672 non-null
                                        object
         date added
                        9668 non-null
                                        int64
     6 release_year 9668 non-null
         rating
                        9331 non-null
                                        object
         duration
                        9668 non-null
                                        object
         listed in
                        9668 non-null
                                        object
     10 description 9668 non-null
                                        object
    dtypes: int64(2), object(9)
    memory usage: 906.4+ KB
[ ] df1.duplicated().sum()
[ ] df1.fillna("No Data", inplace=True)
    df1.isnull().sum()
    type
    title
                     0
    director
                     0
    cast
                     0
    country
    date added
    release_year
    rating
    duration
    listed_in
                     0
    description
                     0
    dtype: int64
FOR DATASET 2(HULU), we will also convert float64 to string
[ ] df2['cast'] = df2['cast'].astype(str)
```

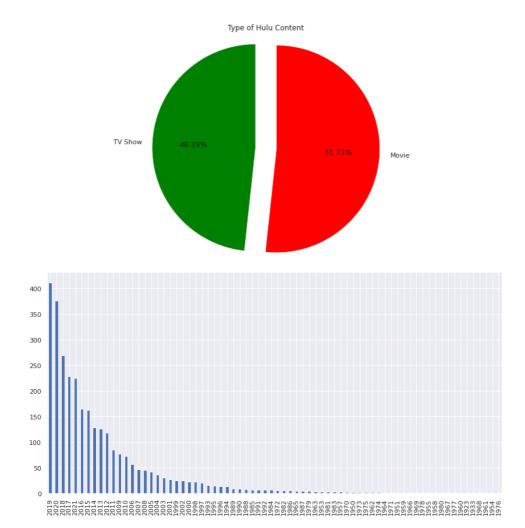
Here, we check the datasets for null and duplicated values as well as missing data. We also convert the float64 column from Hulu dataset to String format.

4.4 Visualization of Datasets

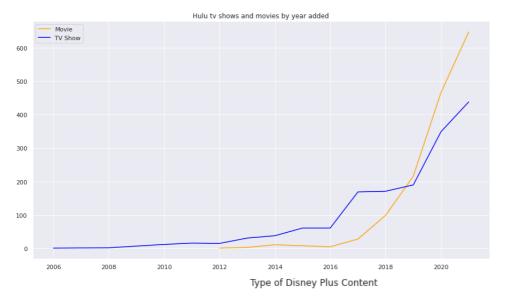
Types of Amazon Prime Content

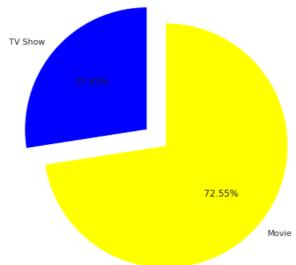


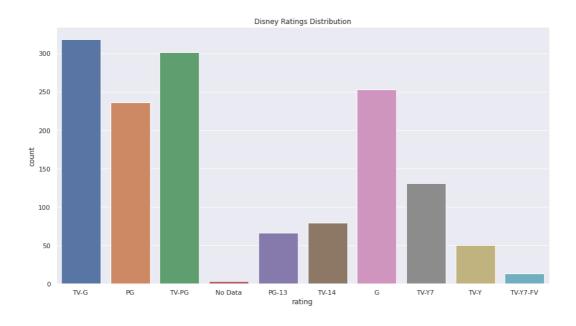


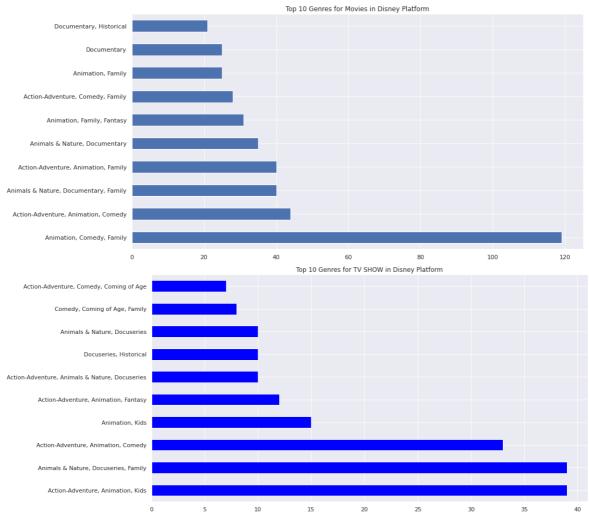


Content by their Release year on Hulu

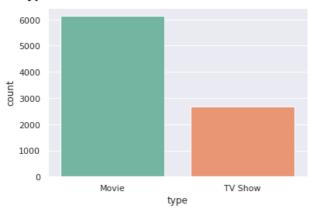




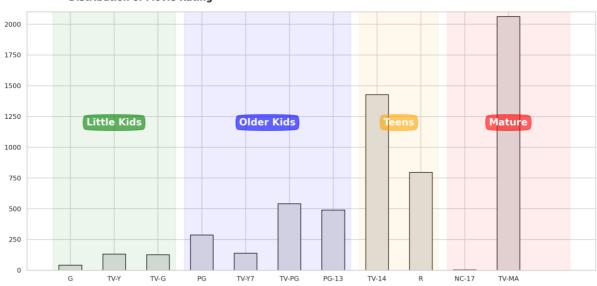


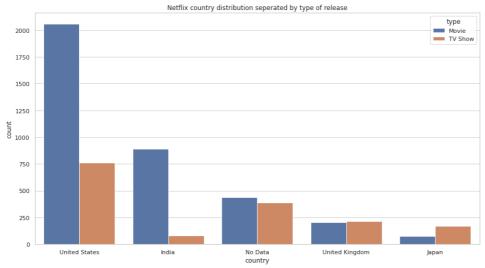


Types of Netflix Content

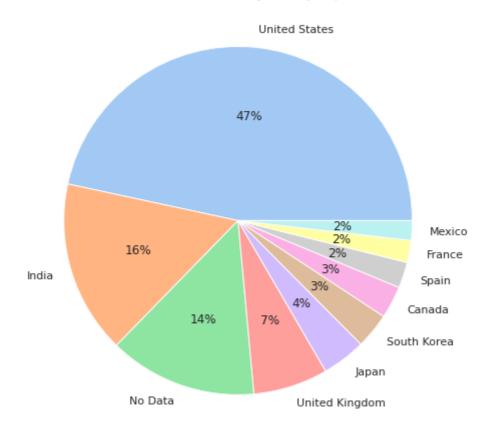




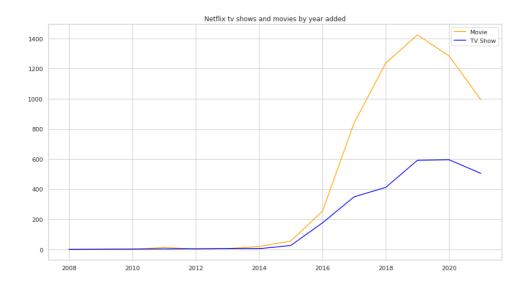




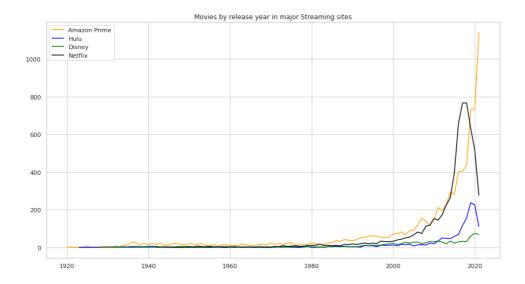
Distribution of release by country (top 10)



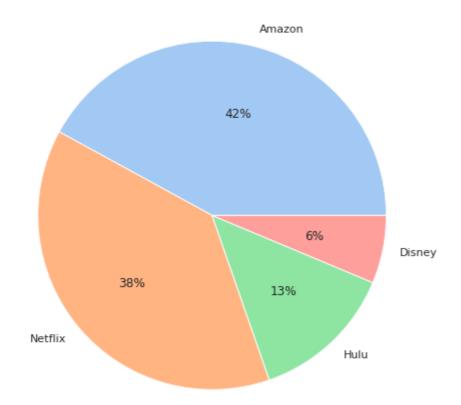
Top 10 Country by content type in country

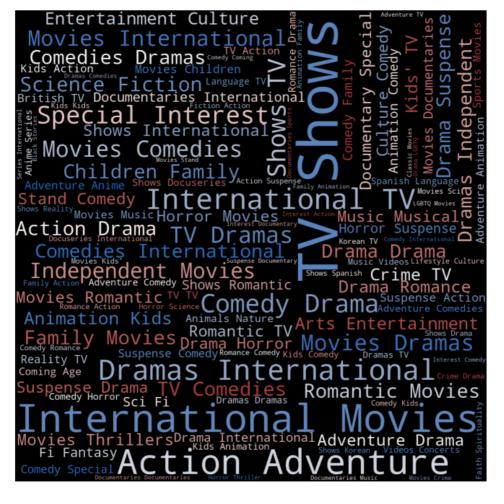


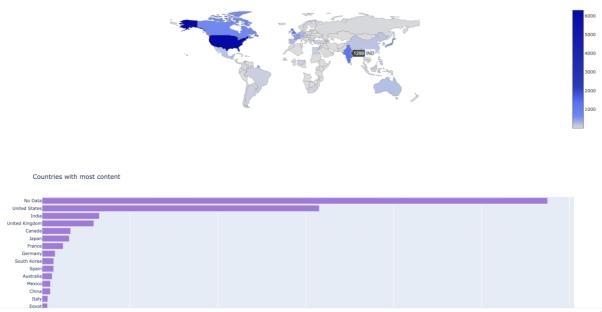
4.5 Creating One unified Dataset and Visualizing it



Distribution of release by platforms

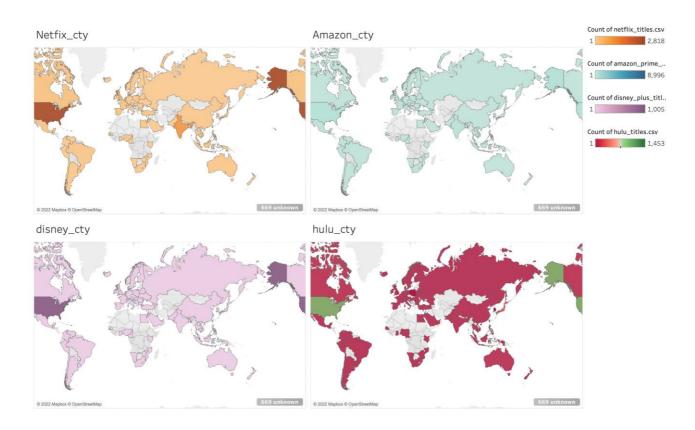




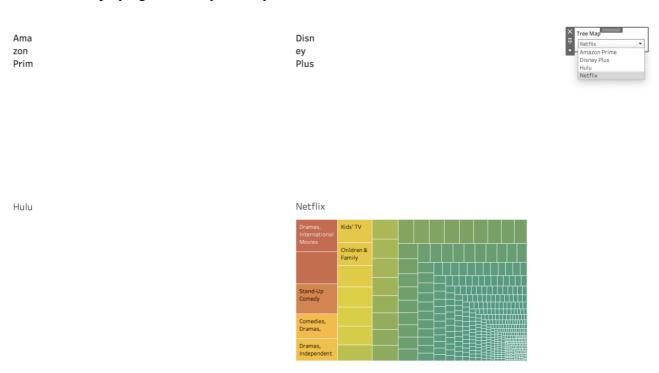


Interactive Plotly Graph in Python

4.6 Creating Tableau Dashboard

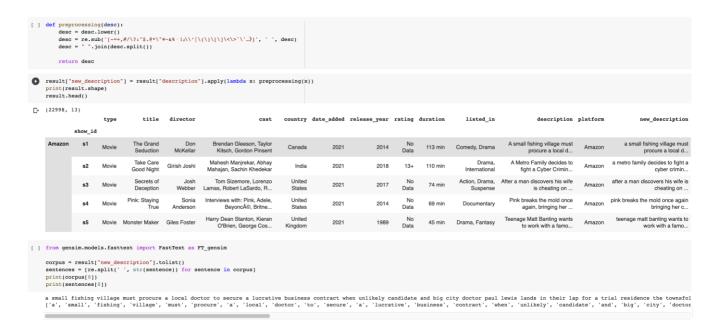


Dashboard displaying content by country in all OTT Platforms



Using Calculated Field to create dynamic Dashboard with a drop-down menu selector

4.7 Creating Clustering and Regression Model



We first preprocess the description field to make it compatible with similarity checks

Then we make clusters using the K-Means algorithm and appending the cluster id with the dataset.

The Data is divided into a total of 49 clusters.



Now, we create the recommendation system

```
[ ] def recommendation_system(title_name):
         top_k = 5
         title_row = result[result["title"] == title_name].copy()
         search_df = result[result["cluster_id"].isin(title_row["cluster_id"])].copy()
         search_df = search_df.drop(search_df[search_df["title"] == title_name].index)
         search_df["Similarity"] = search_df.apply(lambda x: FT_model.wv.similarity(title_row["new_description"], x["new_description"]), axis=1)
         search_df.sort_values(by=["Similarity"], ascending=False, inplace=True)
         return search_df[["title", "Similarity"]].head(top_k)
[ ] recommendation_system("Ernest Saves Christmas")
                                                  title Similarity
              show id
      Netflix
               s1557
                                    A Trash Truck Christmas
                                                          [0.9858199]
      Amazon
               s9378
                                     Noddy Saves Christmas [0.98308843]
               s2658
                                      Dino Dana The Movie
                                                          [0.9823687]
      Netflix
               s7319
                       Little Singham Bandarpur Mein Hu Ha Hu
                                                          [0.9823305]
               s1765
                        Magical Playtime with Mila and Morphle
                                                          [0.9812304]
     Amazon
[ ] recommendation system("National Parks Adventure")
                                  title Similarity
            show id
     Netflix
              s4052
                                   2,215 [0.99168164]
      Hulu
              s490
                           Summer of Soul [0.9916012]
              s682
                     They've Gotta Have Us [0.9912634]
                                          [0.9911077]
```

Our Recommendation System takes a movie or show name as input and then narrows its search space to the cluster that they belong to. Then it runs a similarity check on the description of the entered title with every entry on the cluster.

It then returns a list of similar movies and which OTT platform you can watch that content.

CONCLUSION

From the Visualization we gained a lot of Inferences. Like how each platform values movies more than tv shows. We also found that Amzon and Netflix has the biggest content library with Disney & Hulu slowly building their catalogues. We also saw how US is the biggest producer of OTT Content with India coming at a close Second. We also inferred how the growth of OTT Content libraries has been meteoric in recent years, almost growing exponentially. We also saw the rating distribution between the OTTs and how they favor older teens/Adult markets as their main customer segment.

Finally, we created and tested the recommendation engine. We can see how such engines use clustering to reduce runtime dramatically while producing high quality results. This also highlights the importance of clustering data in large corporate environments like multinational OTT providers.

This proves that clustering isn't just a mere visualization tool but also a very important machine learning implementation that reduces runtimes in such demanding worloads drastically.