Vellore Institute of Technology
(Deemed to be University under section 3 of UGC Act, 1956)

School of Computer Science and Engineering

J Component report

Programme	**: B.Tech (CSE: CORE)**
Course Title	**: Foundation of Data Analytics**
Course Code	**: CSE3505**
Slot	**: F2**

Title: Streaming Content Dashboard

Team Members: **KASHISH BAJAJ (20BCE1790)**

AKSHIT JAIN (20BCE1818)

AKASH RAJ BEHERA (20BCE1829)

Faculty: PRIYADARSHINI R

BONAFIDE CERTIFICATE

Certified that this project report entitled "**Streaming Content Dashboard"** is a bonafide work of **AKASH RAJ BEHERA 20BCE1829, KASHISH BAJAJ 20BCE1790, Akshit Jain 20BCE1818** who carried out the Project work under my supervision and guidance for **CSE3505-FOUNDATION OF DATA ANALYTICS.**

Dr. PRIYADARSHINI R
Associate Professor
School of Computer Science and Engineering (SCOPE)
VIT University, Chennai
Chennai – 600 127

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Streaming Content Dashboard

20BCE1790, KASHISH BAJAJ, Vellore Institute of Technology, Chennai, India

20BCE1818, AKSHIT JAIN, Vellore Institute of Technology, Chennai, India

20BCE1829, AKASH RAJ BEHERA, Vellore Institute of Technology, Chennai, India

What our project claims?

Our project basically is a movie recommendation system where user can get movie recommended from 4 online movie streaming platforms A.K.A. OTT PLATFORMS such as NETFLIX, HULU, AMAZON PRIME & DISNEY HOTSTAR and the movie is recommended in genres for eg. If a user wants to watch action genre movie, the user can choose the online platform the user can that has the greatest number of action movie which is implemented using tableau visualization will be helpful to find a particular movie according to the mood of the user. We use page rank algorithm model, cluster model , CAR (Credible association rule) , a new method to relate and track documents. The CAR does not use prior knowledge of category structure as compared to other automated procedures. linked textual corpus using the relationship of topics in terms of the distribution and the link distribution , discovered rich patterns of topic evolution within built-in features of time-stamped documents. Instead of analyzing documents on the specific interval, the method focuses and treats topics separately as they appear over time in chronological order , retrieval of temporal and event-based knowledge from a huge collection of historical documents. The method uses temporal text mining (TTM) and Topic detection and tracking (TDT) techniques. highlighted topic evolution in text data as an important task. The Text Flow has been introduced; which studies various patterns that appear from various topics. focused on detecting topics with immense information available over the internet. They introduced a new method by combining Suffix Tree Clustering (STC) and Semantic analysis that approaches the problem in two steps. The semantic analysis is used to add significance to the topics and the significance can be measured by applying filters to the words and analyzing structure of words under a cluster which share the same meaning , news collection should be structured such that topic detection and clustering become easy. The vector space model (VSM) is one of the easiest and productive methods that can be used for the representation of topics, and the Information gain algorithm is used for feature selection. The features, then ranked by assigning a score to each of them.

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 findsimilar

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 attractiveto 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. Literature Review

Shubhankar et al. [1] highlighted the main goal of ranking and modeling topic evolution, by an efficient algorithm. The topic, evolution, has become a challenging task over time for the researchers. They suggested the topic as a summary of its content, and also introduced a unique approach, that assigns the rank to a topic by applying PageRank algorithm, without considering the time of research publication [3]. Furthermore, they have categorized topics based on the set of the topic and closed keyword-set. The closed keyword-set were formed such that; phrases were selected from topics of the publications along with a user-defined minimum support. PageRank algorithm has been applied in iterative passion, to assign authorities to score on the research paper. The authority scores, based on popularity in the research community; however, the algorithm also identifies hot topics by evaluating them on a timeline and is shown as landmarks. They also tried to find fading topics; they first checked for topic detection, then evaluated landmark topics, and at the end tried to find fading topics. The algorithm proved as most effective and faster when tested on DBLP dataset.

Song et al. [2] emphasized the use of text clustering for Topic Detection. The text clustering dominates other algorithms in terms of time, computational complexity and cost. There are many ways to transmit data over a network; still, we need methods to avoid noise and irrelevant information. They considered the unstructured and scattered data over the internet as text copra and introduced a two-step algorithm for clustering the text copra. The first step uses C-Process to create overlapping clusters with the help of Canopy Clustering. The Canopy Clustering is usually applied before the K-mean algorithm to speed up clustering of large data-set. In the second step named K-means apply rough clustering on results based on the common points between the clusters. The K-Means uses the X-Means algorithm. The experiments have proved better performance than k-means clustering and single pass algorithms, and proved to be more suitable for detection of online topics.

Wu et al. [4] discussed CAR (Credible association rule) , a new method to relate and track documents. The CAR does not use prior knowledge of category structure as compared to other automated procedures. The other traditional processes detect related documents based on the topic of documents, with the help of some predefined rules or categorization. This method makes use of the term frequency-inverse document frequency (TF-IDF) as a feature pre-selection set. TF-IDF is a numerical statistic which shows how words are important to a document. After the feature subset selection, CAR and minimal clique algorithms were applied. These two algorithms use an adjacency matrix to produce credible association rules. The refinements, removes noise and common words with the high frequency that are not related to the topic of the document. A high level of reliability, availability and performance are achieved by applying refinements like Inverse Document Frequency (IDF) and quasi-maximal cliques.

Jo et al. in [5] proposed algorithms for the topic detection from linked textual corpus using the relationship of topics in terms of the distribution and the link distribution. Their algorithm generates a ranked list of the topics the method has shown effective results with arXiv and Citeseer. Jo et al. in [6] discovered rich patterns of topic evolution within built-in features of time-stamped documents. Instead of analyzing documents on the specific interval, the method focuses and treats topics separately as they appear over time in chronological order. The information is obtained such that; it qualifies the topic as either new or it has some similarity with existing topic. The result was visualized by chronological scanning on a graph known as topic evolution graph. The topological or time restrictions were not considered while building the graph. The nodes of the graph represent topics and the connection between the topic nodes represents the cross-citation relationship. This representation of information projects a huge amount of knowledge about topic evolution. Details about a single topic can be obtained by selecting a seed topic and studying its connections with other nodes. These connections change as time passes, the emergence of new topics adds new nodes to the graph and also changes connections between them. The testing was carried out with the ACM repository.

Jayashri et al. [7] discussed retrieval of temporal and event-based knowledge from a huge collection of historical documents. The method uses temporal text mining (TTM) and Topic detection and tracking (TDT) techniques. The TTM extracts important patterns related to time, like collecting term frequency in a sequence of time; it also helps in keeping track of modification in the words with respect to time. In TDT, a clustering problem called Adaptive Resonance Theory (ART) is used, that tracks unknown topics in the system and assigns them to previously identified topics. The Evaluation of such information is usually carried at the time of its arrival, which helps to consider temporal properties of the topics. The Evolution is implemented using an incremental algorithm. The experiments helped to discover new trends and identify trends that cannot be obtained from documents if analyzed individually.

Cui et al. [8] highlighted topic evolution in text data as an important task. The Text Flow has been introduced; which studies various patterns that appear from various topics. Three-level features selection was conducted namely keywords, critical events, and evolution trends, then these features were visualized via a coherent visualization technique that shows the complex and important relation between them. The Text Flow is an interactive visual analysis tool that helps users analyze how and why the correlated topics change over time. First patterns related to merging/splitting are discovered via hierarchical Dirichlet process employed in incremental passion followed by extraction of keyword correlation and critical events. The result can be visualized by a three-level directed acyclic graph such that the user can deduce various information at any level of consideration. This method helps users visually study the relation between two topics that is best as it represents this relationship in an interactive way.

Jin [9] focused on detecting topics with immense information available over the internet. They introduced a new method by combining Suffix Tree Clustering (STC) and Semantic analysis that approaches the problem in two steps. In the first step feature selection is done with the help of NLP algorithm, by selecting meaningful words for clustering and the weight is assigned to word using term frequency-inverse document frequenting (TF-IDF). The NLP results in parts of the sentences in the form of the noun, verb and named entity. The result of feature selection is supplied to STC to form clusters where the score is assigned to them. TDT is applied to track topics, focusing on topic drifting. This is an inherent difficulty of topic evolution, which occurs over time as new information emerges. The clustered contents are represented via VSM (Vector Space Model) by selecting only top K words that are added to the vector [10]. The semantic analysis is used to add significance to the topics and the significance can be measured by applying filters to the words and analyzing structure of words under a cluster which share the same meaning. The experiments proved that topics can be tracked effectively.

3. 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 OTTplatform.

4. System architecture and design

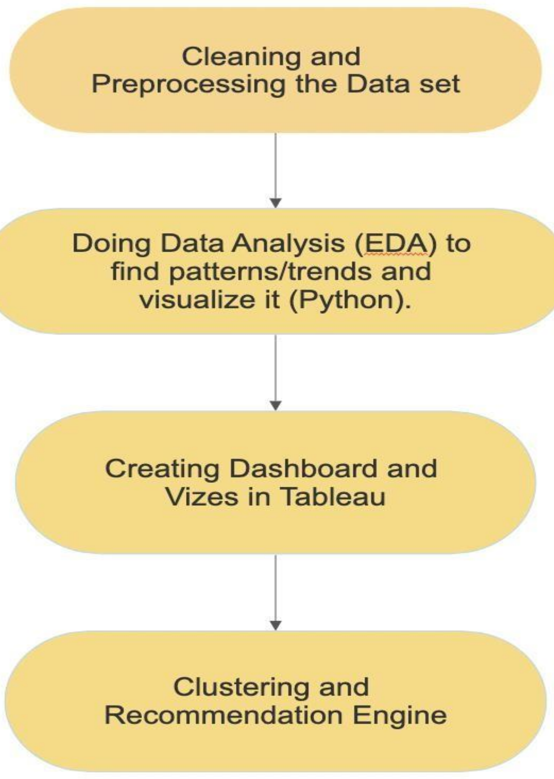

Cleaning and Preprocessing the Data set
Doing Data Analysis (EDA) to find patterns/trends and visualize it (Python).
Creating Dashboard and Vizes in Tableau
Clustering and Recommendation Engine

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 thispurpose.

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) aspossible.

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 all-data 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.

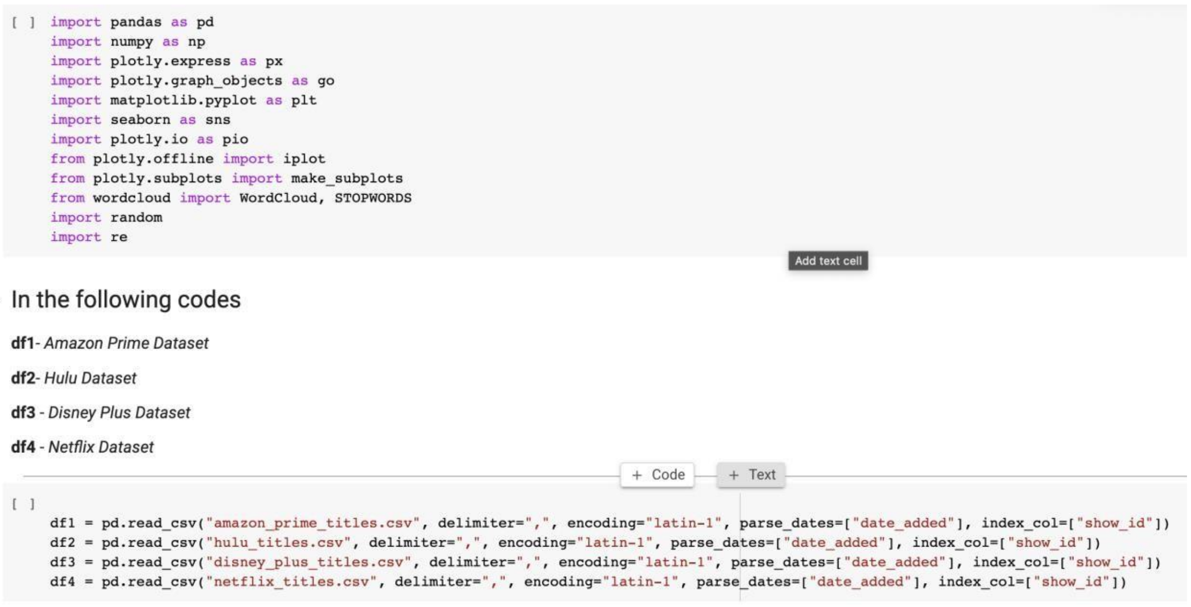
Thus, using K-Means and Text Similarity, it achieves fast and accurate results.

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
```

In the following codes

df1- *Amazon Prime Dataset*

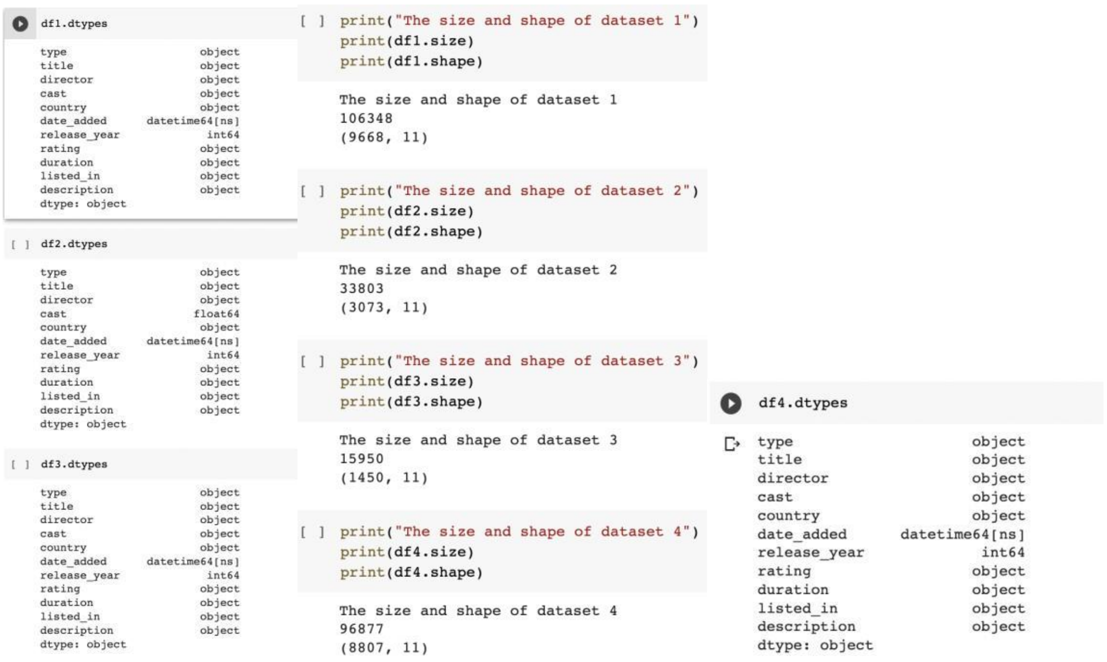
df2- *Hulu Dataset*

df3 - *Disney Plus Dataset*

df4 - *Netflix Dataset*

```
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



```
df1.dtypes
```

```
type                    object
title                   object
director                object
cast                    object
country                 object
date_added      datetime64[ns]
release_year             int64
rating                  object
duration                object
listed_in               object
description             object
dtype: object
```

```
df2.dtypes
```

```
type                    object
title                   object
director                object
cast                   float64
country                 object
date_added      datetime64[ns]
release_year             int64
rating                  object
duration                object
listed_in               object
description             object
dtype: object
```

```
df3.dtypes
```

```
type                    object
title                   object
director                object
cast                    object
country                 object
date_added      datetime64[ns]
release_year             int64
rating                  object
duration                object
listed_in               object
description             object
dtype: object
```

```
print("The size and shape of dataset 1")
print(df1.size)
print(df1.shape)
```

```
The size and shape of dataset 1
106348
(9668, 11)
```

```
print("The size and shape of dataset 2")
print(df2.size)
print(df2.shape)
```

```
The size and shape of dataset 2
33803
(3073, 11)
```

```
print("The size and shape of dataset 3")
print(df3.size)
print(df3.shape)
```

```
The size and shape of dataset 3
15950
(1450, 11)
```

```
print("The size and shape of dataset 4")
print(df4.size)
print(df4.shape)
```

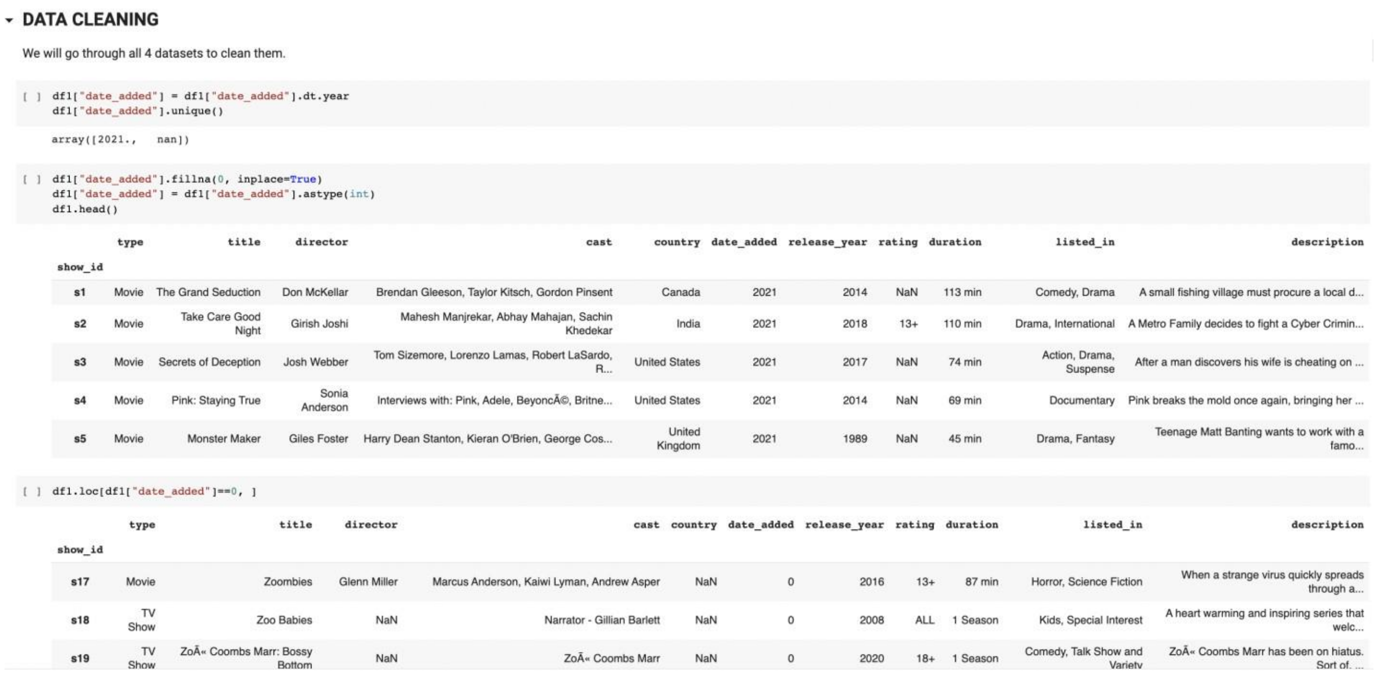
```
The size and shape of dataset 4
96877
(8807, 11)
```

```
df4.dtypes
```

```
type                    object
title                   object
director                object
cast                    object
country                 object
date_added      datetime64[ns]
release_year             int64
rating                  object
duration                object
listed_in               object
description             object
dtype: object
```

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



DATA CLEANING

We will go through all 4 datasets to clean them.

```
df1["date_added"] = df1["date_added"].dt.year
df1["date_added"].unique()
```

```
array([2021.,   nan])
```

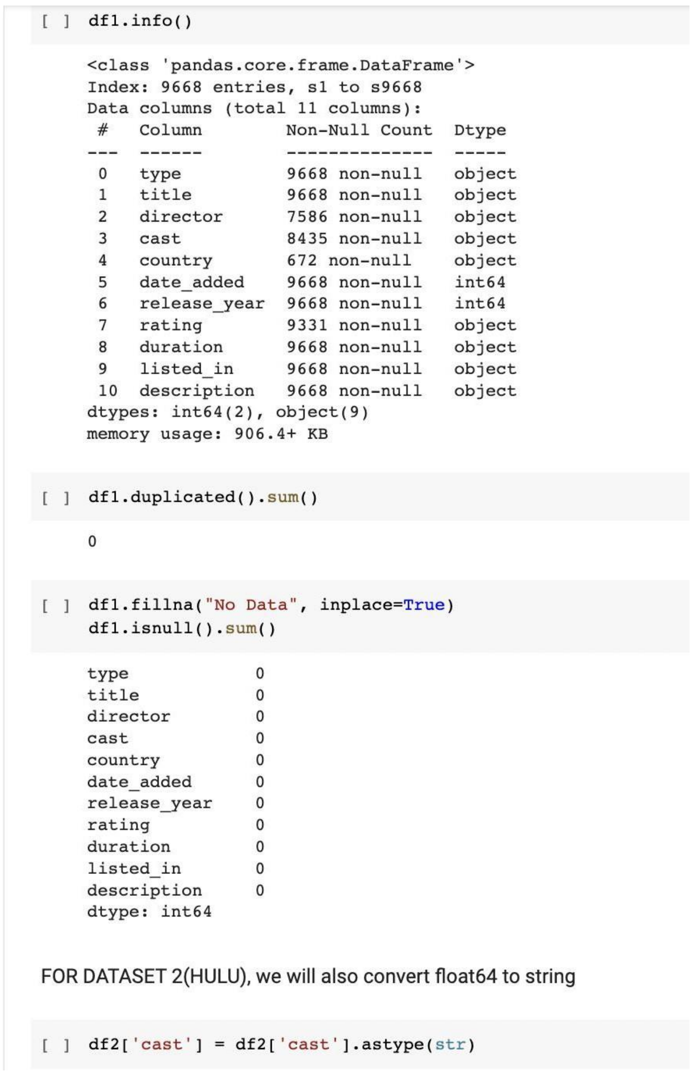
```
df1["date_added"].fillna(0, inplace=True)
df1["date_added"] = df1["date_added"].astype(int)
df1.head()
```

show_id	type	title	director	cast	country	date_added	release_year	rating	duration	listed_in	description
s1	Movie	The Grand Seduction	Don McKellar	Brendan Gleeson, Taylor Kitsch, Gordon Pinsent	Canada	2021	2014	NaN	113 min	Comedy, Drama	A small fishing village must procure a local d...
s2	Movie	Take Care Good Night	Girish Joshi	Mahesh Manjrekar, Abhay Mahajan, Sachin Khedekar	India	2021	2018	13+	110 min	Drama, International	A Metro Family decides to fight a Cyber Crimin...
s3	Movie	Secrets of Deception	Josh Webber	Tom Sizemore, Lorenzo Lamas, Robert LaSardo, R...	United States	2021	2017	NaN	74 min	Action, Drama, Suspense	After a man discovers his wife is cheating on ...
s4	Movie	Pink: Staying True	Sonia Anderson	Interviews with: Pink, Adele, BeyoncÃ©, Britne...	United States	2021	2014	NaN	69 min	Documentary	Pink breaks the mold once again, bringing her ...
s5	Movie	Monster Maker	Giles Foster	Harry Dean Stanton, Kieran O'Brien, George Cos...	United Kingdom	2021	1989	NaN	45 min	Drama, Fantasy	Teenage Matt Banting wants to work with a famo...

```
df1.loc[df1["date_added"]==0, ]
```

show_id	type	title	director	cast	country	date_added	release_year	rating	duration	listed_in	description
s17	Movie	Zoombies	Glenn Miller	Marcus Anderson, Kaiwi Lyman, Andrew Asper	NaN	0	2016	13+	87 min	Horror, Science Fiction	When a strange virus quickly spreads through a...
s18	TV Show	Zoo Babies	NaN	Narrator - Gillian Barlett	NaN	0	2008	ALL	1 Season	Kids, Special Interest	A heart warming and inspiring series that welc...
s19	TV Show	ZoÃ« Coombs Marr: Bossy Bottom	NaN	ZoÃ« Coombs Marr	NaN	0	2020	18+	1 Season	Comedy, Talk Show and Variety	ZoÃ« Coombs Marr has been on hiatus. Sort of. ...

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.



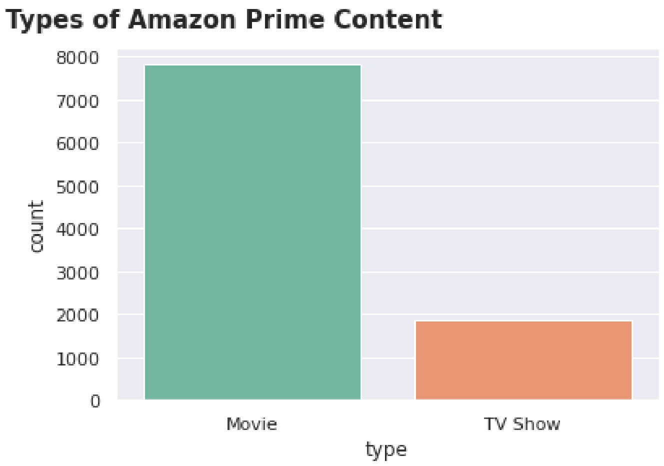
```
[ ] df1.info()

    <class 'pandas.core.frame.DataFrame'>
    Index: 9668 entries, s1 to s9668
    Data columns (total 11 columns):
     #   Column        Non-Null Count  Dtype
    ---  ------        --------------  -----
     0   type          9668 non-null   object
     1   title         9668 non-null   object
     2   director      7586 non-null   object
     3   cast          8435 non-null   object
     4   country       672 non-null    object
     5   date_added    9668 non-null   int64
     6   release_year  9668 non-null   int64
     7   rating        9331 non-null   object
     8   duration      9668 non-null   object
     9   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()

    0

[ ] df1.fillna("No Data", inplace=True)
    df1.isnull().sum()

    type            0
    title           0
    director        0
    cast            0
    country         0
    date_added      0
    release_year    0
    rating          0
    duration        0
    listed_in       0
    description     0
    dtype: int64
```

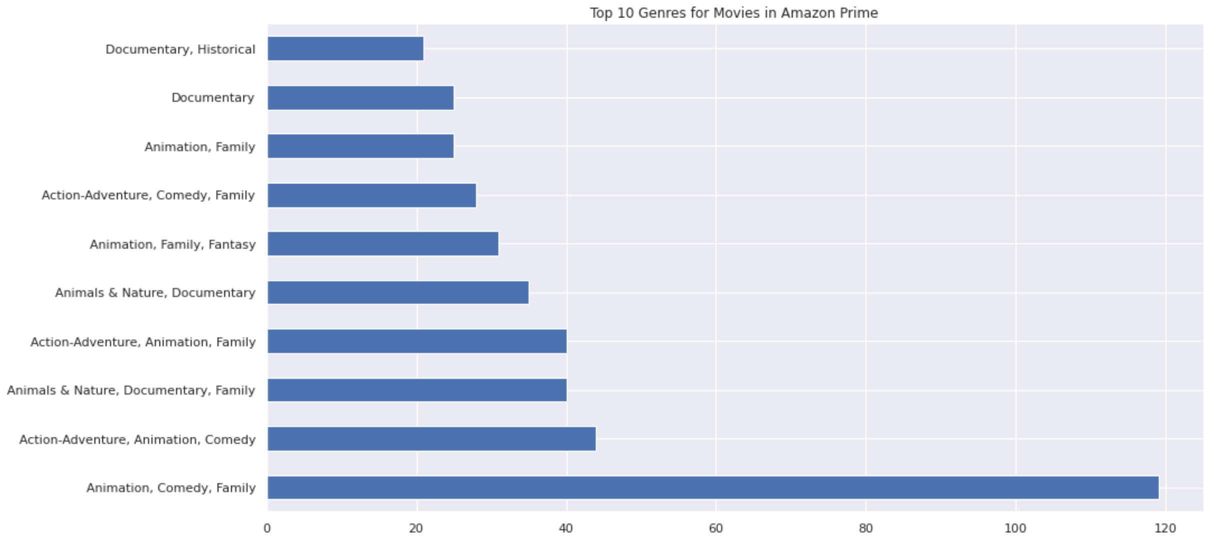
FOR DATASET 2(HULU), we will also convert float64 to string

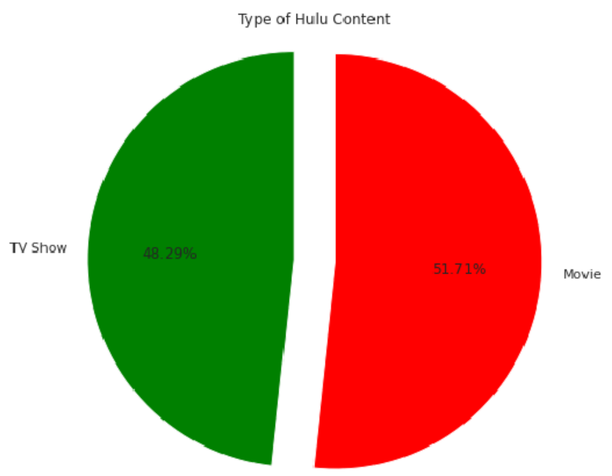
```
[ ] df2['cast'] = df2['cast'].astype(str)
```

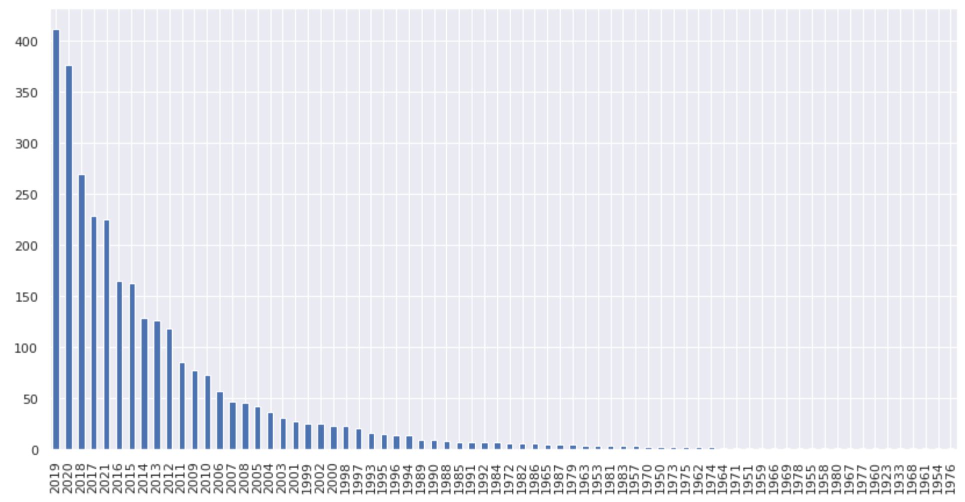
Here, we check the datasets for null and duplicated values as well as missing data. We also convert the float64 column from Hulu dataset to String format.

4.4 Visualization of Datasets

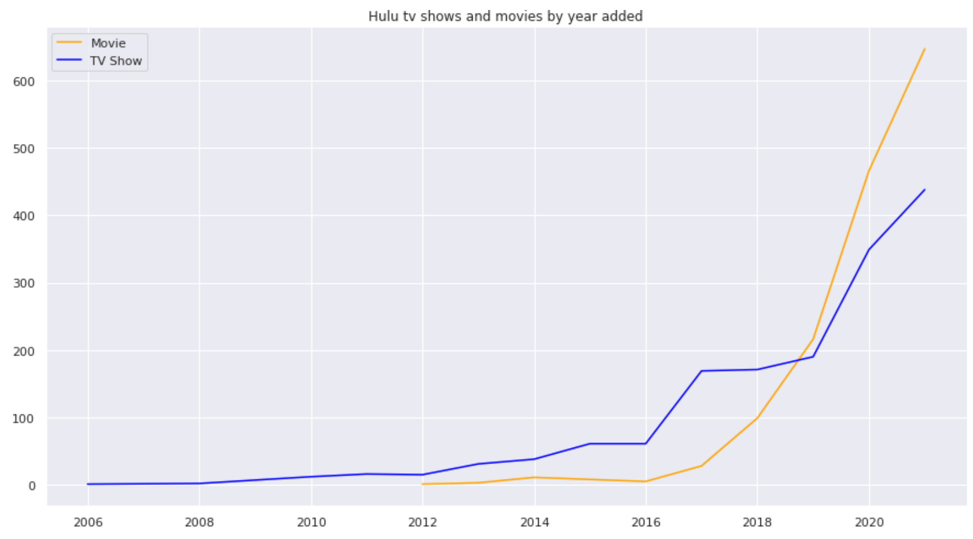

Types of Amazon Prime Content
count
type
Movie
TV Show
0
1000
2000
3000
4000
5000
6000
7000
8000

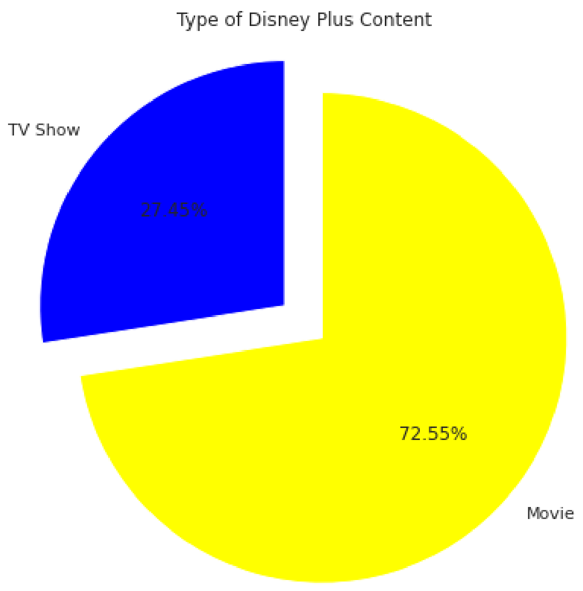

Top 10 Genres for Movies in Amazon Prime
Documentary, Historical
Documentary
Animation, Family
Action-Adventure, Comedy, Family
Animation, Family, Fantasy
Animals & Nature, Documentary
Action-Adventure, Animation, Family
Animals & Nature, Documentary, Family
Action-Adventure, Animation, Comedy
Animation, Comedy, Family
0
20
40
60
80
100
120

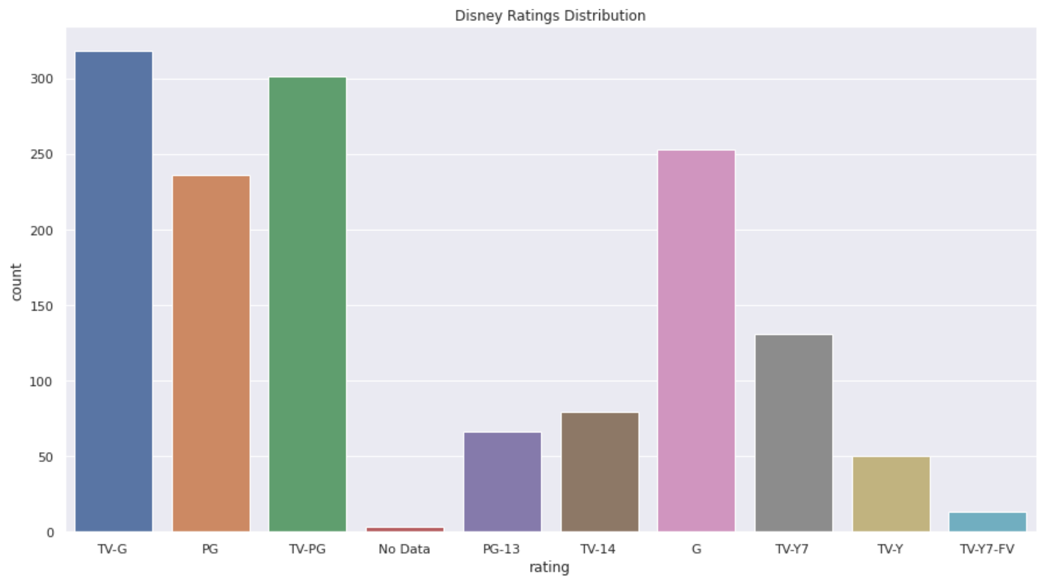


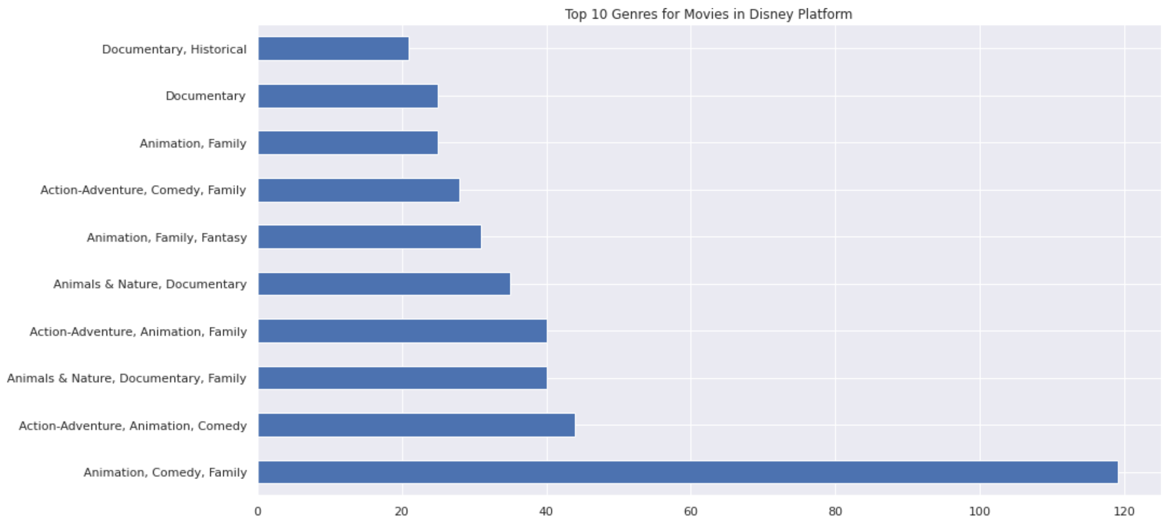


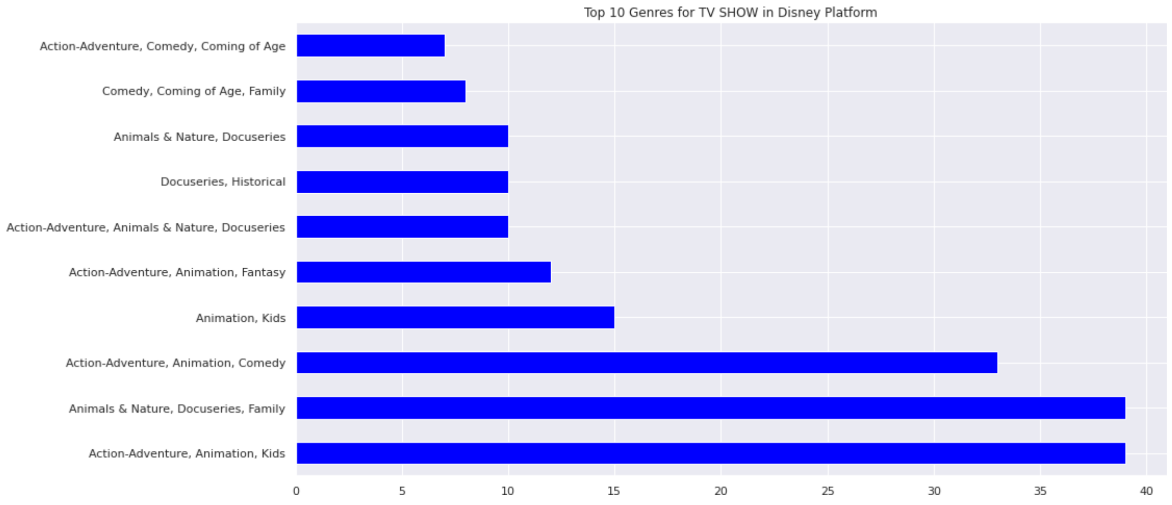
Content by their Release year on Hulu

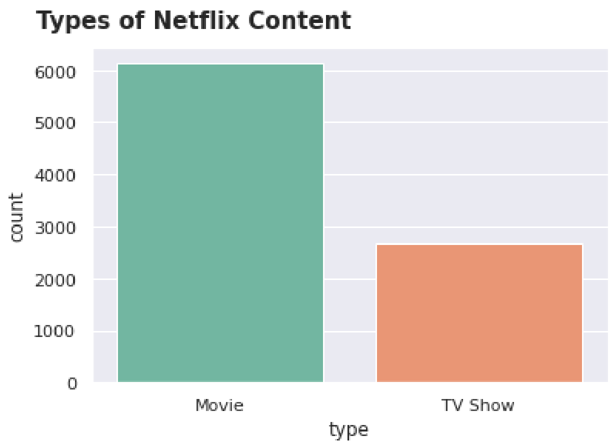

Hulu tv shows and movies by year added
Movie
TV Show
0
100
200
300
400
500
600
2006
2008
2010
2012
2014
2016
2018
2020

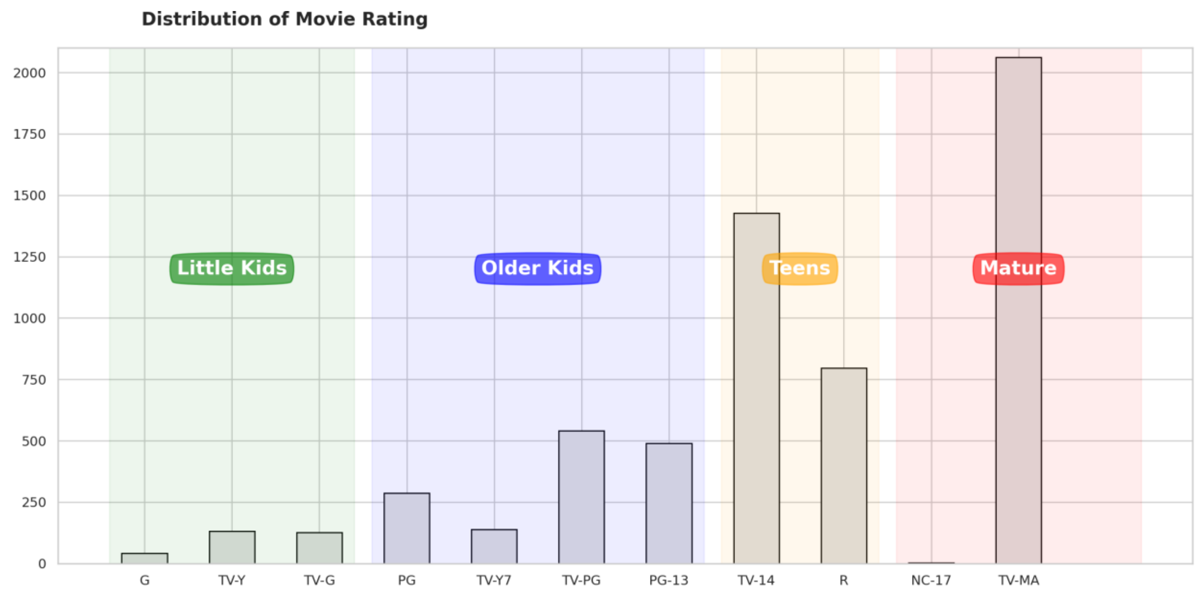

Type of Disney Plus Content
TV Show
27.45%
72.55%
Movie

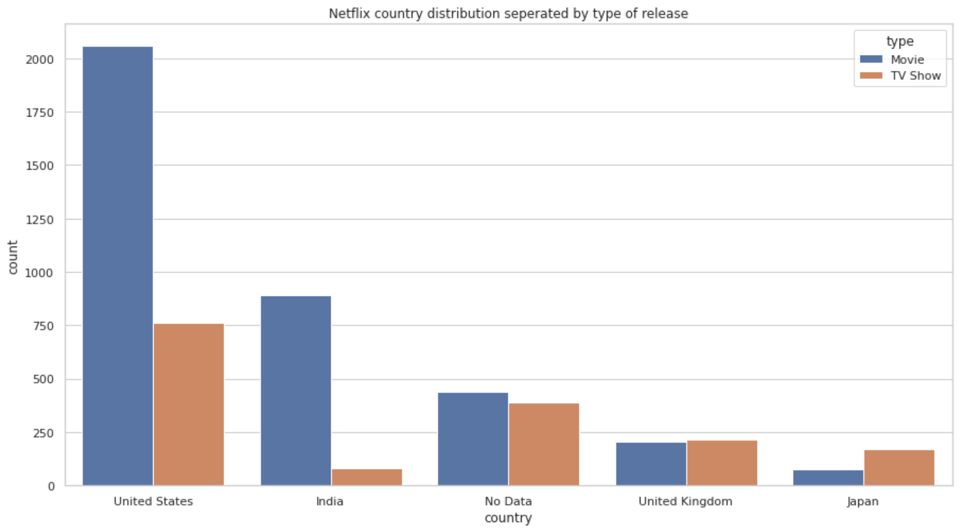

Disney Ratings Distribution
count
0
50
100
150
200
250
300
TV-G
PG
TV-PG
No Data
PG-13
TV-14
G
TV-Y7
TV-Y
TV-Y7-FV
rating

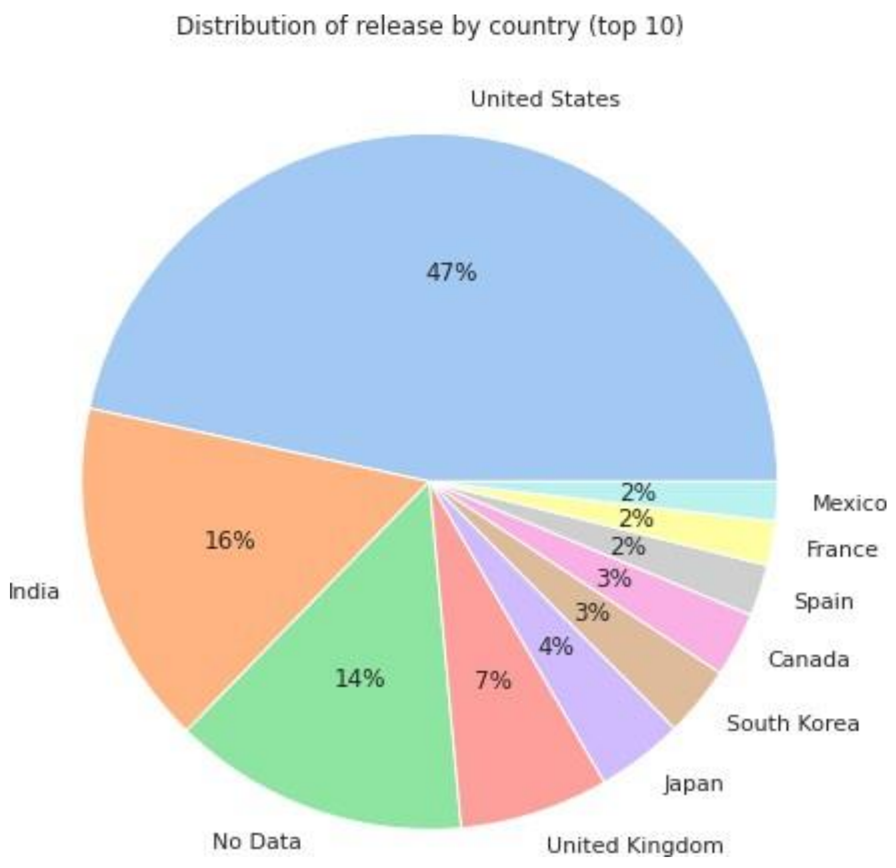

Top 10 Genres for Movies in Disney Platform
Documentary, Historical
Documentary
Animation, Family
Action-Adventure, Comedy, Family
Animation, Family, Fantasy
Animals & Nature, Documentary
Action-Adventure, Animation, Family
Animals & Nature, Documentary, Family
Action-Adventure, Animation, Comedy
Animation, Comedy, Family
0
20
40
60
80
100
120


Top 10 Genres for TV SHOW in Disney Platform
Action-Adventure, Comedy, Coming of Age
Comedy, Coming of Age, Family
Animals & Nature, Docuseries
Docuseries, Historical
Action-Adventure, Animals & Nature, Docuseries
Action-Adventure, Animation, Fantasy
Animation, Kids
Action-Adventure, Animation, Comedy
Animals & Nature, Docuseries, Family
Action-Adventure, Animation, Kids
0
5
10
15
20
25
30
35
40

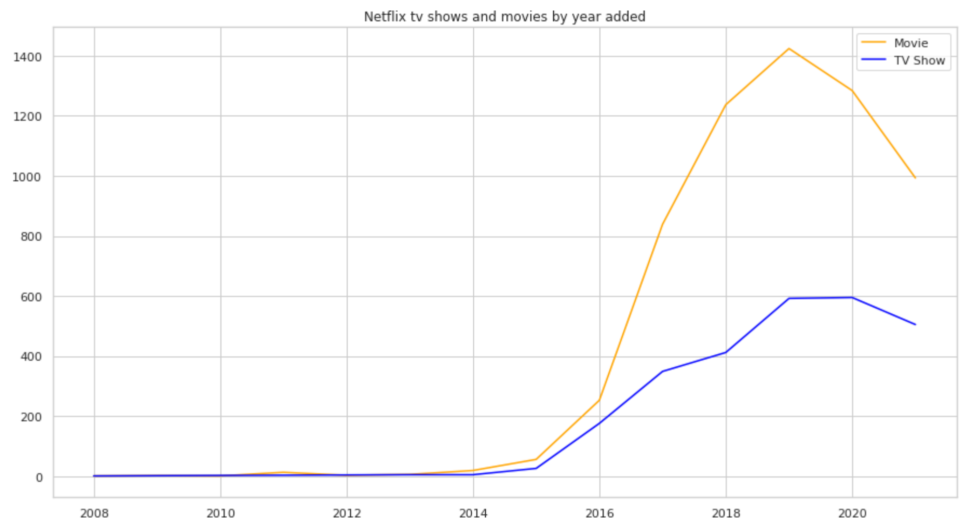

Types of Netflix Content
6000
5000
4000
3000
2000
1000
0
count
Movie
TV Show
type


Distribution of Movie Rating
Little Kids
Older Kids
Teens
Mature
2000
1750
1500
1250
1000
750
500
250
0
G
TV-Y
TV-G
PG
TV-Y7
TV-PG
PG-13
TV-14
R
NC-17
TV-MA

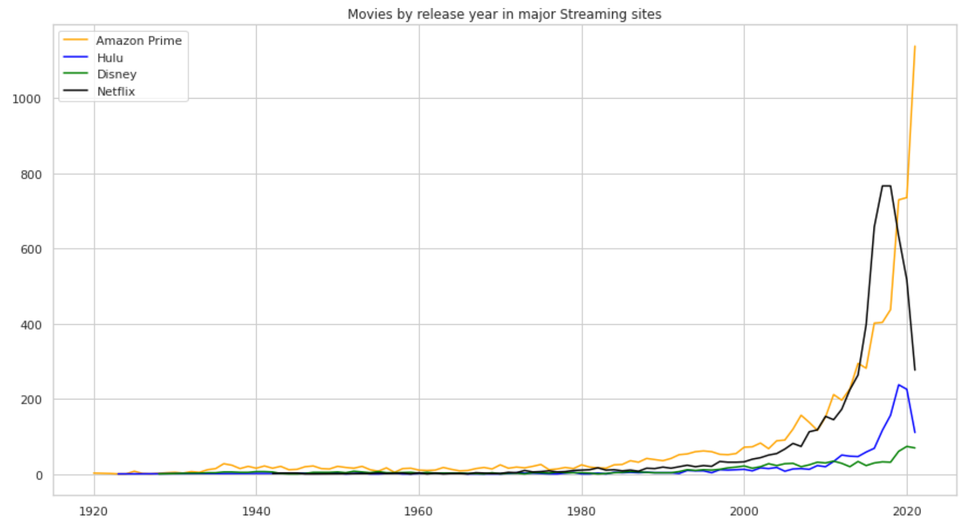

Netflix country distribution seperated by type of release
type
Movie
TV Show
count
2000
1750
1500
1250
1000
750
500
250
0
United States
India
No Data
United Kingdom
Japan
country

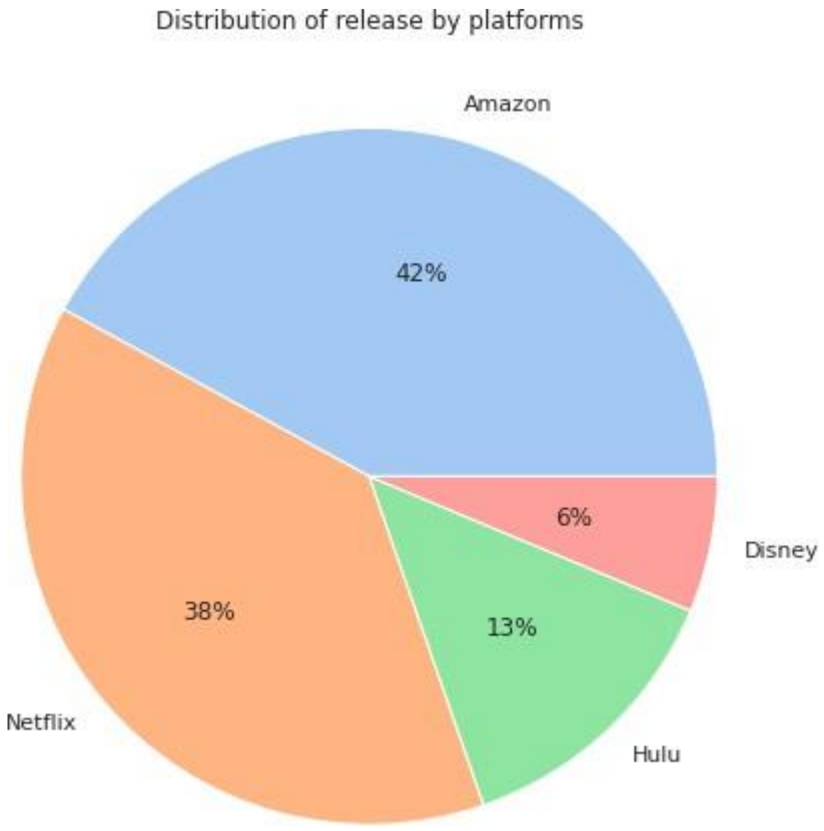


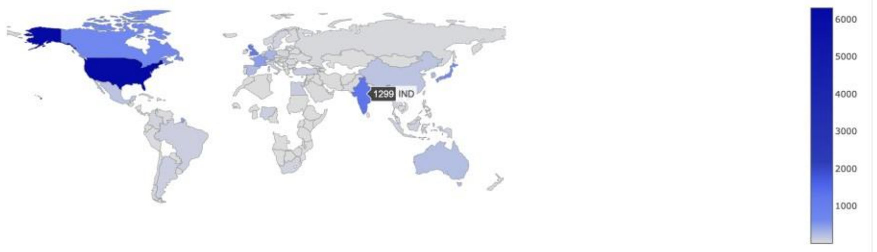
Top 10 Country by content type in country

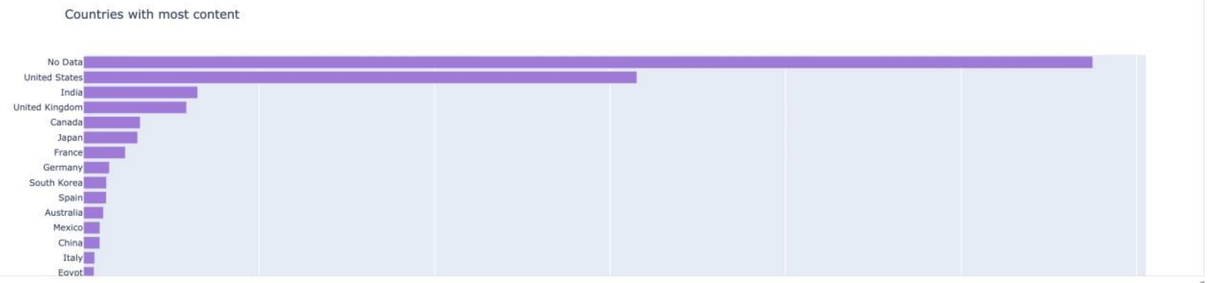


<u>4.5 Creating One unified Dataset and Visualizing it</u>


Movies by release year in major Streaming sites
Amazon Prime
Hulu
Disney
Netflix
1000
800
600
400
200
0
1920
1940
1960
1980
2000
2020

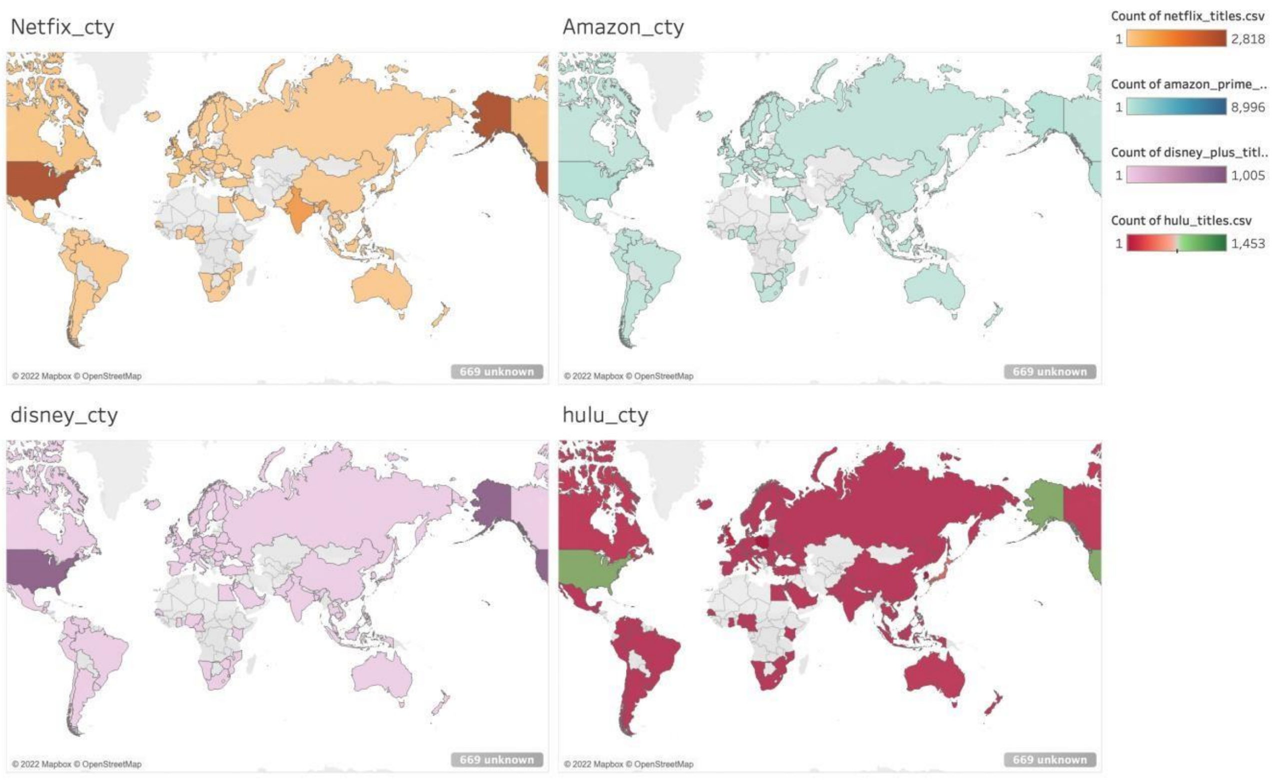

Distribution of release by platforms
Amazon
42%
6%
Disney
38%
13%
Netflix
Hulu



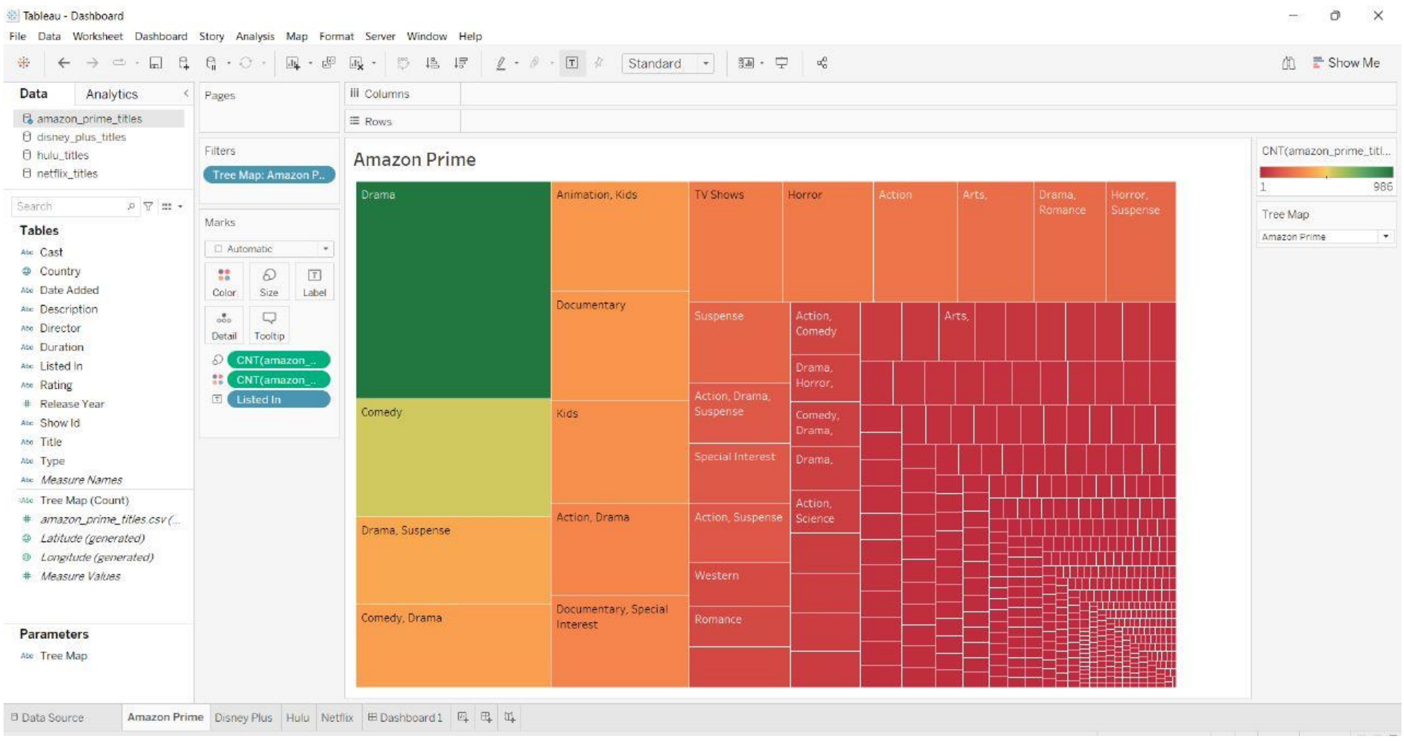


Interactive Plotly Graph in Python

4.6 Creating Tableau Dashboard



Dashboard displaying content by country in all OTT Platforms



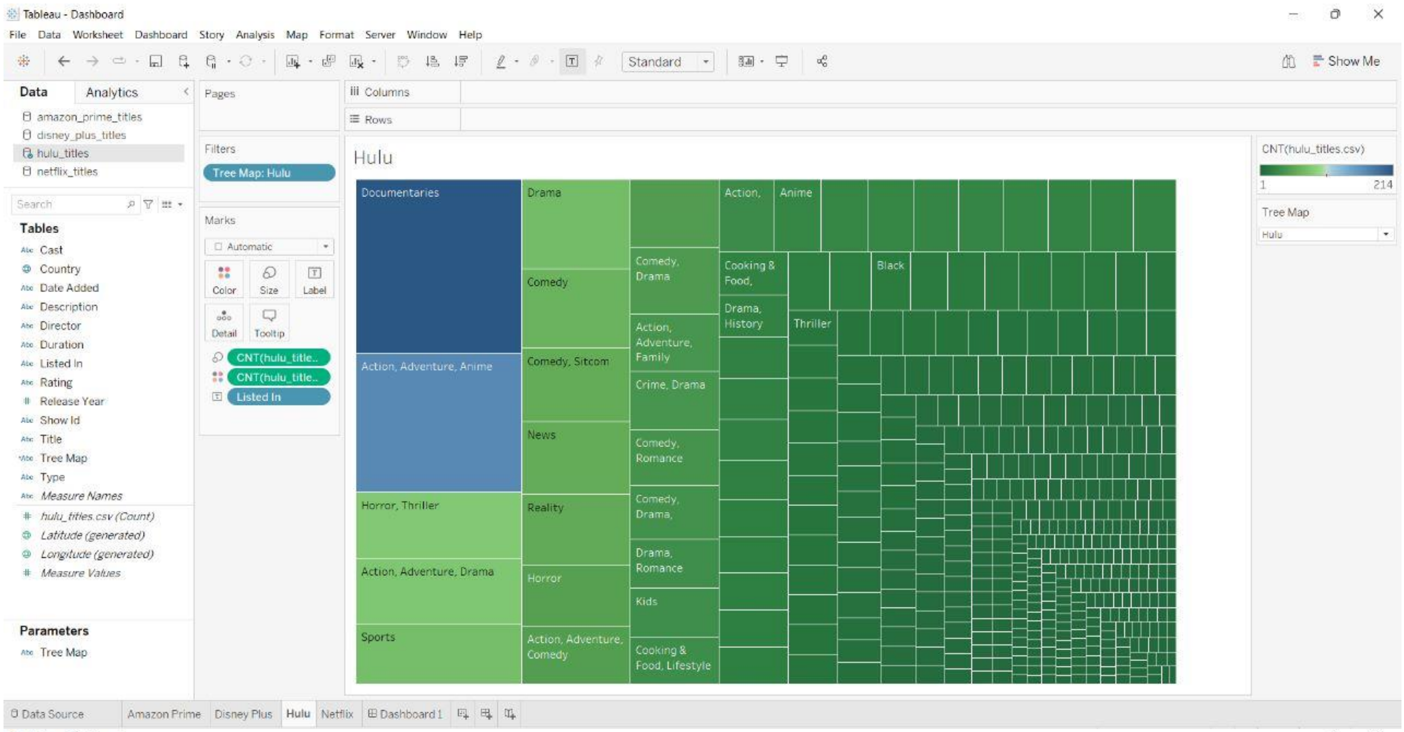


Tableau - Dashboard
File Data Worksheet Dashboard Story Analysis Map Format Server Window Help
Standard
Show Me
Data
Analytics
amazon_prime_titles
disney_plus_titles
hulu_titles
netflix_titles
Tables
Cast
Country
Date Added
Description
Director
Duration
Listed In
Rating
Release Year
Show Id
Title
Tree Map
Type
Measure Names
hulu_titles.csv (Count)
Latitude (generated)
Longitude (generated)
Measure Values
Parameters
Tree Map
Pages
Filters
Tree Map: Hulu
Marks
Automatic
Color
Size
Label
Detail
Tooltip
CNT(hulu_title..
CNT(hulu_title..
Listed In
Columns
Rows
Hulu
Documentaries
Action, Adventure, Anime
Horror, Thriller
Action, Adventure, Drama
Sports
Drama
Comedy
Comedy, Sitcom
News
Reality
Horror
Action, Adventure, Comedy
Comedy, Drama
Action, Adventure, Family
Crime, Drama
Comedy, Romance
Comedy, Drama,
Drama, Romance
Kids
Cooking & Food, Lifestyle
Action,
Anime
Cooking & Food,
Drama, History
Thriller
Black
CNT(hulu_titles.csv)
1
214
Tree Map
Hulu
Data Source
Amazon Prime
Disney Plus
Hulu
Netflix
Dashboard 1

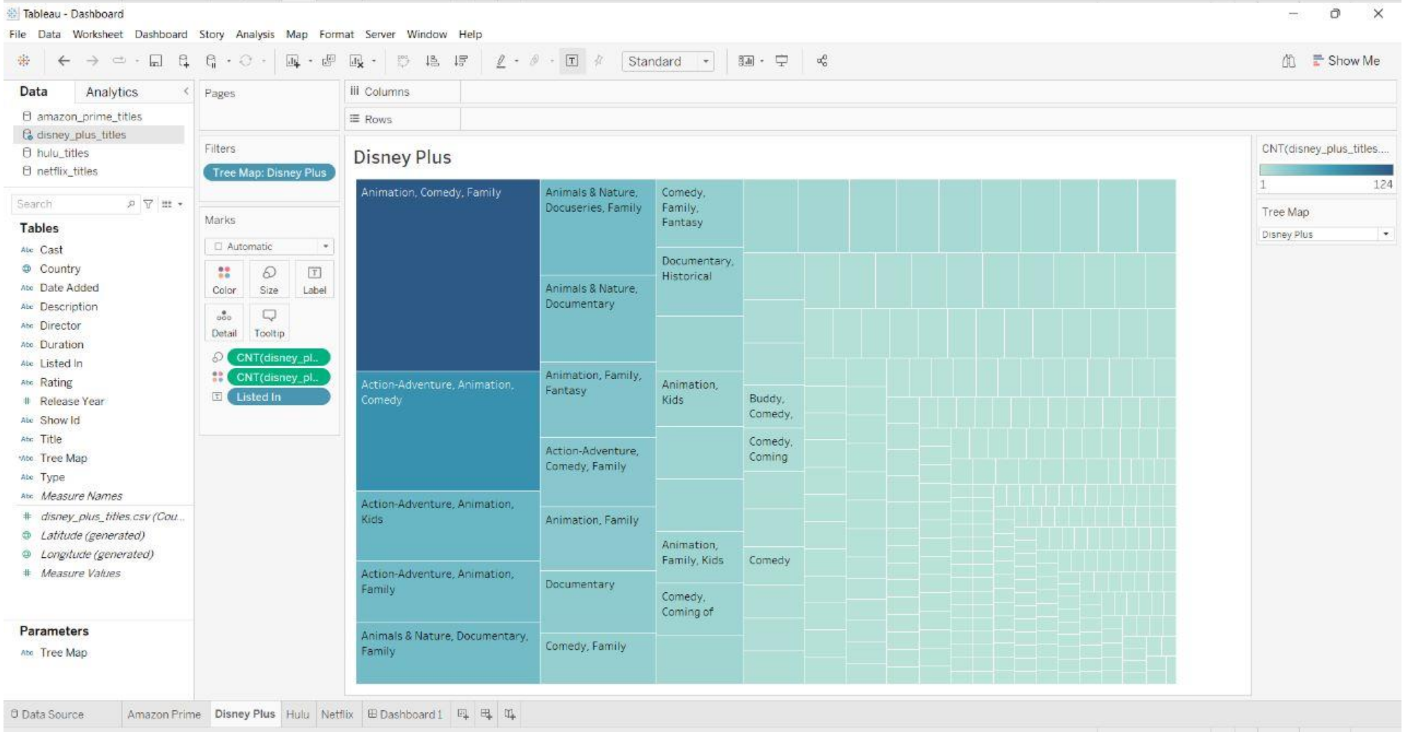


Tableau - Dashboard
File Data Worksheet Dashboard Story Analysis Map Format Server Window Help
Standard
Show Me
Data
Analytics
amazon_prime_titles
disney_plus_titles
hulu_titles
netflix_titles
Tables
Cast
Country
Date Added
Description
Director
Duration
Listed In
Rating
Release Year
Show Id
Title
Tree Map
Type
Measure Names
disney_plus_titles.csv (Cou..
Latitude (generated)
Longitude (generated)
Measure Values
Parameters
Tree Map
Pages
Filters
Tree Map: Disney Plus
Marks
Automatic
Color
Size
Label
Detail
Tooltip
CNT(disney_pl..
CNT(disney_pl..
Listed In
Columns
Rows
Disney Plus
Animation, Comedy, Family
Action-Adventure, Animation, Comedy
Action-Adventure, Animation, Kids
Action-Adventure, Animation, Family
Animals & Nature, Documentary, Family
Animals & Nature, Docuseries, Family
Animals & Nature, Documentary
Animation, Family, Fantasy
Action-Adventure, Comedy, Family
Animation, Family
Documentary
Comedy, Family
Comedy, Family, Fantasy
Documentary, Historical
Animation, Kids
Animation, Family, Kids
Comedy, Coming of
Buddy, Comedy,
Comedy, Coming
Comedy
CNT(disney_plus_titles....
1
124
Tree Map
Disney Plus
Data Source
Amazon Prime
Disney Plus
Hulu
Netflix
Dashboard 1

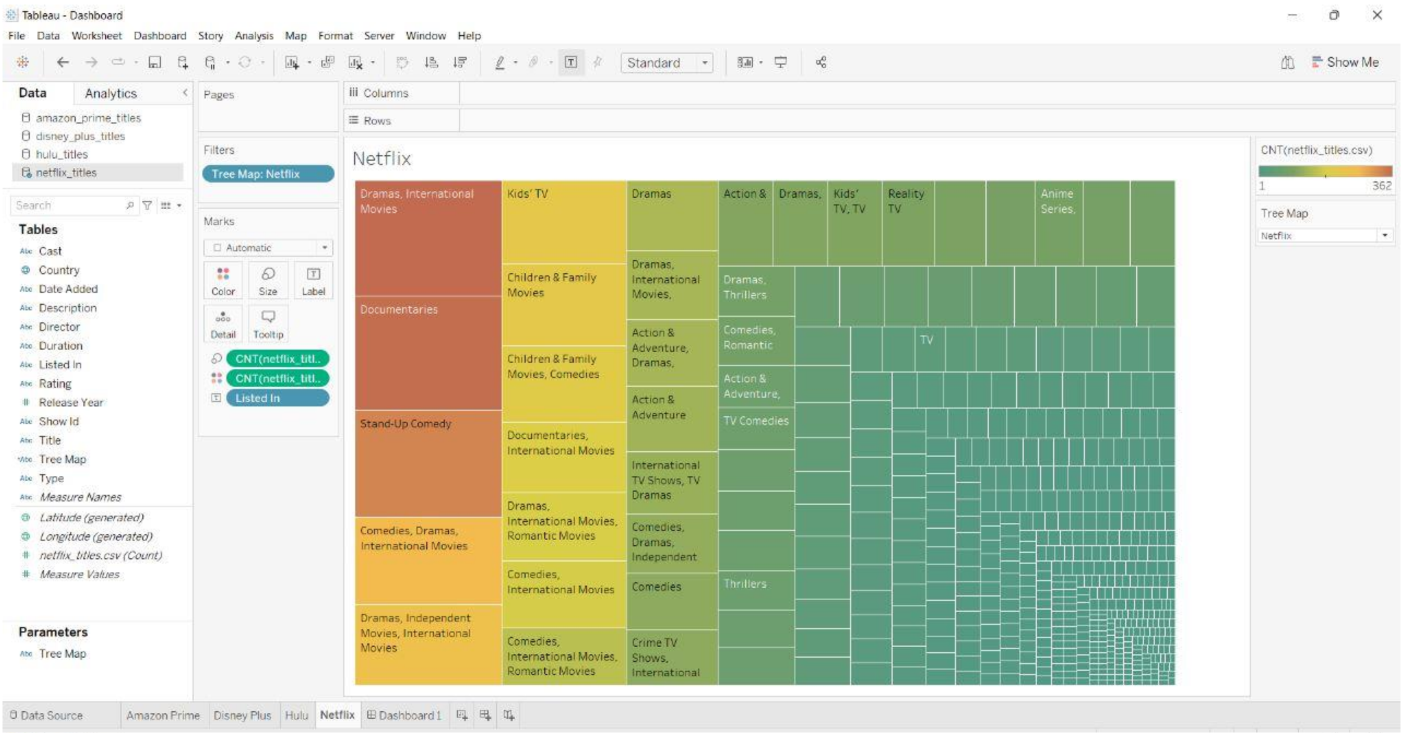


Tableau - Dashboard
File Data Worksheet Dashboard Story Analysis Map Format Server Window Help
Standard
Show Me
Data Analytics
amazon_prime_titles
disney_plus_titles
hulu_titles
netflix_titles
Tables
Cast
Country
Date Added
Description
Director
Duration
Listed In
Rating
Release Year
Show Id
Title
Tree Map
Type
Measure Names
Latitude (generated)
Longitude (generated)
netflix_titles.csv (Count)
Measure Values
Parameters
Tree Map
Pages
Filters
Tree Map: Netflix
Marks
Automatic
Color
Size
Label
Detail
Tooltip
CNT(netflix_titl..
CNT(netflix_titl..
Listed In
Columns
Rows
Netflix
Dramas, International Movies
Documentaries
Stand-Up Comedy
Comedies, Dramas, International Movies
Dramas, Independent Movies, International Movies
Kids' TV
Children & Family Movies
Children & Family Movies, Comedies
Documentaries, International Movies
Dramas, International Movies, Romantic Movies
Comedies, International Movies
Comedies, International Movies, Romantic Movies
Dramas
Dramas, International Movies,
Action & Adventure, Dramas,
Action & Adventure
International TV Shows, TV Dramas
Comedies, Dramas, Independent
Comedies
Crime TV Shows, International
Action &
Dramas,
Kids' TV, TV
Reality TV
Anime Series,
Dramas, Thrillers
Comedies, Romantic
Action & Adventure,
TV Comedies
Thrillers
TV
CNT(netflix_titles.csv)
1
362
Tree Map
Netflix
Data Source
Amazon Prime
Disney Plus
Hulu
Netflix
Dashboard 1

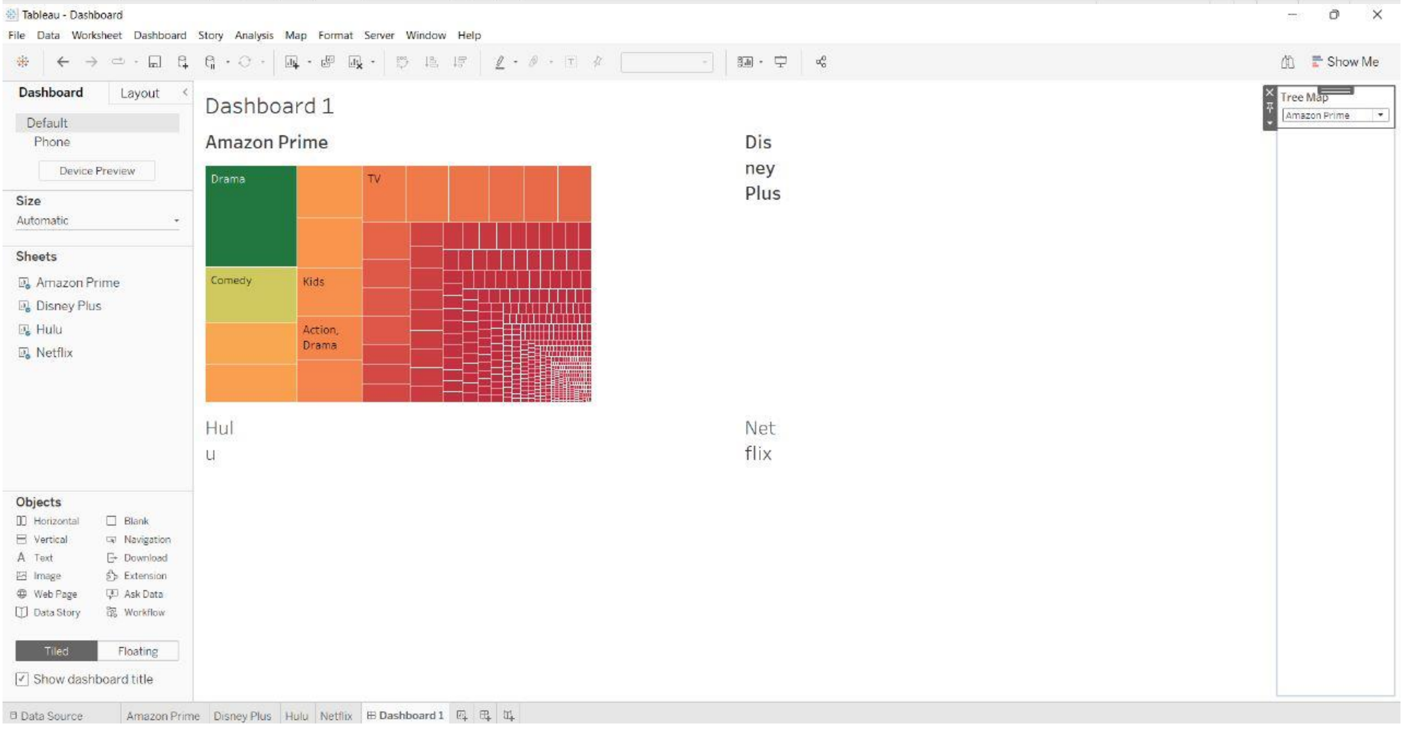


Tableau - Dashboard
File Data Worksheet Dashboard Story Analysis Map Format Server Window Help
Show Me
Dashboard Layout
Default
Phone
Device Preview
Size
Automatic
Sheets
Amazon Prime
Disney Plus
Hulu
Netflix
Objects
Horizontal
Blank
Vertical
Navigation
Text
Download
Image
Extension
Web Page
Ask Data
Data Story
Workflow
Tiled
Floating
Show dashboard title
Dashboard 1
Amazon Prime
Drama
TV
Comedy
Kids
Action, Drama
Dis ney Plus
Hul u
Net flix
Tree Map
Amazon Prime
Data Source
Amazon Prime
Disney Plus
Hulu
Netflix
Dashboard 1

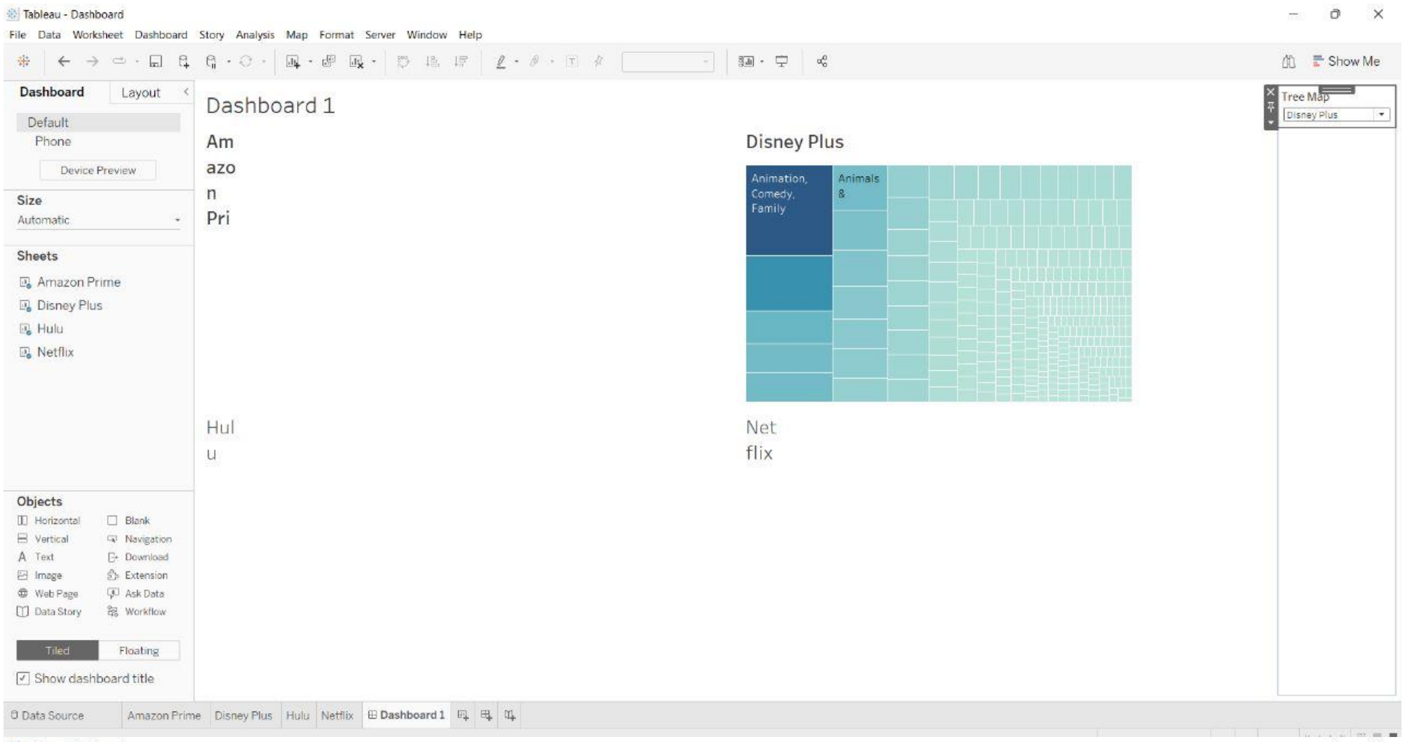


Tableau - Dashboard
File Data Worksheet Dashboard Story Analysis Map Format Server Window Help
Show Me
Dashboard Layout
Default
Phone
Device Preview
Size
Automatic
Sheets
Amazon Prime
Disney Plus
Hulu
Netflix
Objects
Horizontal Blank
Vertical Navigation
Text Download
Image Extension
Web Page Ask Data
Data Story Workflow
Tiled Floating
Show dashboard title
Dashboard 1
Am azo n Pri
Disney Plus
Animation, Comedy, Family
Animals &
Hul u
Net flix
Tree Map
Disney Plus
Data Source Amazon Prime Disney Plus Hulu Netflix Dashboard 1

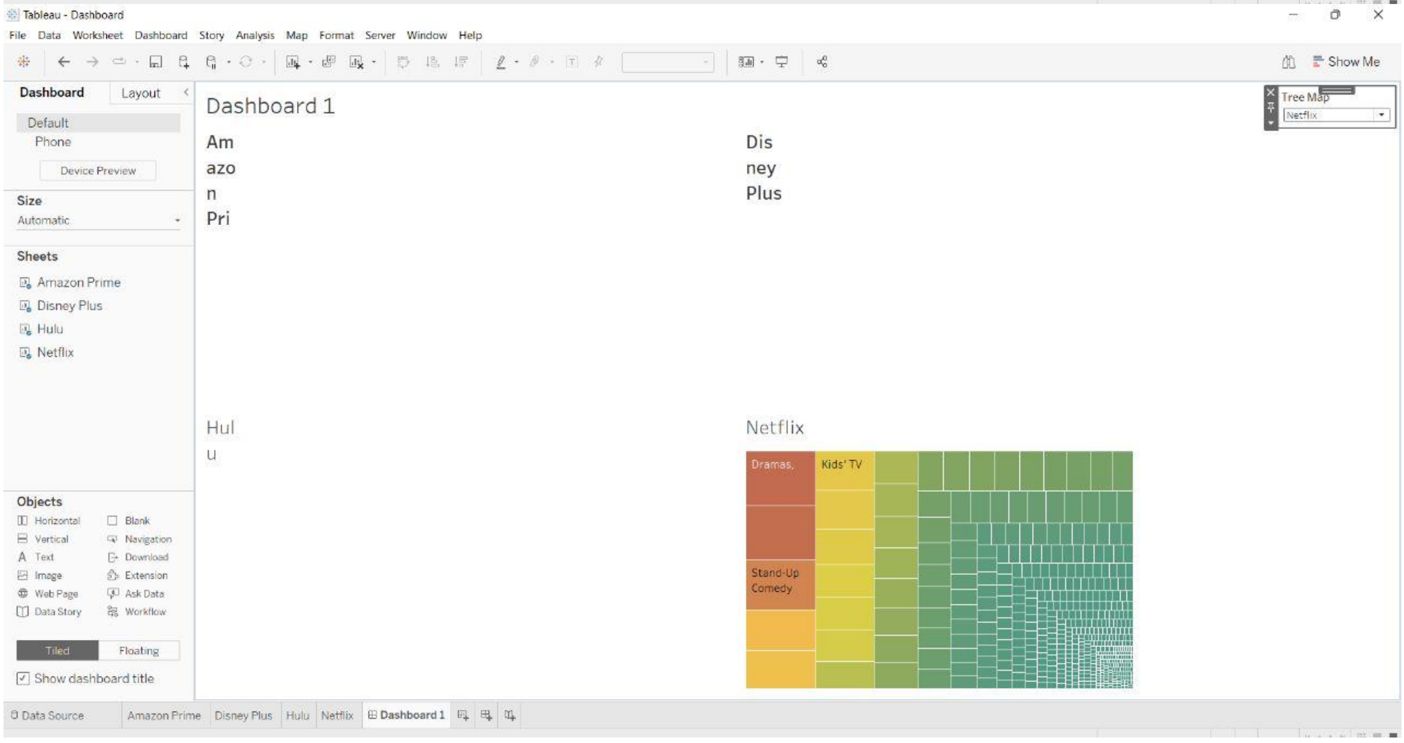
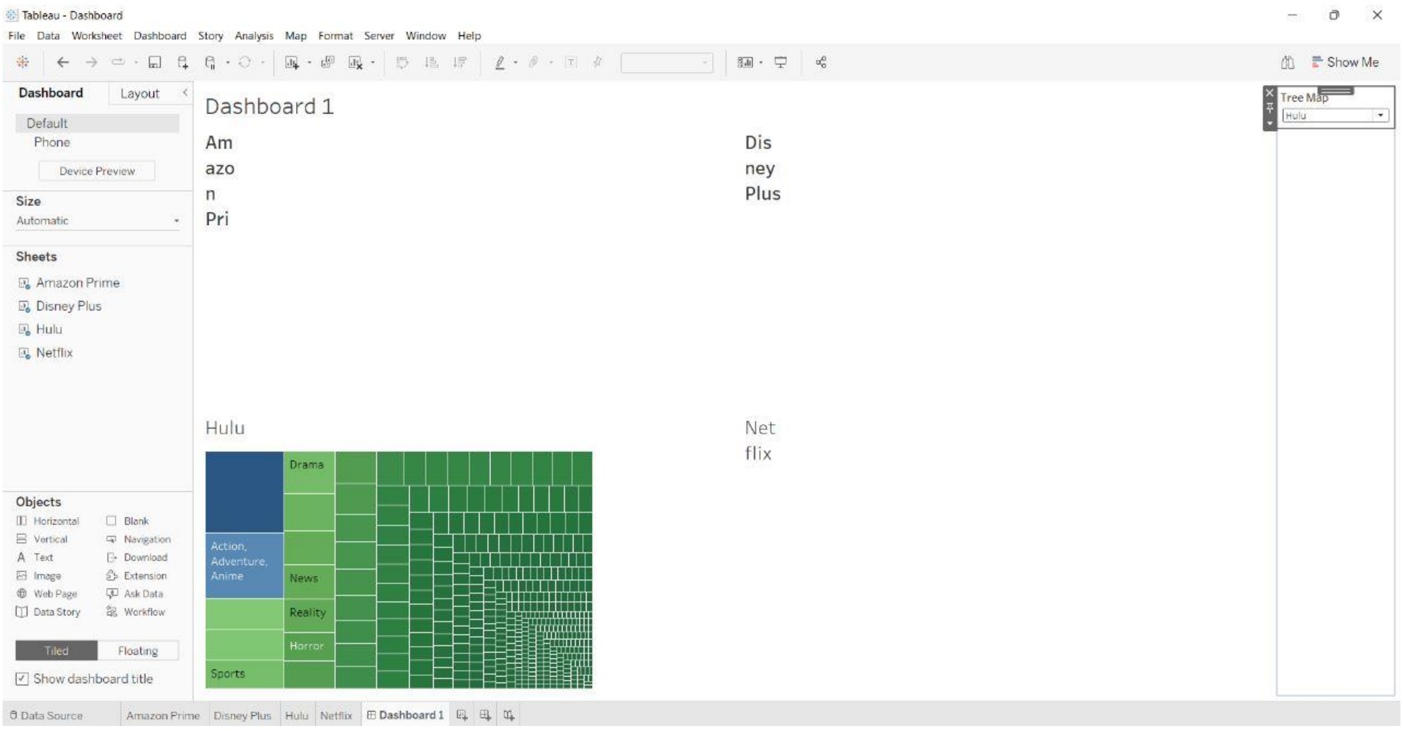
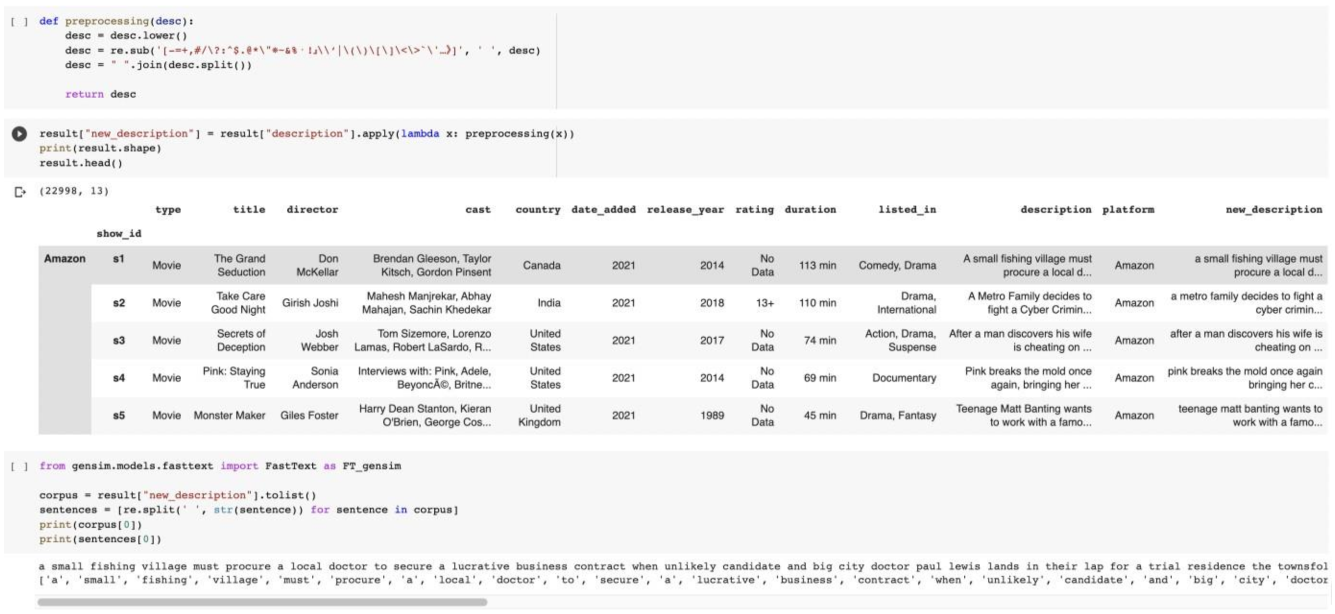


Tableau - Dashboard
File Data Worksheet Dashboard Story Analysis Map Format Server Window Help
Show Me
Dashboard Layout
Default
Phone
Device Preview
Size
Automatic
Sheets
Amazon Prime
Disney Plus
Hulu
Netflix
Objects
Horizontal Blank
Vertical Navigation
Text Download
Image Extension
Web Page Ask Data
Data Story Workflow
Tiled Floating
Show dashboard title
Dashboard 1
Am azo n Pri
Dis ney Plus
Hul u
Netflix
Dramas,
Kids' TV
Stand-Up Comedy
Tree Map
Netflix
Data Source Amazon Prime Disney Plus Hulu Netflix Dashboard 1



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

<u>4.7</u> <u>Creating Clustering and Regression Model</u>



```
[ ] def preprocessing(desc):
        desc = desc.lower()
        desc = re.sub('[-=+,#/\?:^$.@*\"※~&%ㆍ!』\\‘|\(\)\[\]\<\>`\'…》]', ' ', desc)
        desc = " ".join(desc.split())

        return desc
```

```
result["new_description"] = result["description"].apply(lambda x: preprocessing(x))
print(result.shape)
result.head()
```

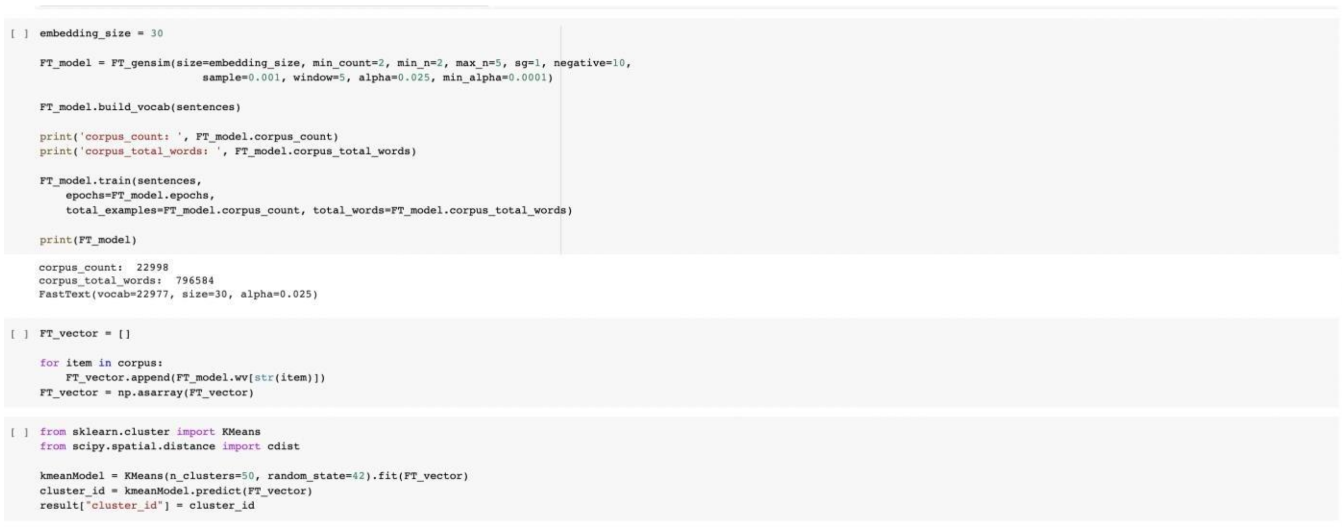
```
(22998, 13)
```

	show_id	type	title	director	cast	country	date_added	release_year	rating	duration	listed_in	description	platform	new_description
Amazon	s1	Movie	The Grand Seduction	Don McKellar	Brendan Gleeson, Taylor Kitsch, Gordon Pinsent	Canada	2021	2014	No Data	113 min	Comedy, Drama	A small fishing village must procure a local d...	Amazon	a small fishing village must procure a local d...
	s2	Movie	Take Care Good Night	Girish Joshi	Mahesh Manjrekar, Abhay Mahajan, Sachin Khedekar	India	2021	2018	13+	110 min	Drama, International	A Metro Family decides to fight a Cyber Crimin...	Amazon	a metro family decides to fight a cyber crimin...
	s3	Movie	Secrets of Deception	Josh Webber	Tom Sizemore, Lorenzo Lamas, Robert LaSardo, R...	United States	2021	2017	No Data	74 min	Action, Drama, Suspense	After a man discovers his wife is cheating on ...	Amazon	after a man discovers his wife is cheating on ...
	s4	Movie	Pink: Staying True	Sonia Anderson	Interviews with: Pink, Adele, BeyoncÃ©, Britne...	United States	2021	2014	No Data	69 min	Documentary	Pink breaks the mold once again, bringing her ...	Amazon	pink breaks the mold once again bringing her c...
	s5	Movie	Monster Maker	Giles Foster	Harry Dean Stanton, Kieran O'Brien, George Cos...	United Kingdom	2021	1989	No Data	45 min	Drama, Fantasy	Teenage Matt Banting wants to work with a famo...	Amazon	teenage matt banting wants to work with a famo...

```
[ ] from gensim.models.fasttext import FastText as FT_gensim

    corpus = result["new_description"].tolist()
    sentences = [re.split(' ', str(sentence)) for sentence in corpus]
    print(corpus[0])
    print(sentences[0])
```

```
a small fishing village must procure a local doctor to secure a lucrative business contract when unlikely candidate and big city doctor paul lewis lands in their lap for a trial residence the townsfol
['a', 'small', 'fishing', 'village', 'must', 'procure', 'a', 'local', 'doctor', 'to', 'secure', 'a', 'lucrative', 'business', 'contract', 'when', 'unlikely', 'candidate', 'and', 'big', 'city', 'doctor
```

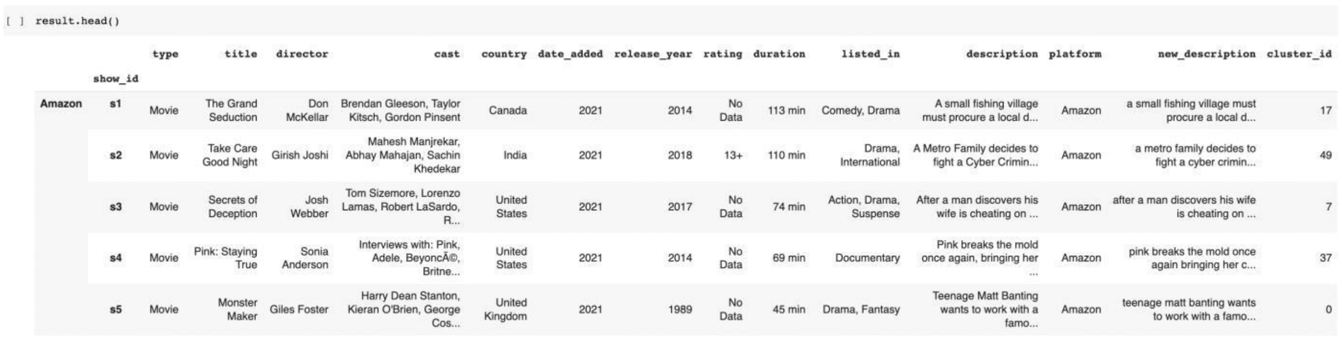
We first preprocess the description field to make it compatible with similarity checks



```
[ ] embedding_size = 30

    FT_model = FT_gensim(size=embedding_size, min_count=2, min_n=2, max_n=5, sg=1, negative=10,
                         sample=0.001, window=5, alpha=0.025, min_alpha=0.0001)

    FT_model.build_vocab(sentences)

    print('corpus_count: ', FT_model.corpus_count)
    print('corpus_total_words: ', FT_model.corpus_total_words)

    FT_model.train(sentences,
        epochs=FT_model.epochs,
        total_examples=FT_model.corpus_count, total_words=FT_model.corpus_total_words)

    print(FT_model)

    corpus_count:  22998
    corpus_total_words:  796584
    FastText(vocab=22977, size=30, alpha=0.025)

[ ] FT_vector = []

    for item in corpus:
        FT_vector.append(FT_model.wv[str(item)])
    FT_vector = np.asarray(FT_vector)

[ ] from sklearn.cluster import KMeans
    from scipy.spatial.distance import cdist

    kmeanModel = KMeans(n_clusters=50, random_state=42).fit(FT_vector)
    cluster_id = kmeanModel.predict(FT_vector)
    result["cluster_id"] = cluster_id
```

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

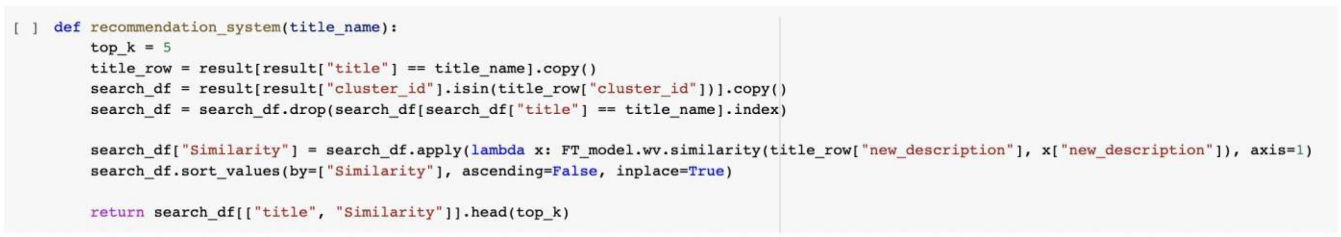
The Data is divided into a total of 49 clusters.



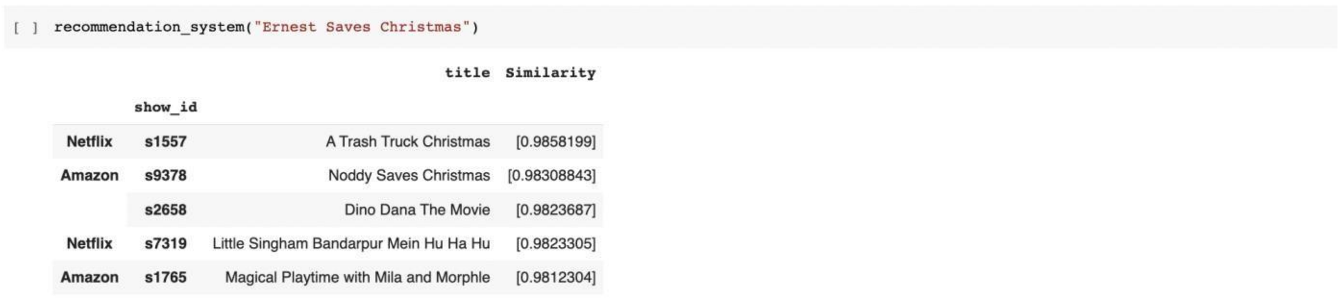
```
[ ] result.head()
```

		type	title	director	cast	country	date_added	release_year	rating	duration	listed_in	description	platform	new_description	cluster_id
	show_id														
Amazon	**s1**	Movie	The Grand Seduction	Don McKellar	Brendan Gleeson, Taylor Kitsch, Gordon Pinsent	Canada	2021	2014	No Data	113 min	Comedy, Drama	A small fishing village must procure a local d...	Amazon	a small fishing village must procure a local d...	17
	s2	Movie	Take Care Good Night	Girish Joshi	Mahesh Manjrekar, Abhay Mahajan, Sachin Khedekar	India	2021	2018	13+	110 min	Drama, International	A Metro Family decides to fight a Cyber Crimin...	Amazon	a metro family decides to fight a cyber crimin...	49
	s3	Movie	Secrets of Deception	Josh Webber	Tom Sizemore, Lorenzo Lamas, Robert LaSardo, R...	United States	2021	2017	No Data	74 min	Action, Drama, Suspense	After a man discovers his wife is cheating on ...	Amazon	after a man discovers his wife is cheating on ...	7
	s4	Movie	Pink: Staying True	Sonia Anderson	Interviews with: Pink, Adele, BeyoncÃ©, Britne...	United States	2021	2014	No Data	69 min	Documentary	Pink breaks the mold once again, bringing her ...	Amazon	pink breaks the mold once again bringing her c...	37
	s5	Movie	Monster Maker	Giles Foster	Harry Dean Stanton, Kieran O'Brien, George Cos...	United Kingdom	2021	1989	No Data	45 min	Drama, Fantasy	Teenage Matt Banting wants to work with a famo...	Amazon	teenage matt banting wants to work with a famo...	0

Now, we create the recommendation system

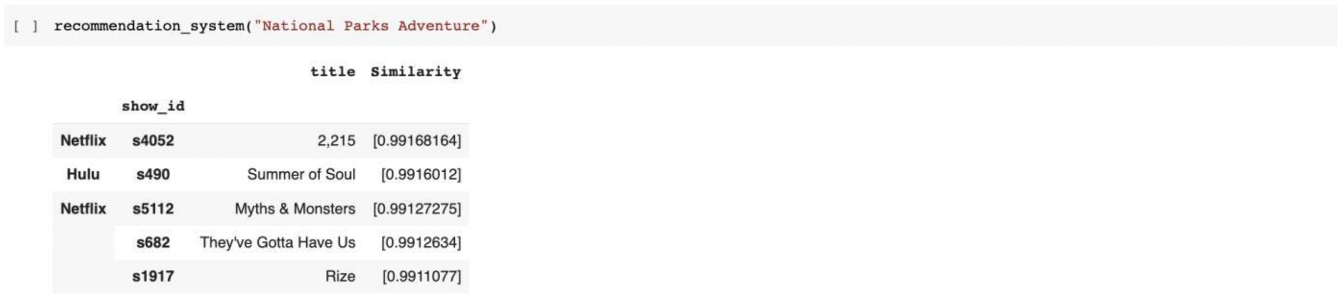


```
[ ] def recommendation_system(title_name):
        top_k = 5
        title_row = result[result["title"] == title_name].copy()
        search_df = result[result["cluster_id"].isin(title_row["cluster_id"])].copy()
        search_df = search_df.drop(search_df[search_df["title"] == title_name].index)

        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]
Amazon	**s1765**	Magical Playtime with Mila and Morphle	[0.9812304]



```
[ ] recommendation_system("National Parks Adventure")
```

		title	Similarity
	show_id		
Netflix	**s4052**	2,215	[0.99168164]
Hulu	**s490**	Summer of Soul	[0.9916012]
Netflix	**s5112**	Myths & Monsters	[0.99127275]
	s682	They've Gotta Have Us	[0.9912634]
	s1917	Rize	[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 Amazon 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.

Appendix: -

Codes: -

```
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

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"])
print("The size and shape of dataset 1")
print(df1.size)
print(df1.shape)

print("The size and shape of dataset 2")
print(df2.size)
print(df2.shape)
print("The size and shape of dataset 3")
print(df3.size)
print(df3.shape)

print("The size and shape of dataset 4")
print(df4.size)
print(df4.shape)

df1.dtypes

df2.dtypes


df3.dtypes


df4.dtypes

df1["date_added"] = df1["date_added"].dt.year
df1["date_added"].unique()


df1["date_added"].fillna(0, inplace=True)
df1["date_added"] = df1["date_added"].astype(int)
df1.head()

df1.loc[df1["date_added"]==0, ]

df1.info()


df1.duplicated().sum()


df1.fillna("No Data", inplace=True)
df1.isnull().sum()


df2['cast'] = df2['cast'].astype(str)


df2["date_added"] = df2["date_added"].dt.year
df2["date_added"].unique()



df2["date_added"].fillna(0, inplace=True)
df2["date_added"] = df2["date_added"].astype(int)
```

```
df2.head()


df2.loc[df2["date_added"]==0, ]
df2.info()
df2.duplicated().sum()

df2.fillna("No Data", inplace=True)
df2.isnull().sum()

df3["date_added"] = df3["date_added"].dt.year
df3["date_added"].unique()

df3["date_added"].fillna(0, inplace=True)
df3["date_added"] = df3["date_added"].astype(int)
df3.head()

df3.loc[df3["date_added"]==0, ]

df3.info()

df3.duplicated().sum()

df3.fillna("No Data", inplace=True)
df3.isnull().sum()

df4["date_added"] = df4["date_added"].dt.year
df4["date_added"].unique()

df4["date_added"].fillna(0, inplace=True)
df4["date_added"] = df4["date_added"].astype(int)
df4.head()

df4.loc[df4["date_added"]==0, ]

df4.info()

df4.duplicated().sum()

df4.fillna("No Data", inplace=True)
df4.isnull().sum()

df1.head()

df2.head()

df3.head()
```

```
df4.head()

sns.set(style="darkgrid")
ax = sns.countplot(x="type", data=df1, palette="Set2")
ax.set_title(f'Types of Amazon Prime Content', fontsize=15, fontweight='bold',
position=(0.20, 1.03))

plt.figure(figsize = (15,8))
plt.title('Top 10 Genres for Movies in Amazon Prime')
df3[df3["type"]=="Movie"]["listed_in"].value_counts()[:10].plot(kind='barh')
plt.show()

d1 = df1[df1["type"] == "TV Show"]
d2 = df1[df1["type"] == "Movie"]

col = "release_year"

vc1 = d1[col].value_counts().reset_index()
vc1 = vc1.rename(columns = {col : "count", "index" : col})
vc1['percent'] = vc1['count'].apply(lambda x : 100*x/sum(vc1['count']))
vc1 = vc1.sort_values(col)

vc2 = d2[col].value_counts().reset_index()
vc2 = vc2.rename(columns = {col : "count", "index" : col})
vc2['percent'] = vc2['count'].apply(lambda x : 100*x/sum(vc2['count']))
vc2 = vc2.sort_values(col)

trace1 = go.Bar(x=vc1[col], y=vc1["count"], name="TV Shows",
marker=dict(color="#a678de"))
trace2 = go.Bar(x=vc2[col], y=vc2["count"], name="Movies",
marker=dict(color="#6ad49b"))
data = [trace1, trace2]
layout = go.Layout(title="Content added over the years", legend=dict(x=0.1, y=1.1,
orientation="h"))
fig = go.Figure(data, layout=layout)
fig.show()

col = "rating"

vc1 = d1[col].value_counts().reset_index()
vc1 = vc1.rename(columns = {col : "count", "index" : col})
vc1['percent'] = vc1['count'].apply(lambda x : 100*x/sum(vc1['count']))
vc1 = vc1.sort_values(col)

vc2 = d2[col].value_counts().reset_index()
vc2 = vc2.rename(columns = {col : "count", "index" : col})
vc2['percent'] = vc2['count'].apply(lambda x : 100*x/sum(vc2['count']))
vc2 = vc2.sort_values(col)
```

```
trace1 = go.Bar(x=vc1[col], y=vc1["count"], name="TV Shows", marker=dict(color="#a678de"))
trace2 = go.Bar(x=vc2[col], y=vc2["count"], name="Movies", marker=dict(color="#6ad49b"))
data = [trace1, trace2]
layout = go.Layout(title="Content added over the years", legend=dict(x=0.1, y=1.1, orientation="h"))
fig = go.Figure(data, layout=layout)
fig.show()

df1['date_added'].value_counts().plot(kind='bar')

plt.figure(figsize=(14, 7))
labels=['TV Show', 'Movie']
plt.pie(df2['type'].value_counts().sort_values(),labels=labels,explode=[0.1,0.1],autopct='%1.2f%%',colors=['green','red'], startangle=90)
plt.title('Type of Hulu Content')
plt.axis('equal')
plt.show()

plt.figure(figsize=(14, 7))
df2['release_year'].value_counts().plot(kind='bar')

plt.figure(figsize = (45,30))
plt.title('Hulu ratings distribution seperated by type of release')
sns.countplot(x='rating', data=df2)
plt.show()

plt.figure(figsize=(15,8))
movie = df2[df2['type'] == 'Movie' ]
tv = df2[df2['type'] == 'TV Show']
movie = movie[movie['date_added']>2000]
tv = tv[tv['date_added']>2000]
added_counts= movie['date_added'].value_counts()
added_tv_counts= tv['date_added'].value_counts()
sns.lineplot(x=added_counts.index,y=added_counts.values, color="orange", label='Movie')
sns.lineplot(x=added_tv_counts.index,y=added_tv_counts.values, color="blue", label='TV Show')
plt.title('Hulu tv shows and movies by year added')
plt.legend()
plt.show()

plt.figure(figsize=(14, 7))
labels=['TV Show', 'Movie']
plt.pie(df3['type'].value_counts().sort_values(),labels=labels,explode=[0.1,0.1],autopct='%1.2f%%',colors=['blue','yellow'], startangle=90)
plt.title('Type of Disney Plus Content')
plt.axis('equal')
plt.show()

plt.figure(figsize = (15,8))
plt.title('Disney Ratings Distribution')
sns.countplot(x='rating', data = df3)
plt.show()

plt.figure(figsize = (15,8))
plt.title('Top 10 Genres for Movies in Disney Platform')
df3[df3["type"]=="Movie"]["listed_in"].value_counts()[:10].plot(kind='barh')
plt.show()

plt.figure(figsize = (15,8))
plt.title('Top 10 Genres for TV SHOW in Disney Platform')
df3[df3["type"]=="TV
Show"]["listed_in"].value_counts()[:10].plot(kind='barh',color='blue')
plt.show()

plt.figure(figsize = (15,8))
plt.title('Disney ratings distribution seperated by type of release')
sns.countplot(x='rating', data=df3, hue='type')
plt.show()

df3['date_added'].value_counts().plot(kind='bar')

df_tv_show = df3[df3['type']=='TV Show']
df_tv_show['duration'].value_counts().plot(kind='bar')

sns.set(style="darkgrid")
ax = sns.countplot(x="type", data=df4, palette="Set2")
ax.set_title(f'Types of Netflix Content', fontsize=15, fontweight='bold', position=(0.20,
1.03))

sns.set_style('whitegrid') # plot with grid
movie = df4[df4['type'] == 'Movie']
rating_order = ['G', 'TV-Y', 'TV-G', 'PG', 'TV-Y7', 'TV-PG', 'PG-13', 'TV-14', 'R', 'NC-
17', 'TV-MA']
movie_rating = movie['rating'].value_counts()[rating_order]
def rating_barplot(data, title, height, h_lim=None):
   fig, ax = plt.subplots(1,1, figsize=(14, 7), dpi=200)
   if h_lim :
      ax.set_ylim(0, h_lim)
   ax.bar(data.index, data, color="#e0e0e0", width=0.52, edgecolor='black')
   color = ['green', 'blue', 'orange', 'red']
   span_range = [[0, 2], [3, 6], [7, 8], [9, 11]]
```

```
  for idx, sub_title in enumerate(['Little Kids', 'Older Kids', 'Teens', 'Mature']):
    ax.annotate(sub_title,
            xy=(sum(span_range[idx])/2 ,height),
            xytext=(0,0), textcoords='offset points',
            va="center", ha="center",
            color="w", fontsize=16, fontweight='bold',
            bbox=dict(boxstyle='round4', pad=0.4, color=color[idx], alpha=0.6))
    ax.axvspan(span_range[idx][0]-0.4,span_range[idx][1]+0.4, color=color[idx],
alpha=0.07)
  ax.set_title(f'Distribution of {title} Rating', fontsize=15, fontweight='bold',
position=(0.20, 1.0+0.03))
  fig.tight_layout()
  plt.show()
rating_barplot(movie_rating, 'Movie', 1200, 2100)


plt.figure(figsize = (15,8))
plt.title('Netflix country distribution seperated by type of release')
sns.countplot(x='country', data=df4, hue='type',
order=df4.country.value_counts().iloc[:5].index)
plt.show()


country_counts = df4['country'].value_counts(sort=True)
country_df = pd.DataFrame(country_counts)
country_df = country_df.reset_index()
country_df.columns = ['country', 'counts']
country_pie_df = country_df.head(10)
plt.figure(figsize = (15,8))
colors = sns.color_palette('pastel')[0:10]
plt.title('Distribution of release by country (top 10)')
plt.pie(country_pie_df['counts'], labels = country_pie_df['country'], colors = colors,
autopct='%.0f%%')
plt.show()


plt.figure(figsize=(15,8))
movie = df4[df4['type'] == 'Movie' ]
tv = df4[df4['type'] == 'TV Show']
movie = movie[movie['date_added']>2000]
tv = tv[tv['date_added']>2000]
added_counts= movie['date_added'].value_counts()
added_tv_counts= tv['date_added'].value_counts()
sns.lineplot(x=added_counts.index,y=added_counts.values, color="orange",
label='Movie')
sns.lineplot(x=added_tv_counts.index,y=added_tv_counts.values, color="blue",
label='TV Show')
plt.title('Netflix tv shows and movies by year added')
plt.legend()
plt.show()

plt.figure(figsize=(15,8))
dd1 = df1[df1['type'] == 'Movie' ]
dd2 = df2[df2['type'] == 'Movie' ]
dd3 = df3[df3['type'] == 'Movie' ]
dd4 = df4[df4['type'] == 'Movie' ]
added_counts1= dd1['release_year'].value_counts()
added_counts2= dd2['release_year'].value_counts()
added_counts3= dd3['release_year'].value_counts()
added_counts4= dd4['release_year'].value_counts()
sns.lineplot(x=added_counts1.index,y=added_counts1.values,                color="orange",
label='Amazon Prime')
sns.lineplot(x=added_counts2.index,y=added_counts2.values,                  color="blue",
label='Hulu')
sns.lineplot(x=added_counts3.index,y=added_counts3.values,                 color="green",
label='Disney')
sns.lineplot(x=added_counts4.index,y=added_counts4.values,                 color="black",
label='Netflix')
plt.title('Movies by release year in major Streaming sites')
plt.legend()
plt.show()


plt.figure(figsize=(15,8))
dt1 = df1[df1['type'] == 'TV Show' ]
dt2 = df2[df2['type'] == 'TV Show' ]
dt3 = df3[df3['type'] == 'TV Show' ]
dt4 = df4[df4['type'] == 'TV Show' ]
dt1 = dt1[dt1['release_year']>1980]
dt2 = dt2[dt2['release_year']>1980]
dt3 = dt3[dt3['release_year']>1980]
dt4 = dt4[dt4['release_year']>1980]
added_countst1= dt1['release_year'].value_counts()
added_countst2= dt2['release_year'].value_counts()
added_countst3= dt3['release_year'].value_counts()
added_countst4= dt4['release_year'].value_counts()
sns.lineplot(x=added_countst1.index,y=added_countst1.values,            color="orange",
label='Amazon Prime')
sns.lineplot(x=added_countst2.index,y=added_countst2.values,              color="blue",
label='Hulu')
sns.lineplot(x=added_countst3.index,y=added_countst3.values,             color="green",
label='Disney')
sns.lineplot(x=added_countst4.index,y=added_countst4.values,             color="black",
label='Netflix')
plt.title('TV SHOWS by release year in major Streaming sites')
plt.legend()
plt.show()


df1['platform'] = 'Amazon'
df2['platform'] = 'Hulu'
df3['platform'] = 'Disney'
df4['platform'] = 'Netflix'


frames = [df1, df2, df3, df4]
result = pd.concat(frames, keys=["Amazon", "Hulu", "Disney", "Netflix"])

platform_counts = result['platform'].value_counts(sort=True)
platform_df = pd.DataFrame(platform_counts)
platform_df = platform_df.reset_index()
platform_df.columns = ['platform', 'counts']
platform_pie_df = platform_df
plt.figure(figsize = (15,8))
colors = sns.color_palette('pastel')[0:10]
plt.title('Distribution of release by platforms')
plt.pie(platform_pie_df['counts'], labels = platform_pie_df['platform'], colors = colors,
autopct='%.0f%%')
plt.show()


text = ' '.join(result['listed_in'])
plt.rcParams['figure.figsize'] = (12,12)
wordcloud = WordCloud(background_color = 'black',colormap='vlag', width = 1200,
height = 1200, max_words = 121).generate(text)
plt.imshow(wordcloud)
plt.axis('off')
plt.show()


country_codes = {'afghanistan': 'AFG', 'albania': 'ALB', 'algeria': 'DZA', 'american
samoa': 'ASM', 'andorra': 'AND', 'angola': 'AGO', 'anguilla': 'AIA',
'antigua and barbuda': 'ATG','argentina': 'ARG','armenia': 'ARM','aruba':
'ABW','australia': 'AUS','austria': 'AUT','azerbaijan': 'AZE','bahamas': 'BHM',
 'bahrain': 'BHR','bangladesh': 'BGD','barbados': 'BRB','belarus': 'BLR','belgium':
'BEL','belize': 'BLZ','benin': 'BEN','bermuda': 'BMU','bhutan': 'BTN',
 'bolivia': 'BOL','bosnia and herzegovina': 'BIH','botswana': 'BWA','brazil':
'BRA','british virgin islands': 'VGB','brunei': 'BRN','bulgaria': 'BGR',
 'burkina faso': 'BFA','burma': 'MMR','burundi': 'BDI','cabo verde':
'CPV','cambodia': 'KHM','cameroon': 'CMR','canada': 'CAN','cayman islands':
'CYM',
 'central african republic': 'CAF','chad': 'TCD','chile': 'CHL','china': 'CHN','colombia':
'COL','comoros': 'COM','congo democratic': 'COD',
 'Congo republic': 'COG','cook islands': 'COK','costa rica': 'CRI',"cote d'ivoire":
'CIV','croatia': 'HRV','cuba': 'CUB','curacao': 'CUW','cyprus': 'CYP',
 'czech republic': 'CZE','denmark': 'DNK','djibouti': 'DJI','dominica':
'DMA','dominican republic': 'DOM','ecuador': 'ECU','egypt': 'EGY',
 'el salvador': 'SLV','equatorial guinea': 'GNQ','eritrea': 'ERI','estonia':
'EST','ethiopia': 'ETH','falkland islands': 'FLK','faroe islands': 'FRO',
 'fiji': 'FJI','finland': 'FIN','france': 'FRA','french polynesia': 'PYF','gabon':
'GAB','gambia, the': 'GMB','georgia': 'GEO','germany': 'DEU',
 'ghana': 'GHA','gibraltar': 'GIB','greece': 'GRC','greenland': 'GRL','grenada':
'GRD','guam': 'GUM','guatemala': 'GTM','guernsey': 'GGY',
 'guinea-bissau': 'GNB','guinea': 'GIN','guyana': 'GUY','haiti': 'HTI','honduras':
'HND','hong kong': 'HKG','hungary': 'HUN','iceland': 'ISL','india': 'IND',
 'indonesia': 'IDN','iran': 'IRN','iraq': 'IRQ','ireland': 'IRL','isle of man': 'IMN','israel':
'ISR','italy': 'ITA','jamaica': 'JAM','japan': 'JPN','jersey': 'JEY',
 'jordan': 'JOR','kazakhstan': 'KAZ','kenya': 'KEN','kiribati': 'KIR','north korea':
'PRK','south korea': 'KOR','kosovo': 'KSV','kuwait': 'KWT',
 'kyrgyzstan': 'KGZ','laos': 'LAO','latvia': 'LVA','lebanon': 'LBN','lesotho':
'LSO','liberia': 'LBR','libya': 'LBY','liechtenstein': 'LIE','lithuania': 'LTU',
 'luxembourg': 'LUX','macau': 'MAC','macedonia': 'MKD','madagascar':
'MDG','malawi': 'MWI','malaysia': 'MYS','maldives': 'MDV','mali': 'MLI','malta':
'MLT',
'marshall islands': 'MHL','mauritania': 'MRT','mauritius': 'MUS','mexico':
'MEX','micronesia': 'FSM','moldova': 'MDA','monaco': 'MCO','mongolia': 'MNG',
 'montenegro': 'MNE','morocco': 'MAR','mozambique': 'MOZ','namibia':
'NAM','nepal': 'NPL','netherlands': 'NLD','new caledonia': 'NCL','new zealand': 'NZL',
 'nicaragua': 'NIC','nigeria': 'NGA','niger': 'NER','niue': 'NIU','northern mariana
islands': 'MNP','norway': 'NOR','oman': 'OMN','pakistan': 'PAK','palau': 'PLW',
 'panama': 'PAN','papua new guinea': 'PNG','paraguay': 'PRY','peru':
'PER','philippines': 'PHL','poland': 'POL','portugal': 'PRT','puerto rico': 'PRI',
 'qatar': 'QAT','romania': 'ROU','russia': 'RUS','rwanda': 'RWA','saint kitts and nevis':
'KNA','saint lucia': 'LCA','saint martin': 'MAF',
 'saint pierre and miquelon': 'SPM','saint vincent and the grenadines': 'VCT','samoa':
'WSM','san marino': 'SMR','sao tome and principe': 'STP',
 'saudi arabia': 'SAU','senegal': 'SEN','serbia': 'SRB','seychelles': 'SYC','sierra leone':
'SLE','singapore': 'SGP','sint maarten': 'SXM','slovakia': 'SVK',
 'slovenia': 'SVN','solomon islands': 'SLB','somalia': 'SOM','south africa': 'ZAF','south
sudan': 'SSD','spain': 'ESP','sri lanka': 'LKA','sudan': 'SDN',
 'suriname': 'SUR','swaziland': 'SWZ','sweden': 'SWE','switzerland': 'CHE','syria':
'SYR','taiwan': 'TWN','tajikistan': 'TJK','tanzania': 'TZA',
 'thailand': 'THA','timor-leste': 'TLS','togo': 'TGO','tonga': 'TON','trinidad and
tobago': 'TTO','tunisia': 'TUN','turkey': 'TUR','turkmenistan': 'TKM',
 'tuvalu': 'TUV','uganda': 'UGA','ukraine': 'UKR','united arab emirates': 'ARE','united
kingdom': 'GBR','united states': 'USA','uruguay': 'URY',
 'uzbekistan': 'UZB','vanuatu': 'VUT','venezuela': 'VEN','vietnam': 'VNM','virgin
islands': 'VGB','west bank': 'WBG','yemen': 'YEM','zambia': 'ZMB',
 'zimbabwe': 'ZWE'}

## countries
```

```
from collections import Counter
colorscale = ["#f7fbff", "#ebf3fb", "#deebf7", "#d2e3f3", "#c6dbef", "#b3d2e9",
"#9ecae1",
   "#85bcdb", "#6baed6", "#57a0ce", "#4292c6", "#3082be", "#2171b5", "#1361a9",
   "#08519c", "#0b4083", "#08306b"
]

def geoplot(ddf):
   country_with_code, country = {}, {}
   shows_countries = ", ".join(result['country'].dropna()).split(", ")
   for c,v in dict(Counter(shows_countries)).items():
      code = ""
      if c.lower() in country_codes:
         code = country_codes[c.lower()]
      country_with_code[code] = v
      country[c] = v

   data = [dict(
         type = 'choropleth',
         locations = list(country_with_code.keys()),
         z = list(country_with_code.values()),
         colorscale = [[0,"rgb(5, 10, 172)"],[0.65,"rgb(40, 60, 190)"],[0.75,"rgb(70, 100,
245)"],\
                  [0.80,"rgb(90, 120, 245)"],[0.9,"rgb(106, 137, 247)"],[1,"rgb(220, 220,
220)"]],
         autocolorscale = False,
         reversescale = True,
         marker = dict(
            line = dict (
               color = 'gray',
               width = 0.5
            ) ),
         colorbar = dict(
            autotick = False,
            title = ''),
        ) ]

   layout = dict(
      title = '',
      geo = dict(
         showframe = False,
         showcoastlines = False,
         projection = dict(
            type = 'Mercator'
         )
      )
   )
```

```
    fig = dict( data=data, layout=layout )
    iplot( fig, validate=False, filename='d3-world-map' )
    return country

country_vals = geoplot(result)
tabs = Counter(country_vals).most_common(25)

labels = [_[0] for _ in tabs][::-1]
values = [_[1] for _ in tabs][::-1]
trace1 = go.Bar(y=labels, x=values, orientation="h", name="",
marker=dict(color="#a678de"))

data = [trace1]
layout = go.Layout(title="Countries with most content", height=700, legend=dict(x=0.1,
y=1.1, orientation="h"))
fig = go.Figure(data, layout=layout)
fig.show()



result.head()



def preprocessing(desc):
    desc = desc.lower()
    desc = re.sub('[-=+,#/\?:^$.@*\"※~&%・!』\\‘|\(\)\[\]\<\>`\'…》]', ' ', desc)
    desc = " ".join(desc.split())

    return desc


result["new_description"] = result["description"].apply(lambda x: preprocessing(x))
print(result.shape)
result.head()


from gensim.models.fasttext import FastText as FT_gensim

corpus = result["new_description"].tolist()
sentences = [re.split(' ', str(sentence)) for sentence in corpus]
print(corpus[0])
print(sentences[0])


embedding_size = 30
```

```
FT_model = FT_gensim(size=embedding_size, min_count=2, min_n=2, max_n=5, sg=1,
negative=10,
                   sample=0.001, window=5, alpha=0.025, min_alpha=0.0001)

FT_model.build_vocab(sentences)

print('corpus_count: ', FT_model.corpus_count)
print('corpus_total_words: ', FT_model.corpus_total_words)

FT_model.train(sentences,
   epochs=FT_model.epochs,
   total_examples=FT_model.corpus_count,
total_words=FT_model.corpus_total_words)

print(FT_model)




FT_vector = []

for item in corpus:
   FT_vector.append(FT_model.wv[str(item)])
FT_vector = np.asarray(FT_vector)




from sklearn.cluster import KMeans
from scipy.spatial.distance import cdist

kmeanModel = KMeans(n_clusters=50, random_state=42).fit(FT_vector)
cluster_id = kmeanModel.predict(FT_vector)
result["cluster_id"] = cluster_id





result.head()




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("Aakhri Adaalat")


recommendation_system("National Parks Adventure")


recommendation_system("Secrets of Deception")
```

References

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FUTURE USE

This report briefly describes simple models that predicts ratings. There are two other widely adopted approaches not discussed here: content-based and collaborative filtering. The recommenderlab package implements these methods and provides an environment to build and test recommendation systems.

Percentage of completion

101% effort, 90% accomplished.
In this project we were able to accomplish 90% of what we thought to accomplish in the beginning. We faced many challenges along our way and were able to find solutions to most of the problems.

PUBLICITY: (github.com)

akshitjain20bce1818/FDA-J-COMP (github.com)
SAME LINK FOR ALL CONTRIBUTORS. (CONTRIBUTORS ARE ADDED FOR THE RESPECTIVE REPOSITORY)

Contributions of the members:

1. Kashish Bajaj : literature survey , research , idea generation
2. Akshit Jain : Data visualization and deployment using tableau
3. Akash Raj Behera : Data cleaning , data set analysis , jupitor notebook .

Documentation for review 1, review 2 and review 3 done in unison.

PPT AND REPORT SUBMITTED IN LMS.

- YES