Youtube Streamers Analysis

Dataset: Top 1000 Youtubers Statistics

Description: This dataset contains valuable information about the top YouTube streamers, including their ranking, categories, subscribers, country, visits, likes, comments, and more.

My task here is to perform a comprehensive analysis of the dataset to extract insights about top YouTube content creators.

I'll start by loading the dataset

```
#load the dataset

import pandas as pd
import matplotlib.pyplot as plt
df = pd.read_csv('C:/Users/PC/Downloads/youtubers_df.csv')
```

Data Exploration

- Exploring the dataset to understand the sturcture and identify key variables
- Check for missing data and outliers

```
#Data Exploration and Cleaning
#Show the first rows of the dataset to understand the structure

print(df.head())
```

```
   Rank       Username           Categories   Suscribers
Country  \
0     1        tseries       Música y baile  249500000.0
India
1     2        MrBeast   Videojuegos, Humor  183500000.0   Estados
Unidos
2     3      CoComelon            Educación  165500000.0
Unknown
3     4       SETIndia                  NaN  162600000.0
India
4     5  KidsDianaShow  Animación, Juguetes  113500000.0
Unknown

        Visits      Likes  Comments  \
0      86200.0     2700.0      78.0
1  117400000.0  5300000.0   18500.0
2    7000000.0    24700.0       0.0
3      15600.0      166.0       9.0
4    3900000.0    12400.0       0.0
```

```
                                               Links
0  http://youtube.com/channel/UCq-Fj5jknLsUf-MWSy...
1  http://youtube.com/channel/UCX6OQ3DkcsbYNE6H8u...
2  http://youtube.com/channel/UCbCmjCuTUZos6Inko4...
3  http://youtube.com/channel/UCpEhnqL0y41EpW2TvW...
4  http://youtube.com/channel/UCk8GzjMOrta8yxDcKf...
```

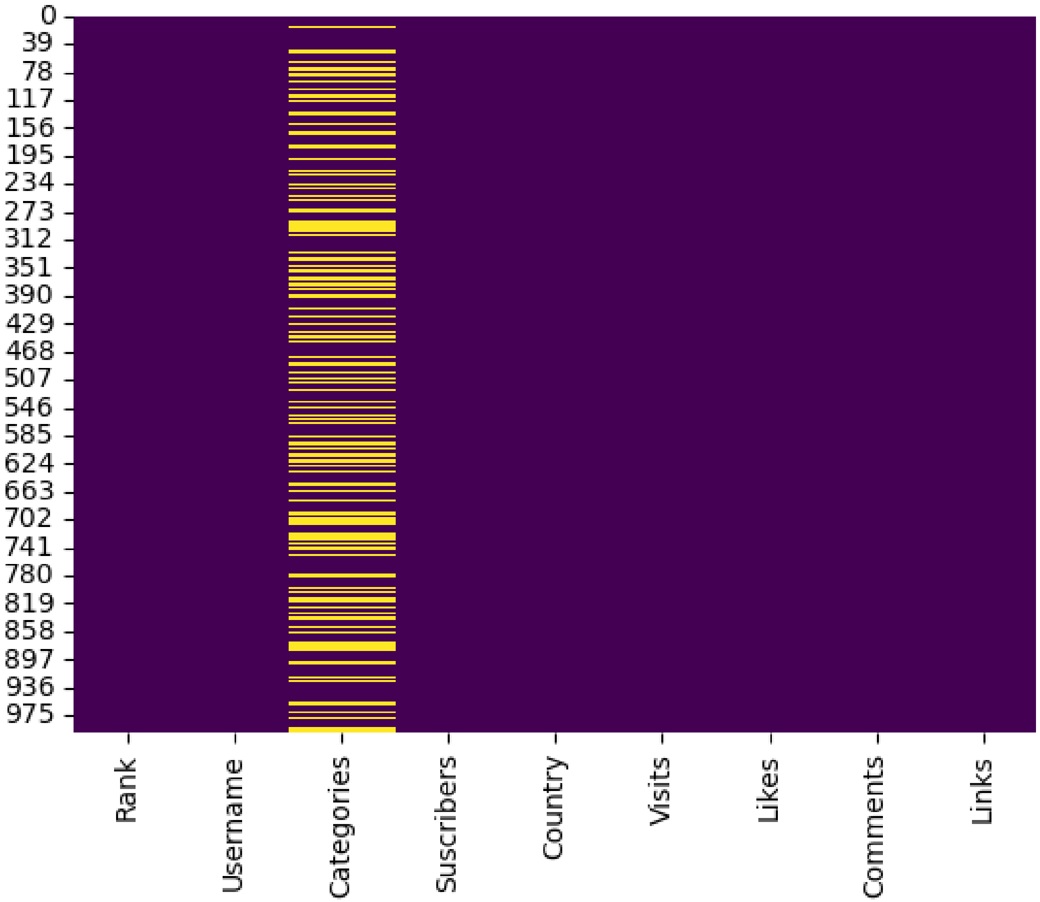
```python
#Show the overview of the dataset including the datatypes and missing
values
print(df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 9 columns):
 #   Column      Non-Null Count  Dtype  
---  ------      --------------  -----  
 0   Rank        1000 non-null   int64  
 1   Username    1000 non-null   object 
 2   Categories  694 non-null    object 
 3   Suscribers  1000 non-null   float64
 4   Country     1000 non-null   object 
 5   Visits      1000 non-null   float64
 6   Likes       1000 non-null   float64
 7   Comments    1000 non-null   float64
 8   Links       1000 non-null   object 
dtypes: float64(4), int64(1), object(4)
memory usage: 70.4+ KB
None
```

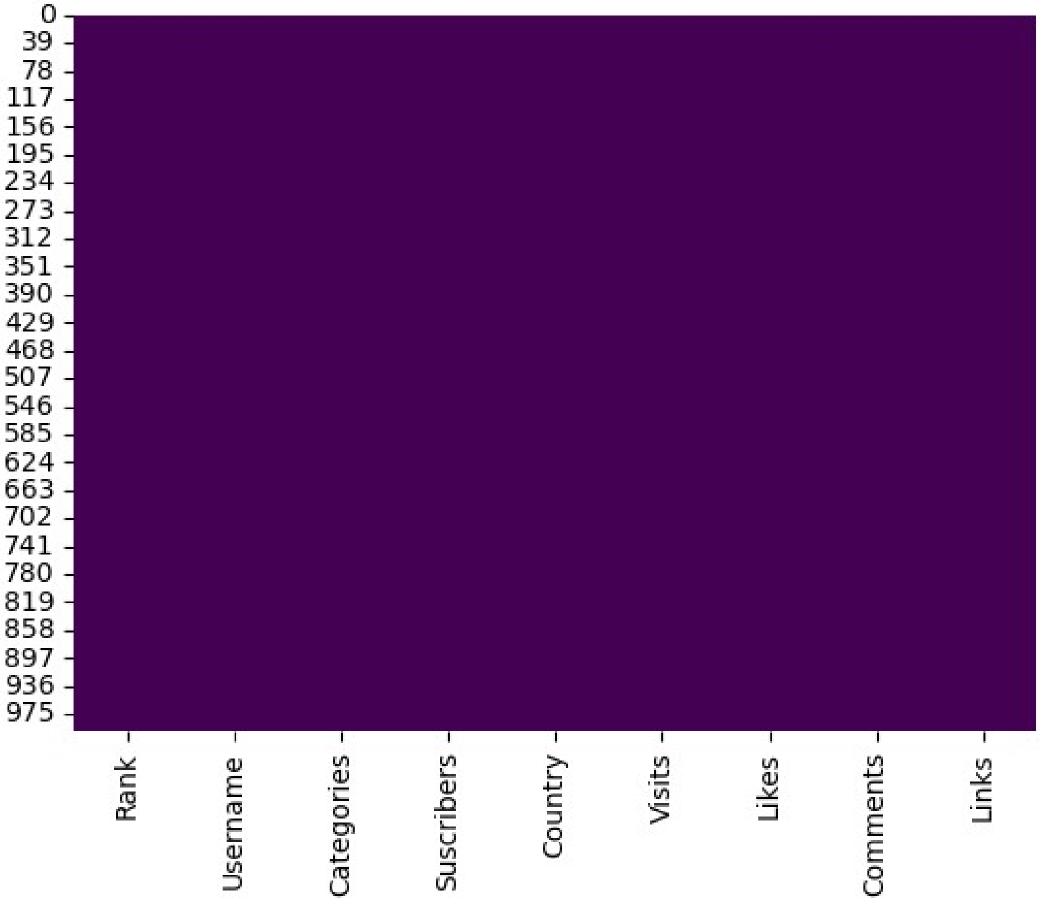
```python
#summary of statistics for numerical columns
print(df.describe())
```

```
              Rank    Suscribers        Visits         Likes
Comments
count  1000.000000  1.000000e+03  1.000000e+03  1.000000e+03
1000.000000
mean    500.500000  2.189440e+07  1.209446e+06  5.363259e+04
1288.768000
std     288.819436  1.682775e+07  5.229942e+06  2.580457e+05
6778.188308
min       1.000000  1.170000e+07  0.000000e+00  0.000000e+00
0.000000
25%     250.750000  1.380000e+07  3.197500e+04  4.717500e+02
2.000000
50%     500.500000  1.675000e+07  1.744500e+05  3.500000e+03
67.000000
75%     750.250000  2.370000e+07  8.654750e+05  2.865000e+04
472.000000
max    1000.000000  2.495000e+08  1.174000e+08  5.300000e+06
154000.000000
```

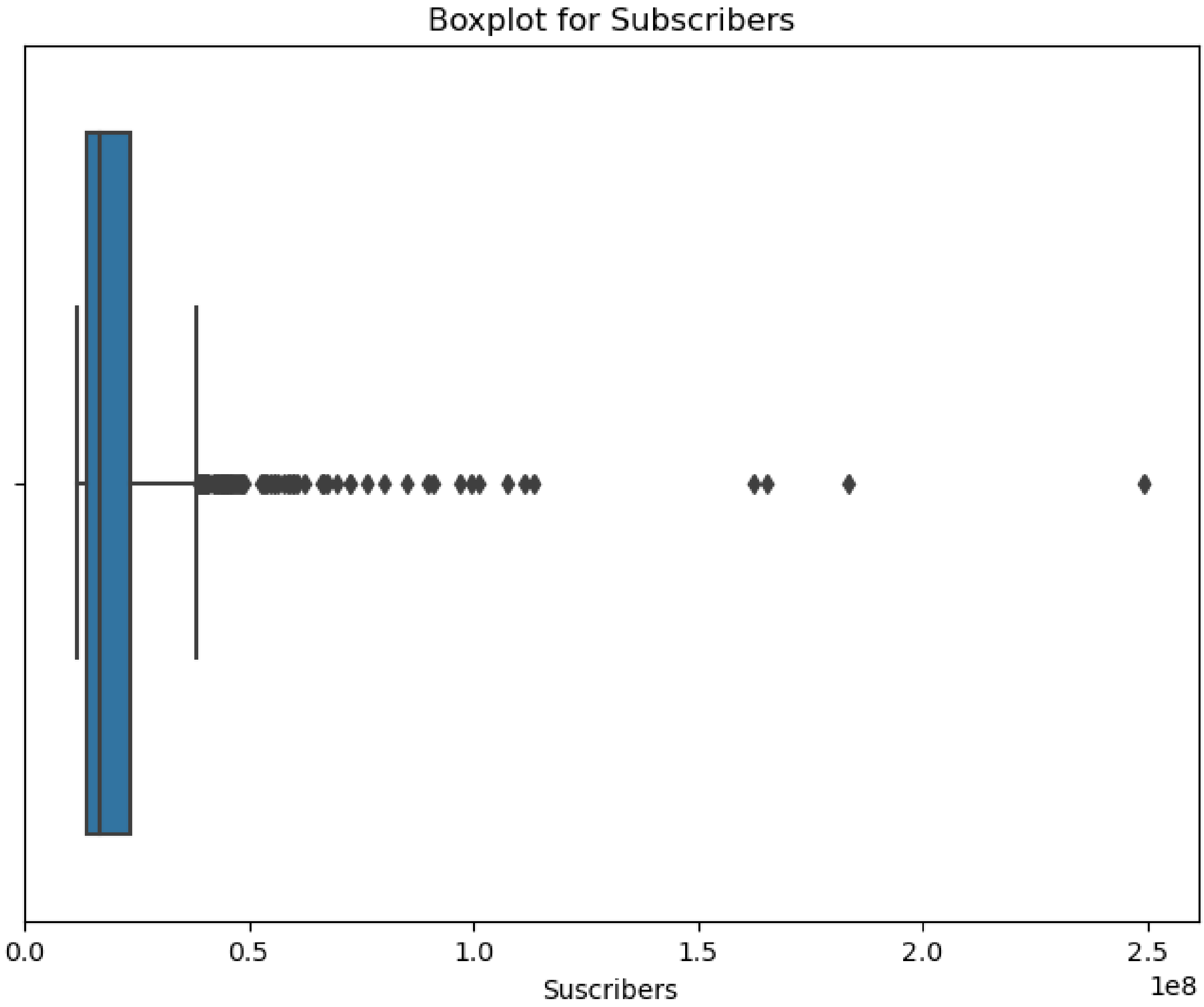
```
#check for missing values
missing_values = df.isnull().sum()
print("Missing Values:\n", missing_values)

Missing Values:
 Rank            0
Username        0
Categories    306
Suscribers      0
Country         0
Visits          0
Likes           0
Comments        0
Links           0
dtype: int64

#Visualise missing values using heat map
import seaborn as sns
sns.heatmap(df.isnull(), cbar=False, cmap='viridis')
plt.show()
```



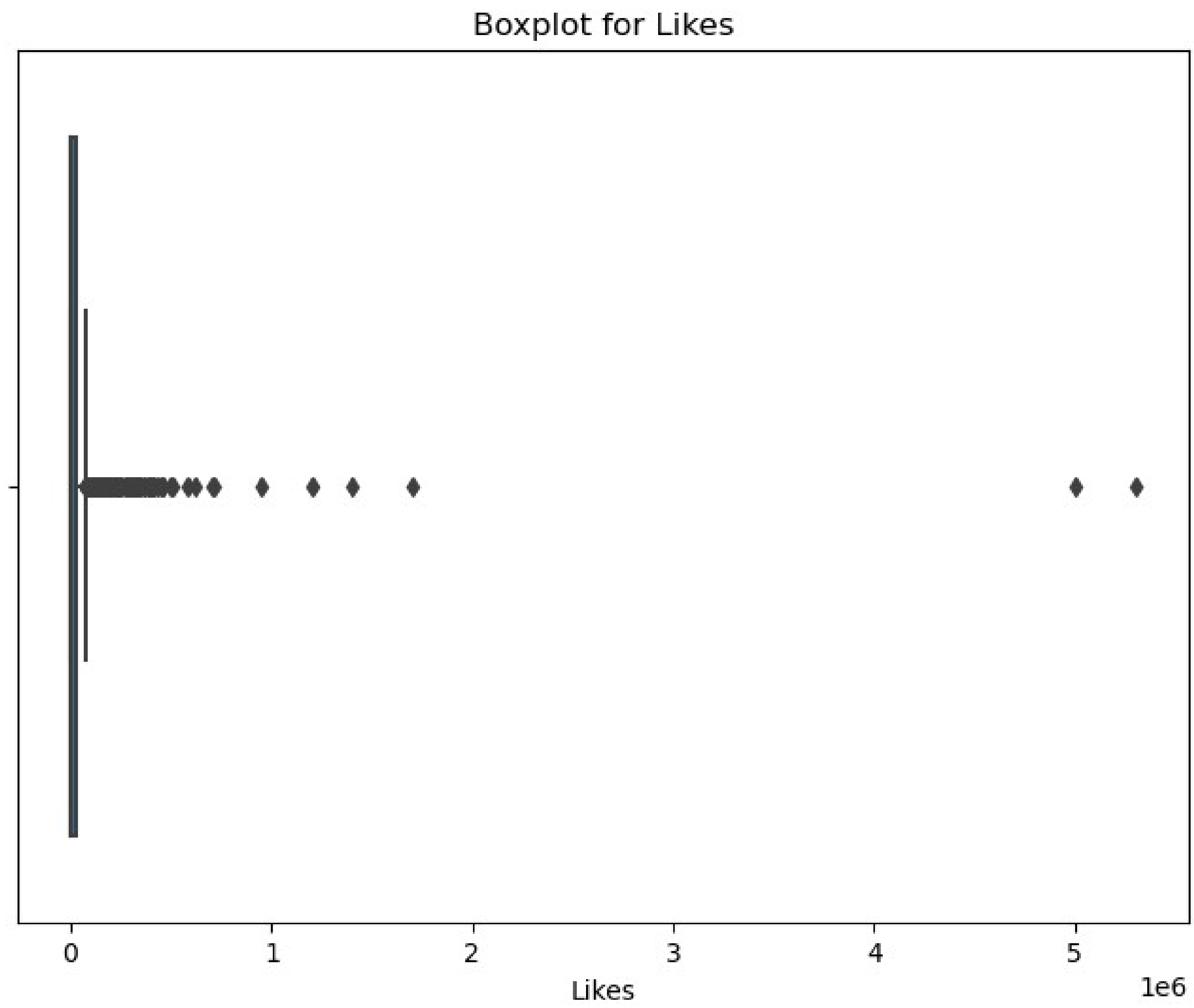
```
#replace the missing values in the Categories column with the most
frequently occuring Category

df['Categories'].fillna(df['Categories'].mode()[0], inplace=True)

#check back for missing values by plotting a heatmap
import seaborn as sns
sns.heatmap(df.isnull(), cbar=False, cmap='viridis')
plt.show()
```



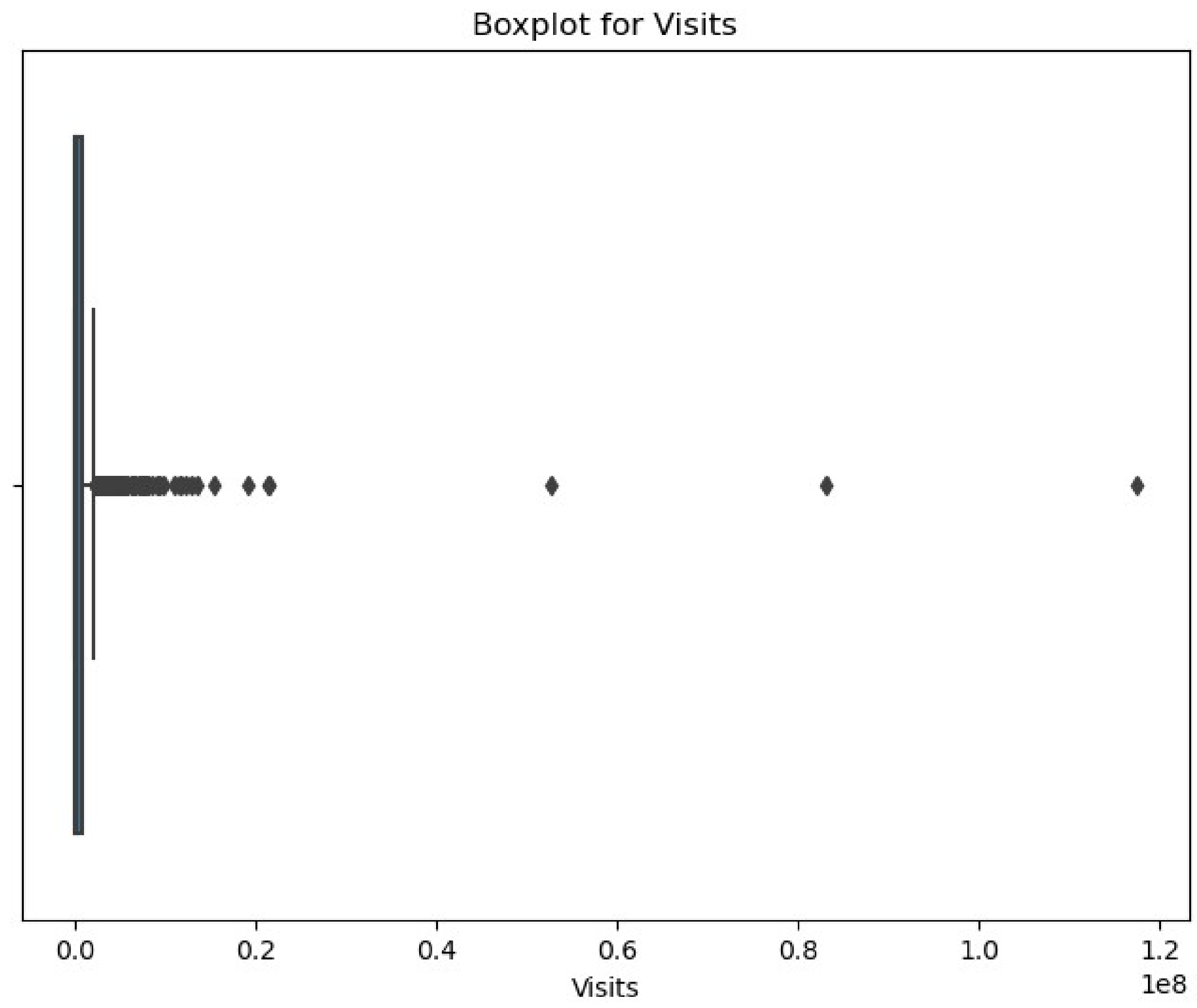
```
#identify outliers using boxplot
plt.figure(figsize=(8,6))
sns.boxplot(x=df['Suscribers'])
plt.title('Boxplot for Subscribers')
plt.show()
```



```
#identify if there are outliers in the 'Likes' column using boxplot

plt.figure(figsize=(8, 6))
sns.boxplot(x=df['Likes'])
plt.title('Boxplot for Likes')
plt.show()
```



```
#identify outliers for the column, Visits by plotting a boxplot

plt.figure(figsize=(8, 6))
sns.boxplot(x=df['Visits'])
plt.title('Boxplot for Visits')
plt.show()
```

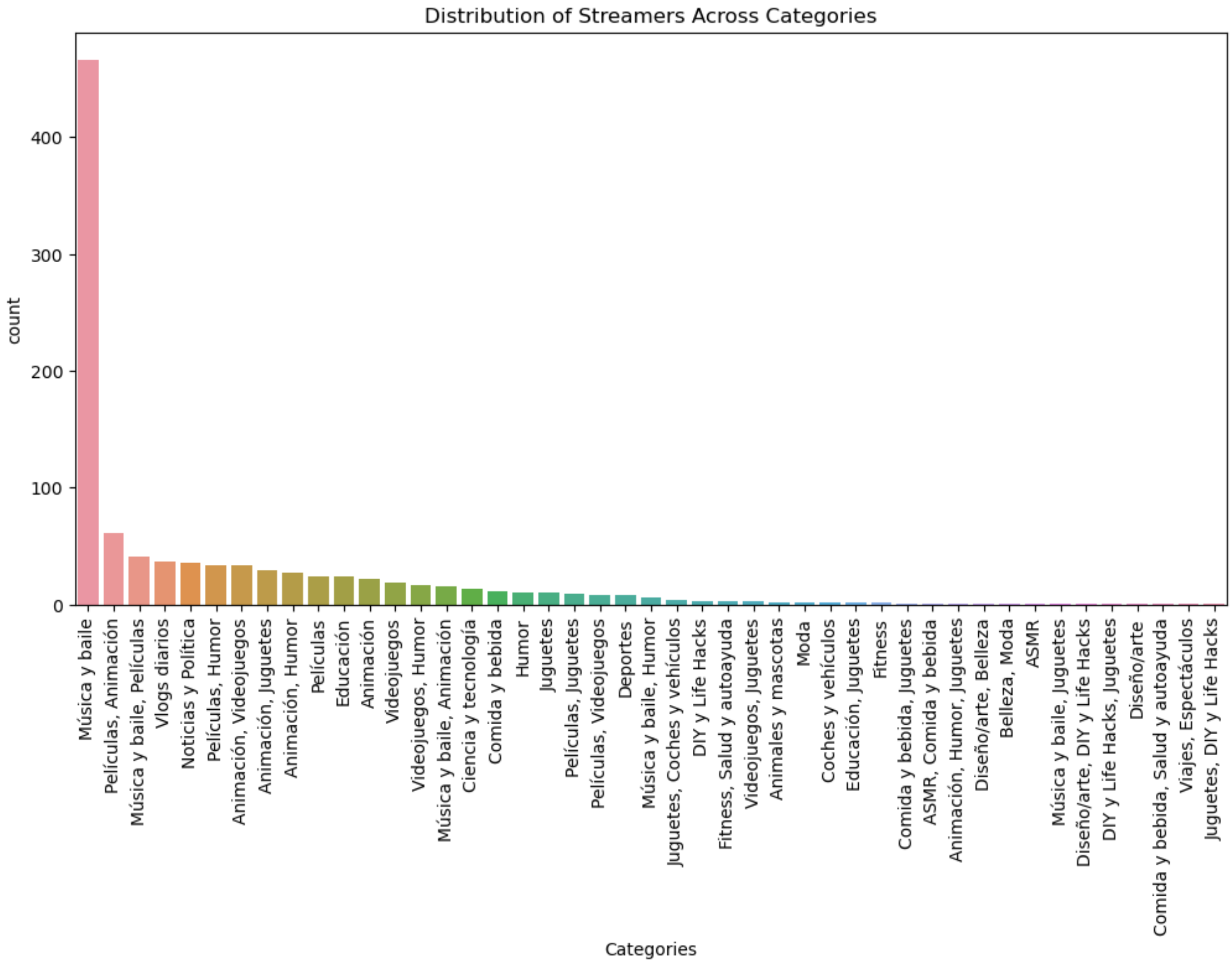


Trend Analysis

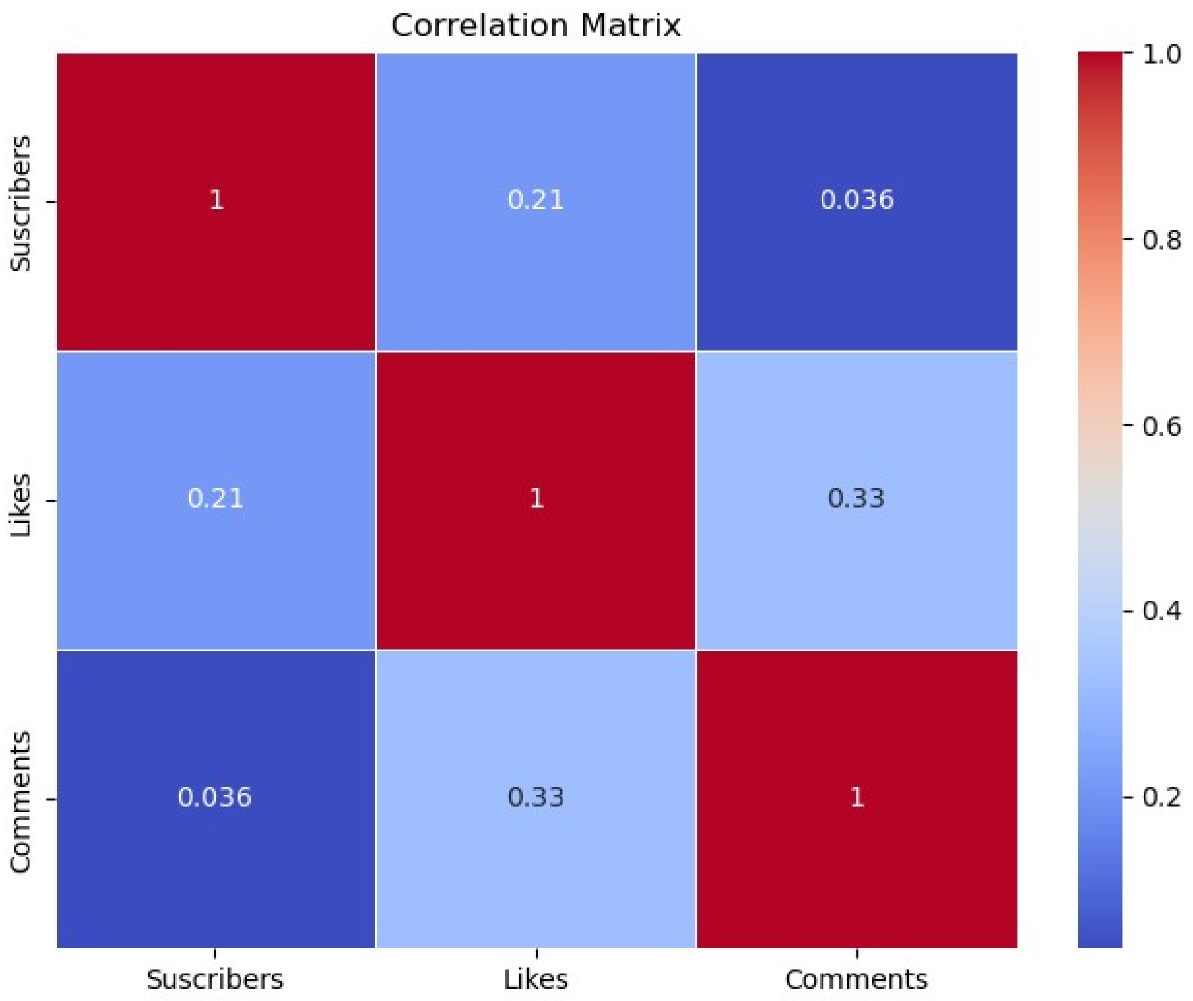
- Identifying trends among the top YouTube streamers. Which categories are the most popular?
- Is there a correlation between the number of subscribers and the number of likes or comments?

```
#define selected columns
selected_columns = ['Suscribers', 'Likes', 'Comments', 'Categories']

#create a subset of the dataframe with relevant columns
subset_df = df[selected_columns]

#identify popular categories
plt.figure(figsize=(12, 6))
sns.countplot(x='Categories', data=subset_df,
order=subset_df['Categories'].value_counts().index)
```

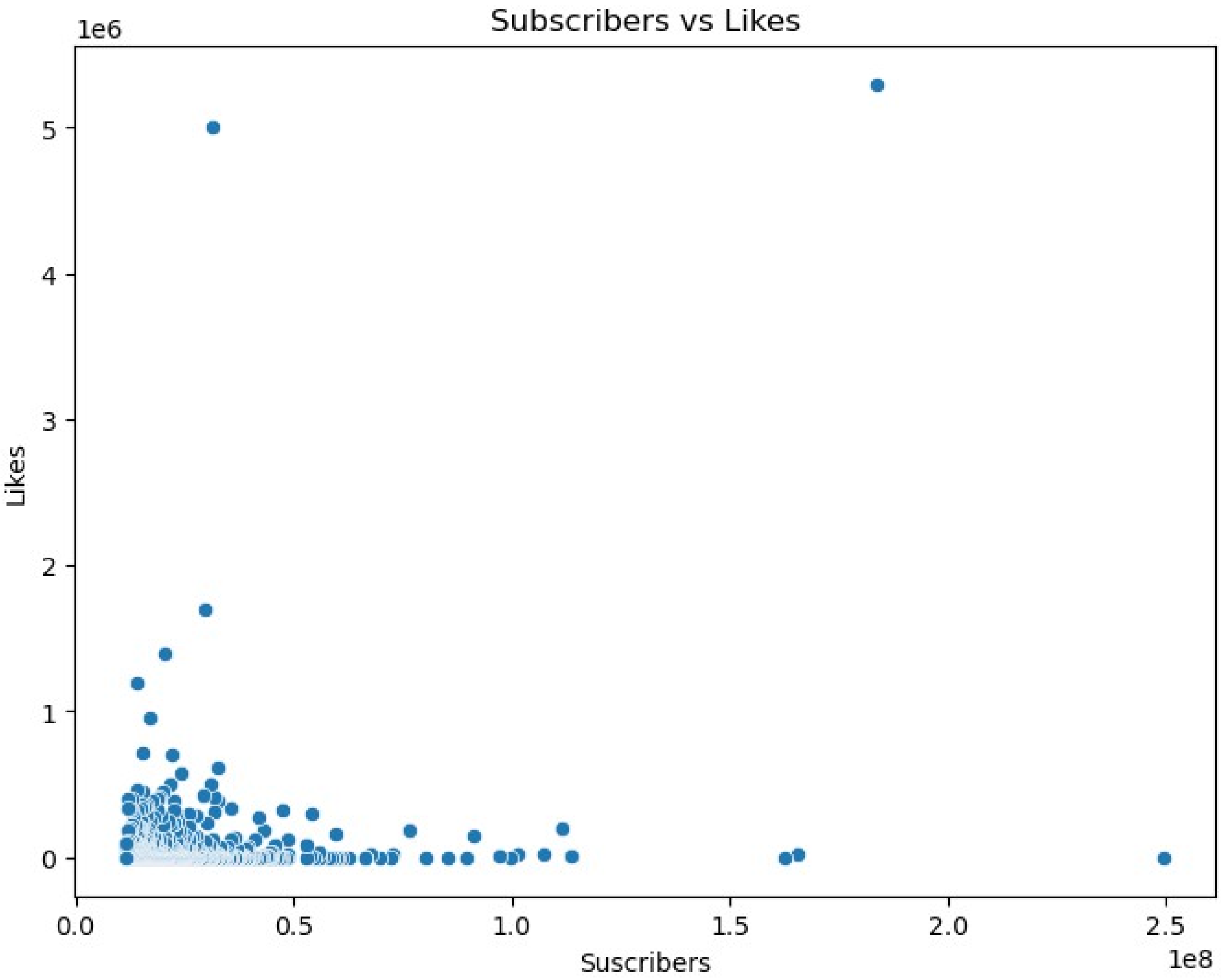
```
plt.xticks(rotation=90)
plt.title('Distribution of Streamers Across Categories')
plt.show()
```



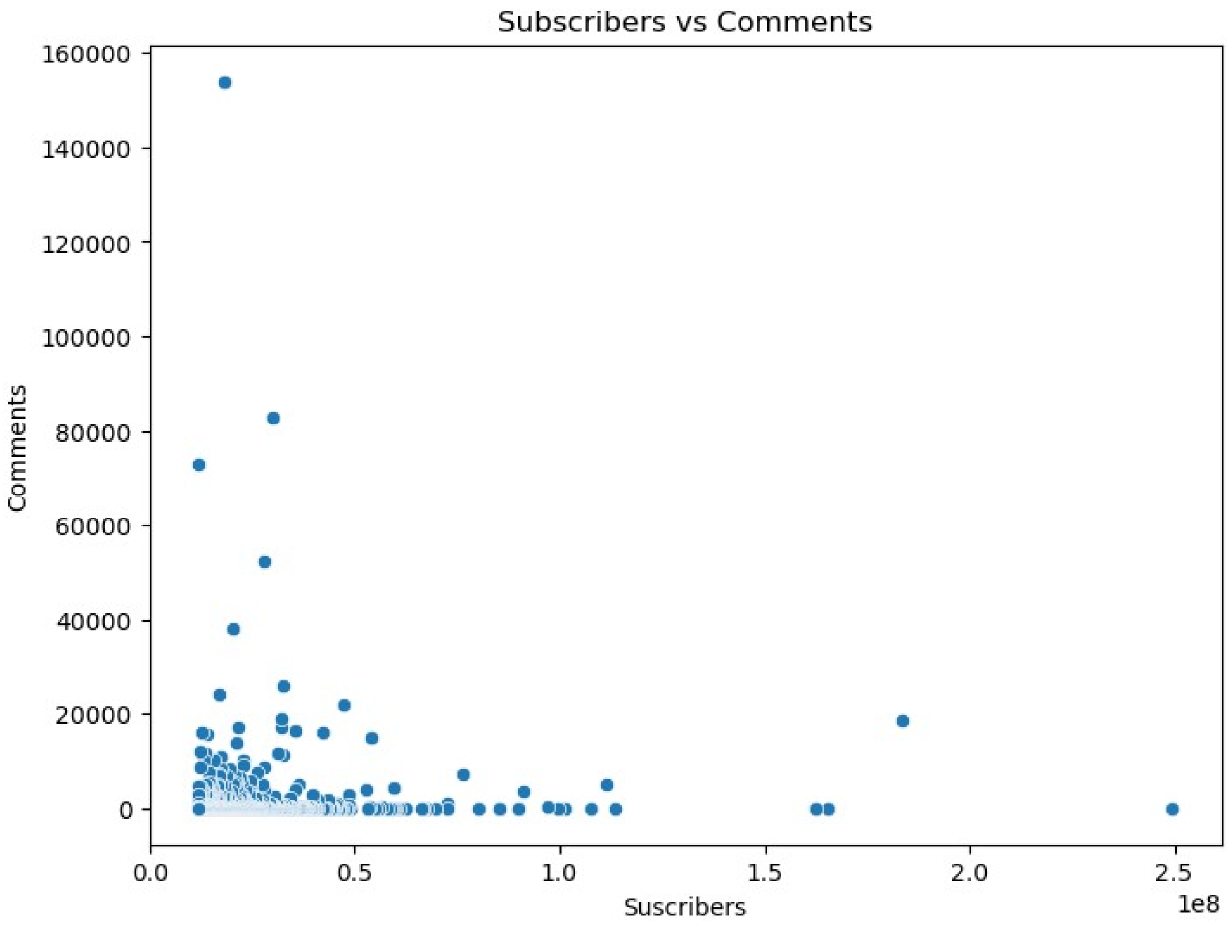
```
#correlation analysis to determine if there is a correlation between
the number of subscribers and the number of likes or comments
correlation_matrix= subset_df[['Suscribers', 'Likes',
'Comments']].corr()

#To visualize the correlation coefficient
plt.figure(figsize=(8, 6))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm',
linewidths=.5)
plt.title('Correlation Matrix')
plt.show()
```



```
#scatterplot of subscribers vs likes
plt.figure(figsize=(8, 6))
sns.scatterplot(x='Suscribers', y='Likes', data=subset_df)
plt.title('Subscribers vs Likes')
plt.show()
```



```
#scatterplot of subscribers vs likes
plt.figure(figsize=(8, 6))
sns.scatterplot(x='Suscribers', y='Comments', data=subset_df)
plt.title('Subscribers vs Comments')
plt.show()
```



Audience Study:

- Analyze the distribution of streamers' audiences by country. Are there regional preferences for specific content categories?

I'll start by checking for unique values in the "Categories" and "Country" columns to understand the distribution of streamers and content categories.

```
#Unique values in the "Country" column

unique_countries = df["Country"].unique()
print("Unique Countries:", unique_countries)

#unique values in the "Categories" column

unique_categories = df['Categories'].unique()
print("Unique Categories:", unique_categories)

Unique Countries: ['India' 'Estados Unidos' 'Unknown' 'Brasil'
'México' 'Rusia' 'Pakistán'
 'Filipinas' 'Indonesia' 'Tailandia' 'Francia' 'Colombia' 'Iraq'
'Japón'
 'Ecuador' 'Argentina' 'Turquía' 'Arabia Saudita' 'El Salvador'
 'Bangladesh' 'Reino Unido' 'Argelia' 'España' 'Perú' 'Egipto'
'Jordania'
 'Marruecos' 'Singapur' 'Somalia']
Unique Categories: ['Música y baile' 'Videojuegos, Humor' 'Educación'
nan
 'Animación, Juguetes' 'Películas, Videojuegos' 'Juguetes'
'Videojuegos'
 'Películas, Animación' 'Películas' 'Noticias y Política'
 'Animación, Humor' 'Música y baile, Animación'
 'Música y baile, Películas' 'Películas, Juguetes' 'Películas, Humor'
 'Vlogs diarios' 'Videojuegos, Juguetes' 'Animación, Videojuegos'
 'Animación' 'Música y baile, Humor' 'Diseño/arte, DIY y Life Hacks'
 'Ciencia y tecnología' 'Fitness, Salud y autoayuda' 'Belleza, Moda'
 'Humor' 'Comida y bebida' 'Deportes' 'Fitness' 'Viajes, Espectáculos'
 'Comida y bebida, Salud y autoayuda' 'Diseño/arte'
 'DIY y Life Hacks, Juguetes' 'Educación, Juguetes'
 'Juguetes, Coches y vehículos' 'Música y baile, Juguetes'
 'Animales y mascotas' 'ASMR' 'Moda' 'DIY y Life Hacks'
 'Diseño/arte, Belleza' 'Coches y vehículos' 'Animación, Humor,
Juguetes'
 'ASMR, Comida y bebida' 'Comida y bebida, Juguetes'
 'Juguetes, DIY y Life Hacks']
```

```
#to check the number of countries entered as "Unknown"

unknown_count = df["Country"].value_counts().get('Unknown', 0)

#print result

print(f"Number of entries named 'Unknown':{unknown_count}")
```

```
Number of entries named 'Unknown':171
```

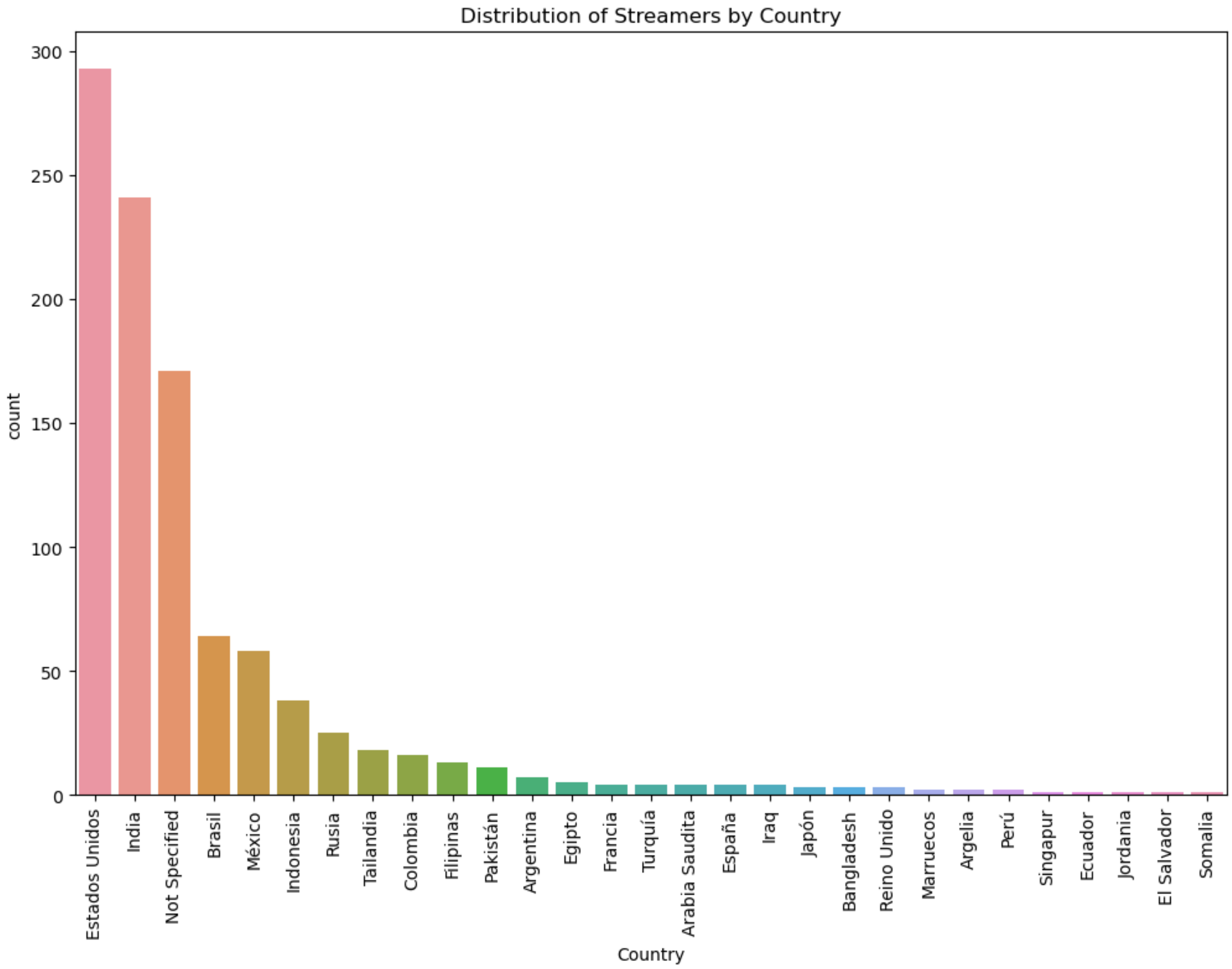
```
#replace 'Unknown' with a more descriptive category

df['Country'].replace('Unknown', 'Not Specified', inplace=True)
```

Visualising Distribution by country

Using a count plot to visialize distribution of streamers by country

```
import seaborn as sns

plt.figure(figsize=(12, 8))
sns.countplot(x='Country', data=df,
order=df['Country'].value_counts().index)
```

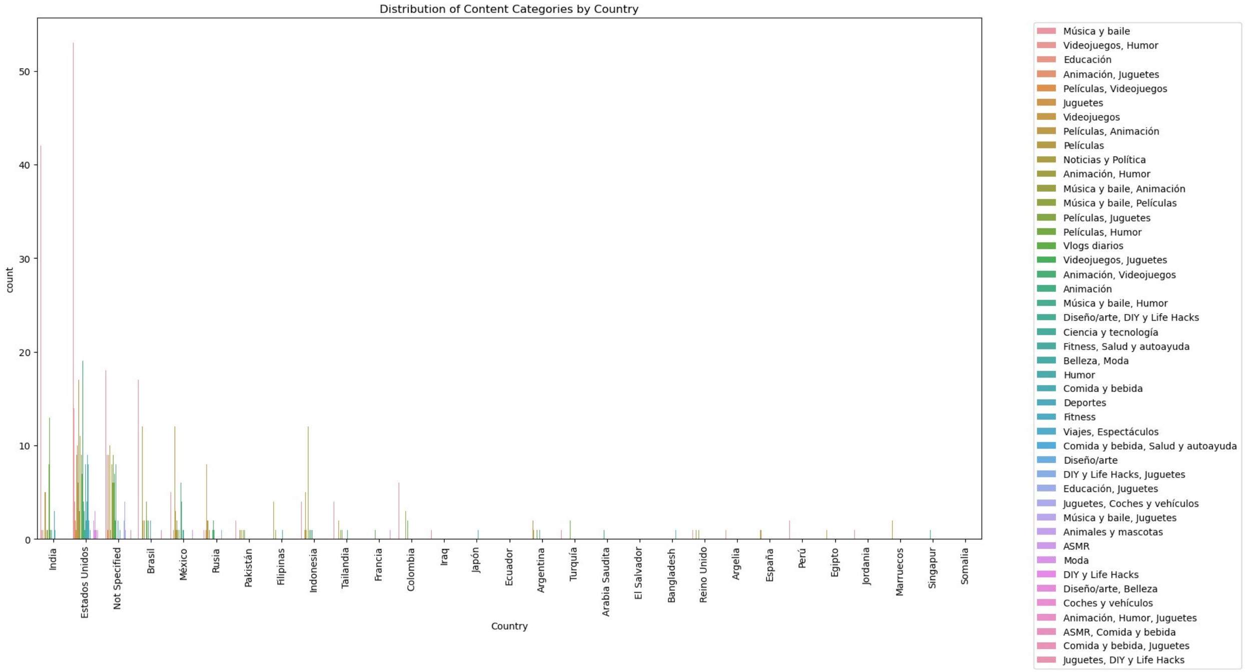
```
plt.xticks(rotation=90)
plt.title('Distribution of Streamers by Country')
plt.show()
```



Exploring Regional Preferences for Categories

- Investigating whether there are regional preferences for particular content categories.
- Using a count plot to investigate distribution of content categories across categories

```
plt.figure(figsize=(18,10))
sns.countplot(x='Country', hue='Categories', data=df)
plt.xticks(rotation=90)
plt.title('Distribution of Content Categories by Country')
plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left')
plt.show()
```



Statistical Analysis

- Performing a statistical analysis (chi-square test) to assess whether the distribution of content categories is different accross different countries

Null Hypothesis: There is no association between the country and content category.

Alternate Hypothesis: There is an association between the country and content category.

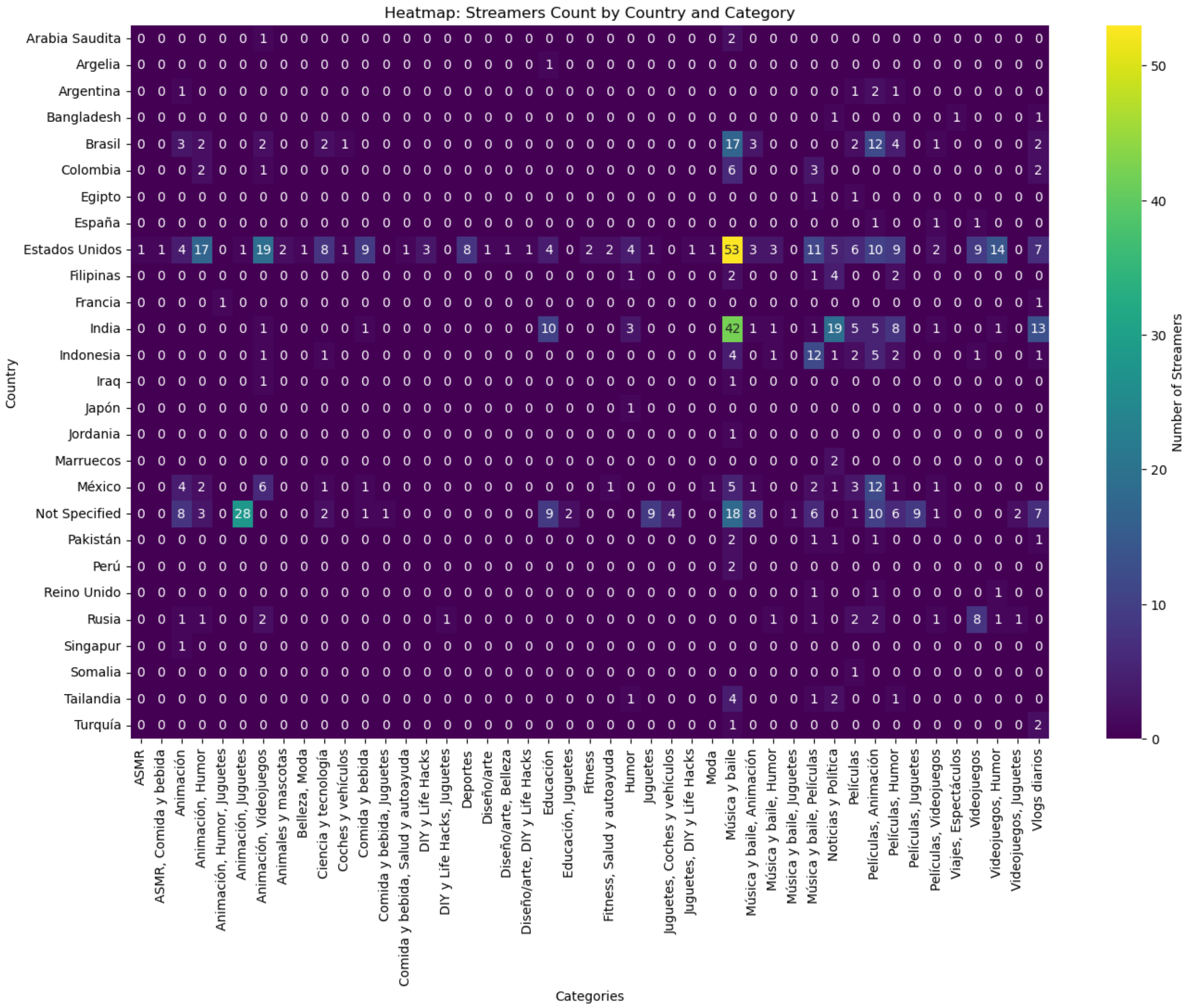
```
from scipy.stats import chi2_contingency

#creating a contingency table

contingency_table = pd.crosstab(df['Country'], df['Categories'])

#perform chi-square test

chi2, p, _, _ = chi2_contingency(contingency_table)
print(f"Chi-square Value: {chi2}, p-value: {p}")

Chi-square Value: 1797.776370988794, p-value: 6.094478820294259e-32
```

Since the p-value is extremely low, we would reject the null hypothesis. It implies that there is strong evidence to suggest that there is an association between the country of streamers and their content categories

Heatmap for Cross-Country Categories

- Visualizing the frequency of each content category across different countries using heatmap

```
plt.figure(figsize=(16, 10))
heatmap_data = df.groupby(['Country',
'Categories']).size().unstack(fill_value=0)
sns.heatmap(heatmap_data, cmap='viridis', annot=True, fmt='d',
cbar_kws={'label': 'Number of Streamers'})
plt.title('Heatmap: Streamers Count by Country and Category')
plt.show()
```



Country	ASMR	ASMR, Comida y bebida	Animación	Animación, Humor	Animación, Humor, Juguetes	Animación, Juguetes	Animación, Videojuegos	Animales y mascotas	Belleza, Moda	Ciencia y tecnología	Coches y vehículos	Comida y bebida	Comida y bebida, Juguetes	Comida y bebida, Salud y autoayuda	DIY y Life Hacks	DIY y Life Hacks, Juguetes	Deportes	Diseño/arte	Diseño/arte, Belleza	Diseño/arte, DIY y Life Hacks	Educación	Educación, Juguetes	Fitness	Fitness, Salud y autoayuda	Humor	Juguetes	Juguetes, Coches y vehículos	Juguetes, DIY y Life Hacks	Moda	Música y baile	Música y baile, Animación	Música y baile, Humor	Música y baile, Juguetes	Música y baile, Películas	Noticias y Política	Películas	Películas, Animación	Películas, Humor	Películas, Juguetes	Películas, Videojuegos	Viajes, Espectáculos	Videojuegos	Videojuegos, Humor	Videojuegos, Juguetes	Vlogs diarios
Arabia Saudita	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Argelia	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Argentina	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	2	1	0	0	0	0	0	0	0
Bangladesh	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	1
Brasil	0	0	3	2	0	0	2	0	0	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	17	3	0	0	0	0	2	12	4	0	1	0	0	0	0	2
Colombia	0	0	0	2	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6	0	0	0	3	0	0	0	0	0	0	0	0	0	0	2
Egipto	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0
España	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	1	0	0	0
Estados Unidos	1	1	4	17	0	1	19	2	1	8	1	9	0	1	3	0	8	1	1	1	4	0	2	2	4	1	0	1	1	53	3	3	0	11	5	6	10	9	0	2	0	9	14	0	7
Filipinas	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	2	0	0	0	1	4	0	0	2	0	0	0	0	0	0	0
Francia	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
India	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	10	0	0	0	3	0	0	0	0	42	1	1	0	1	19	5	5	8	0	1	0	0	1	0	13
Indonesia	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	1	0	12	1	2	5	2	0	0	0	1	0	0	1
Iraq	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Japón	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Jordania	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Marruecos	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0
México	0	0	4	2	0	0	6	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	5	1	0	0	2	1	3	12	1	0	1	0	0	0	0	0
Not Specified	0	0	8	3	0	28	0	0	0	2	0	1	1	0	0	0	0	0	0	0	9	2	0	0	0	9	4	0	0	18	8	0	1	6	0	1	10	6	9	1	0	0	0	2	7
Pakistán	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	1	1	0	1	0	0	0	0	0	0	0	1
Perú	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Reino Unido	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	1	0	0
Rusia	0	0	1	1	0	0	2	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	2	2	0	0	1	0	8	1	1	0
Singapur	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Somalia	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
Tailandia	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	4	0	0	0	1	2	0	0	1	0	0	0	0	0	0	0
Turquía	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2

Performance Metrics

- Calculate and visualize the average number of subscribers, visits, likes, and comments.
- Are there patterns or anomalies in these metrics?

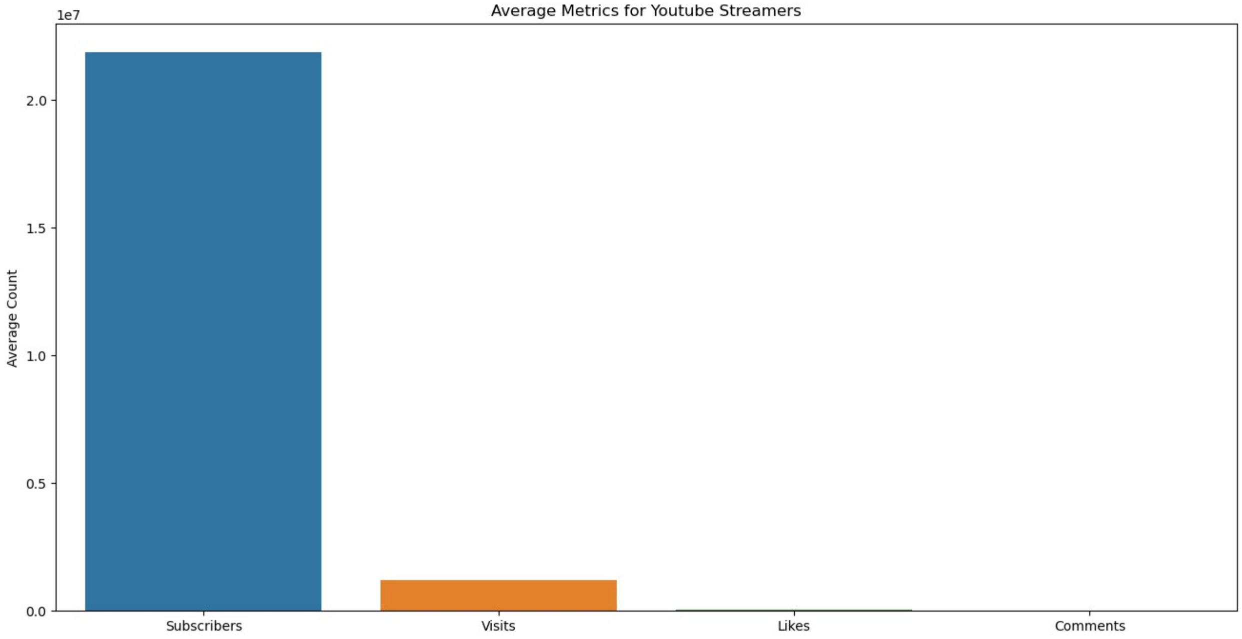
```
#Calculating the average of these metrics

average_subscribers = df['Suscribers'].mean()
average_visits = df['Visits'].mean()
average_likes = df['Likes'].mean()
average_comments = df['Comments'].mean()

#Display the results

print(f"Average Number of Subscribers: {average_subscribers}")
print(f"Average Number of Visits: {average_visits}")
print(f"Avereage Number of Likes: {average_likes}")
print(f"Average Number of Comments: {average_comments}")
```

```
Average Number of Subscribers: 21894400.0
Average Number of Visits: 1209446.3155
Avereage Number of Likes: 53632.592
Average Number of Comments: 1288.768
```

Visualizing the Averages for the Metrics

- Creating a bar plot to visialize the averages of the metrics

```
metrics = ['Subscribers', 'Visits', 'Likes', 'Comments']
averages = [average_subscribers, average_visits, average_likes,
average_comments]

plt.figure(figsize=(16, 8))
sns.barplot(x=metrics, y=averages)
plt.title('Average Metrics for Youtube Streamers')
plt.ylabel('Average Count')
plt.show()
```

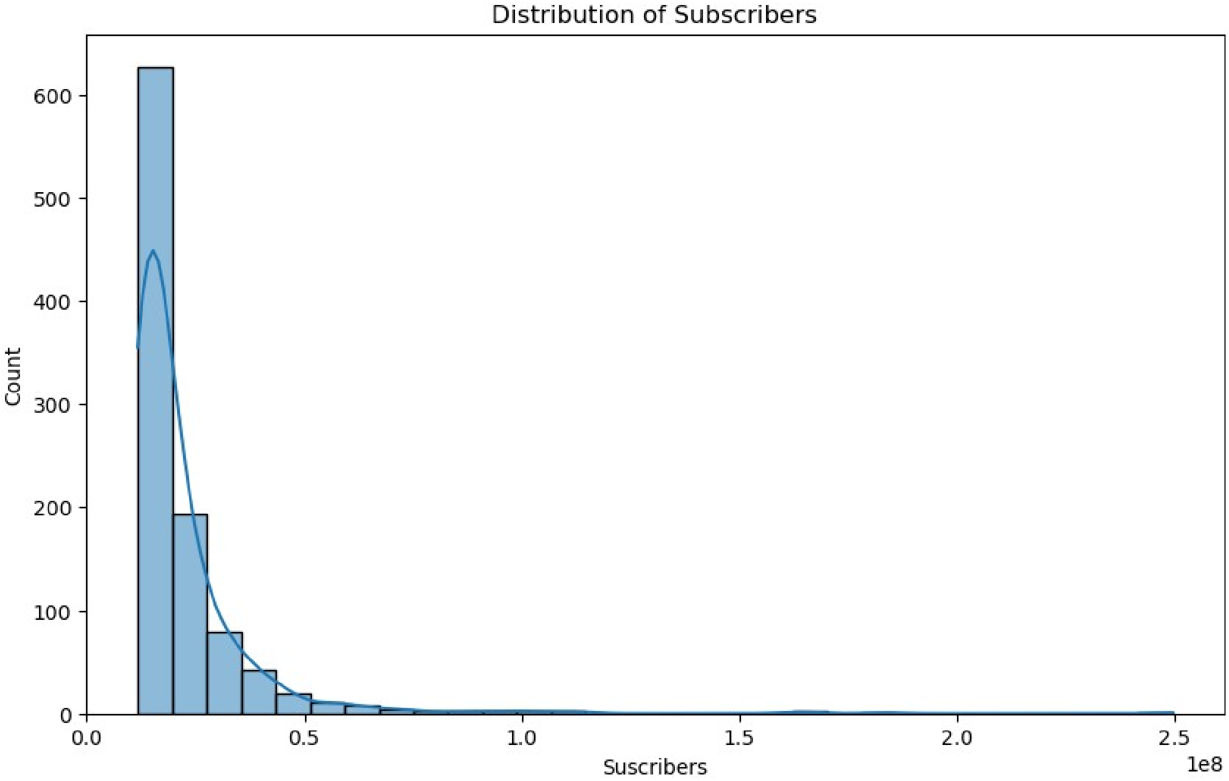


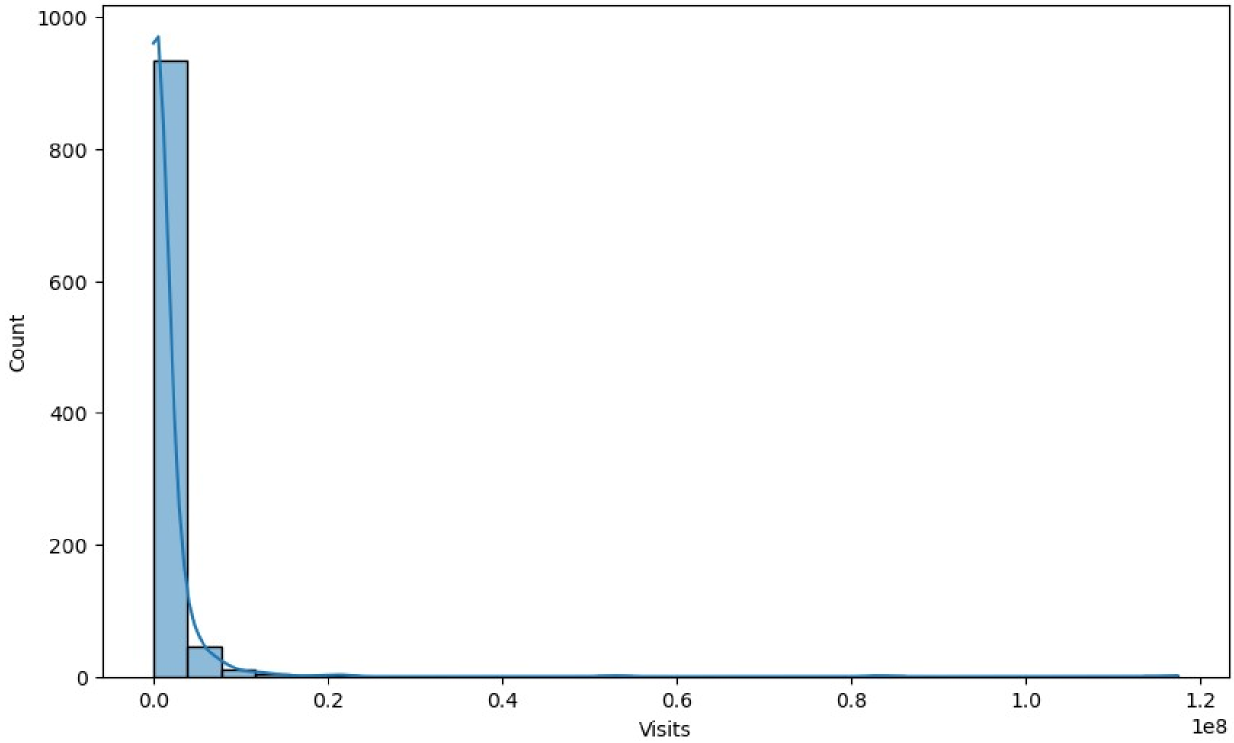
Detecting Patterns or Anomalies

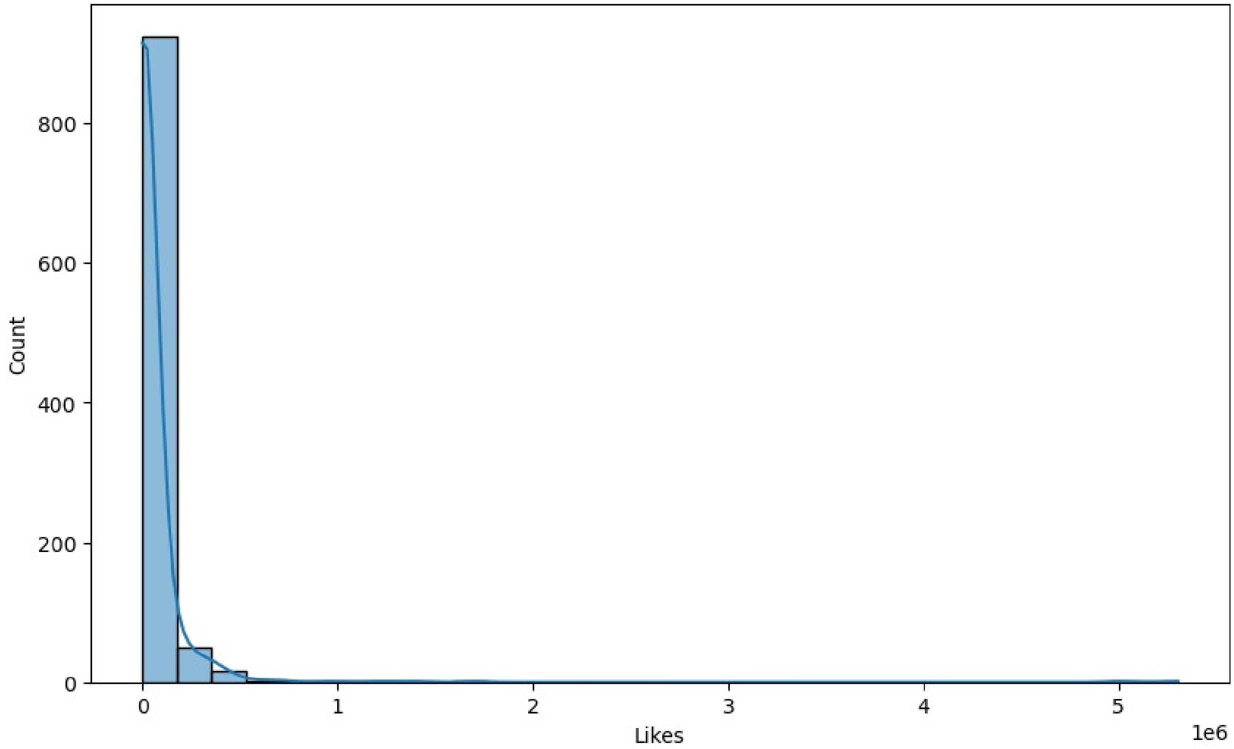
- Visualizing the distrubution of each metric individually using histogram to identify patterns or anomalies

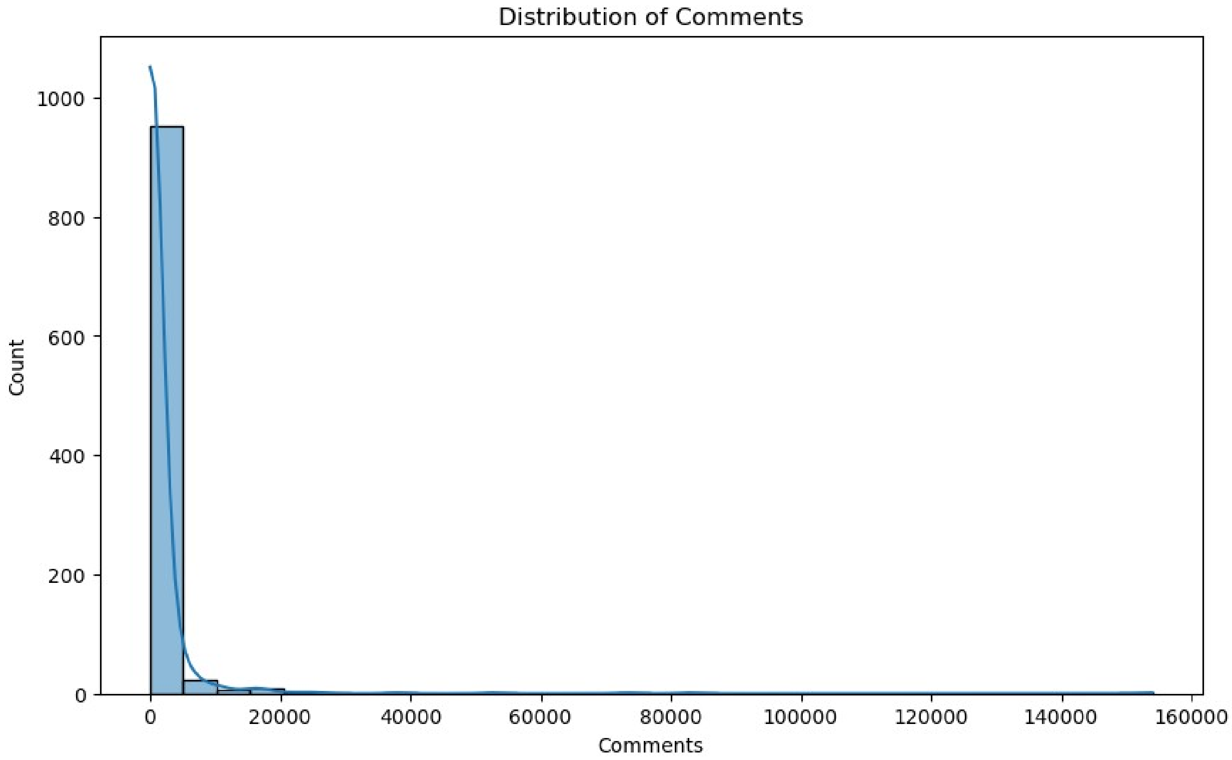
```
#Histogram for the Subscribers Column

plt.figure(figsize=(10, 6))
sns.histplot(df['Suscribers'], bins=30, kde=True)
plt.title('Distribution of Subscribers')
plt.show()

#Histogram for the Visits Column

plt.figure(figsize=(10, 6))
sns.histplot(df['Visits'], bins=30, kde=True)
plt.title('Distribution of Visits')
plt.show()

#Histogram for the Likes Column

plt.figure(figsize=(10, 6))
sns.histplot(df['Likes'], bins=30, kde=True)
plt.title('Distribution of Likes')
plt.show()

#Histogram for the Comments Column

plt.figure(figsize=(10, 6))
sns.histplot(df['Comments'], bins=30, kde=True)
```

```
plt.title('Distribution of Comments')
plt.show()
```




Distribution of Visits

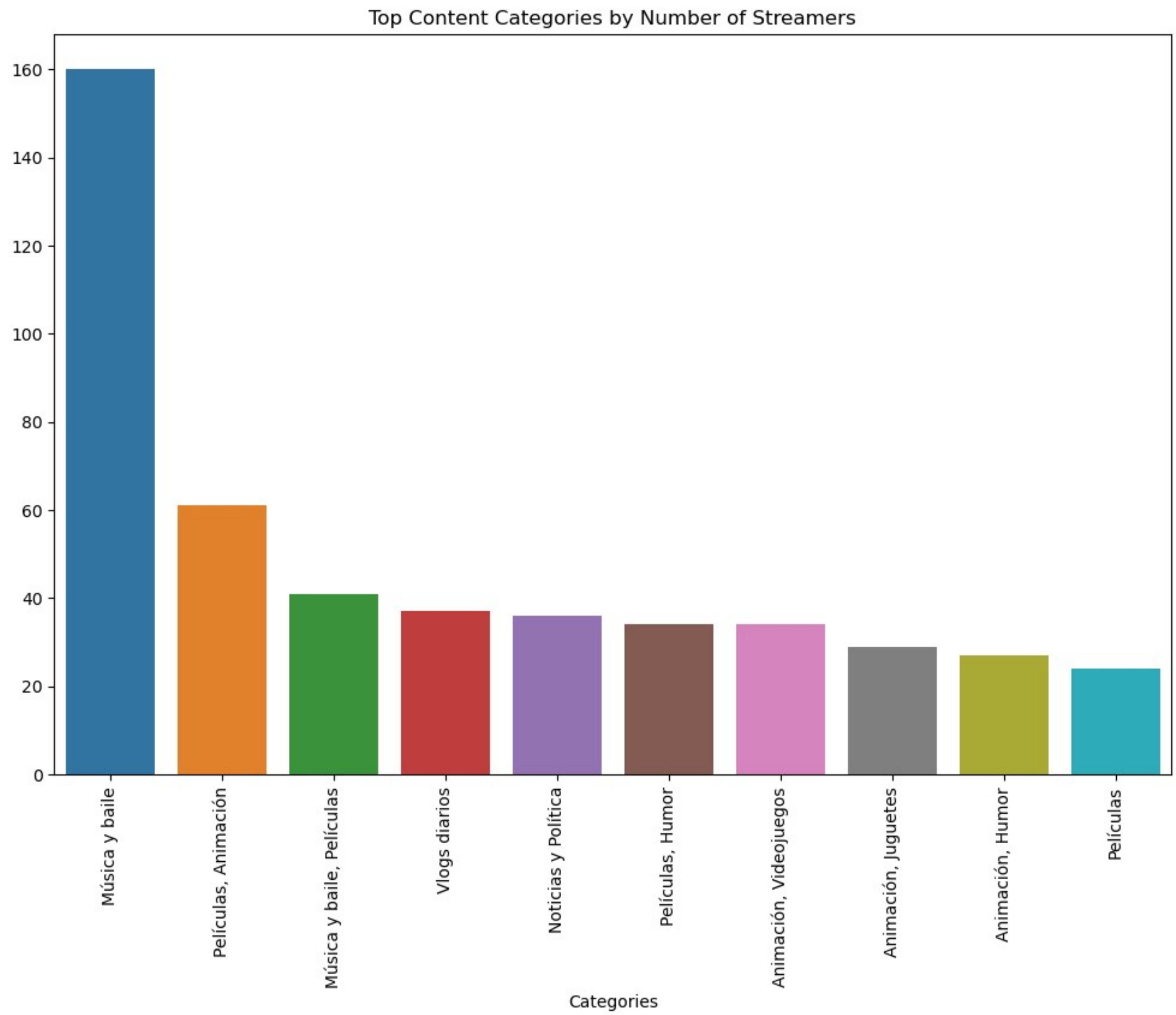

Distribution of Likes



Content Categories:

- Explore the distribution of content categories. Which categories have the highest number of streamers?
- Are there specific categories with exceptional performance metrics?

```
#checking the value counts for the categories with the highest number
of streamers using barplot

top_categories = df['Categories'].value_counts().head(10)
plt.figure(figsize=(12, 8))
sns.barplot(x=top_categories.index, y=top_categories.values)
plt.xticks(rotation=90)
plt.title('Top Content Categories by Number of Streamers')
plt.show()
```



Brands and Collaborations:

- Analyze whether streamers with high performance metrics receive more brand collaborations and marketing campaigns.

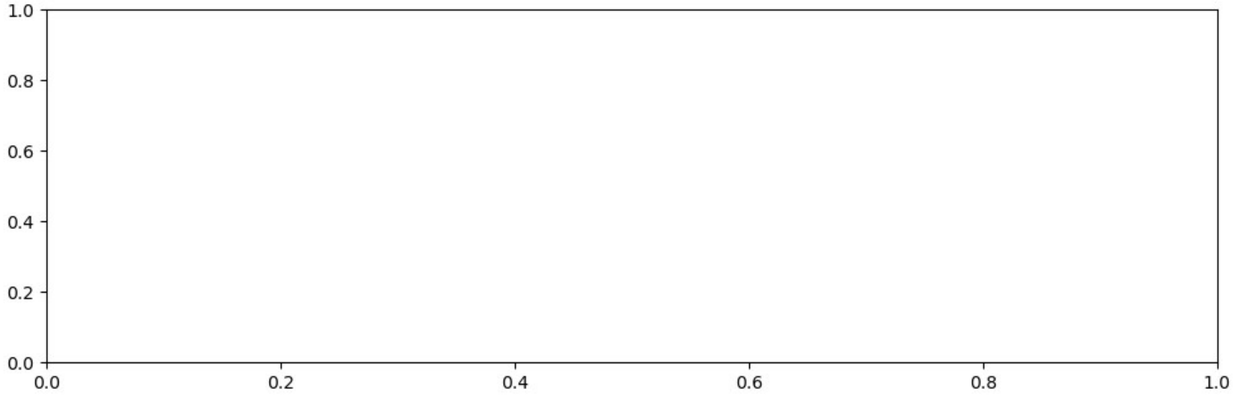
```
#Defining high-performance based on the top quartile of subscribers

subscriber_threshold = df['Suscribers'].quantile(0.75)
df['HighPerformance'] = df['Suscribers'] >= subscriber_threshold
```

Visualizing the Relationship:

Using visualizations to compare the distribution of high-performance streamers and non-high-performance streamers with regard to brand collaborations and marketing campaigns.

```python
plt.figure(figsize=(12, 8))

# Count plot for Brand Collaborations
plt.subplot(2, 1, 1)
sns.countplot(x='HighPerformance', hue='BrandCollaboration', data=df)
plt.title('Distribution of Brand Collaborations by Performance
Metrics')

# Count plot for Marketing Campaigns
plt.subplot(2, 1, 2)
sns.countplot(x='HighPerformance', hue='MarketingCampaign', data=df)
plt.title('Distribution of Marketing Campaigns by Performance
Metrics')

plt.tight_layout()
plt.show()
```

```
----------------------------------------------------------------------
-----
ValueError                                Traceback (most recent call
last)
Cell In[32], line 5
      3 # Count plot for Brand Collaborations
      4 plt.subplot(2, 1, 1)
----> 5 sns.countplot(x='HighPerformance', hue='BrandCollaboration',
data=df)
      6 plt.title('Distribution of Brand Collaborations by Performance
Metrics')
      8 # Count plot for Marketing Campaigns

File ~\anaconda3\Anaconda\Lib\site-packages\seaborn\
categorical.py:2943, in countplot(data, x, y, hue, order, hue_order,
orient, color, palette, saturation, width, dodge, ax, **kwargs)
   2940 elif x is not None and y is not None:
   2941     raise ValueError("Cannot pass values for both `x` and
`y`")
-> 2943 plotter = _CountPlotter(
   2944     x, y, hue, data, order, hue_order,
   2945     estimator, errorbar, n_boot, units, seed,
   2946     orient, color, palette, saturation,
   2947     width, errcolor, errwidth, capsize, dodge
   2948 )
   2950 plotter.value_label = "count"
   2952 if ax is None:

File ~\anaconda3\Anaconda\Lib\site-packages\seaborn\
categorical.py:1530, in _BarPlotter.__init__(self, x, y, hue, data,
order, hue_order, estimator, errorbar, n_boot, units, seed, orient,
color, palette, saturation, width, errcolor, errwidth, capsize, dodge)
   1525 def __init__(self, x, y, hue, data, order, hue_order,
   1526                 estimator, errorbar, n_boot, units, seed,
   1527                 orient, color, palette, saturation, width,
   1528                 errcolor, errwidth, capsize, dodge):
   1529     """Initialize the plotter."""
-> 1530     self.establish_variables(x, y, hue, data, orient,
   1531                              order, hue_order, units)
   1532     self.establish_colors(color, palette, saturation)
   1533     self.estimate_statistic(estimator, errorbar, n_boot, seed)

File ~\anaconda3\Anaconda\Lib\site-packages\seaborn\
categorical.py:541, in _CategoricalPlotter.establish_variables(self,
x, y, hue, data, orient, order, hue_order, units)
    539     if isinstance(var, str):
    540         err = f"Could not interpret input '{var}'"
--> 541         raise ValueError(err)
    543 # Figure out the plotting orientation
    544 orient = infer_orient(
    545     x, y, orient, require_numeric=self.require_numeric
    546 )

ValueError: Could not interpret input 'BrandCollaboration'
```



Benchmarking:

- Identify streamers with above-average performance in terms of subscribers, visits, likes, and comments.
- Who are the top-performing content creators?

```
above_average_criteria = 1.2  # Defining an above average criteris

above_average_subscribers = above_average_criteria *
average_subscribers
above_average_visits = above_average_criteria * average_visits
above_average_likes = above_average_criteria * average_likes
above_average_comments = above_average_criteria * average_comments
```

```
#identifying top performing content creators
top_streamers = df[
    (df['Suscribers'] > above_average_subscribers) &
    (df['Visits'] > above_average_visits) &
    (df['Likes'] > above_average_likes) &
    (df['Comments'] > above_average_comments)
]

#Displaying top performers
print("Top Performing Content Creators:")
print(top_streamers[['Username', 'Categories', 'Suscribers', 'Visits',
'Likes', 'Comments']])
```

```
Top Performing Content Creators:
                 Username              Categories   Suscribers
Visits  \
1                 MrBeast      Videojuegos, Humor  183500000.0
117400000.0
5               PewDiePie  Películas, Videojuegos  111500000.0
2400000.0
26            dudeperfect             Videojuegos   59700000.0
5300000.0
34            TaylorSwift          Música y baile   54100000.0
4300000.0
39            JuegaGerman    Películas, Animación   48600000.0
2000000.0
43               A4a4a4a4        Animación, Humor   47300000.0
9700000.0
58              Mikecrack    Películas, Animación   43400000.0
2200000.0
62         KimberlyLoaiza          Música y baile   42100000.0
5300000.0
64        luisitocomunica                     NaN   41100000.0
2500000.0
96         TotalGaming093  Películas, Videojuegos   36300000.0
1500000.0
98   TechnoGamerzOfficial                     NaN   35600000.0
6200000.0
100            markiplier  Animación, Videojuegos   35500000.0
2100000.0
122               AboFlah  Animación, Videojuegos   32700000.0
3300000.0
123        MRINDIANHACKER                     NaN   32600000.0
6500000.0
131          fedevigevani        Animación, Humor   32000000.0
7700000.0
132                 dream  Animación, Videojuegos   31900000.0
3300000.0
```

```
136              MrBeast2           Vlogs diarios   31300000.0
83100000.0
145         jacksepticeye        Animación, Humor   30400000.0
1600000.0
153             DaFuqBoom        Animación, Humor   29800000.0
52700000.0
176              CrazyXYZ                     NaN   27800000.0
4200000.0
177                DanTDM  Animación, Videojuegos   27800000.0
3500000.0
179           brentrivera      Videojuegos, Humor   27600000.0
6400000.0
180              NichLmao           Vlogs diarios   27500000.0
1500000.0

         Likes  Comments
1    5300000.0   18500.0
5     197300.0    4900.0
26    156500.0    4200.0
34    300400.0   15000.0
39    117100.0    3000.0
43    330400.0   22000.0
58    183400.0    1800.0
62    271300.0   16000.0
64    128900.0    1800.0
96    129400.0    4900.0
98    341800.0   16500.0
100   126500.0    3800.0
122   382000.0   11400.0
123   617400.0   26000.0
131   412200.0   17000.0
132   309200.0   19000.0
136  5000000.0   11600.0
145    83400.0    2300.0
153  1700000.0   82800.0
176   284100.0    8600.0
177   285000.0   52500.0
179   154100.0    5000.0
180    85800.0    1600.0
```

Content Recommendations:

- Propose a system for enhancing content recommendations to YouTube users based on streamers' categories and performance metrics

Enhancing content recommendations on YouTube based on streamers' categories and performance metrics involves leveraging a recommendation system that takes into account user preferences, content categories, and the performance of streamers. Here's a high-level proposal for such a system:

1. **User Profiling:**
   - Develop user profiles based on their viewing history, liked videos, and interactions.
   - Include user preferences for specific content categories, streamer performance metrics (e.g., preferred subscriber count, likes, comments), and historical engagement patterns.
2. **Content Categorization:**
   - Improve and expand the categorization of content on YouTube to include more granular categories or sub-genres.
   - Utilize machine learning techniques for automatic content tagging based on video features, titles, and descriptions.
3. **Streamer Performance Metrics:**
   - Incorporate streamer performance metrics (e.g., subscribers, likes, comments) as additional features in the recommendation system.
   - Consider normalizing performance metrics to account for varying audience sizes.
4. **Collaborative Filtering:**
   - Implement collaborative filtering techniques to recommend content based on the preferences and behaviors of users with similar profiles.
   - Explore both user-based and item-based collaborative filtering approaches.
5. **Content-Based Filtering:**
   - Utilize content-based filtering to recommend videos similar to those the user has already enjoyed, considering content categories and streamer performance metrics.
   - Leverage natural language processing (NLP) techniques to analyze video titles and descriptions.
6. **Hybrid Recommendation System:**
   - Develop a hybrid recommendation system that combines collaborative filtering, content-based filtering, and possibly other recommendation techniques (e.g., matrix factorization, deep learning models).
   - Fine-tune the weighting of different recommendation components based on user feedback and system performance.
7. **Real-Time Updates:**
   - Implement a system that continuously updates user profiles and recommendations in real-time as user preferences evolve and new content becomes available.
   - Regularly update streamer performance metrics to ensure accurate recommendations.
8. **Feedback Loop:**
   - Integrate a feedback loop where users can provide explicit feedback on recommended content.
   - Use implicit feedback signals, such as watch time and engagement, to further refine recommendations.
9. **Diversity in Recommendations:**

    - Ensure diversity in recommendations to expose users to a variety of content categories and streamers.
    - Implement techniques to balance popular content with personalized recommendations.

10. **Privacy Considerations:**
    - Implement privacy-aware features to respect user data and comply with privacy regulations.
    - Provide transparent options for users to control and customize their recommendation settings.
11. **A/B Testing:**
    - Conduct A/B testing to evaluate the performance of the recommendation system.
    - Monitor key metrics such as user engagement, click-through rates, and user satisfaction.

Implementing such a system requires collaboration between data scientists, machine learning engineers, and domain experts to fine-tune the algorithms and ensure effective recommendations. Regularly analyze user feedback and system performance to iteratively improve the recommendation system over time.