YouTube_Trending_Analytics

[ ]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import plotly.express as px
import warnings
warnings.filterwarnings('ignore')
from matplotlib.ticker import FuncFormatter
from matplotlib import ticker
```

[ ]:
```
data = pd.read_csv("DATA/Global_YouTube_Statistics.csv", encoding="ISO-8859-1")

data.head()
```

[ ]:
```
   rank                    Youtuber  subscribers   video views  \
0 1 T-Series 245000000 2.280000e+11 1 2 YouTube Movies
170000000   0.000000e+00   2   3   MrBeast   166000000
2.836884e+10
3     4 Cocomelon - Nursery Rhymes 162000000 1.640000e+11
4     5 SET India  159000000 1.480000e+11

          category                        Title uploads       Country \
0            Music T-Series    20082 India
1            Film & Animation youtubemovies     1 United States
2            Entertainment    MrBeast     741 United States
3            Education Cocomelon - Nursery Rhymes   966 United States
4            Shows SET India  116536      India

  Abbreviation channel_type … subscribers_for_last_30_days \
0           IN         Music …                   2000000.0
1           US         Games …                         NaN
2           US Entertainment …                   8000000.0
3           US      Education …                   1000000.0
4           IN Entertainment …                   1000000.0
   created_year created_month created_date \
0       2006.0           Mar         13.0
1       2006.0           Mar          5.0
2       2012.0           Feb         20.0
3       2006.0           Sep          1.0
4       2006.0           Sep         20.0
Gross tertiary education enrollment (%) Population Unemployment rate \
0                                  28.1 1.366418e+09            5.36
1                                  88.2 3.282395e+08           14.70
```

```
2                              88.2 3.282395e+08          14.70
3                              88.2 3.282395e+08          14.70
4                              28.1 1.366418e+09           5.36
  Urban_population Latitude Longitude
0      471031528.0 20.593684 78.962880
1      270663028.0 37.090240 -95.712891
2      270663028.0 37.090240 -95.712891
3      270663028.0 37.090240 -95.712891
4      471031528.0 20.593684 78.962880

[5 rows x 28 columns]
```

[ ]:
```
data.info()
```

```
<class
'pandas.core.frame.DataFrame'>
RangeIndex: 995 entries, 0 to
994 Data columns (total 28
columns):
#   Column                                  Non-Null Count Dtype
--- ------                                  -------------- -----
0    rank                                   995 non-null  int64
1   Youtuber                                995 non-null  object
2   subscribers                             995 non-null  int64
3   video views                             995 non-null  float64
4   category                                949 non-null  object
5    Title                                  995 non-null  object
6   uploads                                 995 non-null  int64
7   Country                                 873 non-null  object
8   Abbreviation                            873 non-null  object
9   channel_type                            965 non-null  object
 10 video_views_rank                        994 non-null  float64
 11 country_rank                            879 non-null  float64
 12 channel_type_rank                       962 non-null  float64
 13 video_views_for_the_last_30_days        939 non-null  float64
 14 lowest_monthly_earnings                 995 non-null  float64
 15 highest_monthly_earnings                995 non-null  float64
 16 lowest_yearly_earnings                  995 non-null  float64
 17 highest_yearly_earnings                 995 non-null  float64
 18 subscribers_for_last_30_days            658 non-null  float64
 19 created_year                            990 non-null  float64
20 created_month                           990 non-null  object
21 created_date                            990 non-null  float64
 22 Gross tertiary education enrollment (%) 872 non- float64
 null
23 Population                              872 non-null  float64
24 Unemployment rate                       872 non-null  float64
25 Urban_population                        872 non-null  float64
```

```
26 Latitude                                  872 non-null  float64
27 Longitude                                 872 non-null  float64
dtypes: float64(18), int64(3),
object(7) memory usage: 217.8+ KB
```

[ ]:
```
data.columns
```

[ ]:
```
Index(['rank', 'Youtuber', 'subscribers', 'video views', 'category',
'Title',
         'uploads', 'Country', 'Abbreviation', 'channel_type',
         'video_views_rank', 'country_rank', 'channel_type_rank',
         'video_views_for_the_last_30_days', 'lowest_monthly_earnings',
         'highest_monthly_earnings', 'lowest_yearly_earnings',
         'highest_yearly_earnings', 'subscribers_for_last_30_days',
         'created_year', 'created_month', 'created_date',
         'Gross tertiary education enrollment (%)', 'Population',
         'Unemployment rate', 'Urban_population', 'Latitude',
        'Longitude'], dtype='object')
```

[ ]:
```
data.tail()
```

[ ]:
```
     rank               Youtuber subscribers  video views \
990   991          Natan por Aï¿    12300000 9.029610e+09
991 992 Free Fire India Official    12300000 1.674410e+09
992   993                  Panda    12300000 2.214684e+09
993   994            RobTopGames    12300000 3.741235e+08
994   995           Make Joke Of    12300000 2.129774e+09

          category                   Title uploads        Country \
990         Sports            Natan por Aï¿   1200         Brazil
991 People & Blogs Free Fire India Official 1500           India
992            NaN             HybridPanda    2452         United
                                              Kingdom
993         Gaming             RobTopGames      39         Sweden
994         Comedy            Make Joke Of      62          India
   Abbreviation channel_type … subscribers_for_last_30_days \
990          BR Entertainment …                     700000.0
991          IN        Games …                     300000.0
992          GB        Games …                       1000.0
993          SE        Games …                     100000.0
994          IN       Comedy …                     100000.0
     created_year created_month created_date \
990        2017.0          Feb         12.0
991        2018.0          Sep         14.0
992        2006.0          Sep         11.0
993        2012.0          May          9.0
994        2017.0          Aug          1.0
   Gross tertiary education enrollment (%)  Population Unemployment rate
\
```

```
990                              51.3 2.125594e+08         12.08
991                              28.1 1.366418e+09          5.36
992                              60.0 6.683440e+07          3.85
993                              67.0 1.028545e+07          6.48
994                              28.1 1.366418e+09          5.36
    Urban_population   Latitude
Longitude 990     183241641.0 -14.235004
-51.925280
991       471031528.0 20.593684 78.962880
992       55908316.0 55.378051 -3.435973
993       9021165.0 60.128161 18.643501 994   471031528.0 20.593684
          78.962880

[5 rows x 28 columns]
```

[ ]:
```
data.describe()
```

[ ]:
```
          rank  subscribers  video views     uploads video_views_rank \
count 995.00000 9.950000e+02 9.950000e+02   995.000000    9.940000e+02
 mean   498.00000 2.298241e+07 1.103954e+109187.125628    5.542489e+05
 std    287.37606 1.752611e+07 1.411084e+1034151.352254   1.362782e+06
 min    1.00000 1.230000e+07 0.000000e+00     0.000000    1.000000e+00
 25%    249.50000 1.450000e+07 4.288145e+09 194.500000    3.230000e+02
 50%    498.00000 1.770000e+07 7.760820e+09 729.000000    9.155000e+02
 75%    746.50000 2.460000e+07 1.355470e+102667.500000    3.584500e+03
 max    995.00000 2.450000e+08 2.280000e+11 301308.0000004.057944e+06
        country_rank channel_type_rank video_views_for_the_last_30_days
        \
 count   879.000000       962.000000                  9.390000e+02
 mean    386.053470       745.719335                  1.756103e+08
 std    1232.244746      1944.386561                  4.163782e+08
 min       1.000000         1.000000                  1.000000e+00
 25%      11.000000        27.000000                  2.013750e+07
 50%      51.000000        65.500000                  6.408500e+07
 75%     123.000000       139.750000                  1.688265e+08
 max    7741.000000      7741.000000                  6.589000e+09

        lowest_monthly_earnings highest_monthly_earnings … \
 count              995.000000             9.950000e+02 …
 mean             36886.148281             5.898078e+05 …
 std              71858.724092             1.148622e+06 …
 min                  0.000000             0.000000e+00 …
 25%               2700.000000             4.350000e+04 …
 50%              13300.000000             2.127000e+05 …
 75%              37900.000000             6.068000e+05 …
 max             850900.000000             1.360000e+07 …
```

```
       highest_yearly_earnings         subscribers_for_last_30_days
       created_year \

count          9.950000e+02               6.580000e+02  990.000000
mean           7.081814e+06               3.490791e+05 2012.630303
std            1.379704e+07               6.143554e+05    4.512503
min            0.000000e+00               1.000000e+00 1970.000000
25%            5.217500e+05               1.000000e+05 2009.000000
50%            2.600000e+06               2.000000e+05 2013.000000
75%            7.300000e+06               4.000000e+05 2016.000000
max            1.634000e+08               8.000000e+06 2022.000000

       created_date Gross tertiary education enrollment (%)
                                                   Population \
count   990.000000                          872.000000 8.720000e+02
mean     15.746465                           63.627752 4.303873e+08
std       8.777520                           26.106893 4.727947e+08
min       1.000000                            7.600000 2.025060e+05
25%       8.000000                           36.300000 8.335541e+07
50%      16.000000                           68.000000 3.282395e+08
75%      23.000000                           88.200000 3.282395e+08
max      31.000000                          113.100000 1.397715e+09

       Unemployment rate Urban_populationLatitude Longitude
count        872.000000   8.720000e+02 872.000000 872.000000
mean           9.279278    2.242150e+08 26.632783 -14.128146
std            4.888354    1.546874e+08  20.560533  84.760809
min            0.750000   3.558800e+04 -38.416097 -172.104629
25%            5.270000    5.590832e+07 20.593684 -95.712891
50%            9.365000    2.706630e+08 37.090240 -51.925280
75%           14.700000    2.706630e+08  37.090240  78.962880
max           14.720000    8.429340e+08 61.924110 138.252924
[8 rows x 21 columns]
```

[ ]:
```
data.shape
```

[ ]: (995, 28)

[ ]:
```
data.isnull().sum()
```

[ ]:
```
rank                                        0

Youtuber                                    0

subscribers 0 video views    0   category
 46
Title  0 uploads   0
Country                                   122
```

```
Abbreviation      122 channel_type 30
video_views_rank  1 country_rank   116
channel_type_rank 33
video_views_for_the_last_30_days  56
lowest_monthly_earnings      0
highest_monthly_earnings     0
lowest_yearly_earnings 0 highest_yearly_earnings
 0 subscribers_for_last_30_days   337 created_year
 5 created_month  5 created_date   5
Gross tertiary education enrollment (%) 123
Population                              123
Unemployment rate                       123
Urban_population                        123
Latitude     123 Longitude    123
dtype: int64
```

[ ]:
```
data['category'].unique()
```

[ ]:
```
array(['Music', 'Film & Animation', 'Entertainment',
       'Education', 'Shows', nan, 'People & Blogs', 'Gaming',
       'Sports', 'Howto & Style', 'News & Politics', 'Comedy',
       'Trailers', 'Nonprofits & Activism',
       'Science & Technology', 'Movies', 'Pets & Animals',
   'Autos & Vehicles', 'Travel & Events'], dtype=object)
```

[ ]:
```
data['category'].nunique()
```

[ ]: 18

[ ]:
```
data.duplicated().sum()
```

[ ]: 0

[ ]:
```
data = data.dropna()
```

[ ]:
```
data[data['category'].isnull()].head(5)
```

[ ]:
```
Empty DataFrame
Columns: [rank, Youtuber, subscribers, video views, category, Title,
uploads, Country, Abbreviation, channel_type, video_views_rank,
country_rank, channel_type_rank, video_views_for_the_last_30_days,
lowest_monthly_earnings, highest_monthly_earnings,
lowest_yearly_earnings, highest_yearly_earnings,
subscribers_for_last_30_days, created_year, created_month,
created_date, Gross
tertiary education enrollment (%), Population, Unemployment rate,
Urban_population, Latitude, Longitude]
Index: []
```

[0 rows x 28 columns]

```
[ ]: dropped_features = [
         'Abbreviation', 'created_month', 'created_date', 'Latitude', 'Longitude'
     ]
     data = data.drop(data[dropped_features], axis=1)
     data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 554 entries, 0 to 994
Data columns (total 23 columns):

#   Column                                  Non-Null Count Dtype
--- ------                                  -------------- -----
0    rank                                   554 non-null  int64
1    Youtuber                               554 non-null  object
2    subscribers                            554 non-null  int64
3    video views                            554 non-null  float64
4    category                               554 non-null  object
5    Title                                  554 non-null  object
6    uploads                                554 non-null  int64
7    Country                                554 non-null  object
8    channel_type                           554 non-null  object
9   video_views_rank                        554 non-null  float64
 10 country_rank                            554 non-null  float64
 11 channel_type_rank                       554 non-null  float64
 12 video_views_for_the_last_30_days        554 non-null  float64
 13 lowest_monthly_earnings                 554 non-null  float64
 14 highest_monthly_earnings                554 non-null  float64
 15 lowest_yearly_earnings                  554 non-null  float64
 16 highest_yearly_earnings                 554 non-null  float64
 17 subscribers_for_last_30_days            554 non-null  float64
 18 created_year                            554 non-null  float64
 19 Gross tertiary education enrollment (%) 554 non- float64
 null
20 Population                              554 non-null  float64
21 Unemployment rate                       554 non-null  float64
22 Urban_population                        554 non-null  float64
dtypes: float64(15), int64(3),
object(5) memory usage: 103.9+ KB
```

[ ]:
```
numerical_cols = ['subscribers', 'video views', 'uploads',
                  'lowest_monthly_earnings', 'highest_monthly_earnings',
                  'lowest_yearly_earnings', 'highest_yearly_earnings',
                  'video_views_for_the_last_30_days',␣
 ↪'subscribers_for_last_30_days']

correlation_matrix = data[numerical_cols].corr()

correlation_matrix
```

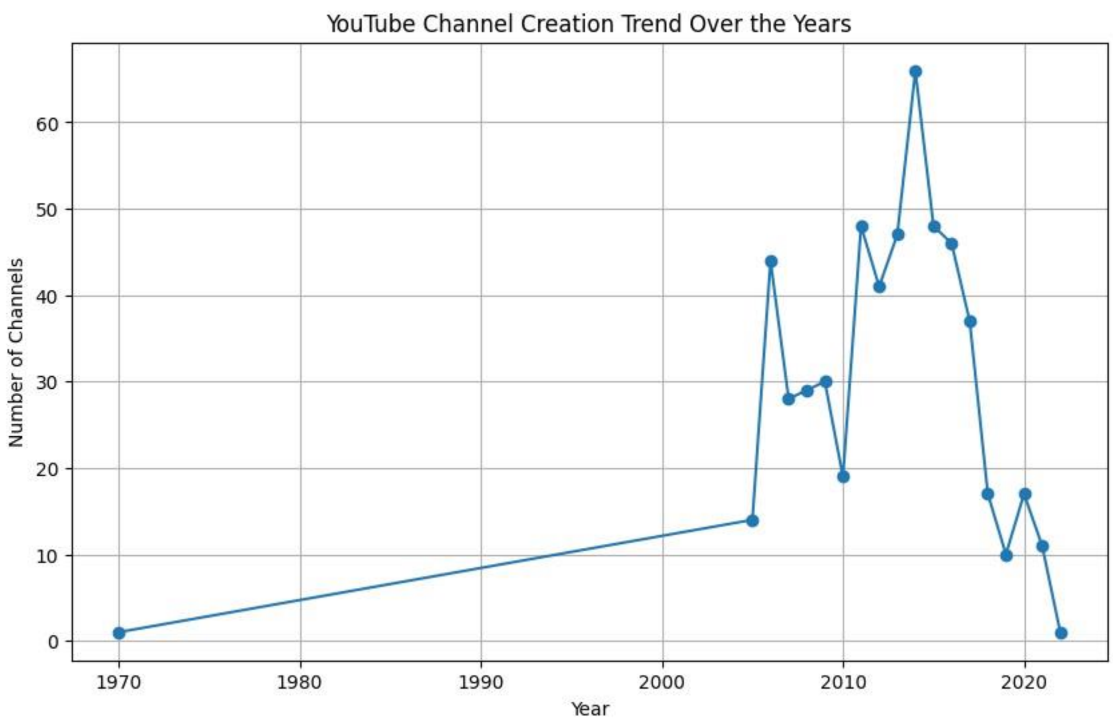
[ ]:
```
                                  subscribers  video views   uploads  \
subscribers                          1.000000     0.850776  0.074791
video views                          0.850776     1.000000  0.147477
uploads                              0.074791     0.147477  1.000000
lowest_monthly_earnings              0.534713     0.637991  0.155557
highest_monthly_earnings             0.534388     0.637376  0.156062
lowest_yearly_earnings               0.534883     0.638861  0.156639
highest_yearly_earnings              0.534721     0.638019  0.155540
video_views_for_the_last_30_days     0.321182     0.360970  0.079308
subscribers_for_last_30_days          0.361800     0.203693   0.009067
                                  lowest_monthly_earnings  \

subscribers                                      0.534713
video views                                      0.637991
uploads                                          0.155557
lowest_monthly_earnings                          1.000000
highest_monthly_earnings                         0.999937
lowest_yearly_earnings                           0.999914
highest_yearly_earnings                          0.999998
video_views_for_the_last_30_days                 0.585838
subscribers_for_last_30_days                     0.616795

                                  highest_monthly_earnings  \
subscribers                                       0.534388
video views                                       0.637376
uploads                                           0.156062
lowest_monthly_earnings                           0.999937
highest_monthly_earnings                          1.000000
lowest_yearly_earnings                            0.999832
highest_yearly_earnings                           0.999935
video_views_for_the_last_30_days                  0.585788
subscribers_for_last_30_days                      0.617150

                                  lowest_yearly_earnings  \
subscribers                                     0.534883
video views                                     0.638861
uploads                                         0.156639
```

```
lowest_monthly_earnings                         0.999914
highest_monthly_earnings                        0.999832
lowest_yearly_earnings                          1.000000
highest_yearly_earnings                         0.999912
video_views_for_the_last_30_days                0.585758
subscribers_for_last_30_days                    0.615874

                                highest_yearly_earnings \
subscribers                                      0.534721
video views                                      0.638019
uploads                                          0.155540
lowest_monthly_earnings                          0.999998
highest_monthly_earnings                         0.999935
lowest_yearly_earnings                           0.999912
highest_yearly_earnings                          1.000000
video_views_for_the_last_30_days                 0.585837
subscribers_for_last_30_days                     0.616816

                                video_views_for_the_last_30_days
\
subscribers                                              0.321182
video views                                              0.360970
uploads                                                  0.079308
lowest_monthly_earnings                                  0.585838
highest_monthly_earnings                                 0.585788
lowest_yearly_earnings                                   0.585758
highest_yearly_earnings                                  0.585837
video_views_for_the_last_30_days                         1.000000
subscribers_for_last_30_days                             0.366320

                                subscribers_for_last_30_days
subscribers                                          0.361800
video views                                          0.203693
uploads                                              0.009067
lowest_monthly_earnings                              0.616795
highest_monthly_earnings                             0.617150
lowest_yearly_earnings                               0.615874
highest_yearly_earnings                              0.616816
video_views_for_the_last_30_days                     0.366320
subscribers_for_last_30_days                         1.000000
```

This code calculates and visualizes the trend in YouTube channel creation over the years using the "created_year" column. Once you've completed this step, you can proceed to the next analysis. If you'd like to continue with the next step or have any questions, please feel free to ask.

[ ]:
```
yearly_trend = data['created_year'].value_counts().sort_index()
```

```
[ ]: # Visualize the YouTube channel creation trend over the years
plt.figure(figsize=(10, 6))
plt.plot(yearly_trend.index, yearly_trend.values, marker='o', linestyle='-')
plt.title('YouTube Channel Creation Trend Over the Years ')
plt.xlabel('Year')
plt.ylabel('Number of Channels')
plt.grid(True)
plt.show()
```



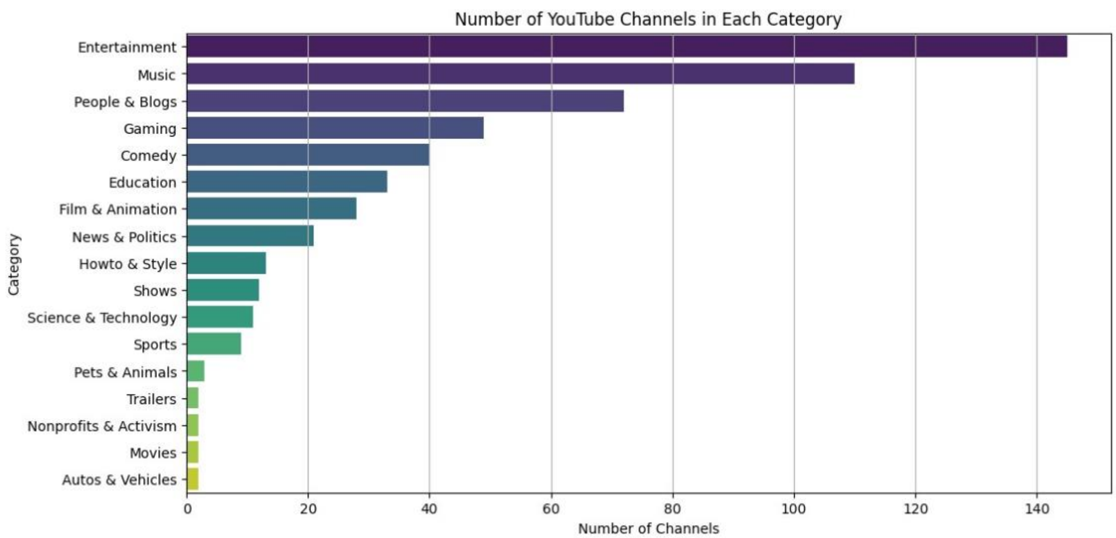
This code calculates and visualizes the number of YouTube channels in each category using a bar plot. It will help you understand which categories have the most channels. If you have any questions or would like to proceed with the next analysis step, please feel free to ask.

```
[ ]: # Calculate the number of channels in each category

category_counts = data['category'].value_counts()
```

```
[ ]: category_counts = category_counts.sort_values(ascending=False)
# Sort the categories by the number of channels in descending order
```

```
[ ]: # Visualize the number of channels in each category using
a bar plot plt.figure(figsize=(12, 6))
sns.barplot(x=category_counts.values,
y=category_counts.index,␣ ↪palette="viridis")
```

```python
plt.title('Number of YouTube Channels in Each Category ')
plt.xlabel('Number of Channels')
plt.ylabel('Category')
plt.grid(axis='x')
plt.show()
```

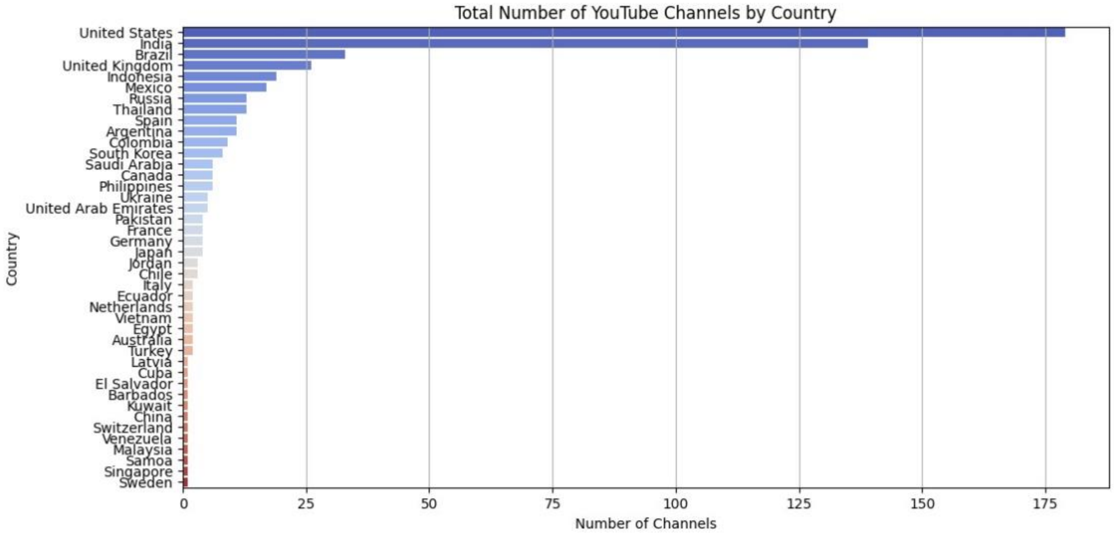


This code calculates and visualizes the total number of YouTube channels from each country using a bar plot. It will provide insights into which countries have the highest number of YouTube channels. If you have any questions or would like to proceed with the next analysis step, please feel free to ask.

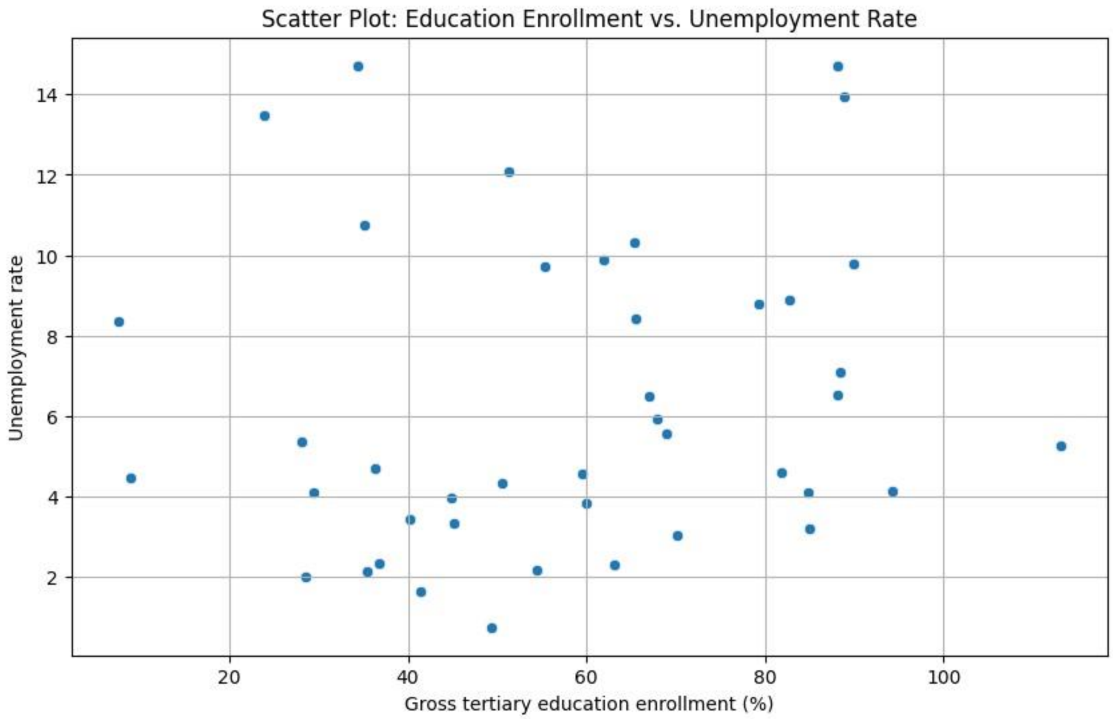
[ ]:
```python
# Calculate the total number of channels from each
country country_counts =
data['Country'].value_counts()
```

[ ]:
```python
# Sort the countries by the total number of channels in descending
order country_counts = country_counts.sort_values(ascending=False)
```

[ ]:
```python
# Visualize the total number of channels from each country using a
bar plot plt.figure(figsize=(12, 6))
sns.barplot(x=country_counts.values, y=country_counts.index,
palette="coolwarm")
plt.title('Total Number of YouTube Channels by Country')
plt.xlabel('Number of Channels')
plt.ylabel('Country')
plt.grid(axis='x')
plt.show()
```



[ ]:
```
# Scatter plot to analyze the relationship between "Gross tertiary education␣
↪enrollment (%)" and "Unemployment rate" plt.figure(figsize=(10,
6)) sns.scatterplot(x='Gross tertiary education enrollment (%)',
y='Unemployment␣
↪rate', data=data) plt.title('Scatter Plot: Education
Enrollment vs. Unemployment Rate') plt.xlabel('Gross
tertiary education enrollment (%)')
plt.ylabel('Unemployment rate') plt.grid(True) plt.show()
```

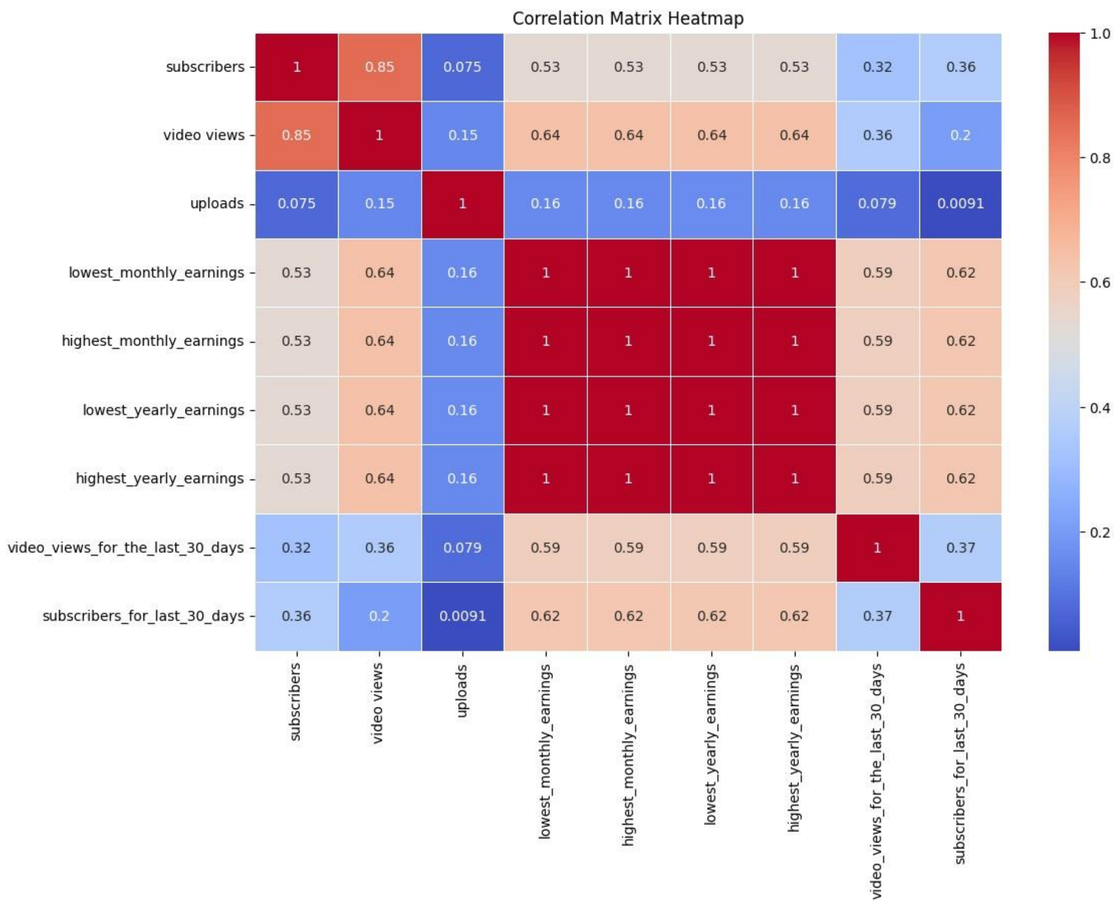


Analysis 2: Correlation Matrix Heatmap

[ ]:
```
# Select numerical columns for correlation analysis
numerical_cols = ['subscribers', 'video views',
'uploads',
         'lowest_monthly_earnings', 'highest_monthly_earnings',
                 'lowest_yearly_earnings',
                 'highest_yearly_earnings',
              'video_views_for_the_last_30_days',␣
 ↪'subscribers_for_last_30_days']
```

[ ]:
```
# Calculate the correlation matrix
correlation_matrix =
data[numerical_cols].corr()
```

[ ]:
```
# Create a heatmap to visualize the correlation matrix
plt.figure(figsize=(12, 8)) sns.heatmap(correlation_matrix,
annot=True, cmap="coolwarm", linewidths=.5)
plt.title('Correlation Matrix Heatmap') plt.show()
```



Explanation: We create a heatmap to visualize the correlation matrix, with annotations to show the correlation coefficients. This heatmap provides insights into how strongly each numerical variable is related to others.

Regression Models:

Linear Regression: To predict the number of subscribers for YouTube channels.

[ ]:
```python
# Import necessary libraries

from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
```

[ ]:
```python
# Select features and target variable
X = data[['video views', 'uploads']]
y = data['subscribers']
```

[ ]:
```python
# Split the data into training and testing sets
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
 ↪random_state=42)
```

[ ]:
```
# Create and train a Linear Regression model
model = LinearRegression()
model.fit(X_train, y_train)
```

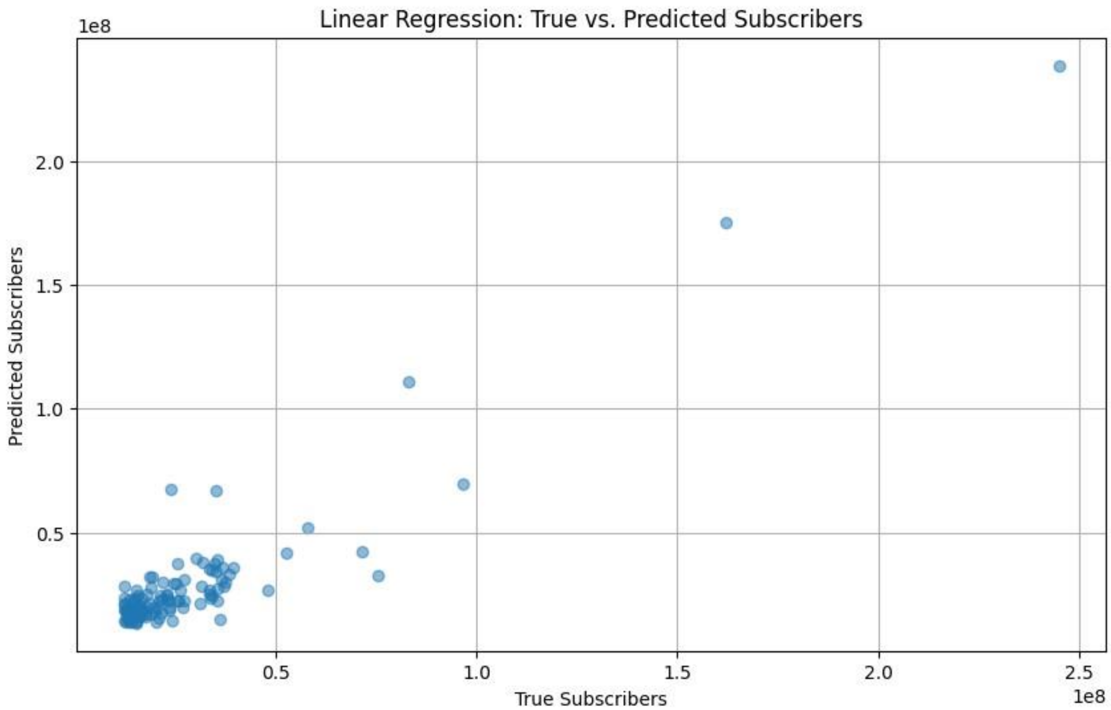
[ ]:
```
LinearRegression()
```

[ ]:
```
# Make predictions on the test set
y_pred = model.predict(X_test)
```

[ ]:
```
# Evaluate the model
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

print("Mean Squared Error:", mse)
print("R-squared:", r2)
```

```
Mean Squared Error: 107379845764229.67
R-squared: 0.8670140324743885
```

[ ]:
```
# Visualize Linear Regression predictions
plt.figure(figsize=(10, 6))
plt.scatter(y_test, y_pred, alpha=0.5)
plt.title('Linear Regression: True vs. Predicted Subscribers ')
plt.xlabel('True Subscribers')
plt.ylabel('Predicted Subscribers')
plt.grid(True)
plt.show()
```



Non-Linear Regression (e.g., Ridge, Lasso, ElasticNet): To handle complex relationships in predicting subscriber counts

[ ]:
```
# Import necessary libraries
from sklearn.linear_model import Ridge, Lasso, ElasticNet
```

[ ]:
```
# Create and train Ridge Regression model
ridge_model = Ridge(alpha=1.0)
ridge_model.fit(X_train, y_train)
```

[ ]: Ridge()

[ ]:
```
# Create and train Lasso Regression model
lasso_model = Lasso(alpha=1.0)
lasso_model.fit(X_train, y_train)
```

[ ]: Lasso()

[ ]:
```
# Create and train ElasticNet Regression model
elasticnet_model = ElasticNet(alpha=1.0,
l1_ratio=0.5) elasticnet_model.fit(X_train, y_train)
```

[ ]: ElasticNet()

[ ]:
```
# Make predictions using each model
ridge_predictions = ridge_model.predict(X_test)
```

```
lasso_predictions = lasso_model.predict(X_test)
elasticnet_predictions =
elasticnet_model.predict(X_test)
```

[ ]:
```
# Evaluate the models ridge_mse =
mean_squared_error(y_test, ridge_predictions) lasso_mse =
mean_squared_error(y_test, lasso_predictions)
elasticnet_mse = mean_squared_error(y_test,
elasticnet_predictions)

print("Ridge Mean Squared Error:", ridge_mse)
print("Lasso Mean Squared Error:", lasso_mse)
print("ElasticNet Mean Squared Error:",
elasticnet_mse)
```

```
Ridge Mean Squared Error: 107379845764229.9
Lasso Mean Squared Error: 107379845764235.2
ElasticNet Mean Squared Error:
107379845764289.69
```

Classification Models:

Decision Trees or Random Forests: To classify channels as successful or not.

[ ]:
```
# Import necessary libraries from sklearn.tree import
DecisionTreeClassifier from sklearn.ensemble import
RandomForestClassifier from sklearn.metrics import
accuracy_score, classification_report

# Load the dataset and preprocess if needed
# Select features and target variable
# Split the data into training and testing sets
```

[ ]:
```
# Create and train a Decision Tree Classifier
decision_tree_model =
DecisionTreeClassifier(random_state=42)
decision_tree_model.fit(X_train, y_train)
```

[ ]: DecisionTreeClassifier(random_state=42)

[ ]:
```
# Create and train a Random Forest Classifier random_forest_model =
RandomForestClassifier(n_estimators=100, random_state=42)
random_forest_model.fit(X_train, y_train)
```

[ ]: RandomForestClassifier(random_state=42)

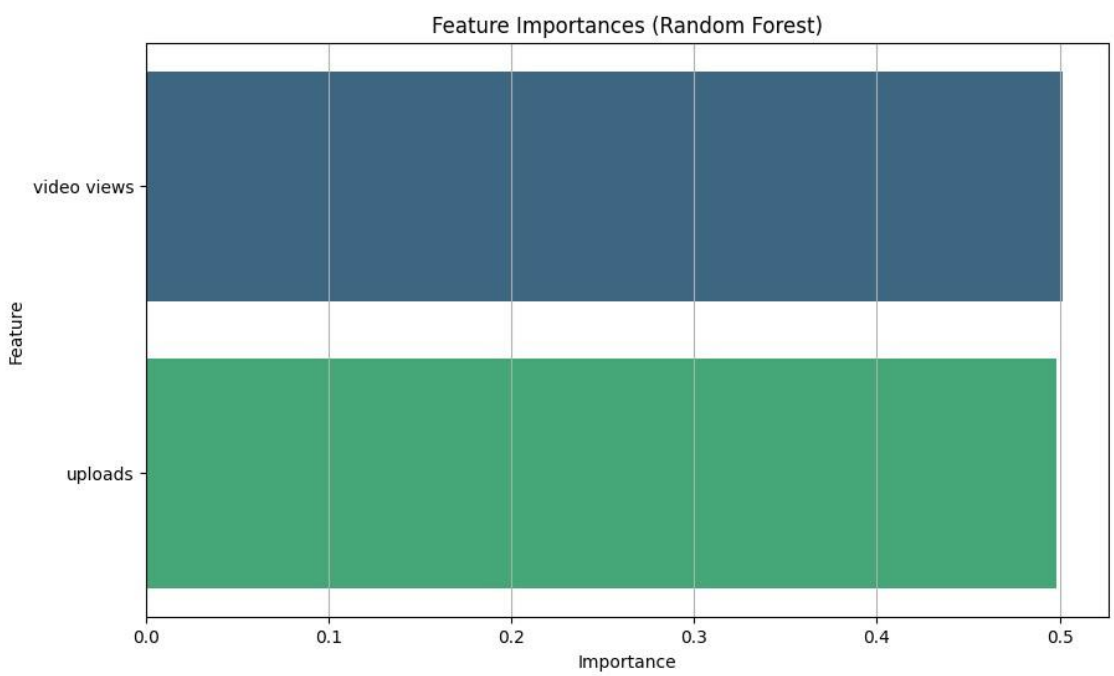
[ ]:
```
# Make predictions on the test set
```

```
decision_tree_predictions = decision_tree_model.predict(X_test)
random_forest_predictions = random_forest_model.predict(X_test)
```

```
[ ]: # Evaluate the models decision_tree_accuracy =
accuracy_score(y_test, decision_tree_predictions)
random_forest_accuracy = accuracy_score(y_test,
random_forest_predictions)

print("Decision Tree Accuracy:", decision_tree_accuracy)
print("Random Forest Accuracy:", random_forest_accuracy)
```

```
Decision Tree Accuracy: 0.009009009009009009
Random Forest Accuracy: 0.009009009009009009
```

```
[ ]: # Visualize feature importances from Random Forest Classifier
importances = random_forest_model.feature_importances_
features = X.columns
plt.figure(figsize=(10, 6))
sns.barplot(x=importances, y=features, palette="viridis")
plt.title('Feature Importances (Random Forest) ')
plt.xlabel('Importance')
plt.ylabel('Feature')
plt.grid(axis='x')
plt.show()
```



Logistic Regression: To predict the channel type (individual or brand).

[ ]:
```
# Import necessary libraries
from sklearn.linear_model import LogisticRegression

# Load the dataset and preprocess if needed
# Select features and target variable
# Split the data into training and testing sets
```

[ ]:
```
# Create and train a Logistic Regression model
logistic_regression_model = LogisticRegression()
logistic_regression_model.fit(X_train, y_train)
```

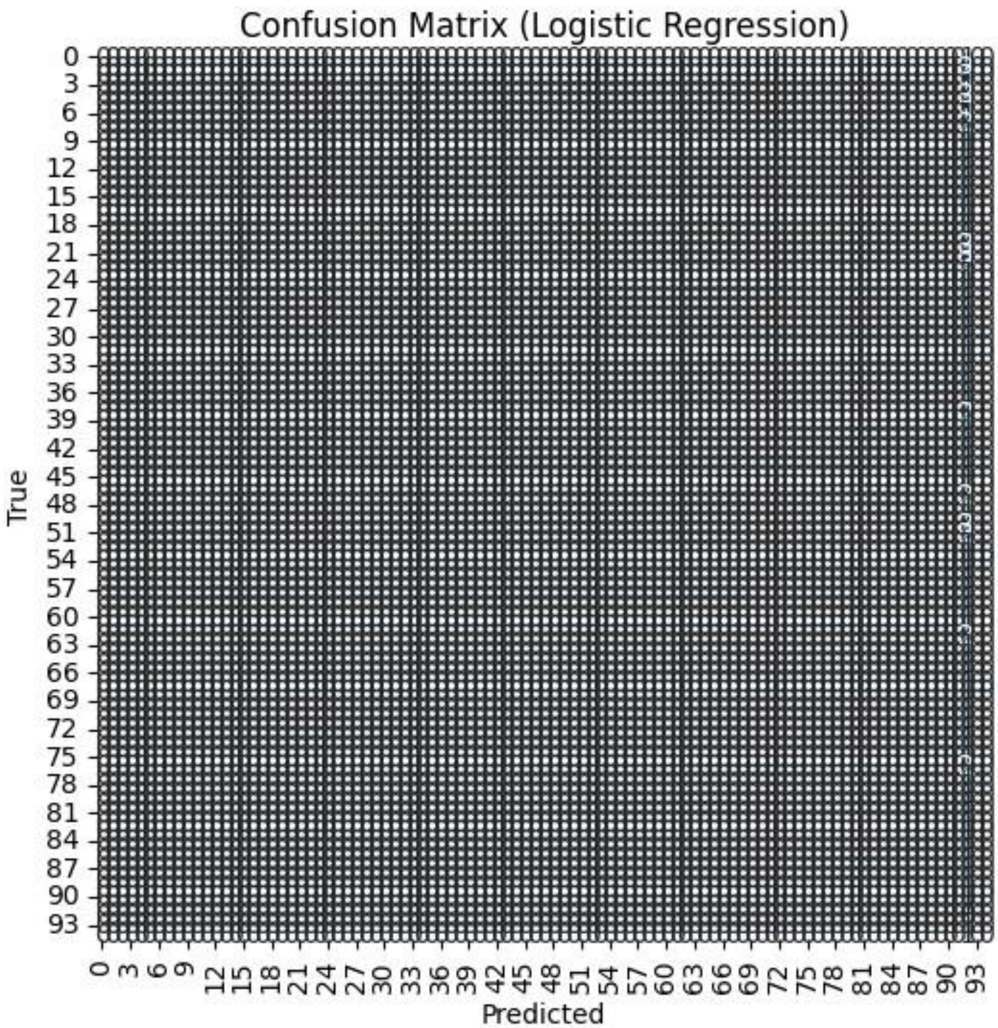
[ ]: LogisticRegression()

[ ]:
```
# Make predictions on the test set
logistic_regression_predictions =
logistic_regression_model.predict(X_test)
```

[ ]:
```
# Evaluate the model
logistic_regression_accuracy = accuracy_score(y_test,␣
↪logistic_regression_predictions) print("Logistic
Regression Accuracy:", logistic_regression_accuracy)
```

Logistic Regression Accuracy: 0.0

[ ]:
```
# Visualize the confusion matrix for Logistic
Regression from sklearn.metrics import
confusion_matrix

conf_matrix = confusion_matrix(y_test,
logistic_regression_predictions) plt.figure(figsize=(6, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues',
cbar=False) plt.title('Confusion Matrix (Logistic
Regression)')
plt.xlabel('Predicted')
plt.ylabel('True')
plt.show()
```



Sentiment Analysis on 'Title' Column:

```
[ ]: # Import the necessary libraries
import nltk
from nltk.corpus import stopwords
from collections import Counter

# Download the stop words list
nltk.download('stopwords')

# Get the titles as text data (assuming your column is named 'Title')
text_data = data['Title']

# Load the stop words list
stop_words = set(stopwords.words('english'))
```

```
# Clean and lowercase the text, remove punctuation
cleaned_text = text_data.str.lower().str.replace('[^\w\s]',
'').str.split()

# Remove stop words from the cleaned text filtered_text = [[word
for word in doc if word not in stop_words] for doc in␣
↪cleaned_text]

# Calculate term frequencies
flat_list = [item for sublist in filtered_text for item in sublist]
term_frequencies = Counter(flat_list)

# Show the most common terms and their frequencies
most_common_terms = term_frequencies.most_common(10)
print(most_common_terms)
```

```
[('-', 26), ('kids', 19), ('tv', 16), ('music', 14), ('official', 12),
('&',
11), ('news', 11), ('rhymes', 9), ('songs', 9), ('ýýýýýýýý', 9)]
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]  C:\Users\pnrde\AppData\Roaming\nltk_data…
[nltk_data]  Package stopwords is already up-to-date!
```

[ ]:

```
# Import the necessary libraries
from textblob import TextBlob

# Get the titles as a list (assuming your column is named 'Title')
titles = data['Title']

# Perform sentiment analysis for each title
sentiments = []
for title in titles:
    analysis = TextBlob(title)
    sentiment = analysis.sentiment.polarity  # Sentiment ranges from -1␣
  ↪(negative) to 1 (positive)
    sentiments.append(sentiment)

# Add the sentiment scores to your dataframe
data['Title_Sentiments'] = sentiments

# Examine the results
data.head()
```

[ ]:

```
   rank                       Youtuber  subscribers   video views  \
0     1                       T-Series    245000000
                                          2.280000e+11
```

```
2    3                  MrBeast   166000000
                                  2.836884e+10
3   4 Cocomelon - Nursery Rhymes  162000000
                                  1.640000e+11
4    5                SET India   159000000
                                  1.480000e+11
8       9   Like Nastya      106000000 9.047906e+10 category
            Title uploads    Country \
0         Music                 T-Series  20082        India
2  Entertainment                 MrBeast    741 United States
3    Education Cocomelon - Nursery Rhymes  966 United States
4         Shows                SET India  116536       India
8 People & Blogs        Like Nastya Vlog    493       Russia
   channel_type video_views_rank … lowest_yearly_earnings \
0        Music            1.0 …            6800000.0
2 Entertainment          48.0 …            4000000.0
3    Education            2.0 …            5900000.0
4 Entertainment           3.0 …            5500000.0
8       People          630.0 …             146800.0
  highest_yearly_earnings subscribers_for_last_30_days created_year
  \
0           108400000.0                2000000.0     2006.0
2            64700000.0                8000000.0     2012.0
3            94800000.0                1000000.0     2006.0
4            87500000.0                1000000.0     2006.0
8             2300000.0                 100000.0     2016.0
Gross tertiary education enrollment (%)Population Unemployment rate \
0                                 28.1 1.366418e+09           5.36
2                                 88.2 3.282395e+08          14.70
3                                 88.2 3.282395e+08          14.70
4                                 28.1 1.366418e+09           5.36
8                                 81.9 1.443735e+08           4.59

  Urban_population Title_Sentiment Title_Sentiments
0     471031528.0           0.0             0.0

2     270663028.0           0.0             0.0

3     270663028.0           0.0             0.0

4     471031528.0           0.0             0.0

8     107683889.0           0.0             0.0

[5 rows x 25 columns]
```