# CS 418 Data Wranglers Final Project Report

# Project Name: Viewer Engagement with YouTube News Videos

Group Members: Reeve Lood, reeveal2@uic.edu, GitHub: WarlordGandhi24 -- Umang Prajapati, upraja2@uic.edu, GitHub: umangp2924 -- Kunal Patel, kpate391@uic.edu, GitHub: kpate391 -- Rimsha Rizvi, rrizvi3@uic.edu, GitHub: rimsharizvi06 -- Deep Patel, dpate329@uic.edu, GitHub: d20patel

Project GitHub: https://github.com/uic-ds-spring-2023/class-project----cs-418-spring-2023-data-wranglers

# Introduction

The data we are analyzing comes from a YouTube engagement survey by Wu et al. (GitHub: https://github.com/avalanchesiqi/youtube-engagement/blob/master/data/README.md). We are using the top_news.json file from the quality videos dataset (https://drive.google.com/drive/folders/1wZwDIR18IHPPTiH1C0dyBbGPR-3MktI7), which contains information about videos of the top 100 most viewed news channels. The question we are answering is this: How does the video topic affect viewer engagement?

# Data

The original dataframe has 6 columns, 5 of which contain dict values. First, a separate dataframe is created for each of those 5 columns. For example, from the statistics column, a new dataframe is created with the dict's keys as its columns. The NA values and duplicates are then dropped from these dataframes. The code used to clean the data is the cleanup.py file.

In [4]:
```
import pandas as pd
pd.options.mode.chained_assignment = None

df = pd.read_json('top_news.json', lines=True)
print('Number of rows:', df.size)
df.head(3)
```

```
Number of rows: 172110
```

Out[4]:

| | topicDetails | statistics | contentDetails | snippet | id | insights |
|---|---|---|---|---|---|---|
| **0** | {'topicCategories': ['https://en.wikipedia.org... | {'commentCount': '0', 'viewCount': '701', 'fav... | {'duration': 'PT11M5S', 'definition': 'sd', 'd... | {'description': '⬇️ Descargá la App de C5N para... | JEibcX5VF1M | {'startDate': '2016-08-21', 'dailyShare': '6,2... |
| **1** | {'topicCategories': ['https://en.wikipedia.org... | {'commentCount': '0', 'viewCount': '889', 'fav... | {'duration': 'PT4M9S', 'definition': 'sd', 'di... | {'description': '⬇️ Descargá la App de C5N para... | CJwOo9Yp3Jk | {'startDate': '2016-08-10', 'dailyShare': '0,0... |
| **2** | {'topicCategories': ['https://en.wikipedia.org... | {'commentCount': '4', 'viewCount': '12720', 'f... | {'duration': 'PT13M11S', 'definition': 'hd', '... | {'description': '', 'title': 'C5N - Road Music... | CbdrzQPgGpI | {'startDate': '2016-07-31', 'dailyShare': '5,2... |

In [3]:
```
import cleanup
topicDetails, statistics, contentDetails, snippets, insights = cleanup.cleanup() # run
```

In [4]:
```
# Final dataframe created for the statistics column.
statistics.head(3)
```

Out[4]:

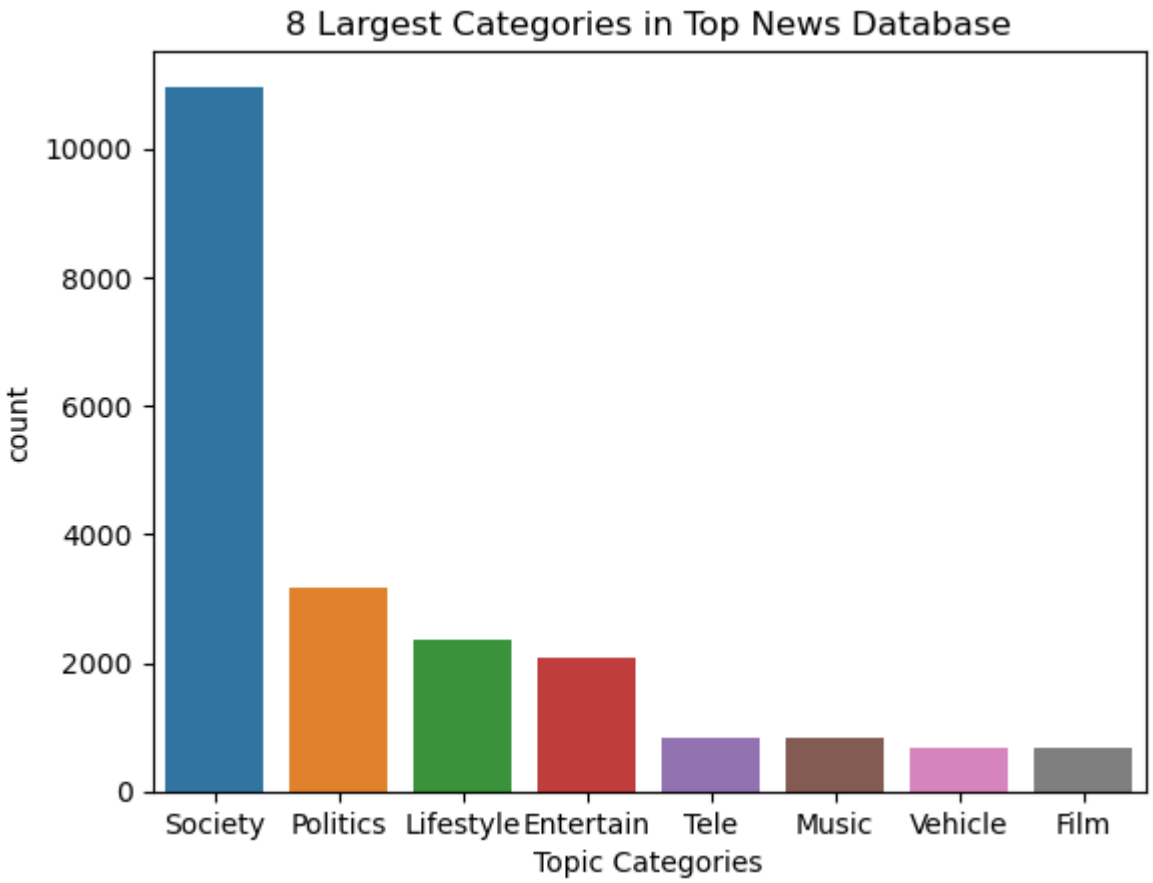
| | commentCount | viewCount | favoriteCount | dislikeCount | likeCount |
|---|---|---|---|---|---|
| **0** | 0 | 701 | 0 | 0 | 9 |
| **1** | 0 | 889 | 0 | 0 | 10 |
| **2** | 4 | 12720 | 0 | 4 | 213 |

# Visualization 1: Bar Chart

For our visualization, we chose to visualize the largest categories in the top news category. Each video in our database has a set of categories that is chosen when uploading a video. This set of categories is obtained from every video and counted in order to obtain the most popular news video genres. From the graph, we can say that by far the most popular is the "Society" tag, which makes sense given that top news is a video genre that primarily focuses on societal events. The most popular genres also include topics such as "Politics" and "Lifestyle", as well as "Music" and "Film". The ability to see these genres and their popularity will allow us to make further insights into the data of videos as a whole.

In [8]:
```
import seaborn as sns
import matplotlib.pyplot as plt
from visualization import *

makeGraph()
```

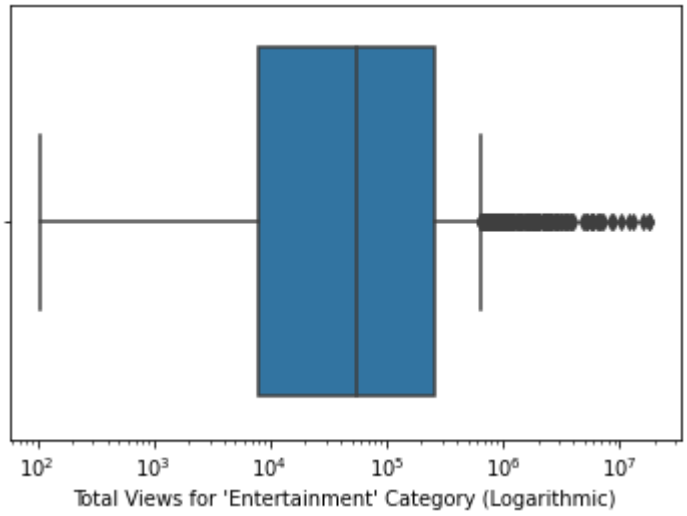



# Visualization 2: Box Plot

For our second visualization, we decided to take a look at the total view count of two specific categories of approximate size and compare the two together to see if on average one has more views than the other. In this example, we chose 'Entertainment' and 'Politics' as the two had approximately similar sizes. We also used a logarithmic scale on the box plot as otherwise there would be too many outliers on either side of the graph. Using this scale, we can see a nice box approximately in the 1000 to 10,000 view range for both categories, but Politics news videos tended to get less views on average than Entertainment news videos although both had similar outliers that reached into the millions of views.

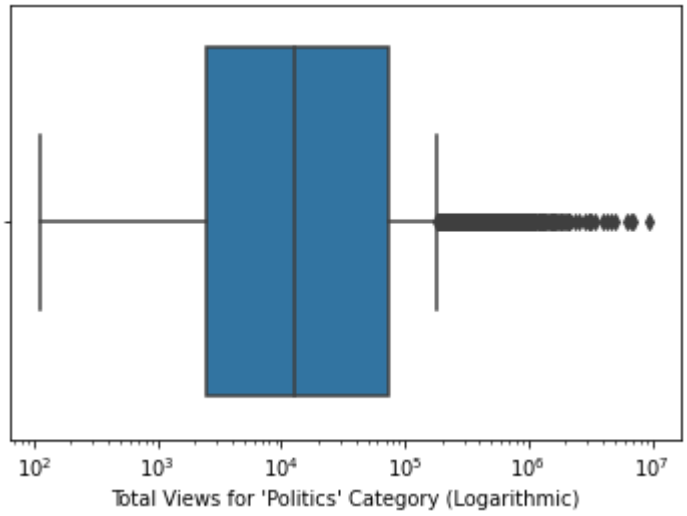
In [11]:
```
import seaborn as sns
import matplotlib.pyplot as plt
from visualization3 import *

makeChart2()
```




In [12]:
```
import seaborn as sns
import matplotlib.pyplot as plt
from visualization3 import *

makeChart3()
```

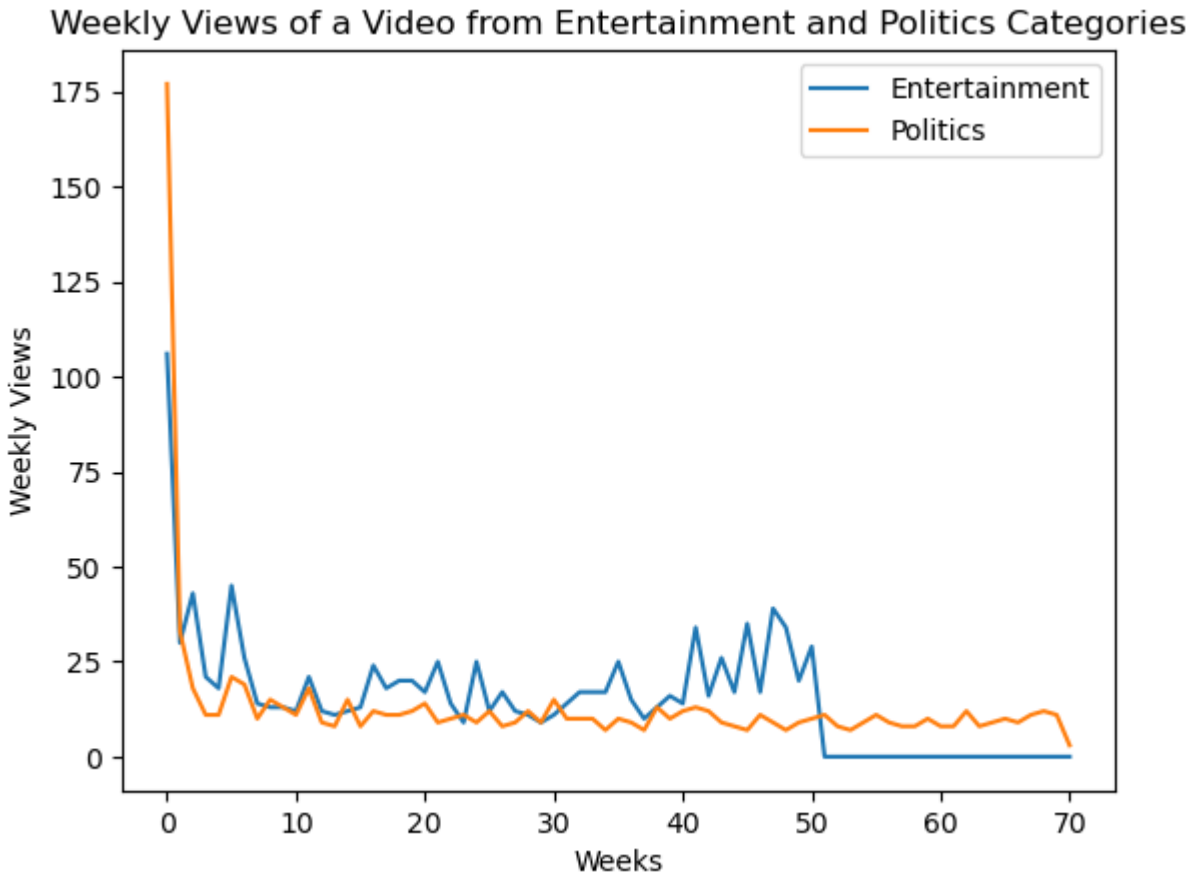



# Visualization 3: Line Graph

This graph delves deeper into the comparison of a video view count between the Entertainment and Politics categories on YouTube. At week 0, the view count of Politics is higher than that of Entertainment. However, as time progresses, the weekly views of Entertainment surpass those of Politics and remain higher until week 50. Notably, the weekly views of Entertainment vary greatly from week to week, while the view counts of Politics drop significantly after week 0 and remain fairly constant. This could be attributed to the possibility that Politics is generally more relevant in the present but may not remain as interesting in the future, resulting in a decline in view counts that fail to regain their initial momentum.

In [6]:
```
import seaborn as sns
import matplotlib.pyplot as plt
```

```
from Visualization2 import *
lineGraphVisualization()
```



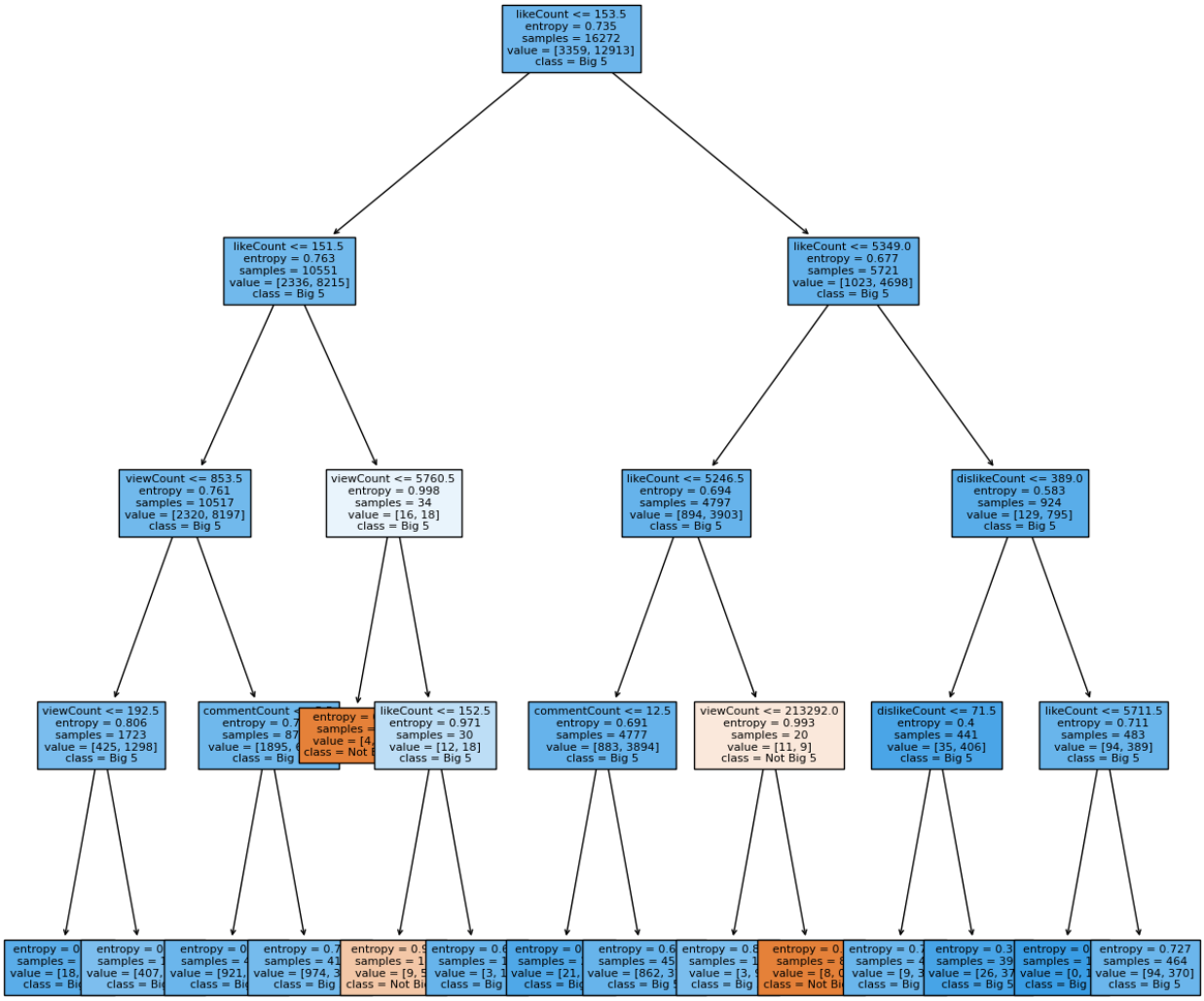

# ML Analysis 1: Decision Tree

The first ML analysis we performed was creating a supervised decision tree classifier that can predict if the video topic category is one of the big five categories (Society, Politics, Lifestyle, Entertainment, and Music) given video statistics (viewCount, dislikeCount, likeCount, etc.). The target column contained binary values: 1 if the video category is in the big 5 and 0 if not. The dataset was split into 70% training, 10% validation, and 20% test data. Training the decision tree classifier with the criterion as entropy and a max tree depth of 4 resulted in a classifier that had a test accuracy of 0.8356. The main inference uncovered was that video engagement statistics can be used to accurately predict if the video category is one of the big 5 categories. Moreover, we learned that expanding the entire tree would give a 100% accuracy on the training data but would overfit the test data. The key was to limit the depth of the tree so that it also does well on the unseen data.

In [2]:
```
import decision_tree
train_accuracy, val_accuracy, test_accuracy, dt = decision_tree.analyze()

print()
print('Train accuracy:', train_accuracy)
print('Validation accuracy:', val_accuracy)
print('Test accuracy:', test_accuracy)
dt;
```

```
Train accuracy: 0.794555063913471
Validation accuracy: 0.7341935483870967
Test accuracy: 0.8356282271944923
```

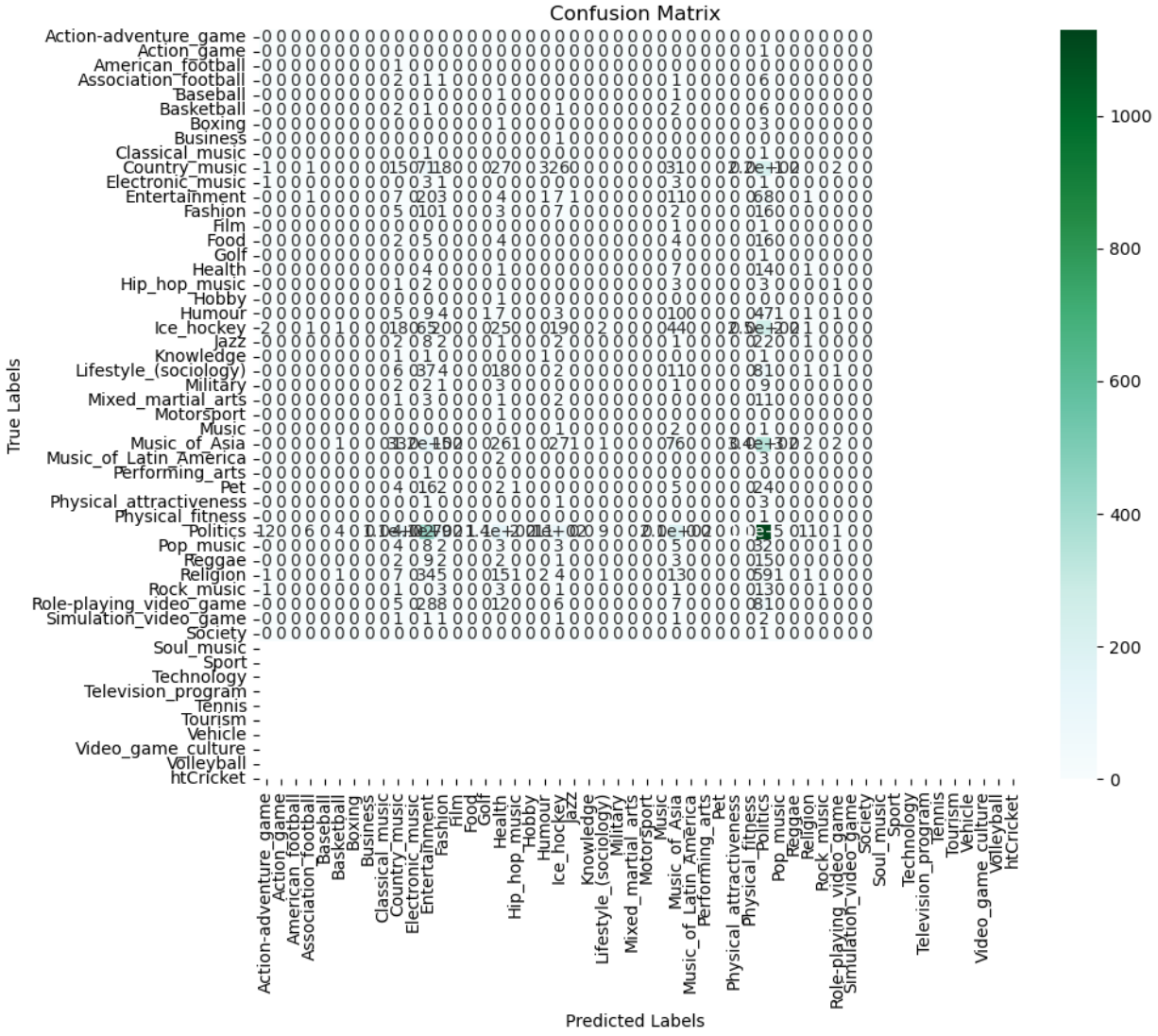



# ML Analysis 2: K-Nearest Neighbors

This analysis employs the K-Nearest Neighbors (KNN) algorithm of machine learning to categorize news articles based on their comment count. The source data is retrieved from a 'top_news.json' file. The analysis involves several preprocessing stages such as computing statistics from the initial dataset, constructing a new dataframe with topic categories, encoding the target labels, partitioning the data into training and testing sets, and normalizing the data. Ultimately, the KNN classifier is trained using the training set, and the accuracy of the model is measured on the test set. The objective is to predict the topic categories based on the comment count, and the performance of the model is expressed as its accuracy.

In [2]:
```
import machine_learning_classifier
machine_learning_classifier.knn_analysis()
```

```
C:\Users\d20patel\anaconda3\lib\site-packages\sklearn\neighbors\_classification.py:228: FutureWarning: Unlike other reduction functions (e.g. `skew`, `kurtosis`), the default behavior of `mode` typically preserves the axis it acts along. In SciPy 1.11.0, this behavior will change: the default value of `keepdims` will become False, the `axis` over which the statistic is taken will be eliminated, and the value None will no longer be accepted. Set `keepdims` to True or False to avoid this warning.
  mode, _ = stats.mode(_y[neigh_ind, k], axis=1)
Accuracy: 0.2601
```




Out[2]:
```
0.2601441812564367
```

# Results

In this project, we aimed to explore the relationship between video topic categories and viewer engagement on YouTube. Using a dataset of the top 100 most viewed news channels, we focused on the quality videos dataset, analyzing video categories, view counts, likes, and dislikes. Our findings suggest that the topic category of a video significantly impacts viewer

engagement, with engagement statistics serving as important predictors of video category topics.

Our analysis included three key visualizations. The bar chart revealed that the most popular video genres were "Society", "Politics", "Lifestyle", "Music", and "Film". The box plot comparison showed that videos in the "Entertainment" category generally received more views than those in the "Politics" category although both had notable outliers in the millions of views. Additionally, the line graph provided insights into the temporal dynamics between the Entertainment and Politics categories. It demonstrated that while Politics had a higher view count at week 0, Entertainment surpassed it in subsequent weeks and maintained a consistently higher viewership.

These findings offer valuable insights for content creators and news channels on YouTube. By optimizing their video topics based on viewer engagement and understanding the interests of their audience, creators and channels can improve their content strategies. Furthermore, our machine learning analyses emphasized the importance of engagement statistics in accurately predicting video category topics. Overall, this project enhances our understanding of the impact of video topic categories on viewer engagement, providing actionable insights for content creators and news channels to enhance their content and engage their audience effectively.