YouTube Videos Analysis

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Outline

- Topic
- Questions We Hope to Answer
- Technologies Used
- Data Source
- Data Exploration Phase
- Data Analysis Phase
- Machine Learning
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- Things We Would Have Done Differently

Topic

Which YouTube video and channel metrics play the biggest role in creating a video that will gain the largest amount of views?

Why

YouTube's dense and diverse arrays of users and content providers pose ample room for analyzing and characterizing the popularity of its videos

Problem Statement

Predict a YouTube video’s success by analyzing the metrics of channels and videos by the topic category of the video.

Research Questions

What features and traits do successful videos have in common across categories?

How do meta-level features drive user engagement and popularity of a video?

Language

Python

SQL

Dashboard

tableau

plotly

Data Storage

PostgreSQL

AWS

Amazon Web Services

Data Source

YouTube Data
API v3

Data Exploration Phase

Categories

- Cooking
- Fitness
- History
- Science
- News
- Music
- Comedy
- Travel

Channels

- Grabbed the top 10 channels from each category.
- Grabbed random channels from each category
- Grabbed top 20 English language channels

Videos

From Each Channel, grab the 50 most recent uploads, and recent comments from each video

Data Source (Code)

- Get list of channels for analysis:
    - Wikipedia - List of most-subscribed YouTube Channels
    - "Best YouTube Channels by Category" - compiled by Clifford Chi
    - "Random Sampling" of channels compiled by Zara Khan
- Feed channel list into YouTube Data API v3

```python
# for loop to get channel details
for channel in video_list:
    response = youtube.channels().list(
        part=['snippet', 'statistics', 'topicDetails', 'contentDetails'],
        id=channel
    ).execute()
    # append response to dataframe
    df = df.append(response['items'], ignore_index=True)
```

- Get 50 most recent videos from each channel

```python
response = youtube.channels().list(
    part=['contentDetails'],
    id=channel_id
).execute()

playlist_id = response['items'][0]['contentDetails']['relatedPlaylists']['uploads']

response = youtube.playlistItems().list(
    part=['contentDetails'],
    playlistId=playlist_id,
    maxResults=50
).execute()
```

- Get recent comments from each video

```python
def get_comments(video_id):
    try:
        results = youtube.commentThreads().list(
            part="snippet",
            videoId=video_id,
            textFormat="plainText",
            maxResults=20
        ).execute()

        comments = []
        for item in results["items"]:
            comment = item["snippet"]["topLevelComment"]["snippet"]["textDisplay"]
            comments.append(comment)
        return comments
    except:
        return None
```

- Get sentiment analysis for comments

```python
for video in comment_df['video_id']:
    comments = get_comments(video)
    if comments is not None:
        comment_df.loc[comment_df['video_id'] == video,
        'sentiment'] = sentiment_analyzer_scores(comments)
```

Ran Channel IDs for Channel Metadata

```python
def channel_information_grabber(video_list, title):
    # create empty dataframe
    df = pd.DataFrame()

    # for loop to get channel details
    for channel in video_list:
        response = youtube.channels().list(
            part=['snippet', 'statistics', 'topicDetails', 'contentDetails'],
            id=channel
        ).execute()
        # append response to dataframe
        df = df.append(response['items'], ignore_index=True)
```

Dropped columns: title, description, thumbnails, default language, topicIds, related Playlists, and category_title

```
id                          object
title                       object
description                 object
customUrl                   object
publishedAt                 object
thumbnails.default.url      object
defaultLanguage             object
viewCount                    int64
subscriberCount              int64
videoCount                   int64
topicIds                    object
topicCategories             object
relatedPlaylists.uploads    object
category_title              object
dtype: object
```

Ran Channel IDs for Top 50 Videos Metadata

```python
# get the 50 videos from each channel in all_channels
video_list = []
for channel in all_channels:
    video_list.append(get_50_videos(channel))

# flatten the list
video_list = [item for sublist in video_list for item in sublist]

# convert to csv
df = pd.DataFrame(video_list)
df.to_csv('video_list.csv', index=False)

video_list
```

```
video_id                              object
channel_id                            object
video_title                           object
video_title_clean                     object
published                datetime64[ns, UTC]
video_views                            int64
video_madeforkids                       bool
video_likes                            int64
video_comment_count                    int64
video_length                          object
video_description                     object
video_tags                            object
dtype: object
```

Dropped columns: video_title, video_madeforkids, video_description, video_tags

Data Source (Tables)

After using the YouTube API, the resulting data was contained in two tables:

Our joined dataframe contains 8603 rows and 13 columns.

- Channels Table
    - Channel ID
    - Channel Name
    - Channel Category
    - View Count
    - Subscriber Count
    - Video Count

Id	Custom Url	Video_category	View Count	Subscriber Cou	Video Count
UCVaXclURQZlal	@news19wltx	Society	150105437	249000	24026
UCQqaNnVhS1v	@channel4come	Humour	132644274	167000	726
UC6YN4FNhAKN	@queencitynew	Society	83768935	125000	11538
UCjlgDApB1OrU	@cookingwithsh	Food	44025876	422000	453
UCf7J0vxbg6Sslj	@britishcomedy	Film	40935727	37800	951

- Videos Table
    - Channel ID
    - Video ID
    - Video Title
    - Published Date
    - Video Length
    - Comment Count
    - Like Count
    - View Count

Channel_id	Video_id	Video_title_clea	Published	Video_length	Video_commen	Video_likes	Video_views
UC0VOyT2OCBK	Sujm6756pZU	Ariana Grande m	2020-10-30 04:0	2:40	14048	300403	13537474
UCbCmjCuTUZo	hqFfJBOrvHw	Humpty Dumpty	2022-09-27 07:0	2:42	0	33185	8768272
UCbCmjCuTUZo	LA2q3QwhG54	Belly Button Dar	2022-07-05 16:0	2:42	0	105966	31790993
UC3gNmTGu-TT	686jgVnwh5M	Morbius 2022 Br	2022-10-31 15:4	2:43	12	111	5855
UC3gNmTGu-TT	RMrcKVzwqyU	Resident Evil Aft	2022-10-27 15:4	2:43	6	105	6452

Data Analysis Phase

Channels Dataframe

	id	customUrl	video_category	viewCount	subscriberCount	videoCount
0	UCVaXclURQZlakiTMzuwHvRw	@news19wltx	Society	150105437	249000	24026
1	UCQqaNnVhS1w_iTeFalJsXog	@channel4comedy	Humour	132644274	167000	726
2	UC6YN4FNhAKN3MDO5DbJSnOA	@queencitynews	Society	83768935	125000	11538
3	UCjlgDApB1OrU_3-1dLMHOZg	@cookingwithshotgunred	Food	44025876	422000	453
4	UCf7J0vxbg6SsljY9587PEiQ	@britishcomedyguide	Film	40935727	37800	951
...	...	...	...	...	...	...
105	UCXsQlHGuoWqukC9vz-uonrg	@collinabroadcast	Tourism	163749185	1460000	91
106	UCdPambxHRj0kdFPNoJFM98A	@georgebenson	Sport	151941207	1020000	1266
107	UC_ptyMRLOsS1Uj0a34a_xCA	@chonnyday	Food	126569583	689000	427
108	UCJsSEDFFnMFvW9JWU6XUn0Q	@seekerstories	Lifestyle	88299661	542000	257
109	UCd5xLBi_QU6w7RGm5TTznyQ	@sundayfundayz	Tourism	75488060	643000	400

Videos Dataframe

channel_id	video_id	video_title_clean	published	video_length	video_comment_count	video_likes	video_views
UCbCmjCuTUZos6Inko4u57UQ	lmH5uqwaFq8	Airplane Song CoComelon Nursery Rhymes Kids Songs	2022-11-01 07:00:15+00:00	2:59	0	19653	3425275
UCbCmjCuTUZos6Inko4u57UQ	0SY0Yn0yF9o	Wheels On The Bus More Nursery Rhymes Kids Son...	2022-10-29 07:00:00+00:00	29:52:00	0	15076	2882582
UCbCmjCuTUZos6Inko4u57UQ	sNyF7BvVfxs	Bingos Bath Song CoComelon Nursery Rhymes Kids...	2022-10-25 07:00:16+00:00	2:49	0	47763	8673081
UCbCmjCuTUZos6Inko4u57UQ	K4kqqCzF-BA	Play Outside at the Beach Song More Nursery Rh...	2022-10-22 07:00:12+00:00	1:01:21	0	57936	11744611
UCbCmjCuTUZos6Inko4u57UQ	gfZmvllWVwY	Halloween Song Dance Dance Party CoComelon Nur...	2022-10-18 07:00:19+00:00	2:39	0	46041	8775011
...	...	...	...	...	...	...	...
UCC7jlYxfWti7WAW8r7ef1RQ	xRi8SGcRDOY	In Paris use the Navigo pass like locals and s...	2022-03-28 15:00:24+00:00	9	0	4	311
UCC7jlYxfWti7WAW8r7ef1RQ	C-34plsWZPk	How to save money in Paris by using the Paris ...	2022-03-27 15:00:04+00:00	4:49	79	166	4642
UCC7jlYxfWti7WAW8r7ef1RQ	L2GdB1gB1ZM	Magical Malta should 100 be on your bucket lis...	2022-03-26 15:00:09+00:00	16	7	133	5091
UCC7jlYxfWti7WAW8r7ef1RQ	89lewFGQQ6E	Is France on your bucket list shorts france tr...	2022-03-25 18:00:03+00:00	16	0	1	31
UCC7jlYxfWti7WAW8r7ef1RQ	QS32cM-BQ6M	Subscribe for more travel tips and inspiration...	2022-03-24 15:00:11+00:00	11	0	2	76

Joining Databases Together

postgres/postgres@AWS

Query Editor

```sql
CREATE TABLE channel_data(
    channel_id varchar NOT NULL,
    custom_url varchar,
    topic_category varchar,
    channel_view_count bigint,
    subscriber_count bigint,
    channel_video_count bigint,
    PRIMARY KEY (channel_id)
);

CREATE TABLE video_data(
    channel_id varchar NOT NULL,
    video_id varchar NOT NULL,
    video_title_clean varchar,
    published_at timestamp,
    video_length varchar,
    comment_count bigint,
    like_count bigint,
    view_count bigint,
FOREIGN KEY (channel_id) REFERENCES channel_data (channel_id)
);
```

```sql
--- join tables together
SELECT c.channel_id,
    c.custom_url,
    c.topic_category,
    c.channel_view_count,
    c.subscriber_count,
    c.channel_video_count,
    v.video_id,
    v.published_at,
    v.video_length,
    v.like_count,
    v.comment_count,
    v.view_count
INTO joined_data
FROM channel_data AS c
INNER JOIN video_data AS v
ON c.channel_id=v.channel_id;

SELECT * FROM joined_data;
```

Joined Data Table

	channel_id	custom_url	topic_category	channel_view_count	subscriber_count	channel_video_count	video_id	video_length	like_count	comment_count	view_count
0	UCbCmjCuTUZos6Inko4u57UQ	@cocomelon	Music	142468175305	146000000	811	lmH5uqwaFq8	2:59	19653	0	3425275
1	UCbCmjCuTUZos6Inko4u57UQ	@cocomelon	Music	142468175305	146000000	811	0SY0Yn0yF9o	29:52:00	15076	0	2882582
2	UCbCmjCuTUZos6Inko4u57UQ	@cocomelon	Music	142468175305	146000000	811	sNyF7BvVfxs	2:49	47763	0	8673081
3	UCbCmjCuTUZos6Inko4u57UQ	@cocomelon	Music	142468175305	146000000	811	K4kqqCzF-BA	1:01:21	57936	0	11744611
4	UCbCmjCuTUZos6Inko4u57UQ	@cocomelon	Music	142468175305	146000000	811	gfZmvllWVwY	2:39	46041	0	8775011

Binned Data Sample View

channel_views_binned	subscribers_binned	video_count_binned	like_count_binned	comment_binned	video_views_binned
1 bil- 100 billion views	5-15 mil subs	5,000-10,000 videos	1,000-5,000 likes	100-500 comments	50,000-500,000
1 mil-5 mil views	10,000-500,000 subs	100-500 videos	less than 50 likes	less than 100 comments	less than 1000 views
1 bil- 100 billion views	5-15 mil subs	500-1500 videos	1,000-5,000 likes	less than 100 comments	50,000-500,000
5 mil- 100 mil	500,000- 1 mil subs	100-500 videos	50-1000 likes	100-500 comments	10,000-50,000 views
1 bil- 100 billion views	5-15 mil subs	greater than 10,000 videos	1,000-5,000 likes	1,000-10,000 comments	50,000-500,000

Combined Topic Categories

```
['Music',
 'Video_game_culture',
 'Lifestyle',
 'Hobby',
 'Hip_hop_music',
 'Entertainment',
 'Action-adventure_game',
 'Rock_music',
 'Pop_music',
 'Film',
 'Knowledge',
 'Food',
 'Physical_fitness',
 'Society',
 'Strategy_video_game',
 'Technology',
 nan,
 'Television_program',
 'Politics',
 'Electronic_music',
 'Sport',
 'Tourism',
 'Classical_music',
 'Christian_music',
 'American_football',
 'Military',
 'Humour']
```

26 to 16 topic categories

```
['Music',
 'Video_game_culture',
 'Lifestyle',
 'Hobby',
 'Entertainment',
 'Film',
 'Knowledge',
 'Food',
 'Physical_fitness',
 'Society',
 'Technology',
 'Television_program',
 'Politics',
 'Sport',
 'Tourism',
 'Humour']
```

Adding Day of Week Published Column

```
#turn published at to day of week published
file["datetime"]=pd.to_datetime(file['published_at'])
file['day_of_week_published']=file['datetime'].dt.day_name()
```

published_at	v
2022-07-22 19:00:16	
2021-06-26 20:00:02	
2019-11-19 20:00:11	
2022-10-28 17:00:27	
2019-09-21 13:00:02	

day_of_week_published
Friday
Saturday
Tuesday
Friday
Saturday

Machine Learning

Our Features

topic_category	subscriber_count	channel_video_count	day_of_week_published	video_length_seconds	viral
Society	5310	617	Tuesday	512.0	0
Lifestyle	9510	195	Friday	9.0	0
Knowledge	417	175	Sunday	34.0	0
Physical_fitness	2720000	1826	Thursday	57.0	0
Film	30300000	8168	Thursday	370.0	0

Target Variable

How did we get the target column?

```python
#make new column that has binary classification. if view count is greather than 1,000,000 then add 1 if less than add 0
def viral(row):
    if row['view_count'] > 1000000:
        return 1
    else:
        return 0
```

✓ 0.1s

```python
#add the viral column
df['viral']=df.apply(lambda row: viral(row), axis=1)
df.sample(5)
```

✓ 0.3s

Encoding and Scaling

```
#encode categorical data
le = LabelEncoder()
df2 = df.copy()
df2['topic_category'] = le.fit_transform(df2['topic_category'])
df2['day'] = le.fit_transform(df2['day_of_week_published'])
df2.sample(5)
```

✓ 0.9s

topic_category	subscriber_count	channel_video_count	day_of_week_published	video_length_seconds	viral	day
0	61800000	2486	Friday	2941.0	0	0
5	679	62	Thursday	1320.0	0	4
9	5240000	46593	Tuesday	487.0	0	5
2	28800	136	Tuesday	216.0	0	5
15	2040000	455	Monday	33381.0	0	1

```python
# Day of Week dictionary
weekday_num = {
    "Sunday": 1,
    "Monday": 2,
    "Tuesday": 3,
    "Wednesday": 4,
    "Thursday": 5,
    "Friday": 6,
    "Saturday": 7
}
```

✓ 0.1s

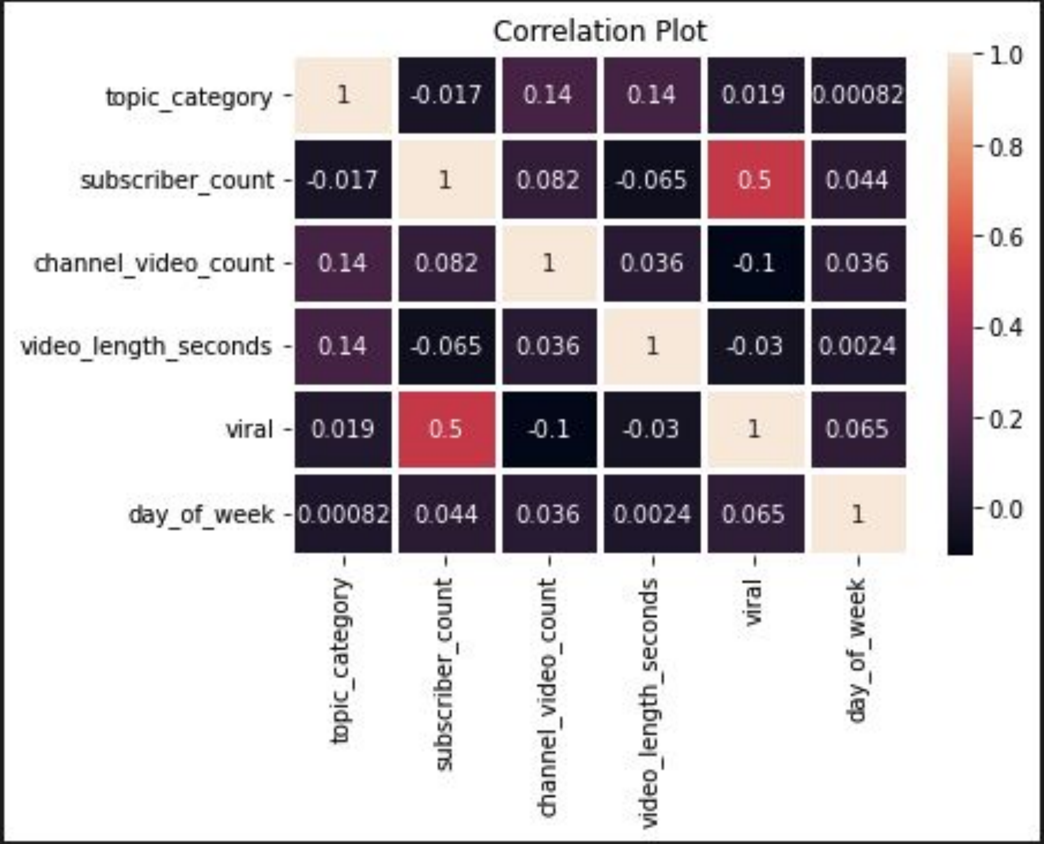
Custom encoding for the days of the week

```python
# weekdays names encoded using the dictionary values
df["day_of_week"] = df["day_of_week_published"].apply(lambda x: weekday_num[x])
df=df.drop(columns=['day','day_of_week_published'])
df.head()
```

✓ 0.1s

	topic_category	subscriber_count	channel_video_count	video_length_seconds	viral	day_of_week
0	7	146000000	811	179.0	1	3
1	7	146000000	811	1792.0	1	7
2	7	146000000	811	169.0	1	3
3	7	146000000	811	3681.0	1	7
4	7	146000000	811	159.0	1	3

Correlation Exploration



Scaling Feature Data

```
stds=StandardScaler()
df_scaled=stds.fit_transform(X.to_numpy())
df_scaled=pd.DataFrame(df_scaled,columns=['topic_category','subscriber_count','channel_video_count','video_length_seconds','day_of_week'])

df_scaled.head()
```

✓ 0.1s

	topic_category	subscriber_count	channel_video_count	video_length_seconds	day_of_week
0	0.215727	4.737927	-0.208141	-0.386398	-0.600557
1	0.215727	4.737927	-0.208141	0.432875	1.591367
2	0.215727	4.737927	-0.208141	-0.391477	-0.600557
3	0.215727	4.737927	-0.208141	1.392333	1.591367
4	0.215727	4.737927	-0.208141	-0.396556	-0.600557

Wait… Our Data is Imbalanced

```
#percentage viral/not viral
print("Viral: ", df.viral.value_counts()[1]/len(df)*100,"%")
print("Not Viral: ", df.viral.value_counts()[0]/len(df)*100,"%")
```

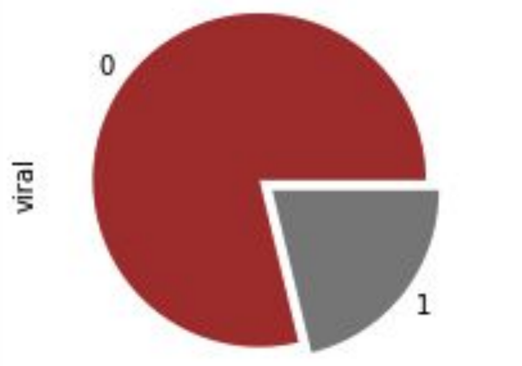
✓ 0.4s

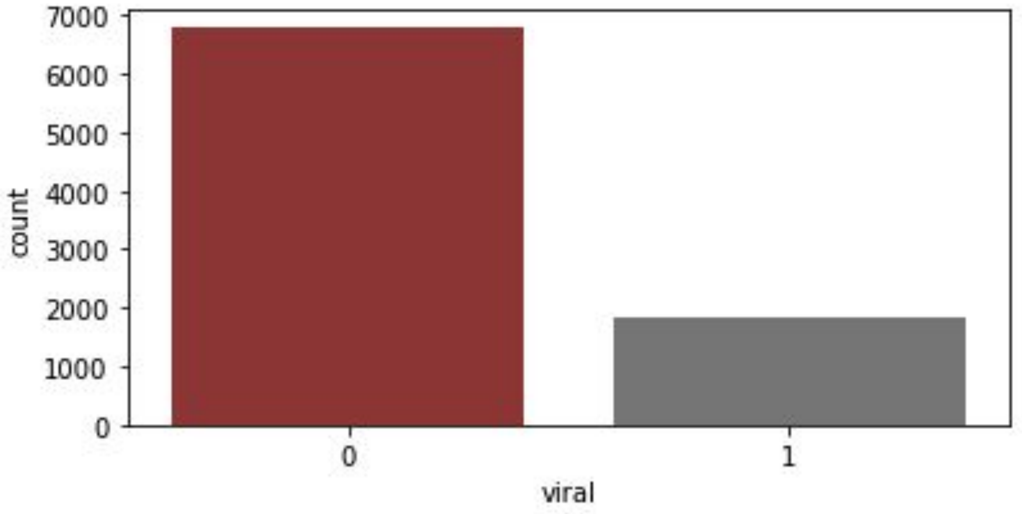
```
Viral:  19.84687163536308 %
Not Viral:  80.15312836463691 %
```

```
y.value_counts()
```

✓ 0.1s

```
0    6700
1    1659
Name: viral, dtype: int64
```





Resampling using SMOTEENN

```
from imblearn.combine import SMOTEENN
from collections import Counter

smote_enn = SMOTEENN(random_state=0)
X_resampled, y_resampled = smote_enn.fit_resample(X, y)
Counter(y_resampled)
```

✓ 1.3s

```
Counter({0: 5822, 1: 5723})
```

Logistic Regression

Simplest binary classification model. However, may be prone to overfitting.

	precision	recall	f1-score	support
0	0.93	0.92	0.92	1675
1	0.68	0.72	0.70	415
accuracy			0.88	2090
macro avg	0.80	0.82	0.81	2090
weighted avg	0.88	0.88	0.88	2090

The precision score was very low.

```
#make predictions
y_pred = classifier.predict(X_test)
#accuracy score
print(accuracy_score(y_test, y_pred))
```

✓ 0.1s

```
0.8755980861244019
```

```
# Display the confusion matrix
from sklearn.metrics import confusion_matrix
confusion_matrix(y_test,y_pred)
```

✓ 0.1s

```
array([[1533,  142],
       [ 118,  297]])
```

Random Forest Classifier

This model is better at handling our numerous variables and big data set.

	precision	recall	f1-score	support
0	0.98	0.94	0.96	1675
1	0.79	0.94	0.86	415
accuracy			0.94	2090
macro avg	0.89	0.94	0.91	2090
weighted avg	0.95	0.94	0.94	2090

```python
# Calculated the balanced accuracy score
y_pred=model.predict(X_test)
balanced_accuracy_score(y_test,y_pred)
```

✓ 0.9s

```
0.939144038841935
```

```python
# Display the confusion matrix
confusion_matrix(y_test, y_pred)
```

✓ 0.7s

```
array([[1568,  107],
       [  24,  391]])
```

Easy Ensemble (AdaBoost) Classifier

This ML Model was used to see if we could get a better accuracy score than the Random Forest Model. However, not the best as we have a lot of outliers in our data.

	pre	rec	spe	f1	geo
0	0.98	0.91	0.91	0.94	0.91
1	0.72	0.91	0.91	0.80	0.91
avg / total	0.92	0.91	0.91	0.92	0.91

```
# Calculated the balanced accuracy score
y_pred=model_eec.predict(X_test)

balanced_accuracy_score(y_test, y_pred)
```

✓ 4.2s

```
0.9094299586405323
```

```
# Display the confusion matrix
confusion_matrix(y_test, y_pred)
```

✓ 0.2s

```
array([[1529,  146],
       [  39,  376]])
```

Trying to Increase Accuracy/Precision Score

```
model = BalancedRandomForestClassifier(max_leaf_nodes=24,n_estimators=120, random_state=1)

# Fitting the model
model.fit(X_resampled, y_resampled)

# Calculated the balanced accuracy score
y_pred=model.predict(X_test)
print("ACCURACY SCORE: ",balanced_accuracy_score(y_test,y_pred))

# Print the imbalanced classification report
print(classification_report(y_test,y_pred))
```

✓ 2.9s

```
ACCURACY SCORE:  0.9106131990649164
              precision    recall  f1-score   support

           0       0.97      0.92      0.95      1675
           1       0.73      0.90      0.81       415

    accuracy                           0.91      2090
   macro avg       0.85      0.91      0.88      2090
weighted avg       0.93      0.91      0.92      2090
```

Trying to Increase Accuracy/Precision Score

```
model = BalancedRandomForestClassifier(max_leaf_nodes=50,n_estimators=50, random_state=1)

# Fitting the model
model.fit(X_resampled, y_resampled)

# Calculated the balanced accuracy score
y_pred=model.predict(X_test)
print("ACCURACY SCORE: ",balanced_accuracy_score(y_test,y_pred))

# Print the imbalanced classification report
print(classification_report(y_test,y_pred))
```

✓ 1.1s

```
ACCURACY SCORE:  0.9247833123538931
              precision    recall  f1-score   support

           0       0.98      0.91      0.95      1675
           1       0.73      0.93      0.82       415

    accuracy                           0.92      2090
   macro avg       0.86      0.92      0.88      2090
weighted avg       0.93      0.92      0.92      2090
```

Trying to Increase Accuracy/Precision Score

```
model = BalancedRandomForestClassifier(max_leaf_nodes= 80,n_estimators=1200, random_state=1)

# Fitting the model
model.fit(X_resampled, y_resampled)

# Calculated the balanced accuracy score
y_pred=model.predict(X_test)
print("ACCURACY SCORE: ",balanced_accuracy_score(y_test,y_pred))

# Print the imbalanced classification report
print(classification_report(y_test,y_pred))
```

✓ 26.5s

```
ACCURACY SCORE:  0.9301672361086135
              precision    recall  f1-score   support

           0       0.98      0.92      0.95      1675
           1       0.75      0.94      0.83       415

    accuracy                           0.93      2090
   macro avg       0.87      0.93      0.89      2090
weighted avg       0.94      0.93      0.93      2090
```

Lets Resample Our Data Again…

Resampling using SMOTE

```
#resample with smote
from imblearn.over_sampling import SMOTE
oversample=SMOTE()
X_smote,y_smote=oversample.fit_resample(X,y)
Counter(y_smote)
```

✓ 0.2s

```
Counter({1: 6700, 0: 6700})
```

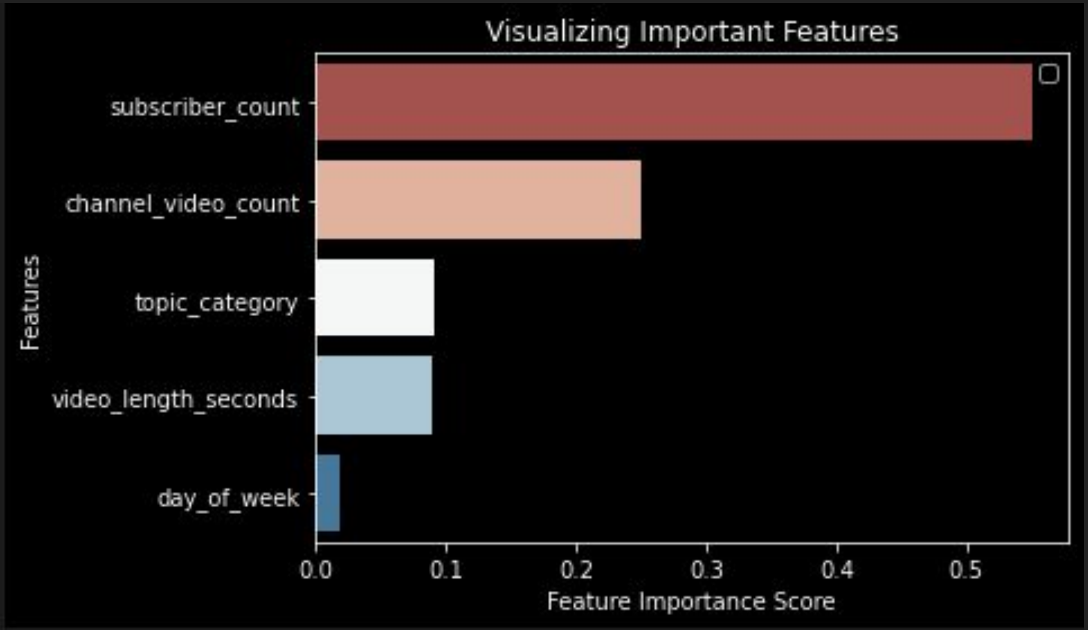
Random Forest with SMOTE

```
ACCURACY SCORE:  0.9942959899298687
```

	precision	recall	f1-score	support
0	1.00	1.00	1.00	1675
1	0.98	0.99	0.99	415
accuracy			1.00	2090
macro avg	0.99	0.99	0.99	2090
weighted avg	1.00	1.00	1.00	2090

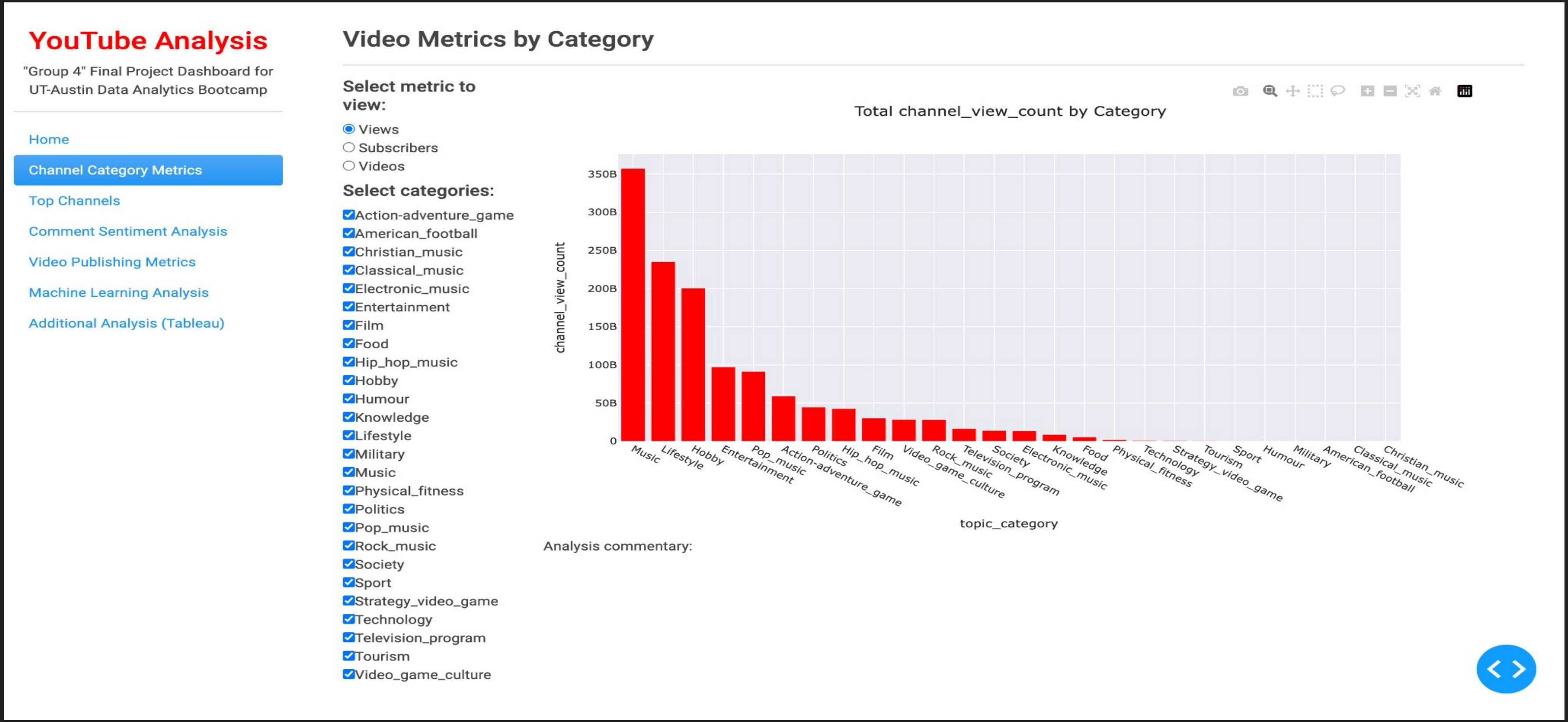
Machine Learning Results

Which YouTube video and channel metrics play the biggest role in creating a video that will gain the largest amount of views?

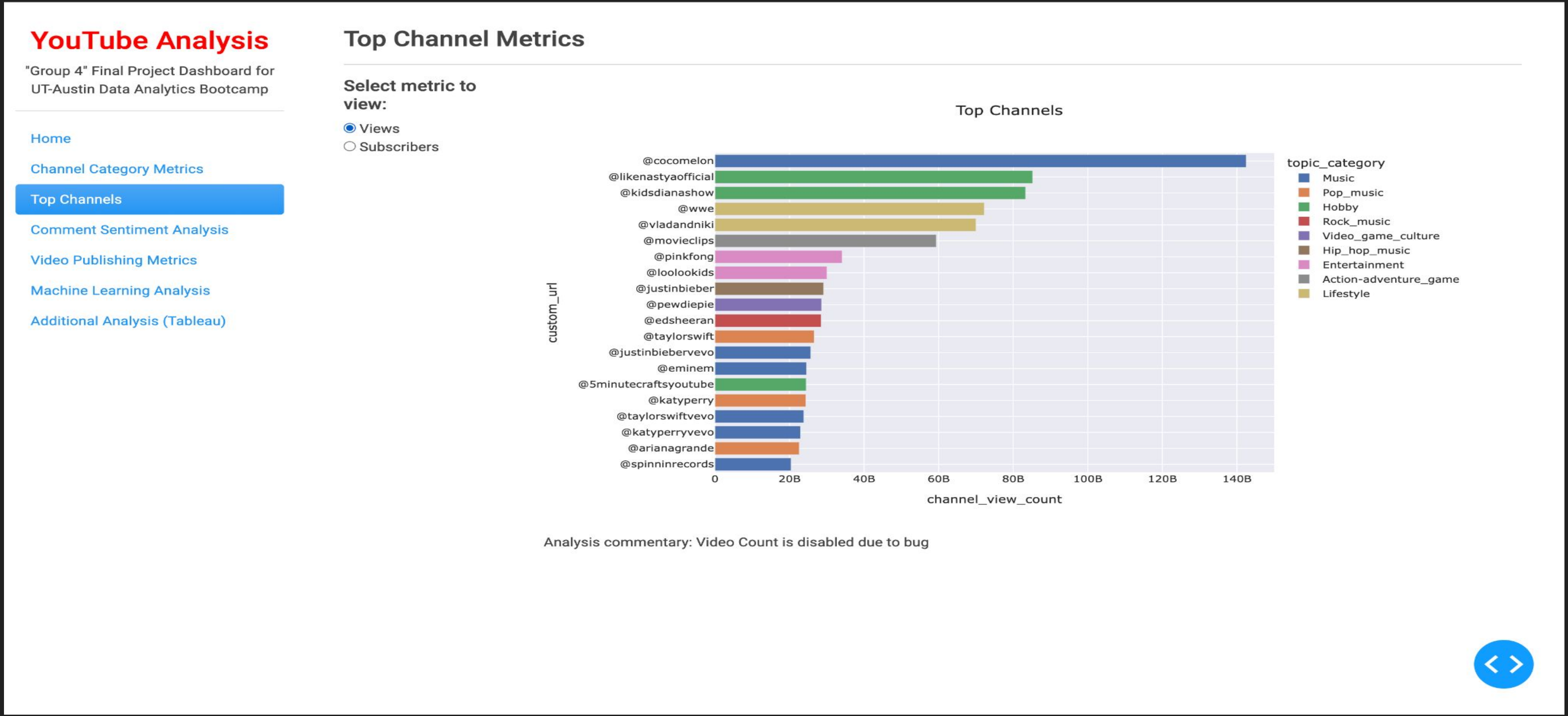


Dashboard

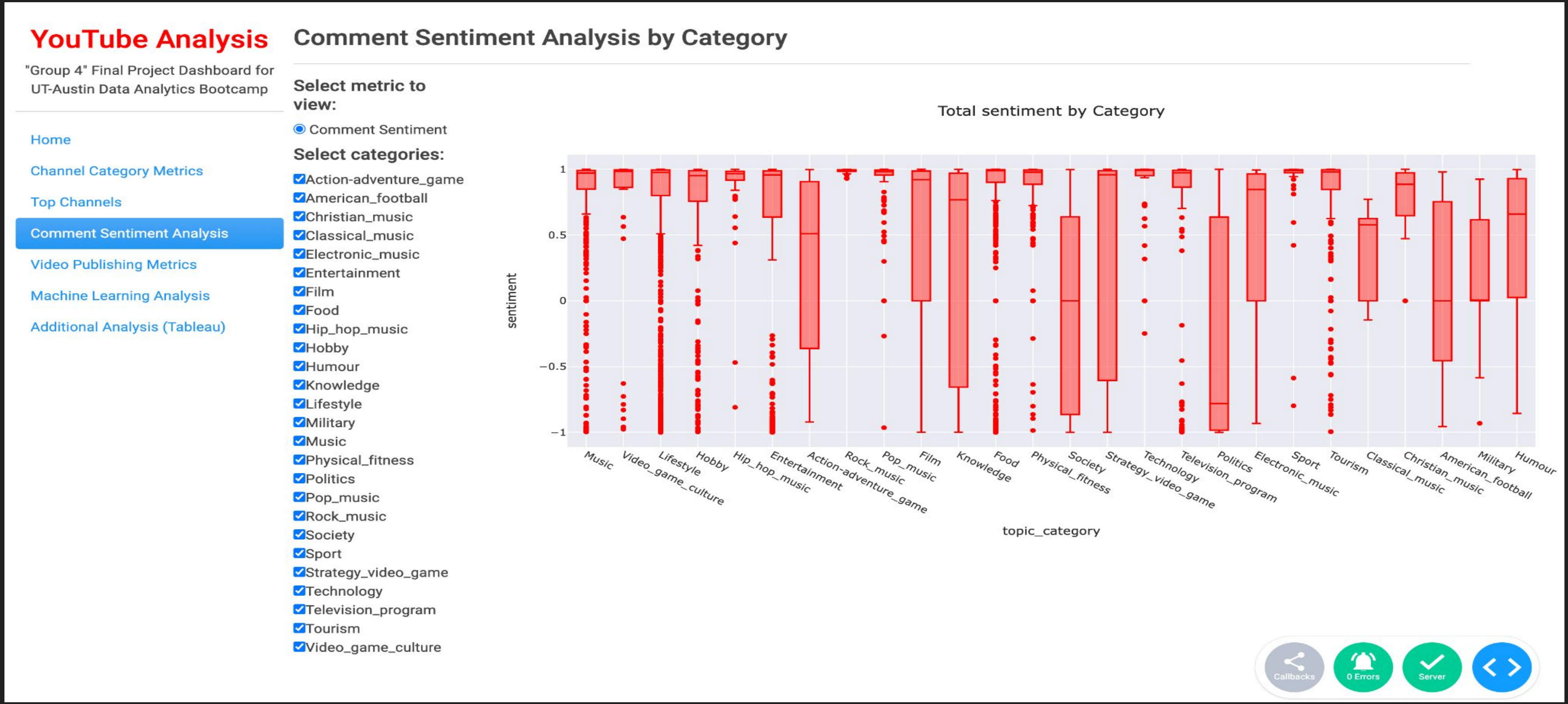
Images of Dashboard



Images of Dashboard



Images of Dashboard



Images of Dashboard

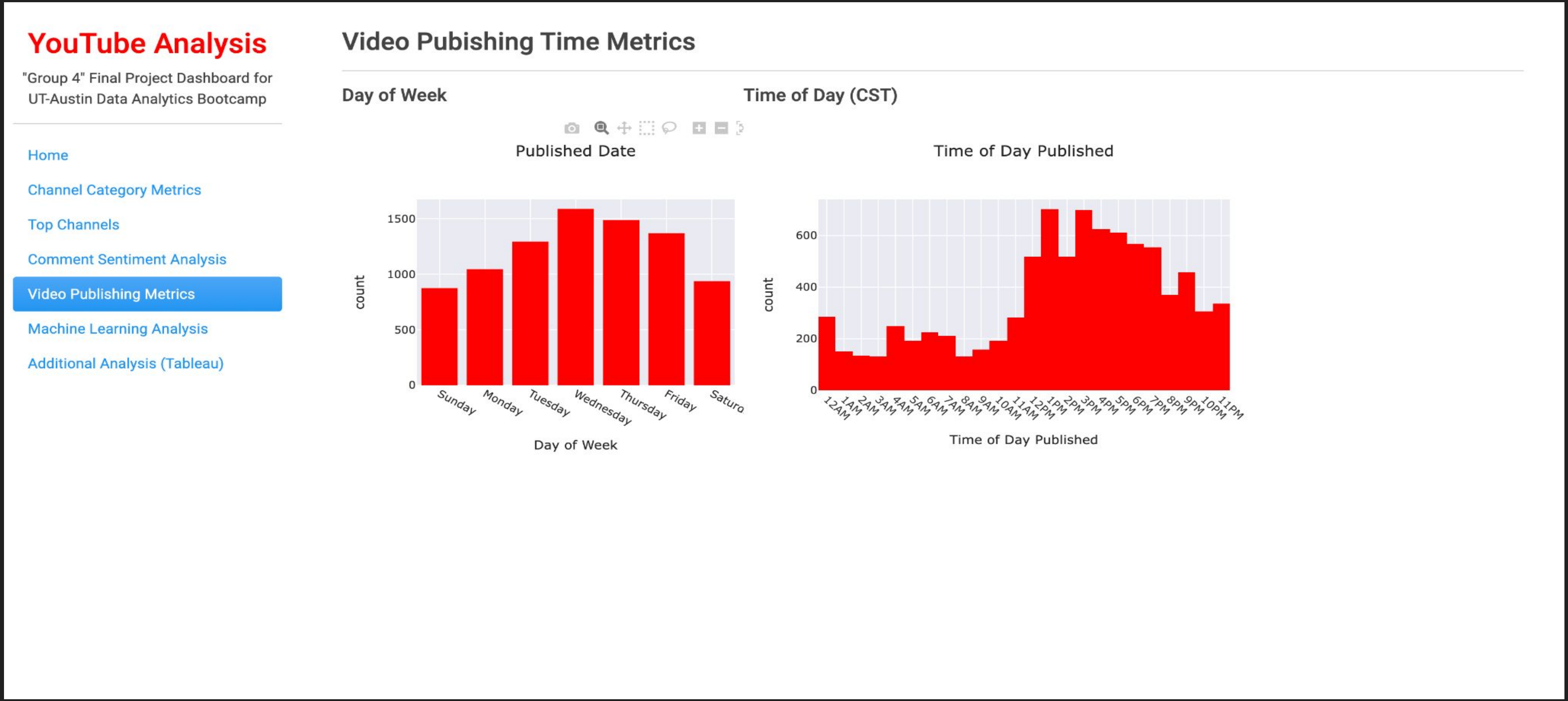
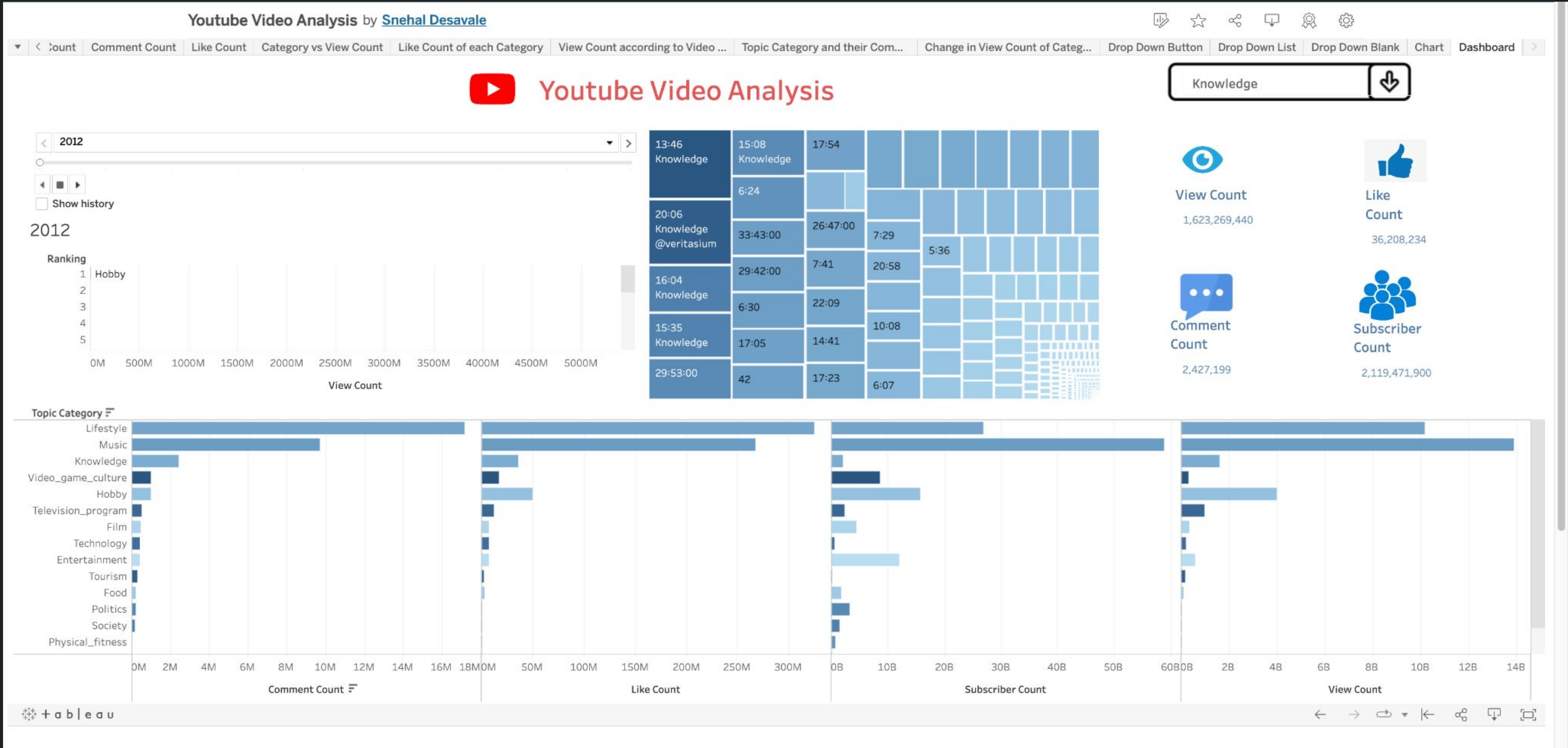


Tableau Dashboard



Recommendations for Future Analysis

- Included the hour video was published as a feature in our machine learning component
- Compare YouTube shorts- requires $

Things We Would Have Done Differently

- Use the full plotly library, not plotly express.
- More time exploring the YouTube API

Any Questions?