Final-Project

March 6, 2022

1 Analysis of Youtube Trending Videos in the U.S. year 2020 - 2021

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1.1 Context

YouTube maintains a list of the top trending videos on the platform. To determine Youtube's top-trending videos, YouTube uses a combination of factors including measuring users interactions (number of views, shares, comments and likes). You can learn more about how Youtube determines its trending video list here .

According to a study by H. Tankovska in early 2021, as of May 2019, more than 500 hours of video were uploaded to YouTube every minute. This equates to approximately 30,000 hours of newly uploaded content per hour. The amount of content on YouTube has increased dramatically as consumer's appetites for online video has grown. In fact, the number of video content hours uploaded every 60 seconds grew by around 40 percent between 2014 and 2019.

1.2 Problem statement

With this information, we took a deeper dive into the top trending videos in the U.S. between August 2020 and April 2021. We used Apache Spark to explore the data and gain insights into characteristics behind trending Youtube videos. We have also used Spark machine learning models to predict views using characteristics that can be controlled by the user uploading the video. The model can potentially be used by Youtube users who are uploading videos and predict the number of views they can receive on their videos.

1.3 Set Up

1.3.1 Importing libraries

Below are the libraries that were used in order to perform EDA (Exploratory data analysis) and Machine Learning using Spark.

[ ]:
```
import pyspark
import pandas as pd
import numpy as np
import re
import requests
from pyspark.sql import SparkSession
from pyspark.sql.functions import col
from os import path
from PIL import Image
from wordcloud import WordCloud, STOPWORDS, ImageColorGenerator
from matplotlib import pyplot as plt
import matplotlib.colors as mc
import seaborn as sns

from pyspark.sql.functions import *
from pyspark.sql.functions import unix_timestamp
from pyspark.sql.functions import hour
from pyspark.sql.functions import isnull, when, count, col
from pyspark.sql.functions import when
from pyspark.sql.functions import countDistinct

#ML Regression Packages
from pyspark.ml.regression import RandomForestRegressor
from pyspark.ml.regression import LinearRegression
#ML Evaluation Packages
from pyspark.ml.evaluation import RegressionEvaluator
from pyspark.ml.evaluation import MulticlassClassificationEvaluator
#ML Data Preparation Packages
from pyspark.ml.feature import StringIndexer
from pyspark.ml.feature import VectorAssembler
#ML Classification Packages
from pyspark.ml.classification import RandomForestClassifier
from pyspark.ml.evaluation import MulticlassClassificationEvaluator

from pyspark.ml.feature import Bucketizer
from pyspark.ml import Pipeline
```

1.3.2 Launch Spark

[ ]:
```
pyspark.__version__
```

[ ]:
```
'3.1.1'
```

1.3.3 Loading the dataset

[ ]:
```
spark = SparkSession \
    .builder \
    .appName('US_youtube_trending_data.csv') \
    .getOrCreate()
```

1.3.4 Creating Spark session

[ ]:
```
spark
```

[ ]:
```
<pyspark.sql.session.SparkSession at 0x7fdd7a5619a0>
```

1.3.5 Loading data into DataFrame

[ ]:
```
df = (spark.read
          .format("csv")
          .option('header', 'true')
          .load("US_youtube_trending_data.csv"))
```

[ ]:
```
df.show(5)
```

```
+-----------+--------------------+--------------------+--------------------+----
---------+----------+--------------------+--------------------+----------+------
+--------+-------------+--------------------+-----------------+----------------+
|   video_id|               title|         publishedAt|           channelId|
channelTitle|categoryId|       trending_date|                tags|view_count|
likes|dislikes|comment_count|
thumbnail_link|comments_disabled|ratings_disabled|
+-----------+--------------------+--------------------+--------------------+----
---------+----------+--------------------+--------------------+----------+------
+--------+-------------+--------------------+-----------------+----------------+
|3C66w5Z0ixs|I ASKED HER TO BE…|2020-08-11T19:20:14Z|UCvtRTOMP2TqYqu51…|
Brawadis|        22|2020-08-12T00:00:00Z|brawadis|prank|ba…|   1514614|156908|
5855|        35313|https://i.ytimg.c…|            FALSE|           FALSE|
|M9Pmf9AB4Mo|Apex Legends | St…|2020-08-11T17:00:10Z|UC0ZV6M2THA81QT9h…|
Apex Legends|        20|2020-08-12T00:00:00Z|Apex Legends|Apex…|
2381688|146739|    2794|        16549|https://i.ytimg.c…|            FALSE|
FALSE|
|J78aPJ3VyNs|I left youtube
fo…|2020-08-11T16:34:06Z|UCYzPXprvl5Y-Sf0g…|jacksepticeye|
24|2020-08-12T00:00:00Z|jacksepticeye|fun…|   2038853|353787|    2628|
40221|https://i.ytimg.c…|            FALSE|           FALSE|
|kXLn3HkpjaA|XXL 2020 Freshman…|2020-08-11T16:38:55Z|UCbg_UMjlHJg_19SZ…|
XXL|        10|2020-08-12T00:00:00Z|xxl freshman|xxl …|    496771| 23251|
1856|         7647|https://i.ytimg.c…|            FALSE|           FALSE|
|VIUo6yapDbc|Ultimate DIY Home…|2020-08-11T15:10:05Z|UCDVPcEbVLQgLZX0R…|
```

```
Mr. Kate|        26|2020-08-12T00:00:00Z|The LaBrant Famil…|   1123889| 45802|
964|         2196|https://i.ytimg.c…|            FALSE|           FALSE|
+-----------+--------------------+--------------------+--------------------+----
---------+----------+--------------------+--------------------+----------+------
+--------+-------------+--------------------+----------------+----------------+
only showing top 5 rows
```

1.3.6 Converting the DataFrame into Pandas

Since the DataFrame configuration is not in a cell format, we converted the DataFrame into panda to get a better look of the data.

[ ]:
```
df.toPandas().head(5)
```

[ ]:
```
      video_id                                              title  \
0  3C66w5Z0ixs                 I ASKED HER TO BE MY GIRLFRIEND…
1  M9Pmf9AB4Mo  Apex Legends | Stories from the Outlands - "Th…
2  J78aPJ3VyNs  I left youtube for a month and THIS is what ha…
3  kXLn3HkpjaA  XXL 2020 Freshman Class Revealed - Official An…
4  VIUo6yapDbc  Ultimate DIY Home Movie Theater for The LaBran…

            publishedAt                channelId   channelTitle categoryId  \
0  2020-08-11T19:20:14Z  UCvtRTOMP2TqYqu51xNrqAzg       Brawadis         22
1  2020-08-11T17:00:10Z  UC0ZV6M2THA81QT9hrVWJG3A   Apex Legends         20
2  2020-08-11T16:34:06Z  UCYzPXprvl5Y-Sf0g4vX-m6g  jacksepticeye         24
3  2020-08-11T16:38:55Z  UCbg_UMjlHJg_19SZckaKajg            XXL         10
4  2020-08-11T15:10:05Z  UCDVPcEbVLQgLZX0Rt6jo34A       Mr. Kate         26

          trending_date                                               tags  \
0  2020-08-12T00:00:00Z  brawadis|prank|basketball|skits|ghost|funny vi…
1  2020-08-12T00:00:00Z  Apex Legends|Apex Legends characters|new Apex …
2  2020-08-12T00:00:00Z  jacksepticeye|funny|funny meme|memes|jacksepti…
3  2020-08-12T00:00:00Z  xxl freshman|xxl freshmen|2020 xxl freshman|20…
4  2020-08-12T00:00:00Z  The LaBrant Family|DIY|Interior Design|Makeove…

  view_count   likes dislikes comment_count  \
0    1514614  156908     5855         35313
1    2381688  146739     2794         16549
2    2038853  353787     2628         40221
3     496771   23251     1856          7647
4    1123889   45802      964          2196

                                thumbnail_link comments_disabled  \
0  https://i.ytimg.com/vi/3C66w5Z0ixs/default.jpg            FALSE
1  https://i.ytimg.com/vi/M9Pmf9AB4Mo/default.jpg            FALSE
2  https://i.ytimg.com/vi/J78aPJ3VyNs/default.jpg            FALSE
3  https://i.ytimg.com/vi/kXLn3HkpjaA/default.jpg            FALSE
```

```
4  https://i.ytimg.com/vi/VIUo6yapDbc/default.jpg             FALSE

  ratings_disabled
0            FALSE
1            FALSE
2            FALSE
3            FALSE
4            FALSE
```

Exploratory Data Analysis

1.3.7 Checking the data types of all columns

This step tells us the types of data we are working with, and can help us make informed decisions on how we want to use the data.

[ ]:
```
df.dtypes
```

[ ]:
```
[('video_id', 'string'),
 ('title', 'string'),
 ('publishedAt', 'string'),
 ('channelId', 'string'),
 ('channelTitle', 'string'),
 ('categoryId', 'string'),
 ('trending_date', 'string'),
 ('tags', 'string'),
 ('view_count', 'string'),
 ('likes', 'string'),
 ('dislikes', 'string'),
 ('comment_count', 'string'),
 ('thumbnail_link', 'string'),
 ('comments_disabled', 'string'),
 ('ratings_disabled', 'string')]
```

1.3.8 Converting data types and including additonal columns

Some columns have their data types inaccurately registered by Spark so we converted them into accurate data types.Selecting data types also makes the Spark run faster. In this step, we have also included additional columns like “hour”, “datediff” and “wordCount” to assist our analysis. Other columns “like view_count_log”, “comment_count_log”, “likes_log” were added as the data was found to be very skewed.

[ ]:
```
dataset = df.withColumn('publishedAt', unix_timestamp("publishedAt",␣
  ↪'%Y-%m-%dT%H:%M:%S.%fZ')) #converting to date, hour and minutes

dataset = df.select(col('video_id').cast('string'),
                    col('title').cast('string'),
                    col('publishedAt').cast('timestamp'),
```

```
                           col('channelId').cast('string'),
                           col('channelTitle').cast('string'),
                           col('categoryId').cast('string'),
                           col('trending_date').cast('date'),
                           col('tags').cast('string'),
                           col('view_count').cast('int'),
                           col('likes').cast('int'),
                           col('dislikes').cast('int'),
                           col('comment_count').cast('int'),
                           col('thumbnail_link').cast('string'),
                           col('comments_disabled').cast('string'),
                           col('ratings_disabled').cast('string')
                          )
dataset = dataset.withColumn("hour", hour("publishedAt")) #hour at which video␣
 ↪was published
dataset = dataset.withColumn("datediff",␣
 ↪datediff(col('trending_date'),col("publishedAt"))) #number of days between␣
 ↪trending date and video published date

dataset = dataset.withColumn("view_count_log", log('view_count')) #converting␣
 ↪views to log
dataset = dataset.withColumn("comment_count_log", log1p("comment_count"))␣
 ↪#using log1p as we want to keep 0 comments in the analysis
dataset = dataset.withColumn("likes_log", log1p("likes")) #using log1p as we␣
 ↪want to keep 0 likes in the analysis

dataset = dataset.withColumn('wordCount', size(split(col('title'), ' ')))␣
 ↪#counting the length of the title
```

Let's check out the result:

[ ]:
```
dataset.dtypes #checking datatype of final dataset
```

[ ]:
```
[('video_id', 'string'),
 ('title', 'string'),
 ('publishedAt', 'timestamp'),
 ('channelId', 'string'),
 ('channelTitle', 'string'),
 ('categoryId', 'string'),
 ('trending_date', 'date'),
 ('tags', 'string'),
 ('view_count', 'int'),
 ('likes', 'int'),
 ('dislikes', 'int'),
 ('comment_count', 'int'),
 ('thumbnail_link', 'string'),
 ('comments_disabled', 'string'),
```

```
 ('ratings_disabled', 'string'),
 ('hour', 'int'),
 ('datediff', 'int'),
 ('view_count_log', 'double'),
 ('comment_count_log', 'double'),
 ('likes_log', 'double'),
 ('wordCount', 'int')]
```

[ ]:
```
dataset.show(5)
```

```
+-----------+--------------------+--------------------+--------------------+-----
--------+----------+-------------+--------------------+----------+------+-------
-+-------------+--------------------+-----------------+----------------+----+---
-----+-----------------+-----------------+-----------------+---------+
|   video_id|               title|        publishedAt|           channelId|
channelTitle|categoryId|trending_date|                tags|view_count|
likes|dislikes|comment_count|
thumbnail_link|comments_disabled|ratings_disabled|hour|datediff|
view_count_log| comment_count_log|         likes_log|wordCount|
+-----------+--------------------+--------------------+--------------------+-----
--------+----------+-------------+--------------------+----------+------+-------
-+-------------+--------------------+-----------------+----------------+----+---
-----+-----------------+-----------------+-----------------+---------+
|3C66w5Z0ixs|I ASKED HER TO BE…|2020-08-11 15:20:14|UCvtRTOMP2TqYqu51…|
Brawadis|        22|   2020-08-12|brawadis|prank|ba…|   1514614|156908|
5855|        35313|https://i.ytimg.c…|            FALSE|           FALSE|  15|
1|14.230671178983725|10.472034764862743|11.963421298452696|        7|
|M9Pmf9AB4Mo|Apex Legends | St…|2020-08-11 13:00:10|UC0ZV6M2THA81QT9h…| Apex
Legends|        20|   2020-08-12|Apex Legends|Apex…|   2381688|146739|
2794|        16549|https://i.ytimg.c…|            FALSE|           FALSE|  13|
1|14.683320037950685|  9.71414138080521|11.896417592267985|       10|
|J78aPJ3VyNs|I left youtube fo…|2020-08-11
12:34:06|UCYzPXprvl5Y-Sf0g…|jacksepticeye|        24|
2020-08-12|jacksepticeye|fun…|   2038853|353787|    2628|
40221|https://i.ytimg.c…|            FALSE|           FALSE|  12|
1|14.527897952793877|10.602169388594548|12.776453142665115|       11|
|kXLn3HkpjaA|XXL 2020 Freshman…|2020-08-11 12:38:55|UCbg_UMjlHJg_19SZ…|
XXL|        10|   2020-08-12|xxl freshman|xxl …|    496771| 23251|    1856|
7647|https://i.ytimg.c…|            FALSE|           FALSE|  12|
1|13.115884434306619| 8.942199454731238|10.054146428821241|        8|
|VIUo6yapDbc|Ultimate DIY Home…|2020-08-11 11:10:05|UCDVPcEbVLQgLZX0R…|
Mr. Kate|        26|   2020-08-12|The LaBrant Famil…|   1123889| 45802|
964|         2196|https://i.ytimg.c…|            FALSE|           FALSE|  11|
1|13.932305550110833|  7.69484807238461|10.732104870140509|        9|
+-----------+--------------------+--------------------+--------------------+-----
--------+----------+-------------+--------------------+----------+------+-------
-+-------------+--------------------+-----------------+----------------+----+---
```

```
-----+-----------------+-----------------+-----------------+---------+
only showing top 5 rows
```

Summarizing data and converting results into pandas to get a better look of the result:

[ ]:
```
dataset.describe().toPandas()
```

[ ]:

	summary	video_id	title
0	count	52991	52991
1	mean	None	None
2	stddev	None	None
3	min	#NAME?	!@#$%$#!! || Dubov vs Carlsen || Airthings Mas…
4	max	zziBybeSAtw	LATE COMEBACK DRAMA! | HIGHLIGHTS | Granada …

	channelId	channelTitle	categoryId
0	52991	52991	52991
1	None	None	18.61810496121983
2	None	None	7.049763252708128
3	UC-2MJlKSq9_pYk5-bdvMhnw	#TeamTrees	1
4	UCzznO4xSV8BKnUBPyswtCUw	NCT DANCE	29

	tags	view_count
0	52991	52991
1	None	2710755.2364552473
2	None	6167696.576334619
3	#1 overall|49ers|BYU|Chris Brockman|Clemson|Da…	0
4	|HyunA|ImNotCool| | |MCD|MCOUNTDOWN| …	232649205

	likes	dislikes	comment_count
0	52991	52991	52991
1	150445.41622162255	3395.891547621294	15568.596289936027
2	417781.47715530026	15523.585060560985	104314.12565911695
3	0	0	0
4	15735533	879354	6065230

	thumbnail_link	comments_disabled
0	52991	52991
1	None	None
2	None	None
3	https://i.ytimg.com/vi/--SvHNpSvpk/default.jpg	FALSE
4	https://i.ytimg.com/vi/zziBybeSAtw/default.jpg	TRUE

	ratings_disabled	hour	datediff
0	52991	52991	52991
1	None	12.889056632258308	4.243324338095149
2	None	5.772991831336436	2.3714927062655975
3	FALSE	0	0

```
4             TRUE                  23                  36

       view_count_log   comment_count_log           likes_log  \
0               52965               52991               52991
1  14.033052952454167   8.288682562422062  10.803081419229423
2   1.1453274961229554   1.844483739556252  1.6791442891251112
3   10.558673226808954                 0.0                 0.0
4   19.265042319098868  15.618083187021625   16.57143202498773

            wordCount
0               52991
1   8.895586042912948
2  3.6649837154565805
3                   1
4                  23
```

1.3.9 Checking for Null values

Most of the columns do not have null values. Only "view_count_log" column have 26 null values. We will be removing this rows in the later analysis

[ ]:
```
dataset.select([count(when(isnull(c), c)).alias(c) for c in dataset.columns]).
↪show()
```

```
+--------+-----+-----------+---------+-----------+----------+-------------+----
+----------+-----+--------+-------------+--------------+-----------------+------
----------+----+--------+--------------+-----------------+---------+---------+
|video_id|title|publishedAt|channelId|channelTitle|categoryId|trending_date|tags
|view_count|likes|dislikes|comment_count|thumbnail_link|comments_disabled|rating
s_disabled|hour|datediff|view_count_log|comment_count_log|likes_log|wordCount|
+--------+-----+-----------+---------+-----------+----------+-------------+----
+----------+-----+--------+-------------+--------------+-----------------+------
----------+----+--------+--------------+-----------------+---------+---------+
|       0|    0|          0|        0|           0|         0|            0|
0|         0|    0|       0|            0|             0|                0|
0|   0|       0|           26|                0|        0|        0|
+--------+-----+-----------+---------+-----------+----------+-------------+----
+----------+-----+--------+-------------+--------------+-----------------+------
----------+----+--------+--------------+-----------------+---------+---------+
```

1.3.10 Statistical summary of numerical columns

This method is used for pulling a statistical summary, such as count, mean, standard deviation, minimum, and maximum values of all numerical data in the DataFrame.

[ ]:

```
dataset.select('comment_count','view_count','likes','dislikes', 'hour',␣
↪'datediff', 'view_count_log', 'comment_count_log','likes_log', 'wordCount').
↪describe().toPandas()
```

[ ]:

summary	comment_count	view_count	likes
count	52991	52991	52991
mean	15568.596289936027	2710755.2364552473	150445.41622162255
stddev	104314.12565911695	6167696.576334619	417781.47715530026
min	0	0	0
max	6065230	232649205	15735533

summary	dislikes	hour	datediff
count	52991	52991	52991
mean	3395.891547621294	12.889056632258308	4.243324338095149
stddev	15523.585060560985	5.772991831336436	2.3714927062655975
min	0	0	0
max	879354	23	36

summary	view_count_log	comment_count_log	likes_log
count	52965	52991	52991
mean	14.033052952454167	8.288682562422062	10.803081419229423
stddev	1.1453274961229554	1.844483739556252	1.6791442891251112
min	10.558673226808954	0.0	0.0
max	19.265042319098868	15.618083187021625	16.57143202498773

summary	wordCount
count	52991
mean	8.895586042912948
stddev	3.6649837154565805
min	1
max	23

The category of trending videos in this DataFrame is characterized by the ID as seen below.

[ ]:
```
dataset.select("categoryId").distinct().show(truncate=False)
```

```
+----------+
|categoryId|
+----------+
|15        |
|29        |
|22        |
|28        |
|27        |
|17        |
|26        |
|19        |
|23        |
```

```
|25         |
|24         |
|1          |
|20         |
|10         |
|2          |
+----------+
```

1.3.11 Transforming categoryId to categoryName

To properly identify each category, we transform the categoryID to correspond with its respective name. For example, categoryID = 1 represents 'Film Animation'. After we transform the category column, we then removed the categoryID column.

[ ]:
```
df_Main = dataset.withColumn("categoryName", when(dataset.categoryId ==␣
 ↪"1","Film & Animation")
                                    .when(dataset.categoryId == "2","Autos &␣
 ↪Vehiclese")
                                    .when(dataset.categoryId == "10","Music")
                                    .when(dataset.categoryId == "15","Pets &␣
 ↪Animals")
                                    .when(dataset.categoryId == "17","Sports")
                                    .when(dataset.categoryId == "19","Travel &␣
 ↪Events")
                                    .when(dataset.categoryId == "20","Gaming")
                                    .when(dataset.categoryId == "22","People &␣
 ↪Blogs")
                                    .when(dataset.categoryId == "23","Comedy")
                                    .when(dataset.categoryId ==␣
 ↪"24","Entertainment")
                                    .when(dataset.categoryId == "25","News &␣
 ↪Politics")
                                    .when(dataset.categoryId == "26","Howto &␣
 ↪Style")
                                    .when(dataset.categoryId == "27","Education")
                                    .when(dataset.categoryId == "28","Science &␣
 ↪Technology")
                                    .when(dataset.categoryId == "29","Nonprofits &␣
 ↪Activisme")
                                    .when(dataset.categoryId.isNull() ,"")
                                    .otherwise(dataset.categoryId))

df_Main.select("categoryName").distinct().show(truncate=False)
```

```
+----------------------+
|categoryName          |
+----------------------+
```

```
|Education             |
|Nonprofits & Activisme|
|Gaming                |
|Entertainment         |
|Travel & Events       |
|Science & Technology  |
|Sports                |
|Howto & Style         |
|Film & Animation      |
|People & Blogs        |
|News & Politics       |
|Pets & Animals        |
|Autos & Vehiclese     |
|Music                 |
|Comedy                |
+----------------------+
```

Then, we take a final look of the DataFrame.

[ ]:
```
df_Main.toPandas().head(5)
```

[ ]:
```
      video_id                                              title  \
0  3C66w5Z0ixs                  I ASKED HER TO BE MY GIRLFRIEND…
1  M9Pmf9AB4Mo  Apex Legends | Stories from the Outlands - "Th…
2  J78aPJ3VyNs  I left youtube for a month and THIS is what ha…
3  kXLn3HkpjaA  XXL 2020 Freshman Class Revealed - Official An…
4  VIUo6yapDbc  Ultimate DIY Home Movie Theater for The LaBran…

          publishedAt                 channelId   channelTitle categoryId  \
0 2020-08-11 15:20:14  UCvtRTOMP2TqYqu51xNrqAzg       Brawadis         22
1 2020-08-11 13:00:10  UC0ZV6M2THA81QT9hrVWJG3A   Apex Legends         20
2 2020-08-11 12:34:06  UCYzPXprvl5Y-Sf0g4vX-m6g  jacksepticeye         24
3 2020-08-11 12:38:55  UCbg_UMjlHJg_19SZckaKajg            XXL         10
4 2020-08-11 11:10:05  UCDVPcEbVLQgLZX0Rt6jo34A       Mr. Kate         26

  trending_date                                              tags  \
0    2020-08-12  brawadis|prank|basketball|skits|ghost|funny vi…
1    2020-08-12  Apex Legends|Apex Legends characters|new Apex …
2    2020-08-12  jacksepticeye|funny|funny meme|memes|jacksepti…
3    2020-08-12  xxl freshman|xxl freshmen|2020 xxl freshman|20…
4    2020-08-12  The LaBrant Family|DIY|Interior Design|Makeove…

   view_count   likes  …                                thumbnail_link  \
0     1514614  156908  …  https://i.ytimg.com/vi/3C66w5Z0ixs/default.jpg
1     2381688  146739  …  https://i.ytimg.com/vi/M9Pmf9AB4Mo/default.jpg
2     2038853  353787  …  https://i.ytimg.com/vi/J78aPJ3VyNs/default.jpg
3      496771   23251  …  https://i.ytimg.com/vi/kXLn3HkpjaA/default.jpg
```

```
4     1123889   45802  …  https://i.ytimg.com/vi/VIUo6yapDbc/default.jpg

   comments_disabled ratings_disabled hour datediff  view_count_log  \
0              FALSE            FALSE   15        1       14.230671
1              FALSE            FALSE   13        1       14.683320
2              FALSE            FALSE   12        1       14.527898
3              FALSE            FALSE   12        1       13.115884
4              FALSE            FALSE   11        1       13.932306

   comment_count_log  likes_log  wordCount    categoryName
0          10.472035  11.963421          7  People & Blogs
1           9.714141  11.896418         10          Gaming
2          10.602169  12.776453         11   Entertainment
3           8.942199  10.054146          8           Music
4           7.694848  10.732105          9   Howto & Style

[5 rows x 22 columns]
```

Total number of videos

[ ]:
```
df_Main.count()
```

[ ]:
```
52991
```

Number of unique videos

[ ]:
```
df_Main.select(countDistinct("video_id")).show()
```

```
+------------------------+
|count(DISTINCT video_id)|
+------------------------+
|                    9038|
+------------------------+
```

1.4 Correlation analysis and heatmap

We visualized the correlation between different parameters. Comments, dislikes, likes are found to be highly correlated to video views which is not surprising as the more views a video gets, there is more possibility of the video receiving more social interactions.

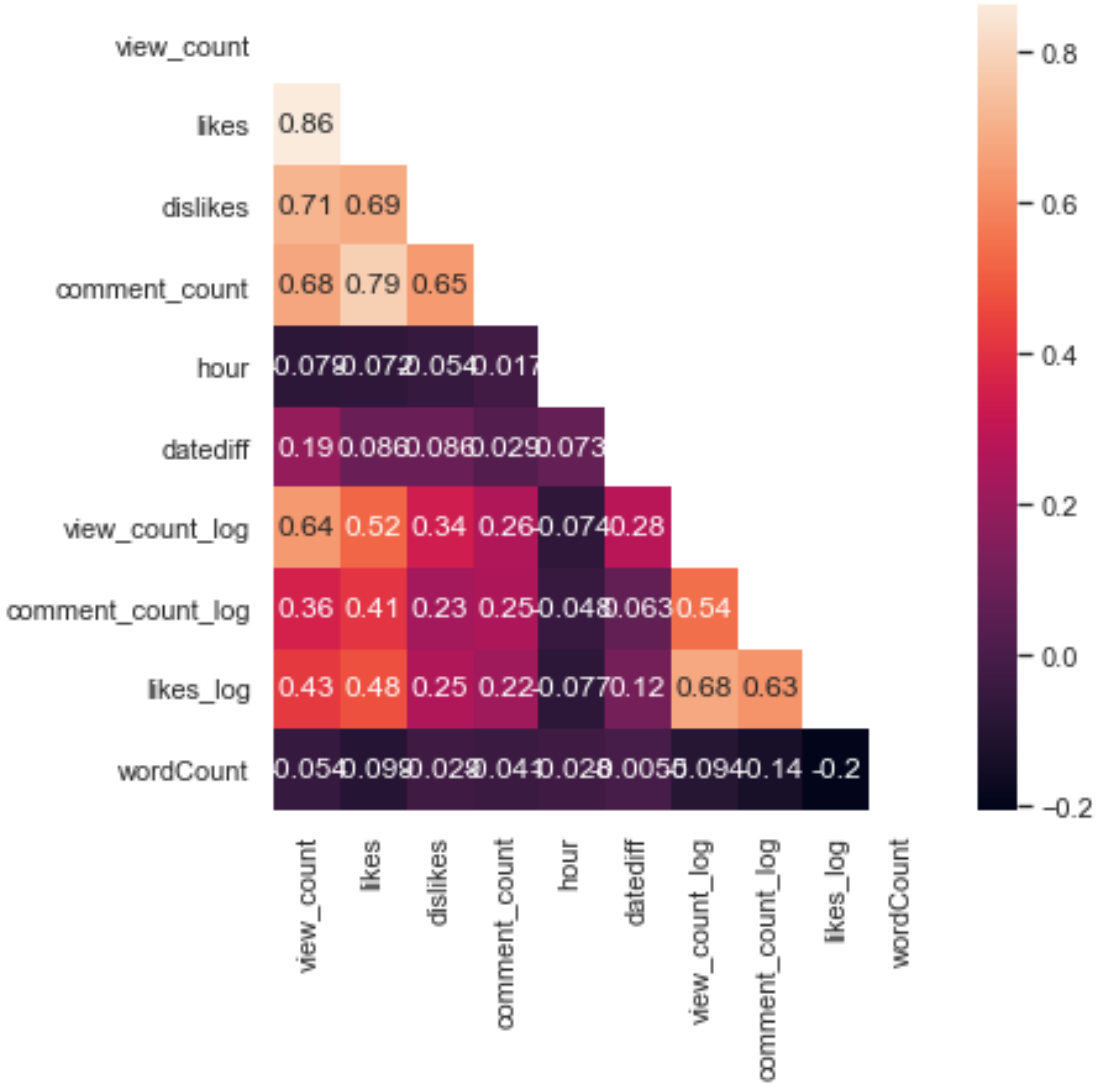
[ ]:
```
DF_DUMMY = df_Main.toPandas()
DF_DUMMY.corr()
```

[ ]:
```
                  view_count     likes  dislikes  comment_count      hour  \
view_count          1.000000  0.864737  0.711494       0.675278 -0.079084
likes               0.864737  1.000000  0.687992       0.785222 -0.072424
dislikes            0.711494  0.687992  1.000000       0.645867 -0.054300
comment_count       0.675278  0.785222  0.645867       1.000000 -0.017223
```

```
hour                -0.079084 -0.072424 -0.054300      -0.017223  1.000000
datediff             0.194113  0.085896  0.086478       0.028850  0.073434
view_count_log       0.641411  0.521933  0.338872       0.258113 -0.073948
comment_count_log    0.358506  0.412541  0.228054       0.250712 -0.048227
likes_log            0.425216  0.476072  0.254974       0.221101 -0.076901
wordCount           -0.053925 -0.099063 -0.028730      -0.040898 -0.027571

                    datediff  view_count_log  comment_count_log  likes_log  \
view_count          0.194113        0.641411           0.358506   0.425216
likes               0.085896        0.521933           0.412541   0.476072
dislikes            0.086478        0.338872           0.228054   0.254974
comment_count       0.028850        0.258113           0.250712   0.221101
hour                0.073434       -0.073948          -0.048227  -0.076901
datediff            1.000000        0.281651           0.063202   0.115138
view_count_log      0.281651        1.000000           0.541897   0.679987
comment_count_log   0.063202        0.541897           1.000000   0.627150
likes_log           0.115138        0.679987           0.627150   1.000000
wordCount          -0.005510       -0.093724          -0.136784  -0.204761

                    wordCount
view_count          -0.053925
likes               -0.099063
dislikes            -0.028730
comment_count       -0.040898
hour                -0.027571
datediff            -0.005510
view_count_log      -0.093724
comment_count_log   -0.136784
likes_log           -0.204761
wordCount            1.000000
```

[ ]:
```
fig, ax = plt.subplots(figsize=(6, 6))
mask = np.zeros_like(DF_DUMMY.corr())
mask[np.triu_indices_from(mask)] = 1
sns.heatmap(DF_DUMMY.corr(), mask= mask, ax= ax, annot= True)
```

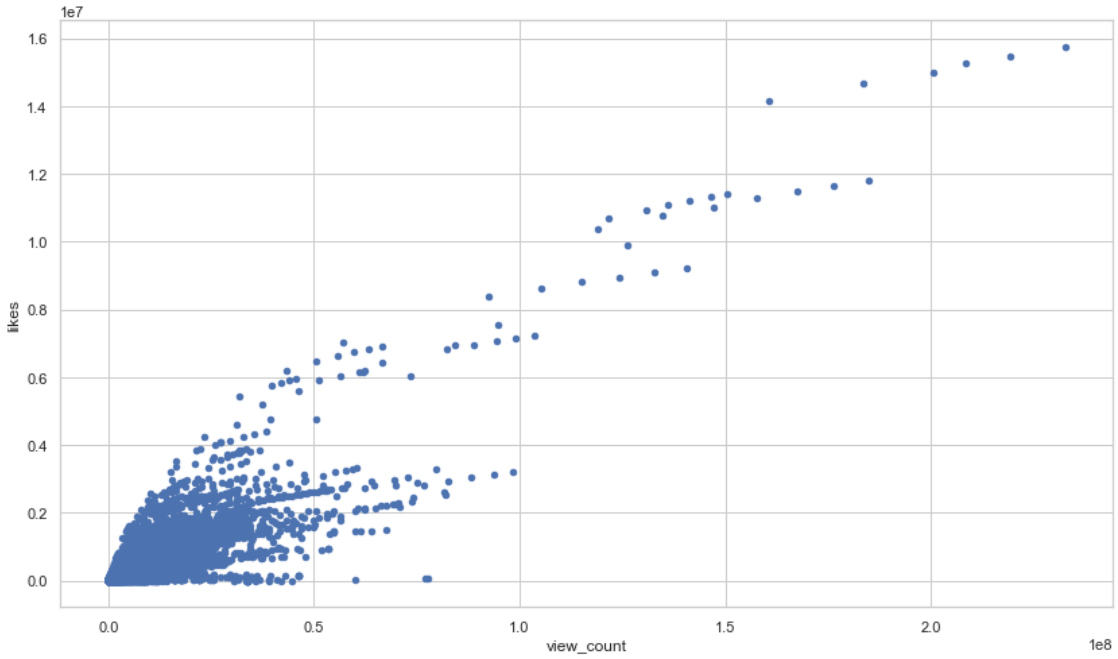
[ ]:
```
<AxesSubplot:>
```



1.4.1 Correlation between views and likes

[ ]:
```
ax = DF_DUMMY.plot(kind='scatter', x='view_count', y='likes', figsize=(14,8))
```

```
*c* argument looks like a single numeric RGB or RGBA sequence, which should be
avoided as value-mapping will have precedence in case its length matches with
*x* & *y*.  Please use the *color* keyword-argument or provide a 2D array with a
single row if you intend to specify the same RGB or RGBA value for all points.
```



Trending Videos and Views

Minimum view count of a trending video

[ ]:
```
df_Main.agg({'view_count': 'min'}).show() # there are videos with zero views
```

```
+---------------+
|min(view_count)|
+---------------+
|              0|
+---------------+
```

1.4.2 Number of trending videos with 0 (zero) view count

Only 26 videos have zero views

[ ]:
```
df_Main.filter(df_Main.view_count == 0).count()
```

[ ]: 26

1.4.3 Maximum view count of a trending video

The maximum number of views in a video is 232649205

[ ]:
```
df_Main.agg({'view_count': 'max'}).show()
```

```
+---------------+
|max(view_count)|
+---------------+
|      232649205|
+---------------+
```

The video is from BTS!

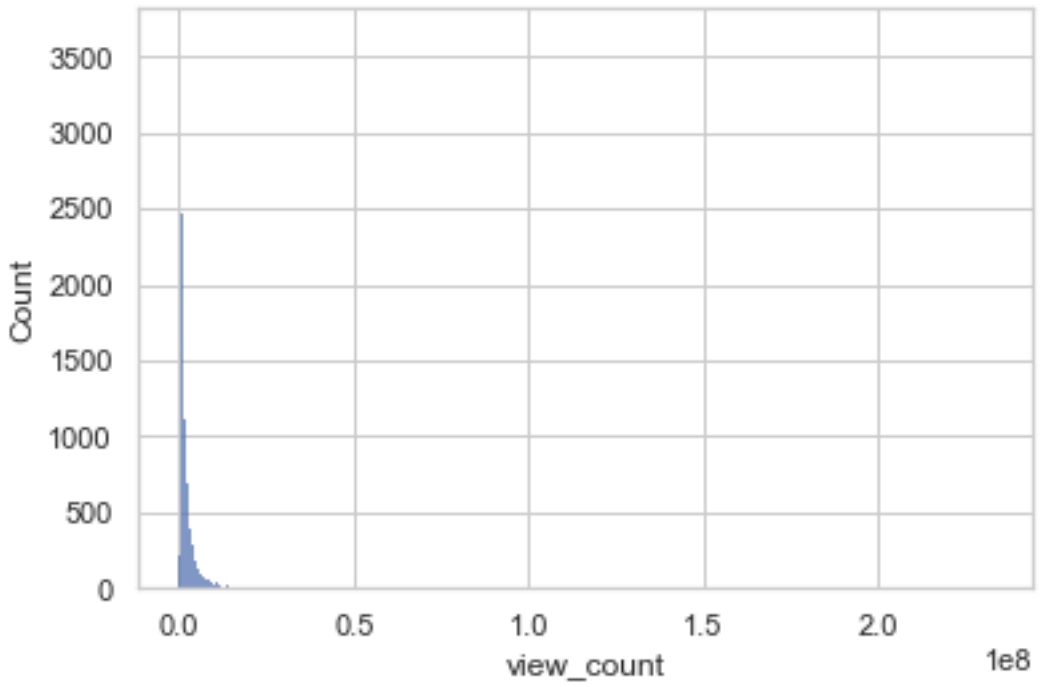
[ ]:
```
df_Main.filter(df_Main.view_count == 232649205).toPandas()
```

[ ]:
```
      video_id                                title         publishedAt  \
0  gdZLi9oWNZg  BTS (   ) 'Dynamite' Official MV 2020-08-20 23:58:10

                  channelId    channelTitle categoryId trending_date  \
0  UC3IZKseVpdzPSBaWxBxundA  Big Hit Labels         10    2020-08-28

                              tags  view_count     likes  …  \
0  BIGHIT|  |   |BTS|BANGTAN|    232649205  15735533  …

                                    thumbnail_link  comments_disabled  \
0  https://i.ytimg.com/vi/gdZLi9oWNZg/default.jpg              FALSE

  ratings_disabled hour datediff  view_count_log  comment_count_log  \
0            FALSE   23        8       19.265042          15.618083

   likes_log  wordCount  categoryName
0  16.571432          5         Music

[1 rows x 22 columns]
```

1.4.4 View count distribution

Based on the below graph, it showed that video views is very skewed

[ ]:
```
sns.set_theme(style="whitegrid")
df_Dummy = df_Main.select("view_count").toPandas()
ax = sns.histplot(x=df_Dummy['view_count']) #histogram of video views
```



1.4.5 View count based on category

Music is the has the highest view count at about 49 million from all categories, followed by Entertainment and Gaming, while Nonprofits & Activism has the lowest view count.

[ ]:
```
df_Main.createOrReplaceTempView("YT_Data")
spark.sql("select categoryName,sum(view_count) Total_View from YT_Data \
          group by categoryName ORDER BY sum(view_count) desc").
 ↪show(truncate=False)
```

```
+----------------------+-----------+
|categoryName          |Total_View |
+----------------------+-----------+
|Music                 |49608723248|
|Entertainment         |28640901805|
|Gaming                |18958853006|
|Sports                |11605344744|
|People & Blogs        |10195523703|
|Science & Technology  |6286576615 |
|Film & Animation      |4353200121 |
|Comedy                |4033999870 |
|News & Politics       |3812392790 |
|Howto & Style         |3133985068 |
|Education             |1383348582 |
|Autos & Vehiclese     |1100550005 |
```

```
|Pets & Animals         |370296727  |
|Travel & Events        |113870468  |
|Nonprofits & Activisme|48063983   |
+----------------------+-----------+
```

1.4.6 Number of days a trending video lasted (a video can be trending for more than 1 day)

Some videos may be trending for days at a time on Youtube, which generates a number of view count. Below are a list of the top 20 videos that were trending for more than a day on the platform between August 2020 and April 2021.

[ ]:
```
df_Main.createOrReplaceTempView("YT_Data")
spark.sql("select title,count(distinct video_id),sum(view_count) Total_View␣
 ↪from YT_Data \
         group by title ORDER BY count(distinct video_id)␣
 ↪desc,sum(view_count)").show(truncate=False)
```

```
+-----------------------------------------------------------------------------
------------------+----------------------+----------+
|title
|count(DISTINCT video_id)|Total_View|
+-----------------------------------------------------------------------------
------------------+----------------------+----------+
|Starlink Mission
|15                      |70373877  |
|We Broke Up
|4                       |45050462  |
|Creative People On Another Level
|4                       |100499120 |
|$1000 if You Can Break This Ball in 1 Minute
|3                       |16098628  |
|we broke up
|3                       |46008685  |
|Most Oddly Satisfying Video to watch before sleep
|3                       |62787020  |
|What is this cute puppy dog doing?#Shorts
|2                       |4663568   |
|Among Us In Real Life
|2                       |4780094   |
|Goodbye.
|2                       |8822067   |
|ENEMIGOS OCULTOS REMIX - OZUNA X T.Y.S X ROCHY X WILMER ROBERTS X SHELOW SHAQ X
MUSICOLOGO X OMEGA|2                       |10171500  |
|Zack Snyder's Justice League - Movie Review
|2                       |10731771  |
|BAD NEWS…
```

```
|2                        |12320172  |
|Wonder Woman 1984 - Movie Review
|2                        |15240001  |
|Friday Night Funkin' - Senpai but every turn a Different Skin Mod is used
|2                        |23806625  |
|I'm Pregnant!!
|2                        |26779011  |
|Shawn Mendes, Camila Cabello - The Christmas Song
|2                        |28708397  |
|"     Switch to me" by DAHYUN and CHAEYOUNG - Melody Project
|2                        |31220022  |
|What Really Happened
|2                        |32362342  |
|I Survived 500 Days in HARDCORE Minecraft…
|2                        |34646003  |
|Most Oddly Satisfying Video to watch before bed
|2                        |35432884  |
+-------------------------------------------------------------------------------
------------------+-----------------------+----------+
only showing top 20 rows
```

1.4.7 Number of video trending based on category

Next, we break down the trending video category based on the number of videos owned by a unique channel. Based on the data, NBA tops other channel at 108 videos that were trending. Despite being at 4th place in terms of view count, Sports as a category tops the total number of trending videos between August 2020 and April 2021.

[ ]:
```
df_Main.createOrReplaceTempView("YT_Data")
spark.sql("select categoryName, channelTitle,count(distinct video_id)  from␣
 ↪YT_Data \
          group by categoryName, channelTitle ORDER BY count(distinct video_id)␣
 ↪desc").show(truncate=False)
```

```
+--------------------+-----------------------------------+--------------------
---+
|categoryName        |channelTitle                       |count(DISTINCT
video_id)|
+--------------------+-----------------------------------+--------------------
---+
|Sports              |NBA                                |108
|
|Sports              |NFL                                |105
|
|Sports              |ESPN                               |44
|
|Sports              |Champions League on CBS Sports     |43
```

```
|
|Gaming               |MrBeast Gaming                       |41
|
|Entertainment        |Saturday Night Live                  |37
|
|Science & Technology|SpaceX                                |36
|
|Entertainment        |SSSniperWolf                         |33
|
|Entertainment        |MrBeast                              |29
|
|Sports               |beIN SPORTS USA                      |28
|
|Sports               |NBC Sports                           |26
|
|Gaming               |Fortnite                             |25
|
|Music                |BLACKPINK                            |25
|
|Sports               |UFC - Ultimate Fighting Championship|24
|
|Entertainment        |James Charles                        |24
|
|Science & Technology|NASA                                  |22
|
|Gaming               |The Game Theorists                   |22
|
|Gaming               |Apex Legends                         |22
|
|Sports               |Dude Perfect                         |22
|
|Entertainment        |Marvel Entertainment                 |21
|
+--------------------+-------------------------------------+----------------------
---+
only showing top 20 rows
```

1.4.8 Maximum number of likes of a trending video

The video has around 15 million likes and appears to be the same video with the highest number of view count.

[ ]:
```
df_dummy = df_Main.agg({'likes': 'max'}).show()
df_Main.filter(df_Main.likes == 15735533).toPandas()
```

```
+----------+
|max(likes)|
```

```
+----------+
|  15735533|
+----------+
```

[ ]:
```
      video_id                                title         publishedAt  \
0  gdZLi9oWNZg  BTS (   ) 'Dynamite' Official MV 2020-08-20 23:58:10

                  channelId    channelTitle categoryId trending_date  \
0  UC3IZKseVpdzPSBaWxBxundA  Big Hit Labels         10    2020-08-28

                              tags  view_count     likes  …  \
0  BIGHIT|  |   |BTS|BANGTAN|    232649205  15735533  …

                                    thumbnail_link  comments_disabled  \
0  https://i.ytimg.com/vi/gdZLi9oWNZg/default.jpg              FALSE

  ratings_disabled hour datediff  view_count_log  comment_count_log  \
0            FALSE   23        8       19.265042          15.618083

   likes_log  wordCount  categoryName
0  16.571432          5         Music

[1 rows x 22 columns]
```

1.4.9 Number of likes based on category

Based on category, Music accumulates the most number of likes, as shown by the top trending video from the previous EDA, while Travel & Events has the least number of likes out of all category.

[ ]:
```
df_Main.groupby('categoryName').agg({'likes': 'max'}).show()
```

```
+--------------------+----------+
|        categoryName|max(likes)|
+--------------------+----------+
|           Education|    376802|
|Nonprofits & Acti…|    230317|
|              Gaming|   2591056|
|       Entertainment|   3871379|
|     Travel & Events|     49693|
|Science & Technology|   1733986|
|              Sports|   1107372|
|       Howto & Style|    678786|
|    Film & Animation|    961910|
|      People & Blogs|   2748677|
|     News & Politics|    634058|
|      Pets & Animals|    247479|
|   Autos & Vehiclese|   1368171|
```

```
|               Music|  15735533|
|              Comedy|   1914930|
+--------------------+----------+
```

1.4.10 Date and category of least and most trending videos

We also look at the number of trending videos and the category from the lowest to the highest count.

[ ]:
```
df_Main.createOrReplaceTempView("YT_Data")
df_Dummy = spark.sql("select categoryName, trending_date, count(distinct␣
 ↪video_id)  from YT_Data \
         group by categoryName, trending_date ORDER BY count(distinct␣
 ↪video_id) desc").toPandas()
df_Dummy.tail(1)
```

[ ]:
```
         categoryName trending_date  count(DISTINCT video_id)
3514  Pets & Animals    2020-09-04                         1
```

[ ]:
```
df_Dummy.head(1)
```

[ ]:
```
   categoryName trending_date  count(DISTINCT video_id)
0         Music    2020-11-24                        65
```

1.4.11 Analysis of most commonly used Title

We identify the most common title used in trending videos, and the result shows that "Official Video" is most commonly used as part of the video title.

[ ]:
```
# Create stopword list:
stopwords = set(STOPWORDS)
stopwords.update(["drink", "now", "wine", "flavor", "flavors"])

DF_Dummy = df_Main.toPandas()
text = " ".join(review for review in DF_Dummy.title)
wordcloud = WordCloud(stopwords=stopwords, width=1920, height=1080,␣
 ↪max_words=100, background_color="white").generate(text)
plt.figure()
plt.imshow(wordcloud, interpolation="bilinear")
plt.axis("off")
plt.show()
```

1.4.12 Analysis of most commonly used Tag

Aside from the title, we also analyze the most common tags used in trending videos. 'among us', 'music', and 'tik tok' are some of the most commonly used tags in trending videos.

```
[ ]: text = " ".join(review for review in DF_Dummy.tags)

wordcloud = WordCloud(stopwords=stopwords, width=1920, height=1080,␣
  ↪max_words=100, background_color="white").generate(text)
plt.figure()
plt.imshow(wordcloud, interpolation="bilinear")
plt.axis("off")
plt.show()
```

Some of the videos have zero views. The number was very low so we removed it.

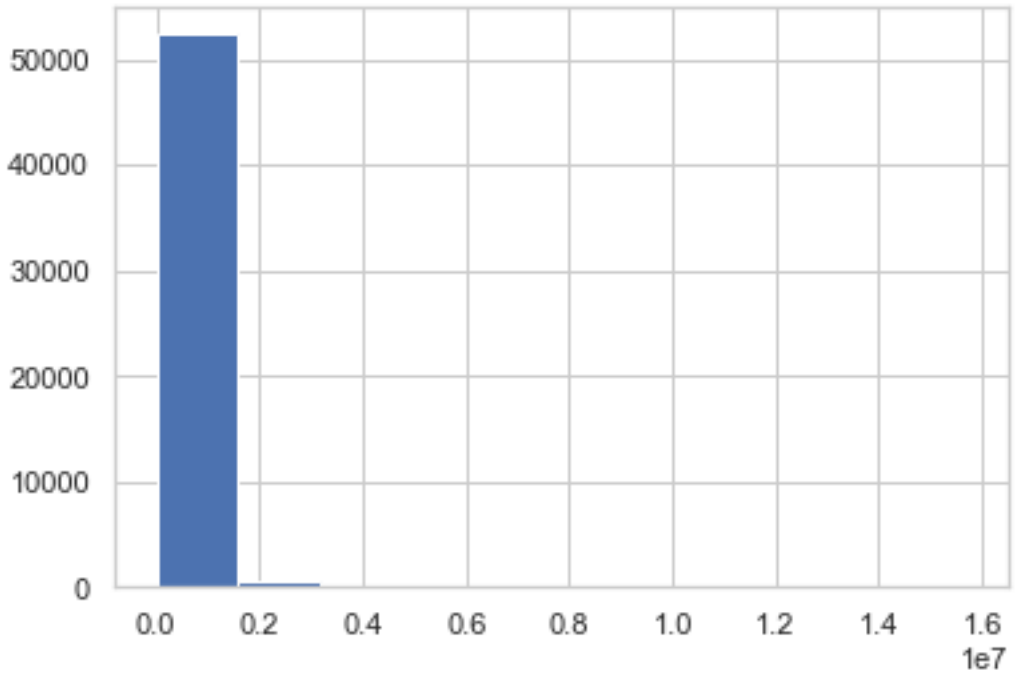
[ ]:
```
DF_DUMMY = DF_DUMMY.loc[DF_DUMMY["view_count"] != 0]
```

[ ]:
```
df_Main = df_Main.where("view_count != 0")
```

The number of trending videos based on likes is skewed as seen in below graph.

[ ]:
```
DF_DUMMY['likes'].hist()
```

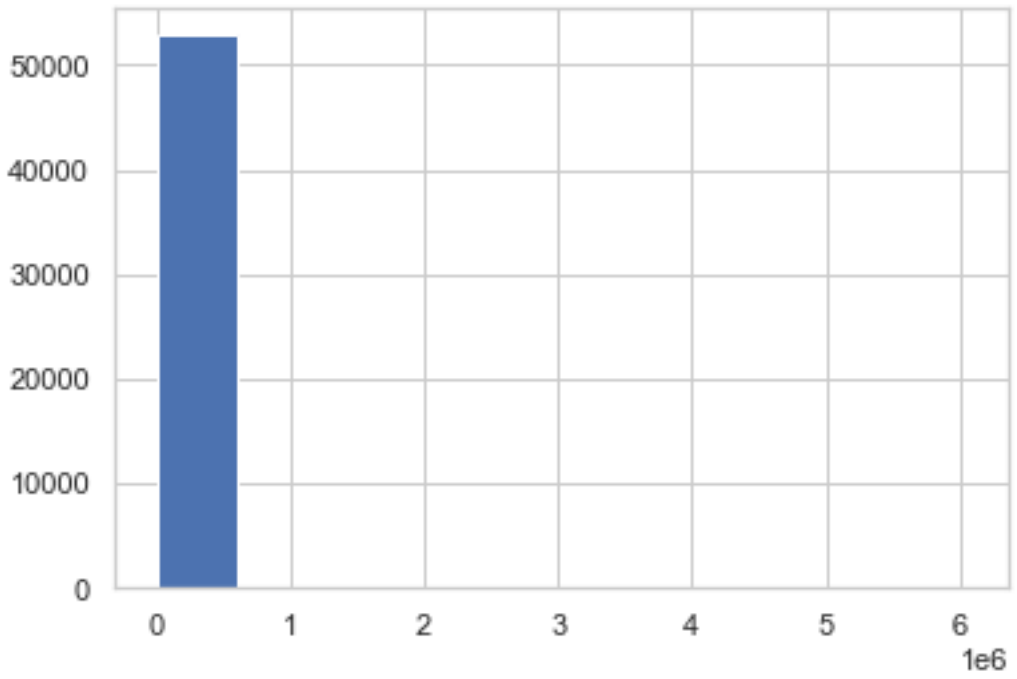
[ ]: <AxesSubplot:>



Likewise, the number of trending videos based on the comments count is skewed as seen in below graph.

[ ]:
```
DF_DUMMY['comment_count'].hist()
```

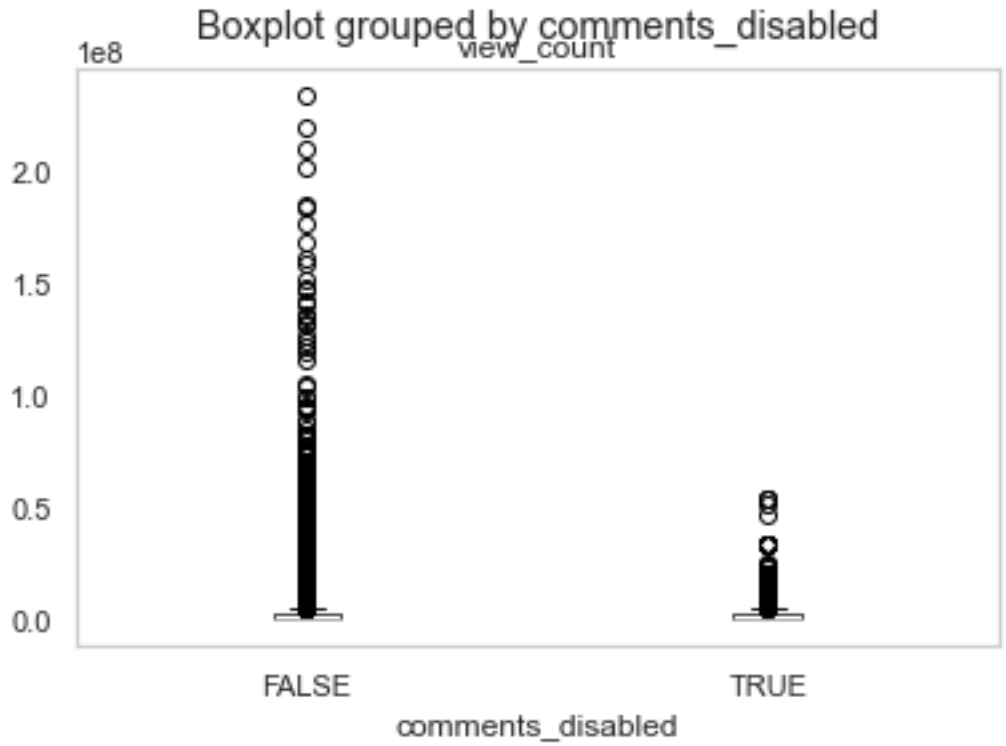
[ ]: <AxesSubplot:>



Some trending videos have their comments section disabled, but the majority of trending videos have their comments section enabled, meaning that viewers can still leave comments on the video.

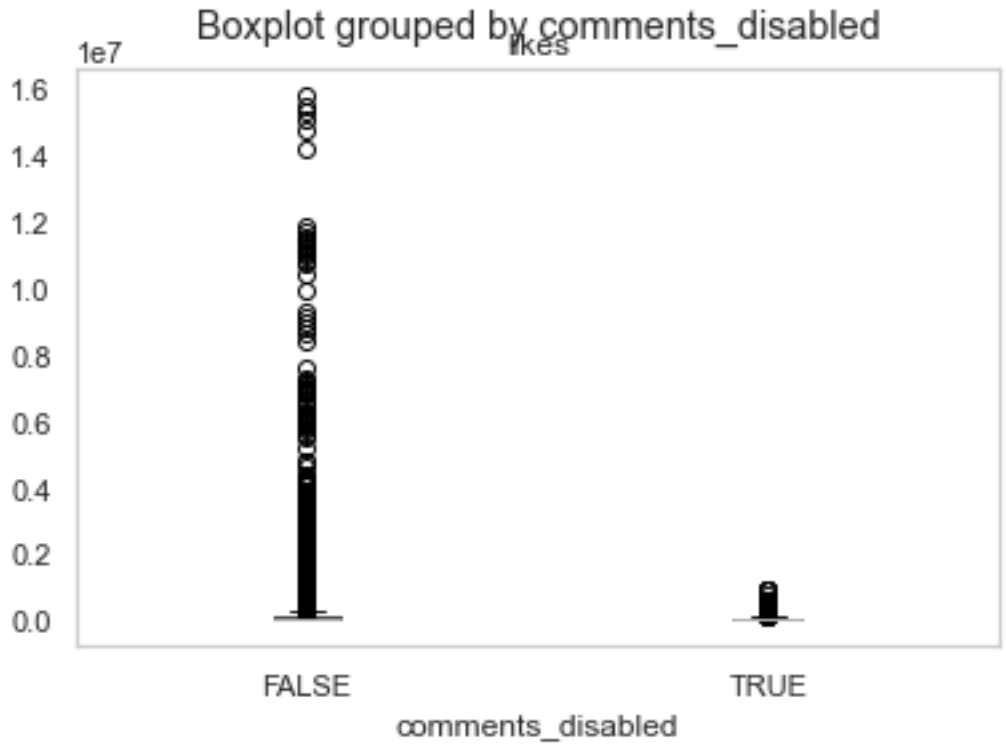
[ ]:
```
DF_DUMMY.boxplot(by = 'comments_disabled', column=['view_count'], grid = False)
```

[ ]:
```
<AxesSubplot:title={'center':'view_count'}, xlabel='comments_disabled'>
```



[ ]:
```
DF_DUMMY.boxplot(by = 'comments_disabled', column=['likes'], grid = False)␣
↪#same trend for likes.
```

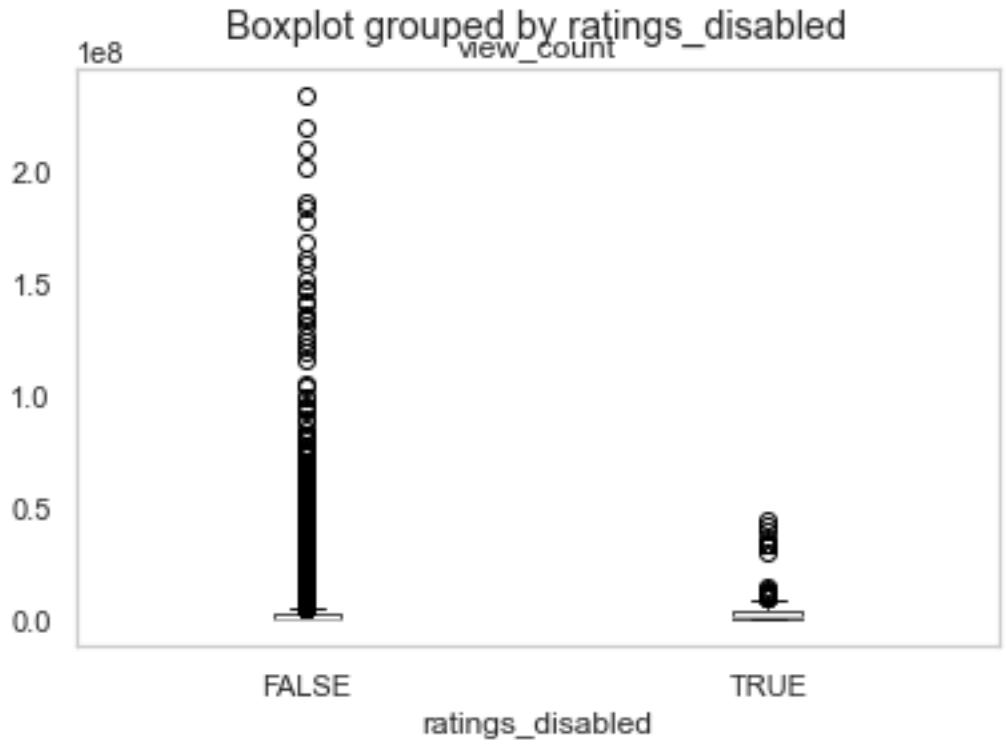
[ ]:
```
<AxesSubplot:title={'center':'likes'}, xlabel='comments_disabled'>
```



Other trending videos can also have their ratings disabled, but the majority of trending videos have their ratings section enabled, meaning that viewers can still view the video's rating.

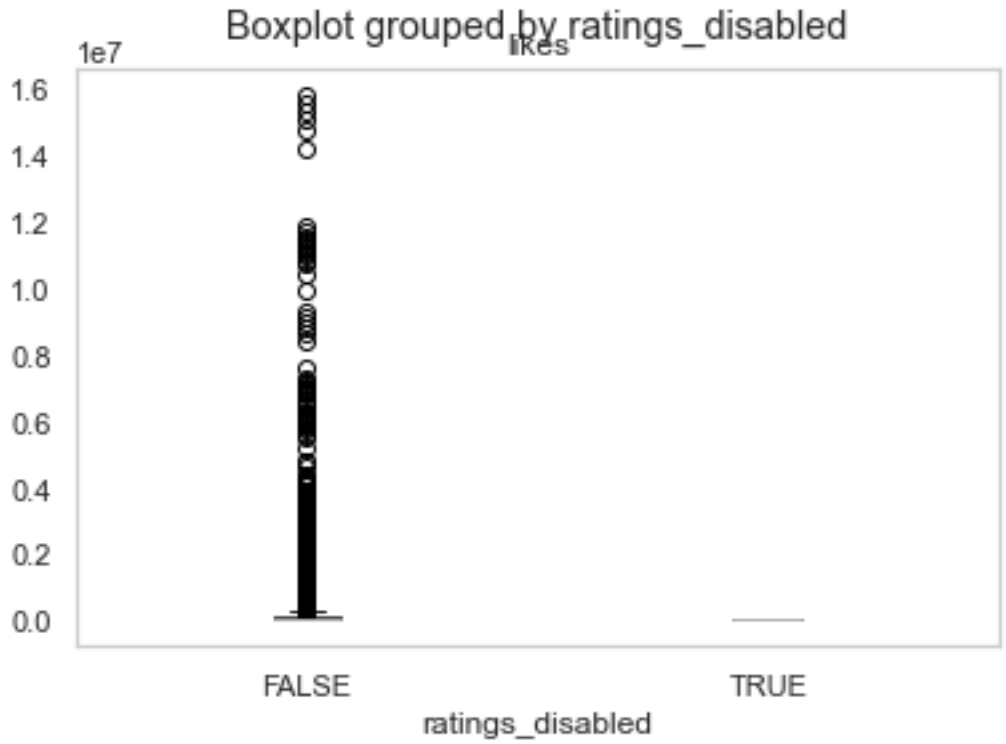
[ ]:
```
DF_DUMMY.boxplot(by = 'ratings_disabled', column=['view_count'], grid = False)
```

[ ]:
```
<AxesSubplot:title={'center':'view_count'}, xlabel='ratings_disabled'>
```



[ ]:
```
DF_DUMMY.boxplot(by = 'ratings_disabled', column=['likes'], grid = False) #␣
↪same trend for likes
```

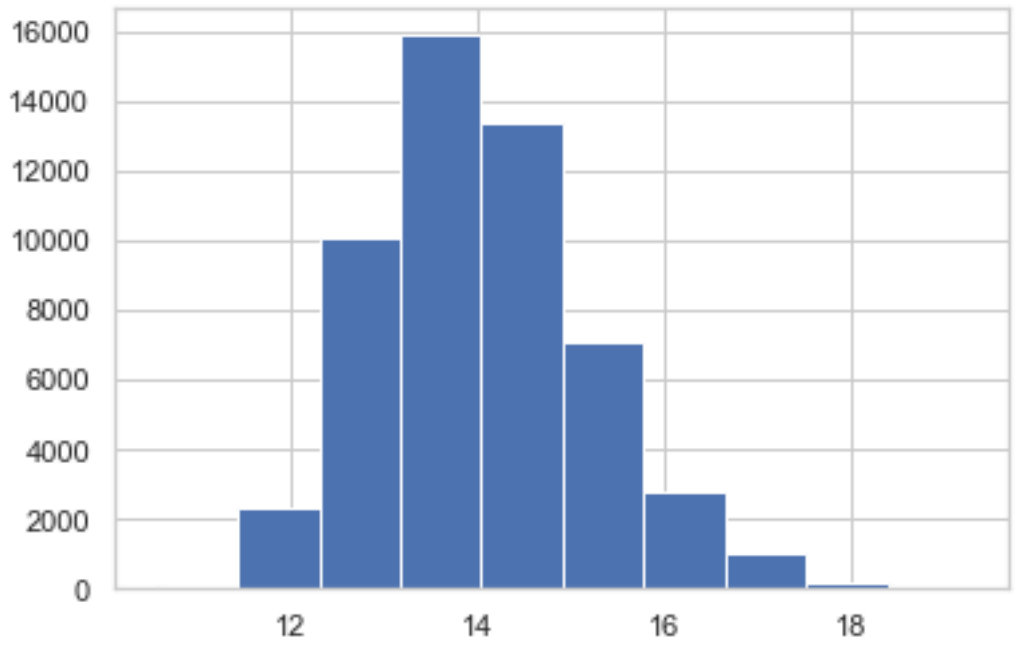
[ ]:
```
<AxesSubplot:title={'center':'likes'}, xlabel='ratings_disabled'>
```



As views were skewed, we decided to use log transformation on the number of views. After using log, it is normally distributed as shown in the histogram below.

[ ]:
```
DF_DUMMY['view_count_log'].hist()
```

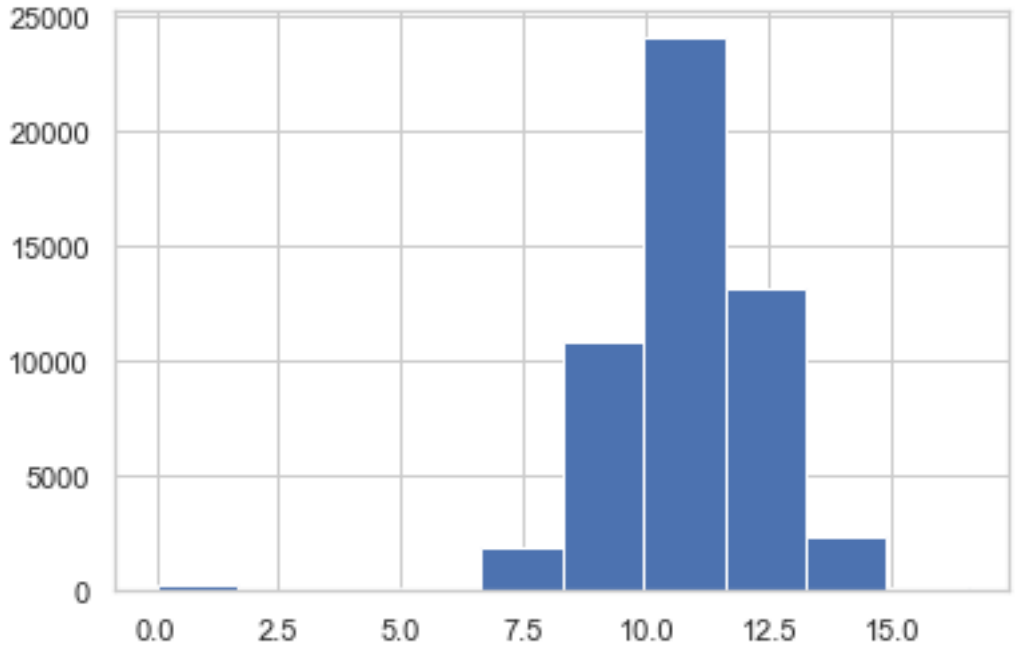
[ ]:
```
<AxesSubplot:>
```



Same applied to likes. It is still little skewed.

[ ]:
```
DF_DUMMY['likes_log'].hist()
```

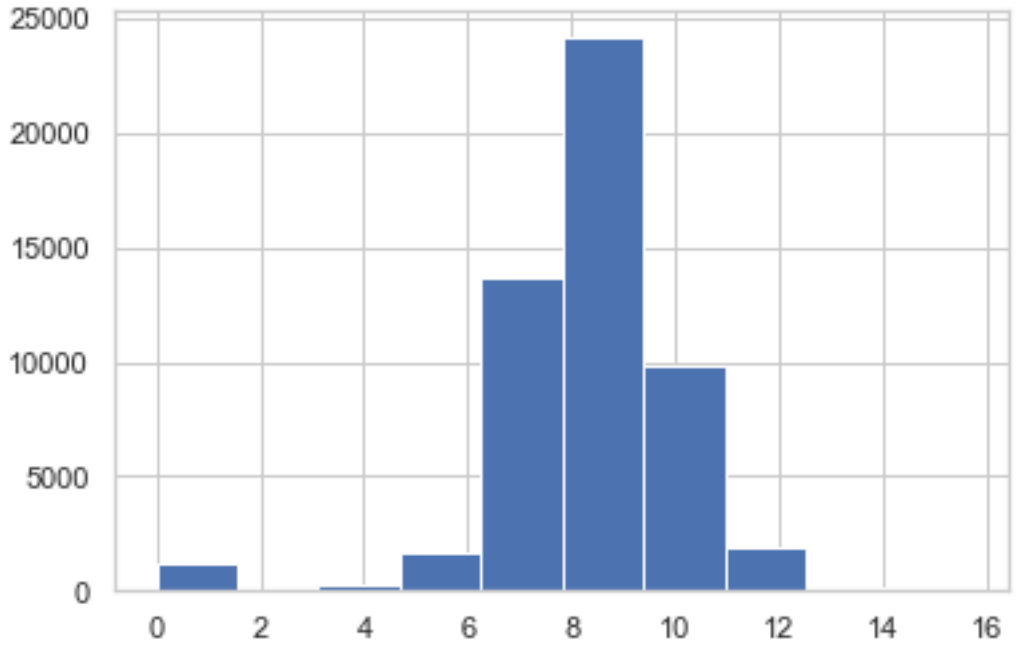
[ ]: <AxesSubplot:>



Same applied to comments.

[ ]:
```
DF_DUMMY['comment_count_log'].hist()
```

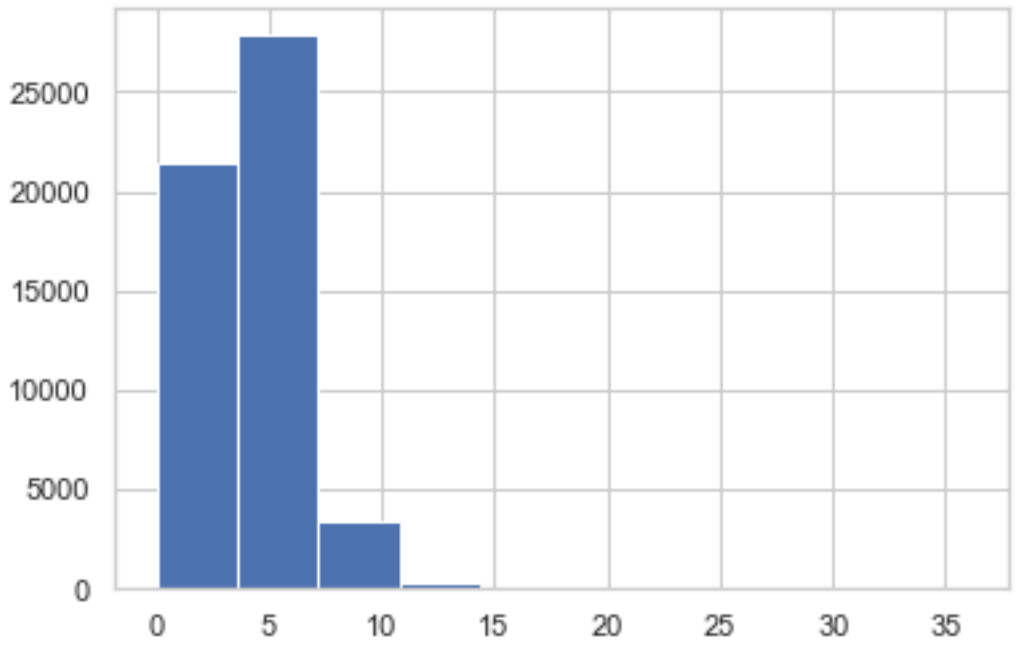
[ ]: <AxesSubplot:>



1.4.13 Most videos become trending within 5 days from the published date

[ ]:
```
DF_DUMMY['datediff'].hist()
```

[ ]: <AxesSubplot:>

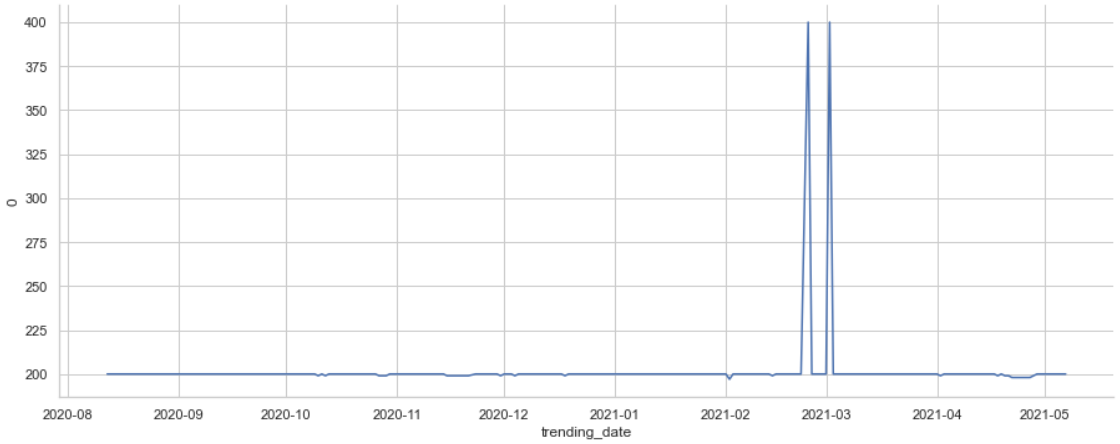


1.4.14 Oddly high number of trending videos

There were two periods between August 2020 and April 2021 where there were siginificantly higher number of trending videos, which occured within the month of February and March 2021. Approximately 400 videos were trending during these times, as opposed to the usual ~200 videos.

[ ]:
```
#finding number of daily trending videos for each day
daily = DF_DUMMY[['trending_date']].value_counts().reset_index().
 ↪sort_values(by='trending_date').reset_index(drop=True)
sns.relplot(data=daily, x='trending_date', y=0,kind='line', aspect=2.5)
```

[ ]:
```
<seaborn.axisgrid.FacetGrid at 0x7fdbe1f3f910>
```

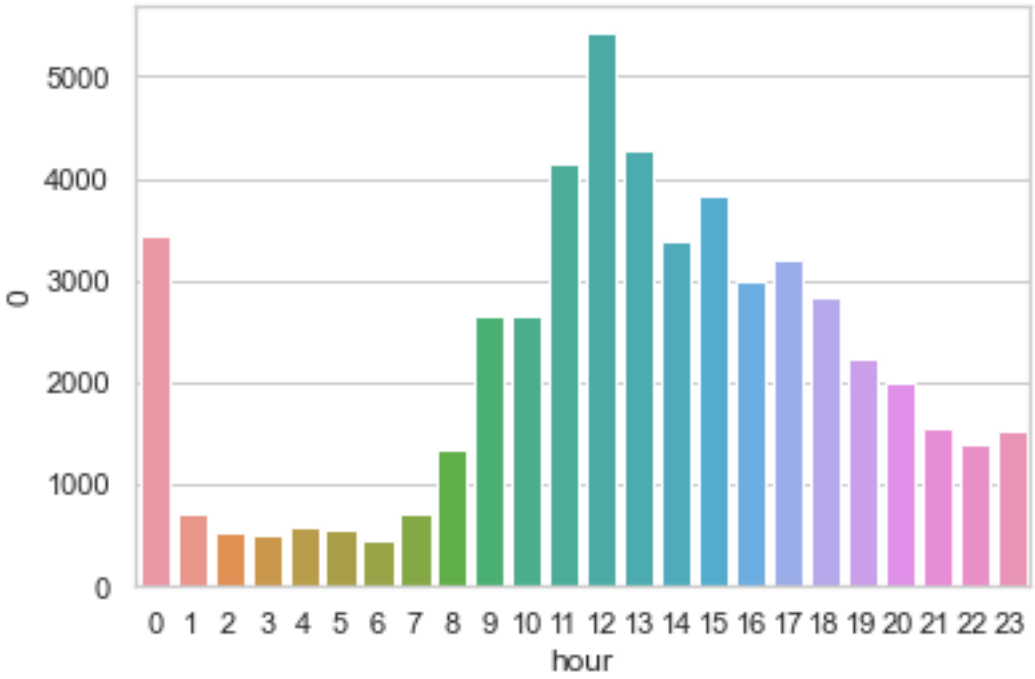


1.4.15 Most of the trending videos were published around noon local time

Another interesting find is that the majority of trending videos were published around midday local time, which might also be the time of the day where there were most traffic on Youtube for domestic viewers.

[ ]:
```
published_hour = DF_DUMMY[['hour']].value_counts().reset_index().
  ↪sort_values(by='hour').reset_index(drop=True)
sns.barplot(data=published_hour, x='hour', y=0)
```

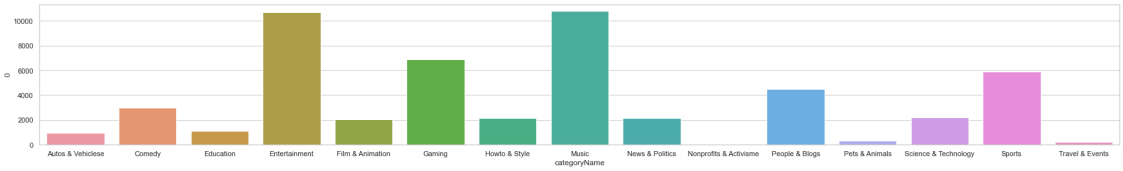
[ ]: <AxesSubplot:xlabel='hour', ylabel='0'>



1.4.16 Most of the trending videos fall into categories Music and Entertainment

[ ]:
```
fig_dims = (30, 4)
fig, ax = plt.subplots(figsize=fig_dims)

category = DF_DUMMY[['categoryName']].value_counts().reset_index().
  ↪sort_values(by='categoryName').reset_index(drop=True)
sns.barplot(data=category, x='categoryName', y=0, ax = ax)
```

[ ]: <AxesSubplot:xlabel='categoryName', ylabel='0'>

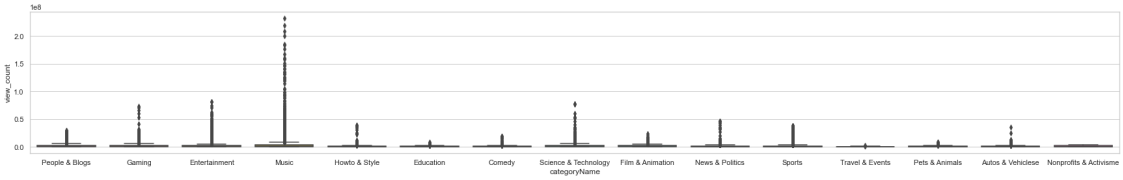


1.4.17 Range in trending video view counts

We look at the range of view counts between each video category. Both Music and Entertainment also had the largest range in video views.

[ ]:
```
fig_dims = (30, 4)
fig, ax = plt.subplots(figsize=fig_dims)
sns.boxplot(y='view_count', x='categoryName', data=DF_DUMMY, ax = ax)
```

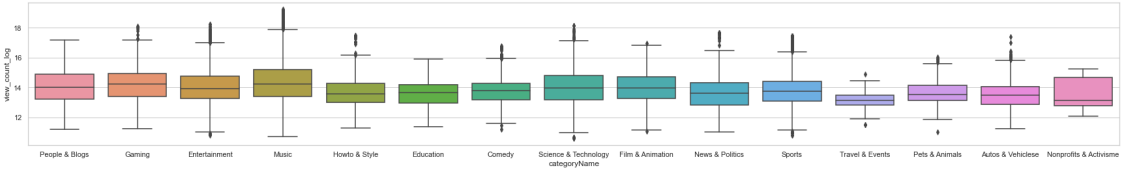
[ ]: <AxesSubplot:xlabel='categoryName', ylabel='view_count'>



As it was hard to see the distribution, we also used log view for this analysis.

[ ]:
```
fig_dims = (30, 4)
fig, ax = plt.subplots(figsize=fig_dims)
sns.boxplot(y='view_count_log', x='categoryName', data=DF_DUMMY, ax = ax)
```

[ ]: <AxesSubplot:xlabel='categoryName', ylabel='view_count_log'>



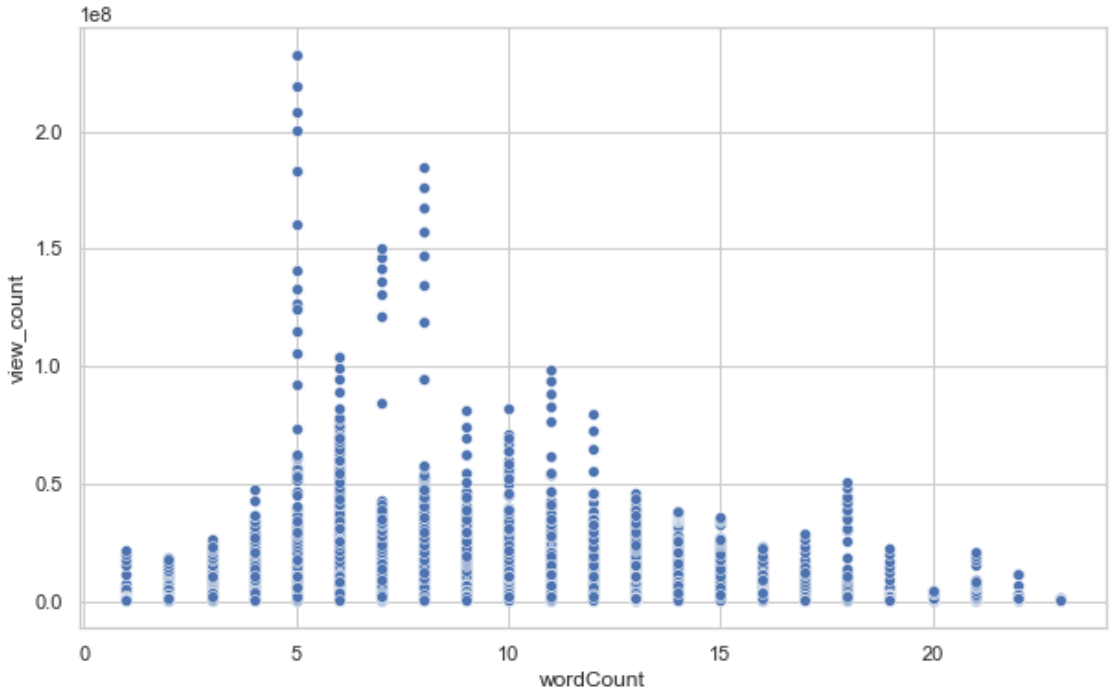
1.4.18 Length of trending video title

The title length of a trending video may be affecting the number of view counts. According to below graph, we see that videos with titles that have between 5-12 words tend have higher view

counts compared to those with lesser or more words. This is also proven by the number of likes, where videos with titles that have between 5-12 words tend to have more likes.

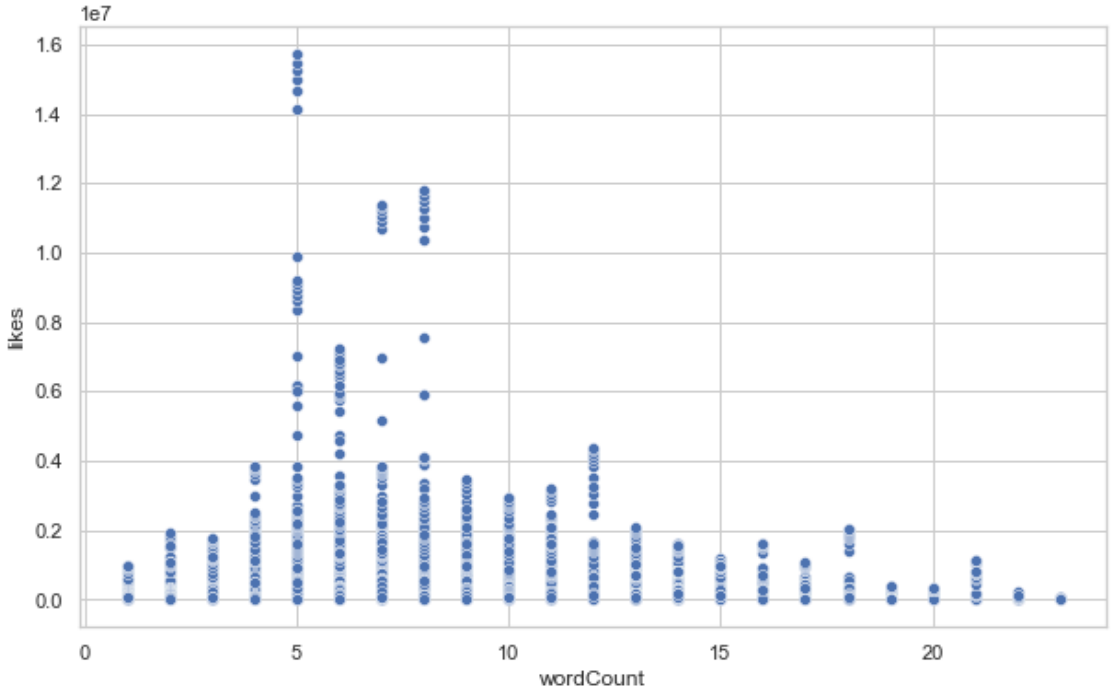
[ ]:
```
fig_dims = (10, 6)
fig, ax = plt.subplots(figsize=fig_dims)
sns.scatterplot(y='view_count', x='wordCount', data=DF_DUMMY, ax = ax)
```

[ ]:
```
<AxesSubplot:xlabel='wordCount', ylabel='view_count'>
```



[ ]:
```
fig_dims = (10, 6)
fig, ax = plt.subplots(figsize=fig_dims)
sns.scatterplot(y='likes', x='wordCount', data=DF_DUMMY, ax = ax)
```

[ ]:
```
<AxesSubplot:xlabel='wordCount', ylabel='likes'>
```



1.5 Machine Learning

We will be using machine learning model to predict for video views. We tested with Random Forest Regression model and Linear regression model. We also tested with Random Forest Classifier model.

Converting columns to binary values: We would like to include "comments_disabled" and "rating_disabled" into our ML model. To include them, we would first need to convert them into binary values.

[ ]:
```
#creating new comments_disabled_binary column
df_Main = StringIndexer(
    inputCol='comments_disabled',
    outputCol='comments_disabled_binary',
    handleInvalid='keep').fit(df_Main).transform(df_Main)

#creating new ratings_disabled_binary column
df_Main = StringIndexer(
    inputCol='ratings_disabled',
    outputCol='ratings_disabled_binary',
    handleInvalid='keep').fit(df_Main).transform(df_Main)
```

Checking the data types of all columns:

[ ]:
```
df_Main.dtypes
```

```
[ ]: [('video_id', 'string'),
      ('title', 'string'),
      ('publishedAt', 'timestamp'),
      ('channelId', 'string'),
      ('channelTitle', 'string'),
      ('categoryId', 'string'),
      ('trending_date', 'date'),
      ('tags', 'string'),
      ('view_count', 'int'),
      ('likes', 'int'),
      ('dislikes', 'int'),
      ('comment_count', 'int'),
      ('thumbnail_link', 'string'),
      ('comments_disabled', 'string'),
      ('ratings_disabled', 'string'),
      ('hour', 'int'),
      ('datediff', 'int'),
      ('view_count_log', 'double'),
      ('comment_count_log', 'double'),
      ('likes_log', 'double'),
      ('wordCount', 'int'),
      ('categoryName', 'string'),
      ('comments_disabled_binary', 'double'),
      ('ratings_disabled_binary', 'double')]
```

Dropping all the columns that are irrelevant for the analyses:

```
[ ]: df_Main = df_Main.drop('ratings_disabled')
     df_Main = df_Main.drop('comments_disabled')
     df_Main = df_Main.drop('thumbnail_link')
     df_Main = df_Main.drop('channelId')
     df_Main = df_Main.drop('channelTitle')
```

Assembling all the features with VectorAssembler The model will using features that can controlled by the user to predict for view views. Comment disabled, ratings disabled, word count, and published hour were included as features for the model.

```
[ ]: required_features = ['comments_disabled_binary',
                        'ratings_disabled_binary',
                        'wordCount',
                        'hour']

     assembler = VectorAssembler(inputCols=required_features, outputCol='features')
     transformed_data = assembler.transform(df_Main)
```

This has created a new column called “features” in the “transformed_data” datafram below:

[ ]:
```
transformed_data.show(5)
```

```
+-----------+--------------------+--------------------+----------+-------------+-
------------------+----------+------+--------+-------------+----+--------+-----
-------------+------------------+------------------+---------+--------------+---
--------------------+-----------------------+-------------------+
|   video_id|               title|        publishedAt|categoryId|trending_date|
tags|view_count| likes|dislikes|comment_count|hour|datediff|    view_count_log|
comment_count_log|         likes_log|wordCount|
categoryName|comments_disabled_binary|ratings_disabled_binary|
features|
+-----------+--------------------+--------------------+----------+-------------+-
------------------+----------+------+--------+-------------+----+--------+-----
-------------+------------------+------------------+---------+--------------+---
--------------------+-----------------------+-------------------+
|3C66w5Z0ixs|I ASKED HER TO BE…|2020-08-11 15:20:14|        22|
2020-08-12|brawadis|prank|ba…|   1514614|156908|    5855|        35313|  15|
1|14.230671178983725|10.472034764862743|11.963421298452696|        7|People &
Blogs|                    0.0|                   0.0| [0.0,0.0,7.0,15.0]|
|M9Pmf9AB4Mo|Apex Legends | St…|2020-08-11 13:00:10|        20|
2020-08-12|Apex Legends|Apex…|   2381688|146739|    2794|        16549|  13|
1|14.683320037950685|  9.71414138080521|11.896417592267985|       10|
Gaming|                     0.0|                   0.0|[0.0,0.0,10.0,13.0]|
|J78aPJ3VyNs|I left youtube fo…|2020-08-11 12:34:06|        24|
2020-08-12|jacksepticeye|fun…|   2038853|353787|    2628|        40221|  12|
1|14.527897952793877|10.602169388594548|12.776453142665115|       11|
Entertainment|                    0.0|
0.0|[0.0,0.0,11.0,12.0]|
|kXLn3HkpjaA|XXL 2020 Freshman…|2020-08-11 12:38:55|        10|
2020-08-12|xxl freshman|xxl …|    496771| 23251|    1856|         7647|  12|
1|13.115884434306619| 8.942199454731238|10.054146428821241|        8|
Music|                    0.0|                   0.0| [0.0,0.0,8.0,12.0]|
|VIUo6yapDbc|Ultimate DIY Home…|2020-08-11 11:10:05|        26|
2020-08-12|The LaBrant Famil…|   1123889| 45802|     964|         2196|  11|
1|13.932305550110833|  7.69484807238461|10.732104870140509|        9| Howto &
Style|                    0.0|                   0.0| [0.0,0.0,9.0,11.0]|
+-----------+--------------------+--------------------+----------+-------------+-
------------------+----------+------+--------+-------------+----+--------+-----
-------------+------------------+------------------+---------+--------------+---
--------------------+-----------------------+-------------------+
only showing top 5 rows
```

Splitting data between testing and training: In order to do ML models, we need to split the datafram into test and train data.

[ ]:
```
(training_data, test_data) = transformed_data.randomSplit([0.8,0.2])
```

1.5.1 ML: Random Forest Regression Model

In this selection, we showed how we tested with Random Forest Regression Model.

[ ]:
```
rf = RandomForestRegressor(labelCol='view_count',
                           featuresCol='features',
                           maxDepth=5)
```

Fitting the model:

[ ]:
```
model = rf.fit(training_data)
```

[ ]:
```
predictions = model.transform(test_data)
```

Evaluating the model: As this is a regression model, we will be RMSE and R^2 to evaluate the model. Ideally, you would like the RMSE to be low and R^2 to be close to 1.

[ ]:
```
evaluator = RegressionEvaluator(
    labelCol='view_count',
    predictionCol='prediction',
    metricName='rmse')
RMSE = evaluator.evaluate(predictions)
print("RMSE on test data = %g" %RMSE)
```

```
RMSE on test data = 6.94448e+06
```

[ ]:
```
pred_evaluator = RegressionEvaluator(predictionCol="prediction",
                 labelCol="view_count",metricName="r2")
print("R Squared (R2) on test data = %g" % pred_evaluator.evaluate(predictions))
```

```
R Squared (R2) on test data = 0.0387524
```

1.5.2 ML: Random Forest Regression Model LogView

As the view values are very skewed, we used logview for the Random Forest Model. We used the same steps as mentioned before.

[ ]:
```
#Log View
rf_log = RandomForestRegressor(labelCol='view_count_log',
                           featuresCol='features',
                           maxDepth=5)
```

[ ]:
```
model_log = rf_log.fit(training_data)
```

[ ]:
```
predictions_log = model_log.transform(test_data)
```

[ ]:
```
evaluator = RegressionEvaluator(
    labelCol='view_count_log',
    predictionCol='prediction',
```

```
    metricName='rmse')
RMSE = evaluator.evaluate(predictions_log)
RMSE
```

[ ]: 1.1224966146056572

[ ]:
```
pred_evaluator = RegressionEvaluator(predictionCol="prediction",
                 labelCol="view_count_log",metricName="r2")
print("R Squared (R2) on test data = %g" % pred_evaluator.
 ↪evaluate(predictions_log))
```

```
R Squared (R2) on test data = 0.0407684
```

When comapred both the model, the model that used log view seems to give a better r^2 and RMSE value.

1.5.3 ML: Linear Regression Model

[ ]:
```
lin_reg = LinearRegression(labelCol='view_count',featuresCol='features')
linear_model = lin_reg.fit(training_data)

#Coefficients from linear model
print("Coefficients: " + str(linear_model.coefficients))
print("\nIntercept: " + str(linear_model.intercept))
```

```
Coefficients:
[139959.70379755078,1101537.330436928,-95107.14814522669,-86528.92587029166]

Intercept: 4667788.422912789
```

RMSE and r^2 values from training data.

[ ]:
```
trainSummary_linear = linear_model.summary
print("RMSE: %f" % trainSummary_linear.rootMeanSquaredError)
print("\nr2: %f" % trainSummary_linear.r2)
```

```
RMSE: 6121722.690005

r2: 0.009820
```

[ ]:
```
predictions_linear = linear_model.transform(test_data)
```

Evaluating linear model using RMSE and r^2 values

[ ]:
```
evaluator = RegressionEvaluator(
    labelCol='view_count',
    predictionCol='prediction',
    metricName='rmse')
RMSE = evaluator.evaluate(predictions_linear)
```

```
print("RMSE on test data = %g" %RMSE)
```

```
RMSE on test data = 6.20454e+06
```

[ ]:
```
pred_evaluator = RegressionEvaluator(predictionCol="prediction",␣
 ↪labelCol="view_count",metricName="r2")
print("R Squared (R2) on test data = %g" % pred_evaluator.
 ↪evaluate(predictions_linear))
```

```
R Squared (R2) on test data = 0.00836203
```

Looking at RMSE and r^2 values from Random Forest regression and Linear regression, we can conclude that random forest is a better model to predict views.

1.6 ML: Classification Model

We also tried predicting views using Classification Model. To do this views had to be converted into categorical values. In our case, views were broken down into 4 categories. Views were broken down according to how the data was distributed and the different quartiles.

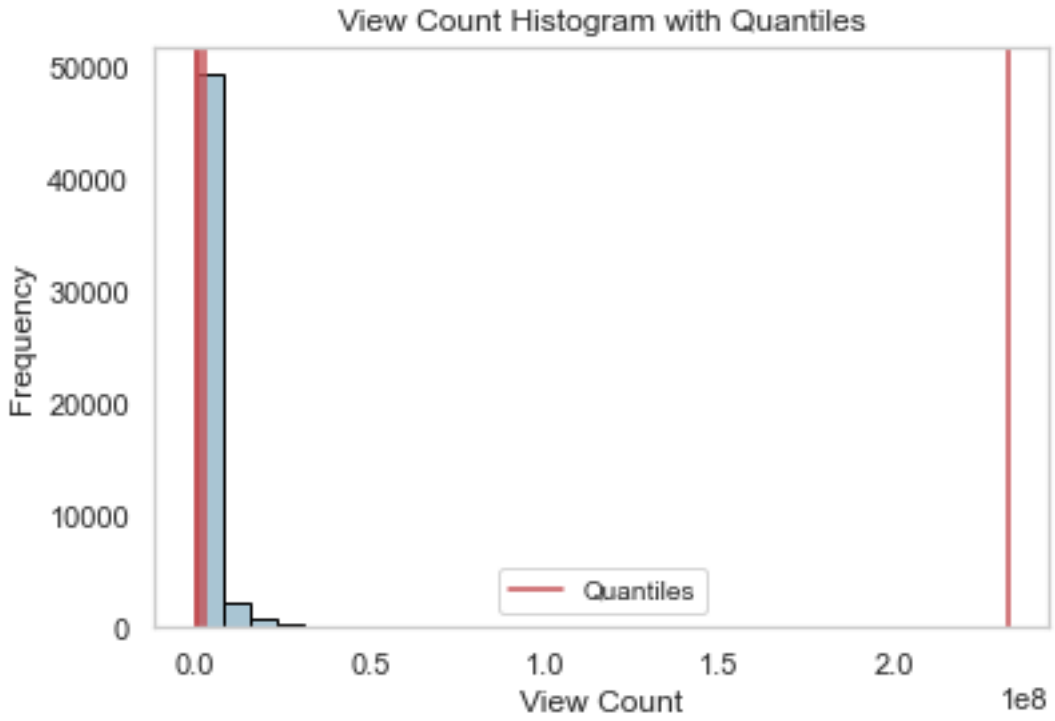
[ ]:
```
quantile_list = [0, .25, .5, .75, 1.]
quantiles = DF_DUMMY['view_count'].quantile(quantile_list)
quantiles # the quartiles of the data
```

[ ]:
```
0.00        38510.0
0.25       547115.0
0.50      1127988.0
0.75      2516799.0
1.00    232649205.0
Name: view_count, dtype: float64
```

Plotting the range a histogram: Visual representation of how the data was broken down is shown below in the histogram.

[ ]:
```
fig, ax = plt.subplots()
DF_DUMMY['view_count'].hist(bins=30, color='#A9C5D3',
                            edgecolor='black', grid=False)
for quantile in quantiles:
    qvl = plt.axvline(quantile, color='r')
ax.legend([qvl], ['Quantiles'], fontsize=10)
ax.set_title('View Count Histogram with Quantiles',
             fontsize=12)
ax.set_xlabel('View Count', fontsize=12)
ax.set_ylabel('Frequency', fontsize=12)
```

[ ]:
```
Text(0, 0.5, 'Frequency')
```



The data was then broken down into the 4 categories and a new column was created called "View_quantile_label".

```
[ ]: quantile_labels = ['0-25Q', '25-50Q', '50-75Q', '75-100Q']
DF_DUMMY['View_quantile_range'] = pd.qcut(
                                          DF_DUMMY['view_count'],
                                          q=quantile_list)
DF_DUMMY['View_quantile_label'] = pd.qcut(
                                          DF_DUMMY['view_count'],
                                          q=quantile_list,
                                          labels=quantile_labels)

DF_DUMMY[['view_count','view_count_log', 'View_quantile_range',
               'View_quantile_label']].iloc[4:9]
```

```
[ ]:    view_count  view_count_log     View_quantile_range View_quantile_label
     4     1123889       13.932306   (547115.0, 1127988.0]              25-50Q
     5      949491       13.763681   (547115.0, 1127988.0]              25-50Q
     6      470446       13.061436   (38509.999, 547115.0]               0-25Q
     7     1050143       13.864437   (547115.0, 1127988.0]              25-50Q
     8     1402687       14.153900  (1127988.0, 2516799.0]              50-75Q
```

In the last section, we did everything on a Pandas dataframe. We now tried to do the same on the Spark dataframe so that the ML can be run efficiently.

[ ]:
```
bucketizer = Bucketizer(splits=[38510,  547115, 1127988, 2516799, 232649205],␣
 ↪inputCol='view_count', outputCol='view_count_category') #categorizing view␣
 ↪data

#Pipeline Stages
stages = [bucketizer]
pipeline = Pipeline(stages=stages)
```

[ ]:
```
df_Main = pipeline.fit(df_Main).transform(df_Main) # fit the pipeline model and␣
 ↪transform the data
```

[ ]:
```
df_Main.show(5)
```

```
+-----------+--------------------+------------------+--------------------+-----
--------+----------+-------------+--------------------+----------+------+-------
-+-------------+--------------------+-----------------+----------------+----+---
-----+-----------------+-----------------+-----------------+---------+-------
-------+------------------------+----------------------+--------------------+
|   video_id|               title|       publishedAt|           channelId|
channelTitle|categoryId|trending_date|                tags|view_count|
likes|dislikes|comment_count|
thumbnail_link|comments_disabled|ratings_disabled|hour|datediff|
view_count_log| comment_count_log|        likes_log|wordCount|  categoryName|co
mments_disabled_binary|ratings_disabled_binary|view_count_category|
+-----------+--------------------+------------------+--------------------+-----
--------+----------+-------------+--------------------+----------+------+-------
-+-------------+--------------------+-----------------+----------------+----+---
-----+-----------------+-----------------+-----------------+---------+-------
-------+------------------------+----------------------+--------------------+
|3C66w5Z0ixs|I ASKED HER TO BE…|2020-08-11 15:20:14|UCvtRTOMP2TqYqu51…|
Brawadis|        22|   2020-08-12|brawadis|prank|ba…|   1514614|156908|
5855|        35313|https://i.ytimg.c…|            FALSE|           FALSE|  15|
1|14.230671178983725|10.472034764862743|11.963421298452696|        7|People &
Blogs|                    0.0|                   0.0|               2.0|
|M9Pmf9AB4Mo|Apex Legends | St…|2020-08-11 13:00:10|UC0ZV6M2THA81QT9h…| Apex
Legends|        20|   2020-08-12|Apex Legends|Apex…|   2381688|146739|
2794|        16549|https://i.ytimg.c…|            FALSE|           FALSE|  13|
1|14.683320037950685|  9.71414138080521|11.896417592267985|       10|
Gaming|                    0.0|                   0.0|               2.0|
|J78aPJ3VyNs|I left youtube fo…|2020-08-11
12:34:06|UCYzPXprvl5Y-Sf0g…|jacksepticeye|        24|
2020-08-12|jacksepticeye|fun…|   2038853|353787|    2628|
40221|https://i.ytimg.c…|            FALSE|           FALSE|  12|
1|14.527897952793877|10.602169388594548|12.776453142665115|       11|
Entertainment|                    0.0|                   0.0|
2.0|
|kXLn3HkpjaA|XXL 2020 Freshman…|2020-08-11 12:38:55|UCbg_UMjlHJg_19SZ…|
```

```
XXL|        10|   2020-08-12|xxl freshman|xxl …|    496771| 23251|    1856|
7647|https://i.ytimg.c…|            FALSE|           FALSE|  12|
1|13.115884434306619| 8.942199454731238|10.054146428821241|        8|
Music|                     0.0|                    0.0|                0.0|
|VIUo6yapDbc|Ultimate DIY Home…|2020-08-11 11:10:05|UCDVPcEbVLQgLZX0R…|
Mr. Kate|        26|   2020-08-12|The LaBrant Famil…|   1123889| 45802|
964|         2196|https://i.ytimg.c…|            FALSE|           FALSE|  11|
1|13.932305550110833|  7.69484807238461|10.732104870140509|        9| Howto &
Style|                     0.0|                    0.0|                1.0|
+-----------+--------------------+------------------+--------------------+-----
--------+----------+-------------+--------------------+----------+------+-------
-+-------------+--------------------+-----------------+----------------+----+---
-----+-----------------+-----------------+-----------------+---------+-------
-------+-----------------------+----------------------+-------------------+
only showing top 5 rows
```

1.7 Random Forest Classifier

We use random forest classifier to run the model. First, we ssemble all the features with VectorAssembler.

[ ]:
```
required_features = ['comments_disabled_binary',
                     'ratings_disabled_binary',
                     'wordCount',
                     'hour']

assembler = VectorAssembler(inputCols=required_features, outputCol='features')
transformed_data = assembler.transform(df_Main)
```

[ ]:
```
transformed_data.show(5)
```

```
+-----------+--------------------+------------------+--------------------+-----
--------+----------+-------------+--------------------+----------+------+-------
-+-------------+--------------------+-----------------+----------------+----+---
-----+-----------------+-----------------+-----------------+---------+-------
-------+-----------------------+----------------------+-------------------+---
----------------+
|   video_id|               title|       publishedAt|           channelId|
channelTitle|categoryId|trending_date|                tags|view_count|
likes|dislikes|comment_count|
thumbnail_link|comments_disabled|ratings_disabled|hour|datediff|
view_count_log| comment_count_log|         likes_log|wordCount|  categoryName|co
mments_disabled_binary|ratings_disabled_binary|view_count_category|
features|
+-----------+--------------------+------------------+--------------------+-----
--------+----------+-------------+--------------------+----------+------+-------
-+-------------+--------------------+-----------------+----------------+----+---
```

```
-----+-----------------+-----------------+-----------------+--------+-------
-------+----------------------+----------------------+------------------+---
---------------+
|3C66w5Z0ixs|I ASKED HER TO BE…|2020-08-11 15:20:14|UCvtRTOMP2TqYqu51…|
Brawadis|        22|   2020-08-12|brawadis|prank|ba…|   1514614|156908|
5855|        35313|https://i.ytimg.c…|            FALSE|           FALSE|  15|
1|14.230671178983725|10.472034764862743|11.963421298452696|        7|People &
Blogs|                     0.0|                    0.0|                2.0|
[0.0,0.0,7.0,15.0]|
|M9Pmf9AB4Mo|Apex Legends | St…|2020-08-11 13:00:10|UC0ZV6M2THA81QT9h…| Apex
Legends|        20|   2020-08-12|Apex Legends|Apex…|   2381688|146739|
2794|        16549|https://i.ytimg.c…|            FALSE|           FALSE|  13|
1|14.683320037950685|  9.71414138080521|11.896417592267985|       10|
Gaming|                     0.0|                    0.0|
2.0|[0.0,0.0,10.0,13.0]|
|J78aPJ3VyNs|I left youtube fo…|2020-08-11
12:34:06|UCYzPXprvl5Y-Sf0g…|jacksepticeye|        24|
2020-08-12|jacksepticeye|fun…|   2038853|353787|    2628|
40221|https://i.ytimg.c…|            FALSE|           FALSE|  12|
1|14.527897952793877|10.602169388594548|12.776453142665115|       11|
Entertainment|                     0.0|                    0.0|
2.0|[0.0,0.0,11.0,12.0]|
|kXLn3HkpjaA|XXL 2020 Freshman…|2020-08-11 12:38:55|UCbg_UMjlHJg_19SZ…|
XXL|        10|   2020-08-12|xxl freshman|xxl …|    496771| 23251|    1856|
7647|https://i.ytimg.c…|            FALSE|           FALSE|  12|
1|13.115884434306619| 8.942199454731238|10.054146428821241|        8|
Music|                     0.0|                    0.0|                0.0|
[0.0,0.0,8.0,12.0]|
|VIUo6yapDbc|Ultimate DIY Home…|2020-08-11 11:10:05|UCDVPcEbVLQgLZX0R…|
Mr. Kate|        26|   2020-08-12|The LaBrant Famil…|   1123889| 45802|
964|         2196|https://i.ytimg.c…|            FALSE|           FALSE|  11|
1|13.932305550110833|  7.69484807238461|10.732104870140509|        9| Howto &
Style|                     0.0|                    0.0|                1.0|
[0.0,0.0,9.0,11.0]|
+-----------+--------------------+------------------+--------------------+-----
--------+----------+-------------+--------------------+----------+------+-------
-+-------------+--------------------+-----------------+---------------+----+---
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---------------+
only showing top 5 rows
```

Next, we split between testing and training. Then, we evaluate our model.

[ ]:
```
(training_data, test_data) = transformed_data.randomSplit([0.8,0.2])
```

Creating the model

[ ]:
```
rf_class = RandomForestClassifier(labelCol='view_count_category',
                                  featuresCol='features',
                                  maxDepth=5)
```

[ ]:
```
model_class = rf_class.fit(training_data)
```

[ ]:
```
predictions = model_class.transform(test_data)
```

[ ]:
```
evaluator = MulticlassClassificationEvaluator(
    labelCol='view_count_category',
    predictionCol='prediction',
    metricName='accuracy')
```

As this is a classification model. We will be using accuracy score to evaluate the model. Accuracy score of this model is 0.3127.

[ ]:
```
accuracy = evaluator.evaluate(predictions)
print('Test Accuracy = ', accuracy)
```

```
Test Accuracy =  0.3127383676582761
```

1.8 Conclusion

Music and Entertainment are the two categories that dominate the top trending videos on Youtube between August 2020 and April 2021. There is a positive correlation between the number of views and likes that a trending video gains, which in turn may impact how these videos are curated to gain the maximum amount of revenue, based on the two aspects and others such as titles, comments, ratings, and tags on how a trending video circulates among the Youtube community.

After testing different models, we can conclude that Random Forest would be better the model to use to predict the number of views. Random Forest Regression model that used log view had a better r^2 and RMSE score. The accuracy score of random forest classfication model is 0.31. The scores from both regression and classification model is pretty low. To improve the model we do hyperparameter tuning and test with different values to improve numbers used for evaluation.