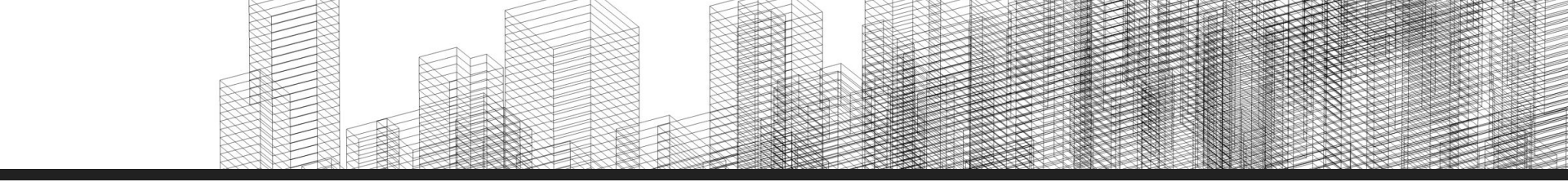
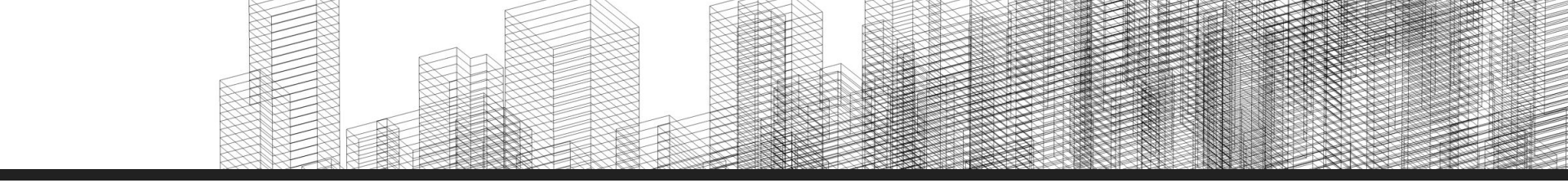


YouTube Trending Videos

Capstone Project 1

Alex Chung
August 2020

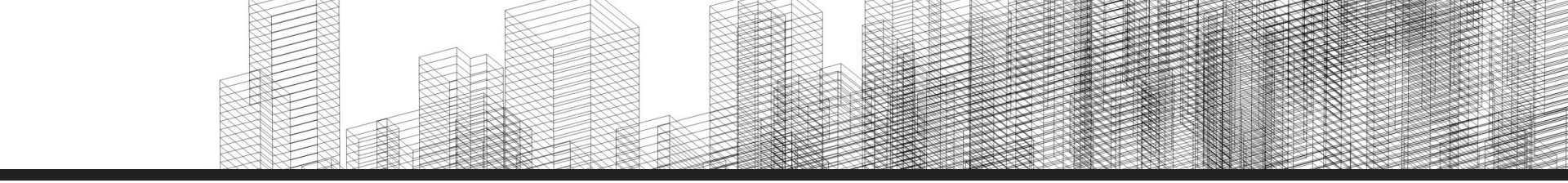


Project Goal:

The goal of this project is to analyze what YouTube videos are trending from a dataset scraped from YouTube's Trending Page in order to find common characteristics of trending videos and attempt to predict and reproduce results.

David Dobrik, one of these trending content creators, for example started his YouTube channel in 2015 and built it to be the fifth-most viewed creator channel on YouTube in 2019 and producing an annual income of $13 million dollars.

This information could be valuable to individual content creators who are interested in increasing their view rates, or for corporate clients or individuals who are interested in using YouTube as an avenue for content creation.



Data Wrangling:

Our data comes from a kaggle project in the following link: Trending YouTube Video Statistics

There are 10 csv files organized by country and one json file with the keys to the category type for the YouTube videos. We start by reading these in:

```
canada = pd.read_csv('CAvideos.csv', encoding='latin-1')
denmark = pd.read_csv('DEvideos.csv', encoding='latin-1')
france = pd.read_csv('FRvideos.csv', encoding='latin-1')
great_britain = pd.read_csv('GBvideos.csv', encoding='latin-1')
india = pd.read_csv('INvideos.csv', encoding='latin-1')
japan = pd.read_csv('JPvideos.csv', encoding='latin-1')
south_korea = pd.read_csv('KRvideos.csv', encoding='latin-1')
mexico = pd.read_csv('MXvideos.csv', encoding='latin-1')
russia = pd.read_csv('RUvideos.csv', encoding='latin-1')
united_states = pd.read_csv('USvideos.csv', encoding='latin-1')

categories = pd.read_json('CA_category_id.json')
```

Exploring the data:

```
ctry = united_states
ctry.columns
```

```
Index(['video_id', 'trending_date', 'title', 'channel_title', 'category_id',
       'publish_time', 'tags', 'views', 'likes', 'dislikes', 'comment_count',
       'thumbnail_link', 'comments_disabled', 'ratings_disabled',
       'video_error_or_removed', 'description'],
      dtype='object')
```

	video_id	trending_date	title	channel_title	category_id	publish_time	tags	views	likes
0	2kyS6SvSYSE	11.14.17	WE WANT TO TALK ABOUT OUR MARRIAGE	CaseyNeistat	22	2017-11-13T17:13:01.000Z	SHANtell martin	748374	57527
1	1ZAPwfrtAFY	11.14.17	The Trump Presidency: Last Week Tonight with J...	LastWeekTonight	24	2017-11-13T07:30:00.000Z	last week tonight trump presidency|"last week ...	2418783	97185

Cleaning the Data:

There are 2 date columns (trending_date and published_time) that are in different formats. We rearrange both to yy.mm.dd and convert the string to Date Time object.

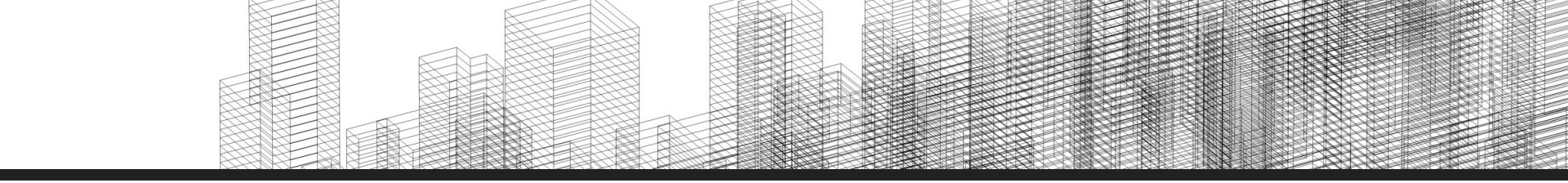
trending_date column:

```
ctry.td2 = ctry.trending_date

for index, row in ctry.iterrows():
    ctry.td2[index] = ctry.td2[index][6:8] + "." + ctry.td2[index][3:5] + "." + ctry.td2[index][0:2]
```

```
ctry.trending_date = pd.to_datetime(ctry.trending_date)
```

```
ctry.trending_date = ctry.trending_date.dt.date
ctry.trending_date
```

```
0        2017-11-14
1        2017-11-14
```



Cleaning the Data:

We do the same for the published date column and create 2 new columns that will give us **time elapsed** between published date of the video to the trending date of the video. And the **average daily views** column (views / time elapsed).

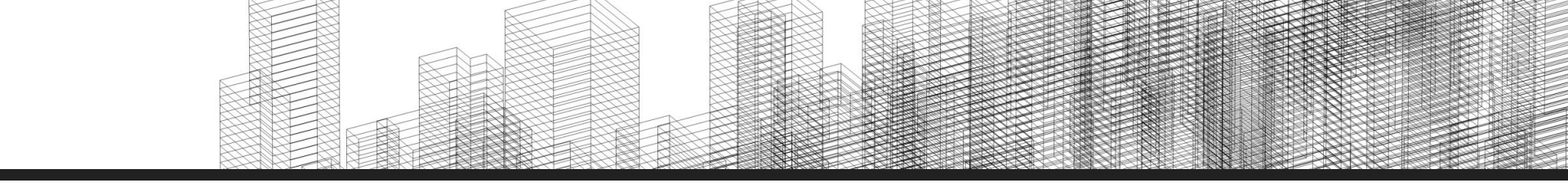
Next we explore the JSON file:

This contains the key to the category id column in the csv files:

```
with open ('CA_category_id.json') as f:
    data = json.load(f)
```

```
data
```

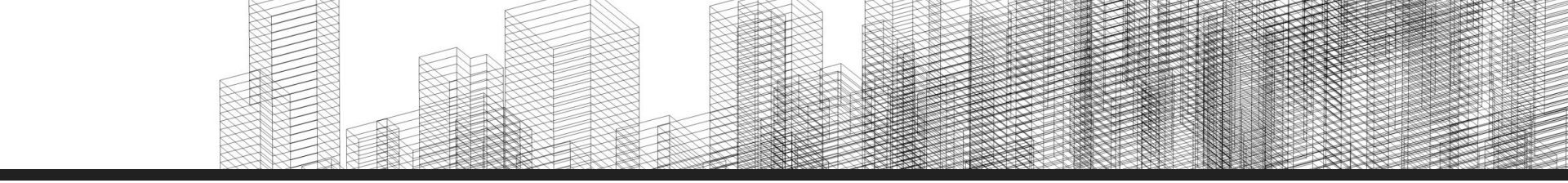

```
{'kind': 'youtube#videoCategoryListResponse',
 'etag': '"ld9biNPKjAjgjV7EZ4EKeEGrhao/1v2mrzYSYG6onNLt2qTj13hkQZk"',
 'items': [{'kind': 'youtube#videoCategory',
   'etag': '"ld9biNPKjAjgjV7EZ4EKeEGrhao/Xy1mB4_yLrHy_BmKmPBggty2mZQ"',
   'id': '1',
   'snippet': {'channelId': 'UCBR8-60-B28hp2BmDPdntcQ',
    'title': 'Film & Animation',
    'assignable': True}},
  {'kind': 'youtube#videoCategory',
   'etag': '"ld9biNPKjAjgjV7EZ4EKeEGrhao/UZ1oLIIz2dxIhO45ZTFR3a3NyTA"',
   'id': '2',
   'snippet': {'channelId': 'UCBR8-60-B28hp2BmDPdntcQ',
    'title': 'Autos & Vehicles',
    'assignable': True}},
```



Next we explore the JSON file:

We see the categories are assigned pairing each ‘id’ and ‘title’.
We create a dict() to hold this pairing and convert to dict() to a series and the series to a panda dataframe:

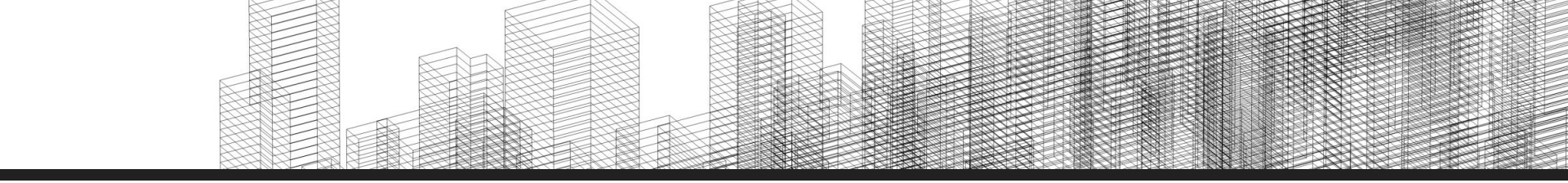
```
category_dict = dict()

for item in data['items']:
    idnum = item['id']
    title = item['snippet']['title']
    category_dict[idnum] = title

s = pd.Series(category_dict, name = 'title')
s.index.name = 'id'

categories_df = pd.DataFrame(s)
categories_df.head()
```



Next we explore the JSON file:

Converting to DataFrame gives us the key to the video categories

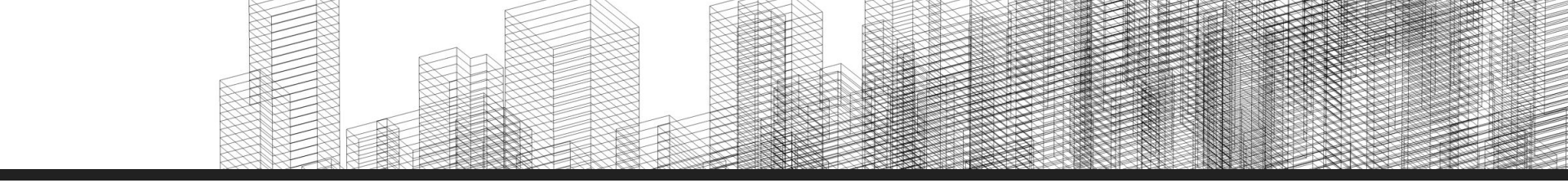
category_id	title
1	Film & Animation
2	Autos & Vehicles
10	Music
15	Pets & Animals
17	Sports
18	Short Movies
19	Travel & Events
20	Gaming
21	Videoblogging
22	People & Blogs
23	Comedy
34	Comedy
24	Entertainment
25	News & Politics
26	Howto & Style
27	Education
28	Science & Technology
30	Movies
31	Anime/Animation
32	Action/Adventure
33	Classics
35	Documentary
36	Drama
37	Family
38	Foreign
39	Horror
40	Sci-Fi/Fantasy
41	Thriller
42	Shorts
43	Shows
44	Trailers



Most Viewed Video Categories:

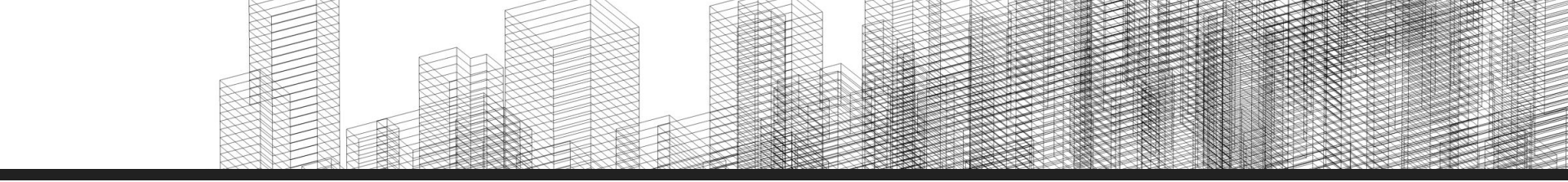
Once we have this we could see the most viewed categories are **Entertainment (24)** followed by **Music(10)** then **How to's and Style(26)** ... Triller(29) and Shows(43) are at the bottom of the list - probably categories you may want to avoid if you want to up your chances of making the trending list:

24	9964
10	6472
26	4146
23	3457
22	3210
25	2487
28	2401
1	2345
17	2174
27	1656
15	920
20	817
19	402
2	384
29	57
43	57



Top 10 Highest Daily Views:

	title	category_id	daily_views	channel_title
35550	BTS (ë°©í□□ì□□ë□□ë□¨) 'FAKE LOVE' Official MV	10	39349927.0	ibighit
3200	Marvel Studios' Avengers: Infinity War Officia...	24	37736281.0	Marvel Entertainment
30750	VENOM - Official Trailer (HD)	24	27973210.0	Sony Pictures Entertainment
4600	YouTube Rewind: The Shape of 2017 | #YouTubeRe...	24	24782158.0	YouTube Spotlight
16181	To Our Daughter	22	20921796.0	Kylie Jenner
24156	Marvel Studios' Avengers: Infinity War - Offic...	24	19716689.0	Marvel Entertainment
30752	Sanju | Official Teaser | Ranbir Kapoor | Rajk...	24	18639195.0	FoxStarHindi
801	Luis Fonsi, Demi Lovato - Ã□chame La Culpa	10	18558186.0	LuisFonsiVEVO
5001	Jurassic World: Fallen Kingdom - Official Trai...	24	18184886.0	Universal Pictures
39149	we broke up	22	16884972.0	David Dobrik
29951	Ariana Grande - No Tears Left To Cry	10	15873034.0	ArianaGrandeVevo



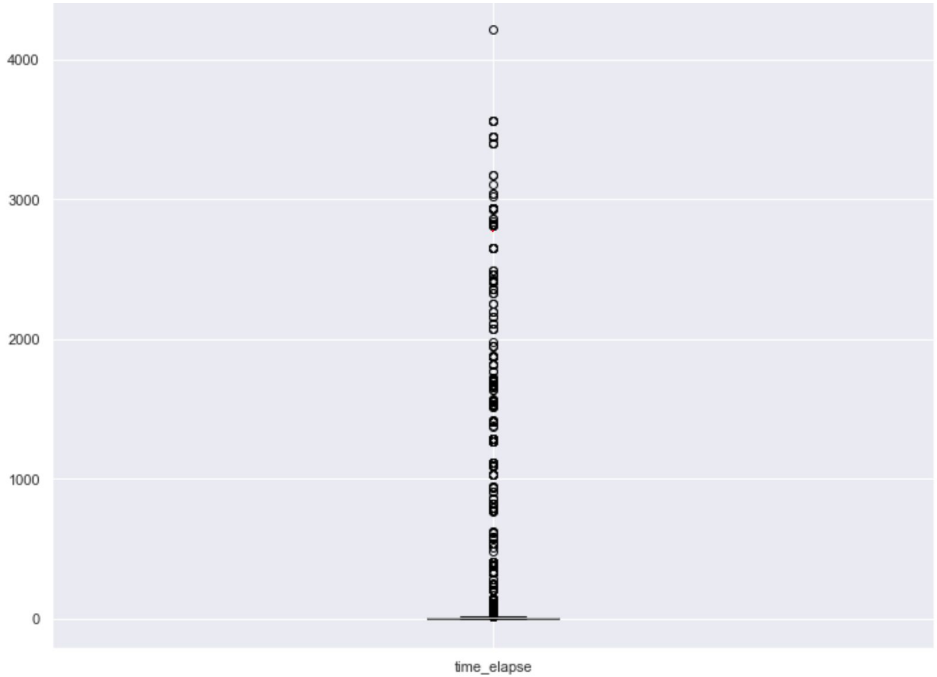
Top 10 Highest Daily Views:

We note a few observations so far:

- Categories 24 and 10 are represented in this list, as welll as another popular category: People and Blog(22)
- Videos which quickly gained views have prior interest for the content, such as movie trailers or music videos: 5 trailers, 3 music videos, 1 YouTube annual summary, 1 is a TV celebrity and 1 was a YouTube celebrity.
- Only one in this list is an individual content creator: David Dobrik. David has created content for over 4 years and has become known in the YouTube community, which made it possible for him to gain large view counts instantly. It is possible to amass this level of views coming out from an unknown status and we want to see more of the characteristics of how these individuals did it.

Visualizing the Data:

We could see that the majority of the data in the time_elapse column are outliers.



Visualizing the Data:

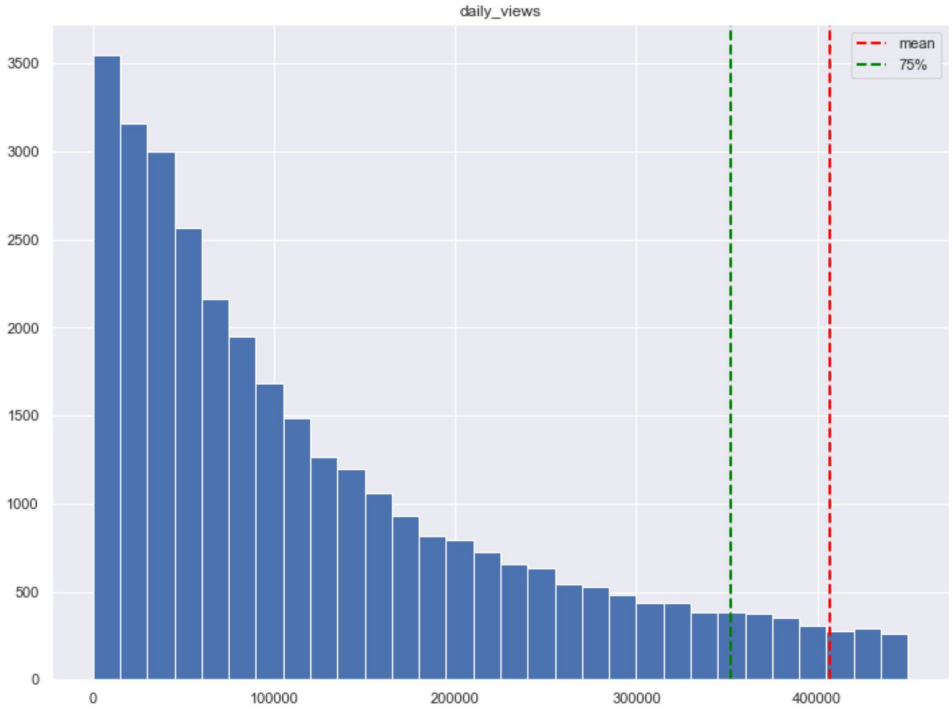
In fact we see that the max time elapsed is 4,215 days but the mean is only 16.8 days and 75% of the videos are within 9 days or less elapsed time from published to trending date.

```
ctry.describe()
```

	category_id	views	likes	dislikes	comment_count	daily_views	time_elapse
count	40949.000000	4.094900e+04	4.094900e+04	4.094900e+04	4.094900e+04	4.082800e+04	40949.000000
mean	19.972429	2.360785e+06	7.426670e+04	3.711401e+03	8.446804e+03	4.067646e+05	16.810423
std	7.568327	7.394114e+06	2.288853e+05	2.902971e+04	3.743049e+04	1.095361e+06	146.014303
min	1.000000	5.490000e+02	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000
25%	17.000000	2.423290e+05	5.424000e+03	2.020000e+02	6.140000e+02	4.760675e+04	3.000000
50%	24.000000	6.818610e+05	1.809100e+04	6.310000e+02	1.856000e+03	1.300480e+05	5.000000
75%	25.000000	1.823157e+06	5.541700e+04	1.938000e+03	5.755000e+03	3.518692e+05	9.000000
max	43.000000	2.252119e+08	5.613827e+06	1.674420e+06	1.361580e+06	3.934993e+07	4215.000000

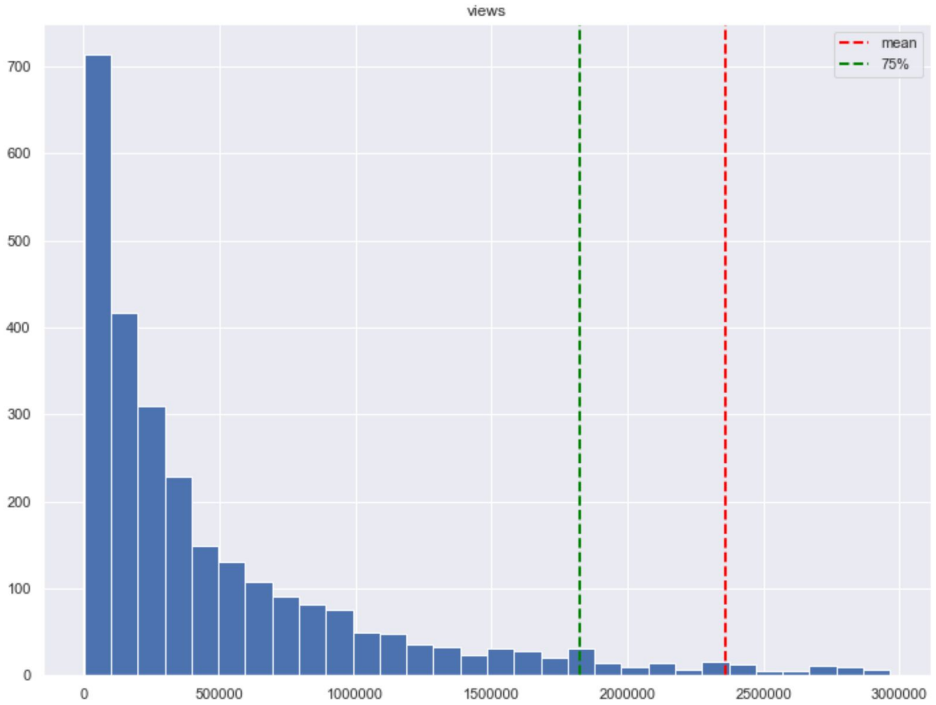
Visualizing the Data:

Another thing to note is the daily views columns - we have a max daily view of 39 million views but the mean is 406,000 daily views with 75% of our videos having 393,000 or less daily views (the views column on the following page shows similar data).



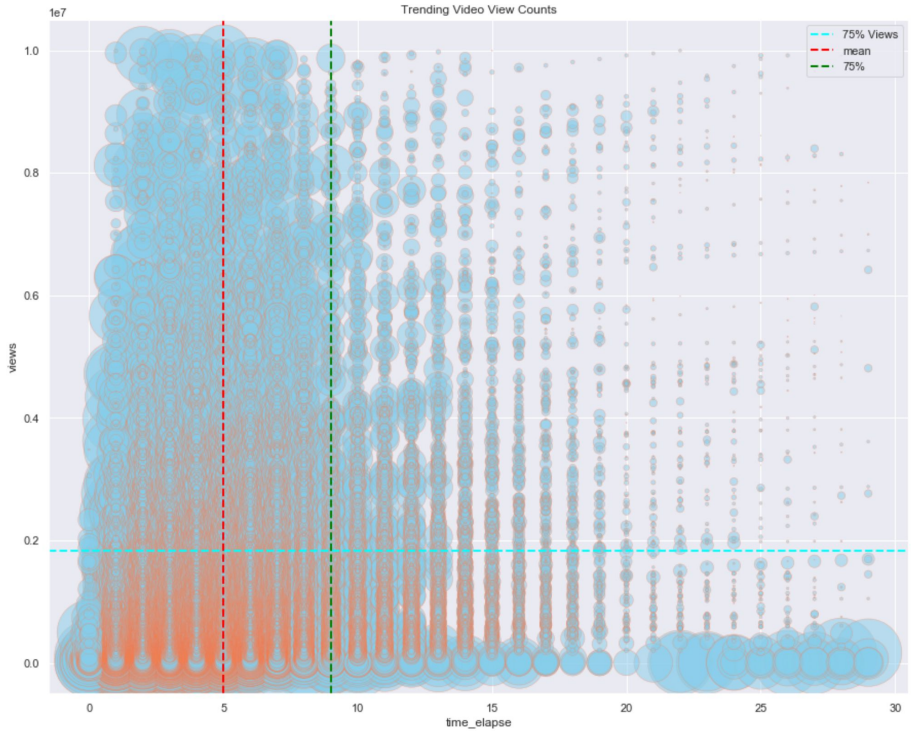
Visualizing the Data:

The histogram of the views column show a similar skew.



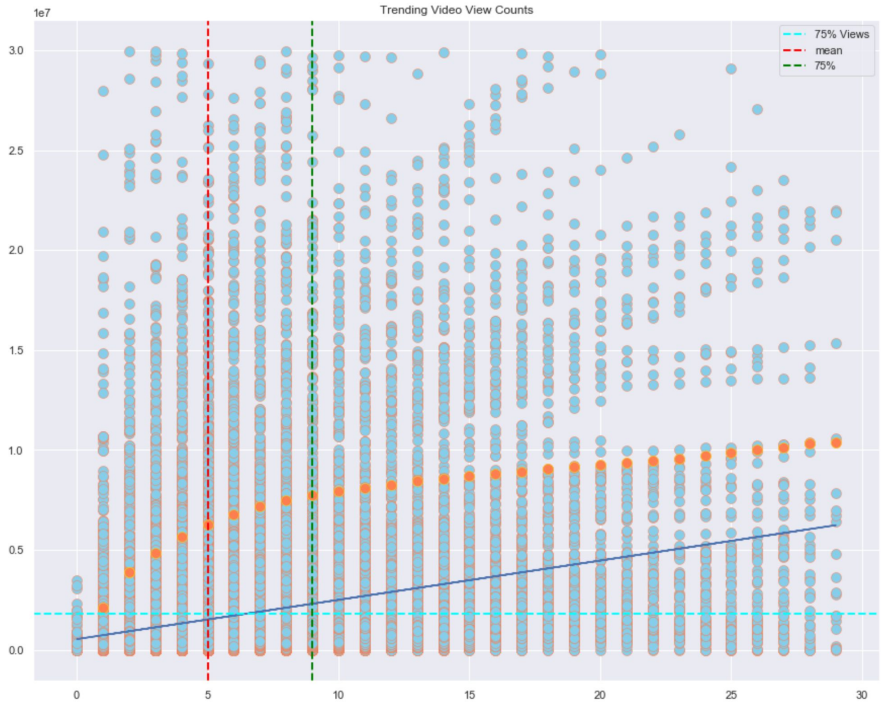
Visualizing the Data:

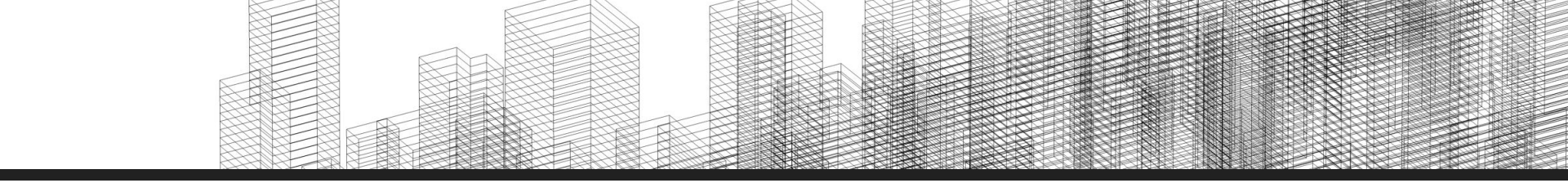
The following 2 graphs show the clustering of data on the bottom left corner of the graph.



Visualizing the Data:

75% of all the videos lie to the left of the green dashed line or below the cyan dashed line

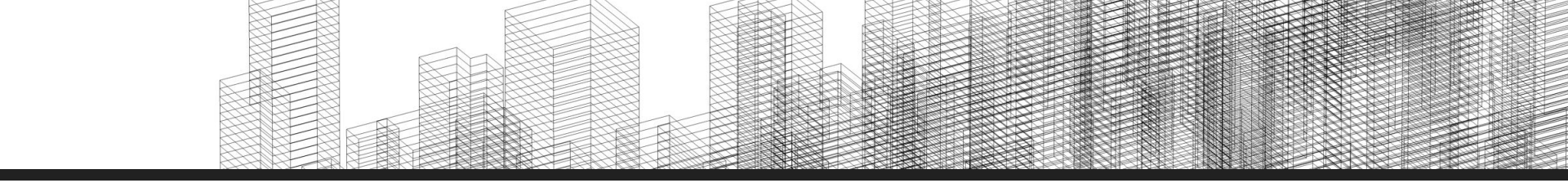




Eliminating Trailers, Music and Corporate Contents:

We see that this list of top views are more representative of individual content creators. They belong more with personal vloggers - many had their starts doing sketch comedies and creating contents that entertain. These generate between 4 to 16 million views on the first day. The histogram of the categories still shows Entertainment as the most popular category.

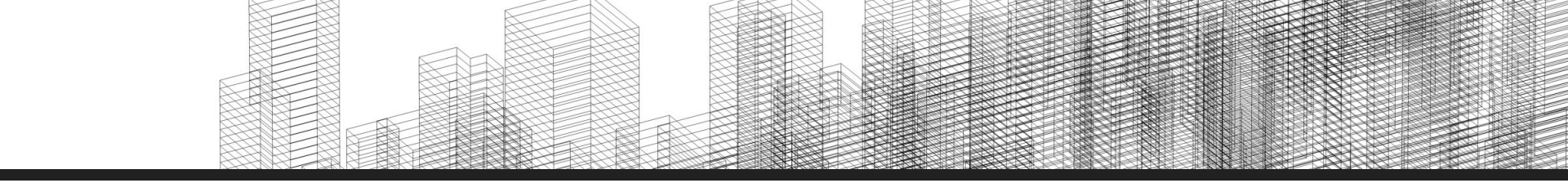
	title	category_id	views	channel_title
39149	we broke up	22	16884972	David Dobrik
10000	So Sorry.	24	13305605	Logan Paul Vlogs
14000	Suicide: Be Here Tomorrow.	29	8041970	Logan Paul Vlogs
4001	42 HOLY GRAIL HACKS THAT WILL SAVE YOU A FORTUNE	26	6315549	5-Minute Crafts
40350	Town Hall 12 Update is Here! (Clash of Clans O...	20	6173038	Clash of Clans
33950	Clash Royale: Meet the Rascals! (New Card!)	20	6142430	Clash Royale
33350	Fortnite with Ninja | Dude Perfect	17	5589612	Dude Perfect
16780	MOMMY AND DAUGHTER SURPRISE DADDY WITH PREGNAN...	22	4990782	The ACE Family
21965	World's Longest LEGO Walk | Dude Perfect	17	4852889	Dude Perfect
6207	Anitta & J Balvin - Downtown (Official Lyric V...	23	4190444	Lele Pons



Applying NLP:

We want to apply Natural Language Processing to some columns (the "title" column) to see if we can gain insight on some words and topics that lead to videos that will get more views.

```
from sklearn.feature_extraction.text import CountVectorizer
import string
import nltk
import re

text = ctry_elim.title

stopwords = nltk.corpus.stopwords.words('english')
ps = nltk.PorterStemmer()

# we set ngram_range for the CountVectorizer to get context around each word
vectorizer = CountVectorizer(min_df=1, analyzer='word', ngram_range=(3, 3))

# we create a function that will get rid of punctuations, tokenize, stem and remove stopwords
def clean_text(text):
    text = "".join([word.lower() for word in text if word not in string.punctuation])
    tokens = re.split('\W+', text)
    text = [ps.stem(word) for word in tokens if word not in stopwords]
    return text

clean_text(text)
```



Applying NLP:

We get a list of features that will be fitted and vectorized.

```
# call `fit` to build the vocabulary
vectorizer.fit(text)

# call `transform` to convert text to a bag of words
x = vectorizer.transform(text)
```

```
Words for each feature:
['000 00 camera', '30 feet under', 'alec steele collab', 'and twitter actually', 'attempt test kitchen', 'before seen videos',
'boseman gets emotional', 'by your name', 'challenge with brian', 'colour blind glasses', 'cut aid over', 'dies after crashin
g', 'drank energy drinks', 'evans make cast', 'feat twin shadow', 'for former first', 'ft tove lo', 'gold games aspen', 'harry
styles canta', 'holiday makeup look', 'if this is', 'interesting electric suv', 'jamie foxx and', 'kelly ambassadors bebe', 'la
var ball article', 'long french fry', 'making new sounds', 'melting every lipstick', 'most subscribed youtubers', 'neck bass so
lo', 'of 50 000', 'on cartoon hangover', 'own way official', 'pizza pouch wearable', 'puppy bowl spot', 'republicans praise tru
mp', 'ryobi tools for', 'sex of kitten', 'smoke behave in', 'stephon marbury and', 'talk through get', 'the call me', 'the ring
s tv', 'thought freestyles on', 'to read fire', 'tried 700 dyson', 'use his music', 'was sexually assaulted', 'while answering
our', 'with ninja dude', 'you in adulthood']
```

Applying NLP:

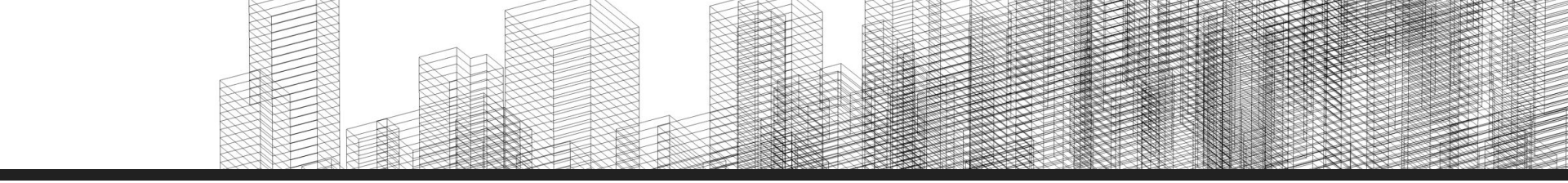
We set our y to videos that gain more that 580,000 views - the threshold for 50% of the videos in this set as a bar to cross and fit with CountVectorizer.

```
X = vectorizer.fit_transform(text)
X = X.tocsc()  # some versions of sklearn return COO format
y = (ctry_elim.views >= 580000)  # this is the threshold for 50% of the videos in this set
```

We split our training and testing set using a testing size of .2 and return pretty similar results from our training and test set.

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

clf.fit(X_train, y_train)
```

```
Accuracy of Training Set: 0.899724289005552
Accuracy of Test Set: 0.8790030211480363
```



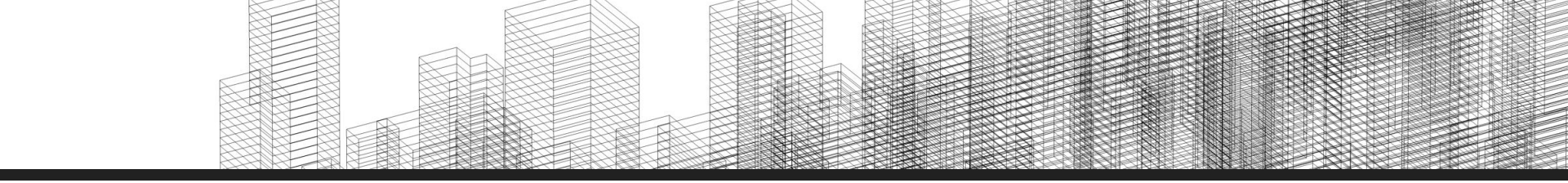
Cross-Validation and hyper-parameter fitting:

We use KFold and a log-likelihood function for our naive bayes classifier. We use an nfold of 5 to split our data into 5 test/train groups

```
from sklearn.model_selection import KFold
def cv_score(clf, X, y, scorefunc):
    result = 0.
    nfold = 5
    for train, test in KFold(nfold).split(X): # split data into train/test groups, 5 times
        clf.fit(X[train], y.iloc[train]) # fit the classifier, passed is as clf.
        result += scorefunc(clf, X[test], y.iloc[test]) # evaluate score function on held-out data
    return result / nfold # average
```

For our naive bayes calculations, we define a log likelihood function to obtain a likelihood estimator by summing up observed results

```
def log_likelihood(clf, x, y):
    prob = clf.predict_log_proba(x)
    good = y
    bad = ~good
    return prob[good, 0].sum() + prob[bad, 1].sum()
```



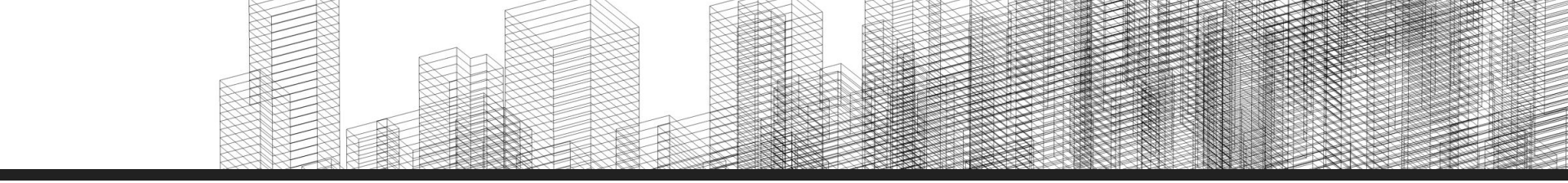
Cross-Validation and hyper-parameter fitting:

We iterate to obtain the best alpha and min_df parameters

```
from sklearn.naive_bayes import MultinomialNB

#the grid of parameters to search over
alphas = [.1, 1, 5]
min_dfs = [1]
```

```
#Find the best value for alpha and min_df, and the best classifier
best_alpha = None
best_min_df = None
maxscore=-np.inf
for alpha in alphas:
    for min_df in min_dfs:
        vectorizer = CountVectorizer(min_df = min_df)
        Xthis, ythis = make_xy(ctry_elim, vectorizer)
        Xtrainthis=Xthis[mask]
        ytrainthis=ythis[mask]
        clf = MultinomialNB(alpha=alpha)
        cvscore = cv_score(clf, Xtrainthis, ytrainthis, log_likelihood)

        if cvscore > maxscore:
            maxscore = cvscore
            best_alpha, best_min_df = alpha, min_df
```

```
best alpha: 5
min_df: 1
```



Cross-Validation and hyper-parameter fitting:

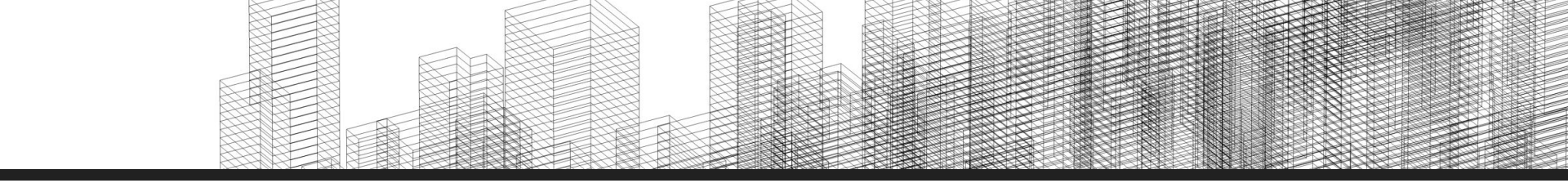
Using these parameters returns training and test accuracy that are pretty close:

```
Accuracy on training data: 0.870191
Accuracy on test data:     0.800104
```

The confusion matrix has less true positives than true negatives but the number still looks good:

```
print(confusion_matrix(ytest, clf.predict(xtest)))
```

```
[[8950 2532]
 [2099 9586]]
```



Cross-Validation and hyper-parameter fitting:

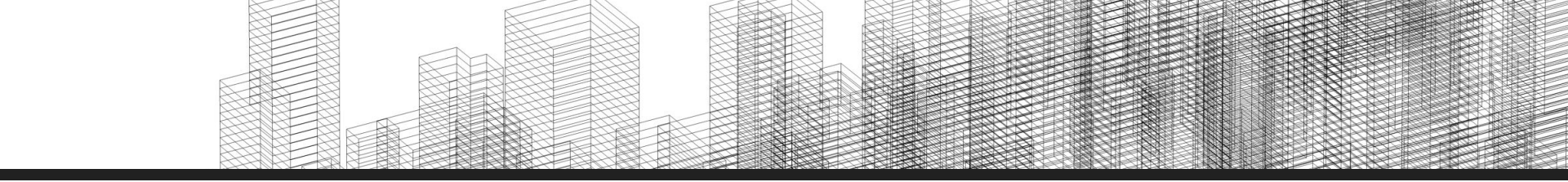
Finally, let's get a list of good words / subjects that predictors of high trending videos

```
words = np.array(vectorizer.get_feature_names())

x = np.eye(xtest.shape[1])
probs = clf.predict_log_proba(x)[:, 0]
ind = np.argsort(probs)

good_words = words[ind[:100]]
bad_words = words[ind[-10:]]

good_prob = probs[ind[:100]]
bad_prob = probs[ind[-10:]]
```

Cross-Validation and hyper-parameter fitting:

```
good_words
```

```
array(['react', 'dude', 'less', 'spider', 'trailers', 'wrong', 'babish',
       'yiay', 'theory', 'lele', 'anwar', 'jibawi', 'bgt', 'pons',
       'twice', 'lucky', 'khalid', 'escape', 'pentatonix', 'mo',
       'mancuso', 'slow', 'rudy', 's9', 'gourmet', 'jason', 'zones',
       'lopez', 'sneaker', 'complex', 'puth', 'guetta', 'shots', 'prison',
       'binging', 'lucas', 'honest', 'lava', 'fast', 'spicy', 'fort',
       'tinashe', 'lovely', 'underwood', 'auditions', 'well', 'bts',
       'collection', 'trick', 'gadgets', 'calories', 'card', 'hacks',
       'perfect', 'ones', 'coca', 'buzzer', 'el', 'wings', 'dear',
       'gomez', 'even', 'tunnel', 'aiko', 'eilish', 'billie', 's5',
       'underground', 'bobby', 'jhenã', 'primitive', 'trainor', 'montana',
       'bags', 'glynne', 'blind', 'jess', 'every', 'anthem', 'galaxy',
       'ant', 'cheap', 'cha', 'flames', 'gauntlet', 'size', 'stirling',
       'khaled', 'vol', 'organized', 'namiko', 'prototype', 'according',
       'graphics', 'lindsey', 'scuba', 'ops', 'dutyâ', 'mama', 'derulo'],
      dtype='<U43')
```



Let's test run video titles to predict what will be a hit:

```
clf.predict_proba(vectorizer.transform(['top 10 ways to make money working from home in 6 months']))
```

```
array([[0.8806663, 0.1193337]])
```

This title has a 11% probability of being a hit.

```
clf.predict_proba(vectorizer.transform(["top 10 ways to make money working from prison you don't have to be sorry about"]))
```

```
array([[0.19830939, 0.80169061]])
```

This one at 80% has a lot better chance.

```
clf.predict_proba(vectorizer.transform(["Why my neighbor brought a dog with the weirdest eyes on holidays with them"]))
```

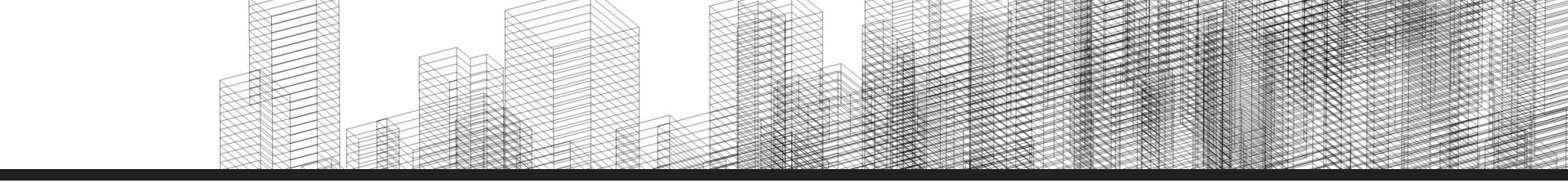
```
array([[0.57510384, 0.42489616]])
```

This one has a 42% chance of being a big hit - although this title peaks my interest, it's predicted to be just a little lower 50% of being a hit.

```
clf.predict_proba(vectorizer.transform(["My perfect nightmares involve falling slowly on the wrong trampoline"]))
```

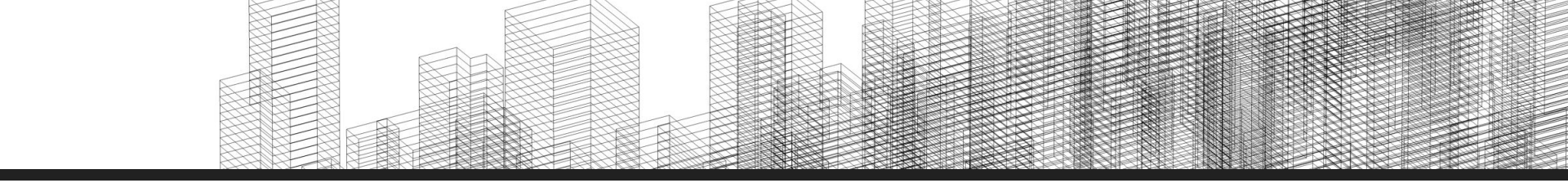
```
array([[0.00599502, 0.99400498]])
```

This scores a high 99% ... because we picked 3 words from the list of good words to form our topic.



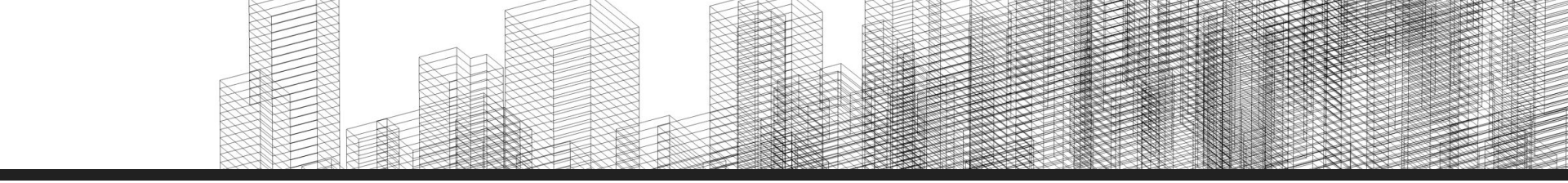
Conclusions:

This short exploration gives us some ideas of what makes a video trend on YouTube. Firstly, we find that movie trailers, music videos and commercially produced videos easily top the list for most viewed videos. This makes sense because these are already established brands and people with celebrity status. We also noted that there are categories that are more popular. Entertainment and Sports tops the list, but right after comes How Tos and Style followed by Comedy, People and Blogs and News and Politics followed by Science and Technology. One way to take advantage of this is to make content in these popular subjects and categories or about them.



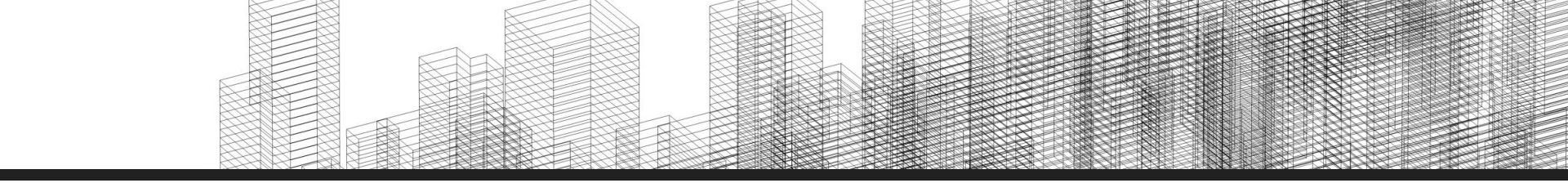
Conclusions:

We find that when we eliminate the movie trailers, music videos and large commercial producers we get more of the regular content creators who create interesting vlog. Some gain views because they posted content that sparked the ire of the viewers and the content goes viral as well as the following apology video. Popular categories remain the same as before. What's interesting about this subset of regular content creators is that they have the potential of creating their own brand and bringing their status and viewership level to match celebrity and commercial producers. They build their viewership from the bottom up rather than from the top down.



Conclusions:

Lastly, we did some NLP to find some predictive words and topics that can generate more views. This list and our list of popular categories can help develop content and subjects that interest the viewers.



Final Thoughts:

YouTube is a visual and audio medium - something that is missing from our data and is a possible direction for future study. There's also something we don't want to discount in these YouTuber's success is qualities like talent, personal charisma, tenacity, work ethic and willingness to take risks. This study provides a kind of cheat code for what type of videos to produce to gain a foothold for success however there's still a matter of work and striving that is ahead for the individual content creator has to put in. It can provide a roadmap to success but each individual has to contribute enough fuel and drive to launch their own journey to the stratosphere.