Introduction

YouTube is the most popular and most used video platfrom in the world today. YouTube has [a list of **trending videos** (https://www.youtube.com/feed/trending)](https://www.youtube.com/feed/trending) that is updated constantly. I will used **Python** with some packages like **Pandas**, **NLTK**,and **Matplotlib** to analyze a dataset includes several countries. I will analyze this data to get insights into YouTube trending videos, to see what is common between these videos. These insights might also be used by people who want to increase popularity of their videos on YouTube.

The dataset that we will use is downloaded from Kaggle [here (https://www.kaggle.com/datasnaek/youtube-new)](https://www.kaggle.com/datasnaek/youtube-new).

Goals of the analysis

We want to answer questions like:

Table of contents

Importing libraries

In [2]:
```
import pandas as pd
pd.set_option('display.max_columns', None) #Dataframe display setting
# import pandas_profiling
import numpy as np
import matplotlib as mpl
from matplotlib import pyplot as plt
import seaborn as sns
import plotnine as p9

import warnings
warnings.filterwarnings('ignore')
import json
import os

%matplotlib inline
```

Read in the dataset

In [3]:
```
files_path = os.getcwd() + '\\youtube'
files = os.listdir(files_path)
csvs = [csv for csv in files if csv.endswith('csv')]
jsons = [json for json in files if json.endswith('json')]
```

In [4]:
```
dfs = []
for csv in csvs:
    df = pd.read_csv(files_path + '\\' + csv)
    df['nation'] = csv[0:2]
    dfs.append(df)
data = pd.concat(dfs) #concatenate all csv files
```

In [5]:
```
cat_dict = {}
with open(files_path + '\\US_category_id.json', 'r') as f:
    j = json.load(f)
    for item in j['items']:
        cat_dict[np.int(item['id'])] = item['snippet']['title']

data['category'] = data.category_id.map(cat_dict).rename(columns={'category_id':'category'
data.head()
```

Out[5]:

	video_id	trending_date	title	channel_title	category_id	publish_time	
0	n1WpP7iowLc	17.14.11	Eminem - Walk On Water (Audio) ft. Beyoncé	EminemVEVO	10	2017-11-10T17:00:03.000Z	Eminem|"V
1	0dBIkQ4Mz1M	17.14.11	PLUSH - Bad Unboxing Fan Mail	iDubbbzTV	23	2017-11-13T17:00:00.000Z	plush|"
2	5qpjK5DgCt4	17.14.11	Racist Superman | Rudy Mancuso, King Bach & Le...	Rudy Mancuso	23	2017-11-12T19:05:24.000Z	racist su
3	d380meD0W0M	17.14.11	I Dare You: GOING BALD!?	nigahiga	24	2017-11-12T18:01:41.000Z	ryan
4	2Vv-BfVoq4g	17.14.11	Ed Sheeran - Perfect (Official Music Video)	Ed Sheeran	10	2017-11-09T11:04:14.000Z	edshee

Data cleaning

Goals:

- Convert features into right data types
- Deal with NA value
- Create possibly useful new features

In [6]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 184755 entries, 0 to 40948
Data columns (total 18 columns):
video_id                  184755 non-null object
trending_date             184755 non-null object
title                     184755 non-null object
channel_title             184755 non-null object
category_id               184755 non-null int64
publish_time              184755 non-null object
tags                      184755 non-null object
views                     184755 non-null int64
likes                     184755 non-null int64
dislikes                  184755 non-null int64
comment_count             184755 non-null int64
thumbnail_link            184755 non-null object
comments_disabled         184755 non-null bool
ratings_disabled          184755 non-null bool
video_error_or_removed    184755 non-null bool
description               178356 non-null object
nation                    184755 non-null object
category                  184755 non-null object
dtypes: bool(3), int64(5), object(10)
memory usage: 23.1+ MB
```

In [7]:
```
data['trending_date'] = pd.to_datetime(data.trending_date, format='%y.%d.%m')
data['publish_time'] = pd.to_datetime(data.publish_time, format='%Y-%m-%dT%H:%M:%S.%fZ')

data.insert(7, 'publish_date', data.publish_time.dt.date)
data['publish_date'] = pd.to_datetime(data.publish_date)
data.insert(7, 'publish_day', data.publish_time.dt.dayofweek)
data.insert(7, 'publish_hour', data.publish_time.dt.hour)

data.description = data.fillna('')
```

In [8]:
```
data.head(3)
```

Out[8]:

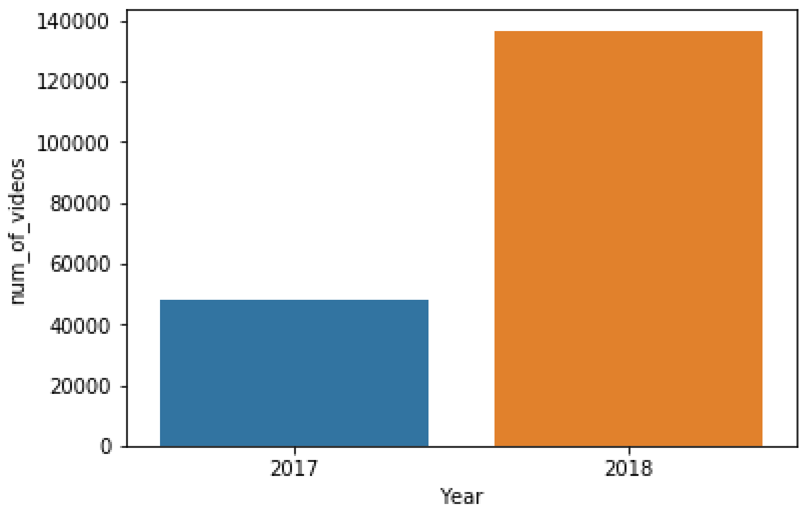
	video_id	trending_date	title	channel_title	category_id	publish_time	
0	n1WpP7iowLc	2017-11-14	Eminem - Walk On Water (Audio) ft. Beyoncé	EminemVEVO	10	2017-11-10 17:00:03	Eminem|"Walk"|'
1	0dBIkQ4Mz1M	2017-11-14	PLUSH - Bad Unboxing Fan Mail	iDubbbzTV	23	2017-11-13 17:00:00	plush|"bad u
2	5qpjK5DgCt4	2017-11-14	Racist Superman | Rudy Mancuso, King Bach & Le...	Rudy Mancuso	23	2017-11-12 19:05:24	racist superma

Dataset collection distribution

In [9]:
```
ydata = data.trending_date.dt.year.value_counts().to_frame().reset_index() \
            .rename(columns={'index': 'year', 'trending_date': 'num_of_videos'})

fig, ax = plt.subplots()
x = ydata.year
y = ydata.num_of_videos
fig = sns.barplot(x=x, y=y, data=ydata)
fig = ax.set(xlabel="Year", ylabel="num_of_videos")

data.trending_date.dt.year.value_counts(normalize = True).to_frame().rename(columns = {'t
```

Out[9]:

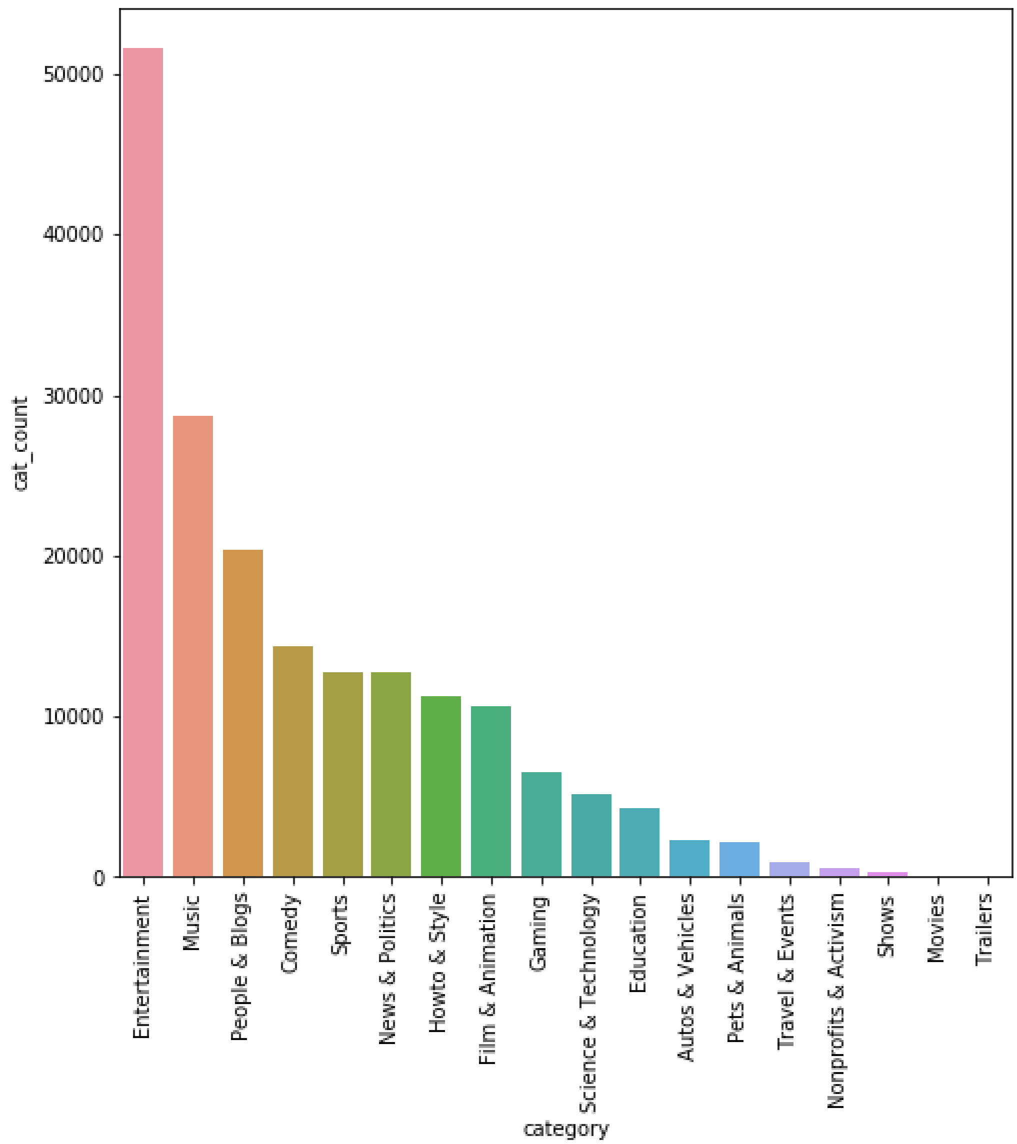
	%_of_videos
2018	0.740316
2017	0.259684



In [10]:
```
cat_data = data.groupby('category').size().sort_values(ascending = False).reset_index(nam
x = cat_data.category
y = cat_data.cat_count
fig, ax = plt.subplots(figsize = (8,8))
sns.barplot(x,y,data = cat_data)
plt.xticks(rotation='vertical')
data.category.value_counts(normalize = True).to_frame().rename(columns={'category':'%_of_
```

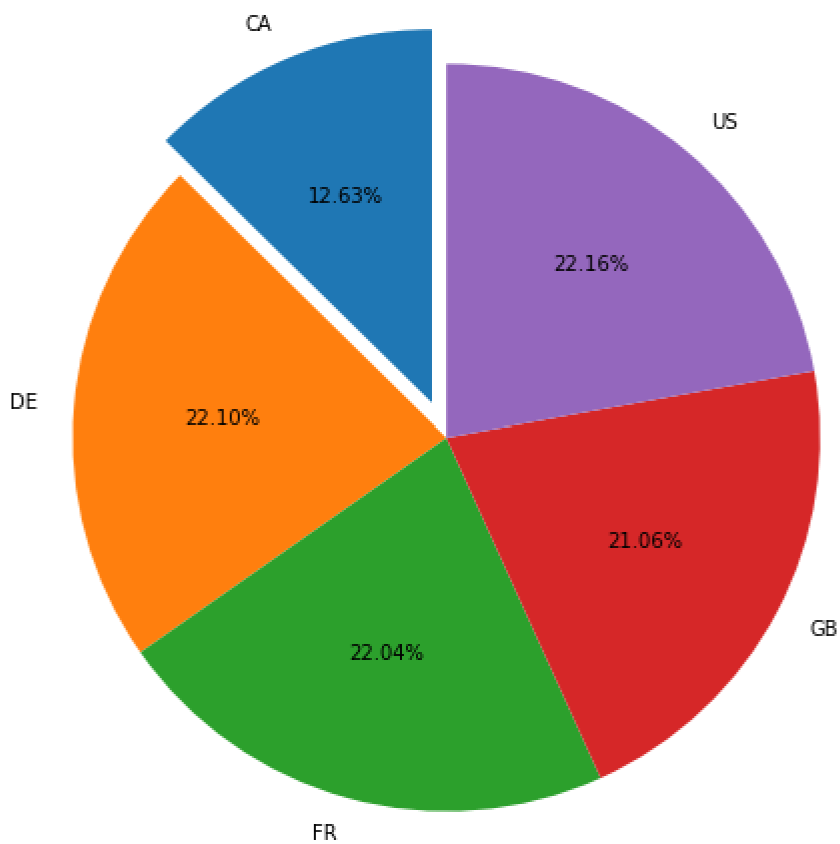
Out[10]:

	%_of_videos
Entertainment	0.279164
Music	0.155168
People & Blogs	0.110032
Comedy	0.077887
Sports	0.069216
News & Politics	0.068897
Howto & Style	0.061021
Film & Animation	0.057709
Gaming	0.035068
Science & Technology	0.027972
Education	0.023474
Autos & Vehicles	0.012324
Pets & Animals	0.011680
Travel & Events	0.005310
Nonprofits & Activism	0.003085
Shows	0.001905
Movies	0.000070
Trailers	0.000016


50000
40000
30000
20000
10000
0
cat_count
Entertainment
Music
People & Blogs
Comedy
Sports
News & Politics
Howto & Style
Film & Animation
Gaming
Science & Technology
Education
Autos & Vehicles
Pets & Animals
Travel & Events
Nonprofits & Activism
Shows
Movies
Trailers
category

In [11]:
```
labels = data.groupby(['nation']).count().index
sizes = data.groupby(['nation']).count()['title']
explode = (0.1, 0, 0, 0, 0)  # only "explode" the 2nd slice (i.e. 'Hogs')

fig, ax = plt.subplots(figsize = (8,8))
ax.pie(sizes, labels=labels, autopct='%1.2f%%',
        shadow=False, explode=explode, startangle=90)
ax.axis('equal')  # Equal aspect ratio ensures that pie is drawn as a circle.
sizes
```

Out[11]:
```
nation
CA    23326
DE    40840
FR    40724
GB    38916
US    40949
Name: title, dtype: int64
```



In [12]:
```
data.shape
```

Out[12]:
```
(184755, 21)
```

- Out of 184755 videos, **74%** of them is collected from 2018 and **26%** of them is collected from 2017;
- **27.9%** of the dataset is related Entertainment, **15.5%** of the dataset is related to Music, and **11%** of the dataset is realted to People & Blogs
- Also, only **12.63%** of the videos is from Canada

Analysis

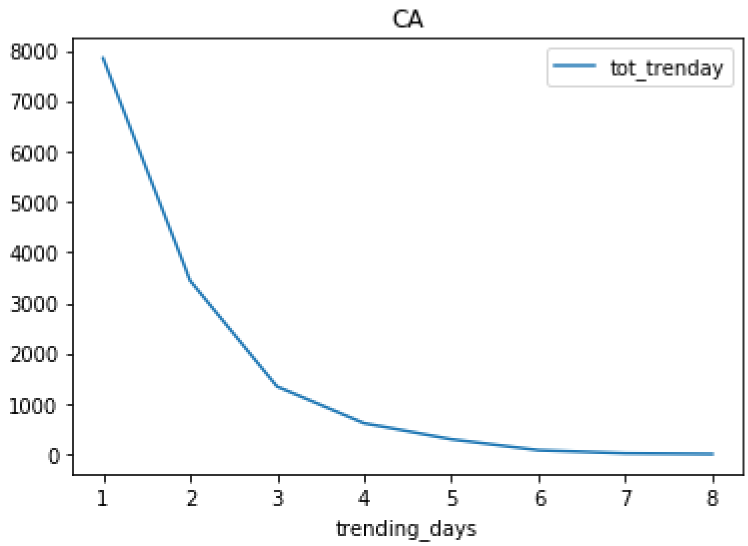
How long usually a video can trend in different countries?

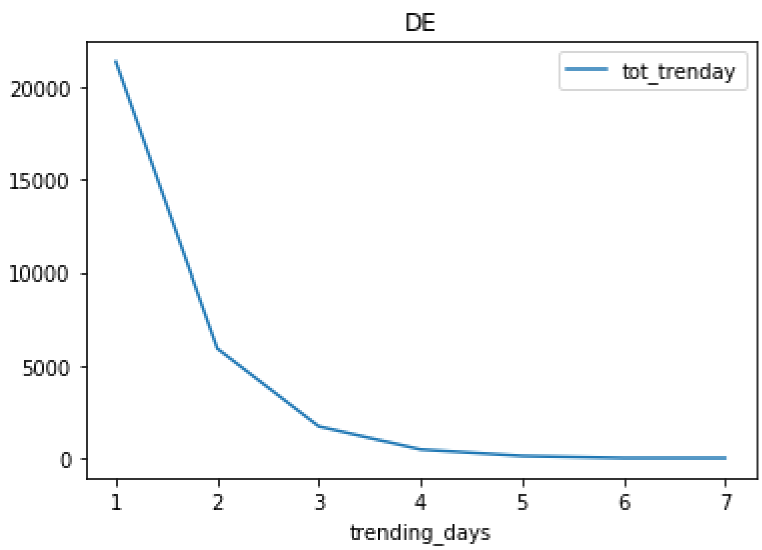
From here we can see that United Kingdom's list has the longest trended Youtube videos (Top 5 in the list is from GB). Also, the US and UK have longer trending days while other countries' videos can only be trended for less than 10 days

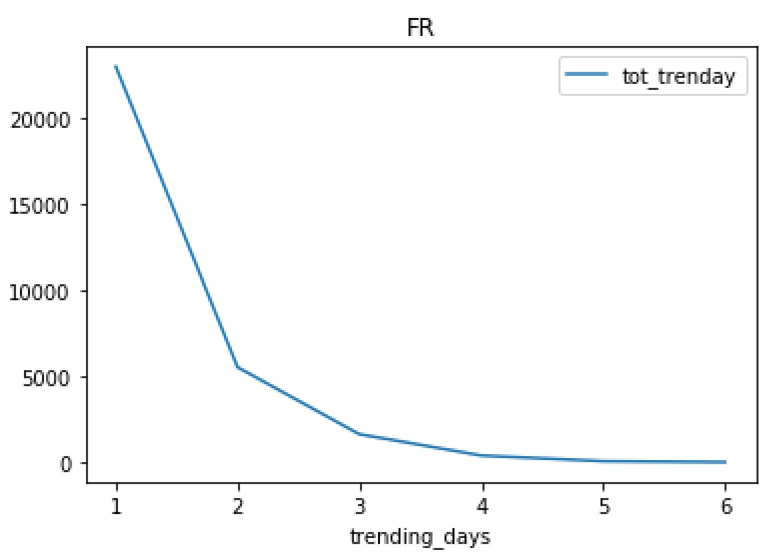
In [13]:
```
fre = data.groupby(['video_id','nation']).size().reset_index(name = 'trending_days').sort_
fre.head(5), fre.tail(5)
```

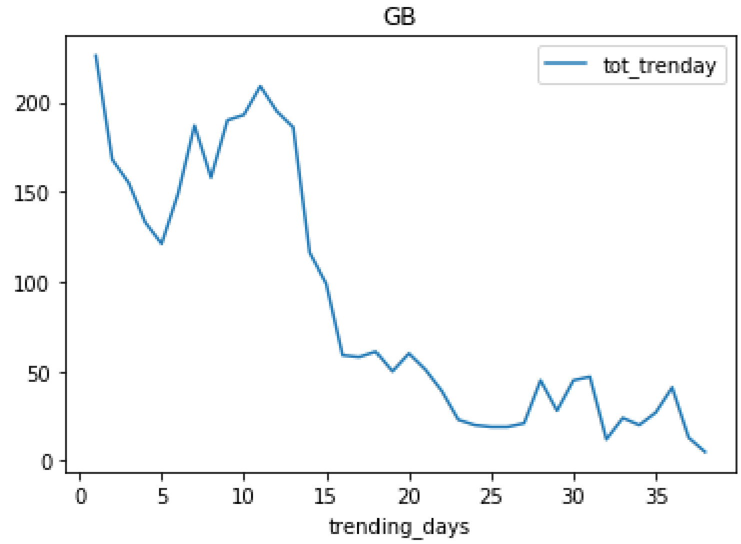
Out[13]:
```
(          video_id nation  trending_days
 76579  u_C4onVrr8U     GB             38
 5219   2z3EUY1aXdY     GB             38
 32284  NooW_RbfdWI     GB             38
 25651  Il-an3K9pjg     GB             38
 16552  BhIEIOOvaBE     GB             38,
           video_id nation  trending_days
 34055  PBjjzcbLCLo     DE              1
 34056  PBsbuFyXSJE     FR              1
 34059  PC1rmoEwIwQ     CA              1
 34060  PC6M5bhy2jE     DE              1
 83479  zzz0_5fMnI8     FR              1)
```

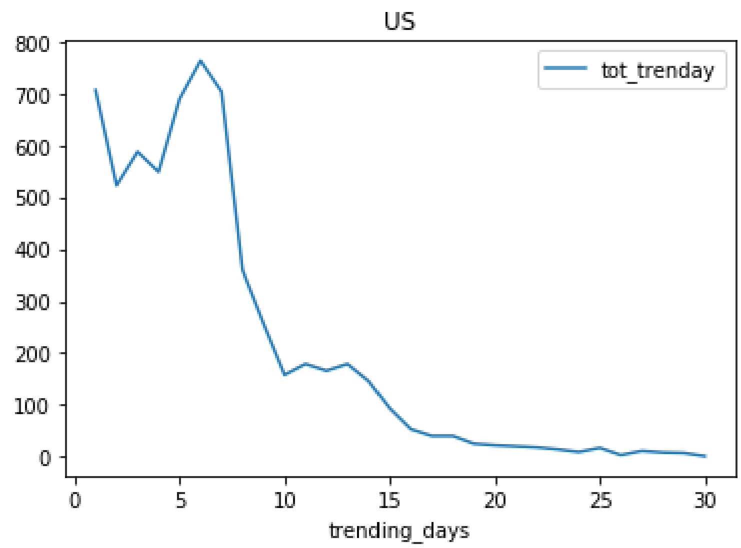
In [14]:
```
nfre = fre.groupby(['nation','trending_days']).size().reset_index(name = 'tot_trenday')
nation_ls = nfre.nation.unique().tolist()
for n in nation_ls:
    nfre[nfre['nation'] == n][['trending_days', 'tot_trenday']].set_index('trending_days')
```





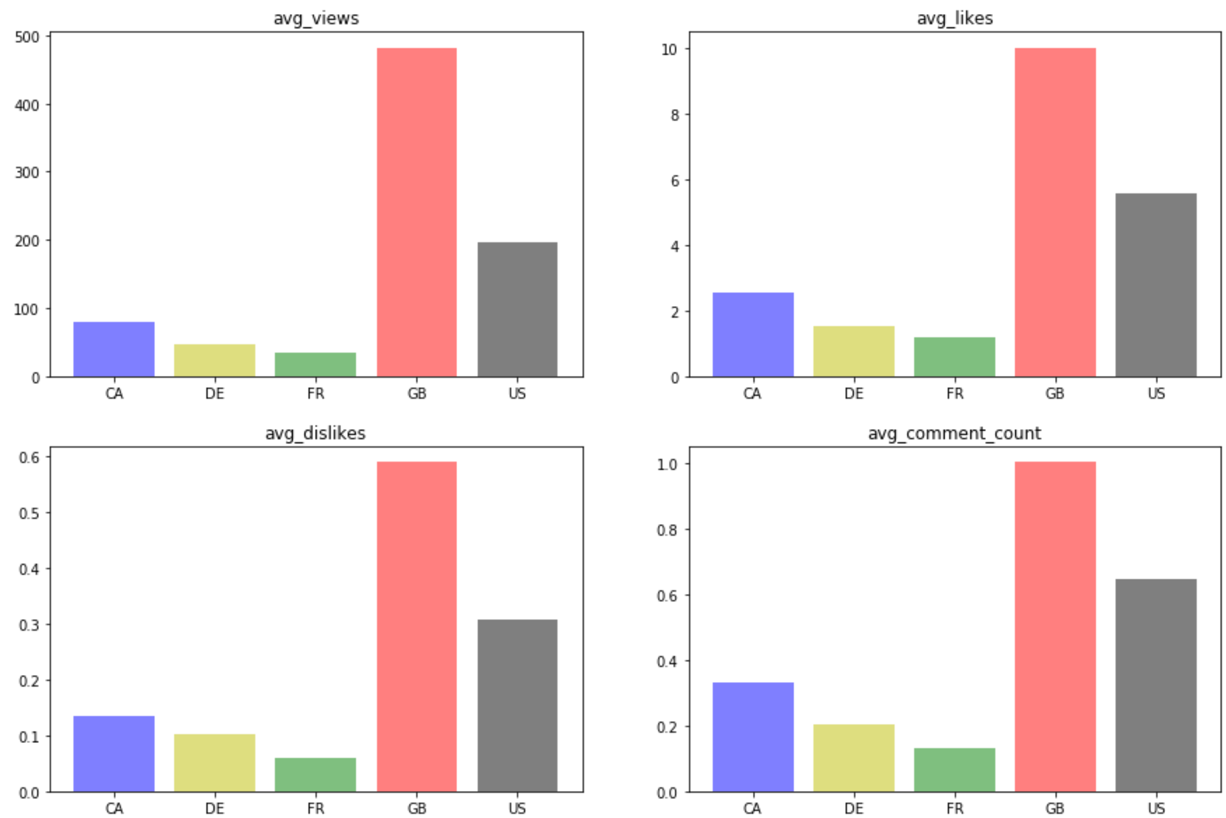






How many views, likes, dislikes, and comments on average in different countries

In [15]:
```
my_df = data.reset_index().sort_values('trending_date').drop_duplicates(['video_id','nati

stats = my_df.groupby('nation')[['views','likes','dislikes','comment_count']].mean().rese
stat_ls = np.array([['views','likes'],['dislikes','comment_count']])

fig, [[ax1, ax2], [ax3, ax4]] = plt.subplots(ncols=2,nrows=2, figsize=(15,10))

for i, axs in enumerate([[ax1, ax2], [ax3, ax4]]):
    for j, ax in enumerate(axs):
        ax.bar(x = stats.nation.tolist(), height = stats[stat_ls[i,j]]/10000,
              color=['b','y','g','r','k'], alpha = 0.5)
        ax.set_title('avg_' + stat_ls[i,j])
```



Variable Correlation

- Above plots indicate that videos with longer trending days have more views, likes, dislikes, and comments;
- However, Adj. R-squared (0.116) and t-scores of each variables show that views, likes, dislikes, and comments are not statistically significant in predicting trending days
- Likes is highly correlated with views and comments while dislikes is highly correlated with comments

In [16]:
```
import statsmodels.api as sm
```

In [17]:
```
full_stat = pd.merge(my_df, fre).sort_values('trending_days',ascending = False)
X = full_stat[['views','likes','dislikes','comment_count']]
y= full_stat.trending_days
X = sm.add_constant(X) #add an intercept for the model
result = sm.OLS(y,X).fit()
print(result.summary())
```

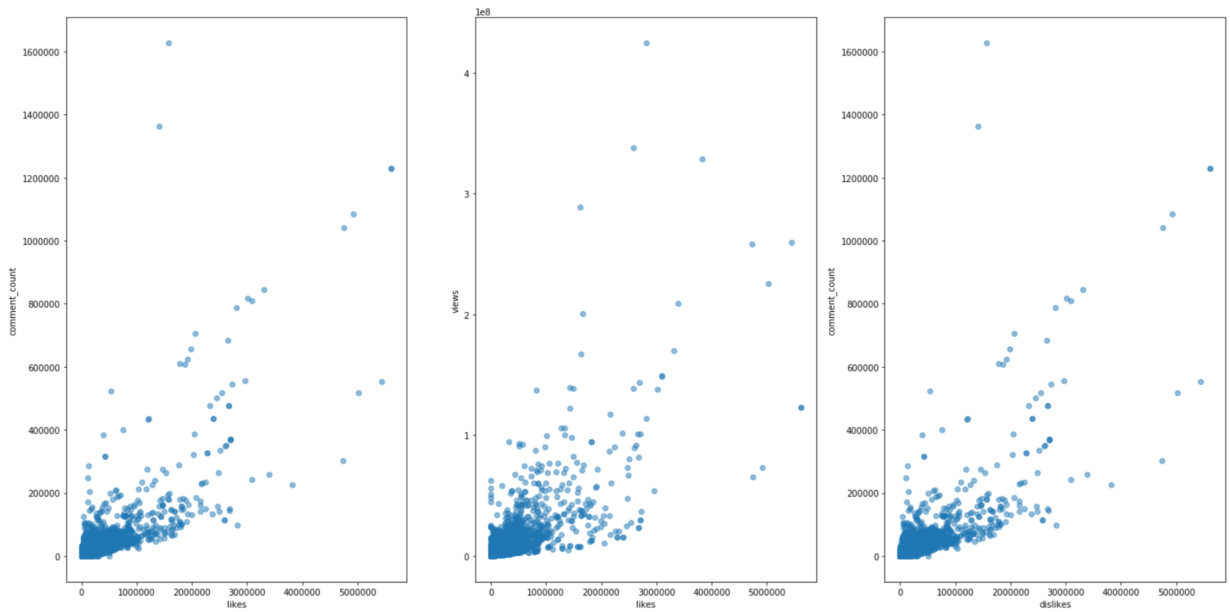
```
                            OLS Regression Results
==============================================================================
Dep. Variable:          trending_days   R-squared:                       0.116
Model:                            OLS   Adj. R-squared:                  0.116
Method:                 Least Squares   F-statistic:                     2742.
Date:                Sat, 20 Jul 2019   Prob (F-statistic):               0.00
Time:                        07:54:38   Log-Likelihood:            -2.1244e+05
No. Observations:               83480   AIC:                         4.249e+05
Df Residuals:                   83475   BIC:                         4.249e+05
Df Model:                           4
Covariance Type:            nonrobust
=================================================================================
                    coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------
const             2.0151      0.011    185.135      0.000       1.994       2.036
views          1.887e-07   3.87e-09     48.778      0.000    1.81e-07    1.96e-07
likes          3.811e-06   2.34e-07     16.273      0.000    3.35e-06    4.27e-06
dislikes      -5.094e-06    9.8e-07     -5.198      0.000   -7.01e-06   -3.17e-06
comment_count -9.523e-06   1.36e-06     -7.007      0.000   -1.22e-05   -6.86e-06
==============================================================================
Omnibus:                    81199.981   Durbin-Watson:                   0.212
Prob(Omnibus):                  0.000   Jarque-Bera (JB):          4853707.624
Skew:                           4.740   Prob(JB):                         0.00
Kurtosis:                      39.132   Cond. No.                     4.89e+06
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specif
ied.
[2] The condition number is large, 4.89e+06. This might indicate that there are
strong multicollinearity or other numerical problems.
```

In [18]:
```
full_stat[['views','likes','dislikes','comment_count']].corr()
```

Out[18]:

	views	likes	dislikes	comment_count
views	1.000000	0.760831	0.416610	0.497356
likes	0.760831	1.000000	0.443768	0.780488
dislikes	0.416610	0.443768	1.000000	0.702464
comment_count	0.497356	0.780488	0.702464	1.000000

In [19]:
```
fig,[ax1, ax2, ax3]= plt.subplots(1,3, figsize = (20,10))

ax1.scatter(x = full_stat.likes, y = full_stat.comment_count, alpha = 0.5)
ax1.set(xlabel = 'likes', ylabel = 'comment_count')
ax2.scatter(x = full_stat.likes, y = full_stat.views, alpha = 0.5)
ax2.set(xlabel = 'likes', ylabel = 'views')
ax3.scatter(x = full_stat.likes, y = full_stat.comment_count, alpha = 0.5)
ax3.set(xlabel = 'dislikes', ylabel = 'comment_count')

plt.tight_layout()
```



Category Analysis

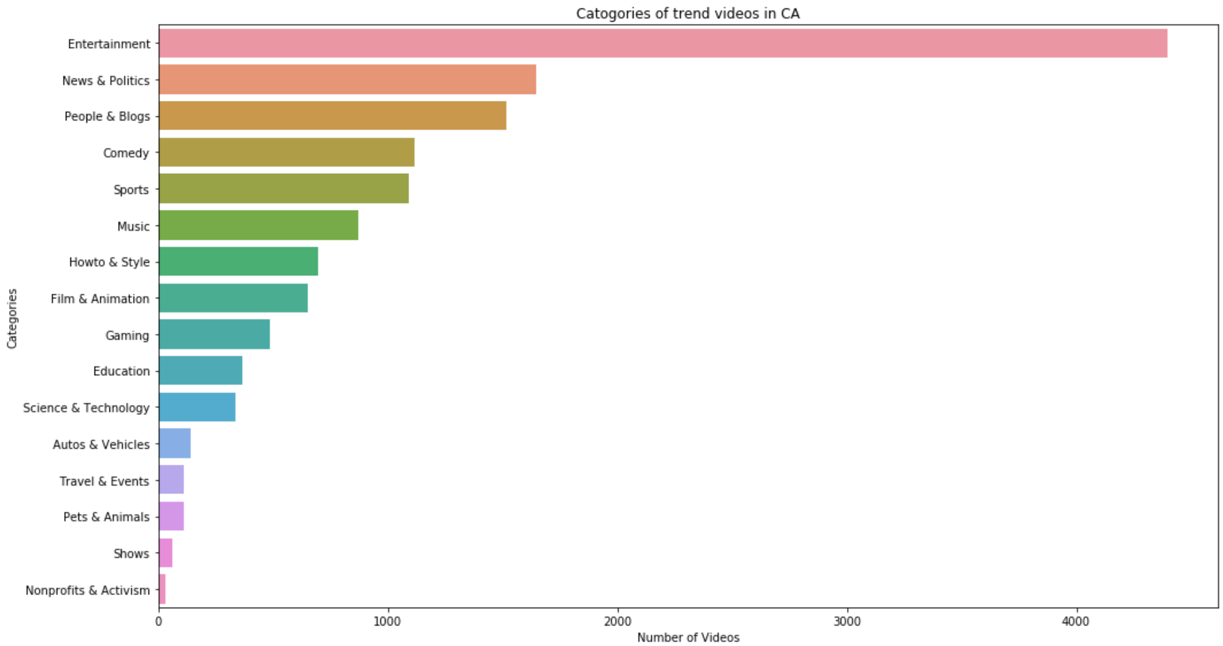
Which category has the most trending videos in different countries? What is the average trending days for each category in dfferent countries?

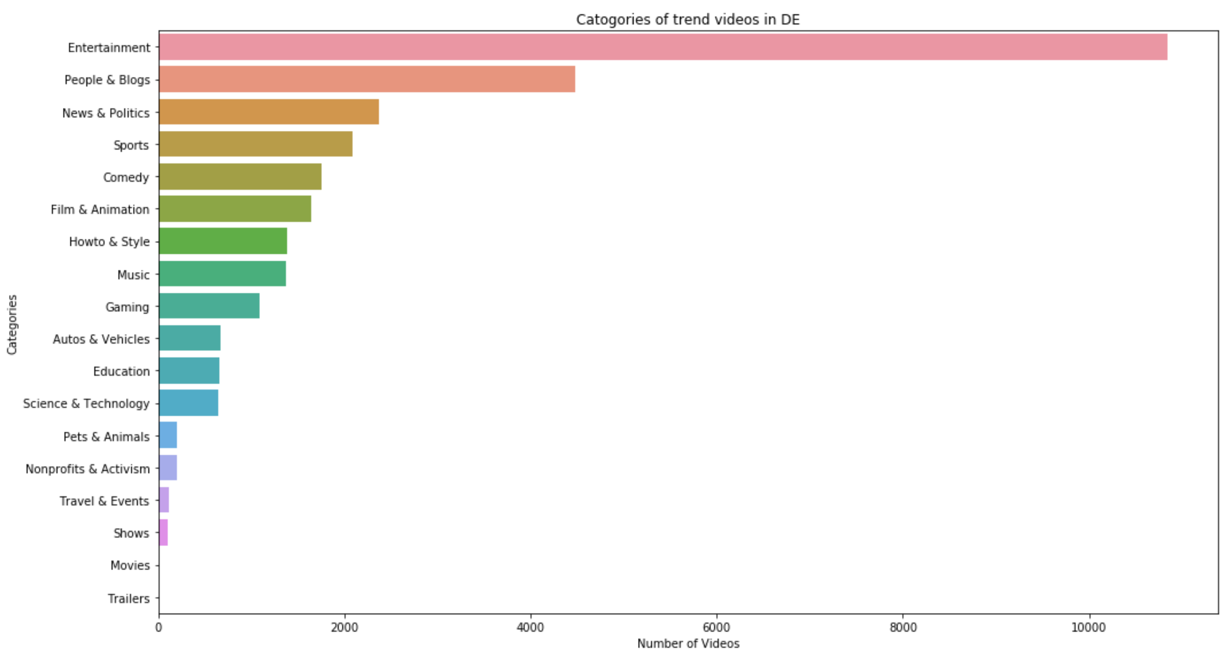
- Entertainment has the most trended video in all the countries
- Obviously, videos in UK and US have much longer average trending days than other coutries; videos in all categories in the UK have long trending days

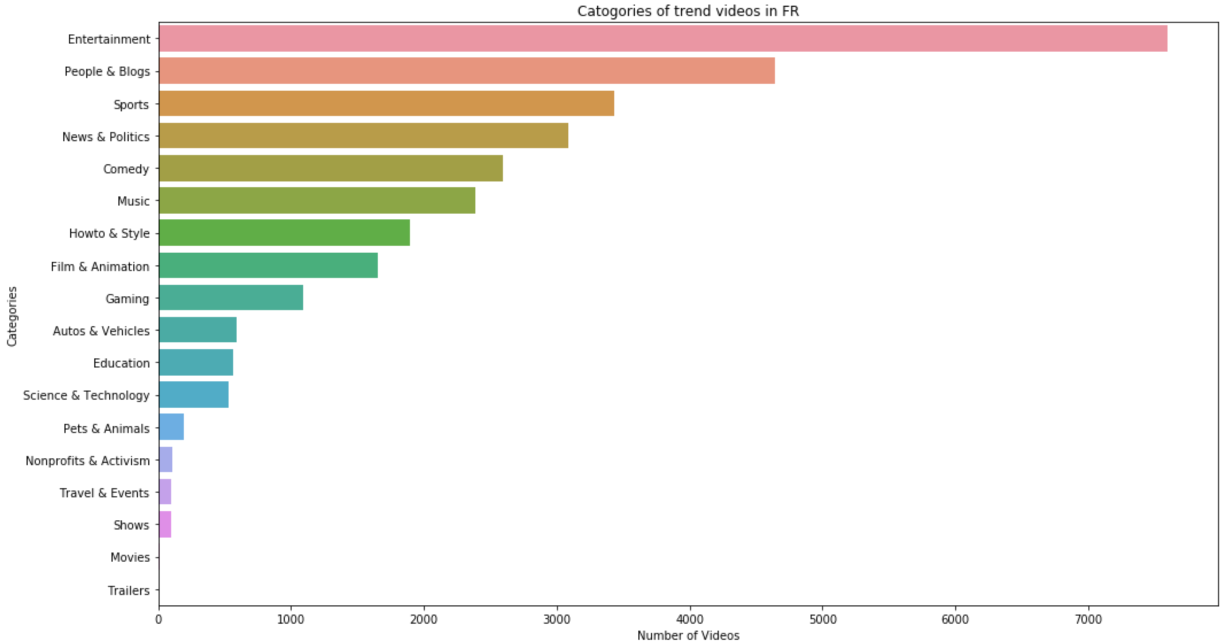
In [20]:
```
# compute how many days it takes to become trended after publish
temp = data.sort_values('trending_date',ascending = False).drop_duplicates(['video_id','n
temp['publish_to_trend'] = temp.trending_date - temp.publish_date
temp['publish_to_trend'] = temp.publish_to_trend.astype('timedelta64[D]').astype(int)
temp = temp[['video_id','nation','publish_to_trend']]
cat_df = pd.merge(full_stat, temp)
```

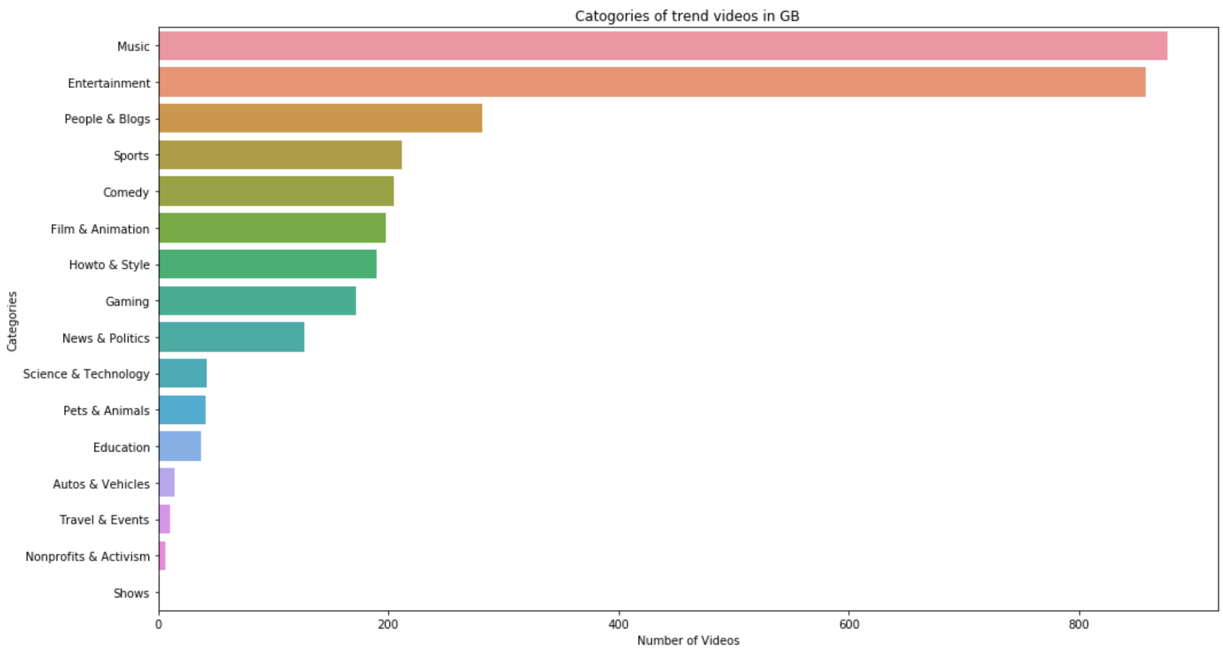
In [21]:
```
def cat_plot(nation, df):
    cat_df_gb = df[df.nation == nation]['category'].value_counts().reset_index()
    plt.figure(figsize=(15,8))
    ax = sns.barplot(y=cat_df_gb['index'],x=cat_df_gb['category'], data=cat_df_gb,orient=
    plt.xlabel("Number of Videos")
    plt.ylabel("Categories")
    plt.title('Catogories of trend videos in ' + nation)
    plt.tight_layout()
```

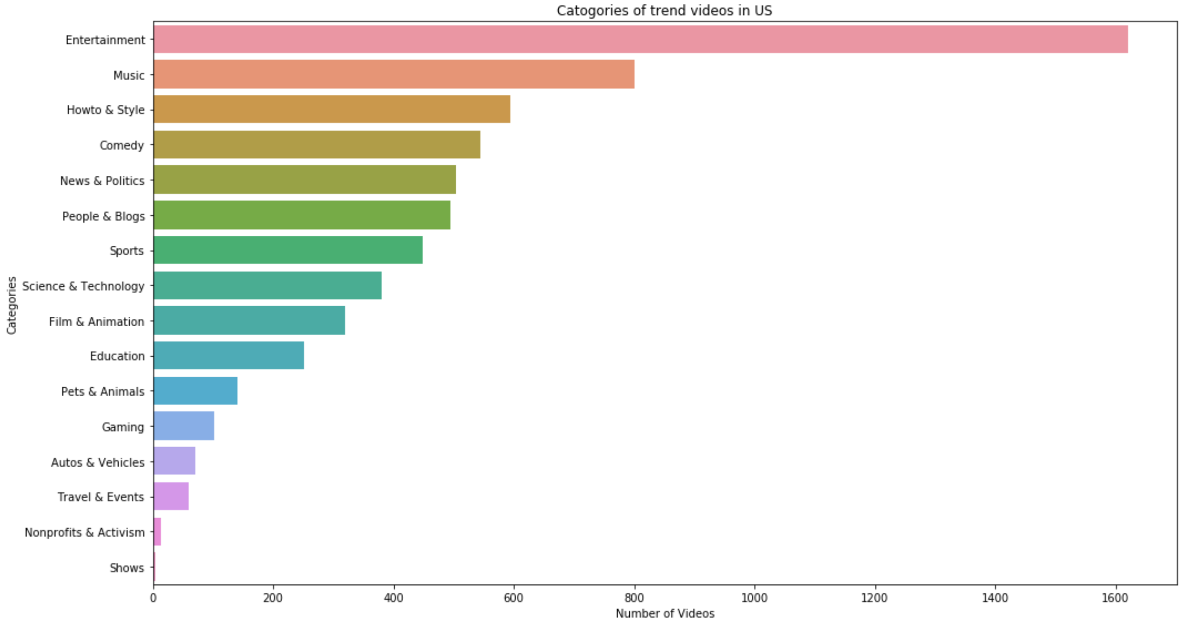
In [22]:
```
for n in nation_ls:
    cat_plot(nation = n, df = cat_df)
```






Catogories of trend videos in FR
Entertainment
People & Blogs
Sports
News & Politics
Comedy
Music
Howto & Style
Film & Animation
Gaming
Autos & Vehicles
Education
Science & Technology
Pets & Animals
Nonprofits & Activism
Travel & Events
Shows
Movies
Trailers
Categories
0
1000
2000
3000
4000
5000
6000
7000
Number of Videos

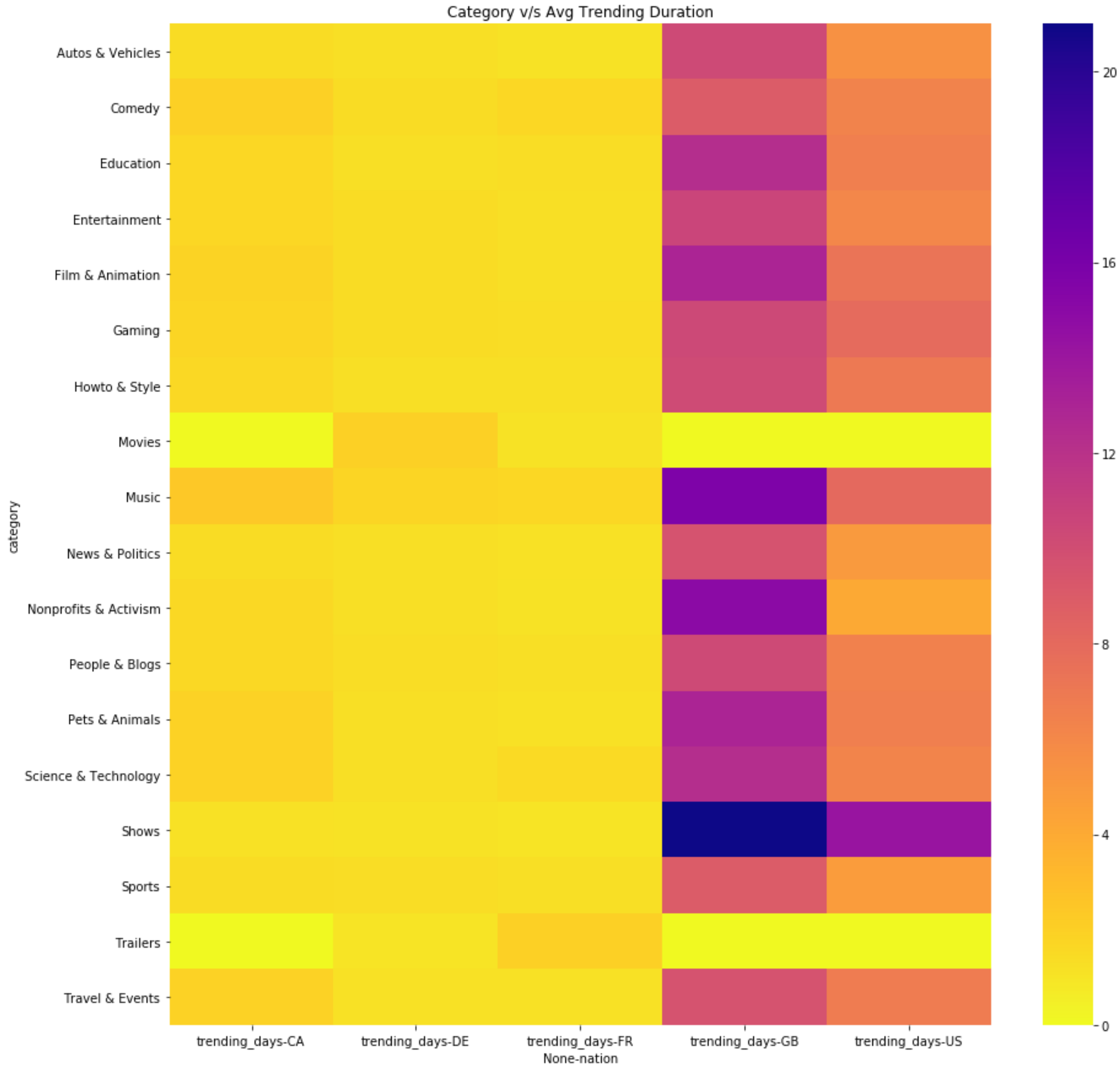

Catogories of trend videos in GB
Music
Entertainment
People & Blogs
Sports
Comedy
Film & Animation
Howto & Style
Gaming
News & Politics
Science & Technology
Pets & Animals
Education
Autos & Vehicles
Travel & Events
Nonprofits & Activism
Shows
Categories
0
200
400
600
800
Number of Videos


Catogories of trend videos in US
Entertainment
Music
Howto & Style
Comedy
News & Politics
People & Blogs
Sports
Science & Technology
Film & Animation
Education
Pets & Animals
Gaming
Autos & Vehicles
Travel & Events
Nonprofits & Activism
Shows
Categories
0
200
400
600
800
1000
1200
1400
1600
Number of Videos

In [23]:
```
cat_trend_days= cat_df.groupby(['category','nation']).mean()[['trending_days']].unstack().
plt.figure(figsize=(15,15))#You can Arrange The Size As Per Requirement
sns.heatmap(cat_trend_days, cmap='plasma_r')
plt.title("Category v/s Avg Trending Duration")
cat_trend_days
```

Out[23]:

	trending_days				
nation	CA	DE	FR	GB	US
category					
Autos & Vehicles	1.450000	1.296131	1.138748	10.285714	5.422535
Comedy	1.995524	1.443746	1.672055	8.951220	6.343750
Education	1.669399	1.274924	1.362832	12.351351	6.613546
Entertainment	1.676444	1.409996	1.292616	10.624709	6.149291
Film & Animation	1.847095	1.446744	1.301750	13.030303	7.340625
Gaming	1.750515	1.436180	1.334249	10.343023	7.932039
Howto & Style	1.565093	1.263577	1.247886	10.205263	6.973064
Movies	0.000000	2.000000	1.100000	0.000000	0.000000
Music	2.440873	1.726744	1.650084	15.702395	8.082397
News & Politics	1.412621	1.238497	1.216926	9.645669	4.932540
Nonprofits & Activism	1.625000	1.267327	1.096154	15.000000	4.071429
People & Blogs	1.637442	1.337877	1.231631	10.301418	6.470707
Pets & Animals	1.920354	1.240196	1.215385	13.024390	6.635714
Science & Technology	1.896450	1.245750	1.502814	12.333333	6.312336
Shows	1.190476	1.077670	1.041667	21.000000	14.250000
Sports	1.474406	1.316595	1.263679	8.990566	4.824053
Trailers	0.000000	1.000000	2.000000	0.000000	0.000000
Travel & Events	1.956140	1.224138	1.226804	9.600000	6.779661

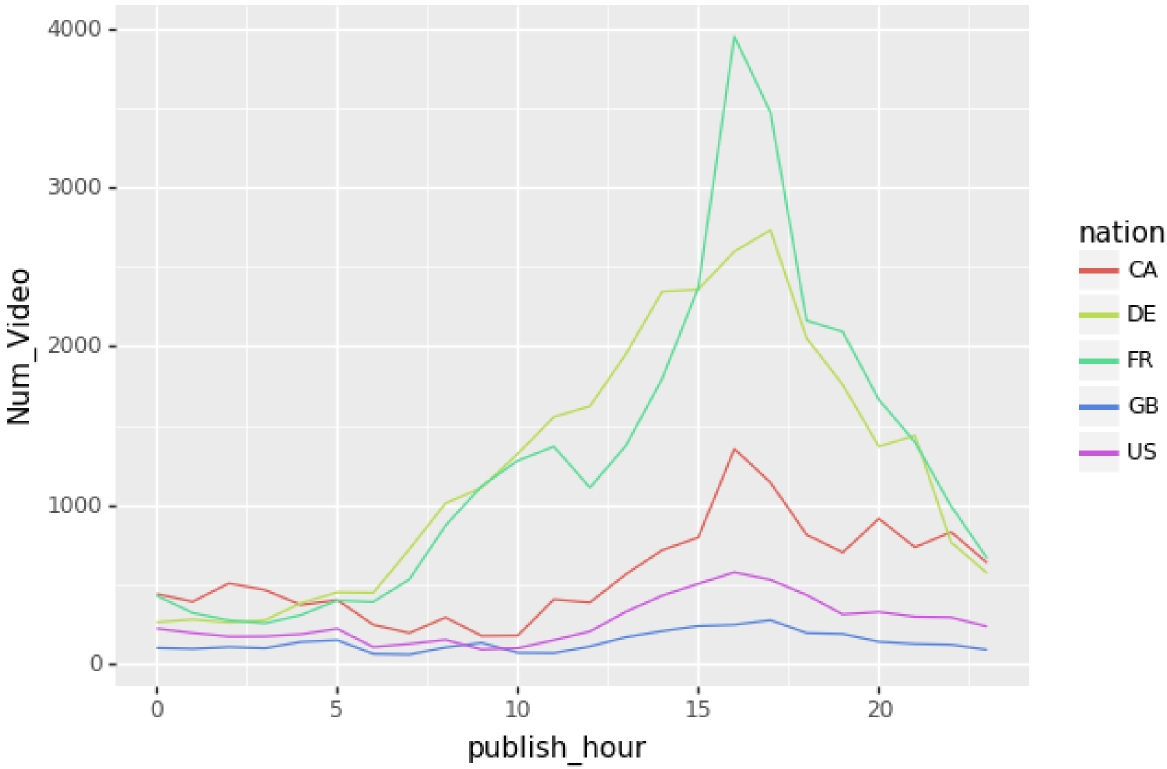


Hour and Day Analysis

What time are videos published the most? What day are videos published the most?

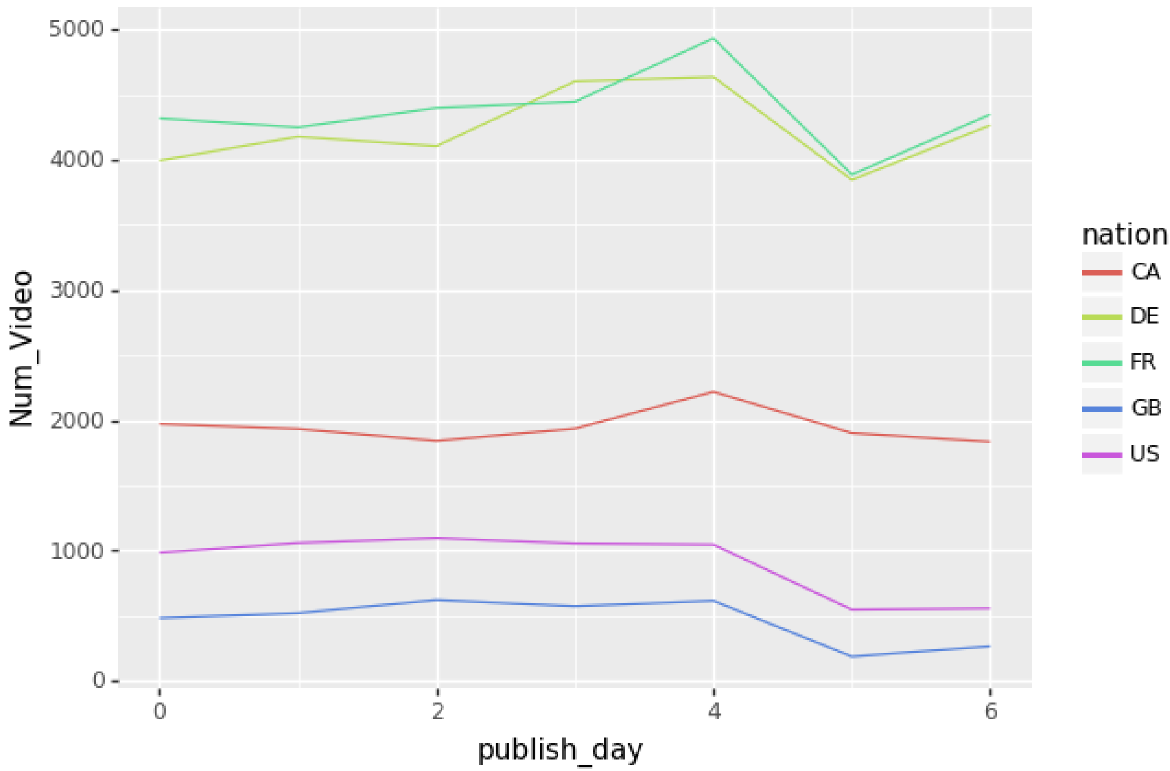
- Climbing up in after 12 p.m and peak at 4 p.m and 5 p.m
- A little bit more videos on Thurseday and less on Weekend

In [24]:
```
hdf = cat_df.groupby('nation').publish_hour.value_counts().to_frame().rename(columns = {'
p9.ggplot(hdf, p9.aes(x = 'publish_hour', y = 'Num_Video', color = 'nation')) + p9.geom_l
```



Out[24]: <ggplot: (30460094)>

In [25]:
```
ddf = cat_df.groupby('nation').publish_day.value_counts().to_frame().rename(columns = {'pu
p9.ggplot(ddf, p9.aes(x = 'publish_day', y = 'Num_Video', color = 'nation')) + p9.geom_li
```



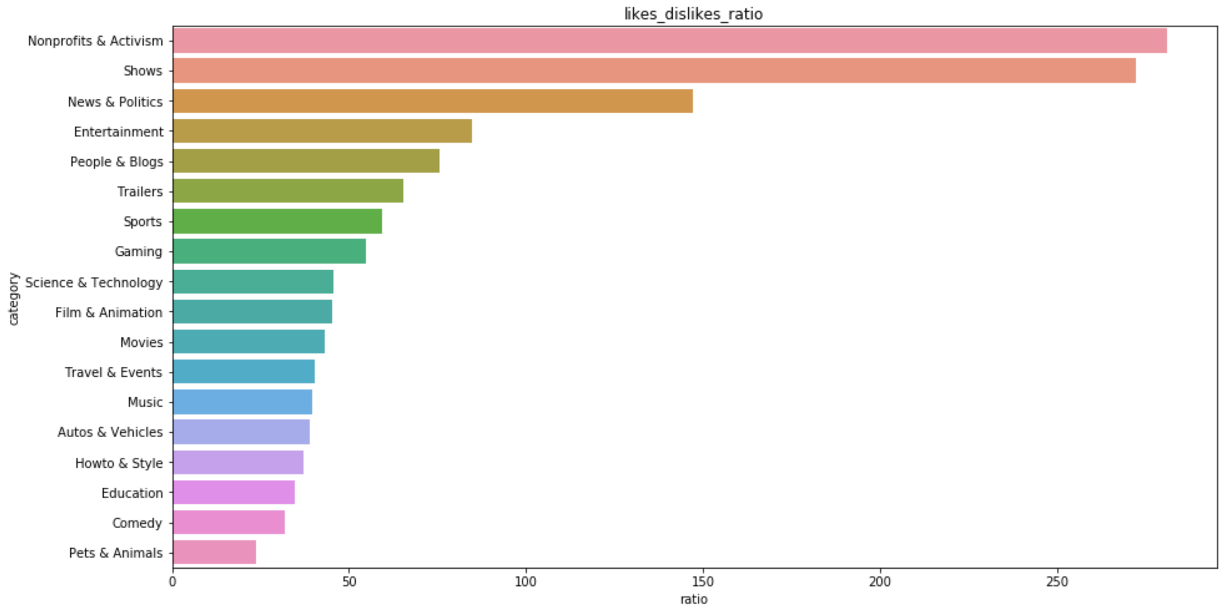
Out[25]: <ggplot: (-9223372036824306684)>

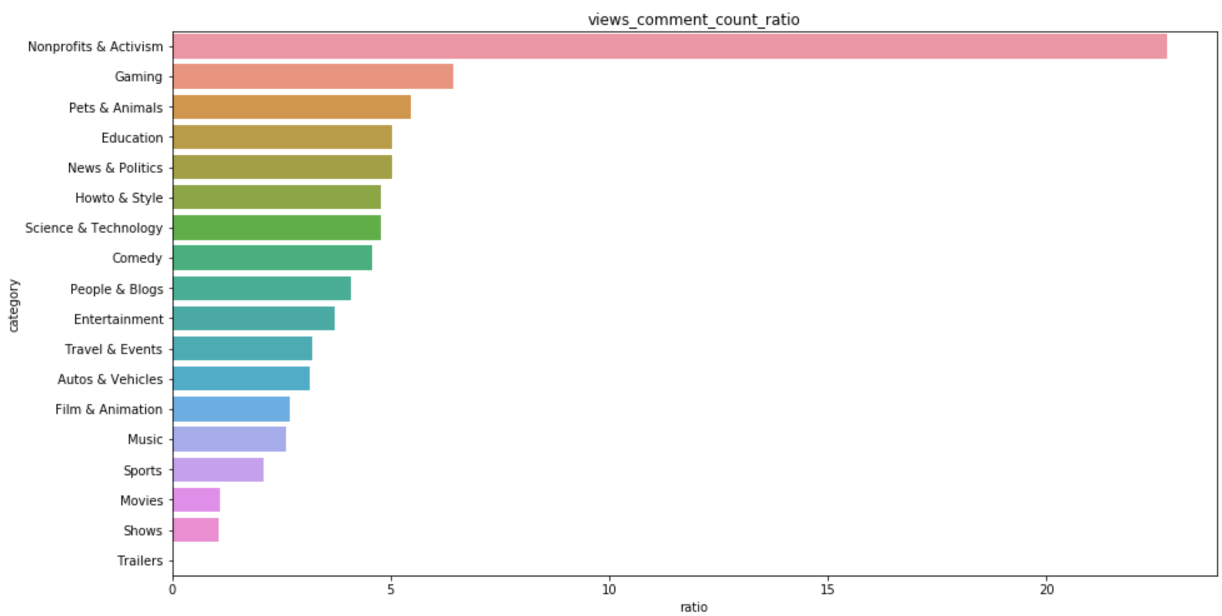
Ratio Analysis

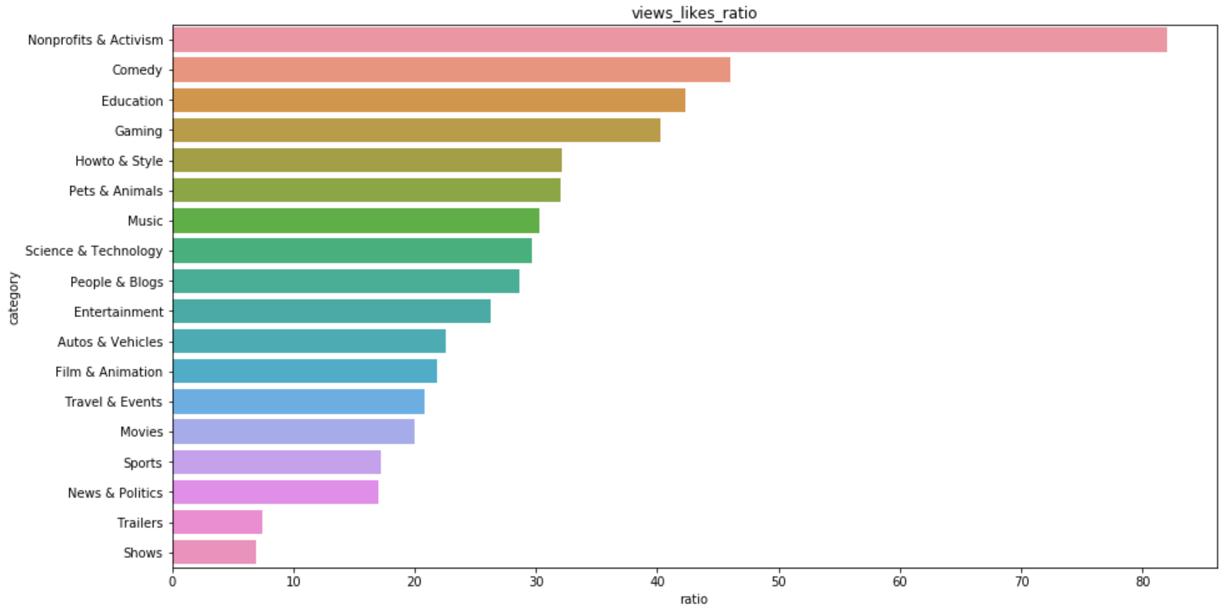
Nonprofits & Activism videos are more controversial and have more acitive posts

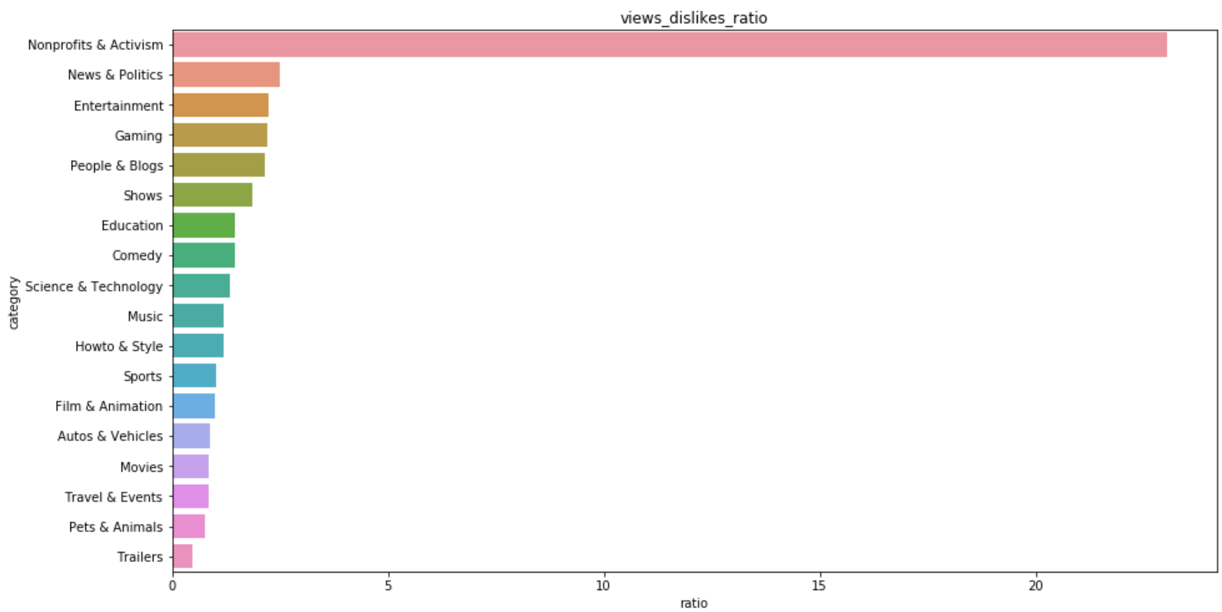
In [26]:
```
def ratio_plot(df, denominator, numerator):
    ratio = df.groupby('category').sum()[numerator] / df.groupby('category').sum()[denomin
    ratio = ratio.sort_values(ascending = False).reset_index()
    ratio.columns = ['category','ratio']
    fig, ax = plt.subplots(figsize = (15,8))
    fig = sns.barplot(x = 'ratio', y = 'category', data = ratio)
    ax.set(title = denominator + '_' + numerator + '_' + 'ratio')
```

In [27]:
```
ratio_plot(cat_df, 'likes', 'dislikes')
ratio_plot(cat_df, 'views', 'comment_count')
ratio_plot(cat_df, 'views', 'likes')
ratio_plot(cat_df, 'views', 'dislikes')
```









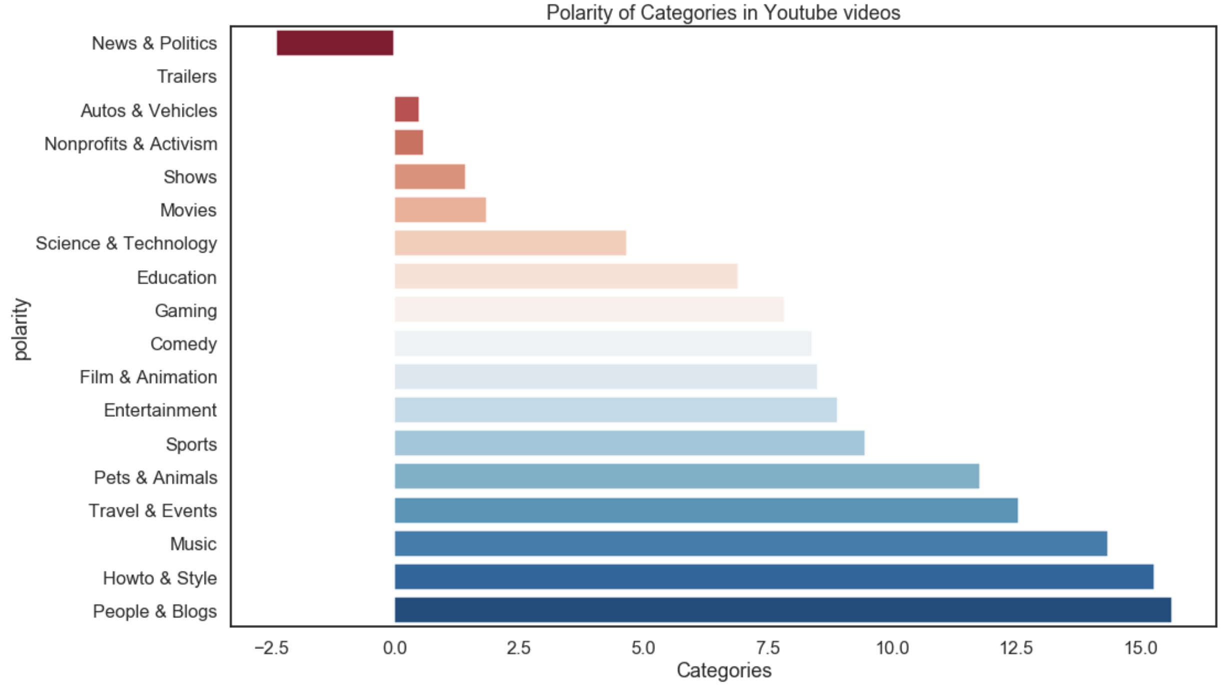
Tags Sentimental Analysis

In [28]:
```
from wordcloud import WordCloud
import nltk
#nltk.download()
from nltk.sentiment import SentimentIntensityAnalyzer
from nltk.corpus import stopwords
from nltk import sent_tokenize, word_tokenize
from wordcloud import WordCloud, STOPWORDS

from collections import Counter
from nltk.tokenize import RegexpTokenizer
import re
```

In [29]:
```
en_stopwords = list(stopwords.words('english'))
de_stopwords = list(stopwords.words('german'))
fr_stopwords = list(stopwords.words('french'))
en_stopwords.extend(de_stopwords)
en_stopwords.extend(fr_stopwords)
```

In [30]:
```
MAX_N = 1000

#remove all the stopwords from the text
en_stopwords = list(stopwords.words('english'))
de_stopwords = list(stopwords.words('german'))
fr_stopwords = list(stopwords.words('french'))
en_stopwords.extend(de_stopwords)
en_stopwords.extend(fr_stopwords)

polarities = list()
category_list = cat_df.category.unique()

for cate in category_list:
    tags_word = cat_df[cat_df['category']==cate]['tags'].str.lower().str.cat(sep=' ')

# removes punctuation,numbers and returns list of words
    tags_word = re.sub('[^A-Za-z]+', ' ', tags_word)
    word_tokens = word_tokenize(tags_word)
    filtered_sentence = [w for w in word_tokens if not w in en_stopwords]
    without_single_chr = [word for word in filtered_sentence if len(word) > 2]

# Remove numbers
    cleaned_data_title = [word for word in without_single_chr if not word.isdigit()]

# Calculate frequency distribution
    word_dist = nltk.FreqDist(cleaned_data_title)
    hnhk = pd.DataFrame(word_dist.most_common(MAX_N),
                    columns=['Word', 'Frequency'])

    compound = .0
    for word in hnhk['Word'].head(MAX_N):
        compound += SentimentIntensityAnalyzer().polarity_scores(word)['compound']

    polarities.append(compound)

category_list = pd.DataFrame(category_list)
polarities = pd.DataFrame(polarities)
tags_sentiment = pd.concat([category_list,polarities],axis=1)
tags_sentiment.columns = ['category','polarity']
tags_sentiment=tags_sentiment.sort_values('polarity').reset_index()

plt.figure(figsize=(16,10))
sns.set(style="white",context="talk")
ax = sns.barplot(x=tags_sentiment['polarity'],y=tags_sentiment['category'], data=tags_sen
plt.xlabel("Categories")
plt.ylabel("polarity")
plt.title("Polarity of Categories in Youtube videos")
```

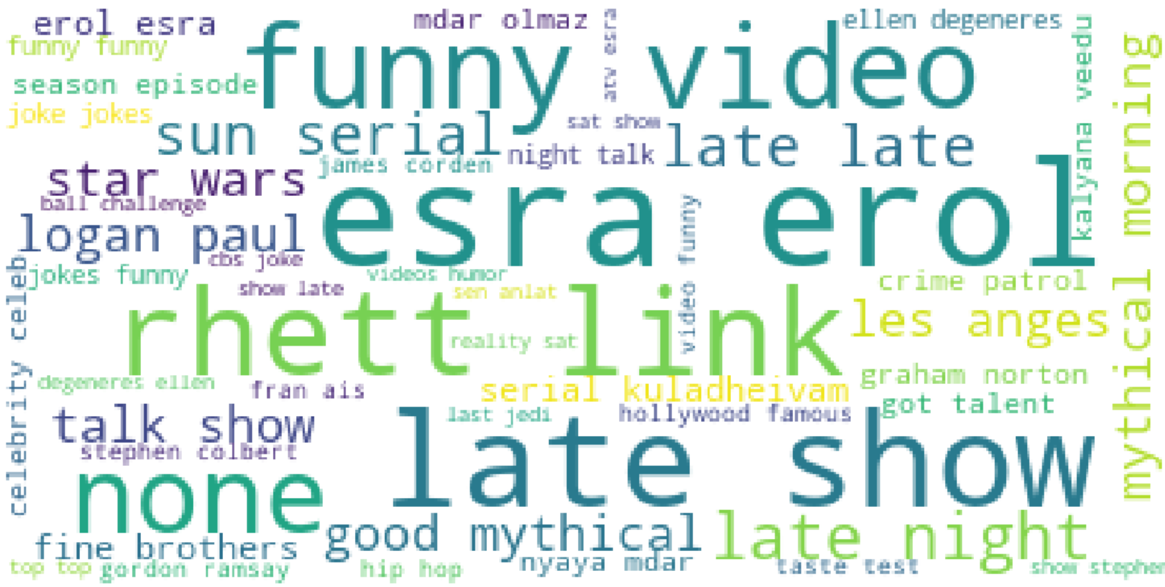
Out[30]:
```
Text(0.5, 1.0, 'Polarity of Categories in Youtube videos')
```



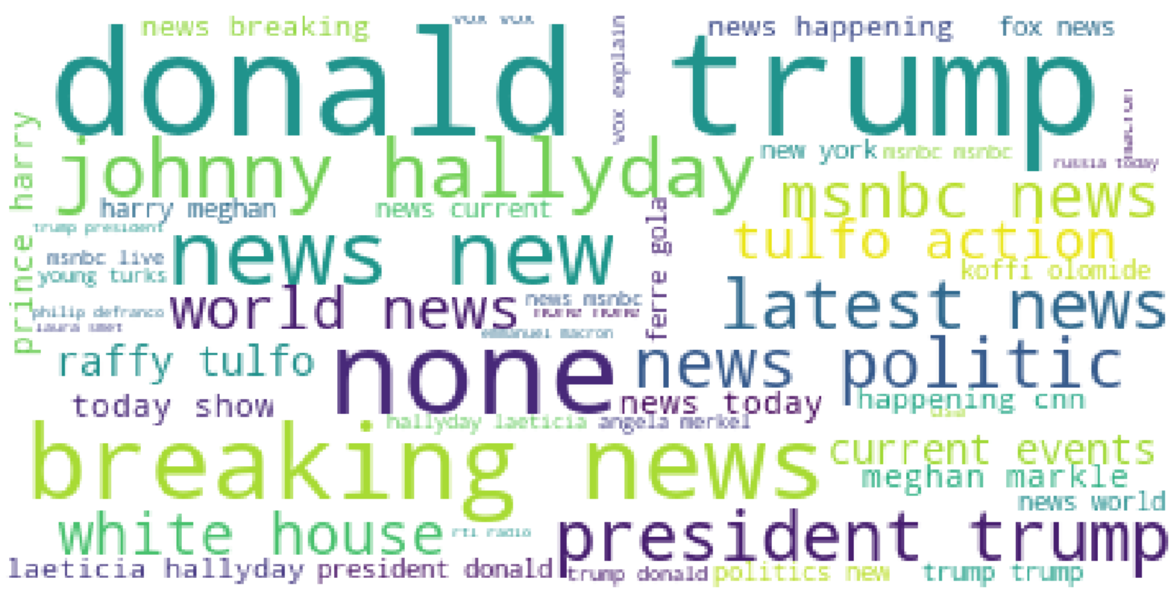
In [31]:
```
def wcloud(data,bgcolor):
    plt.figure(figsize = (20,15))
    cloud = WordCloud(background_color = bgcolor, max_words = 50,  max_font_size = 50)
    cloud.generate(' '.join(data))
    plt.imshow(cloud)
    plt.axis('off')
```

In [32]:
```
def clean_tag(cat):
    tags_word = cat_df[cat_df['category']==cat]['tags'].str.lower().str.cat(sep=' ')
    tags_word = re.sub('[^A-Za-z]+', ' ', tags_word)
    word_tokens = word_tokenize(tags_word)
    filtered_words = [w for w in word_tokens if not w in en_stopwords]
    without_single_chr = [word for word in filtered_words if len(word) > 2]
    cleaned_data = [word for word in without_single_chr if not word.isdigit()]
    return cleaned_data
```

In [33]:
```
wcloud(clean_tag('Entertainment'), 'white')
```



In [34]:
```
wcloud(clean_tag('News & Politics'), 'white')
```



In [35]:
```
wcloud(clean_tag('Nonprofits & Activism'), 'white')
```