Analysis on Trending Youtube Videos

COGS 108 final project

Group 34

Overview

In this project we analyzed youtube trending data of over the course of six months to figure out what the main factors are for a video's popularity. We did data scraping to acquire the lengths of the videos and data cleaning for removing dupilcates and invalid videos. We then used statistical tools to determine the influence of different features on the popularity of a youtube video.

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Research Question

What are the main factors influencing the popularity of a youtube video? Is it possible to estimate the popularity of a video based on its title, category, length, etc.? In this project, we aim to examine the metadata of the videos and its relationship to the views, likes and comment counts as a measure of its popularity.

Background and Prior Work

Youtube is a world-famous video-sharing website on which hundreds of thousands of full-time Youtubers devote their full attention to creating content. The popularity of videos, quantified as viewing statistics, are directly related to these professional Youtubers' income and career paths. Popular videos are generated daily within each category, yet a clearly defined approach to producing such popular videos remains unclear. As a result, a model that could predict a given video's popularity is extraordinarily useful for anyone interested in starting their own YouTube channel. It could also give us some insights into the social impact of YouTube, social media, and video hosting websites in general.

In an article from DIGIDAY, Gwen Miller, VP of content strategy at digital video network Kin Community, indicates that 10 to 16 minutes has become the length of most popular YouTube videos. However because the Youtube algorithm gives YouTubers more income once if they create longer content and insert more ads, catching viewer retention at the same time, more and more YouTubers start to create content which exceeds 12 minutes. Though Miller does not consider dividing the different lengths by categories of videos, they are still considered to be useful for our project as a reference once the research starts. (1)

Trending youtube data has been used to conduct analyses into a few different topics such as: content of video titles, views/likes/dislikes/comment correlation, most popular video category, category of channel with most trending videos, etc.. Youtube data was also compared between different countries to see what similarities or differences existed between youtube video consumption. Some examples of findings include: entertainment videos were the most popular video type in most countries and videos in the US and UK had the longest enduring trending videos. (2)

(1) Peterson, T. (2018, July 3). Retrieved from https://digiday.com/media/creators-making-longer-videos-cater-youtube-algorithm/ (https://digiday.com/media/creators-making-longer-videos-cater-youtube-algorithm/).

(2) Kaggle Dataset: https://www.kaggle.com/datasnaek/youtube-new (https://www.kaggle.com/datasnaek/youtube-new)

Hypothesis

We hypothesize that certain features of the video such as the length of the videos, the title choice and the publish time have an unproportionally large influence on its popularity. We believe there are certain categories of videos that are extremely popular and these categories have similar lengths, title choices, and etc. Therefore, we wonder if the metadata can accurately estimate the video's popularity irrespective of its content.

Dataset(s)

We used a relatively new dataset from a Kaggle challenge titled “Trending YouTube Video Statistics”, which contains features such as views, likes, dislikes, comments, tags and categories of the video. (https://www.kaggle.com/datasnaek/youtube-new (https://www.kaggle.com/datasnaek/youtube-new)). This dataset does not contain the length of the videos so we queried those from the youtube API (https://developers.google.com/youtube/v3 (https://developers.google.com/youtube/v3)).

- Dataset Name: Trending YouTube Video Statistics
- Link to the dataset: https://www.kaggle.com/datasnaek/youtube-new (https://www.kaggle.com/datasnaek/youtube-new)
- Number of observations: 30179 with videos counted multiple times if they are on the trending list more than once and 5567 with duplicates removed

Setup

In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import patsy
import statsmodels.api as sm
import seaborn as sns
import requests
import sys
import json
from scipy.stats import pearsonr
from datetime import datetime
import re
from wordcloud import WordCloud, STOPWORDS
from PIL import Image
from IPython.display import Image as Image_d
from scipy import stats
import nltk
import re
import operator
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
from scipy.stats import ttest_ind,normaltest, gamma
nltk.download('stopwords')
nltk.download('punkt')
```

```
[nltk_data] Downloading package stopwords to /Users/Frank/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package punkt to /Users/Frank/nltk_data...
[nltk_data]   Package punkt is already up-to-date!
```

Out[1]: True

Data Cleaning & Pre-processing

Acquiring video lengths

We first acquired the length of the videos using the youtube API. In the following cell, we turned the dataset on kaggle into a new length.csv file that contains three new columns: hour, min and sec all start with -1 indicating they have not been acquired yet.

In [2]:
```
# US_videos = pd.read_csv('./youtube-new/USvideos.csv')
# row = US_videos.shape[0]
# hour = np.repeat(-1, row)
# min = np.repeat(-1, row)
# sec = np.repeat(-1, row)

# # -1 not scraped, 0 0 0 means not available
# US_videos['hour'] = hour
# US_videos['min'] = min
# US_videos['sec'] = sec

# US_videos.to_csv(r'length.csv', index=False, line_terminator='\r\n')
```

The following function is used to query the youtube api with a video id and returns a string representation of the length of the video.

In [3]:
```
def get_length(video_id):
    searchUrl = "https://www.googleapis.com/youtube/v3/videos?id=" + \
        video_id+"&key="+api_key+"&part=contentDetails"

    request = requests.get(searchUrl)
    if request.status_code == 429:
        print("Temp-Banned due to excess requests, please wait and conti
nue later")
        sys.exit()

    data = request.json()
    if 'items' not in data:
        print(data)
        return "Error"
    return data['items'][0]['contentDetails']['duration']
```

The following is the standardization function to standardize the string representation of the length the youtube API returns to a tuple of hour, minute and seconds. Youtube API returns a string in the format of "PT?H?M?S" but may not have all the characters H,M and S. For example, it may be "PT1H1S" if it's one hour and one seconds long.

In [4]:
```
def standardize_length(input):
    hour = 0
    min = 0
    sec = 0

    input = input.replace('PT', '')
    input = input.upper()
    if 'H' in input:
        hour = input.split('H')[0]
        input = input.split('H')[1]
    if 'M' in input:
        min = input.split('M')[0]
        input = input.split('M')[1]
    if 'S' in input:
        sec = input.split('S')[0]
        input = input.split('S')[1]
    return hour, min, sec
```

Since there's a daily quota limit to the youtube API we can use, the following cell in run multiple time over the course of a week with different api keys to fill in the lengths of the videos. Hour, minute and second are all set to zero if a video's length is not available. This may happen when the video is no longer available on youtube or it's a livestream video. Running the cell directly will cause an error since the api keys are not included in this directory.

In [5]:
```
# with open('./api_keys/YOURAPI.txt', 'r') as file:
#     api_key = file.readline()

# US_videos = pd.read_csv('./length.csv')
# row = US_videos.shape[0]
# hour = np.repeat(-1, row)
# min = np.repeat(-1, row)
# sec = np.repeat(-1, row)

# # -1 not scraped, 0 0 0 means not available

# unavailable_count = 0
# dailyNum = 7000
# startIndex = 0
# first = True
# stop = 0

# # find start Index

# for i, r in US_videos.iterrows():

#     if r['hour'] == -1:
#         startIndex = i
#         break
#     else:
#         hour[i] = r['hour']
#         min[i] = r['min']
#         sec[i] = r['sec']


# # startIndex = 0
# print(startIndex)

# for i, r in US_videos[startIndex: startIndex + dailyNum].iterrows():

#     curr_id = r['video_id']

#     # some videos are unavailable such as: n30k5CwLhS4
#     try:

#         if curr_id == '#NAME?' or curr_id == '#VALUE!':
#             hour[i] = 0
#             min[i] = 0
#             sec[i] = 0
#             unavailable_count += 1
#             continue

#         length = get_length(curr_id)

#         if length == 'Error':
#             print('stopping at: ', i)
#             stop = i
#             break

#         hour[i], min[i], sec[i] = standardize_length(length)
```

```
#         if i % 1000 == 0:
#             print('saving ', startIndex, ' to ', i, 'to disk')
#             US_videos['hour'] = hour
#             US_videos['min'] = min
#             US_videos['sec'] = sec
#             US_videos.to_csv(r'length.csv', index=False,
#                              line_terminator='\r\n')
#     except IndexError:
#         hour[i] = 0
#         min[i] = 0
#         sec[i] = 0
#         unavailable_count += 1
#     except:  # live stream videos
#         hour[i] = 0
#         min[i] = 0
#         sec[i] = 0
#         unavailable_count += 1
#         print('unexpected error(possibly live stream video)')


# print('unavailable videos', unavailable_count)

# US_videos['hour'] = hour
# US_videos['min'] = min
# US_videos['sec'] = sec

# if stop == 0:
#     stop = startIndex + dailyNum
# print(US_videos[stop - 5:stop + 5])
# US_videos.to_csv(r'length.csv', index=False, line_terminator='\r\n')
```

Preprocessing and data wrangling

After acquiring all the lengths of the videos, we stored the data in "US_length.csv" and read that into a dataframe.

In [6]:
```
US_videos = pd.read_csv('US_length.csv')
print(US_videos.shape)
US_videos.head()
```

```
(30179, 19)
```

Out[6]:

	video_id	trending_date	title	channel_title	category_id	publish_time	
0	2kyS6SvSYSE	17.14.11	WE WANT TO TALK ABOUT OUR MARRIAGE	CaseyNeistat	22	2017-11-13T17:13:01.000Z	
1	1ZAPwfrtAFY	17.14.11	The Trump Presidency: Last Week Tonight with J...	LastWeekTonight	24	2017-11-13T07:30:00.000Z	
2	5qpjK5DgCt4	17.14.11	Racist Superman | Rudy Mancuso, King Bach & Le...	Rudy Mancuso	23	2017-11-12T19:05:24.000Z	supe
3	puqaWrEC7tY	17.14.11	Nickelback Lyrics: Real or Fake?	Good Mythical Morning	24	2017-11-13T11:00:04.000Z	
4	d380meD0W0M	17.14.11	I Dare You: GOING BALD!?	nigahiga	24	2017-11-12T18:01:41.000Z	

We get the length of titles and the number of capital letters and store those in separate columns.

In [7]:
```
US_videos['title_length'] = US_videos['title'].str.len()
US_videos['num_of_upper'] = US_videos['title'].str.findall(r'[A-Z]').str
.len()
```

One more thing we need to do is to transform the trending date to datetime format for plotting.

In [8]:
```
US_videos['trending_date'] = pd.to_datetime(US_videos['trending_date'],
format='%y.%d.%m')
```

We then calculate the total number of seconds and store them in a new column and remove the hour, min and sec columns.

In [9]:
```
secs = US_videos['sec'].values
mins = US_videos['min'].values
hours = US_videos['hour'].values
total_time = [s+60*m+3600*h for s,m,h in zip(secs, mins, hours)]
US_videos['total_time'] = total_time
US_videos = US_videos.drop(['sec', 'min', 'hour'], axis = 1)
```

The same video may be on the trending list multiple times. Let's sort the dataframe in terms of title length and the title so see if there are duplicates.

In [10]:
```
sorted_videos = US_videos.sort_values(['title_length', 'title']).set_ind
ex(['title_length', 'title'])
sorted_videos.head()
```

Out[10]:

		video_id	trending_date	channel_title	category_id	publish_time	
title_length	**title**						
4	**Jack**	A9YcrloL3oE	2018-02-22	Unbox Therapy	1	2018-02-21T22:29:33.000Z	therap
	Jack	A9YcrloL3oE	2018-02-23	Unbox Therapy	1	2018-02-21T22:29:33.000Z	therap
	Jack	A9YcrloL3oE	2018-02-24	Unbox Therapy	1	2018-02-21T22:29:33.000Z	therap
	Jack	A9YcrloL3oE	2018-02-25	Unbox Therapy	1	2018-02-21T22:29:33.000Z	therap
	Jack	A9YcrloL3oE	2018-02-26	Unbox Therapy	1	2018-02-21T22:29:33.000Z	therap

As we can see, the video titled "Jack" is on the trending list multiple times.We therefore remove the duplicate videos and keep only the video with the highest view count among those. We also save the original dataframe with duplicates in a separate dataframe to do further analysis.

In [11]:
```
duplicate = US_videos
```

In [12]:
```
uniq = US_videos['title'].unique()

df_extract = pd.DataFrame()
for i in uniq:
    cur_df = US_videos.loc[US_videos['title'] == i]
    max_view = max(cur_df['views'].tolist())
    cur_df = cur_df[cur_df.views == max_view]
    df_extract = df_extract.append(cur_df, sort=False,ignore_index=True)
US_videos = df_extract
print("Done removing duplicates")
```

```
Done removing duplicates
```

In [13]:
```
US_videos.shape
```

Out[13]:
```
(5567, 19)
```

For the publish time, we want to know what time of the day a video is uploaded, so we format the string of the publish time which looks like "2017-11-13T17:13:01.000Z" into a single integer(17) representing the hour of the day it's published and store them in the same column.

In [14]:
```
publish_time = [int(s.split('T')[1].split(':')[0]) for s in US_videos['publish_time'].values]
US_videos['publish_time'] = publish_time
```

Now let's take a look at the cleaned dataframe. This dataframe has no duplicates and all the features in the format we expected.

In [15]:
```
US_videos.head()
```

Out[15]:

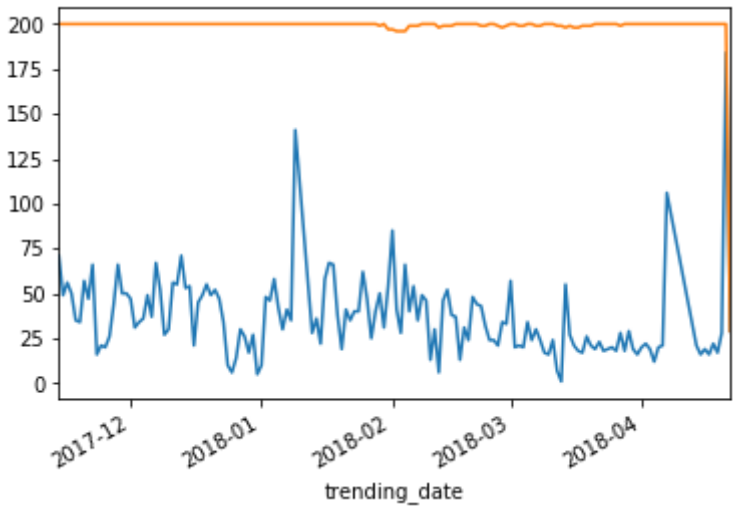
	video_id	trending_date	title	channel_title	category_id	publish_time	
0	2kyS6SvSYSE	2017-11-20	WE WANT TO TALK ABOUT OUR MARRIAGE	CaseyNeistat	22	17	
1	1ZAPwfrtAFY	2017-11-20	The Trump Presidency: Last Week Tonight with J...	LastWeekTonight	24	7	last \
2	5qpjK5DgCt4	2017-11-20	Racist Superman | Rudy Mancuso, King Bach & Le...	Rudy Mancuso	23	19	superma
3	puqaWrEC7tY	2017-11-20	Nickelback Lyrics: Real or Fake?	Good Mythical Morning	24	11	r
4	d380meD0W0M	2017-11-19	I Dare You: GOING BALD!?	nigahiga	24	18	ry

Data Visualization

First we try to see how many trending videos per day are in this dataset. It can be seen that the dataset has about 200 videos per day to begin with (except in the end), but after removing those duplicates, there are only less than half of the videos per day.

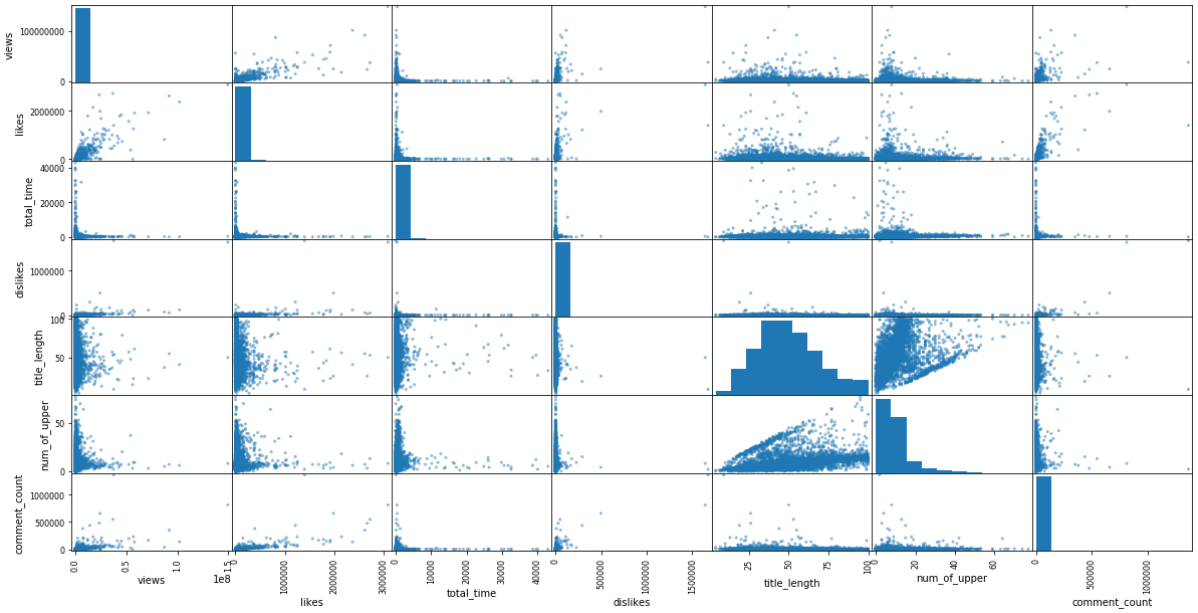
In [16]:
```
US_videos['trending_date'].groupby((US_videos["trending_date"])).count()
.plot()
duplicate['trending_date'].groupby((duplicate["trending_date"])).count()
.plot()
```

Out[16]: <matplotlib.axes._subplots.AxesSubplot at 0x1c21beb8d0>



Then we make a scatter plots of the features to get a visual understanding of the data.

In [17]:
```
pd.plotting.scatter_matrix(US_videos[['views', 'likes', 'total_time', 'd
islikes', 'title_length', 'num_of_upper','comment_count']],figsize=(20,1
0));
```

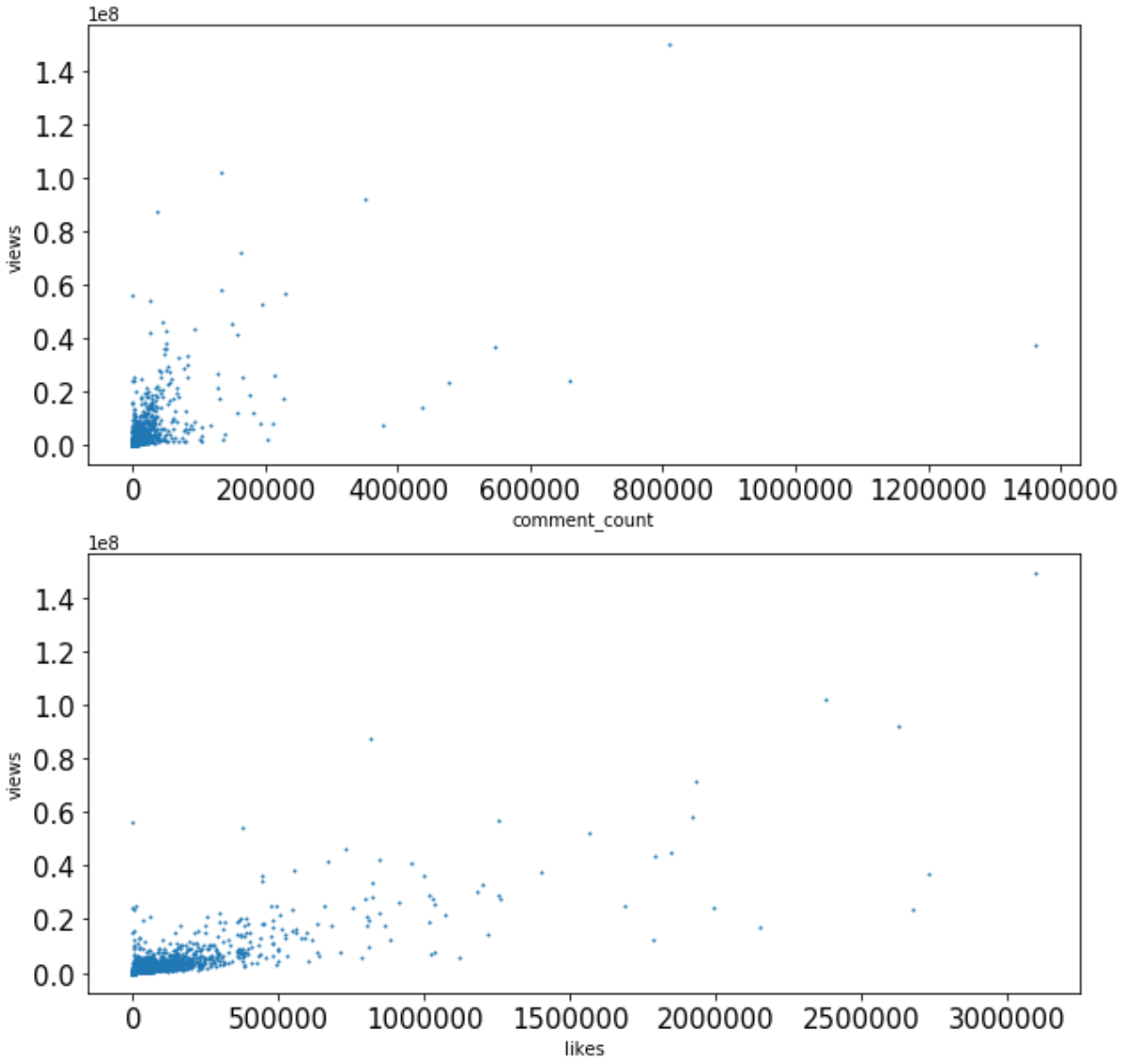


We can see some positive correlations between features such as comment_count and the number of views. This provides a general visual understanding of the data but we'll dive into features we care about in detail.

Before investigating the features, we need to provide a definition of popularity. Therefore we make the following scatter plots for the metrics that indicate popularity of the videos.

In [18]:
```
df = US_videos
fig, axes = plt.subplots(nrows = 2, ncols = 1, figsize = (10,10))
df.plot(kind = 'scatter', x='comment_count', y='views', ax = axes[0], fo
ntsize = 15, s=1)
df.plot(kind = 'scatter', x='likes', y='views', ax = axes[1], fontsize =
15, s = 1)
```

Out[18]: <matplotlib.axes._subplots.AxesSubplot at 0x1c246353c8>



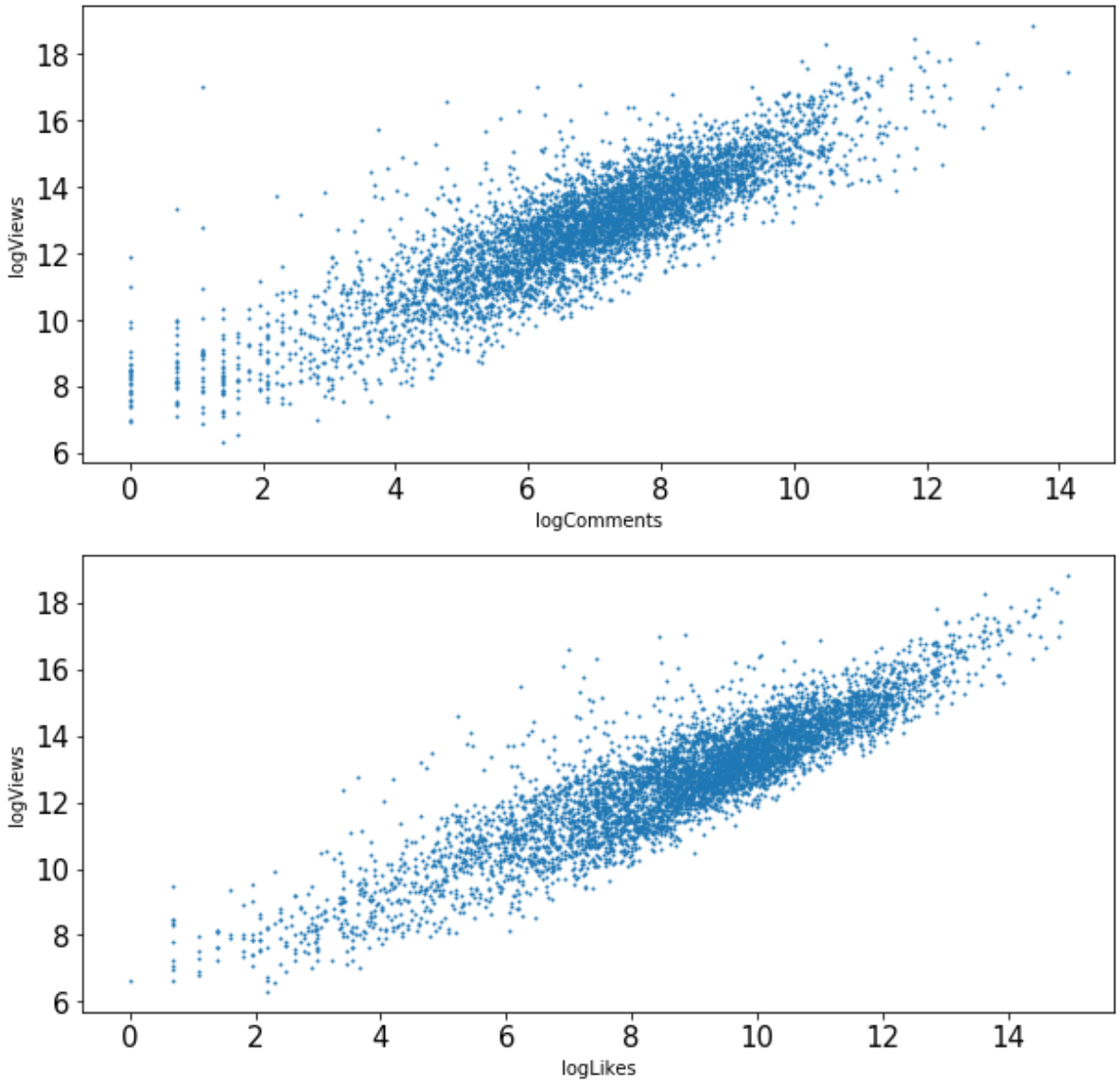
We do a log transform of the views for a better scale.

In [19]:
```
US_videos['logViews'] = np.log(US_videos['views'])
US_videos['logComments'] = np.log(US_videos['comment_count'])
US_videos['logLikes'] = np.log(US_videos['likes'])
```

```
/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:2: Runtime
Warning: divide by zero encountered in log

/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:3: Runtime
Warning: divide by zero encountered in log
  This is separate from the ipykernel package so we can avoid doing imp
orts until
```

In [20]:
```
df = US_videos
fig, axes = plt.subplots(nrows = 2, ncols = 1, figsize = (10,10))
df.plot(kind = 'scatter', x='logComments', y='logViews', ax = axes[0], f
ontsize = 15, s=1)
df.plot(kind = 'scatter', x='logLikes', y='logViews', ax = axes[1], font
size = 15, s = 1)
```

Out[20]: <matplotlib.axes._subplots.AxesSubplot at 0x1c24961c88>



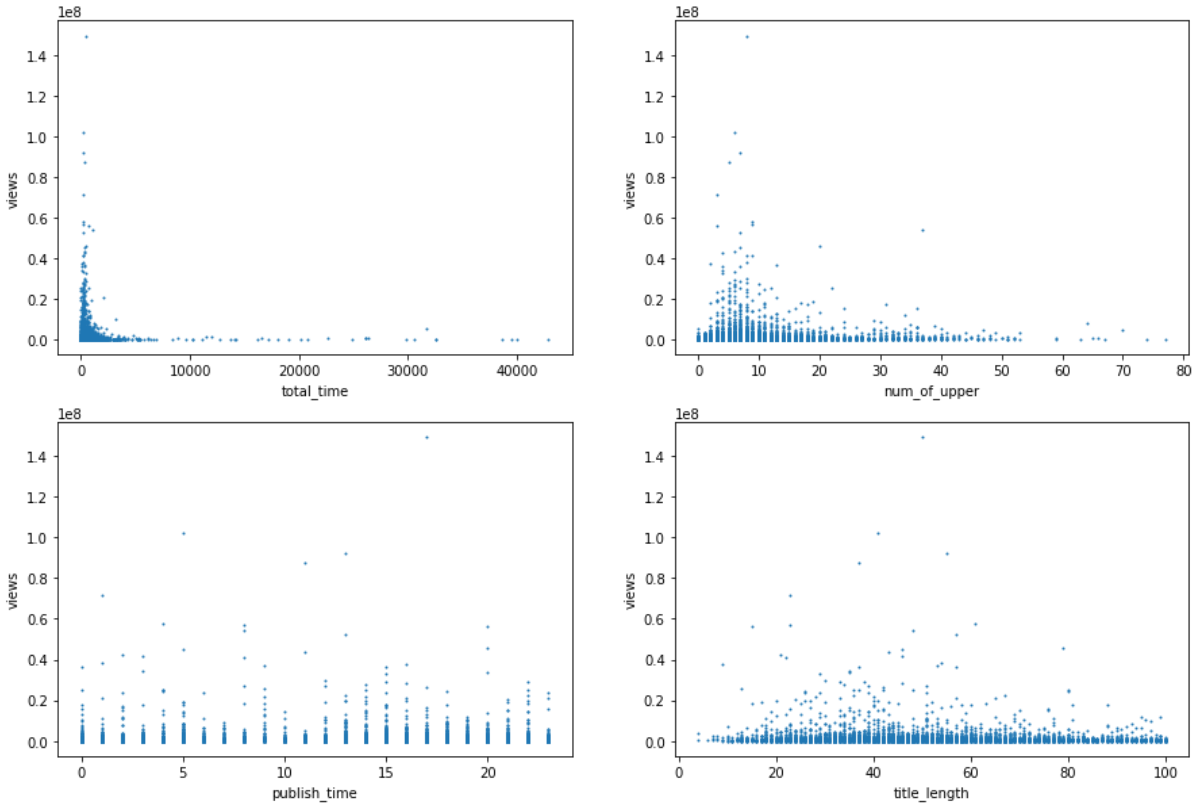
As we can see, the likes, views and comment count are very correlated. This is also expected since videos with higher views typically have higher likes and comment counts(unless comment is disabled). Therefore in our future analysis, we are just using views as an indicator of the popularity of the videos.

Now we investigate into what features are correlated with the popularity of the videos. So we will take a closer look at the following features:

1. Total length of the video
2. Total length of the title
3. The time at which the video is uploaded
4. The number of capital letters in the title

In [21]:
```
fig, axes = plt.subplots(nrows = 2, ncols=2, figsize = (15,10))
US_videos.plot.scatter(ax=axes[0,0], x='total_time', y='views', s =1)
US_videos.plot.scatter(ax=axes[0,1], x='num_of_upper', y='views', s =1)
US_videos.plot.scatter(ax=axes[1,0], x='publish_time', y='views', s =1)
US_videos.plot.scatter(ax=axes[1,1], x='title_length', y='views', s =1)
```

Out[21]: <matplotlib.axes._subplots.AxesSubplot at 0x1c24a72f98>



This gives a general idea of how the features are related to the views of a video.

- for the total_time of the video, we can see that long videos(longer than 10000 seconds) typically are not very popular and the videos with a lot of views typically are relatively short.
- for the number of capital letters in the title, there's peak around 8 characters that have a lot of view counts.
- for the publish time, there does not seem to have a significant correlation with the popularity of the video. There are a couple outliers but the videos published at different hours of the day can all have relatively large views.
- for the view counts and the title length, there also does not seem be a strong relation between the two.

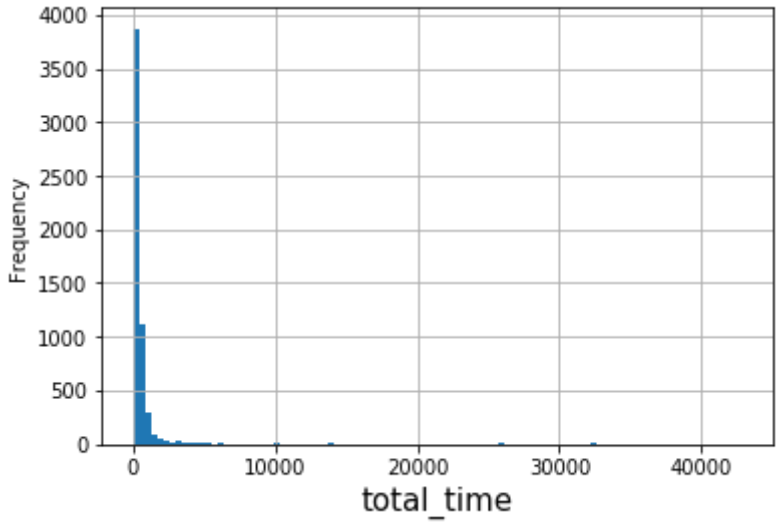
However, in the scatter plots we cannot see how many points belong to a certain range in the x-axis and we cannot determine what's the most frequent title_length, publish_time, etc. among trending videos. Therefore we now go into each of these features in detail in the following analysis.

total_time

We will first examine the "total_time" feature, which is the length of a video. Let's first create a histogram for the total number of seconds.

In [22]:
```
US_videos['total_time'].plot.hist(bins= 100,grid=True)
plt.xlabel("total_time", fontsize=15)
```

Out[22]:
```
Text(0.5, 0, 'total_time')
```



Many videos seems to have nearly 0 lengths. Let's quantify how many videos have 0 second length, which means the length is not valid.

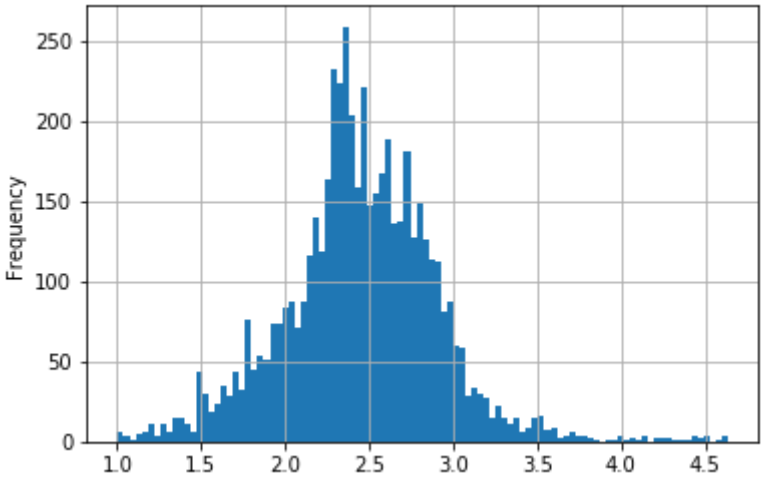
In [23]:
```
print('total number of videos: ', US_videos.shape[0])
print('video with 0 length: ', US_videos[US_videos['total_time'] == 0].s
hape[0])
```

```
total number of videos:  5567
video with 0 length:  340
```

It turns out that only less than 10 percent of the videos have 0 seconds length. The result in the previous graph is because some videos have very long lengths compared to other. Therefore we remove the videos with 0 lengths and do a log transformation of the lengths.

In [24]:
```
np.log10(US_videos[US_videos['total_time'] != 0]['total_time']).plot.his
t(bins= 100,grid=True)
```

Out[24]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1c252c0438>
```



In [25]:
```
print(normaltest(np.log10(US_videos[US_videos['total_time'] != 0]['total
_time'])))
print('average without log transformation:', (US_videos[US_videos['total
_time'] != 0]['total_time']).mean())
print('average video length with log transformation:', 10 ** np.log10(US
_videos[US_videos['total_time'] != 0]['total_time']).mean())
```

```
NormaltestResult(statistic=228.59980507588338, pvalue=2.291833407239999
7e-50)
average without log transformation: 572.72508130859
average video length with log transformation: 279.5926344988227
```

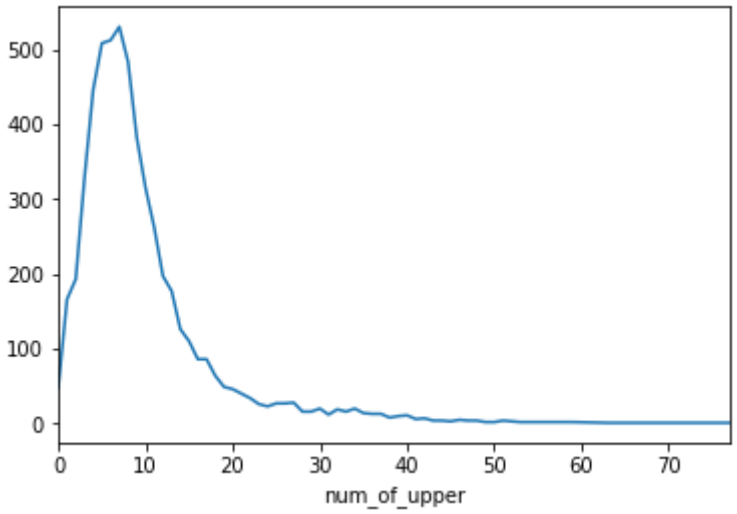
As we can see, the distribution is not likely to be normally distributed. The mean length of the video is sbout 573 seconds which is about 10 minutes, with some outlier videos of very long lengths. With the log transformation, the histogram looks more like a bell shape. We found the mean and use that mean to calculate the average length by using the mean as the exponent, the average length calculated this way is about 280 seconds which is about 4.5 minutes.

num_of_upper

We now examine the number of upper case characters in the title. Again we are not using histogram because we want to capture all the data points.

In [26]:
```
US_videos['num_of_upper'].groupby(US_videos['num_of_upper']).count().plo
t()
```

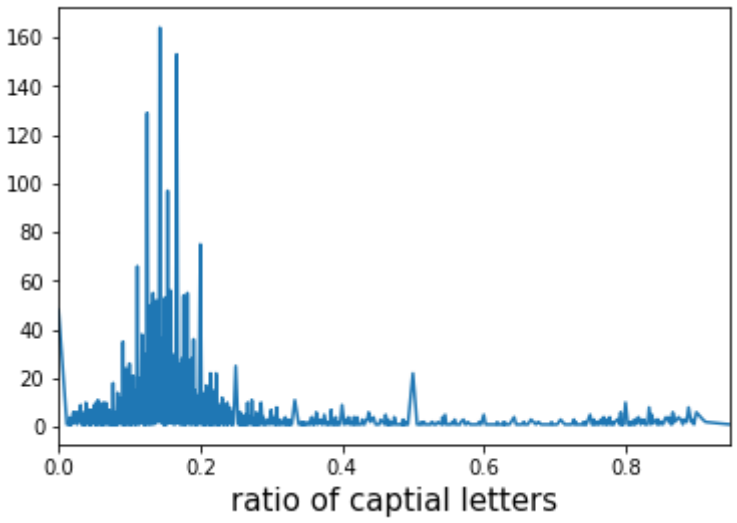
Out[26]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1c254f13c8>
```



It's obvious that the function peaks around 8 upper characters in the title. Let's look at the distribution of ratio of the upper letter characters in the entire title. We made both a line plot and a histrogram for better understanding of the data.

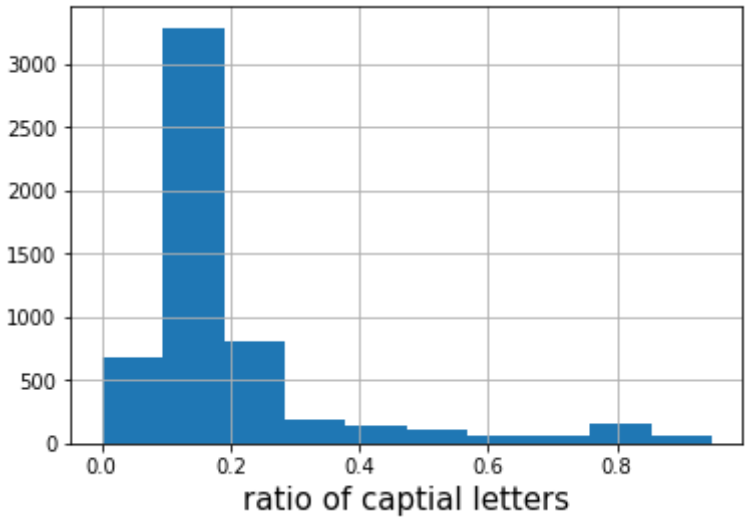
In [27]:
```
ratio = US_videos['num_of_upper']/US_videos['title_length']
ratio.groupby(ratio).count().plot()
plt.xlabel("ratio of captial letters", fontsize=15)
```

Out[27]:
```
Text(0.5, 0, 'ratio of captial letters')
```



In [28]:
```
ratio.hist(bins = 10)
plt.xlabel("ratio of captial letters", fontsize=15)
```

Out[28]:
```
Text(0.5, 0, 'ratio of captial letters')
```



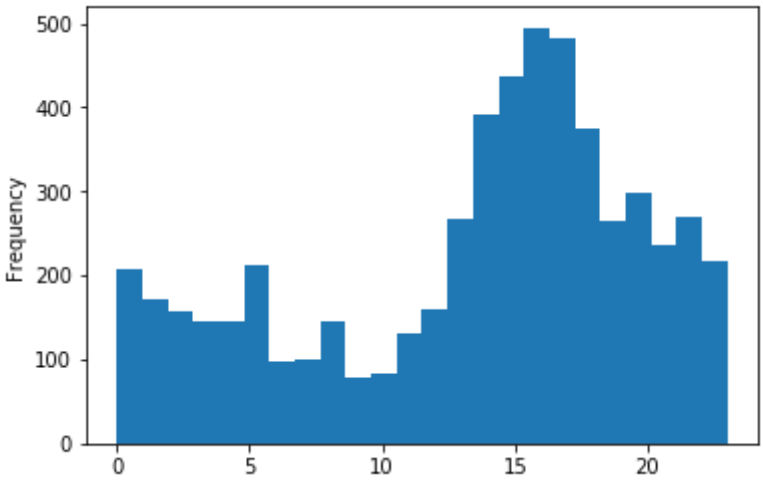
It can be seen that there are around 40 videos that do not use captial letters and most videos have a ratio of 0.1 to 0.2 of capital letters in there titles. There are also a few that use almost all captical letters, indicated by the small peak around 0.8 in the histogram.

publish_time

Next, we want to further visualize the publish time feature in addition to the scatterplot.

```
In [29]: US_videos['publish_time'].plot.hist(bins = 24)
```

```
Out[29]: <matplotlib.axes._subplots.AxesSubplot at 0x1c25313c88>
```



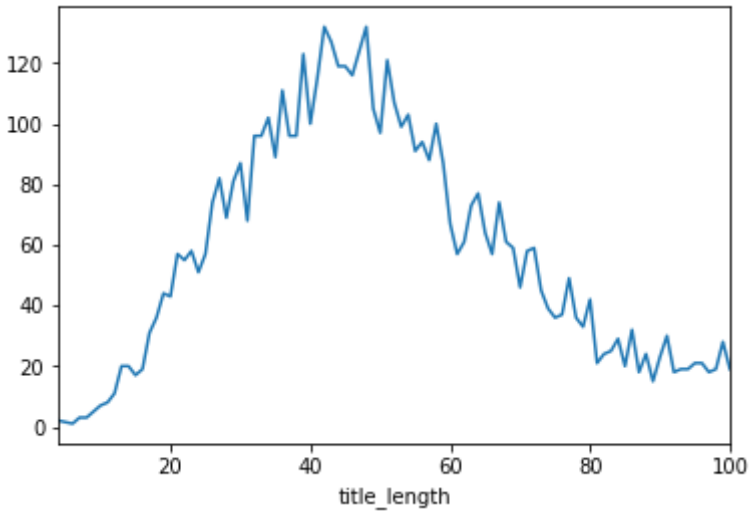
There's a peak around 15. Since the publish time is specified in UTC time and US has multiple time zones from UTC-5 to UTC-10, we can say that most trending videos are published in the morning around 7 to 10 am.

title_length

We check the number of videos with different title lengths. We are not using a histogram since we want to capture the number of videos for all title_lengths and the number of charactesr is a discrete number.

In [30]:
```
US_videos['title_length'].groupby(US_videos['title_length']).count().plo
t()
```

Out[30]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1c25ab7da0>
```



The result shows that videos with title lengths of around 40-60 characters are most common among trending videos.

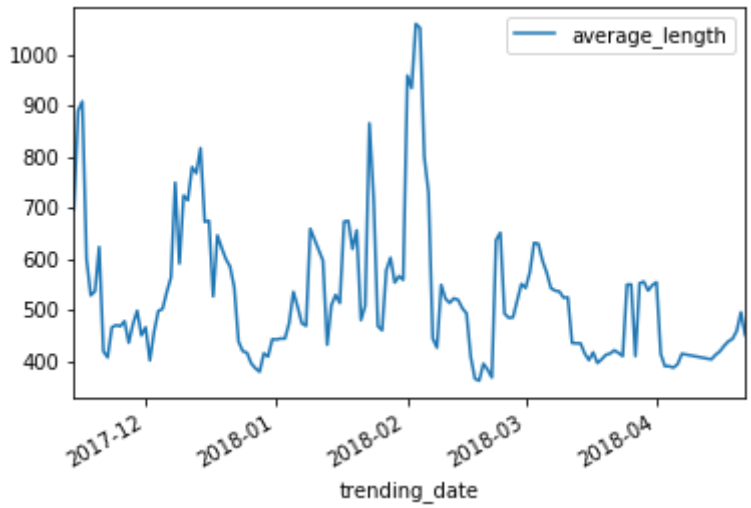
Data Analysis & Results

Average lengths of trending videos over time.

We then check the average lengths of videos each day and plot that length over time to see if there's trend. Here we are using the dataframe without removing the duplicates.

In [31]:
```
lengthOverTime = pd.DataFrame(index = duplicate['trending_date'].groupby
((duplicate['trending_date'])).count().index, columns =['average_length'
])
for date, r in lengthOverTime.iterrows():
    curr_length = duplicate[duplicate['trending_date'] == date]['total_t
ime']
    curr_length = curr_length[curr_length != 0]
    average_length = sum(curr_length) /  curr_length.count()
    lengthOverTime['average_length'][date] = average_length
lengthOverTime.plot()
```

Out[31]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1c25a345f8>
```



In [32]:
```
length_arr = lengthOverTime['average_length'].values
r, p = pearsonr(length_arr.astype(np.float64), np.arange(0, np.size(leng
th_arr)))
r,p
```

Out[32]:
```
(-0.2724783650093921, 0.0006835316762581829)
```

As we can see, there's slight decreasing trend in the the average lengths over the six months. The decreasing rate is relatively small and there are fluctuations, but the small p-value indicates a statistically significant decreasing trend overtime.

Linear regression model for popularity of a video

As shown in the data visualization section, the views of a video is strongly correlated with likes and comment counts, and therefore in this section we are just using the number of views of a video as an indicator for the popularity of a video.

In order to analyze the relationship between the popularity of a video (in this case we are using the views as an indicator), we create linear models to predict the views of a video from the length of the videos and the length of the title.

We drop all the videos with zero lengths and store them in a new dataframe.

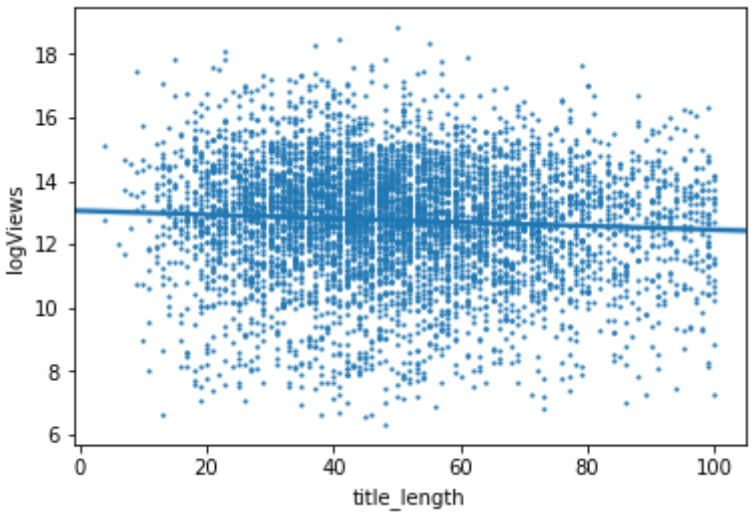
In [33]:
```
US_videos_valid_length = US_videos[US_videos['total_time'] != 0]
```

Here we do a regression of the popularity of videos with the length of the titles.

In [34]:
```
outcome, predictors = patsy.dmatrices('logViews ~ title_length', US_vide
os)

mod = sm.OLS(outcome, predictors)
res = mod.fit()

# Print out the summary results of the model fitting
print(res.summary())

sns.regplot(x='title_length', y='logViews', data=US_videos,scatter_kws={
's':2})
```

```
                            OLS Regression Results
==============================================================================
=======
Dep. Variable:                logViews   R-squared:
0.004
Model:                            OLS   Adj. R-squared:
0.004
Method:                 Least Squares   F-statistic:
22.82
Date:                Tue, 10 Dec 2019   Prob (F-statistic):
1.82e-06
Time:                        14:39:39   Log-Likelihood:
-11265.
No. Observations:                5567   AIC:                             2.
253e+04
Df Residuals:                    5565   BIC:                             2.
255e+04
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
=========
                   coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
---------
Intercept       13.0614      0.067    195.182      0.000      12.930
13.193
title_length    -0.0060      0.001     -4.777      0.000      -0.008
-0.004
==============================================================================
=======
Omnibus:                      217.525   Durbin-Watson:
1.178
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
252.007
Skew:                          -0.465   Prob(JB):
1.89e-55
Kurtosis:                       3.470   Cond. No.
146.
==============================================================================
=======

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
```

Out[34]: <matplotlib.axes._subplots.AxesSubplot at 0x1c2398d470>



It turns out there's a statiscally significant negative relationship between the title length of the popularity, but this explains very little(0.005) of the difference in views.

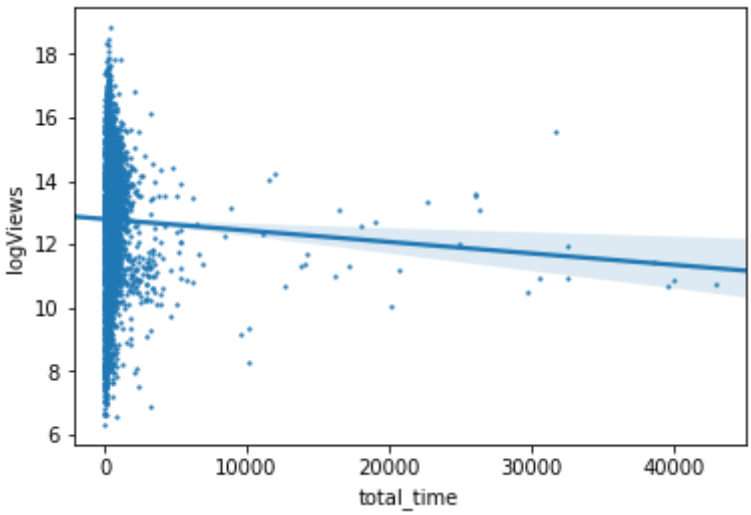
We run a OLS regression on the log of the view counts and the lengths of the video.

In [35]:

```
outcome, predictors = patsy.dmatrices('logViews ~ total_time', US_videos
_valid_length)
mod = sm.OLS(outcome, predictors)
res = mod.fit()
print(res.summary())
sns.regplot(x='total_time', y='logViews', data=US_videos_valid_length,sc
atter_kws={'s':2})
```

```
                            OLS Regression Results
==============================================================================
=======
Dep. Variable:                logViews   R-squared:
0.001
Model:                            OLS   Adj. R-squared:
0.001
Method:                 Least Squares   F-statistic:
7.685
Date:                Tue, 10 Dec 2019   Prob (F-statistic):
0.00559
Time:                        14:39:40   Log-Likelihood:
-10544.
No. Observations:                5227   AIC:                             2.
109e+04
Df Residuals:                    5225   BIC:                             2.
111e+04
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
=======
                 coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
-------
Intercept     12.8010      0.026    487.723      0.000      12.750
12.852
total_time -3.606e-05    1.3e-05     -2.772      0.006   -6.16e-05   -
1.06e-05
==============================================================================
=======
Omnibus:                      200.725   Durbin-Watson:
1.182
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
234.611
Skew:                          -0.454   Prob(JB):
1.13e-51
Kurtosis:                       3.501   Cond. No.
2.10e+03
==============================================================================
=======

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
[2] The condition number is large, 2.1e+03. This might indicate that th
ere are
strong multicollinearity or other numerical problems.
```

Out[35]: <matplotlib.axes._subplots.AxesSubplot at 0x1c23ee4e48>



It can be seen that there's a fairly significant negative relationship between the views and the lengths of the video (p-value is 0.6%), but the R-squared value is 0.001 so the lengths of the video explains very little for the difference in the views.

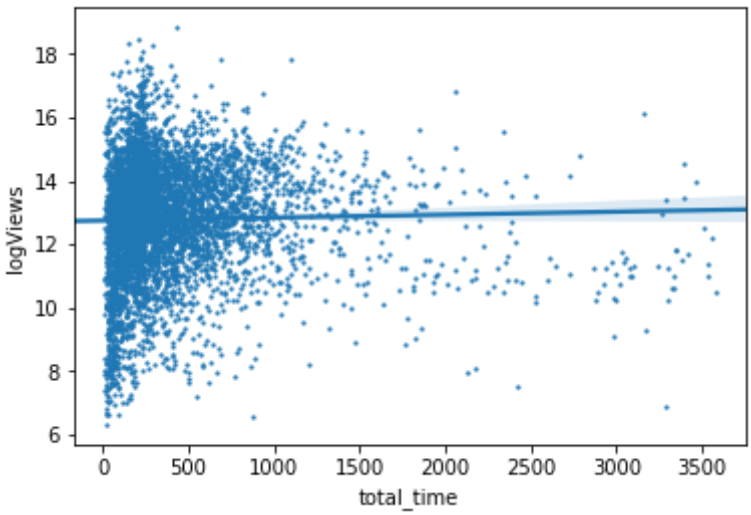
There are some outliers in the graph that certainly skewed the regression. There are a couple very long videos. We removed the outliers videos and run the regression again.

In [36]:

```
outcome, predictors = patsy.dmatrices('logViews ~ total_time', US_videos
_valid_length[US_videos_valid_length['total_time'] < 3600])
mod = sm.OLS(outcome, predictors)
res = mod.fit()
print(res.summary())
sns.regplot(x='total_time', y='logViews', data=US_videos_valid_length[US
_videos_valid_length['total_time'] < 3600],scatter_kws={'s':2})
```

```
                            OLS Regression Results
==============================================================================
=======
Dep. Variable:                logViews   R-squared:
0.001
Model:                            OLS   Adj. R-squared:
0.000
Method:                 Least Squares   F-statistic:
2.682
Date:                Tue, 10 Dec 2019   Prob (F-statistic):
0.102
Time:                        14:39:41   Log-Likelihood:
-10421.
No. Observations:                5163   AIC:                             2.
085e+04
Df Residuals:                    5161   BIC:                             2.
086e+04
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
=======
                 coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
-------
Intercept     12.7537      0.035    369.620      0.000      12.686
12.821
total_time  9.281e-05   5.67e-05      1.638      0.102   -1.83e-05
0.000
==============================================================================
=======
Omnibus:                      194.918   Durbin-Watson:
1.179
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
227.005
Skew:                          -0.451   Prob(JB):
5.09e-50
Kurtosis:                       3.492   Cond. No.
829.
==============================================================================
=======

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
```

Out[36]: <matplotlib.axes._subplots.AxesSubplot at 0x1c23eab898>



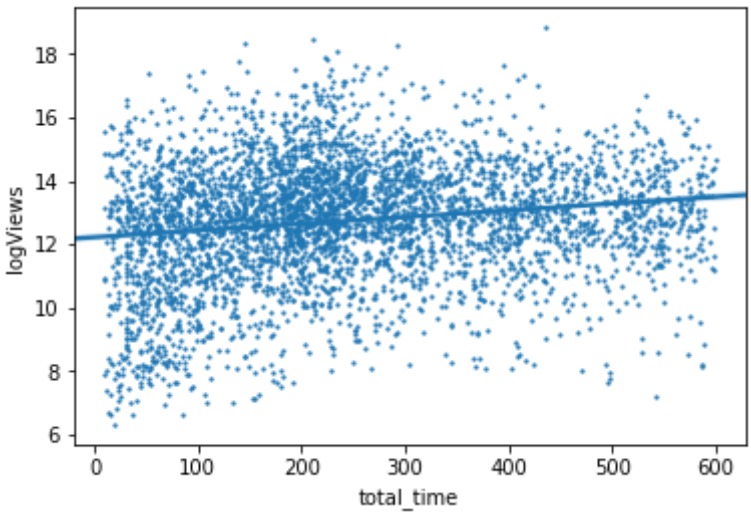
The regression model shown above is for all videos of length less than 3600 seconds (1 hour) and it turns out there's very little relationship between the length of the videos and the popularity in this regression.

In [37]:

```
outcome, predictors = patsy.dmatrices('logViews ~ total_time', US_videos
_valid_length[US_videos_valid_length['total_time'] < 600])
mod = sm.OLS(outcome, predictors)
res = mod.fit()
print(res.summary())
sns.regplot(x='total_time', y='logViews', data=US_videos_valid_length[US
_videos_valid_length['total_time'] < 600],scatter_kws={'s':2})
```

```
                            OLS Regression Results
==============================================================================
=======
Dep. Variable:                logViews   R-squared:
0.028
Model:                            OLS   Adj. R-squared:
0.028
Method:                 Least Squares   F-statistic:
118.5
Date:                Tue, 10 Dec 2019   Prob (F-statistic):
3.12e-27
Time:                        14:39:41   Log-Likelihood:
-8365.2
No. Observations:                4116   AIC:                             1.
673e+04
Df Residuals:                    4114   BIC:                             1.
675e+04
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
=======
                 coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
-------
Intercept     12.2275      0.056    219.008      0.000      12.118
12.337
total_time     0.0021      0.000     10.887      0.000       0.002
0.003
==============================================================================
=======
Omnibus:                       80.540   Durbin-Watson:
1.204
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
88.060
Skew:                          -0.316   Prob(JB):
7.55e-20
Kurtosis:                       3.338   Cond. No.
556.
==============================================================================
=======

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
```

Out[37]: <matplotlib.axes._subplots.AxesSubplot at 0x1c21c58fd0>



The regression model shown above is for all videos of length less than 600 seconds (10 minutes) and there's a statistically significant positive relationship between the views and the lengths of the videos. The R-square is still fairly small, so the lengths of the videos do not explain much about the difference of the popularity.

Word choices in title

In this section, we use all words appeared in titles of given cleaned trending video dataFrame to conduct a word cloud images, given a visually impression of what words are the most popular, or most attracting ones.

Because there are many non-alphabetic words among titles in the dataset, we first cleaned everything non-alphabetic. To maximize the functionability of the world cloud to provide a more meaningful result, we then eliminated all transition words, abjective words and other words that do not mean anything by using wordCloud packages from ULTK.

```
In [38]: df = US_videos
titleLst = df['title'].tolist()

for i in range(len(titleLst)):
    new = re.sub(r"’", '', titleLst[i])
    titleLst[i] = re.sub(r'[^a-zA-Z_]', ' ', new)

with open('titles_non_repeating.txt', 'w') as f:
    for i in range(len(titleLst)):
        newLst = titleLst[i].split(" ")
        length = len(newLst)
        for y in range(length):
            if not (newLst[y] == " ") and not newLst[y] == "" and not le
n(newLst[y]) == 1:
                f.write(str(newLst[y] + ' '))

titleFile = open("titles_non_repeating.txt", "r").read()


def create_word_cloud(string):
    mask = np.array(Image.open("square.png"))
    cloud = WordCloud(background_color="white", max_words=500, mask=mask
,
                      stopwords=set(STOPWORDS), collocations=True)
    cloud.generate(string)
    cloud.to_file("wordCloud_square_collocation500_new.png")


titleFile = titleFile.lower()
create_word_cloud(titleFile)

Image_d(filename='wordCloud_square_collocation500_new.png')
```

Out[38]:

In this word cloud, we set the collocation parameter to true to reflect a more realistic result because if we only know "official" is the biggest word in the word cloud, it does not mean anything in the sense that it won't provide a helpful insight for realizing what kinds of video titles are attracting audiences.

With such collocations,we found that music videos and trailers are very popular words in YouTube video titles. Indeed, it means more for content creators becuase popular words in title can reflect the content of that video in some senses. From this figure, the conclusion can be made that videos related to music, trailer, festivals and videos that are released for the first time are very popular on YouTube. We believe such foundings are helpful because concent creators now can take this word cloud in consideration to help them make related videos that might get popular in the future.

We then find the most used 50 words and analyze whether using these words in the title affects the popularity of a video.

In [39]:
```
df = US_videos

title_list = df['title'].tolist()
title_dict = {}

for i in range(len(title_list)):
    stop_words = set(stopwords.words('english'))
    original = word_tokenize(title_list[i])
    filtered = []

    for j in original:
        lower = j.lower()
        lower = re.sub(r"’", '', lower)
        lower = re.sub(r'[^a-zA-Z_]', ' ', lower)
        if lower not in stop_words and len(lower) > 1 and not lower.issp
ace() \
                and not (" " in lower):
            filtered.append(lower)
        for w in filtered:
            if w not in title_dict:
                title_dict[w] = 1
            else:
                title_dict[w] += 1

sorted_dict = sorted(title_dict.items(), key=operator.itemgetter(1))
count = len(sorted_dict)
top = sorted_dict[count-50: count+1]
top_list = [i[0] for i in top]
print(top_list)
```

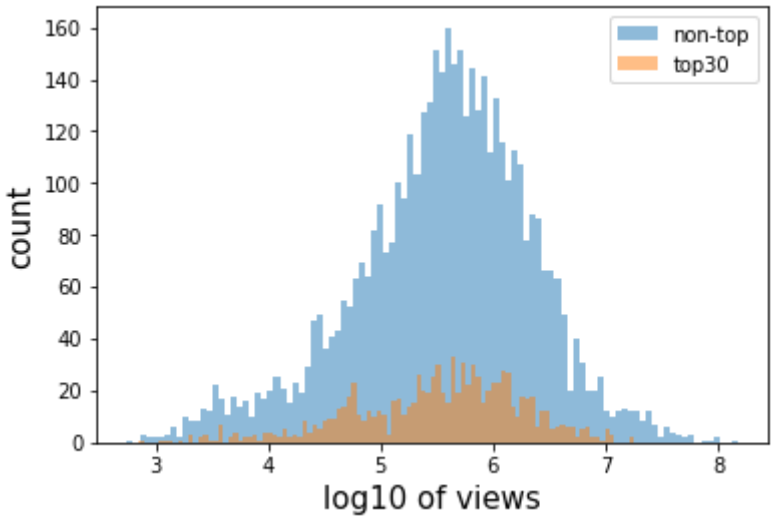
```
['kim', 'house', 'like', 'real', 'audio', 'makes', 'life', 'movie', 'ca
rdi', 'making', 'jedi', 'show', 'year', 'diy', 'man', 'bowl', 'time',
'love', 'watch', 'feat', 'music', 'one', 'makeup', 'get', 'stephen', 'g
ame', 'john', 'hd', 'vs', 'christmas', 'season', 'make', 'super', 'worl
d', 'day', 'top', 'james', 'wars', 'last', 'black', 'full', 'trump', 'b
est', 'star', 'first', 'video', 'live', 'new', 'trailer', 'official']
```

We make two distributions of videos' views. top_d for those videos with titles that include the most used words and non_top for those that do not include these 50 words.

In [40]:
```
top_d = US_videos[US_videos['title'].str.contains('|'.join(top_list))][
'views']
non_top_d = US_videos[~ US_videos['title'].str.contains('|'.join(top_lis
t))]['views']
```

We plot the distributions on a log scale.

In [41]:
```
x1 = np.log10(top_d)
x2 = np.log10(non_top_d)
# x1 = (top_d)
# x2 = (non_top_d)
plt.hist(x2, label = 'non-top', alpha = 0.5, bins=100)
plt.hist(x1, label = 'top30', alpha = 0.5, bins=100)

plt.legend(loc = 'upper right')
plt.xlabel("log10 of views", fontsize=15)

plt.ylabel("count", fontsize=15)
plt.show()
```



It's not exactly clear from the graph which distribution has a higher mean. Let's calculate the mean from the data and run a t-test to tell if the difference is significant.

In [42]:
```
print('average views of videos that include the top 30 words:', top_d.mean())
print('average views of videos that do not include the top 30 words:', non_top_d.mean())
t_val, p_val = ttest_ind(top_d, non_top_d)
t_val, p_val
```

```
average views of videos that include the top 30 words: 979816.2245989305
average views of videos that do not include the top 30 words: 1570220.0578583765
```

Out[42]:
```
(-3.4343834643240876, 0.0005982388999110 18)
```

It can be seen that the average views of those videos with popular words are actually less than those with not. After running the t-test, we can see the difference is actually quite significant. This means that while certain words such as "official", "trailer" appear more frequently than other in trending videos, using these words is actually correlated with less views among all the trending videos.

Average video lengths and title lengths for most popular videos

We now try to determine the average video lengths and title lengths of the most popular videos. We first define popular videos as those with more then 10 million views.

In [43]:
```
popular_videos = US_videos[US_videos['views'] > 10000000]
```

video lengths analysis

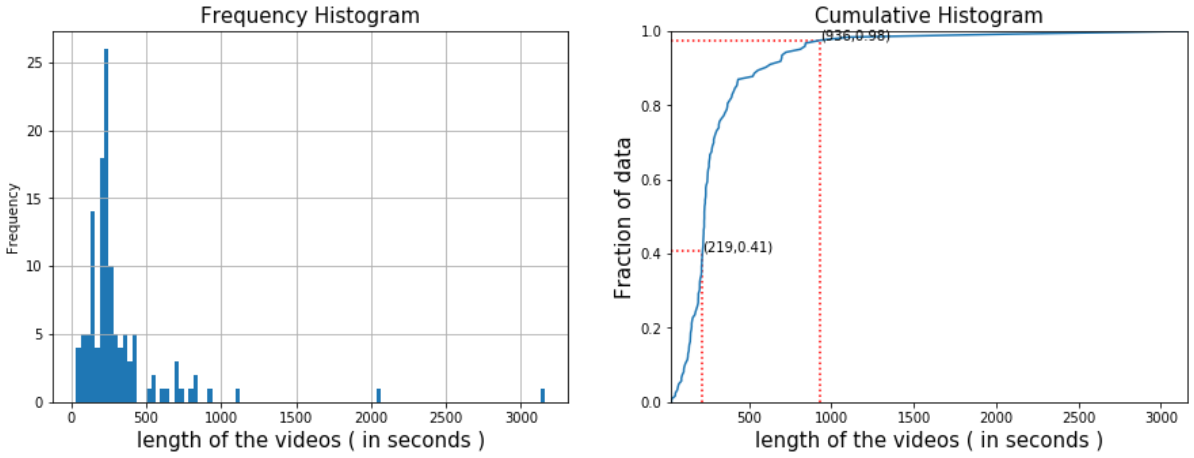
In [44]:
```
print('average length of popular videos (in seconds):', popular_videos['total_time'].mean())
print(normaltest(popular_videos['total_time']))
```

```
average length of popular videos (in seconds): 303.4
NormaltestResult(statistic=175.7153509293746, pvalue=6.98065786323699e-39)
```

The average length of popular videos is about 5 minutes, and the distribution is not normally distributed. We then plot the histogram and cumulative frequency to get a better understanding of the distribution.

In [45]:
```
fig, axes = plt.subplots(nrows = 1,ncols = 2, figsize = (15,5))
popular_videos[popular_videos['total_time'] != 0]['total_time'].plot.his
t(ax = axes[0], bins= 100,grid=True)
axes[0].set_xlabel("length of the videos ( in seconds )", fontsize=15)
axes[0].set_title("Frequency Histogram", fontsize=15)

cdf_length = np.sort(popular_videos[popular_videos['total_time'] != 0][
'total_time'].values)
cdf_prob = np.linspace(0, 1, len(popular_videos[popular_videos['total_ti
me'] != 0]['total_time'].values))
res = plt.plot(cdf_length, cdf_prob)

axes[1].margins(0)

axes[1].set_xlabel("length of the videos ( in seconds )", fontsize=15)
axes[1].set_ylabel("Fraction of data", fontsize=15)
axes[1].set_title("Cumulative Histogram", fontsize=15)

start, end = 50, 120

axes[1].hlines(y=cdf_prob[start], xmin=cdf_length.min(), xmax=cdf_length
[start], color='r', linestyles= "dotted")
axes[1].vlines(x=cdf_length[start], ymin=cdf_prob.min(), ymax=cdf_prob[s
tart], color='r', linestyles= "dotted")
axes[1].text(cdf_length[start], cdf_prob[start], "(" + str(cdf_length[st
art]) + "," + "{0:.2f}".format(cdf_prob[start]) + ")")

axes[1].hlines(y=cdf_prob[end], xmin=cdf_length.min(), xmax=cdf_length[e
nd], color='r', linestyles= "dotted")
axes[1].vlines(x=cdf_length[end], ymin=cdf_prob.min(), ymax=cdf_prob[end
], color='r', linestyles= "dotted")
axes[1].text(cdf_length[end], cdf_prob[end], "(" + str(cdf_length[end])
+ "," + "{0:.2f}".format(cdf_prob[end]) + ")")
```

Out[45]:
```
Text(936, 0.9756097560975611, '(936,0.98)')
```



As we can see, more than half of the popular videos have a length between about 3.5 minutes to 15 minutes.

title length analysis

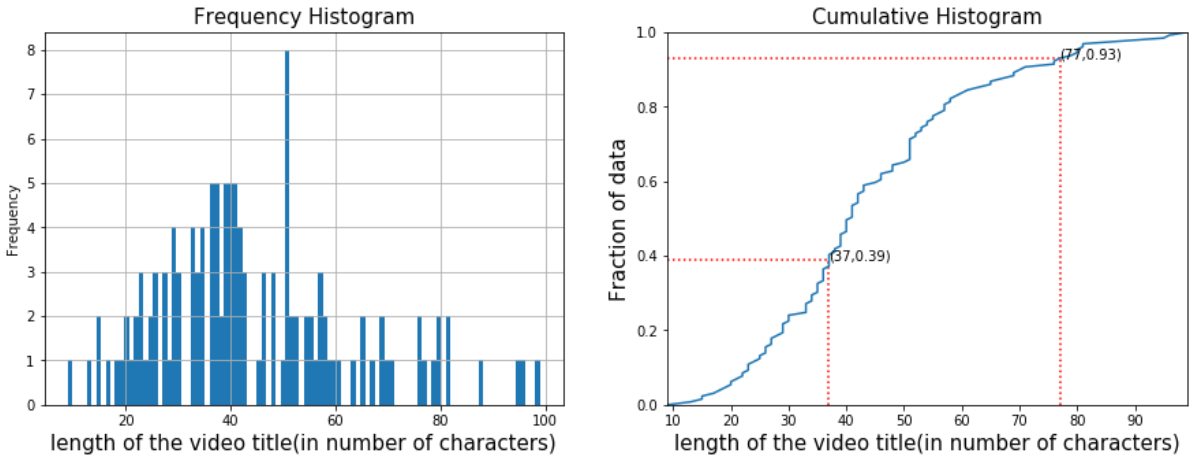
In [46]:
```
print('average title length of popular videos (in number of character
s):', popular_videos['title_length'].mean())
print(normaltest(popular_videos['title_length']))
```

```
average title length of popular videos (in number of characters): 44.16
923076923077
NormaltestResult(statistic=12.796253046636602, pvalue=0.001664673079764
679)
```

The average number of characters in the titles of popular videos is about 44, and the distribution is not normally distributed. Similarly to the video lengths, we plot the histogram and cumulative frequency to get a better understanding of the distribution.

In [47]:
```
fig, axes = plt.subplots(nrows = 1,ncols = 2, figsize = (15,5))
popular_videos['title_length'].plot.hist(ax = axes[0], bins= 100,grid=True)
axes[0].set_xlabel("length of the video title(in number of characters)", fontsize=15)
axes[0].set_title("Frequency Histogram", fontsize=15)

cdf_length = np.sort(popular_videos['title_length'].values)
cdf_prob = np.linspace(0, 1, len(popular_videos['title_length'].values))
res = plt.plot(cdf_length, cdf_prob)

axes[1].margins(0)

axes[1].set_xlabel("length of the video title(in number of characters)", fontsize=15)
axes[1].set_ylabel("Fraction of data", fontsize=15)
axes[1].set_title("Cumulative Histogram", fontsize=15)

start, end = 50, 120

axes[1].hlines(y=cdf_prob[start], xmin=cdf_length.min(), xmax=cdf_length[start], color='r', linestyles= "dotted")
axes[1].vlines(x=cdf_length[start], ymin=cdf_prob.min(), ymax=cdf_prob[start], color='r', linestyles= "dotted")
axes[1].text(cdf_length[start], cdf_prob[start], "(" + str(cdf_length[start]) + "," + "{0:.2f}".format(cdf_prob[start]) + ")")

axes[1].hlines(y=cdf_prob[end], xmin=cdf_length.min(), xmax=cdf_length[end], color='r', linestyles= "dotted")
axes[1].vlines(x=cdf_length[end], ymin=cdf_prob.min(), ymax=cdf_prob[end], color='r', linestyles= "dotted")
axes[1].text(cdf_length[end], cdf_prob[end], "(" + str(cdf_length[end]) + "," + "{0:.2f}".format(cdf_prob[end]) + ")")
```

Out[47]:
```
Text(77, 0.9302325581395349, '(77,0.93)')
```



As we can see, more than half of the popular videos have a title length between about 35 to 80 characters. Given the ratio of capital letter (0.1~0.2) previously determined, there are about 5 to 10 capital letters in the videos. This means spamming the title with capital letters does not necessarily make videos more trendable, however highlighting a part of the title is a common practice.

Ethics & Privacy

Youtubers may exploit this dataset and our analysis to make content for the purpose of making money and gaining a large audience, possibly spreading false or useless information instead of sharing useful information. The social implications of such actions would be widespread; however it should still be noted that gaining a large following on YouTube isn't very easy.

The scope of the dataset may limit the accuracy of how the data reflects the popularity of YouTube videos in the real world, since the data we used only is representative of Trending videos in the US. Because of this, our analysis may be biased.

Conclusion & Discussion

correlation between views and likes and comment counts

As expected, we observe a strong postive correlation between features such as number of views, comment count, and like counts. We therefore define 'popularity' based on view counts for our data anaylsis process.

average lengths of trending videos over time

We have found that among the 6 recent months of data studied, the average length of trending videos tend to be overall decreasing overtime; it is decreasing at a very slight, but still statistically significant, rate.

linear regression models for popularity

With the linear regression models, we found little correlation between the views of a video with either the lengths of the video or the length of the title. However, we can conclude that videos longer than one hour typically don't have very much views compared to other videos in the trending list. Among videos shorter than 10 minutes, there's actually a statistically significant positive correlation between the length and the views. This is probabaly due to the fact that very short videos (less than 1 minutes) typically don't have much views compared to other trending videos as well.

word choice in title

We looked at the actual content in YouTube Video titles and made a visual word cloud of the most popular words used in titles, which include words like "official" and "trailer". However, among all trending videos, those that include the most frequent words like "official" and "trailer" in their title actually have less views on average. Considering the dataset is based on YouTube's trending list which automatically promotes trending videos to target audiences, we can conclude that even though including the top words from the word cloud does not ensure a video to be the most popular videos, it does give us a hint of what contents may have a better chance to be on YouTube's trending list under YouTube's trending list mechanism.

optimal title lengths and video lengths

Among the most viewed videos in the trending list (those with more than 10 million views), we observe that a majority of those have a video length between about 3.5 minutes to 15 minutes. and a title with about 35 to 80 characters.

Limitation

There are certain limitations to the project.

- The dataset is only of trending videos. Other non-trending videos are not included.
- The dataset is only of US region. Trending Youtube videos from other parts of the world are not analyzed.
- Some youtube videos are not available anymore and some trending videos are livestream videos. In either of these two cases, the video length feature would be dropped and not included in the analysis, causing potential bias.