#### Load in the data

- Actual loading script in processor.py
- · Didnt include hear because it makes the notebook more messy

```
In [41]:
           import matplotlib.pyplot as plot
           import numpy as np
 In [9]:
           # Python script to do a lot of the data processessing and make this notebook look cleaner
           import processor
           dataset = processor.load_dataset()
           channels = processor.process_by_chanel( dataset )
In [10]: # Pull out the important info about the trending videos into one table
           # Label is the assigned cataglory
           # Days to trend is publication date - trending date
           dataset.head()
Out[10]:
               trending date
                                      title channel title
                                                          publish time
                                                                                                                 views
                                                                                                                          likes dislikes comment count
                                                                                                         taas
                              WE WANT TO
                  2017-11-14
                              TALK ABOUT
                                                            2017-11-13
           00:00:00+00:00
                                            CaseyNeistat
                                                                                                SHANtell martin
                                                                                                                748374
                                                                                                                         57527
                                                                                                                                   2966
                                                                                                                                                  15954
                                     OUR
                                                        17:13:01+00:00
                                MARRIAGE
                  2017-11-14
                                 Me-O Cats
                                                           2017-04-21
                                               Nobrand
                                                                                          cute|"cats"|"thai"|"eggs"
                                                                                                                 98966
                                                                                                                          2486
                                                                                                                                                   532
              00:00:00+00:00
                                                        06:47:32+00:00
                                Commercial
                              AFFAIRS, EX
                             BOYFRIENDS,
                  2017-11-14
                                                 Shawn
                                                            2017-11-11
                                                                               shawn johnson|"andrew east"|"shawn
                                                                                                                321053
                                                                                                                                   1772
                                                                                                                                                   895
                               $18MILLION
                                                                                                                          4451
              00:00:00+00:00
                                           Johnson East 15:00:03+00:00
                                                                                                  east"| shaw...
                              NET WORTH
                              BLIND(folded)
                                    CAKE
                  2017-11-14
                                                            2017-11-11
                                            Grace Helbig 18:08:04+00:00
                             DECORATING
                                                                       itsgrace|"funny"|"comedy"|"vlog"|"grace"|"helb...
                                                                                                                197062
                                                                                                                          7250
                                                                                                                                    217
                                                                                                                                                   456
              00:00:00+00:00
                                 CONTEST
                                 (with Mo...
                                  Wearing
                  2017-11-14
                                                            2017-11-11
                               Online Dollar
                                                 Safiva
                                                                             wearing online dollar store makeup for a
                                                                                                               2744430 115426
                                                                                                                                   1110
                                                                                                                                                   6541
              00:00:00+00:00
                              Store Makeup
                                               Nygaard 01:19:33+00:00
                                                                                                       week|...
                                For A Week
In [11]: # All the channels that were on trending
           # Count is number of times trended
           # Stats reflect total views, likes, dislikes and comments for each video
           # Days to trend is average across all trending videos
           channels.head()
Out[11]:
                                        channel count
                                                            views
                                                                            dislikes comment_count days_to_trend
                                                                                                                           label
                                          ESPN
           0
                                                   203
                                                       105654218
                                                                    937723
                                                                            108043
                                                                                            387753
                                                                                                         2 132705
                                                                                                                          Sports
           1 The Tonight Show Starring Jimmy Fallon
                                                   197 271426383
                                                                   5981334
                                                                            187407
                                                                                            403655
                                                                                                         3.567450
                                                                                                                         Comedy
           2
                                   TheEllenShow
                                                   193
                                                       253841999
                                                                  6035132
                                                                            193602
                                                                                            344469
                                                                                                         2.611557
                                                                                                                    Entertainment
            3
                                          Netflix
                                                        185818315
                                                                  4211072
                                                                            196212
                                                                                             391350
                                                                                                         3.216193
                                                                                                                    Entertainment
                                                   193 122633963 3272518
                                                                                             558845
                                                                                                         4.479800 News & Politics
                                            Vox
```

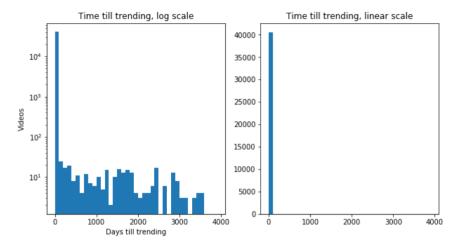
### Look at trending date statistics by videos

```
In [15]: # Huge disperity between median and mean
# Lets see that with data
days_to_trend_mean = dataset['days_to_trend'].mean()
days_to_trend_median = dataset['days_to_trend'].median()
print('It takes ' + str(days_to_trend_mean)[:5] + ' days to trend on average')
print('Median of only ' + str(days_to_trend_median)[:5] + ' days to trend')
```

It takes 16.22 days to trend on average Median of only 4.791 days to trend

```
In [46]: # Looking at it below, wow, some videos take forever to trend? Lets Look at that.
fig, a = plot.subplots(1,2,figsize=(10,5))
bins = np.arange( 0,4000, 100)
a[0].hist( dataset['days_to_trend'].tolist(), log=True, bins=bins )
a[0].set_title('Time till trending, log scale')
a[0].set_ylabel('Videos')
a[0].set_xlabel('Days till trending')
a[1].hist( dataset['days_to_trend'].tolist(), log=False, bins=bins )
a[1].set_title('Time till trending, linear scale')
print('Chart showing how many days some videos took to trend in a logarithmic fassion')
```

Chart showing how many days some videos took to trend in a logarithmic fassion



```
In [47]: # Lets pull one of these videos to make sure
# This video was published in 2006, trended in 2018? Has only a quarter of a million views?
# So you are almost guerenteed to trend immediately or not at all, its very hard for an older video to trend
dataset[dataset['days_to_trend'] > 3000 ][:1]
```

Out[47]:

	trending_date	title	channel_title	publish_time	tags	views	likes	dislikes	comment_count	description	
7054	2018-02-05 00:00:00+00:00	Budweiser - Original Whazzup? ad	dannotv	2006-07-23 08:24:11+00:00	Budweiser "Bud" "Whazzup" "ad"	258506	459	152	82	Original Whazzup ad - however, there is a litt	Er

## By metric breakdown

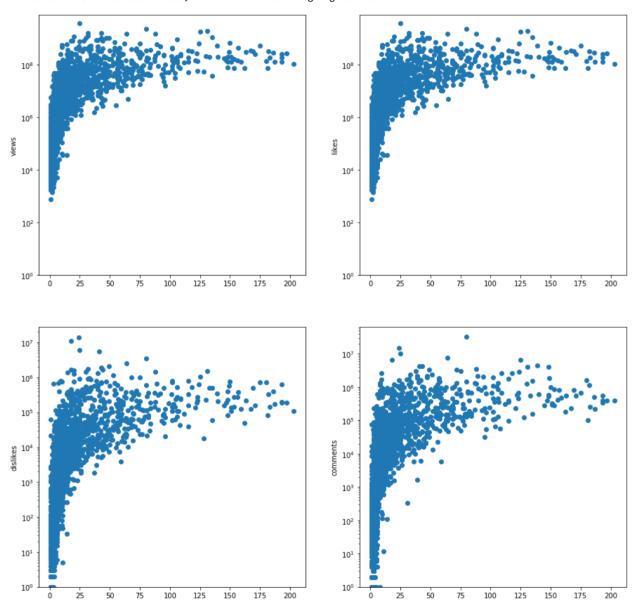
3711.40 dislikes 8446.80 comments

```
In [56]: # Lets get some statistics
    total_trends = channels['count'].sum()
    mean_trending_views = channels['views'].sum() / total_trends
    mean_trending_likes = channels['likes'].sum() / total_trends
    mean_trending_dislikes = channels['dislikes'].sum() / total_trends
    mean_trending_comments = channels['comment_count'].sum() / total_trends
    print('A trending video will have on average:')
    print(str(mean_trending_views)[:10],'views')
    print(str(mean_trending_likes)[:8],'likes')
    print(str(mean_trending_dislikes)[:7],'dislikes')
    print(str(mean_trending_comments)[:7],'comments')

A trending video will have on average:
    2360784.63 views
    74266.70 likes
```

```
In [74]: # Lets plot out some statistics as to the breakdown by channel
fig, a = plot.subplots(2,2,figsize=(15,15))
def add_to_plot(dataX, dataY, i, label):
        a[i//2, i%2].scatter(dataX, dataY, label=label)
        a[i//2, i%2].set_ylabel(label)
        a[i//2, i%2].set_yscale('log')
        a[i//2, i%2].set_yscale('log')
        add_to_plot( channels['count'], channels['views'],0,'views' )
        add_to_plot( channels['count'], channels['views'],1,'likes' )
        add_to_plot( channels['count'], channels['dislikes'],2,'dislikes' )
        add_to_plot( channels['count'], channels['comment_count'],3,'comments' )
        print('Chart showing How different metrics effect trending rate')
        print('X axis is number of times trended, Y axis is value of highlighted metric')
```

Chart showing How different metrics effect trending rate X axis is number of times trended, Y axis is value of highlighted metric

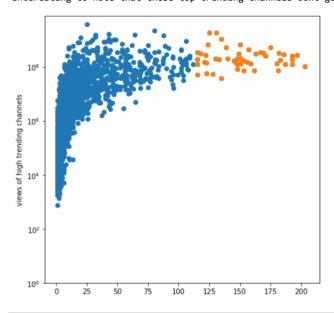


In [76]: # All the charts above look quite similer and seem fairly strongly coorilated
# Notice that there seems to be a hard cutoff on views though, you have to have a certain amount of views to trend.
# Lets look at that in more detail

## By Channel breakdown

```
In [89]: # Lets see if all channels are treated equally here
    # Take top 50 channels by views
    high_views = channels[:50]
    fig, a = plot.subplots(figsize=(7,7))
    a.scatter(channels['count'], channels['views'])
    a.scatter(high_views['count'], high_views['views'])
    a.set_ylabel('views of high trending channels')
    a.set_yscale('log')
    a.set_yscale('log')
    a.set_ylim((1,channels['views'].max()*2))
    print('High trending channels seem to have nothign to do with views')
    print('They have to have a certain cuttof it seems, but after a point it doesnt matter')
    print('Interesting to note that these top trending channels dont get more views, infact they get less per video?')
```

High trending channels seem to have nothign to do with views
They have to have a certain cuttof it seems, but after a point it doesnt matter
Interesting to note that these top trending channels dont get more views, infact they get less per video?

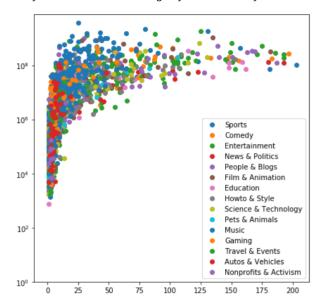


In [90]: # So what does it mean that you can trend over and over but not get many more views than someone who doenst?

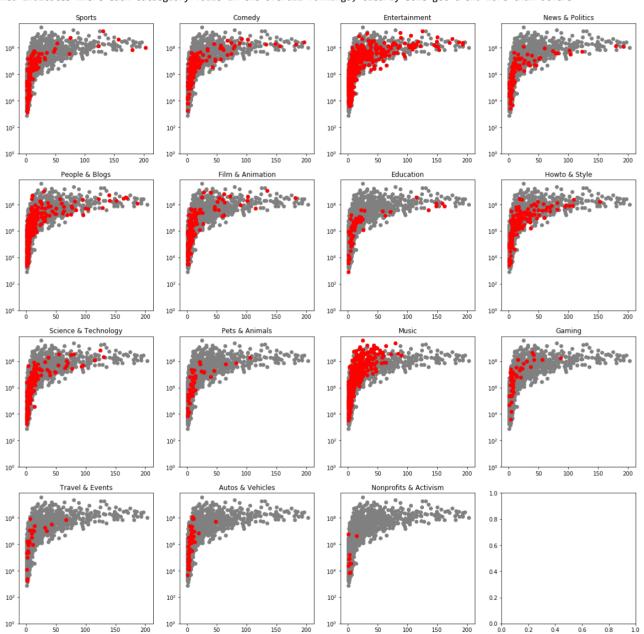
## By Category breakdown

```
In [102]:
    fig, a = plot.subplots(figsize=(7,7))
    def chart_views ( label ):
        data = channels[ channels['label'] == label ]
        a.scatter(data['count'], data['views'], label = label)
        a.set_ylim((1,channels['views'].max()*2))
        a.set_yscale('log')
        all_cats = channels['label'].unique()
        for cat in all_cats:chart_views(cat)
        plot.legend()
        print('messy chart that shows categlory breakdowns by views')
```

messy chart that shows categlory breakdowns by views



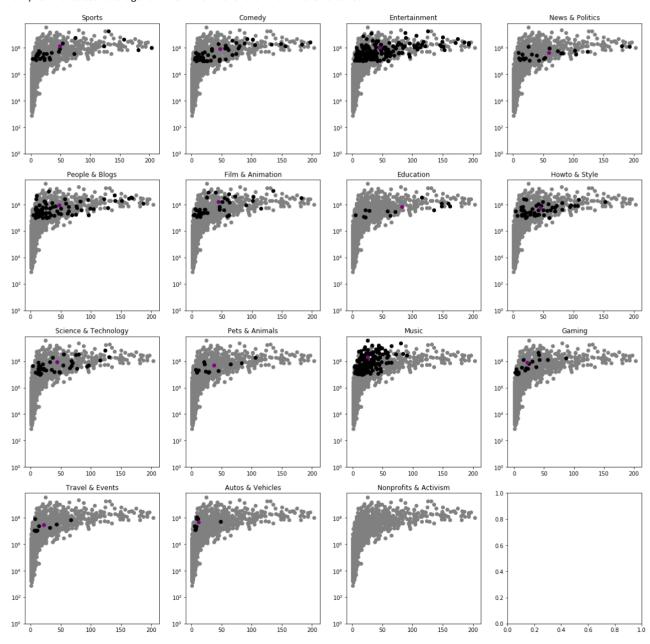
Red indicates where each cataeglory falls in the overall rankings, clearly some get trend more than others



```
In [113]: # Cutting off all data after 10<sup>6</sup> views, lets see where the average video channel falls on the trending amount
            fig, a = plot.subplots(4,4,figsize=(20,20))
            points = []
            def chart_views ( label, i ):
                chart = a[i//4,i%4]
                data = channels[ channels['label'] == label][channels['views'] > 100000000 ]
                chart.scatter(channels['count'], channels['views'], ce'grey')
chart.scatter(data['count'], data['views'], label = label,ce'black')
                _x = data['count'].mean()
_y = data['views'].mean()
                chart.scatter([_x],[_y], label = label,c='purple')
                chart.set_ylim((1,channels['views'].max()*2))
                chart.set_yscale('log')
                chart.set_title(label)
                points.append((label,_x,_y))
            all_cats = channels['label'].unique()
            for (i,cat) in enumerate(all_cats): chart_views(cat,i)
            print('Purlple indicates average channel with more than 10M views trended')
```

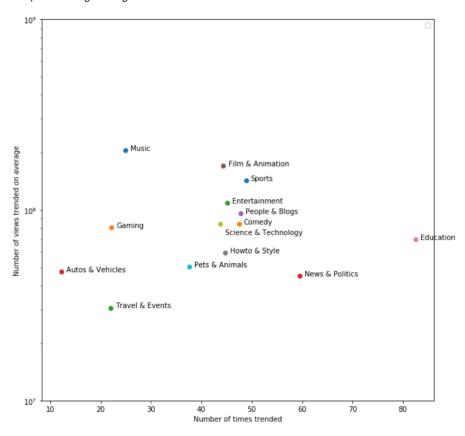
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel\_launcher.py:6: UserWarning: Boolean Series key will be reindexed to match DataFrame index.

Purlple indicates average channel with more than 10M views trended



No handles with labels found to put in legend.

Out[129]: <matplotlib.legend.Legend at 0x2203c25bf60>



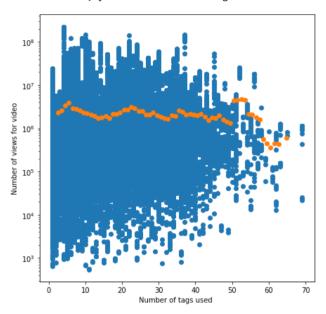
# By Tag Topic breakdown

25 2744430

```
In [148]: import re
           import collections
           import pandas as pd
In [234]: # First of all, how many tags should you have?
           tag_dataset = pd.DataFrame()
tag_dataset['tag_num'] = dataset['tags'].str.split('|').str.len()
           tag_dataset['views'] = dataset['views']
           tag_dataset[:5]
Out[234]:
               tag_num
                          views
            0
                         748374
                          98966
            2
                         321053
            3
                     12
                         197062
```

```
In [252]: # Lets see how video views relate to tag numbers
fig, a = plot.subplots(figsize=(7,7))
group = tag_dataset.groupby('tag_num').mean().reset_index().rolling(4).mean()
a.scatter(tag_dataset['tag_num'],tag_dataset['views'])
a.scatter(group['tag_num'],group['views'])
a.set_ylabel('Number of views for video')
a.set_xlabel('Number of tags used ')
a.set_yscale('log')
print('Blue are videos, yellow is rollind average')
```

Blue are videos, yellow is rollind average



```
In [149]: # What are top videos actually about by tag
pattern = re.compile('[^\\a-zA-Z0-9_]+')
all_tags = '|'.join(dataset['tags']).lower
all_tags = pattern.sub('', all_tags)
all_tags = all_tags.split('|')
print('found ' + str(len(all_tags)) + ' tags')
```

found 808183 tags

```
In [209]: # Lets look at top used tags
    counter=collections.Counter(all_tags)
    print('Videos trended by tag')
    counter.most_common(10)
```

Videos trended by tag

```
In [182]: # Didnt know how to do this with pandas, so its slow in a double for look ;/
           tags_by_video = dataset['tags'].str.split('|').tolist()
           views_by_video = dataset['views']
           combined = dict ()
           for i in range(len(tags_by_video)):
              for tag in tags_by_video[i]:
                   t = pattern.sub('', tag).lower()
                   if combined.get(t):
                       combined[t][0] += views_by_video[i]
                       combined[t][1] += 1
                       combined[t] = [views_by_video[i],1]
               if i % 10000 == 0: print(str(i/len(tags_by_video))[:5] + '%')
          print('processing. . .')
          0.0%
          0.244%
          0.488%
          0.732%
          0.976%
          processing. . .
In [203]: # Create a dataframe to show the tags
           rows = [ {'tag':a,'views':b,'trends':c} for a,(b,c) in combined.items() ]
           tagsData = pd.DataFrame( rows)
In [204]: tagsData = tagsData.drop([tagsData.index[116]])
In [205]: # Clearly music tags trend in most views, but not most number of times
           tagsData.sort_values(by='views',ascending=False)[:5]
Out[205]:
                      tag trends
                                      views
           2692
                           1634
                                 11327075747
                      pop
           3595
                            382
                                 6609541543
                      rap
             23
                           4142
                                 6459300503
                    funny
             48
                           3647
                                 5759029286
                   comedy
                            753
                                 4919357940
            715 musicvideo
```

## Out[206]:

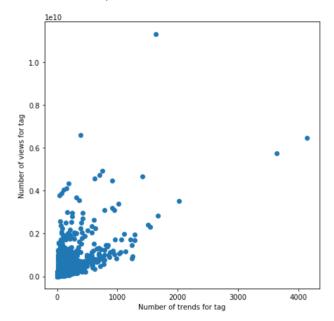
	tag	trends	views
23	funny	4142	6459300503
48	comedy	3647	5759029286
111	howto	2026	3527731838
708	music	1667	2821610384
2692	рор	1634	11327075747

In [206]: # Comedy is dramaticly more likely to trend again when compaired to musical tags

tagsData.sort\_values(by='trends',ascending=False)[:5]

```
In [228]: # Try charting this data
fig, a = plot.subplots(figsize=(7,7))
a.scatter(tagsData['trends'], tagsData['views'])
a.set_ylabel('Number of views for tag')
a.set_xlabel('Number of trends for tag')
print('Not sure if this plot is usefull')
```

Not sure if this plot is usefull



# Finaly, I want to see if telling people like a video actually gets more likes?

Just curious about that

```
In [216]: like_dataset=pd.DataFrame()
           like_dataset['ask_to_like'] = dataset['description'].str.contains("like")
like_dataset['likes'] = dataset['likes']
           like_dataset.head()
Out[216]:
               ask_to_like
                           likes
                    True
                          57527
                           2486
                   False
            2
                           4451
                   False
                    True
                           7250
                   False 115426
In [227]: # Wow! thats actually fairly decisive
           asked_likes = like_dataset[ like_dataset['ask_to_like'] == True]['likes'].mean()
           didnt_ask_likes = like_dataset[ like_dataset['ask_to_like'] == False ]['likes'].mean()
           print('If asked, mean of ' + str(asked_likes)[:8] )
           print('If didnt asked, mean of ' + str(didnt_ask_likes)[:8] )
           print('You saw it here, asking people to leave a video a like actually gets you less likes! ')
           If asked, mean of 60704.67
           If didnt asked, mean of 77105.84
           You saw it here, asking people to leave a video a like actually gets you less likes!
```

### **Conclusions**

What requirements are their to get your video trending?

- You seem to need a certain amount of views and engagement
- It helps to be have your video in a few key cataglories
- · When looking at Frequently Trending Channels:
  - Education, comedy & News channels trend more and with fewer views than anyone else others
  - Music channels will often trend, but only with a high view count, and you shouldnt expect to trend often
  - Gaming chanels are even less likely to trend frequently and need a similarly high number of views
  - News, Comody, and Entertainment channels are among the most over-represented chanels on the trending list
    - Trending hundreds of times with less views than many music video chanels
- Trending before is a high likelyhood of trending again

#### How long till you trend?

- · Trending will happen withing a few days and sharply falls off after that
- Some select older videos will pop on after a while, but reletively rare
- Trend in the first 3 days or dont trend at all if true in vast majority of cases

#### What metrics dont matter?

- · Dislikes dont seem to effect trending at all
- · Views, after about 5 Million, do not have any impact it seems

#### What helps the video do well?

- · Aparently asking for likes is not helpful in getting likes
- Tags by themselves dont seem to indicate much
  - However, you get optimal views with 5ish tags, the more tags the lower the views
  - More than 60 tags and views start to fall fast
  - However, that is relative to other good videos, so += 10 Milion views isnt much in that ranking

In [ ]:	
---------	--