Exploring the data set I was given

Loading it all in

In [191]:
```
import os
import pandas as pd
import json
```

In [192]:
```
cat_path = 'cataglories.json'
vid_path = 'USvideos.csv'
```

In [193]:
```
# Read file sizes, seems like a lot of videos
MB = os.stat(vid_path).st_size / 1000 / 1000
print('Data ' + str(MB) + 'mb')
```

```
Data 62.756152mb
```

In [194]:
```
# Its not really that much, so load it all into memory
raw_videoData = pd.read_csv( vid_path )
with open(cat_path) as f:
  data = json.load(f)
raw_jsonData = pd.DataFrame([ {'label': item['snippet']['title'], 'id' : item['id']}  for (i,item) in enumerate(list(da
ta['items'])) ])
raw_jsonData['id'] = raw_jsonData['id'].astype(int)
```

In [195]:
```
# replace category ID with actual name
combined_data = raw_videoData.merge(raw_jsonData, left_on='category_id', right_on='id')
combined_data.head()
```

Out[195]:

	video_id	trending_date	title	channel_title	category_id	publish_time	tags	views	
0	2kyS6SvSYSE	17.14.11	WE WANT TO TALK ABOUT OUR MARRIAGE	CaseyNeistat	22	2017-11-13T17:13:01.000Z	SHANtell martin	748374	5
1	0mlNzVSJrT0	17.14.11	Me-O Cats Commercial	Nobrand	22	2017-04-21T06:47:32.000Z	cute|"cats"|"thai"|"eggs"	98966	
2	STI2fl7sKMo	17.14.11	AFFAIRS, EX BOYFRIENDS, $18MILLION NET WORTH -...	Shawn Johnson East	22	2017-11-11T15:00:03.000Z	shawn johnson|"andrew east"|"shawn east"|"shaw...	321053	
3	KODzih-pYIU	17.14.11	BLIND(folded) CAKE DECORATING CONTEST (with Mo...	Grace Helbig	22	2017-11-11T18:08:04.000Z	itsgrace|"funny"|"comedy"|"vlog"|"grace"|"helb...	197062	
4	8mhTWqWIQzU	17.14.11	Wearing Online Dollar Store Makeup For A Week	Safiya Nygaard	22	2017-11-11T01:19:33.000Z	wearing online dollar store makeup for a week|...	2744430	11

In [196]:
```
# lots of un-needed columns, lets drop what i dont want for now and leave what sounds interesting
dataset = combined_data.reindex(columns=['trending_date', 'title', 'channel_title', 'publish_time','tags','views','like
s','dislikes','comment_count','description','label'])
dataset.head()
```

Out[196]:

	trending_date	title	channel_title	publish_time	tags	views	likes	dislikes	comment_cou
0	17.14.11	WE WANT TO TALK ABOUT OUR MARRIAGE	CaseyNeistat	2017-11-13T17:13:01.000Z	SHANtell martin	748374	57527	2966	159
1	17.14.11	Me-O Cats Commercial	Nobrand	2017-04-21T06:47:32.000Z	cute|"cats"|"thai"|"eggs"	98966	2486	184	5
2	17.14.11	AFFAIRS, EX BOYFRIENDS, $18MILLION NET WORTH -...	Shawn Johnson East	2017-11-11T15:00:03.000Z	shawn johnson|"andrew east"|"shawn east"|"shaw...	321053	4451	1772	8
3	17.14.11	BLIND(folded) CAKE DECORATING CONTEST (with Mo...	Grace Helbig	2017-11-11T18:08:04.000Z	itsgrace|"funny"|"comedy"|"vlog"|"grace"|"helb...	197062	7250	217	4
4	17.14.11	Wearing Online Dollar Store Makeup For A Week	Safiya Nygaard	2017-11-11T01:19:33.000Z	wearing online dollar store makeup for a week|...	2744430	115426	1110	65

Exploring publication vs days untill trending date

In [197]:
```
import matplotlib.pyplot as plot
```

In [198]:
```
# How long before each video trends on average
trending_time = pd.to_datetime('20' + dataset['trending_date'], format="%Y.%d.%m").dt.tz_localize('UTC')
publish_time = pd.to_datetime(dataset['publish_time'])
delta_time = trending_time - publish_time
trendings =  pd.DataFrame({'time': delta_time, 'days': delta_time / pd.to_timedelta(1, unit='D'), 'cat' : dataset['labe
l']})
trendings.head()
```

Out[198]:

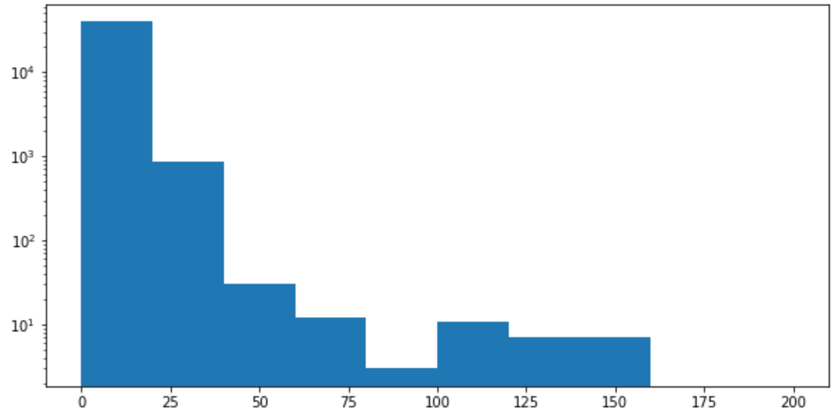
	time	days	cat
0	0 days 06:46:59	0.282627	People & Blogs
1	206 days 17:12:28	206.716991	People & Blogs
2	2 days 08:59:57	2.374965	People & Blogs
3	2 days 05:51:56	2.244398	People & Blogs
4	2 days 22:40:27	2.944757	People & Blogs

In [199]:
```
# Lets look at some stats from these values
print( 'Average time till trending: ', trendings['time'].mean())
print( 'Median time till trending: ', trendings['time'].median())
print('Lots of videos trend within a week, but a few long-term trenders pull up the average')
```

```
Average time till trending:  16 days 05:21:53.236220
Median time till trending:  4 days 18:59:55
Lots of videos trend within a week, but a few long-term trenders pull up the average
```

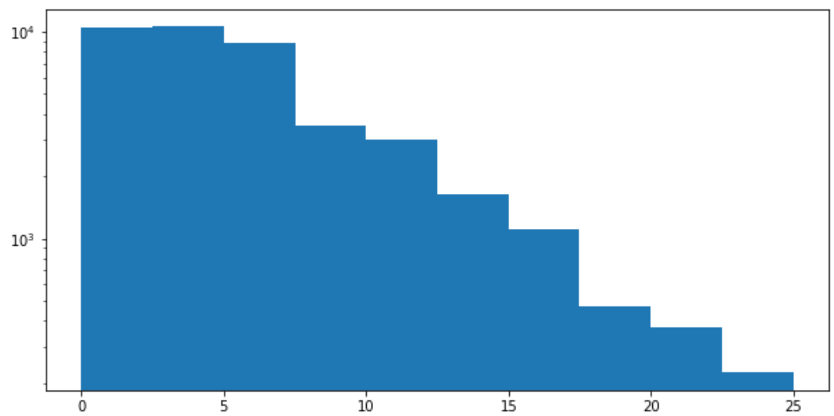
In [200]:
```
# Chart these numbers, log scale was more useful as it shows the range
plot.figure(figsize=(10,5))
plot.hist( trendings['days'].tolist(), range=(0,200), log=True )
```

Out[200]:
```
(array([3.9645e+04, 8.4800e+02, 3.0000e+01, 1.2000e+01, 3.0000e+00,
        1.1000e+01, 7.0000e+00, 7.0000e+00, 0.0000e+00, 0.0000e+00]),
 array([  0.,  20.,  40.,  60.,  80., 100., 120., 140., 160., 180., 200.]),
 <a list of 10 Patch objects>)
```



In [201]:
```
# Zooming into the first 25 days shows a straight logarthmic relationship
plot.figure(figsize=(10,5))
plot.hist( trendings['days'].tolist(), range=(0,25), log=True )
```

Out[201]:
```
(array([10481., 10588.,  8841.,  3536.,  2995.,  1625.,  1108.,   471.,
          372.,   224.]),
 array([ 0. ,  2.5,  5. ,  7.5, 10. , 12.5, 15. , 17.5, 20. , 22.5, 25. ]),
 <a list of 10 Patch objects>)
```

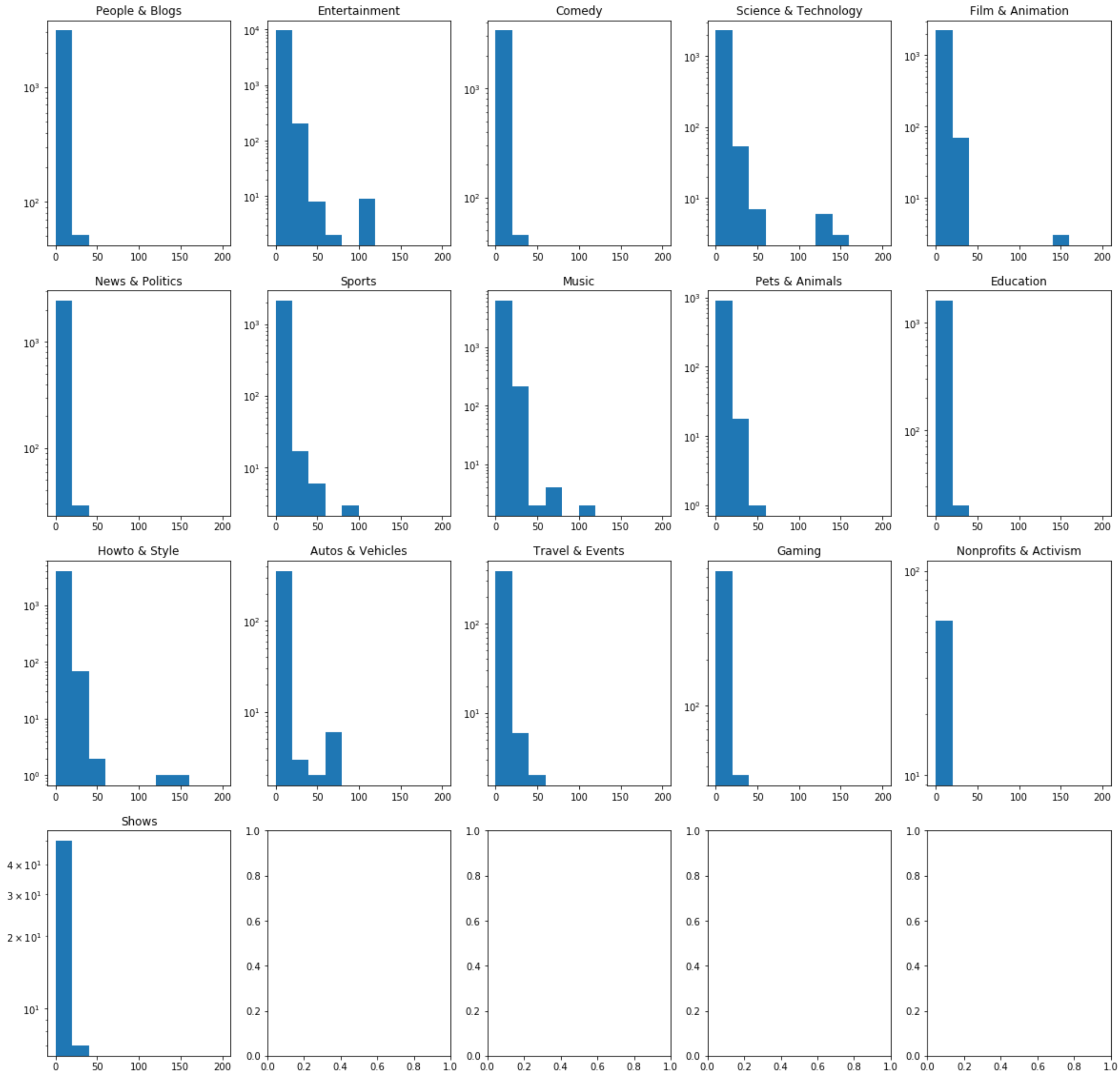


Notes on charts

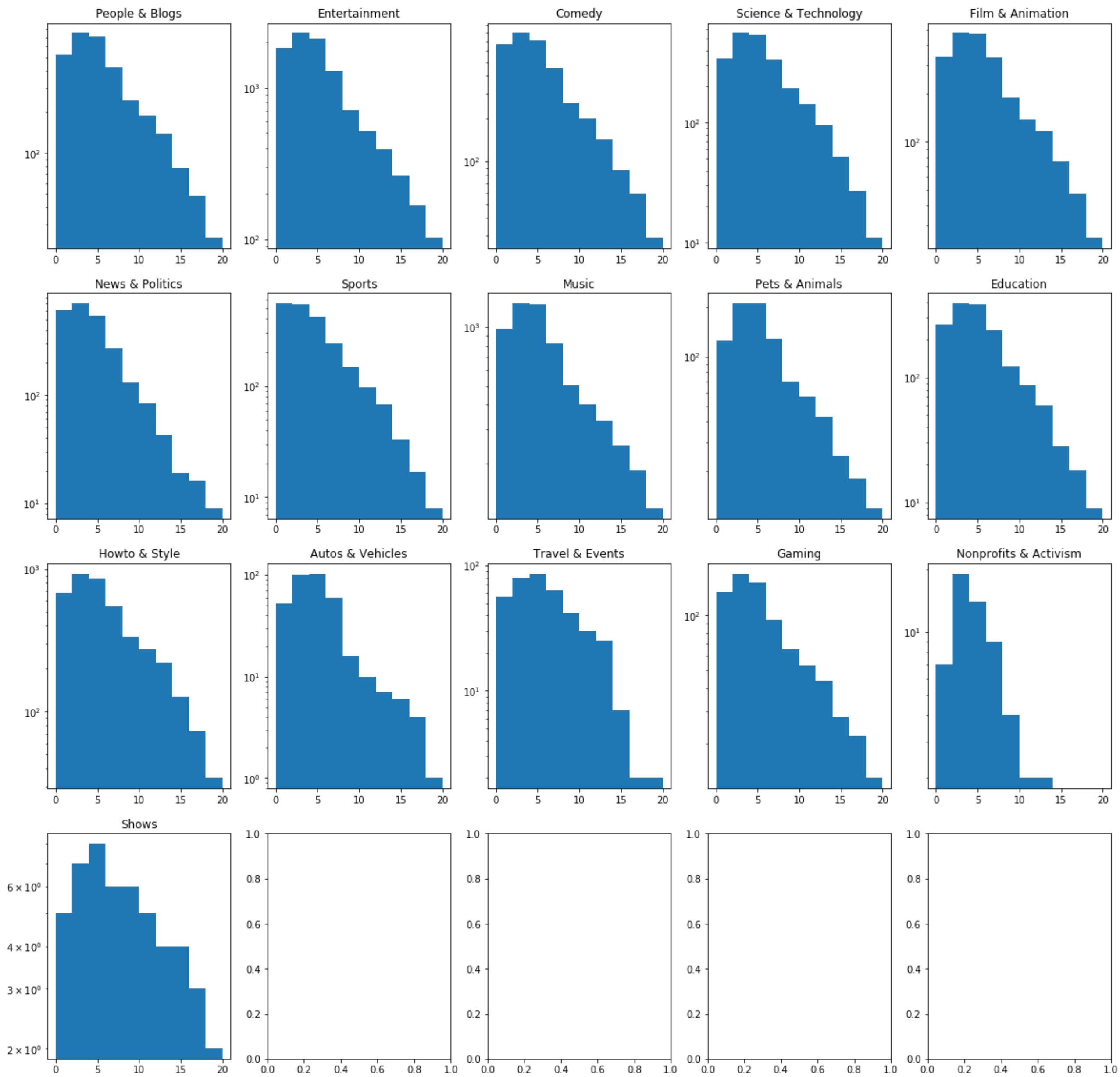
- Trending happens sooner than later in vast majority of cases
- However, older videos get a bump? Why is that

In [213]:
```
# Looking into trending by cataglory
def chartAll (range) :
    all_cats = trendings['cat'].unique()
    fig, axs = plot.subplots(4,5,figsize=(20,20))
    for (i,cat) in enumerate(all_cats):
        x = i // 5
        y = i % 5
        data = trendings['days'][ trendings['cat'] == cat ]
        axs[x,y].hist(data.tolist(), range=(0,range), log=True)
        axs[x,y].set_title(cat)
```

In [214]:
```
# Looking overall
chartAll( 200 )
```



In [215]:
```
# Looking close
chartAll ( 20 )
```



Notes on further charts

- With the exception of Nonprofits & Shows which seems to take a little bit of time to catch on, most cataglories trend quickly at the same rate
- But The cataglory makes a massive difference when it comes to how long a video is elegeble to trend for

Exploring by chanel breakdowns

In [216]:
```
# What chanel does it the best?
trending_by_channel = pd.DataFrame( dataset['channel_title'].value_counts() )
trending_by_channel = pd.DataFrame({ 'channel' : trending_by_channel.index, 'count' : trending_by_channel['channel_titl
e']}).reset_index(drop=True)
trending_by_channel.head()
```

Out[216]:

	channel	count
0	ESPN	203
1	The Tonight Show Starring Jimmy Fallon	197
2	Netflix	193
3	Vox	193
4	TheEllenShow	193

In [217]:
```
# What about total metrics by chanel?
channel_total_metrics = dataset.groupby('channel_title').sum()
```

In [218]:
```
# Total of varius metrics by chanel and trending count
trending_by_channel = trending_by_channel.merge(channel_total_metrics, left_on='channel', right_on='channel_title')
trending_by_channel.head()
```

Out[218]:

	channel	count	views	likes	dislikes	comment_count
0	ESPN	203	105654218	937723	108043	387753
1	The Tonight Show Starring Jimmy Fallon	197	271426383	5981334	187407	403655
2	Netflix	193	185818315	4211072	196212	391350
3	Vox	193	122633963	3272518	615977	558845
4	TheEllenShow	193	253841999	6035132	193602	344469

In [219]:
```
# add in content type
cataglories = pd.DataFrame(dataset.groupby('channel_title')['label'].first())
trending_by_channel = trending_by_channel.merge(cataglories, left_on='channel', right_on='channel_title')
trending_by_channel.head()
```

Out[219]:

	channel	count	views	likes	dislikes	comment_count	label
0	ESPN	203	105654218	937723	108043	387753	Sports
1	The Tonight Show Starring Jimmy Fallon	197	271426383	5981334	187407	403655	Comedy
2	Netflix	193	185818315	4211072	196212	391350	Entertainment
3	Vox	193	122633963	3272518	615977	558845	News & Politics
4	TheEllenShow	193	253841999	6035132	193602	344469	Entertainment

In [221]:
```python
# Now lets look at how some of these chanels stack up!
chanels_by_views = trending_by_channel.sort_values(by='views', ascending=False)
chanels_by_views[:20]
# By views music chanels dominate, but that makes sense.
# With such high views they dont seem to trend that often though.
```

Out[221]:

	channel	count	views	likes	dislikes	comment_count	label
420	ChildishGambinoVEVO	25	3758488765	96700818	6054434	10151289	Music
97	ibighit	80	2235906679	199247121	3467306	31817464	Music
36	Dude Perfect	131	1870085178	60275557	1501477	4009163	Sports
39	Marvel Entertainment	125	1808998971	55873344	1031250	6453560	Entertainment
252	ArianaGrandeVevo	43	1576959172	52170970	1931230	4295333	Music
344	MalumaVEVO	32	1551515831	23278380	1757948	1227634	Music
140	jypentertainment	64	1486972132	44900910	2482131	7575510	Music
83	Sony Pictures Entertainment	88	1432374398	30106808	1414686	3533551	Entertainment
349	FoxStarHindi	32	1238609854	23762509	910745	1782776	Entertainment
507	BeckyGVEVO	20	1182971286	19185287	1616616	1176862	Music
33	20th Century Fox	135	1082872611	24419452	488761	1509224	Film & Animation
247	CalvinHarrisVEVO	43	1042564430	17958660	716558	588676	Music
221	Ed Sheeran	47	1032288961	39279211	769501	1950501	Music
366	Cardi B	30	1026247756	26724811	1431459	1692916	People & Blogs
207	TaylorSwiftVEVO	49	1010955662	39292840	2127542	3352611	Music
55	Universal Pictures	106	883707419	12481737	529442	1351963	Entertainment
285	ZaynVEVO	39	838561451	31695245	777336	2144996	Music
271	Disney•Pixar	40	826815182	13623208	449099	1410747	Film & Animation
242	JenniferLopezVEVO	44	819466359	14238664	1658325	980470	Music
381	Selena Gomez	28	818792483	20165850	346079	1002366	Film & Animation

In [225]:
```python
# What about by engagement? Likes?
chanels_by_likes = trending_by_channel.sort_values(by='likes', ascending=False)
chanels_by_likes[:20]
# Again its music, makes sense again
```

Out[225]:

	channel	count	views	likes	dislikes	comment_count	label
97	ibighit	80	2235906679	199247121	3467306	31817464	Music
420	ChildishGambinoVEVO	25	3758488765	96700818	6054434	10151289	Music
36	Dude Perfect	131	1870085178	60275557	1501477	4009163	Sports
39	Marvel Entertainment	125	1808998971	55873344	1031250	6453560	Entertainment
252	ArianaGrandeVevo	43	1576959172	52170970	1931230	4295333	Music
140	jypentertainment	64	1486972132	44900910	2482131	7575510	Music
207	TaylorSwiftVEVO	49	1010955662	39292840	2127542	3352611	Music
221	Ed Sheeran	47	1032288961	39279211	769501	1950501	Music
285	ZaynVEVO	39	838561451	31695245	777336	2144996	Music
438	Logan Paul Vlogs	24	484356303	31545290	13847251	14870370	Entertainment
117	SMTOWN	72	345614221	31226522	416165	3346026	Music
83	Sony Pictures Entertainment	88	1432374398	30106808	1414686	3533551	Entertainment
82	nigahiga	89	590616191	29395172	656512	2203993	Entertainment
283	BANGTANTV	39	222708704	28718114	104879	1869243	Entertainment
366	Cardi B	30	1026247756	26724811	1431459	1692916	People & Blogs
171	ShawnMendesVEVO	58	442730335	25455119	193107	1461993	Music
32	Safiya Nygaard	139	528434394	25344263	350015	4419873	People & Blogs
33	20th Century Fox	135	1082872611	24419452	488761	1509224	Film & Animation
349	FoxStarHindi	32	1238609854	23762509	910745	1782776	Entertainment
322	Maroon5VEVO	34	516169845	23285980	456914	1360816	Music

In [226]:
```python
# What about by engagement? Likes?
chanels_by_comments = trending_by_channel.sort_values(by='comment_count', ascending=False)
chanels_by_comments[:20]
# Damn you music! Lets just get rid of them, seems to be an outlier group
```

Out[226]:

	channel	count	views	likes	dislikes	comment_count	label
97	ibighit	80	2235906679	199247121	3467306	31817464	Music
438	Logan Paul Vlogs	24	484356303	31545290	13847251	14870370	Entertainment
420	ChildishGambinoVEVO	25	3758488765	96700818	6054434	10151289	Music
140	jypentertainment	64	1486972132	44900910	2482131	7575510	Music
572	YouTube Spotlight	18	791388476	20173324	10924092	6495154	Entertainment
39	Marvel Entertainment	125	1808998971	55873344	1031250	6453560	Entertainment
32	Safiya Nygaard	139	528434394	25344263	350015	4419873	People & Blogs
252	ArianaGrandeVevo	43	1576959172	52170970	1931230	4295333	Music
263	Call of Duty	41	315404711	11553594	5644083	4224430	Gaming
26	jacksfilms	148	199608855	13991372	402276	4074130	Comedy
36	Dude Perfect	131	1870085178	60275557	1501477	4009163	Sports
83	Sony Pictures Entertainment	88	1432374398	30106808	1414686	3533551	Entertainment
207	TaylorSwiftVEVO	49	1010955662	39292840	2127542	3352611	Music
117	SMTOWN	72	345614221	31226522	416165	3346026	Music
108	How Ridiculous	75	612065519	12759049	1003622	3057506	Sports
290	jeffreestar	38	83243512	4798227	100827	3009734	Howto & Style
40	AsapSCIENCE	124	640139160	10761634	622432	2813511	Science & Technology
998	David Dobrik	9	255451991	16537616	802335	2673859	People & Blogs
51	NikkieTutorials	109	250831472	16486069	244633	2673634	Howto & Style
45	James Charles	118	308971512	19723756	517059	2653693	Entertainment

In [229]:
```python
trending_by_channel_musicless = trending_by_channel[ trending_by_channel['label'] != 'Music' ]
trending_by_channel_musicless[:20]
# Removing music, you see a lot of corperate shows, wow
# Late night is trending a lot
# ESPN, VOX, WIRED, CNN
# Big media stuff
```

Out[229]:

	channel	count	views	likes	dislikes	comment_count	label
0	ESPN	203	105654218	937723	108043	387753	Sports
1	The Tonight Show Starring Jimmy Fallon	197	271426383	5981334	187407	403655	Comedy
2	Netflix	193	185818315	4211072	196212	391350	Entertainment
3	Vox	193	122633963	3272518	615977	558845	News & Politics
4	TheEllenShow	193	253841999	6035132	193602	344469	Entertainment
5	The Late Show with Stephen Colbert	187	123675646	1511686	172466	217376	People & Blogs
6	Jimmy Kimmel Live	186	285418753	4844377	389653	514641	Entertainment
7	Late Night with Seth Meyers	183	181602246	2098813	145073	259698	Comedy
8	Screen Junkies	182	319075554	8836325	336492	1130838	Film & Animation
9	NBA	181	72404568	878898	83248	100271	Sports
10	CNN	180	134813215	1688429	735557	1621664	News & Politics
11	Saturday Night Live	175	508000869	5900836	736761	681410	Entertainment
12	WIRED	171	253980390	8295234	154477	543557	Entertainment
13	BuzzFeedVideo	169	319288139	7311734	495874	825334	People & Blogs
14	INSIDER	167	342052217	4121487	124202	230434	People & Blogs
15	The Late Late Show with James Corden	163	296789992	9352398	218041	554303	People & Blogs
16	TED-Ed	162	72834398	2556190	49532	184071	Education
17	Tom Scott	159	128537887	4698666	127322	477971	Education
18	WWE	157	437968663	6714593	376881	829723	Sports
19	CollegeHumor	156	143700307	4892870	269424	414149	Comedy

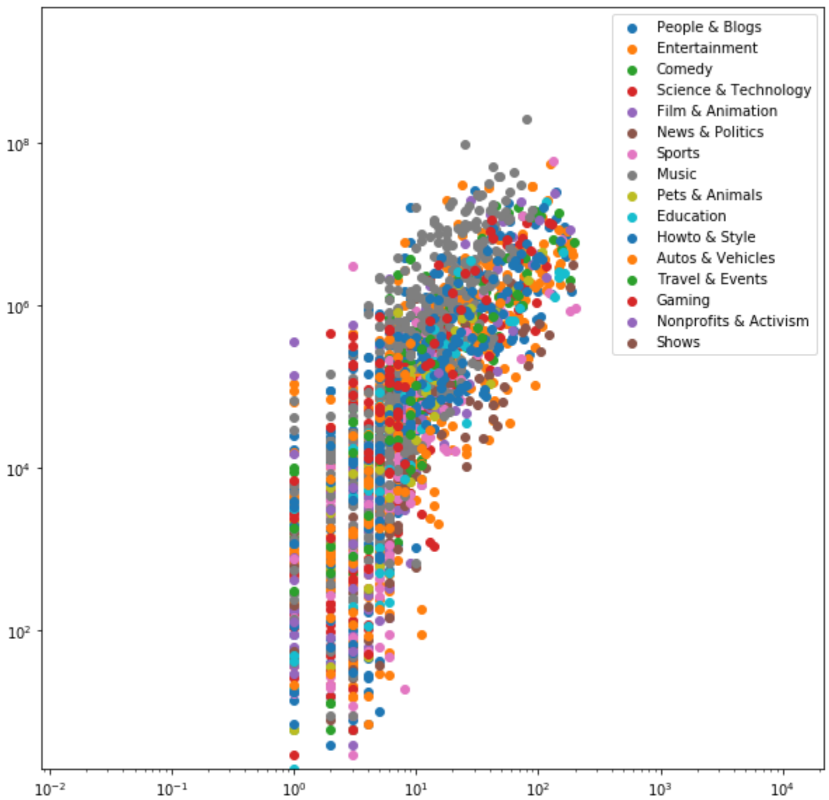
In [231]:
```
trending_by_channel_musicless.sort_values(by='views', ascending=False)[:20]
# Wow, and the chanels that get tons of views dont trend that much in comparison. Interesting
```

Out[231]:

	channel	count	views	likes	dislikes	comment_count	label
36	Dude Perfect	131	1870085178	60275557	1501477	4009163	Sports
39	Marvel Entertainment	125	1808998971	55873344	1031250	6453560	Entertainment
83	Sony Pictures Entertainment	88	1432374398	30106808	1414686	3533551	Entertainment
349	FoxStarHindi	32	1238609854	23762509	910745	1782776	Entertainment
33	20th Century Fox	135	1082872611	24419452	488761	1509224	Film & Animation
366	Cardi B	30	1026247756	26724811	1431459	1692916	People & Blogs
55	Universal Pictures	106	883707419	12481737	529442	1351963	Entertainment
271	Disney•Pixar	40	826815182	13623208	449099	1410747	Film & Animation
381	Selena Gomez	28	818792483	20165850	346079	1002366	Film & Animation
572	YouTube Spotlight	18	791388476	20173324	10924092	6495154	Entertainment
24	Warner Bros. Pictures	150	665142792	5952414	760592	995175	Entertainment
40	AsapSCIENCE	124	640139160	10761634	622432	2813511	Science & Technology
150	Paramount Pictures	62	626892103	7111057	285893	811011	Film & Animation
108	How Ridiculous	75	612065519	12759049	1003622	3057506	Sports
82	nigahiga	89	590616191	29395172	656512	2203993	Entertainment
32	Safiya Nygaard	139	528434394	25344263	350015	4419873	People & Blogs
11	Saturday Night Live	175	508000869	5900836	736761	681410	Entertainment
438	Logan Paul Vlogs	24	484356303	31545290	13847251	14870370	Entertainment
79	Bad Lip Reading	92	476570575	14866609	340444	808214	Comedy
267	Clash Royale	40	465597843	8495526	610654	681138	Gaming

In [264]:
```
# Lets chart this all out to see what trends more or less
# This chart sucks btw haha
def plotCataglory  top_50 = trending_by_channel[:50]
fig, axs = plot.subplots(figsize=(10,10))
axs.set_yscale('log')
axs.set_xscale('log')
all_cats = trendings['cat'].unique()
for (i,cat) in enumerate(all_cats):
    cat_representation = trending_by_channel[trending_by_channel.label == cat]
    plot.scatter(cat_representation['count'], cat_representation['likes'], label=cat)
plot.legend()
```

Out[264]:
```
<matplotlib.legend.Legend at 0x1ceb9a70400>
```



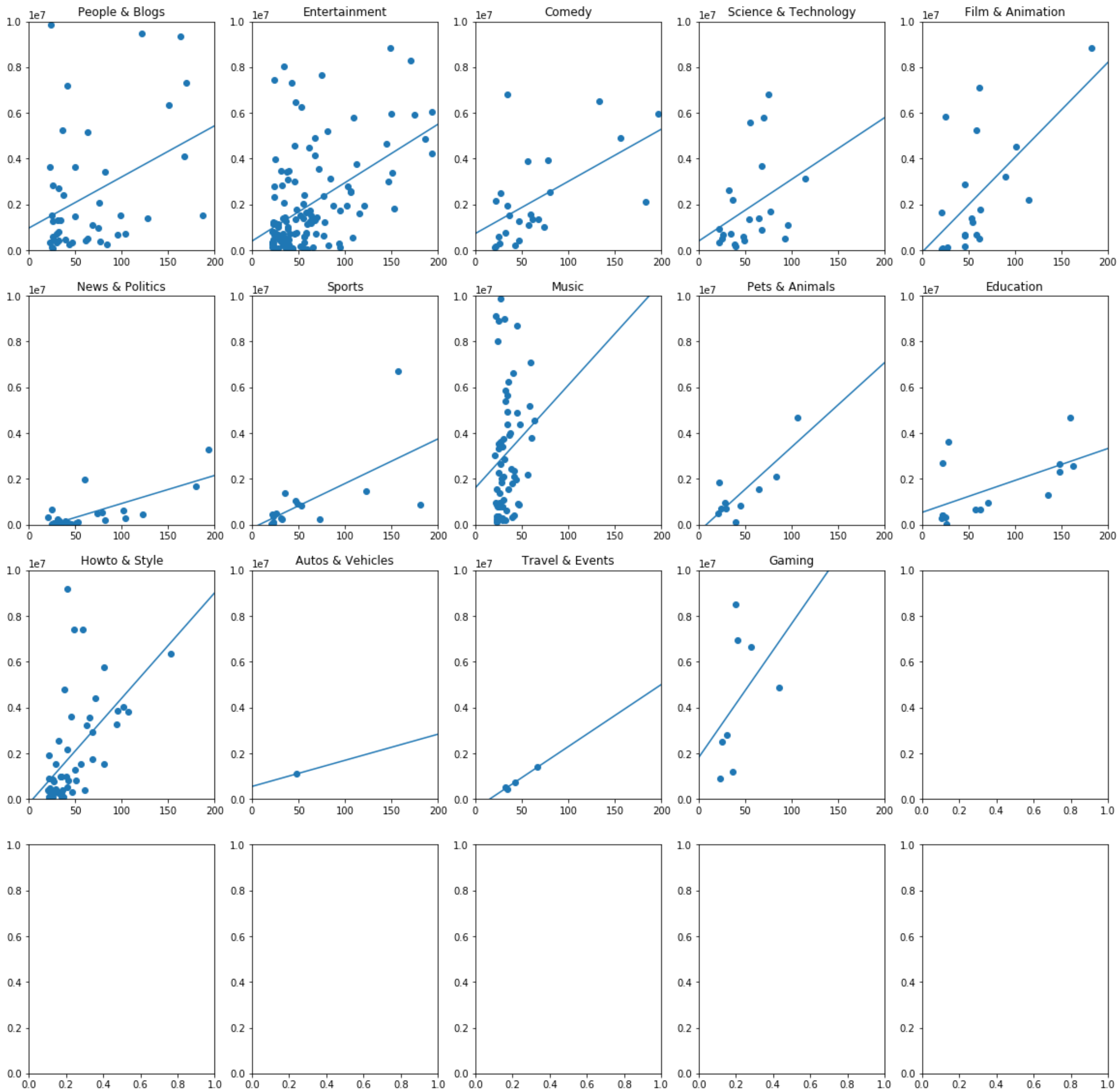
In [320]:
```
import numpy as np
import matplotlib.lines as mlines
```

In [321]:
```
def newline(a, p1, p2):
    xmin, xmax = a.get_xbound()

    if(p2[0] == p1[0]):
        xmin = xmax = p1[0]
        ymin, ymax = ax.get_ybound()
    else:
        ymax = p1[1]+(p2[1]-p1[1])/(p2[0]-p1[0])*(xmax-p1[0])
        ymin = p1[1]+(p2[1]-p1[1])/(p2[0]-p1[0])*(xmin-p1[0])

    l = mlines.Line2D([xmin,xmax], [ymin,ymax])
    a.add_line(l)
    return l
```

In [339]:
```
def chartAll () :
    lines = []
    all_cats = trendings['cat'].unique()
    fig, axs = plot.subplots(4,5,figsize=(20,20))
    for (i,cat) in enumerate(all_cats):

        # Get Data
        cat_representation = trending_by_channel[:500][trending_by_channel.label == cat]
        cat_representation = cat_representation[cat_representation['count'] < 200 ]
        cat_representation = cat_representation[cat_representation['likes'] < 10000000 ]
        xData = cat_representation['count']
        yData = cat_representation['likes']

        if len(cat_representation) is 0: continue

        # Scale Chart
        x = i // 5
        y = i % 5
        axs[x,y].set_xlim((0,200))
        axs[x,y].set_ylim((0,10000000))

        # Chart
        axs[x,y].scatter(xData, yData, label=cat)
        axs[x,y].set_title(cat)

        # Get Trend Line
        z = np.polyfit(x=np.array(xData.values), y=np.array(yData.values), deg=1)
        lines.append((cat,z[0]))

        newline(axs[x,y],(0,z[1]),(1,z[1] + z[0]))

    return lines
```

```
In [340]: # X axis denotes number of times trending
          # Y Axis is number of views on trending videos
          slopeLines = chartAll()
```

```
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:8: UserWarning: Boolean Series key will be reindexed t
o match DataFrame index.

C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:27: RankWarning: Polyfit may be poorly conditioned
```



Particular importance of Education & News and politics

- These two cataglories are highly moved right relative to other cataglories
- It it much easier to trend in these cataglories than others it seems
- Some of these slops are not perfect, Music is ceratinly wrong, should use a methon that minimizes distance not height to line

In [344]:

```
# Line slopes generated for data
slopeLines
```

Out[344]:

```
[('People & Blogs', 22405.30725244264),
 ('Entertainment', 25559.61725749245),
 ('Comedy', 22819.115517921164),
 ('Science & Technology', 27010.445122485333),
 ('Film & Animation', 41565.14214501562),
 ('News & Politics', 12270.516339244816),
 ('Sports', 19525.213522193957),
 ('Music', 44937.291298734366),
 ('Pets & Animals', 36968.19644837616),
 ('Education', 13984.134917312125),
 ('Howto & Style', 46148.17901087852),
 ('Autos & Vehicles', 11426.218749999995),
 ('Travel & Events', 27160.537467700276),
 ('Gaming', 58590.44658119666)]
```

In [355]:

```
# Lets rank trending chance basted on this slope!
# Average out lines
catSlopes = pd.DataFrame ( slopeLines )
catSlopes['trendSlope'] = catSlopes[1] / catSlopes[1].max()

# This ranks the strenght of trending of the cataglories
# Higher is much less likely to trend, needs more views to get onto trending
catSlopes.sort_values(by='trendSlope', ascending=False)
```

Out[355]:

	0	1	trendSlope
13	Gaming	58590.446581	1.000000
10	Howto & Style	46148.179011	0.787640
7	Music	44937.291299	0.766973
4	Film & Animation	41565.142145	0.709418
8	Pets & Animals	36968.196448	0.630959
12	Travel & Events	27160.537468	0.463566
3	Science & Technology	27010.445122	0.461004
1	Entertainment	25559.617257	0.436242
2	Comedy	22819.115518	0.389468
0	People & Blogs	22405.307252	0.382405
6	Sports	19525.213522	0.333249
9	Education	13984.134917	0.238676
5	News & Politics	12270.516339	0.209429
11	Autos & Vehicles	11426.218750	0.195018

In [356]:

```
# Inverted it so higher is more likely to trend, relative strength ish
catSlopes['trendingStrength'] = 1 / ( catSlopes[1] / catSlopes[1].max())
catSlopes.sort_values(by='trendingStrength', ascending=False)
```

Out[356]:

	0	1	trendSlope	trendingStrength
11	Autos & Vehicles	11426.218750	0.195018	5.127720
5	News & Politics	12270.516339	0.209429	4.774897
9	Education	13984.134917	0.238676	4.189780
6	Sports	19525.213522	0.333249	3.000758
0	People & Blogs	22405.307252	0.382405	2.615025
2	Comedy	22819.115518	0.389468	2.567604
1	Entertainment	25559.617257	0.436242	2.292305
3	Science & Technology	27010.445122	0.461004	2.169177
12	Travel & Events	27160.537468	0.463566	2.157190
8	Pets & Animals	36968.196448	0.630959	1.584888
4	Film & Animation	41565.142145	0.709418	1.409605
7	Music	44937.291299	0.766973	1.303827
10	Howto & Style	46148.179011	0.787640	1.269616
13	Gaming	58590.446581	1.000000	1.000000

Conclusion

So it seems like News & Politics / Education / Auto & Vehicles are the key to trending on youtube

Looking at the line and scatter charts above, gaming and music get so many views! but they rairly trend.

On the other hand, News gets hardly any views, but trends all the time.

Late night shows are particularly for topping a lot of the trending charts but none of the view charts

```
In [ ]:
```