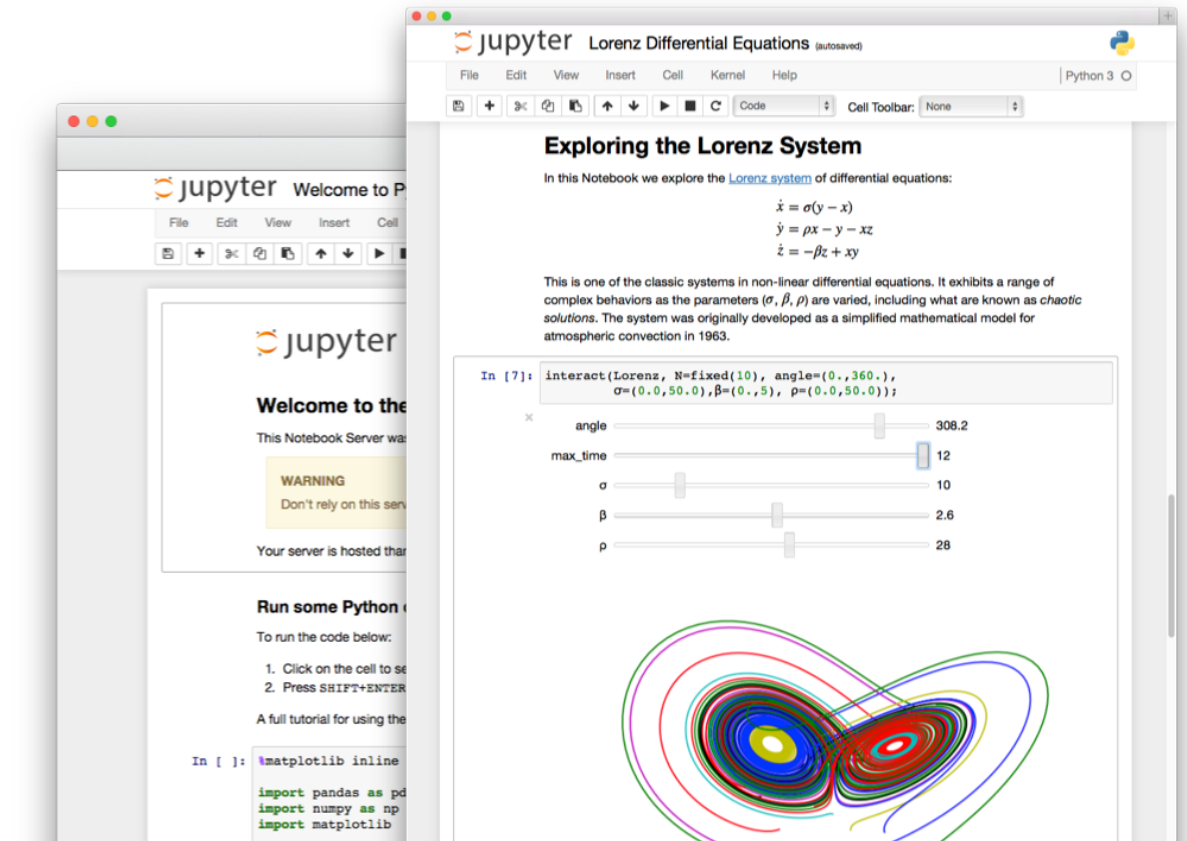


# Instructions ¶

- The latest version of this notebook can always be found and viewed online [here](https://github.com/mdbecker/daa_philly_2015/blob/master/DataPhilly_Analysis.ipynb) ([https://github.com/mdbecker/daa\\_philly\\_2015/blob/master/DataPhilly\\_Analysis.ipynb](https://github.com/mdbecker/daa_philly_2015/blob/master/DataPhilly_Analysis.ipynb)). **It's strongly recommended that you view the online version of this document**
- Instructions for setting up Jupyter Notebook and the required libraries can be found online [here](https://github.com/mdbecker/daa_philly_2015/blob/master/README.md) ([https://github.com/mdbecker/daa\\_philly\\_2015/blob/master/README.md](https://github.com/mdbecker/daa_philly_2015/blob/master/README.md)).
- The repo for this project can be found and forked [here](https://github.com/mdbecker/daa_philly_2015/) ([https://github.com/mdbecker/daa\\_philly\\_2015/](https://github.com/mdbecker/daa_philly_2015/)).

## Jupyter Notebook

The Jupyter Notebook is a web application that allows you to create and share documents that contain live code, equations, visualizations and explanatory text. Uses include: data cleaning and transformation, numerical simulation, statistical modeling, machine learning and much more.



Through Jupyter's kernel and messaging architecture, the Notebook allows code to be run in a range of different programming languages. For each notebook document that a user opens, the web application starts a kernel that runs the code for that notebook. Each kernel is capable of running code in a single programming language and there are kernels available in the following languages

- Python (<https://github.com/ipython/ipython> (<https://github.com/ipython/ipython>))
- Julia (<https://github.com/JuliaLang/IJulia.jl> (<https://github.com/JuliaLang/IJulia.jl>))
- R (<https://github.com/takluyver/IRkernel> (<https://github.com/takluyver/IRkernel>))
- Ruby (<https://github.com/minrk/iruby> (<https://github.com/minrk/iruby>))
- Haskell (<https://github.com/gibiansky/IHaskell> (<https://github.com/gibiansky/IHaskell>))
- Scala (<https://github.com/Bridgewater/scala-notebook> (<https://github.com/Bridgewater/scala-notebook>))
- node.js (<https://gist.github.com/Carreau/4279371> (<https://gist.github.com/Carreau/4279371>))
- Go (<https://github.com/takluyver/igo> (<https://github.com/takluyver/igo>))

<https://github.com/jupyter/notebook/blob/master/docs/source/examples/Notebook/Examples%20and%20Tutorials%20for%20Data%20Science%20Users.ipynb>

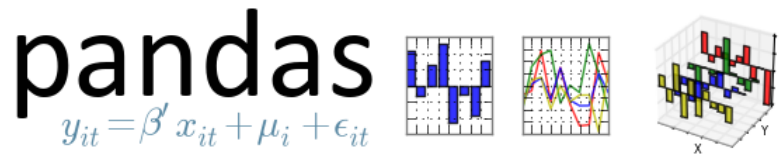
```
In [1]: %matplotlib inline
import seaborn as sns
import pandas as pd
from matplotlib import rcParams

# Modify aesthetics for visibility during presentation
sns.set_style('darkgrid', {'axes.facecolor': '#C2C2C8'})
sns.set_palette('colorblind')

# Make everything bigger for visibility during presentation
rcParams['figure.figsize'] = 20, 10
rcParams['axes.titlesize'] = 'xx-large'
rcParams['axes.labelsize'] = 'x-large'
rcParams['xtick.labelsize'] = 'x-large'
rcParams['ytick.labelsize'] = 'x-large'
rcParams['legend.fontsize'] = 'xx-large'
rcParams['lines.linewidth'] = 4.0
rcParams['grid.linewidth'] = 2.0

# Hide warnings in the notebook
import warnings
warnings.filterwarnings('ignore')
```

## Pandas



Pandas is a library that provides data analysis tools for the Python programming language. You can think of it as Excel on steroids, but in Python.

To start off, I've used the [meetup API \(http://www.meetup.com/meetup\\_api/docs/\)](http://www.meetup.com/meetup_api/docs/) to gather a bunch of data on members of the [DataPhilly meetup group \(http://www.meetup.com/DataPhilly/\)](http://www.meetup.com/DataPhilly/). First let's start off by looking at the events we've had over the past few years. I've loaded the data into a pandas DataFrame and stored it in the file `events.pkl`. A DataFrame is a table

similar to an Excel spreadsheet. Let's load it and see what it looks like:

```
In [2]: events_df = pd.read_pickle('events.pkl')
events_df = events_df.sort_values(by='time')
events_df
```

Out[2]:

	created	name	rating	time	waitlist_count	yes_rsvp_count	id
0	1351948193000	Meet and greet	{u'count': 3, u'average': 5}	1352934000000	0	17	89769502
1	1357781071000	DataPhilly January 2013 Meetup - An Introducti...	{u'count': 6, u'average': 4.17000007629}	1359588600000	0	61	98833672
2	1359732939000	DataPhilly February 2013 Meetup - Data Science...	{u'count': 5, u'average': 5}	1361316600000	0	47	102502622
3	1361647778000	DataPhilly March 2013 Meetup - Data Analysis u...	{u'count': 8, u'average': 5}	1364423400000	0	62	106043892
4	1362506708000	DataPhilly April 2013 Meetup - Machine Learnin...	{u'count': 7, u'average': 4.57000017166}	1366151400000	2	54	107740582
5	1369104714000	DataPhilly June 2013 - Hadoop: BigSheets & Pig	{u'count': 4, u'average': 3}	1370471400000	5	41	120425212
6	1375999505000	DataPhilly August 2013 - Data Science with R	{u'count': 11, u'average': 4.55000019073}	1377037800000	0	77	133803672
7	1378332108000	DataPhilly September 2013 - Data Storytime	{u'count': 9, u'average': 5}	1380234600000	0	64	138415912

8	1381360216000	DataPhilly October 2013 - Data Science Tools a...	{u'count': 11, u'average': 4.73000001907}	1382565600000	0	50	144769822
9	1383762778000	DataPhilly November 2013 - Data in Practice	{u'count': 3, u'average': 4.67000007629}	1384815600000	0	67	149515412
10	1389631621000	DataPhilly January 2014 - Two Hours of Lightni...	{u'count': 6, u'average': 4.82999992371}	1391036400000	0	69	160323532
11	1393608501000	DataPhilly March 2014 - Interactive Data Visua...	{u'count': 9, u'average': 4.67000007629}	1394661600000	0	69	168747852
12	1396956902000	DataPhilly April 2014: Art and Data	{u'count': 4, u'average': 4.75}	1397685600000	0	39	175993712
13	1400001749000	DataPhilly May 2014: Data Discovery	{u'count': 7, u'average': 5}	1400709600000	0	60	182860422
14	1410488369000	Explore All the Data!	{u'count': 2, u'average': 5}	1412719200000	0	44	206754182
15	1414103507000	Explore All the Data!	{u'count': 3, u'average': 4}	1415314800000	0	41	215265722
16	1417659431000	DataPhilly - December 2014	{u'count': 5, u'average': 5}	1418770800000	2	68	219055217
17	1421280214000	DataPhilly & GeoPhilly: Open Data Day Meetup	{u'count': 4, u'average': 4.5}	1424386800000	83	57	219840555
			{u'count': 3,				

<b>18</b>	1423955223000	DataPhilly: March Meetup	{u'average': 4.67000007629}	1426802400000	0	114	220526799
<b>19</b>	1426720048000	DataPhilly: April; Philly Tech Week Edition	{u'count': 9, u'average': 5}	1429221600000	19	115	221245827
<b>20</b>	1442763491000	DataPhilly October	{u'count': 6, u'average': 4.82999992371}	1445551200000	7	139	225488147

You can access values in a DataFrame column like this:

```
In [3]: events_df['yes_rsvp_count']
```

```
Out[3]: 0      17
1      61
2      47
3      62
4      54
5      41
6      77
7      64
8      50
9      67
10     69
11     69
12     39
13     60
14     44
15     41
16     68
17     57
18    114
19    115
20    139
```

```
Name: yes_rsvp_count, dtype: int64
```



You can access a row of a DataFrame using `iloc`:

```
In [4]: events_df.iloc[4]
```

```
Out[4]: created                1362506708000
name          DataPhilly April 2013 Meetup - Machine Learnin...
rating          {u'count': 7, u'average': 4.57000017166}
time                1366151400000
waitlist_count                2
yes_rsvp_count                54
id                107740582
Name: 4, dtype: object
```

We can view the first few rows using the `head` method:

```
In [5]: events_df.head()
```

```
Out[5]:
```

	created	name	rating	time	waitlist_count	yes_rsvp_count	id
0	1351948193000	Meet and greet	{u'count': 3, u'average': 5}	1352934000000	0	17	89769502
1	1357781071000	DataPhilly January 2013 Meetup - An Introducti...	{u'count': 6, u'average': 4.17000007629}	1359588600000	0	61	98833672
2	1359732939000	DataPhilly February 2013 Meetup - Data Science...	{u'count': 5, u'average': 5}	1361316600000	0	47	102502622
3	1361647778000	DataPhilly March 2013 Meetup - Data Analysis u...	{u'count': 8, u'average': 5}	1364423400000	0	62	106043892
4	1362506708000	DataPhilly April 2013 Meetup - Machine Learnin...	{u'count': 7, u'average': 4.57000017166}	1366151400000	2	54	107740582

And similarly the last few using `tail`:

```
In [6]: events_df.tail(3)
```

```
Out[6]:
```

	created	name	rating	time	waitlist_count	yes_rsvp_count	id
18	1423955223000	DataPhilly: March Meetup	{u'count': 3, u'average': 4.67000007629}	1426802400000	0	114	220526799
19	1426720048000	DataPhilly: April; Philly Tech Week Edition	{u'count': 9, u'average': 5}	1429221600000	19	115	221245827
20	1442763491000	DataPhilly October	{u'count': 6, u'average': 4.82999992371}	1445551200000	7	139	225488147

We can see that the `yes_rsvp_count` contains the number of people who RSVPed yes for each event. First let's look at some basic statistics:

```
In [7]: yes_rsvp_count = events_df['yes_rsvp_count']  
yes_rsvp_count.sum(), yes_rsvp_count.mean(), yes_rsvp_count.min(), yes_rsvp_count.max()
```

```
Out[7]: (1355, 64.523809523809518, 17, 139)
```

When we access a single column of the `DataFrame` like this we get a `Series` object which is just a 1-dimensional version of a `DataFrame`.

```
In [8]: type(yes_rsvp_count)
```

```
Out[8]: pandas.core.series.Series
```

We can use the built-in `describe` method to print out a lot of useful stats in a nice tabular format:

```
In [9]: yes_rsvp_count.describe()
```

```
Out[9]: count      21.000000  
mean       64.523810  
std        28.212797  
min        17.000000  
25%        47.000000  
50%        61.000000  
75%        69.000000  
max       139.000000  
Name: yes_rsvp_count, dtype: float64
```

Next I'd like to graph the number of RSVPs over time to see if there are any interesting trends. To do this let's first sum the `waitlist_count` and `yes_rsvp_count` columns and make a new column called `total_RSVP_count`.

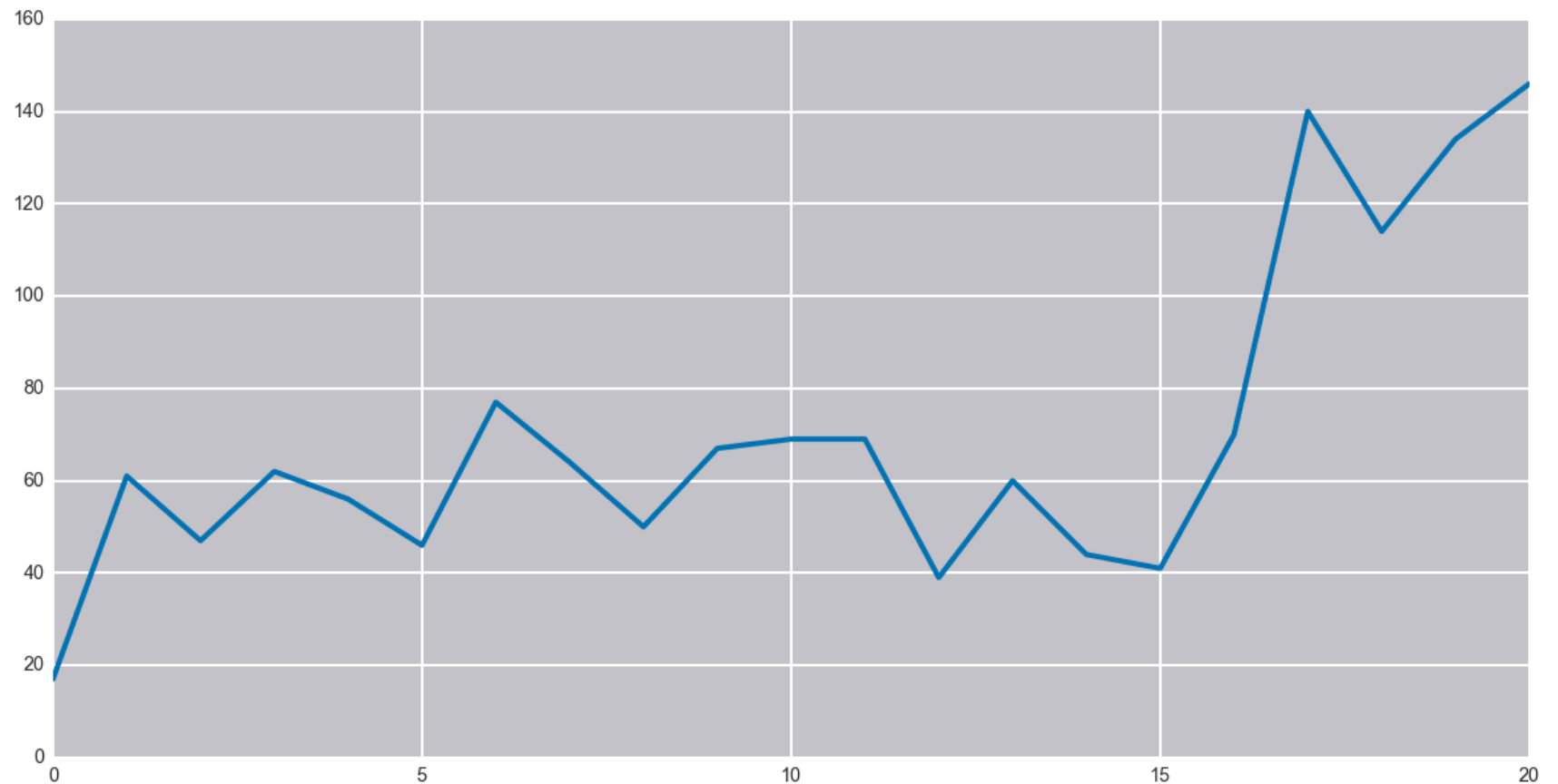
```
In [10]: events_df['total_RSVP_count'] = events_df['waitlist_count'] + events_df['yes_rsvp_count']
events_df['total_RSVP_count']
```

```
Out[10]: 0      17
         1      61
         2      47
         3      62
         4      56
         5      46
         6      77
         7      64
         8      50
         9      67
        10      69
        11      69
        12      39
        13      60
        14      44
        15      41
        16      70
        17     140
        18     114
        19     134
        20     146
Name: total_RSVP_count, dtype: int64
```

We can plot these values using the `plot` method

```
In [11]: events_df['total_RSVP_count'].plot()
```

```
Out[11]: <matplotlib.axes._subplots.AxesSubplot at 0x1045c48d0>
```



The plot method utilizes the `matplotlib` library behind the scenes to draw the plot. This is interesting, but it would be nice to have the dates of the meetups on the X-axis of the plot.

To accomplish this, let's convert the `time` field from a unix epoch timestamp to a python `datetime` utilizing the `apply` method and a function.

```
In [12]: events_df.head(2)
```

```
Out[12]:
```

	created	name	rating	time	waitlist_count	yes_rsvp_count	id	total_RSVP_
0	1351948193000	Meet and greet	{u'count': 3, u'average': 5}	1352934000000	0	17	89769502	17
1	1357781071000	DataPhilly January 2013 Meetup - An Introducti...	{u'count': 6, u'average': 4.17000007629}	1359588600000	0	61	98833672	61

```
In [13]: import datetime
def get_datetime_from_epoch(epoch):
    return datetime.datetime.fromtimestamp(epoch/1000.0)
```

```
In [14]: events_df['time'] = events_df.time.apply(get_datetime_from_epoch)
events_df['time']
```

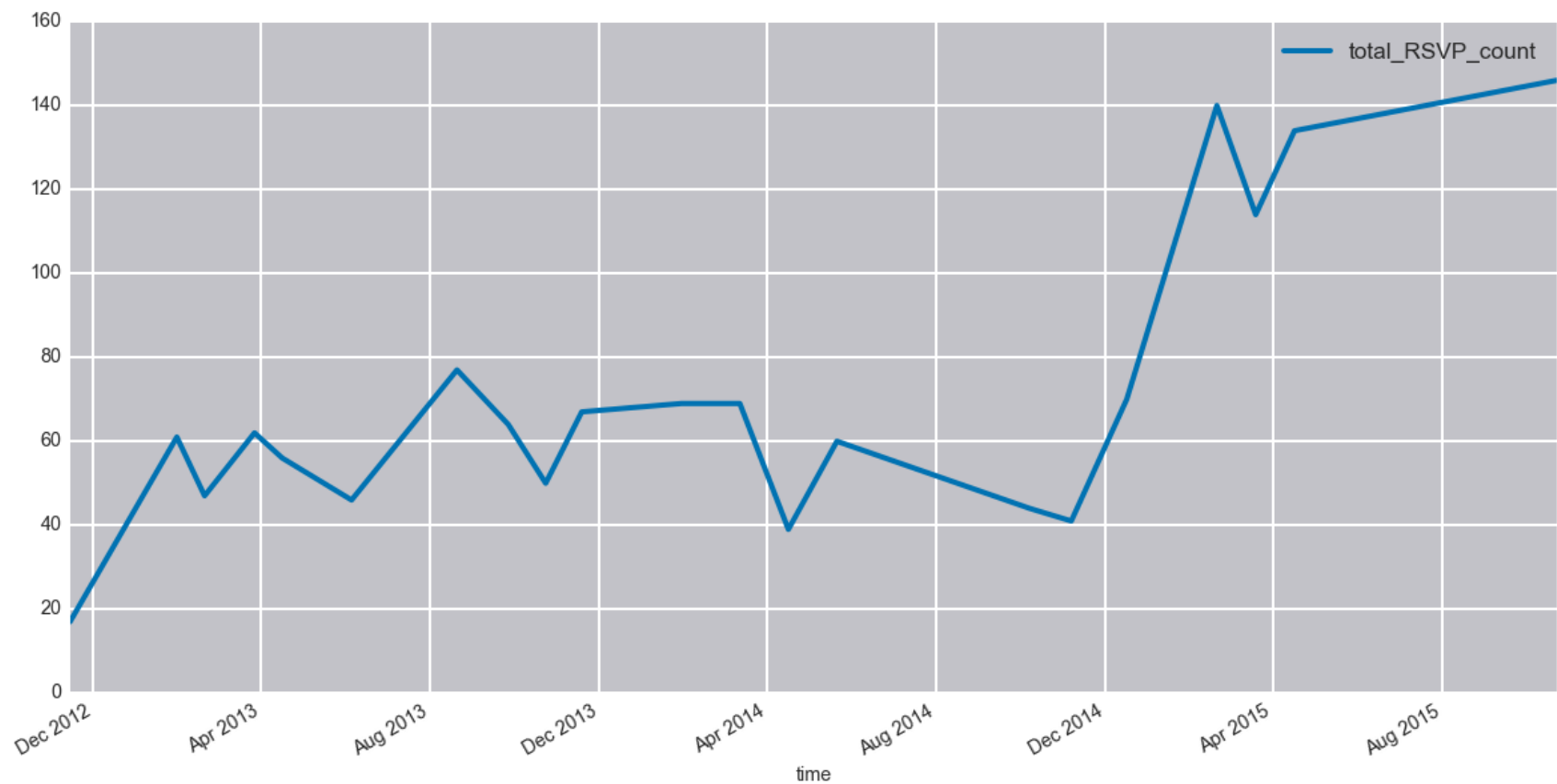
```
Out[14]: 0      2012-11-14 18:00:00
1      2013-01-30 18:30:00
2      2013-02-19 18:30:00
3      2013-03-27 18:30:00
4      2013-04-16 18:30:00
5      2013-06-05 18:30:00
6      2013-08-20 18:30:00
7      2013-09-26 18:30:00
8      2013-10-23 18:00:00
9      2013-11-18 18:00:00
10     2014-01-29 18:00:00
11     2014-03-12 18:00:00
12     2014-04-16 18:00:00
13     2014-05-21 18:00:00
14     2014-10-07 18:00:00
15     2014-11-06 18:00:00
16     2014-12-16 18:00:00
17     2015-02-19 18:00:00
18     2015-03-19 18:00:00
19     2015-04-16 18:00:00
20     2015-10-22 18:00:00
Name: time, dtype: datetime64[ns]
```

Next let's make the `time` column the index of the `DataFrame` using the `set_index` method and then re-plot our data.



```
In [15]: events_df.set_index('time', inplace=True)
events_df[['total_RSVP_count']].plot()
```

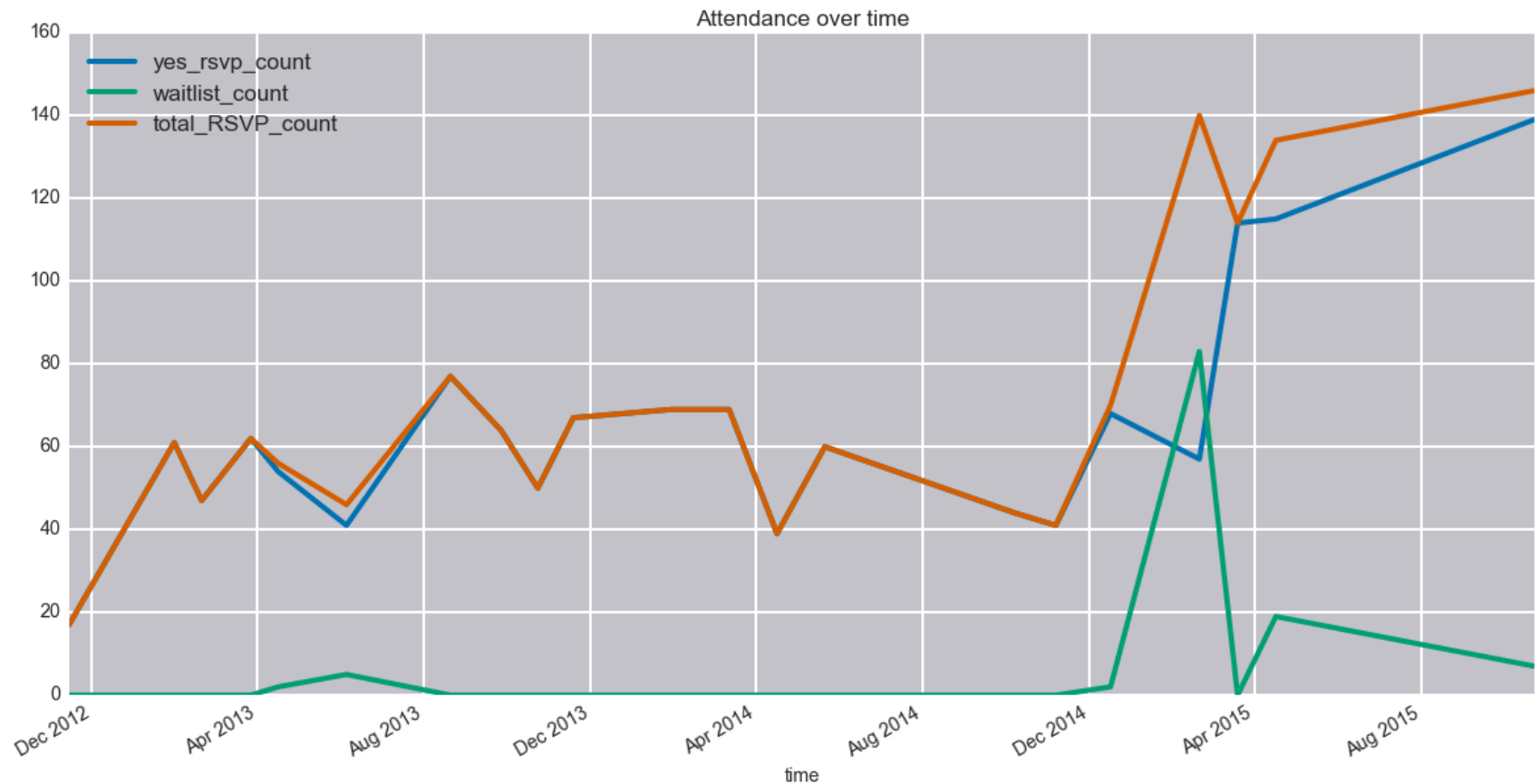
```
Out[15]: <matplotlib.axes._subplots.AxesSubplot at 0x109621550>
```



We can also easily plot multiple columns on the same plot.

```
In [16]: all_rsvps = events_df[['yes_rsvp_count', 'waitlist_count', 'total_RSVP_count']]
all_rsvps.plot(title='Attendance over time')
```

```
Out[16]: <matplotlib.axes._subplots.AxesSubplot at 0x1098fa790>
```



Alright so I'm seeing some interesting trends here. Let's take a look at something different.

The Meetup API also provides us access to member info. Let's have a look at the data we have available:

```
In [17]: members_df = pd.read_pickle('members.pkl')
for column in ['joined', 'visited']:
    members_df[column] = members_df[column].apply(get_datetime_from_epoch)
members_df.head(3)
```

```
Out[17]:
```

	anon_id	anon_name	bio	city	country	gender	hometown	joined	lat	lon	membership_cou
0	0	James	NaN	Philadelphia	us	male	Philadelphia	2015-10-10 21:43:33	39.94	-75.23	0
1	1	Vijay	java software developer in center city philly	Philadelphia	us	male	Philadelphia	2013-11-22 22:32:04	39.96	-75.20	0
2	2	Justin	NaN	Philadelphia	us	male	NaN	2015-06-10 16:18:43	40.00	-75.14	63

You'll notice that I've anonymized the meetup member\_id and the members name. I've also used the python module [SexMachine](https://pypi.python.org/pypi/SexMachine/) (<https://pypi.python.org/pypi/SexMachine/>) to infer members gender based on their first name. Let's have a closer look at the gender breakdown of our members:

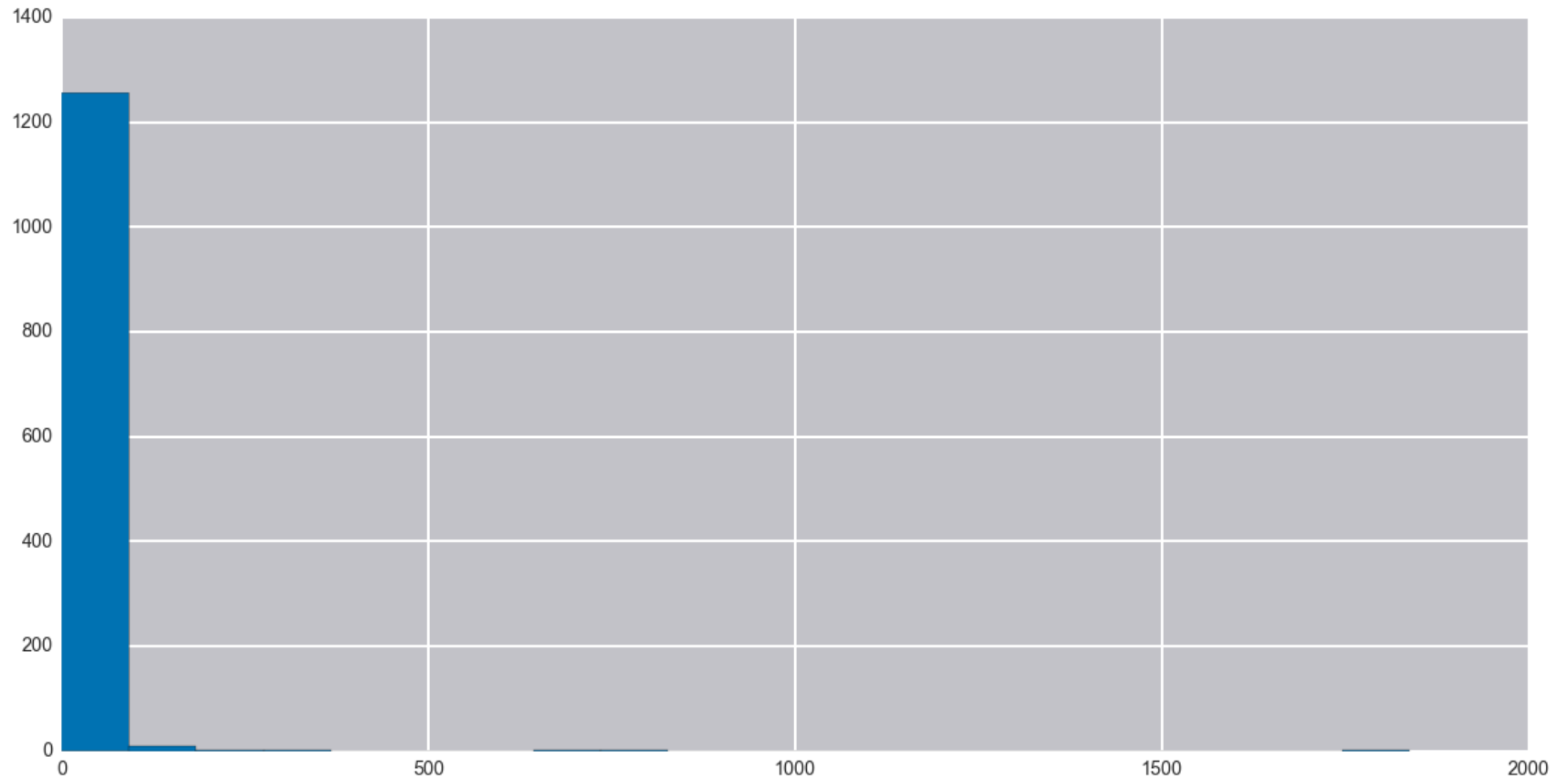
```
In [18]: gender_counts = members_df['gender'].value_counts()  
gender_counts
```

```
Out[18]: male          716  
         andy          257  
         female       175  
         mostly_male    91  
         mostly_female   35  
         Name: gender, dtype: int64
```

Next let's use the `hist` method to plot a histogram of `membership_count`. This is the number of groups each member is in.

```
In [19]: members_df['membership_count'].hist(bins=20)
```

```
Out[19]: <matplotlib.axes._subplots.AxesSubplot at 0x10b30aa10>
```



Something looks odd here let's check out the value\_counts:

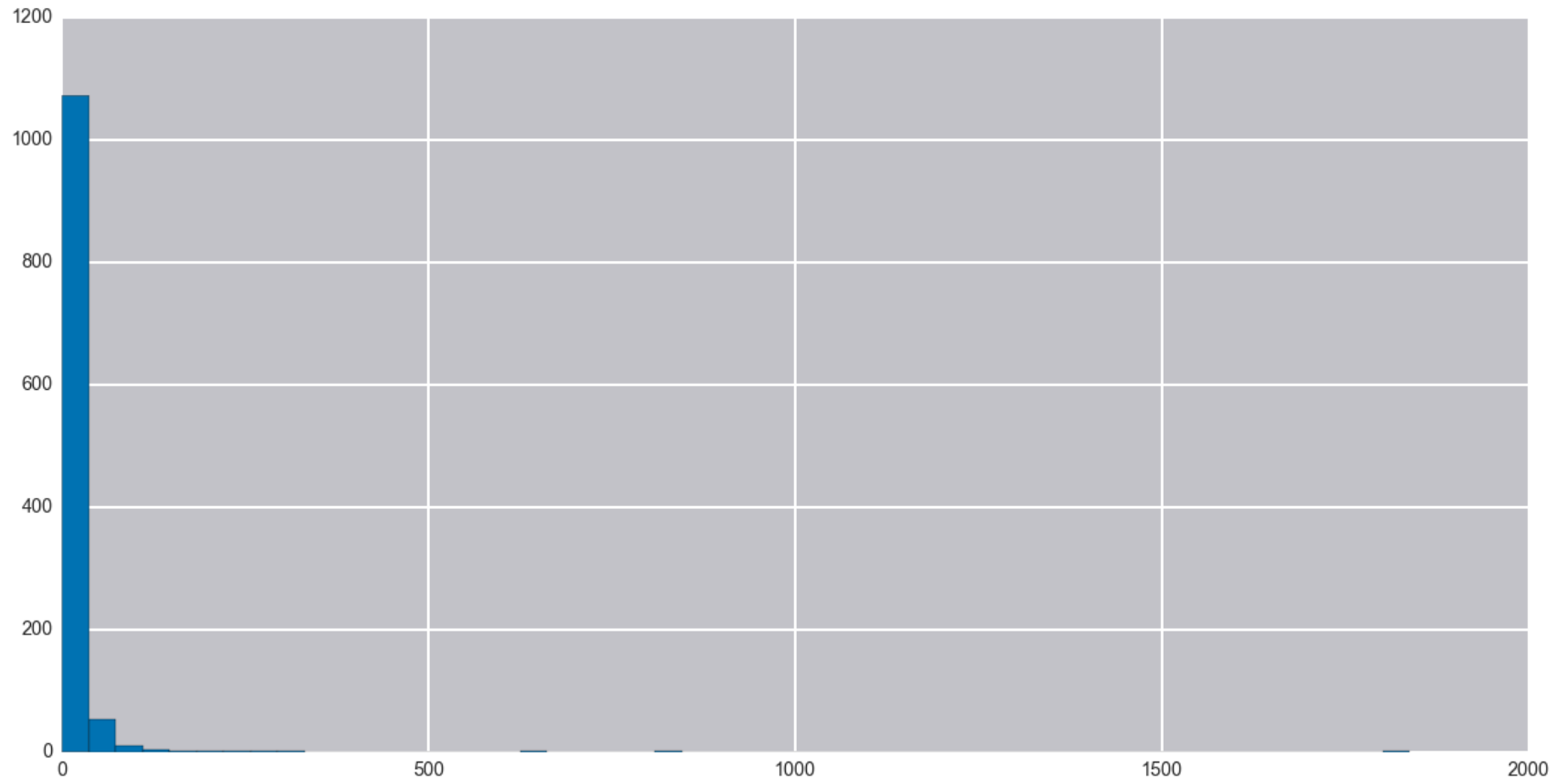
```
In [20]: members_df['membership_count'].value_counts().head()
```

```
Out[20]: 0      124
         2      105
         1       96
         3       86
         5       77
         Name: membership_count, dtype: int64
```

Okay so most members are members of 0 meetup groups?! This seems odd! I did a little digging and came up with the answer; members can set their membership details to be private, and then this value will be zero. Let's filter out these members and recreate the histogram.

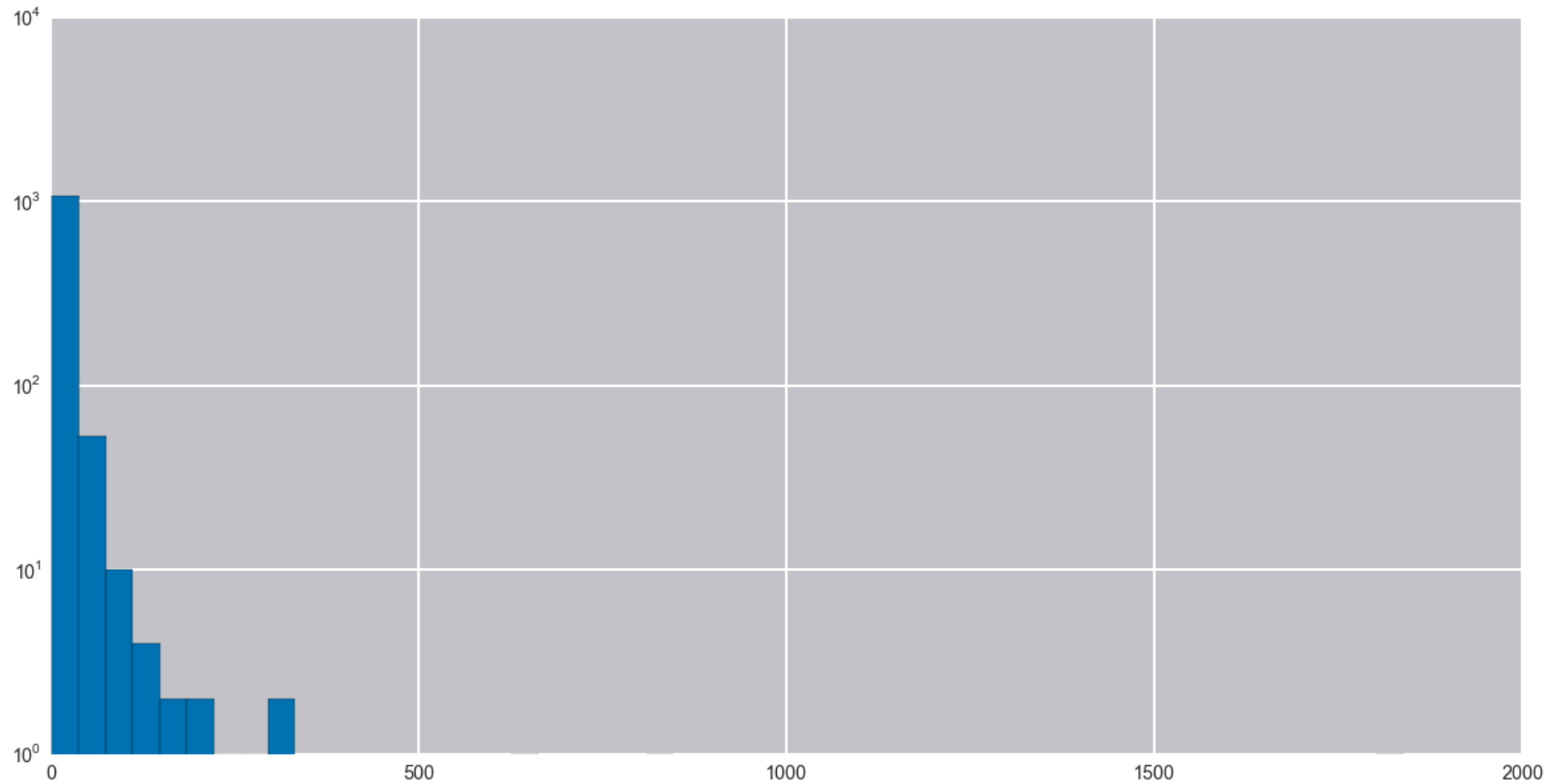
```
In [21]: members_df_non_zero = members_df[members_df['membership_count'] != 0]
members_df_non_zero['membership_count'].hist(bins=50)
```

```
Out[21]: <matplotlib.axes._subplots.AxesSubplot at 0x10b5350d0>
```



Okay so most members are only members of a few meetup groups. There's some outliers that are pretty hard to read, let's try plotting this on a logarithmic scale to see if that helps:

```
In [22]: ax = members_df_non_zero['membership_count'].hist(bins=50)
ax.set_yscale('log')
```



Let's use a mask to filter out the outliers so we can dig into them a little further:

```
In [23]: all_the_meetups = members_df[members_df['membership_count'] > 100]
         filtered = all_the_meetups[['membership_count', 'city', 'country', 'state']]
         filtered.sort_values(by='membership_count', ascending=False)
```

Out[23]:

	membership_count	city	country	state
<b>301</b>	1838	Berlin	de	NaN
<b>25</b>	816	San Francisco	us	CA
<b>141</b>	651	Jerusalem	il	NaN
<b>67</b>	303	Philadelphia	us	PA
<b>420</b>	295	Baltimore	us	MD
<b>1178</b>	278	Princeton	us	NJ
<b>257</b>	241	New York	us	NY
<b>223</b>	207	Scarsdale	us	NY
<b>150</b>	197	Philadelphia	us	PA
<b>174</b>	166	Philadelphia	us	PA
<b>86</b>	166	West Chester	us	PA
<b>449</b>	146	Exton	us	PA
<b>154</b>	119	San Francisco	us	CA
<b>1158</b>	119	Philadelphia	us	PA
<b>1022</b>	113	Levittown	us	PA
<b>868</b>	106	Seattle	us	WA
<b>987</b>	102	San Francisco	us	CA

The people from Philly might actually be legitimate members, let's use a compound mask to filter them out as well:



```
In [24]: all_the_meetups = members_df[
        (members_df['membership_count'] > 100) & (members_df['city'] != 'Philadelphia')
    ]
    filtered = all_the_meetups[['membership_count', 'city', 'country', 'state']]
    filtered.sort_values(by='membership_count', ascending=False)
```

Out[24]:

	membership_count	city	country	state
<b>301</b>	1838	Berlin	de	NaN
<b>25</b>	816	San Francisco	us	CA
<b>141</b>	651	Jerusalem	il	NaN
<b>420</b>	295	Baltimore	us	MD
<b>1178</b>	278	Princeton	us	NJ
<b>257</b>	241	New York	us	NY
<b>223</b>	207	Scarsdale	us	NY
<b>86</b>	166	West Chester	us	PA
<b>449</b>	146	Exton	us	PA
<b>154</b>	119	San Francisco	us	CA
<b>1022</b>	113	Levittown	us	PA
<b>868</b>	106	Seattle	us	WA
<b>987</b>	102	San Francisco	us	CA

That's strange, I don't think we've ever had any members from Berlin, San Francisco, or Jerusalem in attendance :-).

Moving on, we also have all the events that each member RSVPed to:

```
In [25]: rsvps_df = pd.read_pickle('rsvps.pkl')
rsvps_df.head(3)
```

Out[25]:

	102502622	106043892	107740582	120425212	133803672	138415912	144769822	149515412	160323532	16874785
0	0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0	0
2	1	0	0	0	0	0	0	0	0	0

3 rows × 22 columns

We can utilize the pandas merge method to join our members DataFrame and our rsvps DataFrame:

```
In [26]: joined_with_rsvps_df = pd.merge(members_df, rsvps_df, left_on='anon_id', right_on='member_id')
joined_with_rsvps_df.head(3)
```

Out[26]:

	anon_id	anon_name	bio	city	country	gender	hometown	joined	lat	lon	...	206754182
0	4	Edward	NaN	Downingtown	us	male	Philadelphia	2015-05-20 05:24:59	40.02	-75.71	...	0
1	8	John	CTO as SnipSnap, the coupon app	Woodbury	us	male	NaN	2013-01-29 22:49:12	39.83	-75.13	...	0
2	11	John	Founder and CEO of Azavea, a firm that builds ...	Philadelphia	us	male	NaN	2012-11-06 12:18:12	39.95	-75.16	...	0

3 rows x 36 columns

```
In [27]: joined_with_rsvps_df.columns
```

```
Out[27]: Index([      u'anon_id',      u'anon_name',      u'bio',
                u'city',      u'country',      u'gender',
                u'hometown',      u'joined',      u'lat',
                u'lon', u'membership_count',      u'state',
                u'topics',      u'visited',      u'102502622',
                u'106043892',      u'107740582',      u'120425212',
                u'133803672',      u'138415912',      u'144769822',
                u'149515412',      u'160323532',      u'168747852',
                u'175993712',      u'182860422',      u'206754182',
                u'215265722',      u'219055217',      u'219840555',
                u'220526799',      u'221245827',      u'225488147',
                u'89769502',      u'98833672',      u'member_id'],
               dtype='object')
```

Now we have a ton of data, let's see what kind of interesting things we can discover. Let's look at the some stats on male attendees vs. female attendees:

First we can use the `isin` method to make DataFrames for male and female members.

```
In [28]: male_attendees = joined_with_rsvps_df[joined_with_rsvps_df['gender'].isin(['male', 'mostly_male'])
male_attendees.tail(3)
```

Out[28]:

	anon_id	anon_name	bio	city	country	gender	hometown	joined	lat	lon	...	206754182	21526
<b>578</b>	1261	Tom	NaN	Philadelphia	us	male	NaN	2015-10-06 17:50:59	39.96	-75.20	...	0	0
<b>579</b>	1262	Daniel	NaN	Philadelphia	us	male	NaN	2015-10-07 15:48:58	39.97	-75.17	...	0	0
<b>583</b>	1271	Chris	NaN	Philadelphia	us	male	NaN	2015-10-20 15:00:55	39.96	-75.20	...	0	0

3 rows × 36 columns



```
In [29]: female_attendees = joined_with_rsvps_df[joined_with_rsvps_df['gender'].isin(['female', 'mostly_female'])]
female_attendees.tail(3)
```

```
Out[29]:
```

	anon_id	anon_name	bio	city	country	gender	hometown	joined	lat	lon	...	206754182	2152
<b>580</b>	1265	Erin	NaN	Philadelphia	us	female	NaN	2015-10-13 18:13:37	39.95	-75.16	...	0	0
<b>581</b>	1268	Anne	NaN	Philadelphia	us	female	Philadelphia	2015-10-18 15:29:42	39.96	-75.20	...	0	0
<b>582</b>	1269	Stacey	NaN	Philadelphia	us	female	NaN	2015-10-20 09:55:35	39.96	-75.20	...	0	0

3 rows × 36 columns

Next we can use the `sum` method to count the number of male and female attendees per event and create a `Series` for each.

```
In [30]: event_ids = [
    '102502622', '106043892', '107740582', '120425212', '133803672', '138415912', '144769822', '160323532',
    '168747852', '175993712', '182860422', '206754182', '215265722', '219055217', '220526799', '221245827',
    '225488147', '89769502', '98833672'
]
male_attendees[event_ids].sum().head(3)
```

```
Out[30]: 102502622    30
106043892    35
107740582    33
dtype: float64
```

We can then recombine the male and female `Series`' into a new `DataFrame`.

```
In [31]: gender_attendance = pd.DataFrame({'male': male_attendees[event_ids].sum(), 'female': female_atten  
gender_attendance.head(3)
```

Out[31]:

	<b>female</b>	<b>male</b>
<b>102502622</b>	2	30
<b>106043892</b>	6	35
<b>107740582</b>	3	33

And then we can use `merge` again to combine this with our events `DataFrame`.

```
In [32]: events_with_gender_df = pd.merge(events_df, gender_attendance, left_on='id', right_index=True)
events_with_gender_df.head(3)
```

Out[32]:

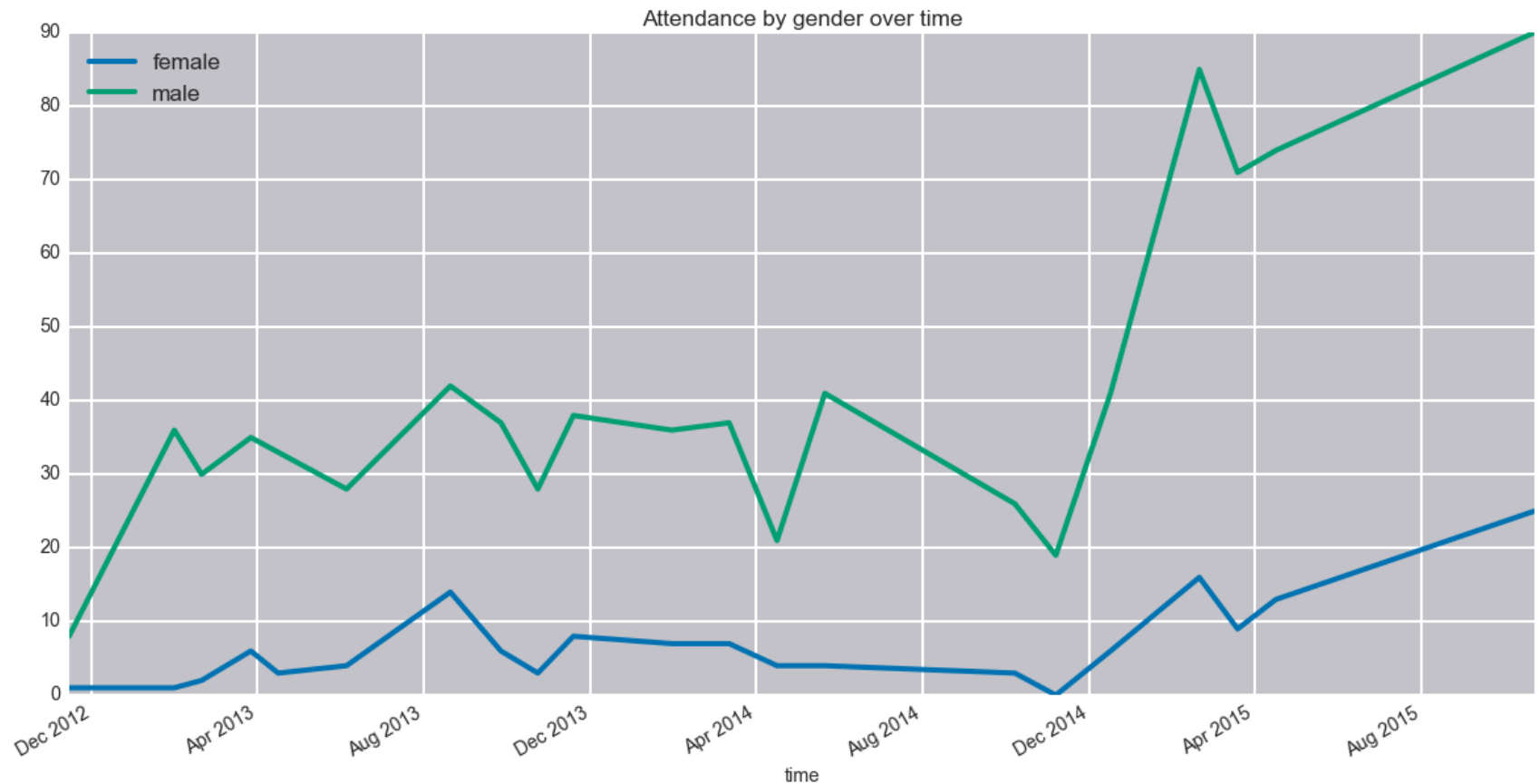
	created	name	rating	waitlist_count	yes_rsvp_count	id	total_RSVP_count	f
time								
<b>2012-11-14 18:00:00</b>	1351948193000	Meet and greet	{u'count': 3, u'average': 5}	0	17	89769502	17	1
<b>2013-01-30 18:30:00</b>	1357781071000	DataPhilly January 2013 Meetup - An Introducti...	{u'count': 6, u'average': 4.17000007629}	0	61	98833672	61	1
<b>2013-02-19 18:30:00</b>	1359732939000	DataPhilly February 2013 Meetup - Data Science...	{u'count': 5, u'average': 5}	0	47	102502622	47	2

The we can plot the attendance by gender over time



```
In [33]: gender_df = events_with_gender_df[['female', 'male']]
gender_df.plot(title='Attendance by gender over time')
```

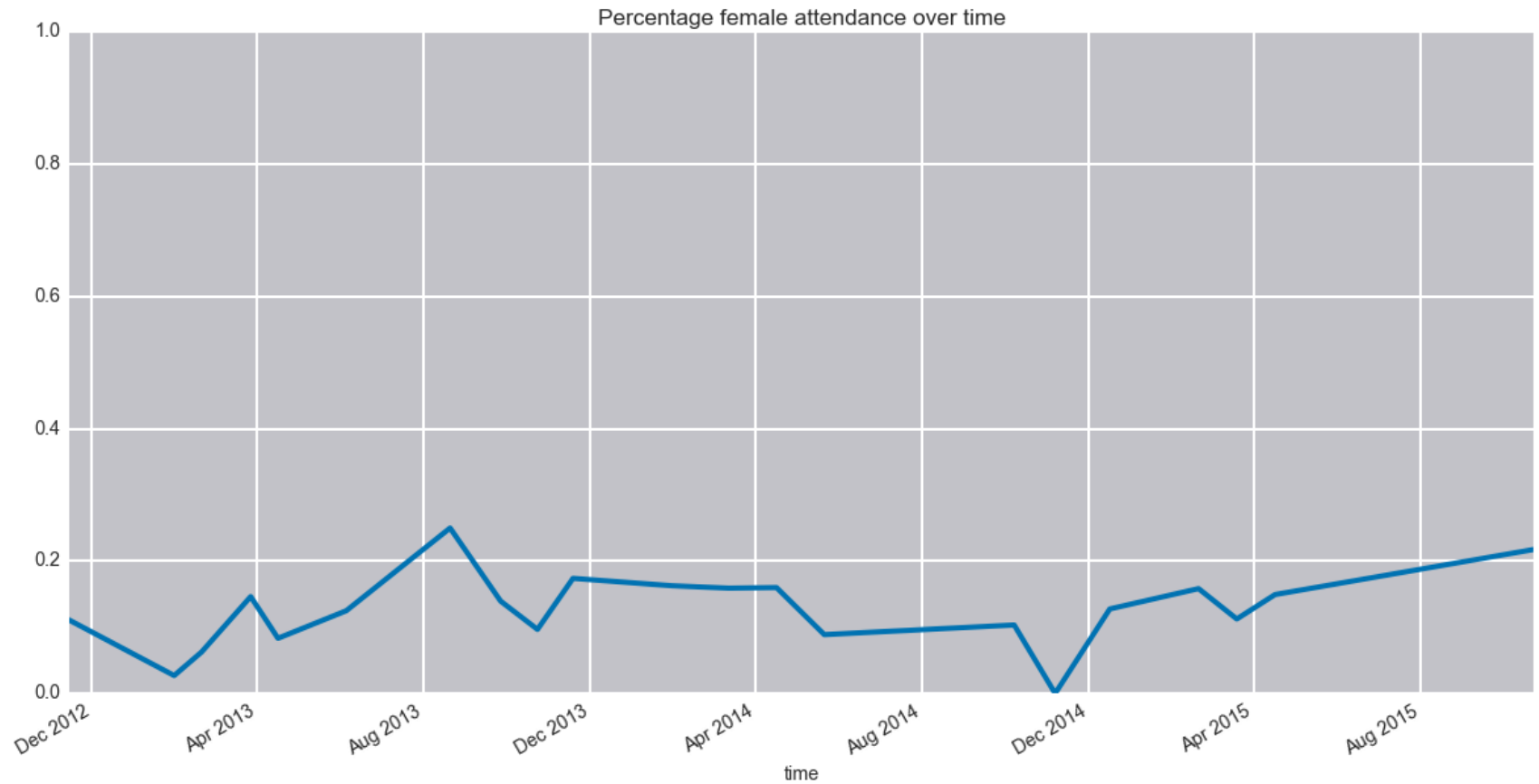
```
Out[33]: <matplotlib.axes._subplots.AxesSubplot at 0x10c266510>
```



This might be easier to interpret by looking at the percentage of females in attendance. We can use the `div` (divide) method to calculate this.

```
In [34]: female_ratio = gender_df['female'].div(gender_df['male'] + gender_df['female'])
female_ratio.plot(title='Percentage female attendance over time', ylim=(0.0, 1.0))
```

```
Out[34]: <matplotlib.axes._subplots.AxesSubplot at 0x10c25c4d0>
```



The members DataFrame also has some other interesting stuff in it. Let's take a look at the topics column.

```
In [35]: members_df['topics'].iloc[0]
```

```
Out[35]: [{u'id': 254, u'name': u'Poker', u'urlkey': u'poker'},
          {u'id': 21067, u'name': u'Collaboration', u'urlkey': u'collaboration'},
          {u'id': 15167, u'name': u'Cloud Computing', u'urlkey': u'cloud-computing'},
          {u'id': 10333, u'name': u'Parents', u'urlkey': u'parents'},
          {u'id': 553, u'name': u'Dungeons & Dragons', u'urlkey': u'dnd'},
          {u'id': 4377, u'name': u'Politics', u'urlkey': u'politics'},
          {u'id': 15992, u'name': u'Games', u'urlkey': u'games'},
          {u'id': 9696, u'name': u'New Technology', u'urlkey': u'newtech'},
          {u'id': 19585, u'name': u'Board Games', u'urlkey': u'board-games'},
          {u'id': 48471,
           u'name': u'Computer programming',
           u'urlkey': u'computer-programming'},
          {u'id': 19197, u'name': u'Activism', u'urlkey': u'activism'},
          {u'id': 226, u'name': u'Acting', u'urlkey': u'acting'},
          {u'id': 17558, u'name': u'Performing Arts', u'urlkey': u'performing-arts'}]
```

Let's see if we can identify any trends in members topics. Let's start off by identifying the most common topics:

```
In [36]: from collections import Counter

topic_counter = Counter()
for m in members_df['topics']:
    topic_counter.update([t['name'] for t in m])
topic_counter.most_common(20)
```

```
Out[36]: [(u'Big Data', 528),
          (u'Data Analytics', 492),
          (u'Computer programming', 473),
          (u'New Technology', 450),
          (u'Open Source', 381),
          (u'Data Mining', 372),
          (u'Software Development', 366),
          (u'Startup Businesses', 359),
          (u'Technology', 314),
          (u'Python', 285),
          (u'Technology Startups', 278),
          (u'Web Development', 277),
          (u'Entrepreneurship', 265),
          (u'Data Visualization', 264),
          (u'Mobile Technology', 227),
          (u'Big Data Analytics', 210),
          (u'Predictive Analytics', 202),
          (u'Mobile Development', 190),
          (u'Web Design', 182),
          (u'Outdoors', 182)]
```

Next let's create a new DataFrame where each column is one of the top 100 topics, and each row is a member. We'll set the values of each cell to be either 0 or 1 to indicate that that member has (or doesn't have) that topic.

```

In [37]: top_100_topics = set([t[0] for t in topic_counter.most_common(100)])
topic_member_map = {}
for i, m in members_df.iterrows():
    if m['topics']:
        top_topic_count = {}
        for topic in m['topics']:
            if topic['name'] in top_100_topics:
                top_topic_count[topic['name']] = 1
        topic_member_map[m['anon_id']] = top_topic_count

top_topic_df = pd.DataFrame(topic_member_map)
top_topic_df.head(3)

```

Out[37]:

	0	2	3	4	5	6	8	9	11	12	...	1261	1262	1264	1266	1267	1268	1269	1271
<b>20's &amp; 30's Social</b>	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	1	NaN	NaN	NaN	NaN	NaN	NaN
<b>Adventure</b>	NaN	NaN	NaN	1	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
<b>Art</b>	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

3 rows × 1088 columns

Okay for what I'm going to do next, I want the rows to be the members and the columns to be the topics. We can use the `T` (transpose) method to fix this.

```
In [38]: top_topic_df = top_topic_df.T
top_topic_df.head(3)
```

```
Out[38]:
```

	20's & 30's Social	Adventure	Art	Bicycling	Big Data	Big Data Analytics	Board Games	Book Club	Business Intelligence	Business Strategy	...	Watching Movies	Web Design	Web Dev
0	NaN	NaN	NaN	NaN	NaN	NaN	1	NaN	NaN	NaN	...	NaN	NaN	NaN
2	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	1	1
3	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN

3 rows × 100 columns

Next we can use the `fillna` method to fill in the missing values with zeros.

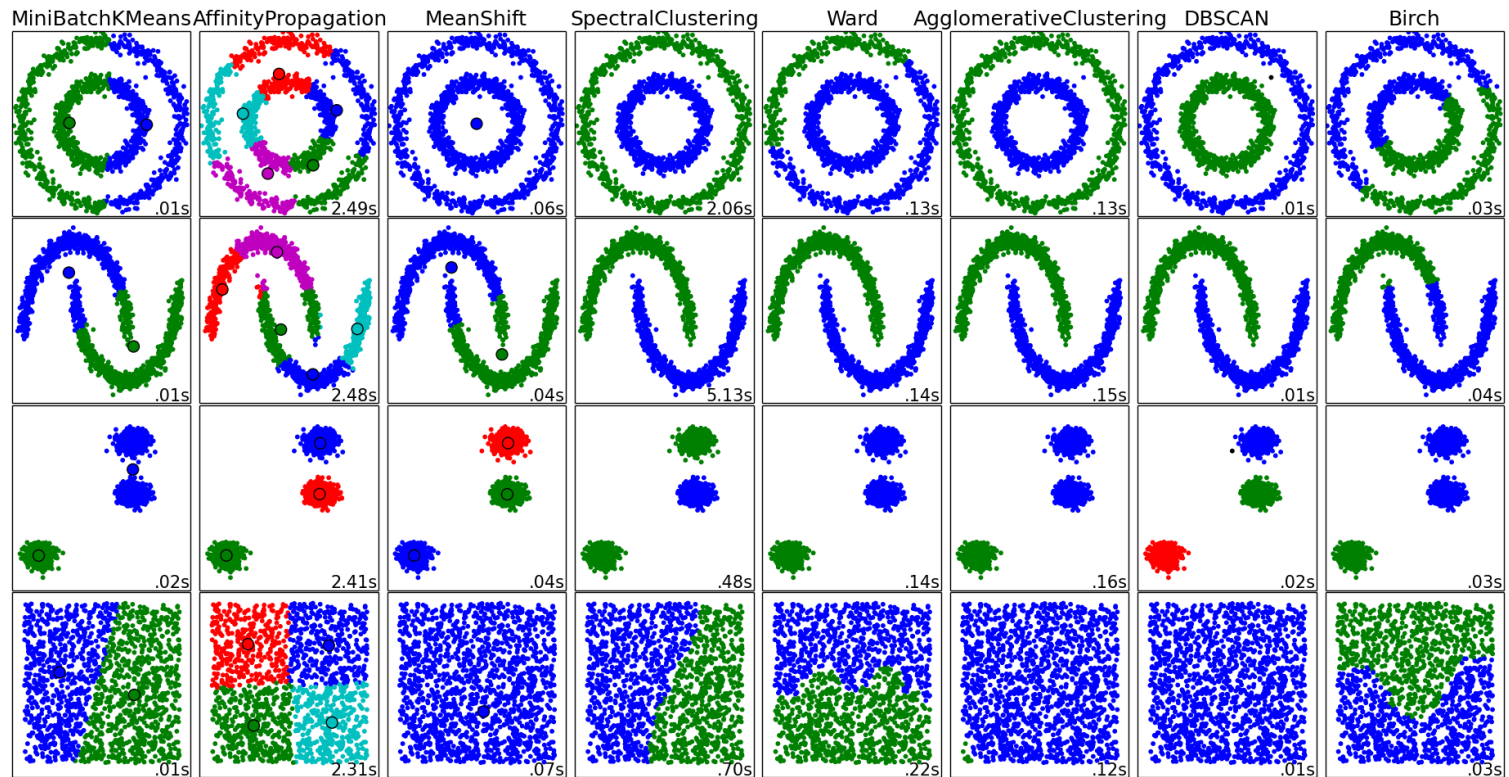
```
In [39]: top_topic_df.fillna(0, inplace=True)
top_topic_df.head(3)
```

```
Out[39]:
```

	20's & 30's Social	Adventure	Art	Bicycling	Big Data	Big Data Analytics	Board Games	Book Club	Business Intelligence	Business Strategy	...	Watching Movies	Web Design	Web Devel
0	0	0	0	0	0	0	1	0	0	0	...	0	0	0
2	0	0	0	0	0	0	0	0	0	0	...	0	1	1
3	0	0	0	0	0	0	0	0	0	0	...	0	0	0

3 rows × 100 columns

Next let's use a [clustering algorithm \(https://en.wikipedia.org/wiki/Cluster\\_analysis\)](https://en.wikipedia.org/wiki/Cluster_analysis) to see if there are any patterns in the topics members are interested in. A clustering algorithm groups a set of data points so that similar objects are in the same group. This is a classic type of [unsupervised machine learning \(https://en.wikipedia.org/wiki/Unsupervised\\_learning\)](https://en.wikipedia.org/wiki/Unsupervised_learning). Below you can find visualisations of how different clustering algorithms perform on various kinds of data:



Kmeans clustering (<http://scikit-learn.org/stable/modules/clustering.html#k-means>) is quick and can scale well to larger datasets.

Let's see how it performs on our dataset:

```
In [40]: from sklearn.cluster import MiniBatchKMeans as KMeans
X = top_topic_df.as_matrix()
n_clusters = 3
k_means = KMeans(init='k-means++', n_clusters=n_clusters, n_init=10, random_state=47)
k_means.fit(X)
k_means.labels_
```

```
Out[40]: array([2, 1, 2, ..., 2, 0, 2], dtype=int32)
```

We've grouped our members into 3 clusters, let's see how many members are in each cluster

```
In [41]: Counter(list(k_means.labels_)).most_common()
```

```
Out[41]: [(2, 637), (1, 293), (0, 158)]
```

Next let's see which topics are most popular in each cluster:



```
In [42]: from collections import defaultdict
```

```
cluster_index_map = defaultdict(list)
for i in range(k_means.labels_.shape[0]):
    cluster_index_map[k_means.labels_[i]].append(top_topic_df.index[i])

for cluster_num in range(n_clusters):
    print 'Cluster {}'.format(cluster_num)
    f = top_topic_df[top_topic_df.index.isin(cluster_index_map[cluster_num])].sum()
    f2 = f[f > 0]
    f3 = f2.sort_values(ascending=False)
    print f3[:10]
    print
```

```
Cluster 0
Outdoors          104
Live Music        98
Dining Out        93
Hiking            86
Fitness           84
Travel            77
Watching Movies   60
Adventure         58
New Technology    57
Intellectual Discussion 54
dtype: float64
```

```
Cluster 1
Computer programming 248
Open Source          236
New Technology        231
Software Development 231
Technology            214
Web Development       211
Big Data              190
Startup Businesses    177
Data Analytics        166
Mobile Technology     158
dtype: float64
```

Cluster 2	
Big Data	291
Data Analytics	286
Data Mining	201
Computer programming	171
New Technology	162
Data Visualization	148
Startup Businesses	130
Python	130
Open Source	123
Big Data Analytics	115
dtype:	float64

So it looks like our biggest cluster (#2) contains members whose primary interest is data science.

The second biggest cluster (#1) contains members whose primary interests are technology, and data science just happens to be one of those interests.

The smallest cluster (#0) contains members whose primary interests are around socializing.

We can also visualize the clusters in 2 dimensions by using PCA (Principal component analysis) (<http://scikit-learn.org/stable/modules/decomposition.html#principal-component-analysis-pca>).

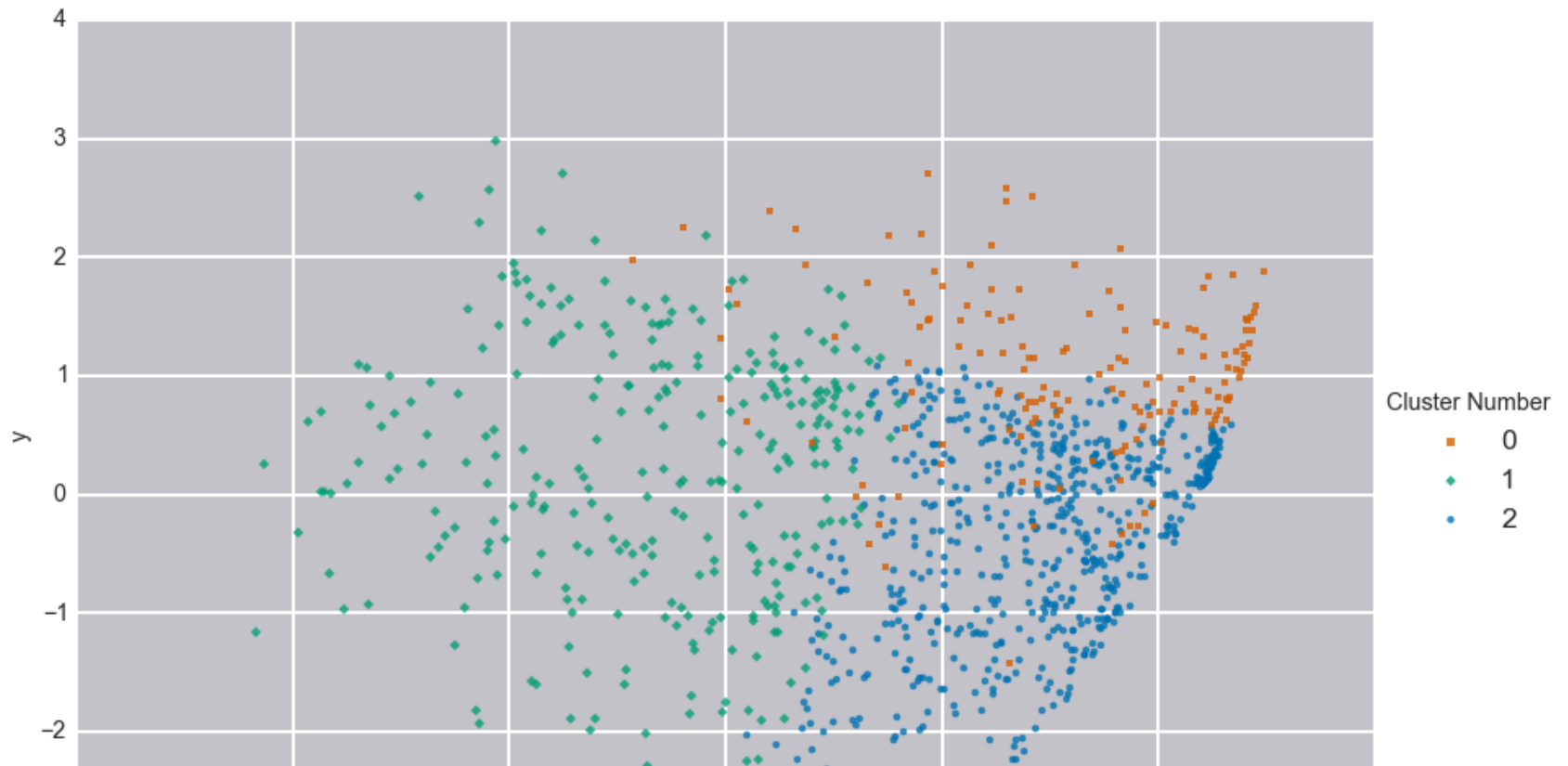
```
In [45]: from sklearn.decomposition import PCA

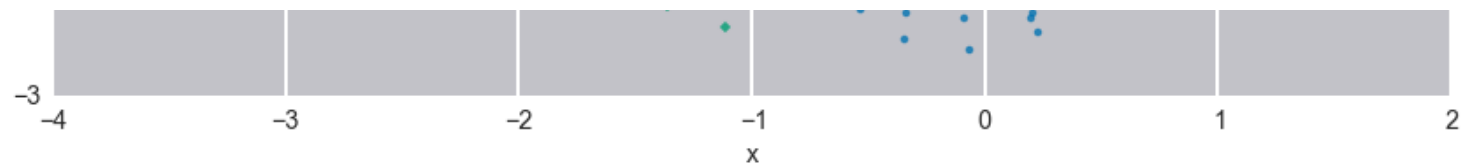
pca = PCA(n_components=2, whiten=True)
X_r = pca.fit(X).transform(X)

pca_data = []
for i in range(X_r.shape[0]):
    cluster_num = k_means.labels_[i]
    pca_data.append({'x': X_r[i, 0], 'y': X_r[i, 1], 'Cluster Number': cluster_num})

pca_df = pd.DataFrame(pca_data)
markers = ['o', 'D', 's']
ax = sns.lmplot(x="x", y="y", hue="Cluster Number", data=pca_df, fit_reg=False, legend=False, size=10)
ax.add_legend(label_order = sorted(ax._legend_data.keys(), key = int))
```

Out[45]: <seaborn.axisgrid.FacetGrid at 0x10df903d0>





In [ ]: