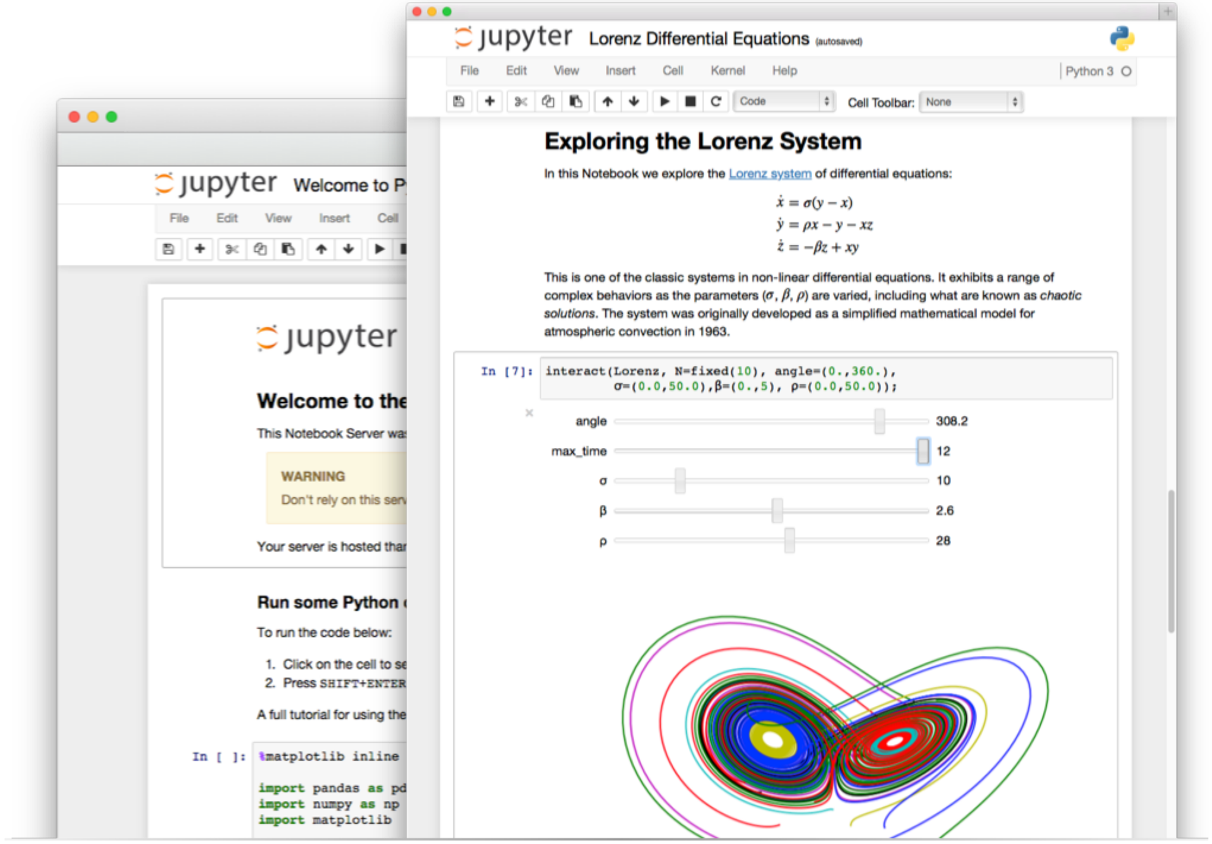
Instructions

- 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).
- 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).
- The repo for this project can be found and forked here (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))

The default kernel runs Python code. The notebook provides a simple way for users to pick which of these kernels is used for a given notebook.

Jupyter examples and tutorials can be found in the Jupyter github repo here (https://github.com/jupyter/notebook/blob/master/docs/source/examples/Notebook/Examples%20and%20Tutorials%2(

Initializing our environment

First let's start off by initilizing our environment

- `%matplotlib inline` initilizes matplotlib (http://matplotlib.org/) so that we can display graphs and charts in our notebook.
- `import seaborn as sns` imports seaborn (https://web.stanford.edu/~mwaskom/software/seaborn/) a graphing library built on top of matplotlib.
- `import pandas as pd` imports pandas (http://pandas.pydata.org/) a tool I'll explain in the next section.

Hint: If you've installed Jupyter Notebook and you're running this on your machine, you can use the run button ⏭ in the toolbar at the top of the page to execute each cell

Click on the cell above and the cell below. You'll notice that the cell above is Markdown (https://daringfireball.net/projects/markdown/). You can edit it by double clicking on it. The cell below contains Python code which can be modified and execute. If the code has any output it will be printed out below the cell with **Out [n]:** in front of it.

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/) to gather a bunch of data on members of the DataPhilly meetup group (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,				

18	1423955223000	DataPhilly: March Meetup	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

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`.

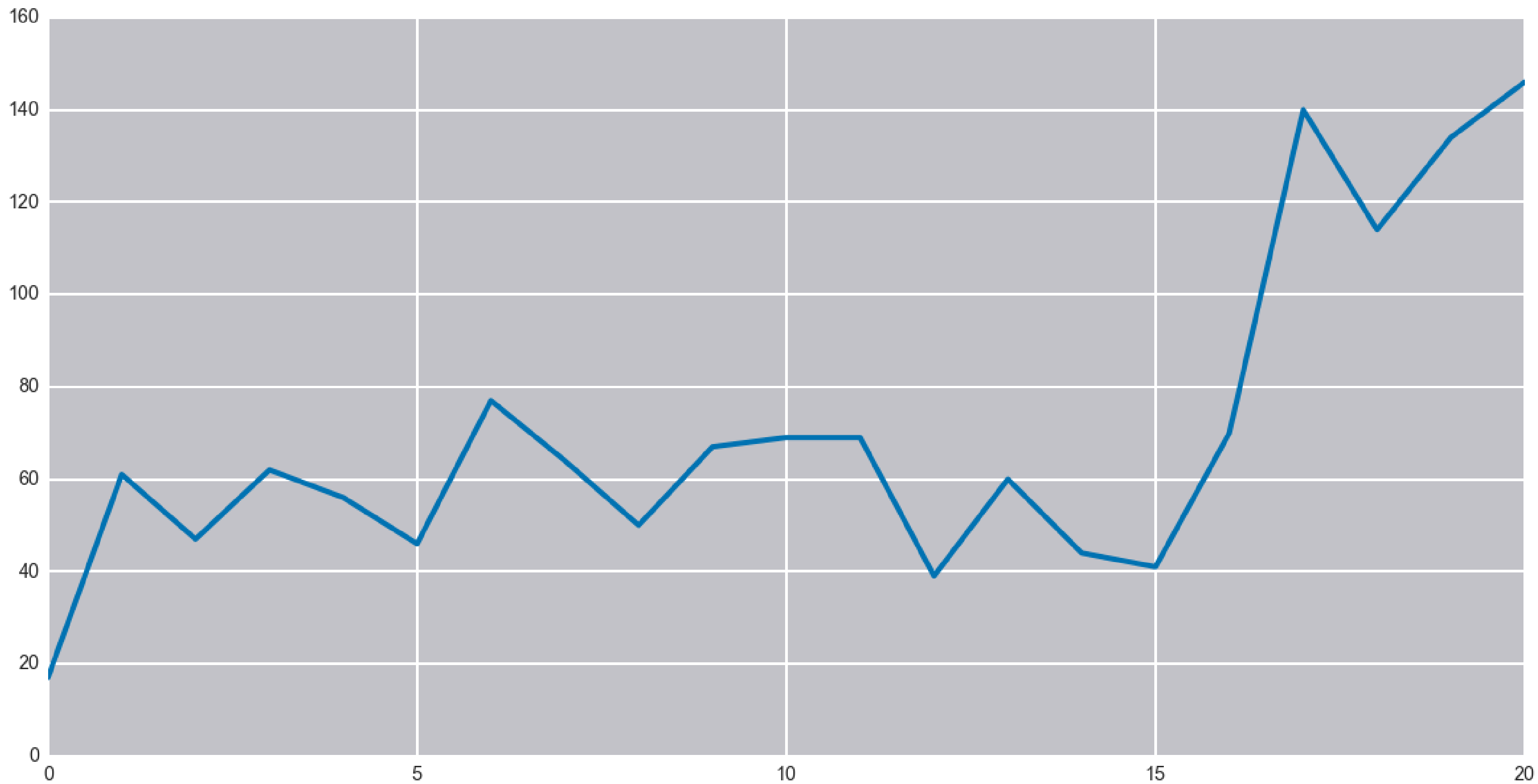
In [10]:
```
events_df['total_RSVP_count'] = events_df['waitlist_count'] + events_df['yes_rsvp_count']
events_df['total_RSVP_count']
```

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)
```

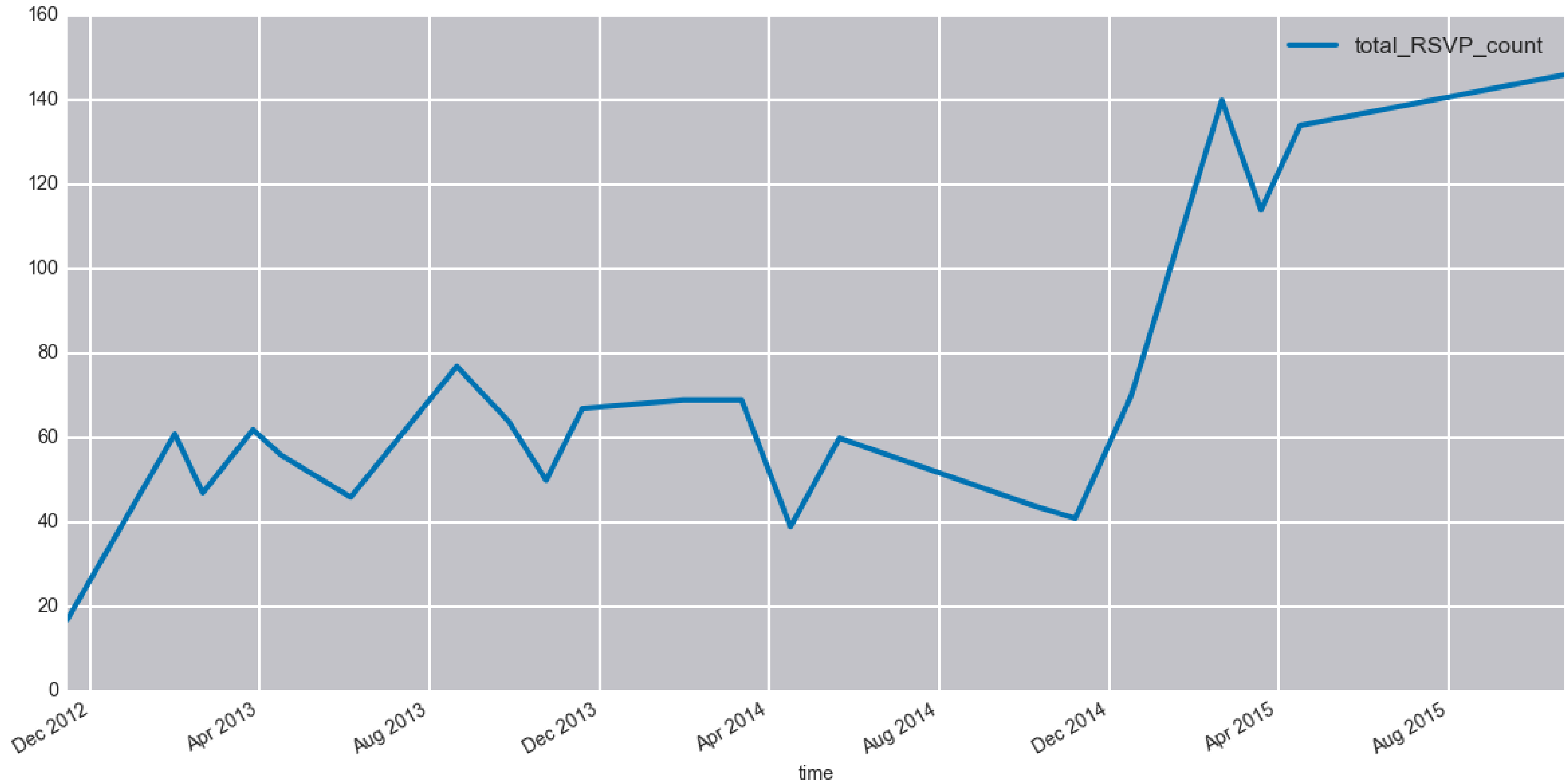
```
In [14]: events_df['time'] = events_df.time.apply(get_datetime_from_epoch)
         events_df['time']
```

```
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()
```

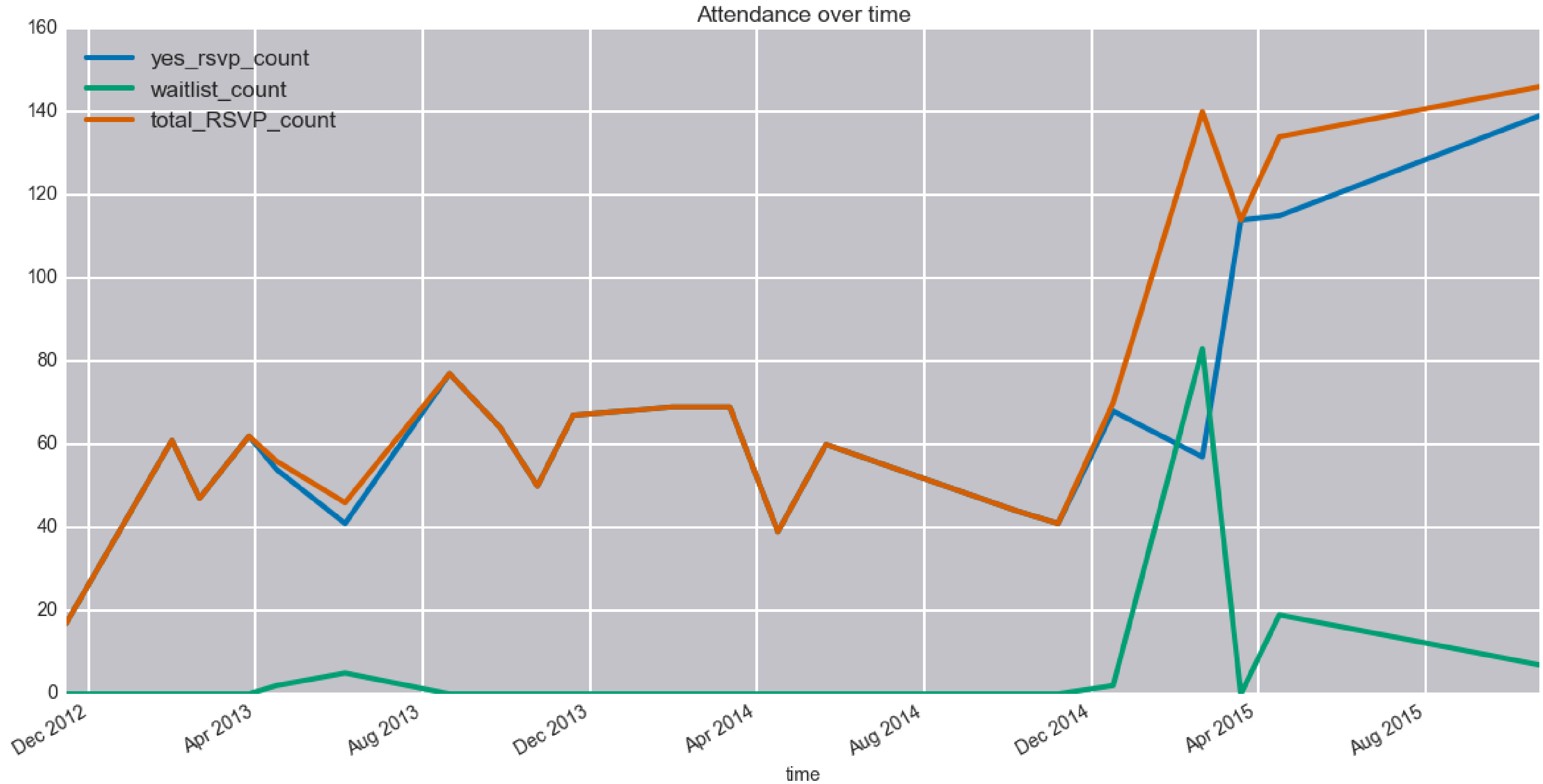
Out[15]: <matplotlib.axes._subplots.AxesSubplot at 0x109621550>



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]:
```python
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 anonimized the meetup member_id and the members name. I've also used the python module `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:

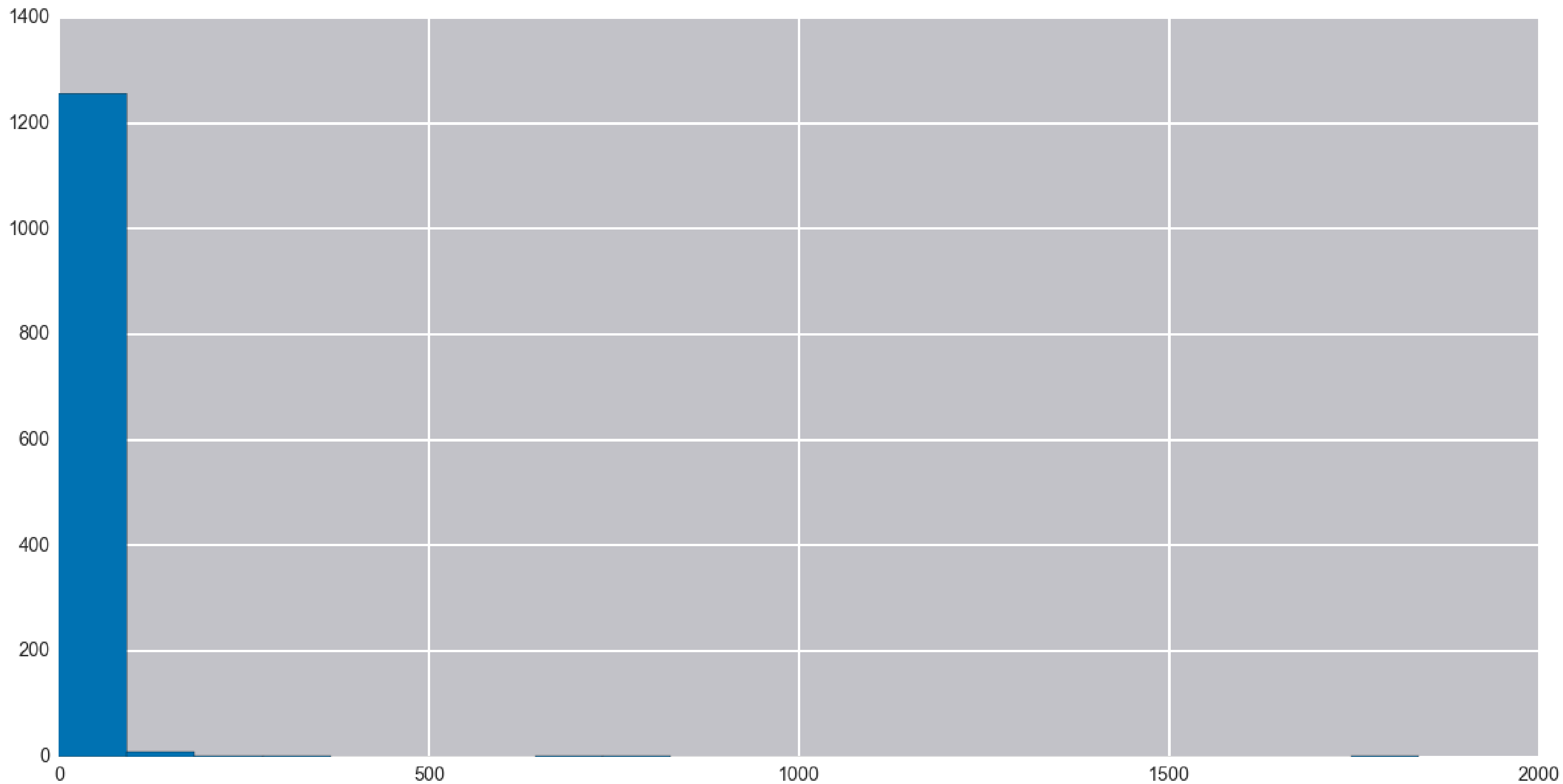
In [18]:
```
gender_counts = members_df['gender'].value_counts()
gender_counts
```

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`:

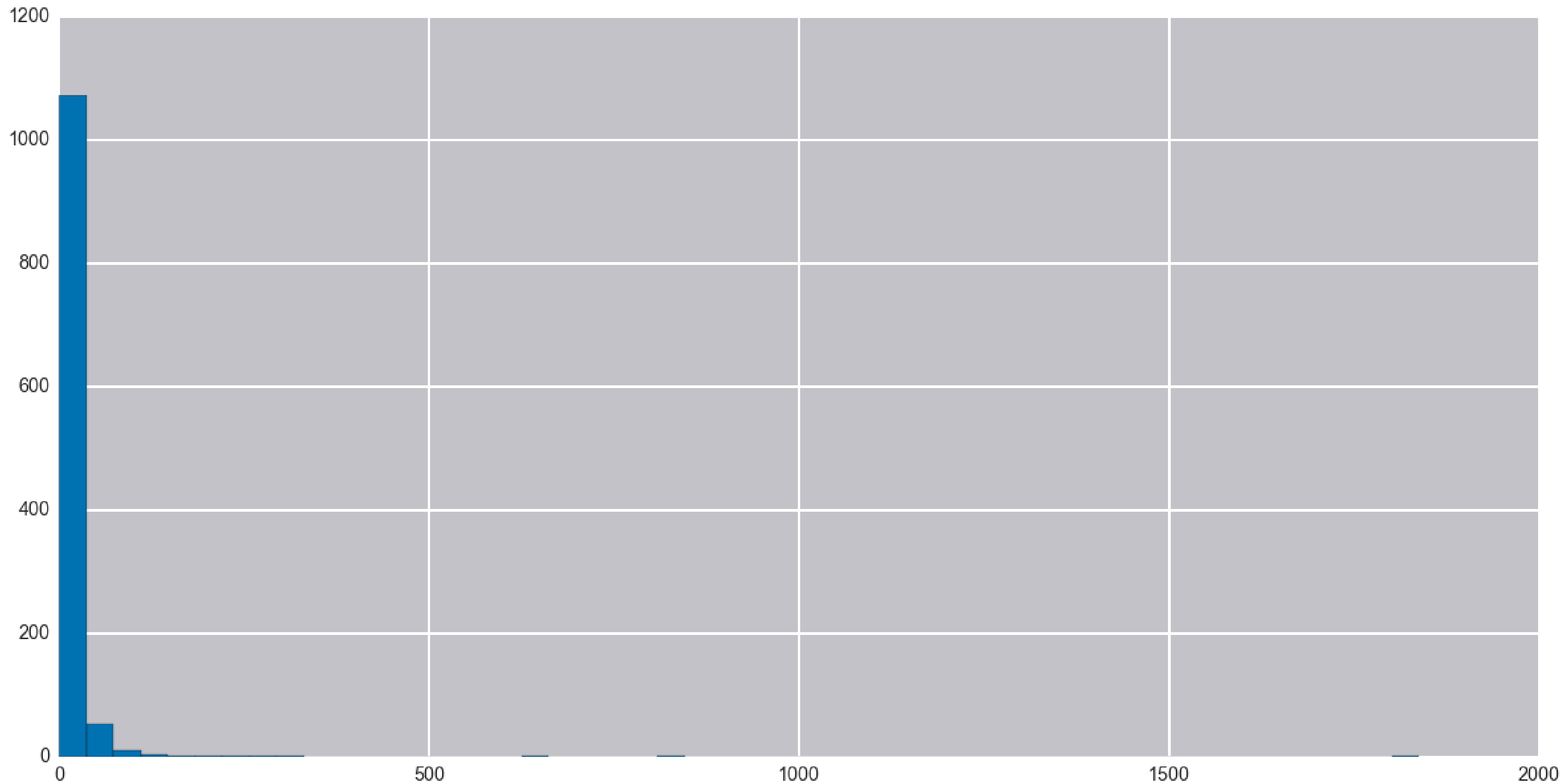
In [20]:
```
members_df['membership_count'].value_counts().head()
```

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.

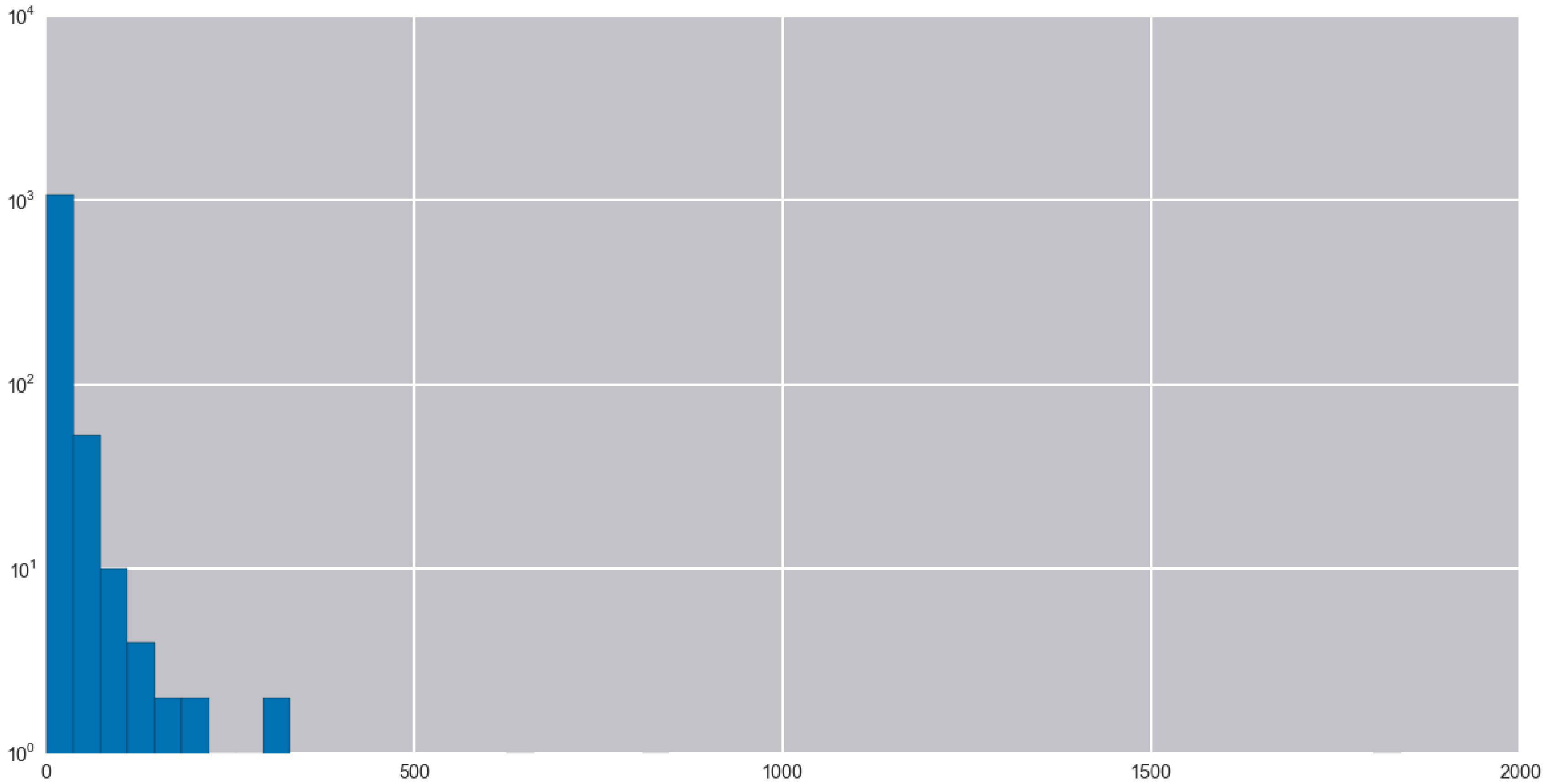
In [21]:
```
members_df_non_zero = members_df[members_df['membership_count'] != 0]
members_df_non_zero['membership_count'].hist(bins=50)
```

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 logaritmic 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
301	1838	Berlin	de	NaN
25	816	San Francisco	us	CA
141	651	Jerusalem	il	NaN
67	303	Philadelphia	us	PA
420	295	Baltimore	us	MD
1178	278	Princeton	us	NJ
257	241	New York	us	NY
223	207	Scarsdale	us	NY
150	197	Philadelphia	us	PA
174	166	Philadelphia	us	PA
86	166	West Chester	us	PA
449	146	Exton	us	PA
154	119	San Francisco	us	CA
1158	119	Philadelphia	us	PA
1022	113	Levittown	us	PA
868	106	Seattle	us	WA
987	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
301	1838	Berlin	de	NaN
25	816	San Francisco	us	CA
141	651	Jerusalem	il	NaN
420	295	Baltimore	us	MD
1178	278	Princeton	us	NJ
257	241	New York	us	NY
223	207	Scarsdale	us	NY
86	166	West Chester	us	PA
449	146	Exton	us	PA
154	119	San Francisco	us	CA
1022	113	Levittown	us	PA
868	106	Seattle	us	WA
987	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 × 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
578	1261	Tom	NaN	Philadelphia	us	male	NaN	2015-10-06 17:50:59	39.96	-75.20	...	0	0
579	1262	Daniel	NaN	Philadelphia	us	male	NaN	2015-10-07 15:48:58	39.97	-75.17	...	0	0
583	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_fe
female_attendees.tail(3)
```

Out[29]:

	anon_id	anon_name	bio	city	country	gender	hometown	joined	lat	lon	...	206754182	2152
580	1265	Erin	NaN	Philadelphia	us	female	NaN	2015-10-13 18:13:37	39.95	-75.16	...	0	0
581	1268	Anne	NaN	Philadelphia	us	female	Philadelphia	2015-10-18 15:29:42	39.96	-75.20	...	0	0
582	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 femal attendees per event and create a `Series` for each.

In [30]:
```
event_ids = [
    '102502622', '106043892', '107740582', '120425212', '133803672', '138415912', '144769822', '1
    '160323532', '168747852', '175993712', '182860422', '206754182', '215265722', '219055217', '2
    '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]:

	female	male
102502622	2	30
106043892	6	35
107740582	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)
```

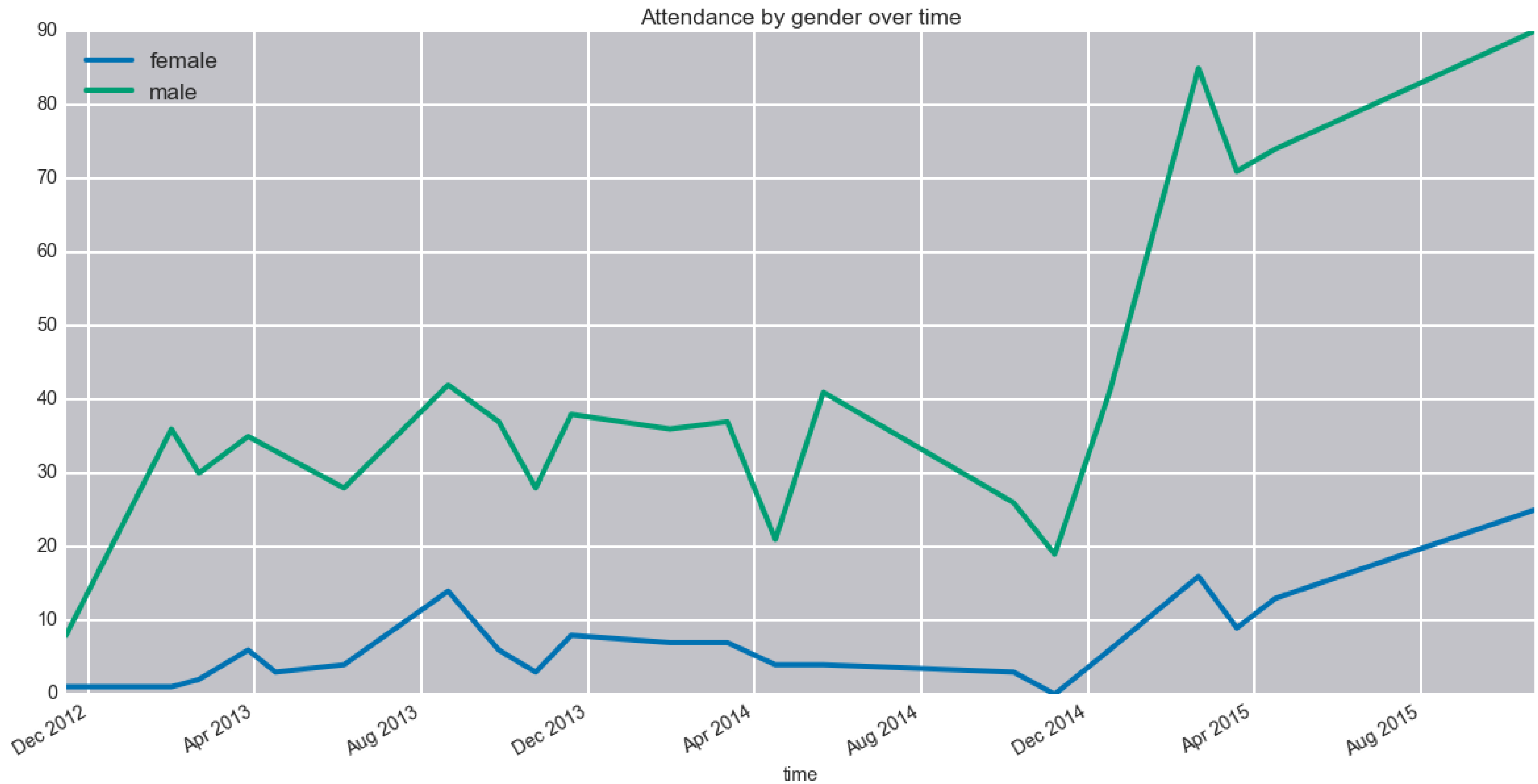
Out[32]:

	created	name	rating	waitlist_count	yes_rsvp_count	id	total_RSVP_count	f
time								
2012-11-14 18:00:00	1351948193000	Meet and greet	{u'count': 3, u'average': 5}	0	17	89769502	17	1
2013-01-30 18:30:00	1357781071000	DataPhilly January 2013 Meetup - An Introducti...	{u'count': 6, u'average': 4.17000007629}	0	61	98833672	61	1
2013-02-19 18:30:00	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')
```

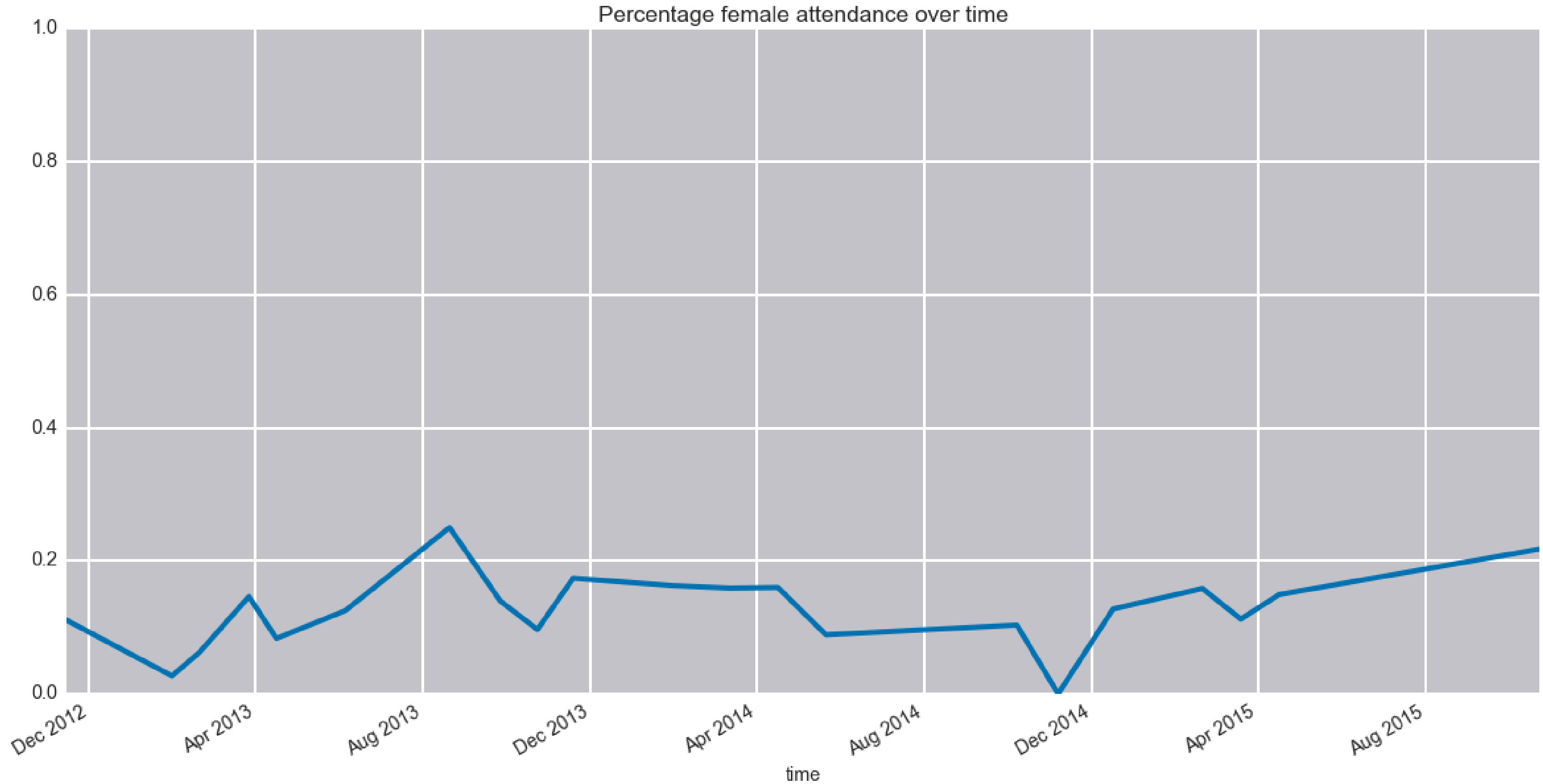
Out[33]: <matplotlib.axes._subplots.AxesSubplot at 0x10c266510>



This might be easier to interpret by looking at the percentage of females in attendance. We can use the `div` (divide) methode 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]:
```python
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
20's & 30's Social	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	1	NaN	NaN	NaN	NaN	NaN	NaN
Adventure	NaN	NaN	NaN	1	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Art	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.

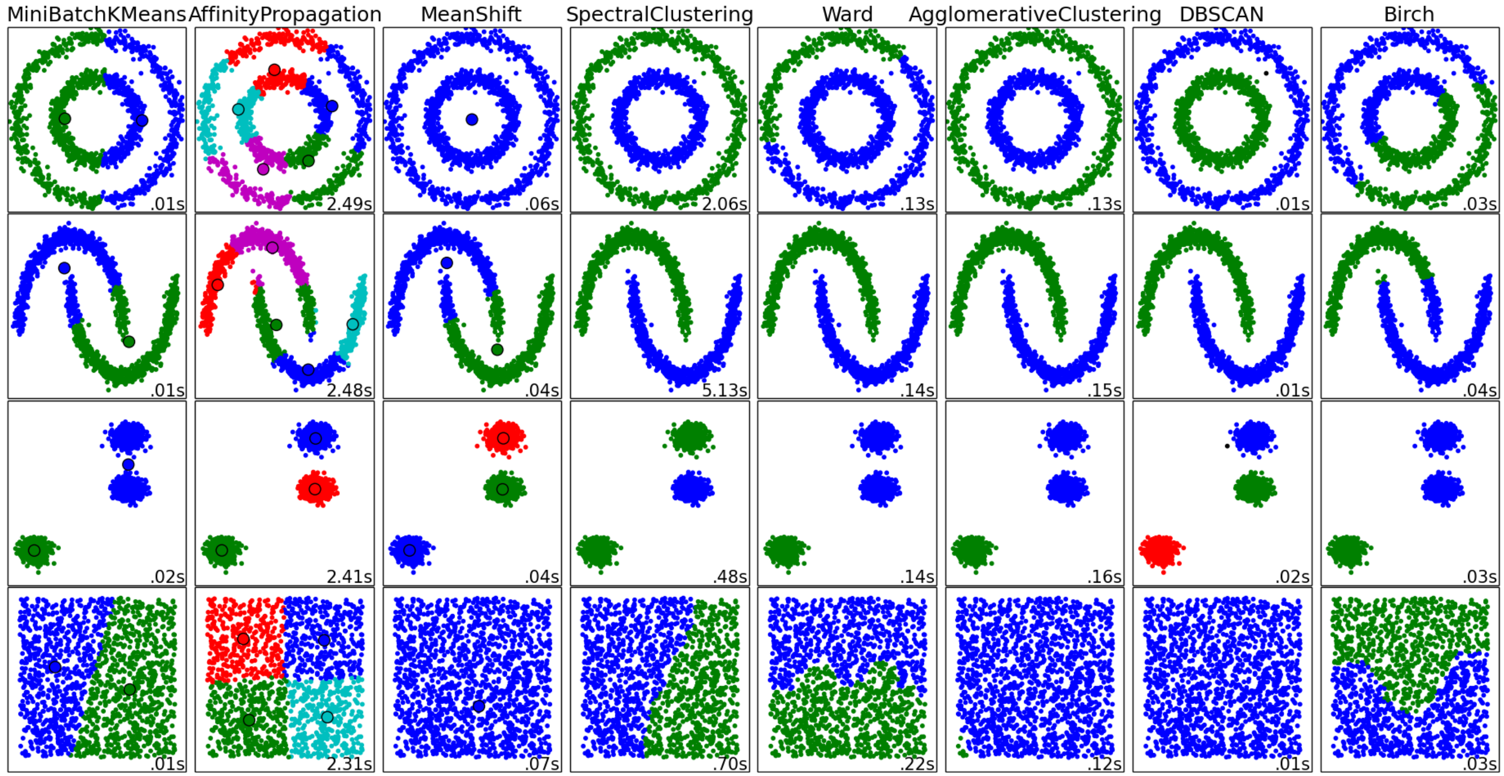
In [39]:
```
top_topic_df.fillna(0, inplace=True)
top_topic_df.head(3)
```

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

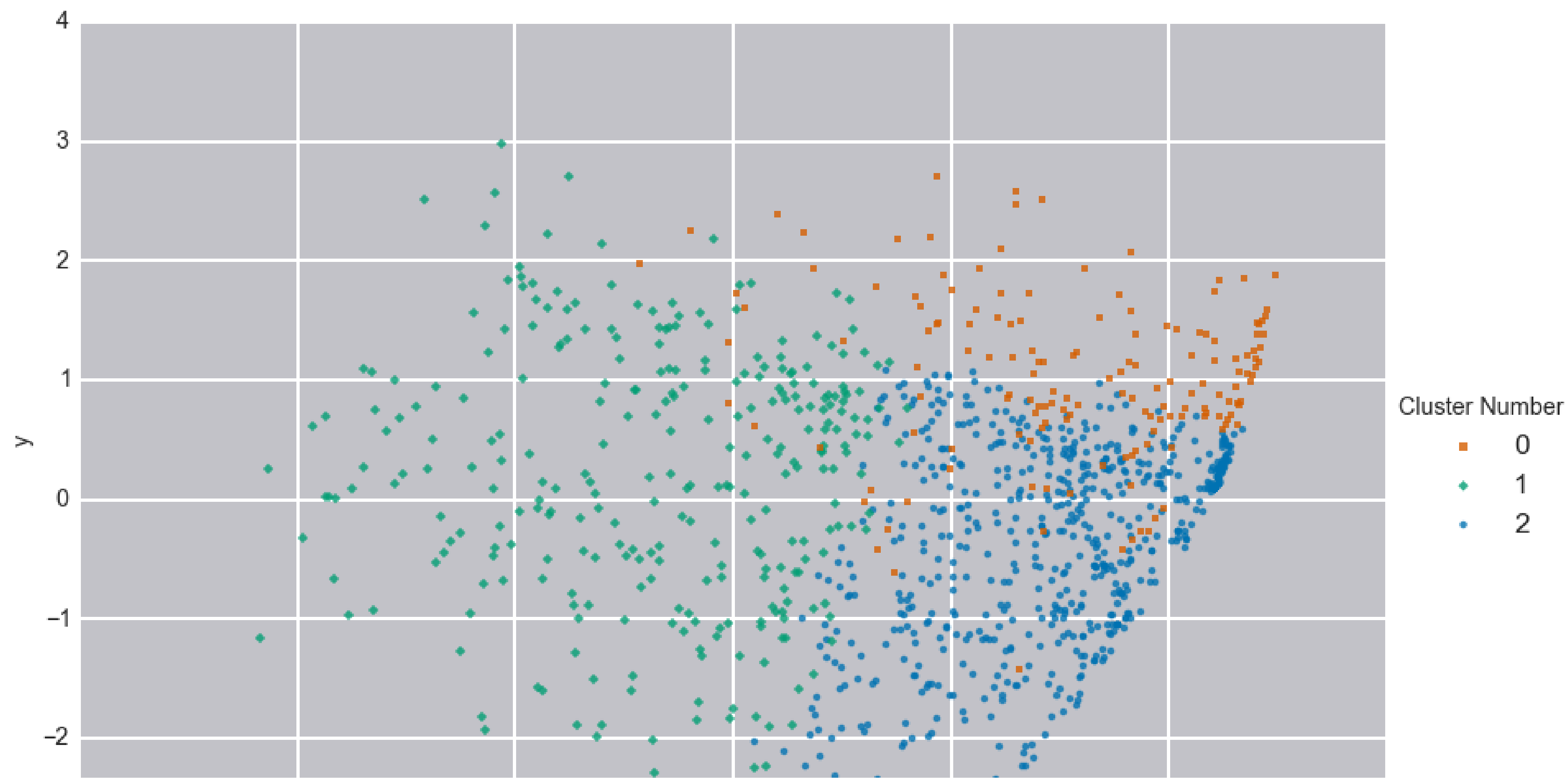
The second biggest cluster (#1) contains members whose primary interests are technology, and data science just happens to be one of those interests.

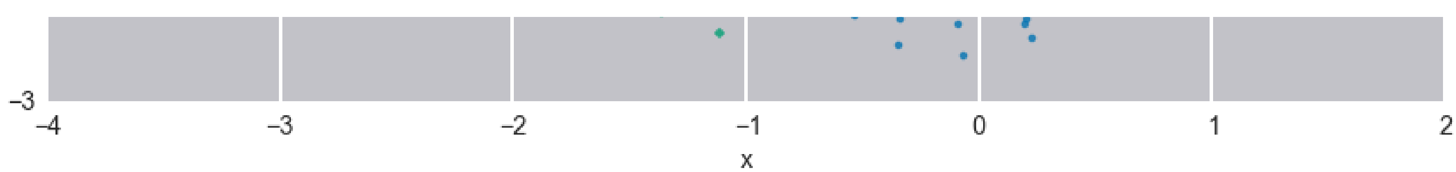
The smallest cluster (#0) contains members whose primary interests are around socializing.

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, siz
ax.add_legend(label_order = sorted(ax._legend_data.keys(), key = int))
```

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





In [ ]: