Lab 2 ¶

Introduction

With this lab data grouping and graphing will be explored. There is always a great deal of information you can gather by grouping and comparing various columns within a dataframe. In addition for data summarization graphing is an important tool to have.

HTTP data will be used for this exercise. The data was generated from various PCAPs that have been collected that contain both legitimate traffic as well as traffic relating to exploit kits. While no malicious traffic is contained within the log file there are malicious domains and URLS (it's recommended you don't visit them). While this traffic was generated by running Bro over a series of PCAPS, similar data can be obtained from various Web Proxies, this is a nice cross over example of what is possible with your own data.

Some goals will be understand when the data was generated, what systems generated, high-level stats about the traffic, and the types of data transferred within the connections.

Exercises

File Input

Using what you learned in the last lab cread in the log (csv) file provided for you.

Hints

- The file name is in the current directory and is called *http.log*
- There is no header to the file
- It's *[TAB]* seperated
- The fields are: 'ts', 'uid', 'id.orig_h', 'id.orig_p', 'id.resp_h', 'id.resp_p', 'trans_depth', 'method', 'host', 'uri', 'referrer', 'user_agent', 'request_body_len', 'response_body_len', 'status_code', 'status_msg', 'info_code', 'info_msg', 'filename', 'tags', 'username', 'password', 'proxied', 'orig_fuids', 'orig_mime_types', 'resp_fuids', 'resp_mime_types', 'sample'

In [1]:
```
import pandas as pd
http_df = pd.read_csv("http.log", header=None, sep="\t", names=['ts', 'uid', 'id
```

I kept getting a permission error. So I copied the log file from inside the http.log directory into the Lab_2 directory

Clean-up the timestamp

Now that you've got the data imported, cleanup up the timestamp column *ts*. Don't forget to re-assign back to the *ts* column.

In [2]:
```
from datetime import datetime
```

In [3]:
```
http_df.head()
```

Out[3]:

	ts	uid	id.orig_h	id.orig_p	id.resp_h	id.resp_p	trans_de
0	1.338423e+09	ChBJ7L2l1Vcl8PmMxh	192.168.88.10	1030	188.121.46.128	80	
1	1.338423e+09	CKH7Eu1pUtdXF8KKq8	192.168.88.10	1031	50.28.53.156	80	
2	1.338423e+09	CMjfL821GNMgnPFTa9	192.168.88.10	1034	188.72.248.160	80	
3	1.338423e+09	Ckt4Bw4pZVSaU17gSg	192.168.88.10	1035	69.63.148.95	80	
4	1.338423e+09	ChBJ7L2l1Vcl8PmMxh	192.168.88.10	1030	188.121.46.128	80	

5 rows × 28 columns

In [4]:
```
http_df.shape
```

Out[4]:
```
(807537, 28)
```

The .shape command list the number of rows (first coordinate) and columns (second coordinate)

In [5]:
```
http_df['ts'] = [datetime.fromtimestamp(float(date)) for date in http_df['ts'].va
http_df.head()
```

Out[5]:

	ts	uid	id.orig_h	id.orig_p	id.resp_h	id.resp_p	trans_
0	2012-05-30 17:09:27.177343	ChBJ7L2l1Vcl8PmMxh	192.168.88.10	1030	188.121.46.128	80	
1	2012-05-30 17:09:28.343725	CKH7Eu1pUtdXF8KKq8	192.168.88.10	1031	50.28.53.156	80	
2	2012-05-30 17:09:29.124170	CMjfL821GNMgnPFTa9	192.168.88.10	1034	188.72.248.160	80	
3	2012-05-30 17:09:29.142869	Ckt4Bw4pZVSaU17gSg	192.168.88.10	1035	69.63.148.95	80	
4	2012-05-30 17:09:29.602005	ChBJ7L2l1Vcl8PmMxh	192.168.88.10	1030	188.121.46.128	80	

5 rows × 28 columns

For converting timestamps from string to dates I typically use pd.to_datetime, but my results were not matching up with the code the author used in the last lab. So, I will continue to use his code for the timestamp conversion.

I did linked some documentation for pd.to_datetime and datetime.fromtimestamp.

https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.to_datetime.html (https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.to_datetime.html)
https://docs.python.org/3/library/datetime.html#datetime.date.fromtimestamp (https://docs.python.org/3/library/datetime.html#datetime.date.fromtimestamp)

In [ ]:
```
#http_df['ts'] = pd.to_datetime(http_df['ts'], unit='s')
#http_df.head()
```

In the next cell the timestamp column is set to be the new index of the dataframe. By default dataframes are indexed by the row number, and by indexing by timestamp it's easier to perform various types of time series analysis. After the assignment a quick **head()** is performed, and in the output you'll see that the *ts* has moved "down and to the left". The new location of the *ts* heading indicates that it is now the index, and has replaced the default.

In [6]:
```
http_df = http_df.set_index('ts')
http_df.head()
```

Out[6]:

ts	uid	id.orig_h	id.orig_p	id.resp_h	id.resp_p	trans_dep
2012-05-30 17:09:27.177343	ChBJ7L2l1Vcl8PmMxh	192.168.88.10	1030	188.121.46.128	80	
2012-05-30 17:09:28.343725	CKH7Eu1pUtdXF8KKq8	192.168.88.10	1031	50.28.53.156	80	
2012-05-30 17:09:29.124170	CMjfL821GNMgnPFTa9	192.168.88.10	1034	188.72.248.160	80	
2012-05-30 17:09:29.142869	Ckt4Bw4pZVSaU17gSg	192.168.88.10	1035	69.63.148.95	80	
2012-05-30 17:09:29.602005	ChBJ7L2l1Vcl8PmMxh	192.168.88.10	1030	188.121.46.128	80	

5 rows × 27 columns

In [7]:
```
http_df.shape
```

Out[7]:
```
(807537, 27)
```

Since the dataframe is now indexed by the ts column, the number of columns was reduced from 28 to 27.

Selecting Based on Index Values

With the default indexing in dataframes you can select elements or slices of elements based on numbers (similarly to how lists work in Python). With a time indexed dataframe various parts of dates, or whole dates, can be used to select rows.

A year can be used eg: 2012, a year and month '2012-02' or a year, month and day '2012-02-20'.

In [8]:
```
http_df['2012-02-20':'2012-02-23'][http_df.columns.tolist()[2:7]].head()
```

Out[8]:

ts	id.orig_p	id.resp_h	id.resp_p	trans_depth	method
2012-02-21 13:41:14.255273	1030	173.245.61.14	80	1	GET
2012-02-21 13:41:14.453622	1031	74.125.45.157	80	1	GET
2012-02-21 13:41:14.532165	1031	74.125.45.157	80	2	GET
2012-02-21 13:41:14.694098	1031	74.125.45.157	80	3	GET
2012-02-21 13:41:14.777528	1031	74.125.45.157	80	4	GET

The results show the rows where the ts column is between '2012-02-20' and '2012-02-23' and the columns indexed between 2 and 7, exclusively.

In [9]:
```
http_df['2012-02-20':'2012-02-23']['id.orig_h'].head()
```

Out[9]:
```
ts
2012-02-21 13:41:14.255273    192.168.4.10
2012-02-21 13:41:14.453622    192.168.4.10
2012-02-21 13:41:14.532165    192.168.4.10
2012-02-21 13:41:14.694098    192.168.4.10
2012-02-21 13:41:14.777528    192.168.4.10
Name: id.orig_h, dtype: object
```

Similarly, a range of dates can be extracted when the column name is explicitly called instead of using a list.

In [10]:
```
len(http_df.index)
```

Out[10]:
```
807537
```

The len command is showing how long (the length) is the index of http_df.

Time Resampling

Time indexed information can be resampled and summarized.

Below is a resampling on day *D* that will count up the number of occurrences per day. Try various date selections to get a feel for how the sampling works and how it can be used to summarize data.

In [11]:
```
%time
temp_df = http_df['2012-02-20':'2012-02-25']
temp_df.resample("D").count().head()
```

```
Wall time: 0 ns
```

Out[11]:

ts	uid	id.orig_h	id.orig_p	id.resp_h	id.resp_p	trans_depth	method	host	uri	referrer	.
2012-02-20	1581	1581	1581	1581	1581	1581	1581	1581	1581	1581	.
2012-02-21	589	589	589	589	589	589	589	589	589	589	.
2012-02-22	2573	2573	2573	2573	2573	2573	2573	2573	2573	2573	.
2012-02-23	428	428	428	428	428	428	428	428	428	428	.
2012-02-24	1982	1982	1982	1982	1982	1982	1982	1982	1982	1982	.

5 rows × 27 columns

The percent sign (%) in front of time is a magic command native to Jupyter Notebooks. %time will display the time it took to run the commands in the cell.
I modified the line containing the resample command due to a depreciation warning. The daily counts are displayed across the columns. There are other (more interesting) quantitative methods to use on resample like mean and sum.

https://blog.dominodatalab.com/lesser-known-ways-of-using-notebooks/ (https://blog.dominodatalab.com/lesser-known-ways-of-using-notebooks/)

https://www.geeksforgeeks.org/python-pandas-dataframe-resample/ (https://www.geeksforgeeks.org/python-pandas-dataframe-resample/)

Try the resample example from above with some of the other options for resample. Replace the *D* with some other values to get different frequencies.

Alias	Description
B	business day frequency
C	custom business day frequency (experimental)
D	calendar day frequency
W	weekly frequency
M	month end frequency
BM	business month end frequency
CBM	custom business month end frequency

Alias	Description
MS	month start frequency
BMS	business month start frequency
CBMS	custom business month start frequency
Q	quarter end frequency
BQ	business quarter end frequency
QS	quarter start frequency
BQS	business quarter start frequency
A	year end frequency
BA	business year end frequency
ASyear	start frequency
BAS	business year start frequency
H	hourly frequency
T	minutely frequency
S	secondly frequency
L	milliseonds
U	microseconds

In [12]:
```
http_df['2012-02-20':'2012-02-25'].resample("H").count().head()
```

Out[12]:

ts	uid	id.orig_h	id.orig_p	id.resp_h	id.resp_p	trans_depth	method	host	uri	referrer
2012-02-20 11:00:00	951	951	951	951	951	951	951	951	951	951
2012-02-20 12:00:00	0	0	0	0	0	0	0	0	0	0
2012-02-20 13:00:00	0	0	0	0	0	0	0	0	0	0
2012-02-20 14:00:00	127	127	127	127	127	127	127	127	127	127
2012-02-20 15:00:00	503	503	503	503	503	503	503	503	503	503

5 rows × 27 columns

The hourly counts between 2012-02-20 and 2012-02-25 are displayed across the columns.

The head command can be removed to reveal the rest of the timestamps for ts.

Graphing Time Series Data

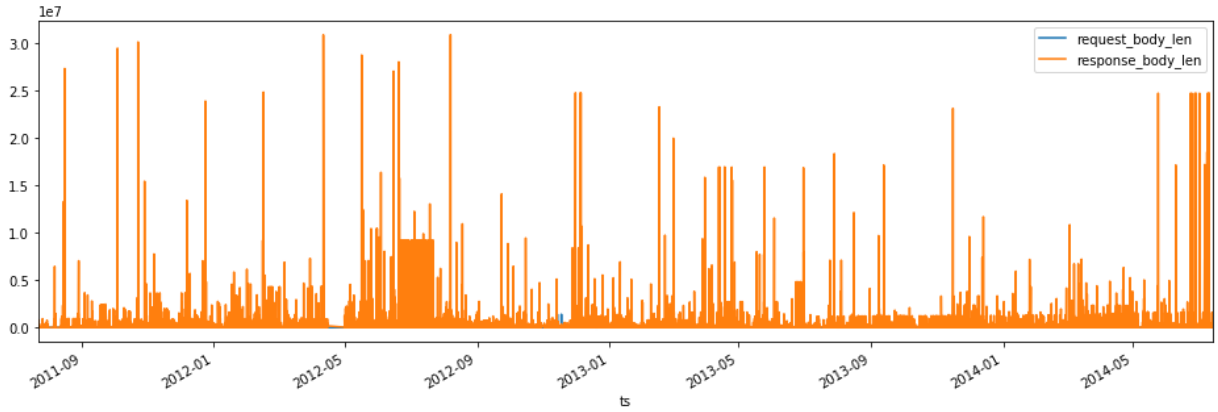
After getting a grasp on the various ways to look at time indexed data, it's useful to display it visually. With this section the same progression as above will be used.

The cell below will generate a time series graph of both the request and response bodies, summed up over their timestamps.

In [14]:
```
import matplotlib
from matplotlib import rcParams, pyplot as plt
rcParams['figure.figsize'] = (16.0, 5.0)
rcParams['agg.path.chunksize'] = 10000

df = http_df[['request_body_len','response_body_len']]
df.plot()
```

Out[14]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x13b2815d898>
```



I was getting a NameError issue for pylab, so I modified the import command. See below
https://stackoverflow.com/questions/35463670/what-is-the-preferred-way-to-import-pylab-at-a-function-level-in-python-2-7 (https://stackoverflow.com/questions/35463670/what-is-the-preferred-way-to-import-pylab-at-a-function-level-in-python-2-7)

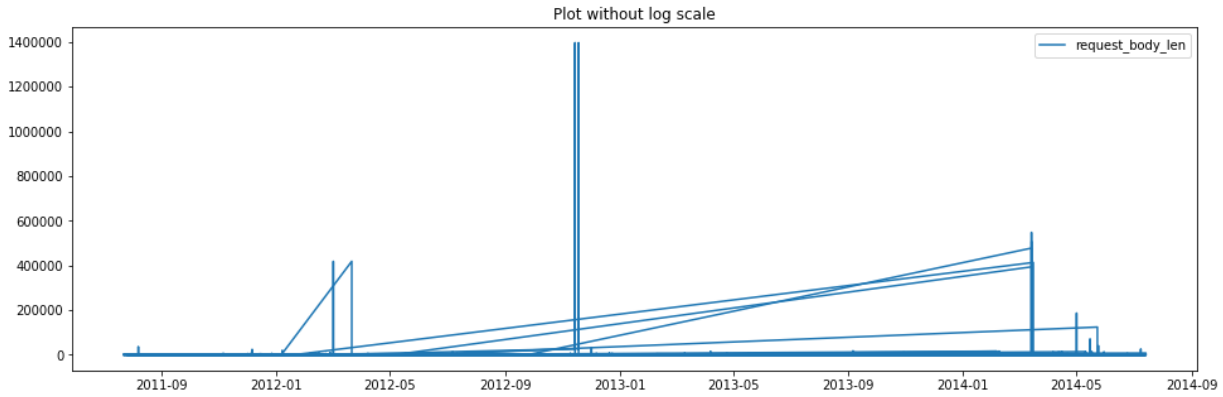
rcParams is used to set the plot to a certain length and width.

I ran the cell twice since the figure did not show up the first time.

The time series plot looks neat, but the magnitude of response_body_len (10^7) makes it hard to visualize request_body_len. Maybe a logarithm scale would useful or normalize the variables individually so that they are on the same scale.

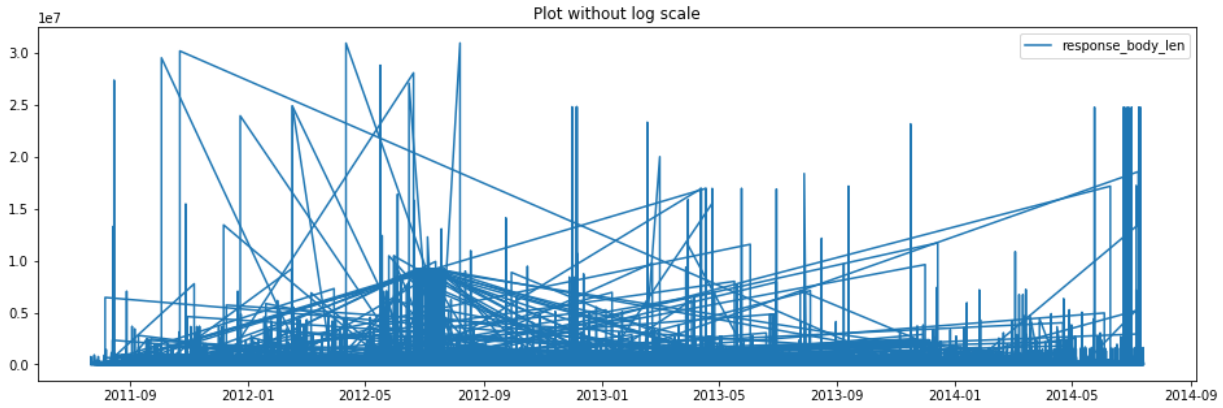
In [15]:
```
plt.plot(df.index,df.request_body_len)
plt.legend(['request_body_len'])
plt.title('Plot without log scale')
plt.plot()
```

Out[15]: []



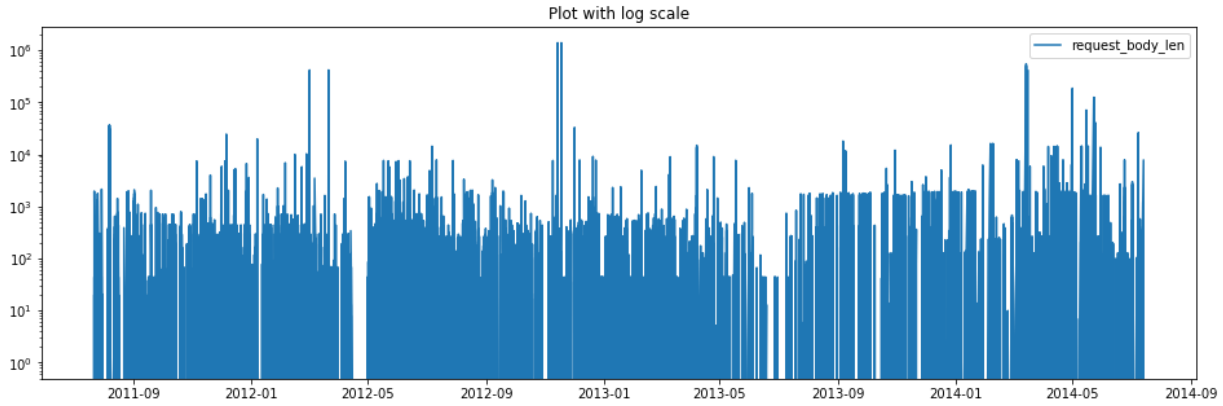
In [16]:
```
plt.plot(df.index,df.response_body_len)
plt.legend(['response_body_len'])
plt.title('Plot without log scale')
plt.plot()
```

Out[16]: []



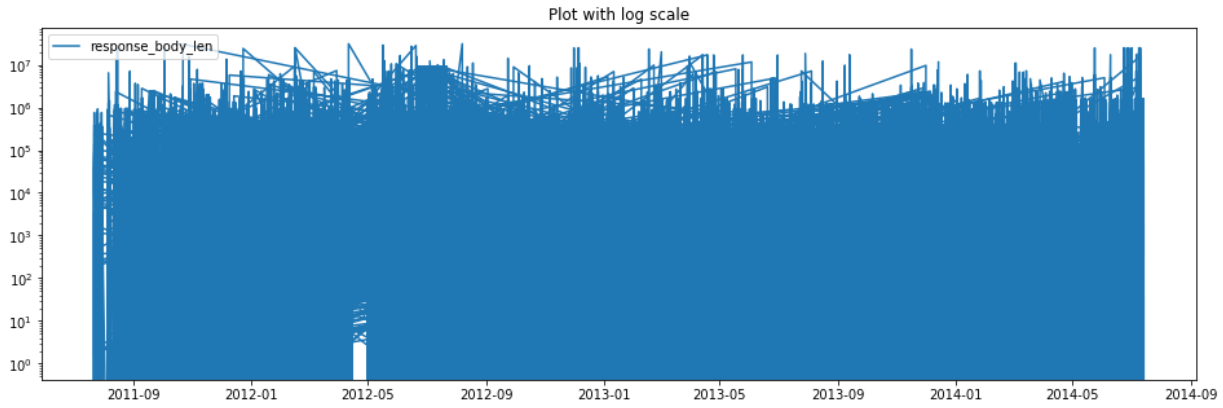
In [17]:
```
plt.plot(df.index,df.request_body_len)
plt.legend(['request_body_len'])
plt.title('Plot with log scale')
plt.yscale("log")
plt.plot()
```

Out[17]: []



In [18]:
```
plt.plot(df.index,df.response_body_len)
plt.legend(['response_body_len'])
plt.title('Plot with log scale')
plt.yscale("log")
plt.plot()
```

Out[18]: []



I have plotted the variables separately, before and after applying the logarithmic (log) scale on the y-axis. We can see the trends of request_body_len better with the log scale. Yet the response_body_len plot looks all over the place and dense.
https://stackoverflow.com/questions/46374209/logarithmic-scale-in-python (https://stackoverflow.com/questions/46374209/logarithmic-scale-in-python)

The last plot had an OverflowError issue: https://stackoverflow.com/questions/37470734/matplotlib-giving-error-overflowerror-in-draw-path-exceeded-cell-block-limit (https://stackoverflow.com/questions/37470734/matplotlib-giving-error-overflowerror-in-draw-path-exceeded-cell-block-limit)

I did use matplotlib commands to create plots which uses quite a few series of commands to create the final result.

A small copy of the HTTP dataframe **http_df** is stored in **df** it only contains 2 columns *[request_body_len, response_body_len]*, this enables the comparison of the request and response body lengths.

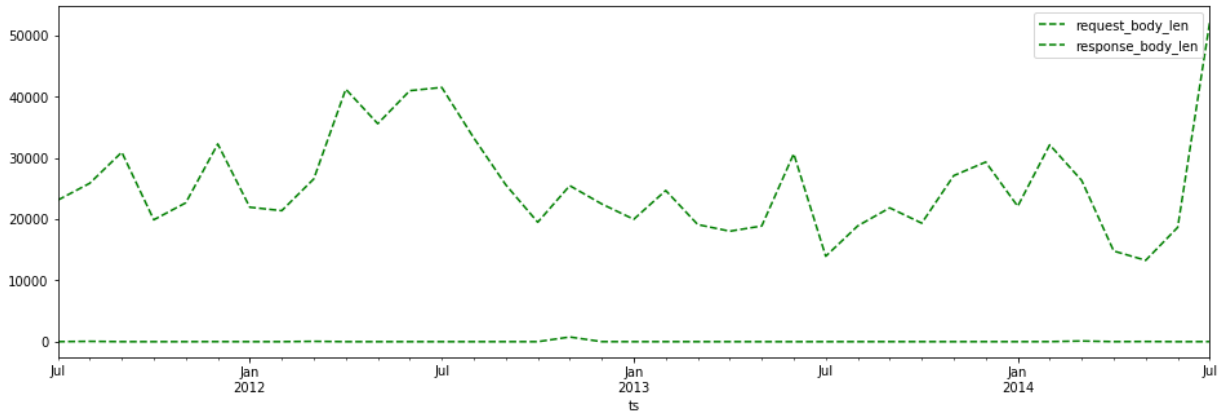
Below is another way to graph the resampled data. In this case the data is resampled on *month*, and when no **how** parameter is passed to **resample()** it defaults to *mean*.

Hint

If you're going to use anything but *'count'* as the paremeter to **how**, you need to make sure it's numeric data.

In [19]:
```
resamp = df.resample("M").mean()
resamp.plot(style='g--')
```

Out[19]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x13b11f94fd0>
```

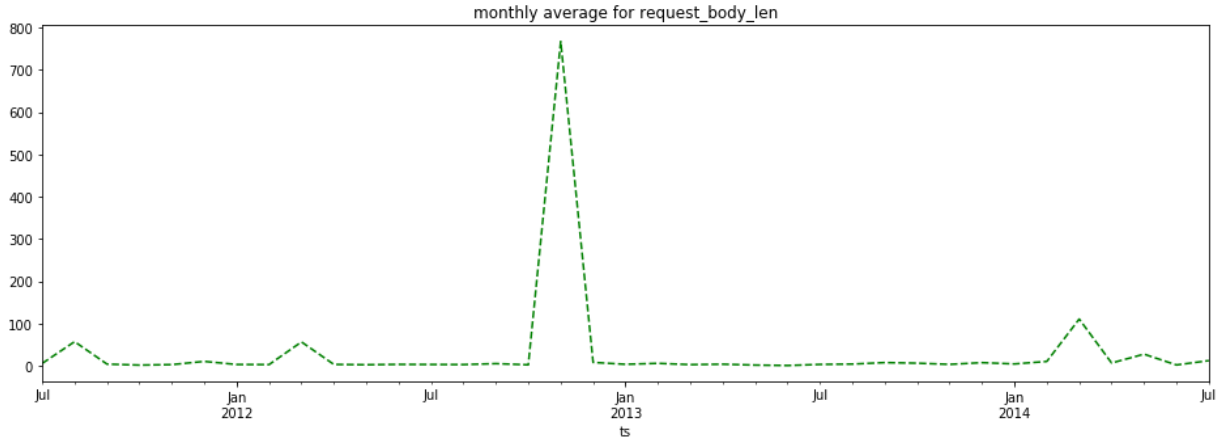


I just added the mean command at the end to get the graph since how is deprecated: https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.DataFrame.resample.html (https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.DataFrame.resample.html)

The colors look too similar. I am guessing the flat-like line at the bottom is request_body_len and the curvy line is response_body_len.

In [20]:
```
resamp = df.request_body_len.resample("M").mean()
resamp.plot(style='g--',title='monthly average for request_body_len')
```

Out[20]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x13b296449b0>
```



I plotted the resamp plot for only request_body_len. The values are quite small in comparison to the resampling of response_body_len so that is why request_body_len looks like a flat line in the plot before this one.

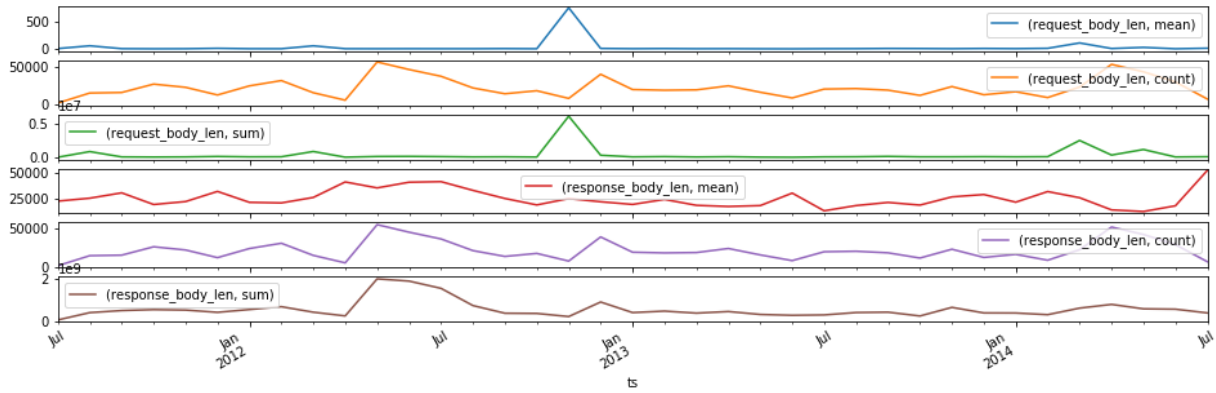
This plot does show an abnormally large average length for the body of the request for the month of November 2013.

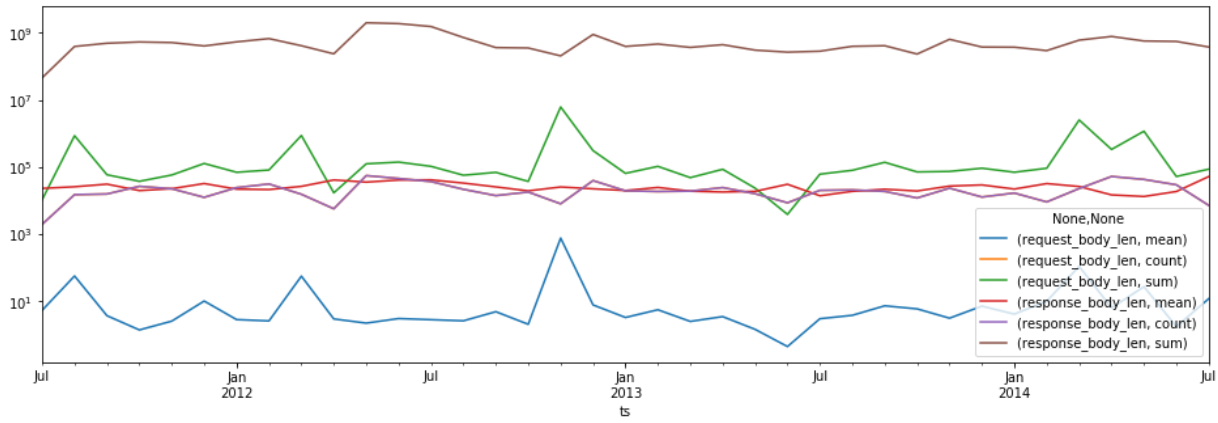
Graphing Multiple Views (Time Series)

It's possible to graph multiple **how** methods as well. This can help identify different patterns in the data.

In [21]:
```
resamp = df.resample("M").agg(['mean', 'count', 'sum'])
resamp.plot(subplots=True)
resamp.plot(logy=True)
```

Out[21]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x13b2950ceb8>
```





Instead of using how, I applied .agg to get similar results as the solution: https://stackoverflow.com/questions/22128218/pandas-how-to-apply-multiple-functions-to-dataframe (https://stackoverflow.com/questions/22128218/pandas-how-to-apply-multiple-functions-to-dataframe)

For some reason only two lines was plotted for the last figures, so I added logy=True in the plot command. https://kanoki.org/2019/09/16/dataframe-visualization-with-pandas-plot/ (https://kanoki.org/2019/09/16/dataframe-visualization-with-pandas-plot/)

Above, the response_body_len sum really sticks out in the bottom graph, but viewing the smaller graphs above it's possible to see that it's not because of an increase in the number of requests (it's simply because more information was received, in aggregate, over all the connections).

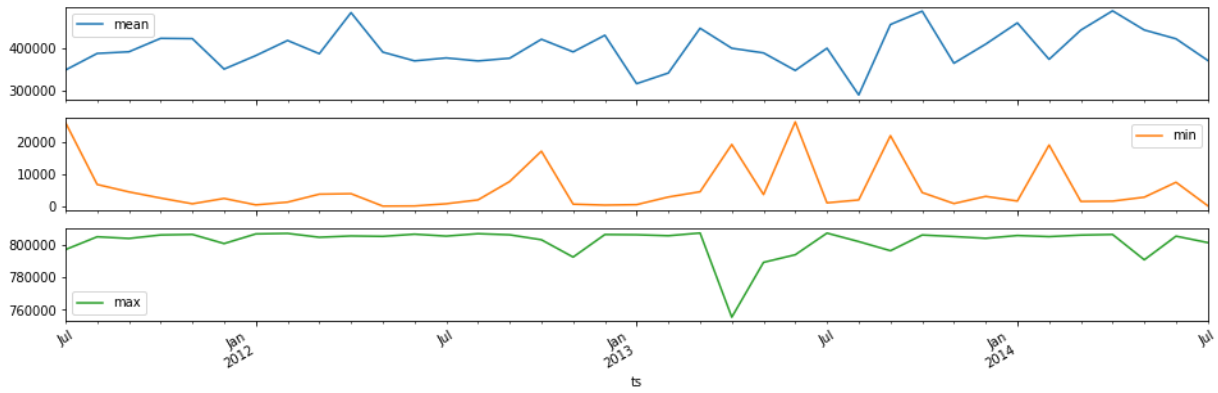
Below, the *count* column was added for you, try doing the same type graph as above and incorporate **np.min** and **np.max** into your resampling.

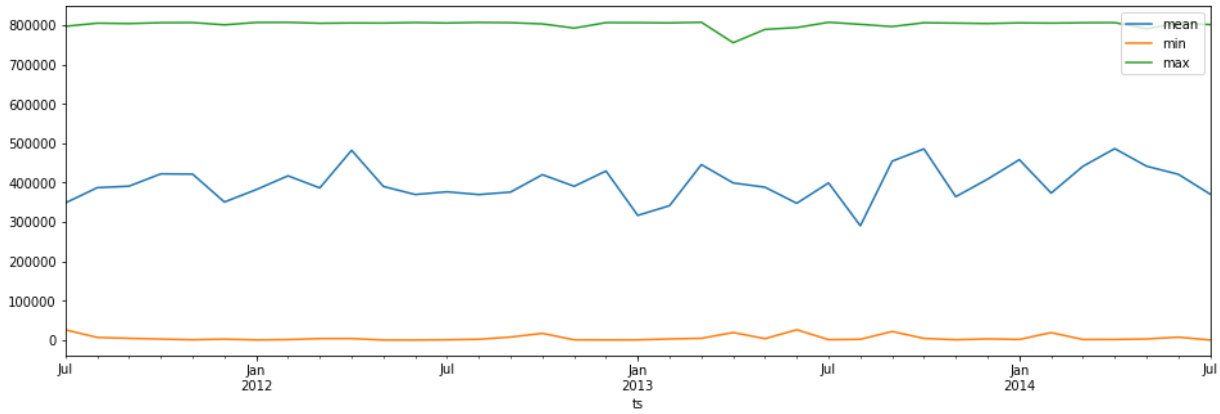
Hint

Do not put single quotes around **np.min** or **np.max**.

In [22]:
```
pd.options.mode.chained_assignment = None
df['count'] = 1
df=df['count'].cumsum()
resamp = df.resample("M").agg(['mean', 'min', 'max'])
resamp.plot(subplots=True)
resamp.plot()
```

Out[22]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x13b12494828>
```





I had an issue with the SettingWithCopyWarning. I could figure out which line to debug so I disabled chained assignments.

https://stackoverflow.com/questions/49728421/pandas-dataframe-settingwithcopywarning-a-value-is-trying-to-be-set-on-a-copy (https://stackoverflow.com/questions/49728421/pandas-dataframe-settingwithcopywarning-a-value-is-trying-to-be-set-on-a-copy)

Dataframe Grouping

Another useful way to look at data is how different groups of values look with one another. For this pandas offers the **groupby()** command. It allows you to specify an arbitrary list of columns in your dataframe that are evaluated left-to-right in terms of grouping.

The example below shows how *resp_mime_type* (filetype returned by the server) breaks down, and then per-filetype what *user_agents* requested those files. You can see the number of entries per-column per-value in the table.

In [23]:
```
http_df.groupby(['resp_mime_types','user_agent']).count()
```

Out[23]:

resp_mime_types	user_agent
-	
	B2BFB2BDDEC2B5B7C7B1C1A786819A9D94A8C4C5C7CBC4DEC5C7C2DEAE8FC2C
	Googlebot/2.1 (+http://www.google.c
	Inte
	Micro
	Microsoft Internet Explorer/1.0 (
	Microsoft-CryptoAPI/5.1
	Microsoft-WebDAV-MiniF
	Mozilla/1.22 (compatible; MSIE 10.0;
	Mozilla/3.0 (compatible;
	Mozilla/4.0 (Windows XP 5.1)
	Mozilla/4.0 (Windows; U; Windows NT 5.1; en-US; rv:1.9.2.10) Gecko/2009801003
	Mozilla/4.0 (compatible. MSIE 8.0. Win
	Mozilla/4.0 (compatible; 2600.xpsp_sp2_rtm.040803-2158; uid=1b88000074050000a7 6.
	Mozilla/4.0 (compatible; MSIE 10.0; Windows NT 6
	Mozilla/4.0 (compatible; MSIE 2.0; Windows NT 5.0; Trident/4.0; SLCC2; .NET CLR 2.(CLR 3.5.30729; .NET CLR 3.0.30729; Media C
	Mozilla/4.0 (compatible; MSIE 4.01; Win
	Mozilla/4.0 (compatible; MSIE 5.01; Win
...	

resp_mime_types	
text/x-c	Mozilla/4.0 (compatible; MSIE 6.0; Windows
	Mozilla/4.0 (compatible; MSIE 6.0; Win
	Mozilla/4.0 (compatible; MSIE 7.0; Windows NT 5.
	Mozilla/4.0 (compatible; MSIE 8.0; Windows NT 5.
	Mozilla/5.0 (Windows NT 5.1) AppleWebKit/537.4 (KHTML, like Gecko) Chrome
	Mozilla/5.0 (Windows NT 6.1; WOW64; rv:17.0) Gecko/20100101 Firefox/17.0 AlexaToo
	Mozilla/5.0 (Windows NT 6.3; Trident/7.0; Touch; rv:11
	Mozilla/5.0 (Windows; U; Windows NT 6.0; en-GB; rv:1.9.2.26) Gecko/20120128 F .NET CLR 3.5.30729; .NET4.0C) ;Sh
	Mozilla/5.0 (compatible; MSIE 10.0; Windows NT 6.
	Mozilla/5.0 (compatible; MSIE 10.0; Windows NT 6.1; WOW6
text/x-c++	Mozilla/4.0 (compatible; MSIE 6.0; Windows
	Mozilla/4.0 (compatible; MSIE 8.0; Windows NT 5.
text/x-pascal	Mozilla/4.0 (compatible; MSIE 6.0; Windows
	Mozilla/4.0 (compatible; MSIE 8.0; Windows NT 5.
text/x-php	Mozilla/4.0 (compatible; MSIE 6.0; Windows
video/mp2p	Mozilla/4.0 (compatible; MSIE 6.0; Windows
video/mp4	Mozilla/4.0 (compatible; MSIE 6.0; Windows
	Mozilla/4.0 (compatible; MSIE 8.0; Windows NT 5.
	Mozilla/5.0 (Windows NT 5.1) AppleWebKit/537.4 (KHTML, like Gecko) Chrome
	Mozilla/5.0 (compatible; MSIE 10.0; Windows NT 6.1; WOW6
video/x-flv	Mozilla/4.0 (compatible; MSIE 6.0; Windows
	Mozilla/4.0 (compatible; MSIE 8.0; Windows NT 5.
	Mozilla/5.0 (Windows NT 5.1) AppleWebKit/537.4 (KHTML, like Gecko) Chrome
video/x-ms-asf	Mozilla/4.0 (compatible; MSIE 6.0; Windows
	NSPlay
	NSPlayer/9.0.0.3250
	Windows-Media-Player
video/x-msvideo	Mozilla/4.0 (compatible; MSIE 6.0; Windows
	Windows-Media-Player

1503 rows × 25 columns

Information like this, gives us insight into what are the most and least common user agents per

filetype. We can also see some interesting interesting user agents paired with a filetype.

It's also possible to select rows (as learned in Lab 1) and then do a **groupby()** to look at various sub views of the data.

This looks at all rows associated with those 2 different *user_agent*s, and then shows how many entries are in the data per-user-agent per-filetype.

In [24]:
```
http_df[http_df['user_agent'].isin(
    ['Mozilla/4.0 (compatible; MSIE 6.0; Windows NT 5.1; SV1)',
     'Mozilla/4.0 (compatible; MSIE 8.0; Windows NT 5.1; Trident/4.0)'])].groupby
```

Out[24]:

		uid	id.orig_h	id.orig_p	id.resp_h	id.resp_p	trans_depth	
resp_mime_types	**user_agent**							
-	**Mozilla/4.0 (compatible; MSIE 6.0; Windows NT 5.1; SV1)**	64458	64458	64458	64458	64458	64458	
	Mozilla/4.0 (compatible; MSIE 8.0; Windows NT 5.1; Trident/4.0)	45411	45411	45411	45411	45411	45411	
application/msword	**Mozilla/4.0 (compatible; MSIE 6.0; Windows NT 5.1; SV1)**	1	1	1	1	1	1	

I have not used .isin() myself, but it looks handy to filter values/records. I have linked the documentation below for it.

https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.DataFrame.isin.html (https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.DataFrame.isin.html)

Use the pre-defined filetypes below to come up with a couple of interesting views on the data that involve the **groupby()** function.

In [25]:
```
executable_types = set(['application/x-dosexec', 'application/octet-stream', 'bi
common_exploit_types = set(['application/x-java-applet','application/pdf','appli
```

Both the variables executable_types and common_exploit_types are Python sets, created by using lists.

https://www.programiz.com/python-programming/set (https://www.programiz.com/python-programming/set)

Graphing Groupby Data

One advantage of the **groupby()** command is being able to graph the output to get another view into the data. One popular way to do this is via a bar graph.

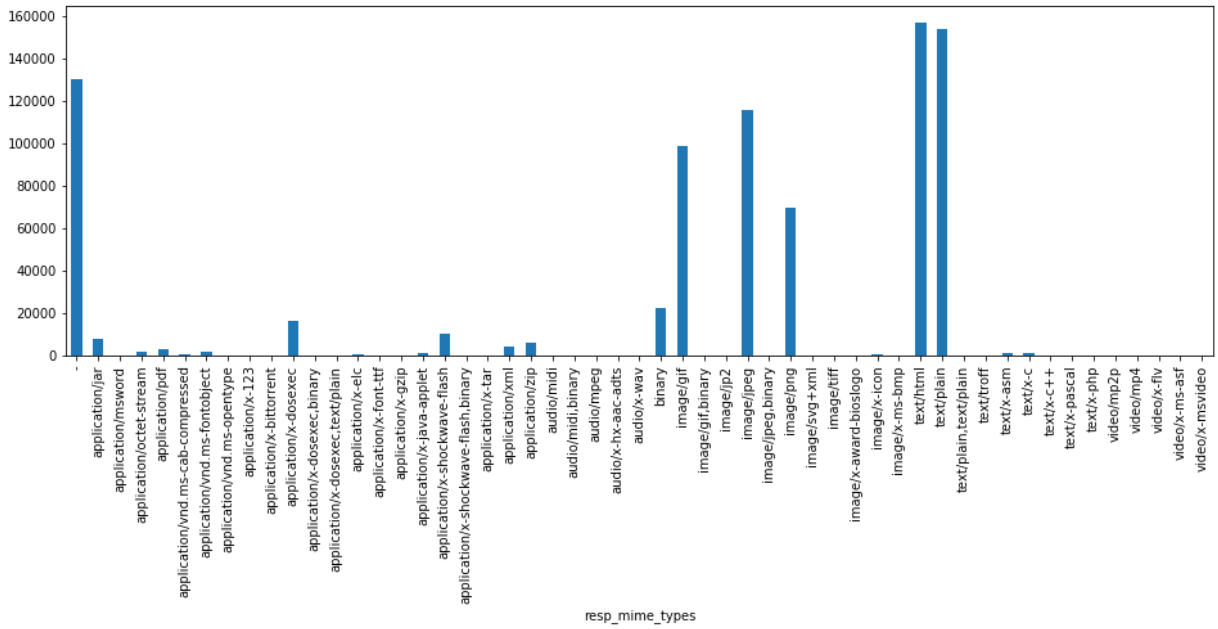
In the next cell there are a couple of things going on. First, a column named *count* is created and every row in that column is assigned the value of 1. This creates a column that we can use pandas to sum on since it has a value of 1 for each row.

In the second line, the dataframe is grouped by *resp_mime_types* and then only the *count* column is viewed/returned from the **groupby()** command. The result is then passed to the **sum()** function, this causes the sum on the *count* column, which due to the trick above has a value of 1 for each row. Combined this gets the number of files in each filetype. The result is simply plotted with **plot()**.

Any surprising results? What could they possibly indicate?

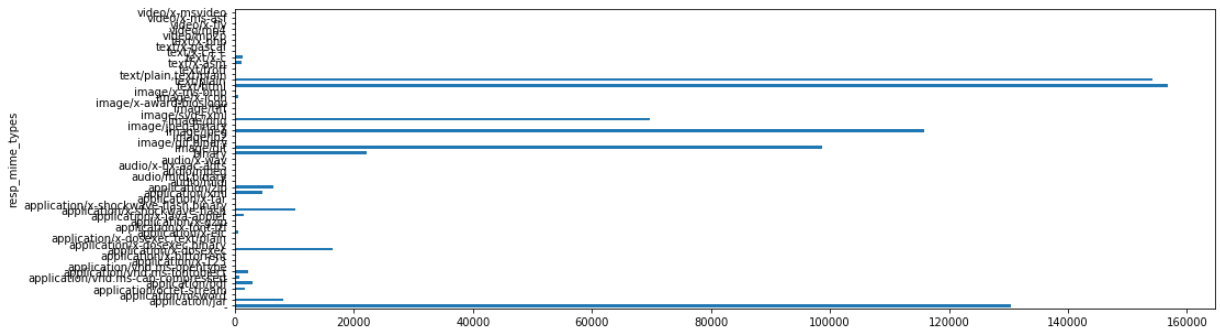
In [26]:
```
http_df['count'] = 1
http_df.groupby('resp_mime_types')['count'].sum().plot(kind='bar')
```

Out[26]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x13b126d8400>
```



In [27]:
```
http_df.groupby('resp_mime_types')['count'].sum().plot.barh()
```

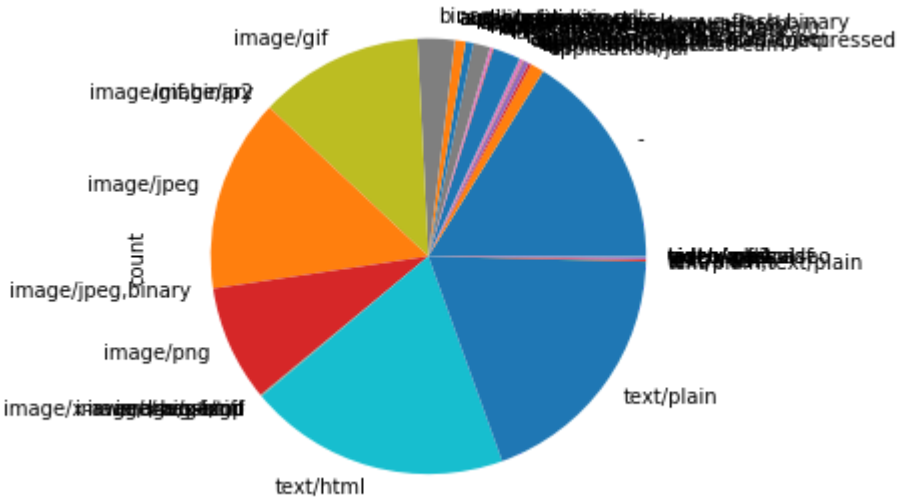
Out[27]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x13b11f94630>
```



If the labels are long in the x-axis of a bar chart, I would create use a horizontal bar chart instead. The labels are still hard to read, so I created a pie chart. Some of the labels are readable, but for issues like this I would maybe try to plot the top values, create a table, or create an interactive plot using HoloViz.

In [28]:
```
http_df.groupby('resp_mime_types')['count'].sum().plot.pie()
```

Out[28]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x13b11dd0898>
```



In [29]:
```
http_df.groupby('resp_mime_types')['count'].sum().sort_values(ascending=False).h
```

Out[29]:
```
resp_mime_types
text/html     156818
text/plain    154173
-             130441
image/jpeg    115827
image/gif      98738
Name: count, dtype: int64
```

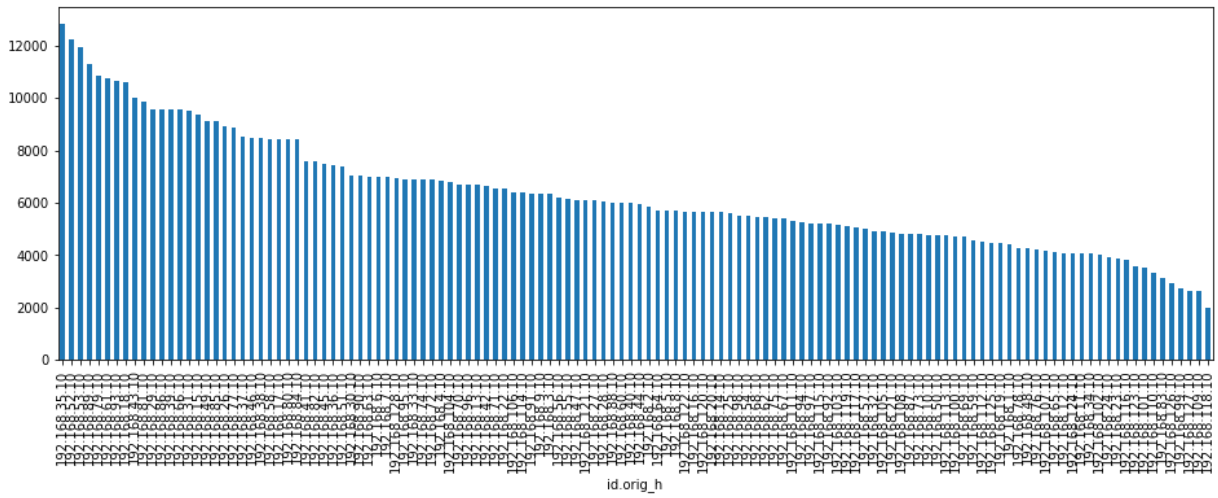
Above is a table showing the top five resp_mime_types.

The technique above can be used to look at the number of samples associated with each IP in dataset.

What kinds of conclusions can you draw based on the graph below?

In [31]:
```
http_df.groupby('id.orig_h')['count'].sum().sort_values(ascending=False).plot(ki
```

Out[31]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x13b123cef98>
```



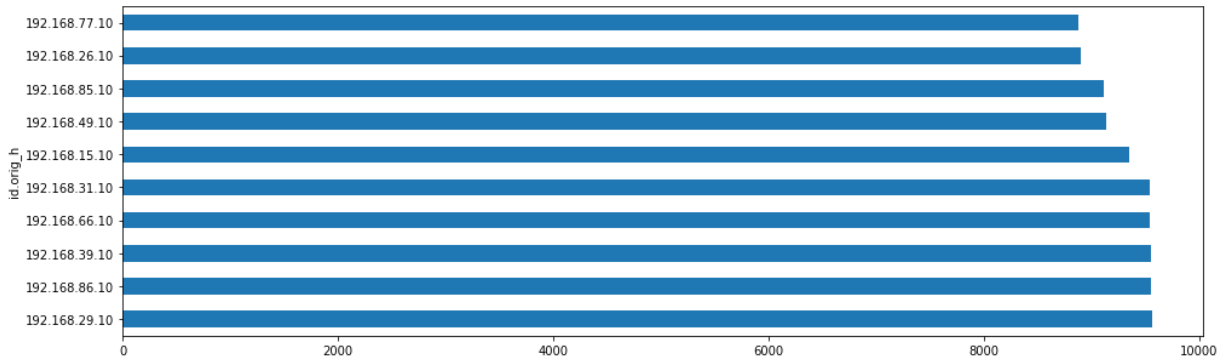
There was error when using .order() so I replaced it with .sort_values().

That's a lot of IP addresses! Bonus question: How many different source IP addresses are in the data set?

Remember above when we said you could access elements in a dataframe that weren't indexed by a timestamp like a regular Python array? Well, it's possible to do the same with dataframes produced by **groupby()**. By sliding around the dataset below what can you learn about the IP addresses that wasn't possible to see because of the resolution of the graph above?

```
In [32]: http_df.groupby('id.orig_h')['count'].sum().sort_values(ascending=False)[10:20].
```

```
Out[32]: <matplotlib.axes._subplots.AxesSubplot at 0x13b1230d4a8>
```



Stacked Groupby Graphs With Bonus Colors

Once you learn the basic bar graph, it's time to kick it up a notch by looking at the relationship between two different columns. This can be done with stacked bar charts.

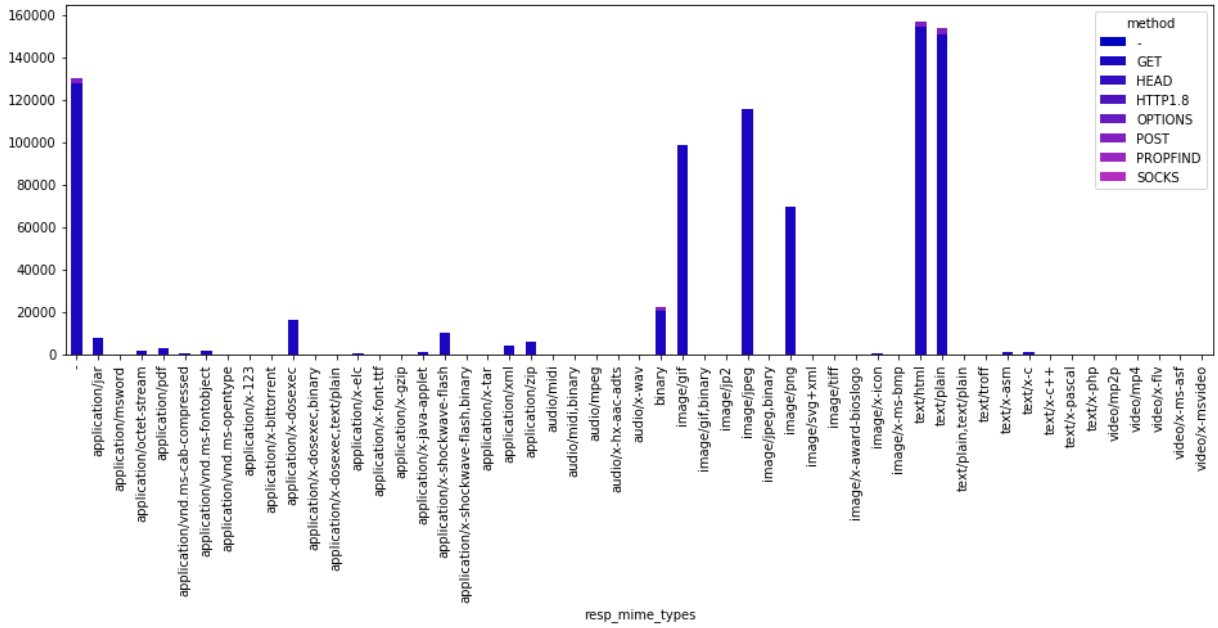
In this case the relationship between filetype and HTTP method can be explored. Perhaps one or two HTTP methods are more responsible for specific filetypes vs. others. Custom colors can be created with the values in the **colors** list, and passed into the graph with **color=colors**. Similar to the examples above we're using our added *count* column to get the number of things. In this example multiple tiers are used for **groupby()** since the breakdown of methods by filetype are being explored. The **unstack()** function "expands" the grouped columns, and **fillna(0)** fills all non-values with zero (since these won't impact the sum).

What happens when you remove the custom color labels?

Bonus: Create a new cell and take a look at what the dataframe looks like without the **plot()** or other commands stacked on top of one another. This is useful to do to understand the output of each function in the chain.

In [33]:
```
colors = [(x/10.0, x/40.0, 0.75) for x in range(len(http_df['method'].unique().t
http_df.groupby(['resp_mime_types','method'])['count'].sum().unstack('method').f
    color=colors, kind='bar', stacked=True, grid=False)
```

Out[33]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x13b122a5d68>
```



The colors are difficult to see in the stacked bar chart. I would have used a different color mapping or modify the RGB values.

In [34]:
```
http_df.groupby(['resp_mime_types','method'])['count'].sum().unstack('method').f
```

Out[34]:

method	-	GET	HEAD	HTTP1.8	OPTIONS	POST	PROPFIND	SOCKS
resp_mime_types								
-	55.0	127796.0	51.0	12.0	107.0	2407.0	11.0	2.0
application/jar	0.0	8078.0	0.0	0.0	0.0	0.0	0.0	0.0
application/msword	0.0	3.0	0.0	0.0	0.0	0.0	0.0	0.0
application/octet-stream	0.0	1715.0	0.0	0.0	0.0	11.0	0.0	0.0
application/pdf	0.0	2912.0	0.0	0.0	0.0	0.0	0.0	0.0
application/vnd.ms-cab-compressed	0.0	778.0	0.0	0.0	0.0	0.0	0.0	0.0
application/vnd.ms-fontobject	0.0	2191.0	0.0	0.0	0.0	0.0	0.0	0.0
application/vnd.ms-opentype	0.0	48.0	0.0	0.0	0.0	0.0	0.0	0.0
application/x-123	0.0	71.0	0.0	0.0	0.0	0.0	0.0	0.0
application/x-bittorrent	0.0	4.0	0.0	0.0	0.0	0.0	0.0	0.0
application/x-dosexec	0.0	16446.0	0.0	0.0	0.0	63.0	0.0	0.0
application/x-dosexec,binary	0.0	26.0	0.0	0.0	0.0	0.0	0.0	0.0
application/x-dosexec,text/plain	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0
application/x-elc	0.0	571.0	0.0	0.0	0.0	0.0	0.0	0.0
application/x-font-ttf	0.0	45.0	0.0	0.0	0.0	0.0	0.0	0.0
application/x-gzip	0.0	45.0	0.0	0.0	0.0	0.0	0.0	0.0
application/x-java-applet	0.0	1519.0	0.0	0.0	0.0	0.0	0.0	0.0
application/x-shockwave-flash	1.0	10092.0	0.0	0.0	0.0	2.0	0.0	0.0
application/x-shockwave-flash,binary	0.0	2.0	0.0	0.0	0.0	0.0	0.0	0.0
application/x-tar	0.0	2.0	0.0	0.0	0.0	0.0	0.0	0.0
application/xml	0.0	4484.0	0.0	0.0	0.0	94.0	27.0	0.0
application/zip	0.0	6420.0	0.0	0.0	0.0	0.0	0.0	0.0
audio/midi	0.0	7.0	0.0	0.0	0.0	0.0	0.0	0.0
audio/midi,binary	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0
audio/mpeg	0.0	27.0	0.0	0.0	0.0	0.0	0.0	0.0
audio/x-hx-aac-adts	0.0	2.0	0.0	0.0	0.0	1.0	0.0	0.0
audio/x-wav	0.0	12.0	0.0	0.0	0.0	0.0	0.0	0.0
binary	0.0	20502.0	0.0	0.0	0.0	1709.0	0.0	0.0
image/gif	9.0	98691.0	0.0	0.0	0.0	38.0	0.0	0.0

method resp_mime_types	-	GET	HEAD	HTTP1.8	OPTIONS	POST	PROPFIND	SOCKS
image/gif,binary	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0
image/jp2	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0
image/jpeg	4.0	115823.0	0.0	0.0	0.0	0.0	0.0	0.0
image/jpeg,binary	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0
image/png	2.0	69664.0	0.0	0.0	0.0	0.0	0.0	0.0
image/svg+xml	0.0	47.0	0.0	0.0	0.0	0.0	0.0	0.0
image/tiff	0.0	7.0	0.0	0.0	0.0	0.0	0.0	0.0
image/x-award-bioslogo	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0
image/x-icon	0.0	509.0	0.0	0.0	0.0	0.0	0.0	0.0
image/x-ms-bmp	0.0	206.0	0.0	0.0	0.0	0.0	0.0	0.0
text/html	64.0	154265.0	0.0	0.0	262.0	2127.0	100.0	0.0
text/plain	34.0	150612.0	0.0	0.0	9.0	3508.0	10.0	0.0
text/plain,text/plain	0.0	0.0	0.0	0.0	0.0	4.0	0.0	0.0
text/troff	0.0	236.0	0.0	0.0	0.0	0.0	0.0	0.0
text/x-asm	0.0	1169.0	0.0	0.0	0.0	20.0	0.0	0.0
text/x-c	0.0	1311.0	0.0	0.0	0.0	0.0	0.0	0.0
text/x-c++	0.0	28.0	0.0	0.0	0.0	0.0	0.0	0.0
text/x-pascal	0.0	32.0	0.0	0.0	0.0	0.0	0.0	0.0
text/x-php	0.0	7.0	0.0	0.0	0.0	0.0	0.0	0.0
video/mp2p	0.0	2.0	0.0	0.0	0.0	0.0	0.0	0.0
video/mp4	0.0	81.0	0.0	0.0	0.0	0.0	0.0	0.0
video/x-flv	0.0	287.0	0.0	0.0	0.0	0.0	0.0	0.0
video/x-ms-asf	0.0	7.0	0.0	0.0	0.0	0.0	0.0	0.0
video/x-msvideo	0.0	5.0	0.0	0.0	0.0	0.0	0.0	0.0

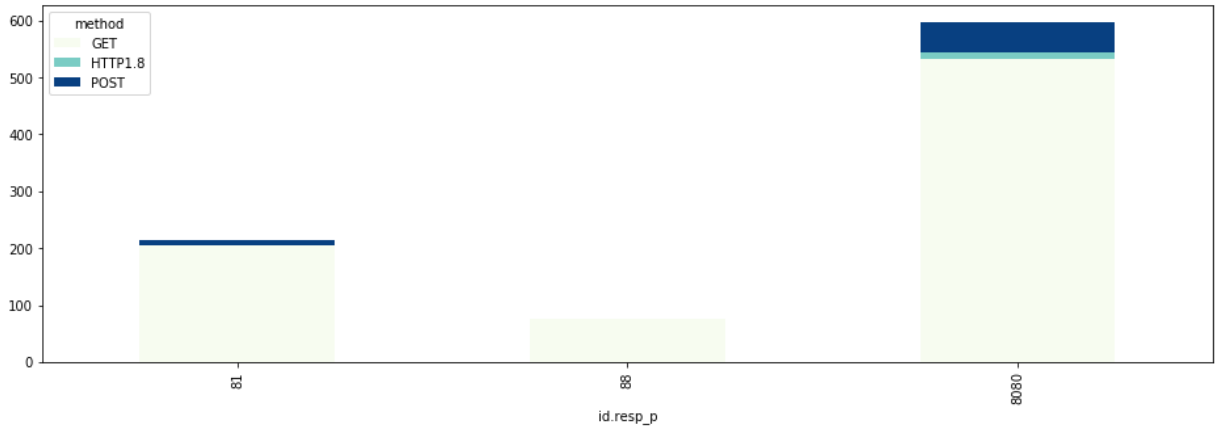
When removing the plot command, we get a table of the resulting sum. There is quite a bit of sparsity (zeroes). In addition, GET is the most common method across the different filetypes.

Final Exercise

The final challenge is using all the techniques from above to create a stacked bar chart that shows: only for destination ports 81, 88, and 8080 how many of each HTTP method is associated with each port. The **plot()** command is present to show another way to specify different custom colors.

In [35]:
```
'].isin(
by(['id.resp_p','method'])['count'].sum().unstack('method').fillna(0).plot(colorm
```

Out[35]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x13b2d7009b0>
```



Use .isin() to filter the destination ports (id.resp_p) for 81, 88, and 8080. Apply .groupby() with .unstack() to create a table where each row is a value for id.resp_p and each column is a value for method.

In [36]:
```
http_df[http_df['id.resp_p'].isin(
    [81, 88, 8080])].groupby(['id.resp_p','method'])['count'].sum().unstack('metl
```

Out[36]:

method	GET	HTTP1.8	POST
id.resp_p			
81	206.0	0.0	9.0
88	76.0	0.0	0.0
8080	532.0	12.0	53.0

Final comment:
This lab gave a good introduction to time series plotting and grouping columns in dataframe. Time series allows us to look at data over time and baseline behavior. Though without additional context, it can be difficult to determine if abnormal behavior needs futher investigation. The techniques used in this lab to filter and group data is quite useful to drill down on points of interest.

Tables and charts are great to present information, but I would be careful about presenting too much information such that it makes it difficult for the reader to understand. This is a general problem with security datasets as there tends to be too much data to summarize it in a digestible manner. In addition, it takes practice to understand which data visualization technique is best for your data. Other comestic issues are making sure the labels are a decent font size and are readable, picking distinguishable colors, transformaing the data to be on the same scale.