Lab 1

Introduction

This is a basic introduction to IPython and pandas functionality. [Pandas (http://pandas.pydata.org/)](http://pandas.pydata.org/) (Python Data Analysis Library) "is an open source, BSD-licensed library providing high-performance, easy-to-use data structures and data analysis tools for the Python programming language." It (pandas) provides [dataframe (http://pandas.pydata.org/pandas-docs/stable/dsintro.html#dataframe)](http://pandas.pydata.org/pandas-docs/stable/dsintro.html#dataframe) functionality for reading/accessing/manipulating data in memory. You can think of a data frame as a table of indexed values.

What you're currently looking at is an IPython Notebook, this acts as a way to interactively use the python interpreter as well as a way to display graphs/charts/images/markdown along with code. IPython is commonly used in scientific computing due to its flexibility. Much more information is available on the [IPython (http://ipython.org/)](http://ipython.org/) website.

Often data is stored in files, and the first goal is to get that information off of disk and into a dataframe. Since we're working with limited resources in this VM we'll have to use samples of some of the files. Don't worry though, the same techniques apply if you're not sampling the files for exploration.

Tip

If you ever want to know the various keyboard shortcuts, just click on a (non-code) cell or the text "In []" to the left of the cell, and press the *H* key. Or select *Help* from the menu above, and then *Keyboard Shortcuts*.

Exercises

File sampling

First off, let's take a look at a log file generated from [Bro (http://www.bro.og/)](http://www.bro.og/) this log is similar to netflow logs as well. However, this log file is rather large and doesn't fit in memory.

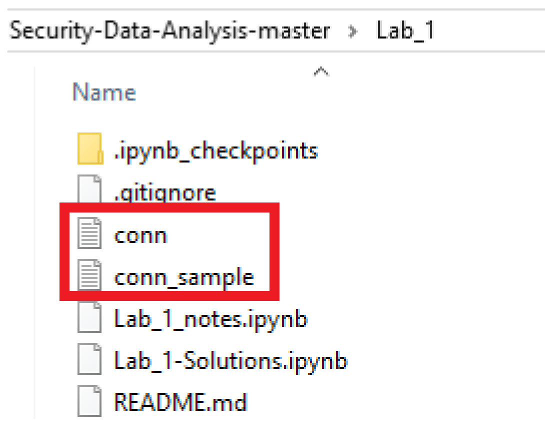
As part of the first exercise, figure out what setting the variable **sample_percent** should be in order to read in between 200k and 300k worth of (randomly selected) lines from the file. Change the variable, after doing that either click the *play* button above (it's the arrow) or hit the *[Shift]+ [Enter]* keys as the same time.

In [1]:
```python
import random
logfile = 'conn.log'
sample_percent = .01
num_lines = sum(1 for line in open(logfile))
slines = set(sorted(random.sample(range(num_lines), int(num_lines * sample_perce
print("%s lines in %s, using a sample of %s lines" %(num_lines, logfile, len(sli
```

```
22694356 lines in conn.log, using a sample of 226943 lines
```

This notebook was previously coded using Python 2 so I had to make a couple of changes.
Debugging Comments:

- I modified the print statement
- I kept getting a permission error. So I copied the log file from inside the conn.log directory folder
- xrange does not exist in Python 3 so I used range instead



File Creation

Awesome! Now that you have a subset of lines to work with, let's write them to another file so we'll have something to practice reading in. Simply hit *[Shift]+[Enter]* below to run the code in the cell and create a new file.

In [2]:
```python
outfile = 'conn_sample.log'
f = open(outfile, 'w+')
i = open(logfile, 'r+')
linecount = 0
for line in i:
    if linecount in slines:
        f.write(line)
    linecount += 1
f.close()
i.close()
```

This code creates a file called conn_sample.log and it contains a subset of data from the original file, conn.log. The file was created using a loop over logfile and a condition over slines.

File Input (CSV)

This next cell does a couple of things, first it imports pandas so we can create a dataframe, and then it reads our newly created file from above into memory. You can see the separator is specified to "\t" because Bro produces tab-delimited files by default. In this case we've also specified what we should call the columns in the dataframe.

In [3]:
```
import pandas as pd
conn_df = pd.read_csv(outfile, sep="\t", header=None, names=['ts','uid','id.orig_
```

The data is read into a pandas dataframe, which helps for data manipulation and visualization. The file didn't contain any header with the column names, so they were inputted manually using the names variable.

Verifying Input

Now (in theory) the contents of the file should be in a nicely laid-out dataframe.

For this next exercise, experiment with calling the **head()** and **tail()** method to see the values at the beginning and end of the dataframe. You can also pass a number to **head()** and **tail()** to specify the number of lines you want to see. Remember to click *play* or press *[Shift]+[Enter]* to execute the code in the cell after you change it.

In [4]:
```
conn_df.head()
```

Out[4]:

	ts	uid	id.orig_h	id.orig_p	id.resp_h	id.resp_p	proto
0	1.331901e+09	CzzTdG1vmwELxPECo6	192.168.202.79	46243	192.168.229.254	443	tcp
1	1.331901e+09	C3WlGc3MKqYX4yew4i	192.168.202.79	50798	192.168.229.251	80	tcp
2	1.331901e+09	CgyJe94ZUZCLDEm4Ed	192.168.202.79	46579	192.168.229.254	443	tcp
3	1.331901e+09	CwV1MF8pLSHKwAQA4	192.168.202.76	51673	149.5.45.166	80	tcp
4	1.331901e+09	CyTR8y2igFLhViL5K3	192.168.202.79	57151	192.168.229.251	143	tcp

5 rows × 22 columns

The command .head() gives us a peek at column names and some of the values in the conn.log dataset. By default it shows the top 5 rows.

Data Summarization

Now create a new cell below this one. This can be accomplished by clicking on this cell once, and then clicking the +* icon towards the top or selecting *Insert* from above and then selecting *Insert Cell Below*. After creating the new cell, it's time to learn about the **describe()** method that can be called on dataframes. This will give you a numeric summarization of all columns that contain numbers.

Try it out!

In [5]:
```
conn_df.describe()
```

Out[5]:

	ts	id.orig_p	id.resp_p	missed_bytes	orig_pkts	orig_ip_bytes
count	2.269430e+05	226943.000000	226943.000000	226943.0	226943.000000	226943.000000
mean	1.331949e+09	42723.213692	20410.488506	0.0	1.372472	121.946255
std	4.276083e+04	15336.893052	20623.902724	0.0	6.463269	1935.458915
min	1.331901e+09	0.000000	0.000000	0.0	0.000000	0.000000
25%	1.331908e+09	36044.000000	2111.000000	0.0	1.000000	44.000000
50%	1.331928e+09	44316.000000	10180.000000	0.0	1.000000	48.000000
75%	1.331997e+09	54494.000000	37786.000000	0.0	1.000000	60.000000
max	1.332018e+09	65534.000000	65535.000000	0.0	1034.000000	718677.000000

The command .describe() is handy to look at the summary statistics of the dataset.

Data Types

Wait a second, isn't the ts column supposed to be a timestamp? Perhaps this column would be better suited as a time data type vs. a number.

Run the cell below to see what type of information Python stored in each column.

In [6]:
```
conn_df.dtypes
```

Out[6]:
```
ts                 float64
uid                 object
id.orig_h           object
id.orig_p            int64
id.resp_h           object
id.resp_p            int64
proto               object
service             object
duration            object
orig_bytes          object
resp_bytes          object
conn_state          object
local_orig          object
missed_bytes         int64
history             object
orig_pkts            int64
orig_ip_bytes        int64
resp_pkts            int64
resp_ip_bytes        int64
tunnel_parents      object
threat             float64
sample             float64
dtype: object
```

Converting Column Types

Time to change the ts column to a datetime object! We will accomplish that by using a simple function provided called *to_datetime()*. The cell below runs this function on the ts column (what should be a time stamp), and then re-assigns this column back to the dataframe in the same place. A new timestamp column could have been added to the dataframe as well so both the float value and the datetime object columns are present.

Run the cell below to convert the column type.

In [7]:
```
from datetime import datetime
conn_df['ts'] = [datetime.fromtimestamp(float(date)) for date in conn_df['ts'].va
```

The code uses a for loop to convert the ts column to a datetime object. Another option could be using an apply command: conn_df['ts'].apply(pandas.to_datetime)

In [8]:
```
conn_df.dtypes
```

Out[8]:
```
ts                  datetime64[ns]
uid                         object
id.orig_h                   object
id.orig_p                    int64
id.resp_h                   object
id.resp_p                    int64
proto                       object
service                     object
duration                    object
orig_bytes                  object
resp_bytes                  object
conn_state                  object
local_orig                  object
missed_bytes                 int64
history                     object
orig_pkts                    int64
orig_ip_bytes                int64
resp_pkts                    int64
resp_ip_bytes                int64
tunnel_parents              object
threat                     float64
sample                     float64
dtype: object
```

In [9]:
```
conn_df.head()
```

Out[9]:

	ts	uid	id.orig_h	id.orig_p	id.resp_h	id.resp_p	proto
0	2012-03-16 05:30:00.810	CzzTdG1vmwELxPECo6	192.168.202.79	46243	192.168.229.254	443	tcp
1	2012-03-16 05:30:03.080	C3WlGc3MKqYX4yew4i	192.168.202.79	50798	192.168.229.251	80	tcp
2	2012-03-16 05:30:04.360	CgyJe94ZUZCLDEm4Ed	192.168.202.79	46579	192.168.229.254	443	tcp
3	2012-03-16 05:30:08.740	CwV1MF8pLSHKwAQA4	192.168.202.76	51673	149.5.45.166	80	tcp
4	2012-03-16 05:30:12.480	CyTR8y2igFLhViL5K3	192.168.202.79	57151	192.168.229.251	143	tcp

5 rows × 22 columns

Looking at the results above, the conversion was successful. The ts column is now in datetime format.

Data Value Exploration

Verify that the conversion was successful. What is the datatype of the column now?

Scroll back up the page and note where you ran the **describe()** function. You'll see under the threat and sample columns there is likely the value of *NaN*. This stands for Not a Number and is a special value assigned to empty column values. There are a few ways to explore what values a column has. Two of these are **value_counts()** and **unique()**.

Try them below on different columns. You can create new cells or if you want to get more than the last command worth of output you can put a print statement in front.

What happens when you run them on a column with IPs (*id.orig_h, id.resp_h*)? What about sample or threat?

In [10]:
```
conn_df['sample'].unique()
```

Out[10]:
```
array([nan])
```

In [11]:
```
conn_df['id.orig_h'].unique()
```

Out[11]:
```
array(['192.168.202.79', '192.168.202.76', '192.168.202.71',
       '192.168.202.100', 'fe80::216:47ff:fe9d:f2c3', '192.168.202.85',
       '192.168.202.89', '192.168.202.97', '192.168.202.103',
       '192.168.203.61', 'fe80::c62c:3ff:fe37:efc', '192.168.202.83',
       '2001:dbb:c18:155:2449:14f1:f324:7497', '192.168.202.101',
       '192.168.202.93', '192.168.203.62', '192.168.202.106',
       '192.168.204.70', '192.168.202.81', '192.168.202.108',
       '192.168.202.73', '192.168.202.96', 'fe80::20c:29ff:fef0:f164',
       '192.168.202.102', '192.168.202.75', '192.168.202.110', '0.0.0.0',
       '192.168.203.45', '192.168.204.45', '192.168.202.87',
       'fe80::216:47ff:fe9d:f2c2', '192.168.27.103',
       'fe80::216:47ff:fe9d:f2d4', '192.168.202.65', '192.168.202.116',
       '192.168.202.68', '192.168.203.63', '::', '192.168.202.115',
       '192.168.27.102', '192.168.202.90', '192.168.26.100',
       '192.168.51.38', '192.168.24.100', '192.168.203.64', '172.19.2.66',
       '192.168.202.94', 'fe80::c62c:3ff:fe30:7333', '192.168.202.95',
       '192.168.202.109', '192.168.28.100', '192.168.202.80',
       '192.168.27.100', 'fe80::216:47ff:fe9d:f2c5', '192.168.202.112',
       '192.168.202.84', 'fe80::216:47ff:fe9d:f2d5',
       'fe80::216:47ff:fe9d:f2c8', 'fe80::216:47ff:fe9d:f2d6',
       '192.168.204.1', '192.168.202.1', 'fe80::216:47ff:fe9d:f2c7',
       '192.168.202.63', 'fe80::216:47ff:fe9d:f2c4', '192.168.204.57',
       '192.168.207.4', '192.168.202.117', '192.168.202.107',
       '192.168.202.88', '192.168.229.156', '192.168.22.253',
       '192.168.22.252', '192.168.202.77', 'fe80::216:47ff:fe9d:f2c1',
       'fe80::20c:29ff:fe4e:9e86', 'fe80::20c:29ff:fe93:209e',
       '192.168.202.92', 'fe80::4c3a:e571:4cfc:b70c', '192.168.205.253',
       '192.168.202.78', '10.10.117.209', '192.168.202.49',
       '192.168.27.25', '192.168.25.25', '192.168.28.25',
       '192.168.202.91', '192.168.202.119', '192.168.229.252',
       '192.168.26.254', '192.168.202.113', '192.168.26.25',
       '192.168.202.118', '192.168.23.25', 'fe80::4c9b:aad8:8a6a:7bb0',
       'fe80::9c8a:5786:bbb0:3db8', '192.168.202.121', '172.16.6.57',
       '2001:dbb:c18:202:20c:29ff:fe93:571e', '192.168.204.60',
       '192.168.22.25', '192.168.25.100', '192.168.24.25',
       '192.168.25.203', 'fe80::a800:4ff:fe00:a04',
       '2001:dbb:c18:204:a800:4ff:fe00:a04', '192.168.202.123',
       'fe80::4172:3555:4717:3e0c', '192.168.21.25',
       'fe80::65ca:c6cd:7ae0:ac8c', '2001:dbb:c18:204:20c:29ff:fe4e:9e86',
       'fe80::5e26:aff:fe6a:4084', '192.168.25.152', '192.168.202.69',
       '2001:dbb:c18:202:d4bc:e39f:84ad:5001', '192.168.202.122',
       '192.168.202.125', '192.168.21.1', '192.168.21.203',
       '192.168.23.202', '10.10.10.10', 'fe80::62fb:42ff:feef:5440',
       '192.168.202.98', '192.168.202.120', '192.168.202.129',
       '192.168.202.4', 'fe80::226:9eff:fe23:5ee4', '192.168.21.202',
       'fe80::3e07:54ff:fe1c:a665', '192.168.202.131', '192.168.21.103',
       '192.168.23.100', '192.168.204.59', '192.168.202.64',
       '192.168.227.83', '192.168.202.138', '192.168.203.65',
       '192.168.203.66', 'fe80::bc5c:15c1:ec81:1e08', '192.168.202.140',
       '192.168.202.139', 'fe80::beae:c5ff:fe9e:f3b6', '192.168.202.141',
       '192.168.202.133', '192.168.202.137', 'fe80::d69a:20ff:fef9:b49c',
       '192.168.202.135', '192.168.202.143',
       '2001:dbb:c18:202:20c:29ff:fe18:b667', 'fe80::20c:29ff:fe8e:385a',
       '192.168.202.144', '2001:dbb:c18:202:20c:29ff:fe41:4be7',
       'fe80::11a:f507:d853:a03d', '192.168.202.222', '192.168.202.240',
```

```
 '172.16.6.100', 'fe80::2c0:caff:fe5f:6869', '192.168.27.152',
 '2001:dbb:c18:202:20c:29ff:febd:1154', '192.168.202.136',
 '192.168.202.149', '2001:dbb:c18:202:a800:4ff:fe00:a04',
 'fe80::216:47ff:fe9d:f2c6', 'fe80::21d:72ff:fe8c:a569',
 '192.168.202.44', '192.168.202.41', '192.168.202.43',
 'fe80::ba8d:12ff:fe53:a8d8', '192.168.202.145', '192.168.202.152',
 '192.168.202.62', 'fe80::dcad:beff:feef:beef', '192.168.21.254',
 '192.168.27.1', '192.168.202.153', '192.168.202.33',
 '192.168.202.40', '192.168.202.150',
 '2001:dbb:c18:202:223:dfff:fe97:4e12', 'fe80::d840:5635:ef48:b032',
 '192.168.202.157', '192.168.202.42', '192.168.202.155'],
dtype=object)
```

In [12]:
```
conn_df['id.resp_h'].value_counts()
```

Out[12]:
```
192.168.206.44             49025
192.168.22.254              4333
192.168.229.254             4302
192.168.229.101             3549
192.168.27.102              3505
192.168.27.100              3337
192.168.23.1                3233
192.168.27.254              3174
192.168.27.101              3166
192.168.28.25               3101
192.168.27.1                3083
192.168.24.253              3001
192.168.22.1                2769
192.168.229.156             2756
192.168.229.251             2698
192.168.21.100              2683
192.168.27.253              2611
192.168.229.252             2564
192.168.22.253              2502
192.168.229.153             2502
192.168.229.1               2452
192.168.27.103              2443
192.168.22.252              2428
192.168.22.25               2371
192.168.21.1                2213
192.168.27.152              2210
192.168.21.25               2061
192.168.21.103              1967
192.168.28.202              1965
192.168.24.202              1856
                           ...
192.168.26.214                 1
172.16.3.121                   1
192.168.26.233                 1
172.16.7.185                   1
172.16.4.254                   1
172.16.8.159                   1
172.16.3.176                   1
192.168.23.243                 1
192.168.27.204                 1
192.168.23.158                 1
172.16.3.73                    1
172.16.5.223                   1
172.16.5.87                    1
172.16.8.23                    1
111.221.77.147                 1
192.168.229.208                1
172.16.7.203                   1
172.16.1.231                   1
192.168.229.109                1
172.16.1.103                   1
192.168.26.250                 1
192.168.26.168                 1
ff02::1:ff53:a8d8              1
192.168.26.211                 1
```

```
192.168.202.100             1
172.16.4.108                1
192.168.22.214              1
172.16.8.171                1
fe80::20c:29ff:fe93:209e    1
172.16.7.9                  1
Name: id.resp_h, Length: 2750, dtype: int64
```

In [13]:
```
conn_df['threat'].unique()
```

Out[13]:
```
array([nan])
```

The values in the threat and sample columns are NaN while the values in the id.orig_h and id.resp_h are IPv4 or IPv6 addresses.

The command .unique() list the unique values. The command .value_counts() shows the counts of each value in descending order.

Remove Columns

Another useful operation on a dataframe is removing and adding columns. Since the threat and sample columns contain only *NaNs*, we can safely remove them and not impact any analysis that may be performed.

Below the sample column is removed (dropped), add a similar line to drop the *threat* column and use a method from above to verify they are no longer in the dataframe.

In [14]:
```
conn_df.drop('sample', axis=1, inplace=True)
```

Can you think of other columns to remove? Select a few and remove them as well. What does your dataframe look like now? (Insert additional cells as needed)

In [15]:
```
conn_df.drop('threat', axis=1, inplace=True)
```

Looking at the unique values in the local_orig column, I would also remove it from the dataset. This column does not seem useful for analysis.

In [16]:
```
conn_df['local_orig'].unique()
```

Out[16]:
```
array(['-'], dtype=object)
```

In [17]:
```
conn_df.drop('local_orig', axis=1, inplace=True)
```

Instead of dropping the columns, we can also replace the values with number zero or the string 'NA'.

In [18]:
```python
conn_df.head()
```

Out[18]:

	ts	uid	id.orig_h	id.orig_p	id.resp_h	id.resp_p	proto
0	2012-03-16 05:30:00.810	CzzTdG1vmwELxPECo6	192.168.202.79	46243	192.168.229.254	443	tcp
1	2012-03-16 05:30:03.080	C3WlGc3MKqYX4yew4i	192.168.202.79	50798	192.168.229.251	80	tcp
2	2012-03-16 05:30:04.360	CgyJe94ZUZCLDEm4Ed	192.168.202.79	46579	192.168.229.254	443	tcp
3	2012-03-16 05:30:08.740	CwV1MF8pLSHKwAQA4	192.168.202.76	51673	149.5.45.166	80	tcp
4	2012-03-16 05:30:12.480	CyTR8y2igFLhViL5K3	192.168.202.79	57151	192.168.229.251	143	tcp

Looking at the results, the columns threat, sample, and local_orig has been removed.

Row Selection

You can use column values to select rows from the dataframes (and even only view specific columns). First, select all rows that contain *SSL* traffic by running the cell below.

In [19]:
```python
conn_df[conn_df['service'] == 'ssl'].head()
```

Out[19]:

	ts	uid	id.orig_h	id.orig_p	id.resp_h	id.resp_p	prc
0	2012-03-16 05:30:00.810	CzzTdG1vmwELxPECo6	192.168.202.79	46243	192.168.229.254	443	t
2	2012-03-16 05:30:04.360	CgyJe94ZUZCLDEm4Ed	192.168.202.79	46579	192.168.229.254	443	t
5765	2012-03-16 05:47:37.420	Cy7R1f3DzWehzZlaLd	192.168.202.79	52473	192.168.229.254	443	t
5829	2012-03-16 05:47:49.640	CpdleG4wcHvlh7jBU4	192.168.202.79	52955	192.168.229.254	443	t
5892	2012-03-16 05:48:02.630	CkpUlX1s6SqzuCJEnf	192.168.202.79	53335	192.168.229.254	443	t

Next we can assign that result to a dataframe, and then look at all all the *SSL* connections that happen over ports other than 443.

In [20]:
```
ssl_df = conn_df[conn_df['service'] == 'ssl']
ssl_df[ssl_df['id.resp_p'] != 443].head()
```

Out[20]:

	ts	uid	id.orig_h	id.orig_p	id.resp_h	id.resp_p	pr
41277	2012-03-16 06:32:55.860	Cd0faF3BHwypesYLS5	192.168.202.110	47416	192.168.27.253	8089	
41567	2012-03-16 06:33:40.960	CCqJ9U1kyQJ2gimpCj	192.168.202.110	48971	192.168.27.253	8089	
41575	2012-03-16 06:33:43.160	CdIJrf2YD0GxxnqS8l	192.168.202.110	49030	192.168.27.253	8089	
41664	2012-03-16 06:33:56.870	Cyu6FjB8RpkUZUGR1	192.168.202.110	49556	192.168.27.253	8089	
42629	2012-03-16 06:36:26.280	CpFTBJ1zBUJusKTWJ7	192.168.202.110	54043	192.168.27.253	8089	

You can see the individual column selections above eg: *conn_df['service']*, and *ssl_df['id.resp_p']* respectively. You can use these to view output of specific columns.

For example, run the cell below to see all the individual values of originator bytes associated with a *SSL* connection over port 443.

In [21]:
```
ssl_df[ssl_df['id.resp_p'] == 443]['orig_bytes'].head()
```

Out[21]:
```
0       539
2       547
5765    558
5829    545
5892    546
Name: orig_bytes, dtype: object
```

Final Exercise

Use all of the techniques above to display the unique ports and originator IPs (bonus points for the number of connections of each) associated with all *HTTP* connections **NOT** over port 80. (Hint, create a new dataframe for easier manipulation)

In [22]:
```
http_df = conn_df[conn_df['service'] == 'http']
http_df[http_df['id.resp_p'] != 80].head()
```

Out[22]:

	ts	uid	id.orig_h	id.orig_p	id.resp_h	id.resp_p	pr
5574	2012-03-16 05:46:57.140	CbrIg71dmMXffENDC5	192.168.202.79	38937	192.168.229.153	5357	
5675	2012-03-16 05:47:17.760	Cx5lMj37kAzvVSip7e	192.168.202.79	39519	192.168.229.153	5357	
5784	2012-03-16 05:47:42.390	CFA6Fr4D77CLr5zZwj	192.168.202.79	40606	192.168.229.153	5357	
5818	2012-03-16 05:47:48.910	CUJXMf3W9dNHU2tGOd	192.168.202.79	40815	192.168.229.153	5357	
5872	2012-03-16 05:47:57.980	CIl9j51UpVHSnMC276	192.168.202.79	41091	192.168.229.153	5357	

First, I created a dataframe called http_df that contains all of the HTTP connections. Then, I applied a condition to look at all HTTP connectons other than port 80.

In [29]:
```
http_df[http_df['id.resp_p'] != 80]['id.orig_h'].value_counts()
```

Out[29]:
```
192.168.202.110    437
192.168.202.140     74
192.168.202.138     68
192.168.202.79      17
192.168.204.45      15
192.168.202.108      7
192.168.202.144      2
192.168.202.102      1
192.168.202.96       1
192.168.202.68       1
192.168.202.95       1
192.168.202.112      1
192.168.202.103      1
192.168.202.100      1
192.168.203.45       1
192.168.202.4        1
192.168.202.80       1
Name: id.orig_h, dtype: int64
```

In [30]:
```
http_df[http_df['id.resp_p'] != 80]['id.resp_p'].value_counts()
```

Out[30]:
```
3128    206
8080    179
8000    155
5488     74
5357     16
Name: id.resp_p, dtype: int64
```

The results shows the unique values and the count of the connections of both the ports and originator IPs.

I did cheated a little bit since I did not understood that the final exercise asked for unique values from BOTH columns. In addition, there are two different columns having port information. How would anyone know to use the id.resp_p column?

In [28]:
```
print(http_df[http_df['id.resp_p'] != 80][['id.resp_p','id.orig_h']].drop_duplica
```

```
        id.resp_p        id.orig_h
5574         5357   192.168.202.79
5893         5488   192.168.202.79
13854        8080   192.168.202.96
15233        8080   192.168.203.45
20116        8080  192.168.202.102
29197        3128  192.168.202.110
29627        5357  192.168.202.110
29742        8000  192.168.202.110
31640        8080  192.168.202.110
51025        5357   192.168.204.45
51157        8000   192.168.204.45
53344        8000  192.168.202.112
70028        8000  192.168.202.108
73909        8000   192.168.202.80
83220        5488  192.168.202.110
86182        8000   192.168.202.79
100331       8000  192.168.202.100
103856       8000   192.168.202.95
110168       8000    192.168.202.4
130480       3128   192.168.204.45
165616       8000  192.168.202.103
166996       8000  192.168.202.140
167272       8080  192.168.202.140
172995       3128  192.168.202.140
184872       8000  192.168.202.144
207281       3128  192.168.202.138
208604       8000  192.168.202.138
220140       3128   192.168.202.68
```

I used the .drop_duplicates() to display the unique ports per originator IPs.

Final comment:
This lab gives a gentle and superb introduction to exploratory data analysis. More specifically, the pandas dataframe techniques on the connections log dataset. Some of these techniques are what I use for my own data projects.

Yet, the columns seemed to be abbreviated and are confusing to understand. It would be nice to have some descriptions. I do agree that this lab has quite a bit of hand-holding.

I think it is a good habit to drop columns not useful for analysis. It also reduces the number of columns to feed into a machine learning algorithm. Since the threat column contains only NaNs, it would be difficult to use machine learning to classify a connection as threat or not.