python_data_science_intro

March 20, 2019

In [1]:
```
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### PRESENTED: python hack night, 2/19/19
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```

In [2]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
```

1 Pandas

pandas is a python library that provides a dataframe structure (think excel spreadsheet). It contains built in data manipulation and statistics functions. This notebook will use dataframes built from python dicts and read from csv's. It has a built in read function for many formats, see http://pandas.pydata.org/pandas-docs/version/0.15/io.html for complete list.

In [3]:
```
# Example 1 - creating a dataframe
```

In [4]:
```
# create a new dataframe and store it under 'dataframe'
dataframe = pd.DataFrame(
 {'col1': [1, 2, 3, 4, 5, 6],
 'col2': ['a', 'b', 'b', 'a', 'a', 'b'],
 'col3': [130, 145, 145, 123, 140, 157]})
```

In [5]:
```
# print the dataframe to the output
dataframe.head()
```

Out[5]:
```
 col1 col2 col3
0 1 a 130
1 2 b 145
2 3 b 145
3 4 a 123
4 5 a 140
```

In [6]:
```
# count the number of times a value occurs in a column
dataframe['col2'].value_counts()
```

```
Out[6]: b 3
        a 3
        Name: col2, dtype: int64
```

```
In [7]: # filter the dataframe based on column values
        dataframe[dataframe['col3'].gt(140) & dataframe['col1'].gt(2)]
```

```
Out[7]:  col1 col2 col3
        2 3 b 145
        5 6 b 157
```

```
In [8]: # a filter just takes a boolean mask as input
        dataframe['col3'].gt(140) & dataframe['col1'].gt(2)
```

```
Out[8]: 0 False
        1 False
        2 True
        3 False
        4 False
        5 True
        dtype: bool
```

```
In [9]: # add a column, that is the sum of two columns
        dataframe['col4'] = dataframe['col1'] + dataframe['col3']
        dataframe
```

```
Out[9]:  col1 col2 col3 col4
        0 1 a 130 131
        1 2 b 145 147
        2 3 b 145 148
        3 4 a 123 127
        4 5 a 140 145
        5 6 b 157 163
```

```
In [10]: # define some complicated function, and apply it to each value in a column (series)
         def mod_col_3(val):
          """if val gt 140 return 1, else return 0"""
          if val > 140:
          output = 1
          else:
          output = 0
          return output

         # the apply function returns a new series, it will not change the input series
         # we will assign the result to a new column in the df
         dataframe['col5'] = dataframe['col3'].apply(mod_col_3)
         dataframe
```

```
Out[10]:  col1 col2 col3 col4 col5
         0 1 a 130 131 0
```

```
1 2 b 145 147 1
2 3 b 145 148 1
3 4 a 123 127 0
4 5 a 140 145 0
5 6 b 157 163 1
```

In [11]:
```python
# get statistics automatically on all numeric columns
dataframe.describe()
```

Out[11]:
```
 col1 col3 col4 col5
count 6.000000 6.000000 6.000000 6.000000
mean 3.500000 140.000000 143.500000 0.500000
std 1.870829 12.066483 12.988456 0.547723
min 1.000000 123.000000 127.000000 0.000000
25% 2.250000 132.500000 134.500000 0.000000
50% 3.500000 142.500000 146.000000 0.500000
75% 4.750000 145.000000 147.750000 1.000000
max 6.000000 157.000000 163.000000 1.000000
```

In [12]:
```python
#take the mean of col3
dataframe.col3.mean()
```

Out[12]:
```
140.0
```

2 matplotlib

matplotlib is the most standard plotting library for python, however there are many more to chose from.

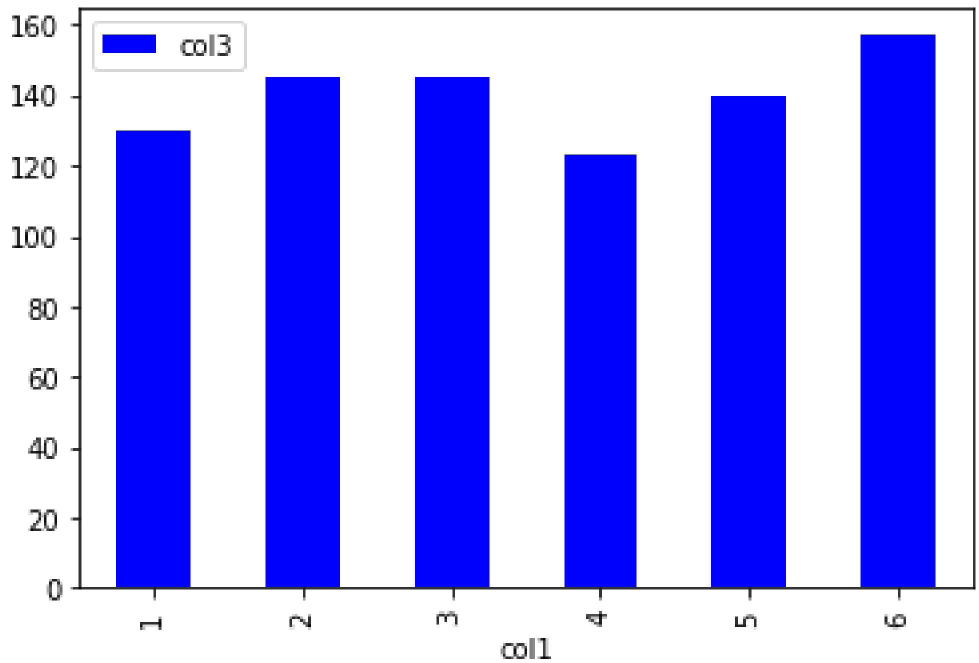
In [13]:
```python
# pandas has some matplotlib functionality built in
```

In [14]:
```python
dataframe
```

Out[14]:
```
 col1 col2 col3 col4 col5
0 1 a 130 131 0
1 2 b 145 147 1
2 3 b 145 148 1
3 4 a 123 127 0
4 5 a 140 145 0
5 6 b 157 163 1
```

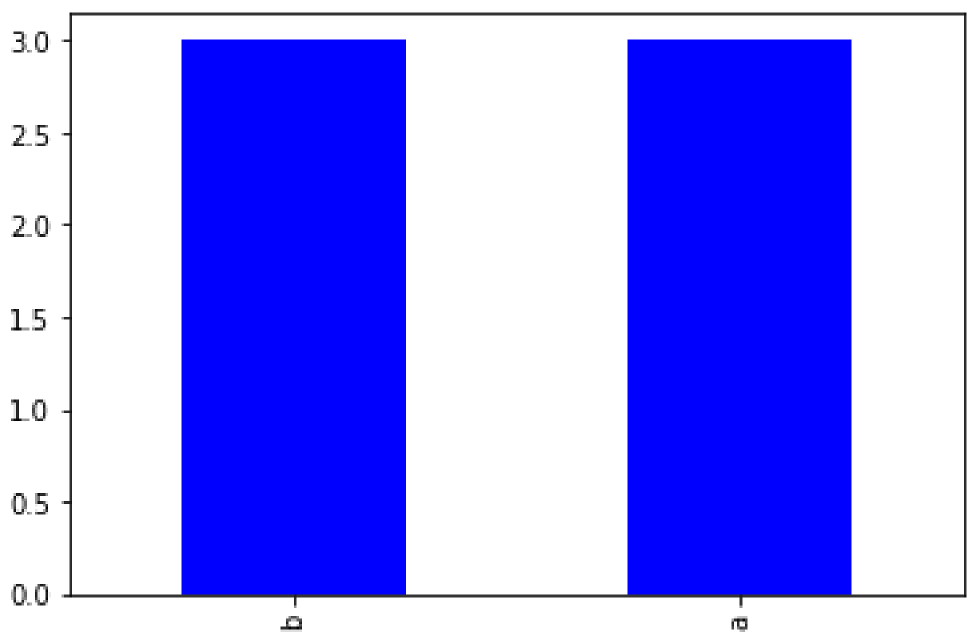
In [15]:
```python
# example bar plot
dataframe.plot(x='col1', y='col3', kind='bar', color='b')
```

Out[15]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x118f2a390>
```



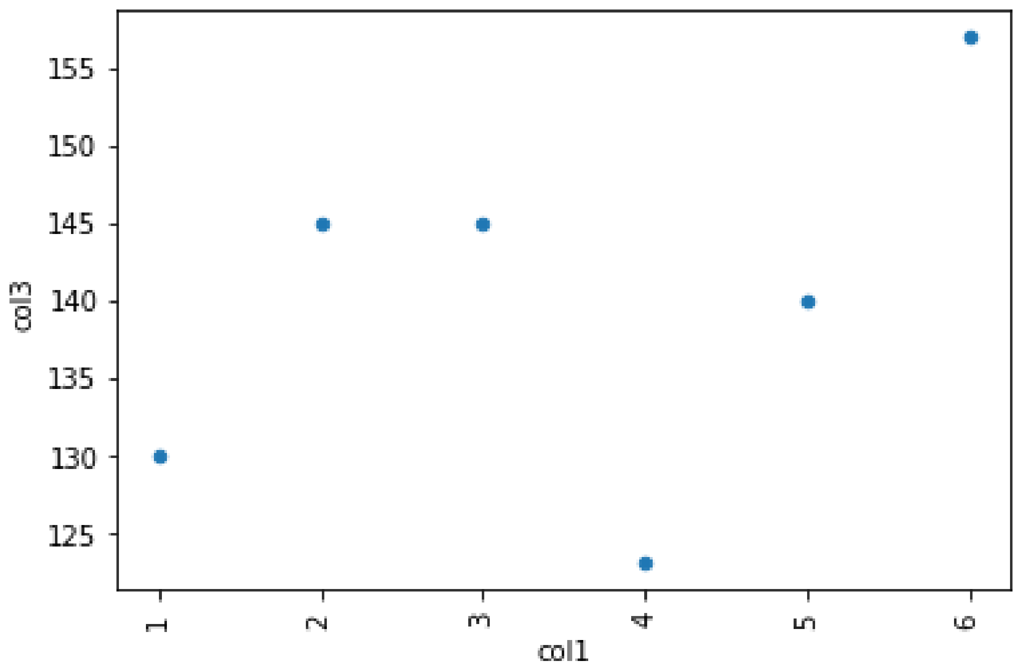
In [16]: dataframe['col2'].value_counts().plot(kind='bar', color='b')

Out[16]: <matplotlib.axes._subplots.AxesSubplot at 0x11b625550>



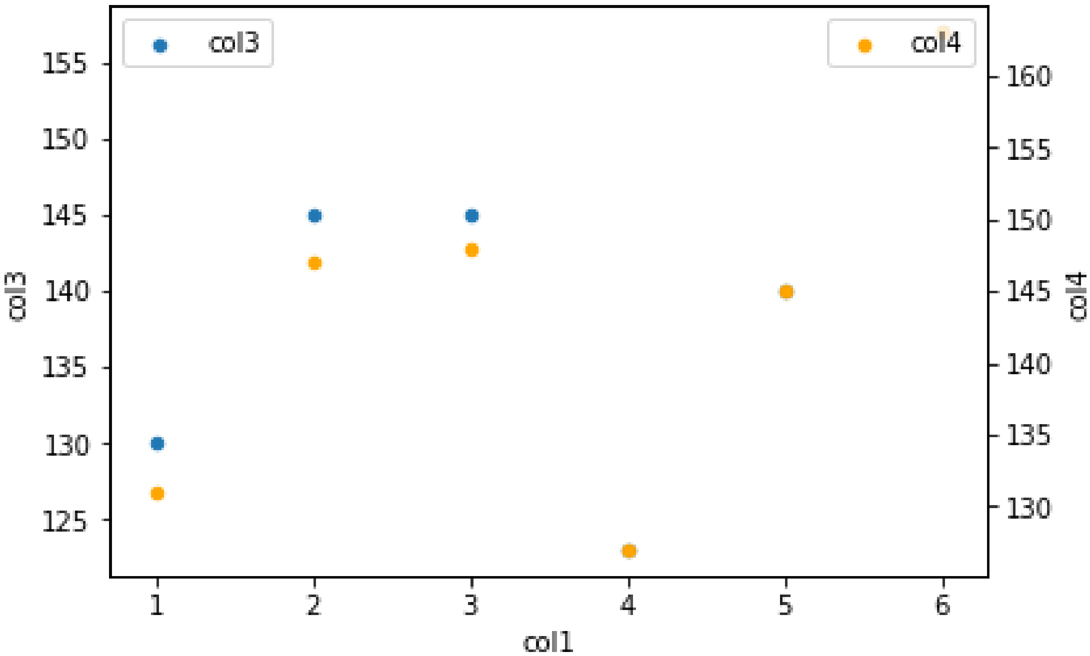
In [17]:
```
# example scatter plot
dataframe.plot('col1', 'col3', kind='scatter', rot=90)
```

Out[17]: <matplotlib.axes._subplots.AxesSubplot at 0x11b6a7e10>



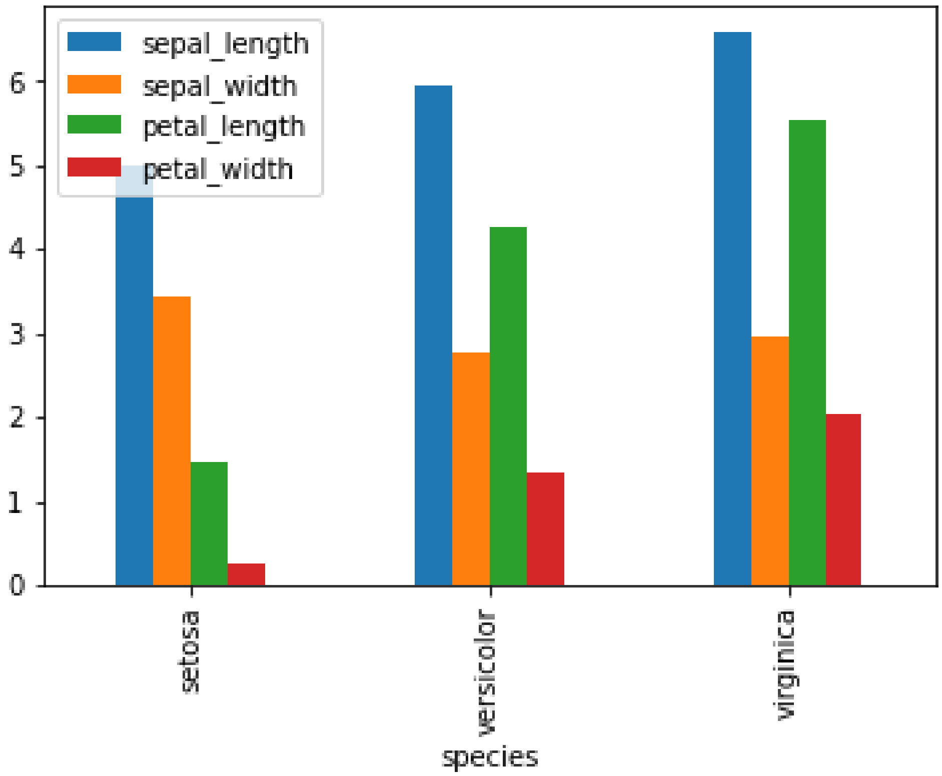
In [18]:
```
# dual y-axis
ax = dataframe.plot('col1', 'col3', kind='scatter', label='col3')
ax2 = ax.twinx() #pyplot
dataframe.plot('col1', 'col4', kind='scatter', ax=ax2, label='col4', color='orange')
ax2.legend(loc=1) #pyplot
```

Out[18]: <matplotlib.legend.Legend at 0x11b848a58>

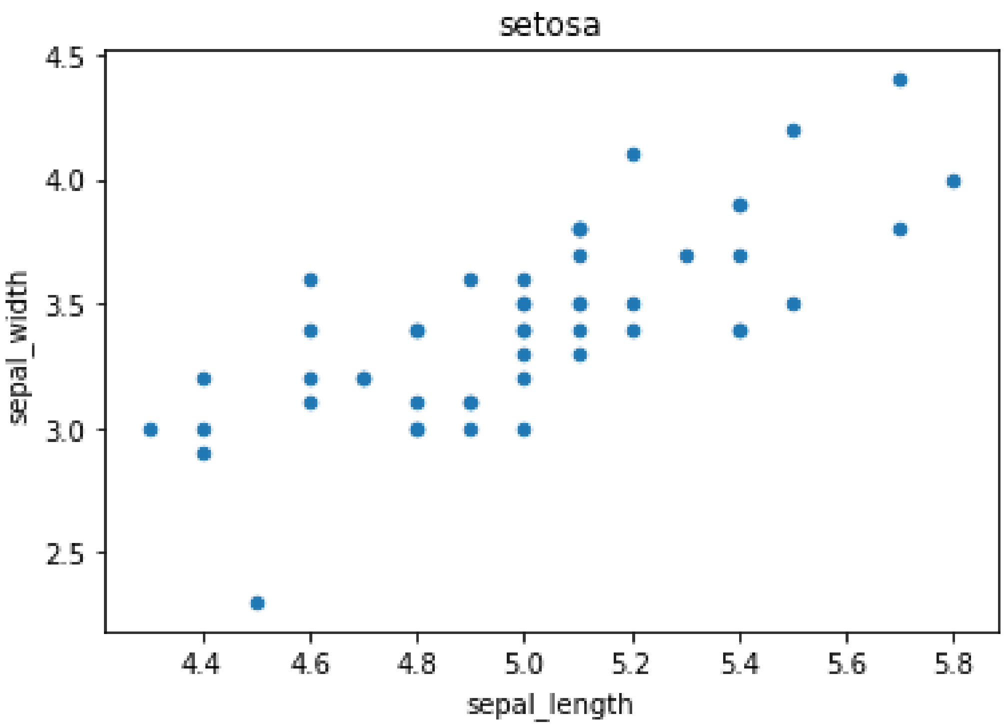


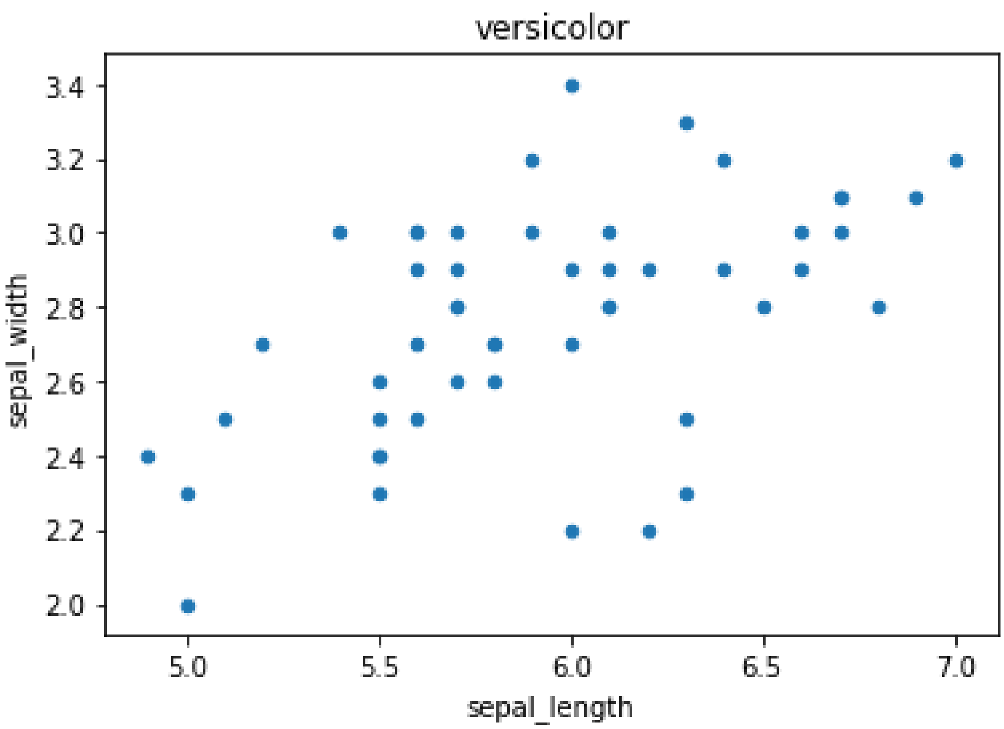
2.1 data from csv

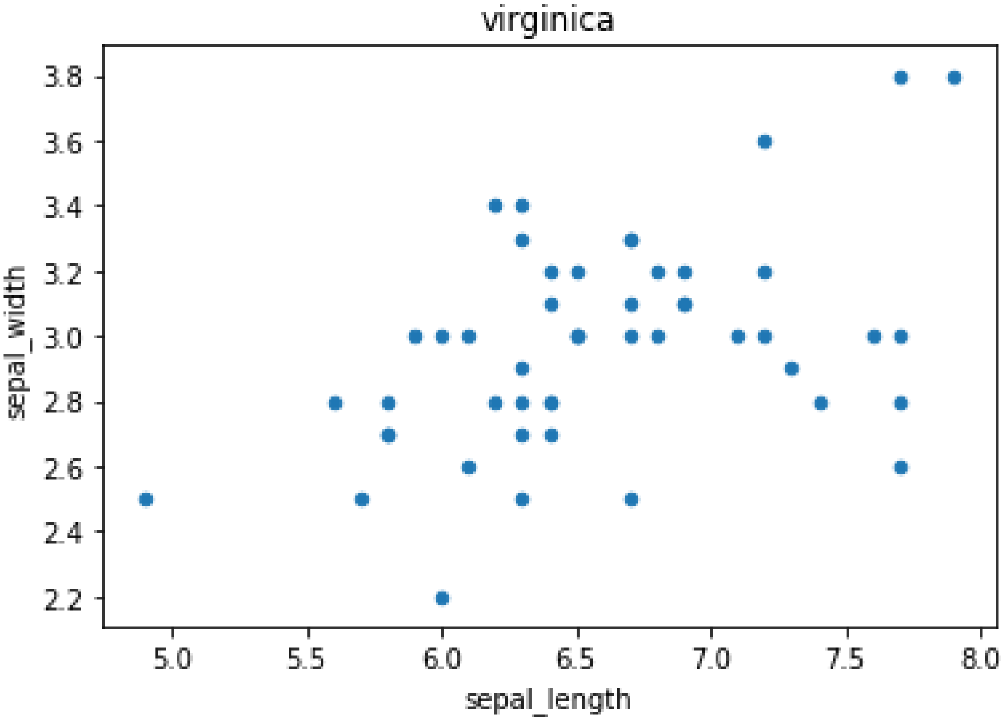
```
In [19]: ### this section will introduce reading csv, groupby, merge and pivot_table functions

In [20]: iris = pd.read_csv('https://raw.githubusercontent.com/mwaskom/seaborn-data/master/iris

In [21]: iris.shape

Out[21]: (150, 5)

In [22]: iris.head()

Out[22]:  sepal_length sepal_width petal_length petal_width species
        0 5.1 3.5 1.4 0.2 setosa
        1 4.9 3.0 1.4 0.2 setosa
        2 4.7 3.2 1.3 0.2 setosa
        3 4.6 3.1 1.5 0.2 setosa
        4 5.0 3.6 1.4 0.2 setosa

In [23]: # check avg of each value based on species
         iris.groupby('species').mean().plot(kind='bar')

Out[23]: <matplotlib.axes._subplots.AxesSubplot at 0x11b89ddd8>
```




```
In [24]: grouped = iris.groupby('species').agg({'sepal_length': ['mean','std'],
          'sepal_width': 'count'})

In [25]: grouped

Out[25]:  sepal_length sepal_width
          mean std count
         species
         setosa 5.006 0.352490 50
         versicolor 5.936 0.516171 50
         virginica 6.588 0.635880 50

In [26]: grouped.columns.values

Out[26]: array([('sepal_length', 'mean'), ('sepal_length', 'std'),
          ('sepal_width', 'count')], dtype=object)

In [27]: grouped.columns = ['_'.join(col).strip() for col in grouped.columns.values]

In [28]: # iterate through subset of dataframe
         # each "df" in forloop is a filtered dataframe based on the groupby argument
         # "grp" will contain the column val, or list of values, that the current df is filter
         for grp, df in iris.groupby('species'):
          df.plot('sepal_length','sepal_width', kind='scatter', title=grp)
```


setosa
4.5
4.0
3.5
3.0
2.5
sepal_width
4.4
4.6
4.8
5.0
5.2
5.4
5.6
5.8
sepal_length


versicolor
3.4
3.2
3.0
2.8
2.6
2.4
2.2
2.0
sepal_width
5.0
5.5
6.0
6.5
7.0
sepal_length




```
In [29]: exercise = pd.read_csv('https://raw.githubusercontent.com/mwaskom/seaborn-data/master/
```

```
In [30]: exercise.head()
```

```
Out[30]:  id diet pulse time kind
         0 1 low fat 85 1 min rest
         1 1 low fat 85 15 min rest
         2 1 low fat 88 30 min rest
         3 2 low fat 90 1 min rest
         4 2 low fat 92 15 min rest
```

```
In [31]: exercise['time'].unique()
```

```
Out[31]: array(['1 min', '15 min', '30 min'], dtype=object)
```

```
In [32]: exercise.pivot_table(index=['diet','kind'], columns='time', values='pulse', aggfunc='
```

```
Out[32]: time 1 min 15 min 30 min
         diet kind
         low fat rest 97 97 94
          running 98 132 120
          walking 95 103 104
         no fat rest 100 99 100
          running 103 135 150
          walking 103 109 103
```

In [33]:
```
df1 = pd.DataFrame({'employee': ['Bob', 'Jake', 'Lisa', 'Sue'],
 'group': ['Accounting', 'Engineering', 'Engineering', 'HR']})
df2 = pd.DataFrame({'employee': ['Lisa', 'Bob', 'Jake', 'Sue'],
 'hire_date': [2004, 2008, 2012, 2014]})
```

In [34]:
```
df1
```

Out[34]:

	employee	group
0	Bob	Accounting
1	Jake	Engineering
2	Lisa	Engineering
3	Sue	HR

In [35]:
```
df2
```

Out[35]:

	employee	hire_date
0	Lisa	2004
1	Bob	2008
2	Jake	2012
3	Sue	2014

In [36]:
```
df1.merge(df2, on=['employee'], how='left')
```

Out[36]:

	employee	group	hire_date
0	Bob	Accounting	2008
1	Jake	Engineering	2012
2	Lisa	Engineering	2004
3	Sue	HR	2014

2.2 Putting it all together

In [37]:
```
### In this example, we look at (fake) test results
### we will create fake date labels, find the number of passes and fails in each,
### then average the fails by day, which will give you yield (pass/fail is 1,0)
### In addition, for those widgets that passed or failed, we will plot a box plot
### to show the distribution of some parameter, could be temperature, time
### completing some process step etc...

### the end chart will show by day, how many parts were tested, the yield of those pa
### and the distribution of some parameter, so you can see the change over time and r
### to the parameter
```

In [38]:
```
### create a fake time index. Use pd.Series to create a single column
date_index = pd.Series(['2018-03-03']*10 + ['2018-03-04']*12 + ['2018-03-05']*18 + ['
date_index = pd.to_datetime(date_index)
# print out preview of what the "column" looks like
date_index.head()
```

Out[38]:
```
0 2018-03-03
1 2018-03-03
2 2018-03-03
3 2018-03-03
4 2018-03-03
Name: date, dtype: datetime64[ns]
```

In [39]:
```
### use random numbers to generate pass and fail data
from random import choices, gauss
test1_yld = pd.Series(choices(population=[0, 1], weights=[30, 70], k=91), name='test1_
test2_yld = pd.Series(choices([0, 1], [10, 90], k=91), name='test2_pass_fail')

### create fake process parameter. Think seconds a widget spent at process step x
process_param = pd.Series([gauss(20, 4) for i in range(91)], name='process_param')
```

In [40]:
```
### we will also create a fake "widget_id"
widget_id = pd.Series([i for i in range(len(date_index))], name='widget_id')
```

In [41]:
```
### concat the fail data together, think of the python zip() function
### the resulting dataframe will have for each date, a number of passes and fails
### think of this as a single widget per row
example_df = pd.concat([date_index, test1_yld, test2_yld, process_param, widget_id], a
example_df.head()
```

Out[41]:

	date	test1_pass_fail	test2_pass_fail	process_param	widget_id
0	2018-03-03	1	1	16.154771	0
1	2018-03-03	1	1	23.180473	1
2	2018-03-03	1	1	17.247763	2
3	2018-03-03	1	1	19.270181	3
4	2018-03-03	1	1	28.049684	4

In [42]:
```
### summarize the average pass value by date. This will be your yield trend
### you can also aggregate the "nunique" pandas function to count the unique number o
yield_trend = example_df.groupby('date').agg({'test1_pass_fail': 'mean',
 'test2_pass_fail': 'mean',
 'widget_id': lambda rows: rows.nunique()}) #rows is the *grouped* series of data

# rename the columns
yield_trend.rename(columns = {'test1_pass_fail': 'test1_yld',
 'test2_pass_fail': 'test2_yld',
 'widget_id': 'num_widgets'},
 inplace=True)

# print the dataframe
yield_trend
```

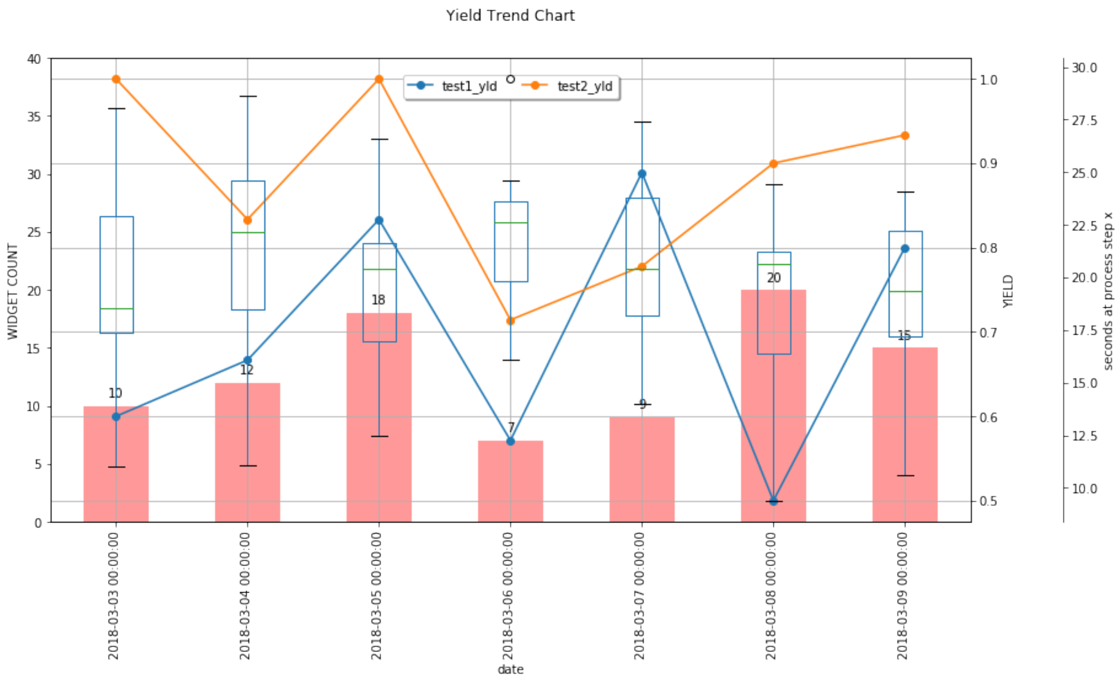
Out[42]:

	test1_yld	test2_yld	num_widgets
date			
2018-03-03	0.600000	1.000000	10

```
2018-03-04 0.666667 0.833333 12
2018-03-05 0.833333 1.000000 18
2018-03-06 0.571429 0.714286 7
2018-03-07 0.888889 0.777778 9
2018-03-08 0.500000 0.900000 20
2018-03-09 0.800000 0.933333 15
```

In [43]:
```python
# set up global plot size
from pylab import rcParams
rcParams['figure.figsize'] = 13, 7
```

In [44]:
```python
# plot bar chart for widget count in graph (1st y axis)
ax = yield_trend.plot(y='num_widgets', kind='bar', alpha=0.4, color='r', legend=None)

# for each bar, put a text label above it with the actual count value
for p in ax.patches:
 ax.annotate(np.round(p.get_height(),decimals=2), (p.get_x()+p.get_width()/2., p.get_h

# establish your 2nd and 3rd y axis and positions
ax2 = ax.twinx()
ax3 = ax.twinx()
ax3.spines["right"].set_position(("axes", 1.1))

# on your 3rd y axis, plot a boxplot. This will show for each date, this distribution
bp = example_df.boxplot(column='process_param', by='date', ax=ax3, widths = 0.25, retu

# for each yield column, make a line plot, your label will be you column in the legen
for col in ['test1_yld', 'test2_yld']:
 ax2.plot(ax.get_xticks(), yield_trend[col], label=col, marker='o');
ax2.legend(loc='lower center', bbox_to_anchor=(0.5, 0.90),
 fancybox=True, shadow=True, ncol=5);

plt.suptitle('Yield Trend Chart')
plt.title('')

ax2.grid(True, axis='y')
ax.grid(True, axis='x')
ax3.grid(False)
ax.set_ylabel('WIDGET COUNT')
ax2.set_ylabel('YIELD')
ax3.set_ylabel('seconds at process step x')
ax.set_ylim(0, 40);

len(plt.gca().get_xticks());
# plt.show();
```



Yield Trend Chart
test1_yld
test2_yld
WIDGET COUNT
YIELD
seconds at process step x
date
2018-03-03 00:00:00
2018-03-04 00:00:00
2018-03-05 00:00:00
2018-03-06 00:00:00
2018-03-07 00:00:00
2018-03-08 00:00:00
2018-03-09 00:00:00
10
12
18
7
9
20
15