9.2 Customized Visualizations using Seaboarn

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Section: CPE22S3

Course: Computational Thinking with Python

Course Code: CPE311

Instructions

- **Create a Python notebook to answer all shown procedures, exercises and analysis in this section**

Resources

- **Download the following datasets: fb_stock_prices_2018.csv Download fb_stock_prices_2018.csv, earthquakes-1.csv**

Procedures

9.4 Introduction to Seaborn

```
%matplotlib inline
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
import pandas as pd
fb = pd.read_csv(
'data/fb_stock_prices_2018.csv', index_col='date', parse_dates=True
)
quakes = pd.read_csv('data/earthquakes.csv')
quakes
```

	mag	magType	time	place	tsunami	parsed_place
0	1.35	ml	1539475168010	9km NE of Aguanga, CA	0	California
1	1.29	ml	1539475129610	9km NE of Aguanga, CA	0	California
2	3.42	ml	1539475062610	8km NE of Aguanga, CA	0	California
3	0.44	ml	1539474978070	9km NE of Aguanga, CA	0	California
4	2.16	md	1539474716050	10km NW of Avenal, CA	0	California
...	...	...	...	...	...	...
9327	0.62	md	1537230228060	9km ENE of Mammoth Lakes, CA	0	California
9328	1.00	ml	1537230135130	3km W of Julian, CA	0	California
9329	2.40	md	1537229908180	35km NNE of Hatillo, Puerto Rico	0	Puerto Rico
9330	1.10	ml	1537229545350	9km NE of Aguanga, CA	0	California
9331	0.66	ml	1537228864470	9km NE of Aguanga, CA	0	California

Next steps: View recommended plots

Categorical data

A 7.5 magnitude earthquake on September 28, 2018 near Palu, Indonesia caused a devastating tsunami afterwards. Let's take a look at some visualizations to understand what magTypes are used in Indonesia, the range of magnitudes there, and how many of the earthquakes are accompanied by a tsunami

```
quakes.assign(time=lambda x: pd.to_datetime(x.time, unit='ms')).set_index('time').loc['2018-09-28'].query(
    "parsed_place == 'Indonesia' and tsunami == 1 and mag == 7.5")
```

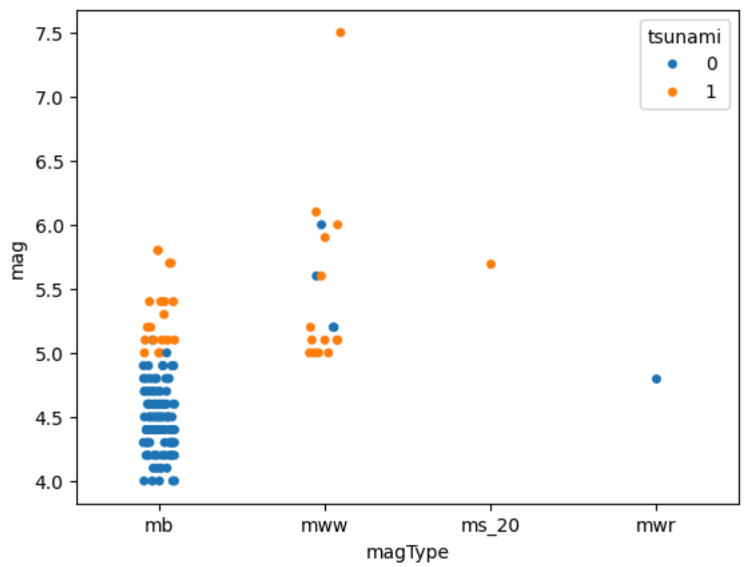
time	mag	magType	place	tsunami	parsed_place
2018-09-28 10:02:43.480	7.5	mww	78km N of Palu, Indonesia	1	Indonesia

stripplot()

The stripplot() function helps us visualize categorical data on one axis and numerical data on the other. We also now have the option of coloring our points using a column of our data (with the hue parameter). Using a strip plot, we can see points for each earthquake that was measured with a given magType and what its magnitude was; however, it isn't too easy to see density of the points due to overlap

```
sns.stripplot(
x='magType',
y='mag',
hue='tsunami',
data=quakes.query('parsed_place == "Indonesia"')
)
```

```
<Axes: xlabel='magType', ylabel='mag'>
```

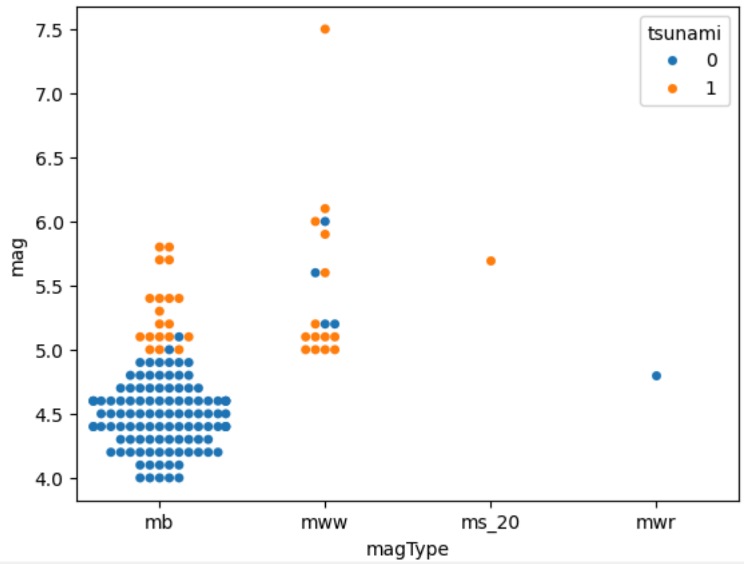


swarmplot()

The bee swarm plot helps address this issue be keeping the points from overlapping. Notice how many more points we can see for the blue section of the mb magType

```
sns.swarmplot(
x='magType',
y='mag',
hue='tsunami',
data=quakes.query('parsed_place == "Indonesia"')
)
```

```
<Axes: xlabel='magType', ylabel='mag'>
/usr/local/lib/python3.10/dist-packages/seaborn/categorical.py:3398: UserWarning: 10.2%
  warnings.warn(msg, UserWarning)
```



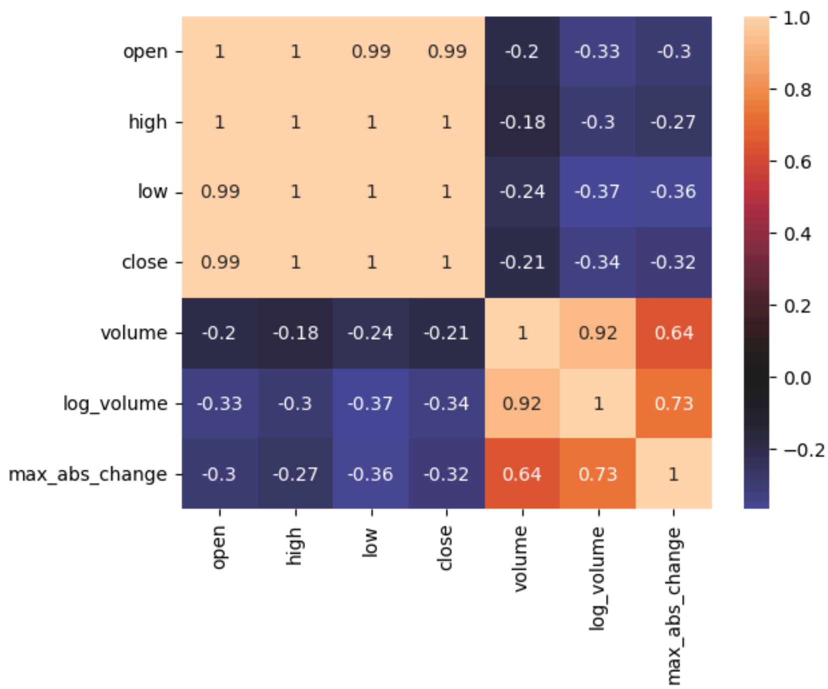
Correlations and Heatmaps

heatmap()

An easier way to create correlation matrix is to use seaborn

```
sns.heatmap(
fb.sort_index().assign(
log_volume=np.log(fb.volume),
max_abs_change=fb.high - fb.low
).corr(),annot=True, center=0
)
```

```
<Axes: >
```

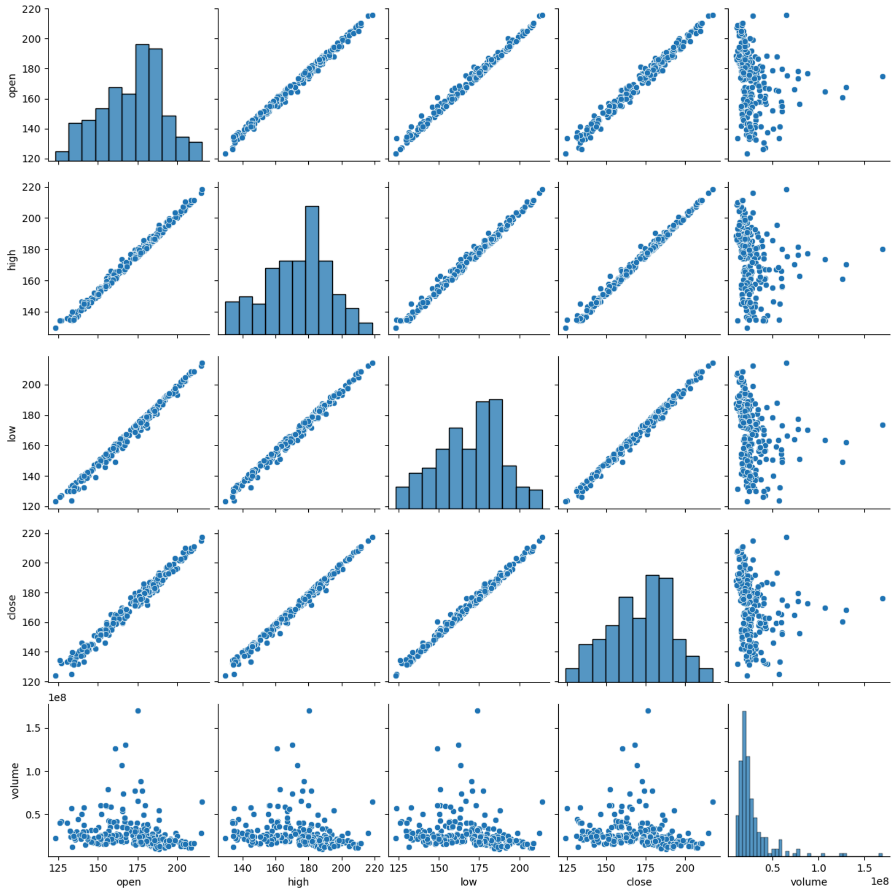


pairplot()

The pair plot is seaborn's answer to the scatter matrix we saw in the pandas subplotting notebook

```
sns.pairplot(fb)
```

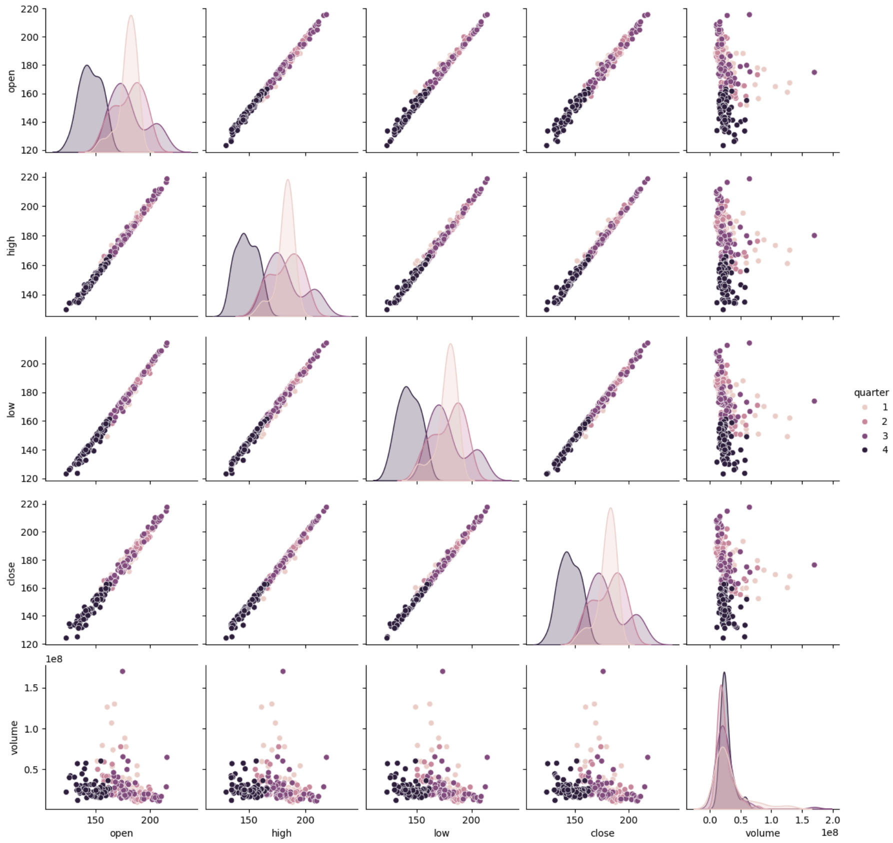
```
<seaborn.axisgrid.PairGrid at 0x7ac9c8b0ea10>
```



Just as with pandas we can specify what to show along the diagonal; however, seaborn also allows us to color the data based on another column (or other data with the same shape)

```
sns.pairplot(
fb.assign(quarter=lambda x: x.index.quarter),
diag_kind='kde',
hue='quarter'
)
```

<seaborn.axisgrid.PairGrid at 0x7ac9c8b86140>

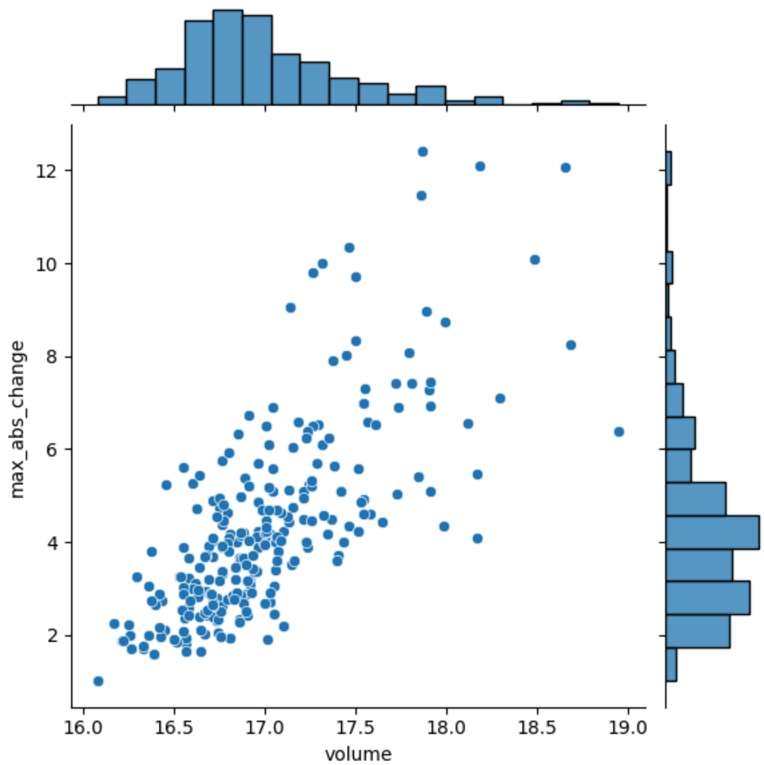


jointplot()

The joint plot allows us to visualize the relationship between two variables, like a scatter plot. However, we get the added benefit of being able to visualize their distributions at the same time (as a histogram or KDE). The default options give us a scatter plot in the center and histograms on the sides

```
sns.jointplot(
x='volume',
y='max_abs_change',
data=fb.assign(
volume=np.log(fb.volume),
max_abs_change=fb.high - fb.low
)
)
```

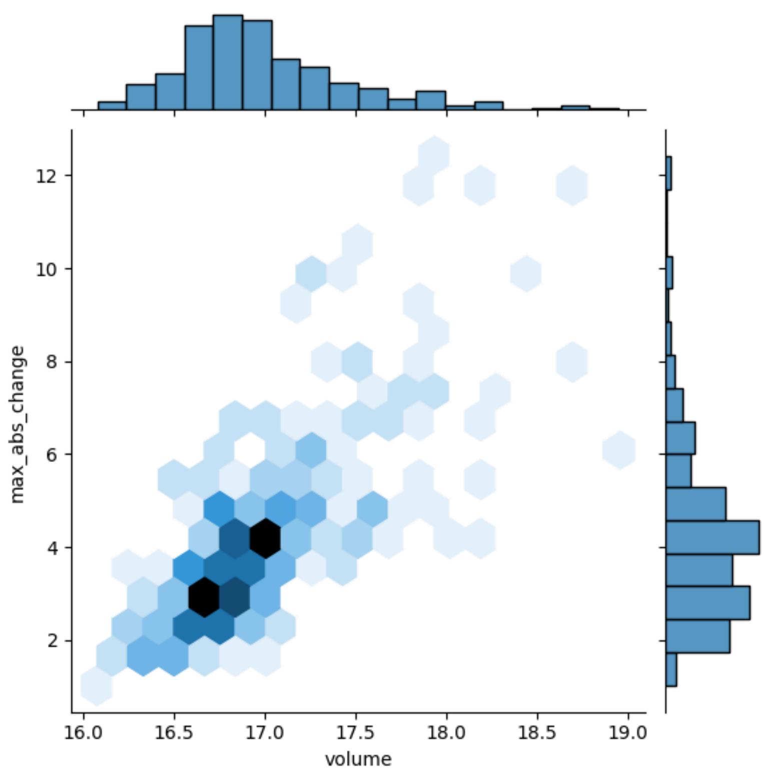
<seaborn.axisgrid.JointGrid at 0x7ac9b870b910>



By changing the kind argument, we can change how the center of the plot is displayed. For example, we can pass kind='hex' for hexbins:

```
sns.jointplot(
x='volume',
y='max_abs_change',
kind='hex',
data=fb.assign(
volume=np.log(fb.volume),
max_abs_change=fb.high - fb.low
)
)
```

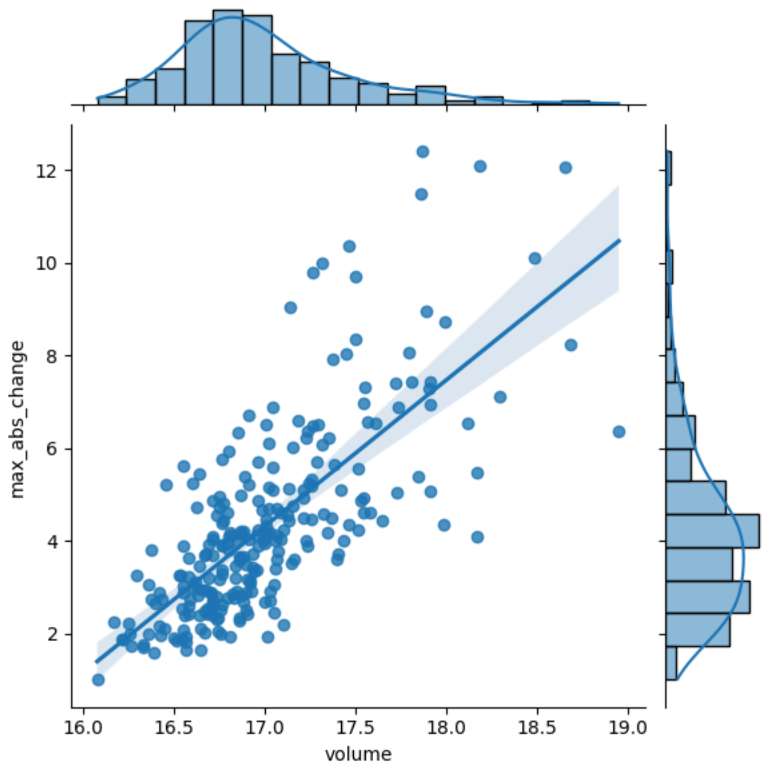
```
<seaborn.axisgrid.JointGrid at 0x7ac9b84f3370>
```



If we specify kind='reg' instead, we get a regression line in the center and KDEs on the sides

```
sns.jointplot(
x='volume',
y='max_abs_change',
kind='reg',
data=fb.assign(
volume=np.log(fb.volume),
max_abs_change=fb.high - fb.low
)
)
```

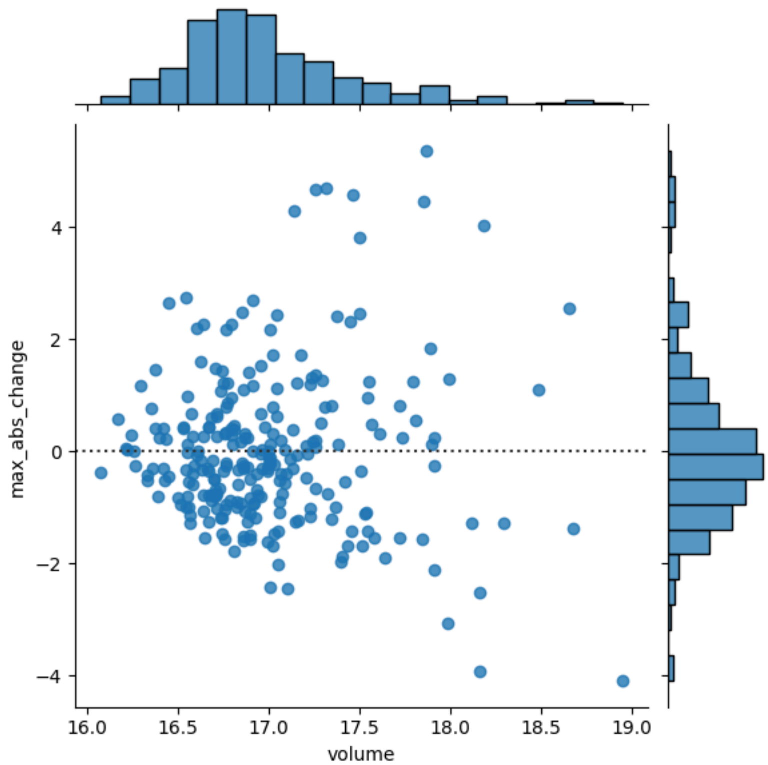
```
<seaborn.axisgrid.JointGrid at 0x7ac9f7b09150>
```



If we pass kind='resid' , we get the residuals from the aforementioned regression

```
sns.jointplot(
x='volume',
y='max_abs_change',
kind='resid',
data=fb.assign(
volume=np.log(fb.volume),
max_abs_change=fb.high - fb.low
)
)
```

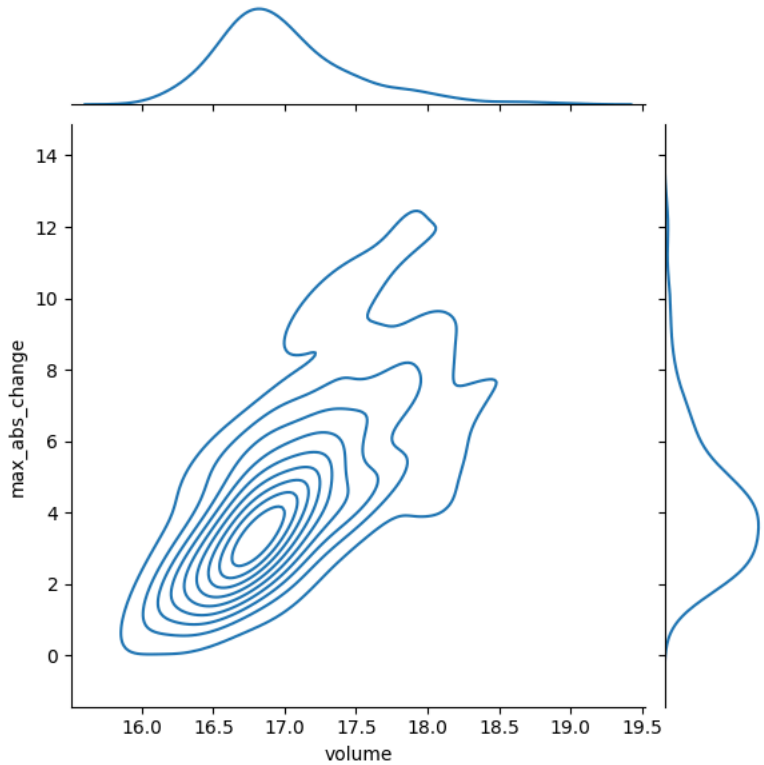
```
<seaborn.axisgrid.JointGrid at 0x7ac9b8262290>
```



Finally, if we pass kind='kde' , we get a contour plot of the joint density estimate with KDEs along the sides:

```
sns.jointplot(
x='volume',
y='max_abs_change',
kind='kde',
data=fb.assign(
volume=np.log(fb.volume),
max_abs_change=fb.high - fb.low
)
)
```

```
<seaborn.axisgrid.JointGrid at 0x7ac9b80eaaa0>
```



Regression plots

We are going to use seaborn to visualize a linear regression between the log of the volume traded in Facebook stock and the maximum absolute daily change (daily high stock price - daily low stock price). To do so, we first need to isolate this data

```
fb_reg_data = fb.assign(
volume=np.log(fb.volume),
max_abs_change=fb.high - fb.low
).iloc[:,-2:]

fb_reg_data
```

date	volume	max_abs_change
2018-01-02	16.714286	4.0300
2018-01-03	16.642029	3.4500
2018-01-04	16.446024	2.1104
2018-01-05	16.423706	1.9700
2018-01-08	16.705589	2.5700
...	...	...
2018-12-24	16.909549	6.7200
2018-12-26	17.497450	8.3500
2018-12-27	17.256009	5.3200
2018-12-28	16.934680	3.7200
2018-12-31	17.019285	4.6900

251 rows × 2 columns

Next steps: View recommended plots

Since we want to visualize each column as the regressor, we need to look at permutations of their order. Permutations and combinations (among other things) are made easy in Python with itertools , so let's import it

itertools gives us efficient iterators. Iterators are objects that we loop over, exhausting them. This is an iterator from itertools ; notice how the second loop doesn't do anything

```
import itertools

iterator = itertools.repeat("I'm an iterator", 1)
for i in iterator:
  print(f'-->{i}')
print('This printed once because the iterator has been exhausted')
for i in iterator:
  print(f'-->{i}')
```

```
-->I'm an iterator
This printed once because the iterator has been exhausted
```

```
iterable = list(itertools.repeat("I'm an iterable", 1))
for i in iterable:
  print(f'-->{i}')
print('This prints again because it\'s an iterable:')
for i in iterable:
  print(f'-->{i}')
```

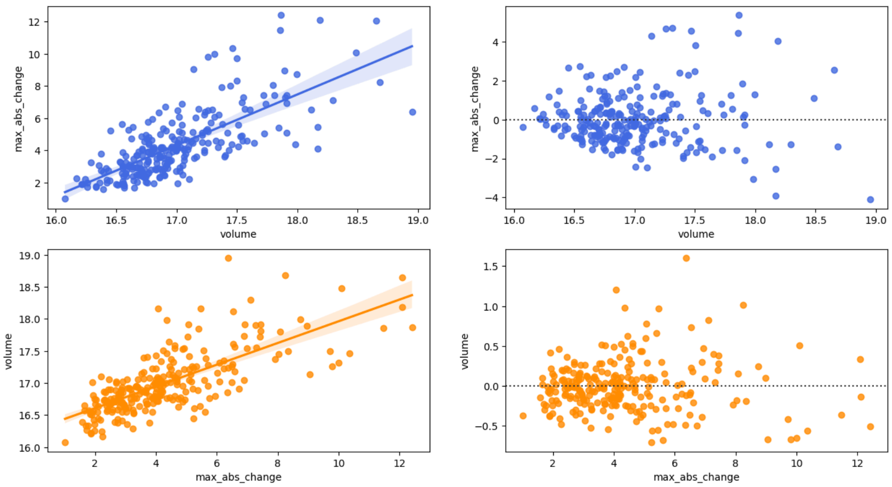
```
-->I'm an iterable
This prints again because it's an iterable:
-->I'm an iterable
```

The reg_resid_plots() function from the reg_resid_plot.py module in this folder uses regplot() and residplot() from seaborn along with itertools to plot the regression and residuals side-by-side

```
import itertools
import matplotlib.pyplot as plt
import seaborn as sns
def reg_resid_plots(data):

  num_cols = data.shape[1]
  permutation_count = num_cols * (num_cols - 1)
  fig, ax = plt.subplots(permutation_count, 2, figsize=(15, 8))
  for (x, y), axes, color in zip(
    itertools.permutations(data.columns, 2),
    ax,
    itertools.cycle(['royalblue', 'darkorange'])):
    for subplot, func in zip(axes, (sns.regplot, sns.residplot)):
      func(x=x, y=y, data=data, ax=subplot, color=color)
  plt.close()
  return fig
```

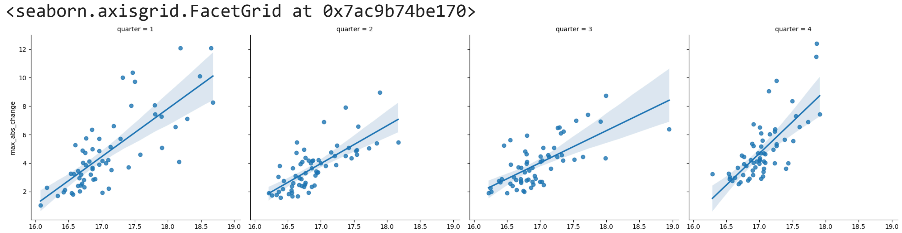
```
reg_resid_plots(fb_reg_data)
```



We can use lmplot() to split our regression across subsets of our data. For example, we can perform a regression per quarter on the Facebook stock data

```
sns.lmplot(
x='volume',
y='max_abs_change',
data=fb.assign(
volume=np.log(fb.volume),
max_abs_change=fb.high - fb.low,
quarter=lambda x: x.index.quarter
),
col='quarter'
)
```

```
<seaborn.axisgrid.FacetGrid at 0x7ac9b74be170>
```



Distributions

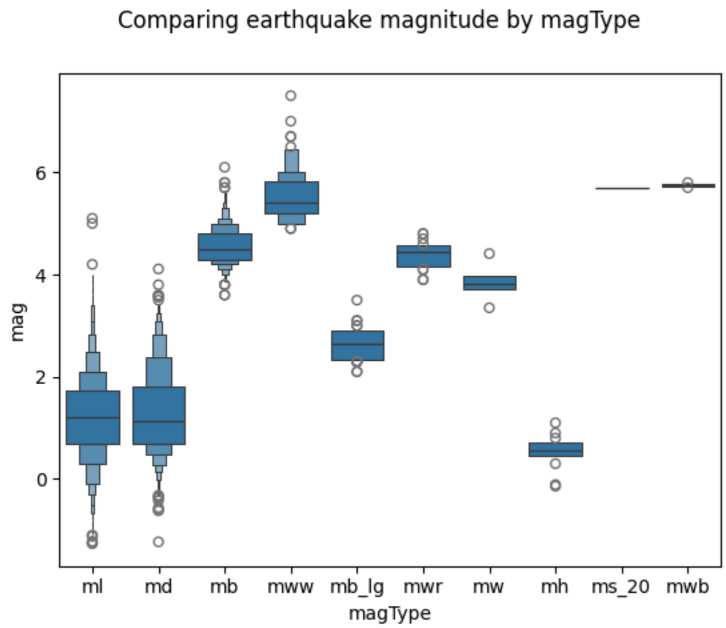
Seaborn provides some new plot types for visualizing distributions in additional to its own versions of the plot types we discussed in chapter 5 (in this notebook).

boxenplot()

The boxenplot is a box plot that shows additional quantiles:

```
sns.boxenplot(
x='magType', y='mag', data=quakes[['magType', 'mag']]
)
plt.suptitle('Comparing earthquake magnitude by magType')
```

```
Text(0.5, 0.98, 'Comparing earthquake magnitude by magType')
```



violinplot()

Box plots lose some information about the distribution, so we can use violin plots which combine box plots and KDEs:

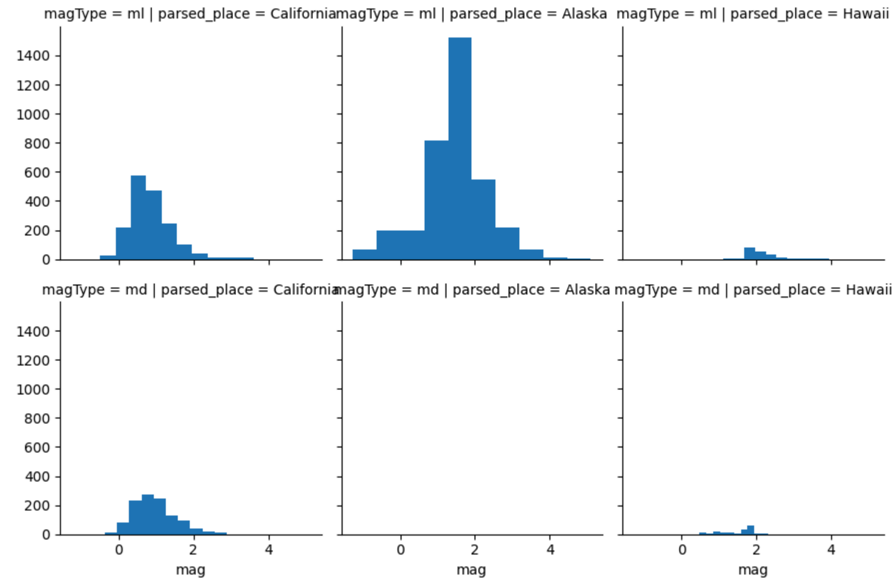
```
fig, axes = plt.subplots(figsize=(10, 5))
sns.violinplot(
x='magType', y='mag', data=quakes[['magType', 'mag']],
ax=axes, scale='width' # all violins have same width
)
plt.suptitle('Comparing earthquake magnitude by magType')
```

Faceting

We can create subplots across subsets of our data by faceting. First, we create a FacetGrid specifying how to layout the plots (which categorical column goes along the rows and which one along the columns). Then, we call the map() method of the FacetGrid and pass in the plotting function we want to use (along with any additional arguments). Let's make histograms showing the distribution of earthquake magnitude in California, Alaska, and Hawaii faceted by magType and parse_placed

```
g = sns.FacetGrid(
quakes[
(quakes.parsed_place.isin([
'California', 'Alaska', 'Hawaii'
]))\
```

```
& (quakes.magType.isin(['ml', 'md']))
],
row='magType',
col='parsed_place'
)
g = g.map(plt.hist, 'mag')
```



9.5 Formatting Plots

```
%matplotlib inline
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import seaborn as sns
fb = pd.read_csv(
'data/fb_stock_prices_2018.csv', index_col='date', parse_dates=True)
fb
```

date	open	high	low	close	volume
2018-01-02	177.68	181.58	177.5500	181.42	18151903
2018-01-03	181.88	184.78	181.3300	184.67	16886563
2018-01-04	184.90	186.21	184.0996	184.33	13880896
2018-01-05	185.59	186.90	184.9300	186.85	13574535
2018-01-08	187.20	188.90	186.3300	188.28	17994726
...	...	...	...	...	...
2018-12-24	123.10	129.74	123.0200	124.06	22066002
2018-12-26	126.00	134.24	125.8900	134.18	39723370
2018-12-27	132.44	134.99	129.6700	134.52	31202509
2018-12-28	135.34	135.92	132.2000	133.20	22627569
2018-12-31	134.45	134.64	129.9500	131.09	24625308

251 rows × 5 columns

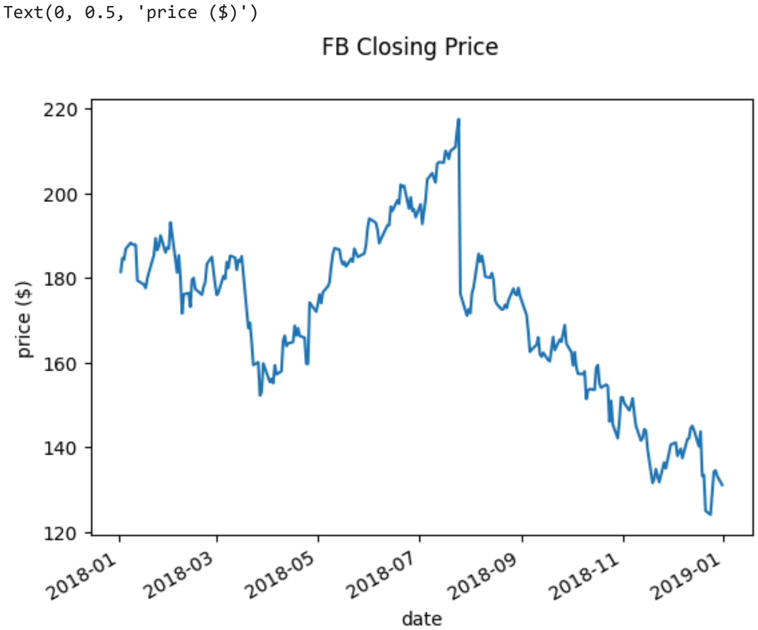
Next steps: View recommended plots

Titles and Axis Labels

- **plt.suptitle() adds a title to plots and subplots**
- **plt.title() adds a title to a single plot. Note if you use subplots, it will only put the title on the last subplot, so you will need to use plt.suptitle()**
- **plt.xlabel() labels the x-axis**
- **plt.ylabel() labels the y-axis**

```
fb.close.plot()
plt.suptitle('FB Closing Price')
plt.xlabel('date')
plt.ylabel('price ($)')
```

```
Text(0, 0.5, 'price ($)')
```

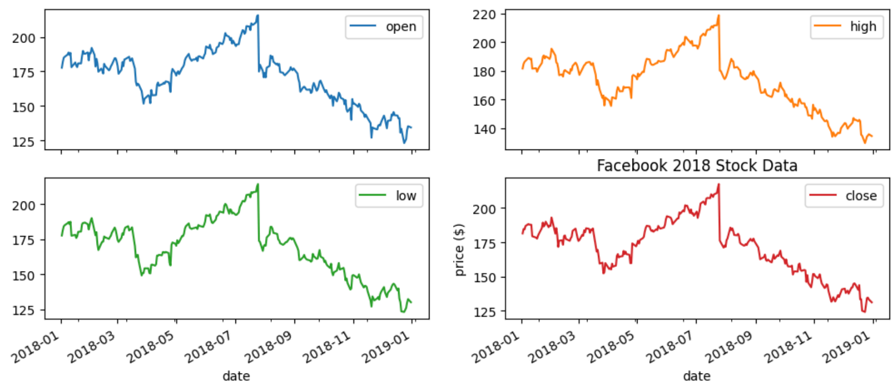


plt.suptitle() vs. plt.title()

Check out what happens when we call plt.title() with subplots

```
fb.iloc[:,:4].plot(subplots=True, layout=(2, 2), figsize=(12, 5))
plt.title('Facebook 2018 Stock Data')
plt.xlabel('date')
plt.ylabel('price ($)')
```

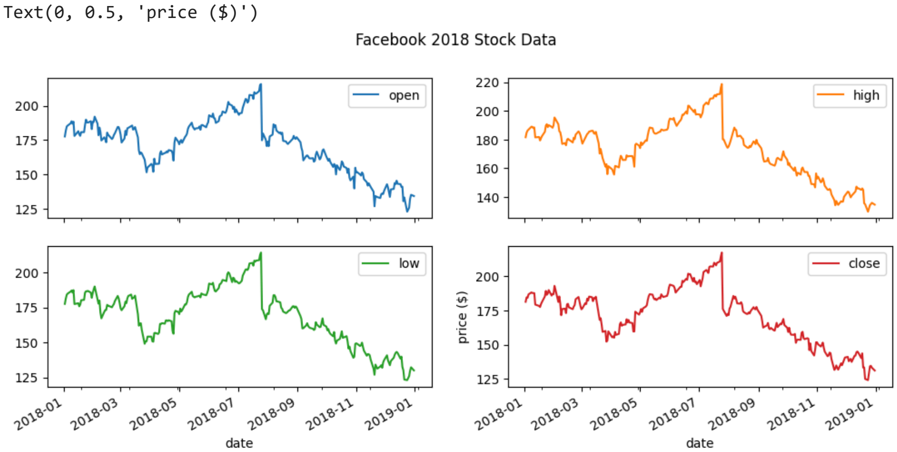
```
Text(0, 0.5, 'price ($)')
```



Simply getting into the habit of using plt.suptitle() instead of plt.title()will save you this confusion

```
fb.iloc[:,:4].plot(subplots=True, layout=(2, 2), figsize=(12, 5))
plt.suptitle('Facebook 2018 Stock Data')
plt.xlabel('date')
plt.ylabel('price ($)')
```

```
Text(0, 0.5, 'price ($)')
```



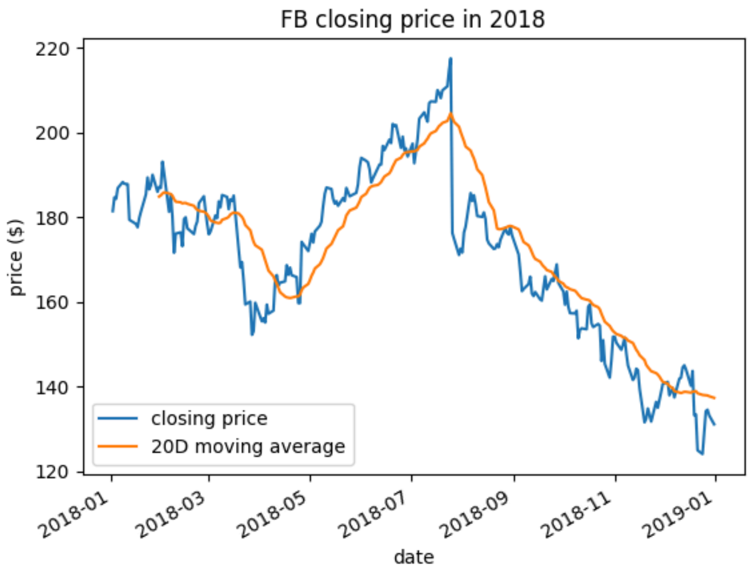
Legends

plt.legend() adds a legend to the plot. We can specify where to place it with the loc parameter

```
fb.assign(
ma=lambda x: x.close.rolling(20).mean()
).plot(
y=['close', 'ma'],
```

```
title='FB closing price in 2018',
label=['closing price', '20D moving average']
)
plt.legend(loc='lower left')
plt.ylabel('price ($)')
```

```
Text(0, 0.5, 'price ($)')
```



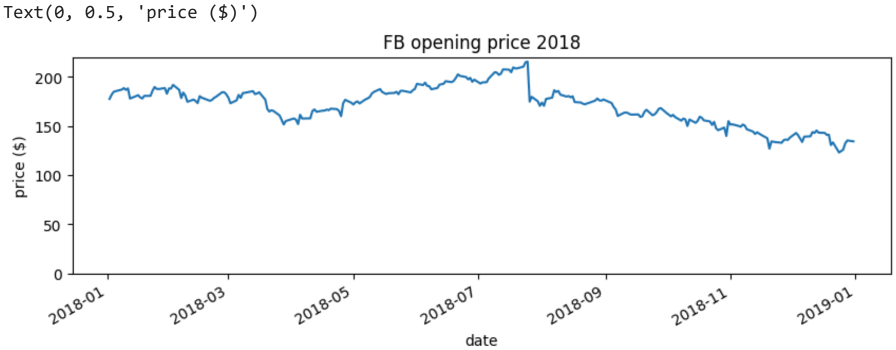
Formatting Axes

Specifying axis limits

plt.xlim() and plt.ylim() can be used to specify the minimum and maximum values for the axis. Passing None will have matplotlib determine the limit

```
fb.open.plot(figsize=(10, 3), title='FB opening price 2018')
plt.ylim(0, None)
plt.ylabel('price ($)')
```

```
Text(0, 0.5, 'price ($)')
```



Formatting the Axis Ticks

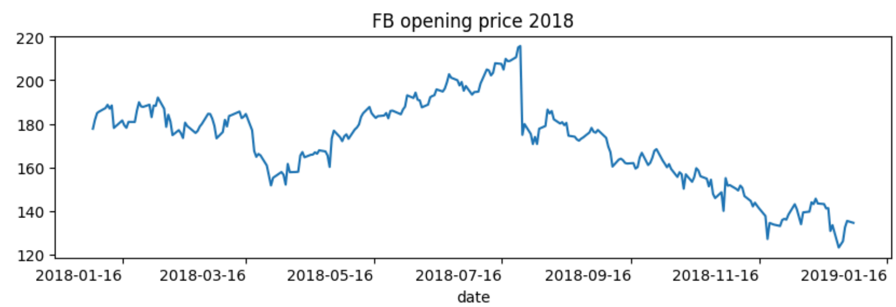
We can use plt.xticks() and plt.yticks() to provide tick labels and specify, which ticks to show. Here, we show every other month

```
import calendar
fb.open.plot(figsize=(10, 3), rot=0, title='FB opening price 2018')
locs, labels = plt.xticks()
plt.xticks(locs + 15 , calendar.month_name[1::2])
plt.ylabel('price ($)')
```

```
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
<ipython-input-42-49f9a03c7ca6> in <cell line: 4>()
      2 fb.open.plot(figsize=(10, 3), rot=0, title='FB opening price 2018')
      3 locs, labels = plt.xticks()
----> 4 plt.xticks(locs + 15 , calendar.month_name[1::2])
      5 plt.ylabel('price ($)')

3 frames
/usr/local/lib/python3.10/dist-packages/matplotlib/axis.py in set_ticklabels(self,
labels, minor, fontdict, **kwargs)
   1967             # remove all tick labels, so only error for > 0 labels
   1968             if len(locator.locs) != len(labels) and len(labels) != 0:
-> 1969                 raise ValueError(
   1970                     "The number of FixedLocator locations"
   1971                     f" ({len(locator.locs)}), usually from a call to"

ValueError: The number of FixedLocator locations (7), usually from a call to set_ticks,
does not match the number of labels (6).
```



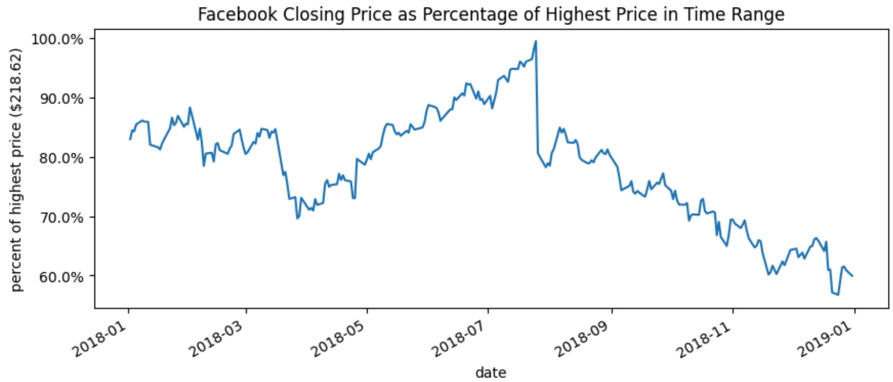
Using ticker

PercentFormatter

We can use ticker.PercentFormatter and specify the denominator (xmax) to use when calculating the percentages. This gets passed to the set_major_formatter() method of the xaxis or yaxis on the Axes

```
import matplotlib.ticker as ticker
ax = fb.close.plot(
figsize=(10, 4),
title='Facebook Closing Price as Percentage of Highest Price in Time Range'
)
ax.yaxis.set_major_formatter(
ticker.PercentFormatter(xmax=fb.high.max())
)
ax.set_yticks([
fb.high.max()*pct for pct in np.linspace(0.6, 1, num=5)
]) # show round percentages only (60%, 80%, etc.)
ax.set_ylabel(f'percent of highest price (${fb.high.max()})')
```

```
Text(0, 0.5, 'percent of highest price ($218.62)')
```

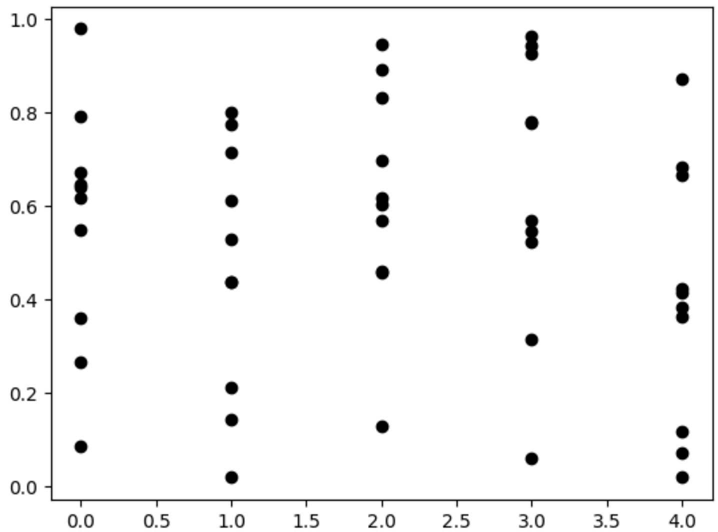


MultipleLocator

Say we have the following data. The points only take on integer values for x

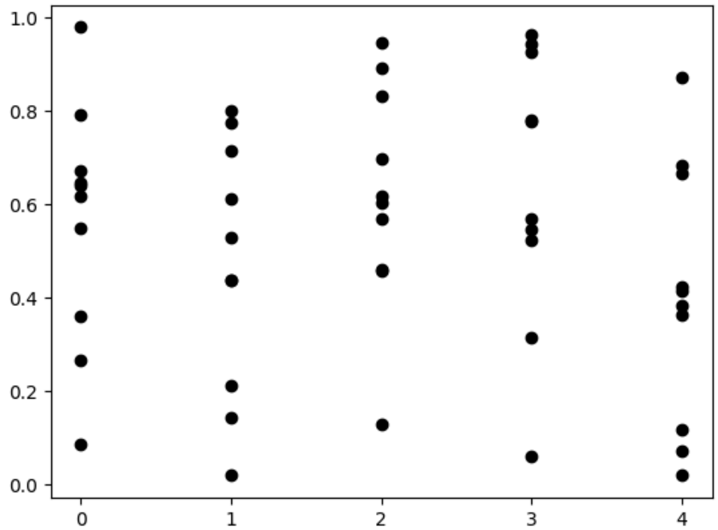
```
fig, ax = plt.subplots(1, 1)
np.random.seed(0)
ax.plot(np.tile(np.arange(0, 5), 10), np.random.rand(50), 'ko')
```

```
[<matplotlib.lines.Line2D at 0x7ac9b6700f40>]
```



If we don't want to show decimal values on the x-axis, we can use the MultipleLocator . This will give ticks for all multiples of a number specified with the base parameter. To get integer values, we use base=1

```
fig, ax = plt.subplots(1, 1)
np.random.seed(0)
ax.plot(np.tile(np.arange(0, 5), 10), np.random.rand(50), 'ko')
ax.get_xaxis().set_major_locator(
ticker.MultipleLocator(base=1)
)
```



9.6 Customizing Visualizations

```
%matplotlib inline
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
fb = pd.read_csv('data/fb_stock_prices_2018.csv', index_col='date', parse_dates=True)
fb
```

date	open	high	low	close	volume
2018-01-02	177.68	181.58	177.5500	181.42	18151903
2018-01-03	181.88	184.78	181.3300	184.67	16886563
2018-01-04	184.90	186.21	184.0996	184.33	13880896
2018-01-05	185.59	186.90	184.9300	186.85	13574535
2018-01-08	187.20	188.90	186.3300	188.28	17994726
...	...	...	...	...	...
2018-12-24	123.10	129.74	123.0200	124.06	22066002
2018-12-26	126.00	134.24	125.8900	134.18	39723370
2018-12-27	132.44	134.99	129.6700	134.52	31202509
2018-12-28	135.34	135.92	132.2000	133.20	22627569
2018-12-31	134.45	134.64	129.9500	131.09	24625308

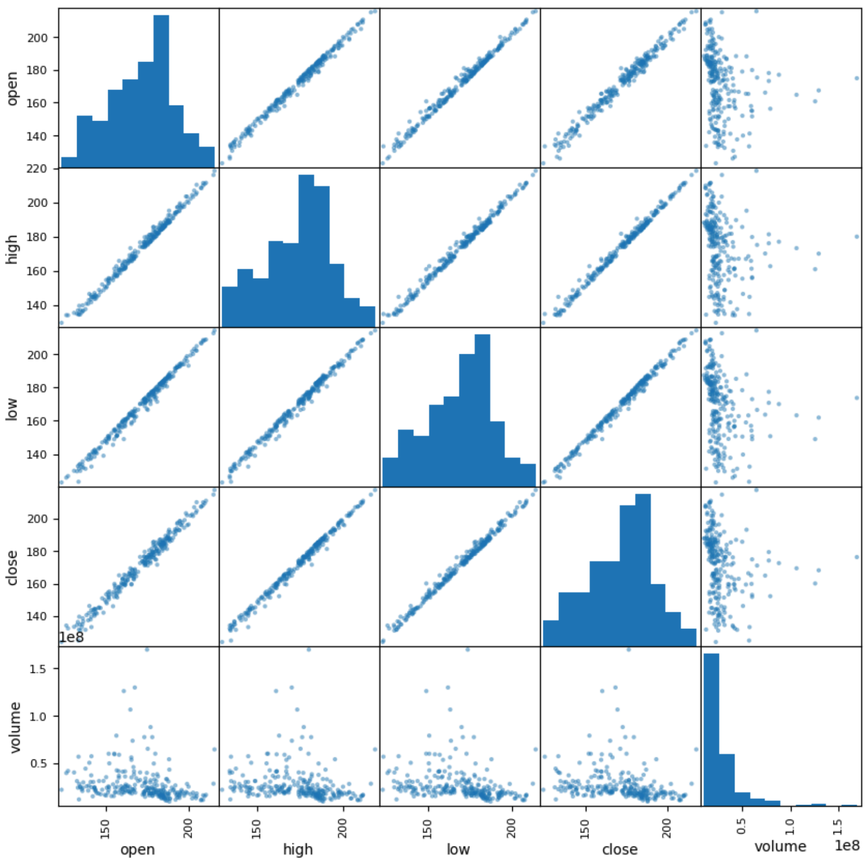
251 rows × 5 columns

Next steps: View recommended plots

Scatter matrix

```
from pandas.plotting import scatter_matrix
scatter_matrix(fb, figsize=(10, 10))
```

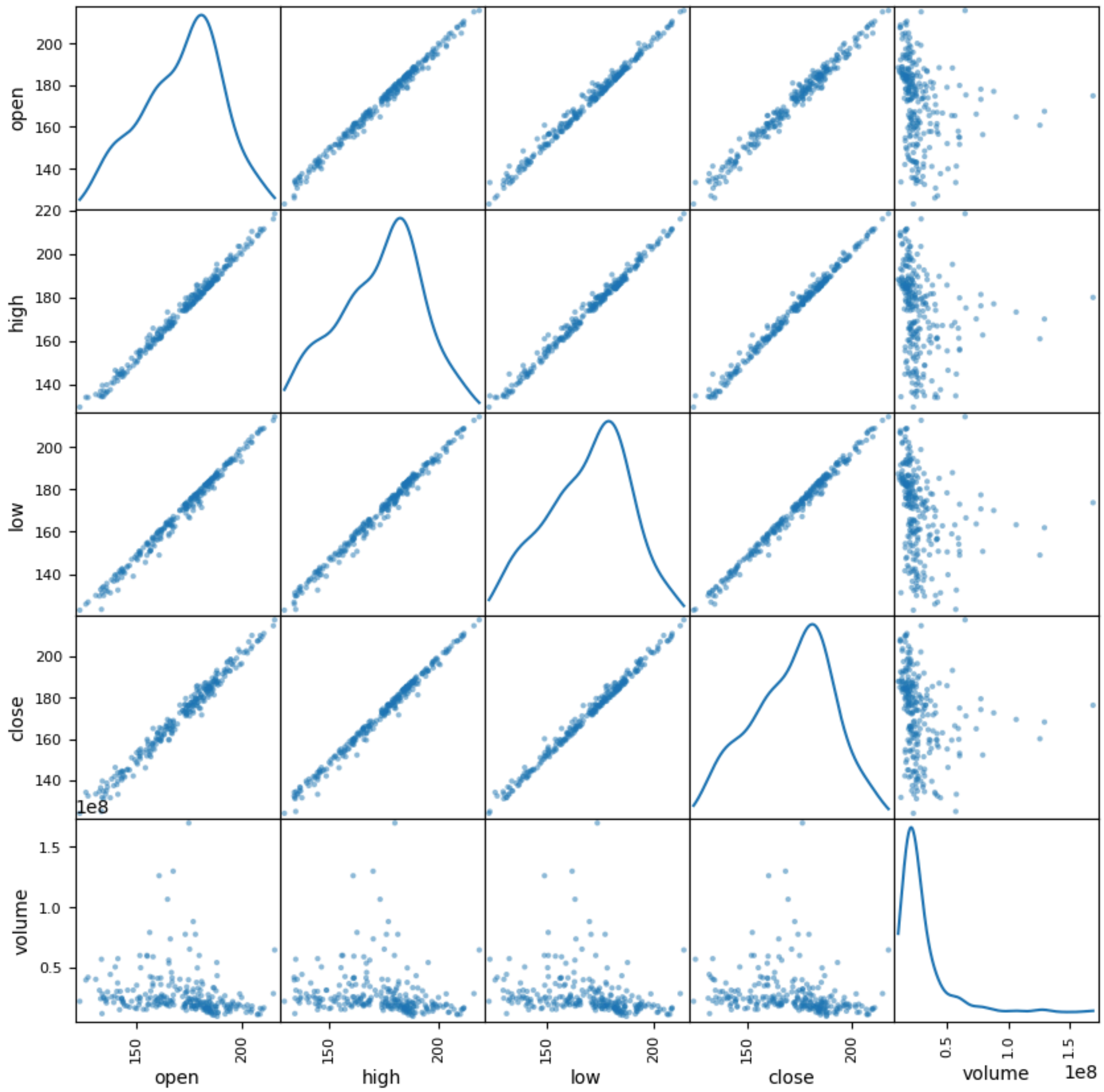
```
[<Axes: xlabel='open', ylabel='high'>,
 <Axes: xlabel='high', ylabel='high'>,
 <Axes: xlabel='low', ylabel='high'>,
 <Axes: xlabel='close', ylabel='high'>,
 <Axes: xlabel='volume', ylabel='high'>],
[<Axes: xlabel='open', ylabel='low'>,
 <Axes: xlabel='high', ylabel='low'>,
 <Axes: xlabel='low', ylabel='low'>,
 <Axes: xlabel='close', ylabel='low'>,
 <Axes: xlabel='volume', ylabel='low'>],
[<Axes: xlabel='open', ylabel='close'>,
 <Axes: xlabel='high', ylabel='close'>,
 <Axes: xlabel='low', ylabel='close'>,
 <Axes: xlabel='close', ylabel='close'>,
 <Axes: xlabel='volume', ylabel='close'>],
[<Axes: xlabel='open', ylabel='volume'>,
 <Axes: xlabel='high', ylabel='volume'>,
 <Axes: xlabel='low', ylabel='volume'>,
 <Axes: xlabel='close', ylabel='volume'>,
 <Axes: xlabel='volume', ylabel='volume'>]], dtype=object)
```



Changing the diagonal from histograms to KDE

```
scatter_matrix(fb, figsize=(10, 10), diagonal='kde')
```

```
array([[<Axes: xlabel='open', ylabel='open'>,
        <Axes: xlabel='high', ylabel='open'>,
        <Axes: xlabel='low', ylabel='open'>,
        <Axes: xlabel='close', ylabel='open'>,
        <Axes: xlabel='volume', ylabel='open'>],
       [<Axes: xlabel='open', ylabel='high'>,
        <Axes: xlabel='high', ylabel='high'>,
        <Axes: xlabel='low', ylabel='high'>,
        <Axes: xlabel='close', ylabel='high'>,
        <Axes: xlabel='volume', ylabel='high'>],
       [<Axes: xlabel='open', ylabel='low'>,
        <Axes: xlabel='high', ylabel='low'>,
        <Axes: xlabel='low', ylabel='low'>,
        <Axes: xlabel='close', ylabel='low'>,
        <Axes: xlabel='volume', ylabel='low'>],
       [<Axes: xlabel='open', ylabel='close'>,
        <Axes: xlabel='high', ylabel='close'>,
        <Axes: xlabel='low', ylabel='close'>,
        <Axes: xlabel='close', ylabel='close'>,
        <Axes: xlabel='volume', ylabel='close'>],
       [<Axes: xlabel='open', ylabel='volume'>,
        <Axes: xlabel='high', ylabel='volume'>,
        <Axes: xlabel='low', ylabel='volume'>,
        <Axes: xlabel='close', ylabel='volume'>,
        <Axes: xlabel='volume', ylabel='volume'>]], dtype=object)
```



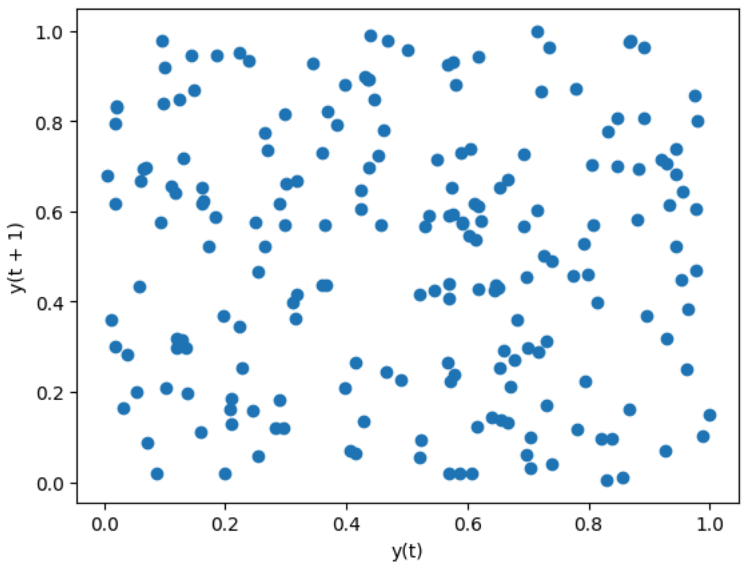
Lag plot

Lag plots let us see how the variable correlations with past observations of itself. Random data has no pattern

```
from pandas.plotting import lag_plot
np.random.seed(0) # make this repeatable
```

```
lag_plot(pd.Series(np.random.random(size=200)))
```

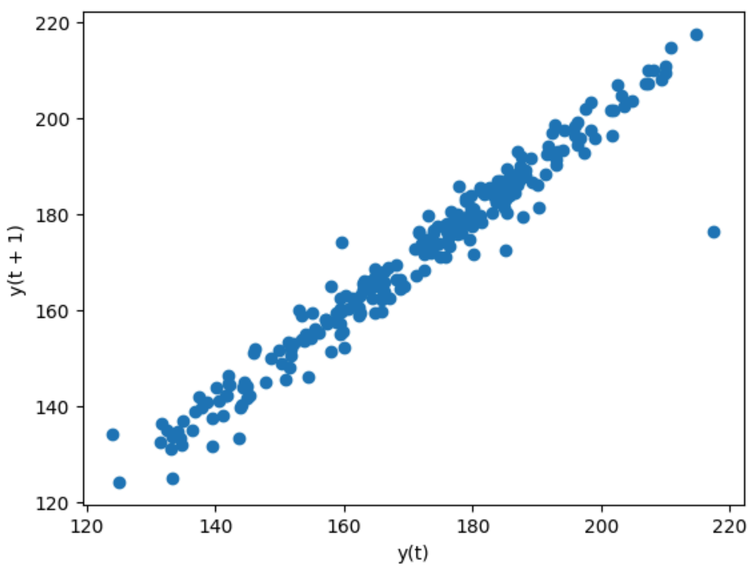
<Axes: xlabel='y(t)', ylabel='y(t + 1)'>



Data with some level of correlation to itself (autocorrelation) may have patterns. Stock prices are highly auto-correlated:

```
lag_plot(fb.close)
```

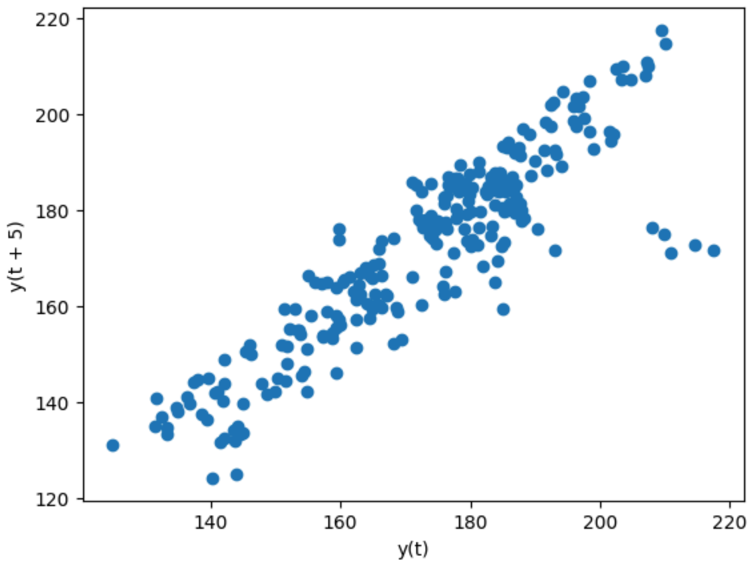
<Axes: xlabel='y(t)', ylabel='y(t + 1)'>



The default lag is 1, but we can alter this with the lag parameter. Let's look at a 5 day lag (a week of trading activity)

```
lag_plot(fb.close, lag=5)
```

```
<Axes: xlabel='y(t)', ylabel='y(t + 5)'>
```

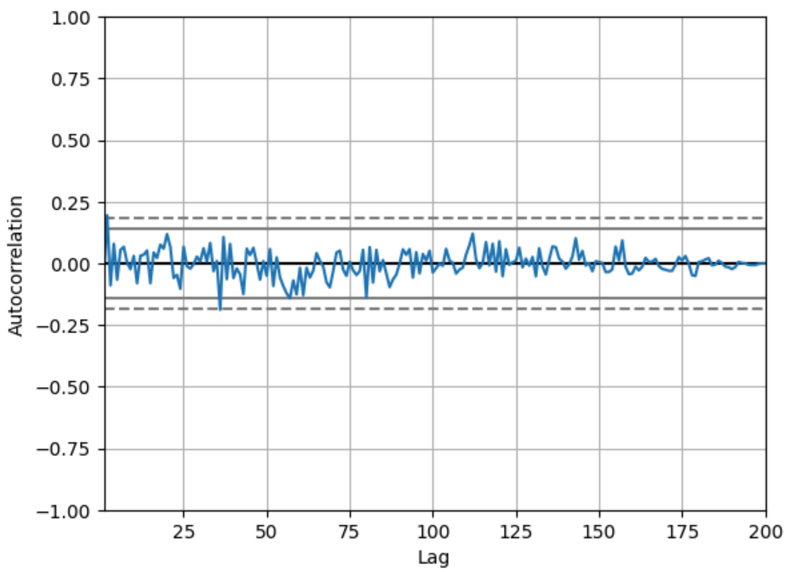


Autocorrelation plots

We can use the autocorrelation plot to see if this relationship may be meaningful or just noise. Random data will not have any significant autocorrelation (it stays within the bounds below)

```
from pandas.plotting import autocorrelation_plot
np.random.seed(0) # make this repeatable
autocorrelation_plot(pd.Series(np.random.random(size=200)))
```

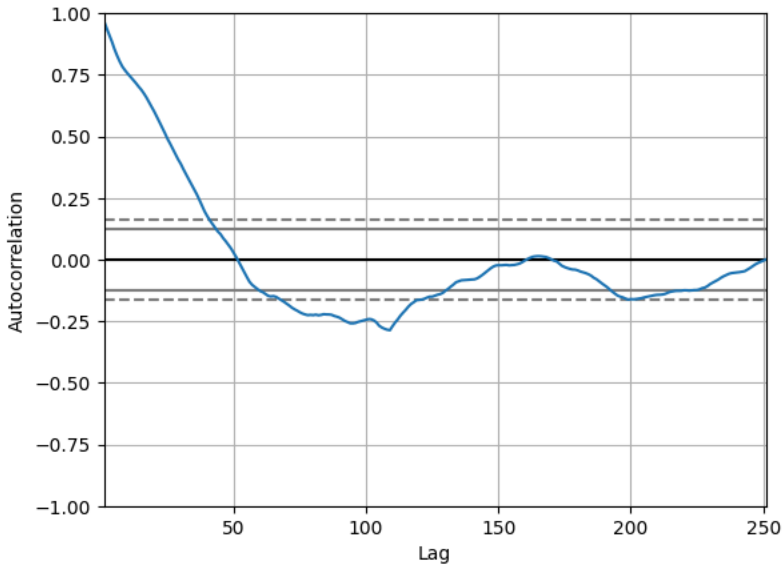
```
<Axes: xlabel='Lag', ylabel='Autocorrelation'>
```



Stock data, on the other hand, does have significant autocorrelation

```
autocorrelation_plot(fb.close)
```

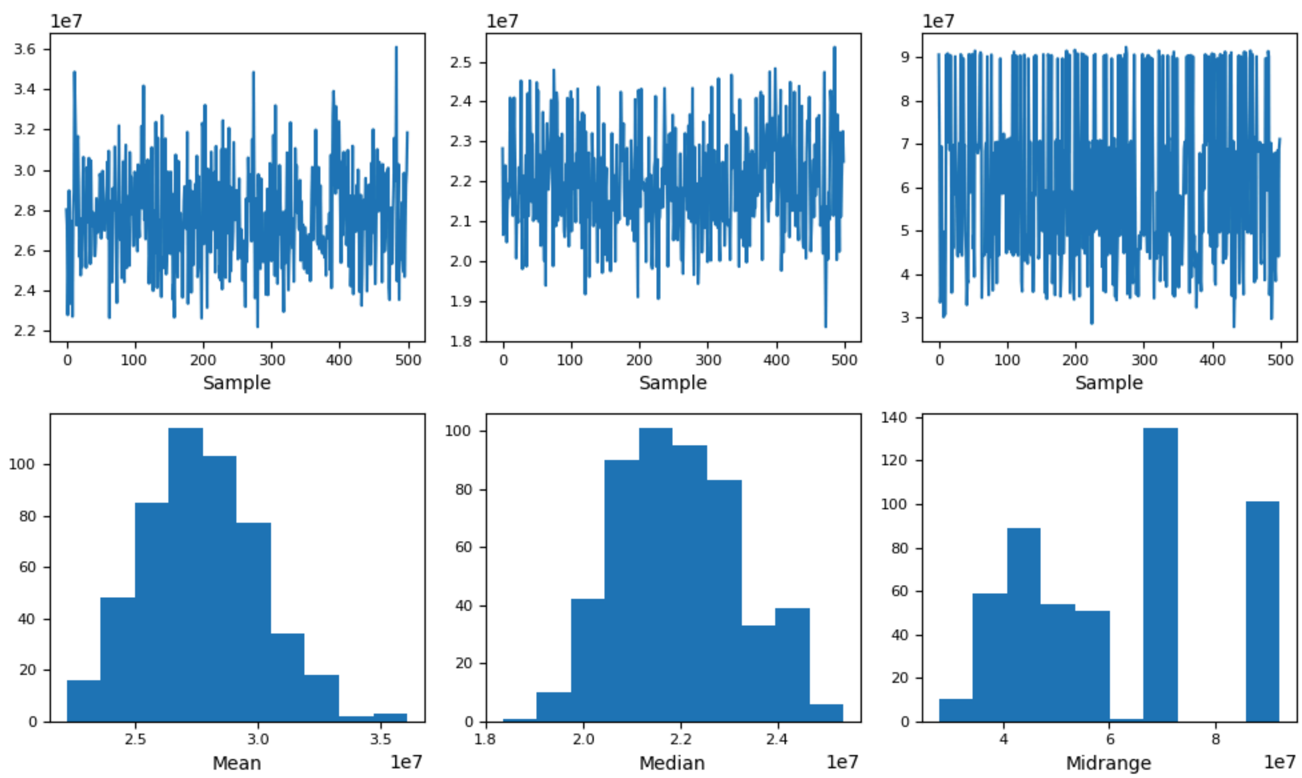
```
<Axes: xlabel='Lag', ylabel='Autocorrelation'>
```



Bootstrap plot

This plot helps us understand the uncertainty in our summary statistics

```
from pandas.plotting import bootstrap_plot
fig = bootstrap_plot(fb.volume, fig=plt.figure(figsize=(10, 6)))
```



Supplementary Activity

```
eq = pd.read_csv('data/earthquakes.csv')
eq
```

	mag	magType	time	place	tsunami	parsed_place
0	1.35	ml	1539475168010	9km NE of Aguanga, CA	0	California
1	1.29	ml	1539475129610	9km NE of Aguanga, CA	0	California
2	3.42	ml	1539475062610	8km NE of Aguanga, CA	0	California
3	0.44	ml	1539474978070	9km NE of Aguanga, CA	0	California
4	2.16	md	1539474716050	10km NW of Avenal, CA	0	California
...	...	...	...	...	...	...
9327	0.62	md	1537230228060	9km ENE of Mammoth Lakes, CA	0	California
9328	1.00	ml	1537230135130	3km W of Julian, CA	0	California
9329	2.40	md	1537229908180	35km NNE of Hatillo, Puerto Rico	0	Puerto Rico
9330	1.10	ml	1537229545350	9km NE of Aguanga, CA	0	California
9331	0.66	ml	1537228864470	9km NE of Aguanga, CA	0	California

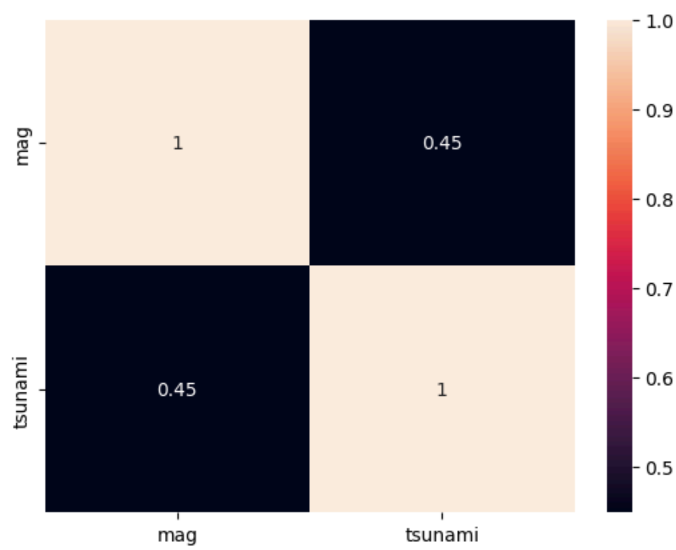
9332 rows × 6 columns

Next steps: View recommended plots

1. Using seaborn, create a heatmap to visualize the correlation coefficients between earthquake magnitude and whether there was a tsunami with the magType of mb.

```
eq2 = eq.query('magType == "mb"')[['mag','tsunami']] # accessing only the Tsunami with magType of mb
sns.heatmap(eq2.corr(), #identifying if there is a correlation
          annot = True)
```

```
<Axes: >
```

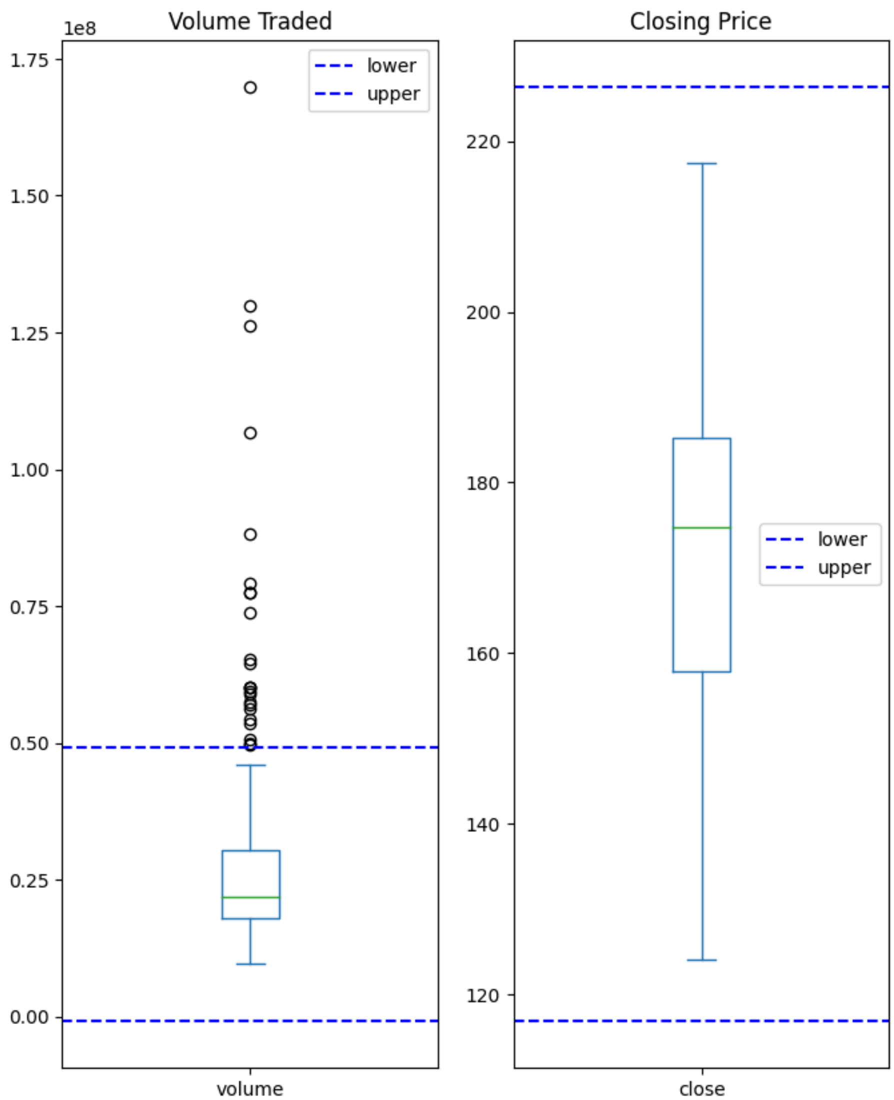


2. Create a box plot of Facebook volume traded and closing prices, and draw reference lines for the bounds of a Tukey fence with a multiplier of 1.5. The bounds will be at Q1 - 1.5 * IQR and Q3 + 1.5 * IQR. Be sure to use the quantile() method on the data to make this easier. (Pick whichever orientation you prefer for the plot, but make sure to use subplots.)

```
columns = ['volume', 'close']
subset = fb[columns]
qtl = subset.quantile([0.25, 0.75])
qtl.loc['iqr',:] = qtl.loc[0.75,:] - qtl.loc[0.25,:]

axes = subset.plot(
    kind='box',
    subplots=True,
    figsize=(8, 10),
    title=['Volume Traded', 'Closing Price'])

for ax, col in zip(axes, columns):
  stats = qtl[col]
  lower = stats.loc[0.25] - 1.5 * stats['iqr']
  upper = stats.loc[0.75] + 1.5 * stats['iqr']
  for bound, name in zip([lower, upper], ['lower', 'upper']):
    ax.axhline( bound, color='blue', linestyle='dashed', label=name )
    ax.legend()
```



3. Fill in the area between the bounds in the plot from exercise #2.