Introduction to Seaborn

About the Data

In this notebook, we will be working with 2 datasets:

Facebook's stock price throughout 2018 (obtained using the stock_analysis package) Earthquake data from September 18, 2018 - October 13, 2018 (obtained from the US Geological Survey (USGS) using the USGS API) Setup

```
%matplotlib inline
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
import pandas as pd

fb = pd.read_csv(
'/content/fb_stock_prices_2018.csv', index_col='date', parse_dates=True
)

quakes = pd.read_csv('/content/earthquakes.csv')
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"
)
```

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

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"
)
```

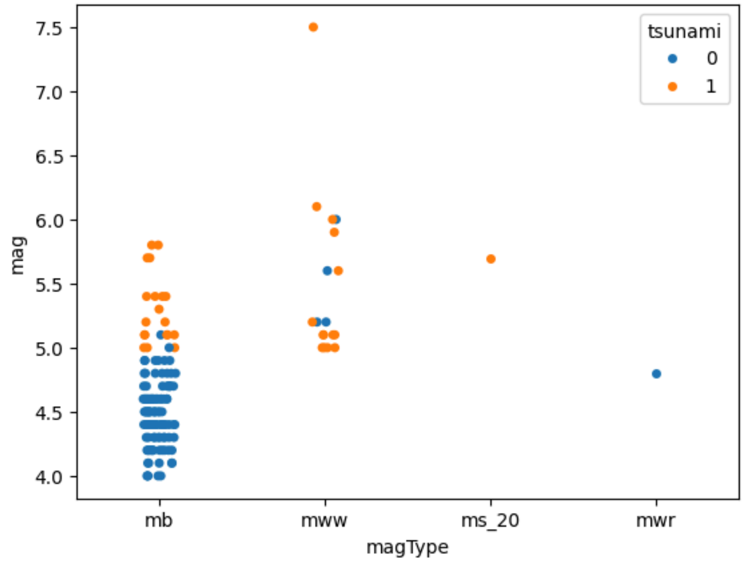
	mag	magType	place	tsunami	parsed_place
time					
2018-09-28 10:02:43.480	7.5	mww	78km N of Palu, Indonesia	1	Indonesia

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'>
```

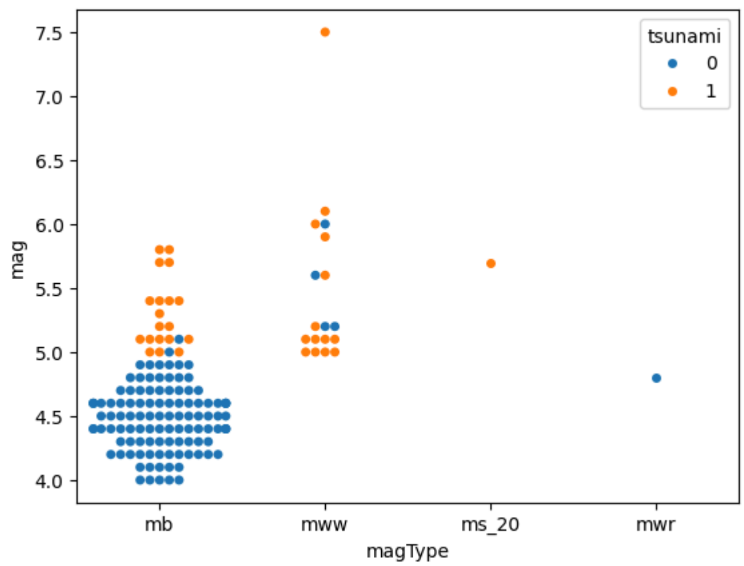


swarmplot()

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% of the points cannot be placed; you may want to
  warnings.warn(msg, UserWarning)
```



Correlations and Heatmaps

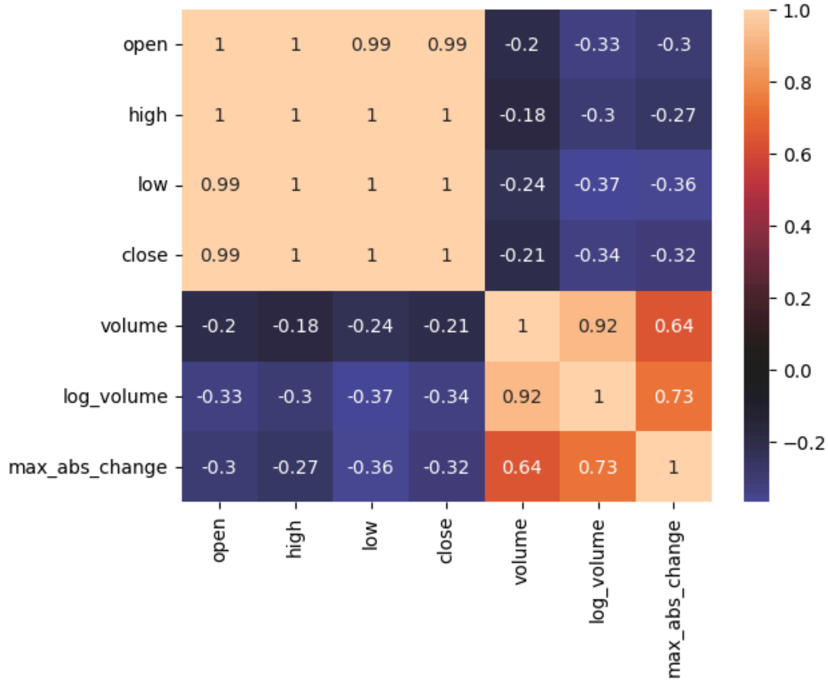
heatmap()

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: >
```

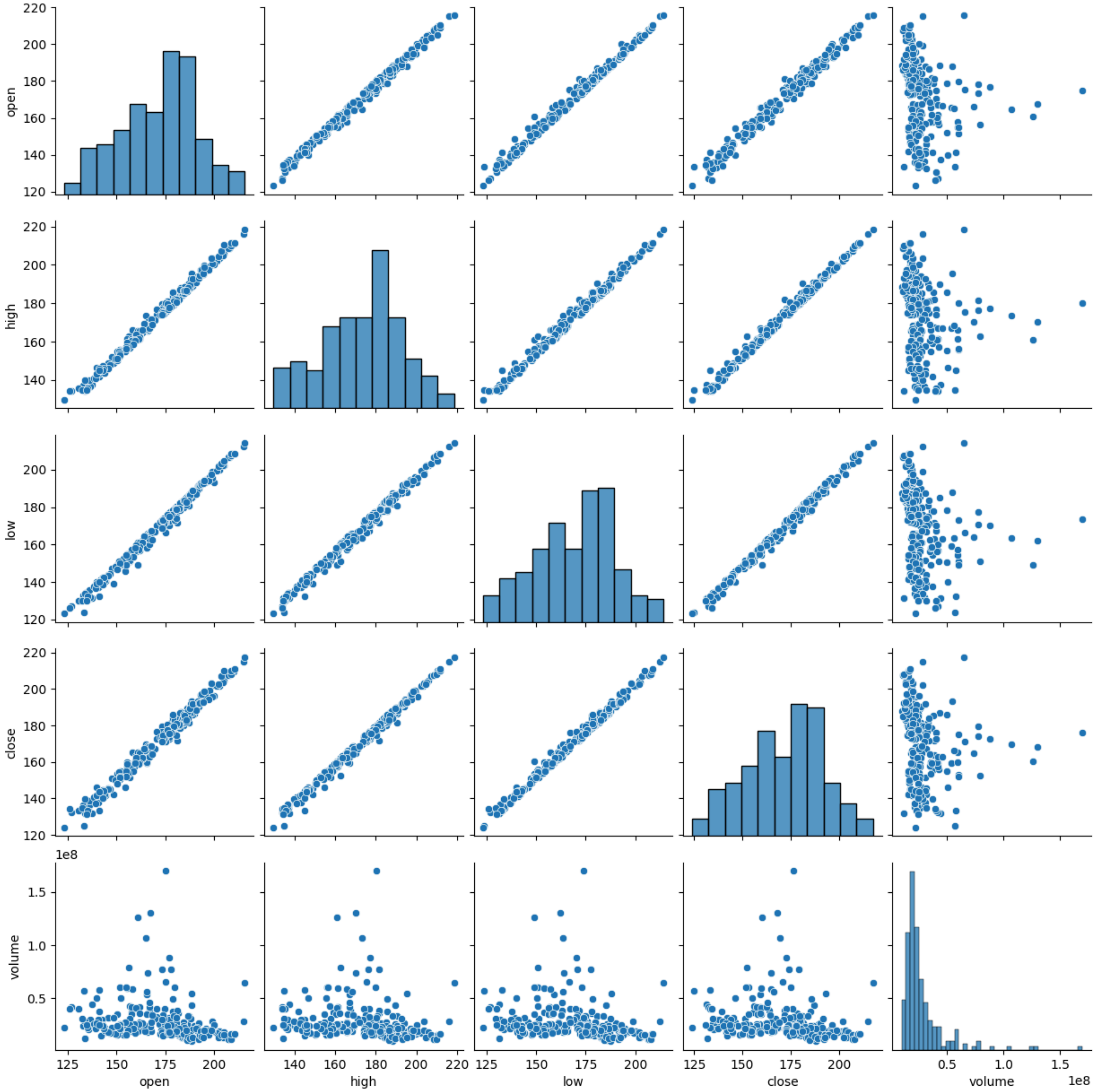


pairplot()

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

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

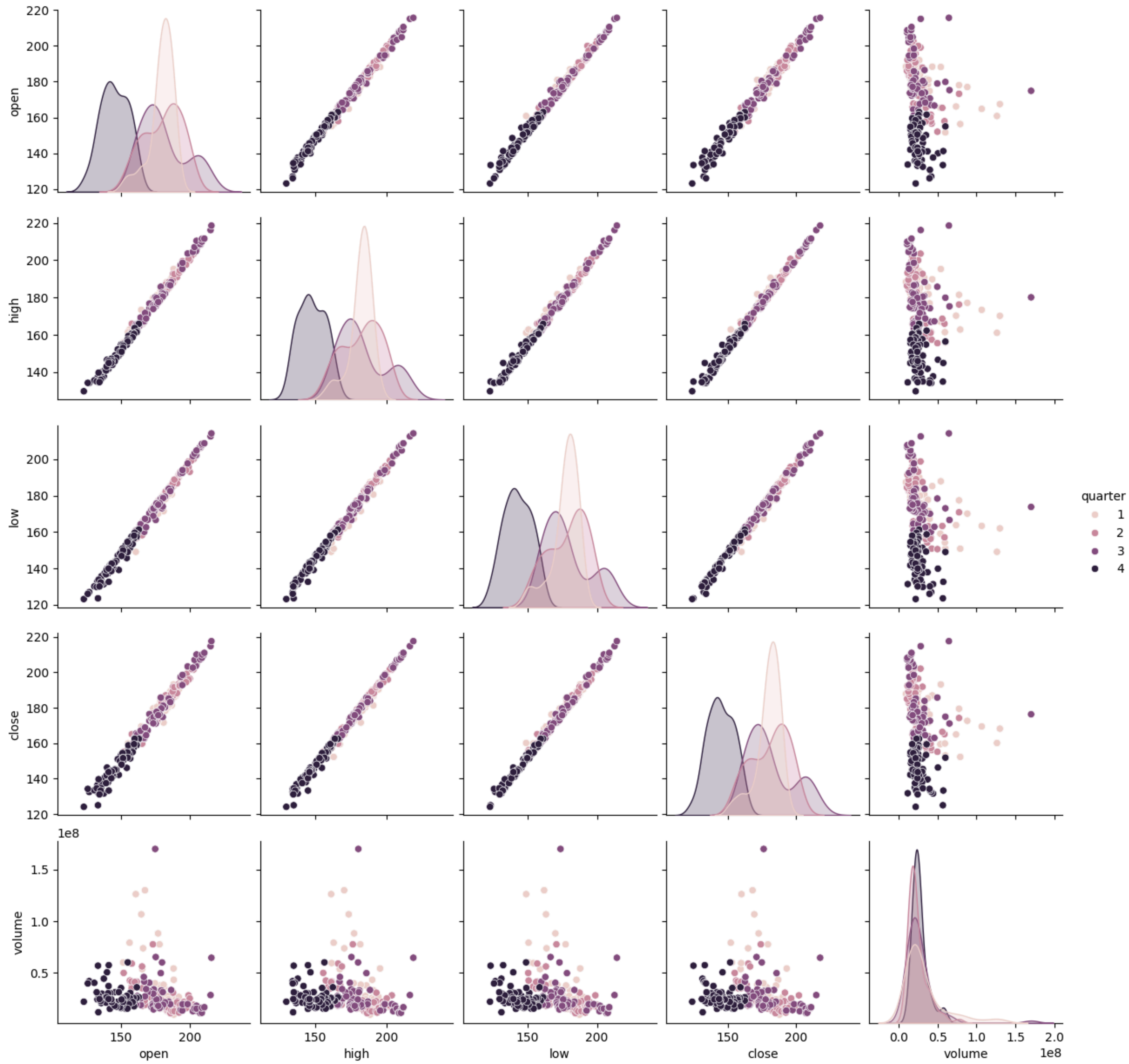
```
<seaborn.axisgrid.PairGrid at 0x79cf0d1ef430>
```



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 0x79cf0f6970a0>
```

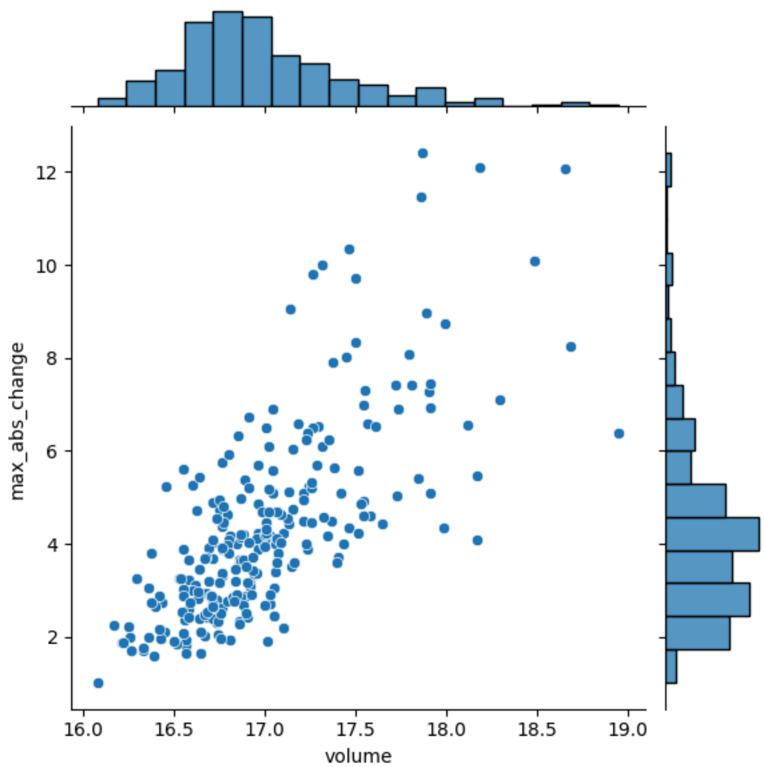


jointplot()

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
)
)
```

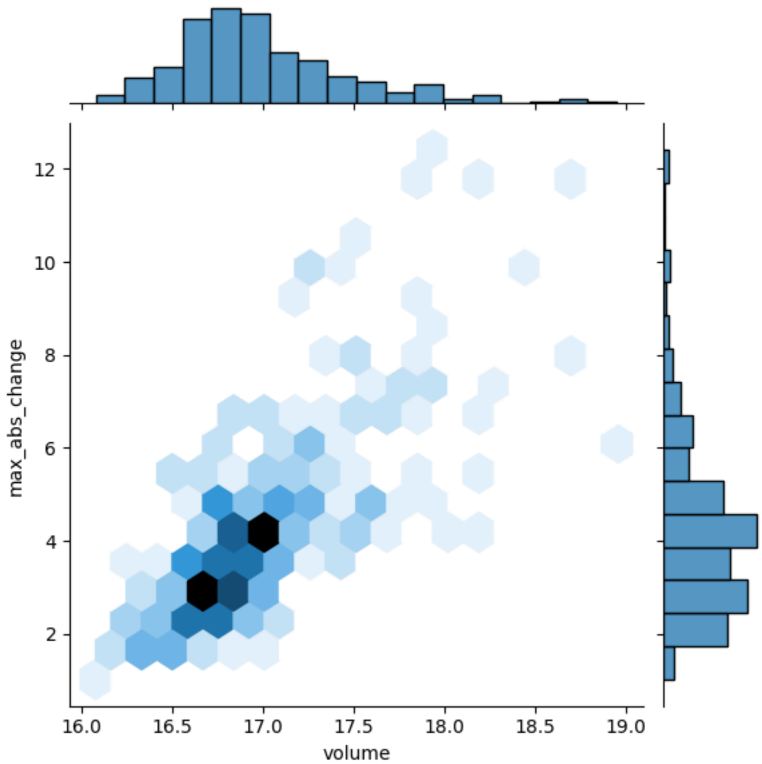
```
<seaborn.axisgrid.JointGrid at 0x79cf0f4aaaa0>
```



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
)
)
```

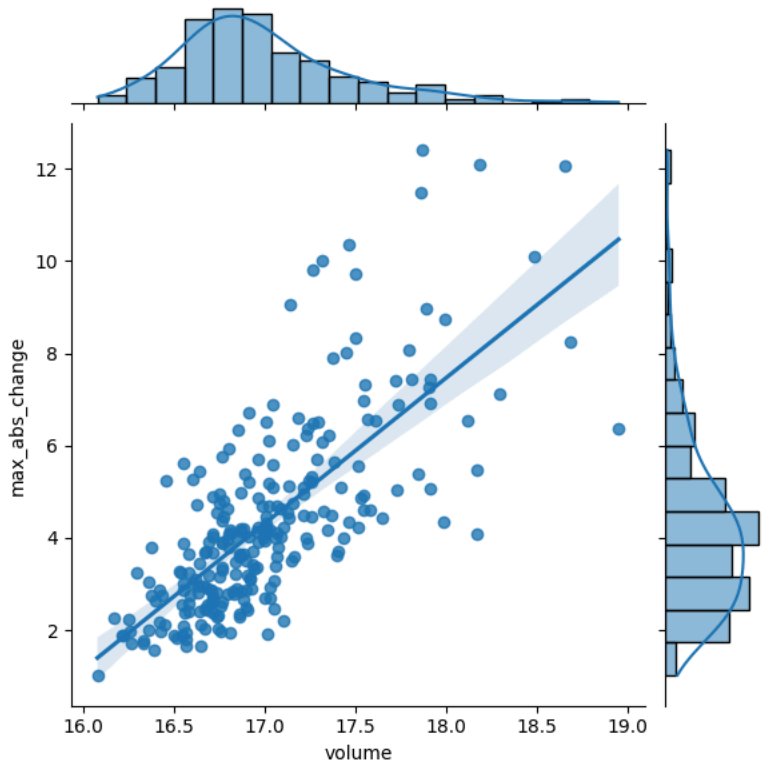
```
<seaborn.axisgrid.JointGrid at 0x79cf04cc3520>
```



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
)
)
```

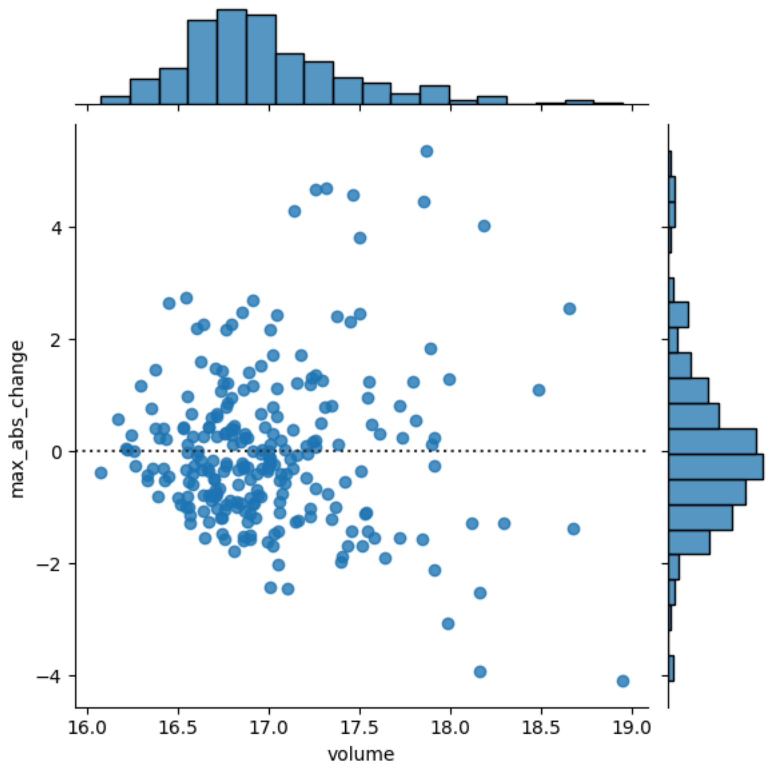
```
<seaborn.axisgrid.JointGrid at 0x79cf04f144c0>
```



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
)
)
```

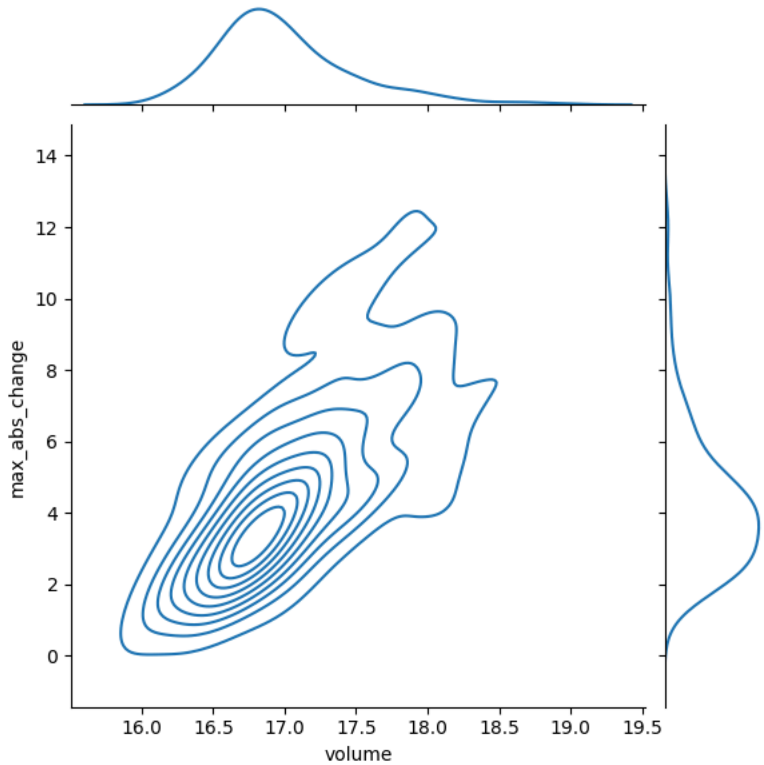
```
<seaborn.axisgrid.JointGrid at 0x79cf05a323b0>
```



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 0x79cf0f341540>
```



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:]
```

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:

```
import itertools
```

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:

```
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
```

Iterables are objects that can be iterated over. When entering a loop, an iterator is made from the iterable to handle the iteration. Iterators are iterables, but not all iterables are iterators. A list is an iterable. If we turn that iterator into an iterable (a list in this case), the second loop runs:

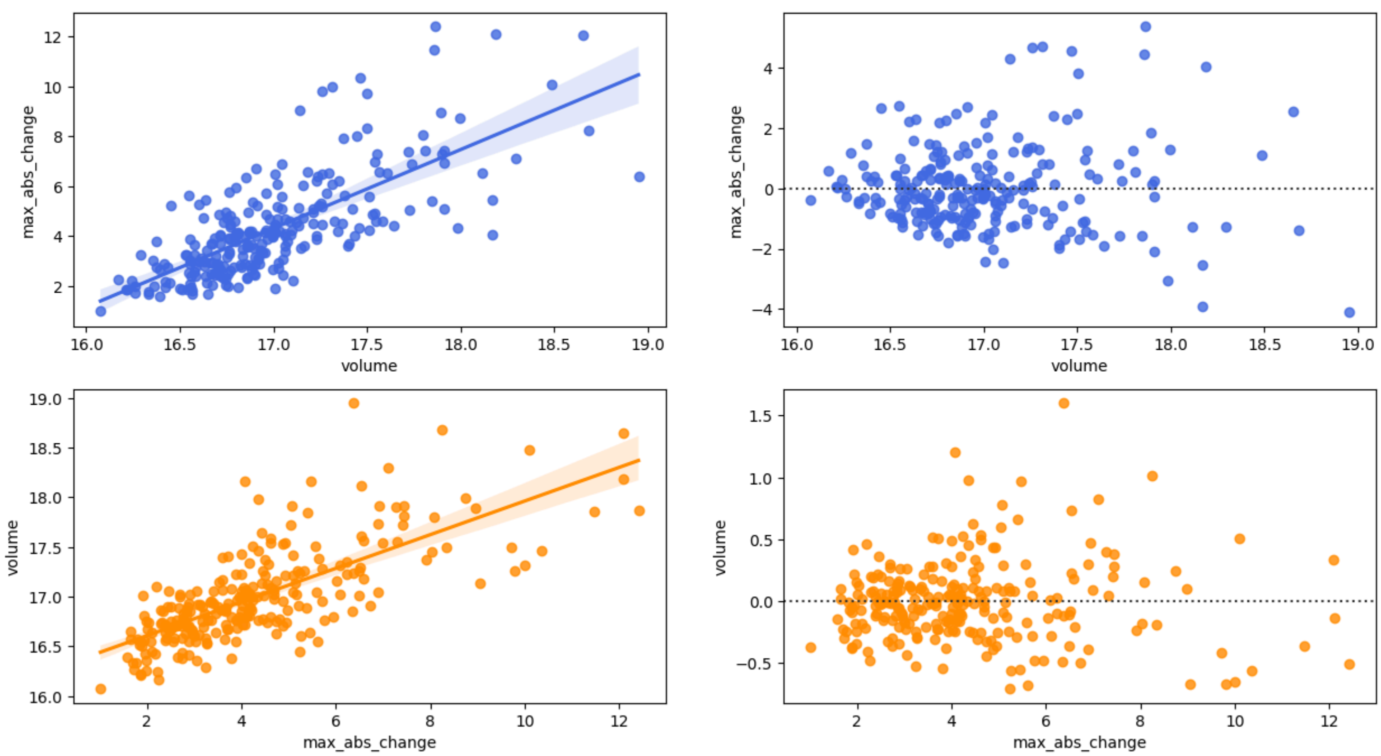
```
iterable = list(itertools.repeat("I'm an iterable", 1))
for i in iterable:
  print(f'-->{i}')
print('This prints again because it\'s an iterable:')
```

```
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

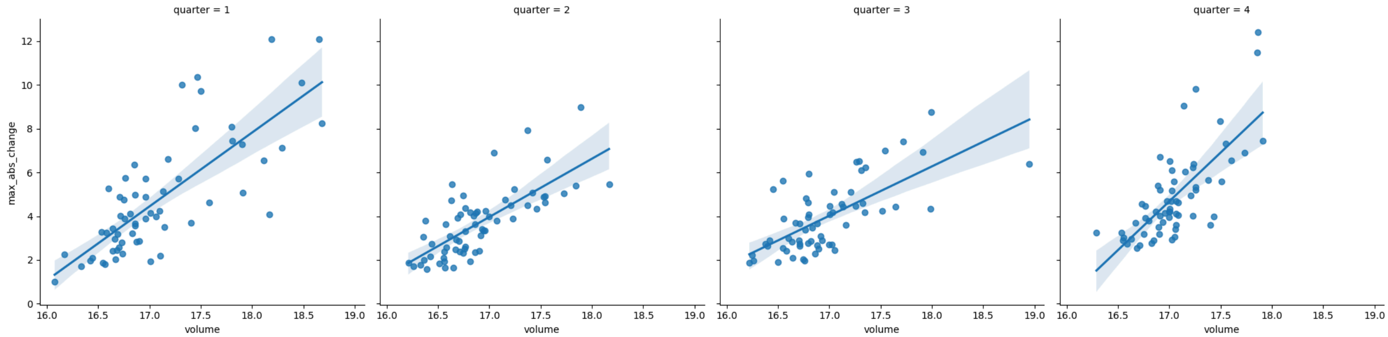
```
from reg_resid_plot import reg_resid_plots
reg_resid_plots(fb_reg_data)
```



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 0x79cf04942110>
```



Distributions

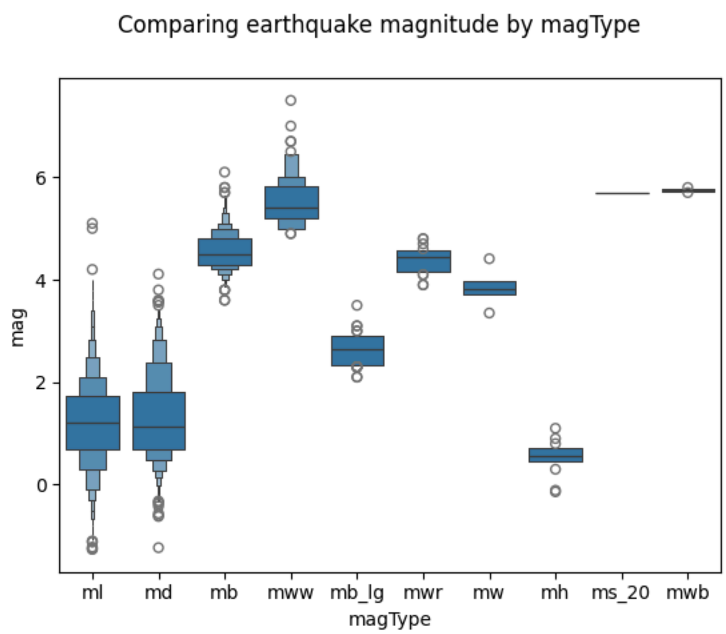
Seaborn provides some new plot types for visualizing distributions in additional to its own versions of the plot types we discussed in chapter 5 (in this notebook).

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')
```

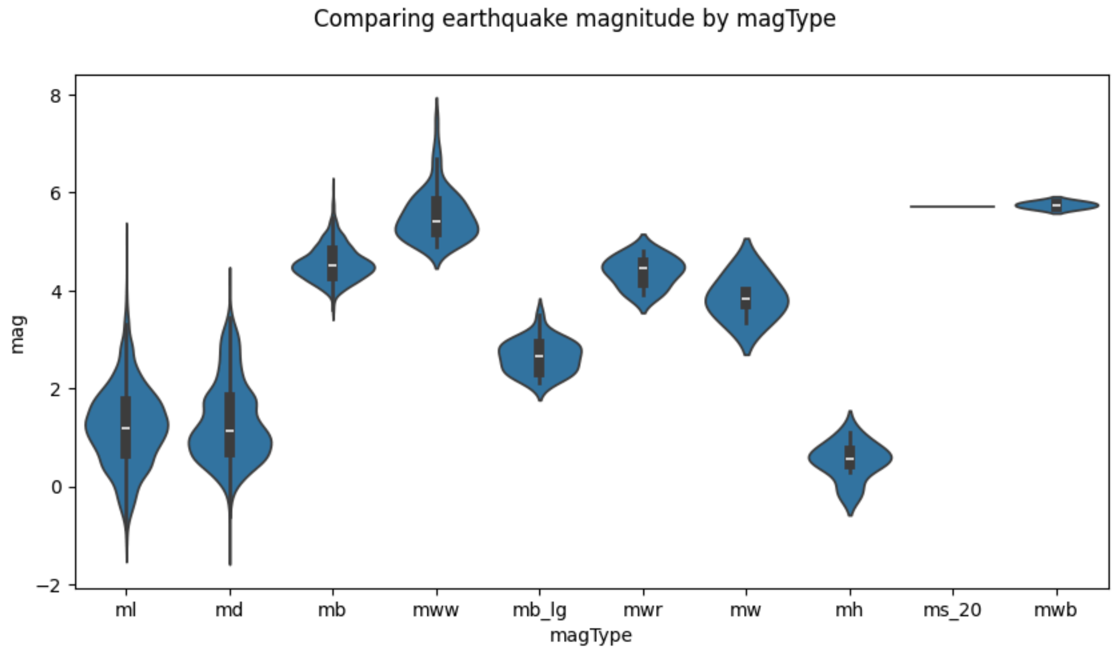


violinplot()

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, density_norm='width' # all violins have same width
)
plt.suptitle('Comparing earthquake magnitude by magType')
```

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

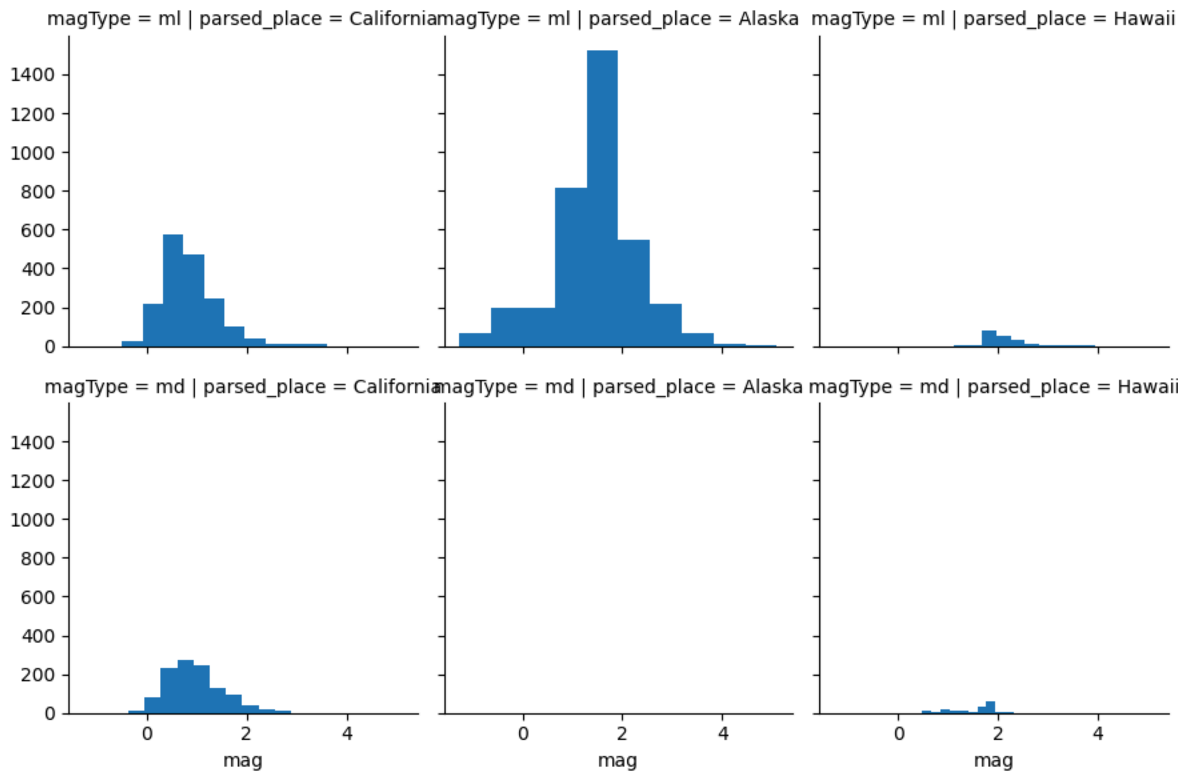


Faceting

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**

About the Data

In this notebook, we will be working with Facebook's stock price throughout 2018 (obtained using the stock_analysis package).

Setup

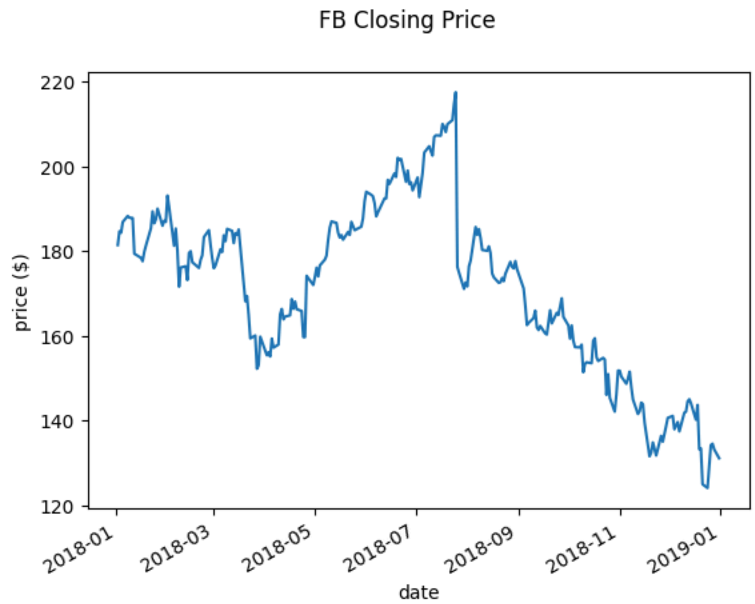
```
%matplotlib inline
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import seaborn as sns
fb = pd.read_csv(
'/content/fb_stock_prices_2018.csv', index_col='date', parse_dates=True
)
```

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 ($)')
```

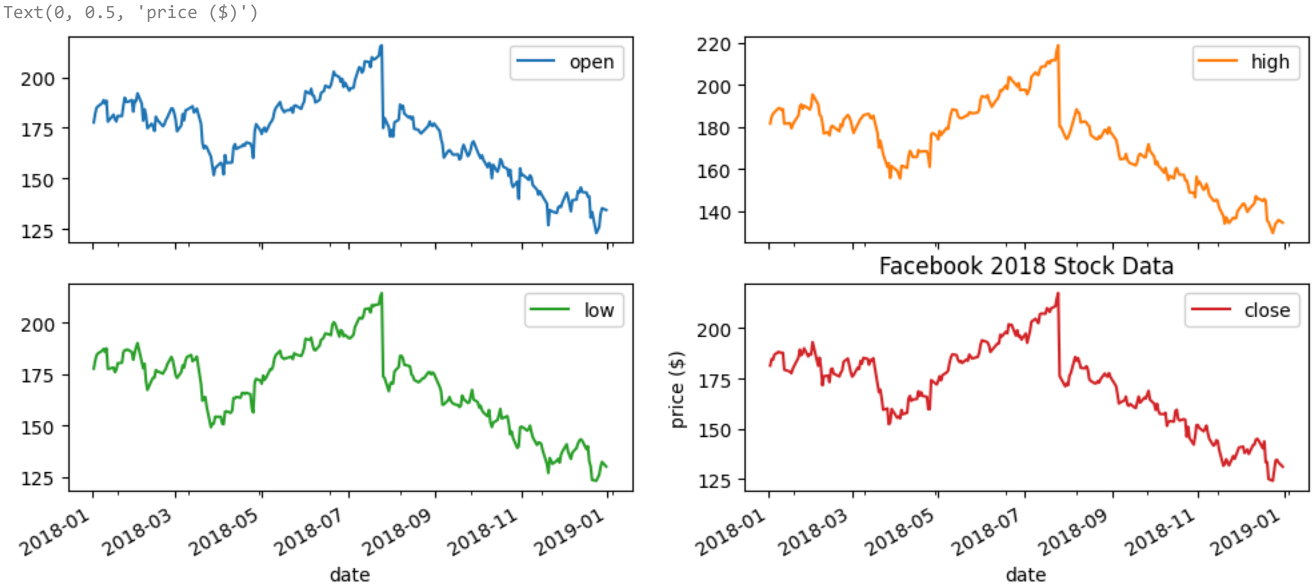


plt.suptitle() vs. plt.title()

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 ($)')
```

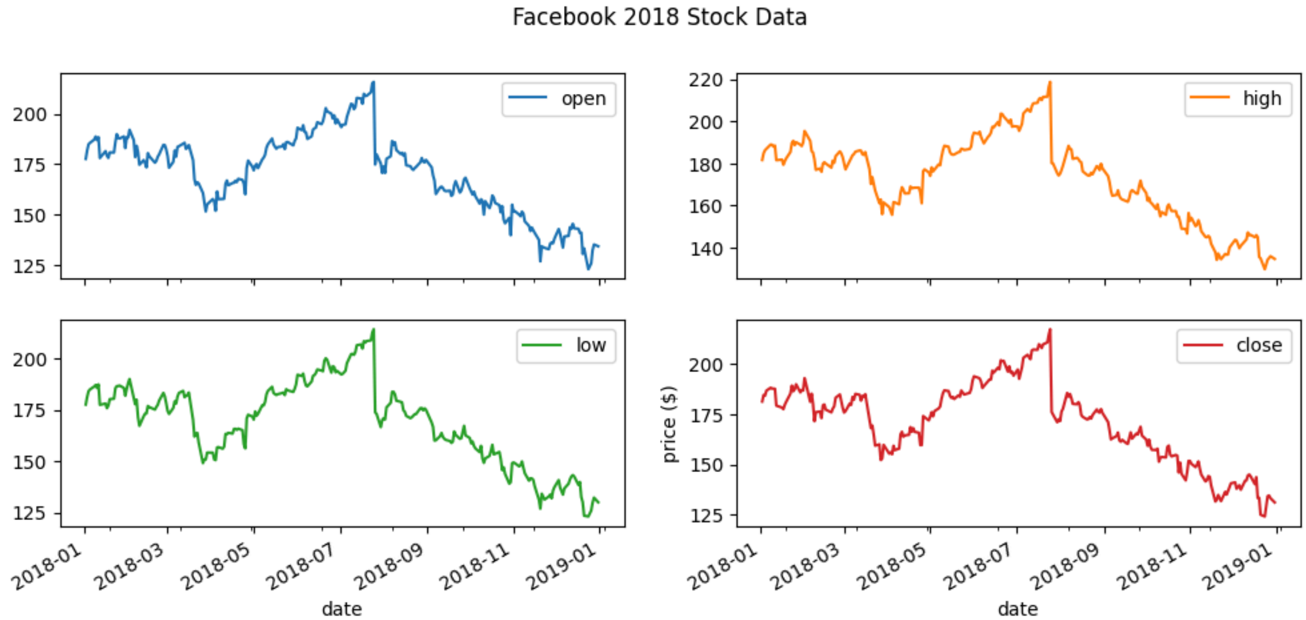
```
Text(0, 0.5, 'price ($)')
```



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 ($)')
```

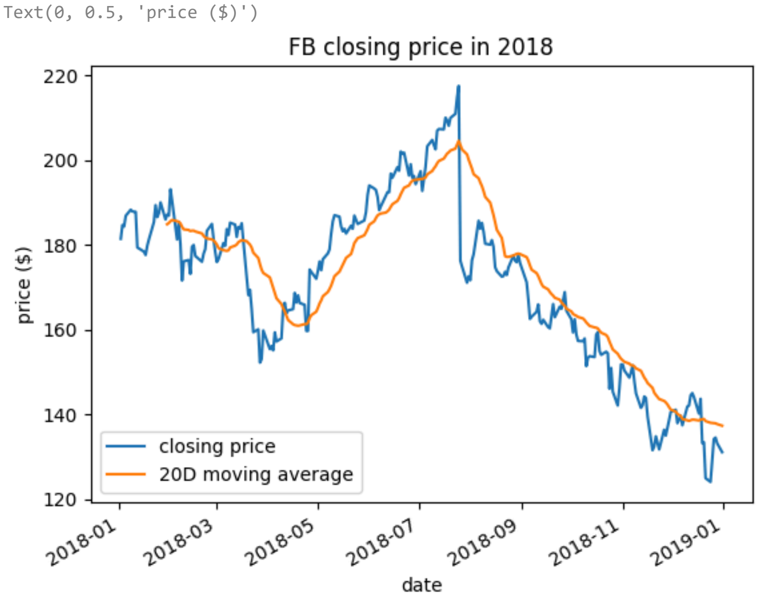


Legends

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 ($)')
```



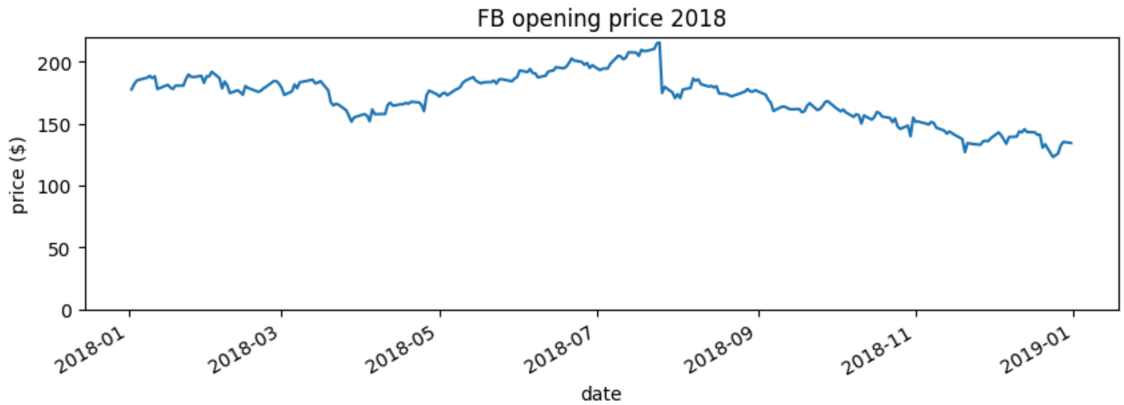
Formatting Axes

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:

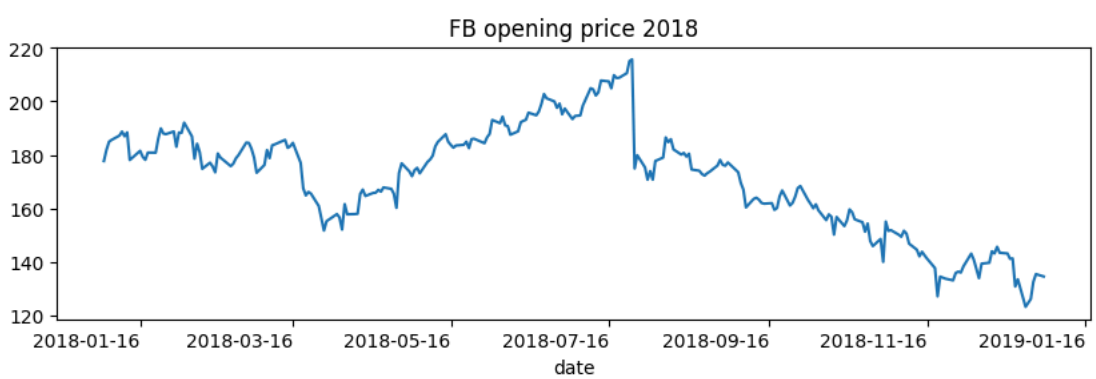
```
import calendar

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-36-dcb2ef525d0e> in <cell line: 5>()
      3 fb.open.plot(figsize=(10, 3), rot=0, title='FB opening price 2018')
      4 locs, labels = plt.xticks()
----> 5 plt.xticks(locs + 15 , calendar.month_name[1::2])
      6 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

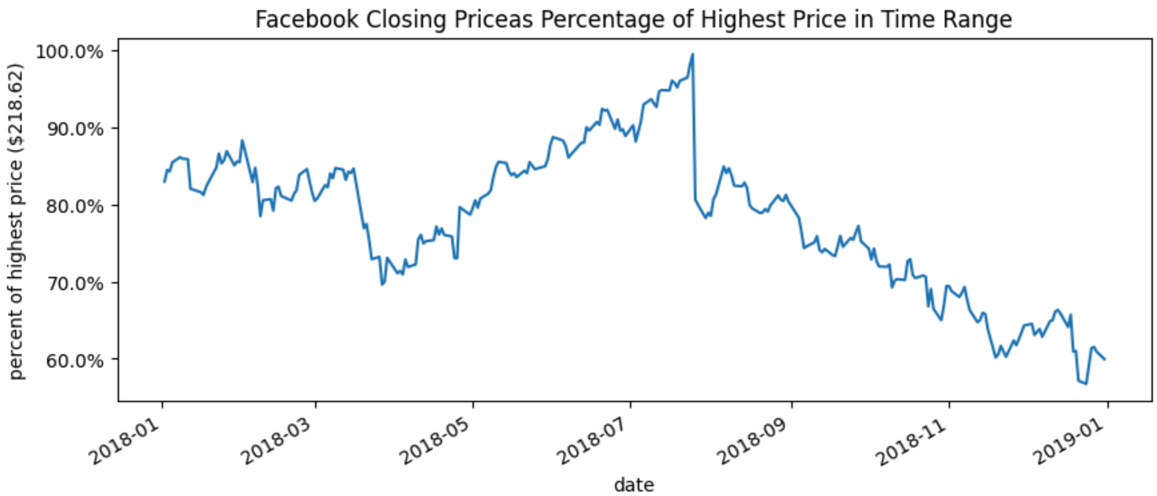
PercentFormatter

We can use ticker.PercentFormatter and specify the denominator (xmax) to use when calculationg 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 Priceas 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)
])
ax.set_ylabel(f'percent of highest price (${fb.high.max()})')
```

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

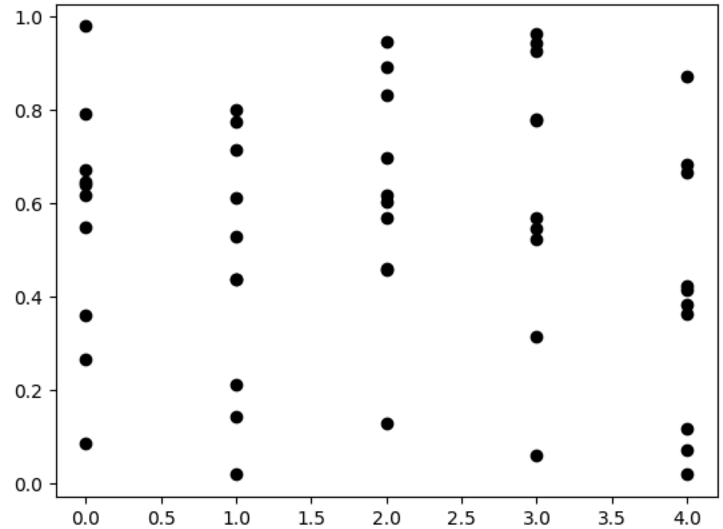


MultipleLocator

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

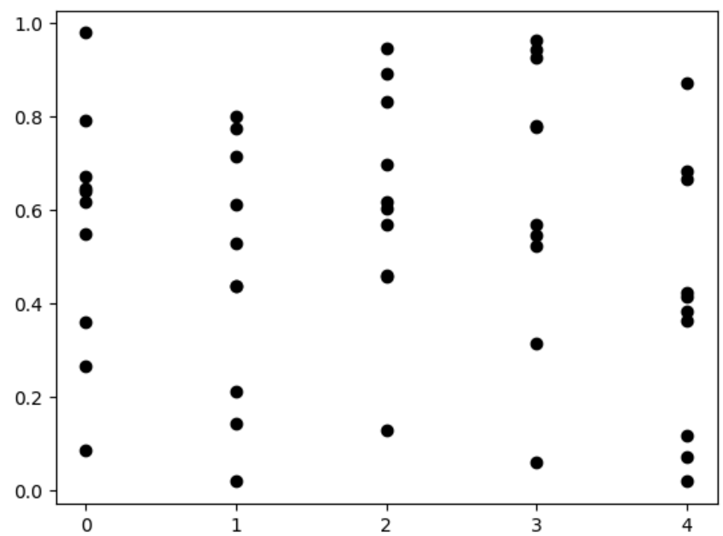
```
fig, ax = plt.subplots(1, 1)
np.random.seed(0)
ax.plot(np.tile(np.arange(0, 5), 10), np.random.rand(50), 'ko')
```

```
[<matplotlib.lines.Line2D at 0x79cefbf8f970>]
```



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**

pandas.plotting subpackage

Pandas provides some extra plotting functions for a few select plot types.

About the Data

In this notebook, we will be working with Facebook's stock price throughout 2018 (obtained using the stock_analysis package).

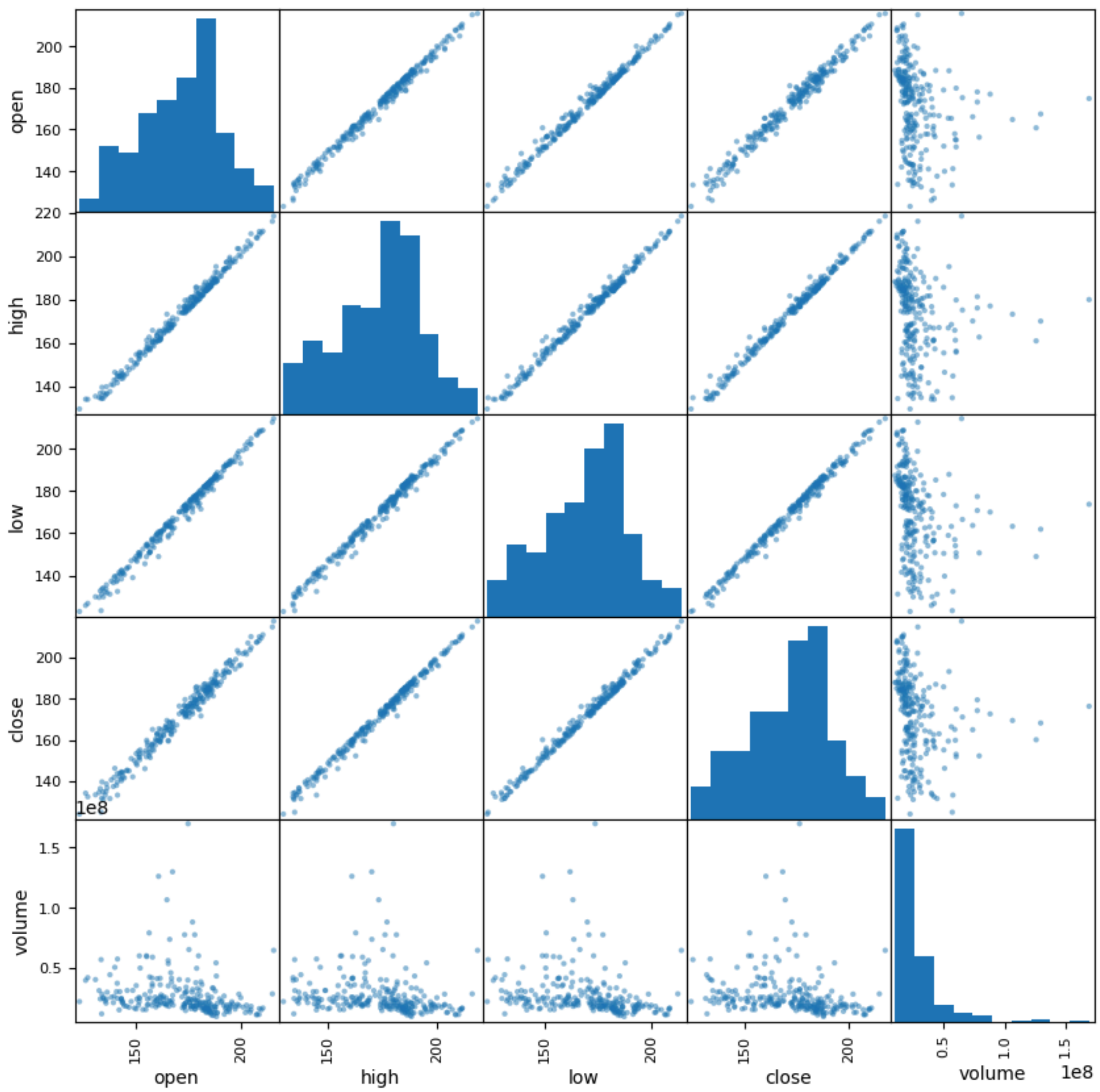
Setup

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

Scatter matrix

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

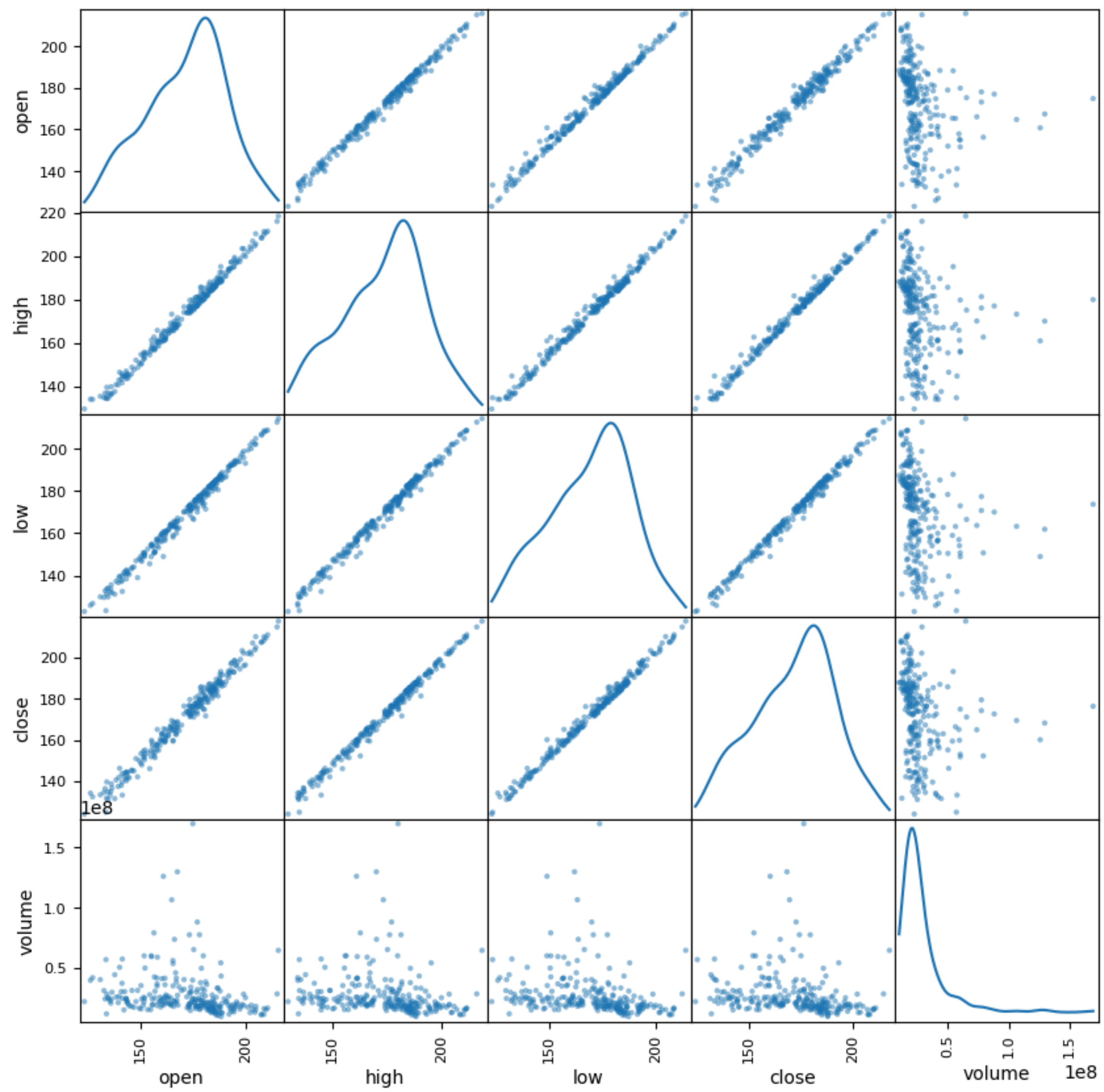
```
array([[<Axes: xlabel='open', ylabel='open'>,
        <Axes: xlabel='high', ylabel='open'>,
        <Axes: xlabel='low', ylabel='open'>,
        <Axes: xlabel='close', ylabel='open'>,
        <Axes: xlabel='volume', ylabel='open'>],
       [<Axes: xlabel='open', ylabel='high'>,
        <Axes: xlabel='high',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



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)
```

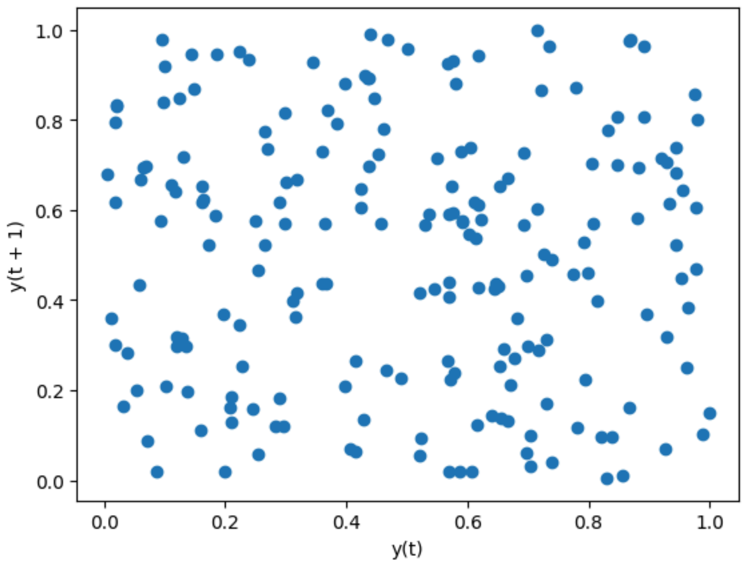


Lag plot

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)))
```

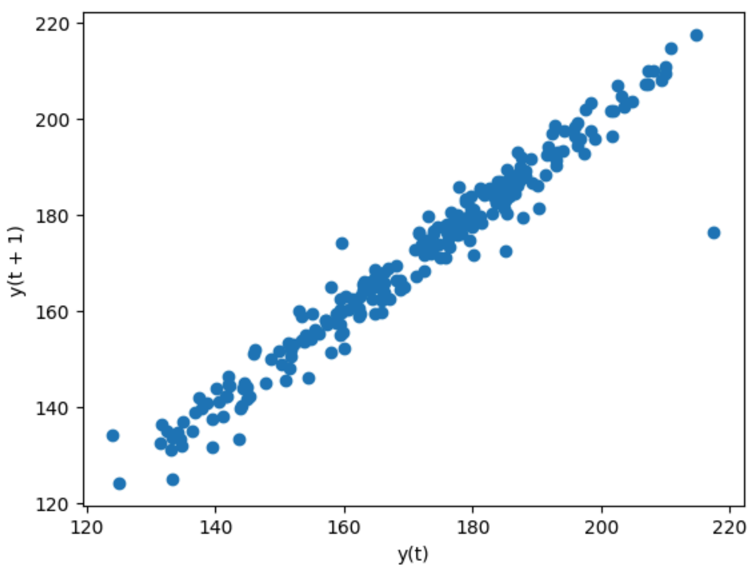
```
<Axes: xlabel='y(t)', ylabel='y(t + 1)'>
```



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

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

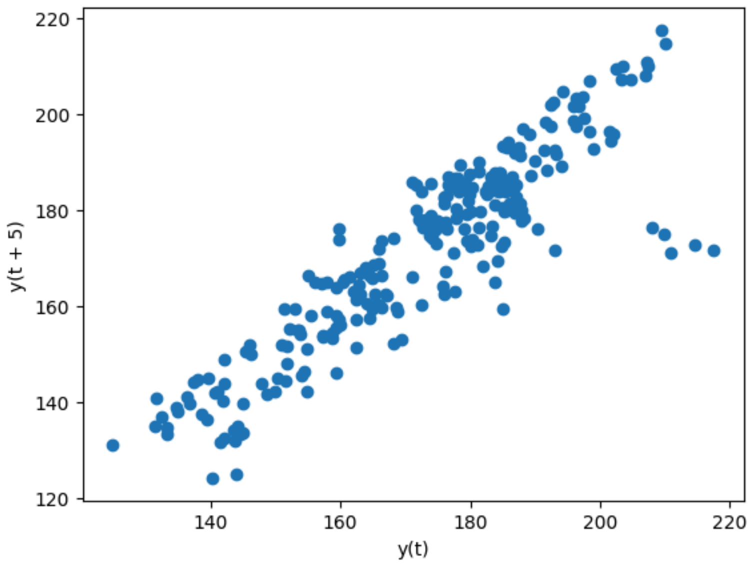
```
<Axes: xlabel='y(t)', ylabel='y(t + 1)'>
```



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)'>
```

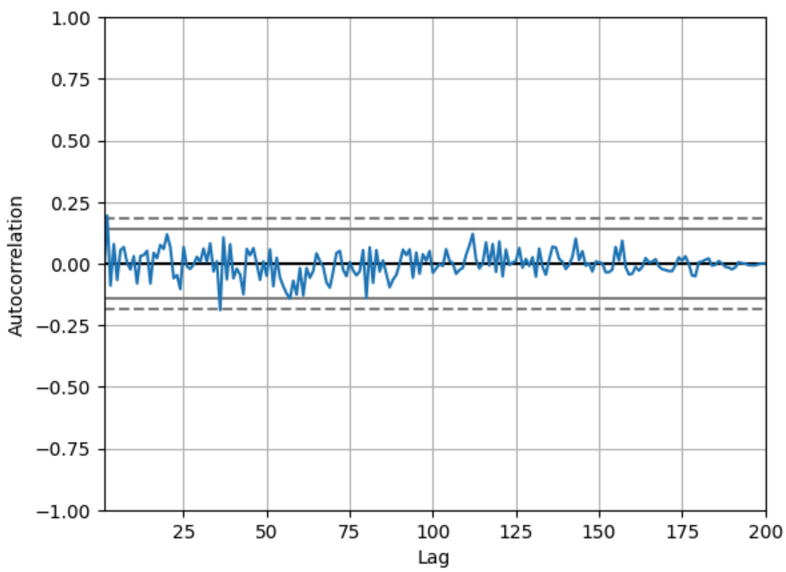


Autocorrelation plots

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)))
```

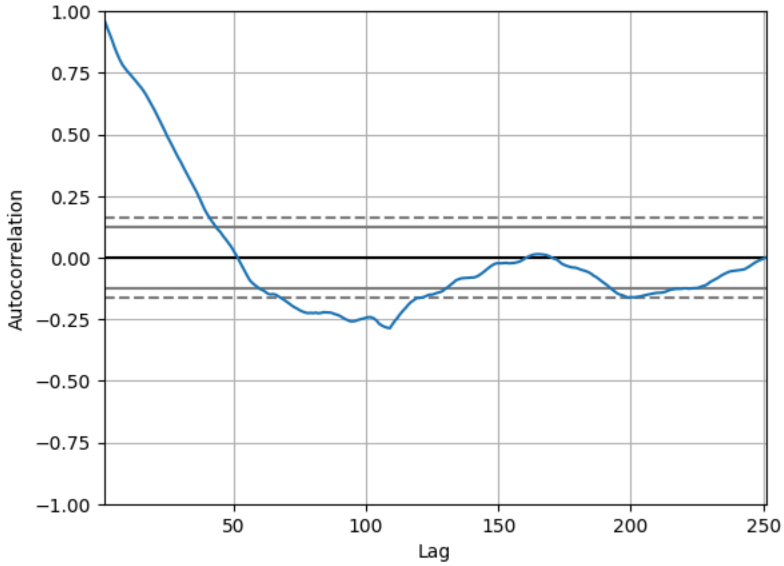
```
<Axes: xlabel='Lag', ylabel='Autocorrelation'>
```



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

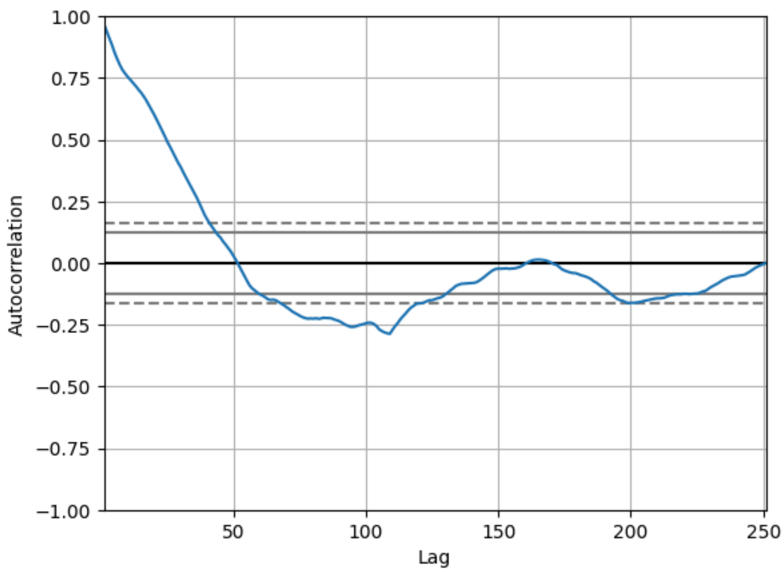
```
autocorrelation_plot(fb.close)
```

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




```
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)))
```