Hands-on Activity 9.2 Customized Visualizations using Seaborn

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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
- 9.5 Formatting Plots
- 9.6 Customizing Visualizations

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

In [87]:
```
%matplotlib inline
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
import pandas as pd

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

quakes = pd.read_csv('earthquakes.csv')
```

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.

In [25]:
```
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"
)
```

Out[25]:

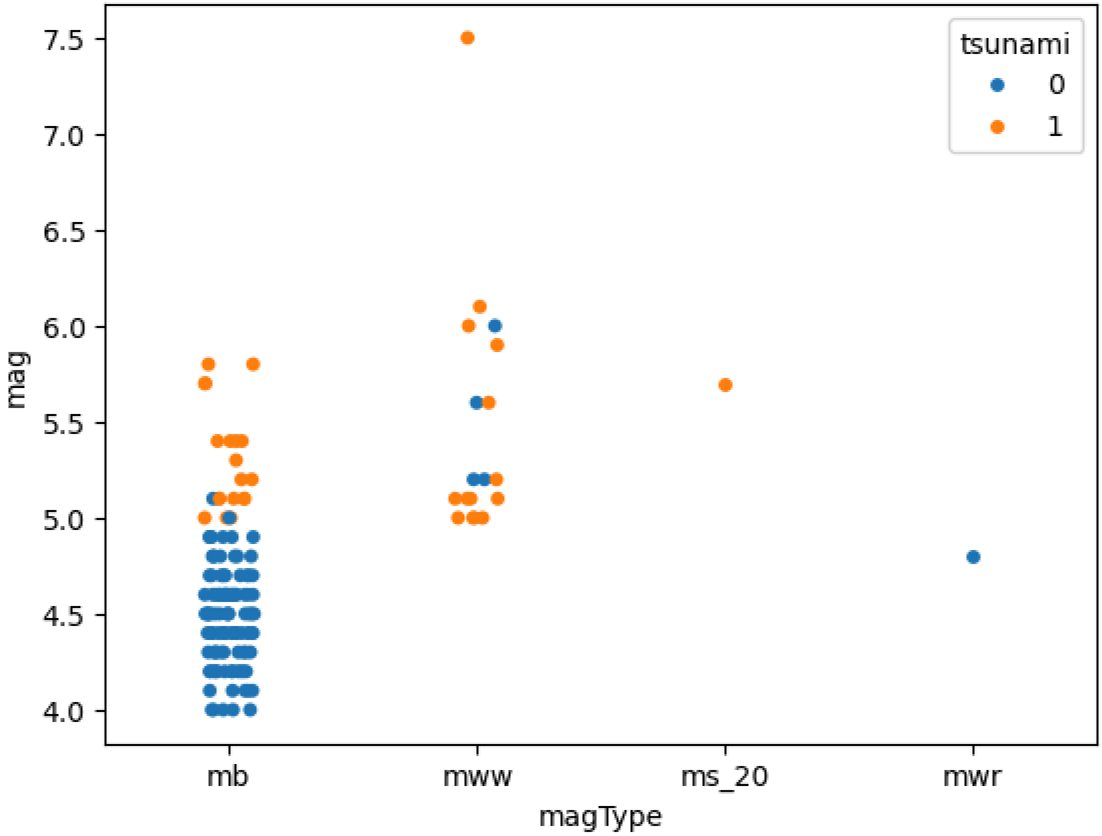
	mag	magType	place	tsunami	parsed_place
time					
2018-09-28 10:02:43.480	7.5	mww	78km N of Palu, Indonesia	1	Indonesia

`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:

In [28]:
```
sns.stripplot(
    x='magType',
    y='mag',
    hue='tsunami',
    data=quakes.query('parsed_place == "Indonesia"')
)
```

Out[28]: `<Axes: xlabel='magType', ylabel='mag'>`



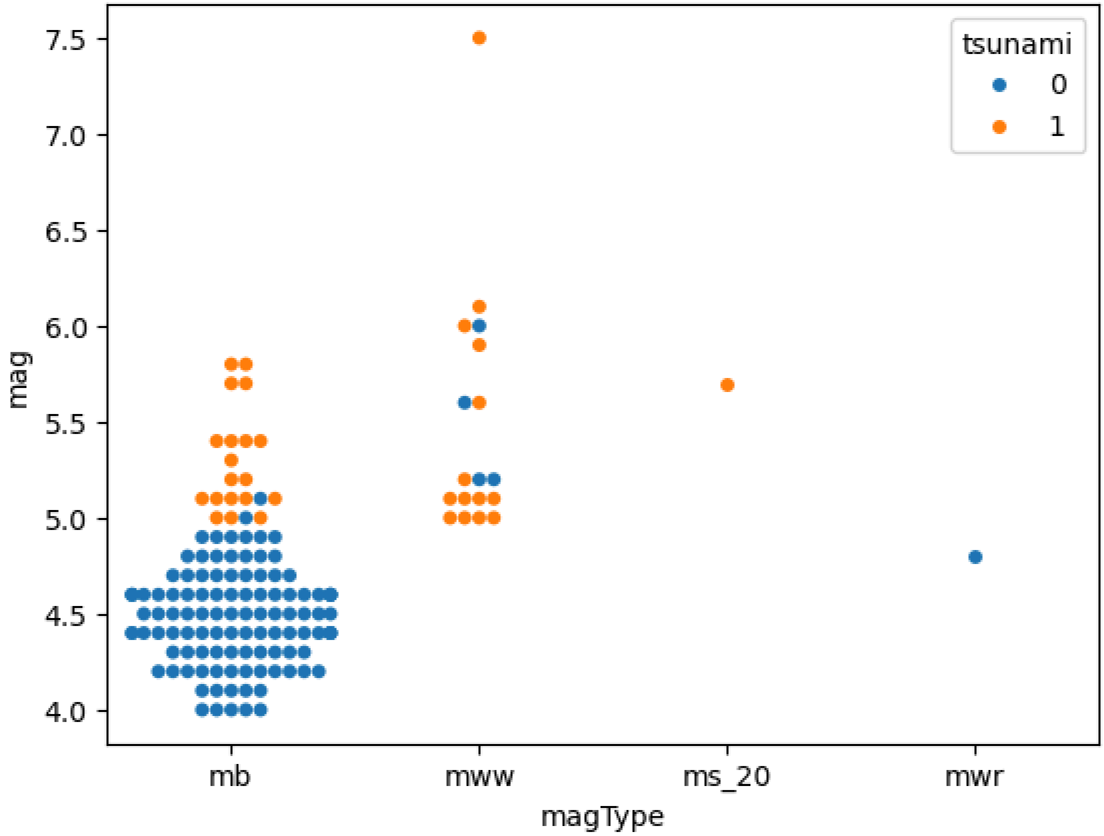
`swarmplot()`

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`:

In [30]:
```
sns.swarmplot(
    x='magType',
    y='mag',
    hue='tsunami',
    data=quakes.query('parsed_place == "Indonesia"')
)
```

Out[30]: `<Axes: xlabel='magType', ylabel='mag'>`

```
C:\Users\micki\anaconda3\Lib\site-packages\seaborn\categorical.py:3399: UserWarning:
10.2% of the points cannot be placed; you may want to decrease the size of the marke
rs or use stripplot.
  warnings.warn(msg, UserWarning)
```



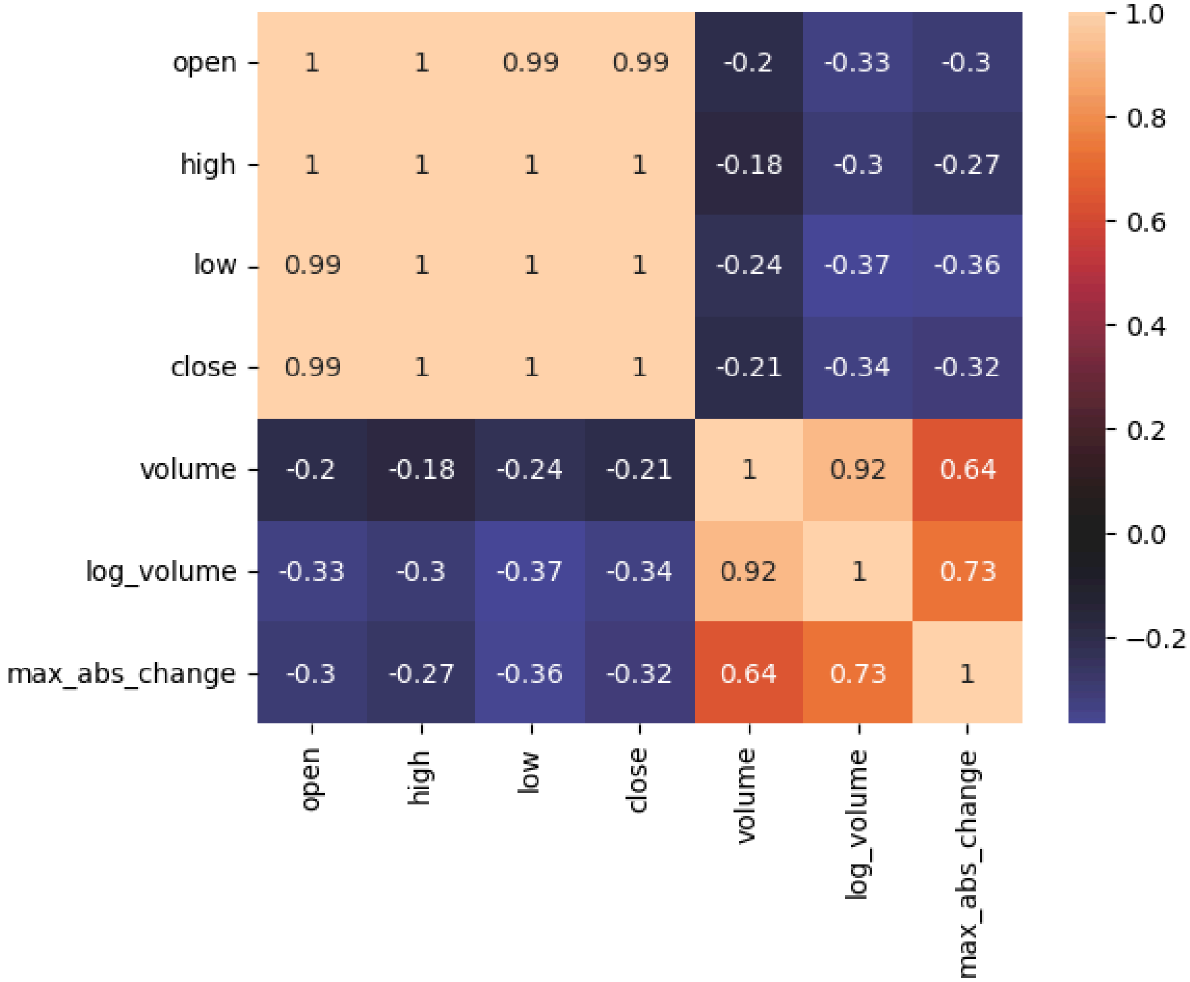
Correlation and Heatmaps

`heatmap()`

An easier way to create correlation matrix is to use `seaborn`:

In [34]:
```
sns.heatmap(
    fb.sort_index().assign(
    log_volume=np.log(fb.volume),
    max_abs_change=fb.high - fb.low
).corr(),
    annot=True, center=0
)
```

Out[34]: `<Axes: >`

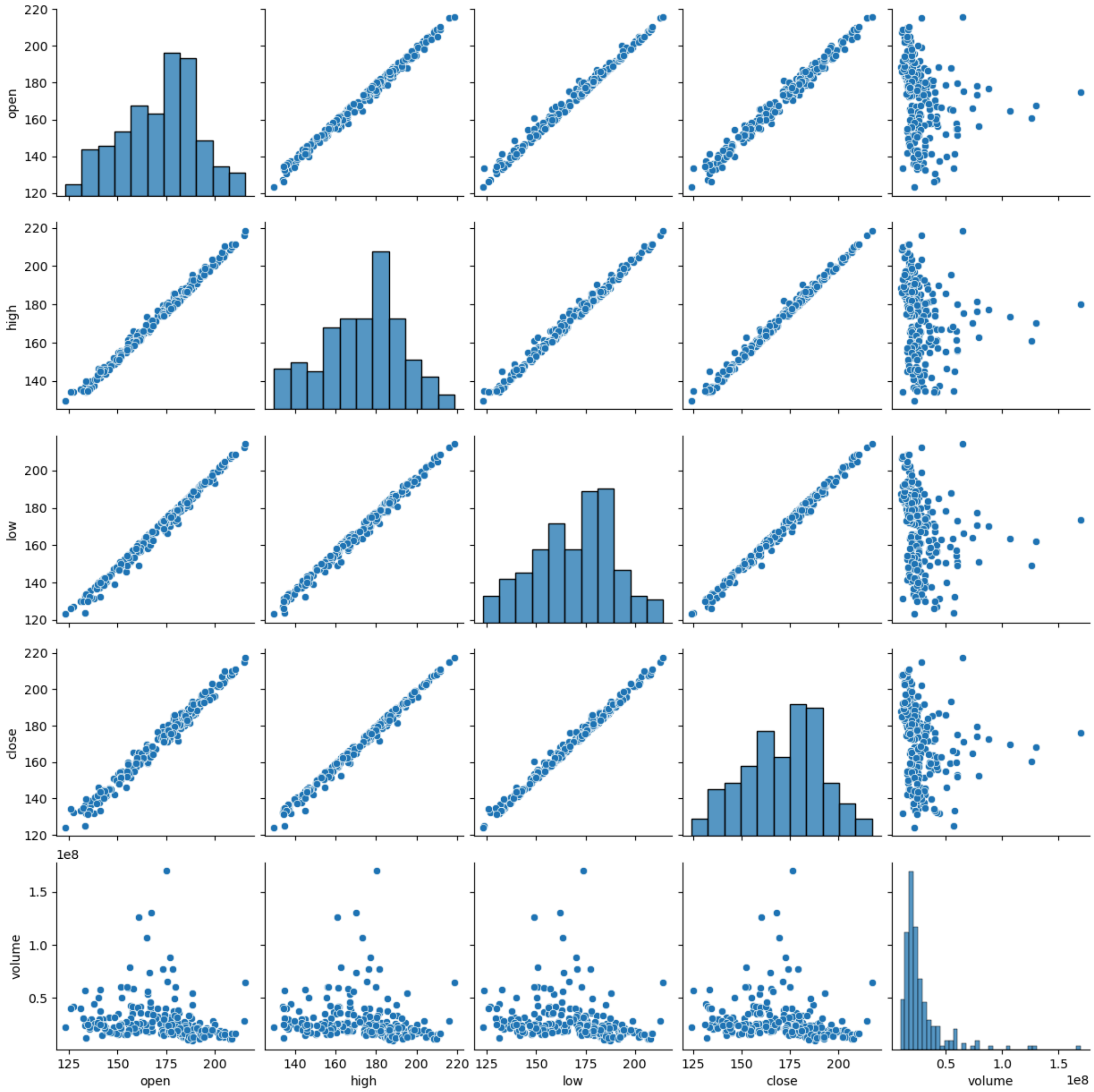


`pairplot()`

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

In [36]:
```
sns.pairplot(fb)
```

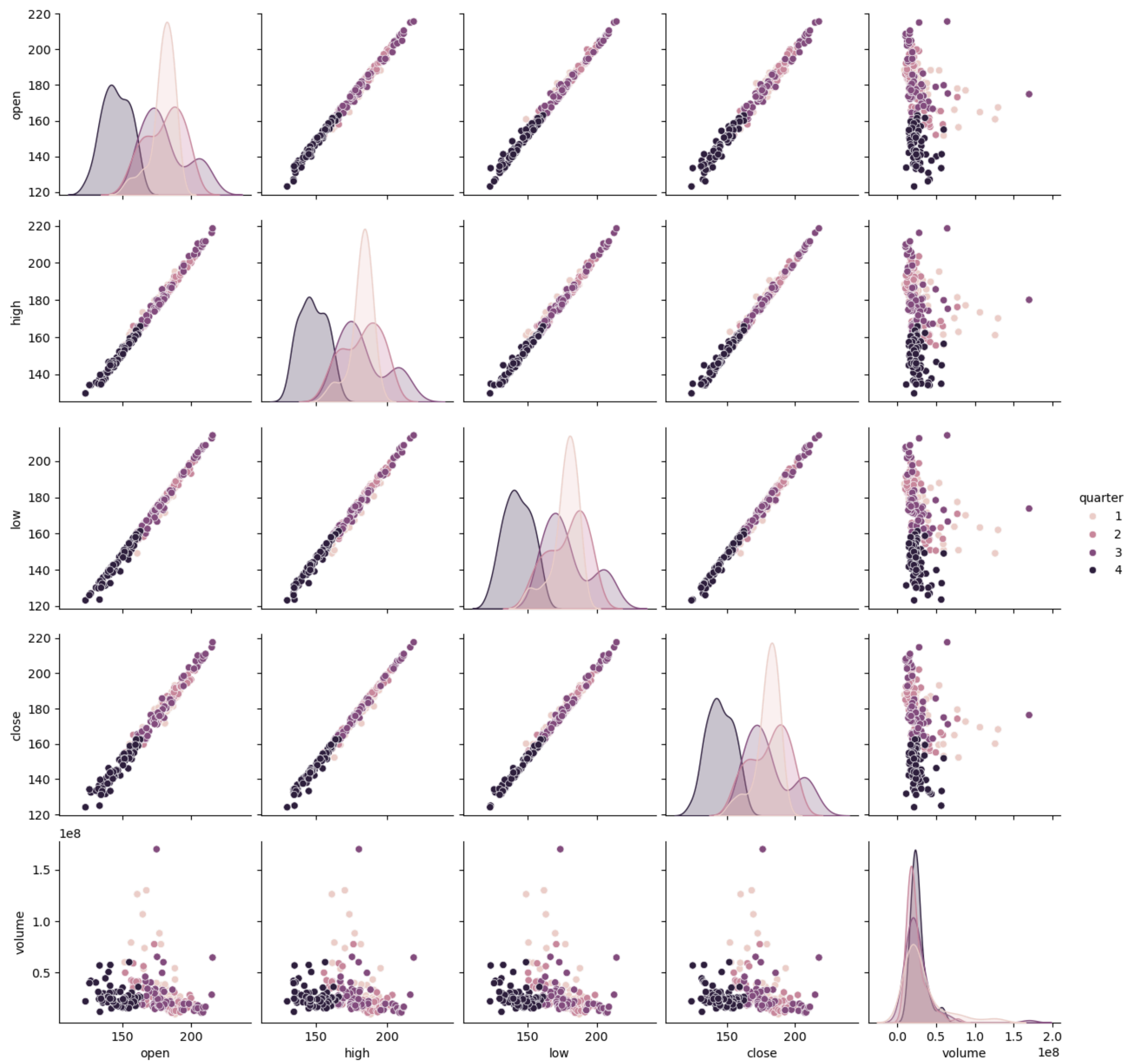
Out[36]: `<seaborn.axisgrid.PairGrid at 0x1d058ba4ce0>`



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):

In [38]:
```
sns.pairplot(
    fb.assign(quarter=lambda x: x.index.quarter),
    diag_kind='kde',
    hue='quarter'
)
```

Out[38]: <seaborn.axisgrid.PairGrid at 0x1d061df9ee0>

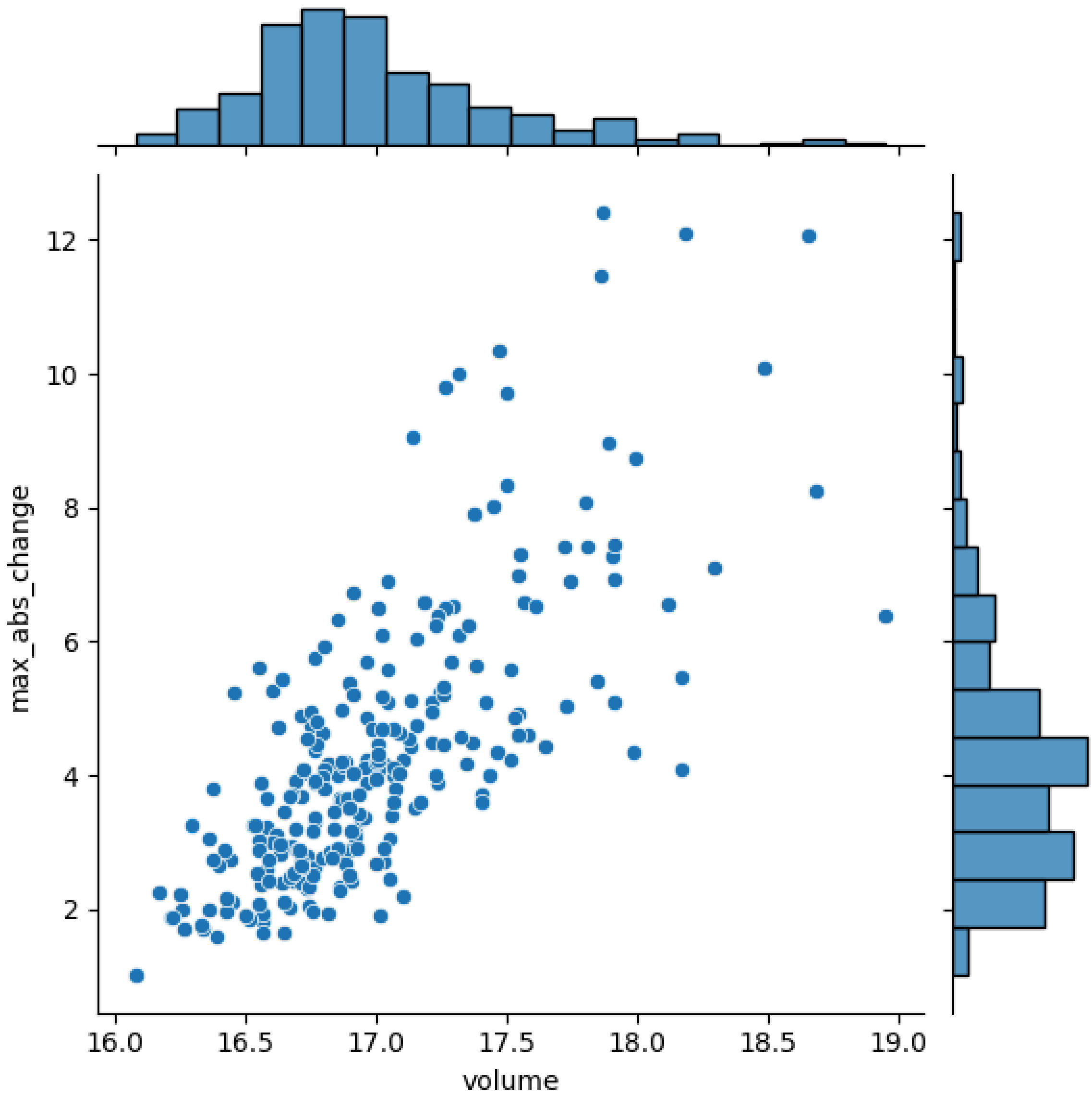


`jointplot()`

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:

In [40]:
```
sns.jointplot(
    x='volume',
    y='max_abs_change',
    data=fb.assign(
        volume=np.log(fb.volume),
        max_abs_change=fb.high - fb.low
    )
)
```

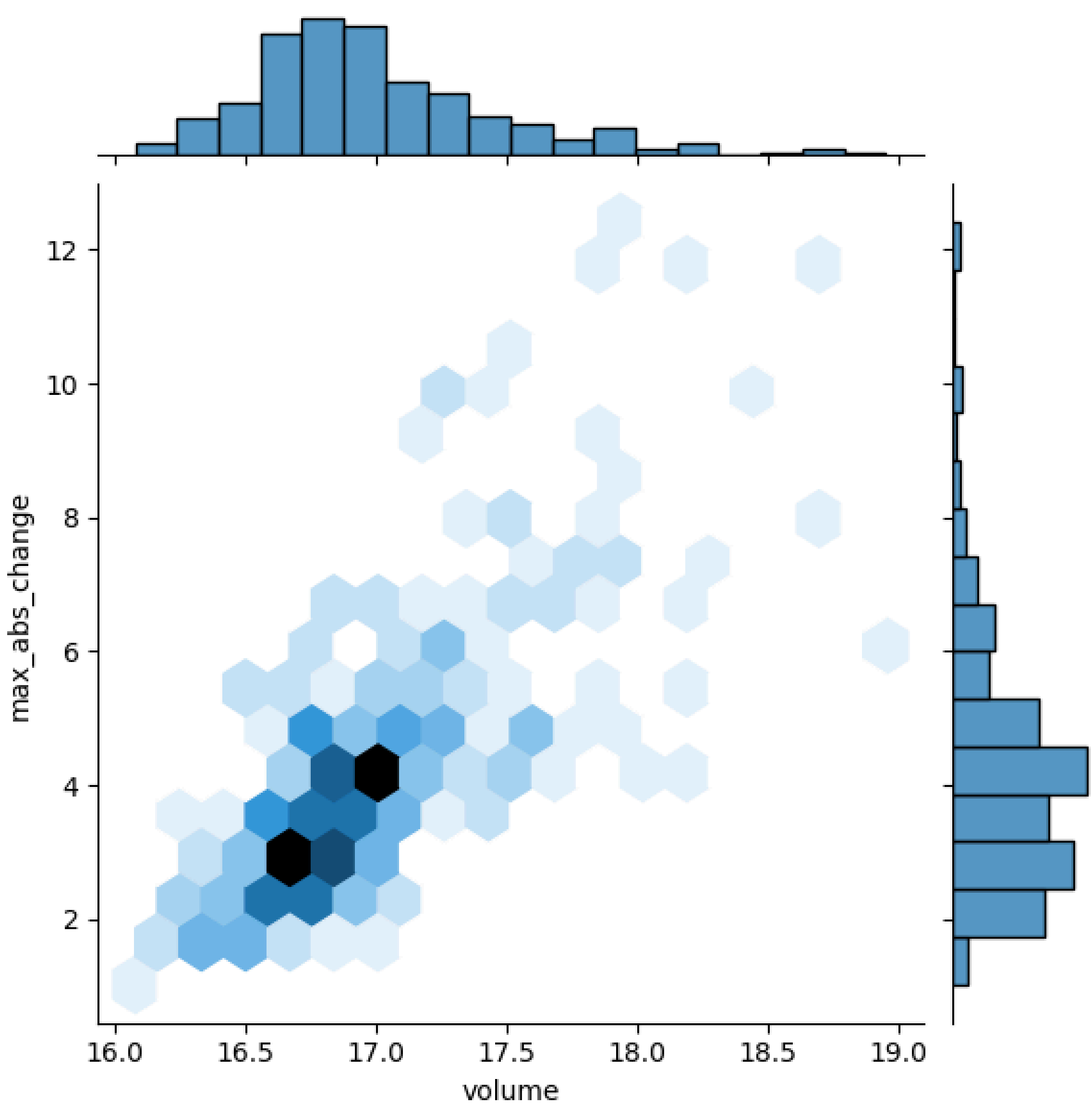
Out[40]: `<seaborn.axisgrid.JointGrid at 0x1d062784770>`



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:

In [42]:
```
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
    )
)
```

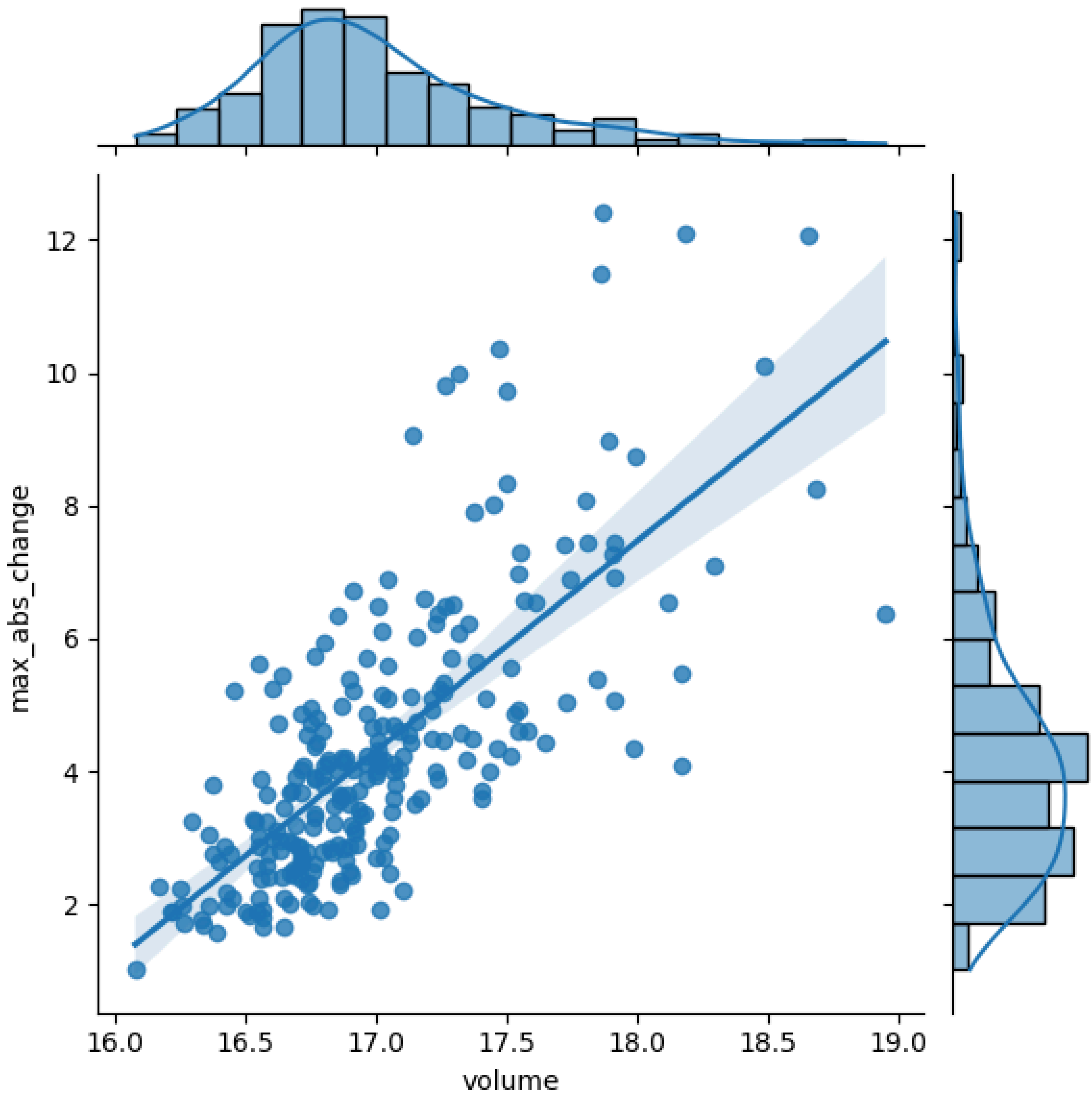
Out[42]: <seaborn.axisgrid.JointGrid at 0x1d05f87acc0>



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

In [44]:
```
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
    )
)
```

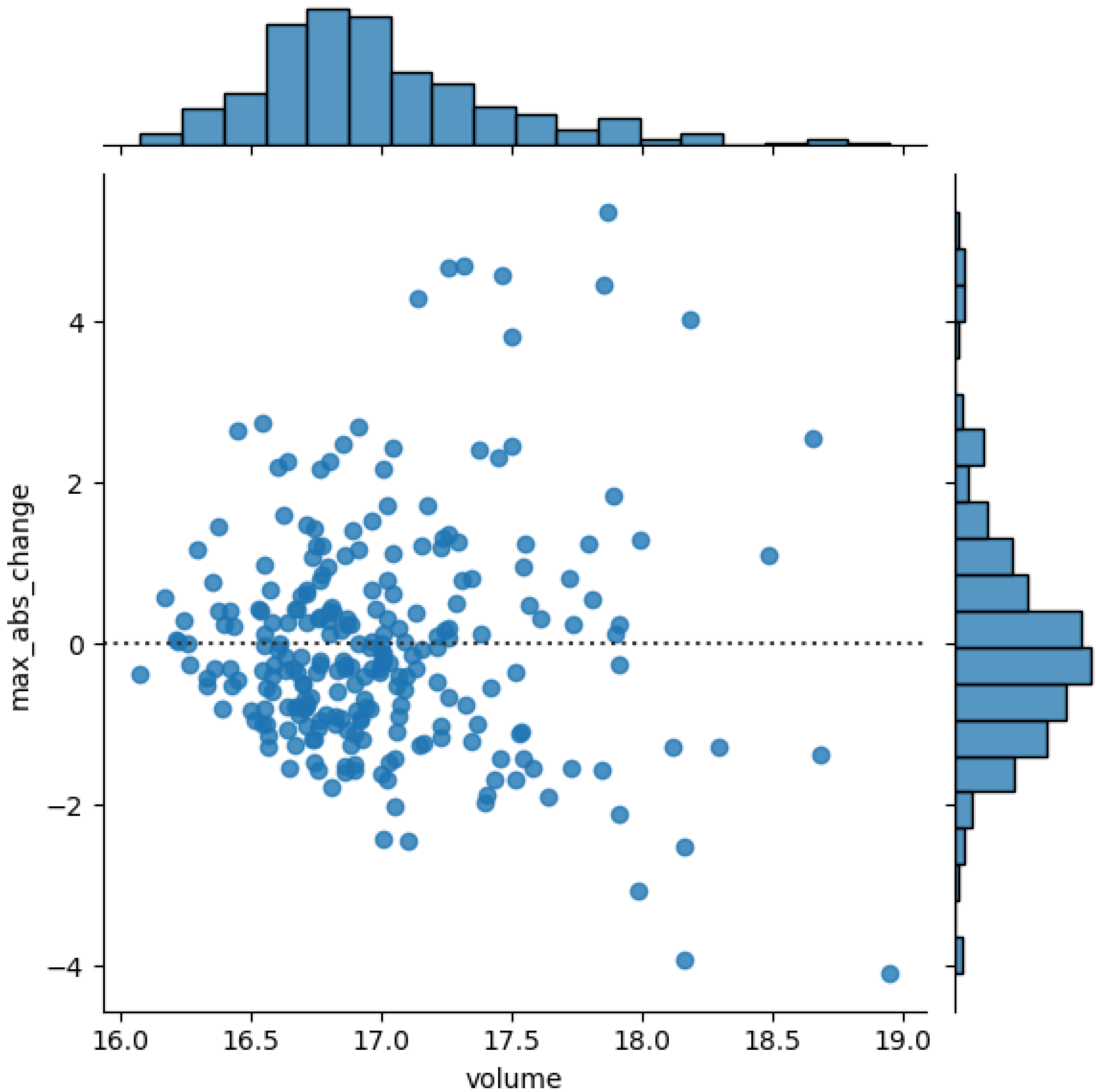
Out[44]: <seaborn.axisgrid.JointGrid at 0x1d0648fc2c0>



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

In [46]:
```
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
    )
)
```

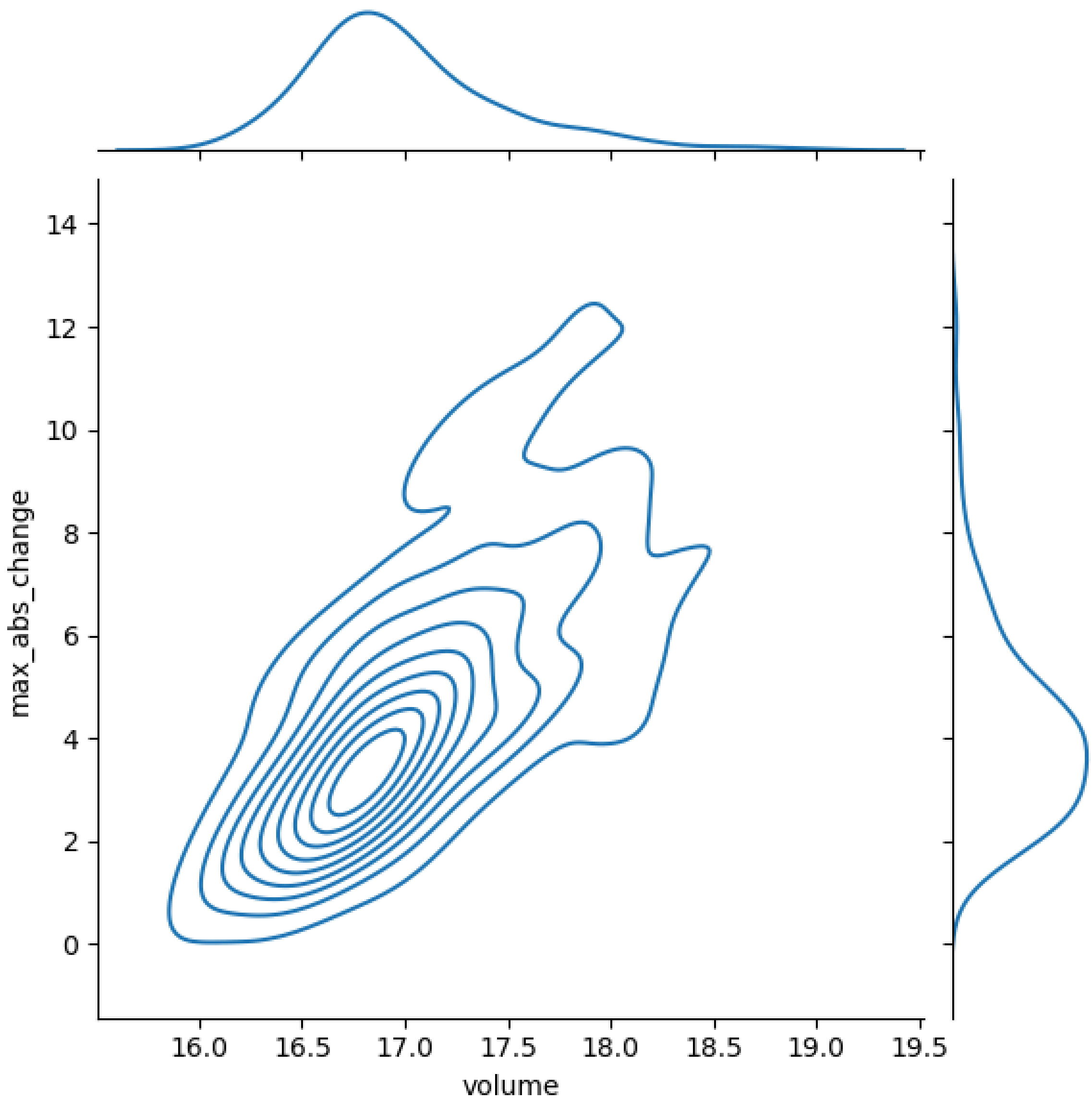
Out[46]: <seaborn.axisgrid.JointGrid at 0x1d064d5c650>



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

In [49]:
```
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
    )
)
```

Out[49]: <seaborn.axisgrid.JointGrid at 0x1d065a3c770>



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:

In [51]:
```python
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

In [53]:
```python
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:

In [56]:
```
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:

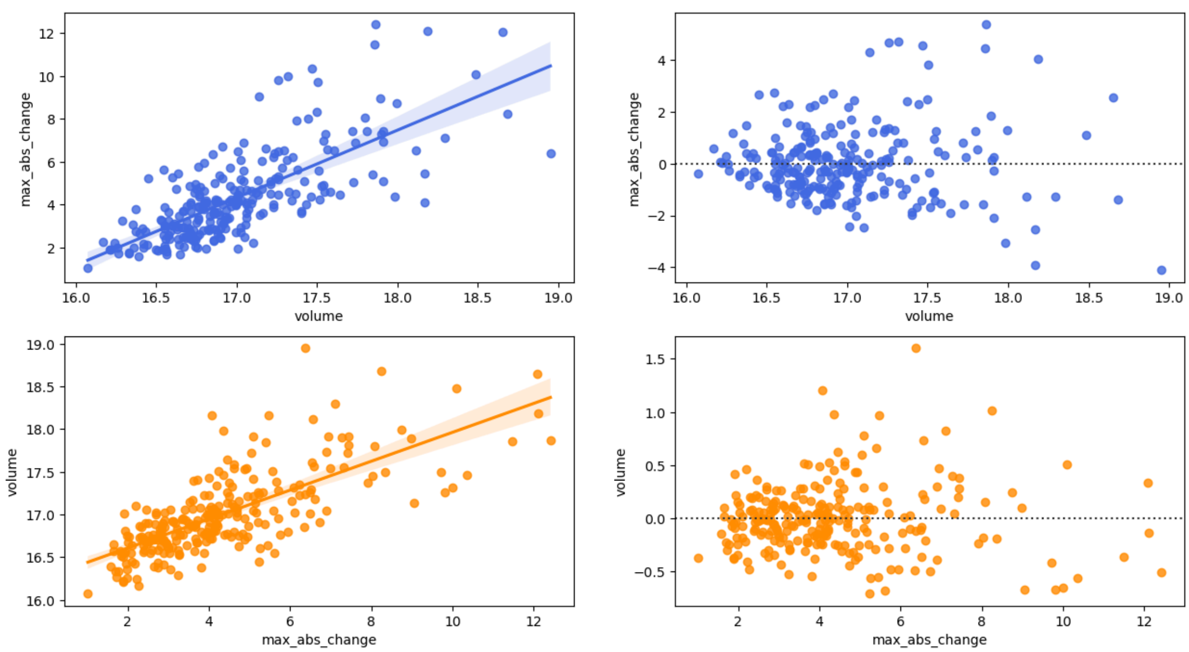
In [ ]:
```
iterable = list(itertools.repeat("I'm an iterable", 1))

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:

In [62]:
```
from reg_resid_plot import reg_resid_plots
reg_resid_plots(fb_reg_data)
```

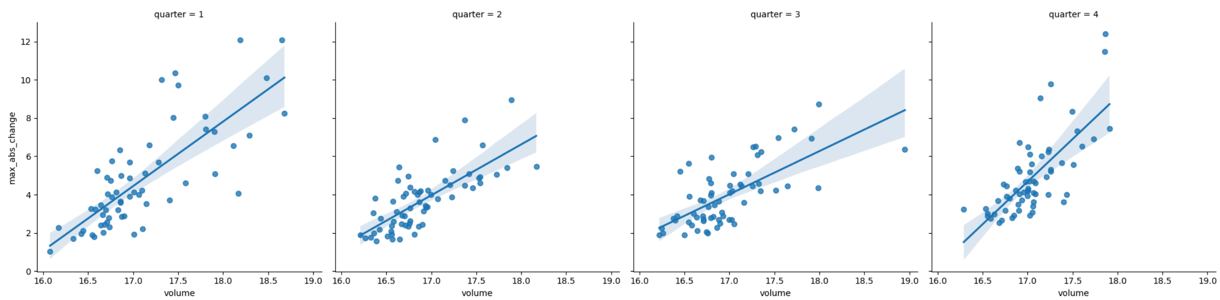
Out[62]:



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:

In [74]:
```
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'
)
```

Out[74]: <seaborn.axisgrid.FacetGrid at 0x1d064604fe0>



Distributions

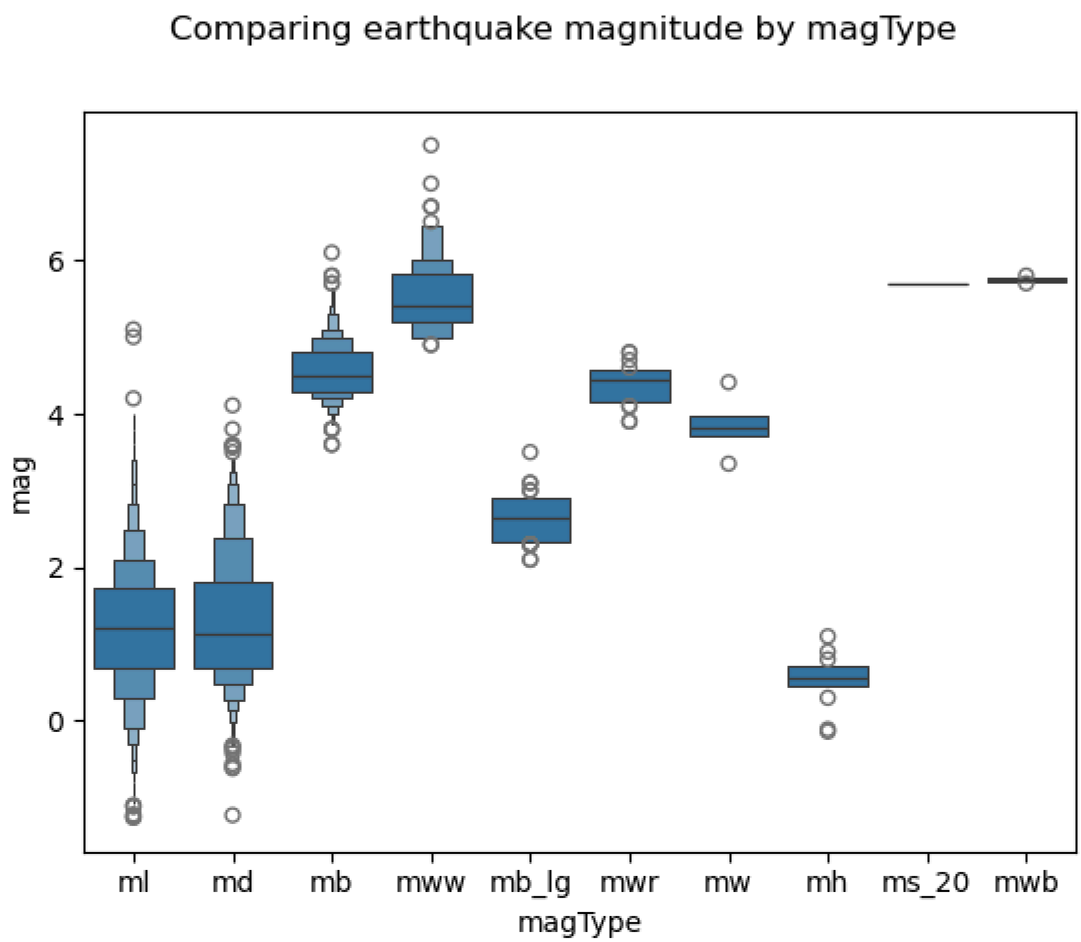
Seaborn provides some new plot types for visualizing distributions in additional to its own versions of the plot types we discussed in chapter 5 (in this notebook).

`boxenplot()`

The boxenplot is a box plot that shows additional quantiles:

In [80]:
```
sns.boxenplot(
    x='magType', y='mag', data=quakes[['magType', 'mag']]
)
plt.suptitle('Comparing earthquake magnitude by magType')
```

Out[80]: Text(0.5, 0.98, 'Comparing earthquake magnitude by magType')



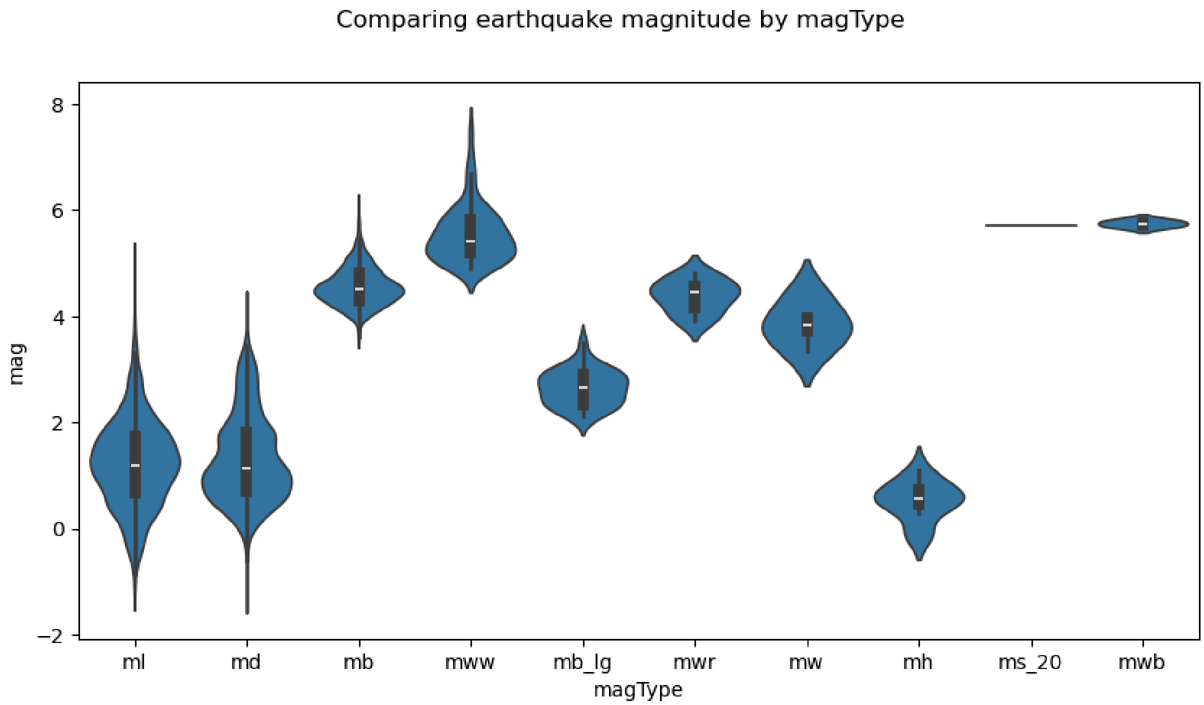
`violinplot()`

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

In [82]:
```
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')
```

```
C:\Users\micki\AppData\Local\Temp\ipykernel_11308\897263406.py:2: FutureWarning:

The `scale` parameter has been renamed and will be removed in v0.15.0. Pass `density
_norm='width'` for the same effect.
  sns.violinplot(
```

Out[82]: `Text(0.5, 0.98, 'Comparing earthquake magnitude by magType')`

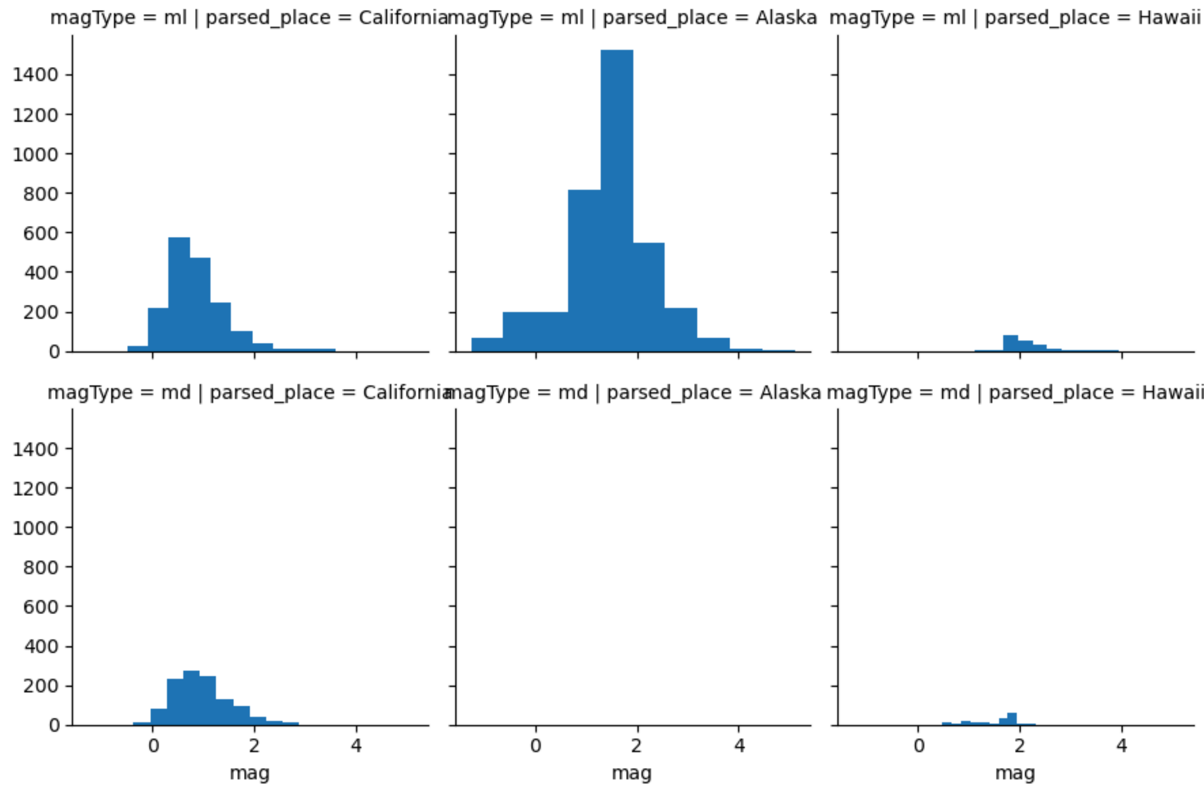


Faceting

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 :

In [85]:
```
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')
```



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

In [99]:
```
%matplotlib inline
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import seaborn as sns
fb = pd.read_csv(
    'fb_stock_prices_2018.csv', index_col='date', parse_dates=True
)
```

Titles and Axis Labels

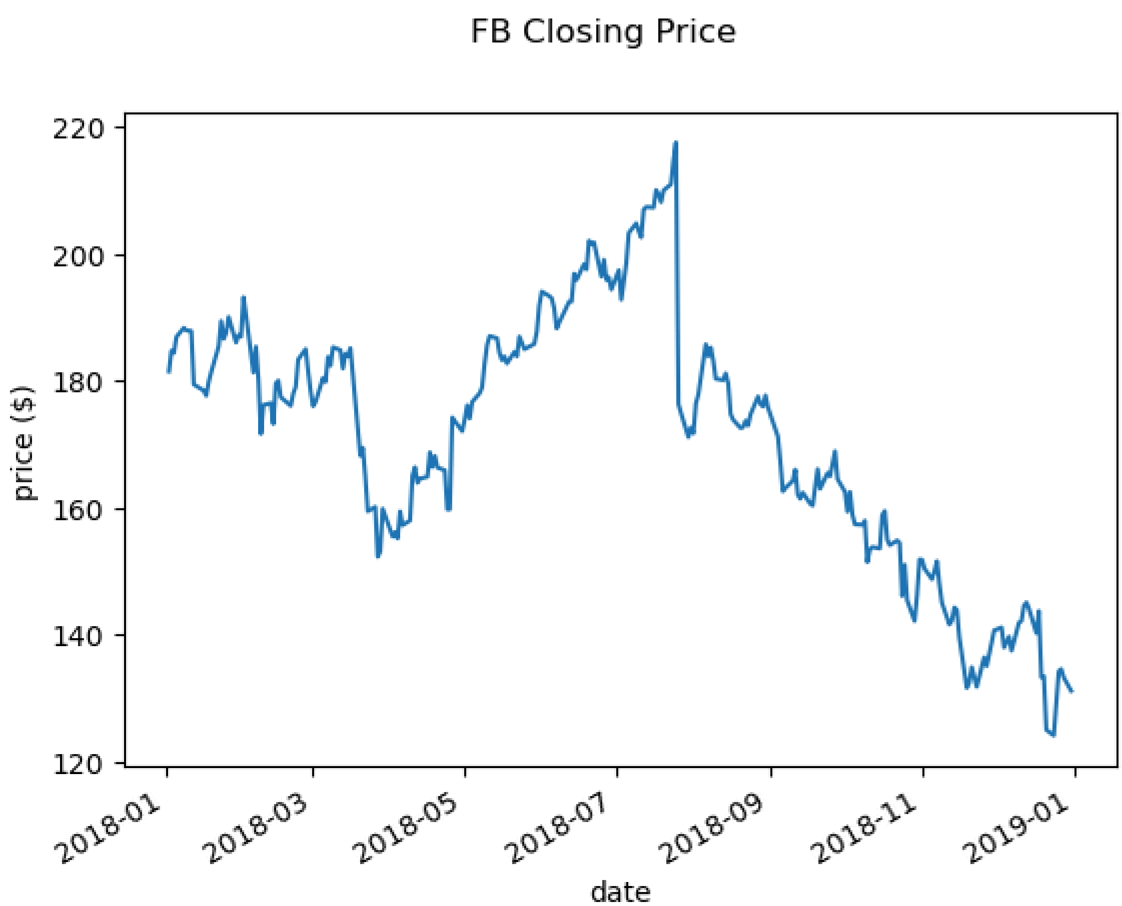
- plt.suptitle() adds a title to plots and subplots
- plt.title() adds a title to a single plot. Note if you use subplots, it will only - put the title on the last subplot, so you will need to use plt.suptitle()
- plt.xlabel() labels the x-axis
- plt.ylabel() labels the y-axis

In [102…

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

Out[102…

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



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

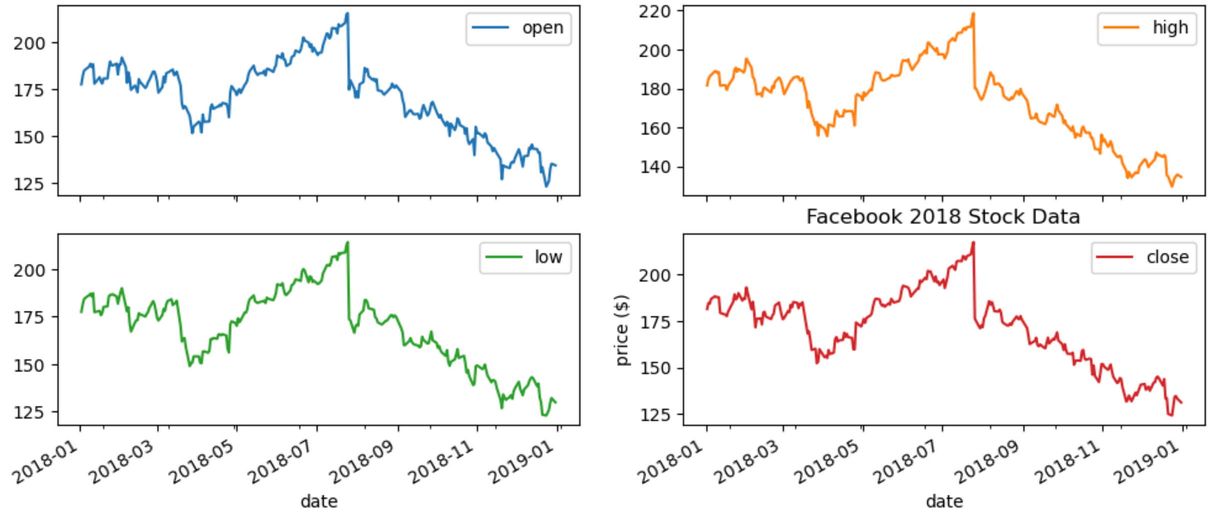
Check out what happens when we call plt.title() with subplots:

In [105…

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

Out[105…

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



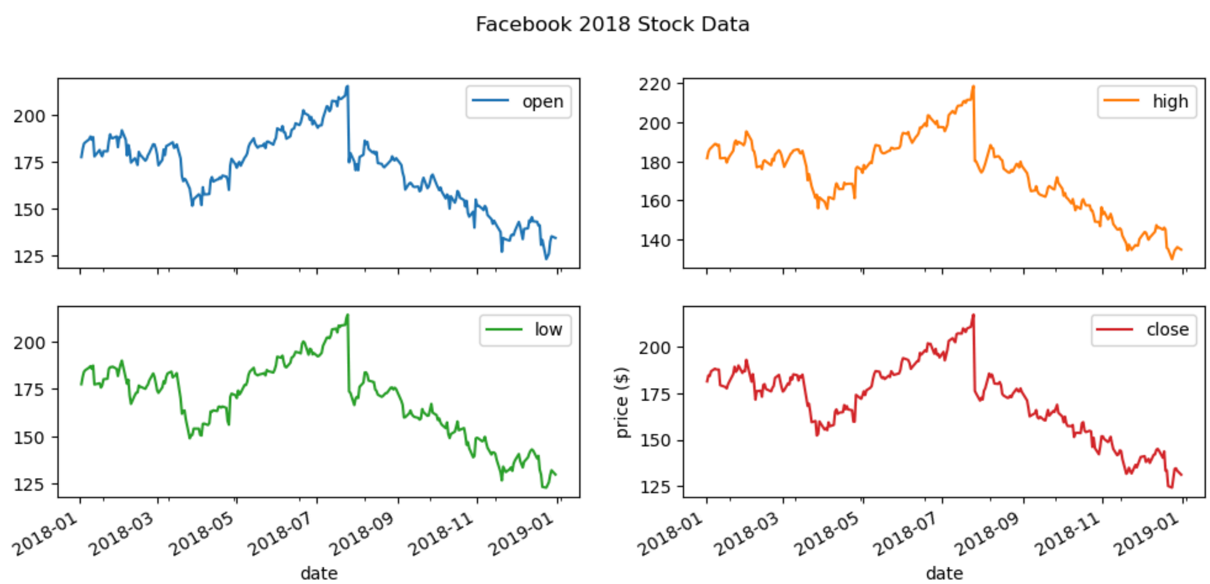
Simply getting into the habit of using plt.suptitle() instead of plt.title() will save you this confusion:

In [108…

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

Out[108…

```
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:

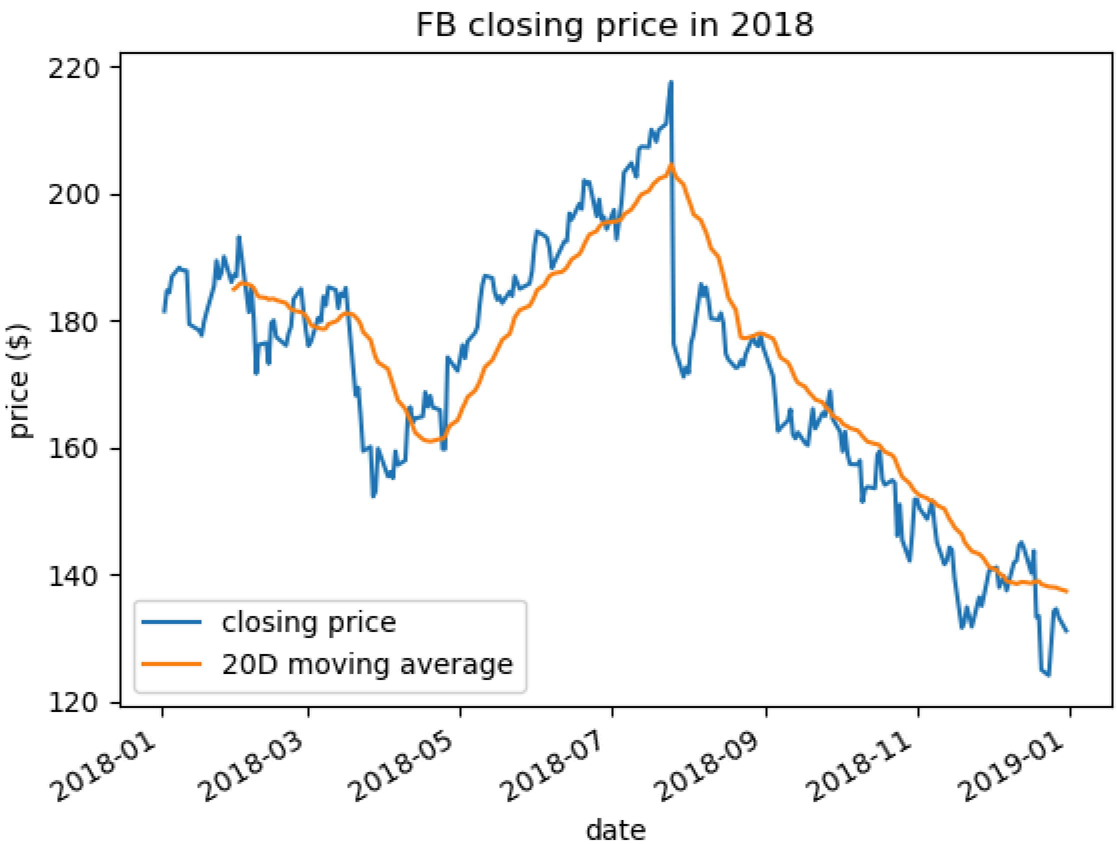
In [111…

```
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 ($)')
```

Out[111…

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



Formatting Axes

Specifying axis limits

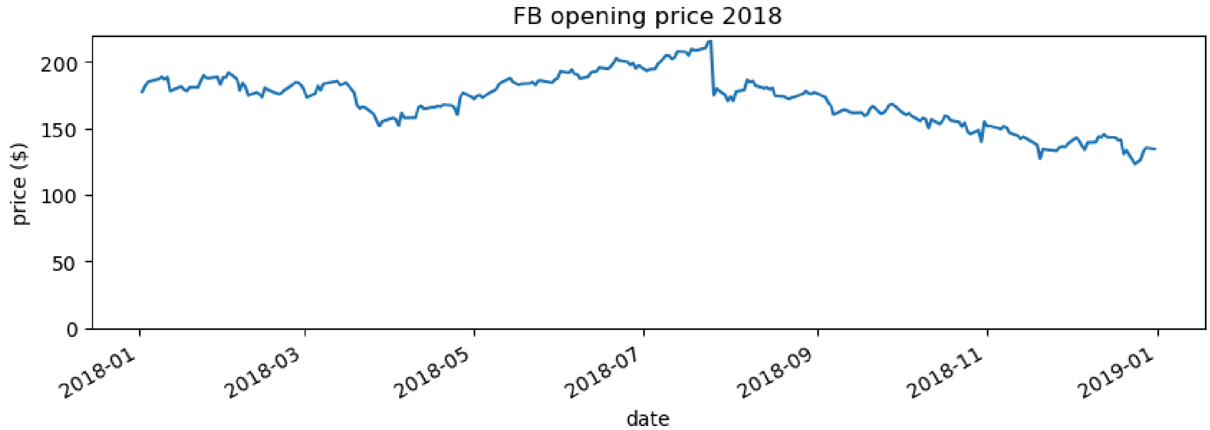
`plt.xlim()` and `plt.ylim()` can be used to specify the minimum and maximum values for the axis. Passing `None` will have `matplotlib` determine the limit.

In [114…

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

Out[114…

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

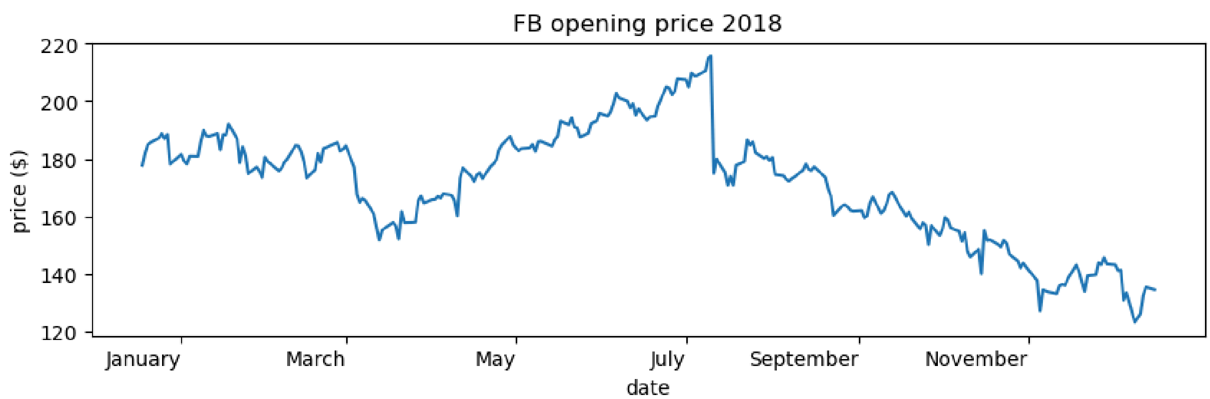


Formatting the Axis Ticks

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

In [123…
```
import calendar

fb.open.plot(figsize=(10, 3), rot=0, title='FB opening price 2018')
locs, labels = plt.xticks()
plt.xticks(locs[:6] + 15 , calendar.month_name[1::2])
    # added '[:6]' to match the number of ticks
plt.ylabel('price ($)')
```

Out[123…
```
Text(0, 0.5, 'price ($)')
```



Using `ticker`

`PercentFormatter`

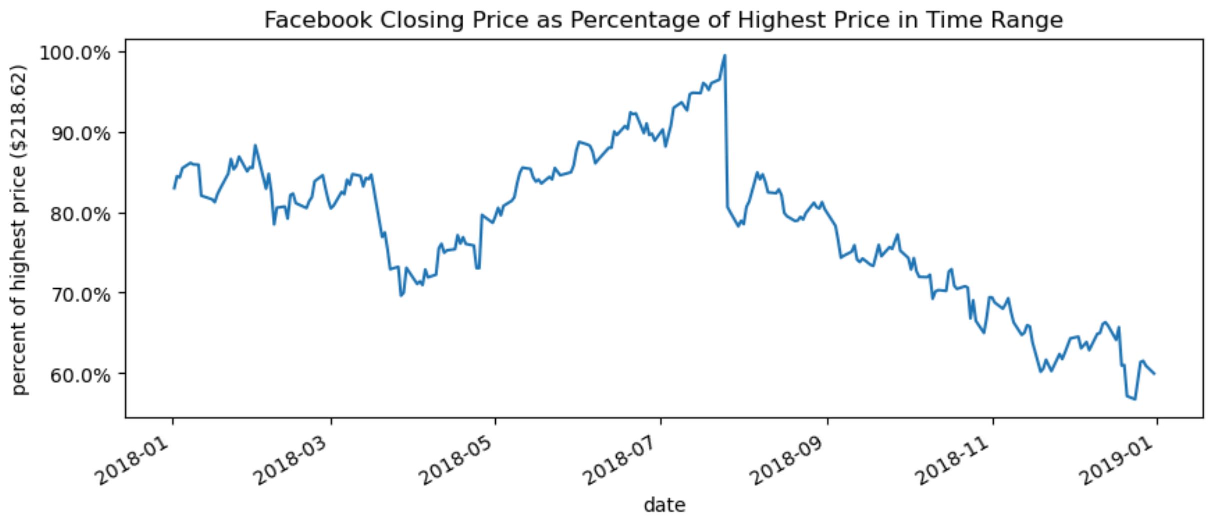
We can use `ticker.PercentFormatter` and specify the denominator (`xmax`) to use when calculating the percentages. This gets passed to the `set_major_formatter()` method of the `xaxis` or `yaxis` on the `Axes` .

In [128…
```
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()})')
```

Out[128…

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



`MultipleLocator`

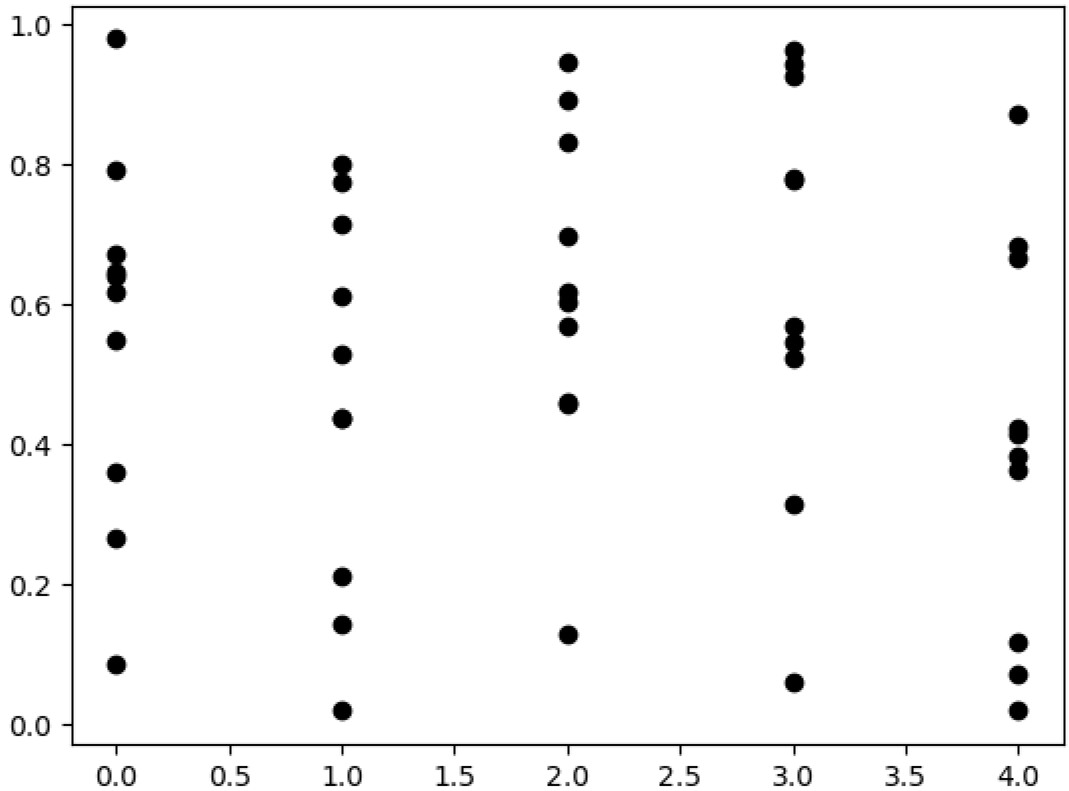
Say we have the following data. The points only take on integer values for `x`.

In [131…

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

Out[131…

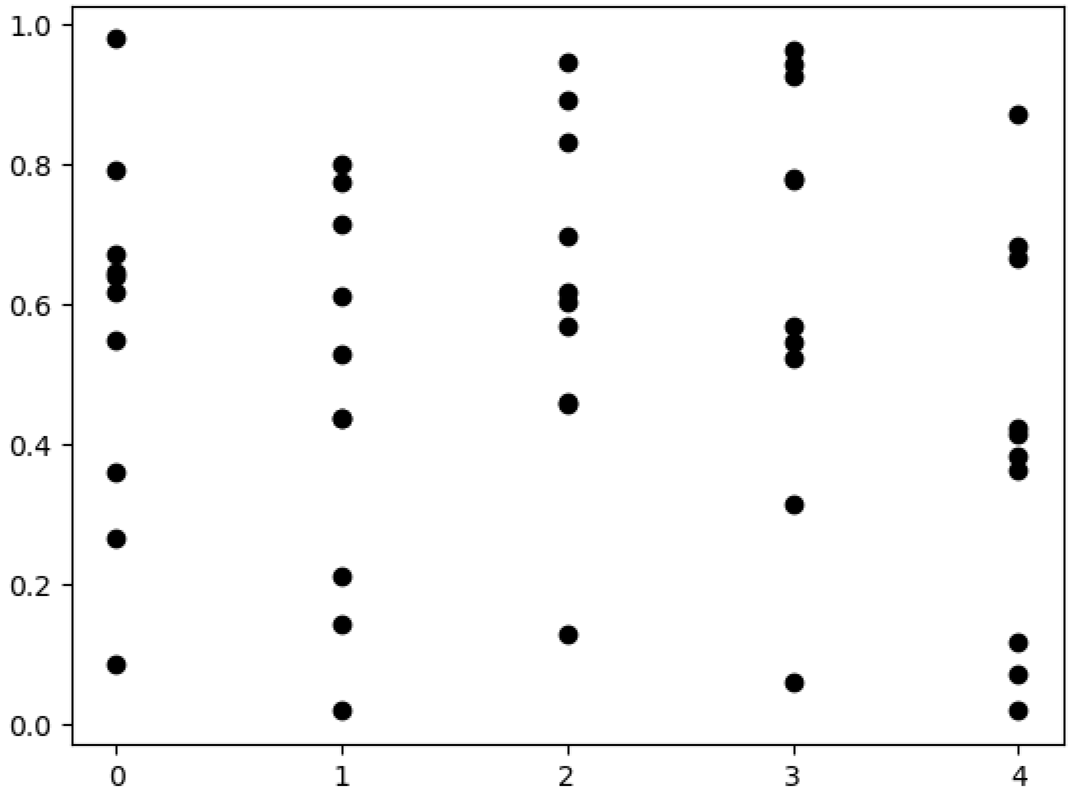
```
[<matplotlib.lines.Line2D at 0x1d06fb1c440>]
```



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 :

In [134…

```
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)
)
```



Pandas Plotting Subpackage

`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

In [141…

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

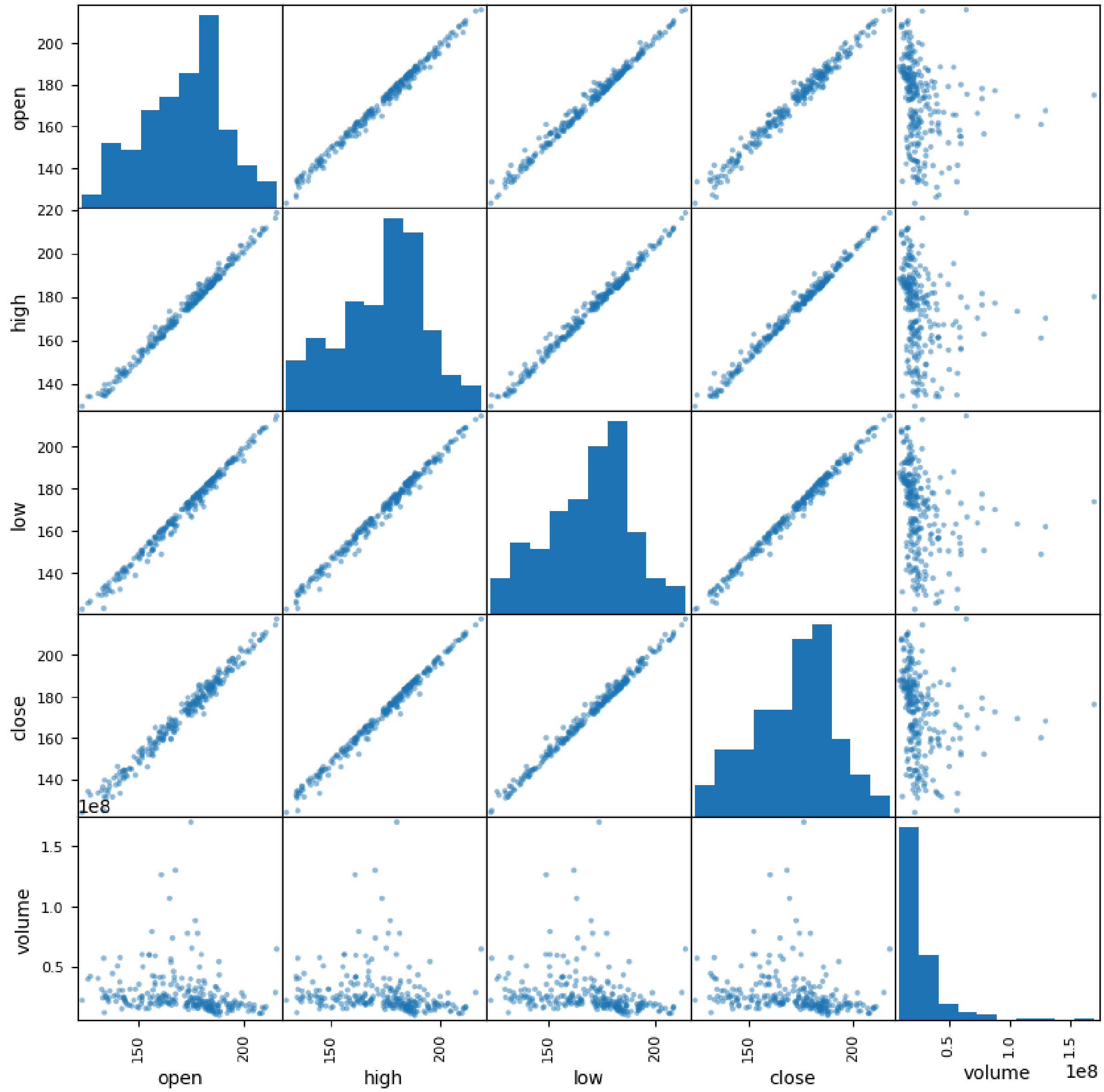
Scatter matrix

In [144…

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

Out[144…

```
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)
```

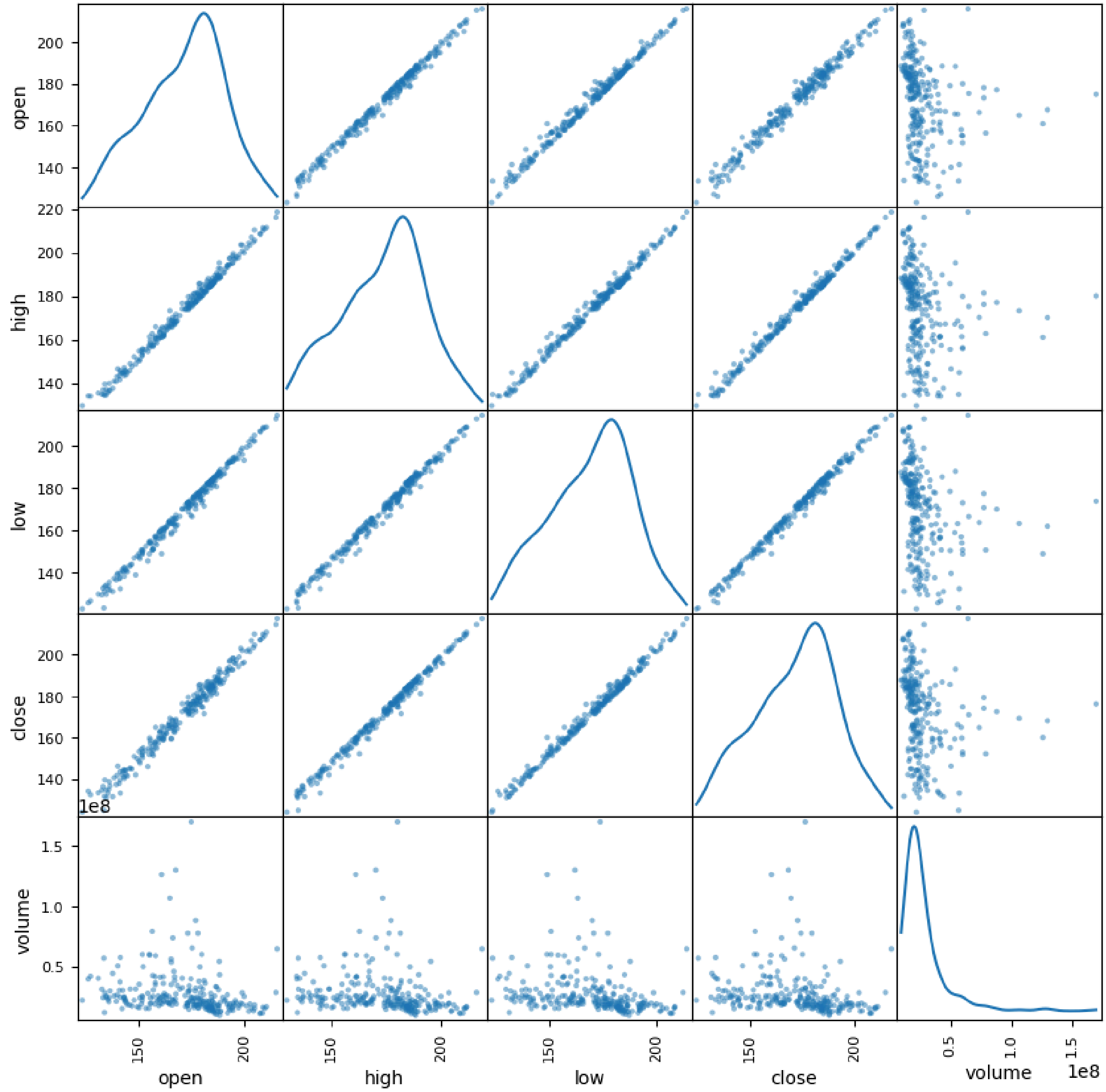


Changing the diagonal from histograms to KDE:

In [146…

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

Out[146…
```
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

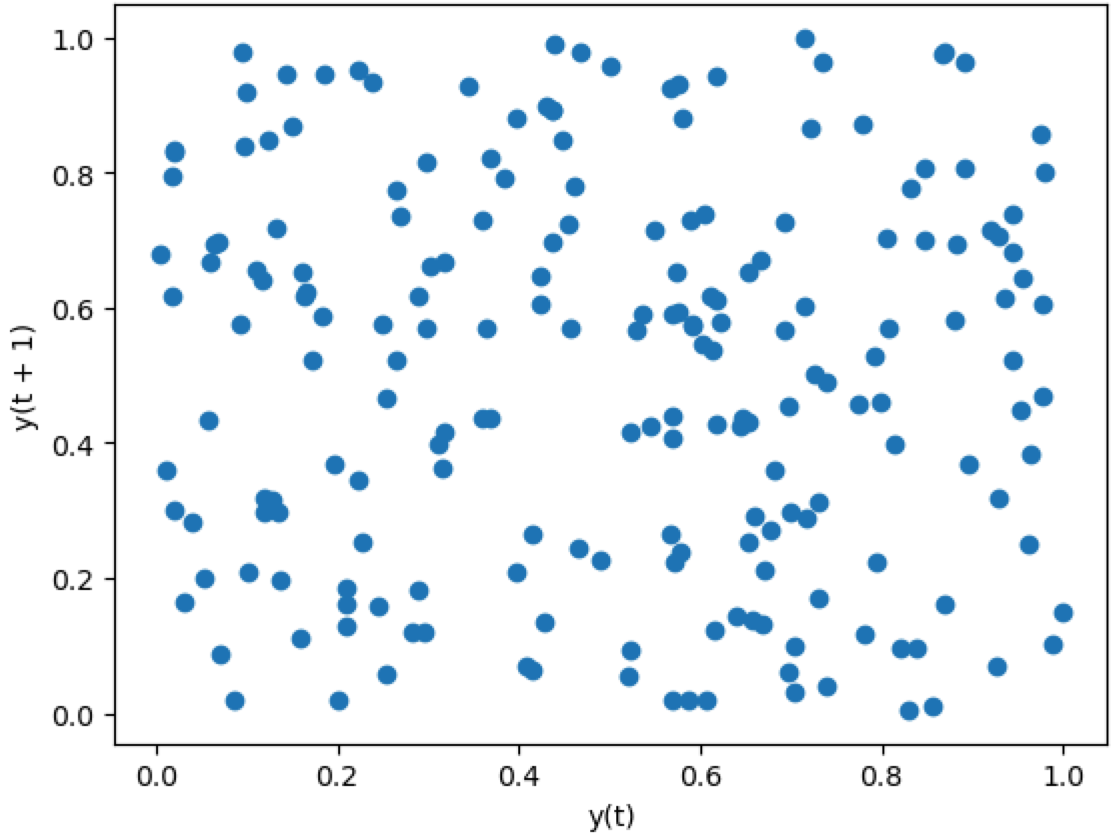
Lag plots let us see how the variable correlations with past observations of itself. Random data has no pattern:

In [149…

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

Out[149…

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



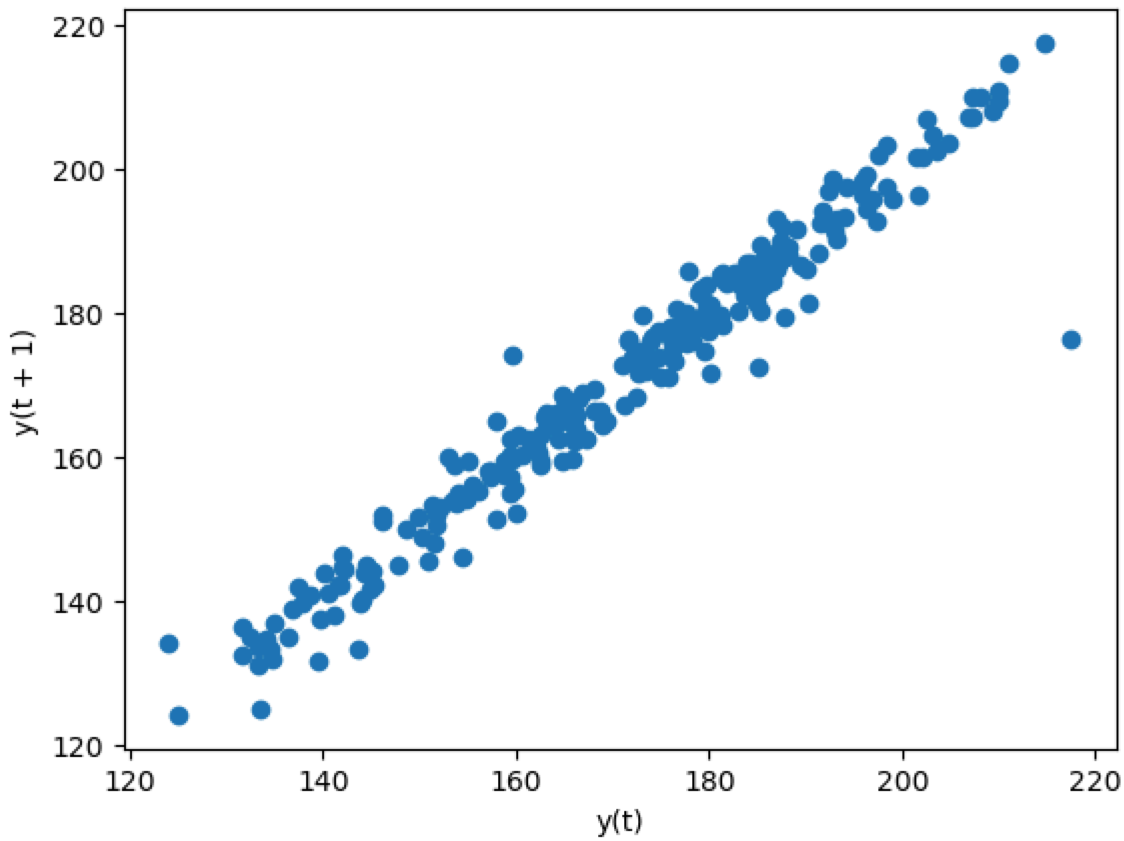
Data with some level of correlation to itself (autocorrelation) may have patterns. Stock prices are highly auto-correlated:

In [152…

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

Out[152…

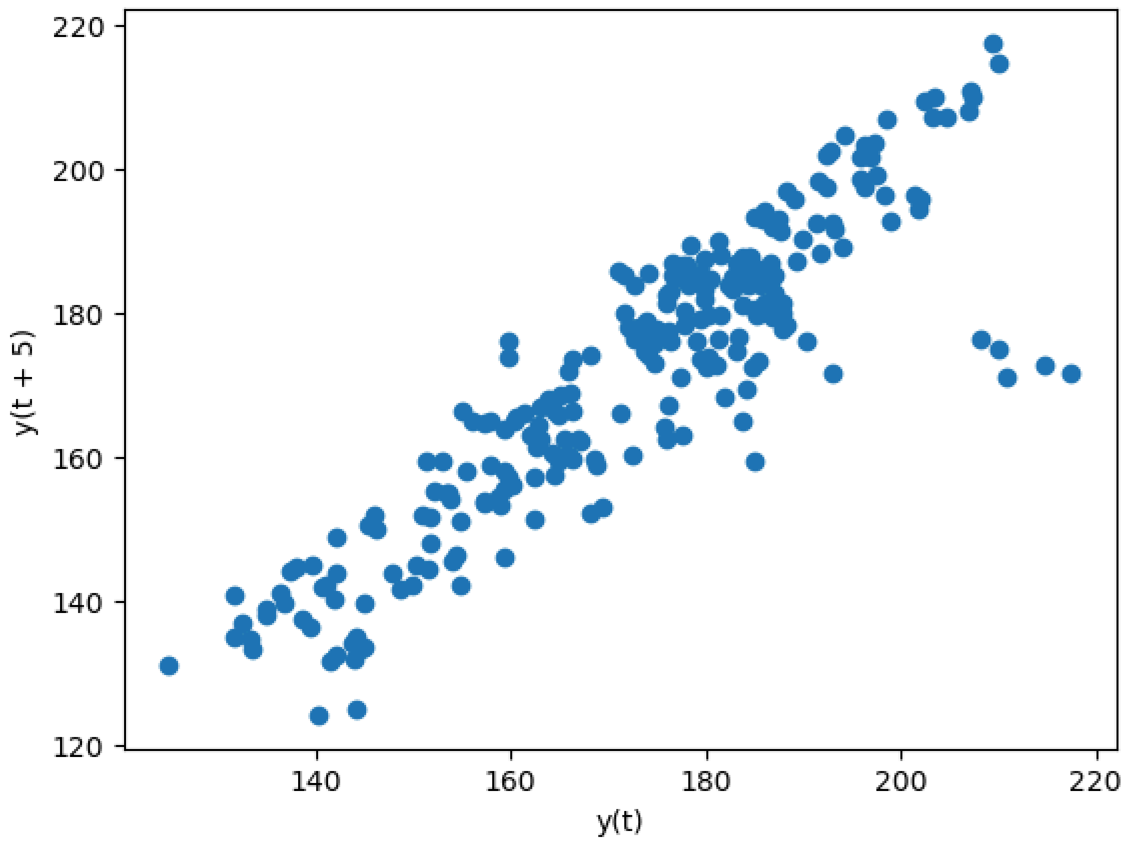
```
<Axes: xlabel='y(t)', ylabel='y(t + 1)'>
```



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):

In [155…
```
lag_plot(fb.close, lag=5)
```

Out[155…
```
<Axes: xlabel='y(t)', ylabel='y(t + 5)'>
```



Autocorrelation plots

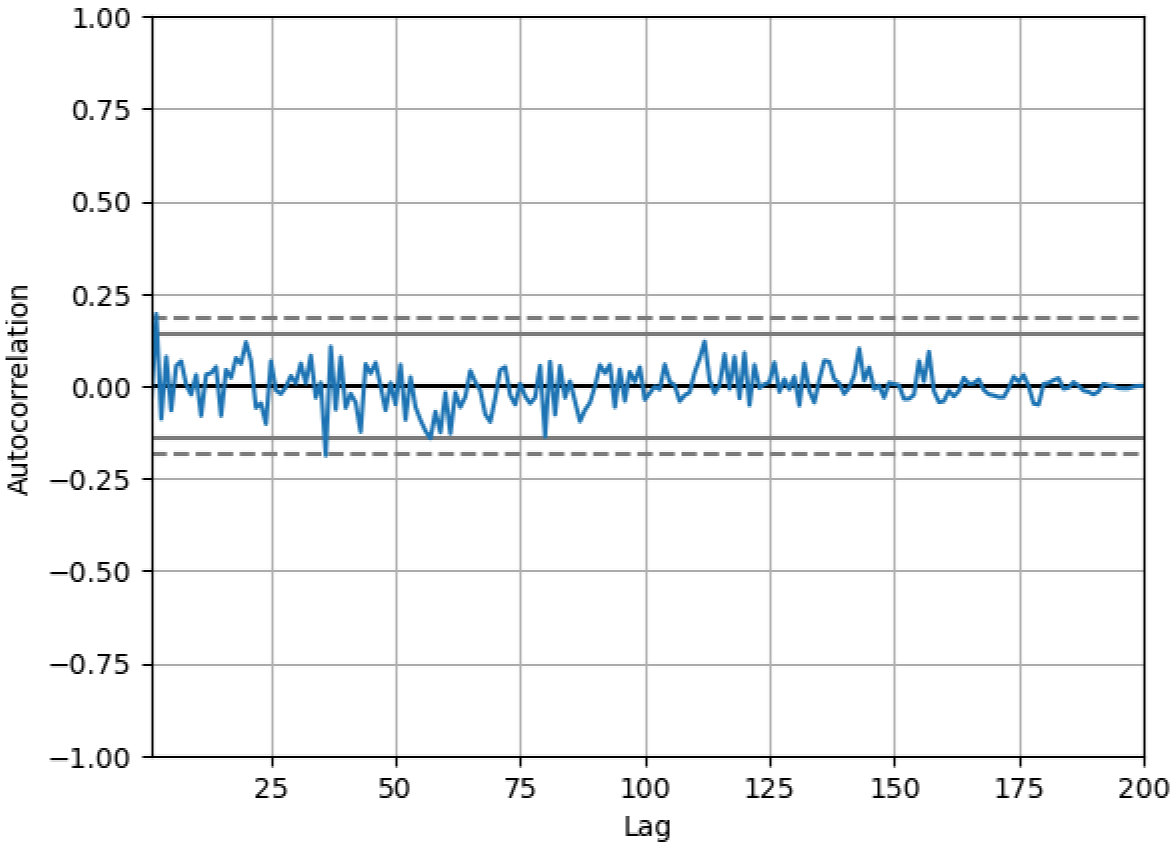
We can use the autocorrelation plot to see if this relationship may be meaningful or just noise. Random data will not have any significant autocorrelation (it stays within the bounds below):

In [158…

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

Out[158…

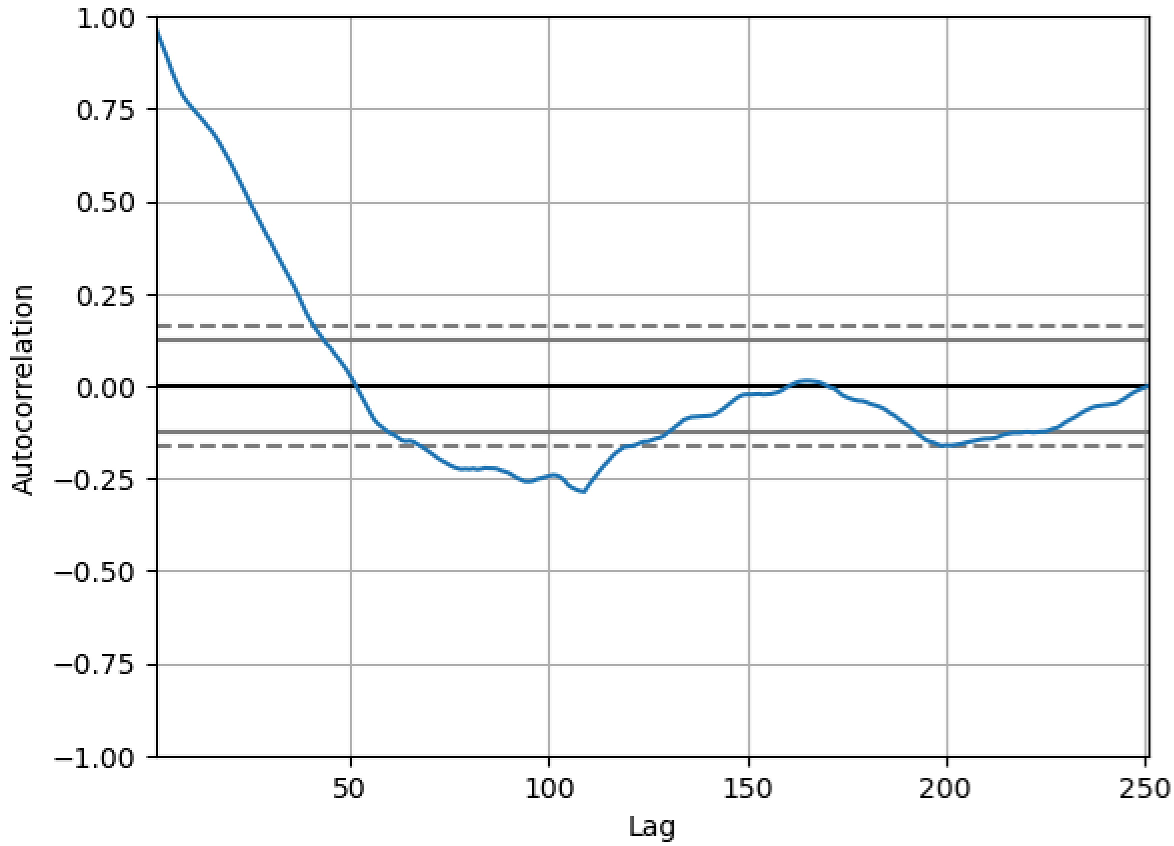
```
<Axes: xlabel='Lag', ylabel='Autocorrelation'>
```



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

In [161…
```
autocorrelation_plot(fb.close)
```

Out[161…
```
<Axes: xlabel='Lag', ylabel='Autocorrelation'>
```

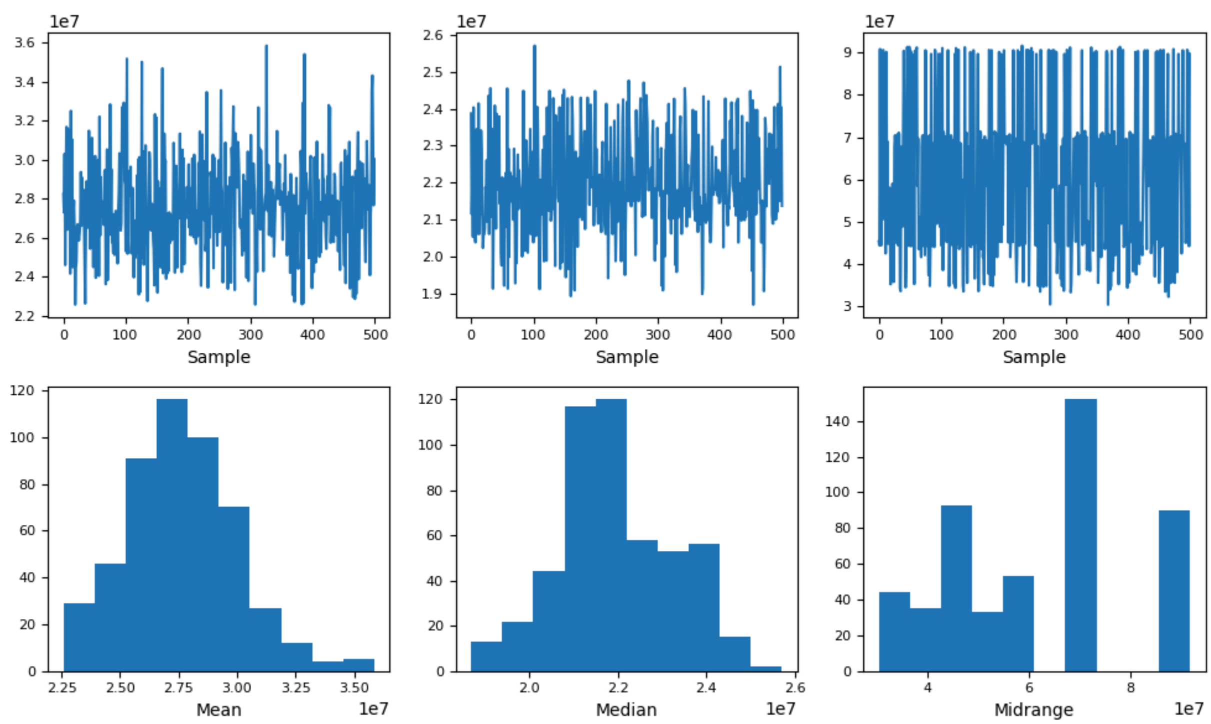


Bootstrap plot

This plot helps us understand the uncertainty in our summary statistics:

In [164…

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



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

Data Analysis

> The first procedure discussed using Seaborn to make sense of data through different kinds of plots. I looked at earthquake data and Facebook's 2018 stock prices using strip plots, swarm plots, and heatmaps to spot patterns and connections. Then, I used jointplots and pairplots to get a better look at how the data was spread out and how variables relate to each other. Regression and residual plots showed us trends and how far off some points were. Lastly, I also learned how to use violin plots, boxen plots, and FacetGrids to compare different groups in the data.

> The second procedure talked about improving the readability and presentation of plots using Matplotlib formatting tools. Some of the key techniques included adding clear titles with suptitle() and proper axis labels, customizing legends for clarity, and adjusting axis limits and tick labels for better scaling and interpretation. Also, there were also Formatter tools introduced like PercentFormatter and MultipleLocator --- which were used to display percentages and control tick intervals, making the visualizations more informative and easier to understand.

Supplementary Activity

Using the CSV files provided and what we have learned so far in this module complete the following exercises:

Task 1

> 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.

In [180…

```
# Import all relevant modules
%matplotlib inline

import pandas as pd
```

```
import matplotlib.pyplot as plt
import seaborn as sns
```

In [182…

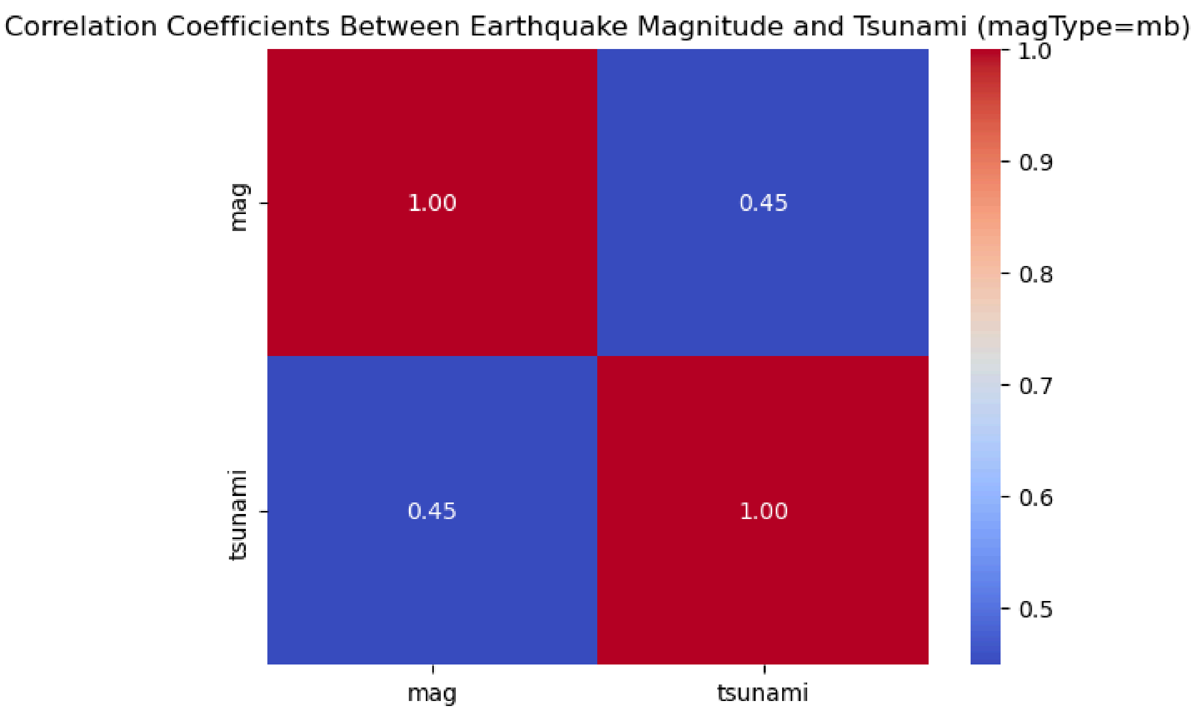
```
# Read the relevant file (.csv)
quakes = pd.read_csv('earthquakes-1.csv')
```

In [196…

```
# Filter the magType
mb_earthquakes = quakes[quakes['magType'] == 'mb']

# Check how strongly earthquake magnitude ('mag') is related to tsunami occurrence
corr_mtx = mb_earthquakes[['mag', 'tsunami']].corr()

# Set-up the heatmap
fig, ax = plt.subplots(figure=(8,6))

sns.heatmap(
    corr_mtx,
    annot=True,
    cmap='coolwarm',
    fmt='.2f',
    ax=ax
)

ax.set_title('Correlation Coefficients Between Earthquake Magnitude and Tsunami (ma
```

Out[196…

```
Text(0.5, 1.0, 'Correlation Coefficients Between Earthquake Magnitude and Tsunami
(magType=mb)')
```



Task 2

> 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.)

In [239…
```
# Import relevant modules
%matplotlib inline
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [241…
```
# Import relevant file(.csv)
fb = pd.read_csv('fb_stock_prices_2018.csv')
```

> A. Calculate the quartiles and IQR for volume traded and closing prices

In [244…
```
# --- Volume ---
volume_quartiles = fb['volume'].quantile([0.25, 0.75])
volume_q1 = volume_quartiles.loc[0.25]
volume_q3 = volume_quartiles.loc[0.75]
volume_iqr = volume_q3 - volume_q1

# --- Close ---
close_quartiles = fb['close'].quantile([0.25, 0.75])
close_q1 = close_quartiles.loc[0.25]
close_q3 = close_quartiles.loc[0.75]
close_iqr = close_q3 - close_q1
```

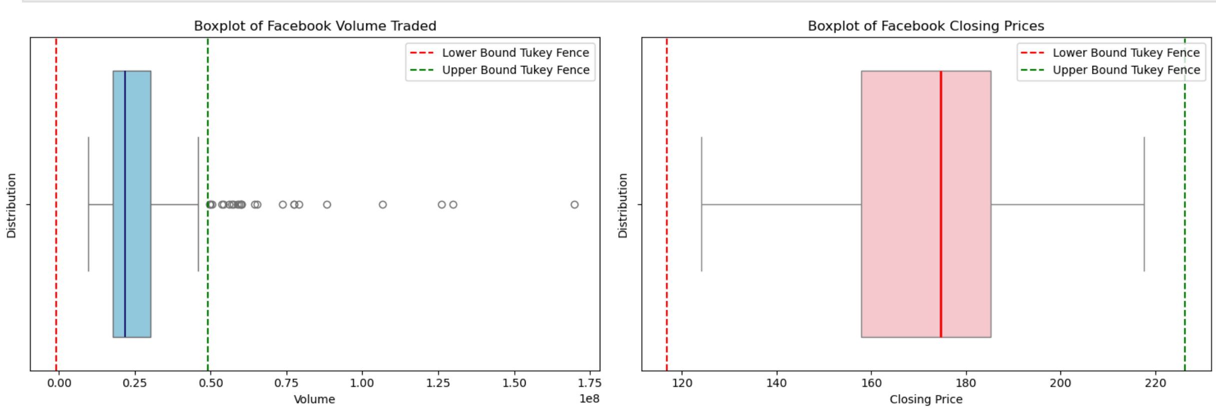
> B. Calculate the Tukey fence bounds for volume and closing price

In [247…
```
# Calculate the Tukey fence bounds for volume
volume_fence_lower = volume_q1 - 1.5 * volume_iqr
volume_fence_upper = volume_q3 + 1.5 * volume_iqr

# Calculate the Tukey fence bounds for closing price
close_fence_lower = close_q1 - 1.5 * close_iqr
close_fence_upper = close_q3 + 1.5 * close_iqr
```

> C. Set-up the subplots

In [291…
```
fig, axes = plt.subplots(ncols=2, figsize=(15, 5))

# --- Boxplot for Volume ---
sns.boxplot(
    x='volume',
    data=fb,
    ax=axes[0],
    color='skyblue',
    medianprops=dict(color='midnightblue', linewidth=1.5)
)
axes[0].axvline(
```

```
    x=volume_fence_lower,
    color='red',
    linestyle='--',
    label='Lower Bound Tukey Fence'
)
axes[0].axvline(
    x=volume_fence_upper,
    color='green',
    linestyle='--',
    label='Upper Bound Tukey Fence'
)
axes[0].set_title('Boxplot of Facebook Volume Traded')
axes[0].set_xlabel('Volume')
axes[0].set_ylabel('Distribution')
axes[0].legend()

# --- Boxplot for Closing Price ---
sns.boxplot(
    x='close',
    data=fb,
    ax=axes[1],
    color='pink',
    medianprops=dict(color='red', linewidth=2)
)
axes[1].axvline(
    x=close_fence_lower,
    color='red',
    linestyle='--',
    label='Lower Bound Tukey Fence'
)
axes[1].axvline(
    x=close_fence_upper,
    color='green',
    linestyle='--',
    label='Upper Bound Tukey Fence'
)
axes[1].set_title('Boxplot of Facebook Closing Prices')
axes[1].set_xlabel('Closing Price')
axes[1].set_ylabel('Distribution')
axes[1].legend()

plt.tight_layout()
```



Task 3

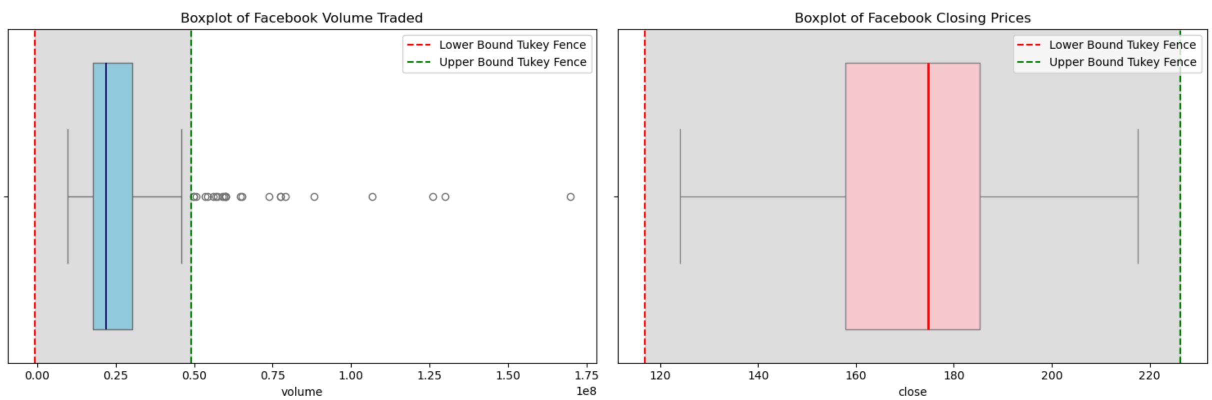
> 3. Fill in the area between the bounds in the plot from exercise #2.

> A. Modification A: fill the area between the bounds entirely
>
> Observation: the shading tells that data from the right in subplot of volume, are outliers

In [301…

```
fig, axes = plt.subplots(ncols=2, figsize=(15, 5))

# --- Boxplot for Volume ---
sns.boxplot(
    x='volume',
    data=fb,
    ax=axes[0],
    color='skyblue',
    medianprops=dict(color='midnightblue', linewidth=1.5)
)
axes[0].axvline(
    x=volume_fence_lower,
    color='red',
    linestyle='--',
    label='Lower Bound Tukey Fence'
)
axes[0].axvline(
    x=volume_fence_upper,
    color='green',
    linestyle='--',
    label='Upper Bound Tukey Fence'
)
# --- Fill between the bounds ----
axes[0].axvspan(
    volume_fence_lower,
    volume_fence_upper,
    color='gray', alpha=0.25)

axes[0].set_title('Boxplot of Facebook Volume Traded')
axes[0].legend()

# --- Boxplot for Closing Price ---
sns.boxplot(
    x='close',
    data=fb,
    ax=axes[1],
    color='pink',
    medianprops=dict(color='red', linewidth=2)
)
axes[1].axvline(
    x=close_fence_lower,
    color='red',
    linestyle='--',
```

```
    label='Lower Bound Tukey Fence'
)
axes[1].axvline(
    x=close_fence_upper,
    color='green',
    linestyle='--',
    label='Upper Bound Tukey Fence'
)
# Fill between the bounds
axes[1].axvspan(
    close_fence_lower,
    close_fence_upper,
    color='gray',
    alpha=0.25)

axes[1].set_title('Boxplot of Facebook Closing Prices')
axes[1].legend()

plt.tight_layout()
plt.show()
```

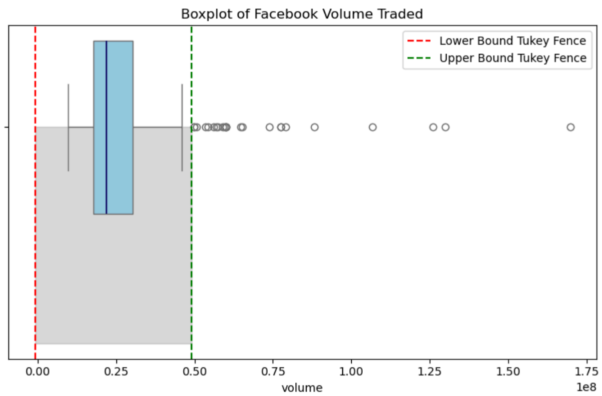


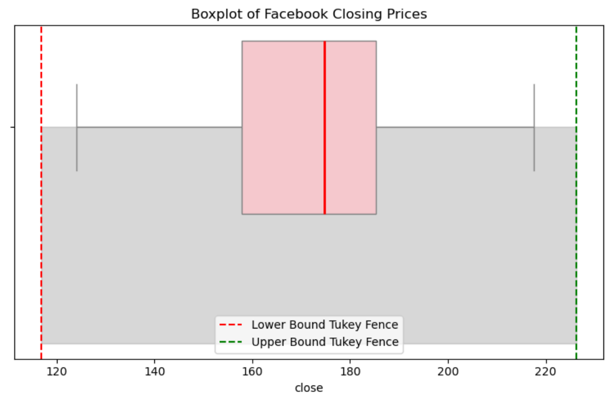
> B. Modification B: shaded partially by the whiskers

In [299…

```
fig, axes = plt.subplots(ncols=2, figsize=(15, 5))

# --- Boxplot for Volume ---
sns.boxplot(
    x='volume',
    data=fb,
    ax=axes[0],
    color='skyblue',
    medianprops=dict(color='midnightblue', linewidth=1.5)
)
axes[0].axvline(
    x=volume_fence_lower,
    color='red',
    linestyle='--',
    label='Lower Bound Tukey Fence'
)
axes[0].axvline(
    x=volume_fence_upper,
    color='green',
```

```
    linestyle='--',
    label='Upper Bound Tukey Fence'
)
# --- Fill between the bounds ----
axes[0].fill_betweenx([0, 1],
                      volume_fence_lower,
                      volume_fence_upper,
                      color='gray',
                      alpha=0.3)

axes[0].set_title('Boxplot of Facebook Volume Traded')
axes[0].legend()

# --- Boxplot for Closing Price ---
sns.boxplot(
    x='close',
    data=fb,
    ax=axes[1],
    color='pink',
    medianprops=dict(color='red', linewidth=2)
)
axes[1].axvline(
    x=close_fence_lower,
    color='red',
    linestyle='--',
    label='Lower Bound Tukey Fence'
)
axes[1].axvline(
    x=close_fence_upper,
    color='green',
    linestyle='--',
    label='Upper Bound Tukey Fence'
)
# --- Fill between the bounds ---
axes[1].fill_betweenx([0, 1],
                      close_fence_lower,
                      close_fence_upper,
                      color='gray',
                      alpha=0.3)

axes[1].set_title('Boxplot of Facebook Closing Prices')
axes[1].legend()

plt.tight_layout()
plt.show()
```





Task 4

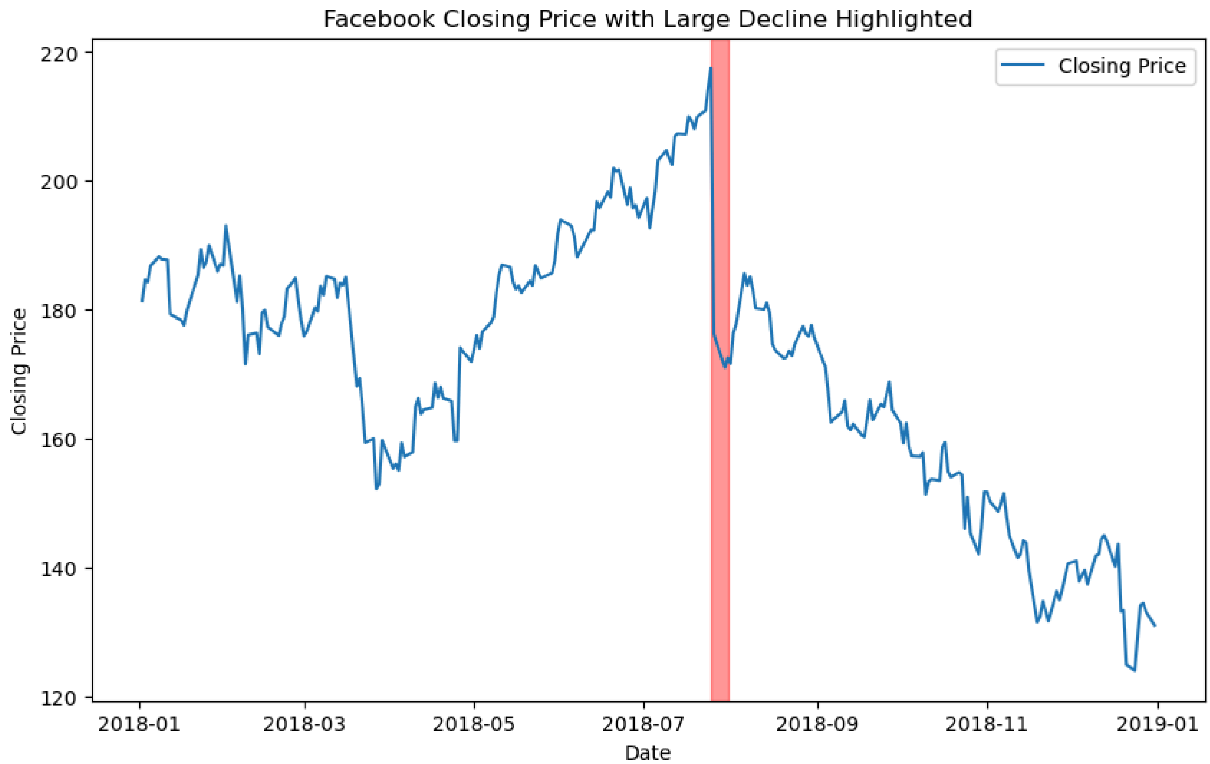
> 4. Use axvspan() to shade a rectangle from '2018-07-25' to '2018-07-31', which marks the large decline in Facebook price on a line plot of the closing price.

In [375…

```
fb_data = pd.read_csv('fb_stock_prices_2018.csv')
```

In [377…

```
fb_data['date'] = pd.to_datetime(fb_data['date'])
fb_data.set_index('date', inplace=True)

fig, ax = plt.subplots(figsize=(10, 6))

# Plot the closing price
ax.plot(fb_data.index, fb_data['close'], label='Closing Price')

# Highlight the decline period with axvspan
ax.axvspan(pd.to_datetime('2018-07-25'), pd.to_datetime('2018-07-31'), color='red',

ax.set_xlabel('Date')
ax.set_ylabel('Closing Price')
ax.set_title('Facebook Closing Price with Large Decline Highlighted')

ax.legend()
plt.show()
```



Task 5

> 5. Using the Facebook stock price data, annotate the following three events on a line plot of the closing price:

- Disappointing user growth announced after close on July 25, 2018
- Cambridge Analytica story breaks on March 19, 2018 (when it affected the market)
- FTC launches investigation on March 20, 2018

In [445…

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

fb5 = fb_data.copy()
```

In [492…

```
fb_close = fb['close']
events = [
    ('Disappointing user growth announced after close', pd.to_datetime('2018-07-25'
    ('Cambridge Analytica story breaks', pd.to_datetime('2018-03-19')),
    ('FTC launches investigation', pd.to_datetime('2018-03-20'))
]

fig, ax = plt.subplots(figsize=(8, 4))

ax.plot(fb_close.index, fb_close.values, label='Closing Price', color='green')

for event, date in events:
    y_value = fb_close.loc[date]
```

```
    jitter = np.random.uniform(-20, -25)  # vertical offset to avois overlap
    ax.annotate(
        event,
        xy=(date, y_value),
        xytext=(pd.Timestamp('2019-02-25'), y_value + jitter),
        arrowprops=dict(arrowstyle='->', alpha=0.4)
    )

ax.grid(True, alpha=0.25)
ax.set_ylabel('Price ($)')
ax.set_title('Facebook Closing Price')
ax.legend()

plt.show()
```

Task 6

> 6. Modify the reg_resid_plots() function to use a matplotlib colormap instead of cycling between two colors. Remember, for this use case, we should pick a qualitative colormap or make our own.

In [31]:
```
import pandas as pd
fb = pd.read_csv('fb_stock_prices_2018.csv', index_col='date', parse_dates=True)
```

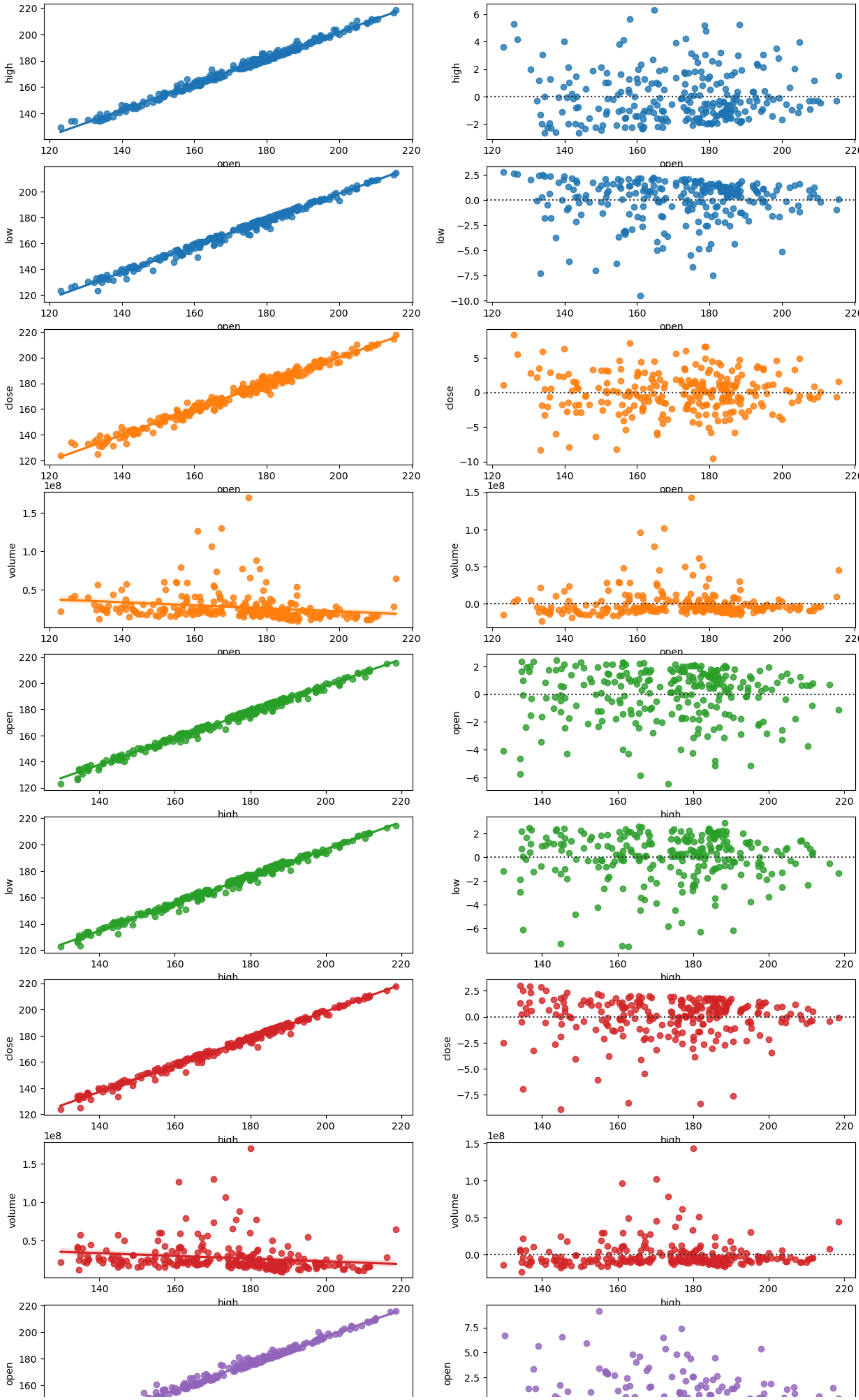
In [49]:
```
import itertools
import matplotlib.pyplot as plt
import seaborn as sns
from matplotlib import cm  # <-- use cm for colormaps

def reg_resid_plots(data):
    num_cols = data.shape[1]
    permutation_count = num_cols * (num_cols - 1)

    colormap = cm.get_cmap('tab10', permutation_count)
    colors = [colormap(i) for i in range(permutation_count)]

    fig, ax = plt.subplots(permutation_count, 2, figsize=(15, 60))

    for i, ((x, y), axes) in enumerate(zip(itertools.permutations(data.columns, 2),
        color = colors[i]
```

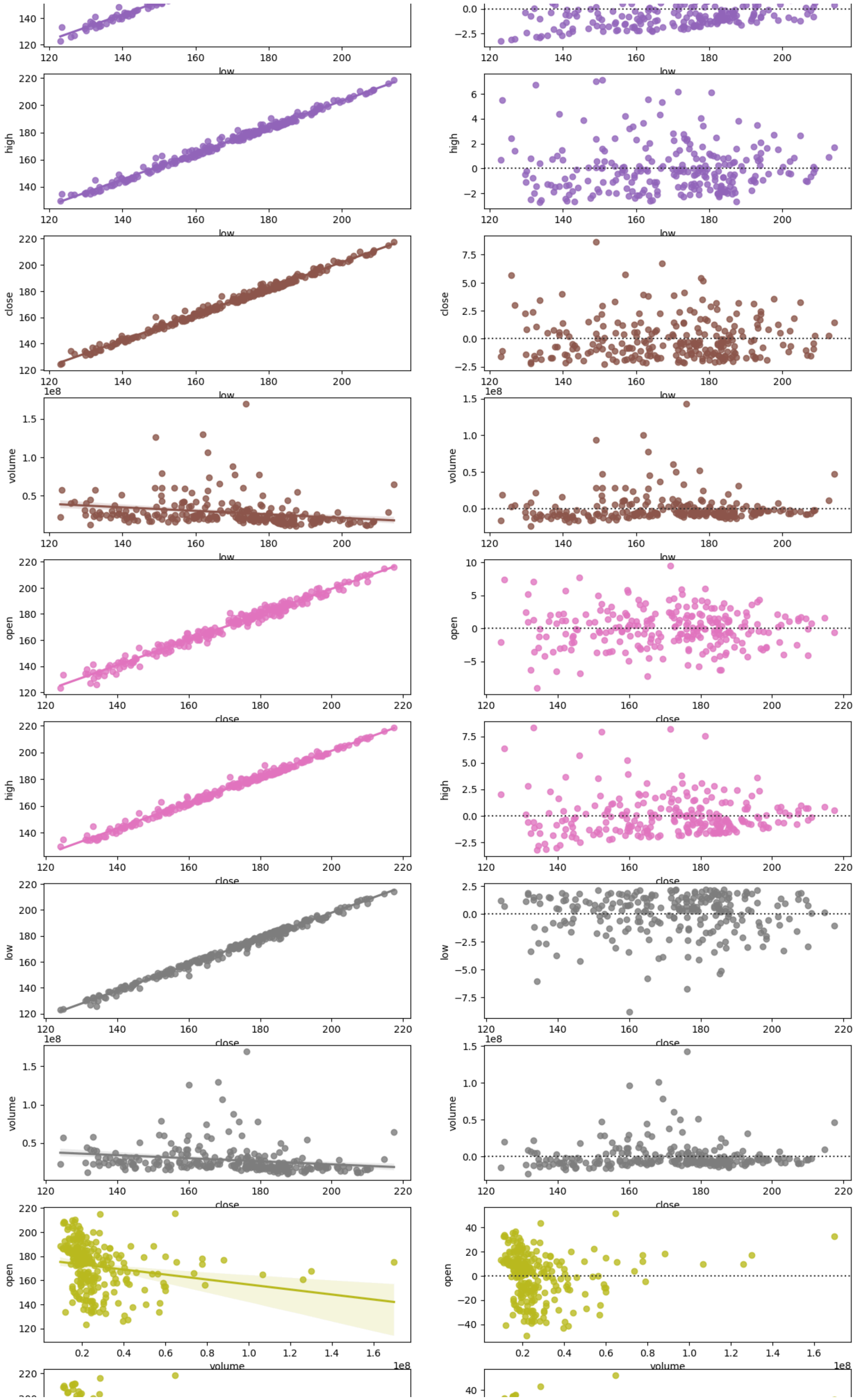
```
        for subplot, func in zip(axes, (sns.regplot, sns.residplot)):
            func(x=x, y=y, data=data, ax=subplot, color=color)
    plt.close()
    return fig
```

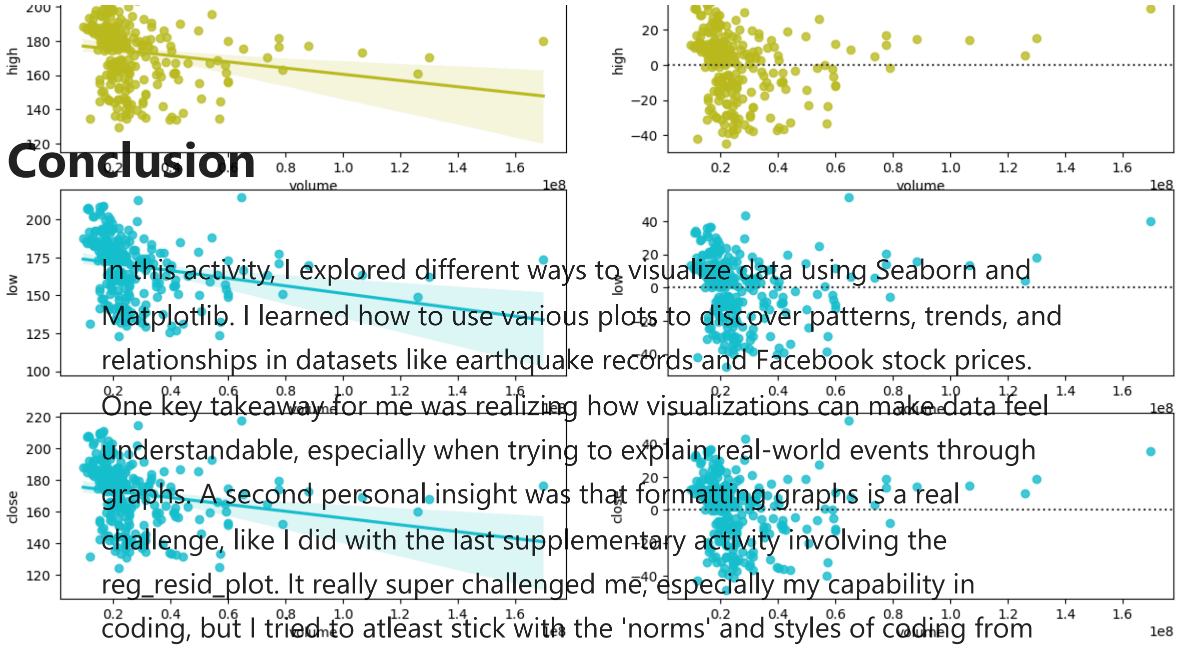
In [51]:
```
# tRY
reg_resid_plots(fb)
```

```
C:\Users\micki\AppData\Local\Temp\ipykernel_29300\31896281.py:10: MatplotlibDeprecationWarning: The get_cmap function was deprecated in Matplotlib 3.7 and will be removed two minor releases later. Use ``matplotlib.colormaps[name]`` or ``matplotlib.colormaps.get_cmap(obj)`` instead.
  colormap = cm.get_cmap('tab10', permutation_count)
```

Out[51]:




low
high
low
close
low
1e8
volume
low
open
close
high
close
low
close
1e8
volume
close
open
volume
1e8



Conclusion

In this activity, I explored different ways to visualize data using Seaborn and Matplotlib. I learned how to use various plots to discover patterns, trends, and relationships in datasets like earthquake records and Facebook stock prices.

> One key takeaway for me was realizing how visualizations can make data feel understandable, especially when trying to explain real-world events through graphs. A second personal insight was that formatting graphs is a real challenge, like I did with the last supplementary activity involving the reg_resid_plot. It really super challenged me, especially my capability in coding, but I tried to atleast stick with the 'norms' and styles of coding from previous numbers. Lastly, I saw how much clarity and communication can the combination of seaborn and matplotlib do in creating visuals. This is important in creating a well-formatted graph, and I thinks that's is important in conveying analysis. Overall, this activity showed me how powerful Seaborn is, and that with more hands-on practice, I can start creating more meaningful visual stories.
