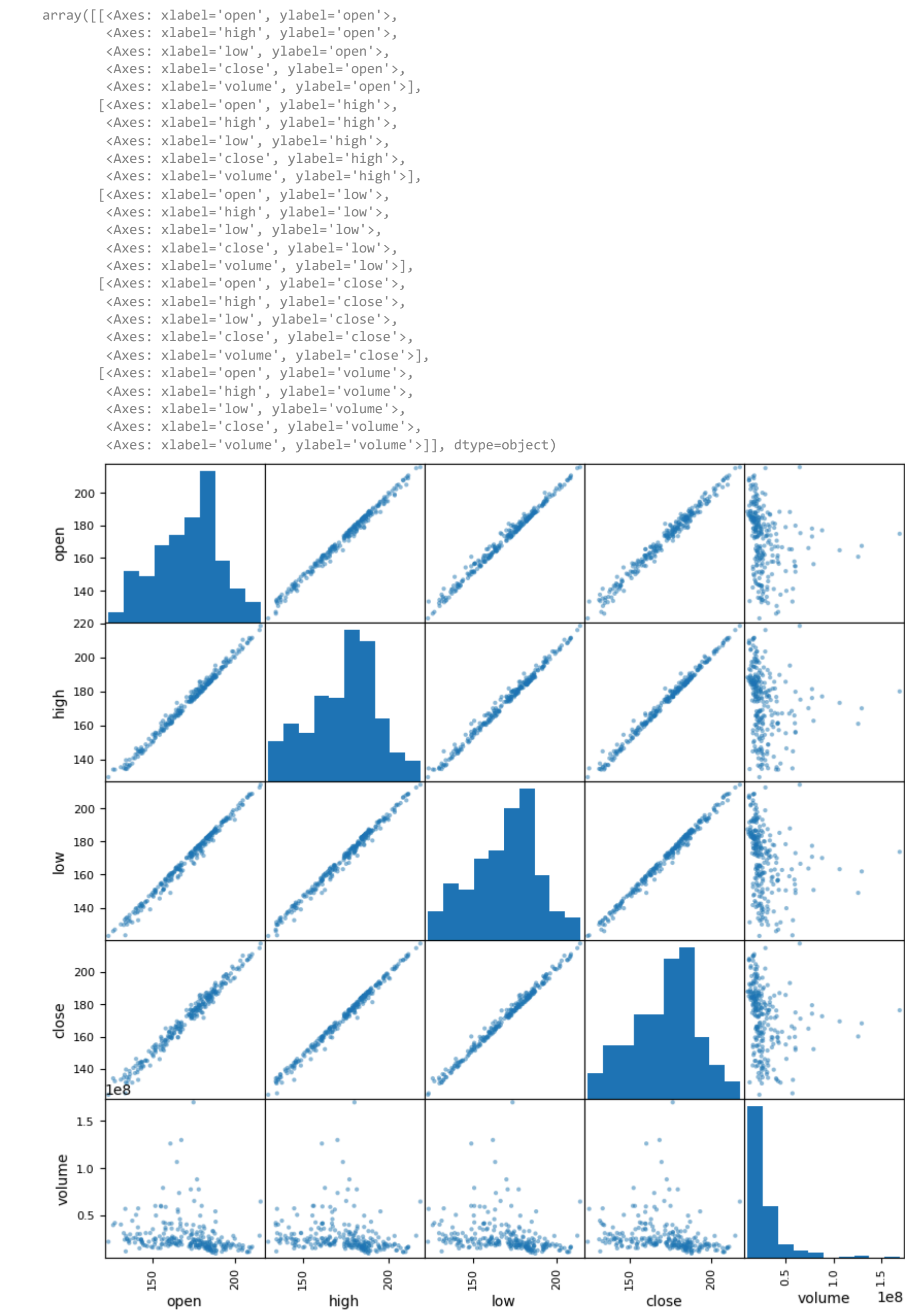


▼ pandas.plotting subpackage

▼ Setup

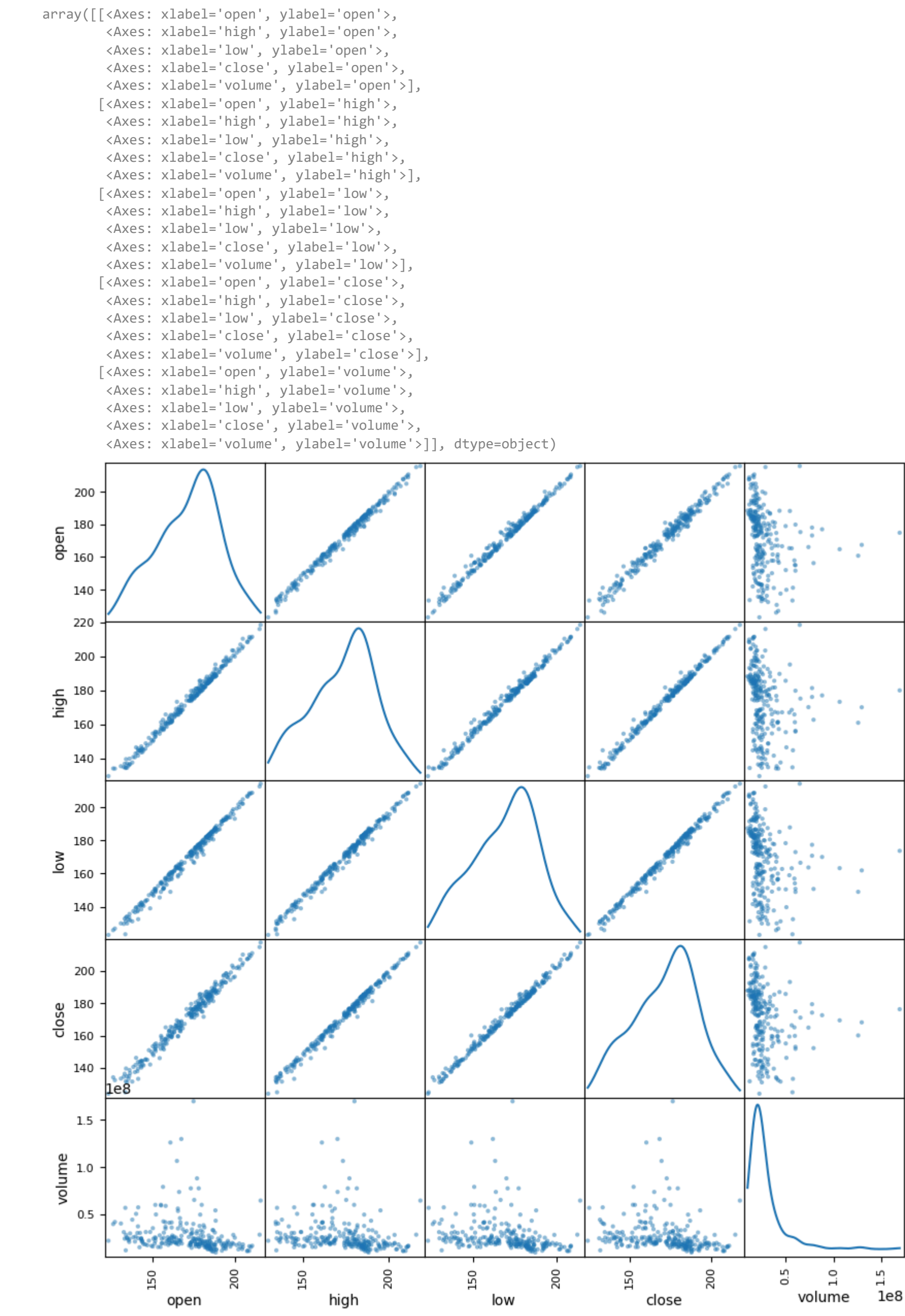
```
%matplotlib inline
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
fb = pd.read_csv(
    'fb_stock_prices_2018.csv', index_col='date', parse_dates=True
)
```

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



Changing the diagonal from histograms to KDE:

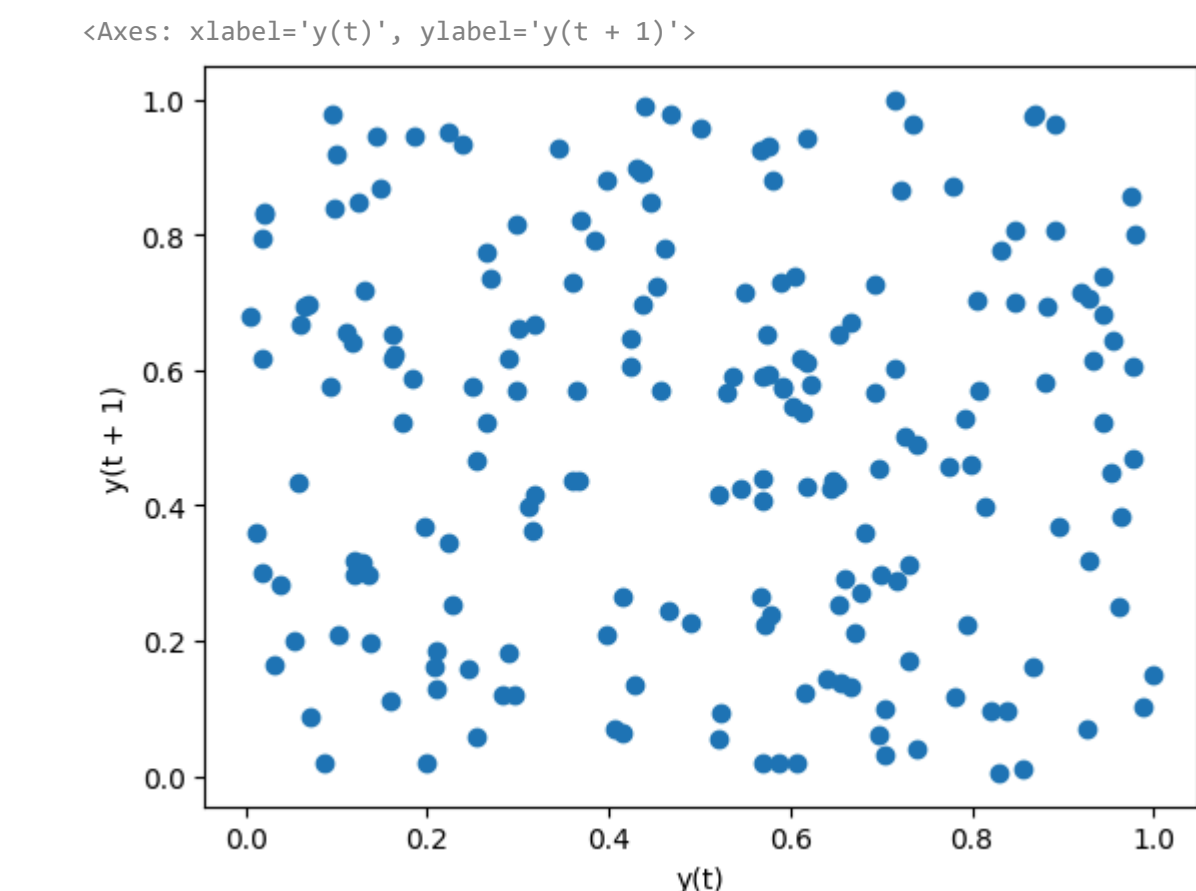
```
scatter_matrix(fb, figsize=(10, 10), diagonal='kde') # change the diagonal section to kde
```



▼ Lag plot

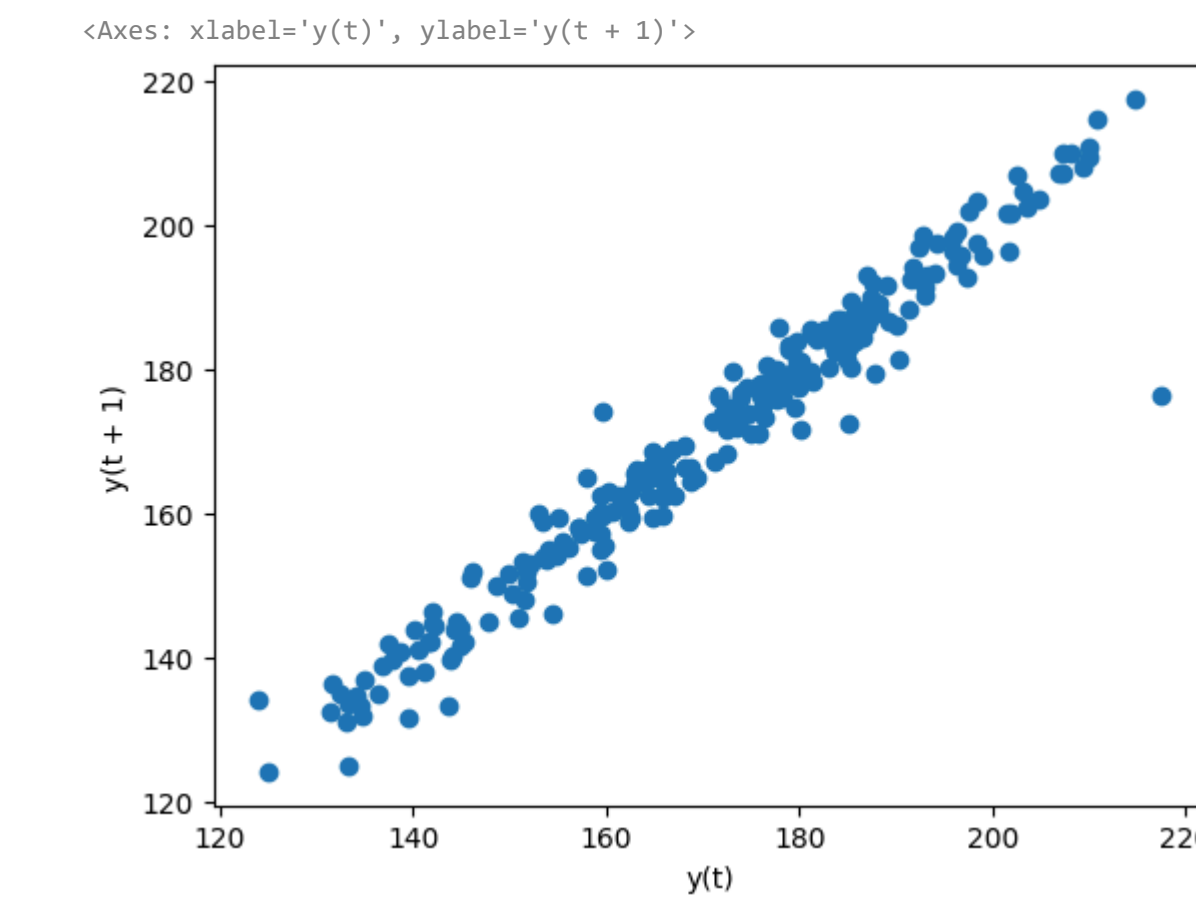
Lag plots let us see how the variable correlations with past observations of itself. Random data has no pattern:

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

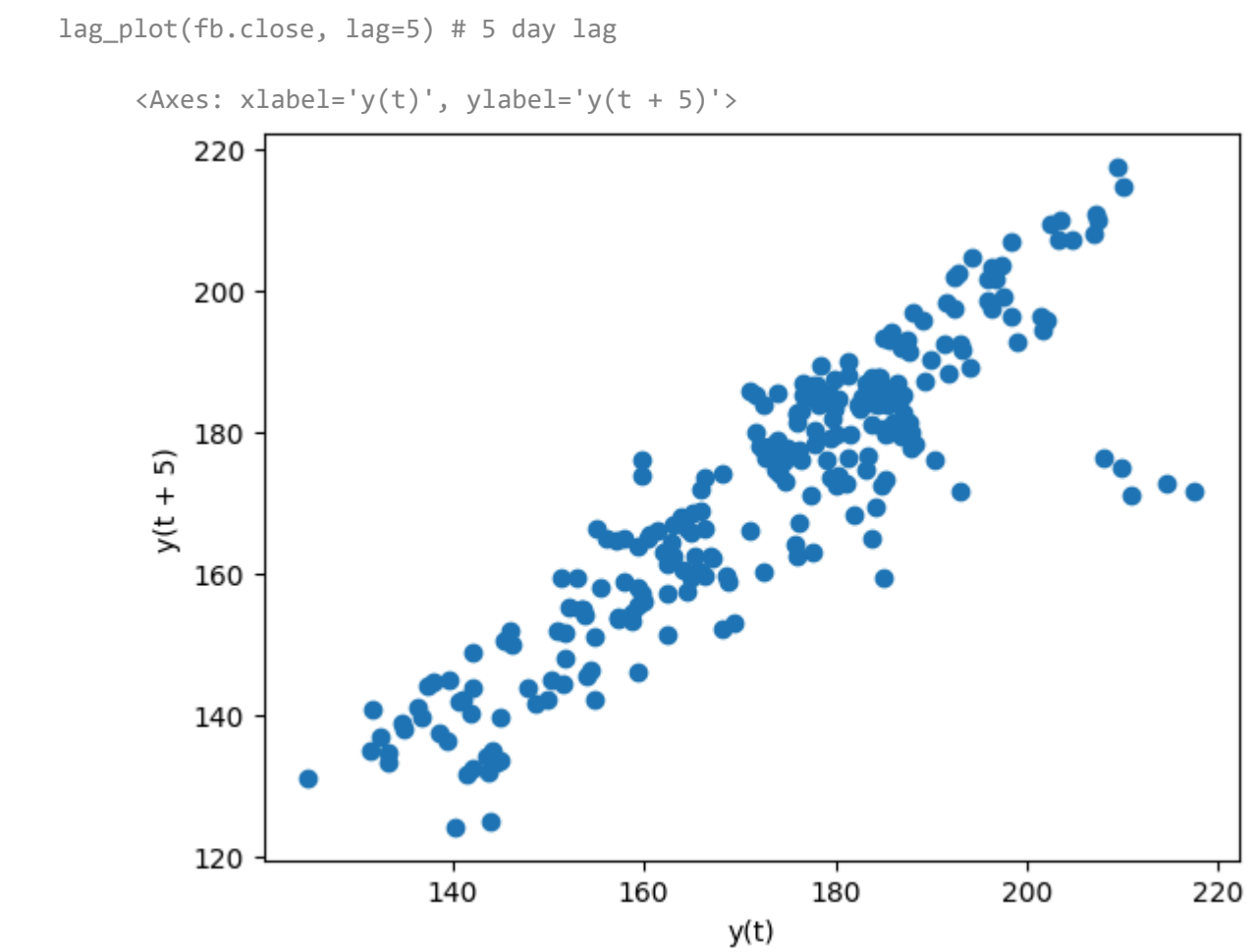


Data with some level of correlation to itself (autocorrelation) may have patterns. Stock prices are highly auto-correlated:

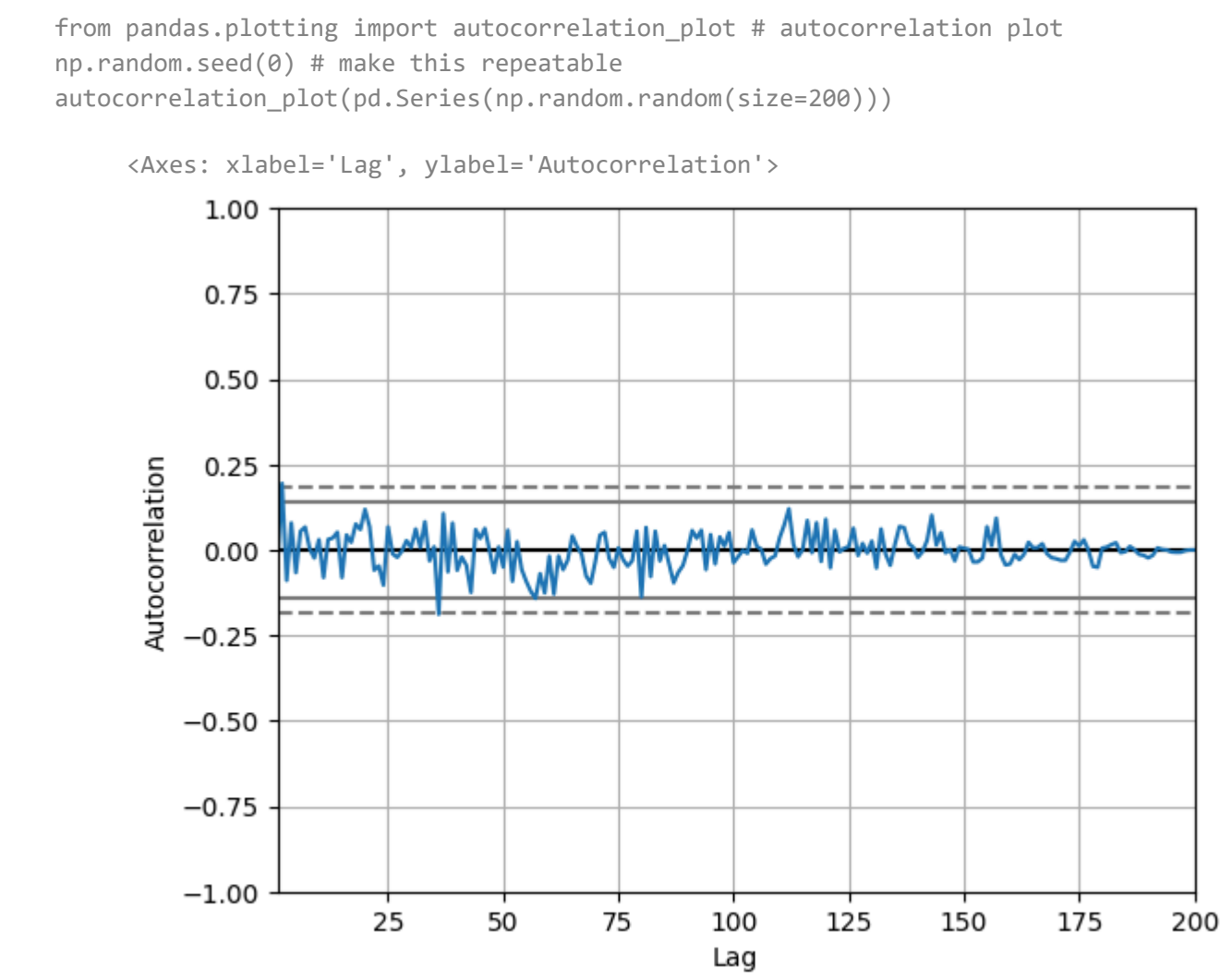
```
lag_plot(fb.close) # lag plotting closing price shows the correlation between the plots
```



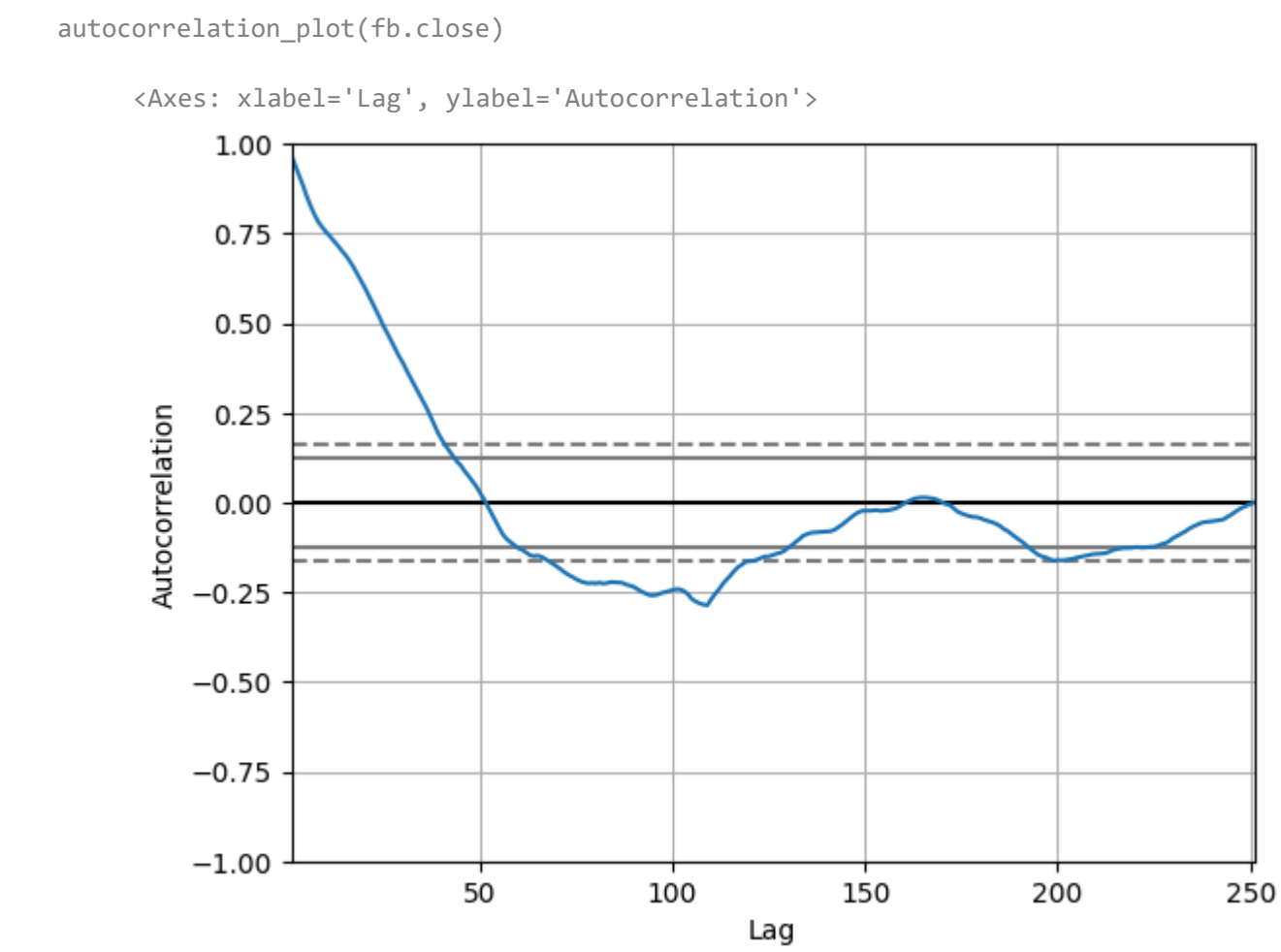
The default lag is 1, but we can alter this with the parameter. Let's look at a 5 day lag (a week of trading activity):



Autocorrelation plots



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



Bootstrap plot

This plot helps us understand the uncertainty in our summary statistics

```
from pandas.plotting import bootstrap_plot # bootstrap_plot that helps understand uncertainty in summary statistics
fig = bootstrap_plot(fb.volume, fig=plt.figure(figsize=(10, 6)))
```

