Machine learning for finance

MACHINE LEARNING FOR FINANCE IN PYTHON

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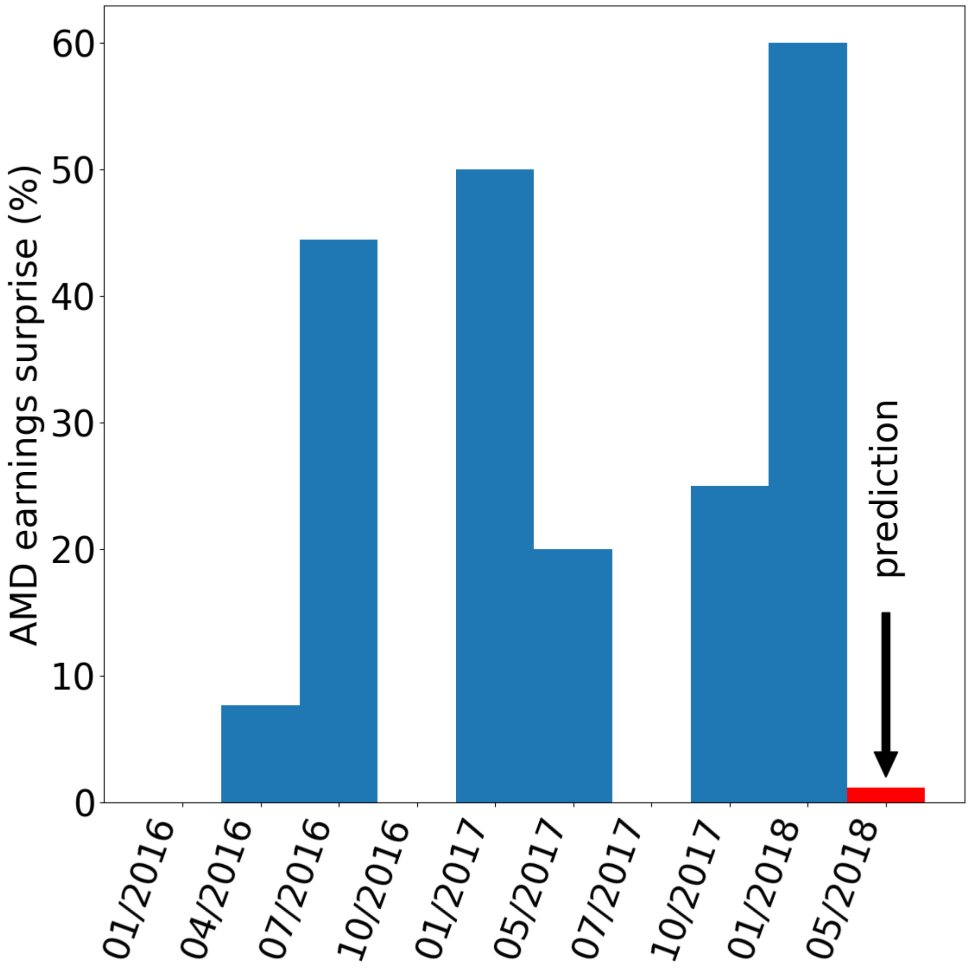
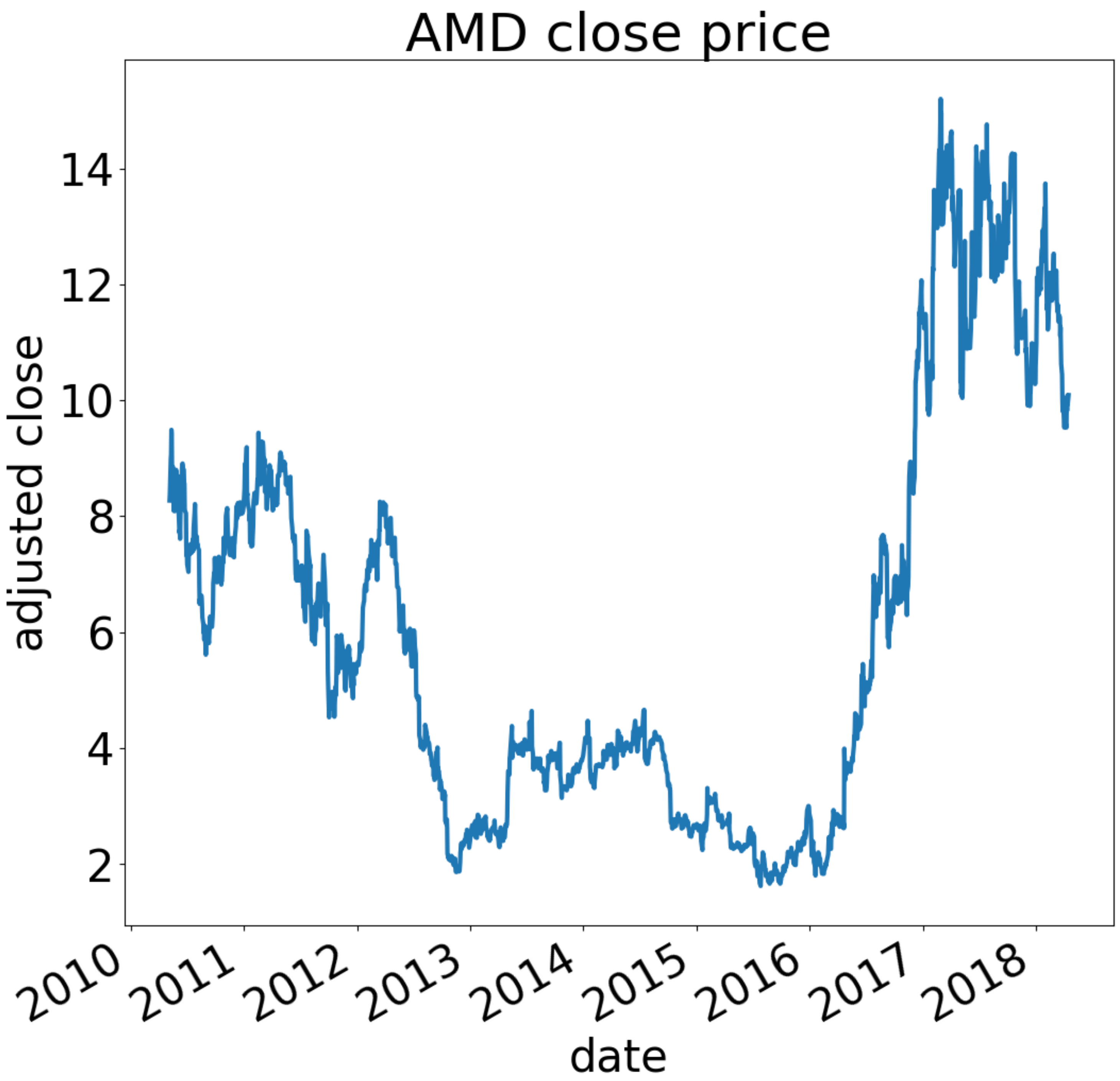
Data Science Professor

Machine Learning in Finance

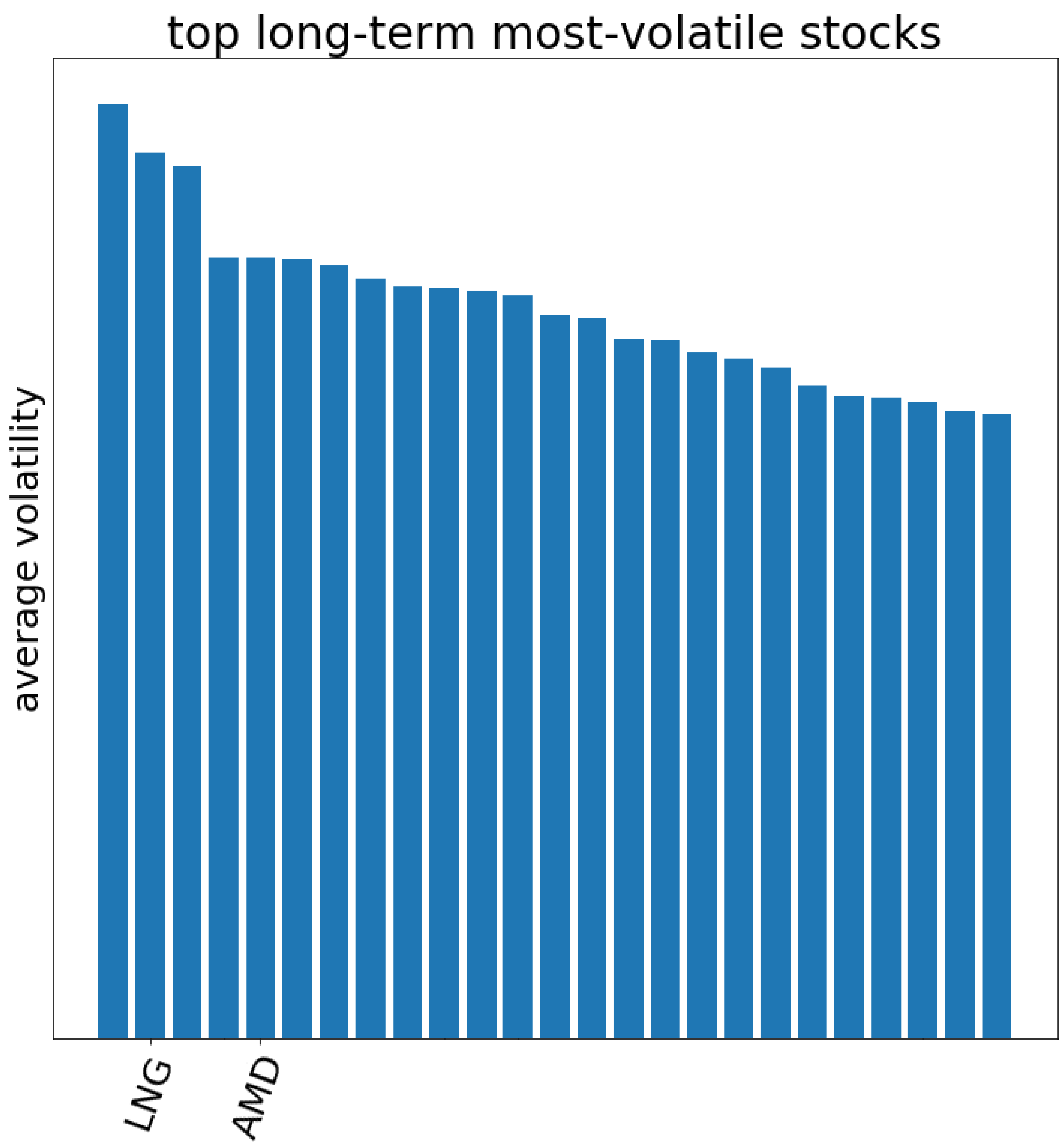


source: **https://www.zacks.com/stock/quote/AMD**

JPM report: **http://valuesimplex.com/articles/JPM.pdf**



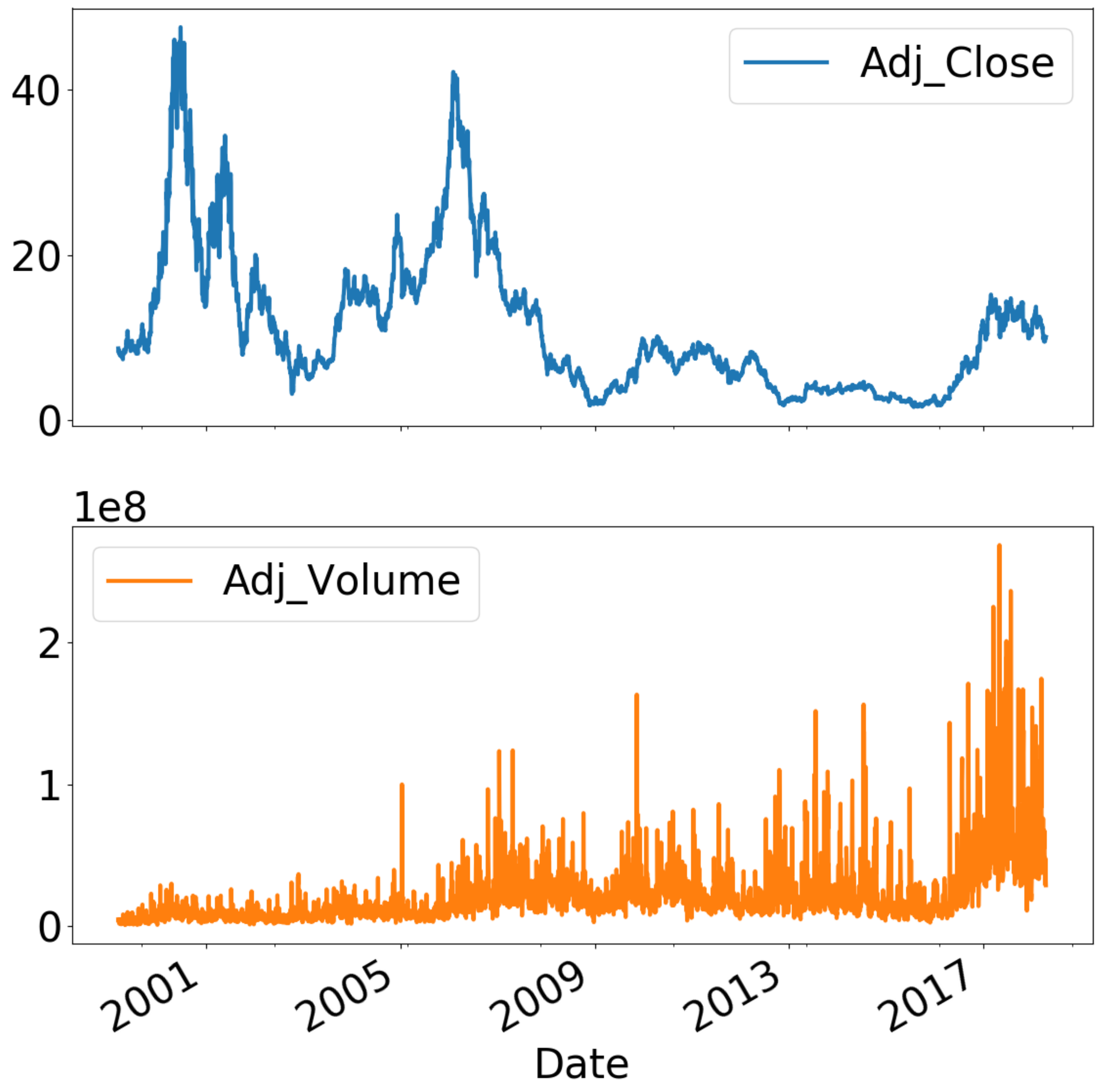
AMD close price
14
12
10
8
6
4
2
adjusted close
2010
2011
2012
2013
2014
2015
2016
2017
2018
date


top long-term most-volatile stocks
average volatility
LNG
AMD

Understanding the data

```
print(amd_df.head())
```

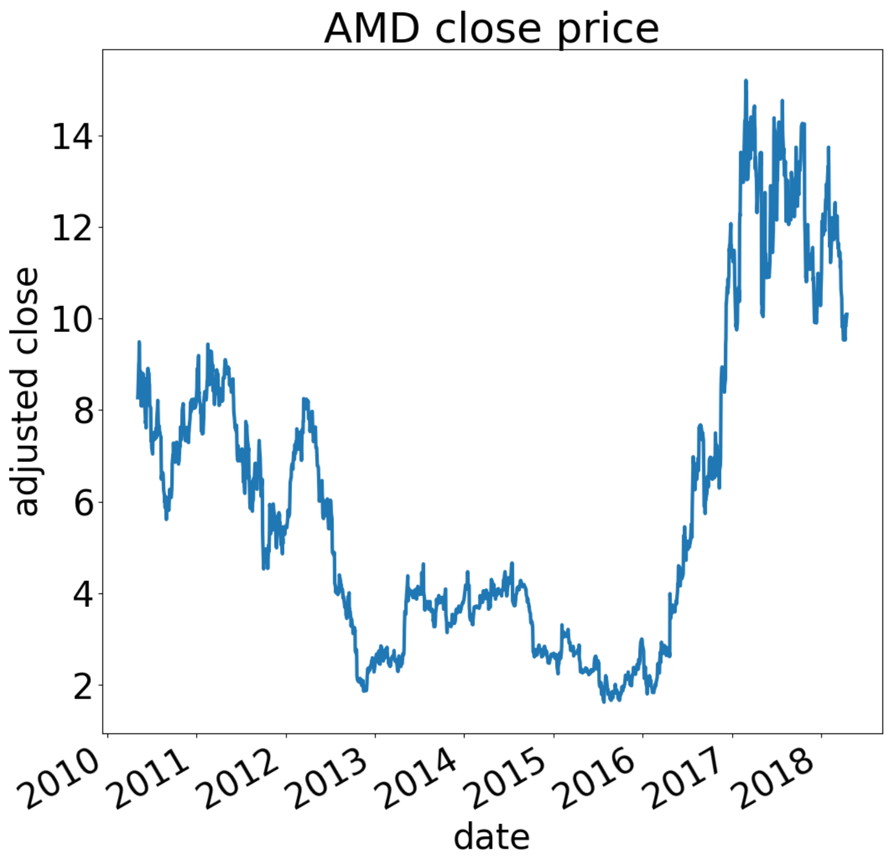
```
            Adj_Close  Adj_Volume
Date
1999-03-10      8.690   4871800.0
1999-03-11      8.500   3566600.0
1999-03-12      8.250   4126800.0
1999-03-15      8.155   3006400.0
1999-03-16      8.500   3511400.0
```



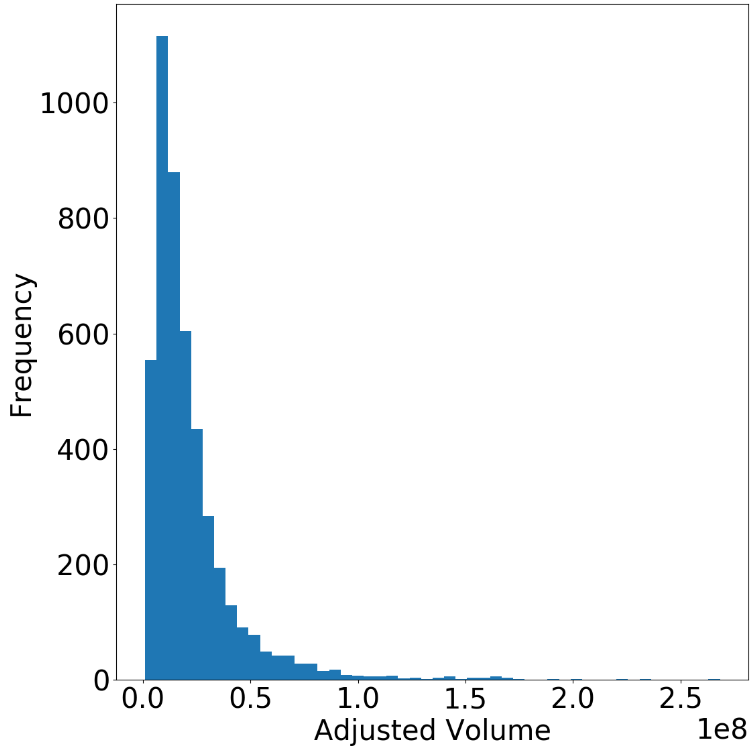
Adj_Close
40
20
0
1e8
Adj_Volume
2
1
0
2001
2005
2009
2013
2017
Date

EDA plots

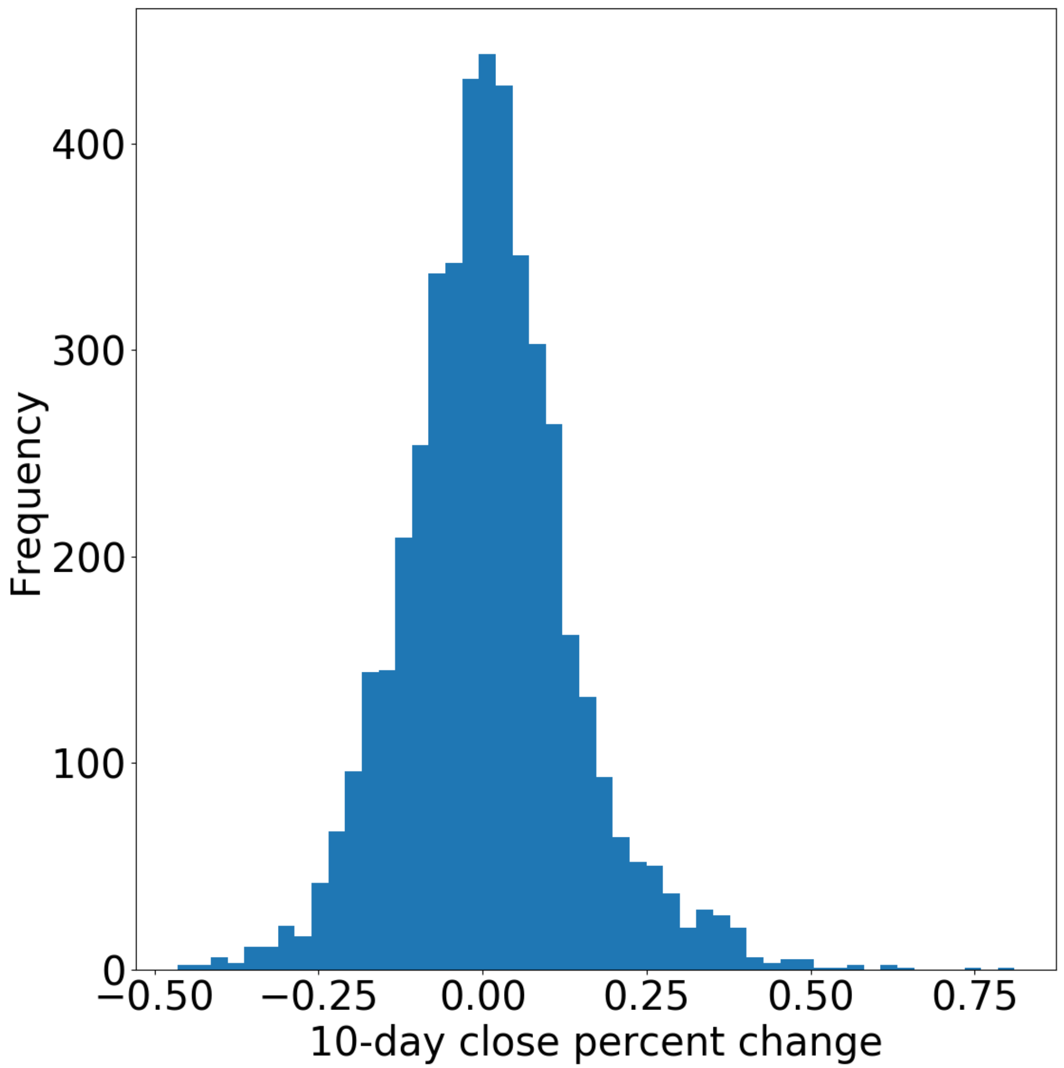
```
amd_df['Adj_Close'].plot()
plt.show()
```



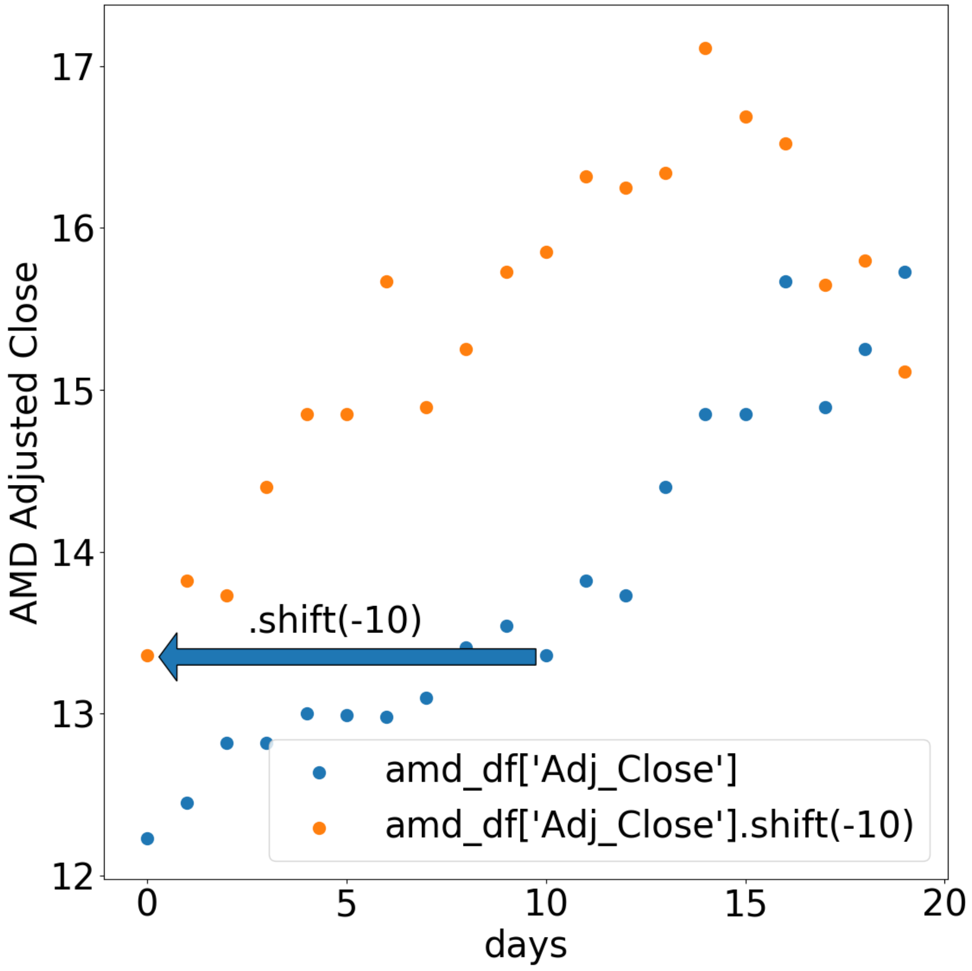

```
# clears the plot area
plt.clf()
vol = amd_df['Adj_Volume']
vol.plot.hist(bins=50)
plt.show()
```



```
amd_df['10d_close_pct'] = amd_df['Adj_Close'].pct_change(10)
amd_df['10d_close_pct'].plot.hist(bins=50)
plt.show()
```



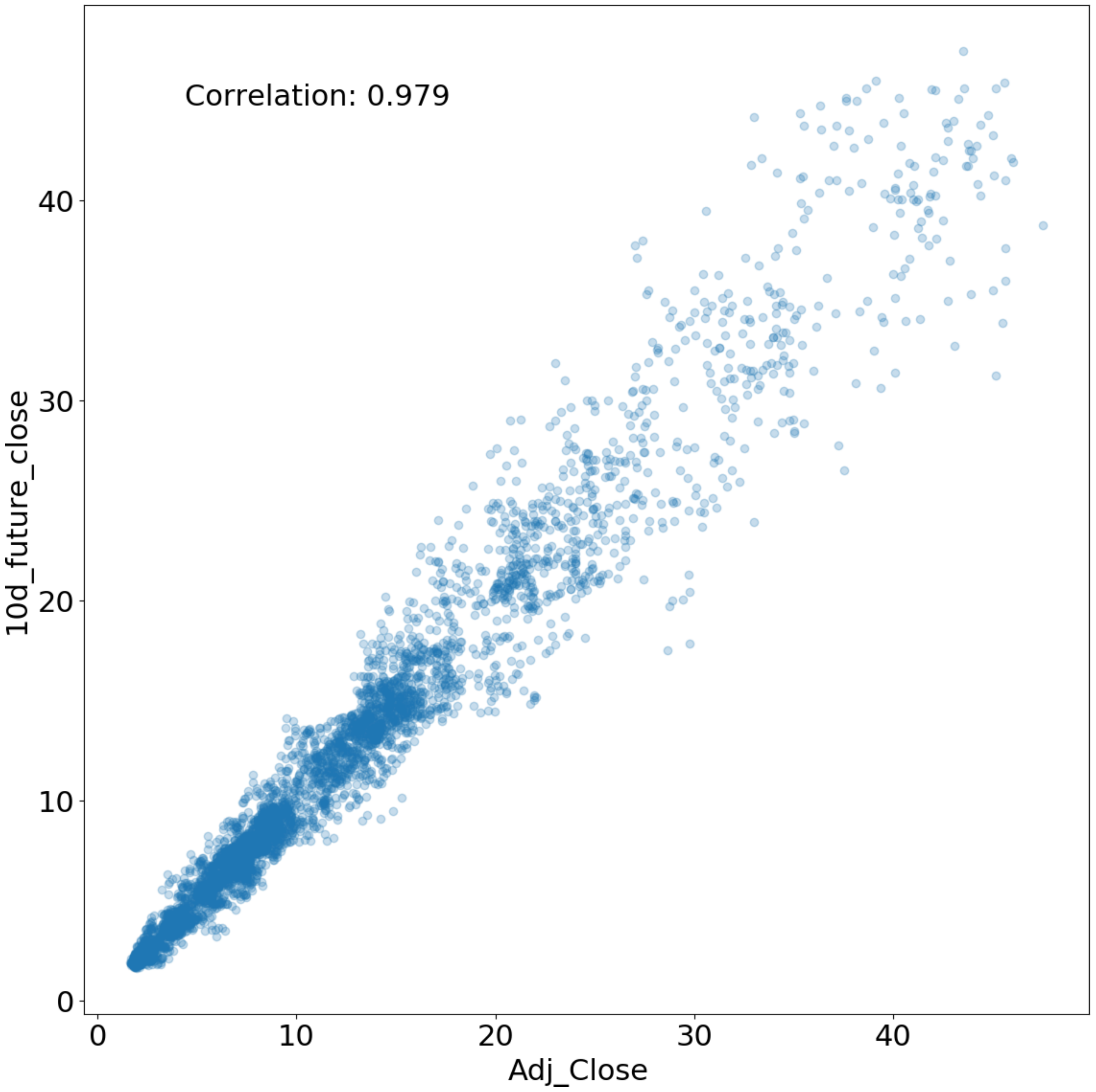
```python
amd_df['10d_future_close'] = amd_df['Adj_Close'].shift(-10)
amd_df['10d_future_close_pct'] = amd_df['10d_future_close'].pct_change(10)
```

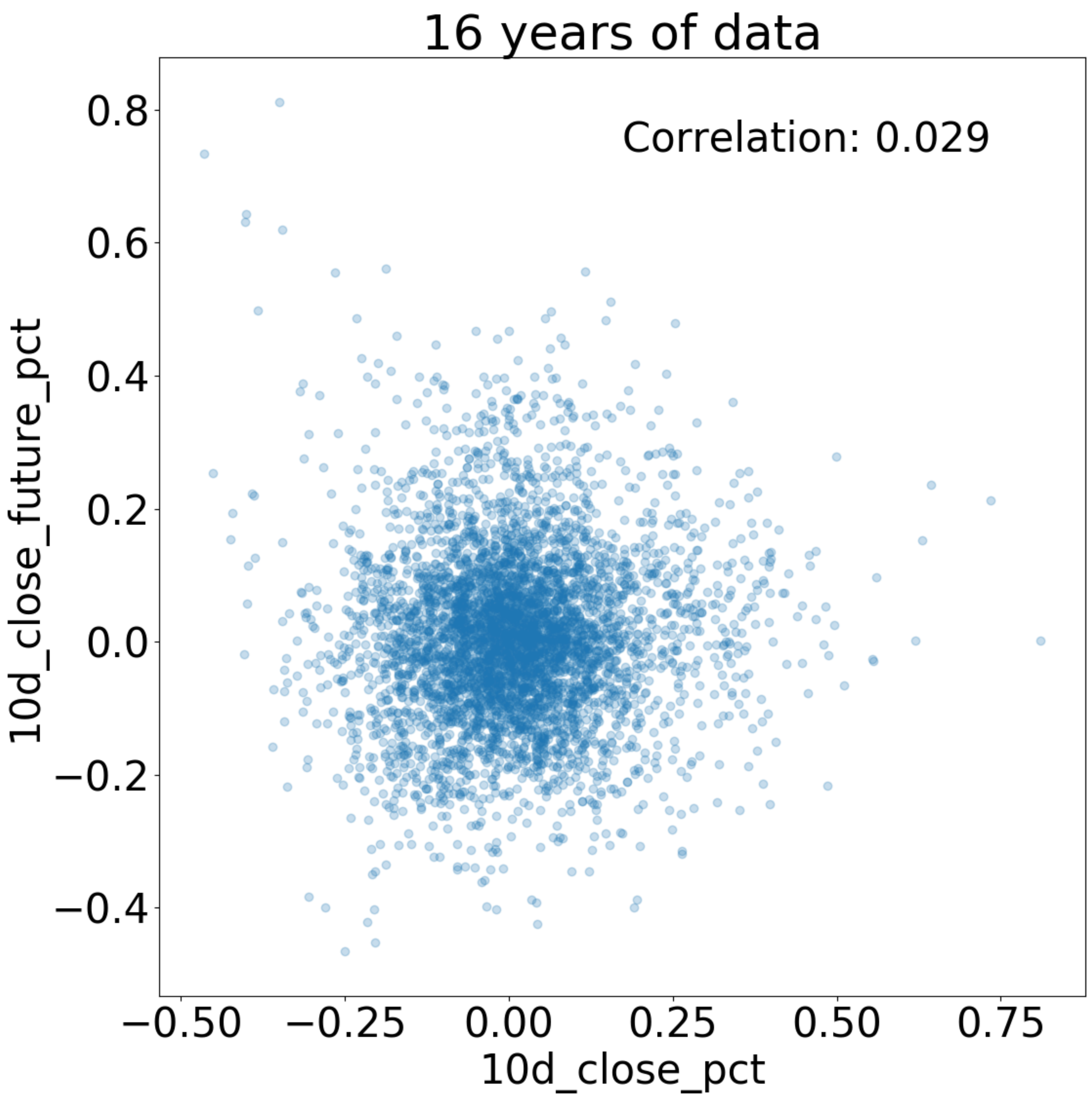


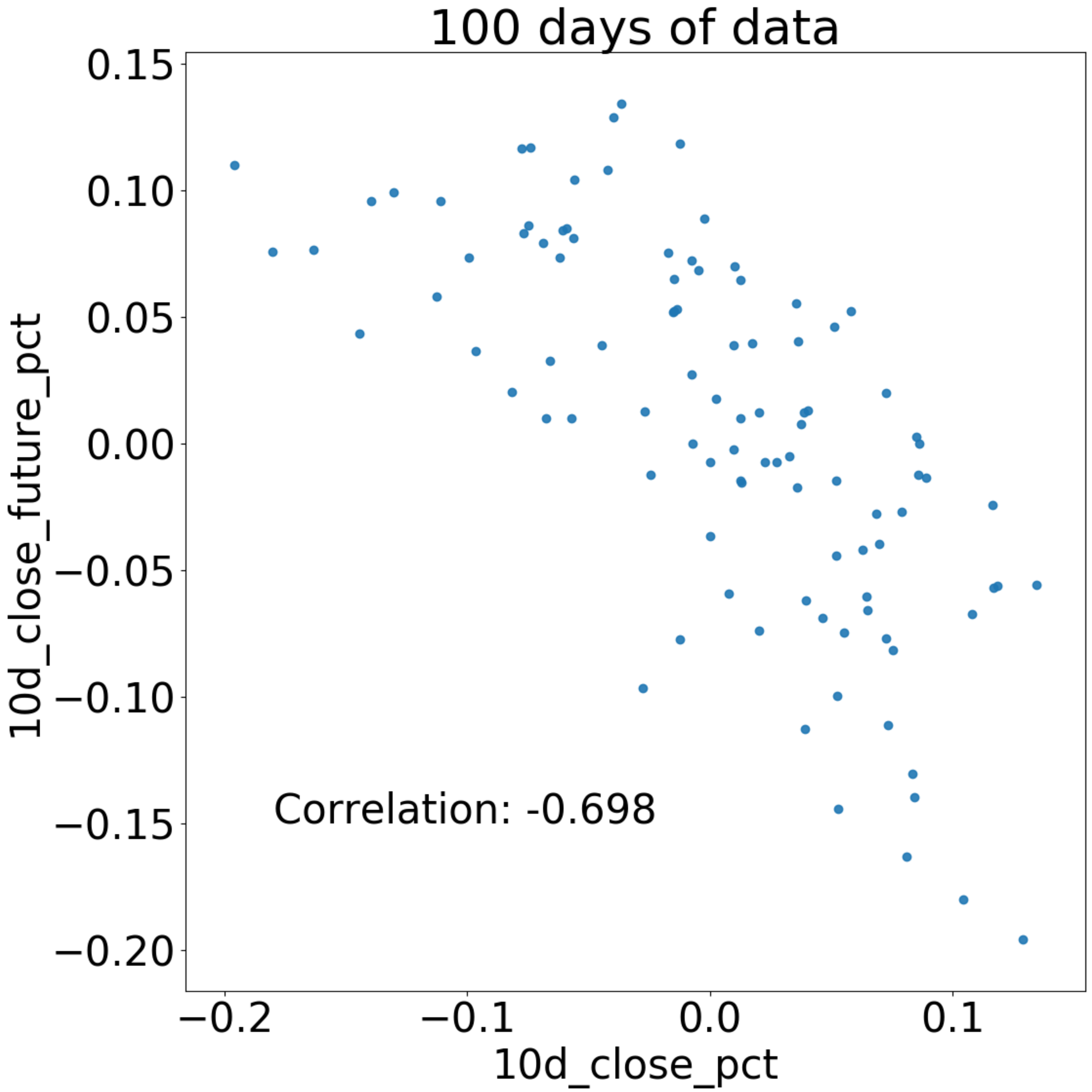
```python
corr = amd_df.corr()
print(corr)
```

```
                    10d_future_close_pct  10d_future_close  10d_close_pct  \
10d_future_close_pct              1.000000          0.070742       0.030402
10d_future_close                  0.070742          1.000000       0.082828
10d_close_pct                     0.030402          0.082828       1.000000
Adj_Close                        -0.083982          0.979345       0.073843
Adj_Volume                       -0.024456         -0.122473       0.044537

                      Adj_Close  Adj_Volume
10d_future_close_pct  -0.083982   -0.024456
10d_future_close       0.979345   -0.122473
10d_close_pct          0.073843    0.044537
Adj_Close              1.000000   -0.119437
Adj_Volume            -0.119437    1.000000
```


Correlation: 0.979
40
30
20
10
0
10d_future_close
0
10
20
30
40
Adj_Close


16 years of data
Correlation: 0.029
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4
10d_close_future_pct
−0.50
−0.25
0.00
0.25
0.50
0.75
10d_close_pct



100 days of data
0.15
0.10
0.05
0.00
−0.05
−0.10
−0.15
−0.20
10d_close_future_pct
Correlation: -0.698
−0.2
−0.1
0.0
0.1
10d_close_pct

Let's do some EDA!

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Data transforms, features, and targets

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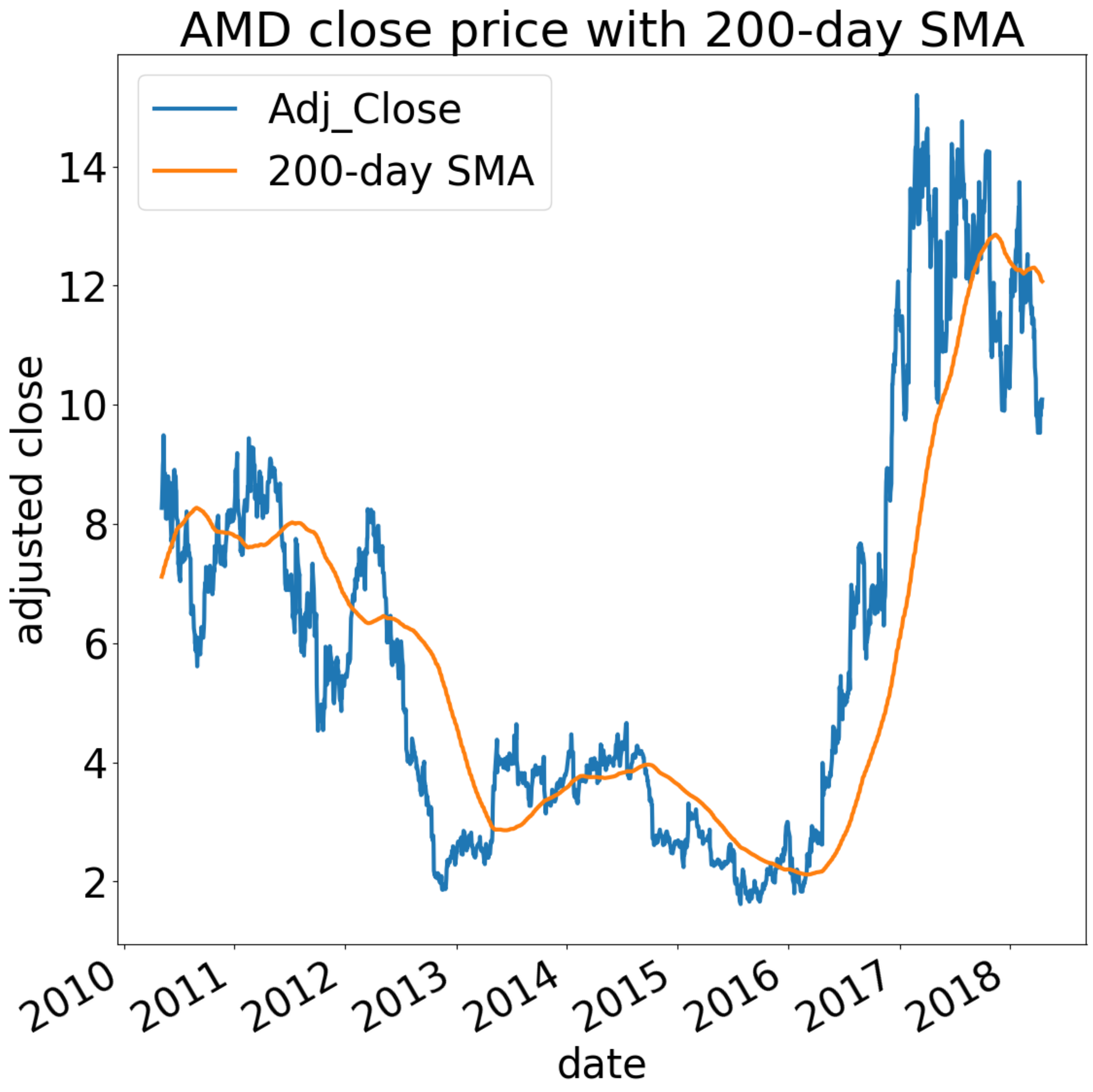
Making features and targets

```
features = amd_df[['10d_close_pct', 'Adj_Volume']]
targets = amd_df['10d_future_close_pct']
print(type(features))
```

```
pandas.core.series.DataFrame
```

```
print(type(targets))
```

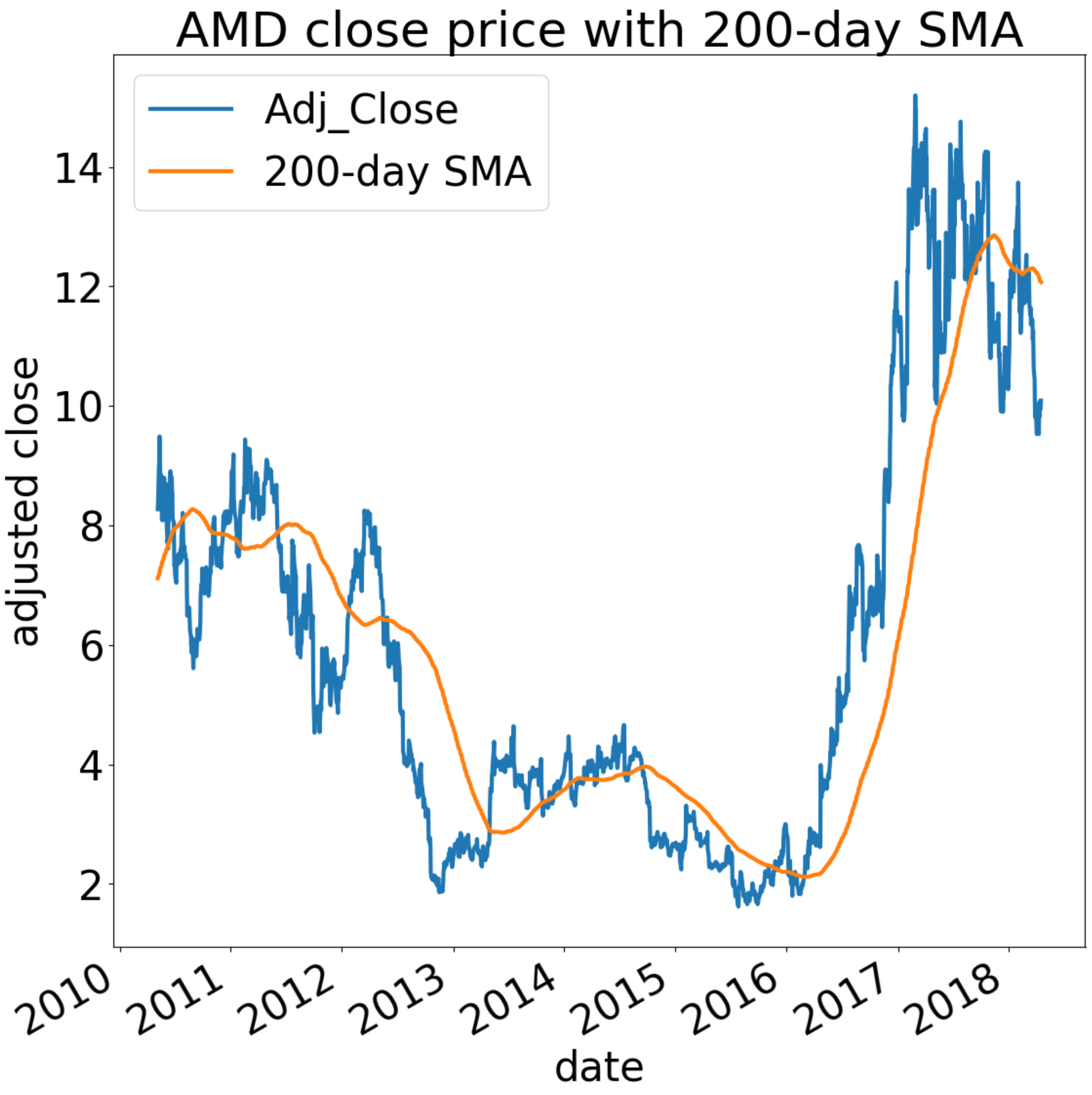
```
pandas.core.series.Series
```

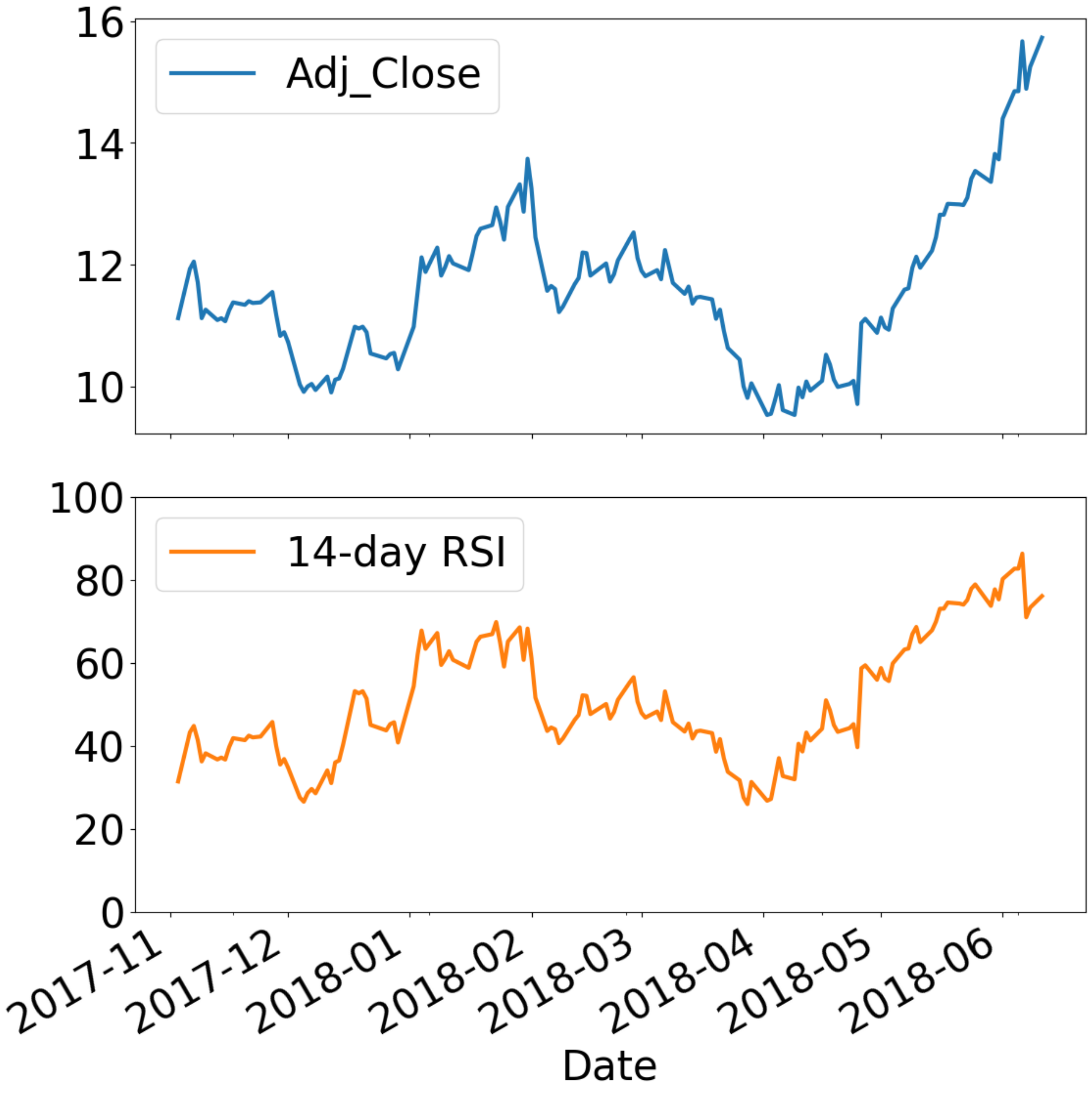

AMD close price with 200-day SMA
Adj_Close
200-day SMA
adjusted close
2
4
6
8
10
12
14
2010
2011
2012
2013
2014
2015
2016
2017
2018
date

Moving averages

Moving averages:

- use *n* past days to get average
- common values for *n*: 14, 50, 200


AMD close price with 200-day SMA
Adj_Close
200-day SMA
adjusted close
2
4
6
8
10
12
14
2010
2011
2012
2013
2014
2015
2016
2017
2018
date



Adj_Close
16
14
12
10
14-day RSI
100
80
60
40
20
0
2017-11
2017-12
2018-01
2018-02
2018-03
2018-04
2018-05
2018-06
Date

$$RSI = 100 - \frac{100}{1 + RS}$$

$$RS = \frac{\text{Average gain over } n \text{ periods}}{\text{Average loss over } n \text{ periods}}$$

Calculating SMA and RSI

```
import talib
amd_df['ma200'] = talib.SMA(amd_df['Adj_Close'].values, timeperiod=200)
amd_df['rsi200'] = talib.RSI(amd_df['Adj_Close'].values, timeperiod=200)
```

Finally, our features

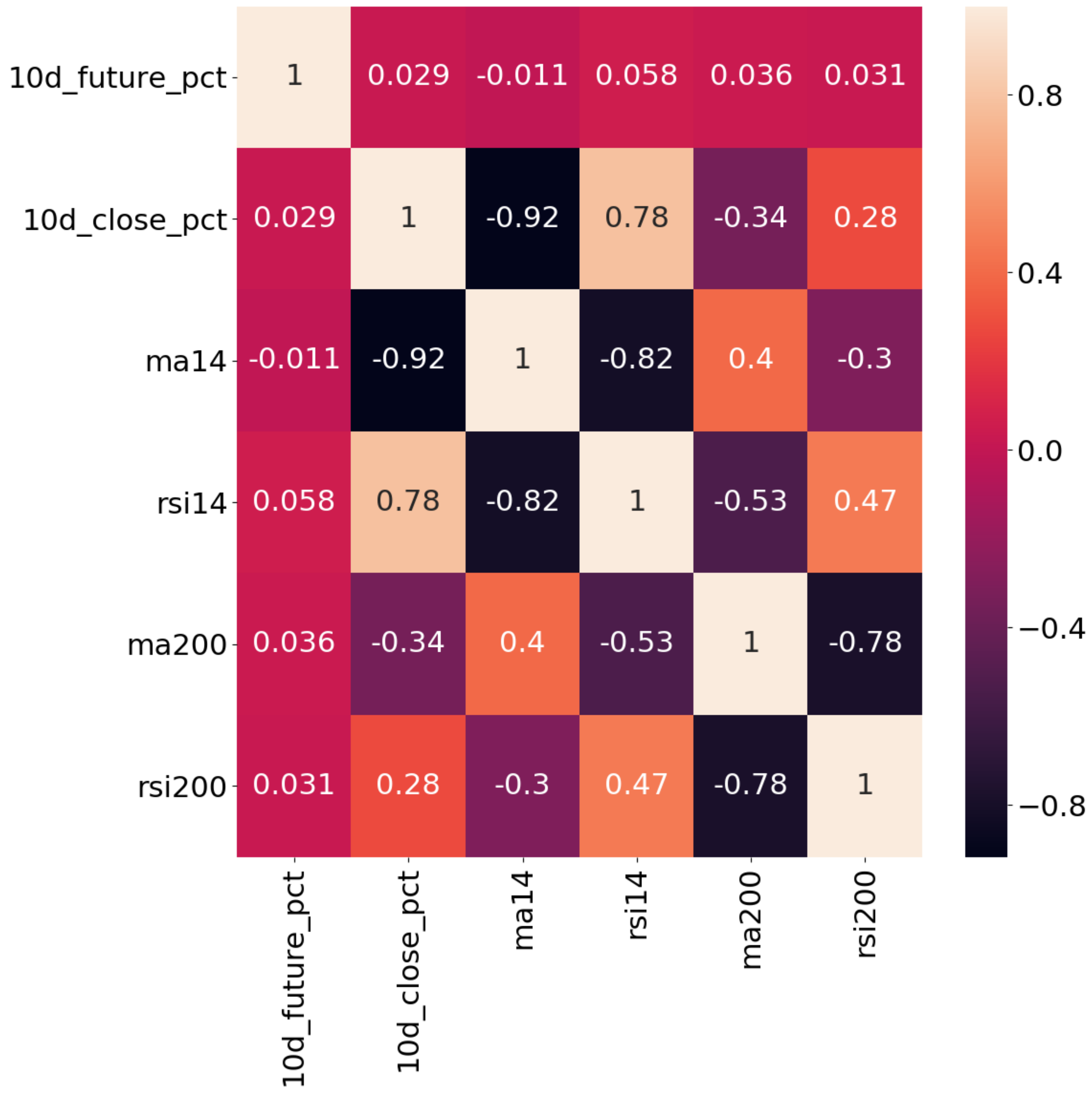
```
feature_names = ['10d_close_pct', 'ma200', 'rsi200']
features = amd_df[feature_names]
targets = amd_df['10d_future_close_pct']

feature_target_df = amd_df[feature_names + '10d_future_close_pct']
```

Check correlations

```
import seaborn as sns


corr = feature_target_df.corr()
sns.heatmap(corr, annot=True)
```


10d_future_pct
10d_close_pct
ma14
rsi14
ma200
rsi200
1 0.029 -0.011 0.058 0.036 0.031
0.029 1 -0.92 0.78 -0.34 0.28
-0.011 -0.92 1 -0.82 0.4 -0.3
0.058 0.78 -0.82 1 -0.53 0.47
0.036 -0.34 0.4 -0.53 1 -0.78
0.031 0.28 -0.3 0.47 -0.78 1
0.8
0.4
0.0
−0.4
−0.8

Let's create features and targets!

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Linear modeling with financial data

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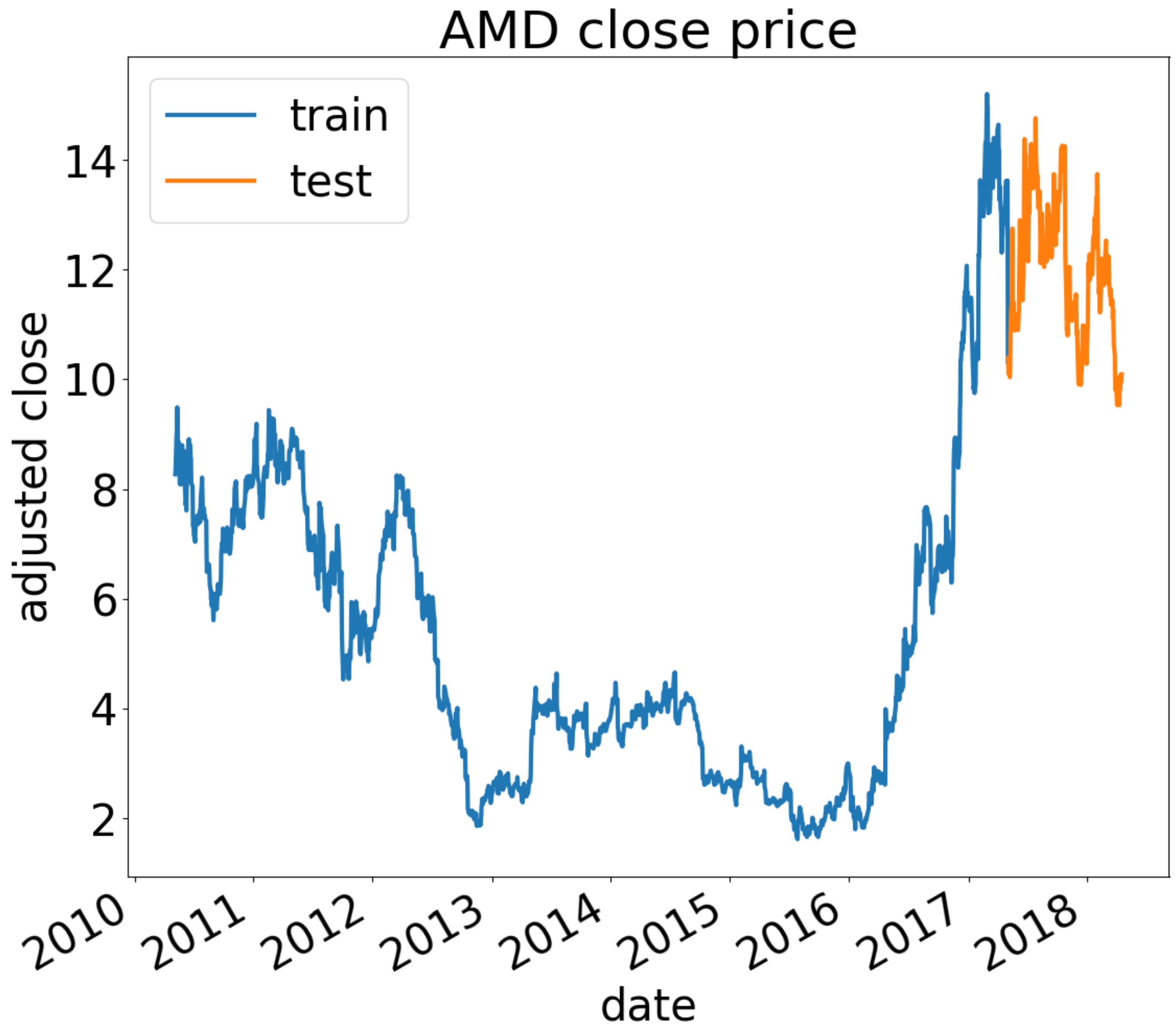

AMD close price
train
test
14
12
10
8
6
4
2
adjusted close
2010
2011
2012
2013
2014
2015
2016
2017
2018
date

Make train and test sets

```
import statsmodels.api as sm
linear_features = sm.add_constant(features)
train_size = int(0.85 * targets.shape[0])
train_features = linear_features[:train_size]
train_targets = targets[:train_size]
test_features = linear_features[train_size:]
test_targets = targets[train_size:]
```

```
some_list[start:stop:step]
```

Linear modeling

```
model = sm.OLS(train_targets, train_features)
results = model.fit()
```

Linear modeling

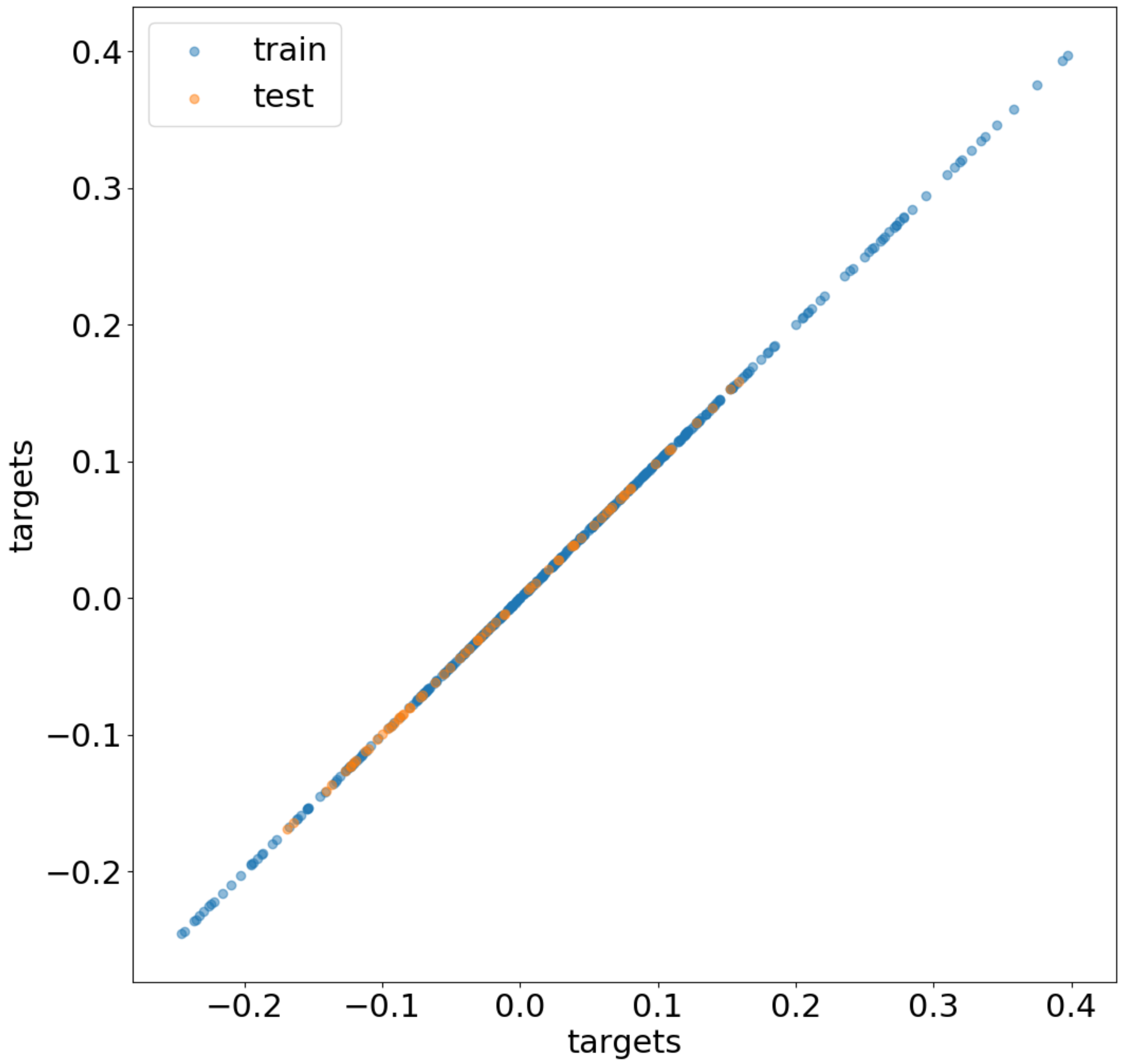
```
print(results.summary())
```

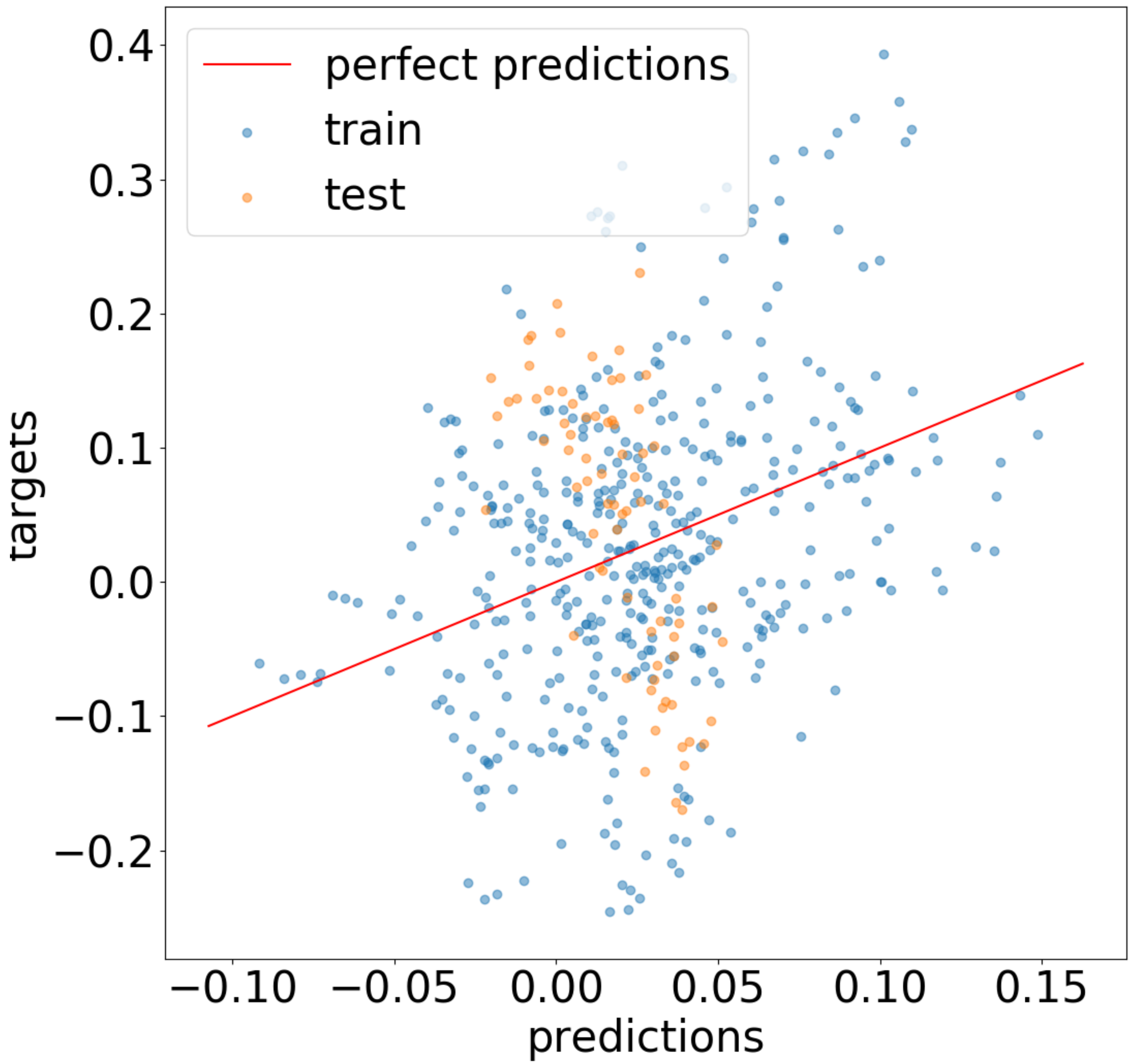
```
Dep. Variable:         10d_future_pct   R-squared:                       0.157
Model:                            OLS   Adj. R-squared:                  0.146
Method:                 Least Squares   F-statistic:                     15.55
Date:                Thu, 19 Apr 2018   Prob (F-statistic):              4.79e-14
Time:                        11:41:05   Log-Likelihood:                  336.53
No. Observations:                 425   AIC:                            -661.1
Df Residuals:                     419   BIC:                            -636.8
Df Model:                           5
Covariance Type:            nonrobust
============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
<hr />--------------------------------------------------------------------------------
const           1.3305      0.323      4.117      0.000       0.695       1.966
10d_close_pct   0.0906      0.098      0.927      0.355      -0.102       0.283
ma14            0.3313      0.209      1.585      0.114      -0.080       0.742
rsi14          -0.0013      0.001     -1.044      0.297      -0.004       0.001
ma200          -0.4090      0.053     -7.712      0.000      -0.513      -0.305
rsi200         -0.0224      0.003     -6.610      0.000      -0.029      -0.016
============================================================================
Omnibus:                        3.571   Durbin-Watson:                   0.209
Prob(Omnibus):                  0.168   Jarque-Bera (JB):                3.323
Skew:                           0.202   Prob(JB):                        0.190
Kurtosis:                       3.159   Cond. No.                        5.47e+03
```

p-values

```
print(results.pvalues)
```

```
const            4.630428e-05
10d_close_pct    3.546748e-01
ma14             1.136941e-01
rsi14            2.968699e-01
ma200            9.126405e-14
rsi200           1.169324e-10
```


train
test
0.4
0.3
0.2
0.1
0.0
−0.1
−0.2
targets
−0.2
−0.1
0.0
0.1
0.2
0.3
0.4
targets


perfect predictions
train
test
targets
predictions
0.4
0.3
0.2
0.1
0.0
−0.1
−0.2
−0.10
−0.05
0.00
0.05
0.10
0.15

Time to fit a linear model!

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