pandas Foundations

What is pandas?

- Python library for data analysis
- High-performance containers for data analysis
- Data structures with a lot of functionality
    - Meaningful labels
    - Time series functionality
    - Handling missing data
    - Relational operations

What you will learn

- How to work with pandas
    - Data import & export in various formats
- Exploratory Data Analysis using pandas
    - Statistical & graphical methods
- Using pandas to model *time series*
    - Time indexes, resampling

PANDAS FOUNDATIONS

See you in the course!

PANDAS FOUNDATIONS

Review of pandas DataFrames

pandas DataFrames

- Example: DataFrame of Apple Stock data

Date	Open	High	Low	Close	Volume	Adj Close
2014-09-16	99.80	101.26	98.89	100.86	66818200	100.86
2014-09-15	102.81	103.05	101.44	101.63	61216500	101.63
2014-09-12	101.21	102.19	101.08	101.66	62626100	101.66
...	...	...	...	...	...	...

Indexes and columns

```
In [1]: import pandas as pd

In [2]: type(AAPL)
Out[2]: pandas.core.frame.DataFrame

In [3]: AAPL.shape
Out[3]: (8514, 6)

In [4]: AAPL.columns
Out[4]:
Index(['Open', 'High', 'Low', 'Close', 'Volume', 'Adj Close'],
dtype=‘object’)

In [5]: type(AAPL.columns)
Out[5]: pandas.indexes.base.Index
```

Indexes and columns

```
In [6]: AAPL.index
Out[6]:
DatetimeIndex(['2014-09-16', '2014-09-15', '2014-09-12',
               '2014-09-11', '2014-09-10', '2014-09-09',
               '2014-09-08', '2014-09-05', '2014-09-04',
               '2014-09-03',
               ...
               '1980-12-26', ‘1980-12-24', '1980-12-23',
               '1980-12-22', '1980-12-19', '1980-12-18',
               '1980-12-17', '1980-12-16', '1980-12-15',
               '1980-12-12'],
              dtype='datetime64[ns]', name='Date', length=8514,
              freq=None)

In [7]: type(AAPL.index)
Out[7]: pandas.tseries.index.DatetimeIndex
```

Slicing

```
In [8]: AAPL.iloc[:5,:]
Out[8]:
              Open    High     Low   Close     Volume  Adj Close
Date
2014-09-16   99.80  101.26   98.89  100.86   66818200     100.86
2014-09-15  102.81  103.05  101.44  101.63   61216500     101.63
2014-09-12  101.21  102.19  101.08  101.66   62626100     101.66
2014-09-11  100.41  101.44   99.62  101.43   62353100     101.43
2014-09-10   98.01  101.11   97.76  101.00  100741900     101.00

In [9]: AAPL.iloc[-5:,:]
Out[9]:
             Open   High    Low  Close     Volume  Adj Close
Date
1980-12-18  26.63  26.75  26.63  26.63   18362400       0.41
1980-12-17  25.87  26.00  25.87  25.87   21610400       0.40
1980-12-16  25.37  25.37  25.25  25.25   26432000       0.39
1980-12-15  27.38  27.38  27.25  27.25   43971200       0.42
1980-12-12  28.75  28.87  28.75  28.75  117258400       0.45
```

head()

```
In [10]: AAPL.head(5)
Out[10]:
             Open    High     Low   Close     Volume  Adj Close
Date
2014-09-16   99.80  101.26   98.89  100.86   66818200     100.86
2014-09-15  102.81  103.05  101.44  101.63   61216500     101.63
2014-09-12  101.21  102.19  101.08  101.66   62626100     101.66
2014-09-11  100.41  101.44   99.62  101.43   62353100     101.43
2014-09-10   98.01  101.11   97.76  101.00  100741900     101.00

In [11]: AAPL.head(2)
Out[11]:
             Open    High     Low   Close    Volume  Adj Close
Date
2014-09-16   99.80  101.26   98.89  100.86  66818200     100.86
2014-09-15  102.81  103.05  101.44  101.63  61216500     101.63
```

tail()

```
In [12]: AAPL.tail()
Out[12]:
             Open   High    Low  Close     Volume  Adj Close
Date
1980-12-18  26.63  26.75  26.63  26.63   18362400       0.41
1980-12-17  25.87  26.00  25.87  25.87   21610400       0.40
1980-12-16  25.37  25.37  25.25  25.25   26432000       0.39
1980-12-15  27.38  27.38  27.25  27.25   43971200       0.42
1980-12-12  28.75  28.87  28.75  28.75  117258400       0.45

In [13]: AAPL.tail(3)
Out[13]:
             Open   High    Low  Close     Volume  Adj Close
Date
1980-12-16  25.37  25.37  25.25  25.25   26432000       0.39
1980-12-15  27.38  27.38  27.25  27.25   43971200       0.42
1980-12-12  28.75  28.87  28.75  28.75  117258400       0.45
```

info()

```
In [14]: AAPL.info()
Out[14]:
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 8514 entries, 2014-09-16 to 1980-12-12
Data columns (total 6 columns):
Open          8514 non-null float64
High          8514 non-null float64
Low           8514 non-null float64
Close         8514 non-null float64
Volume        8514 non-null int64
Adj Close     8514 non-null float64
dtypes: float64(5), int64(1)
memory usage: 465.6 KB
```

Broadcasting

```
In [15]: import numpy as np

In [16]: AAPL.iloc[::3, -1] = np.nan

In [17]: AAPL.head(6)
Out[17]:
              Open    High     Low   Close     Volume  Adj Close
Date
2014-09-16   99.80  101.26   98.89  100.86   66818200        NaN
2014-09-15  102.81  103.05  101.44  101.63   61216500     101.63
2014-09-12  101.21  102.19  101.08  101.66   62626100     101.66
2014-09-11  100.41  101.44   99.62  101.43   62353100        NaN
2014-09-10   98.01  101.11   97.76  101.00  100741900     101.00
2014-09-09   99.08  103.08   96.14   97.99  189560600      97.99
2014-09-08   99.30   99.31   98.05   98.36   46277800        NaN
```

Assigning scalar value to column slice *broadcasts* value to each row.

Broadcasting

```
In [18]: AAPL.info()
Out[18]:
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 8514 entries, 2014-09-16 to 1980-12-12
Data columns (total 6 columns):
Open          8514 non-null float64
High          8514 non-null float64
Low           8514 non-null float64
Close         8514 non-null float64
Volume        8514 non-null int64
Adj Close     5676 non-null float64
dtypes: float64(5), int64(1)
memory usage: 465.6 KB
```

Series

```
In [19]: low = AAPL['Low']

In [20]: type(low)
Out[20]: pandas.core.series.Series

In [21]: low.head()
Out[21]:
Date
2014-09-16     98.89
2014-09-15    101.44
2014-09-12    101.08
2014-09-11     99.62
2014-09-10     97.76
Name: Low, dtype: float64

In [22]: lows = low.values

In [23]: type(lows)
Out[23]: numpy.ndarray
```

Let's practice!

Building DataFrames from scratch

DataFrames from CSV files

```
In [1]: import pandas as pd

In [2]: users = pd.read_csv('datasets/users.csv', index_col=0)

In [3]: print(users)
Out[3]:
  weekday    city  visitors  signups
0     Sun  Austin       139        7
1     Sun  Dallas       237       12
2     Mon  Austin       326        3
3     Mon  Dallas       456        5
```

DataFrames from dict (1)

```
In [1]: import pandas as pd

In [2]: data = {'weekday': ['Sun', 'Sun', 'Mon', 'Mon'],
   ...:         'city': ['Austin', 'Dallas', 'Austin', 'Dallas',
   ...:         'visitors': [139, 237, 326, 456],
   ...:         'signups': [7, 12, 3, 5]}

In [3]: users = pd.DataFrame(data)

In [4]: print(users)
Out[4]:
  weekday    city  visitors  signups
0     Sun  Austin       139        7
1     Sun  Dallas       237       12
2     Mon  Austin       326        3
3     Mon  Dallas       456        5
```

DataFrames from dict (2)

```
In [1]: import pandas as pd

In [2]: cities = ['Austin', 'Dallas', 'Austin', 'Dallas']

In [3]: signups = [7, 12, 3, 5]

In [4]: visitors = [139, 237, 326, 456]

In [5]: weekdays = ['Sun', 'Sun', 'Mon', 'Mon']

In [6]: list_labels = ['city', 'signups', 'visitors', 'weekday']

In [7]: list_cols = [cities, signups, visitors, weekdays]

In [8]: zipped = list(zip(list_labels, list_cols))
```

DataFrames from dict (3)

```
In [9]: print(zipped)
Out[9]:
[('city', ['Austin', 'Dallas', 'Austin', 'Dallas']), ('signups',
[7, 12, 3, 5]), ('visitors', [139, 237, 326, 456]), ('weekday',
['Sun', 'Sun', 'Mon', 'Mon'])]

In [10]: data = dict(zipped)

In [11]: users = pd.DataFrame(data)

In [12]: print(users)
Out[12]:
  weekday    city  visitors  signups
0     Sun  Austin       139        7
1     Sun  Dallas       237       12
2     Mon  Austin       326        3
3     Mon  Dallas       456        5
```

Broadcasting

```
In [13]: users['fees'] = 0 # Broadcasts to entire column

In [14]: print(users)
Out[14]:
     city  signups  visitors weekday  fees
0  Austin        7       139     Sun     0
1  Dallas       12       237     Sun     0
2  Austin        3       326     Mon     0
3  Dallas        5       456     Mon     0
```

Broadcasting with a dict

```
In [1]: import pandas as pd

In [2]: heights = [ 59.0, 65.2, 62.9, 65.4, 63.7, 65.7, 64.1 ]

In [3]: data = {'height': heights, 'sex': 'M'}

In [4]: results = pd.DataFrame(data)

In [5]: print(results)
Out[5]:
   height sex
0    59.0   M
1    65.2   M
2    62.9   M
3    65.4   M
4    63.7   M
5    65.7   M
6    64.1   M
```

Index and columns

```
In [6]: results.columns = ['height (in)', 'sex']

In [7]: results.index = ['A', 'B', 'C', 'D', 'E', 'F', 'G']

In [8]: print(results)
Out[8]:
   height (in) sex
A         59.0   M
B         65.2   M
C         62.9   M
D         65.4   M
E         63.7   M
F         65.7   M
G         64.1   M
```

Let's practice!

Importing & exporting data

Original CSV file

- Dataset: Sunspot observations collected from SILSO

```
1818,01,01,1818.004, -1,1
1818,01,02,1818.007, -1,1
1818,01,03,1818.010, -1,1
1818,01,04,1818.012, -1,1
1818,01,05,1818.015, -1,1
1818,01,06,1818.018, -1,1
                ...
```

Source: SILSO, Daily total sunspot number (http://www.sidc.be/silso/infossntotdaily)

Datasets from CSV files

```
In [1]: import pandas as pd

In [2]: filepath = 'ISSN_D_tot.csv'

In [3]: sunspots = pd.read_csv(filepath)

In [4]: sunspots.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 71921 entries, 0 to 71920
Data columns (total 6 columns):
1818        71921 non-null int64
01          71921 non-null int64
01.1        71921 non-null int64
1818.004    71921 non-null float64
 -1         71921 non-null int64
1           71921 non-null int64
dtypes: float64(1), int64(5)
memory usage: 3.3 MB
```

Datasets from CSV files

```
In [5]: sunspots.iloc[10:20, :]
Out[5]:
    1818  01  01.1  1818.004  -1  1
10  1818   1    12  1818.034  -1  1
11  1818   1    13  1818.037  22  1
12  1818   1    14  1818.040  -1  1
13  1818   1    15  1818.042  -1  1
14  1818   1    16  1818.045  -1  1
15  1818   1    17  1818.048  46  1
16  1818   1    18  1818.051  59  1
17  1818   1    19  1818.053  63  1
18  1818   1    20  1818.056  -1  1
19  1818   1    21  1818.059  -1  1
```

Problems

- CSV file has no column headers
    - Columns 0-2: Gregorian date (year, month, day)
    - Column 3: Date as fraction as year
    - Column 4: Daily total sunspot number
    - Column 5: Definitive/provisional indicator (1 or 0)
- Missing values in column 4: indicated by -1
- Dates representation inconvenient

Using header keyword

```
In [6]: sunspots = pd.read_csv(filepath, header=None)

In [7]: sunspots.iloc[10:20, :]
Out[7]:
       0  1   2         3   4  5
10  1818  1  11  1818.031  -1  1
11  1818  1  12  1818.034  -1  1
12  1818  1  13  1818.037  22  1
13  1818  1  14  1818.040  -1  1
14  1818  1  15  1818.042  -1  1
15  1818  1  16  1818.045  -1  1
16  1818  1  17  1818.048  46  1
17  1818  1  18  1818.051  59  1
18  1818  1  19  1818.053  63  1
19  1818  1  20  1818.056  -1  1
```

Using names keyword

```
In [8]: col_names = ['year', 'month', 'day', 'dec_date',
   ...:              'sunspots', 'definite']

In [9]: sunspots = pd.read_csv(filepath, header=None,
   ...:                        names=col_names)

In [10]:  sunspots.iloc[10:20, :]
Out[10]:
    year  month  day  dec_date  sunspots  definite
10  1818      1   11  1818.031        -1         1
11  1818      1   12  1818.034        -1         1
12  1818      1   13  1818.037        22         1
13  1818      1   14  1818.040        -1         1
14  1818      1   15  1818.042        -1         1
15  1818      1   16  1818.045        -1         1
16  1818      1   17  1818.048        46         1
17  1818      1   18  1818.051        59         1
18  1818      1   19  1818.053        63         1
19  1818      1   20  1818.056        -1         1
```

Using na_values keyword (1)

```
In [11]: sunspots = pd.read_csv(filepath, header=None,
    ...:                        names=col_names, na_values='-1')

In [12]: sunspots.iloc[10:20, :]
Out[12]:
    year  month  day  dec_date  sunspots  definite
10  1818      1   11  1818.031        -1         1
11  1818      1   12  1818.034        -1         1
12  1818      1   13  1818.037        22         1
13  1818      1   14  1818.040        -1         1
14  1818      1   15  1818.042        -1         1
15  1818      1   16  1818.045        -1         1
16  1818      1   17  1818.048        46         1
17  1818      1   18  1818.051        59         1
18  1818      1   19  1818.053        63         1
19  1818      1   20  1818.056        -1         1
```

Using na_values keyword (2)

```
In [13]: sunspots = pd.read_csv(filepath, header=None,
    ...:                        names=col_names, na_values=' -1')

In [14]: sunspots.iloc[10:20, :]
Out[14]:
    year  month  day  dec_date  sunspots  definite
10  1818      1   11  1818.031       NaN         1
11  1818      1   12  1818.034       NaN         1
12  1818      1   13  1818.037      22.0         1
13  1818      1   14  1818.040       NaN         1
14  1818      1   15  1818.042       NaN         1
15  1818      1   16  1818.045       NaN         1
16  1818      1   17  1818.048      46.0         1
17  1818      1   18  1818.051      59.0         1
18  1818      1   19  1818.053      63.0         1
19  1818      1   20  1818.056       NaN         1
```

Using na_values keyword (3)

```
In [15]: sunspots = pd.read_csv(filepath, header=None,
    ...: names=col_names, na_values={'sunspots':[' -1']})

In [16]: sunspots.iloc[10:20, :]
Out[16]:
    year  month  day  dec_date  sunspots  definite
10  1818      1   11  1818.031       NaN         1
11  1818      1   12  1818.034       NaN         1
12  1818      1   13  1818.037      22.0         1
13  1818      1   14  1818.040       NaN         1
14  1818      1   15  1818.042       NaN         1
15  1818      1   16  1818.045       NaN         1
16  1818      1   17  1818.048      46.0         1
17  1818      1   18  1818.051      59.0         1
18  1818      1   19  1818.053      63.0         1
19  1818      1   20  1818.056       NaN         1
```

Using parse_dates keyword

```
In [17]: sunspots = pd.read_csv(filepath, header=None,
    ...: names=col_names, na_values={'sunspots':[' -1']},
    ...: parse_dates=[[0, 1, 2]])

In [18]: sunspots.iloc[10:20, :]
Out[18]:
   year_month_day  dec_date  sunspots  definite
10     1818-01-11  1818.031       NaN         1
11     1818-01-12  1818.034       NaN         1
12     1818-01-13  1818.037      22.0         1
13     1818-01-14  1818.040       NaN         1
14     1818-01-15  1818.042       NaN         1
15     1818-01-16  1818.045       NaN         1
16     1818-01-17  1818.048      46.0         1
17     1818-01-18  1818.051      59.0         1
18     1818-01-19  1818.053      63.0         1
19     1818-01-20  1818.056       NaN         1
```

Inspecting DataFrame

```
In [19]: sunspots.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 71922 entries, 0 to 71921
Data columns (total 4 columns):
year_month_day    71922 non-null datetime64[ns]
dec_date          71922 non-null float64
sunspots          68675 non-null float64
definite          71922 non-null int64
dtypes: datetime64[ns](1), float64(2), int64(1)
memory usage: 2.2 MB
```

Using dates as index

```
In [20]: sunspots.index = sunspots['year_month_day']

In [21]: sunspots.index.name = 'date'

In [22]: sunspots.info()
Out[22]:
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 71922 entries, 1818-01-01 to 2014-11-30
Data columns (total 4 columns):
year_month_day    71922 non-null datetime64[ns]
dec_date          71922 non-null float64
sunspots          68675 non-null float64
definite          71922 non-null int64
dtypes: datetime64[ns](1), float64(2), int64(1)
memory usage: 2.7 MB
```

Trimming redundant columns

```
In [23]: cols = ['sunspots', 'definite']

In [24]: sunspots = sunspots[cols]

In [25]: sunspots.iloc[10:20, :]
Out[25]:
            sunspots  definite
date
1818-01-11       NaN         1
1818-01-12       NaN         1
1818-01-13      22.0         1
1818-01-14       NaN         1
1818-01-15       NaN         1
1818-01-16       NaN         1
1818-01-17      46.0         1
1818-01-18      59.0         1
1818-01-19      63.0         1
1818-01-20       NaN         1
```

Writing files

```
In [26]: out_csv = 'sunspots.csv'

In [27]: sunspots.to_csv(out_csv)

In [28]: out_tsv = 'sunspots.tsv'

In [29]: sunspots.to_csv(out_tsv, sep='\t')

In [30]: out_xlsx = 'sunspots.xlsx'

In [31]: sunspots.to_excel(out_xlsx)
```

Let's practice!

Plotting with pandas

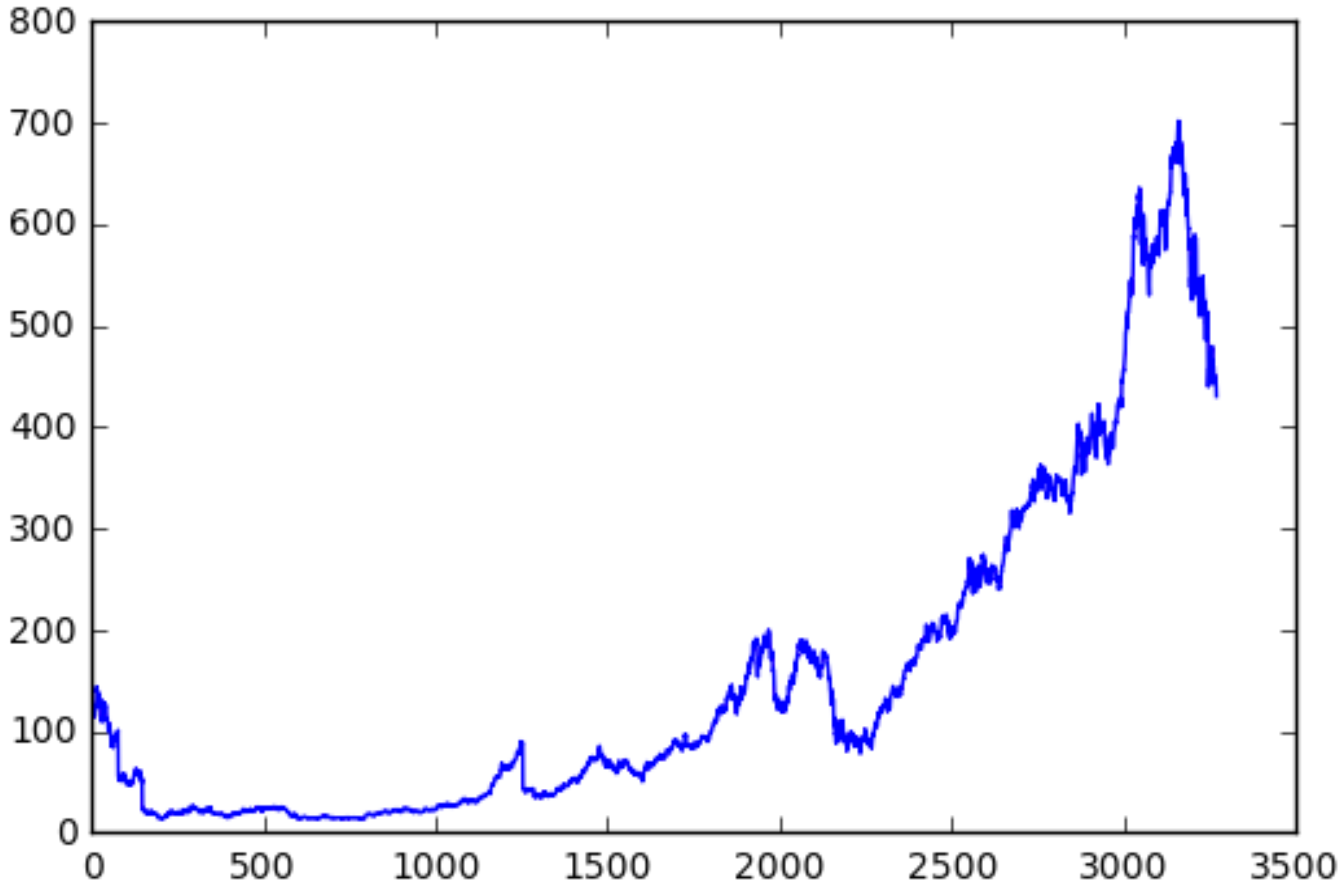
AAPL stock data

```
In [1]: import pandas as pd

In [2]: import matplotlib.pyplot as plt

In [3]: aapl = pd.read_csv('aapl.csv', index_col='date',
   ...:                   parse_dates=True)

In [4]: aapl.head(6)
Out[4]:
            adj_close   close    high     low    open    volume
date
2000-03-01      31.68  130.31  132.06  118.50  118.56  38478000
2000-03-02      29.66  122.00  127.94  120.69  127.00  11136800
2000-03-03      31.12  128.00  128.23  120.00  124.87  11565200
2000-03-06      30.56  125.69  129.13  125.00  126.00   7520000
2000-03-07      29.87  122.87  127.44  121.12  126.44   9767600
2000-03-08      29.66  122.00  123.94  118.56  122.87   9690800
```

Plotting arrays (matplotlib)

```
In [5]: close_arr = aapl['close'].values

In [6]: type(close_arr)
Out[6]: numpy.ndarray

In [7]: plt.plot(close_arr)
Out[7]: [<matplotlib.lines.Line2D at 0x115550358>]

In [8]: plt.show()
```

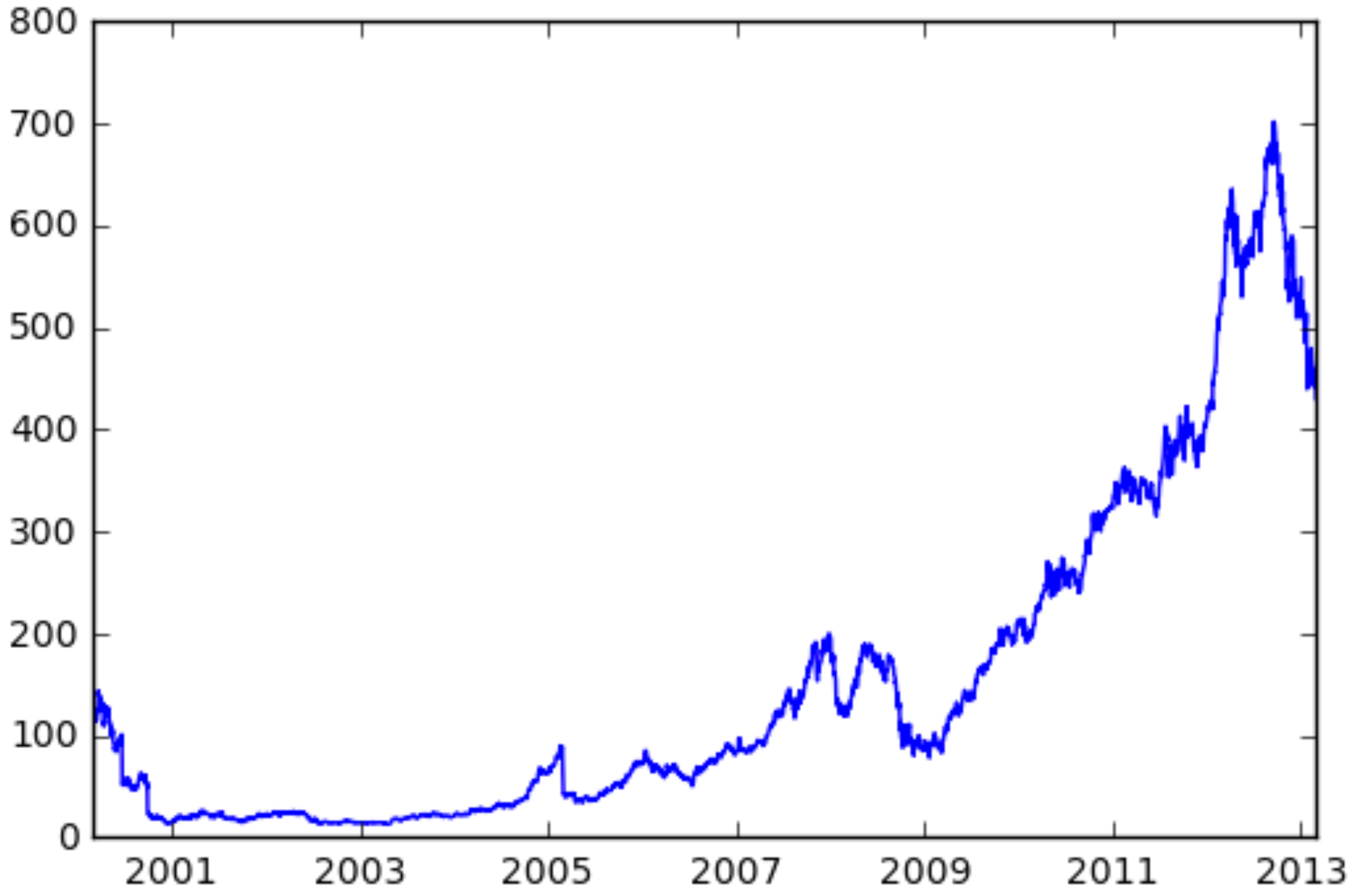
Plotting arrays (Matplotlib)



Plotting Series (matplotlib)

```
In [9]: close_series = aapl['close']

In [10]: type(close_series)
Out[10]: pandas.core.series.Series

In [11]: plt.plot(close_series)
Out[11]: [<matplotlib.lines.Line2D at 0x11801cd30>]

In [12]: plt.show()
```

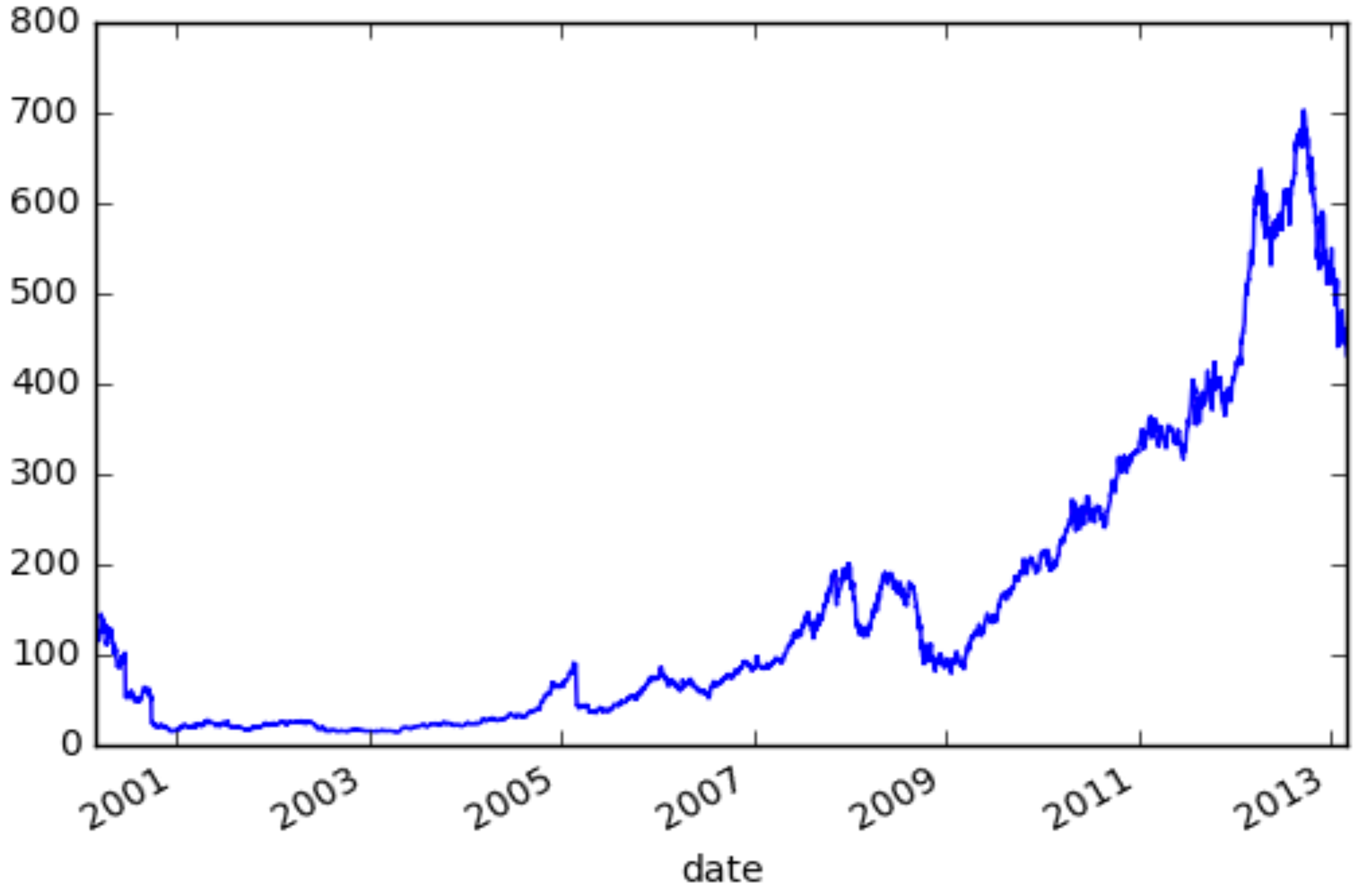
Plotting Series (matplotlib)



Plotting Series (pandas)

```
In [13]: close_series.plot()  # plots Series directly

In [14]: plt.show()
```

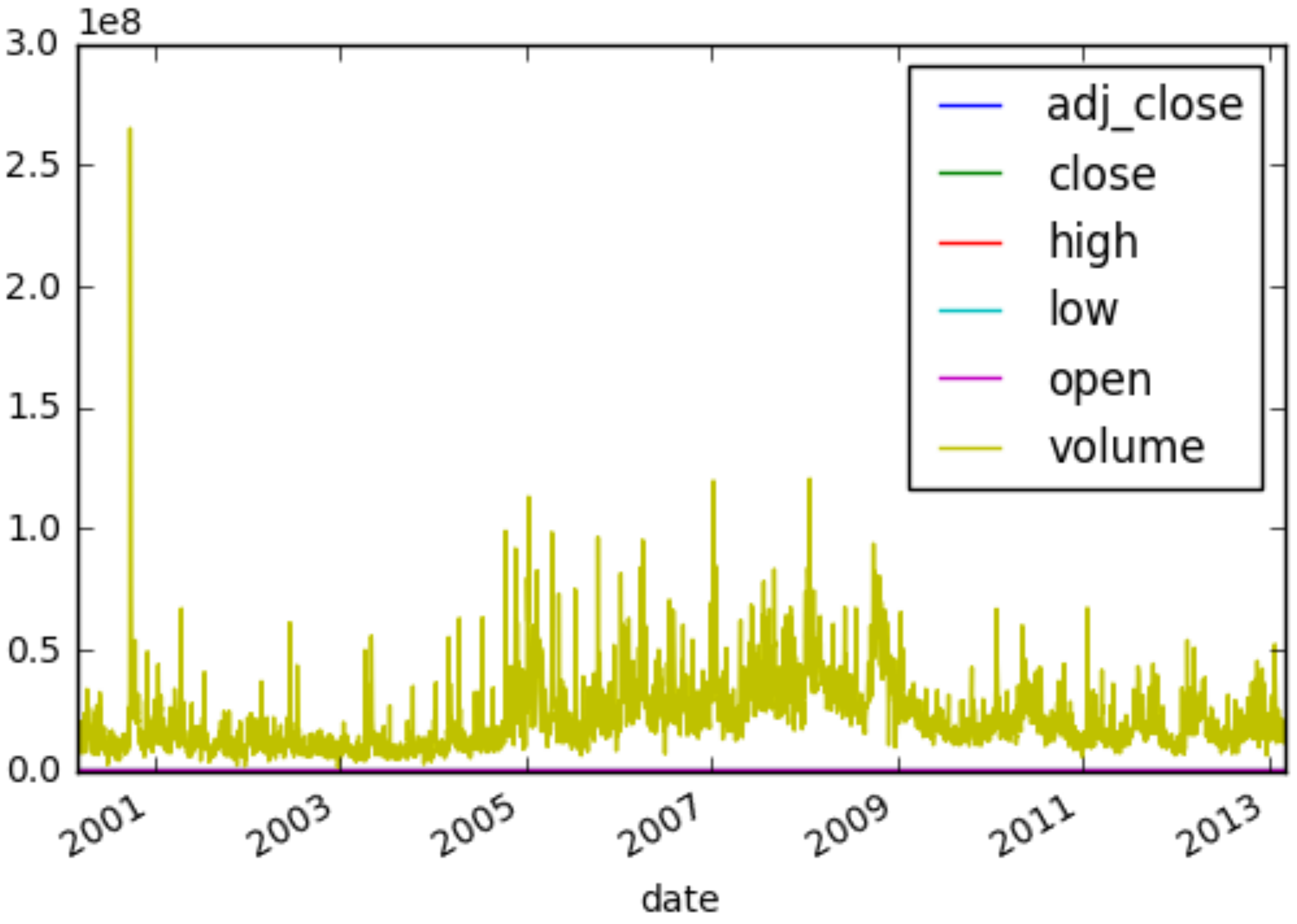
Plotting Series (pandas)



Plotting DataFrames (pandas)

```
In [15]: aapl.plot()  # plots all Series at once
Out[15]: <matplotlib.axes._subplots.AxesSubplot at 0x118039b38>

In [16]: plt.show()
```

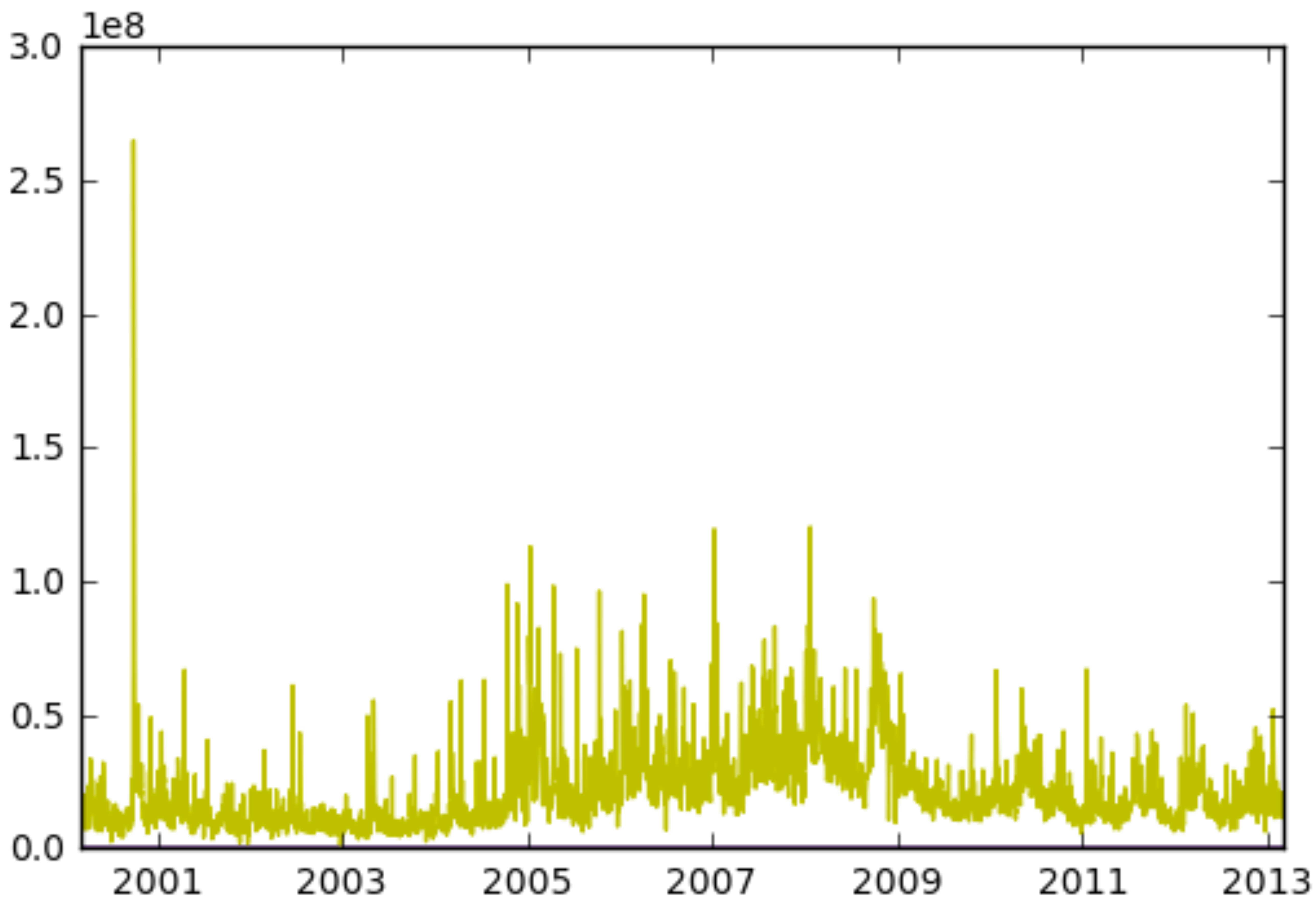
Plotting DataFrames (pandas)



Plotting DataFrames (matplotlib)

```
In [17]: plt.plot(aapl) # plots all columns at once
Out[17]:
 <matplotlib.lines.Line2D at 0x1156290f0>,
 <matplotlib.lines.Line2D at 0x1156525f8>,
 <matplotlib.lines.Line2D at 0x1156527f0>,
 <matplotlib.lines.Line2D at 0x1156529e8>,
 <matplotlib.lines.Line2D at 0x115652be0>,
 <matplotlib.lines.Line2D at 0x115652dd8>

In [18]: plt.show()
```

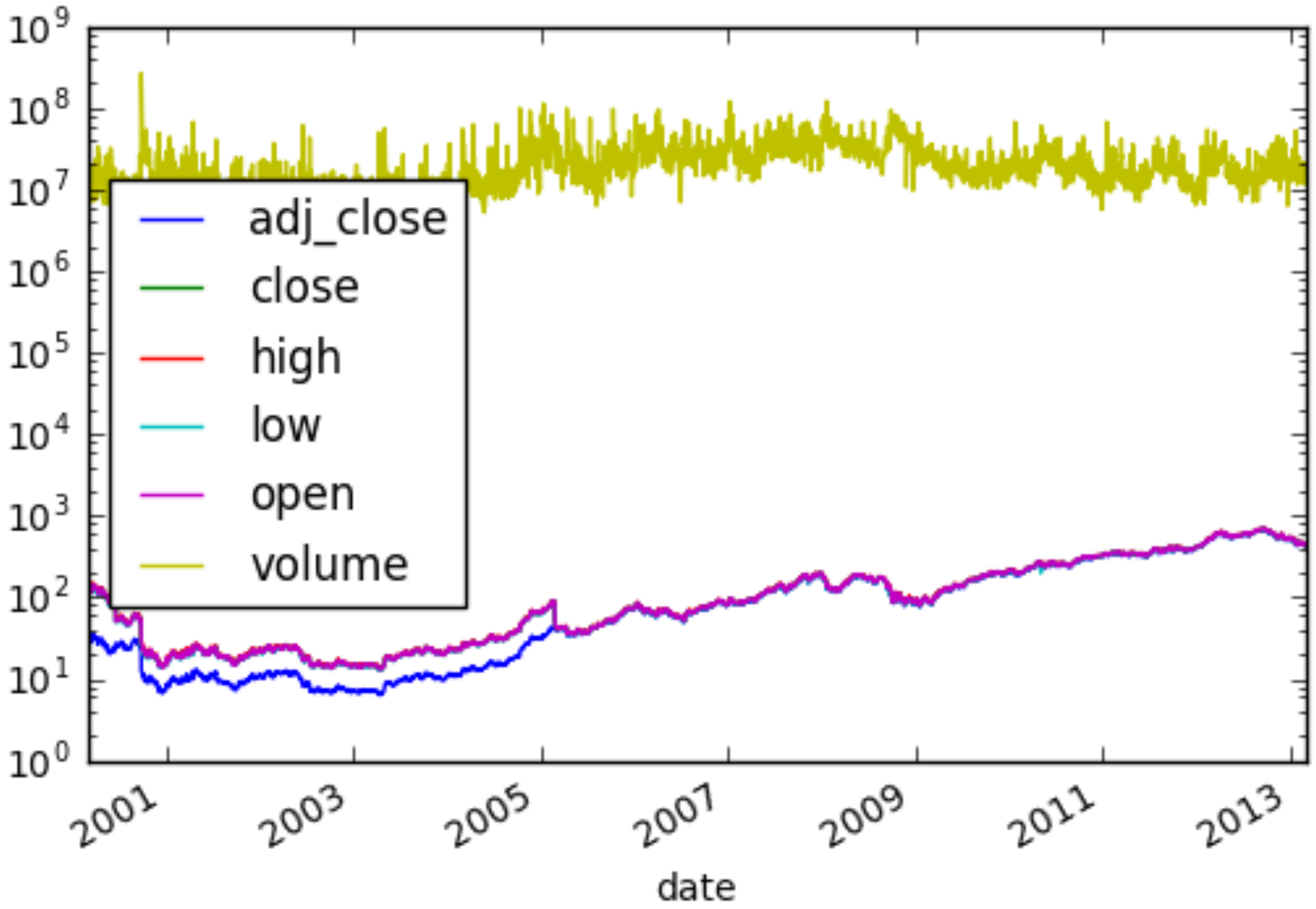
Plotting DataFrames (matplotlib)



Fixing scales

```
In [19]: aapl.plot()
Out[19]: <matplotlib.axes._subplots.AxesSubplot at 0x118afe048>

In [20]: plt.yscale('log') # logarithmic scale on vertical axis

In [21]: plt.show()
```

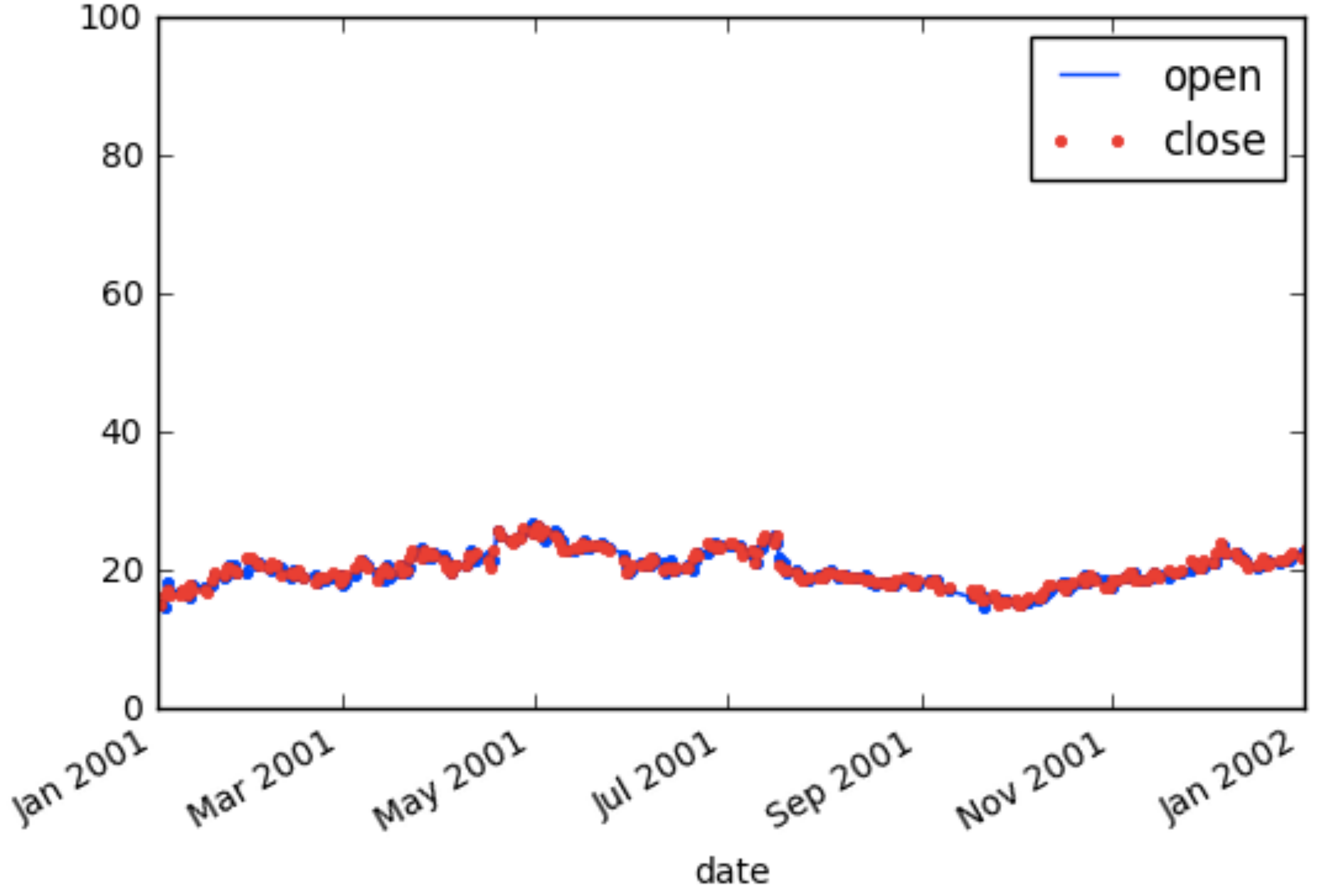
Fixing scales



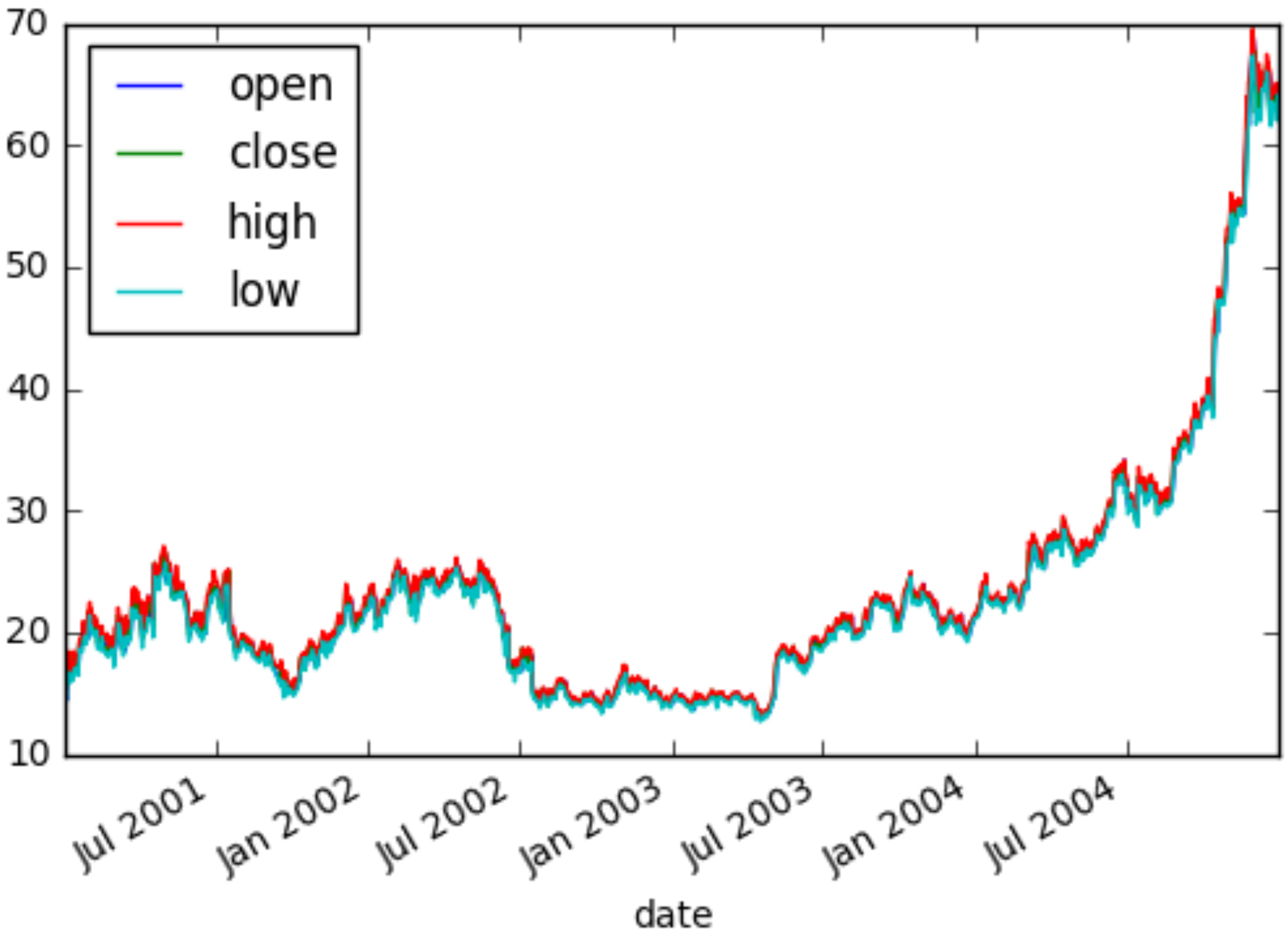
Customizing plots

```
In [22]: aapl['open'].plot(color='b', style='.-', legend=True)
Out[22]: <matplotlib.axes._subplots.AxesSubplot at 0x11a17db38>

In [23]: aapl['close'].plot(color='r', style='.', legend=True)
Out[23]: <matplotlib.axes._subplots.AxesSubplot at 0x11a17db38>

In [24]: plt.axis(('2001', '2002', 0, 100))
Out[24]: ('2001', '2002', 0, 100)

In [25]: plt.show()
```

Customizing plots



Saving plots



Saving plots

```
In [26]: aapl.loc['2001':'2004',['open', 'close', 'high',
    ...:             'low']].plot()
Out[26]: <matplotlib.axes._subplots.AxesSubplot at 0x11ab42978>

In [27]: plt.savefig('aapl.png')

In [28]: plt.savefig('aapl.jpg')

In [29]: plt.savefig('aapl.pdf')

In [30]: plt.show()
```

Let's practice!

Visual exploratory data analysis

The iris data set

- Famous data set in pattern recognition
- 150 observations, 4 features each
    - Sepal length
    - Sepal width
    - Petal length
    - Petal width
- 3 species: setosa, versicolor, virginica

Source: R.A. Fisher, Annual Eugenics, 7, Part II, 179-188 (1936), http://archive.ics.uci.edu/ml/datasets/Iris

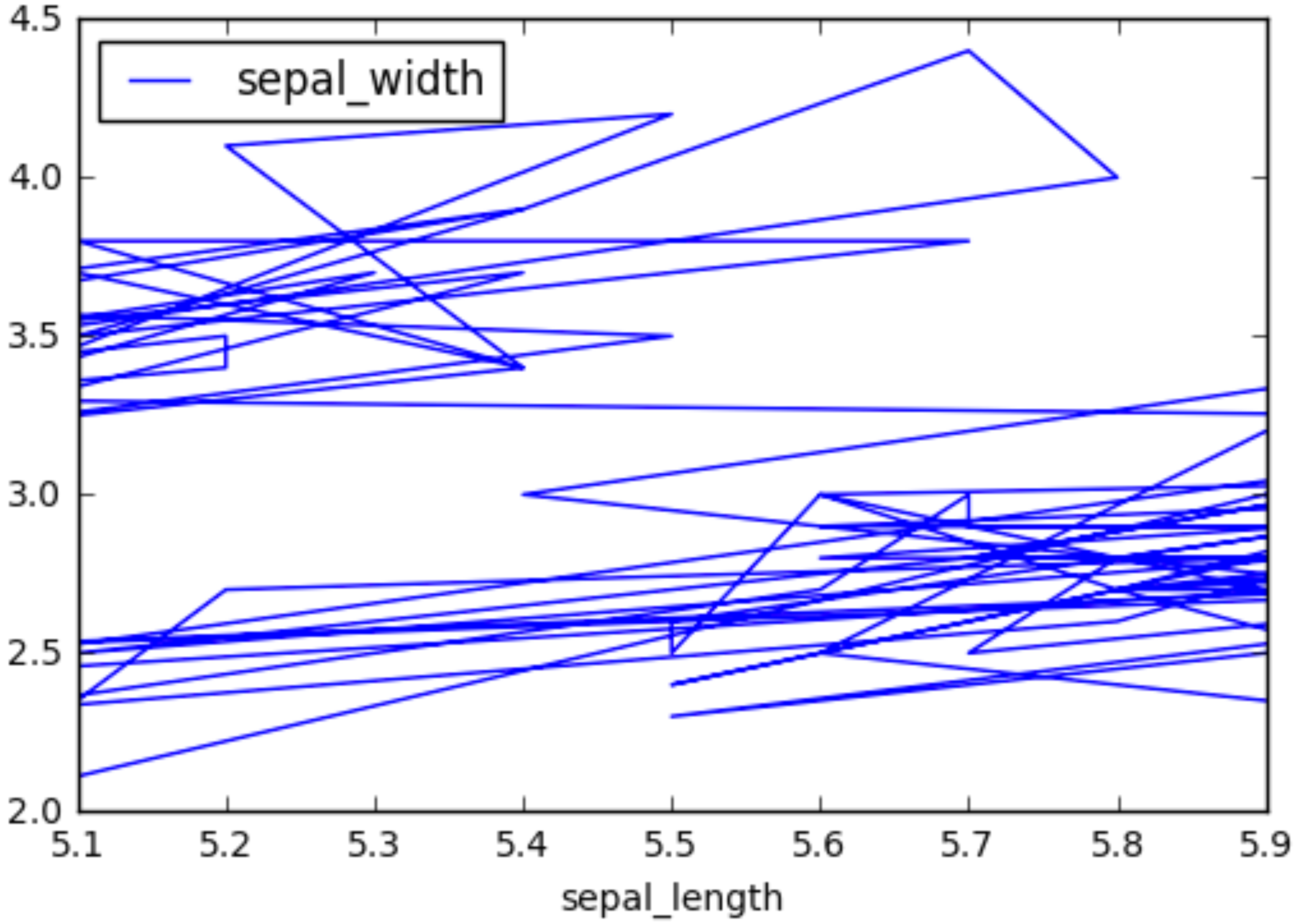
Data import

```
In [1]: import pandas as pd

In [2]: import matplotlib.pyplot as plt

In [3]: iris = pd.read_csv('iris.csv', index_col=0)

In [4]: print(iris.shape)
(150, 5)
```

Line plot

```
In [5]: iris.head()
Out[5]:
   sepal_length  sepal_width  petal_length  petal_width species
0           5.1          3.5           1.4          0.2  setosa
1           4.9          3.0           1.4          0.2  setosa
2           4.7          3.2           1.3          0.2  setosa
3           4.6          3.1           1.5          0.2  setosa
4           5.0          3.6           1.4          0.2  setosa

In [6]: iris.plot(x='sepal_length', y='sepal_width')

In [7]: plt.show()
```

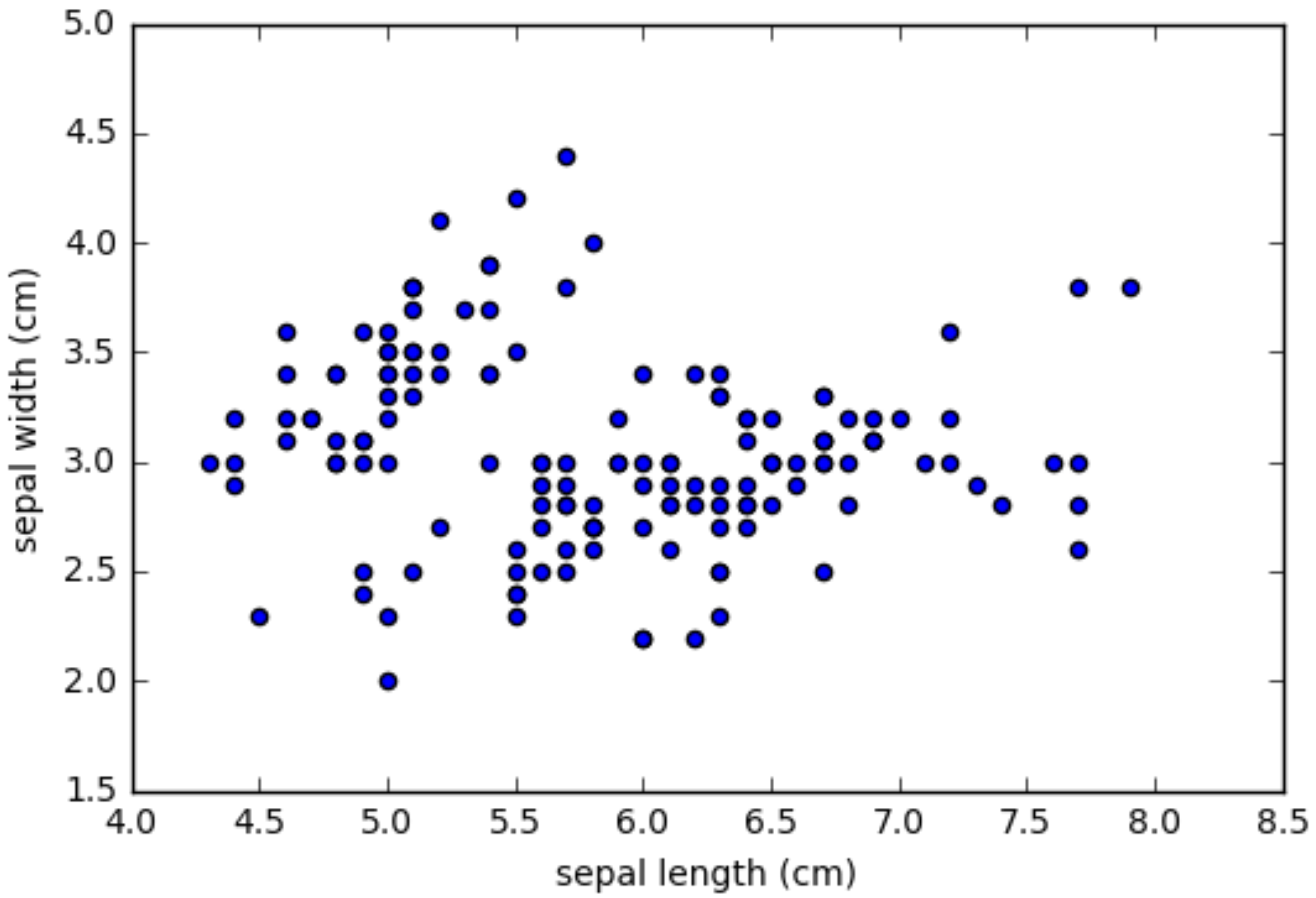
Line plot


sepal_width
4.5
4.0
3.5
3.0
2.5
2.0
5.1
5.2
5.3
5.4
5.5
5.6
5.7
5.8
5.9
sepal_length

Scatter plot

```
In [8]: iris.plot(x='sepal_length', y='sepal_width',
   ...:           kind='scatter')

In [9]: plt.xlabel('sepal length (cm)')

In [10]: plt.ylabel('sepal width (cm)')

In [11]: plt.show()
```

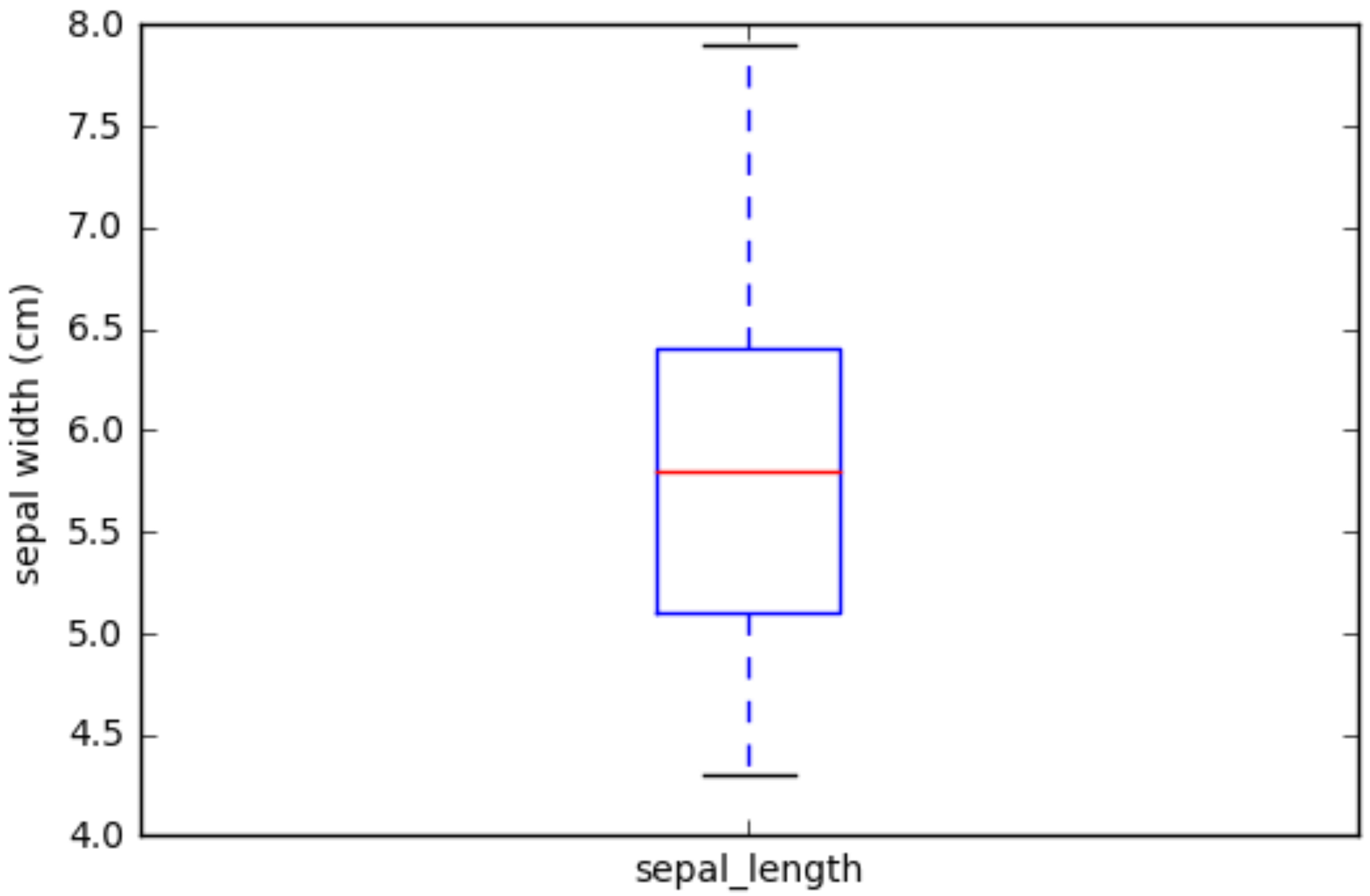
Scatter plot



Box plot

```
In [12]: iris.plot(y='sepal_length', kind='box')

In [13]: plt.ylabel('sepal width (cm)')

In [14]: plt.show()
```

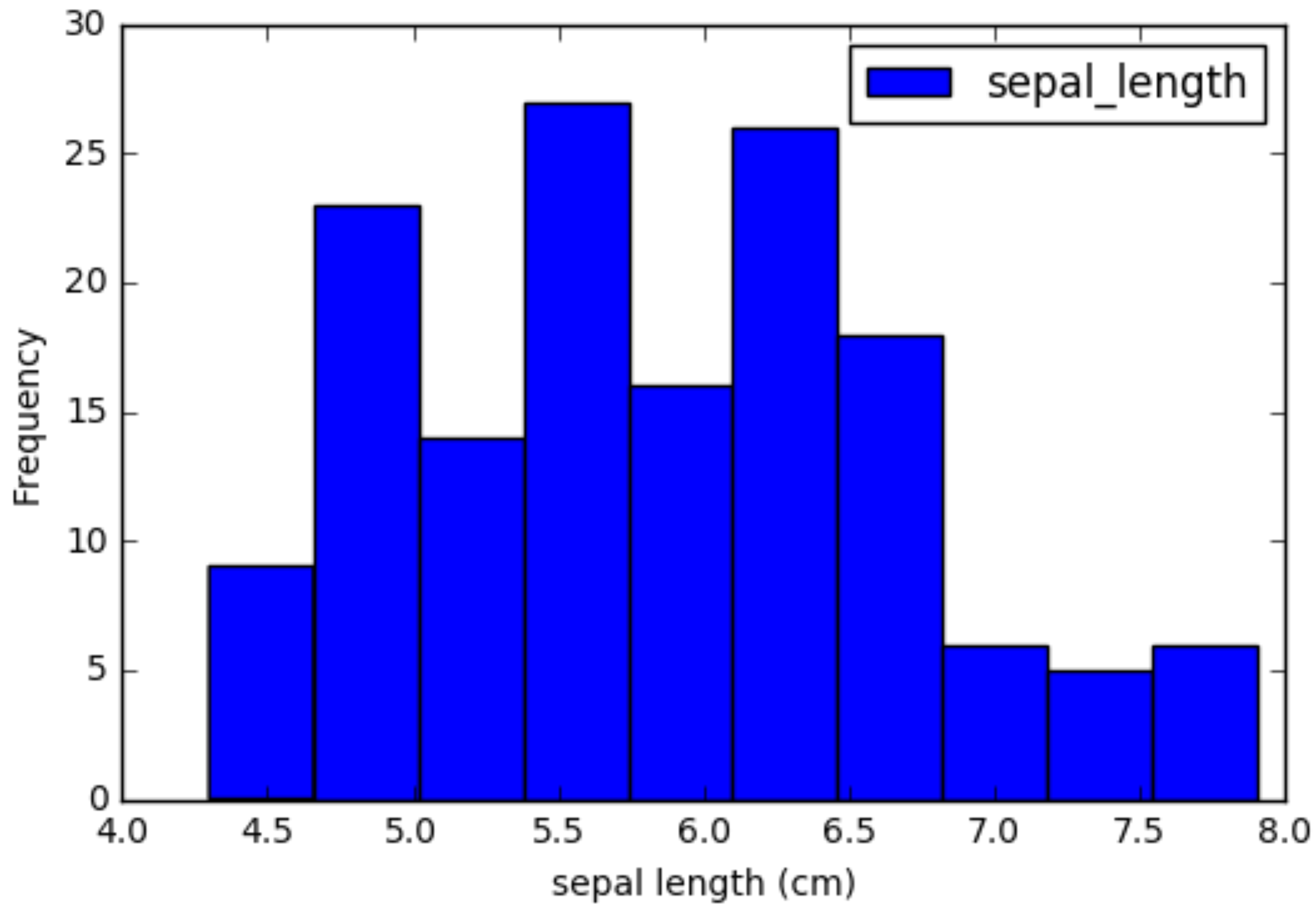
Box plot



Histogram

```
In [15]: iris.plot(y='sepal_length', kind='hist')

In [16]: plt.xlabel('sepal length (cm)')

In [17]: plt.show()
```

Histogram


sepal_length
Frequency
30
25
20
15
10
5
0
4.0
4.5
5.0
5.5
6.0
6.5
7.0
7.5
8.0
sepal length (cm)

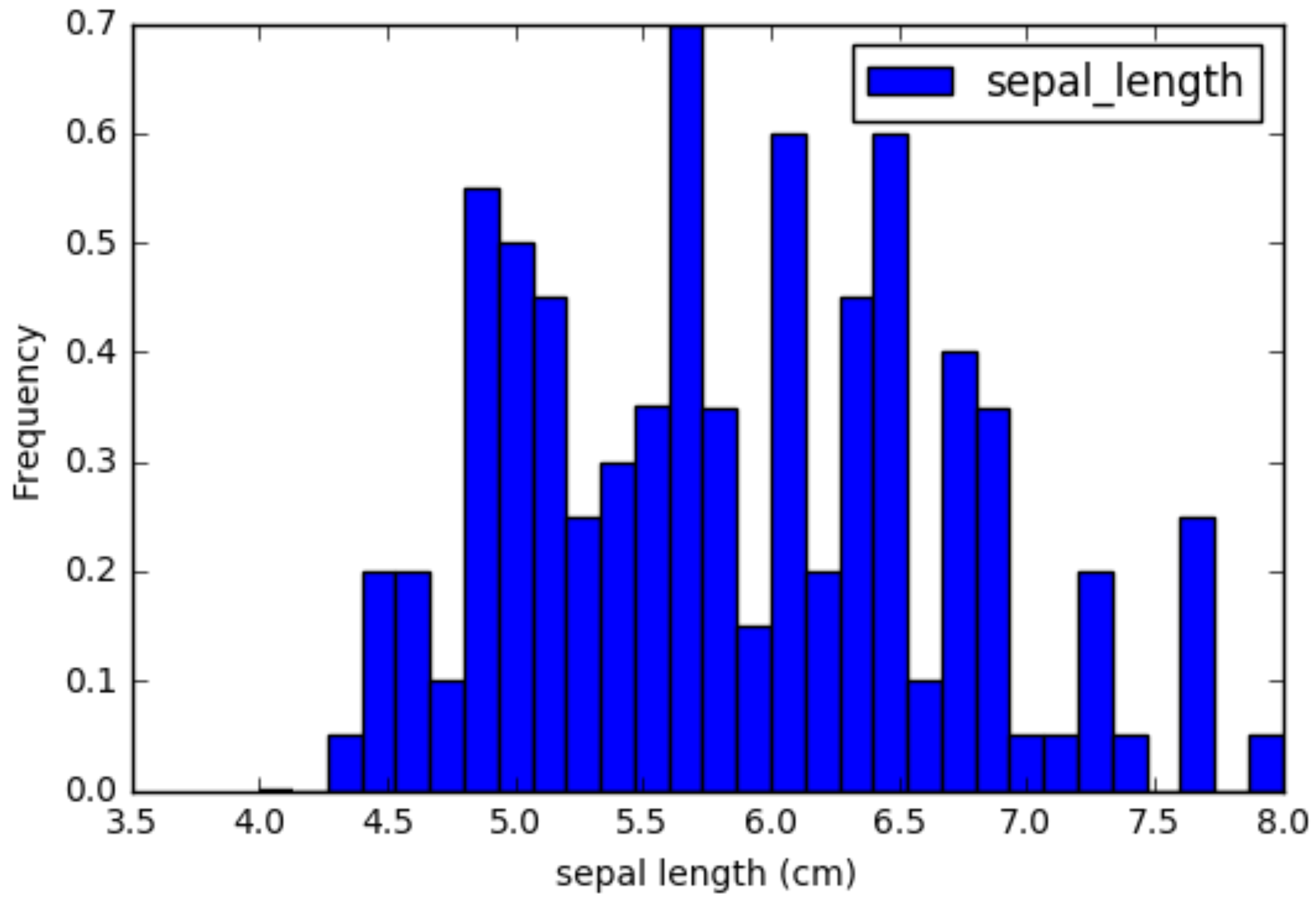
Histogram options

- *bins* (integer): number of intervals or bins
- *range* (tuple): extrema of bins (minimum, maximum)
- *normed* (boolean): whether to normalize to one
- *cumulative* (boolean): compute Cumulative Distribution Function (CDF)
- ... more Matplotlib customizations

Customizing histogram

```
In [18]: iris.plot(y='sepal_length', kind='hist',
    ...:           bins=30, range=(4,8), normed=True)

In [19]: plt.xlabel('sepal length (cm)')

In [20]: plt.show()
```

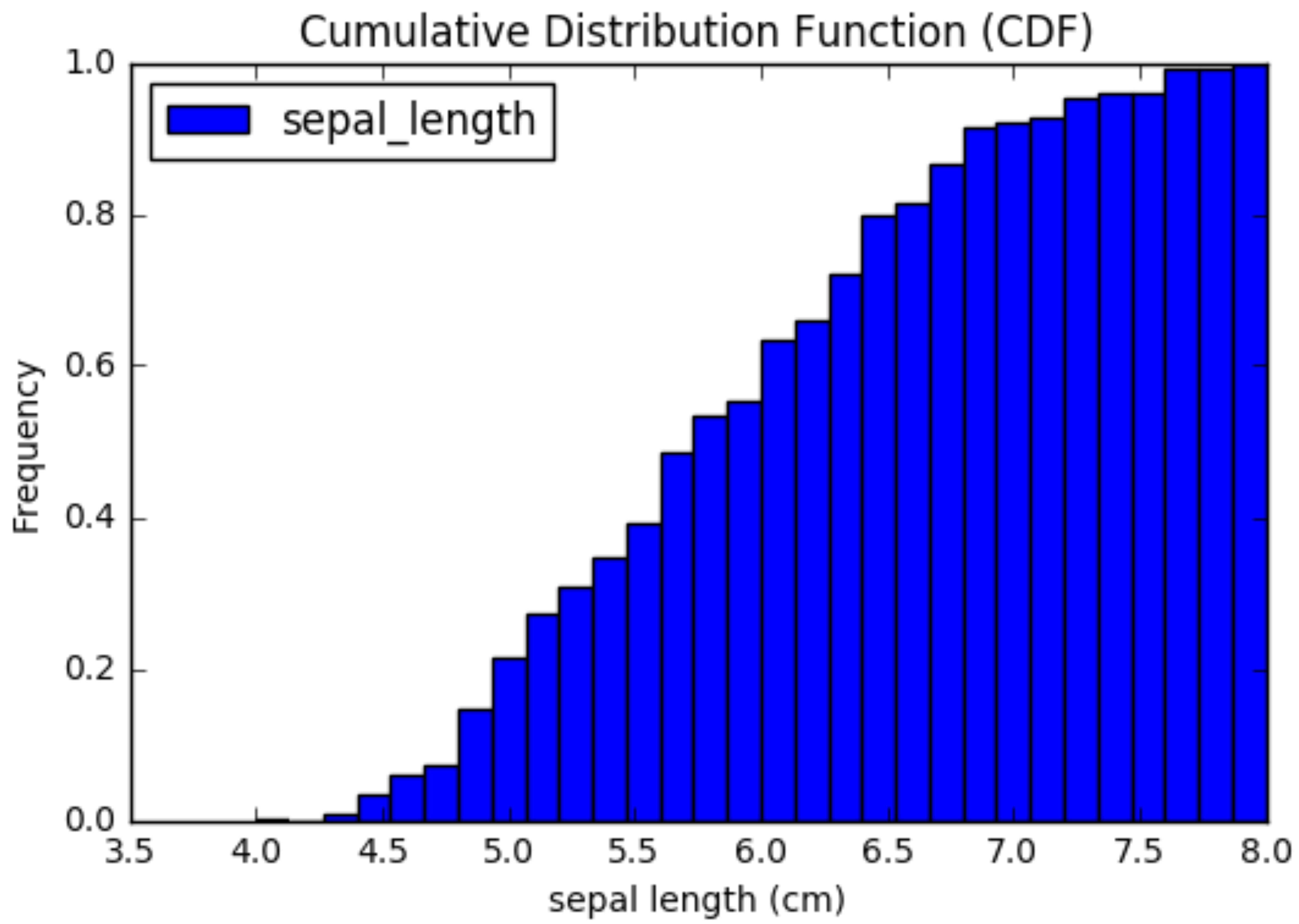
Customizing histogram



Cumulative distribution

```
In [21]: iris.plot(y='sepal_length', kind='hist', bins=30,
    ...:           range=(4,8), cumulative=True, normed=True)

In [22]: plt.xlabel('sepal length (cm)')

In [23]: plt.title('Cumulative distribution function (CDF)')

In [24]: plt.show()
```

Cumulative distribution



Word of warning

- Three different DataFrame plot idioms
    - *iris.plot(kind='hist')*
    - *iris.plt.hist()*
    - *iris.hist()*
- Syntax/results differ!
- Pandas API still evolving: check documentation!

Let’s practice!

PANDAS FOUNDATIONS

Statistical exploratory data analysis

Summarizing with describe()

```
In [1]: iris.describe() # summary statistics
Out[1]:
       sepal_length  sepal_width  petal_length  petal_width
count    150.000000   150.000000    150.000000   150.000000
mean       5.843333     3.057333      3.758000     1.199333
std        0.828066     0.435866      1.765298     0.762238
min        4.300000     2.000000      1.000000     0.100000
25%        5.100000     2.800000      1.600000     0.300000
50%        5.800000     3.000000      4.350000     1.300000
75%        6.400000     3.300000      5.100000     1.800000
max        7.900000     4.400000      6.900000     2.500000
```

Describe

- *count*: number of entries
- *mean*: average of entries
- *std*: standard deviation
- min: minimum entry
- *25%*: first quartile
- *50%*: median or second quartile
- *75%*: third quartile
- *max*: maximum entry

Counts

```
In [2]: iris['sepal_length'].count() # Applied to Series
Out[2]: 150

In [3]: iris['sepal_width'].count() # Applied to Series
Out[3]: 150

In [4]: iris[['petal_length', 'petal_width']].count() # Applied
    ...: to DataFrame
Out[4]:
petal_length    150
petal_width     150
dtype: int64

In [5]: type(iris[['petal_length', 'petal_width']].count()) #
    ...: returns Series
Out[5]: pandas.core.series.Series
```

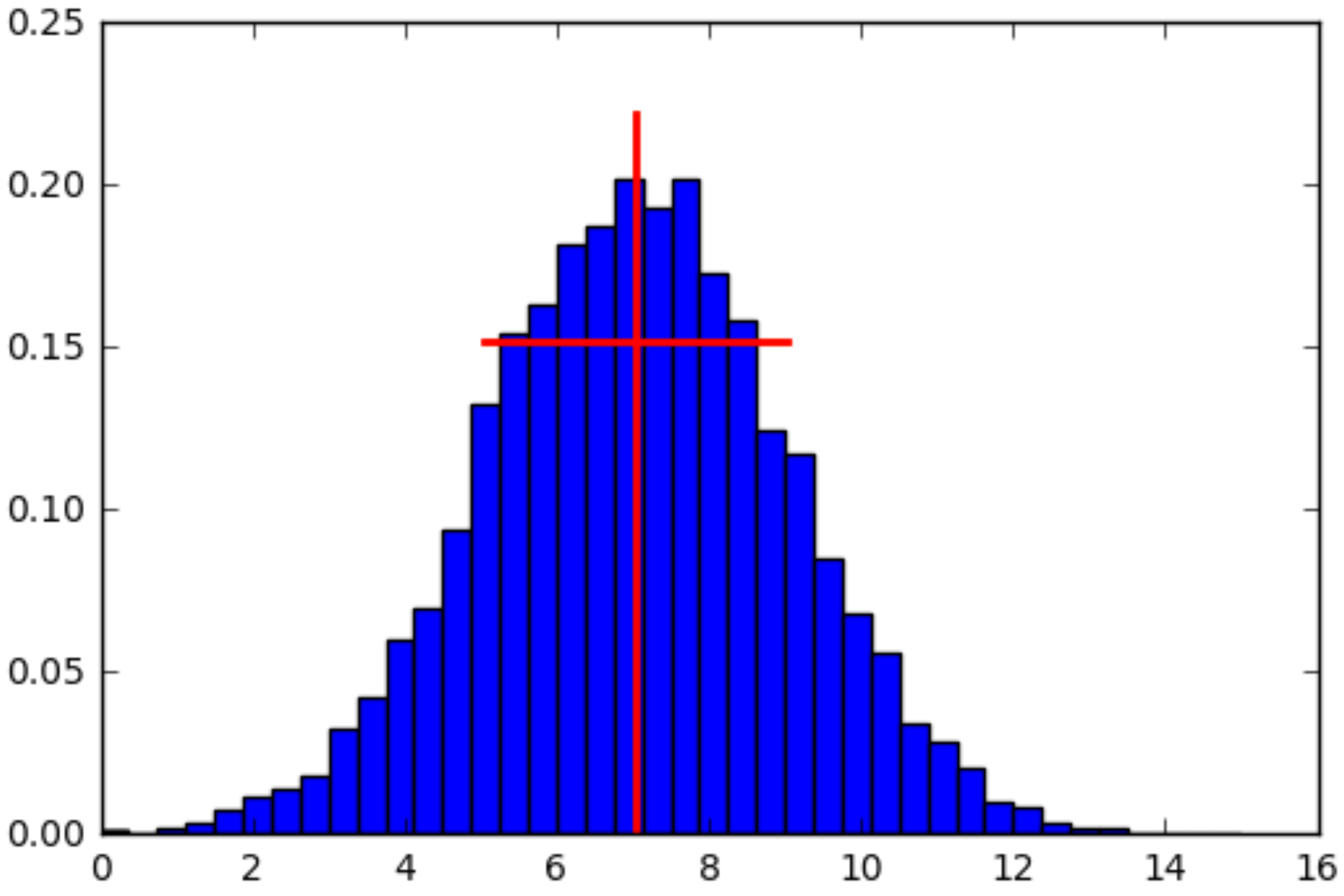
Averages

```
In [6]: iris['sepal_length'].mean() # Applied to Series
Out[6]: 5.843333333333335

In [7]: iris.mean() # Applied to entire DataFrame
Out[7]:
sepal_length    5.843333
sepal_width     3.057333
petal_length    3.758000
petal_width     1.199333
dtype: float64
```

Standard deviations

```
In [8]: iris.std()
Out[8]:
sepal_length    0.828066
sepal_width     0.435866
petal_length    1.765298
petal_width     0.762238
dtype: float64
```

Mean and standard deviation on a bell curve



Medians

```
In [9]: iris.median()
Out[9]:
sepal_length    5.80
sepal_width     3.00
petal_length    4.35
petal_width     1.30
dtype: float64
```

Medians & 0.5 quantiles

```
In [10]: iris.median()
Out[10]:
sepal_length    5.80
sepal_width     3.00
petal_length    4.35
petal_width     1.30
dtype: float64

In [11]: q = 0.5

In [12]: iris.quantile(q)
Out[12]:
sepal_length    5.80
sepal_width     3.00
petal_length    4.35
petal_width     1.30
dtype: float64
```

Inter-quartile range (IQR)

```
In [13]: q = [0.25, 0.75]

In [14]: iris.quantile(q)
Out[14]:
      sepal_length  sepal_width  petal_length  petal_width
0.25           5.1          2.8           1.6          0.3
0.75           6.4          3.3           5.1          1.8
```

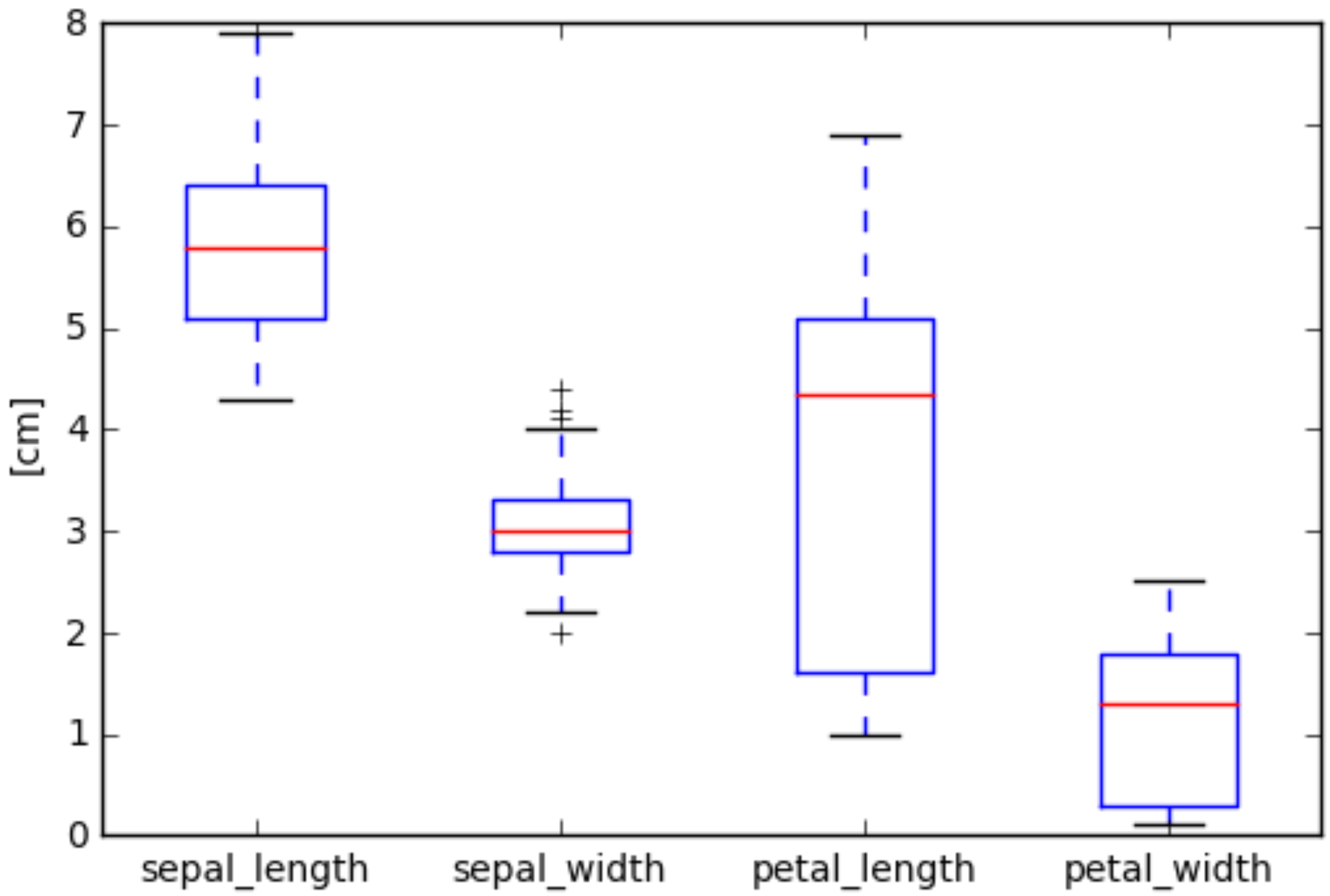
Ranges

```
In [15]: iris.min()
Out[15]:
sepal_length       4.3
sepal_width          2
petal_length         1
petal_width        0.1
species         setosa
dtype: object

In [16]: iris.max()
Out[16]:
sepal_length          7.9
sepal_width           4.4
petal_length          6.9
petal_width           2.5
species         virginica
dtype: object
```

Box plots

```
In [17]: iris.plot(kind= 'box')
Out[17]: <matplotlib.axes._subplots.AxesSubplot at 0x118a3d5f8>

In [18]: plt.ylabel('[cm]')
Out[18]: <matplotlib.text.Text at 0x118a524e0>

In [19]: plt.show()
```

Box plots


8
7
6
5
4
3
2
1
0
[cm]
sepal_length
sepal_width
petal_length
petal_width

Percentiles as quantiles

```
In [20]: iris.describe() # summary statistics
Out[20]:
       sepal_length  sepal_width  petal_length  petal_width
count    150.000000   150.000000    150.000000   150.000000
mean       5.843333     3.057333      3.758000     1.199333
std        0.828066     0.435866      1.765298     0.762238
min        4.300000     2.000000      1.000000     0.100000
25%        5.100000     2.800000      1.600000     0.300000
50%        5.800000     3.000000      4.350000     1.300000
75%        6.400000     3.300000      5.100000     1.800000
max        7.900000     4.400000      6.900000     2.500000
```

Let's practice!

Separating populations

```
In [1]: iris.head()
Out[1]:
   sepal_length  sepal_width  petal_length  petal_width species
0           5.1          3.5           1.4          0.2  setosa
1           4.9          3.0           1.4          0.2  setosa
2           4.7          3.2           1.3          0.2  setosa
3           4.6          3.1           1.5          0.2  setosa
4           5.0          3.6           1.4          0.2  setosa
```

Describe species column

```
In [2]: iris['species'].describe()
Out[2]:
count        150
unique         3
top       setosa
freq          50
Name: species, dtype: object
```

count: # non-null entries
unique: # distinct values
top: most frequent category
freq: # occurrences of top

Unique & factors

```
In [3]: iris['species'].unique()
Out[3]: array(['setosa', 'versicolor', 'virginica'], dtype=object)
```

Filtering by species

```
In [4]: indices = iris['species'] == 'setosa'

In [5]: setosa = iris.loc[indices,:] # extract new DataFrame

In [6]: indices = iris['species'] == 'versicolor'

In [7]: versicolor = iris.loc[indices,:] # extract new DataFrame

In [8]: indices = iris['species'] == 'virginica'

In [9]: virginica = iris.loc[indices,:] # extract new DataFrame
```

Checking species

```
In [10]: setosa['species'].unique()
Out[10]: array(['setosa'], dtype=object)

In [11]: versicolor['species'].unique()
Out[11]: array(['versicolor'], dtype=object)

In [12]: virginica['species'].unique()
Out[12]: array(['virginica'], dtype=object)

In [13]: del setosa['species'], versicolor['species'],
    ...: virginica['species']
```

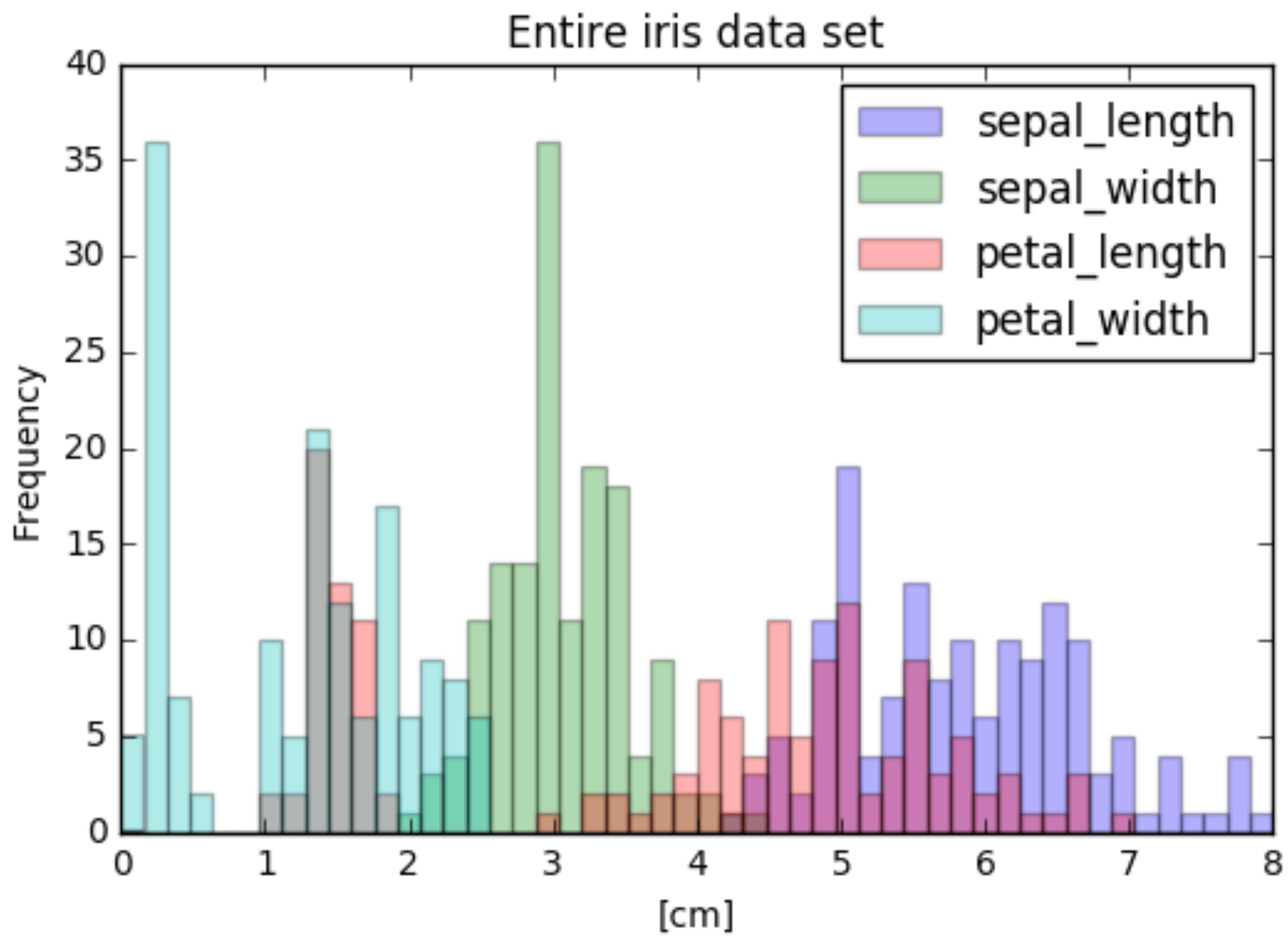
Checking indexes

```
In [14]: setosa.head(2)
Out[14]:
   sepal_length  sepal_width  petal_length  petal_width
0           5.1          3.5           1.4          0.2
1           4.9          3.0           1.4          0.2

In [15]: versicolor.head(2)
Out[15]:
    sepal_length  sepal_width  petal_length  petal_width
50           7.0          3.2           4.7          1.4
51           6.4          3.2           4.5          1.5

In [16]: virginica.head(2)
Out[16]:
     sepal_length  sepal_width  petal_length  petal_width
100           6.3          3.3           6.0          2.5
101           5.8          2.7           5.1          1.9
```

Visual EDA: all data

```
In [17]: iris.plot(kind= 'hist', bins=50, range=(0,8), alpha=0.3)

In [18]: plt.title('Entire iris data set')

In [19]: plt.xlabel('[cm]')

In [20]: plt.show()
```

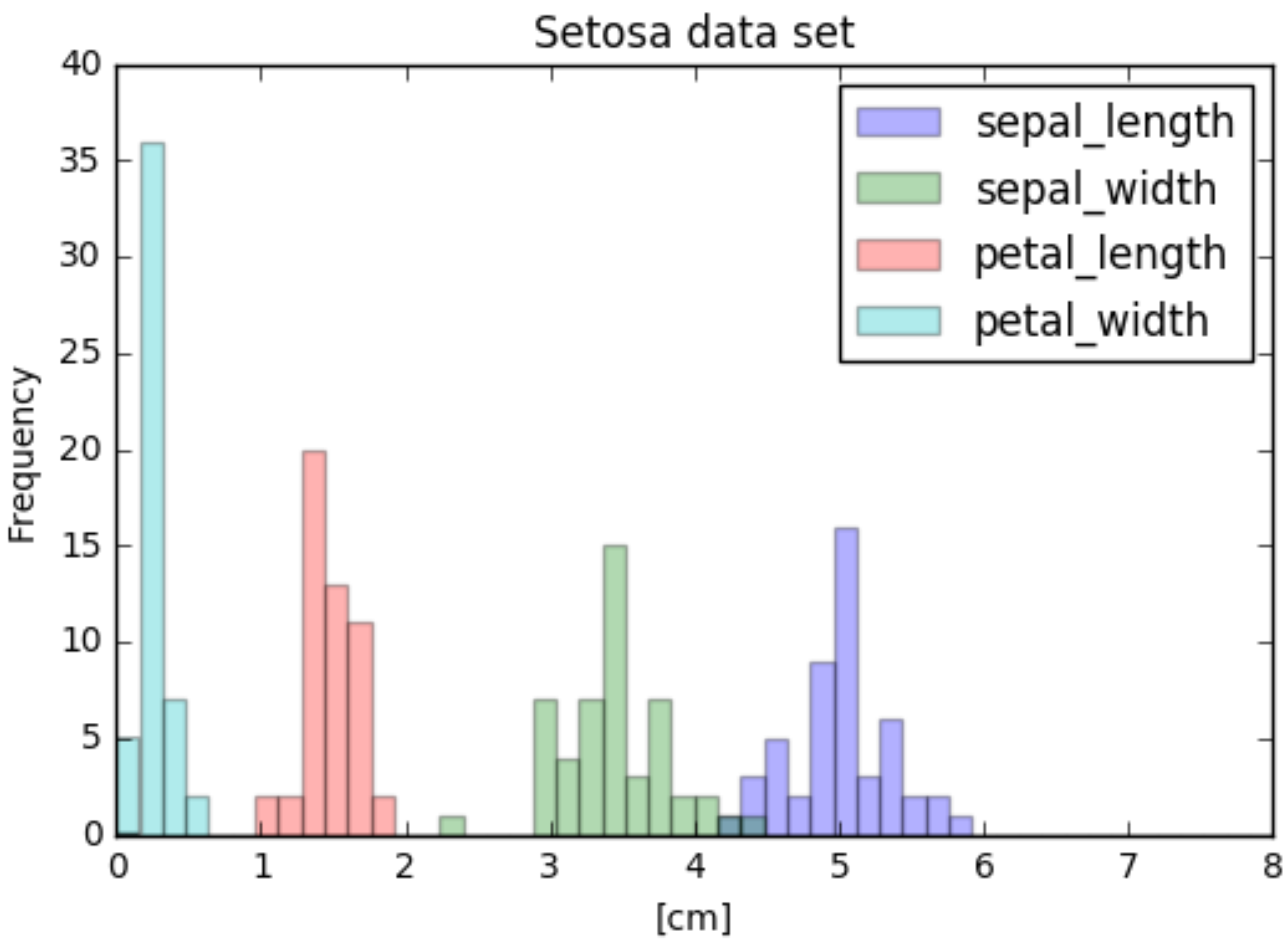
Visual EDA: all data



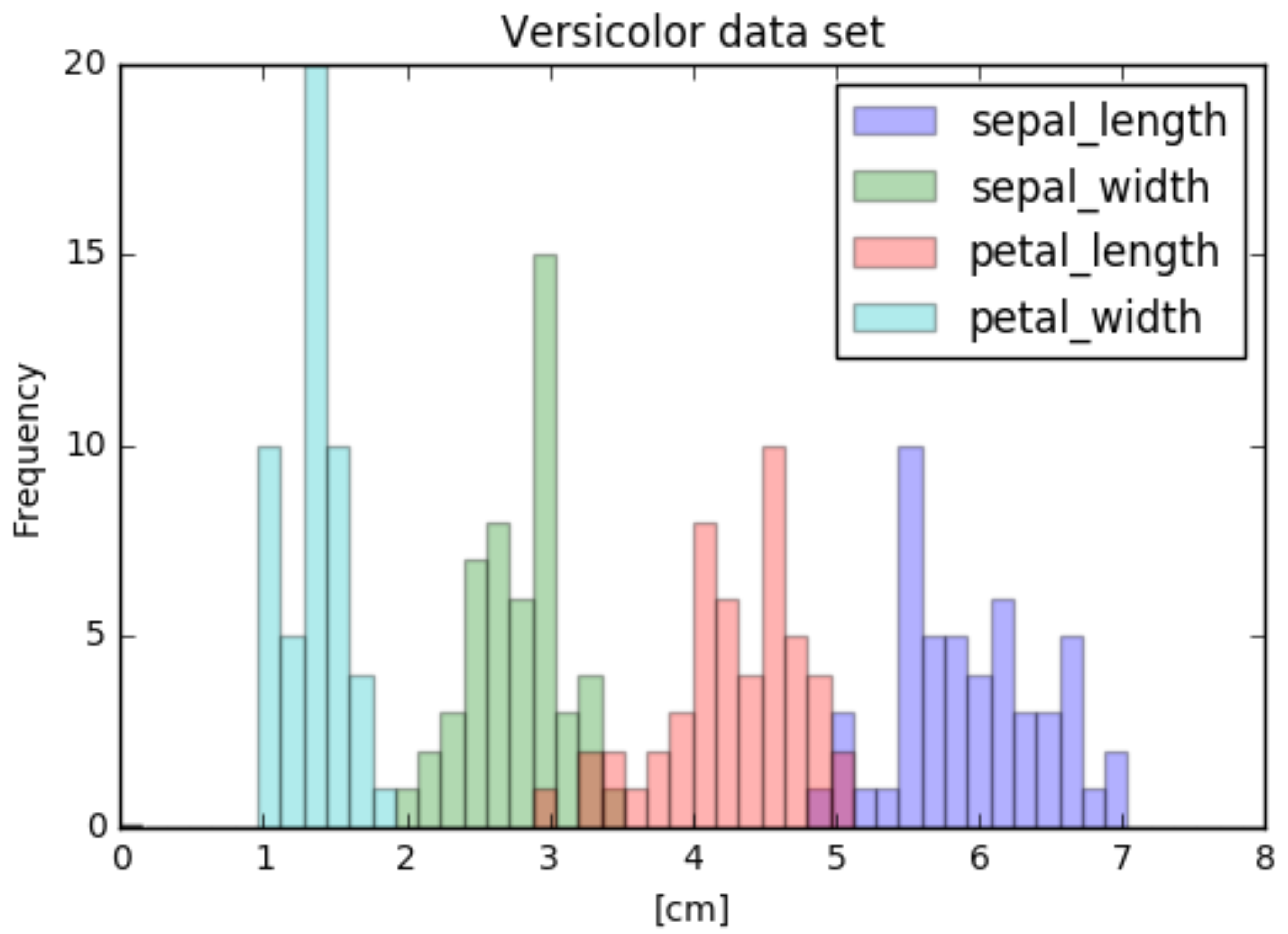
Visual EDA: individual factors

```
In [21]: setosa.plot(kind='hist', bins=50, range=(0,8), alpha=0.3)

In [22]: plt.title('Setosa data set’)

In [23]: plt.xlabel('[cm]')

In [24]: versicolor.plot(kind='hist', bins=50, range=(0,8), alpha=0.3)

In [25]: plt.title('Versicolor data set’)

In [26]: plt.xlabel('[cm]')

In [27]: virginica.plot(kind='hist', bins=50, range=(0,8), alpha=0.3)

In [28]: plt.title('Virginica data set’)

In [29]: plt.xlabel('[cm]')

In [30]: plt.show()
```

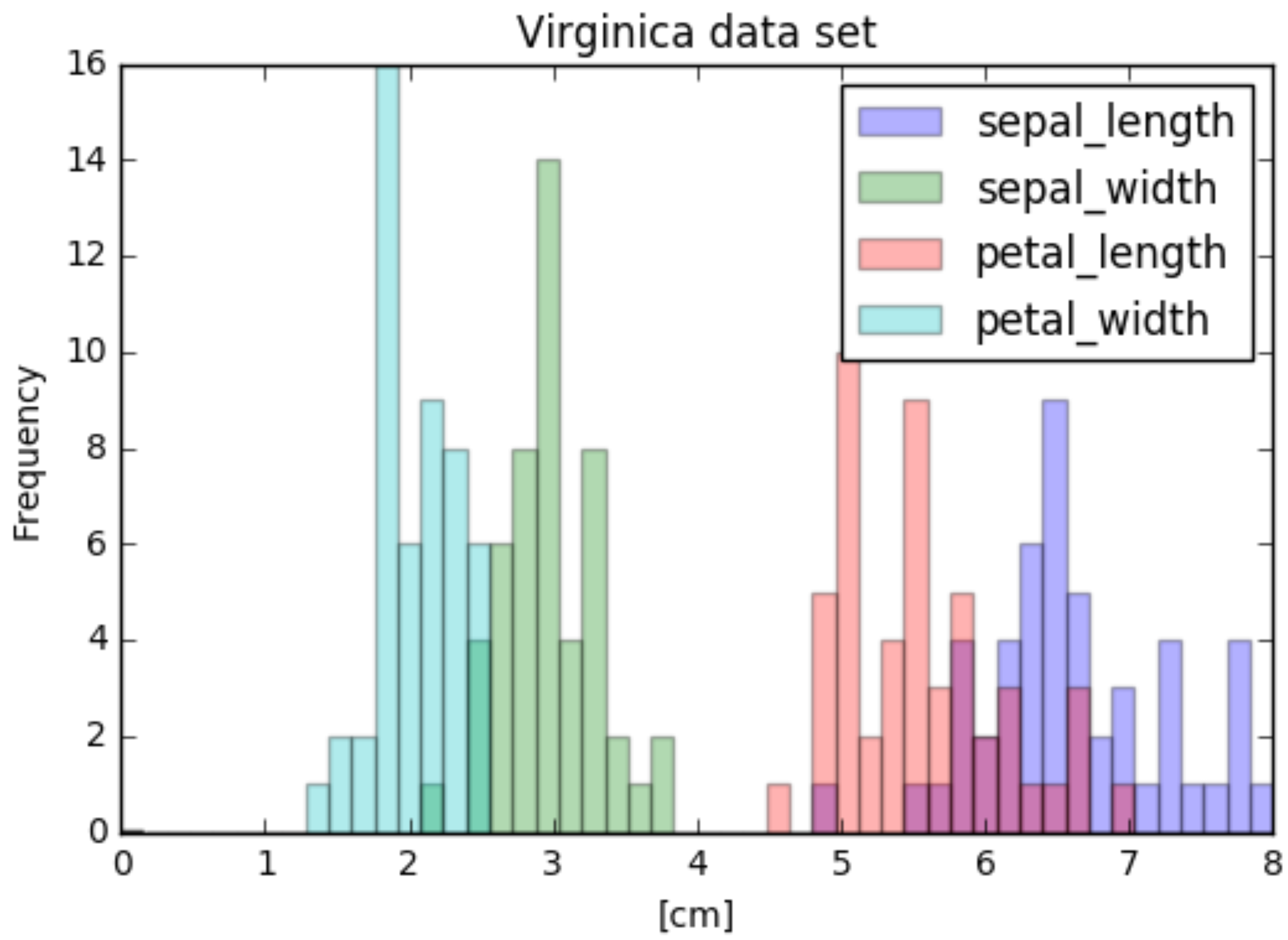
Visual EDA: Setosa data



Visual EDA: Versicolor data



Visual EDA: Virginica data



Statistical EDA: describe()

```
In [31]: describe_all = iris.describe()

In [32]: print(describe_all)
Out[32]:
       sepal_length  sepal_width  petal_length  petal_width
count    150.000000   150.000000    150.000000   150.000000
mean       5.843333     3.057333      3.758000     1.199333
std        0.828066     0.435866      1.765298     0.762238
min        4.300000     2.000000      1.000000     0.100000
25%        5.100000     2.800000      1.600000     0.300000
50%        5.800000     3.000000      4.350000     1.300000
75%        6.400000     3.300000      5.100000     1.800000
max        7.900000     4.400000      6.900000     2.500000

In [33]: describe_setosa = setosa.describe()

In [34]: describe_versicolor = versicolor.describe()

In [35]: describe_virginica = virginica.describe()
```

Computing errors

```
In [36]: error_setosa = 100 * np.abs(describe_setosa -
    ...: describe_all)

In [37]: error_setosa = error_setosa/describe_setosa

In [38]: error_versicolor = 100 * np.abs(describe_versicolor -
    ...: describe_all)

In [39]: error_versicolor = error_versicolor/describe_versicolor

In [40]: error_virginica = 100 * np.abs(describe_virginica -
    ...: describe_all)

In [41]: error_virginica = error_verginica/describe_virginica
```

Viewing errors

```
In [42]: print(error_setosa)
         sepal_length  sepal_width  petal_length  petal_width
count      200.000000   200.000000    200.000000   200.000000
mean        16.726595    10.812913    157.045144   387.533875
std        134.919250    14.984768    916.502136   623.284534
min          0.000000    13.043478      0.000000     0.000000
25%          6.250000    12.500000     14.285714    50.000000
50%         16.000000    11.764706    190.000000   550.000000
75%         23.076923    10.204082    223.809524   500.000000
max         36.206897     0.000000    263.157895   316.666667
```

Let's practice!

Indexing time series

Using pandas to read datetime objects

- read_csv() function
    - Can read strings into datetime objects
    - Need to specify 'parse_dates=True'
- ISO 8601 format
    - yyyy-mm-dd hh:mm:ss

Product sales CSV

	Date	Company	Product	Units
0	2015-02-02 08:30:00	Hooli	Software	3
1	2015-02-02 21:00:00	Mediacore	Hardware	9
2	2015-02-03 14:00:00	Initech	Software	13
3	2015-02-04 15:30:00	Streeplex	Software	13
4	2015-02-04 22:00:00	Acme Coporation	Hardware	14

Parse dates

```
In [1]: import pandas as pd

In [2]: sales = pd.read_csv('sales-feb-2015.csv',
   ...:                     parse_dates=True, index_col= 'Date')
```

Parse dates

```
In [3]: sales.head()
Out[3]:
                              Company   Product  Units
Date
2015-02-02 08:30:00             Hooli  Software      3
2015-02-02 21:00:00         Mediacore  Hardware      9
2015-02-03 14:00:00           Initech  Software     13
2015-02-04 15:30:00         Streeplex  Software     13
2015-02-04 22:00:00  Acme Coporation  Hardware     14
```

Parse dates

```
In [4]: sales.info()
DatetimeIndex: 19 entries, 2015-02-02 08:30:00 to 2015-02-26
09:00:00
Data columns (total 3 columns):
Company     19 non-null object
Product     19 non-null object
Units       19 non-null int64
dtypes: int64(1), object(2)
memory usage: 608.0+ bytes
```

Selecting single datetime

```
In [5]: sales.loc['2015-02-19 11:00:00', 'Company']
Out[5]: ‘Mediacore’
```

Selecting whole day

```
In [6]: sales.loc['2015-2-5']
Out[6]:
                              Company   Product  Units
Date
2015-02-05 02:00:00  Acme Coporation  Software     19
2015-02-05 22:00:00            Hooli   Service     10
```

Partial datetime string selection

- Alternative formats:
  - sales.loc['February 5, 2015']
  - sales.loc['2015-Feb-5']
- Whole month: sales.loc['2015-2']
- Whole year: sales.loc['2015']

Selecting whole month

```
In [7]: sales.loc['2015-2']
Out[7]:
                            Company   Product  Units
Date
2015-02-02 08:30:00           Hooli  Software      3
2015-02-02 21:00:00       Mediacore  Hardware      9
2015-02-03 14:00:00         Initech  Software     13
2015-02-04 15:30:00       Streeplex  Software     13
2015-02-04 22:00:00  Acme Coporation  Hardware     14
2015-02-05 02:00:00  Acme Coporation  Software     19
2015-02-05 22:00:00           Hooli   Service     10
2015-02-07 23:00:00  Acme Coporation  Hardware      1
2015-02-09 09:00:00       Streeplex   Service     19
2015-02-09 13:00:00       Mediacore  Software      7
2015-02-11 20:00:00         Initech  Software      7
2015-02-11 23:00:00           Hooli  Software      4
2015-02-16 12:00:00           Hooli  Software     10
2015-02-19 11:00:00       Mediacore  Hardware     16
…
```

Slicing using dates/times

```
In [8]: sales.loc['2015-2-16':'2015-2-20']
Out[8]:
                       Company   Product  Units
Date
2015-02-16 12:00:00      Hooli  Software     10
2015-02-19 11:00:00  Mediacore  Hardware     16
2015-02-19 16:00:00  Mediacore   Service     10
```

Convert strings to datetime

```
In [9]: evening_2_11 = pd.to_datetime(['2015-2-11 20:00',
   ...: '2015-2-11 21:00', '2015-2-11 22:00', '2015-2-11 23:00'])

In [10]: evening_2_11
Out[10]:
DatetimeIndex(['2015-02-11 20:00:00', '2015-02-11 21:00:00',
               '2015-02-11 22:00:00', '2015-02-11 23:00:00'],
              dtype='datetime64[ns]', freq=None)
```

Reindexing DataFrame

```
In [11]: sales.reindex(evening_2_11)
Out[11]:
                    Company   Product  Units
2015-02-11 20:00:00 Initech  Software    7.0
2015-02-11 21:00:00     NaN       NaN    NaN
2015-02-11 22:00:00     NaN       NaN    NaN
2015-02-11 23:00:00   Hooli  Software    4.0
```

Filling missing values

```
In [12]: sales.reindex(evening_2_11, method='ffill')
Out[12]:
                    Company   Product  Units
2015-02-11 20:00:00 Initech  Software      7
2015-02-11 21:00:00 Initech  Software      7
2015-02-11 22:00:00 Initech  Software      7
2015-02-11 23:00:00   Hooli  Software      4

In [13]: sales.reindex(evening_2_11, method='bfill')
Out[13]:
                    Company   Product  Units
2015-02-11 20:00:00 Initech  Software      7
2015-02-11 21:00:00   Hooli  Software      4
2015-02-11 22:00:00   Hooli  Software      4
2015-02-11 23:00:00   Hooli  Software      4
```

Let's practice!

Resampling time series data

Sales data

```
In [1]: import pandas as pd

In [2]: sales = pd.read_csv('sales-feb-2015.csv',
   ...:                     parse_dates=True, index_col= 'Date')

In [3]: sales.head()
Out[3]:
                             Company   Product  Units
Date
2015-02-02 08:30:00            Hooli  Software      3
2015-02-02 21:00:00        Mediacore  Hardware      9
2015-02-03 14:00:00          Initech  Software     13
2015-02-04 15:30:00        Streeplex  Software     13
2015-02-04 22:00:00  Acme Coporation  Hardware     14
```

Resampling

- Statistical methods over different time intervals
  - mean(), sum(), count(), etc.
- Down-sampling
  - reduce datetime rows to slower frequency
- Up-sampling
  - increase datetime rows to faster frequency

Aggregating means

```
In [4]: daily_mean = sales.resample('D').mean()

In [5]: daily_mean
Out[5]:
             Units
Date
2015-02-02     6.0
2015-02-03    13.0
2015-02-04    13.5
2015-02-05    14.5
2015-02-06     NaN
2015-02-07     1.0
2015-02-08     NaN
2015-02-09    13.0
2015-02-10     NaN
2015-02-11     5.5
2015-02-12     NaN
2015-02-13     NaN
2015-02-14     NaN
```

Verifying

```
In [6]: print(daily_mean.loc['2015-2-2'])
Units    6.0
Name: 2015-02-02 00:00:00, dtype: float64

In [7]: print(sales.loc['2015-2-2', 'Units'])
Date
2015-02-02 08:30:00    3
2015-02-02 21:00:00    9
Name: Units, dtype: int64

In [8]: sales.loc['2015-2-2', 'Units'].mean()
Out[8]: 6.0
```

Method chaining

```
In [9]: sales.resample('D').sum()
Out[9]:
             Units
Date
2015-02-02     6.0
2015-02-03    13.0
2015-02-04    13.5
2015-02-05    14.5
2015-02-06     NaN
2015-02-07     1.0
2015-02-08     NaN
2015-02-09    13.0
2015-02-10     NaN
2015-02-11     5.5
2015-02-12     NaN
2015-02-13     NaN
```

Method chaining

```
In [10]: sales.resample('D').sum().max()
Out[10]:
Units    29.0
dtype: float64
```

Resampling strings

```
In [11]: sales.resample('W').count()
Out[11]:
            Company  Product  Units
Date
2015-02-08        8        8      8
2015-02-15        4        4      4
2015-02-22        5        5      5
2015-03-01        2        2      2
```

Resampling frequencies

Input	Description
‘min’, ‘ T’	minute
‘H’	hour
‘D’	day
‘B’	business day
‘W’	week
‘M’	month
‘Q’	quarter
‘A’	year

Multiplying frequencies

```
In [12]: sales.loc[:,'Units'].resample('2W').sum()
Out[12]:
Date
2015-02-08    82
2015-02-22    79
2015-03-08    14
Freq: 2W-SUN, Name: Units, dtype: int64
```

Upsampling

```
In [13]: two_days = sales.loc['2015-2-4': '2015-2-5', 'Units']

In [13]: two_days
Out[13]:
Date
2015-02-04 15:30:00    13
2015-02-04 22:00:00    14
2015-02-05 02:00:00    19
2015-02-05 22:00:00    10
Name: Units, dtype: int64
```

Upsampling and filling

```
In [14]: two_days.resample('4H').ffill()
Out[14]:
Date
Date
2015-02-04 12:00:00     NaN
2015-02-04 16:00:00    13.0
2015-02-04 20:00:00    13.0
2015-02-05 00:00:00    14.0
2015-02-05 04:00:00    19.0
2015-02-05 08:00:00    19.0
2015-02-05 12:00:00    19.0
2015-02-05 16:00:00    19.0
2015-02-05 20:00:00    19.0
Freq: 4H, Name: Units, dtype: float64
```

Let's practice!

PANDAS FOUNDATIONS

Manipulating time series data

Sales data

```
In [1]: import pandas as pd

In [2]: sales = pd.read_csv('sales-feb-2015.csv',
   ...:                     parse_dates=['Date'])

In [3]: sales.head()
Out[3]:
                 Date         Company   Product  Units
0 2015-02-02 08:30:00           Hooli  Software      3
1 2015-02-02 21:00:00       Mediacore  Hardware      9
2 2015-02-03 14:00:00         Initech  Software     13
3 2015-02-04 15:30:00       Streeplex  Software     13
4 2015-02-04 22:00:00  Acme Coporation  Hardware     14
```

String methods

```
In [4]: sales['Company'].str.upper()
Out[4]:
0                  HOOLI
1              MEDIACORE
2                INITECH
3              STREEPLEX
4        ACME COPORATION
5        ACME COPORATION
6                  HOOLI
7        ACME COPORATION
8              STREEPLEX
9              MEDIACORE
10               INITECH
11                 HOOLI
12                 HOOLI
13             MEDIACORE
14             MEDIACORE
15             MEDIACORE
…
```

Substring matching

```
In [5]: sales['Product'].str.contains('ware')
Out[5]:
0       True
1       True
2       True
3       True
4       True
5       True
6      False
7       True
8      False
9       True
10      True
11      True
12      True
13      True
14     False
…
```

Boolean arithmetic

```
In [6]: True + False
Out[6]: 1

In [7]: True + True
Out[7]: 2

In [8]: False + False
Out[8]: 0
```

Boolean reduction

```
In [9]: sales['Product'].str.contains('ware').sum()
Out[9]: 14
```

Datetime methods

```
In [9]: sales['Date'].dt.hour
Out[9]:
0      8
1     21
2     14
3     15
4     22
5      2
6     22
7     23
8      9
9     13
10    20
11    23
12    12
13    11
14    16
…
```

Set timezone

```
In [10]: central = sales['Date'].dt.tz_localize('US/Central')

In [11]: central
Out[11]:
0     2015-02-02 08:30:00-06:00
1     2015-02-02 21:00:00-06:00
2     2015-02-03 14:00:00-06:00
3     2015-02-04 15:30:00-06:00
4     2015-02-04 22:00:00-06:00
5     2015-02-05 02:00:00-06:00
6     2015-02-05 22:00:00-06:00
7     2015-02-07 23:00:00-06:00
8     2015-02-09 09:00:00-06:00
9     2015-02-09 13:00:00-06:00
10    2015-02-11 20:00:00-06:00
11    2015-02-11 23:00:00-06:00
12    2015-02-16 12:00:00-06:00
…
Name: Date, dtype: datetime64[ns, US/Central]
```

Convert timezone

```
In [12]: central.dt.tz_convert('US/Eastern')
Out[12]:
0     2015-02-02 09:30:00-05:00
1     2015-02-02 22:00:00-05:00
2     2015-02-03 15:00:00-05:00
3     2015-02-04 16:30:00-05:00
4     2015-02-04 23:00:00-05:00
5     2015-02-05 03:00:00-05:00
6     2015-02-05 23:00:00-05:00
7     2015-02-08 00:00:00-05:00
8     2015-02-09 10:00:00-05:00
9     2015-02-09 14:00:00-05:00
10    2015-02-11 21:00:00-05:00
11    2015-02-12 00:00:00-05:00
12    2015-02-16 13:00:00-05:00
13    2015-02-19 12:00:00-05:00
14    2015-02-19 17:00:00-05:00
…
Name: Date, dtype: datetime64[ns, US/Eastern]
```

Method chaining

```
In [13]: sales['Date'].dt.tz_localize('US/Central').
    ...: dt.tz_convert('US/Eastern')
Out[13]:
0     2015-02-02 09:30:00-05:00
1     2015-02-02 22:00:00-05:00
2     2015-02-03 15:00:00-05:00
3     2015-02-04 16:30:00-05:00
4     2015-02-04 23:00:00-05:00
5     2015-02-05 03:00:00-05:00
6     2015-02-05 23:00:00-05:00
7     2015-02-08 00:00:00-05:00
8     2015-02-09 10:00:00-05:00
9     2015-02-09 14:00:00-05:00
10    2015-02-11 21:00:00-05:00
11    2015-02-12 00:00:00-05:00
12    2015-02-16 13:00:00-05:00
13    2015-02-19 12:00:00-05:00
14    2015-02-19 17:00:00-05:00
…
Name: Date, dtype: datetime64[ns, US/Eastern]
```

World Population

```
In [14]: population = pd.read_csv('world_population.csv',
    ...: parse_dates=True, index_col= 'Date')

In [15]: population
Out[15]:
              Population
Date
1960-12-31  2.087485e+10
1970-12-31  2.536513e+10
1980-12-31  3.057186e+10
1990-12-31  3.644928e+10
2000-12-31  4.228550e+10
2010-12-31  4.802217e+10
```

Upsample population

```
In [16]: population.resample('A').first()
Out[16]:
              Population
Date
1960-12-31  2.087485e+10
1961-12-31           NaN
1962-12-31           NaN
1963-12-31           NaN
1964-12-31           NaN
1965-12-31           NaN
1966-12-31           NaN
1967-12-31           NaN
1968-12-31           NaN
1969-12-31           NaN
1970-12-31  2.536513e+10
1971-12-31           NaN
1972-12-31           NaN
```

Interpolate missing data

```
In [17]: population.resample('A').first().interpolate('linear')
Out[17]:
              Population
Date
1960-12-31  2.087485e+10
1961-12-31  2.132388e+10
1962-12-31  2.177290e+10
1963-12-31  2.222193e+10
1964-12-31  2.267096e+10
1965-12-31  2.311999e+10
1966-12-31  2.356902e+10
1967-12-31  2.401805e+10
1968-12-31  2.446707e+10
1969-12-31  2.491610e+10
1970-12-31  2.536513e+10
1971-12-31  2.588580e+10
1972-12-31  2.640648e+10
```

Let’s practice!

PANDAS FOUNDATIONS

Time series visualization

Topics

- Line types
- Plot types
- Subplots

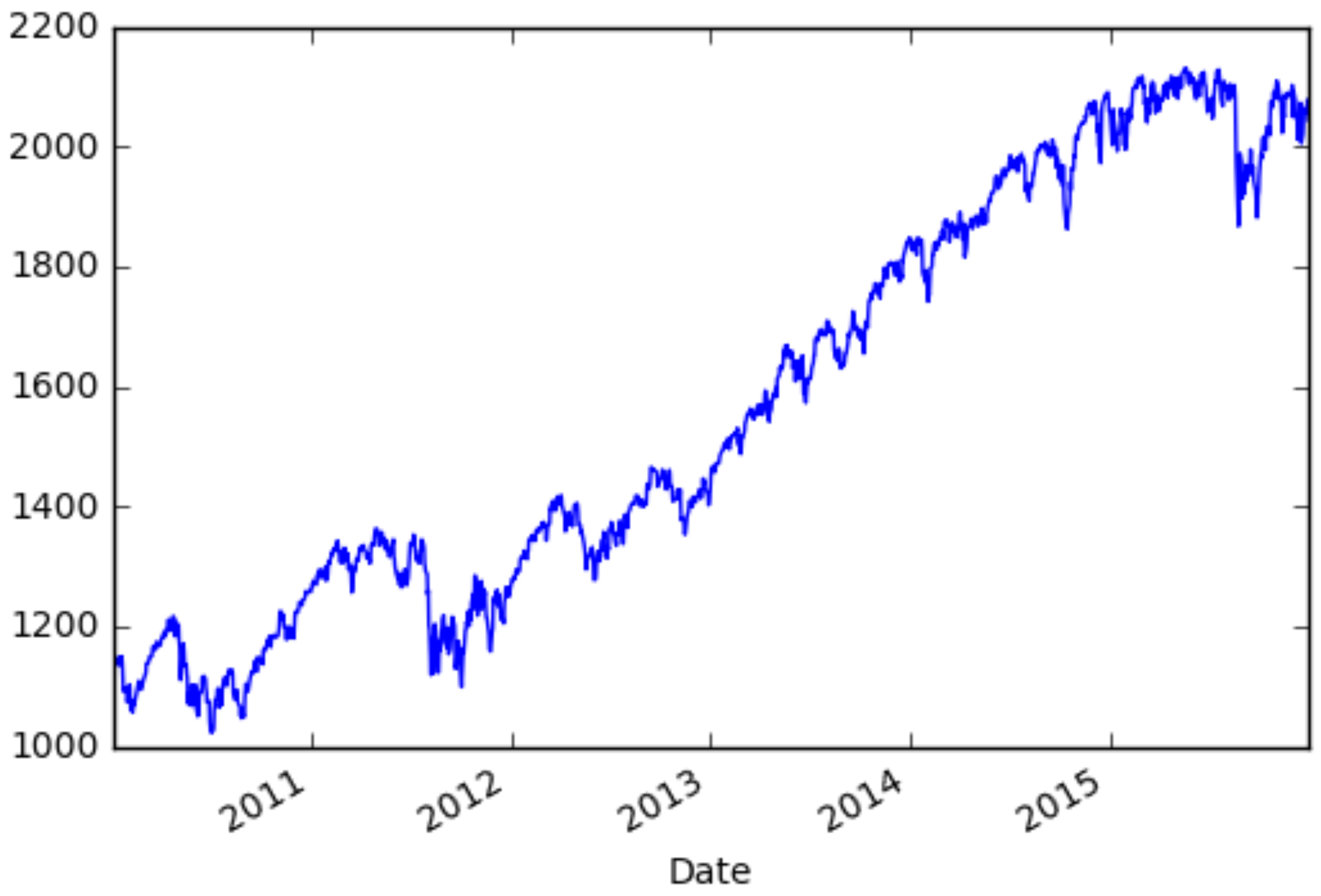
S&P 500 Data

```
In [1]: import pandas as pd

In [2]: import matplotlib.pyplot as plt

In [3]: sp500 = pd.read_csv('sp500.csv', parse_dates=True,
   ...:                     index_col= 'Date')

In [4]: sp500.head()
Out[4]:
                   Open         High          Low        Close      Volume    Adj Close
Date
2010-01-04  1116.560059  1133.869995  1116.560059  1132.989990  3991400000  1132.989990
2010-01-05  1132.660034  1136.630005  1129.660034  1136.520020  2491020000  1136.520020
2010-01-06  1135.709961  1139.189941  1133.949951  1137.140015  4972660000  1137.140015
2010-01-07  1136.270020  1142.459961  1131.319946  1141.689941  5270680000  1141.689941
2010-01-08  1140.520020  1145.390015  1136.219971  1144.979980  4389590000  1144.979980
```

Pandas plot

```
In [5]: sp500['Close'].plot()

In [6]: plt.show()
```

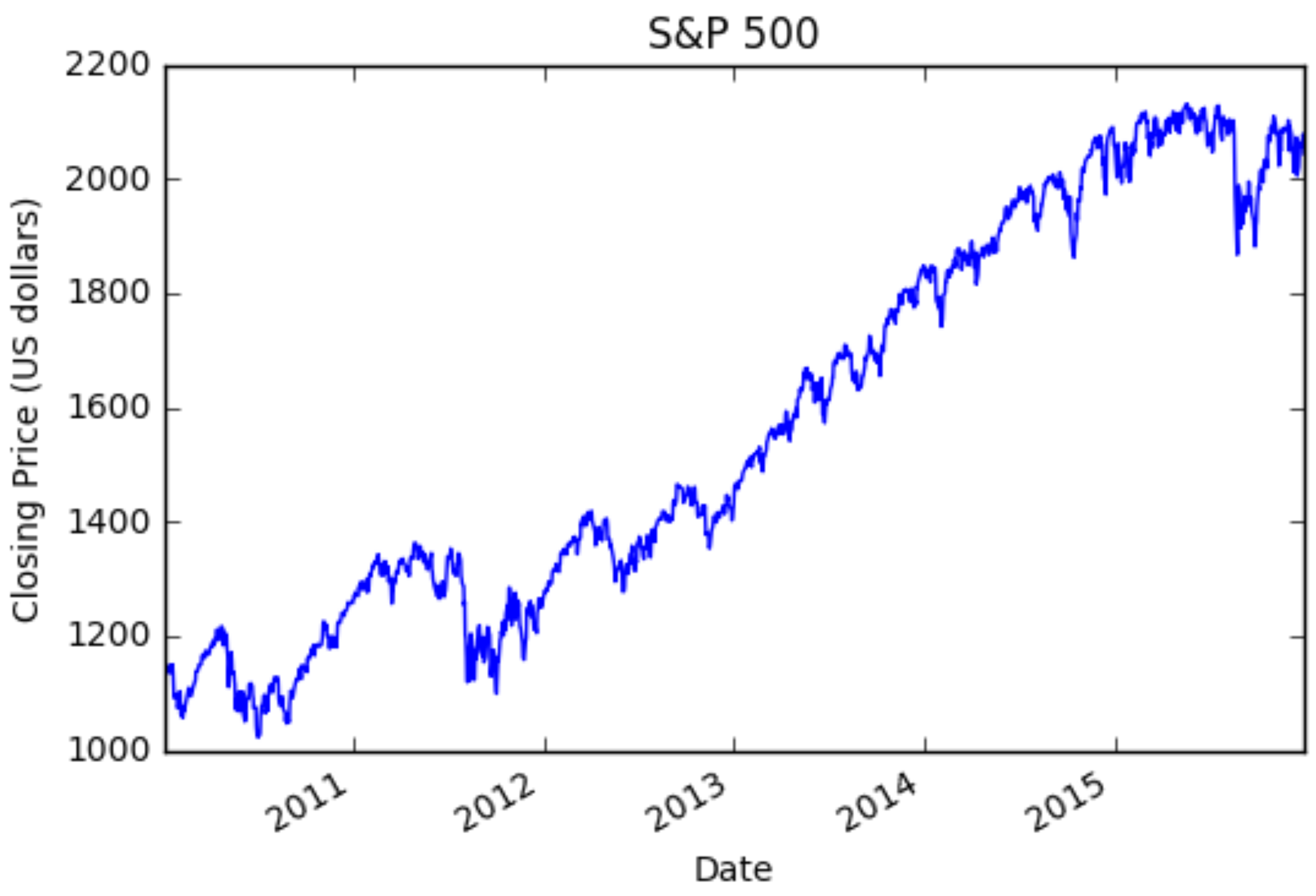
Default plot



Labels and title

```
In [7]: sp500['Close'].plot(title='S&P 500')

In [8]: plt.ylabel('Closing Price (US Dollars)')

In [9]: plt.show()
```

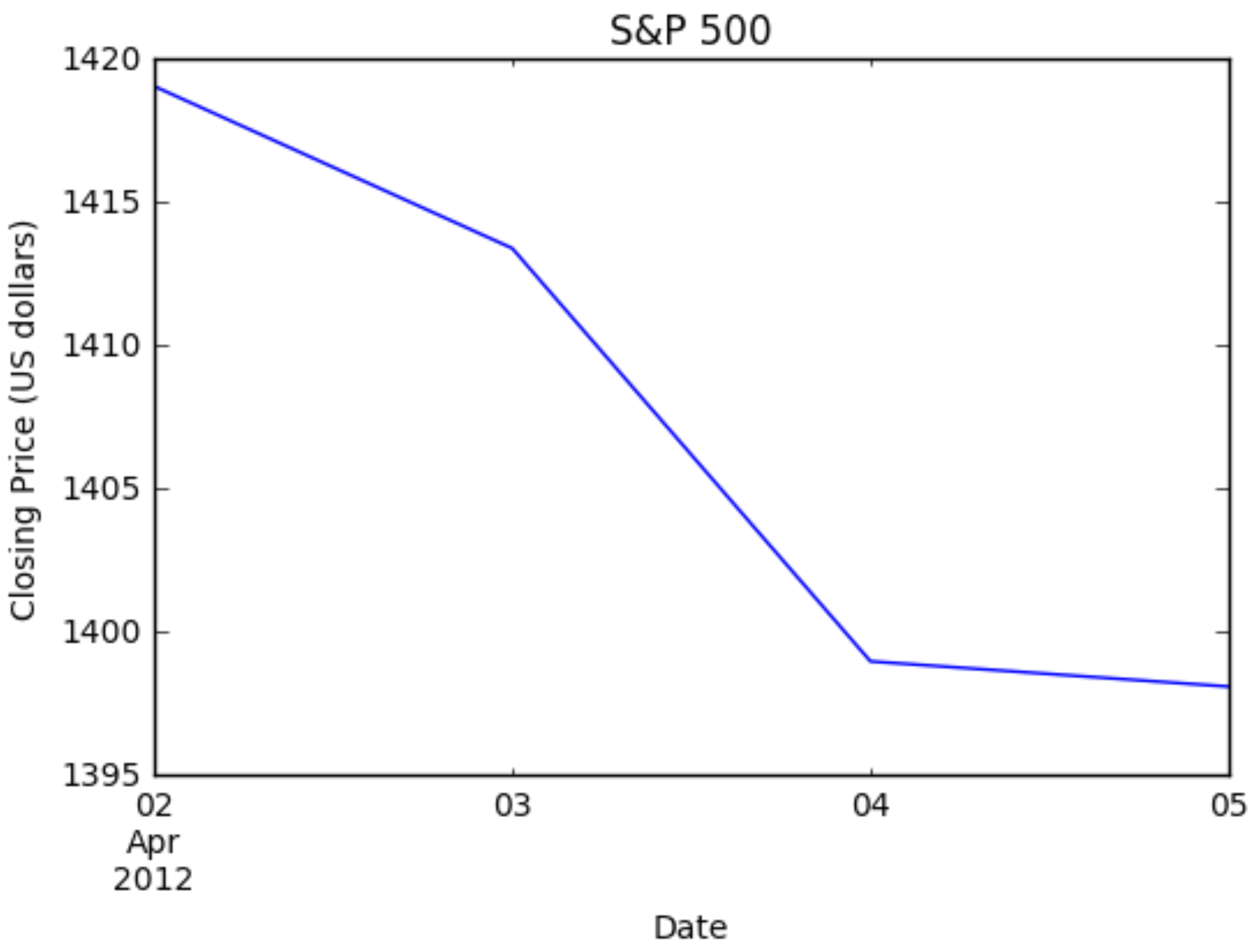
Labels and title



One week

```
In [10]: sp500.loc['2012-4-1':'2012-4-7', 'Close'].plot(title='S&P
    ...: 500')

In [11]: plt.ylabel('Closing Price (US Dollars)')

In [12]: plt.show()
```

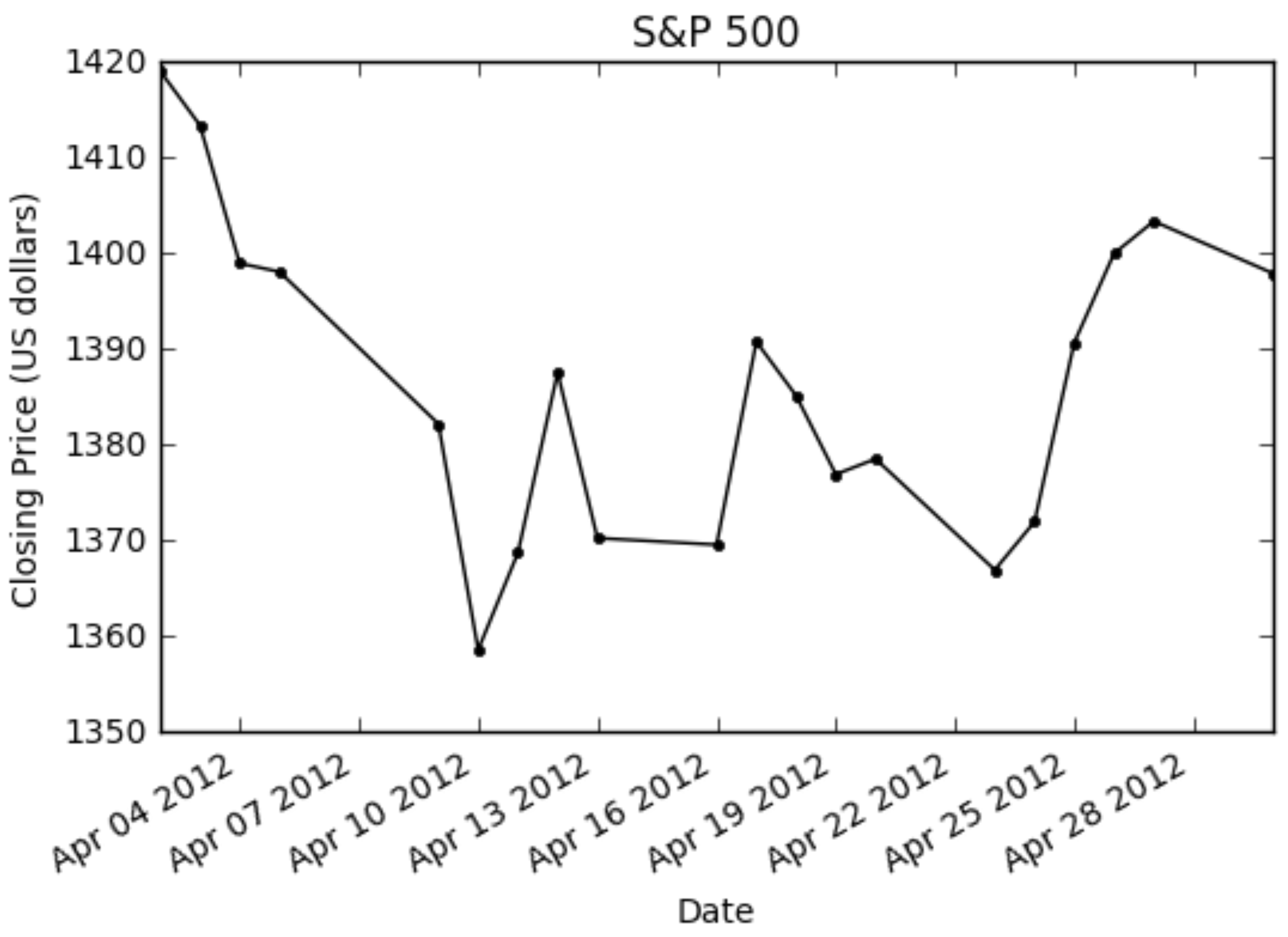
One week


S&P 500
Closing Price (US dollars)
1420
1415
1410
1405
1400
1395
02
Apr
2012
03
04
05
Date

Plot styles

```
In [13]: sp500.loc['2012-4', 'Close'].plot(style='k.-',
    ...:                                   title='S&P500')

In [14]: plt.ylabel('Closing Price (US Dollars)')

In [15]: plt.show()
```

One week


S&P 500
Closing Price (US dollars)
1420
1410
1400
1390
1380
1370
1360
1350
Apr 04 2012
Apr 07 2012
Apr 10 2012
Apr 13 2012
Apr 16 2012
Apr 19 2012
Apr 22 2012
Apr 25 2012
Apr 28 2012
Date

More plot styles

- Style format string
    - color (k: black)
    - marker (. : dot)
    - line type (-: solid)

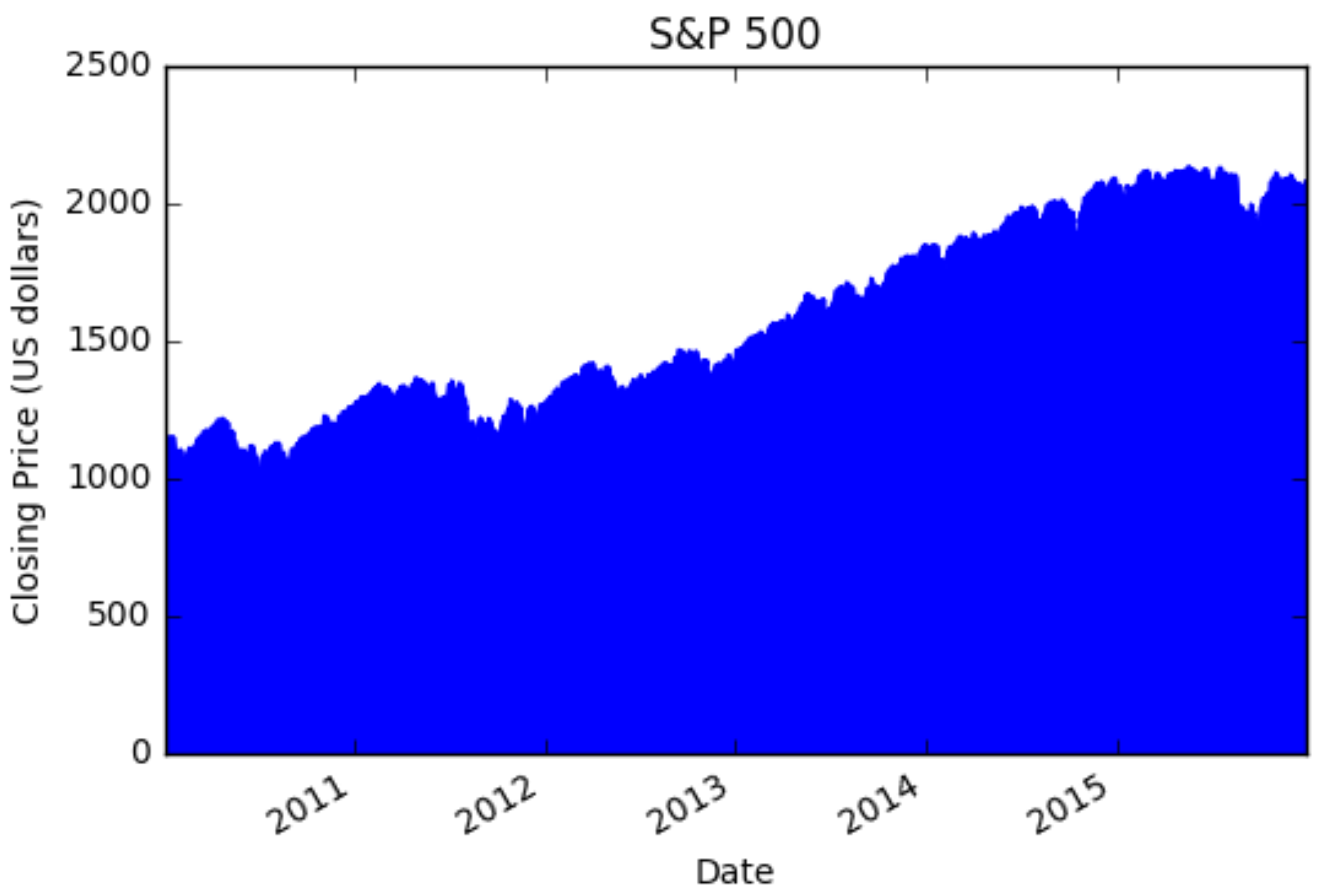
More plot styles

Color	Marker	Line
b: blue	o: circle	: dotted
g: green	*: star	–: dashed
r: red	s: square	
c: cyan	+: plus	

Area plot

```
In [16]: sp500['Close'].plot(kind='area', title='S&P 500')

In [17]: plt.ylabel('Closing Price (US Dollars)')

In [18]: plt.show()
```

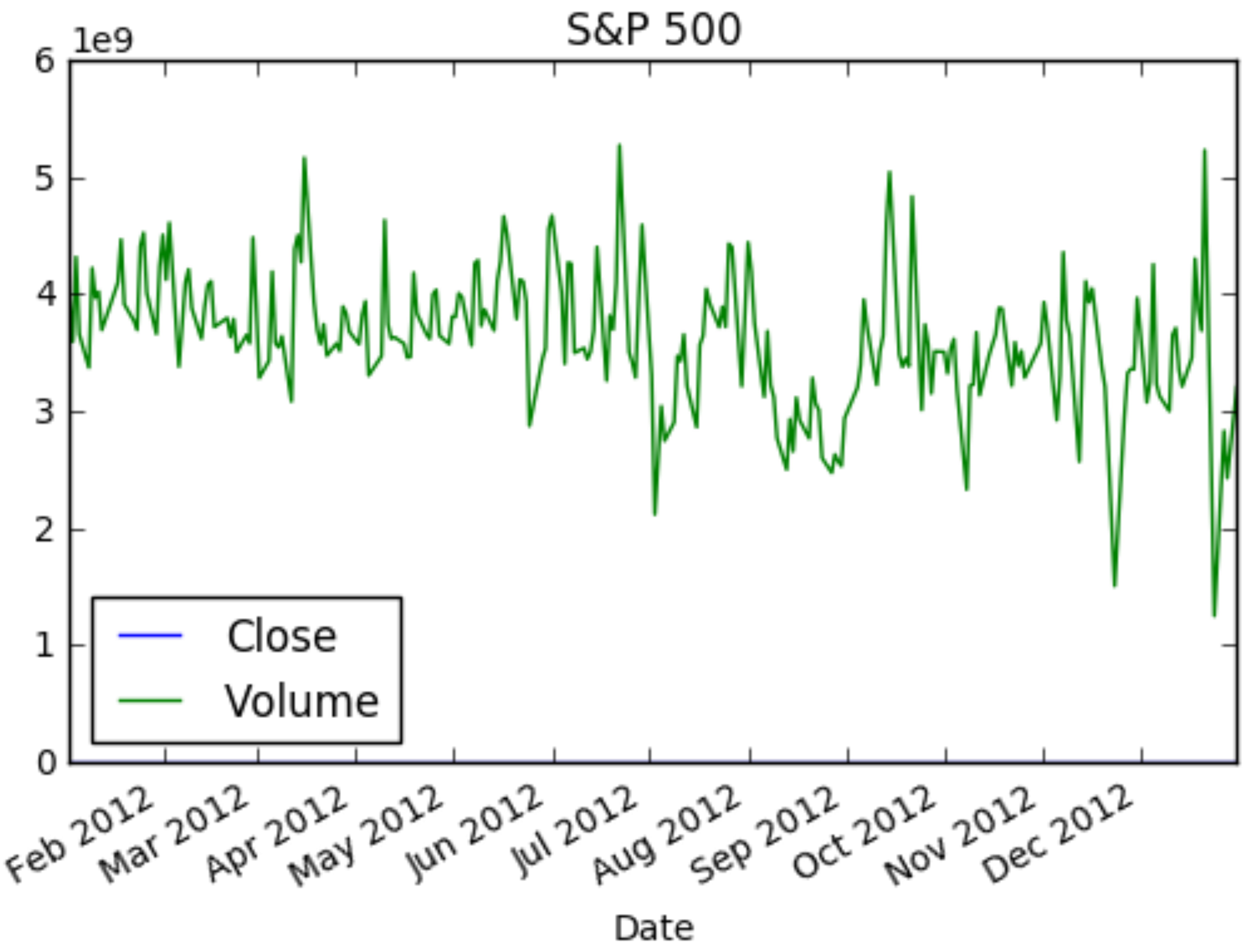
Area plot


S&P 500
Closing Price (US dollars)
2500
2000
1500
1000
500
0
2011
2012
2013
2014
2015
Date

Multiple columns

```
In [19]: sp500.loc['2012', ['Close','Volume']].plot(title='S&P
    ...: 500')

In [20]: plt.show()
```

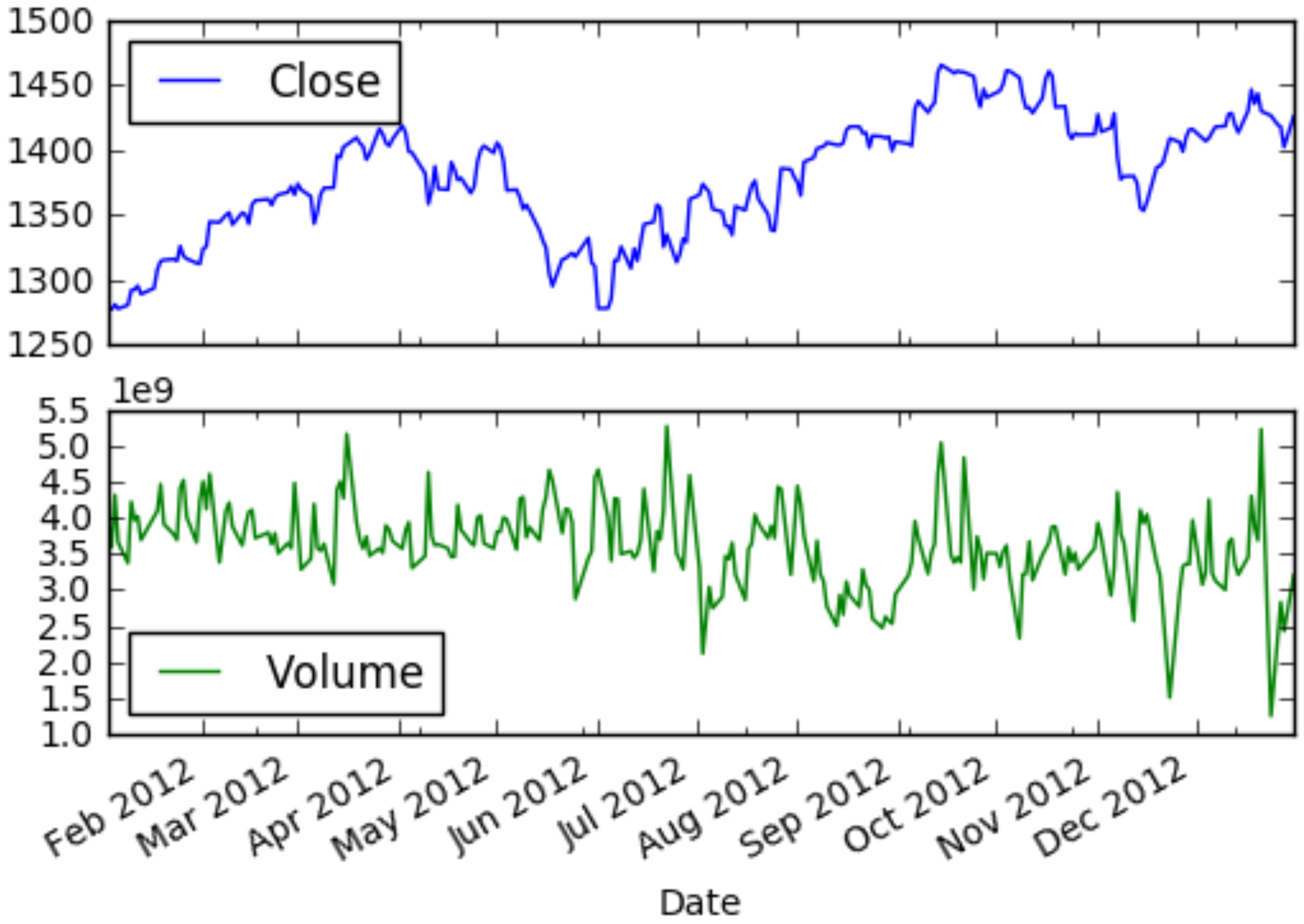
Multiple columns



Subplots

```
In [21]: sp500.loc['2012', ['Close','Volume']].plot(subplots=True)

In [22]: plt.show()
```

Subplots


1500
1450
1400
1350
1300
1250
Close
1e9
5.5
5.0
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
Volume
Feb 2012
Mar 2012
Apr 2012
May 2012
Jun 2012
Jul 2012
Aug 2012
Sep 2012
Oct 2012
Nov 2012
Dec 2012
Date

Let's practice!

Reading and cleaning the data

Case study

- Comparing observed weather data from two sources

	Temperature	DewPoint	Pressure	Date
0	46.2	37.5	1.0	20100101 00:00
1	44.6	37.1	1.0	20100101 01:00
2	44.1	36.9	1.0	20100101 02:00
3	43.8	36.9	1.0	20100101 03:00
4	43.5	36.8	1.0	20100101 04:00

	Date	Wban	...	station_pressure	sea_level_pressure
0	2011-01-01 00:53:00	13904	...	29.42	29.95
1	2011-01-01 01:53:00	13904	...	29.49	30.01
2	2011-01-01 02:53:00	13904	...	29.49	30.01
3	2011-01-01 03:53:00	13904	...	29.51	30.03
4	2011-01-01 04:53:00	13904	...	29.51	30.04

Source: National Oceanic & Atmospheric Administration, www.noaa.gov/climate

Climate normals of Austin, TX from 1981-2010

	Temperature	DewPoint	Pressure	Date
0	46.2	37.5	1.0	20100101 00:00
1	44.6	37.1	1.0	20100101 01:00
2	44.1	36.9	1.0	20100101 02:00
3	43.8	36.9	1.0	20100101 03:00
4	43.5	36.8	1.0	20100101 04:00
5	43.0	36.5	1.0	20100101 05:00
6	43.1	36.3	1.0	20100101 06:00
7	42.3	35.9	1.0	20100101 07:00
8	42.5	36.2	1.0	20100101 08:00
9	45.9	37.8	1.0	20100101 09:00

Source: National Oceanic & Atmospheric Administration, www.noaa.gov/climate

Weather data of Austin, TX from 2011

	Date	Wban	date	Time	StationType	...	relative_humidity	wind_speed	wind_direction	station_pressure	sea_level_pressure
0	2011-01-01 00:53:00	13904	20110101	5300	12	...	24.0	15.0	360	29.42	29.95
1	2011-01-01 01:53:00	13904	20110101	15300	12	...	23.0	10.0	340	29.49	30.01
2	2011-01-01 02:53:00	13904	20110101	25300	12	...	22.0	15.0	010	29.49	30.01
3	2011-01-01 03:53:00	13904	20110101	35300	12	...	27.0	7.0	350	29.51	30.03
4	2011-01-01 04:53:00	13904	20110101	45300	12	...	25.0	11.0	020	29.51	30.04
5	2011-01-01 05:53:00	13904	20110101	55300	12	...	28.0	6.0	010	29.53	30.06
6	2011-01-01 06:53:00	13904	20110101	65300	12	...	29.0	7.0	360	29.57	30.10
7	2011-01-01 07:53:00	13904	20110101	75300	12	...	29.0	11.0	020	29.59	30.12
8	2011-01-01 08:53:00	13904	20110101	85300	12	...	25.0	15.0	020	29.62	30.16
9	2011-01-01 09:53:00	13904	20110101	95300	12	...	22.0	18.0	010	29.65	30.19

Source: National Oceanic & Atmospheric Administration, www.noaa.gov/climate

Reminder: read_csv()

- Useful keyword options
  - names: assigning column labels
  - index_col: assigning index
  - parse_dates: parsing datetimes
  - na_values: parsing NaNs

Let's practice!

Statistical exploratory data analysis

Reminder: time series

- Index selection by date time
- Partial datetime selection
- Slicing ranges of datetimes

```
In [1]: climate2010['2010-05-31 22:00:00'] # datetime

In [2]: climate2010['2010-06-01'] # Entire day

In [3]: climate2010['2010-04'] # Entire month

In [4]: climate2010[‘2010-09':'2010-10'] # 2 months
```

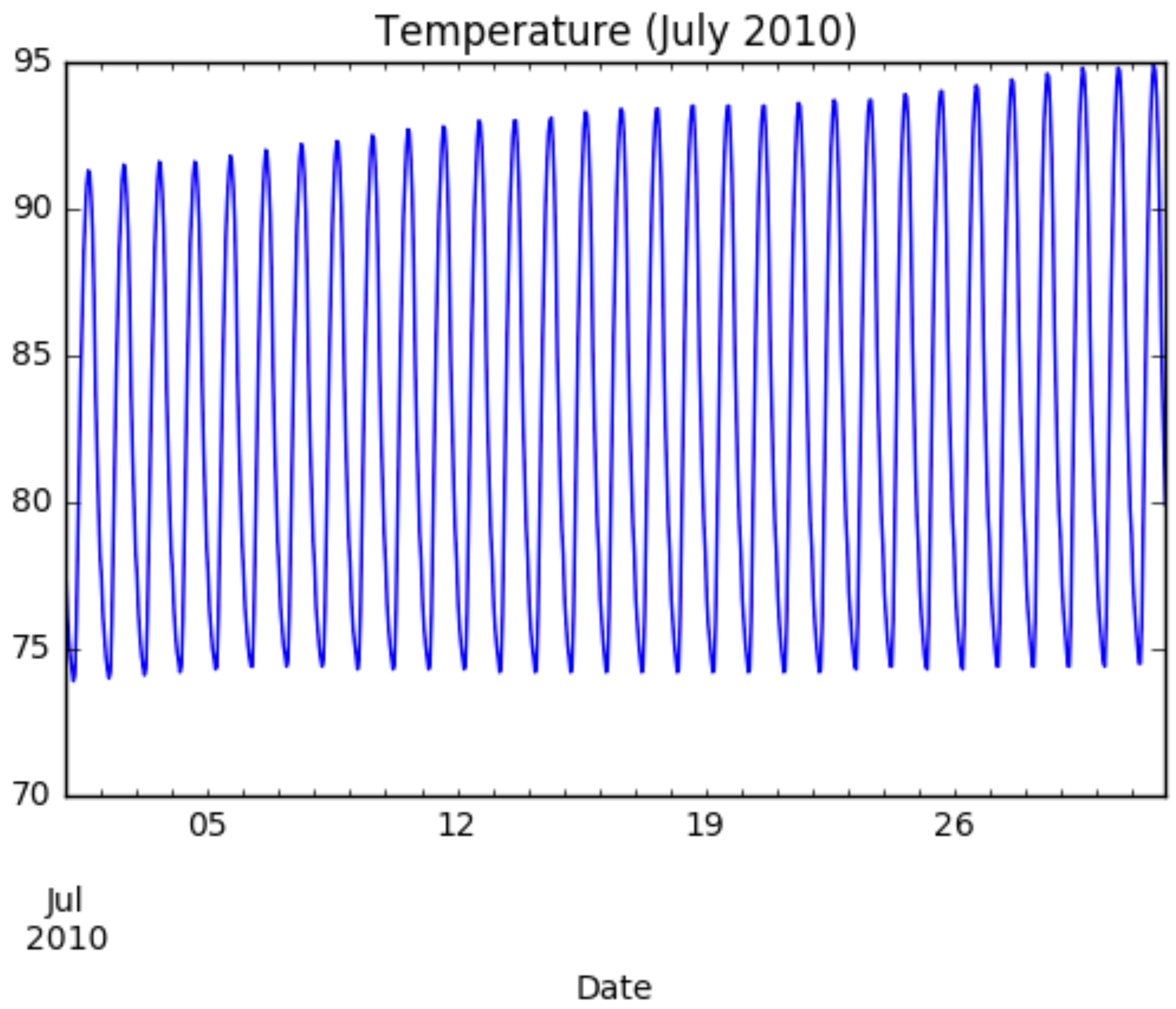
Reminder: statistics methods

- Methods for computing statistics:
  - describe(): summary
  - mean(): average
  - count(): counting entries
  - median(): median
  - std(): standard deviation

Let's practice!

Visual exploratory data analysis

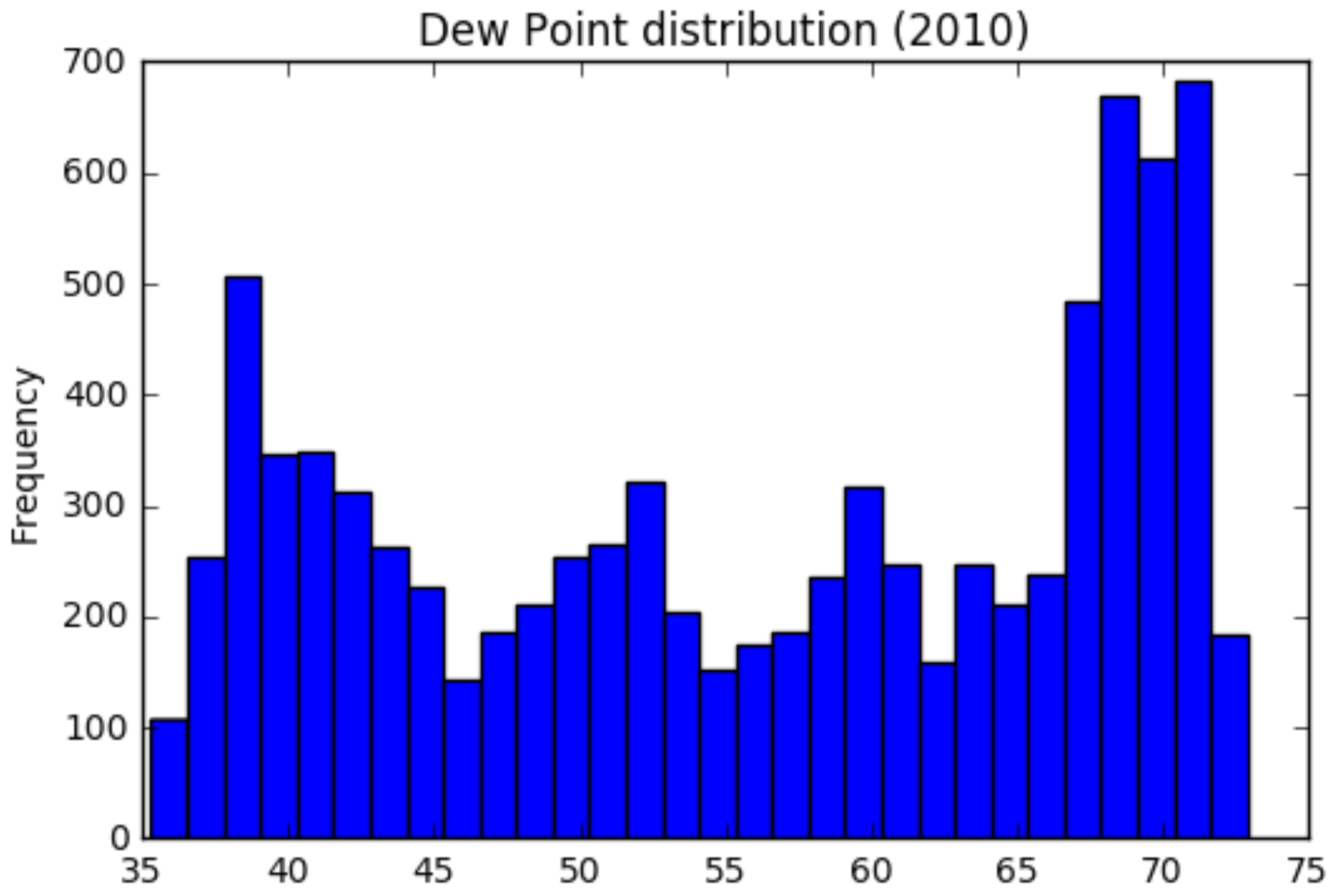
Line plots in pandas



Line plots in pandas

```
In [1]: import matplotlib.pyplot as plt

In [2]: climate2010.Temperature['2010-07'].plot()

In [3]: plt.title('Temperature (July 2010)')

In [4]: plt.show()
```

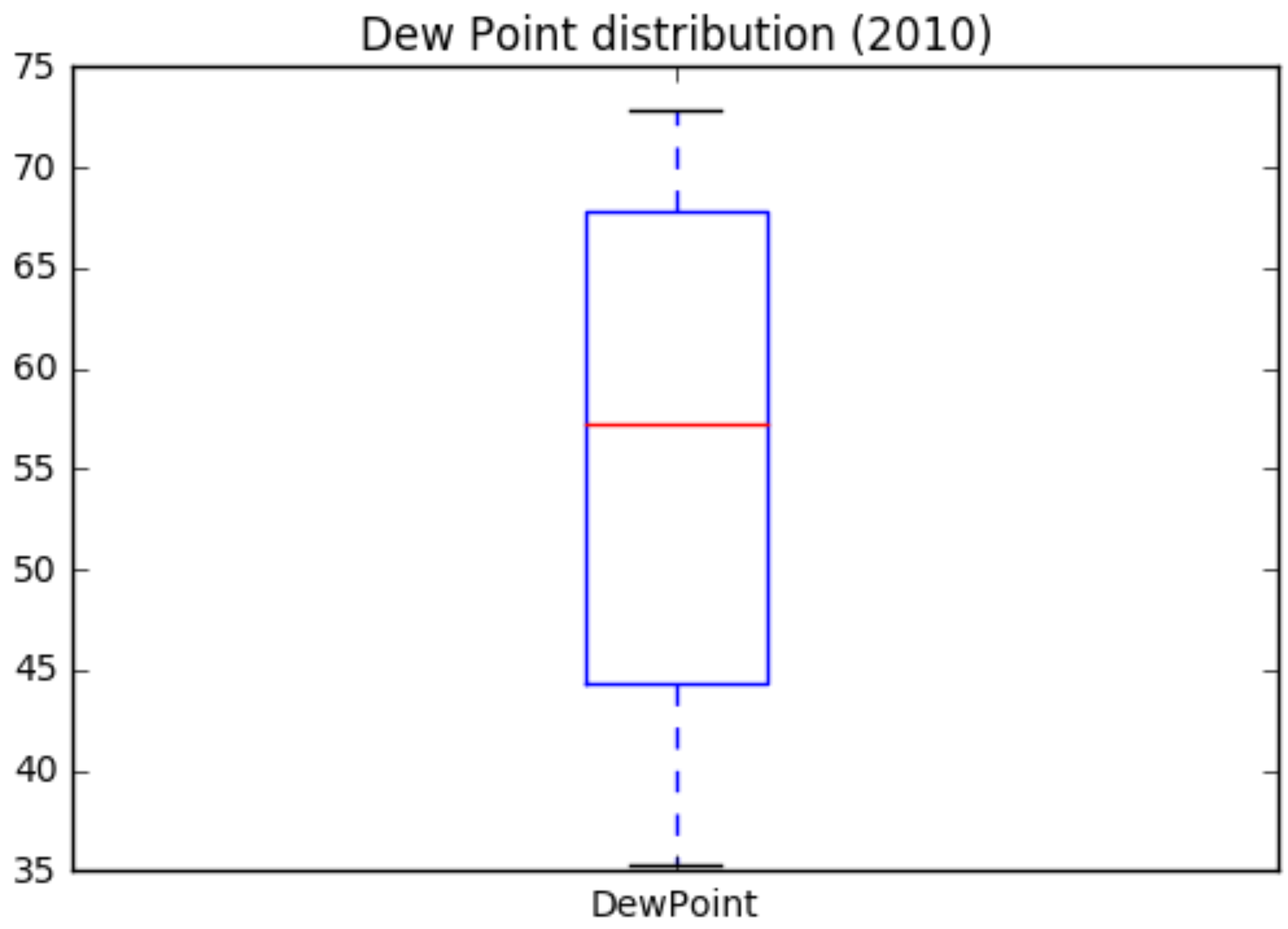
Histograms in pandas



Histograms in pandas

```
In [5]: climate2010['DewPoint'].plot(kind= 'hist', bins=30)

In [6]: plt.title('Dew Point distribution (2010)')

In [7]: plt.show()
```

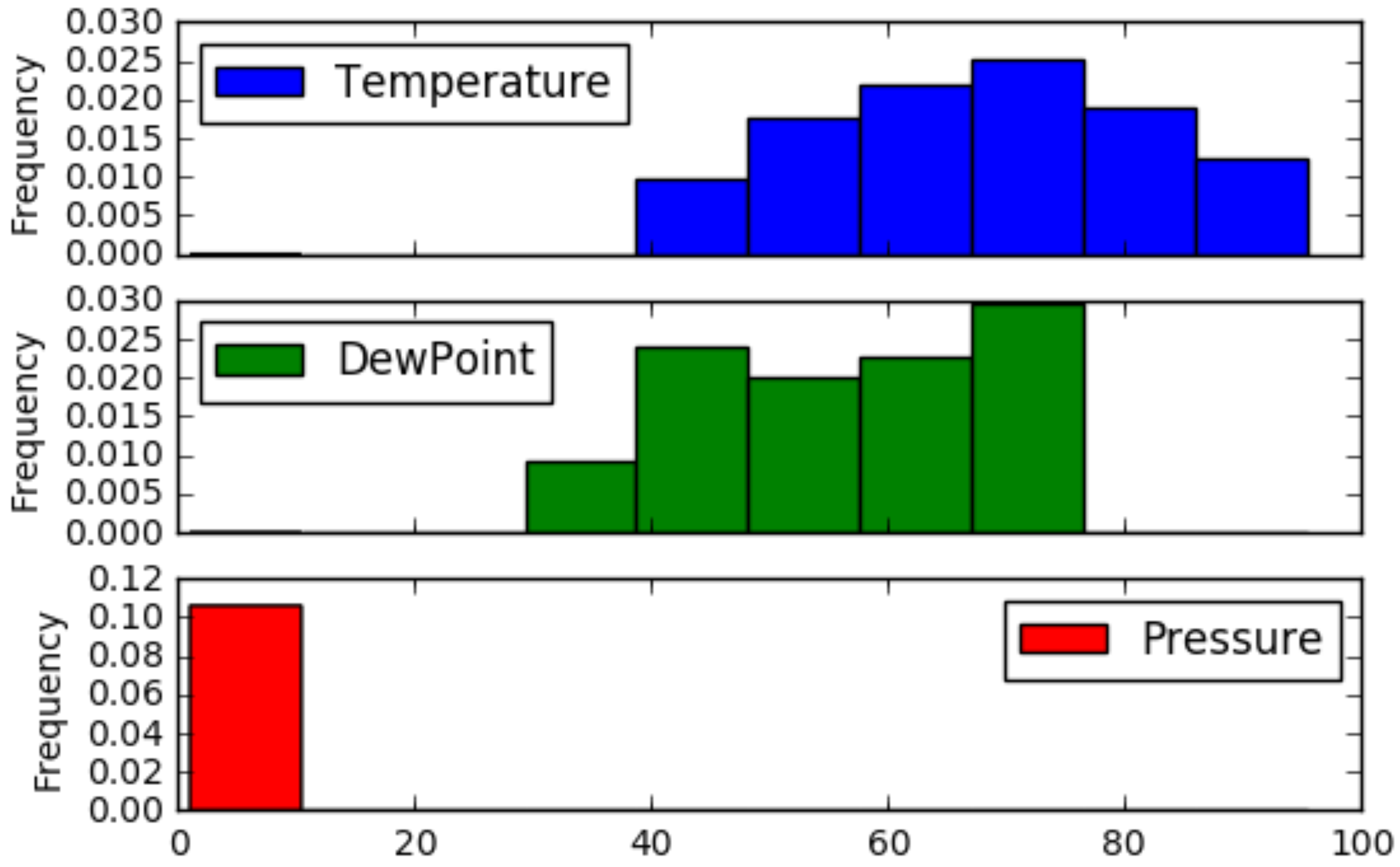
Box plots in pandas



Box plots in pandas

```
In [8]: climate2010['DewPoint'].plot(kind='box')

In [9]: plt.title('Dew Point distribution (2010)')

In [10]: plt.show()
```

Subplots in pandas



Subplots in pandas

```
In [11]: climate2010.plot(kind='hist', normed=True, subplots=True)

In [12]: plt.show()
```

Let’s practice!

Final thoughts

You can now...

- Import many types of datasets and deal with import issues
- Export data to facilitate collaborative data science
- Perform statistical and visual EDA natively in pandas

See you in the next course!

In [1]:
```python
dict = {
"country":["Brazil", "Russia", "India", "China", "South Africa"],
"capital":["Brasilia", "Moscow", "New Delhi", "Beijing", "Pretoria"],
"area":[8.516, 17.10, 3.286, 9.597, 1.221],
"population":[200.4, 143.5, 1252, 1357, 52.98] }
print(dict)
```

```
{'country': ['Brazil', 'Russia', 'India', 'China', 'South Africa'], 'capital': ['Bra
silia', 'Moscow', 'New Delhi', 'Beijing', 'Pretoria'], 'area': [8.516, 17.1, 3.286,
9.597, 1.221], 'population': [200.4, 143.5, 1252, 1357, 52.98]}
```

In [2]:
```python
import pandas as pd
x=pd.DataFrame(dict)
print(x)
```

```
        country    capital    area  population
0        Brazil   Brasilia   8.516      200.40
1        Russia     Moscow  17.100      143.50
2         India  New Delhi   3.286     1252.00
3         China    Beijing   9.597     1357.00
4  South Africa   Pretoria   1.221       52.98
```

In [3]:
```python
x.index = ["BR", "RU", "IN", "CH", "SA"]
print(x)
```

```
         country    capital    area  population
BR        Brazil   Brasilia   8.516      200.40
RU        Russia     Moscow  17.100      143.50
IN         India  New Delhi   3.286     1252.00
CH         China    Beijing   9.597     1357.00
SA  South Africa   Pretoria   1.221       52.98
```

In [44]:
```python
x= pd.read_csv("H:\std.csv")
print(x)
```

```
   rollno  sub1  sub2  sub3
0      90    90  95.0   100
1      91    98  94.0    63
2      92    63   NaN    47
3      93    95  94.0    75
4      94    65   NaN    69
5      95    82  89.0    85
```

In [5]:
```python
x['country']
```

Out[5]:
```
BR          Brazil
RU          Russia
IN           India
CH           China
SA    South Africa
Name: country, dtype: object
```

In [6]:
```python
type(x["country"])
```

Out[6]:
```
pandas.core.series.Series
```

Column Access [ ]

In [7]:
```
x[['country']]
```

Out[7]:

	country
BR	Brazil
RU	Russia
IN	India
CH	China
SA	South Africa

In [8]:
```
x[["country", "capital"]]
```

Out[8]:

	country	capital
BR	Brazil	Brasilia
RU	Russia	Moscow
IN	India	New Delhi
CH	China	Beijing
SA	South Africa	Pretoria

Row Access

In [33]:
```
x.iloc[0:2,0:2]
```

Out[33]:

	country	capital
BR	Brazil	Brasilia
RU	Russia	Moscow

loc - (label-based)

iloc- (integer position-based)

In [10]:
```
#Row as Pandas Series
print(x.loc['RU'])
#DataFrame
print(x.loc[['RU']])
```

```
country       Russia
capital       Moscow
area            17.1
population     143.5
Name: RU, dtype: object
   country capital  area  population
RU  Russia  Moscow  17.1       143.5
```

In [11]:
```
x.loc[["RU", "IN", "CH"]]
```

Out[11]:

	country	capital	area	population
RU	Russia	Moscow	17.100	143.5
IN	India	New Delhi	3.286	1252.0
CH	China	Beijing	9.597	1357.0

In [12]:
```
x.loc[["RU", "IN", "CH"], ["country", "capital"]]
```

Out[12]:

	country	capital
RU	Russia	Moscow
IN	India	New Delhi
CH	China	Beijing

In [13]:
```
x.loc[:,['country','capital']]
```

Out[13]:

	country	capital
BR	Brazil	Brasilia
RU	Russia	Moscow
IN	India	New Delhi
CH	China	Beijing
SA	South Africa	Pretoria

In [14]:
```
x.iloc[[0]]
```

Out[14]:

	country	capital	area	population
BR	Brazil	Brasilia	8.516	200.4

In [15]:
```
x.iloc[[1,2,3]]
```

Out[15]:

	country	capital	area	population
RU	Russia	Moscow	17.100	143.5
IN	India	New Delhi	3.286	1252.0
CH	China	Beijing	9.597	1357.0

In [16]:
```
x.iloc[:,[0,2]]
```

Out[16]:

	country	area
BR	Brazil	8.516
RU	Russia	17.100
IN	India	3.286
CH	China	9.597
SA	South Africa	1.221

In [17]:
```python
x[x["area"] > 8]
```

Out[17]:

	country	capital	area	population
BR	Brazil	Brasilia	8.516	200.4
RU	Russia	Moscow	17.100	143.5
CH	China	Beijing	9.597	1357.0

In [18]:
```python
x[x.iloc[:,2]>8]
```

Out[18]:

	country	capital	area	population
BR	Brazil	Brasilia	8.516	200.4
RU	Russia	Moscow	17.100	143.5
CH	China	Beijing	9.597	1357.0

In [34]:
```python
import numpy as np
print(x)
```

```
         country    capital    area  population  newcol  new
BR        Brazil   Brasilia   8.516      200.40     6.0    6
RU        Russia     Moscow  17.100      143.50     6.0    6
IN         India  New Delhi   3.286     1252.00     5.0    5
CH         China    Beijing   9.597     1357.00     5.0    5
SA  South Africa   Pretoria   1.221       52.98    12.0   12
```

In [20]:
```python
x[np.logical_and(x["area"] > 8, x["area"] < 10)]
```

Out[20]:

	country	capital	area	population
BR	Brazil	Brasilia	8.516	200.4
CH	China	Beijing	9.597	1357.0

In [21]:
```python
for i in x:
    print(i)
```

```
country
capital
area
population
```

In [22]:
```
for l,r in x.iterrows():
    print(l)
    print(r)
```

```
BR
country           Brazil
capital         Brasilia
area               8.516
population         200.4
Name: BR, dtype: object
RU
country        Russia
capital        Moscow
area             17.1
population      143.5
Name: RU, dtype: object
IN
country            India
capital        New Delhi
area               3.286
population          1252
Name: IN, dtype: object
CH
country         China
capital       Beijing
area            9.597
population       1357
Name: CH, dtype: object
SA
country       South Africa
capital           Pretoria
area                 1.221
population           52.98
Name: SA, dtype: object
```

In [23]:
```
for l,r in x.iterrows():
    print(l,":",r['country'])
```

```
BR : Brazil
RU : Russia
IN : India
CH : China
SA : South Africa
```

In [46]:
```
for l,r in x.iterrows():
    x.loc[l,"totalmarks"]=r['sub1']+r['sub2']+r['sub3']
```

In [47]:
```
print(x)
```

```
   rollno  sub1  sub2  sub3  totalmarks
0      90    90  95.0   100       285.0
1      91    98  94.0    63       255.0
2      92    63   NaN    47         NaN
3      93    95  94.0    75       264.0
4      94    65   NaN    69         NaN
5      95    82  89.0    85       256.0
```

In [26]:
```
x['new']=x['country'].apply(len)
```

In [27]:
```
x
```
Out[27]:

	country	capital	area	population	newcol	new
BR	Brazil	Brasilia	8.516	200.40	6.0	6
RU	Russia	Moscow	17.100	143.50	6.0	6
IN	India	New Delhi	3.286	1252.00	5.0	5
CH	China	Beijing	9.597	1357.00	5.0	5
SA	South Africa	Pretoria	1.221	52.98	12.0	12

In [28]:
```
x.loc[['RU','IN','CH']]
```
Out[28]:

	country	capital	area	population	newcol	new
RU	Russia	Moscow	17.100	143.5	6.0	6
IN	India	New Delhi	3.286	1252.0	5.0	5
CH	China	Beijing	9.597	1357.0	5.0	5

In [45]:
```
x.info()
```
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6 entries, 0 to 5
Data columns (total 4 columns):
rollno     6 non-null int64
sub1       6 non-null int64
sub2       4 non-null float64
sub3       6 non-null int64
dtypes: float64(1), int64(3)
memory usage: 272.0 bytes
```

In [48]:
```
x.to_csv("abc.csv")
```

In [49]:
```
x.to_excel("dat.xlsx")
```

In [32]:
```
x.iloc[:3,1:3]
```
Out[32]:

	capital	area
BR	Brasilia	8.516
RU	Moscow	17.100
IN	New Delhi	3.286

In [ ]:

In [5]:
```
import pandas as pd
data=pd.read_csv('C:\\Users\\iraga\\Desktop\\python\\iris.csv')
print(data.tail())
```

```
     sepal.length  sepal.width  petal.length  petal.width    variety
145           6.7          3.0           5.2          2.3  Virginica
146           6.3          2.5           5.0          1.9  Virginica
147           6.5          3.0           5.2          2.0  Virginica
148           6.2          3.4           5.4          2.3  Virginica
149           5.9          3.0           5.1          1.8  Virginica
```

In [7]:
```
edata=pd.ExcelFile('C:\\Users\\iraga\\Desktop\\python\\logins.xlsx')
print(edata.sheet_names)
```

```
['sheet', 'sheet1']
```

In [10]:
```
df1=edata.parse(0)
print(df1.head(20))
```

```
     username  password                           email
0   CHDFAC001  Infy@123           kamravikas@akgec.ac.in
1   CHDFAC002  Infy@123         rawatgaurav@akgec.ac.in
2   CHDFAC003  Infy@123           seema.baghae@gmail.com
3   CHDFAC004  Infy@123       tannuchanana1990@gmail.com
4   CHDFAC005  Infy@123        sivajyothi.cse@anits.edu.in
5   CHDFAC006  Infy@123            meena.it@anits.edu.in
6   CHDFAC007  Infy@123              mnprasadu@gmail.com
7   CHDFAC008  Infy@123            paramesh.u@gmail.com
8   CHDFAC009  Infy@123  suvarnashirke@atharvacoe.ac.in
9   CHDFAC010  Infy@123     nidaparkar@atharvacoe.ac.in
10  CHDFAC011  Infy@123             geethu0517@gmail.com
11  CHDFAC012  Infy@123       ravindra.meegada99@gmail.com
12  CHDFAC013  Infy@123      promila.verma@baddiuniv.ac.in
13  CHDFAC014  Infy@123  priyanka.sharma@baddiuniv.ac.in
14  CHDFAC015  Infy@123       prashanthbabubandi@gmail.com
15  CHDFAC016  Infy@123        prasanth.k@becbapatla.ac.in
16  CHDFAC017  Infy@123            pardeep308@yahoo.co.in
17  CHDFAC018  Infy@123                ashiarya@gmail.com
18  CHDFAC019  Infy@123         vasanthasena_it@cbit.ac.in
19  CHDFAC020  Infy@123          gnyanadeepa_it@cbit.ac.in
```

In [6]:
```
df1=edata.parse(1)
df1.head()
```

Out[6]:

	username	password	email
0	CHDFAC104	Infy@123	varsha469@gmail.com
1	CHDFAC105	Infy@123	jhdevare@mitaoe.ac.in
2	CHDFAC106	Infy@123	stwarpe@comp.maepune.ac.in
3	CHDFAC107	Infy@123	kanwalpreetsingh_pu@yahoo.com
4	CHDFAC108	Infy@123	manishkumar.3006@poornima.org

In [4]:
```
df1=edata.parse('sheet')
df1.head()
```

Out[4]:

	username	password	email
0	CHDFAC001	Infy@123	kamravikas@akgec.ac.in
1	CHDFAC002	Infy@123	rawatgaurav@akgec.ac.in
2	CHDFAC003	Infy@123	seema.baghae@gmail.com
3	CHDFAC004	Infy@123	tannuchanana1990@gmail.com
4	CHDFAC005	Infy@123	sivajyothi.cse@anits.edu.in

In [5]:
```
df1=edata.parse('sheet1')
df1.head()
```

Out[5]:

	username	password	email
0	CHDFAC104	Infy@123	varsha469@gmail.com
1	CHDFAC105	Infy@123	jhdevare@mitaoe.ac.in
2	CHDFAC106	Infy@123	stwarpe@comp.maepune.ac.in
3	CHDFAC107	Infy@123	kanwalpreetsingh_pu@yahoo.com
4	CHDFAC108	Infy@123	manishkumar.3006@poornima.org

In [ ]: