PANDAS FOUNDATIONS

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

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See you in the course!

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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
```

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Let’s practice!

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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
```

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Let’s practice!

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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)
```

PANDAS FOUNDATIONS

Let’s practice!

PANDAS FOUNDATIONS

Plotting with pandas

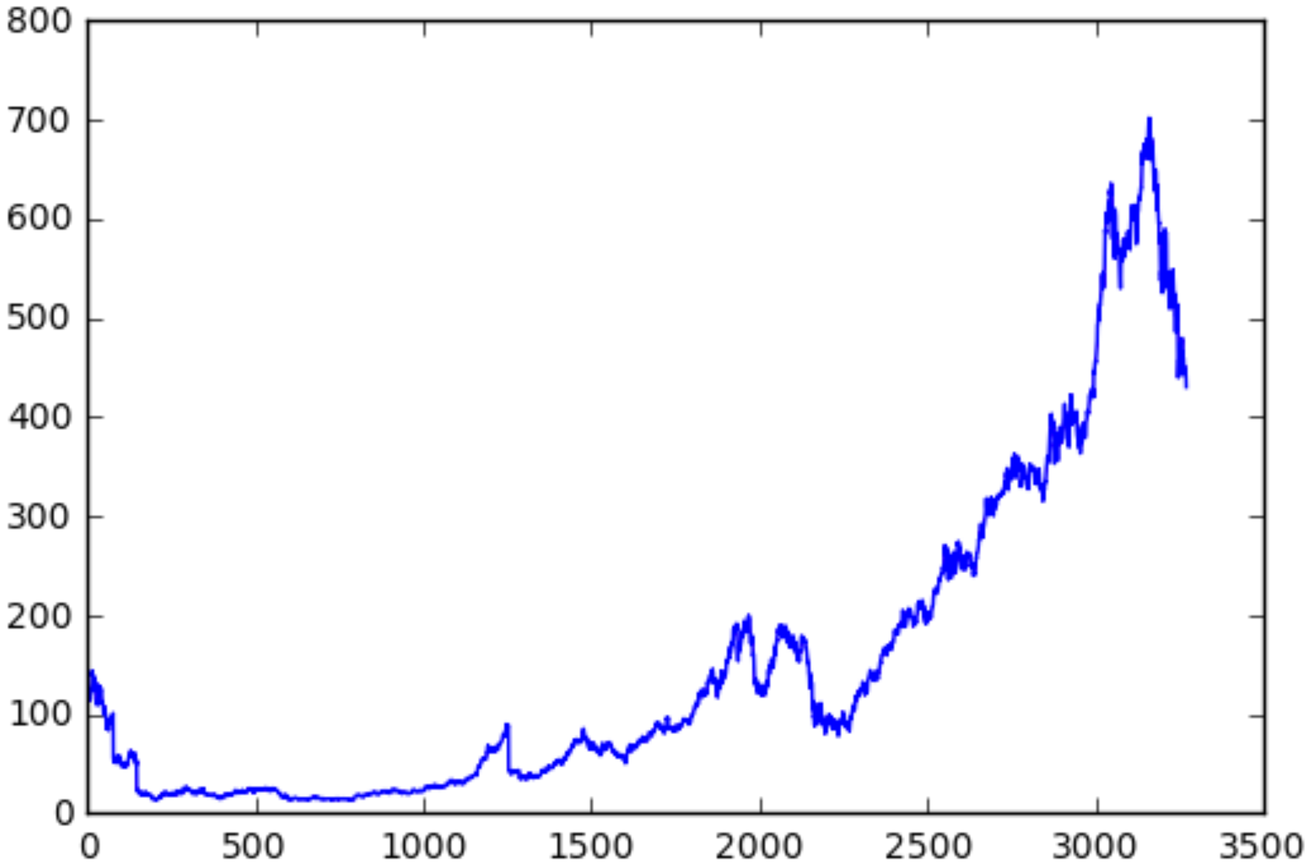
AAPL stock data

```
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()
```

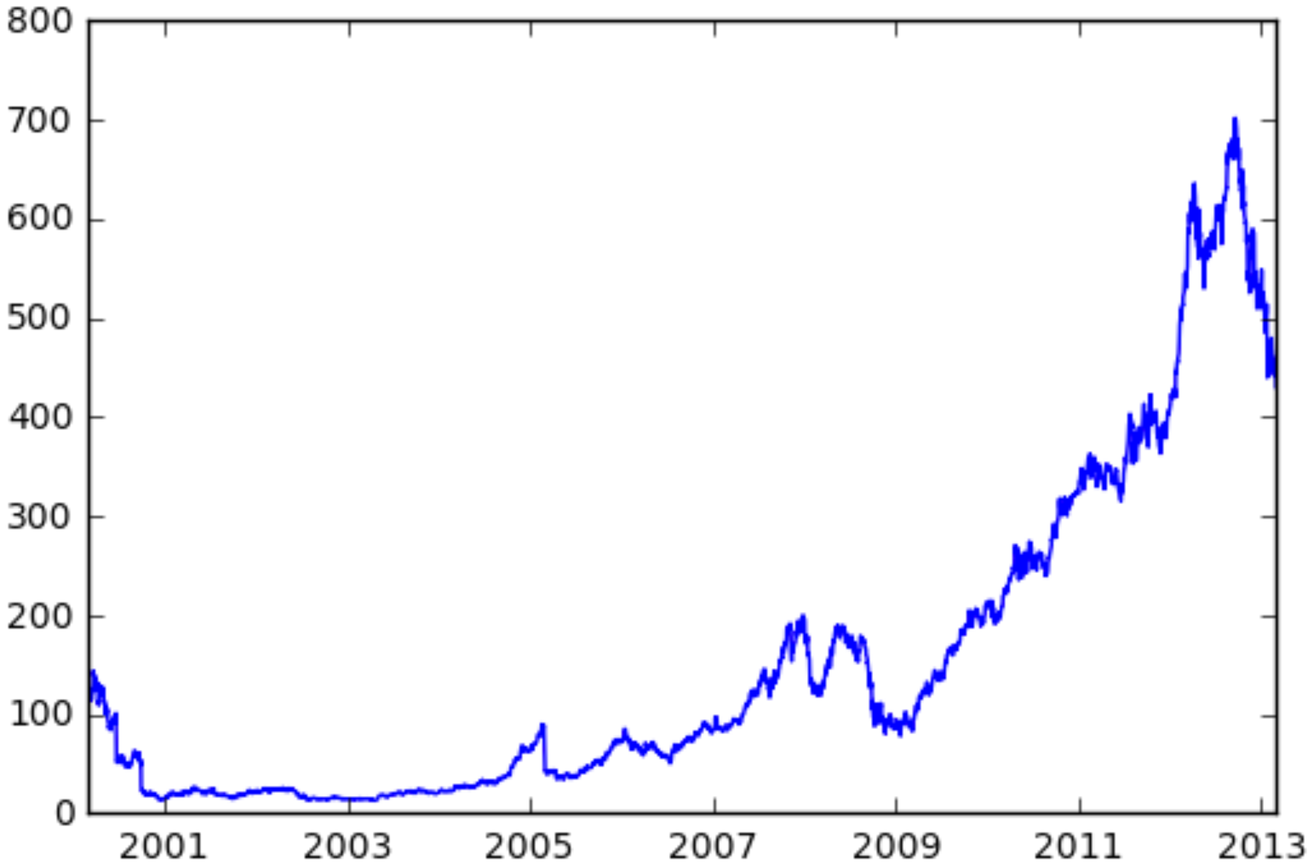
Plotting arrays (Matplotlib)



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()
```

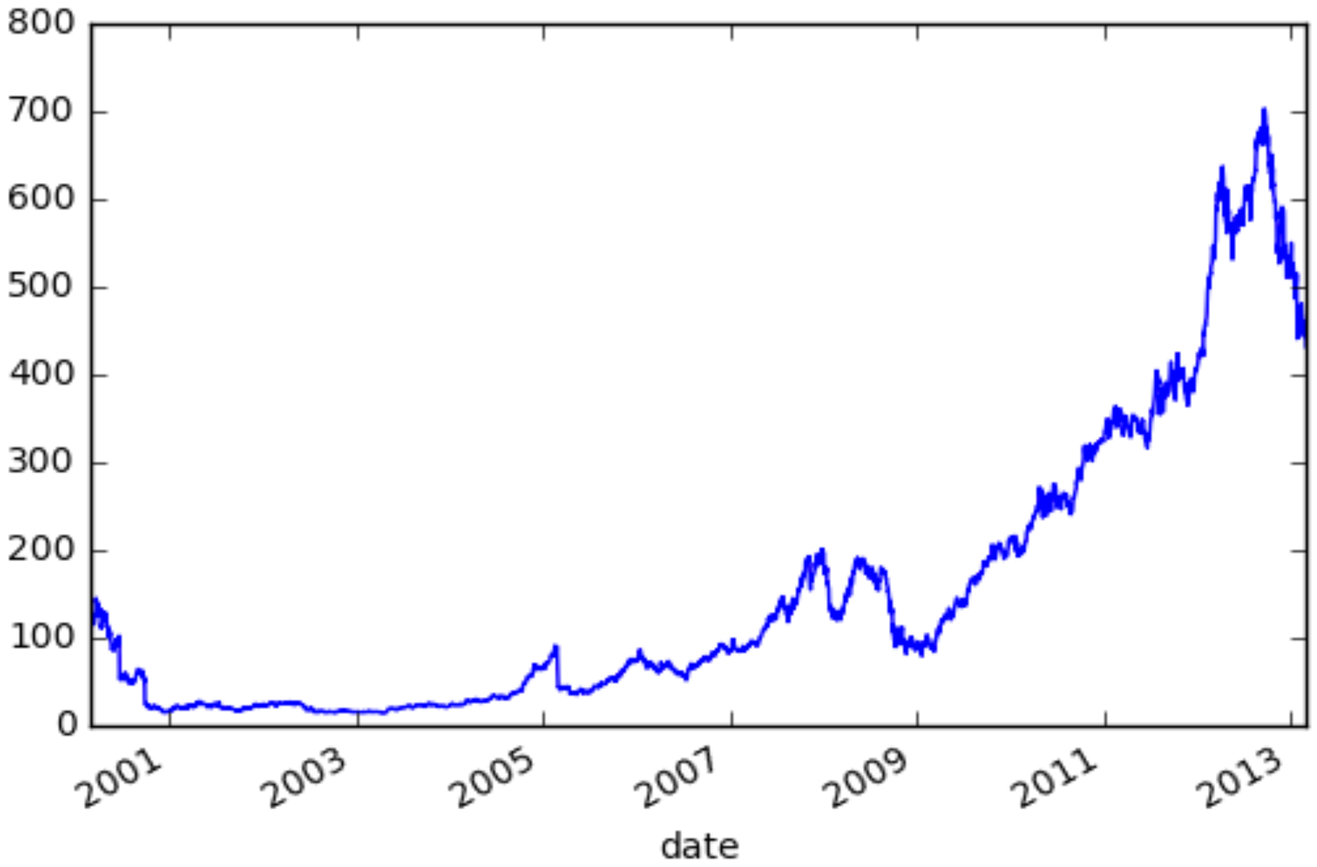
Plotting Series (matplotlib)



Plotting Series (pandas)

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

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

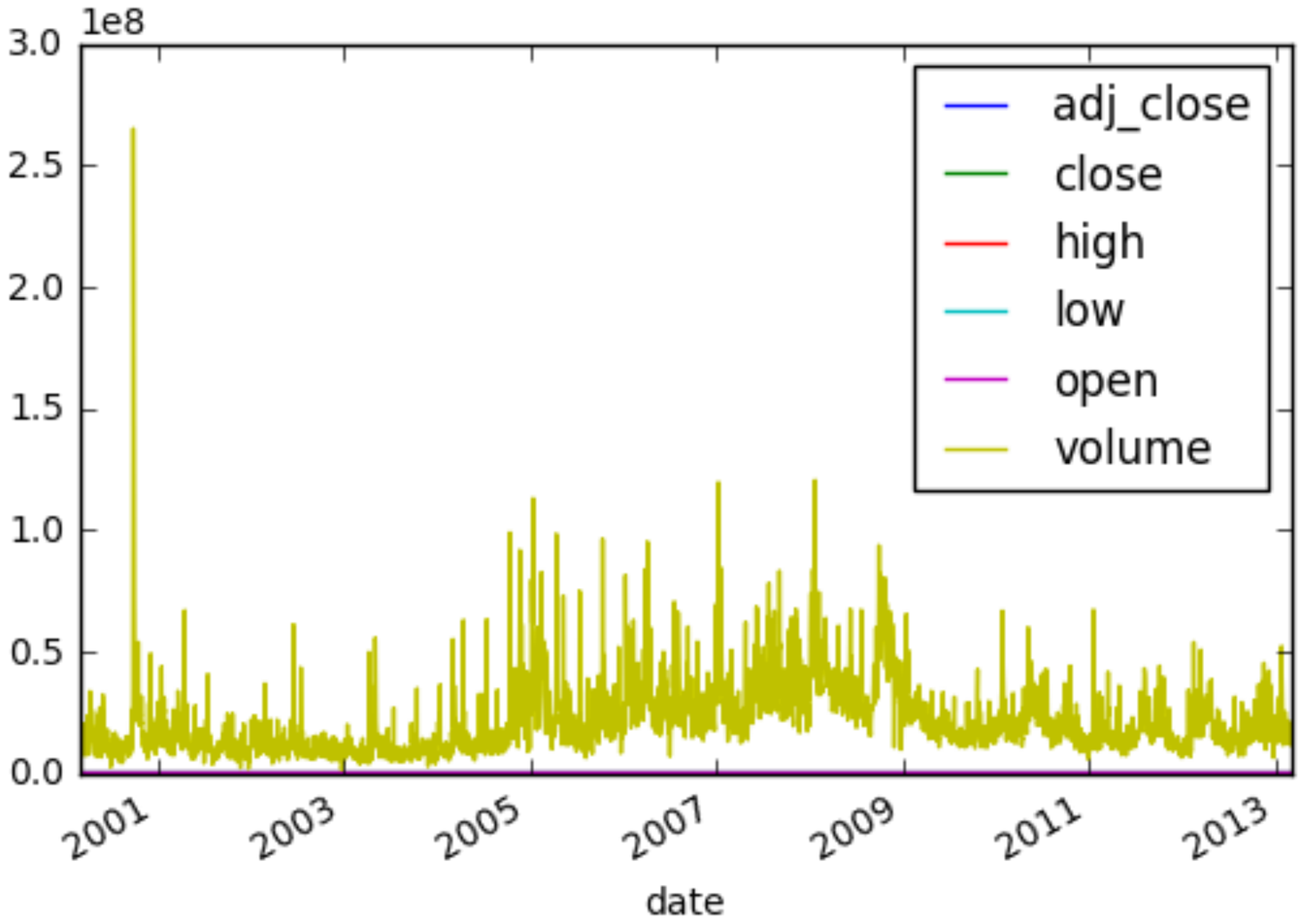
Plotting Series (pandas)



Plotting DataFrames (pandas)

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

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

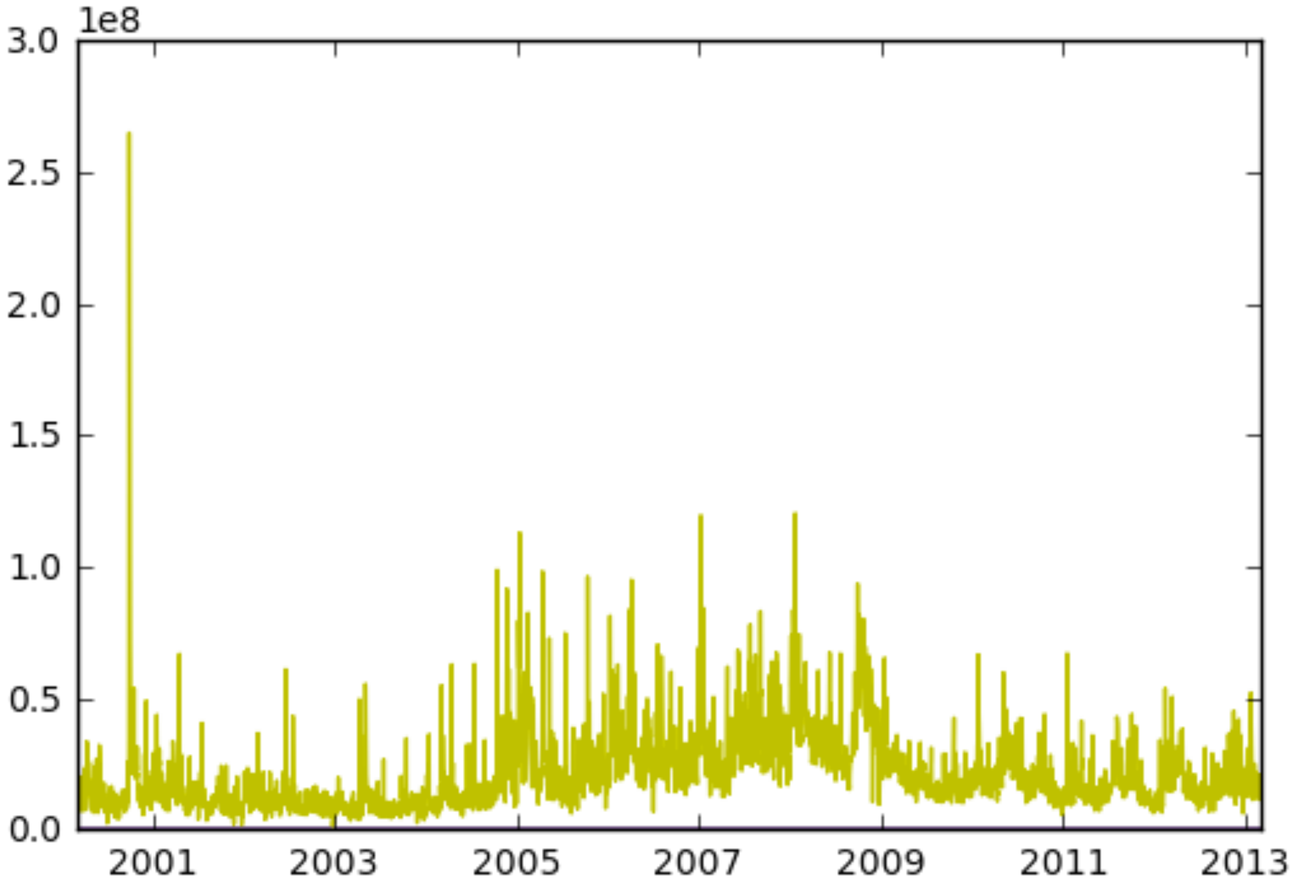
Plotting DataFrames (pandas)



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()
```

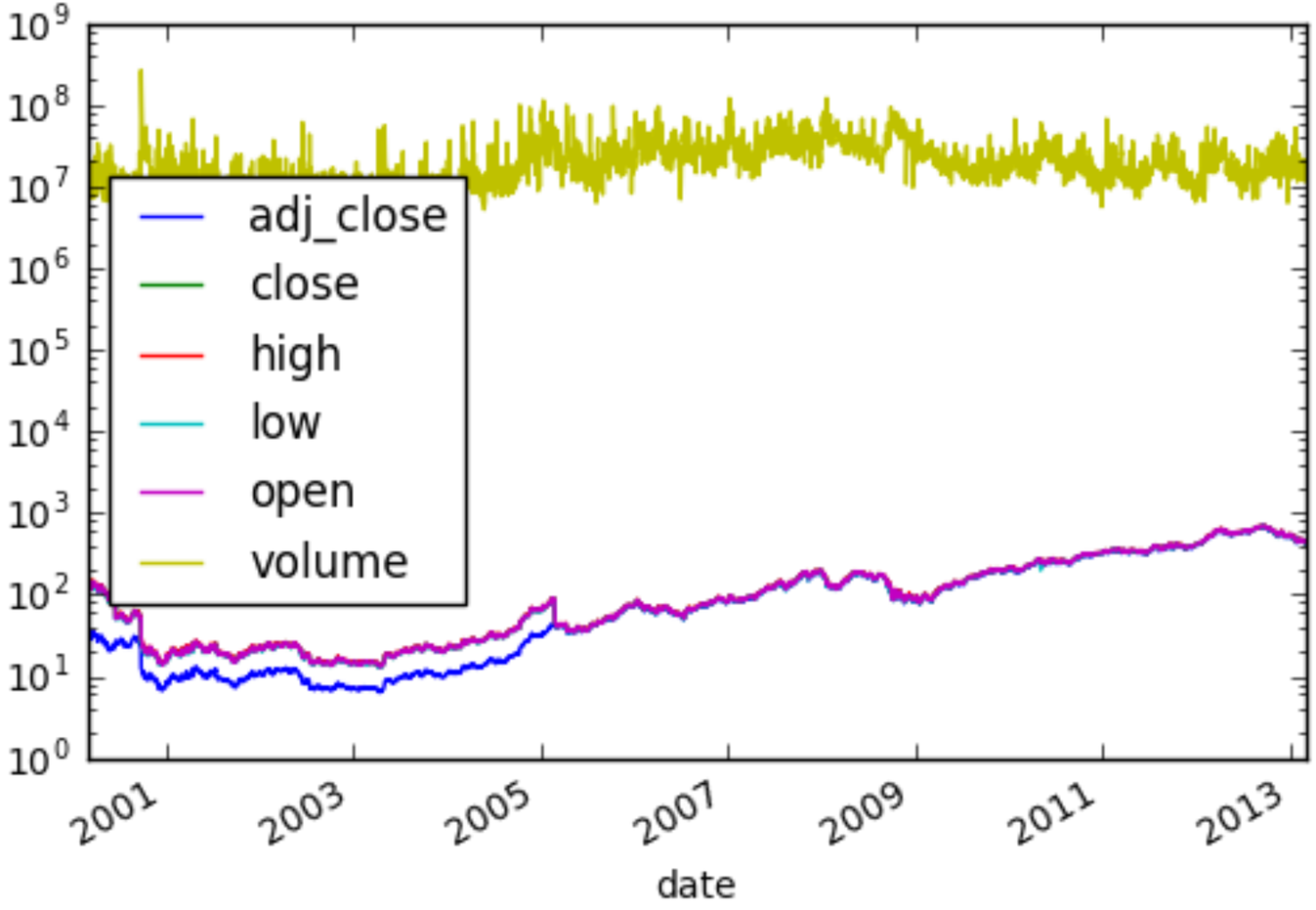
Plotting DataFrames (matplotlib)



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()
```

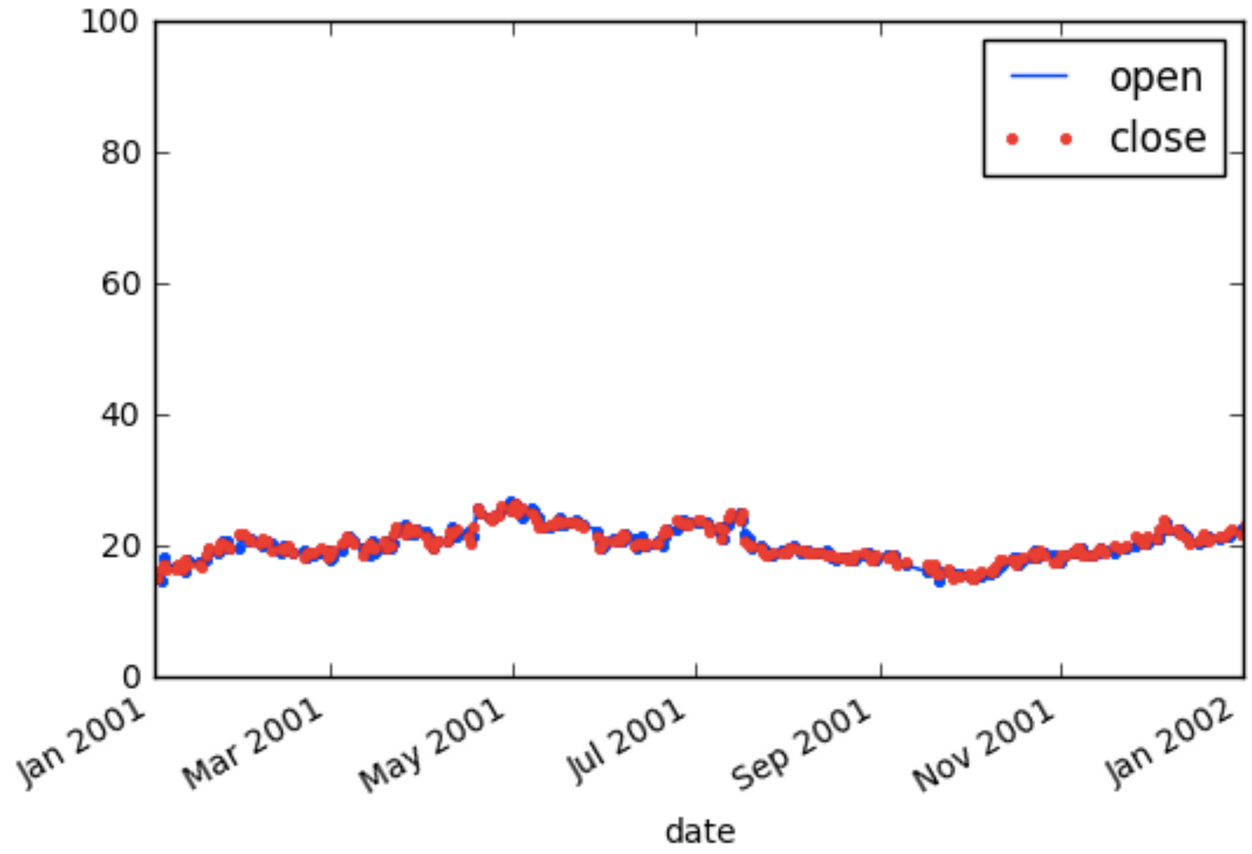
Fixing scales



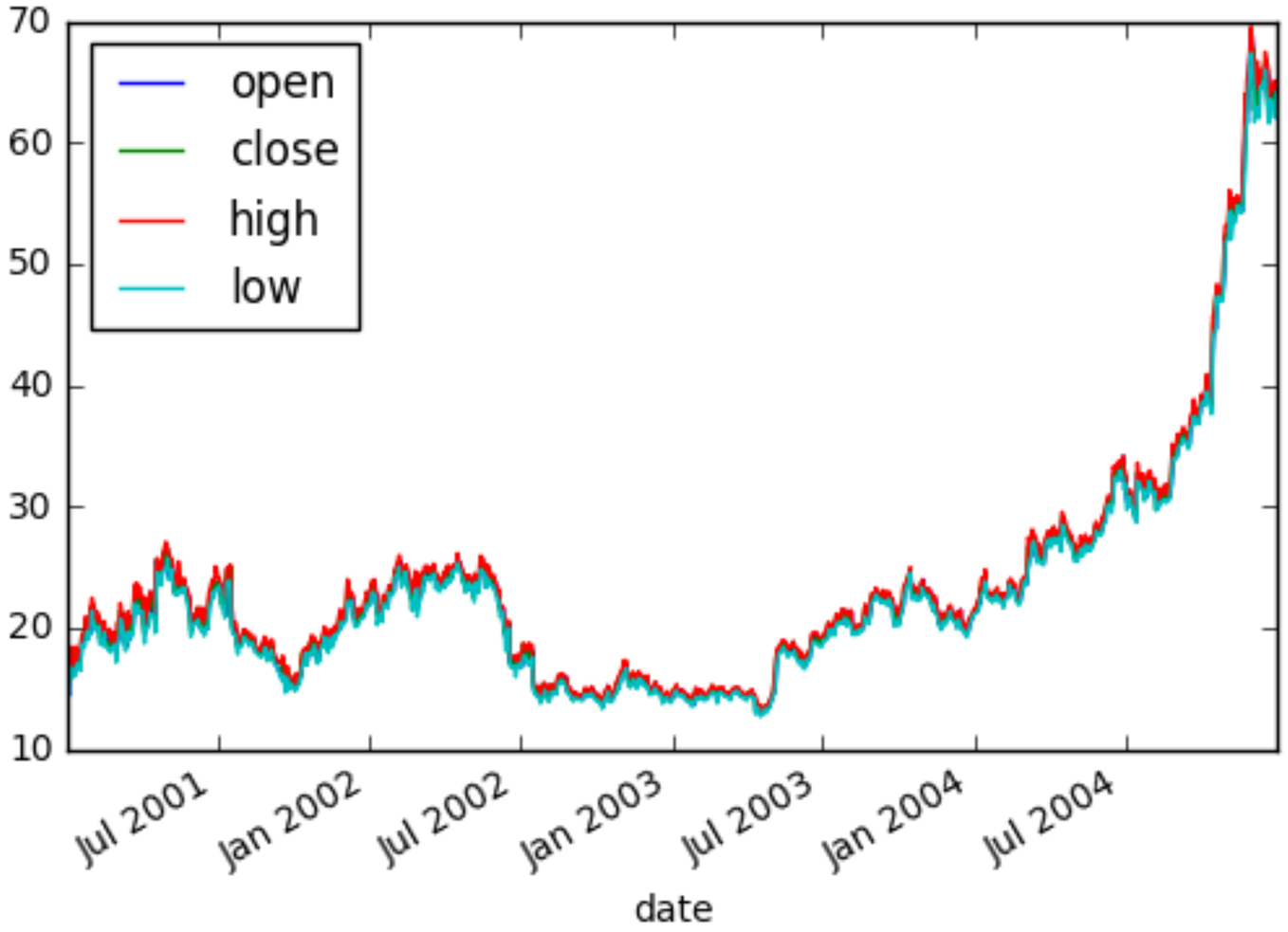
Customizing plots

```
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()
```

PANDAS FOUNDATIONS

Let’s practice!

PANDAS FOUNDATIONS

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

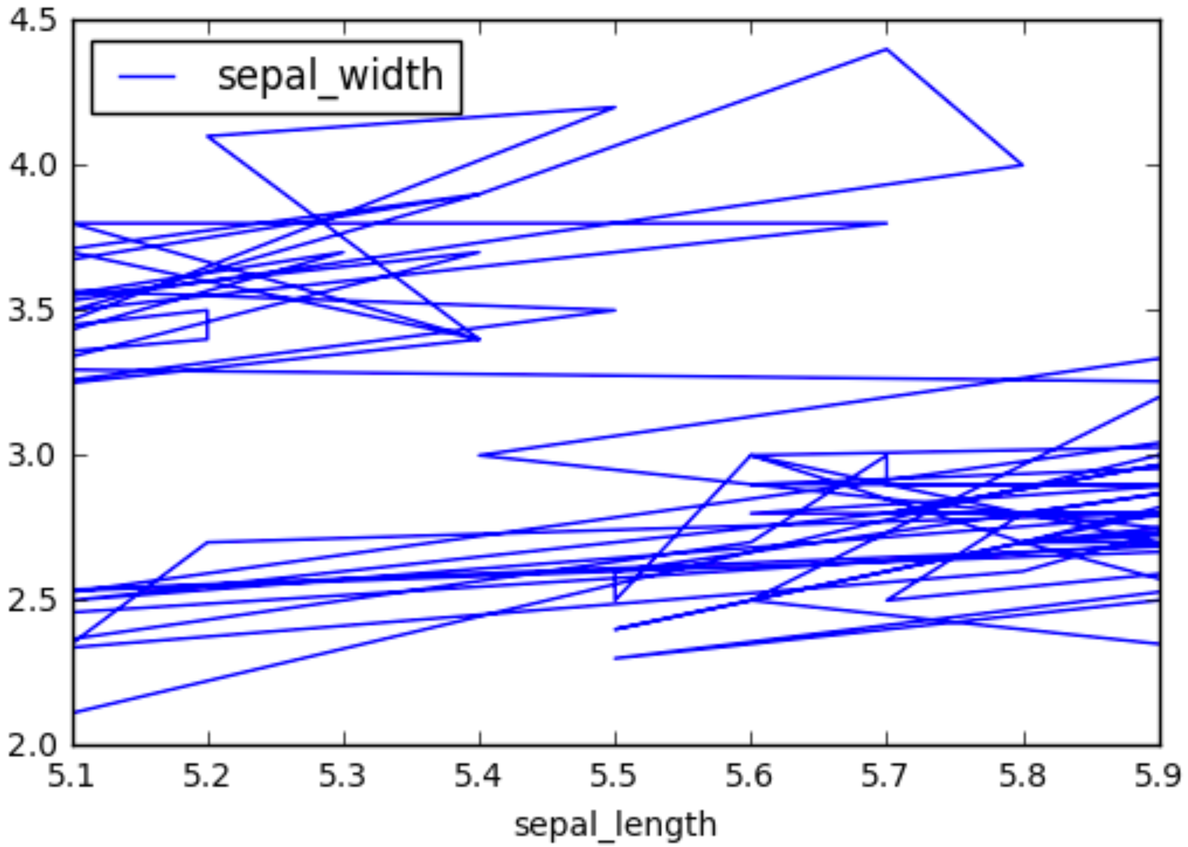
Data import

```
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()
```

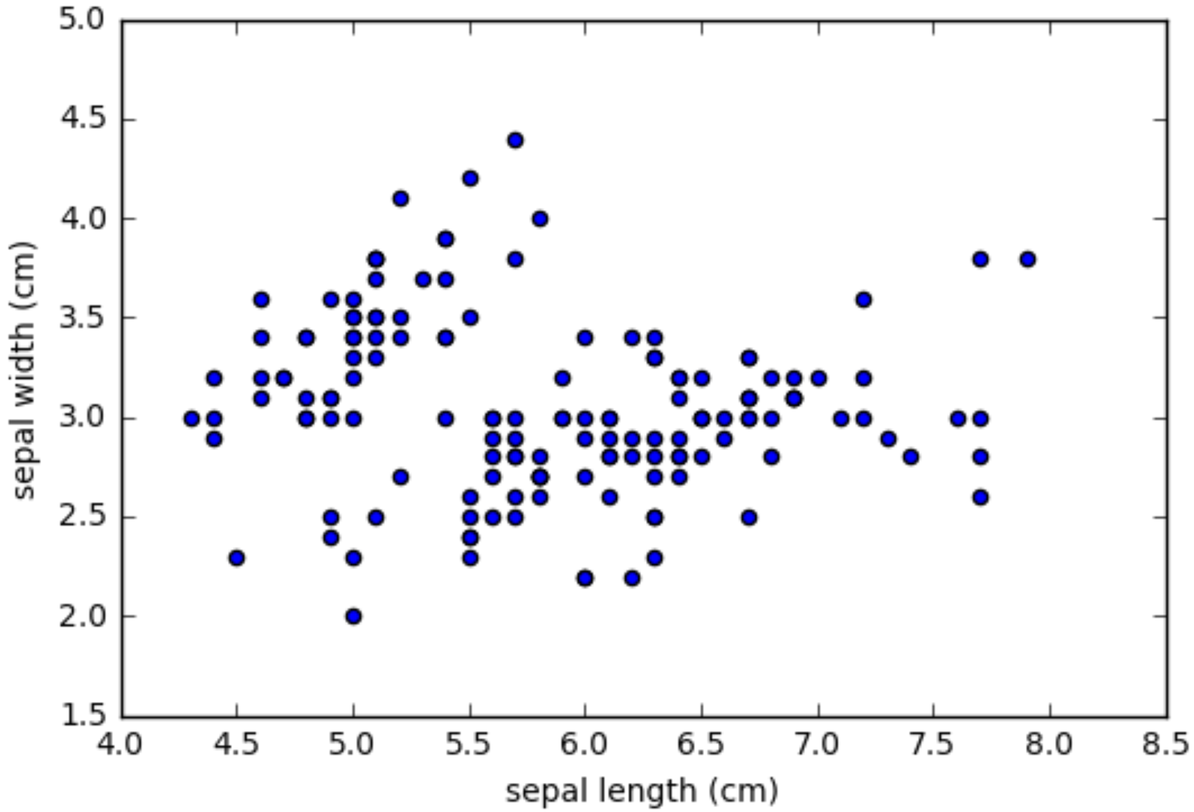
Line plot


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()
```

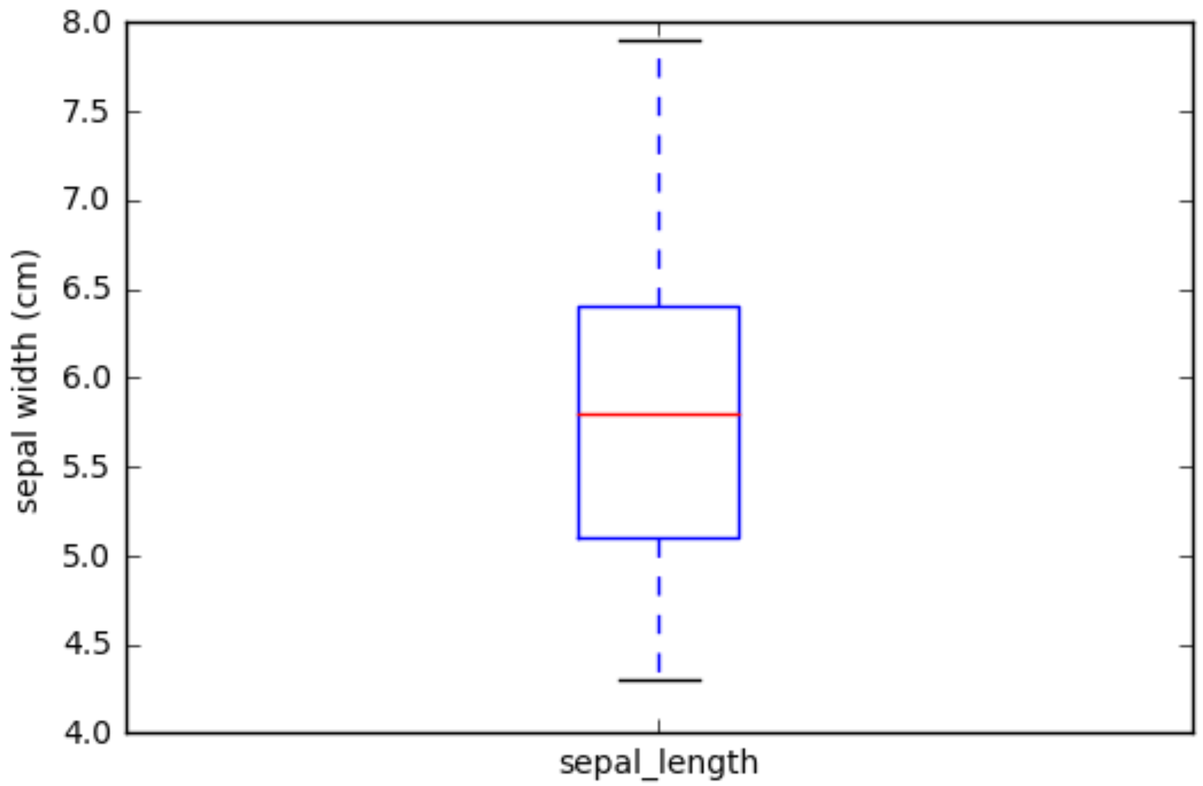
Scatter plot



Box plot

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

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

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

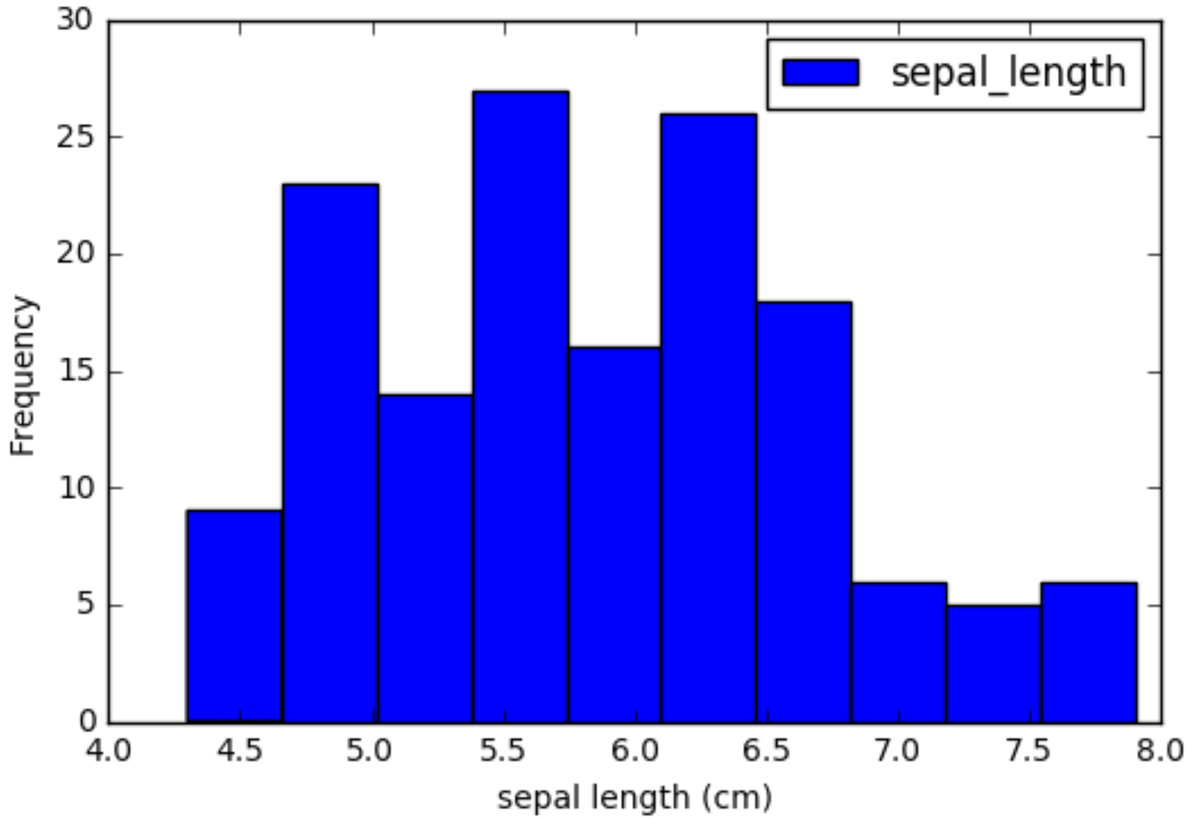
Box plot



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

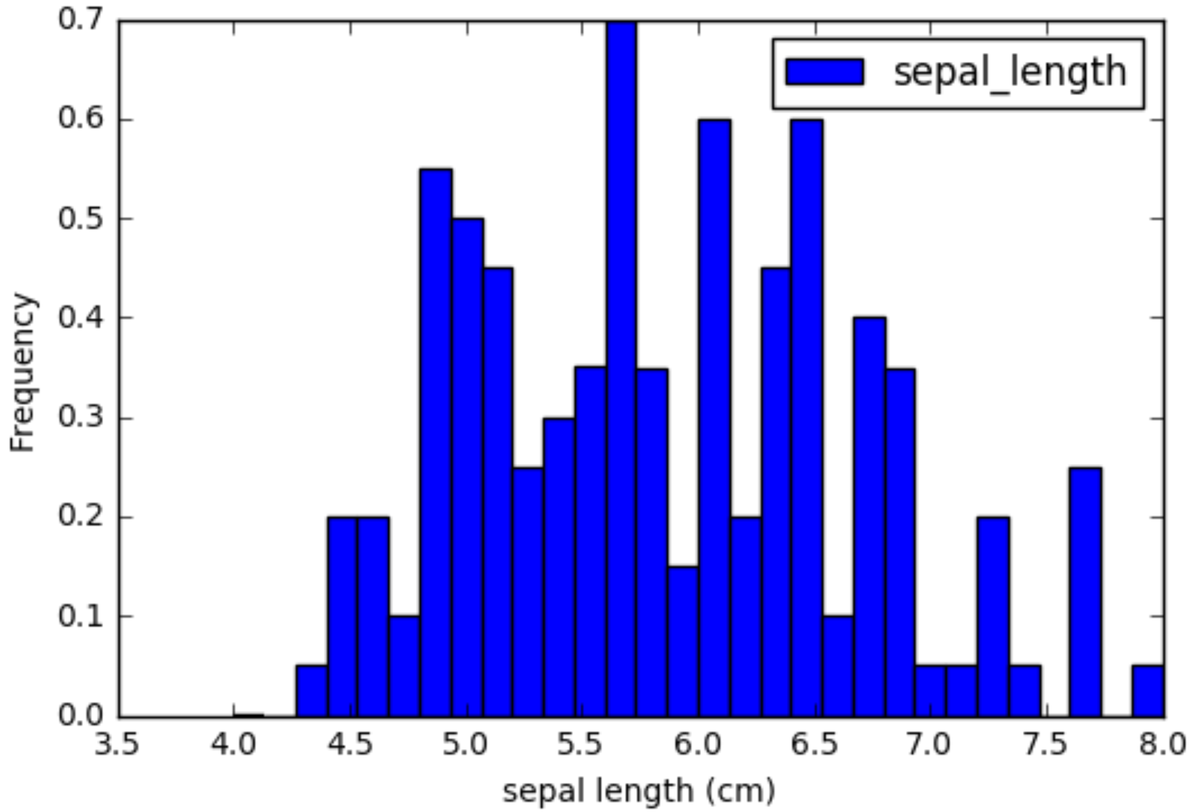
Histogram options

- *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()
```

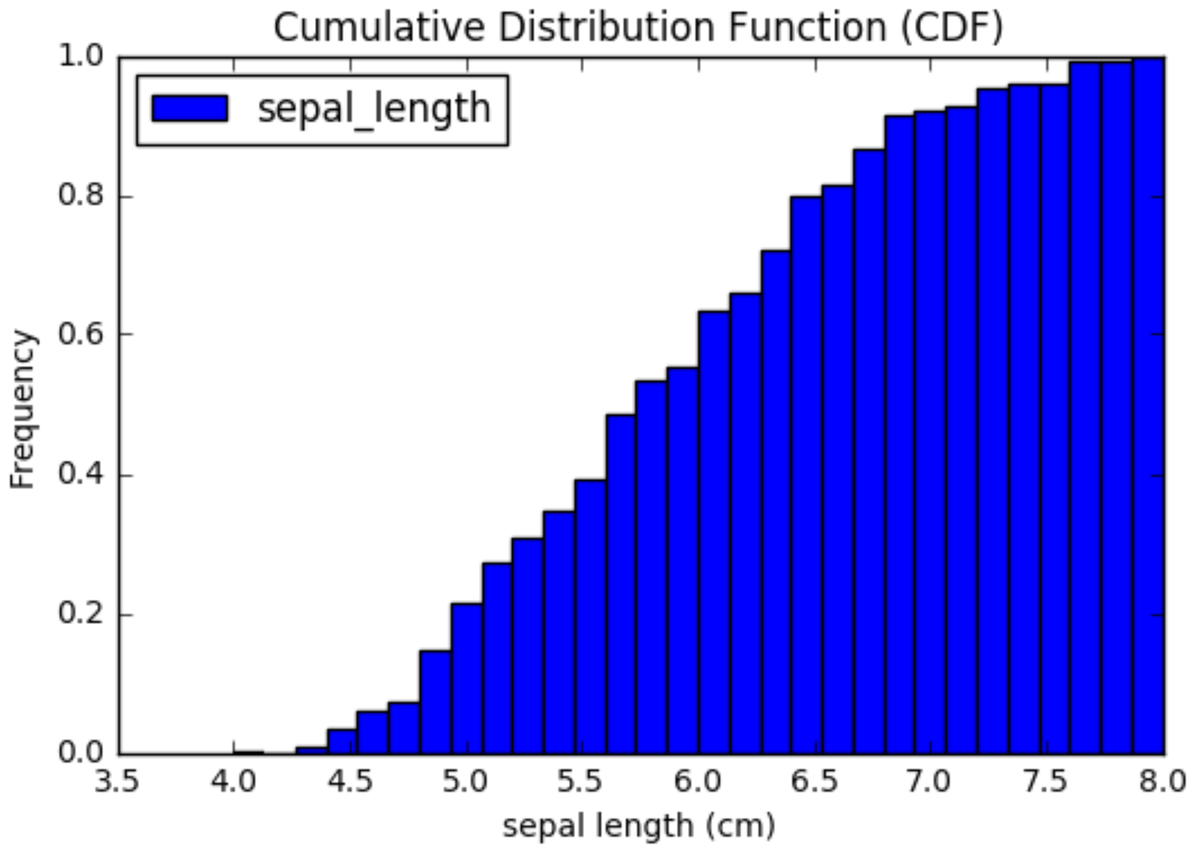
Customizing histogram



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!

PANDAS FOUNDATIONS

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
```

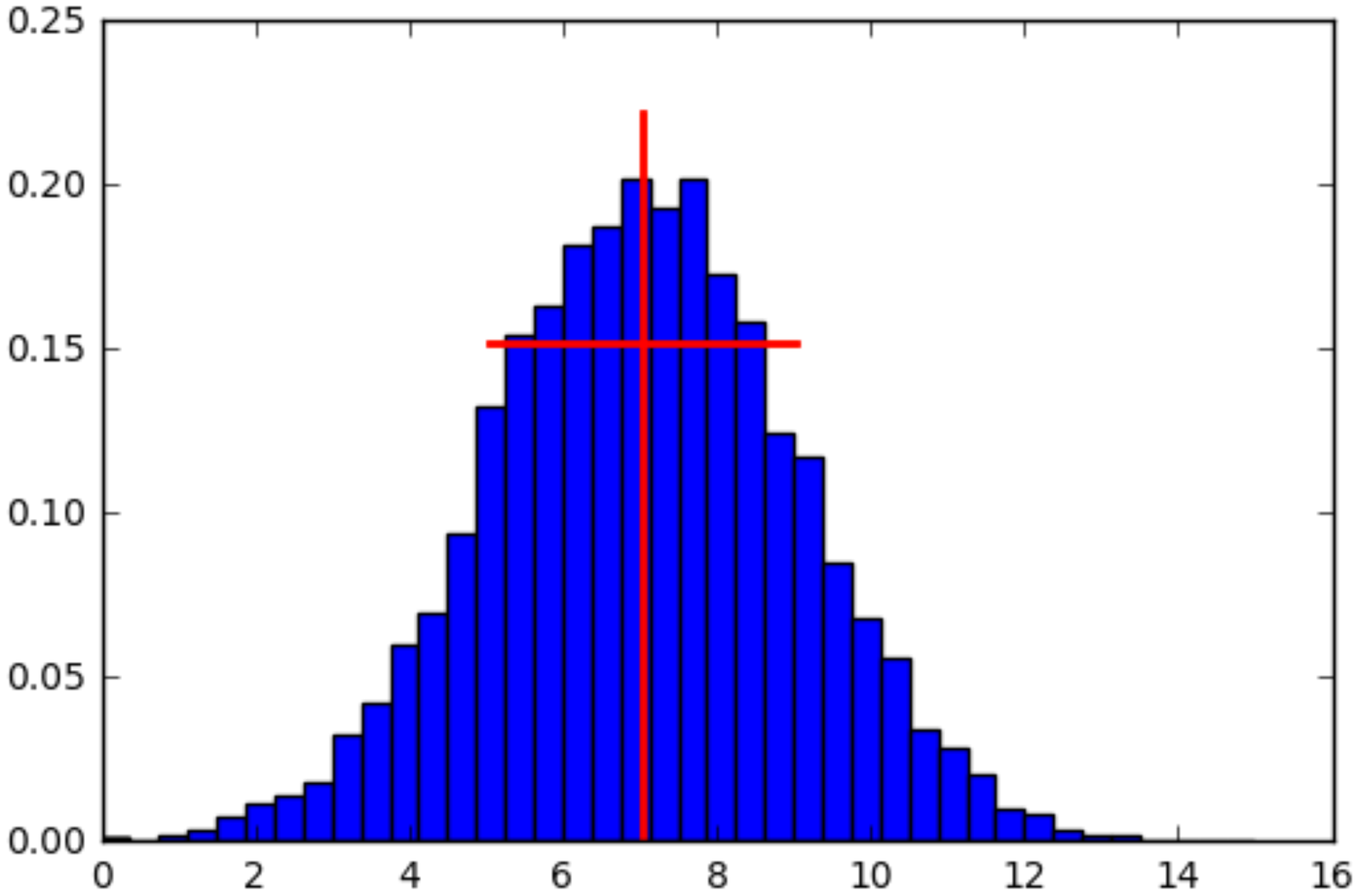
Averages

```
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
```

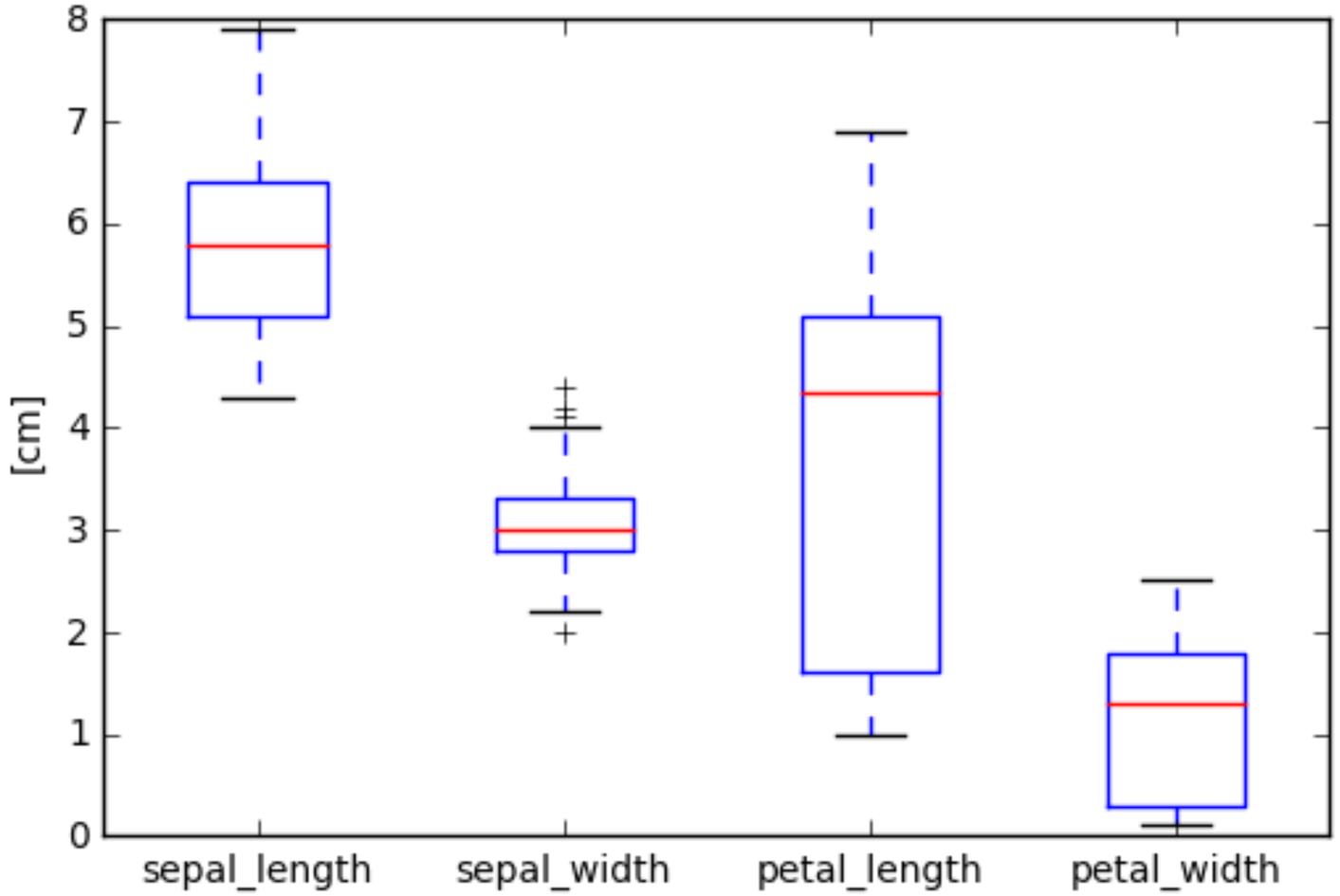
Ranges

```
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
```

PANDAS FOUNDATIONS

Let’s practice!

PANDAS FOUNDATIONS

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']
```

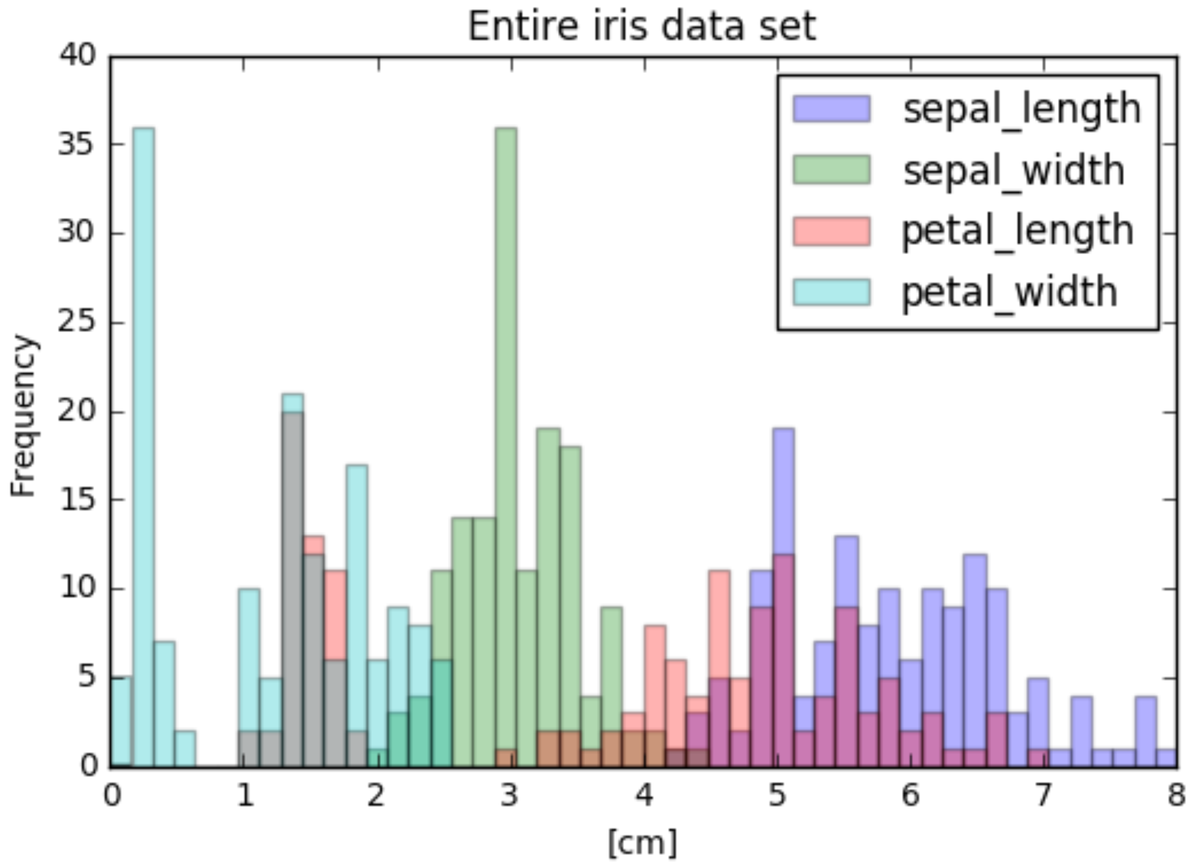
Checking indexes

```
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()
```

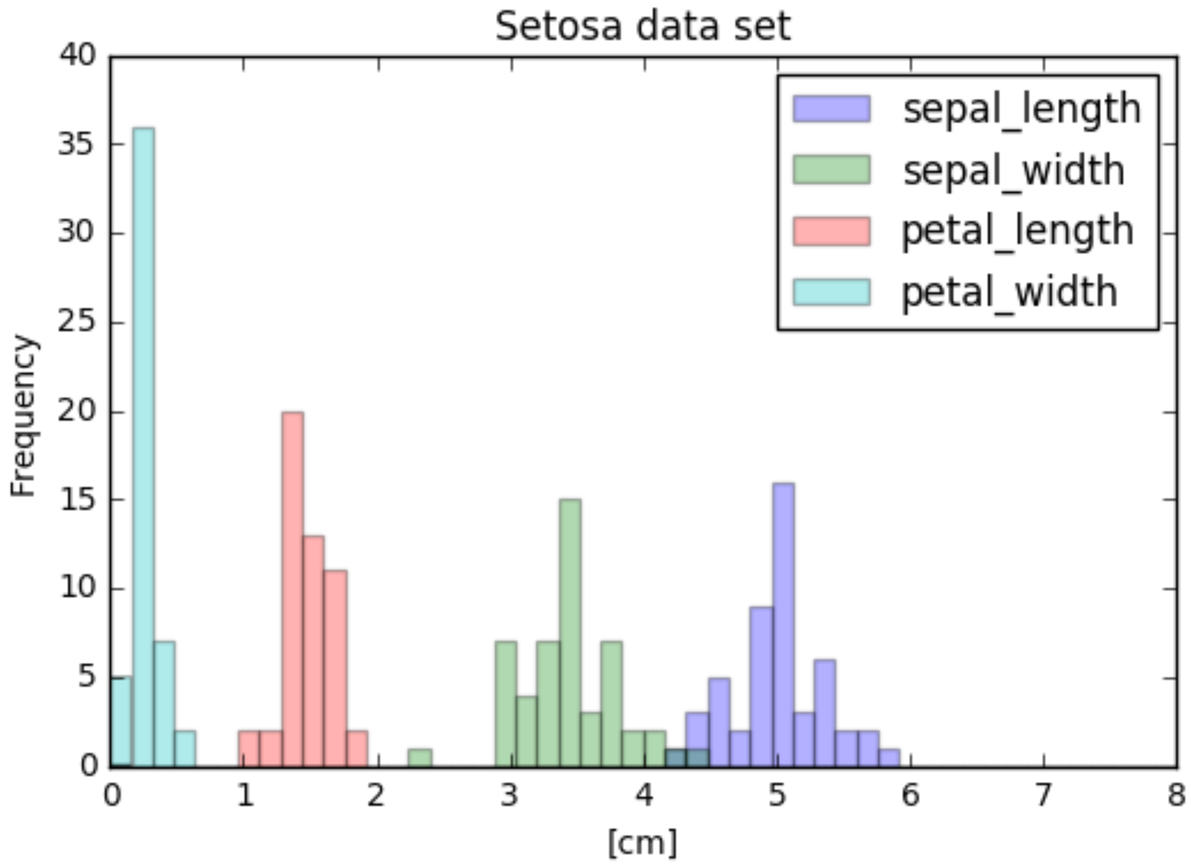
Visual EDA: all data



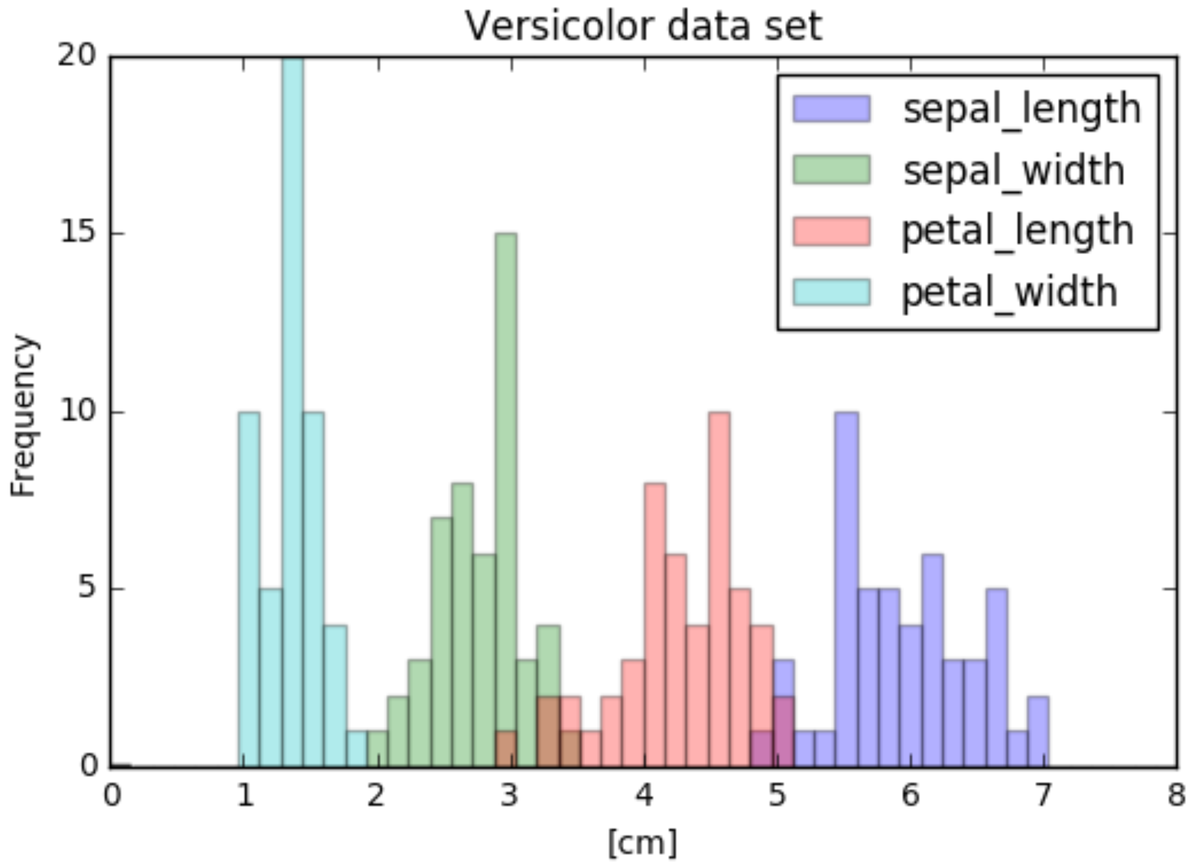
Visual EDA: individual factors

```
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()
```

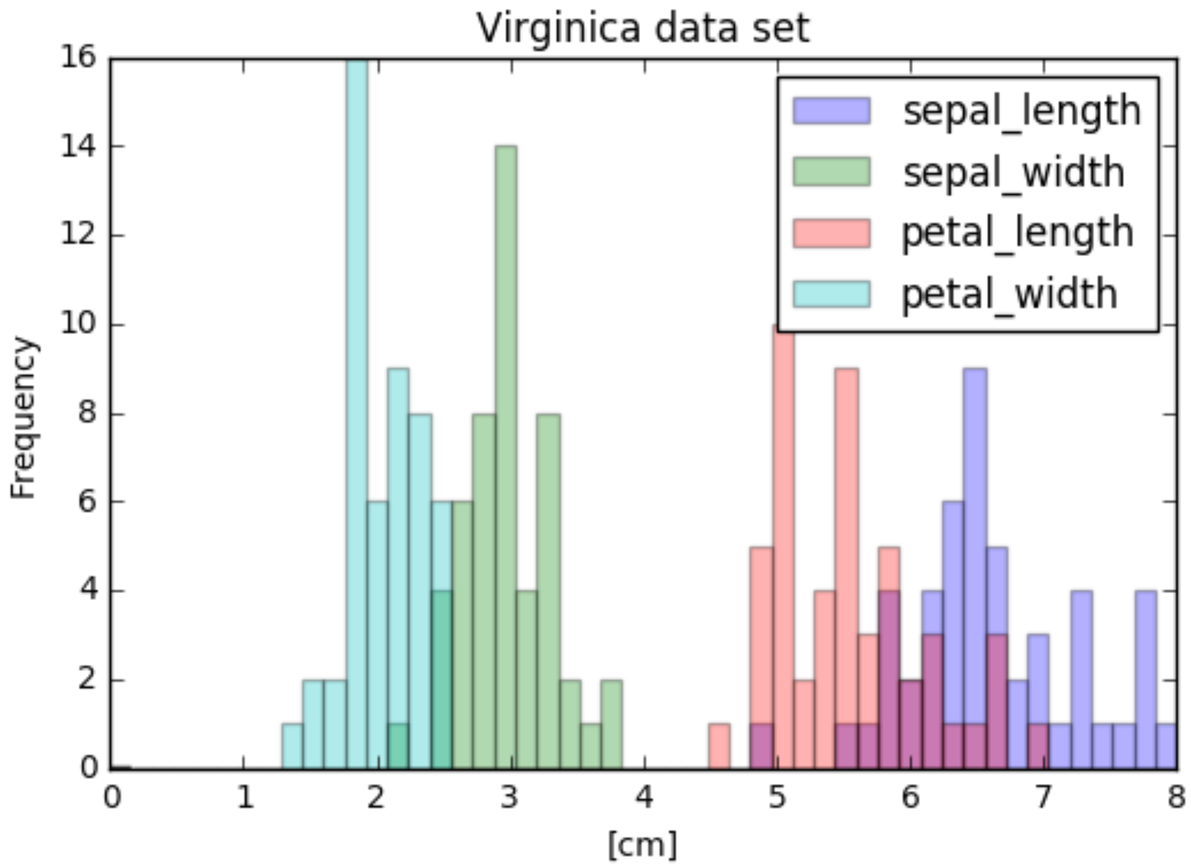
Visual EDA: Setosa data



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
```

PANDAS FOUNDATIONS

Let’s practice!

PANDAS FOUNDATIONS

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]:
```

Date	Company	Product	Units
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
```

PANDAS FOUNDATIONS

Let’s practice!

PANDAS FOUNDATIONS

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
```

PANDAS FOUNDATIONS

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
```

PANDAS FOUNDATIONS

Let’s practice!

PANDAS FOUNDATIONS

Time series visualization

Topics

- Line types
- Plot types
- Subplots

S&P 500 Data

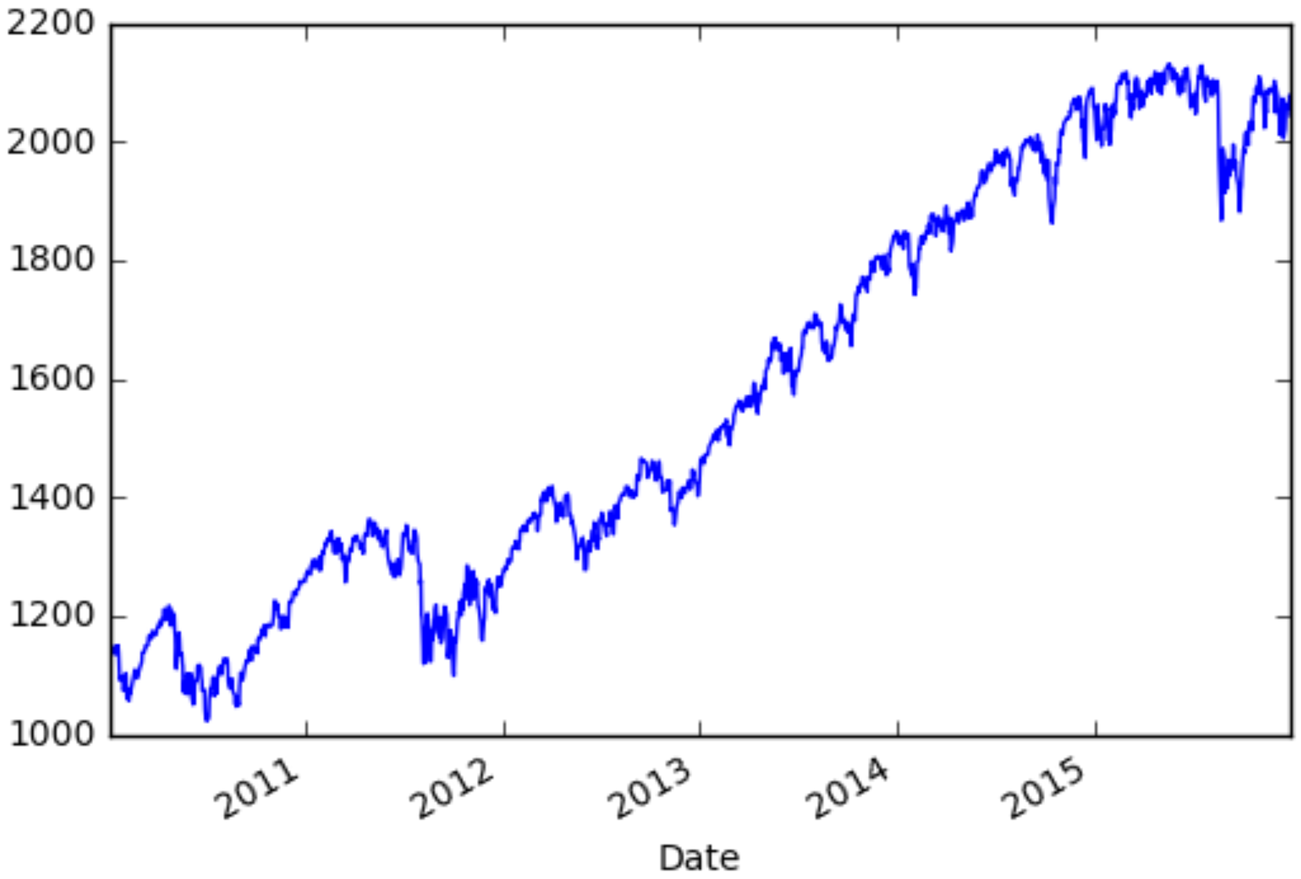
```
In [1]: import pandas as pd

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]:
```

Date	Open	High	Low	Close	Volume	Adj Close
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()
```

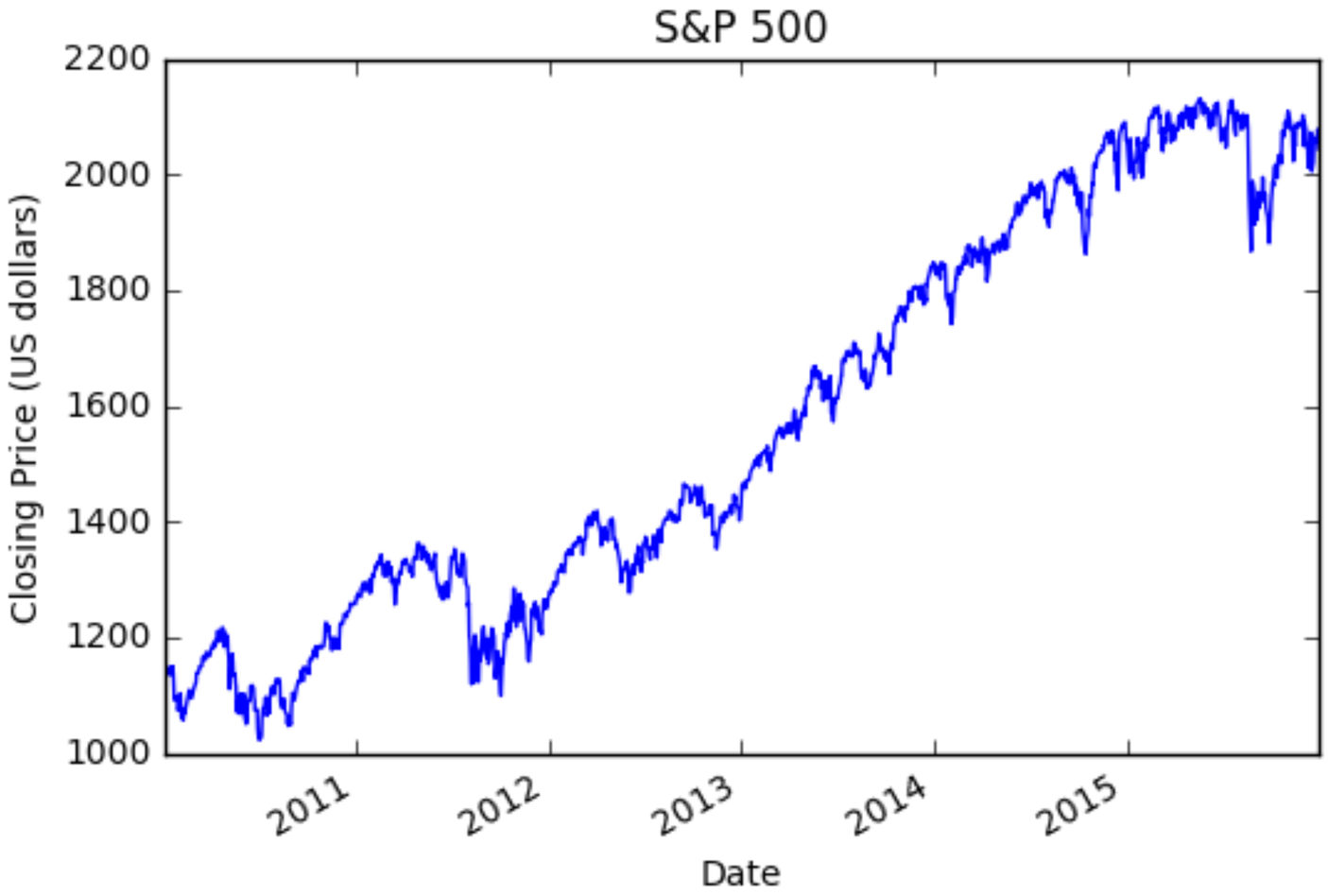
Default plot



Labels and title

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

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

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

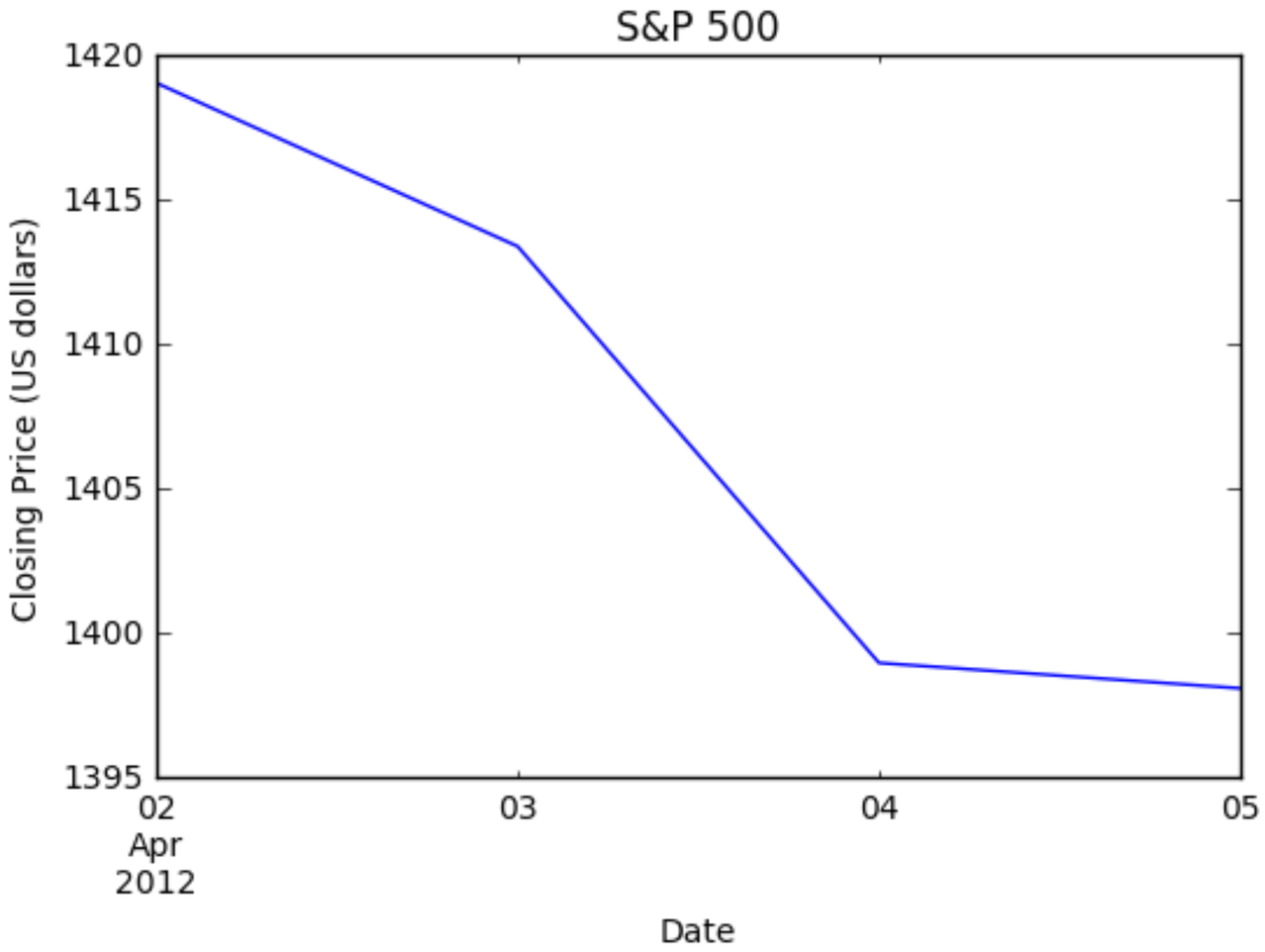
Labels and title



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()
```

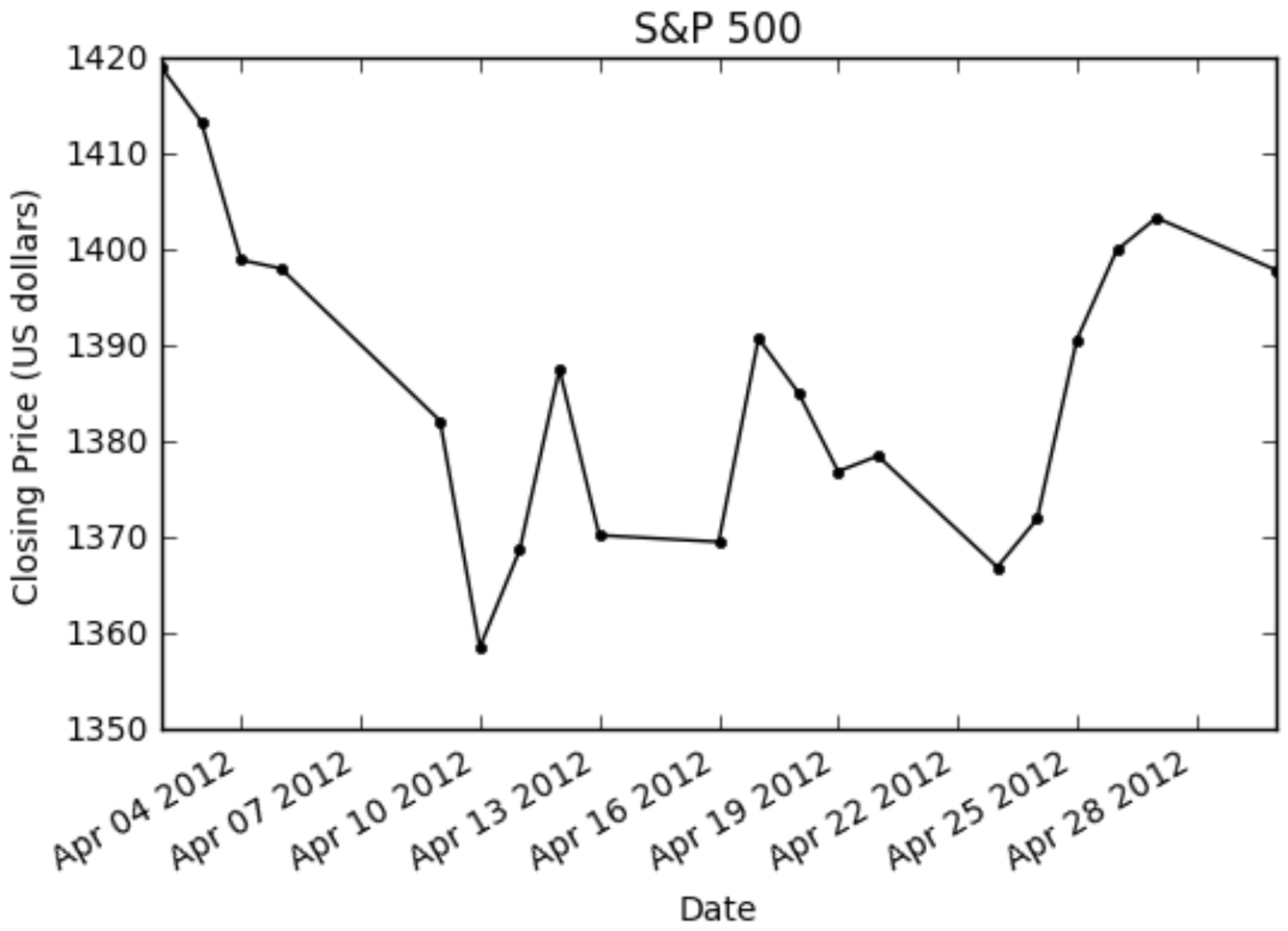
One week


S&P 500
1420
1415
1410
1405
1400
1395
Closing Price (US dollars)
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)

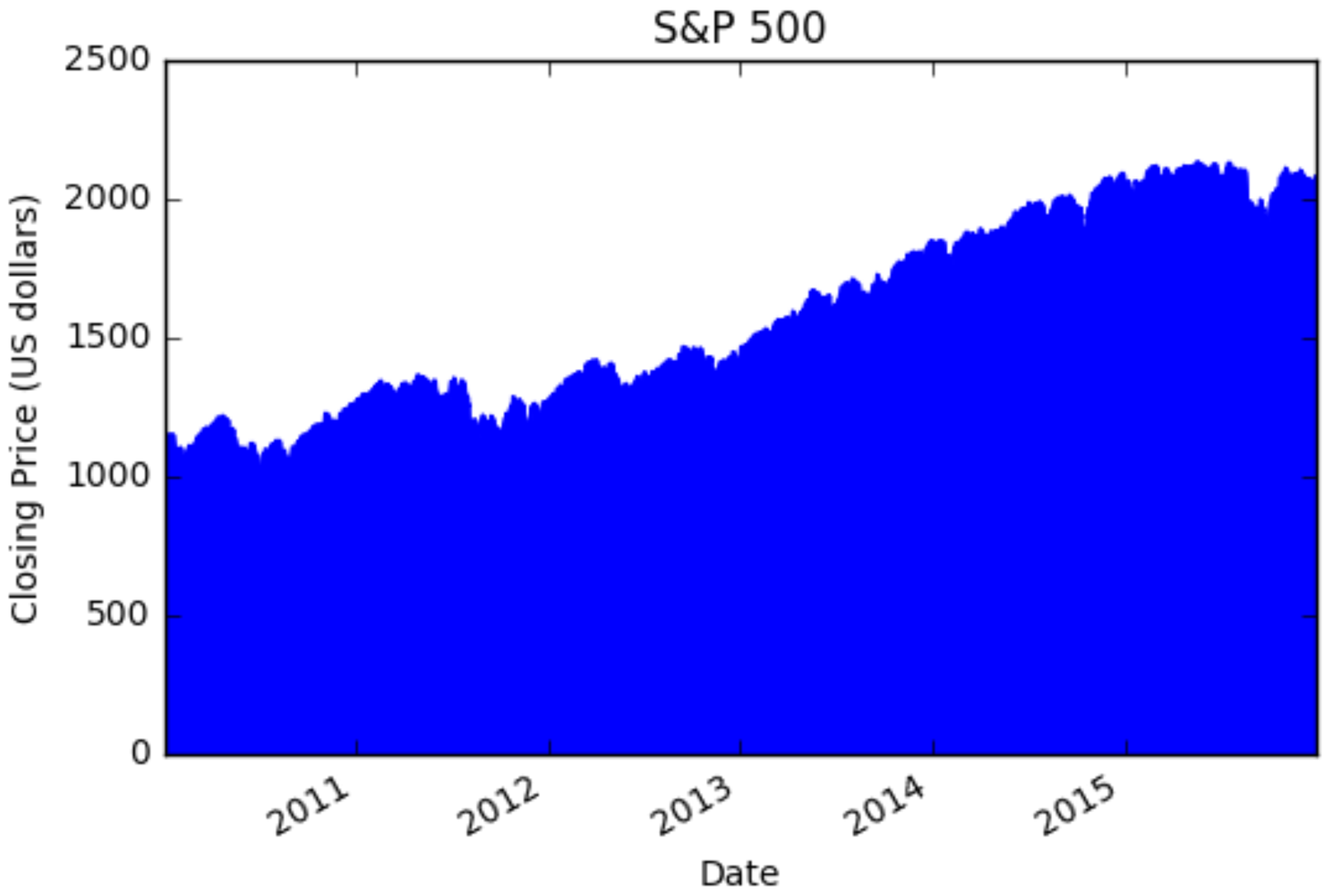
More plot styles

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()
```

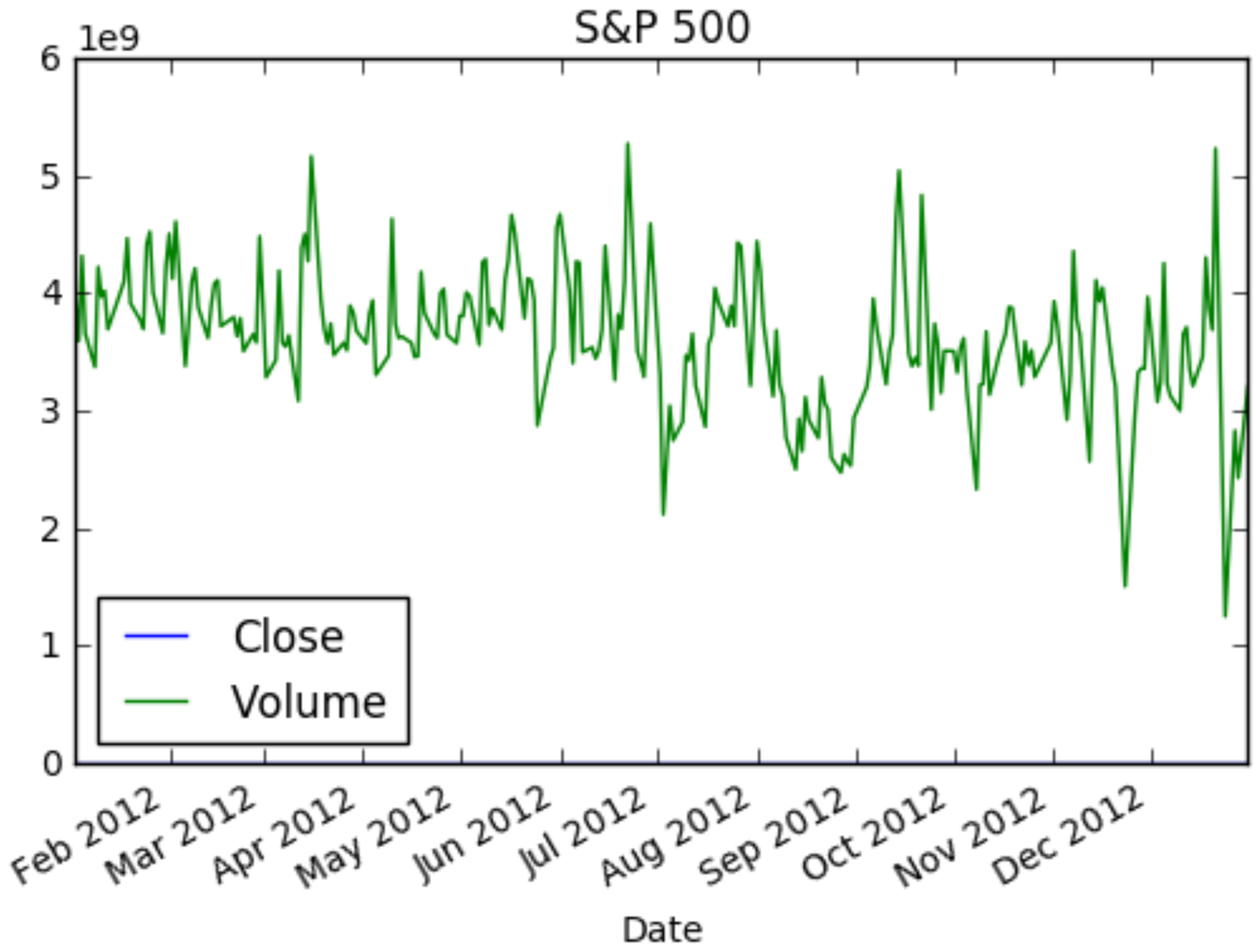
Area plot


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()
```

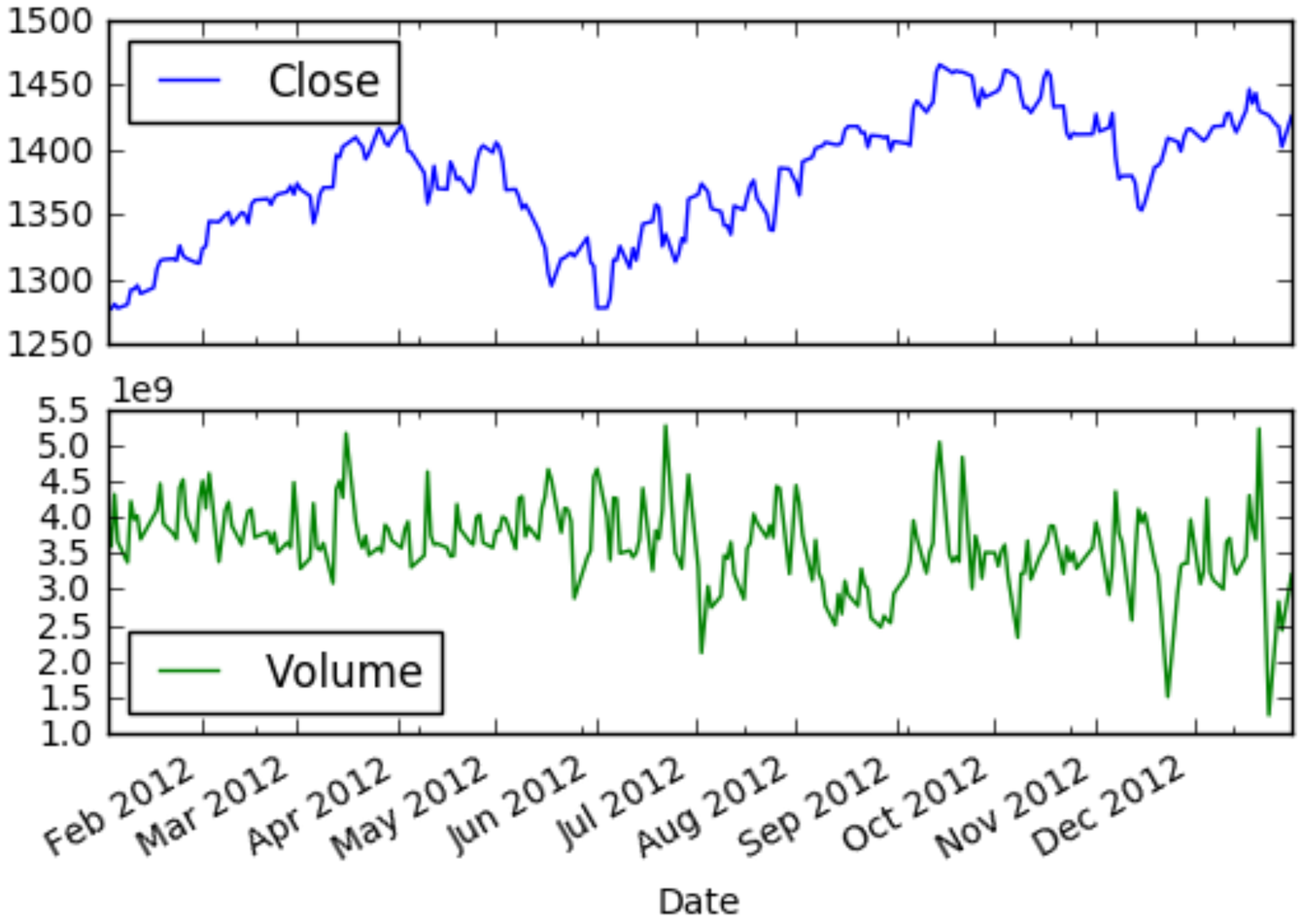
Multiple columns



Subplots

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

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

Subplots


Close
1500
1450
1400
1350
1300
1250
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

PANDAS FOUNDATIONS

Let’s practice!

PANDAS FOUNDATIONS

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

PANDAS FOUNDATIONS

Let’s practice!

PANDAS FOUNDATIONS

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

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Let’s practice!

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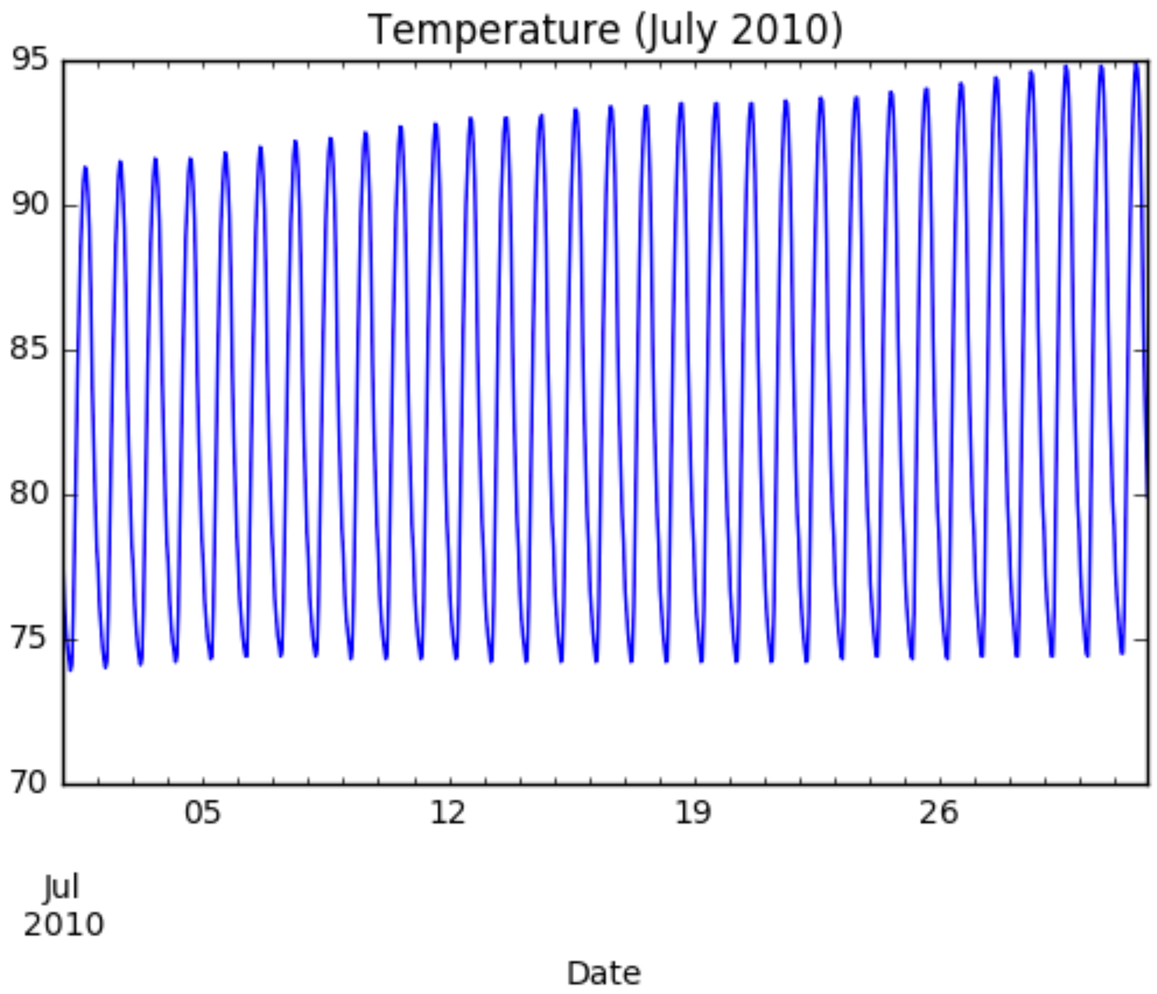
Visual exploratory data analysis

Line plots in pandas



Line plots in pandas

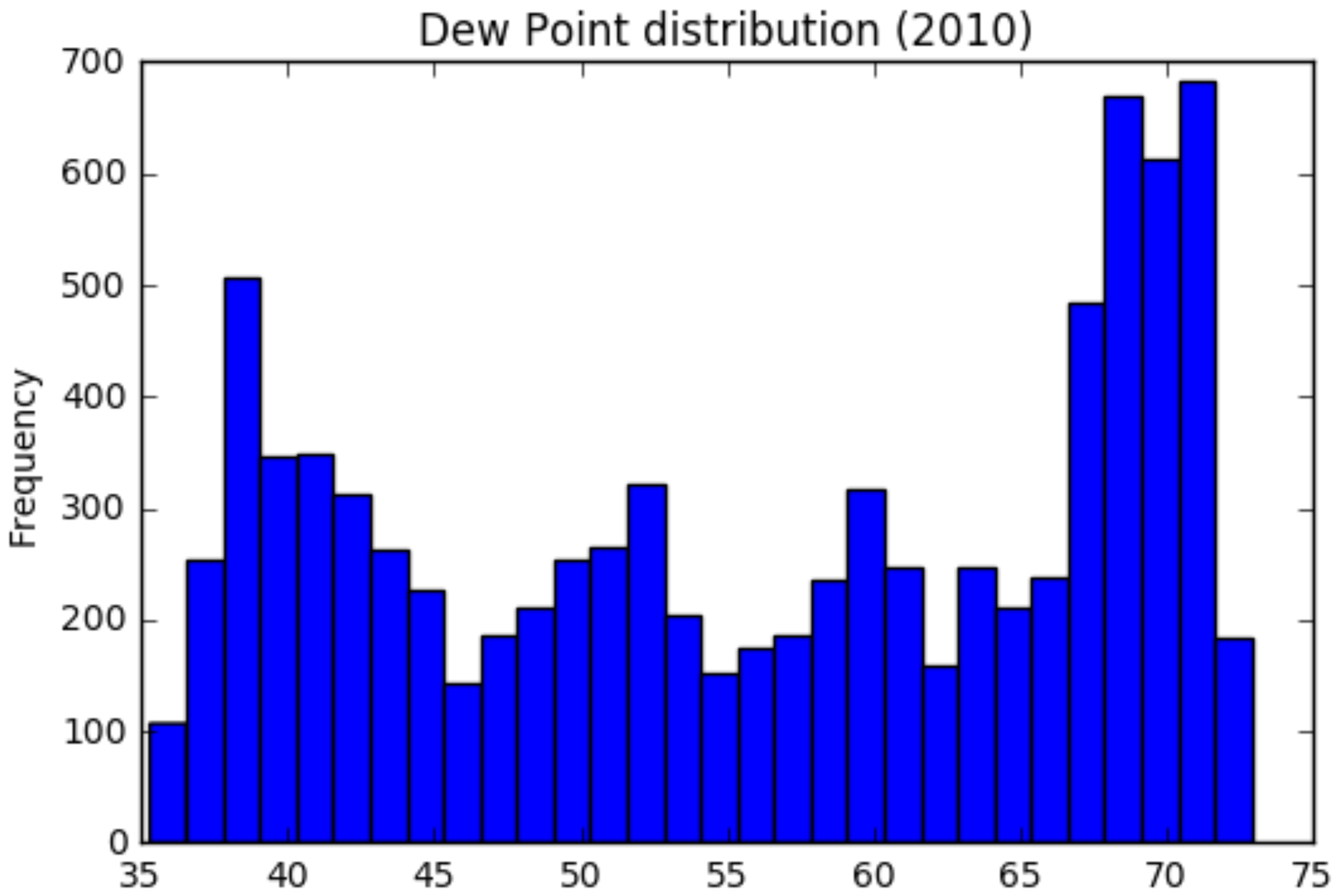
```
In [1]: import matplotlib.pyplot as plt

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

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

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

Histograms in pandas



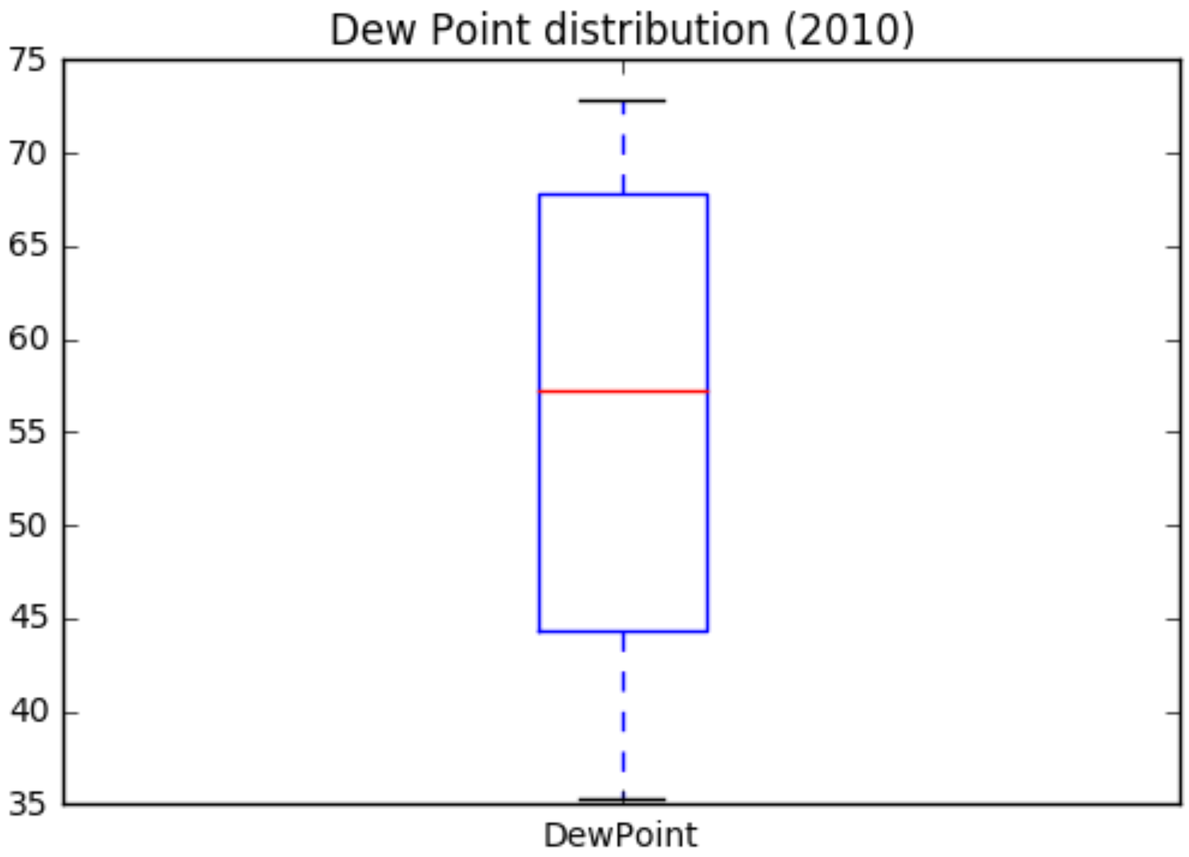
Histograms in pandas

```
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



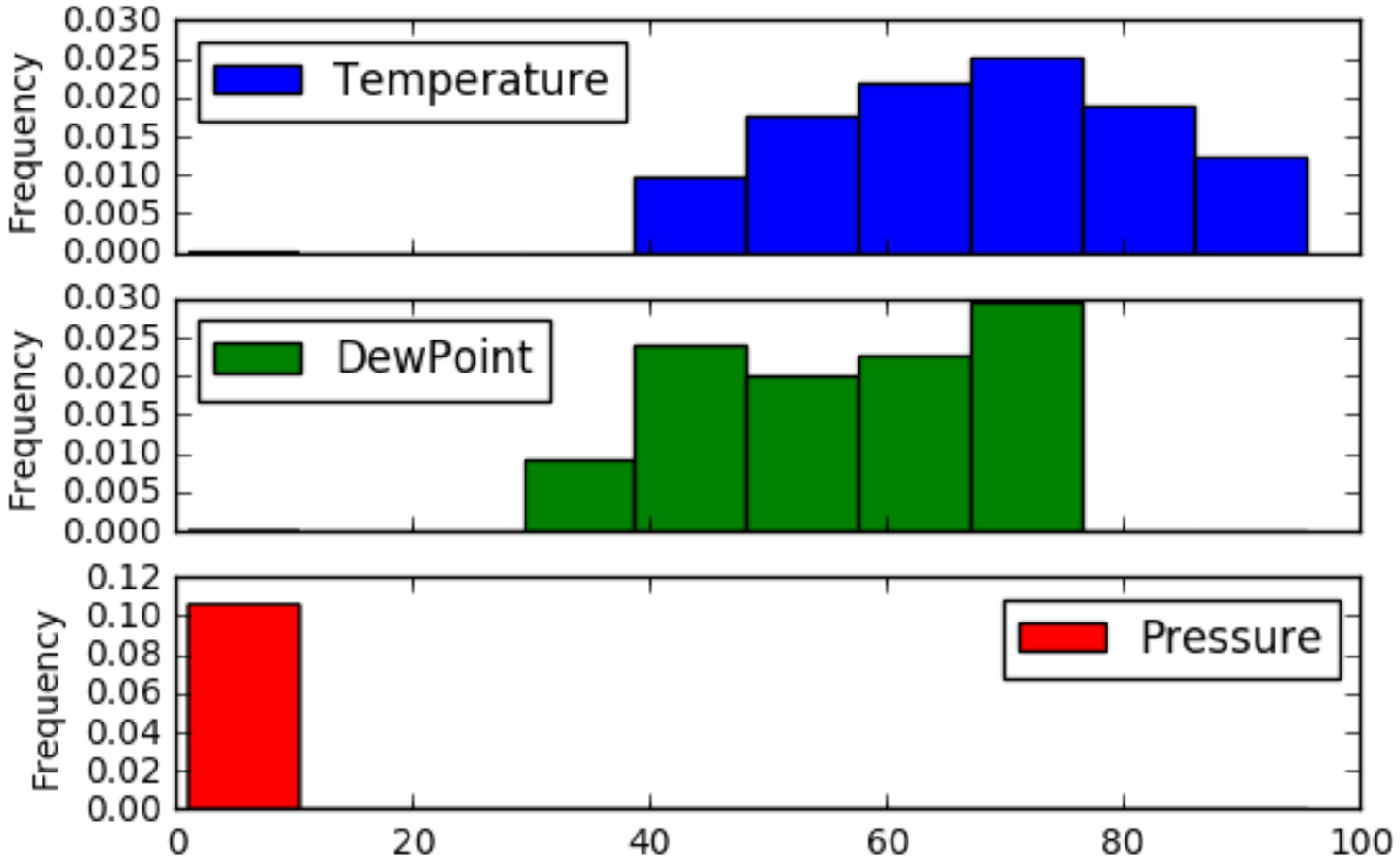
Box plots in pandas

```
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()
```

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Let’s practice!

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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

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See you in the next course!