Unit 8: Data input and output

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Contents

1 Data input and output

In this unit we discuss input and output, or I/O for short. We focus exclusively on I/O routines used to load and store data from files that are relevant for numerical computation and data analysis.

1.1 I/O with NumPy

1.1.1 Loading text data

We have already encountered the most basic, and probably most frequently used NumPy I/O routine, `np.loadtxt()`. We often use files that store data as text files containing character-separated values (CSV) since virtually any application supports this data format. The most important I/O functions to process text data are:

- `np.loadtxt()`: load data from a text file.
- `np.genfromtxt()`: load data from a text file and handle missing data.
- `np.savetxt()`: save a NumPy array to a text file.

There are a few other I/O functions in NumPy, for example to write arrays as raw binary data. We won't cover them here, but you can find them in the official documentation.

Imagine we have the following tabular data from FRED, where the first two rows look as follows:

Year	GDP	CPI	UNRATE
1948	2118.5	24.0	3.8
1949	2106.6	23.8	6.0

To load this CSV file as a NumPy array, we use `loadtxt()`. As in the previous unit, it is advantageous to globally set the path to the `data/` directory that can point either to the local directory or to the `data/` directory on GitHub.

[1]:
```
# Uncomment this to use files in the local data/ directory
# DATA_PATH = '../data'

# Load data directly from GitHub
DATA_PATH = 'https://raw.githubusercontent.com/richardfoltyn/MLFP-ECON5130/main/data'
```

[2]:
```
import numpy as np


# relative path to CSV file
file = f'{DATA_PATH}/FRED.csv'

# load CSV
data = np.loadtxt(file, skiprows=1, delimiter=',')
data[:2]        # Display first two rows
```

[2]:
```
array([[1948. , 2118.5,   24. ,    3.8],
       [1949. , 2106.6,   23.8,    6. ]])
```

The default settings will in many cases be appropriate to load whatever CSV file we might have. However, we'll occasionally want to specify the following arguments to override the defaults:

- `delimiter`: Character used to separate individual fields (default: space).
- `skiprows=n`: Skip the first `n` rows. For example, if the CSV file contains a header with variable names, `skiprows=1` needs to be specified as NumPy by default cannot process these names.
- `dtype`: Enforce a particular data type for the resulting array.
- `encoding`: Set the character encoding of the input data. This is usually not needed, but can be required to import data with non-latin characters that are not encoded using Unicode.

While `loadtxt()` is simple to use, it quickly reaches its limits with more complex data sets. For example, when we try to load our sample of universities with `loadtxt()`, we get the following error:

[3]:
```
import numpy as np

file = f'{DATA_PATH}/universities.csv'

# Try to load CSV data that contains strings
# This will result in an error!
data = np.loadtxt(file, delimiter=';', skiprows=1)
```

```
ValueError: could not convert string to float: '"University of Glasgow"'
```

This code fails for two reasons:

1. The file contains strings and floats, and `loadtxt()` by default cannot load mixed data.
2. There are missing values (empty fields), which `loadtxt()` cannot handle either.

We can address the first issue by creating a so-called structured array, i.e., an array that contains fields with mixed data. This is accomplished by constructing a special `dtype` object that specifies the field names and their data types:

[4]:
```
# Define names and data types for fields in CSV file
#   Data types are defined using two tokens:
#       1.  The main data type (U: unicode string, f: float, i: integer)
#       2.  The precision or field width
dtypes = np.dtype([('Institution', 'U30'),      # unicode string of length 30
```

```
                    ('Country', 'U20'),          # unicode string of length 20
                    ('Founded', 'i4'),           # integer, 4 bytes
                    ('Students', 'i4'),
                    ('Staff', 'i4'),
                    ('Admin', 'i4'),
                    ('Budget', 'f8'),            # float, 8 bytes
                    ('Russell', 'i1')])          # integer, 1 byte

data = np.loadtxt(file, delimiter=';', skiprows=1, dtype=dtypes)
```

```
ValueError: could not convert string to float: ''
```

However, this still fails because the of a few missing values.

We can get around this by using `genfromtxt()`, which is more flexible and can also deal with missing data:

[5]:
```
# load data using genfromtxt()
# We still need to specify the dtype defined above!
data = np.genfromtxt(file, delimiter=';', dtype=dtypes, encoding='utf8',
                     skip_header=1)

# Determine rows with missing data:
#   - missing integers are coded as -1
#   - missing floats are coded as np.nan
missing = (data['Staff'] < 0) | (data['Admin'] < 0) | np.isnan(data['Budget'])

# print rows with missing values
data[missing]
```

[5]:
```
array([('"University of Strathclyde"', '"Scotland"', 1964, 22640,   -1, 3200,
304.4, 0),
       ('"University of Oxford"', '"England"', 1096, 24515, 7000,   -1, 2450. ,
1),
       ('"University of Manchester"', '"England"', 2004, 40250, 3849,   -1,
1095.4, 1),
       ('"University of Birmingham"', '"England"', 1825, 35445, 4020,   -1,
673.8, 1),
       ('"University of Nottingham"', '"England"', 1798, 30798, 3495,   -1,
656.5, 1),
       ('"University of Stirling"', '"Scotland"', 1967,  9548,   -1, 1872,
113.3, 0),
       ('"Swansea University"', '"Wales"', 1920, 20620,   -1, 3290,     nan, 0)],
      dtype=[('Institution', '<U30'), ('Country', '<U20'), ('Founded', '<i4'),
('Students', '<i4'), ('Staff', '<i4'), ('Admin', '<i4'), ('Budget', '<f8'),
('Russell', 'i1')])
```

While the CSV file can now be processed without errors, you see that NumPy does not remove the double quotes around strings such as the university names. Instead of trying to fix this, it is advisable to just use pandas to load this kind of data which handles all these problems automatically. We examine this alternative below.

1.1.2 Saving data to text files

To save a NumPy array to a CSV file, there is a logical counterpart to `np.loadtxt()` which is called `np.savetxt()`.

[6]:
```
import numpy as np
import os.path
```

```python
import tempfile

# Generate some random data on [0,1)
data = np.random.default_rng(123).random(size=(10, 5))

# create temporary directory
d = tempfile.TemporaryDirectory()

# path to CSV file
file = os.path.join(d.name, 'data.csv')

# Print destination file - this will be different each time
print(f'Saving CSV file to {file}')

# Write NumPy array to CSV file. The fmt argument specifies
# that data should be saved as floating-point using a
# field width of 8 characters and 5 decimal digits.
np.savetxt(file, data, delimiter=';', fmt='%8.5f')
```

```
Saving CSV file to /tmp/tmpoej8m64y/data.csv
```

The above code creates a 10×5 matrix of random floats and stores these in the file `data.csv` using 5 significant digits.

We store the destination file in a temporary directory which we create as follows:

- Because we cannot know in advance on which system this code is run (e.g., the operating system and directory layout), we cannot hard-code a file path.
- Moreover, we do not know whether the code is run with write permissions in any particular folder.
- We work around this issue by asking the Python runtime to create a writeable temporary directory *for the system where the code is being run*.
- We use the routines in the `tempfile` module to create this temporary directory.

Of course, on your own computer you do not need to use a temporary directory, but can instead use any directory where your user has write permissions. For example, on Windows you could use something along the lines of

```
file = 'C:/Users/Path/to/file.txt'
np.savetxt(file, data, delimiter=';', fmt='%8.5f')
```

You can even use relative paths. To store a file in the current working directory it is sufficient to just pass the file name:

```
file = 'file.txt'
np.savetxt(file, data, delimiter=';', fmt='%8.5f')
```

1.2 I/O with pandas

Pandas's I/O routines are more powerful than those implemented in NumPy:

- They support reading and writing numerous file formats.
- They support heterogeneous data without having to specify the data type in advance.
- They gracefully handle missing values.

For these reasons, it is often preferable to directly use pandas to process data instead of NumPy.

The most important routines are:

- `read_csv()`, `to_csv()`: Read or write CSV text files
- `read_fwf()`: Read data with fixed field widths, i.e., text data that does not use delimiters to separate fields.
- `read_excel()`, `to_excel()`: Read or write Excel spreadsheets

- `read_stata()`, `to_stata()`: Read or write Stata's `.dta` files.

For a complete list of I/O routines, see the official documentation.

To illustrate, we repeat the above examples using pandas's `read_csv()`. Since the FRED data contains only floating-point data, the result is very similar to reading in a NumPy array.

[7]:
```python
import pandas as pd

# relative path to CSV file
file = f'{DATA_PATH}/FRED.csv'

df = pd.read_csv(file, sep=',')
df.head(2)           # Display the first 2 rows of data
```

[7]:
```
   Year     GDP   CPI  UNRATE
0  1948  2118.5  24.0     3.8
1  1949  2106.6  23.8     6.0
```

The difference between NumPy and pandas become obvious when we try to load our university data: this works out of the box, without the need to specify any data types or to handle missing values:

[8]:
```python
import pandas as pd

# relative path to CSV file
file = f'{DATA_PATH}/universities.csv'

df = pd.read_csv(file, sep=';')
df.tail(3)       # show last 3 rows
```

[8]:
```
                   Institution           Country  Founded  Students   Staff  \
20      University of Stirling          Scotland     1967      9548     NaN
21  Queen's University Belfast  Northern Ireland     1810     18438  2414.0
22          Swansea University             Wales     1920     20620     NaN

     Admin  Budget  Russell
20  1872.0   113.3        0
21  1489.0   369.2        1
22  3290.0     NaN        0
```

Note that missing values are correctly converted to `np.nan` and the double quotes surrounding strings are automatically removed!

Unlike NumPy, pandas can also process other popular data formats such as MS Excel files (or OpenDocument spreadsheets):

[9]:
```python
import pandas as pd

# Excel file containing university data
file = f'{DATA_PATH}/universities.xlsx'

df = pd.read_excel(file, sheet_name='universities')
df.head(3)
```

[9]:
```
                 Institution   Country  Founded  Students   Staff   Admin  \
0     University of Glasgow   Scotland     1451     30805  2942.0  4003.0
1   University of Edinburgh   Scotland     1583     34275  4589.0  6107.0
2  University of St Andrews   Scotland     1413      8984  1137.0  1576.0

   Budget  Russell
0   626.5        1
1  1102.0        1
2   251.2        0
```

The routine read_excel() takes the argument sheet_name to specify the sheet that should be read.

- Note that the Python package openpyxl needs to be installed in order to read files from Excel 2003 and above.
- To read older Excel files (.xls), you need the package xlrd.

Finally, we often encounter text files with fixed field widths, since this is a commonly used format in older applications (for example, fixed-width files are easy to create in Fortran). To illustrate, the fixed-width variant of our FRED data looks like this:

```
Year GDP    CPI  UNRATE
1948 2118.5   24     3.8
1949 2106.6 23.8       6
1950 2289.5 24.1     5.2
1951 2473.8   26     3.3
1952 2574.9 26.6       3
```

You see that the column Year occupies the first 5 characters, the GDP column the next 7 characters, and so on. To read such files, the width (i.e., the number of characters) has to be explicitly specified:

[10]:
```
import pandas as pd

# File name of FRED data, stored as fixed-width text
file = f'{DATA_PATH}/FRED-fixed.csv'

# field widths are passed as list to read_fwf()
df = pd.read_fwf(file, widths=[5, 7, 5, 8])
df.head(3)
```

[10]:
```
   Year     GDP   CPI  UNRATE
0  1948  2118.5  24.0     3.8
1  1949  2106.6  23.8     6.0
2  1950  2289.5  24.1     5.2
```

Here the widths argument accepts a list that contains the number of characters to be used for each field.

1.3 Retrieving macroeconomic / financial data from the web

1.3.1 Federal Reserve Economic Data (FRED)

FRED, provided by the Federal Reserve of St. Louis, is likely the most important macroeconomic online database (at least for US-centric data). fredapi is a Python API for the FRED data which provides a wrapper for the FRED web service (see also the project's GitHub page).

Before accessing FRED, you need to install fredapi into your Python environment as follows:

```
pip install --no-deps fredapi
```

Important:

- The --no-deps argument might be required for Anaconda users as otherwise the conda-provided versions of numpy and pandas could be overwritten.
- Anaconda users should *not* use the fredapi package provided in conda-forge as that one is outdated and will not work.

To use FRED, you additional need an API key which can be requested at https://fred.stlouisfed.org/docs/api/api_key.html. Unlike with some other APIs we discuss below, it is not possible to make a request without a key. Once you have a key, you can specify it in several ways:

1. On your local machine, set the environment variable FRED_API_KEY to store the key and it will be picked up automatically. This only works if you run a Python environment locally.

2. Store it in a file and pass the file name when creating a `Fred` instance:

   ```
   from fredapi import Fred
   fred = Fred(api_key_file='path_to_file')
   ```

3. Pass the string containing the API key as a parameter:

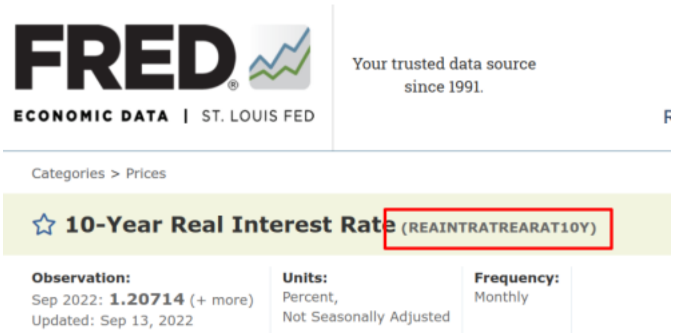
   ```
   from fredapi import Fred
   fred = Fred(api_key='INSERT API KEY HERE')
   ```

The following code assumes that the `FRED_API_KEY` variable has been set up and might not work in your environment if that is not the case.

Examples:

[11]:
```
# Uncomment next line to install fredapi in your local or cloud-hosted Python environment
↪(Binder or Google Colab)
#! pip install --no-deps fredapi
```

In order to retrieve any data, we first need to identify the series name. This is easiest done by searching for the data on FRED using your browser and copying the series name, highlighted in red in the screenshot below.



For example, if we want to retrieve the 10-year real interest rate, the corresponding series name is `REAINTRATREARAT10Y`. The FRED web page contains additional useful information such as the time period for which the data is available, the data frequency (monthly, quarterly, annual) and whether it's seasonally adjusted.

To download and plot the 10-year real interest rate, we proceed as follows:

[12]:
```
from fredapi import Fred

# Create instance assuming API key is stored as environment variable
fred = Fred()

# or specify API key directly
# fred = Fred(api_key='INSERT API KEY HERE')

# Download observations starting from the year 2000 onward
series = fred.get_series('REAINTRATREARAT10Y', observation_start='2000-01-01')
```

[13]:
```
# Print first 5 observations
series.head(5)
```

[13]:
```
2000-01-01    3.411051
2000-02-01    3.513343
2000-03-01    3.440347
2000-04-01    3.202967
2000-05-01    3.360531
dtype: float64
```

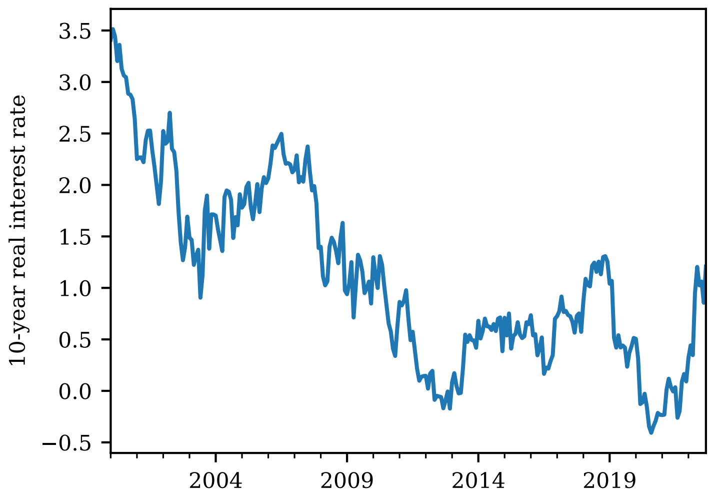
The data is returned as a pandas `Series` object with the corresponding dates set as the index.

[14]:
```
series.info()
```

```
<class 'pandas.core.series.Series'>
DatetimeIndex: 273 entries, 2000-01-01 to 2022-09-01
Series name: None
Non-Null Count  Dtype
--------------  -----
273 non-null    float64
dtypes: float64(1)
memory usage: 4.3 KB
```

[15]:
```
# Plot interest rate time series
series.plot(ylabel='10-year real interest rate')
```

[15]: `<AxesSubplot:ylabel='10-year real interest rate'>`



Other popular time series available on FRED are the CPI, real GDP and the unemployment rate.

1.3.2 Yahoo! Finance data

`yfinance` is a user-written library to access data from Yahoo! Finance using the public API (see the project's GitHub repository for detailed examples). This project is not affiliated with Yahoo! Finance and is intended for personal use only. Before using the library, it needs to be installed from PyPi as follows:

```
pip install yfinance
```

[16]:
```
# When running via Google Colab, uncomment and execute the following line
#! pip install yfinance
```

`yfinance` allows us to retrieve information for a single symbol via properties of the `Ticker` object, or for multiple ticker symbols at once.

Example: Retrieving data for a single symbol

We first use the API to retrieve data for a single symbol, in this case the S&P 500 index which has the (somewhat unusual) ticker symbol `^GSPS`. One can easily find the desired ticker symbol by searching for some stock, index, currency or other asset on Yahoo! Finance.

[17]:
```
import yfinance as yf

# Symbol for S&P 500 index
```

```
symbol = '^GSPC'

# Create ticker object
ticker = yf.Ticker(symbol)
```

We can now use the attributes of the `ticker` object to get all sorts of information. For example, we can get some meta data from the `info` attribute as follows:

[18]:
```
# Descriptive name and asset class
shortname = ticker.info['shortName']
quoteType = ticker.info['quoteType']

# 52-week low and high
low = ticker.info['fiftyTwoWeekLow']
high = ticker.info['fiftyTwoWeekHigh']

print(f'{shortname} is an {quoteType}')
print(f'{shortname} 52-week range: {low} - {high}')

# To see which keys are available, use the keys() method
# ticker.info.keys()
```

```
S&P 500 is an INDEX
S&P 500 52-week range: 3584.13 - 4818.62
```

We use the `history` attribute to get detailed price data. Unless we want all available data, we should select the relevant period using the `start=...` and `end=...` arguments.

[19]:
```
# Retrieve daily index values data for this year
daily = ticker.history(start='2022-01-01', end='2022-03-31')

# Print first 5 rows
daily.head()
```

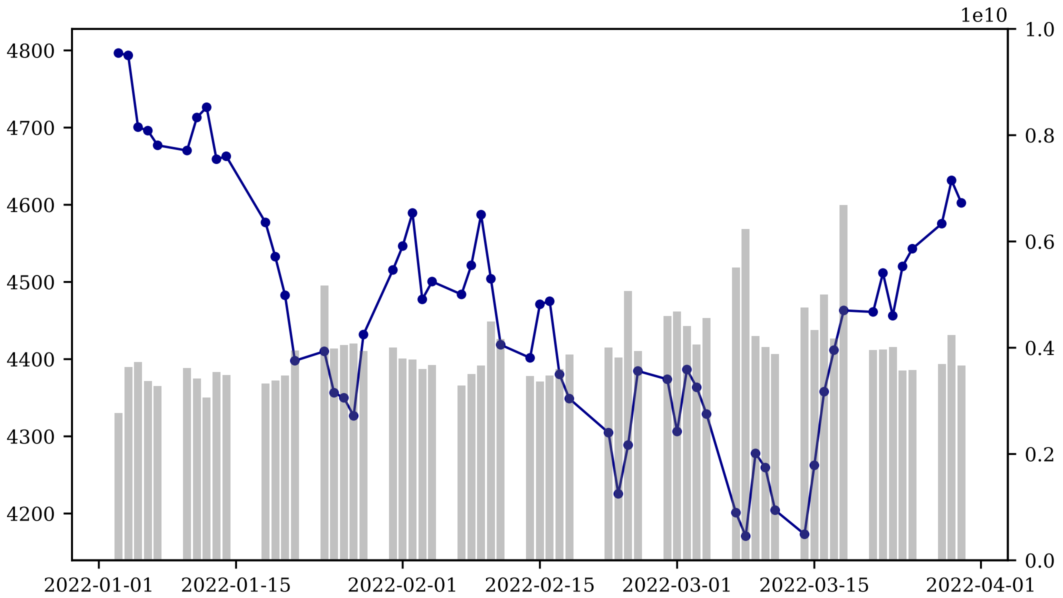
[19]:
```
                   Open         High          Low        Close      Volume  \
Date
2022-01-03  4778.140137  4796.640137  4758.169922  4796.560059  2775190000
2022-01-04  4804.509766  4818.620117  4774.270020  4793.540039  3641050000
2022-01-05  4787.990234  4797.700195  4699.439941  4700.580078  3733540000
2022-01-06  4693.390137  4725.009766  4671.259766  4696.049805  3371250000
2022-01-07  4697.660156  4707.950195  4662.740234  4677.029785  3279870000

            Dividends  Stock Splits
Date
2022-01-03          0             0
2022-01-04          0             0
2022-01-05          0             0
2022-01-06          0             0
2022-01-07          0             0
```

We can then use this data to plot the daily closing price and trading volume.

[20]:
```
import matplotlib.pyplot as plt

fix, ax = plt.subplots(1, 1, figsize=(7,4))

# Plot closing price
ax.plot(daily.index, daily['Close'], color='darkblue', marker='o', ms=3, lw=1)

# Create secondary y-axis for trading volume
ax2 = ax.twinx()
```

```python
# Plot trading volume as bar chart
ax2.bar(daily.index, daily['Volume'], color='#666666', alpha=0.4, zorder=-1, lw=0)
ax2.set_ylim((0.0, 1.0e10))
```

[20]: (0.0, 10000000000.0)



Example: Retrieving data for multiple symbols

We can download trading data for multiple symbols at once using the `download()` function. Unlike the `Ticker` class, this immediately returns a `DataFrame` containing data similar to the `history` method we called previosuly, but now the column index contains an additional level for each ticker symbol. For example, to get the trading data for Amazon and Microsoft for the last 3 months, we proceed as follows:

[21]:
```python
import yfinance as yf

# Get data for Amazon (AMZN) and Microsoft (MSFT) for the last three months.
# valid intervals for the 'period' argument are:
#   1m,2m,5m,15m,30m,60m,90m,1h,1d,5d,1wk,1mo,3mo
data = yf.download("AMZN MSFT", period='3mo')
data.head()
```

```
[*********************100%***********************]  2 of 2 completed
```

[21]:
```
             Adj Close              Close                    High  \
                  AMZN        MSFT       AMZN        MSFT       AMZN
Date
2022-07-05  113.500000  262.293274  113.500000  262.850006  114.080002
2022-07-06  114.330002  265.646118  114.330002  266.209991  115.480003
2022-07-07  116.330002  267.831482  116.330002  268.399994  116.989998
2022-07-08  115.540001  267.093079  115.540001  267.660004  116.580002
2022-07-11  111.750000  263.949738  111.750000  264.510010  114.300003

                               Low                    Open              \
                  MSFT        AMZN        MSFT        AMZN        MSFT
Date
2022-07-05  262.980011  106.320000  254.740005  107.599998  256.160004
2022-07-06  267.989990  112.010002  262.399994  113.209999  263.750000
2022-07-07  269.059998  113.489998  265.019989  113.849998  265.119995
2022-07-08  268.100006  113.690002  263.290009  114.599998  264.790009
```

```
2022-07-11  266.529999  110.870003  262.179993  114.080002  265.649994

              Volume
                AMZN      MSFT
Date
2022-07-05  76583700  22941000
2022-07-06  66958900  23824400
2022-07-07  57872300  20859900
2022-07-08  45719700  19658800
2022-07-11  53487600  19455200
```

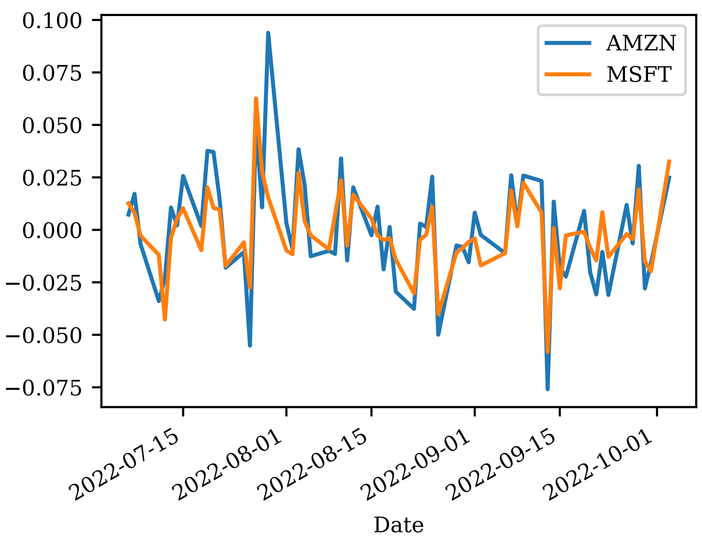
To extract data for a particular symbol, we have to take into account the hierarchical column index:

[22]:
```python
# Use hierarchical indexing to get data for Amazon
data[('Close', 'AMZN')].head()
```

[22]:
```
Date
2022-07-05    113.500000
2022-07-06    114.330002
2022-07-07    116.330002
2022-07-08    115.540001
2022-07-11    111.750000
Name: (Close, AMZN), dtype: float64
```

[23]:
```python
# Plot daily returns for both stocks
returns = data['Close'].diff() / data['Close']
returns.plot(y=['AMZN', 'MSFT'])
```

[23]: <AxesSubplot:xlabel='Date'>



1.3.3 NASDAQ data API (formerly quandl)

The NASDAQ stock exchange provides an open-source Python library hosted on GitHub to access various types of financial data (not only those traded on NASDAQ), see here for details. The detailed API documentation can be found at here. This data API was formerly known as quandl which is no longer actively maintained but might still work.

Before using this service, you need to make sure that the Python package is installed. Depending on how you launched this notebook, you may need to execute the following code to install `nasdaq-data-link`:

```
pip install nasdaq-data-link
```

Various types of data are available via this service and can be found using the online search at `https://data.nasdaq.com/search`.

- Data come from various data provides. To select a data set, you usually have to specify a string of the form `'PROVIDER/SERIES'` where `'PROVIDER'` is the name of the provider (e.g., `'FRED'` or `'BOE'`) and `'SERIES'` is the name of the time series.
- Most of these data require a subscription or at least a free NASDAQ account. Once you have an account, you will need to get an API key and specify it when retrieving data. See the above links for details.
- Some commercial data series include sample data that can be used without a subscription but requires a free NASDAQ account.
- Some data series are freely available without a subscription or an account. These are often taken from other freely available data sets such as FRED or blockchain.com. We'll be using these to demonstrate how the API works.

  Important: Even for freely available data, NASDAQ imposes a cap of 50 calls per day. You need to register to get around this.

The data is returned as pandas `DataFrame` object (or alternatively as an NumPy array).

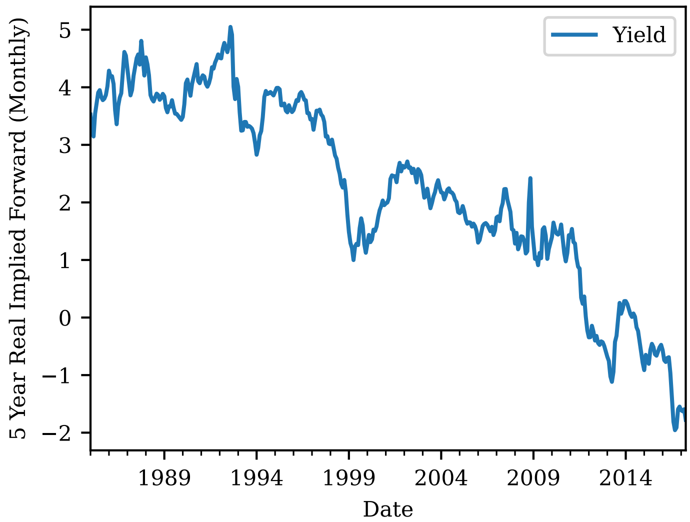
[24]:
```
# When running via Google Colab, uncomment and execute the following line
#! pip install nasdaq-data-link
```

Example: Data from the Bank of England

Let's start by retrieving some macroeconomic times series from the Bank of England (BOE). It's not always straightforward to find the name of the time series one is looking for, but you can see some of the available time series here. The name will vary depending on the type of data (interest rate, exchange rate), the frequency and how it is aggregated (daily, last day of the month, monthly average) and a currency pair, if applicable.

[25]:
```
# Retrieve 5-year real implied yield on UK government bonds
import nasdaqdatalink as ndl
df = ndl.get('BOE/IUMASRIF')

# Rename column which is always called 'Value'
df = df.rename(columns={'Value': 'Yield'})

# Plot time series
df.plot(ylabel='5 Year Real Implied Forward (Monthly)')
```

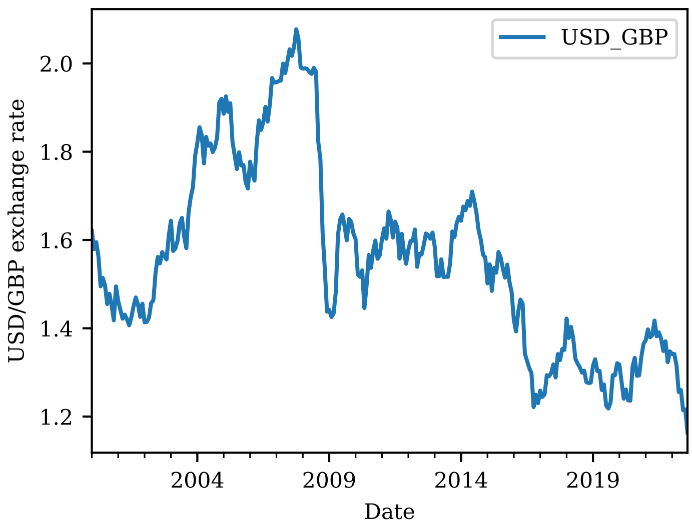
[25]:
```
<AxesSubplot:xlabel='Date', ylabel='5 Year Real Implied Forward (Monthly)'>
```



As another example, we retrieve the US dollar / Sterling exchange rate at a monthly frequency (this is determined by the name of the time series used where `ML` requests the monthly series, using the last observation for each month). Note that we can pass additional arguments, for example restricting the time period we want to retrieve using `start_date` and `end_date`.

[26]:
```
# Get USD / GDP exchange rate using the last observation for each month.
df = ndl.get('BOE/XUMLUSS', start_date='2000-01-31')
df = df.rename(columns={'Value': 'USD_GBP'})

# Plot USD/GBP time series
df.plot(ylabel='USD/GBP exchange rate')
```

[26]: `<AxesSubplot:xlabel='Date', ylabel='USD/GBP exchange rate'>`



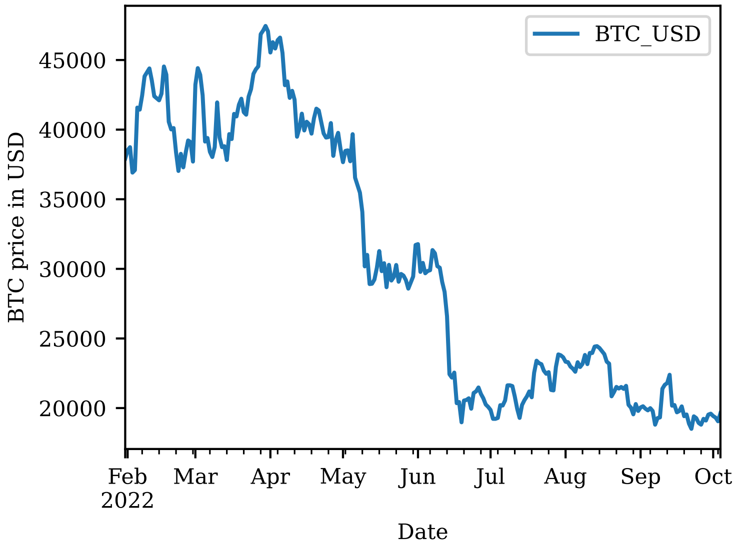
Example: Data from blockchain.com

The NASDAQ data link also supports retrieving data on cryptocurrencies. For example, there is a freely accessible time series for the price of Bitcoin in USD.

[27]:
```
import nasdaqdatalink as ndl

# Retrieve price of BTC in USD for 2022
df = ndl.get('BCHAIN/MKPRU', start_date='2022-01-31')
```

```python
# Change column name to something more descriptive
df = df.rename(columns={'Value': 'BTC_USD'})

# Plot time series
df.plot(ylabel='BTC price in USD')
```

[27]: <AxesSubplot:xlabel='Date', ylabel='BTC price in USD'>



Example: Historical stock data

As a final example, we obtain the trading data for the stock of Apple (ticker symbol `AAPL`) for the year 2001. Such data is often not available without a subscription or a login, but it works if the requested time period is sufficiently far in the past!

[28]:
```python
# Retrieve stock data for Apple (ticker symbol AAPL)
df = ndl.get("WIKI/AAPL", start_date='2000-01-01', end_date='2000-12-31')
```

Unlike in the previous examples, this data contains not only a single value, but a whole range of variables including the opening and closing price, the trading volume, etc.:

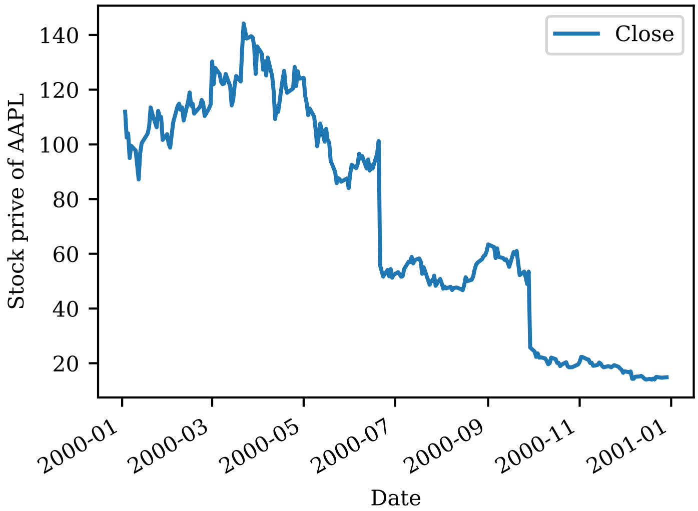
[29]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 252 entries, 2000-01-03 to 2000-12-29
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   Open         252 non-null    float64
 1   High         252 non-null    float64
 2   Low          252 non-null    float64
 3   Close        252 non-null    float64
 4   Volume       252 non-null    float64
 5   Ex-Dividend  252 non-null    float64
 6   Split Ratio  252 non-null    float64
 7   Adj. Open    252 non-null    float64
 8   Adj. High    252 non-null    float64
 9   Adj. Low     252 non-null    float64
 10  Adj. Close   252 non-null    float64
 11  Adj. Volume  252 non-null    float64
dtypes: float64(12)
memory usage: 25.6 KB
```

To plot a specific column, we can use the `y=...` argument to `DataFrame.plot()`.

```
[30]: df.plot(y='Close', ylabel='Stock prive of AAPL')
```

```
[30]: <AxesSubplot:xlabel='Date', ylabel='Stock prive of AAPL'>
```



1.3.4 Pandas Datareader

`pandas-datareader` is a Python library that fetches online data from multiple sources and returns them as pandas `DataFrame` objects. Despite its name, this library is not included in `pandas` and may need to be installed separately, e.g., by running

```
pip install pandas-datareader
```

The aim is to provide a uniform API to access data from multiple sources, including those we covered earlier. See the official documentation for supported data sources and how to access them.

```
[31]: # Uncomment and execute the following line if running in Google Colab
      # ! pip install pandas-datareader
```

Example: Downloading data from FRED

As a first illustration, we fetch macroeconomic data from FRED, but instead of `fredapi` we use `pandas-datareader` and set the data source to `'fred'`. No API key is required for this particular data source, but this is not true for all data sources supported by `pandas-datareader`.

Note that we find the name of the series we want to download in the same way as previously discussed in the section on FRED.

```
[32]: # The convention is to import this library as web
      import pandas_datareader.data as web

      # define start and end dates
      start_date = "2000-01-01"
      end_date = "2021-12-31"

      # Specify series name as first and 'fred' data source as second argument
      gdp = web.DataReader('GDP', 'fred', start_date, end_date)

      # Show first 3 observations
      gdp.head(3)
```

[32]:
```
                  GDP
DATE
2000-01-01  10002.179
2000-04-01  10247.720
2000-07-01  10318.165
```

We can also fetch multiple series at the same time, for example the CPI and the unemployment rate.

[33]:
```
data = web.DataReader(['CPIAUCSL', 'UNRATE'], data_source='fred', start='2020-01-01')
data.head(3)
```

[33]:
```
            CPIAUCSL  UNRATE
DATE
2020-01-01   258.682     3.5
2020-02-01   259.007     3.5
2020-03-01   258.165     4.4
```

Example: Download data from Yahoo! Finance

As another example, we can use `pandas-datareader` as a client for Yahoo! Finance by specifying `'yahoo'` as the data source. As with `yfinance` we discussed earlier, we use the search function on Yahoo! Finance to identify the ticker symbol for the data series we are interested in.

The example below also illustrates that we can optionally use instances of `datetime` to define the sample period instead of plain strings.

[34]:
```
import pandas_datareader.data as web
import datetime

# Instead of strings, we can define period in terms of datetime objects:
# Sample period: 2011-01-1 to 2021-12-31
start = datetime.datetime(2011, 1, 1)
end = datetime.datetime(2021, 12, 31)

# Fetch stock price data for Tesla (ticker symbol TSLA)
data = web.DataReader('TSLA', data_source='yahoo', start=start, end=end)

data.head(3)
```

[34]:
```
                High       Low      Open     Close      Volume  Adj Close
Date
2011-01-03  1.800000  1.726667  1.789333  1.774667  19245000.0   1.774667
2011-01-04  1.796667  1.734667  1.777333  1.778000  17811000.0   1.778000
2011-01-05  1.793333  1.746000  1.765333  1.788667  21700500.0   1.788667
```

1.4 Pickling

A wholly different approach to data I/O is taken by Python's built-in `pickle` module. Almost any Python object can be dumped into a binary file and read back using `pickle.dump()` and `pickle.load()`.

The big advantage over other methods is that hierarchies of objects are automatically supported. For example, we can pickle a list containing a `tuple`, a string and a NumPy array:

[35]:
```
import numpy as np
import pickle
import tempfile
import os.path

# Generate 2d array of integers
arr = np.arange(10).reshape((2, -1))
tpl = (1, 2, 3)
```

```python
text = 'Pickle is very powerful!'

# data: several nested containers and strings
data = [tpl, text, arr]

# create temporary directory
d = tempfile.TemporaryDirectory()
# Binary destination file
file = os.path.join(d.name, 'data.bin')

# print destination file path
print(f'Pickled data written to {file}')

with open(file, 'wb') as f:
    pickle.dump(data, f)
```

```
Pickled data written to /tmp/tmp9ahjcb3i/data.bin
```

We can then read back the data as follows:

[36]:
```python
# load pickle data from above
with open(file, 'rb') as f:
    data = pickle.load(f)

# expand data into its components
tpl, text, arr = data
arr          # prints previously generated 2d array
```

[36]:
```
array([[0, 1, 2, 3, 4],
       [5, 6, 7, 8, 9]])
```

The above example introduces a few concepts we have not encountered so far:

1. The built-in function `open()` is used to open files for reading or writing.
   - The second argument indicates whether a file should be read-only, `r`, or writeable, `w`.
   - The `b` sets the file mode to *binary*, i.e., its contents are *not* human-readable text.
2. We usually access files using a so-called *context manager*. A context manager is created via the `with` statement.

   A big advantage of using a context manager is that the file resource made available as `f` in the block following `with` is automatically cleaned up as soon as the block exits. This is particularly important when writing data.

So why not always use `pickle` to load and store data?

1. Pickling is Python-specific and no other application can process pickled data.
2. The pickle protocol can change in a newer version of Python, and you might not be able to read back your old pickled objects.
3. Even worse, because projects such as NumPy and pandas implement their own pickling routines, you might not even be able to unpickle old DataFrames when you upgrade to a newer pandas version!
4. `pickle` is not secure: It is possible to construct binary data that will execute arbitrary code when unpickling, so you don't want to unpickle data from untrusted sources.
5. Some objects cannot be pickled automatically. For example, this applies to any classes defined with Numba or Cython, unless special care is taken to implement the pickle protocol.

`pickle` is great for internal use when you do not need to exchange data with others and have complete control over your computing environment (i.e., you can enforce a specific version of Python and the libraries you are using). For anything else, you should avoid it.