Module 8: File I/O and Error Handling

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Last time we covered data structures (lists, tuples, dictionaries, sets) in Python that allow us to work with more powerful data items than just the individual numbers, strings and Booleans that we had used before. We also discussed the important difference between call by value and call by reference.

Until now the course dealt with the basics of imperative programming in Python, and you have learned about the most important concepts that you need as a programmer. We will now leave the relatively secluded, controlled environment that we were in so far and look at how to read and write data from and to files, access online resources, use external libraries, and connected to that how to make programs more robust against errors that come from “the outside”.

Today we will cover how to read and write files in general, how to deal with CSV files in particular, and how to handle runtime errors that can for example be caused by user inputs or file operations.

Next time (after the midterm exam) we will have a look at fetching data and other resources from the internet, and how to interact with web services from within Python programs.

Reading and Writing Files

Python distinguishes between only two types of files: text and binary. Basically, anything that is not a text file is regarded as a binary. Text files are sequences of lines, which are themselves sequences of characters that are terminated with a special end-of-line (EOL) character, often the newline character. The content of text files can be processed with the common string manipulation functionality, while processing binary files requires knowledge about their structure. For the moment we are only concerned with text files.

To open a file, first a file object needs to be created with the `open()` function:

```
<file_object> = open(<filename>, <mode>)
```

`<filename>` is the name (path) of the file to open, and `<mode>` specifies for which kind of processing the file is opened ("r" for reading content, "w" for writing content, "a" for appending content, or "r+" for a special read and write mode). For example:

In [14]:
```
# create a file object in reading mode
file = open("data/shorttext.txt", "r")
print(file)
file.close()
```

```
<_io.TextIOWrapper name='data/shorttext.txt' mode='r' encoding='UTF-8'>
```

When the file is opened, operations according to the chosen mode can be carried out. When all operations on the file have been performed, the file should be closed again to avoid unintended side effects:

```
file.close()
```

Play around with the following code examples and a small text file if your choice to see what happens. Add printouts to visualize what has been read by the different commands.

For example, when opened in reading mode we can call different functions for reading content from the file:

In [15]:
```
# creating a file object in reading mode
file = open("data/shorttext.txt", "r")

# file.read() to read all characters in the file
#content = file.read()
#print(content)

# file.read(n) to read the first/next n characters of the file
first_n = file.read(10)
print(first_n)

# file.readline() to read a (the first/next) line of the file
#first_line = file.readline()
#print(first_line)

# file.readlines to read the content of the files line by line
#lines = file.readlines()
#print(lines)

# close file
file.close()
```

```
Invisible
```

When opened in writing mode, we can call diffent functions to write text into the file:

In [16]:
```
# creating a file object in writing mode
file = open("data/textdump.txt", "w")

# file.write to write (or append) text to a file
file.write("Hello World!\n")
file.write("It's cold today...\n")
file.writelines(["Another line\n", "and another line\n"])

# close file
file.close()
```

Change this example from writing to appending mode (parameter "a") and see what the difference is.

With the `with` -statement, Python provides an alternative, elegant way to handle files. It also takes care of closing the file, so it is a good idea to make it a habit to use it for file handling (and never forget closing):

In [17]:
```
with open("data/shorttext.txt", "r") as file:
    content = file.read()

with open("data/newtext.txt", "w") as file:
    file.write("Hello World!\n")
    file.write("It's cold today...\n")
    file.writelines(["Another line\n", "and another line\n"])
```

Note that here is also a short and elegant way to iterate over all lines of a file, without explicitly calling `readlines()` before:

```
for line in file:
    <do something with line>
```

As a more complete example, see the following code to read the text from a file, encrypt it using the Caesar cipher, and write it into another file:

In [18]:
```
from caesarcipher import CaesarCipher

with open("data/shorttext.txt", "r") as file:
    content = file.read()

content_encrypted = CaesarCipher(content, offset=3)

with open("data/shorttext_encrypted.txt", "w") as file:
    file.write(content_encrypted.encoded)
```

This code produces no output on the command line, but if you try it with a text file yourself, you will see the effect in the new file that is created.

Dealing With CSV Files

Let's look at another kind of text file, that you will frequently come across when working on data science problems: CSV files. CSV stands for "comma-separated values" and means that commas are used to separate the values in a line from each other. Sometimes also other characters are used as separators, such as the tabulator "\t" or the semicolon ";", so don't be confused if you see that. As such, CSV files are a simple means to represent tabular data. The following example is based on the Dutch municipalities data set from Kaggle (https://www.kaggle.com/justinboon/municipalities-of-the-netherlands/data (https://www.kaggle.com/justinboon/municipalities-of-the-netherlands/data)), stored in the file dutch_municipalities.csv. We can open and read this file as in the examples above:

In [19]:
```
with open("data/dutch_municipalities.csv", "r") as csvfile:
    print(csvfile.read())
```

```
municipality    province        latitude        longitude       surface_km2
population      avg_household_income_2012       avg_woz_2014    university
Aa en Hunze     Drenthe 53.010.485      6.749.528       278.9   25243   35500
225000  0
Aalburg Noord-Brabant   51.751.294      5.057.085       53.17   12859   39100
249000  0
Aalsmeer        Noord-Holland   52.262.164      4.761.922       32.29   30792
40900   276000  0
Aalten  Gelderland      51.926.667      6.580.678       96.57   27030   33300
194000  0
Achtkarspelen   Friesland       53.210.357      6.153.565       103.98  28002
30500   165000  0
Alblasserdam    Zuid-Holland    51.870.337      4.670.202       10.06   19822
35500   195000  0
Albrandswaard   Zuid-Holland    51.858.068      4.423.187       23.75   25044
42700   255000  0
Alkmaar Noord-Holland   52.632.842      4.755.037       31.2    94906   32300
181000  0
Almelo  Overijssel      52.367.027      6.668.492       69.4    72435   31000
```

In this form (as one long string) the content of the CSV file is of course not of too much use, as it is difficult to access individual elements from it. Instead of reading the content file completely, we could read it line by line (getting a list of lines), and then split the lines at the separator to create a list or dictionary of the elements in each row of the table, resulting in big list of lists or list of dictionaries. Luckily, however, CSV files are so common that there is a package called csv that provides this and other frequently needed functionality for working with CSV files (please refer to the online documentation at https://docs.python.org/3/library/csv.html (https://docs.python.org/3/library/csv.html) for full reference). Here are some examples of what working with the package can look like:

In [20]:
```python
# import the csv library
import csv

# csv.reader returns the content of the file as list of lists of strings
with open("data/dutch_municipalities.csv", "r") as csvfile:
    csvreader = csv.reader(csvfile, delimiter='\t')
    for row in csvreader:
        print(row[0])
```

```
municipality
Aa en Hunze
Aalburg
Aalsmeer
Aalten
Achtkarspelen
Alblasserdam
Albrandswaard
Alkmaar
Almelo
Almere
Alphen aan den Rijn
Alphen-Chaam
Ameland
Amersfoort
Amstelveen
Amsterdam
Apeldoorn
Appingedam
Arnhem
```

In [21]:
```python
# csv.DictReader returns the content of the file as list of dictionaries, using the
with open("data/dutch_municipalities.csv", "r") as csvfile:
    csvreader = csv.DictReader(csvfile, delimiter='\t')
    for row in csvreader:
        print(f'{row["municipality"]}: {row["university"]}')
```

```
Aa en Hunze: 0
Aalburg: 0
Aalsmeer: 0
Aalten: 0
Achtkarspelen: 0
Alblasserdam: 0
Albrandswaard: 0
Alkmaar: 0
Almelo: 0
Almere: 0
Alphen aan den Rijn: 0
Alphen-Chaam: 0
Ameland: 0
Amersfoort: 0
Amstelveen: 0
Amsterdam: 2
Apeldoorn: 0
Appingedam: 0
Arnhem: 0
Assen: 0
```

In [22]:
```
# same as the previous example, but printing only municipalitiers with and average
with open("data/dutch_municipalities.csv", "r") as csvfile:
    csvreader = csv.DictReader(csvfile, delimiter='\t')
    for row in csvreader:
        if int(row["university"]) > 0:
            print(f'{row["municipality"]}: {row["university"]}')
```

```
Amsterdam: 2
Delft: 1
Eindhoven: 1
Enschede: 1
Groningen: 1
Leiden: 1
Maastricht: 1
Nijmegen: 1
Rotterdam: 1
Tilburg: 1
Utrecht: 1
Wageningen: 1
```

If you want to do more advanced things with the data from CSV files, like for example merge, join, or concatenate tables from different CSV files, you can absolutely do that with CSV files read in as above and the knowledge about loops, conditions, list, dictionaries etc. that you have, but it can be a bit tricky. This is why when such operations are (likely to be) needed, it is usually recommended to use the pandas library (http://pandas.pydata.org/ (http://pandas.pydata.org/)), which has some specialized functions for this.

Pandas has an own function for reading CSV files, which returns the result as a so-called data frame, as shown in the following example:

In [23]:
```
import pandas as pd

df = pd.read_csv('data/dutch_municipalities.csv', sep="\t")
print(df)
```

```
            municipality       province    latitude  longitude  surface_km2  \
0             Aa en Hunze        Drenthe  53.010.485  6.749.528       278.90
1                 Aalburg  Noord-Brabant  51.751.294  5.057.085        53.17
2                Aalsmeer  Noord-Holland  52.262.164  4.761.922        32.29
3                  Aalten     Gelderland  51.926.667  6.580.678        96.57
4              Achtkarspelen      Friesland  53.210.357  6.153.565       103.98
5              Alblasserdam   Zuid-Holland  51.870.337  4.670.202        10.06
6              Albrandswaard   Zuid-Holland  51.858.068  4.423.187        23.75
7                    Alkmaar  Noord-Holland  52.632.842  4.755.037        31.20
8                     Almelo     Overijssel  52.367.027  6.668.492        69.40
9                     Almere      Flevoland  52.350.785  5.264.702       248.77
10   Alphen aan den Rijn   Zuid-Holland  52.111.222  4.647.251       132.49
11              Alphen-Chaam  Noord-Brabant  51.509.135  4.861.589        93.51
12                   Ameland      Friesland  53.440.564  5.658.766       268.50
13                Amersfoort        Utrecht  52.156.111  5.387.827        63.86
14                Amstelveen  Noord-Holland  52.311.421  4.870.087        44.08
15                 Amsterdam  Noord-Holland  52.370.216  4.895.168       219.30
16                 Apeldoorn     Gelderland  52.211.157  5.969.923       341.15
17                Appingedam      Groningen  53.320.678  6.854.422        24.58
18                    Arnhem     Gelderland  51.985.103  5.898.730       101.54
```

Data frames are two-dimensional labeled data structures, very much like tables. The rows are labeled by an index (typically ascending from 0), and the columns are labeled by the column names, corresponding to the kind of data that is contained in them. See https://pandas.pydata.org/pandas-docs/stable/dsintro.html#dataframe (https://pandas.pydata.org/pandas-docs/stable/dsintro.html#dataframe) for further details.

Data frames have a number of attributes, such as the column labels, the row indices and the types of the data in the columns (see a full list at https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.DataFrame.html (https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.DataFrame.html)), that can be accessed as illustrated below:

In [24]:
```
print(df.index)
print(df.columns)
print(df.dtypes)
```

```
RangeIndex(start=0, stop=380, step=1)
Index(['municipality', 'province', 'latitude', 'longitude', 'surface_km2',
       'population', 'avg_household_income_2012', 'avg_woz_2014',
       'university'],
      dtype='object')
municipality                 object
province                     object
latitude                     object
longitude                    object
surface_km2                 float64
population                  float64
avg_household_income_2012   float64
avg_woz_2014                float64
university                    int64
dtype: object
```

Via the `iloc` attribute we can access a row by its index, for example:

In [25]:
```
print(df.iloc[39])
print(type(df.iloc[39]))
```

```
municipality                   De Bilt
province                       Utrecht
latitude                     52.109.272
longitude                     5.180.968
surface_km2                       67.13
population                        42013
avg_household_income_2012         43100
avg_woz_2014                     338000
university                            0
Name: 39, dtype: object
<class 'pandas.core.series.Series'>
```

Apparently, such single row of a data frame is of type “Series” (see https://pandas.pydata.org/pandas-docs/stable/reference/series.html (https://pandas.pydata.org/pandas-docs/stable/reference/series.html) for full reference), which basically means a one-dimensional labeled data structure. Series are iterable. You have maybe already noticed that many functions in, e.g., pandas and matplotlib take Series as input, and this is one way to get them.

Slicing works with `iloc`, too, so a range of indices can be used to access several rows at a time. The result is of type “DataFrame” again:

In [26]:
```
print(df.iloc[39:42])
print(type(df.iloc[39:42]))
```

```
   municipality       province    latitude  longitude  surface_km2  \
39      De Bilt        Utrecht  52.109.272  5.180.968        67.13
40   Binnenmaas   Zuid-Holland  51.796.188  4.548.157        75.57
41       Bladel  Noord-Brabant  51.362.963  5.213.639        75.62

    population  avg_household_income_2012  avg_woz_2014  university
39     42013.0                    43100.0      338000.0           0
40     28682.0                    39300.0      231000.0           0
41     19825.0                    37200.0      272000.0           0
<class 'pandas.core.frame.DataFrame'>
```

Similarly, a list of indices (not necessarily a range) can be used:

In [27]:
```
print(df.iloc[[38,40,42]])
print(type(df.iloc[[38,40,42]]))
```

```
   municipality       province    latitude  longitude  surface_km2  \
38    Beverwijk  Noord-Holland  52.486.984  4.657.447        20.09
40   Binnenmaas   Zuid-Holland  51.796.188  4.548.157        75.57
42     Blaricum  Noord-Holland  52.272.669  5.248.080        15.56

    population  avg_household_income_2012  avg_woz_2014  university
38     40052.0                    32500.0      178000.0           0
40     28682.0                    39300.0      231000.0           0
42      9112.0                    51600.0      536000.0           0
<class 'pandas.core.frame.DataFrame'>
```

The `iloc` access can also be used for indexing at both axes of the data frame, including accessing a single element (note the different resulting data types):

In [28]:
```
print(df.iloc[1:3,1:3])
print(type(df.iloc[1:3,1:3]))
print(df.iloc[3,3])
print(type(df.iloc[3,3]))
```

```
       province    latitude
1  Noord-Brabant  51.751.294
2  Noord-Holland  52.262.164
<class 'pandas.core.frame.DataFrame'>
6.580.678
<class 'str'>
```

Very similar to `iloc`, the loc attribute can be used to access (groups of) rows and columns by their labels. For example (note the difference in the interpretation of the range now that the labels of the indexes are used):

In [29]:
```
print(df.loc[1:3,"population"])
```

```
1    12859.0
2    30792.0
3    27030.0
Name: population, dtype: float64
```

Without using any attributes, just in pairs of square brackets, columns in a dataframe can be addressed by their name. For example, to access the “murders_2014” column of our example data frame, it’s name can be used as reference:

In [30]:
```
print(df["population"])
print(type(df["population"]))
```

```
0       25243.0
1       12859.0
2       30792.0
3       27030.0
4       28002.0
5       19822.0
6       25044.0
7       94906.0
8       72435.0
9      196156.0
10     106809.0
11       9712.0
12       3565.0
13     150943.0
14      85135.0
15     853312.0
16     157535.0
17      12049.0
18     150817.0
19      67209.0
20      16479.0
21       6617.0
22      24344.0
23      47375.0
24      54176.0
25      10475.0
26      16268.0
27       8919.0
28      13593.0
29      18956.0
        ...
350     25487.0
351     13977.0
352     23906.0
353     41010.0
354     23170.0
355     23031.0
356     13843.0
357     28873.0
358     21654.0
359     50607.0
360     23592.0
361     15751.0
362     12386.0
363     14407.0
364    150911.0
365     27207.0
366     16588.0
367     13661.0
368     21543.0
369     61337.0
370     32254.0
371    123614.0
372      8089.0
373     18767.0
374     40878.0
375     21374.0
376     47154.0
377     22148.0
378     44546.0
379    123211.0
```

```
Name: population, Length: 380, dtype: float64
<class 'pandas.core.series.Series'>
```

Again, the output is a Series, so this is another way to get this data structure.

Accessing several columns at once is also possible, the result is a data frame:

In [31]:
```
print(df[["municipality","population"]])
print(type(df[["municipality","population"]]))
```

```
            municipality  population
0             Aa en Hunze     25243.0
1                 Aalburg     12859.0
2                Aalsmeer     30792.0
3                  Aalten     27030.0
4            Achtkarspelen     28002.0
5             Alblasserdam     19822.0
6            Albrandswaard     25044.0
7                  Alkmaar     94906.0
8                   Almelo     72435.0
9                   Almere    196156.0
10   Alphen aan den Rijn    106809.0
11           Alphen-Chaam      9712.0
12                Ameland      3565.0
13              Amersfoort    150943.0
14              Amstelveen     85135.0
15               Amsterdam    853312.0
16               Apeldoorn    157535.0
17              Appingedam     12049.0
18                  Arnhem    150817.0
19                   Assen     67209.0
20                   Asten     16479.0
21          Baarle-Nassau      6617.0
22                   Baarn     24344.0
23            Barendrecht     47375.0
24              Barneveld     54176.0
25                   Bedum     10475.0
26                    Beek     16268.0
27                Beemster      8919.0
28                  Beesel     13593.0
29            Berg en Dal     18956.0
..                    ...         ...
350     Weststellingwerf     25487.0
351            Westvoorne     13977.0
352               Wierden     23906.0
353               Wijchen     41010.0
354            Wijdemeren     23170.0
355   Wijk bij Duurstede     23031.0
356                Winsum     13843.0
357           Winterswijk     28873.0
358           Woensdrecht     21654.0
359                Woerden     50607.0
360              De Wolden     23592.0
361            Wormerland     15751.0
362            Woudenberg     12386.0
363            Woudrichem     14407.0
364              Zaanstad    150911.0
365            Zaltbommel     27207.0
366             Zandvoort     16588.0
367               Zederik     13661.0
368               Zeewolde     21543.0
369                  Zeist     61337.0
370               Zevenaar     32254.0
371            Zoetermeer    123614.0
372           Zoeterwoude      8089.0
373               Zuidhorn     18767.0
374               Zuidplas     40878.0
375                Zundert     21374.0
376                Zutphen     47154.0
377      Zwartewaterland     22148.0
378           Zwijndrecht     44546.0
```

```
379               Zwolle    123211.0

[380 rows x 2 columns]
<class 'pandas.core.frame.DataFrame'>
```

Another handy feature is to filter data frames based on certain criteria. For example, we might only want to see the data of municipalities with at least 150,000 inhabitants:

In [32]:
```
print(df[df["population"]>=150000])
```

```
      municipality       province    latitude  longitude  surface_km2  \
9           Almere      Flevoland  52.350.785  5.264.702       248.77
13      Amersfoort        Utrecht  52.156.111  5.387.827        63.86
15       Amsterdam  Noord-Holland  52.370.216  4.895.168       219.30
16       Apeldoorn     Gelderland  52.211.157  5.969.923       341.15
18          Arnhem     Gelderland  51.985.103  5.898.730       101.54
52           Breda  Noord-Brabant  51.571.915  4.768.323       128.68
92       Eindhoven  Noord-Brabant  51.441.642  5.469.722        88.87
96        Enschede     Overijssel  52.221.537  6.893.662       142.72
116  's-Gravenhage   Zuid-Holland  52.070.498  4.300.700        98.12
117      Groningen      Groningen  53.219.383  6.566.502        83.75
122        Haarlem  Noord-Holland  52.387.388  4.646.219        32.09
221       Nijmegen     Gelderland  51.812.563  5.837.226        57.60
272      Rotterdam   Zuid-Holland  51.924.420  4.477.733       325.79
306        Tilburg  Noord-Brabant  51.560.596  5.091.914       119.18
315        Utrecht        Utrecht  52.090.737  5.121.420        99.21
364       Zaanstad  Noord-Holland  52.457.966  4.751.043        83.24

     population  avg_household_income_2012  avg_woz_2014  university
9      196156.0                    34900.0      182000.0           0
13     150943.0                    36900.0      222000.0           0
15     853312.0                    31400.0      231000.0           2
16     157535.0                    34800.0      208000.0           0
18     150817.0                    30500.0      175000.0           0
52     179999.0                    35200.0      221000.0           0
92     220782.0                    32000.0      209000.0           1
96     158542.0                    29600.0      155000.0           1
116    508592.0                    31800.0      188000.0           0
117    198108.0                    28500.0      157000.0           1
122    155205.0                    34300.0      229000.0           0
221    168499.0                    30900.0      191000.0           1
272    618467.0                    29600.0      148000.0           1
306    210382.0                    31600.0      187000.0           1
315    328577.0                    34300.0      223000.0           1
364    150911.0                    33300.0      177000.0           0
```

Or the data for the province of Utrecht:

In [33]:
```
print(df[df["province"]=="Utrecht"])
```

```
            municipality province    latitude  longitude  surface_km2  \
13             Amersfoort  Utrecht  52.156.111  5.387.827        63.86
22                  Baarn  Utrecht  52.213.182  5.286.410        33.01
39               De Bilt  Utrecht  52.109.272  5.180.968        67.13
57                Bunnik  Utrecht  52.066.528  5.200.776        37.57
58             Bunschoten  Utrecht  52.240.642  5.367.070        34.81
88                 Eemnes  Utrecht  52.253.746  5.261.275        33.70
157                Houten  Utrecht  52.002.991  5.185.760        58.99
160          IJsselstein  Utrecht  52.017.765  5.040.300        21.68
186              Leusden  Utrecht  52.131.793  5.429.469        58.89
192                Lopik  Utrecht  51.974.861  4.945.148        78.98
213             Montfoort  Utrecht  52.036.213  4.951.859        38.20
218            Nieuwegein  Utrecht  52.024.821  5.091.819        25.65
250             Oudewater  Utrecht  52.024.163  4.868.417        40.10
261             Renswoude  Utrecht  52.074.661  5.538.173        18.51
264                Rhenen  Utrecht  51.962.140  5.571.116        43.76
270       De Ronde Venen  Utrecht  52.206.680  4.886.773       116.98
288                 Soest  Utrecht  52.176.352  5.299.197        46.43
297       Stichtse Vecht  Utrecht  52.144.755  5.033.208       106.82
315              Utrecht  Utrecht  52.090.737  5.121.420        99.21
316  Utrechtse Heuvelrug  Utrecht  52.052.203  5.282.495       134.09
321            Veenendaal  Utrecht  52.026.301  5.554.431        19.72
327                Vianen  Utrecht  51.990.276  5.103.033        42.39
355   Wijk bij Duurstede  Utrecht  51.975.600  5.338.450        50.25
359               Woerden  Utrecht  52.079.829  4.862.724        92.92
362            Woudenberg  Utrecht  52.082.175  5.426.595        36.82
369                 Zeist  Utrecht  52.090.601  5.233.253        48.65

     population  avg_household_income_2012  avg_woz_2014  university
13     150943.0                    36900.0      222000.0           0
22      24344.0                    38600.0      290000.0           0
39      42013.0                    43100.0      338000.0           0
57      14619.0                    42600.0      271000.0           0
58      20547.0                    39400.0      250000.0           0
88       8773.0                    40100.0      291000.0           0
157     48427.0                    42900.0      261000.0           0
160     34268.0                    39300.0      234000.0           0
186     28967.0                    41000.0      267000.0           0
192     14000.0                    39500.0      267000.0           0
213     13639.0                    41200.0      264000.0           0
218     61017.0                    35200.0      206000.0           0
250      9868.0                    39600.0      283000.0           0
261      4928.0                    39200.0      281000.0           0
264     19123.0                    37100.0      255000.0           0
270     42648.0                    42700.0      300000.0           0
288     45430.0                    38700.0      273000.0           0
297     63823.0                    40800.0      270000.0           0
315    328577.0                    34300.0      223000.0           1
316     47939.0                    41400.0      305000.0           0
321     63207.0                    34800.0      210000.0           0
327     19573.0                    37400.0      219000.0           0
355     23031.0                    39500.0      261000.0           0
359     50607.0                    39900.0      251000.0           0
362     12386.0                    38800.0      281000.0           0
369     61337.0                    39700.0      301000.0           0
```

Or for the municipalities in the province of Utrecht with at least 150,000 inhabitants:

In [34]:
```
print(df[(df["population"]>=150000) & (df["province"]=="Utrecht")])
```

```
    municipality province    latitude  longitude  surface_km2  population  \
13    Amersfoort  Utrecht  52.156.111  5.387.827        63.86    150943.0
315      Utrecht  Utrecht  52.090.737  5.121.420        99.21    328577.0

     avg_household_income_2012  avg_woz_2014  university
13                     36900.0      222000.0           0
315                    34300.0      223000.0           1
```

Note that are several other clever ways to access (ranges of) values in data frames, but discussing them all would be out of scope of this lecture. We will see some of them in the examples later on, but if you are interested in digging deeper into this, please refer to the official “Indexing and Selecting Data” guide at http://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html (http://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html) or ask Google if you are looking for hints how to index best in a specific situation.

In the following we will look at a few methods that pandas data frames provide. This selection is by no means complete, either, but you can find the full list at https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.DataFrame.html (https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.DataFrame.html).

For example, there are methods to easily sum up values, or get basic statistic information like the max, min, mean and median values. Just to show a few:

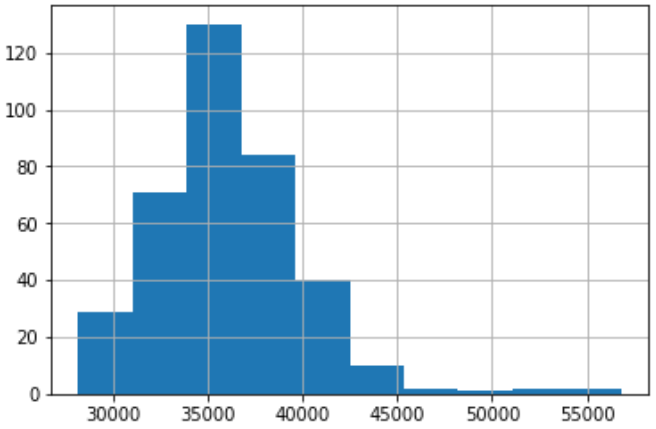
In [35]:
```
print(f"Population was {df['population'].sum()} in total.")
print(f"The maximum population in a municipality was "\
      f"{df['population'].max()}.")
print(f"The average population per municipality was "\
      f"{df['population'].mean():.3f}.")
print(f"The average population per municipality with at "\
      f"least 1 university was "\
      f"{df[df['university']>=1]['population'].mean():.3f}.")
```

```
Population was 16589696.0 in total.
The maximum population in a municipality was 853312.0.
The average population per municipality was 44121.532.
The average population per municipality with at least 1 university was 261600.250.
```

The `hist` method can be used to plot simple histograms from data:

In [36]:
```
print(df["avg_household_income_2012"].hist())
```

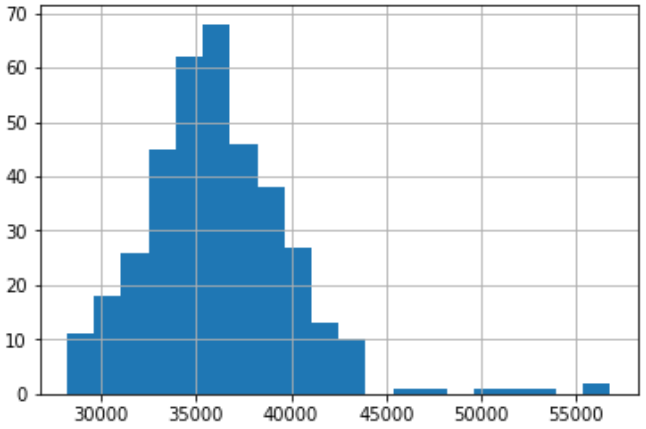
```
AxesSubplot(0.125,0.125;0.775x0.755)
```



Or, with a larger number of bins:

In [37]:
```
print(df["avg_household_income_2012"].hist(bins=20))
```

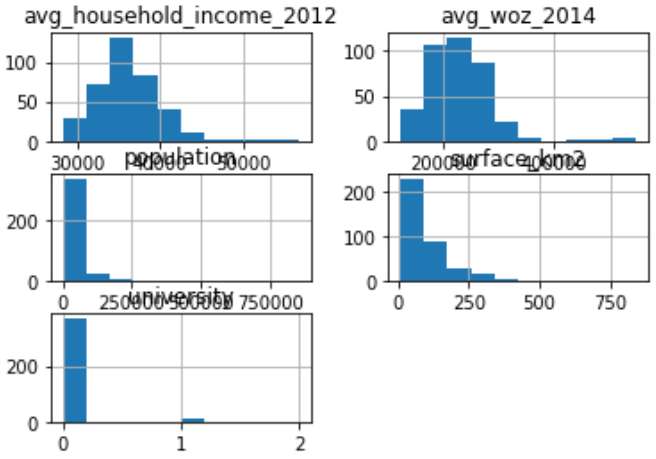
```
AxesSubplot(0.125,0.125;0.775x0.755)
```



If a data frame contains several columns with numeric values, the `hist` method will create histograms for all of them. For example, when called on the whole data frame:

In [38]:
```
print(df.hist())
```

```
[[<matplotlib.axes._subplots.AxesSubplot object at 0x7f5744122750>
  <matplotlib.axes._subplots.AxesSubplot object at 0x7f5742f30bd0>]
 [<matplotlib.axes._subplots.AxesSubplot object at 0x7f5742ee2ed0>
  <matplotlib.axes._subplots.AxesSubplot object at 0x7f5742f0eb90>]
 [<matplotlib.axes._subplots.AxesSubplot object at 0x7f5742ec0e90>
  <matplotlib.axes._subplots.AxesSubplot object at 0x7f5742e6bb50>]]
```



The possibilities for making histograms with `hist()` more “beautiful” are a bit limited, so other libraries should be used when a better design is wanted. However, for a quick check of the distribution of data in a data frame it is very suitable.

As a last example for today, we want to sort the data in the data frame according to average household income (descending), instead of having them sorted by municipality, like it is now. The `sort_values()` method is what we need:

In [39]:
```
sorted_df = df.sort_values("avg_household_income_2012", ascending=False)
print(sorted_df)
```

```
            municipality       province    latitude  longitude  surface_km2  \
273            Rozendaal     Gelderland  52.009.785  5.966.507        27.92
43           Bloemendaal  Noord-Holland  52.404.947  4.620.185        45.18
340            Wassenaar   Zuid-Holland  52.142.910  4.401.213        62.37
42              Blaricum  Noord-Holland  52.272.669  5.248.080        15.56
177                Laren  Noord-Holland  52.256.817  5.224.155        12.41
133            Heemstede  Noord-Holland  52.351.063  4.620.300         9.64
231            Oegstgeest   Zuid-Holland  52.186.226  4.474.810         7.97
176        Lansingerland   Zuid-Holland  51.998.714  4.516.263        56.37
249         Ouder-Amstel  Noord-Holland  52.285.929  4.913.383        25.78
39               De Bilt        Utrecht  52.109.272  5.180.968        67.13
336              Waalre  Noord-Brabant  51.387.833  5.443.202        22.66
157              Houten        Utrecht  52.002.991  5.185.760        58.99
351           Westvoorne   Zuid-Holland  51.887.279  4.084.461        97.48
270       De Ronde Venen        Utrecht  52.206.680  4.886.773       116.98
206      Midden-Delfland   Zuid-Holland  51.954.201  4.288.310        49.38
6          Albrandswaard   Zuid-Holland  51.858.068  4.423.187        23.75
57                 Bunnik        Utrecht  52.066.528  5.200.776        37.57
332          Voorschoten   Zuid-Holland  52.123.790  4.438.598        11.56
255   Rijnaaker Nootdorp   Zuid-Holland  52.012.608  4.427.255        28.61
```

Note that the index column was sorted with the rest of the data, too. So, if we want to have indices there running up from 0, we need to reset the index:

In [40]:
```
sorted_reindexed_df = sorted_df.reset_index(drop=True)
print(sorted_reindexed_df)
```

```
            municipality       province    latitude  longitude  surface_km2  \
0              Rozendaal     Gelderland  52.009.785  5.966.507        27.92
1            Bloemendaal  Noord-Holland  52.404.947  4.620.185        45.18
2              Wassenaar   Zuid-Holland  52.142.910  4.401.213        62.37
3                Blaricum  Noord-Holland  52.272.669  5.248.080        15.56
4                   Laren  Noord-Holland  52.256.817  5.224.155        12.41
5              Heemstede  Noord-Holland  52.351.063  4.620.300         9.64
6              Oegstgeest   Zuid-Holland  52.186.226  4.474.810         7.97
7          Lansingerland   Zuid-Holland  51.998.714  4.516.263        56.37
8           Ouder-Amstel  Noord-Holland  52.285.929  4.913.383        25.78
9                De Bilt        Utrecht  52.109.272  5.180.968        67.13
10               Waalre  Noord-Brabant  51.387.833  5.443.202        22.66
11               Houten        Utrecht  52.002.991  5.185.760        58.99
12            Westvoorne   Zuid-Holland  51.887.279  4.084.461        97.48
13        De Ronde Venen        Utrecht  52.206.680  4.886.773       116.98
14       Midden-Delfland   Zuid-Holland  51.954.201  4.288.310        49.38
15         Albrandswaard   Zuid-Holland  51.858.068  4.423.187        23.75
16                Bunnik        Utrecht  52.066.528  5.200.776        37.57
17           Voorschoten   Zuid-Holland  52.123.790  4.438.598        11.56
18    Rijnaaker Nootdorp   Zuid-Holland  52.012.608  4.427.255        28.61
```

Finally, note that data frames can easily be saved as CSV files with the `to_csv()` method. For example:

In [41]:
```
sorted_reindexed_df.to_csv('data/dutch_municipalities_sorted.csv')
```

We will see more about data frames in the following lecture(s).

Error Handling

There are basically two kinds of errors that can be detected by the Python interpreter: syntax (aka parsing) errors and exceptions (aka runtime or execution-time errors). `SyntaxErrors` are caused by syntactically incorrect code (like invalid variable names, forgotten indentations, braces, quotation marks or colons, etc.; Spyder will often already point you to them). They are fixed by correcting the code accordingly. Syntactically correct code can however still cause exceptions during exection. For example, a division by zero will result in a `ZeroDivisonError`, and a type mismatch between str and int will result in a `TypeError`. We say that an exception is "thrown" at runtime when the respective error occurs, and we can add code to "catch" and handle it if that happens (and thus prevent the program from simply crashing). That is done by the try-and-except construct in Python. Simply put, it defines what should be tried, and what happens if that goes wrong:

```
try:
    <do something>
except <error>:
    <do something to react on error>
```

For example, a `ValueError` is thrown when the user's input is not convertible into an integer, so we can catch it and display an error message accordingly:

In [42]:
```
try:
    x = int(input("Please enter a number: "))
except ValueError:
    print("That was no valid number.")
```

```
Please enter a number:  23
```

In this case, it would in practice be handy if the user is asked to try again, until (s)he enters a valid input. Maybe even encapsulated into a function, to have a specific, error-handling reader available for reuse:

In [43]:
```
def read_integer(prompt):
    while True:
        try:
            x = int(input(prompt))
            return x
        except ValueError:
            print("That was no valid number. Try again.")

# in main program:
number = read_integer("Please enter a number:" )
```

```
---------------------------------------------------------------------------
KeyboardInterrupt                         Traceback (most recent call last)
<ipython-input-43-e031ff325090> in <module>
      8
      9 # in main program:
---> 10 number = read_integer("Please enter a number:" )

<ipython-input-43-e031ff325090> in read_integer(prompt)
      2     while True:
      3         try:
----> 4             x = int(input(prompt))
      5             return x
      6         except ValueError:

~/anaconda3/lib/python3.7/site-packages/ipykernel/kernelbase.py in raw_input(self,
prompt)
    858             self._parent_ident,
    859             self._parent_header,
--> 860             password=False,
    861         )
    862

~/anaconda3/lib/python3.7/site-packages/ipykernel/kernelbase.py in _input_request
(self, prompt, ident, parent, password)
    899             except KeyboardInterrupt:
    900                 # re-raise KeyboardInterrupt, to truncate traceback
--> 901                 raise KeyboardInterrupt("Interrupted by user") from None
    902             except Exception as e:
    903                 self.log.warning("Invalid Message:", exc_info=True)

KeyboardInterrupt: Interrupted by user
```

As another example: When handling files, it can easily happen that the path to the file to be opened is not correct, and the file cannot be opened. Then the `FileNotFoundError` can be caught to prevent the program from crashing because of that:

In [ ]:
```
filename = input("Enter file name: ")
while True:
    try:
        with open(filename, "r") as file:
            print(file.read())
        break
    except FileNotFoundError:
        print("File not found. Please try again.")
        filename = input("Enter file name: ")
```

There are several built-in exceptions in Python. We cannot go through them all, but you find them listed at https://docs.python.org/3/library/exceptions.html (https://docs.python.org/3/library/exceptions.html).

Often several things can potentially go wrong, so that it makes sense to catch several exceptions:

In [ ]:
```
number1 = read_integer("Enter number 1: ")
number2 = read_integer("Enter number 2: ")
try:
    print(number1 * number2)
    print(number1 / number2)
except (FloatingPointError, OverflowError, ZeroDivisionError):
    print("Something went wrong with the calculation.")
```

Or in a more specific variant, distinguishing between division by zero and all other kinds of errors:

In [ ]:
```
number1 = read_integer("Enter number 1: ")
number2 = read_integer("Enter number 2: ")
try:
    print(number1 * number2)
    print(number1 / number2)
except ZeroDivisionError:
    print("Division by 0!")
except:
    print("Something went wrong with the calculation.")
```

As you can maybe guess from the previous example, and except clause with no specific error defined will catch all (remaining) errors that happen in the try clause. In such a case, it is often useful to assign a name to the exception that is caught, so that the error-handling code can check its type or get the underlying error message, to deal with the exception accordingly. For example:

In [ ]:
```
number1 = read_integer("Enter number 1: ")
number2 = read_integer("Enter number 2: ")
try:
    print(number1 * number2)
    print(number1 / number2)
except Exception as err:
    print("Error handling for:", err)
```

Finally, note that with the `raise` statement it is also possible to let your own code throw one of the predefined or also self-defined exceptions:

In [ ]:
```
temperature = read_integer("Enter temperature: ")
try:
    if 0 < temperature < 100:
        print("Water is liquid.")
    else:
        raise Exception("incompatible temperature", temperature)
except Exception as err:
    print(err)
```

In practice it needs a bit of experience to decide how and where to implement error-handling behavior in a software. In the scope of the projects that you are working on in this course, it would not be feasible to surround each individual statement by try-and-except clauses. As a practical rule, error-handling should be implemented at places where things can easily go wrong, such as reading input from the user (even users with a lot of goodwill make typos), handling files (working with file systems is always prone to unexpected behavior) or accessing online resources and services (communication with them can be affected by network problems etc.). Generally, the less control the programmer (or their code) has over what happens, the more error-handling is a good idea.

Exercises

Please use Quarterfall to submit and check your answers.

1. Interview Anonymization

Imagine you are a journalist, and you have written a text about an interview with somebody. Because the person wants to remain unrecognized, you have to replace their name through a fictive one everywhere in the text before it gets published. Write a Python program that reads the file containing the interview text, replaces all occurrences of the original name by a new one (the `str.replace()` function can be used here), and saves the changed text in the file. You can use the text file "interview-with-a-syrian-refugee.txt" or create an own one.

2. Longest Word

Reuse your code from exercise 5.5 (Text Analysis) to create a function that finds the longest word in a text. Apply it to the text file that you used for exercise 1 above. The output should be something like:

```
The longest word in the text is "responsibility".
```

3. Randomized Story-Telling

One of the simple pen-and-paper games I remember from my childhood days goes as follows: A paper sheet is divided into four columns for the questions “Who?”, “Does what?”, “How?” and “Where?”. The first player would write down a person in the first column, then fold it away, the second would fill in a verb, fold it away, etc. After the fourth column has been filled, the complete sentence is read out. It could then be something like “My brother is showering excessively at the gas station.”

Write a program that creates a user-defined number of such random sentences. The file `“inputs.csv”` contains a list of possible answers to all of the four questions. Take the values from there. Feel free to add further words to the CSV file to create more variation. The output of the program should be something like:

```
How many sentences do you want to create? 3
My granny is dancing massively at the fair.
The butcher is travelling aggressively in bed.
My grandpa is reading nicely in the bathroom.
```

4. Population and Universities per Province

Write a Python program that reads in the CSV file `"dutch_municipalities.csv"` that we already used in the lecture. Sum up the population and universities for each province and write the result into a new CSV file `“dutch_provinces.csv”`, in alphabetical order of the province names. Its content should look like:

```
province,population,murders
Drenthe,488892,0
Flevoland,400179,5
Friesland,580537,2
[...]
Utrecht,1254034,6
Zeeland,380619,3
Zuid-Holland,3579503,22
```

5. Error Handling

Add adequate "try and except" error handling to your code for exercises 1.-4. Include it in all code that you write from now on, at least when dealing with user inputs, file reading/writing operations, and accessing resources or services on the web.

Extras for the Weekend

Exercise 3 was hopefully a bit of fun, but of course we generated a very simple kind of prose text there. The website https://eh.bard.edu/generating-algorithmic-poetry/ (https://eh.bard.edu/generating-algorithmic-poetry/) describes how to use Python to automatically generate poems in the style of Shakespeare or Dickinson. Have a look if you find that interesting!

In [ ]: