# Day 1, Part 3: Pandas and Data I/O

## Introduction to Python

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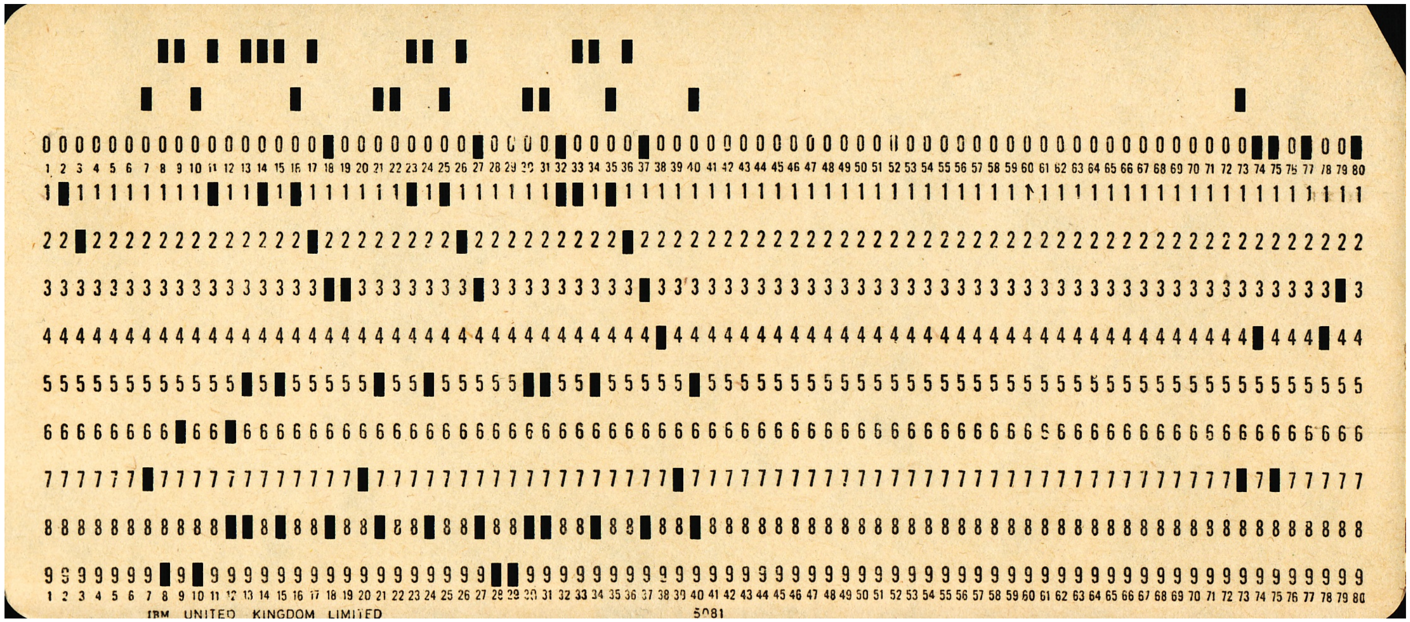
RECSM Summer School 2023

# Rectangular data

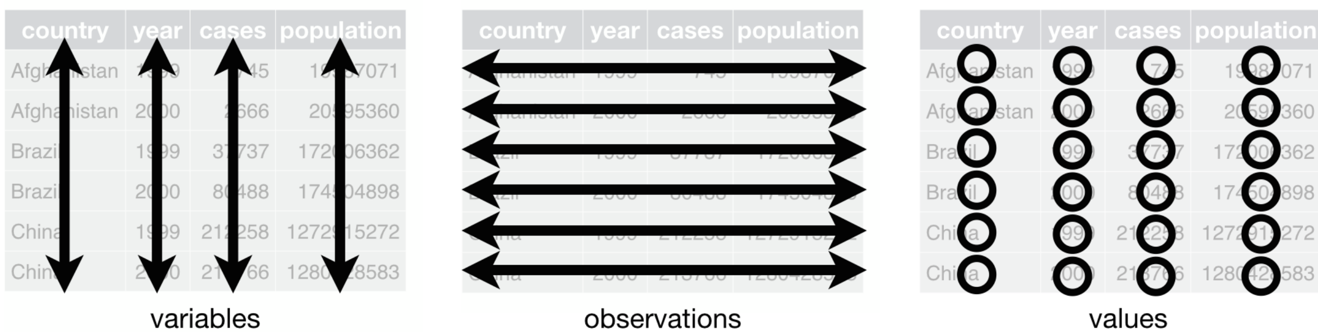



History of rectangular data goes back to punchcards with origins in US census data processing.

Source: Wikipedia

# Tidy data

- Tidy data is a specific subset of rectangular data, where:
    - Each variable is in a column
    - Each observation is in a row
    - Each value is in a cell




Source: [R for Data Science]

# Data in Python

- Python can hold and manipulate > 1 dataset at the same time
- Python stores objects in memory
- The limit on the size of data is determined by your computer memory
- Most functionality for dealing with data is provided by external libraries

# Numerical analysis in Python

- As opposed to other programming languages (Julia, R, MatLab), Python provides very bare bones functionality for numeric analysis.
- E.g. no built-in matrix/array object type, limited mathematical and statistical functions

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In [1]:
```
# Representing 3x3 matrix with list
mat = [[1, 2, 3],
       [4, 5, 6],
       [7, 8, 9]]
```

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```

In [2]:
```
# Subsetting 2nd row, 3rd element
mat[1][2]
```

Out[2]:
```
6
```

# Numerical analysis in Python

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       [7, 8, 9]]
```

In [2]:

```python
# Subsetting 2nd row, 3rd element
mat[1][2]
```

Out[2]:

```
6
```

In [3]:

```python
# Naturally, this representation
# breaks down rather quickly
mat * 2
```

Out[3]:

```
[[1, 2, 3], [4, 5, 6], [7, 8, 9], [1, 2, 3], [4, 5, 6], [7, 8,
9]]
```

# NumPy - numerical analysis in Python

- NumPy (**Num**eric **Py**thon) package provides the basis of numerical computing in Python:
    - multidimensional array
    - mathematical functions for arrays
    - array data I/O
    - linear algebra, RNG, FFT, ...

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    - multidimensional array
    - mathematical functions for arrays
    - array data I/O
    - linear algebra, RNG, FFT, ...

In [4]:

```
# Using 'as' allows to avoid typing full name
# each time the module is referred to
import numpy as np
```

# NumPy array

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- It is the backbone of data frames, operating behind the scenes

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In [5]:
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arr = np.array([[1, 2, 3],
                [4, 5, 6],
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```

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                [4, 5, 6],
                [7, 8, 9]])
```

In [6]:
```
arr[1][2]
```

Out[6]:
```
6
```

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In [5]:
```
arr = np.array([[1, 2, 3],
                [4, 5, 6],
                [7, 8, 9]])
```

In [6]:
```
arr[1][2]
```

Out[6]:
```
6
```

In [7]:
```
arr * 2
```

Out[7]:
```
array([[ 2,  4,  6],
       [ 8, 10, 12],
       [14, 16, 18]])
```

# Working with arrays

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In [8]:
```
# Object type
type(arr)
```

Out[8]:
```
numpy.ndarray
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# Array dimensionality
arr.ndim
```

Out[9]:
```
2
```

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Out[9]:

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2
```

In [10]:

```
# Array size
arr.shape
```

Out[10]:

```
(3, 3)
```

# Working with arrays

In [8]:
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Out[9]:
```
2
```

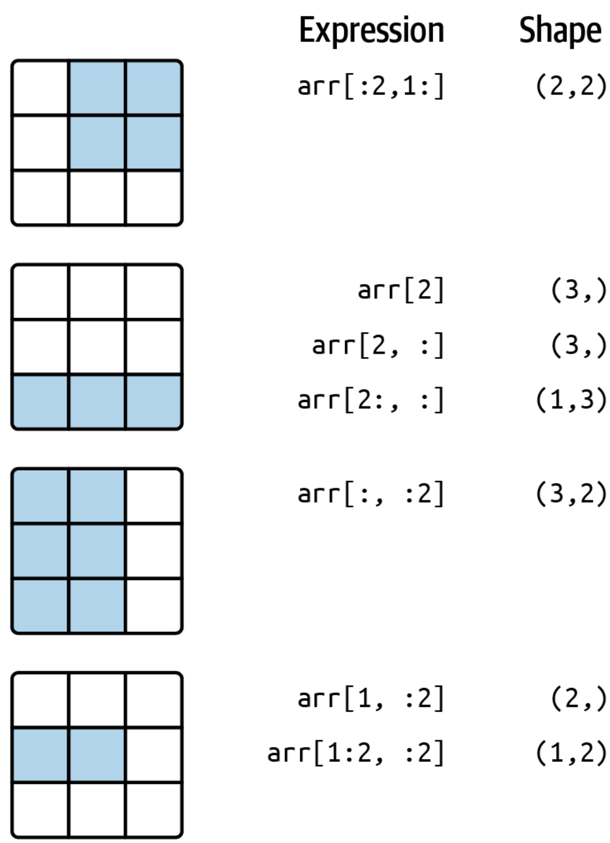
In [10]:
```
# Array size
arr.shape
```

Out[10]:
```
(3, 3)
```

In [11]:
```
# Calculating summary statistics on array
# axis indicates the dimension
# compare to R's `apply(arr, 1, mean)`
# note that every list within a list
# is treated as a column (not row)
arr.mean(axis = 0)
```

Out[11]:
```
array([4., 5., 6.])
```

# Array indexing and slicing




Source: Python for Data Analysis

# Pandas

- Standard Python library does not have data type for tabular data
- However, `pandas` library has become the de facto standard for data manipulation
- pandas is built upon (and often used in conjuction with) other computational libraries
- E.g. `numpy` (array data type), `scipy` (linear algebra) and `scikit-learn` (machine learning)

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import pandas as pd
```

# Series

- *Series* is a one-dimensional array-like object

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In [13]:
```
sr1 = pd.Series([150.0, 120.0, 3000.0])
sr1
```

Out[13]:
```
0     150.0
1     120.0
2    3000.0
dtype: float64
```

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In [14]:
```
sr1[0] # Slicing is simiar to standard Python objects
```

Out[14]:
```
150.0
```

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In [14]:
```
sr1[0] # Slicing is simiar to standard Python objects
```

Out[14]:
```
150.0
```

In [15]:
```
sr1[sr1 > 200]
```

Out[15]:
```
2    3000.0
dtype: float64
```

# Indexing in Series

- Another way to think about Series is as a ordered dictionary

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In [16]:
```
d = {'apple': 150.0, 'banana': 120.0, 'watermelon': 3000.0}
```

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- Another way to think about Series is as a ordered dictionary

In [16]:
```
d = {'apple': 150.0, 'banana': 120.0, 'watermelon': 3000.0}
```

In [17]:
```
sr2 = pd.Series(d)
sr2
```

Out[17]:
```
apple          150.0
banana         120.0
watermelon    3000.0
dtype: float64
```

# Indexing in Series

- Another way to think about Series is as a ordered dictionary

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d = {'apple': 150.0, 'banana': 120.0, 'watermelon': 3000.0}
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In [17]:
```
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```

Out[17]:
```
apple          150.0
banana         120.0
watermelon    3000.0
dtype: float64
```

In [18]:
```
sr2[0] # Recall that this slicing would be impossible for standard dict
```

Out[18]:
```
150.0
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apple          150.0
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```

In [18]:
```
sr2[0] # Recall that this slicing would be impossible for standard dict
```

Out[18]:
```
150.0
```

In [19]:
```
sr2.index
```

Out[19]:
```
Index(['apple', 'banana', 'watermelon'], dtype='object')
```

# DataFrame - the workhorse of data analysis

- *DataFrame* is a rectangular table of data

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In [20]:
```
data = {'fruit': ['apple', 'banana', 'watermelon'], # DataFrame can be
        'weight': [150.0, 120.0, 3000.0],           # a dict of equal-l
        'berry': [False, True, True]}
df = pd.DataFrame(data)
df
```

Out[20]:

| | fruit | weight | berry |
|---|---|---|---|
| **0** | apple | 150.0 | False |
| **1** | banana | 120.0 | True |
| **2** | watermelon | 3000.0 | True |

# Indexing in DataFrame

- DataFrame has both row and column indices
- `DataFrame.loc()` provides method for *label* location
- `DataFrame.iloc()` provides method for *index* location

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- DataFrame has both row and column indices
- `DataFrame.loc()` provides method for *label* location
- `DataFrame.iloc()` provides method for *index* location

In [21]:
```
df.iloc[0] # First row
```

Out[21]:
```
fruit      apple
weight     150.0
berry      False
Name: 0, dtype: object
```

# Indexing in DataFrame

- DataFrame has both row and column indices
- `DataFrame.loc()` provides method for *label* location
- `DataFrame.iloc()` provides method for *index* location

In [21]:
```
df.iloc[0] # First row
```

Out[21]:
```
fruit      apple
weight     150.0
berry      False
Name: 0, dtype: object
```

In [22]:
```
df.iloc[:,0] # First column
```

Out[22]:
```
0         apple
1        banana
2    watermelon
Name: fruit, dtype: object
```

# Summary of indexing in DataFrame

| Expression | Selection Operation |
|---|---|
| `df[val]` | Column or sequence of columns +convenience (e.g. slice) |
| `df.loc[lab_i]` | Row or subset of rows by label |
| `df.loc[:, lab_j]` | Column or subset of columns by label |
| `df.loc[lab_i, lab_j]` | Both rows and columns by label |
| `df.iloc[i]` | Row or subset of rows by integer position |
| `df.iloc[:, j]` | Column or subset of columns by integer position |
| `df.iloc[i, j]` | Both rows and columns by integer position |
| `df.at[lab_i, lab_j]` | Single scalar value by row and column label |
| `df.iat[i, j]` | Single scalar value by row and column integer position |

Extra: Pandas documentation on indexing

# Subsetting in DataFrame

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In [23]:

```
df.iloc[:2] # Select the first two rows (with convenience shortcut for
```

Out[23]:

| | fruit | weight | berry |
|---|---|---|---|
| **0** | apple | 150.0 | False |
| **1** | banana | 120.0 | True |

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In [24]:

```
df[:2]  # Shortcut
```

Out[24]:

| | fruit | weight | berry |
|---|---|---|---|
| **0** | apple | 150.0 | False |
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In [24]:
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```

Out[24]:

| | fruit | weight | berry |
|---|---|---|---|
| 0 | apple | 150.0 | False |
| 1 | banana | 120.0 | True |

In [25]:
```
df.loc[:, ['fruit', 'berry']] # Select the columns 'fruit' and 'berry'
```

Out[25]:

| | fruit | berry |
|---|---|---|
| 0 | apple | False |
| 1 | banana | True |
| 2 | watermelon | True |

# Subsetting in DataFrame

In [23]:
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df.iloc[:2] # Select the first two rows (with convenience shortcut for
```

Out[23]:

| | fruit | weight | berry |
|---|---|---|---|
| **0** | apple | 150.0 | False |
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In [24]:
```
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Out[24]:

| | fruit | weight | berry |
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| **0** | apple | 150.0 | False |
| **1** | banana | 120.0 | True |

In [25]:
```
df.loc[:, ['fruit', 'berry']] # Select the columns 'fruit' and 'berry'
```

Out[25]:

| | fruit | berry |
|---|---|---|
| **0** | apple | False |
| **1** | banana | True |
| **2** | watermelon | True |

In [26]:
```
df[['fruit', 'berry']] # Shortcut
```

Out[26]:

| | fruit | berry |
|---|---|---|
| **0** | apple | False |
| **1** | banana | True |
| **2** | watermelon | True |

# Columns in DataFrame

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In [27]:
```
df.columns # Retrieve the names of all columns
```

Out[27]:
```
Index(['fruit', 'weight', 'berry'], dtype='object')
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In [28]:
```
df.columns[0] # This Index object is subsettable
```

Out[28]:
```
'fruit'
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df.columns # Retrieve the names of all columns
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Out[27]:
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```
df.columns[0] # This Index object is subsettable
```

Out[28]:
```
'fruit'
```

In [29]:
```
df.columns.str.startswith('fr') # As column names are strings, we can a
```

Out[29]:
```
array([ True, False, False])
```

# Columns in DataFrame

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df.columns # Retrieve the names of all columns
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Out[27]:
```
Index(['fruit', 'weight', 'berry'], dtype='object')
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Out[28]:
```
'fruit'
```

In [29]:
```
df.columns.str.startswith('fr') # As column names are strings, we can a
```

Out[29]:
```
array([ True, False, False])
```

In [30]:
```
df.iloc[:,df.columns.str.startswith('fr')] # This is helpful with more
```

Out[30]:

| | fruit |
|---|---|
| **0** | apple |
| **1** | banana |
| **2** | watermelon |

# Filtering in DataFrame

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In [31]:
```
df[df.loc[:,'berry'] == False] # Select rows where fruits are not berri
```

Out[31]:

| | fruit | weight | berry |
|---|---|---|---|
| **0** | apple | 150.0 | False |

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In [32]:
```
df[df['berry'] == False] # The same can be achieved with more concise s
```

Out[32]:

| | fruit | weight | berry |
|---|---|---|---|
| **0** | apple | 150.0 | False |

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In [31]:
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In [32]:
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df[df['berry'] == False] # The same can be achieved with more concise s
```

Out[32]:

| | fruit | weight | berry |
|---|---|---|---|
| **0** | apple | 150.0 | False |

In [33]:
```
weight200 = df[df['weight'] > 200] # Create new dataset with rows where
weight200
```

Out[33]:

| | fruit | weight | berry |
|---|---|---|---|
| **2** | watermelon | 3000.0 | True |

# Variable transformation

- Lambda functions can be used to transform data with `map()` method

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In [34]:
```
df['fruit'].map(lambda x: x.upper())
```

Out[34]:
```
0         APPLE
1        BANANA
2    WATERMELON
Name: fruit, dtype: object
```

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Out[34]:
```
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1        BANANA
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Name: fruit, dtype: object
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In [35]:
```
transform = lambda x: x.capitalize()
```

# Variable transformation

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df['fruit'].map(lambda x: x.upper())
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```
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1        BANANA
2    WATERMELON
Name: fruit, dtype: object
```

In [35]:
```
transform = lambda x: x.capitalize()
```

In [36]:
```
transformed = df['fruit'].map(transform)
```

# Variable transformation

- Lambda functions can be used to transform data with `map()` method

```
In [34]: df['fruit'].map(lambda x: x.upper())
```

```
Out[34]: 0         APPLE
         1        BANANA
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```

```
In [35]: transform = lambda x: x.capitalize()
```

```
In [36]: transformed = df['fruit'].map(transform)
```

```
In [37]: transformed
```

```
Out[37]: 0         Apple
         1        Banana
         2    Watermelon
         Name: fruit, dtype: object
```

# File object

- File object in Python provides the main interface to external files
- In contrast to other core types, file objects are created not with a literal,
- But with a function, `open()`:

```
<variable_name> = open(<filepath>, <mode>)
```

# Data input and output

- Modes of file objects allow to:
    - ( `r` )ead a file (default)
    - ( `w` )rite an object to a file
    - e( `x` )clusively create, failing if a file exists
    - ( `a` )ppend to a file
- You can `r+` mode if you need to read and write to file

# Data output example

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In [38]:
```
f = open('../temp/test.txt', 'w') # Create a new file object in write m
```

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In [38]:
```
f = open('../temp/test.txt', 'w') # Create a new file object in write m
```

In [39]:
```
f.write('This is a test file.') # Write a string of characters to it
```

Out[39]:
```
20
```

# Data output example

In [38]:
```
f = open('../temp/test.txt', 'w') # Create a new file object in write m
```

In [39]:
```
f.write('This is a test file.') # Write a string of characters to it
```

Out[39]:
```
20
```

In [40]:
```
f.close() # Flush output buffers to disk and close the connection
```

# Data input example

- To avoid keeping track of open file connections, `with` statement can be used

Extra: Python documentation on with statement

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- To avoid keeping track of open file connections, `with` statement can be used

Extra: Python documentation on with statement

In [41]:

```
with open('../temp/test.txt', 'r') as f: # Note that we use 'r' mode fo
    text = f.read()
```

# Data input example

- To avoid keeping track of open file connections, `with` statement can be used

Extra: Python documentation on with statement

In [41]:
```
with open('../temp/test.txt', 'r') as f: # Note that we use 'r' mode fo
    text = f.read()
```

In [42]:
```
text
```

Out[42]:
```
'This is a test file.'
```

# Reading and writing data in `pandas`

- `pandas` provides high-level methods that takes care of file connections
- These methods all follow the same `read_<format>` and `to_<format>` name patterns
- CSV (comma-separated value) files are the standard of interoperability

```
<variable_name> = pd.read_<format>(<filepath>)
```

```
<variable_name>.to_<format>(<filepath>)
```

# Reading data in `pandas` example

- We will use the data from Kaggle 2021 Machine Learning and Data Science Survey
- For more information you can read the executive summary
- Or explore the winning Python Jupyter Notebooks

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- We will use the data from Kaggle 2021 Machine Learning and Data Science Survey
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- Or explore the winning Python Jupyter Notebooks

In [43]:
```
# We specify that we want to combine first two rows as a header
kaggle2021 = pd.read_csv('../data/kaggle_survey_2021_responses.csv', he
```

```
/tmp/ipykernel_279893/1791299071.py:2: DtypeWarning: Columns (19
5,201) have mixed types. Specify dtype option on import or set l
ow_memory=False.
  kaggle2021 = pd.read_csv('../data/kaggle_survey_2021_response
s.csv', header = [0,1])
```

# Visual data inspection

# Visual data inspection

In [44]:
```
kaggle2021.head() # Returns the top n (n=5 default) rows
```

Out[44]:

| | Time from Start to Finish (seconds) | Q1 | Q2 | Q3 | Q4 | Q5 | |
|---|---|---|---|---|---|---|---|
| | Duration (in seconds) | What is your age (# years)? | What is your gender? - Selected Choice | In which country do you currently reside? | What is the highest level of formal education that you have attained or plan to attain within the next 2 years? | Select the title most similar to your current role (or most recent title if retired): - Selected Choice | For how year you writin program |
| **0** | 910 | 50-54 | Man | India | Bachelor’s | Other | 5-1( |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | | | | degree | | |
| **1** | 784 | 50-54 | Man | Indonesia | Master’s degree | Program/Project Manager | 20+ |
| **2** | 924 | 22-24 | Man | Pakistan | Master’s degree | Software Engineer | 1-3 |
| **3** | 575 | 45-49 | Man | Mexico | Doctoral degree | Research Scientist | 20+ |
| **4** | 781 | 45-49 | Man | India | Doctoral degree | Other | < 1 |

5 rows × 369 columns

# Visual data inspection continued

# Visual data inspection continued

In [45]:
```
kaggle2021.tail() # Returns the bottom n (n=5 default) rows
```

Out[45]:

| | Time from Start to Finish (seconds) | Q1 | Q2 | Q3 | Q4 | Q5 | |
|---|---|---|---|---|---|---|---|
| | Duration (in seconds) | What is your age (# years)? | What is your gender? - Selected Choice | In which country do you currently reside? | What is the highest level of formal education that you have attained or plan to attain within the next 2 years? | Select the title most similar to your current role (or most recent title if retired): - Selected Choice | For how r years you l writing ( ar programm |
| **25968** | 1756 | 30-34 | Man | Egypt | Bachelor’s | Data | 1-3 y |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | | | | degree | Analyst | |
| **25969** | 253 | 22-24 | Man | China | Master's degree | Student | 1-3 y |
| **25970** | 494 | 50-54 | Man | Sweden | Doctoral degree | Research Scientist | I have r written |
| **25971** | 277 | 45-49 | Man | United States of America | Master's degree | Data Scientist | 5-10 y |
| **25972** | 255 | 18-21 | Man | India | Bachelor's degree | Business Analyst | I have r written |

5 rows × 369 columns

# Reading in other (non-`.csv`) data files

- Pandas can read in file other than `.csv` (comma-separated value)
- Common cases include STATA `.dta`, SPSS `.sav` and SAS `.sas`
- Use `pd.read_stata(path)`, `pd.read_spss(path)` and `pd.read_sas(path)`
- Check here for more examples

# Writing data out in `pandas`

- Note that when writing data out we start with the object name storing the dataset
- I.e. `df.to_csv(path)` as opposed to `df = pd.read_csv(path)`
- Pandas can also write out into other data formats
- E.g. `df.to_excel(path)`, `df.to_stata(path)`

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- Note that when writing data out we start with the object name storing the dataset
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In [46]:
```
kaggle2021.to_csv('../temp/kaggle2021.csv')
```

# Additional pandas materials

Books:

- McKinney, Wes. 2022. *Python for Data Analysis: Data Wrangling with pandas, NumPy, and Jupyter*. 3rd ed. Sebastopol, CA: O'Reilly Media

  **From the original author of the library!**

Online:

- Pandas Getting Started Tutorials
- Pandas Documentation (intermediate and advanced)

# Tomorrow

- Exploratory data analysis
- Data visualization