Python - Data Analysis Essentials

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It's nice to have you here today

About You

- Your major / occupation
- Your programming experience
- Your goals for this course

About me

- Bachelor in CS
- Master in Neural Systems and Computation
- Work at ces ag which make the speed traps in Zürich ;)
- I mainly program with Python and C++
- I used to build model rockets :)

Learning Objectives for This Course

- The main goal is to get a better picture on the essential Python libraries (NumPy and pandas) for preparing, cleaning, transforming and aggregating your data for analysis
- You get IPython notebooks that contain the slides' content (one notebook for the NumPy part and one for pandas part), so you can experiment with all the material at home
- Learn how to visualize different datasets using Seaborn

Timeline

Part 1: Introduction, Course objectives, Python basics, Setting up Pycharm, Jupyter, Getting started with numpy theory(array creation, slicing, utility functions) and exercises(puzzles)

Part 2: Continue Numpy theory(concatenating, splitting, universal functions, aggregations, boolean masking, reading and writing data) and exercises(puzzles)

Part 3: Pandas theory(series and dataframe creation, basic dataframe and series methods, data selection, universal functions) and exercises(puzzles)

Part 4: Continue Pandas theory(Reading and writing data, aggregations, filters, groupby) and exercises(finish puzzles, 3 case studies), visualizations using Seaborn, small visualization example of covid

Please Feel Free to Always Ask Questions

- Questions are a natural part of the learning process and you're always allowed to ask them
- **Asking questions is an integral part of this course**
- Even if you have a feeling that you're question might "not be good enough," or you don't understand a concept "even if it should be easy to do so," please ask the question nonetheless
  - For one, it gives me the possibility to try and come up with better / clearer explanations
- In case you have any questions after the course, please feel free to contact me via email at bubanja.kaju@gmail.com

Learning By Doing (and Making Errors)

- **Programming is best learned by doing**
- Don't be afraid to try stuff out in Python and make errors
  - Errors are a vital part of the learning process and help you understand situations much better

- If you should get stuck on an error during a programming exercise, please always feel free to call for my help or the help of fellow students
- Also, don't be afraid to use pen and paper to solve the exercises or when you are trying to understand a specific concept
  - For one, it helps a lot to step away from the computer from time to time
  - It also helps a lot to write down the immediate steps when trying to understand a complicated concept

Feedback

- I'm very thankful for all the feedback I get (be it positive or negative), since I want you to feel comfortable and I love to improve my courses and my teaching skills
  - Course is moving too fast?
  - I'm not speaking clearly enough?
  - Please feel free to inform me about anything whenever you feel like it ☺

Checkpoint System

- Just sticking to a rigid schedule makes no sense
- That is why we will use a checkpoint system
- After some theory you will be presented with a checkpoint
- When a majority of the people solved the checkpoint(Please raise your hand in Teams to indicate this) we will continue with the course/look at the solutions together
- If you finished the checkpoint feel free to look at the next slides/exercises or just do something else private. But please have Teams open somewhere, so that you notice when we continue again.

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Course Outline for Today

1. Organization
2. An Introduction to IPython and Jupyter
3. Setting up Pycharm
4. Important Basics of the Python Programming Language
5. Storing and Operating on Data with NumPy

An Introduction to IPython and Jupyter

Python, the Programming Language

- Goal: we want be able to give the computer instructions to do specific things, e.g. reading a file, computing the sum between two numbers, and so on

- Python is a *formal language* which we humans can read, type, and use to formulate instructions for the computer
  - "Formal language" means that there exists a specific set of rules we have to follow when writing code with it

- The Python *interpreter* then translates our code to *machine code*, which can be directly executed by our computer
  - The interpreter is the interface between a human and a computer

Python Code Is Often Quite Readable

– Idea for a program:

IDEE

1. Number 1 has value 2
2. Number 2 has value 10
3. Number 3 has value 18.3
4. Compute Number 1 * Number 2 + Number 3
5. Print the result

– Corresponding Python code:

CODE

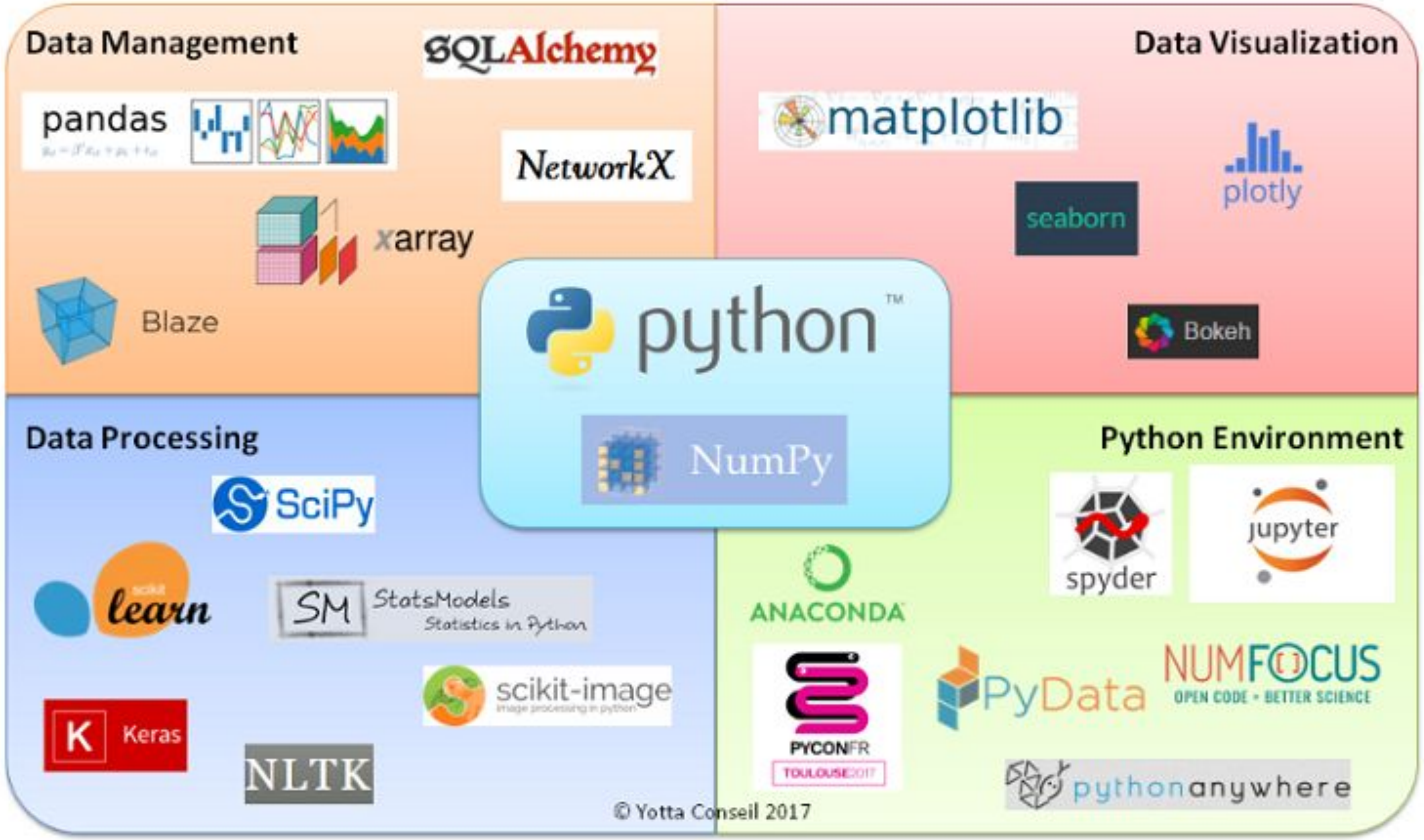
```
number_1 = 2
number_2 = 10
number_3 = 18.3
result = number_1  * number_2 + number_3
print(result)
```

Python Code Is Portable

– Python code can be interpreted and run / executed using any current operating system, e.g. Windows, OS X, and Linux

The Python Ecosystem Is Huge

- Python already comes with a lot of useful tools and libraries
- Nonetheless, there also exist thousands of third-party modules and libraries which can be used to accomplish various tasks, NumPy and Pandas being just two of them
  - https://awesome-python.com/



IPython: Interactive Python

- Interactive computing in Python
- Offers introspection: We can inspect values and errors, time our functions, and more
- Offers tab completion and history
- Offers a browser-based notebook interface with support for code, text, mathematical expressions and more (it's called *Jupyter* nowadays)
    - A notebook runs Python / IPython statements

IPython: Interactive Python

– We are going to run all the code in this course with IPython
– IPython supports Python 3.*

Help and Documentation in IPython

- How do I call a function? What arguments and options does It have?
- What does the source code of this Python value / object look like?
- What is in this package I imported?
- What variables / attributes or methods does this value / object have?

Help and Documentation in IPython

– We can access documentation with `?`

IPYTHON

```
In [1]: print?
Docstring:
print(value, ..., sep=' ', end='\n', file=sys.stdout, flush=False)

Prints the values to a stream, or to sys.stdout by default.
```

– This notation works for about anything, including object methods and functions (as we will see later)

Help and Documentation in IPython

– We can access source code with `??`

IPYTHON

```
In [1]: def myfun(lst):
   ...:     for e in lst:
   ...:         print(e)
   ...:

In [2]: myfun??
Signature: myfun(lst)
Docstring: <no docstring>
Source:
def myfun(lst):
    for e in lst:
        print(e)
File:      ~/<ipython-input-9-42be41fecbd8>
Type:      function
```

Help on Methods in IPython

– We can check the documentation for specific methods with **?** in IPython

IPYTHON

```
In [1]: lst = [1,2,3]
In [2]: lst.index?
Docstring:
L.index(value, [start, [stop]]) -> integer -- return first index of value.
Raises ValueError if the value is not present.
```

– IPython also provides tab-completion, meaning it will show all available methods for a specific value

- Lets check out the tab-completion in IPython **{Live Coding}**

Shell Commands in IPython

- The shell is a way to interact textually with your computer
  - Operating systems existed long before graphical user interfaces as we know and use today
- We can create folders, files, copy and delete them, and more with a shell
  - Basically, we can submit a lot of commands via shell to the computer

Shell Commands in IPython

- Common shell commands
  - `pwd`: Print the working directory (where we currently are in the file system)
  - `ls`: List working directory contents
  - `cd`: Change directory
  - `mkdir`: Make new directory
- In IPython we can use these shell commands by prefixing them with `!`

Running External Code with %run

– We can use a text editor to write code and use IPython to run it with `%run`

print.py

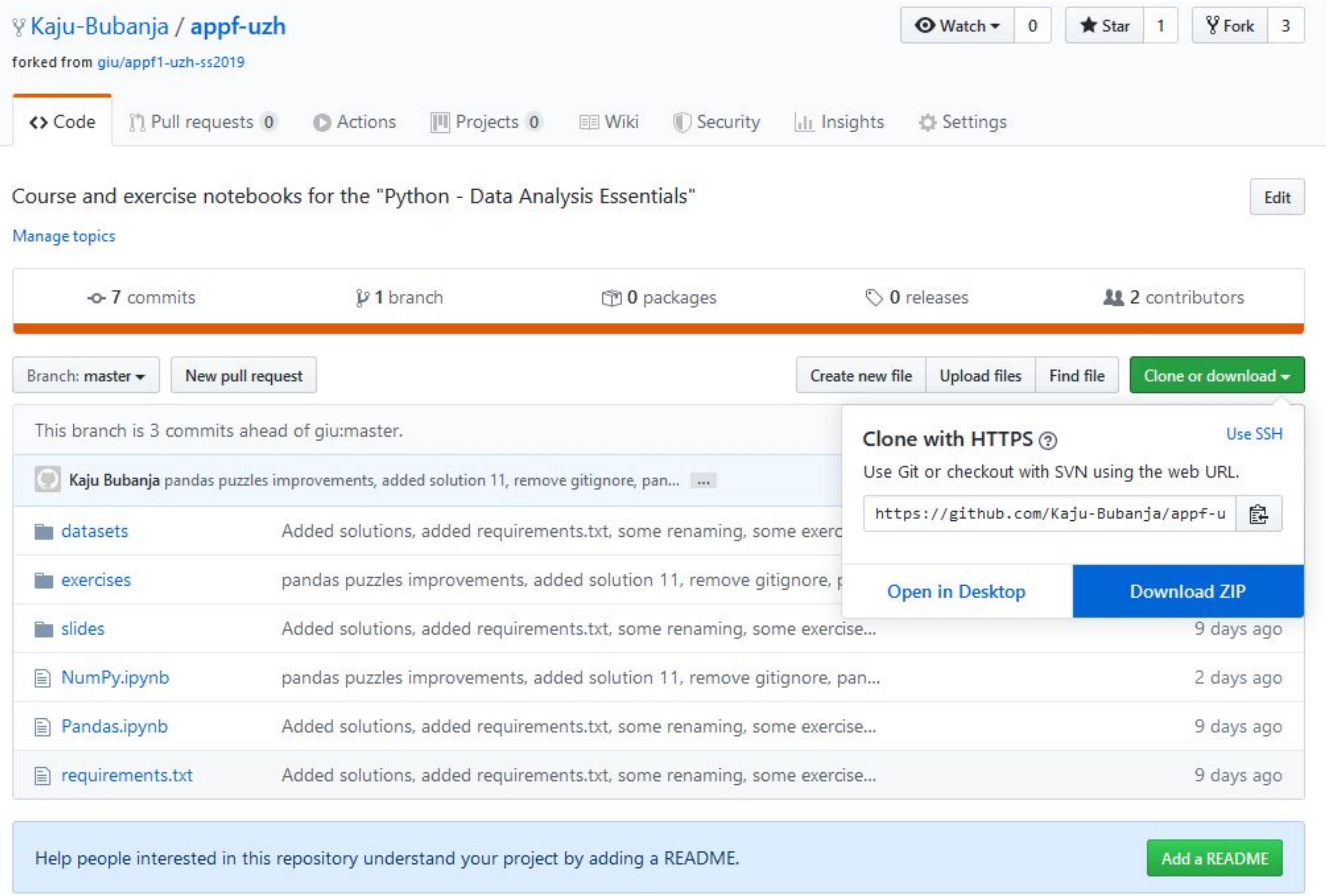
```python
def fun(lst):
  for e in lst:
    print(e)

fun([1,2,3,4])
```

IPYTHON

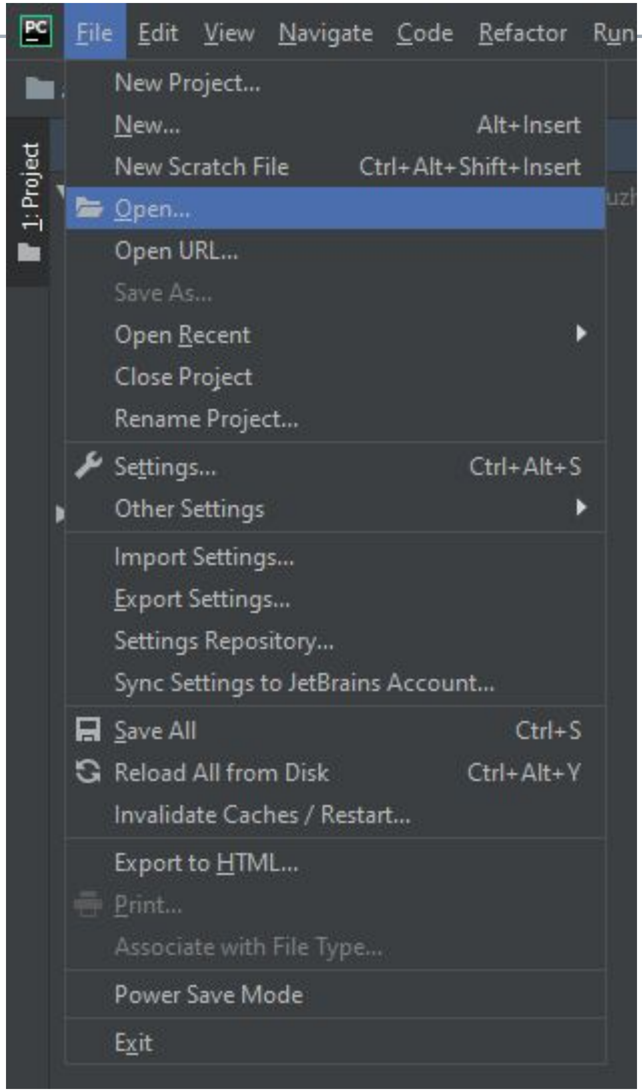
```
In [1]: %run print.py
1
2
3
4
```

Setting up Pycharm

Download the repository



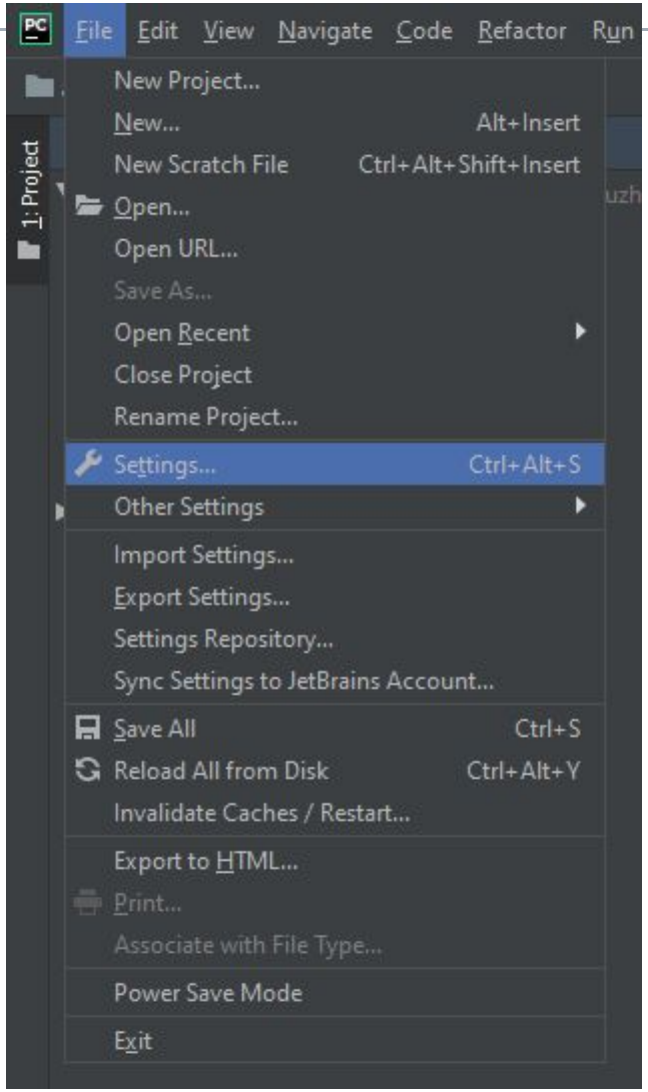
Open unzipped folder



Settings

Windows: File->Settings

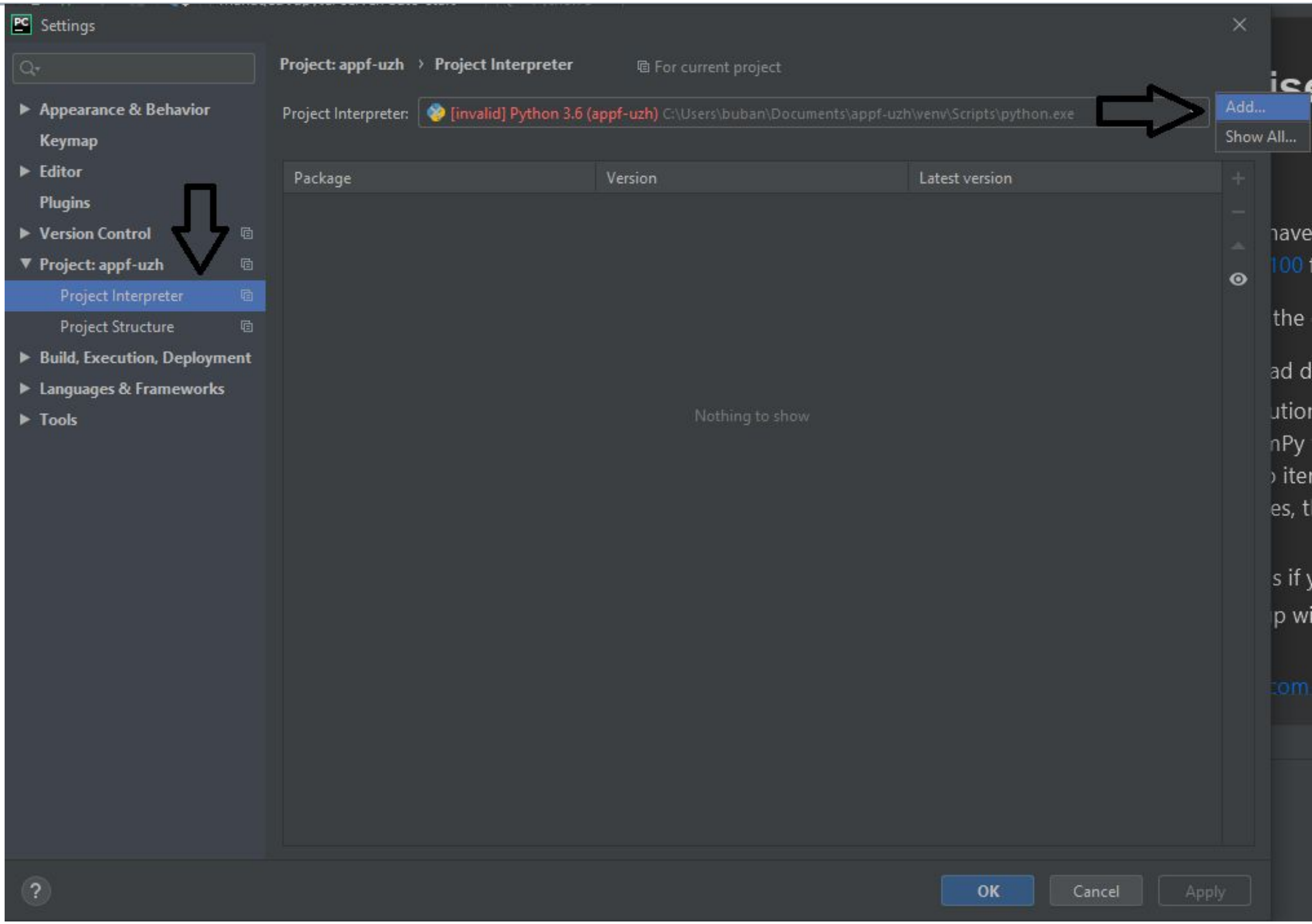
Mac: Pycharm->Preferences



Project interpreter

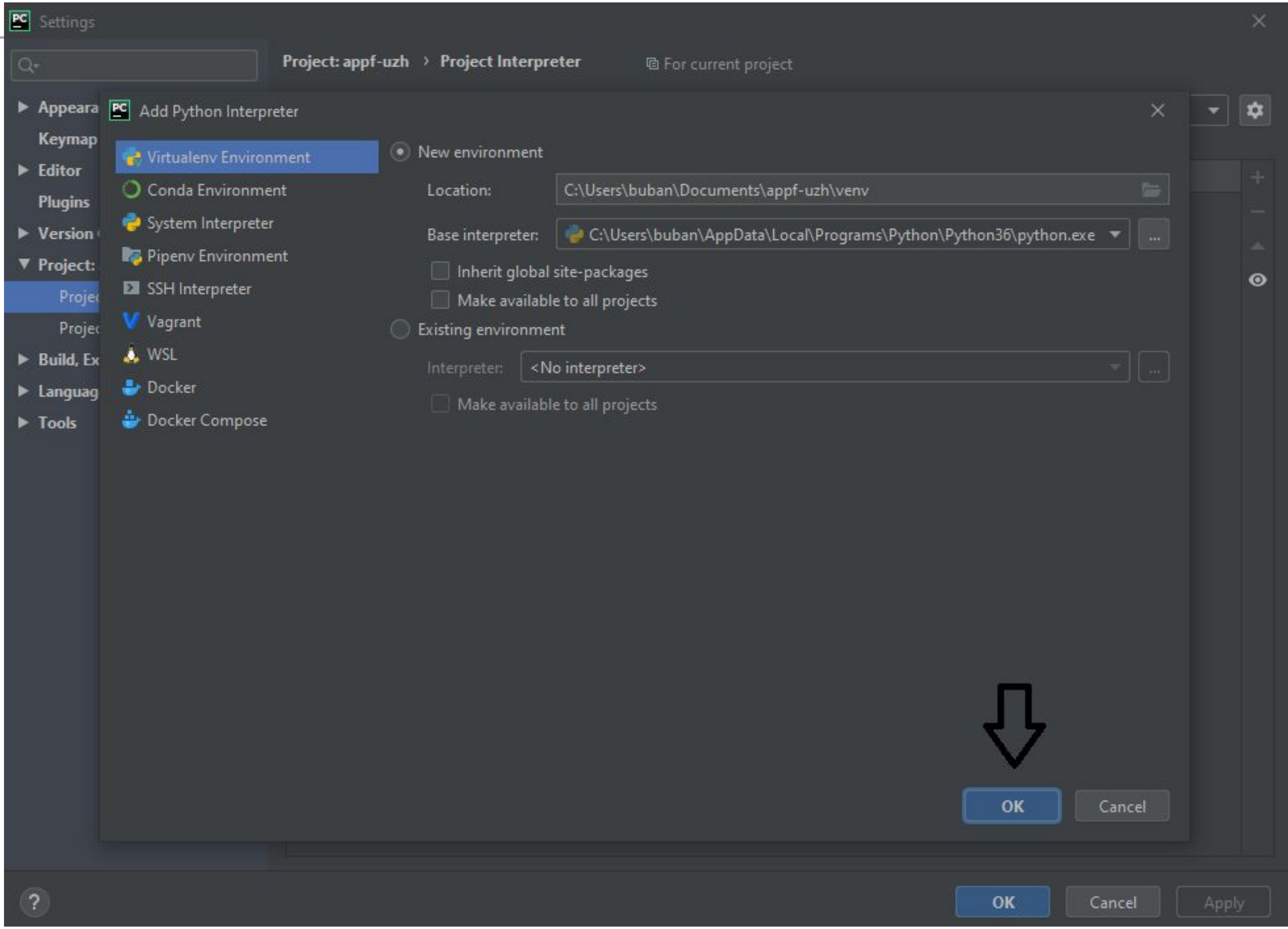
Version 3.6 works for sure,

But other version should also work

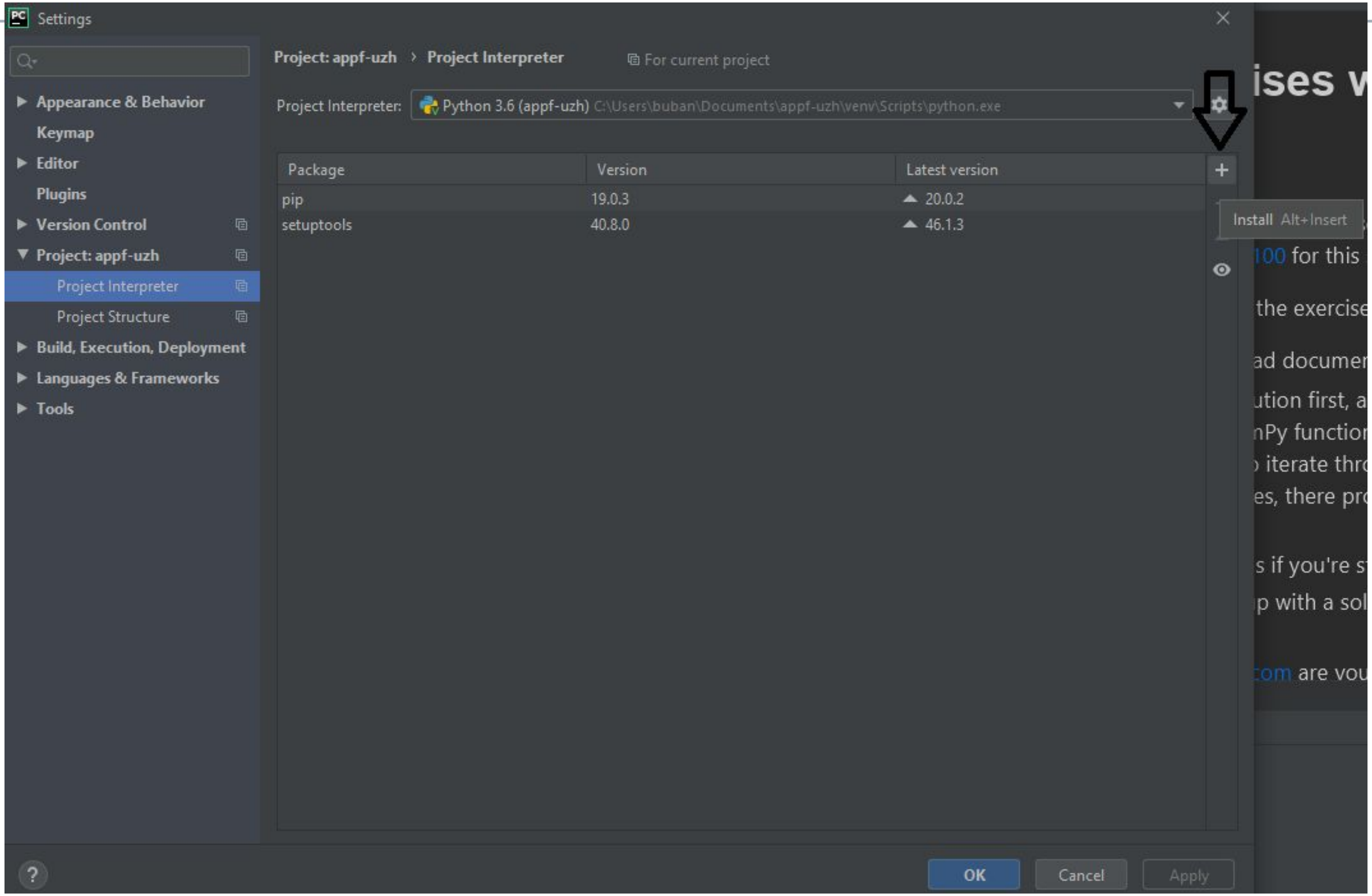


Create environment

Select your python interpreter



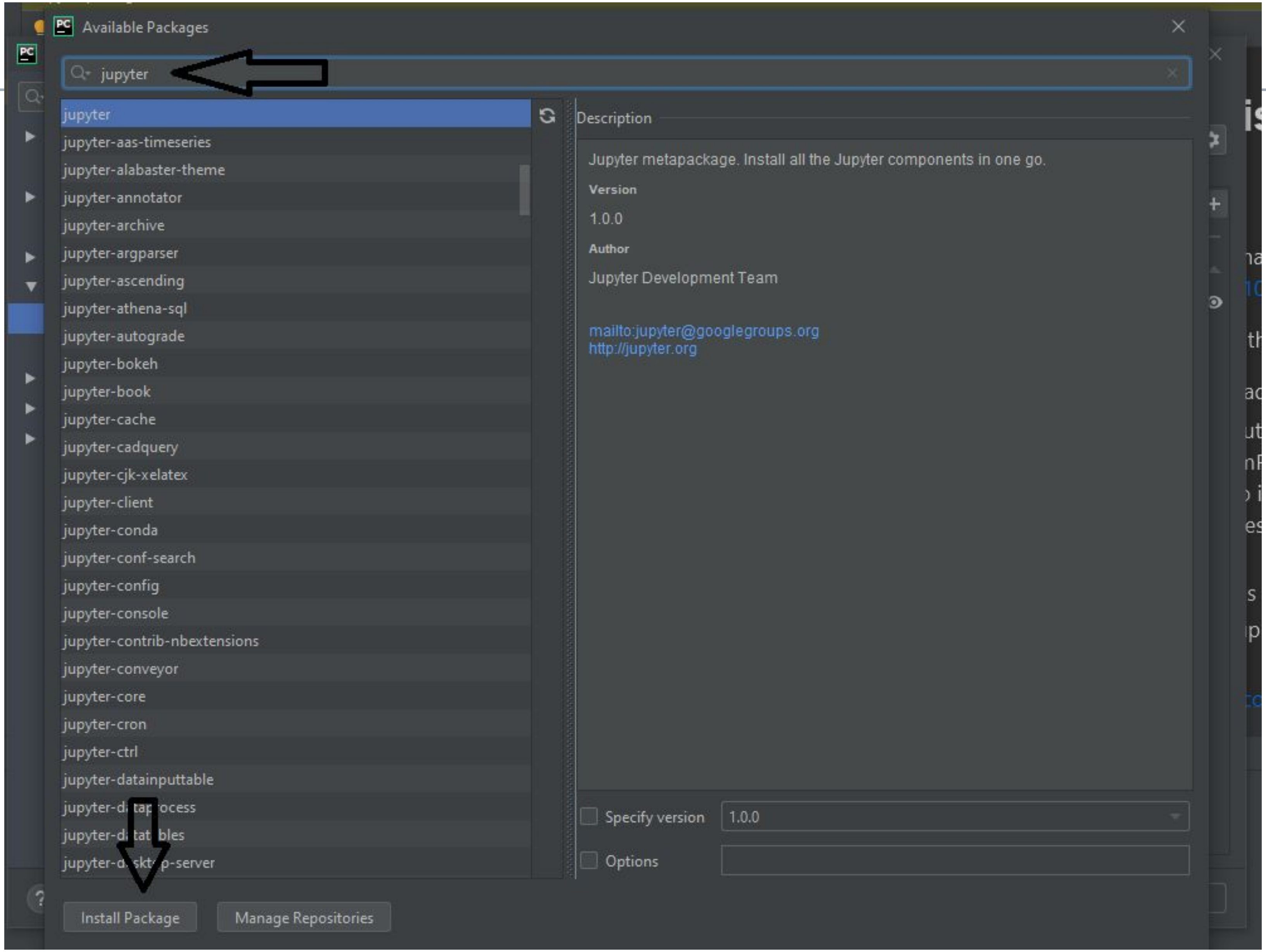
Add packages



Install packages

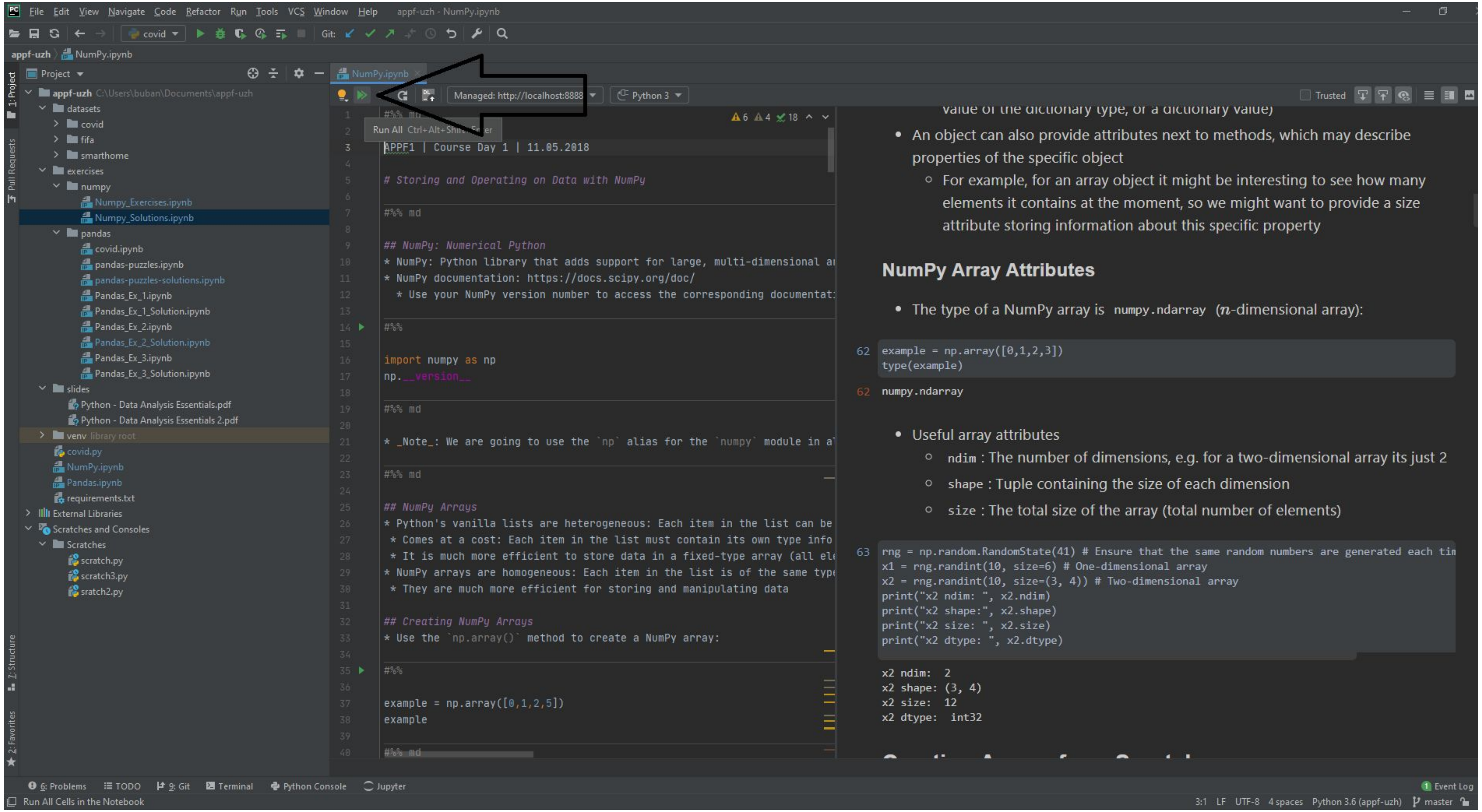
Install following packages:

- jupyter
- numpy
- pandas
- xlrd



Checkpoint 1

- Pycharm is set up
- You have the course package downloaded
- The virtual environment setup with the needed packages
- You can run all the cells in the Numpy Notebook



Important Basics of the Python Programming Language

(…at least for this course)

Learning Objectives

- You know
  - what values, variables and statements are
  - about datatypes like int, float, str, list, tuple, dict
  - how to use lists and dictionaries and their differences

Values and Data Types

- *Values* are fundamental things like the number `2` or `1.234`, or the string `Hello`
- A *data type* is a category for values, and a value always belongs to a single data type
  - Integer data type: `-1, -100, 0, 12, 34`
  - Float data type: `-1.324, 0.14123, 10.1, 100.0`
  - String data type: `‘Hello’, ‘Word’, ‘Spaces are included’`
  - List data type: `[1,2,3,4]`
  - Tuple data type: `("A", "B", "C")`
  - Dictionary data type: `{"k1": 1, "k2": 132}`

Storing Values in Variables

- A *variable* is like a box where you can store a single value
- Assigning a value to a variable is done with an *assignment statement*:

CODE
```
myNumber = 123
```

  - `myNumber` is the variable name, and `123` is the value stored within this variable
- Since a variable stores a value, a variable also belongs to a data type, which we can query with the `type` function:

CODE
```
type(myNumber)
```

Statements, Expressions, and Operators

- A *statement* is an instruction that the Python interpreter can execute
- An *expression* is a combination of values, variables, operators, and calls to functions
  - Expressions need to be *evaluated*
  - The evaluation of an expression always produces a single value
- An operator is a special token that represents a computation like an addition, multiplication, and division
  - Values that the operator works on are called *operands*

The List Data Type

1. Initialization of a list: (*Note*: A list can contain elements of different data types)

CODE
```
lst = ["one", "two", 3, 4, 5]
```

2. Accessing elements: (*Note*: First element in the list is at the index `0`)

CODE
```
el1 = lst[0]
eln = lst[-1]
```

3. Changing values: (*Note*: A Python list is a *mutable* data structure)

CODE
```
lst[0] = "abc"
lst[4] = 423.132
```

The List Data Type

4. Accessing slices: (*Note*: The slice goes up to, but will not include, the value at the second index)

CODE

```
sl1 = lst[2:3]
sl2 = lst[1:]
```

5. Removing elements: (*Note*: Removing an element changes the underlying list structure)

CODE

```
del lst[2]
```

6. Iterating over a list's elements:

CODE

```
for el in lst:
  print(el)
```

7. Check if a value exists in a list:

CODE

```
val_exists = "one" in lst
```

The Tuple Data Type

1. Initialization of a tuple: (*Note*: A tuple can contain elements of different data types)

CODE
```
tpl = (1, 2, 3, "four", 5)
```

2. Accessing elements: (*Note*: First element in the tuple is at the index `0`)

CODE
```
t1 = tpl[0]
eln = tpl[-1]
```

3. We cannot change elements of a tuple, since it's an *immutable* data structure.
   What we can do instead is copy its elements into a mutable data structure:

CODE
```
lst = list(tpl)
lst[0] = 34
lst[4] = "abc"
```

The Tuple Data Type

4. Accessing slices: (*Note*: The slice goes up to, but will not include, the value at the second index)

CODE
```
sl1 = tpl[2:3]
sl2 = tpl[1:]
```

5. We cannot remove elements from a tuple, since it's an *immutable* data structure.
6. Iterating over a tuple's elements:

CODE
```
for el in tpl:
  print(el)
```

7. Check if a value exists in a tuple:

CODE
```
val_exists = 1 in tpl
```

The Dictionary Data Type

1. Initialization of a dictionary: (*Note*: all keys must be of the same data type; values can be *anything*)

CODE
```
dct = {"k1": "v1", "k2": "v2"}
```

2. Accessing values: (*Note*: We access a value by its corresponding key)

CODE
```
v1 = dct["k1"]
v2 = dct["k2"]
```

3. Changing values: (*Note*: A Python dictionary is a *mutable* data structure)

CODE
```
dct["k1"] = "v1new"
```

The Dictionary Data Type

4. Accessing slices is not possible, since the data type of the key is not always integer
5. Removing elements:

CODE
```
del dct["k1"]
```

6. Iterating over a list's key-value pairs:

CODE
```
for (k,v) in dct.items():
  print(k, ": ", v, sep="")
```

7. Check if an entry exists for a specific *key*:

CODE
```
entry_exists = "k1" in dct
```

Dictionaries vs. Lists

- Lists are ordered
  - First item in a list is located at the index 0
  - We can slice lists
  - Trying to access an index that is out of range results in an error message
- Dictionaries are unordered
  - There is no "first" item, since we can only access items using keys
  - We cannot slice dictionaries
  - Trying to access a key that does not exist results in an error message

Dictionaries vs. Lists

– Lists are ordered; the order of the elements matters:

CODE

```
l1 = [1,2,3,4]
l2 = [2,1,3,4]

print(l1 == l2)
```

INTERP.

OUTPUT

```
False
```

– Dictionaries are unordered; the order of the elements does not matter:

CODE

```
d1 = {"a":13, "b":14}
d2 = {"b":14, "a":13}

print(d1 == d2)
```

INTERP.

OUTPUT

```
True
```

Functions and Methods

Learning Objectives

- You know
  - how to write a function
  - how to call a method
  - how to use tab-completion to help you with methods
  - that different data types may provide different methods

Functions

CODE

```
def hello():
  print('Hello World')

hello()
```

- A *function* is defined by using the `def` keyword
- The code in the block that follows the def statement is called the *function body*
  - This code is only executed when the function gets called, not when it's first defined
- The `hello()` after the function definition is a *function call*
  - A function call is just a functions name followed by parentheses, possibly with some arguments in between the parentheses

Functions with Arguments

- We can define functions that take in *arguments*, which are typed between the parentheses
  - For example, the `print()` function takes an argument, namely the string we want to have printed on the screen

CODE

```
def hello(name):
  print('Hello, ' + name)

hello('Giuseppe')
```

Functions with Return Values

- Functions can evaluate to a value, which is called the *return value* of the function
  - For example, if we pass the argument `'Hello'` to the `len()` function, it will evaluate to the integer value `5`, which is the length of the string we passed
- We can specify what a function should return by using the return statement followed by the value we want to return:

CODE

```
def sqr(x):
  return x*x

sqr_of_two = sqr(2)
print(str(sqr_of_two))
```

- *Note*: Functions without return value always evaluate to `None`

Methods

- A *method* is the same thing as a function, except it is called on an object
  - Function call: `my_fun(a,b,c)`
  - Method call: `my_list.index("k")`
    - We called the `index` method on the value of `my_list`, which is of type `list`
- Each data type (`str`, `list`, `dict`, etc.) has its own set of methods
  - The `list` data type has several useful methods for finding, adding, removing, and manipulating values in a list
- A method always acts on the value it has been called on
  - `list1.index("k")` □ `index("k")` acts on the value of `list1`
  - `list2.index("e")` □ `index("e")` acts on the value of `list2`

Finding a value in a List: The `index()` Method

– The list data type provides an `index()` method, to which we can pass a value. If that value exists in the list, the index of the value is returned, else Python produces a `ValueError` error

CODE

```python
n = ["one", "two", "three", "four"]

ind1 = n.index("two")
print("Index of 'two': " + str(ind1))

ind2 = n.index("five")
```

INTERPRETER

OUTPUT

```
Index of 'two': 1

Traceback (most recent call last):
  File "<stdin>", line 1, in <module>
ValueError: 'five' is not in list
```

Adding Values to a List: The `append()` and `insert()` Methods

- We can add new values to a list by calling the `append()` and `insert()` methods
- The `append()` method call adds the argument to the end of the list
- The `insert()` method call requires two arguments: the first argument is the index for the new value, and the second argument is the new value to be inserted

In-Place Changes

- Both the `append()` and `insert()` methods will change the list on which they're called on
- We call these kind of changes *in-place changes*

Adding Values to a List: The `append()` and `insert()` Methods

– Lets append a new value at the end of a list:

CODE

```
alpha = ["a", "b", "c"]

alpha.append("d")

print(alpha)
```

Adding Values to a List: The `append()` and `insert()` Methods

– Lets add a new element at index `1` of the list:

CODE

```
alpha = ["a", "b", "c"]

alpha.insert(1, "w")

print(alpha)
```

– *Note*: After adding the new element, all previously existing elements at index 1, 2, and above are moved to the right. This can be a costly operation if we insert elements in very large lists like this

Adding Values to a List: The `append()` and `insert()` Methods

– Note: It's not `alpha = alpha.append("d")` or `alpha = alpha.insert(1, "w")`
  – Both functions do not return the modified list `alpha` (both calls evaluate to `None`)
  – The list `alpha` is rather modified *in place* (a list is a *mutable* data type)

Different Methods for Different Data Types

- Methods belong to a single data type
  - `append()` and `insert()` are list methods and can be called only on lists, not on other values such as strings or integers

CODE

```
num = 1023

# What might happen here?
num.insert(1, "w")
```

Removing Values from Lists (In-Place): The `remove()` Method

- We can pass a value we want to be removed to the `remove()` method of a specific list:

CODE

```
alpha = ["a", "b", "c"]

alpha.remove("a")

print(alpha)
```

- *Note:* If you know the index of the value we want to remove, we can still use the `del` operator for the removal; if you know the value, just use the `remove()` method

Sorting the Values in a List (In-Place): The `sort()` Method

– We can sort lists of strings or numbers by calling the `sort()` method on a specific list:

CODE

```
alpha = ["c", "a", "b"]
alpha.sort()
print(alpha)

num = [3.14, 10, 1, -23, 0.4]
num.sort()
print(num)
```

INTERPRETER

OUTPUT

```
['a', 'b', 'c']
[-23, 0.4, 1, 3.14, 10]
```

Learning Objectives

- You know
  - how to write a function
  - how to call a method
  - how to use tab-completion to help you with methods
  - that different data types may provide different methods

Universität
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IT Training and Continuing Education

Storing and Operating on Data with NumPy

Python Data Science Handbook

- This part of the course is heavily based on Jake Vanderplas' "Python Data Science Handbook"
- You can find the official online version here: https://jakevdp.github.io/PythonDataScienceHandbook/
- Repository with lots of Jupyter notebooks on the subject:
  https://github.com/jakevdp/PythonDataScienceHandbook/tree/master/notebooks

Learning Objectives

- You know:
  - How to create one- and two-dimensional NumPy arrays
  - How to access these arrays
  - How to use the aggregation functions
  - How to work with Boolean arrays
  - How to read and write files with NumPy

Autosave Your Notebook(Only needed if not working in Pycharm)

- Activate autosave for your current notebook by using `%autosave`:
- Only needed if not working in Pycharm. Pycharm saves everything automatically per default.
- Do not enable if working in Pycharm, since the Jupyter autosave function and the Pycharm autosave function will interfere with each other.

```
In  [1]: %autosave 30

         Autosaving every 30 seconds
```

JUPYTER NB

NumPy: Numerical Python

- NumPy: Python library that adds support for large, multi-dimensional arrays and matrices, along with a large collection of high-level mathematical functions to operate on these arrays
- NumPy documentation: https://docs.scipy.org/doc/
  - Use your NumPy version number to access the corresponding documentation

JUPYTER NB

```
In  [1]: import numpy as np
         np.__version__

Out [1]: '1.15.4'
```

- *Note*: We are going to use the `np` alias for the `numpy` module in all the code samples on the following slides

NumPy Arrays

- Python's vanilla lists are heterogeneous: Each item in the list can be of a different data type
  - Comes at a cost: Each item in the list must contain its own type info and other information
  - It is much more efficient to store data in a fixed-type array (all elements are of the same type)
- NumPy arrays are homogeneous: Each item in the list is of the same type
  - They are much more efficient for storing and manipulating data

- NOTE: Colloquially the terms array, vector, matrix have all the same meaning namely they denote a np.array([1,2,3]). There are differences for the terms depending on the field(linear algebra, computer science...), but for this course they all mean the same thing

NumPy Arrays

– Use the `np.array()` method to create a NumPy array:

JUPYTER NB

```
In [1]:  example = np.array([0,1,2,3])
     example

Out [1]: array([1, 2, 3, 4])
```

Multidimensional NumPy Arrays

- *One-dimensional* array: we only need *one coordinate* to address a single item, namely an integer index
- *Multidimensional* array: we now need *multiple indices* to address a single item
  - For an n-dimensional array we need up to n indices to address a single item
  - We're going to mainly work with two-dimensional arrays in this course, i.e. $n = 2$

JUPYTER NB

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

Out [1]:

1	2	3
4	5	6
7	8	9

(Visual aid only, not real output)

Two-Dimensional NumPy Arrays

– Two-dimensional NumPy arrays have *rows* (horizontally) and *columns* (vertically)

	Column 0	Column 1	Column 2
Row 0	1	2	3
Row 1	4	5	6
Row 2	7	8	9

Array Indexing

- Array indexing for one-dimensional arrays works as usual: `onedim[0]`
- Accessing items in a two-dimensional array requires you to specify two indices: `twodim[0,1]`
  - First index is the row number (here `0`), second index is the column number (here `1`)

	Col. 0	Col. 1	Col. 2
Row 0	1	**2**	3
Row 1	4	5	6
Row 2	7	8	9

twodim

Objects in Python

- Almost everything in Python is an *object*, with its properties and methods
  - For example, a dictionary is an object that provides an `items()` method, which can only be called on a dictionary object (which is the same as a *value of the dictionary type,* or *a dictionary value*)
- An object can also provide *attributes* next to methods, which may describe properties of the specific object
  - For example, for an array object it might be interesting to see how many elements it contains at the moment, so we might want to provide a *size attribute* storing information about this specific property

NumPy Array Attributes

– The type of a NumPy array is **numpy.ndarray** (*n-dimensional array*)

JUPYTER NB

```
In [1]:  example = np.array([0,1,2,3])
         type(example)

Out [1]: np.ndarray
```

– Useful array attributes
  – **ndim**: The number of dimensions, e.g. for a two-dimensional array its just 2
  – **shape**: Tuple containing the size of each dimension
  – **size**: The total size of the array (total number of elements)

Creating Arrays from Scratch

- NumPy provides a wide range of functions for the creation of arrays:
  https://docs.scipy.org/doc/numpy-1.15.4/reference/routines.array-creation.html#routines-array-creation
  - For example: `np.arange`, `np.zeros`, `np.ones`, `np.linspace`, etc.
- NumPy also provides functions to create arrays filled with random data:
  https://docs.scipy.org/doc/numpy-1.15.1/reference/routines.random.html
  - For example: `np.random.random`, `np.random.randint`, etc.

NumPy Data Types

– Use the keyword **dtype** to specify the data type of the array elements:

JUPYTER NB

```
In [1]:  floats = np.array([0,1,2,3], dtype="float32")
         floats

Out [1]: array([0., 1., 2., 3.], dtype=float32)
```

– Overview of available data types: https://docs.scipy.org/doc/numpy-1.15.4/user/basics.types.html

Array Slicing: One-Dimensional Subarrays

– Let `x` be a one-dimensional NumPy array
– The NumPy slicing syntax follows that of the standard Python list:

`x[start:stop:step]`

Slice	Description
`x[:5]`	First five elements
`x[5:]`	All elements after index 5
`x[4:7]`	Middle subarray
`x[::2]`	Every other element
`x[1::2]`	Every other element, starting at index 1
`x[::-1]`	All elements, reversed
`x[5::-1]`	Reverses all elements up until index 5 (included)

Array Slicing: Multidimensional Subarrays

– Let `Y` be a two-dimensional NumPy array. Multiple slices are now separated by commas:

```
Y[start:stop:step, start:stop:step]
```

Slice	Description
`Y[:2, :3]`	First two rows and first three columns
`Y[:3, ::2]`	First three rows and every other column
`Y[::-1, ::-1]`	Reverse rows and columns
`Y[:, 0]`	First column
`Y[2, :]`	Third row
`Y[2]`	Same as `Y[2, :]`, so third row again

Array Views and Copies

- With Python lists, the slices will be *copies*: If we modify the subarray, only the copy gets changed
- With NumPy arrays, the slices will be *direct views*: If we modify the subarray, the original array gets changed, too
  - Very useful: When working with large datasets, we don't need to copy any data (costly operation)
- Creating copies: we can use the `copy()` method of a slice to create a copy of the specific subarray
  - *Note*: The type of a slice is again `numpy.ndarray`

Array Slicing: Multidimensional Subarrays

– Since we're working with direct views, we can update the data using array slicing:

Y =

100	24	0
41	30	12
10	5	53

`Y[:,1] = [1,2,3]`

(Result)

100	1	0
41	2	12
10	3	53

Reshaping

– We can use the `reshape()` method on an NumPy array to actually change its shape:

JUPYTER NB

```
In  [1]: grid = np.arange(1, 10).reshape((3, 3))
         print(grid)

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

– For this to work, the size of the initial array must match the size of the reshaped array

– *Important*: `reshape()` will return a new view if possible; otherwise, it will be a copy

  – *Remember*: In case of a view, if you change an entry of the reshaped array, it will also change the initial array

Array Concatenation and Splitting

- *Concatenation*, or joining of two or multiple arrays in NumPy can be accomplished through the functions `np.concatenate`, `np.vstack`, and `np.hstack`
  - Join multiple two-dimensional arrays: `np.concatenate([twodim1, twodim2,…], axis=0)`
    - A two-dimensional array has two axes: The first running vertically downwards across rows (axis 0), and the second running horizontally across columns (axis 1)
- The opposite of *concatenation* is splitting, which is provided by the functions `np.split`, `np.hsplit` (split horizontally), and `np.vsplit` (split vertically)
  - For each of these we can pass a list of indices giving the split points

Faster Operations Instead of Slow `for` Loops

- Looping over arrays to operate on each element can be a quite slow operation in Python

Lets check this out on a concrete example, which we will be timing using IPython's `%timeit` magic command **{Live Coding}**

- One of the reasons why the for loop approach is so slow is because of the type-checking and function dispatches that must be done at each iteration of the cycle
  - Python needs to examine the object's type and do a dynamic lookup of the correct function to use for that type

NumPy's Universal Functions

- NumPy provides very fast, vectorized operations which are implemented via *universal functions* (ufuncs), whose main purpose is to quickly execute repeated operations on values in NumPy arrays
  - A *vectorized operation* is performed on the array, which will then be applied to each element
- Instead of computing the reciprocal using a for loop, lets do it by using a universal function:

```
In  [1]: %timeit (1.0 / big_array)
```
JUPYTER NB

Lets time this new approach in our Jupyter notebook **{Live Coding}**

- We can use ufuncs to apply an operation between a scalar and an array, but we can also operate between two arrays

```
In  [1]: np.array([4,5,6]) / np.array([1,2,3])
```
JUPYTER NB

NumPy's Universal Functions

Operator	Equivalent ufunc	Description
`+`	`np.add`	Addition
`-`	`np.subtract`	Subtraction
`-`	`np.negative`	Unary negation (e.g., `-2`)
`*`	`np.multiply`	Multiplication
`/`	`np.divide`	Division
`//`	`np.floor_divide`	Floor division (e.g., `3 // 2 = 1`)
`**`	`np.power`	Exponentiation (e.g., `3**2 = 8`)
`%`	`np.mod`	Modulus/remainder (e.g., `9 % 4 = 1`)

Advanced Ufunc Features: Specifying Output and Aggregates

- ufuncs provide a few specialized features
- We can specify where to store a result (useful for large calculations)
  - If no `out` argument is provided, a newly-allocated array is returned (can be costly memory-wise)

JUPYTER NB

```
In  [1]: np.multiply(x,10, out=y)
```

- *Reduce*: Repeatedly apply a given operation to the elements of an array until only one single result remains
  - For example, `np.add.reduce(x)` applies addition to the elements until the one result remains, namely the sum of all elements
- *Accumulate*: Almost same as reduce, but also stores the intermediate results of the computation

Lets see how these advanced ufunc features work {Live Coding}

Aggregations

- If we want to compute summary statistics for the data in question, aggregates are very useful
  - Common summary statistics: mean, standard deviation, median, minimum, maximum, quantiles, etc.
- NumPy provides fast built-in aggregation function for working with arrays:

JUPYTER NB

```
In  [1]: %timeit np.max(x) # NumPy ufunc
         %timeit max(x)    # Python function
```

- Summing values in an array:

JUPYTER NB

```
In  [1]: %timeit np.sum(x) # NumPy ufunc
         %timeit sum(x)    # Python function
```

Lets check out other aggregation functions {Live Coding}

Some Other Aggregate Functions

Function Name	Description
`np.sum`	Compute sum of elements
`np.prod`	Compute product of elements
`np.mean`	Compute mean of elements
`np.std`	Compute standard deviation
`np.min`	Find minimum value
`np.max`	Find maximum value
`np.argmin`	Find index of minimum value
`np.argmax`	Find index of maximum value
`np.median`	Compute median of elements
`np.percentile`	

Multidimensional Aggregates

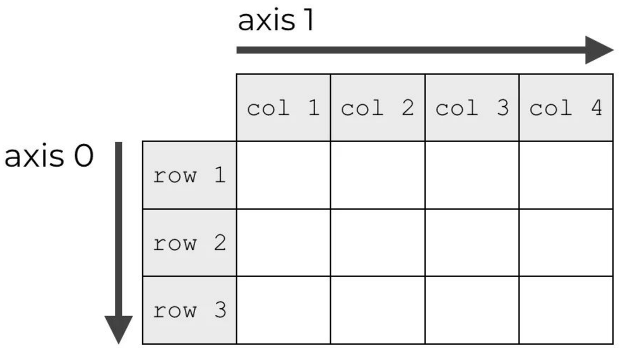
- By default, each NumPy aggregation function will return the aggregate over the entire array
- Aggregation functions take an additional argument specifying the axis along which the aggregate is computed
  - For example, we can find the minimum value within each column by specifying `axis=0`:

JUPYTER NB

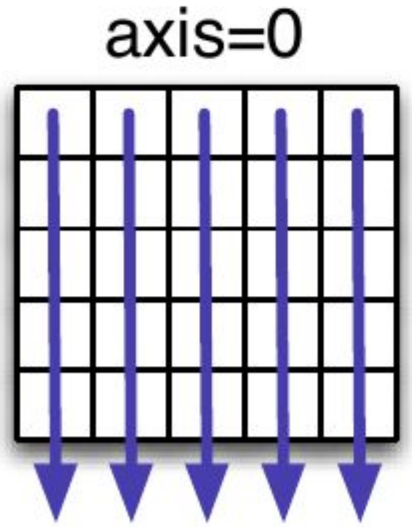
```
In  [1]: twodim.min(axis=0)
Out [1]: array([ … ]) # Array containing min. of each column
```

Lets check out why `axis=0` returns a result in regard to the columns and lets visualize these results by switching between the axes in a two-dim. array {Live Coding}

Bsp: a = array([[1, 2],
[3, 4]])

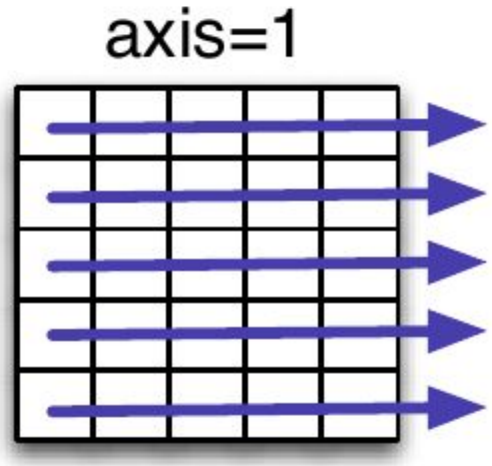


a.sum(axis=0)



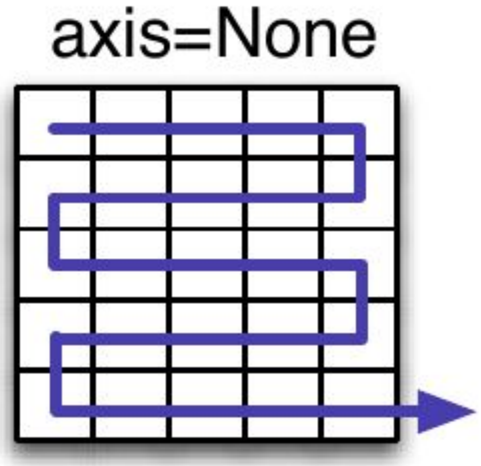
array([4, 6])

a.sum(axis=1)



array([3, 7])

a.sum()



10

Checkpoint 2

- *For the exercises there is a tip for each exercise. Check out the function documentation on: https://numpy.org/doc/ to find out more about it. This can often be useful and reading the manual of something is often the fastest way to learn about it.*
- *This being said don't be afraid to ask if you don't understand something.*
- You read and ran the cells in the Numpy notebook up until Multidimensional Aggregates
- You finished the Numpy exercises up to exercise 20(without 20)

The Boolean Data Type

- Boolean data type: `True`, `False` (only two possible values)
- *Comparison operators* compare two values and evaluate to a single Boolean value
  - The comparison operators are `==`, `!=`, `<`, `>`, `<=`, and `>=`
- *Boolean operators* are used to compare Boolean values
  - The Boolean operators are `or`, `and`, and `not`
- We can mix Boolean and comparison operators to create *conditions*

• Lets see the Boolean and comparison operators in action **{Live Coding}**

Comparison Operators as ufuncs

- NumPy also implements comparison operators as element-wise ufuncs
- The result of these comparison operators is always an array with a Boolean data type:

JUPYTER NB

```
In  [1]: np.array([1,2,3]) < 2
```

Operator	Equivalent ufunc
`==`	`np.equal`
`!=`	`np.not_equal`
`<`	`np.less`
`<=`	`np.less_equal`
`>`	`np.greater`
`>=`	`np.greater_equal`

Comparison Operators as ufuncs

– It is also possible to do an element-by-element comparison of two arrays:

JUPYTER NB

```
In  [1]: np.array([1,2,3]) < np.array([0,4,2])
```

{Live Coding}

These ufuncs will work on arrays of any size and shape.
Lets see an example on how a multidimensional example looks like

Working with Boolean Arrays: Counting Entries

– The `np.count_nonzero()` function will count the number of `True` entries in a Boolean array:

JUPYTER NB

```
In  [1]: nums = np.array([1,2,3,4,5])
         np.count_nonzero(nums < 4)

Out [1]: 3
```

– We can also use the `np.sum()` function to accomplish the same. In this case, True is interpreted as 1 and False as 0:

JUPYTER NB

```
In  [1]: np.sum(nums < 4)

Out [1]: 3
```

Lets checkout the `np.any()` and `np.all()` functions in relation to Boolean arrays **{Live Coding}**

Working with Boolean Arrays: Boolean Operators

- NumPy also implements bitwise logic operators as element-wise ufuncs
- We can use these bitwise logic operators to construct compound conditions (consisting of multiple conditions)

Operator	Equivalent ufunc
`&`	`np.bitwise_and`
`|`	`np.bitwise_or`
`^`	`np.bitwise_xor`
`~`	`np.bitwise_not`

These ufuncs will work on arrays of any size and shape. {Live Coding}
Lets see an example on how a multidimensional example looks like

Boolean Arrays as Masks

- In the previous slides we looked at aggregates computed directly on Boolean arrays
- Once we have a Boolean array from lets say a comparison, we can select the entries that meet the condition by using the Boolean array as a *mask*

`x`

3	1	5
10	32	100
-1	3	4

`x<5`

True	True	False
False	False	False
True	True	True

`x[x<5]`

3	1	5
10	32	100
-1	3	4

(Result)

```
array([3,1,-1,3,4])
```

Lets checkout more examples using this masking operation {Live Coding}

Checkpoint 3

- You read and ran the cells in the Numpy notebook up until Reading and Writing Data with Numpy
- You solved the Numpy exercises 20-60(including 60)

Reading and Writing Data with NumPy

- We can use the `np.savetxt()` function to save NumPy data to a file
- We can use the `np.loadtxt()` function to load data from a file
  - *Remember:* We can only store elements of a single type in a NumPy array
- Use the shell commands `!ls`, `!pwd`, and `!cd` to navigate the file system if necessary

Lets checkout how we can read and write files with NumPy **{Live Coding}**

Comma-Separated Values (CSV)

- CSV files are simplified spreadsheets stored as plaintext files
  - Excel for example allows to export spreadsheets as CSV files
- CSV files
  - Don't have types for their values – everything is a string
  - Don't have settings for font size or color
  - Can't specify cell width and heights
  - And more

Comma-Separated Values (CSV)

– Each line in a CSV file represents a row in the spreadsheet, and commas separate the cells in the row:

```
4/5/2015 13:34,Apples,73
4/5/2015 3:41,Cherries,85
4/6/2015 12:46,Pears,14
4/8/2015 8:59,Oranges,52
```

Source: Automate the Boring Stuff with Python

Reading CSV Data with NumPy

- Some CSV data contains a mix between numbers and strings, or might have missing values
- We can use the `np.genfromtxt()` function to load mixed data from such a file into a NumPy array

Lets import the FIFA 2019 CSV file using `numpy.genfromtxt()` **{Live Coding}**

Dataset source: https://www.kaggle.com/karangadiya/fifa19

Learning Objectives

- You know:
  - How to create one- and two-dimensional NumPy arrays
  - How to access these arrays
  - How to use the aggregation functions
  - How to work with Boolean arrays
  - How to read and write files with NumPy

Questions

– If you have any questions, information, or more about any topic of today's course, feel free to write me at bubanja.kaju@gmail.com