Introduction to Python for Data Science

Veerasak Kritsanapraphan

About myself?

- Graduated from San Francisco State University in Master of Science in Computer Information System, 1997
- PhD. at Chulalongkorn University, research focus on Data Science, Big Data, Mobile Computing and Internet of Thing (IOT)
- Senior Director, Arise by Infinitas (KTB)
- Instructor for Software Park in Data Science, Generative AI, Prompt Engineering

Introduce yourself?

- What is your name/position/role in your organization?
- Tell you a bit about yourself?
- What is your passion?
- What is your expectation for this class?

Slide and Solutions

- https://github.com/vkrit/python-for-data-science

Agenda

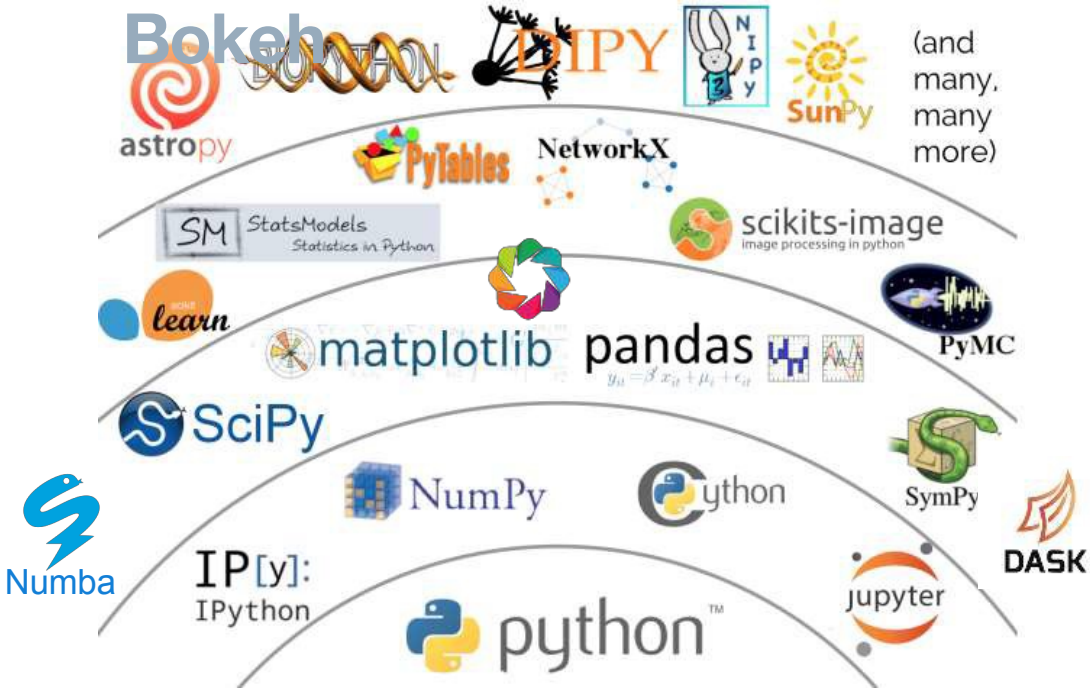
Agenda

- Python Eco-system
- Anaconda
- Python Scripting
- Jupyter Notebook
- Basic Python
- Data Structure
- String
- Iteration
- Conditional Construct
- Python Libraries
- Python Graphics

Agenda

- Exploratory Data Analysis using Panda
- Data Wrangling
- Statistics
- Inferential Statistics
- Hypothesis Testing
- Linear Regression

Python Ecosystem



Anaconda

2012 – Anaconda Open Source History

Company

ANACONDA
Powered by Continuum Analytics

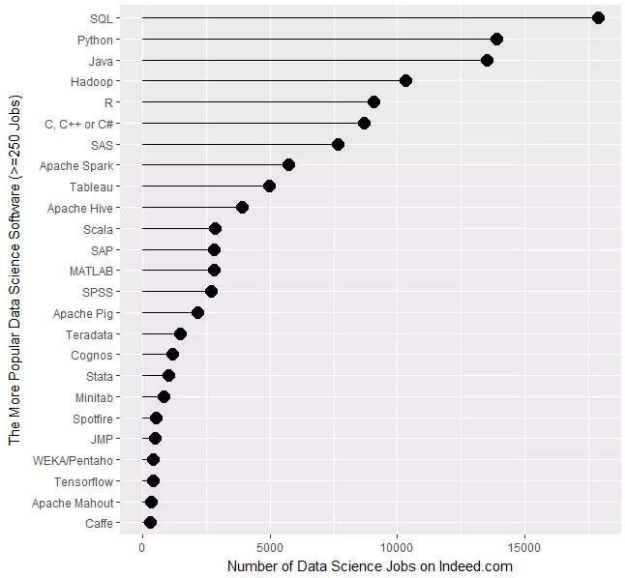
Enterprise **software, support** and **services** to empower people who change the world to get rapid insight from **all** of their data — built on **open-source** that we contribute to and sustain.

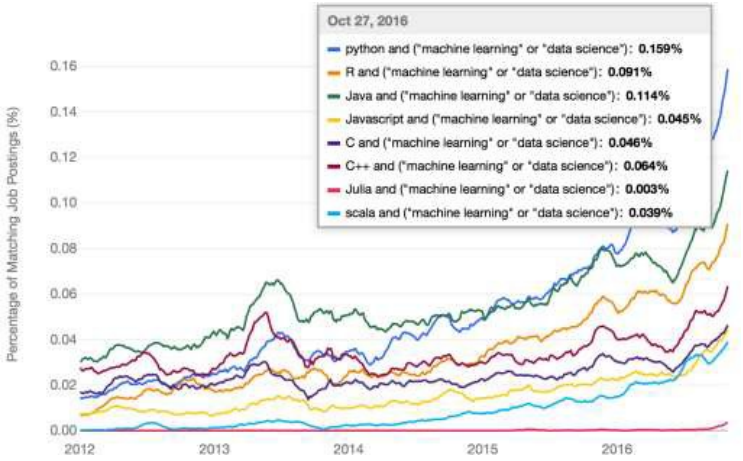
Community

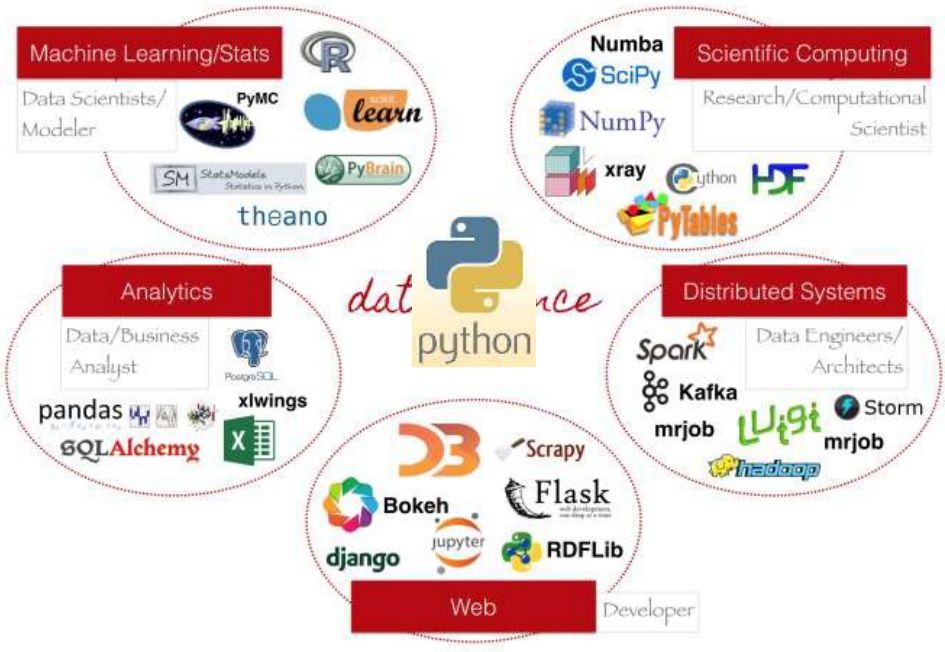
PyData

NUMFOCUS
OPEN CODE = BETTER SCIENCE

Data Science is growing with Python leading the way







ANACONDA

Bringing Technology Together

Accelerate adoption of Data Science

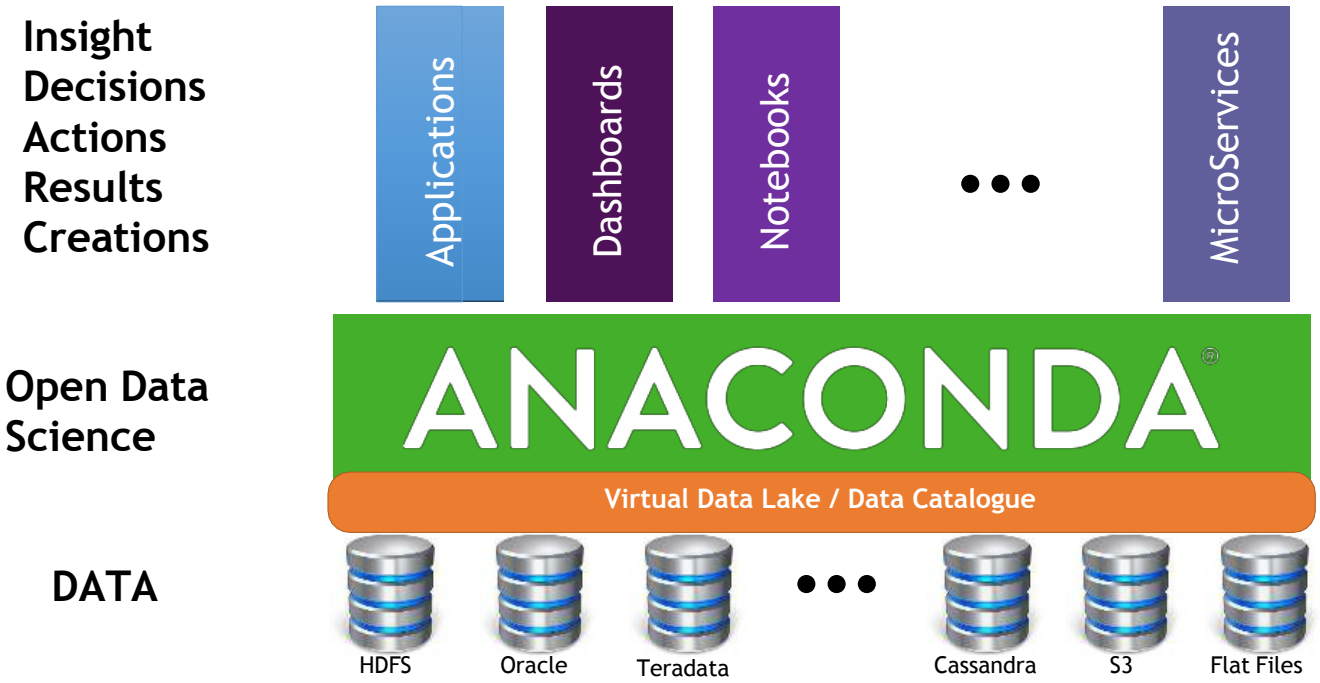
http://continuum.io/downloads

ANACONDA®

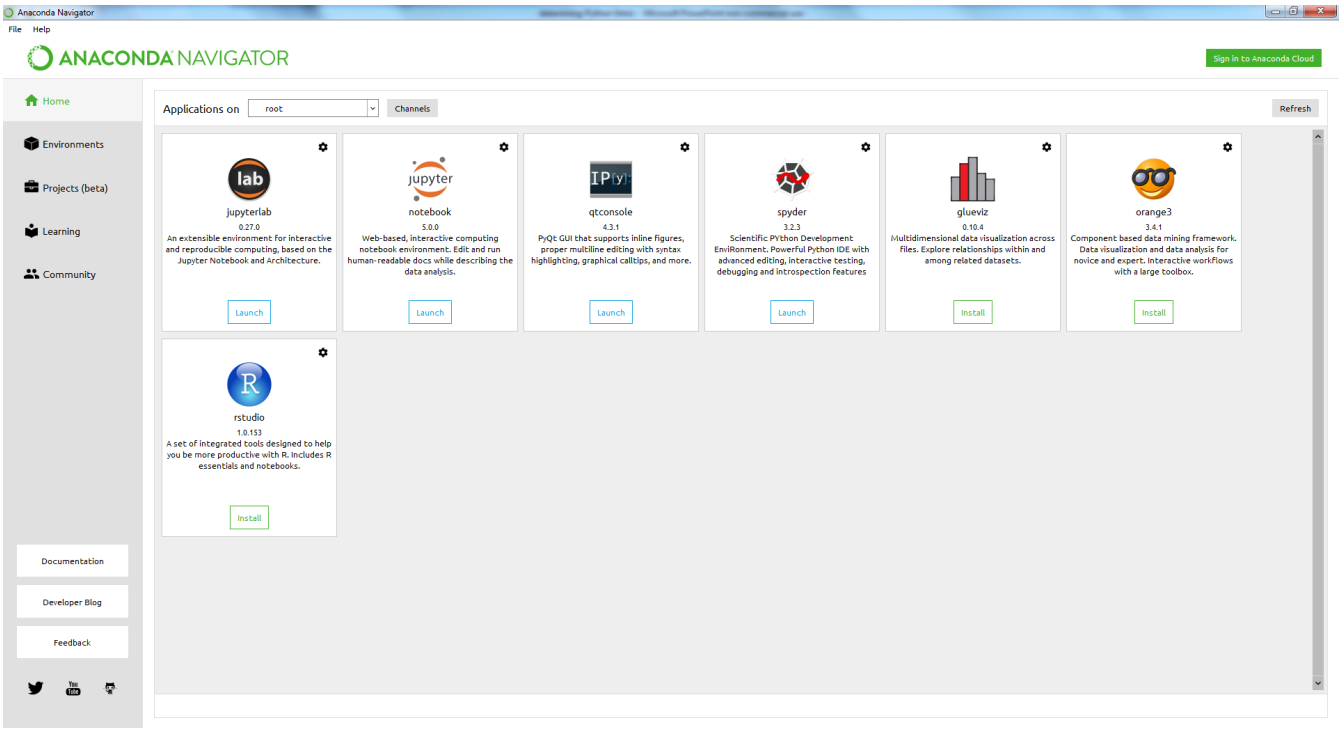
PYTHON & R OPEN SOURCE ANALYTICS

NumPy	SciPy	Pandas	Scikit-learn	Jupyter/IPython	
Numba	Matplotlib	Spyder	TensorFlow	Cython	Theano
Scikit-image	NLTK	Dask	Caffe	dplyr	shiny
ggplot2	tidyr			**& 1000+ packages**	

CONDA®



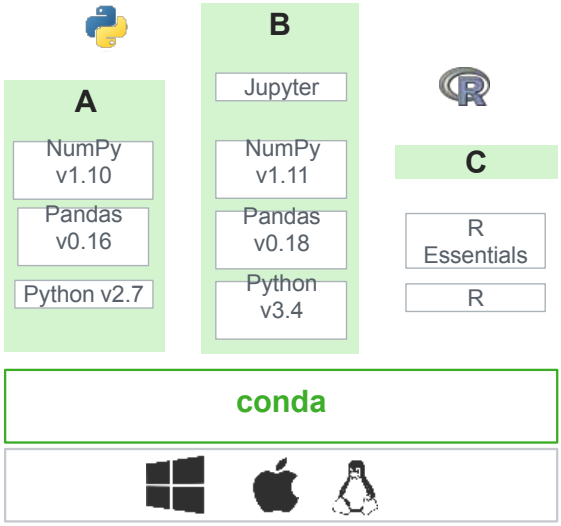
Anaconda Navigator



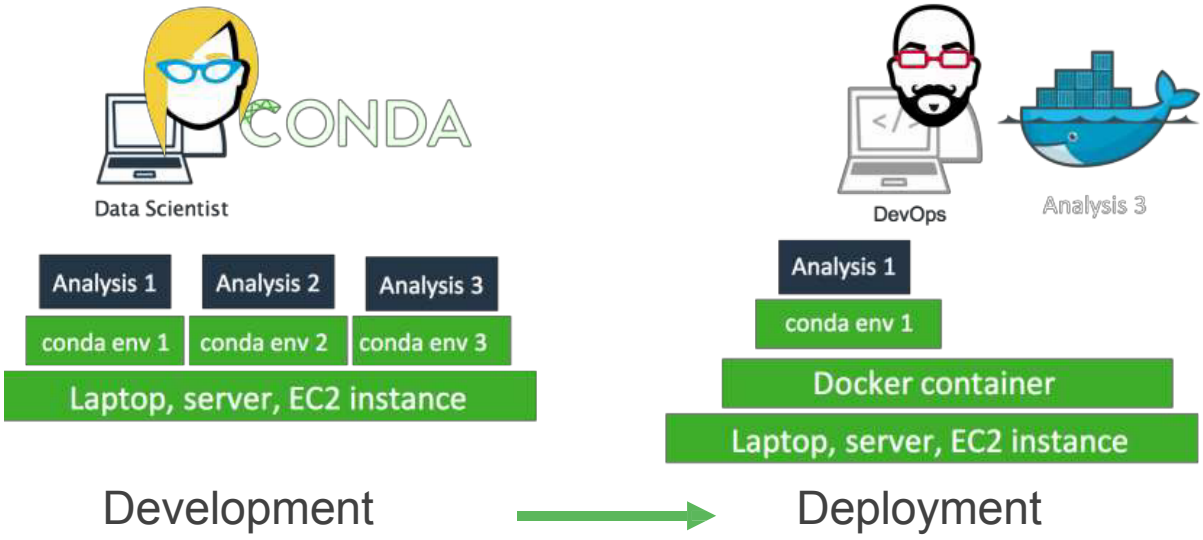
Conda Sandboxing Technology

- **Language** independent
- **Platform** independent
- No special privileges required
- No VMs or containers
- Enables:
  - **Reproducibility**
  - **Collaboration**
  - **Scaling**

"conda – package everything"



Conda for Deployment



CONDA

```
$ conda install python=2.7
$ conda install pandas
$ conda install -c r r
$ conda install -c conda-forge tensorflow
```

Install dependencies

```
name: myenv
channels:
  - chdoig
  - r
  - foo
dependecies:
  - python=2.7
  - r
  - r-ldavis
  - pandas
  - mongodb
  - spark=1.5
  - pip
  - pip:
      - flask-migrate
      - bar=1.4
```

```
$ conda env create
$ source activate myenv
```

nage multiple environments

```
$ anaconda-project run plot —show
```

```
$ conda kapsel run plot --show
```

Deploy an interactive visualization

26

Python Scripting

About Python

- Development started in the 1980's by Guido van Rossum.
  - Only became popular in the last decade or so.
- Python 2.x currently dominates, but Python 3.x is the future of Python.
- Interpreted, very-high-level programming language.
- Supports a multitude of programming paradigms.
  - OOP, functional, procedural, logic, structured, etc.
- General purpose.
  - Very comprehensive standard library includes numeric modules, crypto services, OS interfaces, networking modules, GUI support, development tools, etc.

Philosophy

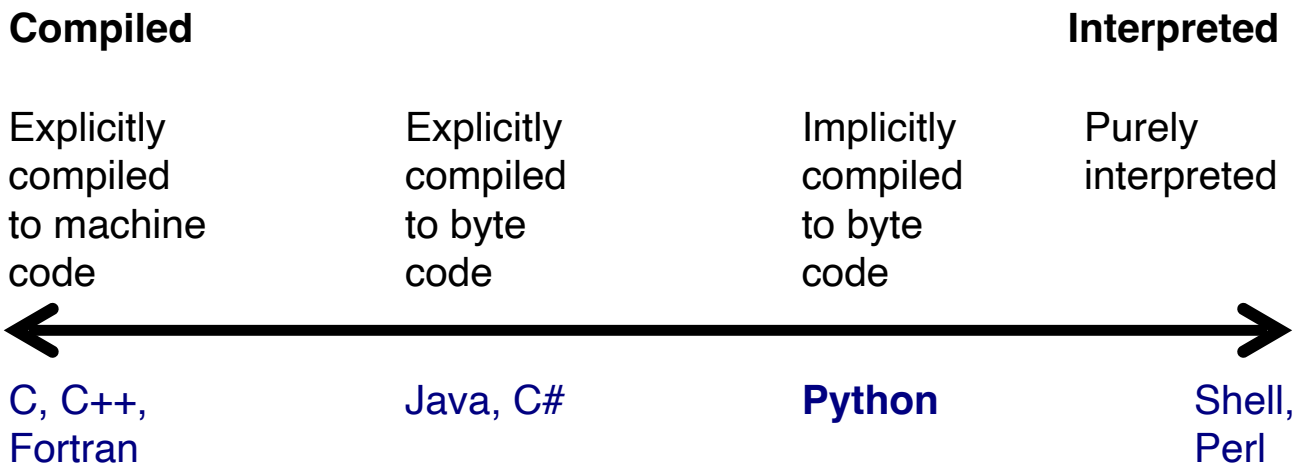
- From *The Zen of Python* (https://www.python.org/dev/peps/pep-0020/)

Beautiful is better than ugly.
Explicit is better than implicit.
Simple is better than complex.
Complex is better than complicated.
Flat is better than nested.
Sparse is better than dense.
Readability counts.
Special cases aren't special enough to break the rules.
Although practicality beats purity.
Errors should never pass silently.
Unless explicitly silenced.
In the face of ambiguity, refuse the temptation to guess.
There should be one-- and preferably only one --obvious way to do it.
Although that way may not be obvious at first unless you're Dutch.
Now is better than never.
Although never is often better than *right* now.
If the implementation is hard to explain, it's a bad idea.
If the implementation is easy to explain, it may be a good idea.
Namespaces are one honking great idea -- let's do more of those!

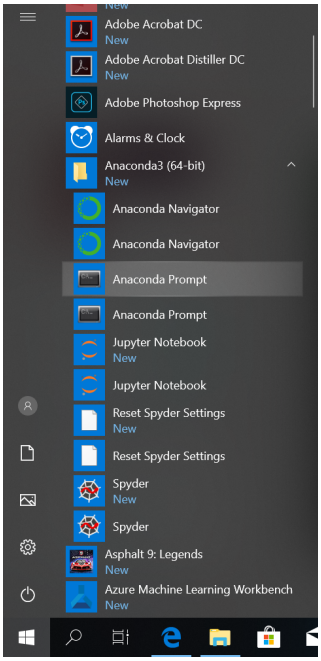
Notable Features

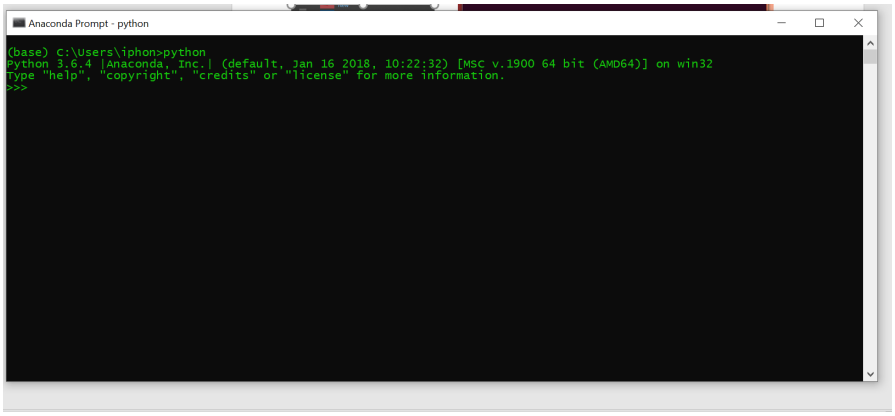
- Easy to learn.
- Supports quick development.
- Cross-platform.
- Open Source.
- Extensible.
- Embeddable.
- Large standard library and active community.
- Useful for a wide variety of applications.

What sort of language is Python?

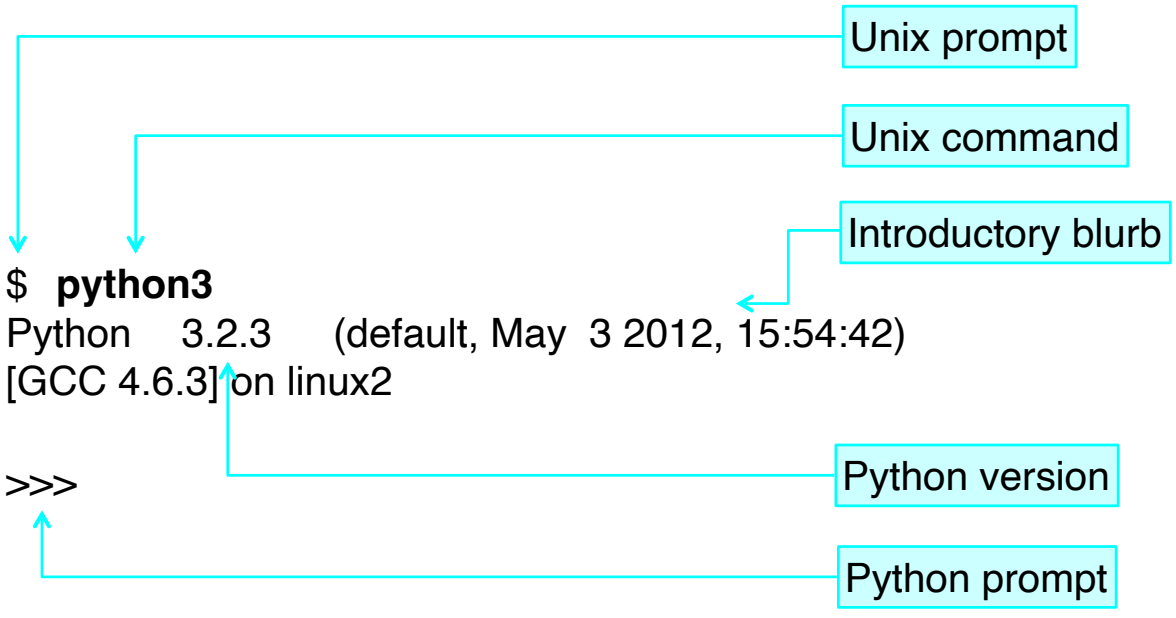


Running Python — 1





Running Python — 2

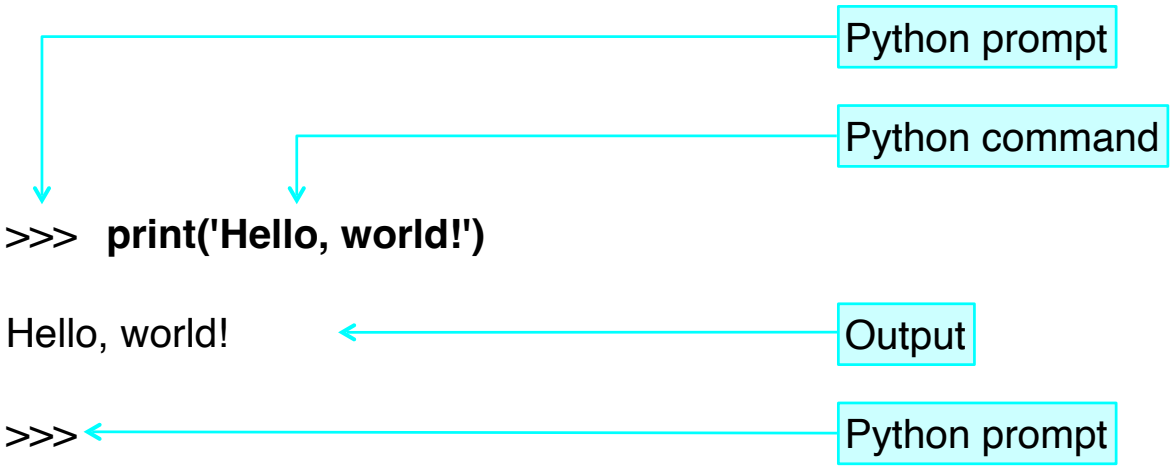


Quitting Python

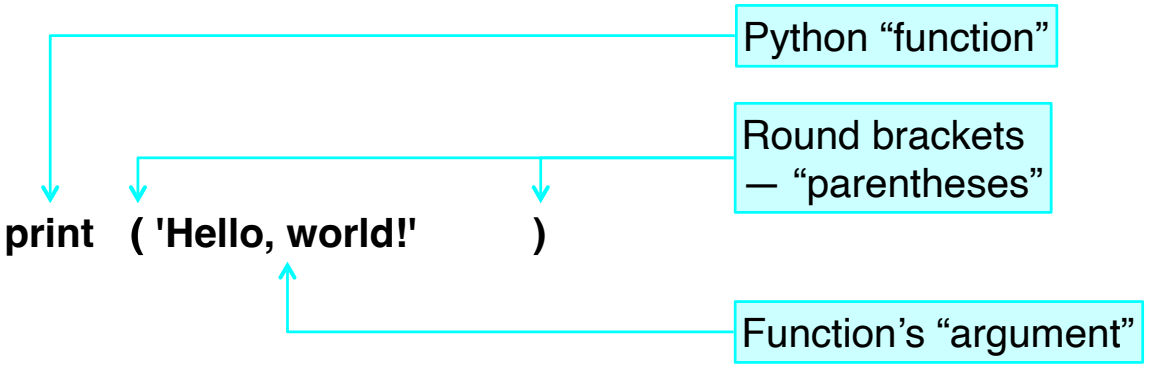
```
>>> exit()
>>> quit()
>>> Ctrl + D
```

Any one of these

A first Python command



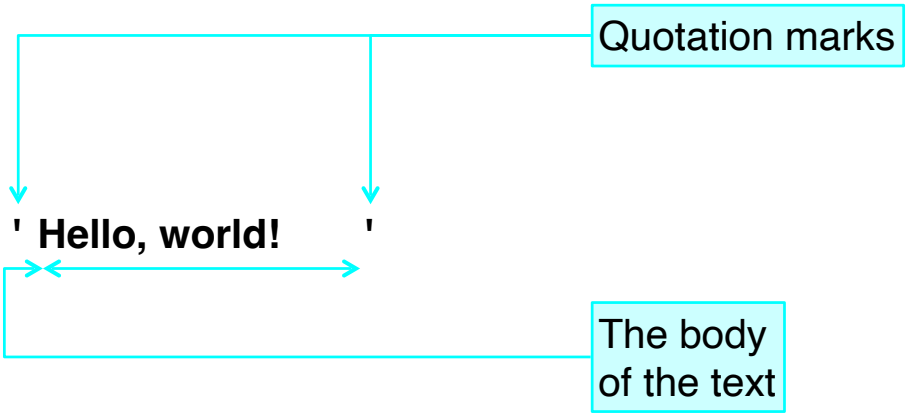
Python commands



print ≠ PRINT

“Case sensitive”

Python text



The quotes are not
part of the text itself.

Quotes?

print → Command

'print' → Text

Python scripts

File in home directory

Run from *Unix* prompt

```
print('Hello, world!')
```

hello1.py

```
$ python3 hello1.py
Hello, world!
$
```

Unix prompt

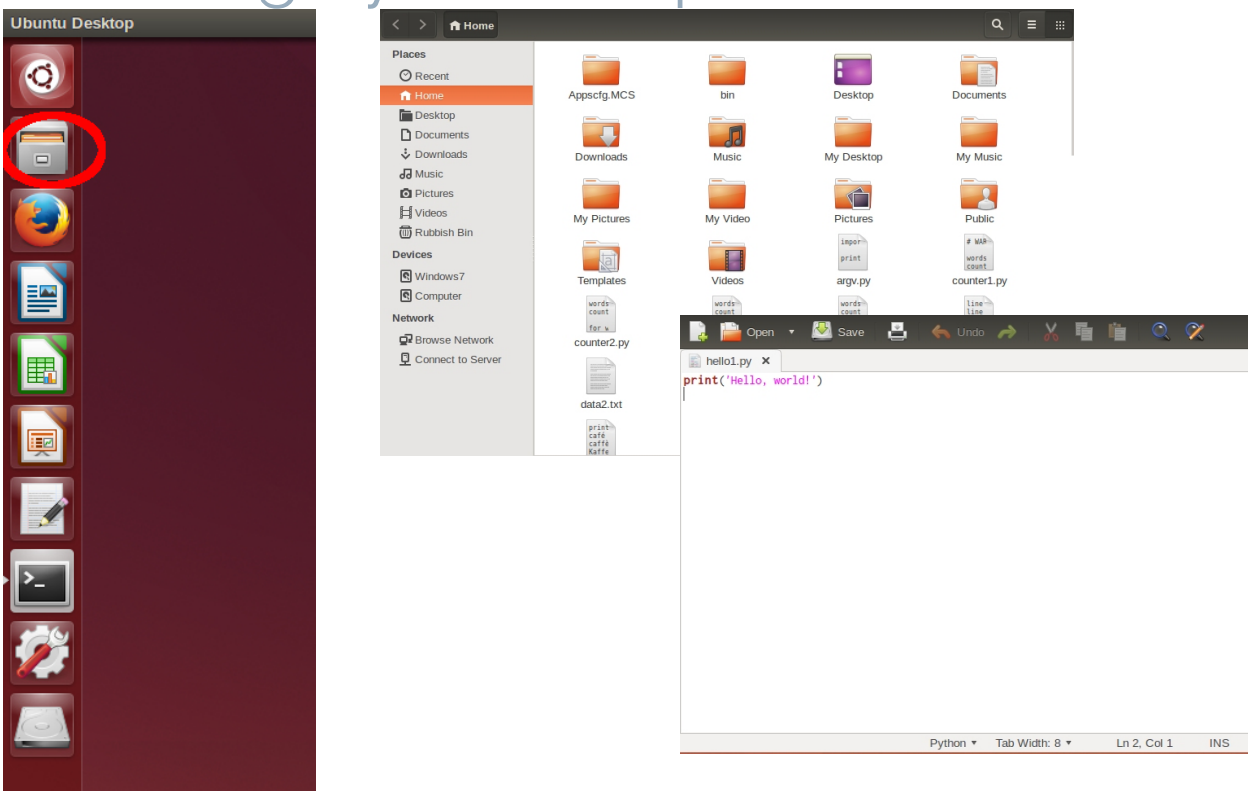
Unix command to run Python

Python script

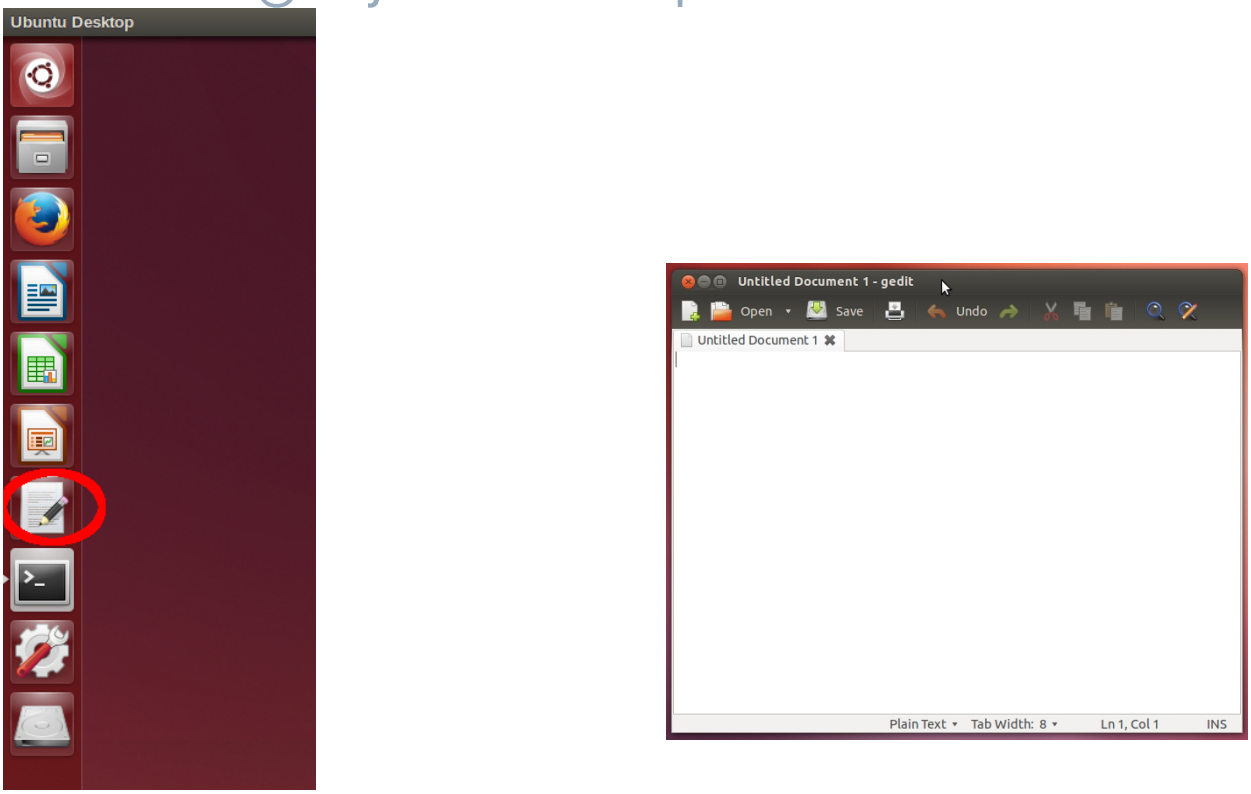
Python script's output

Unix prompt

Editing Python scripts — 1



Editing Python scripts — 2



Exercise 1

1. Print “Goodbye, cruel world!” from interactive Python.
2. Edit exercise1.py to print the same text.
3. Run the modified exercise1.py script.

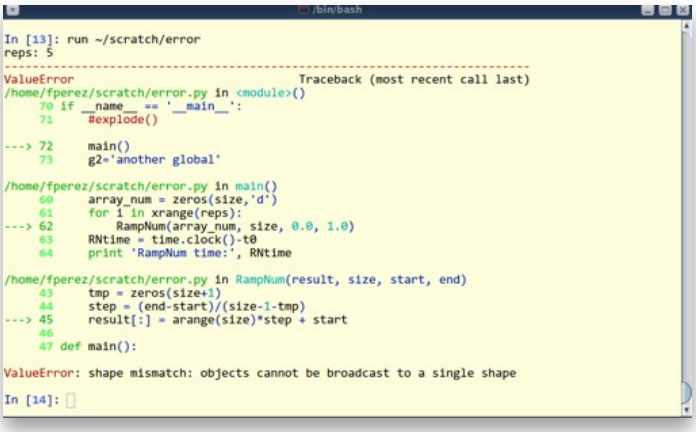
❢ Please ask if you have questions.

Jupyter

A bit of History

- Fernando Perez, 2001, CU Boulder
  (instead of writing a physics dissertation):

- Python can replace the collection of bash, perl, C/C++ Script. But the Python REPL can be better.



NOVEMBER 2001: "JUST AN AFTERNOON HACK"

- 259 Line Python script. (https://gist.github.com/fperez/1579699)
- sys.ps1 -> In [N].
- sys.displayhook -> Out[N], caches
- results. Plotting, Numeric, etc.

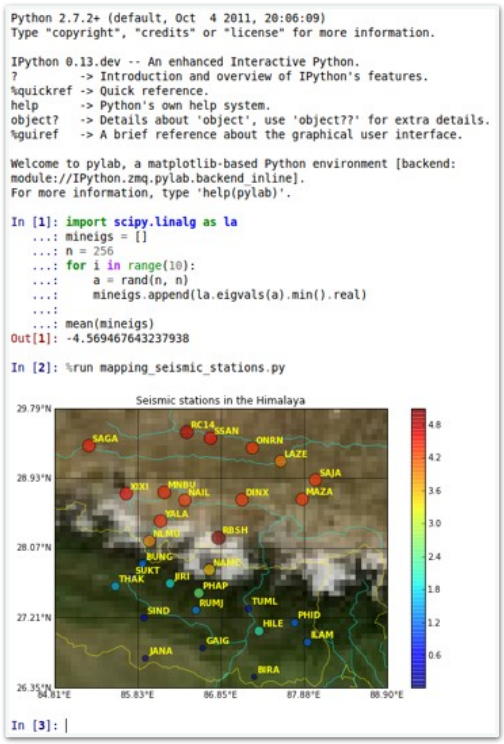
2014 (OPENHUB STATS)

- 19,279 commits
- 442 contributors
- Total Lines: 187,326
- Number of Languages : 7 (JS, CSS, HTML, …)

Improve over the terminal

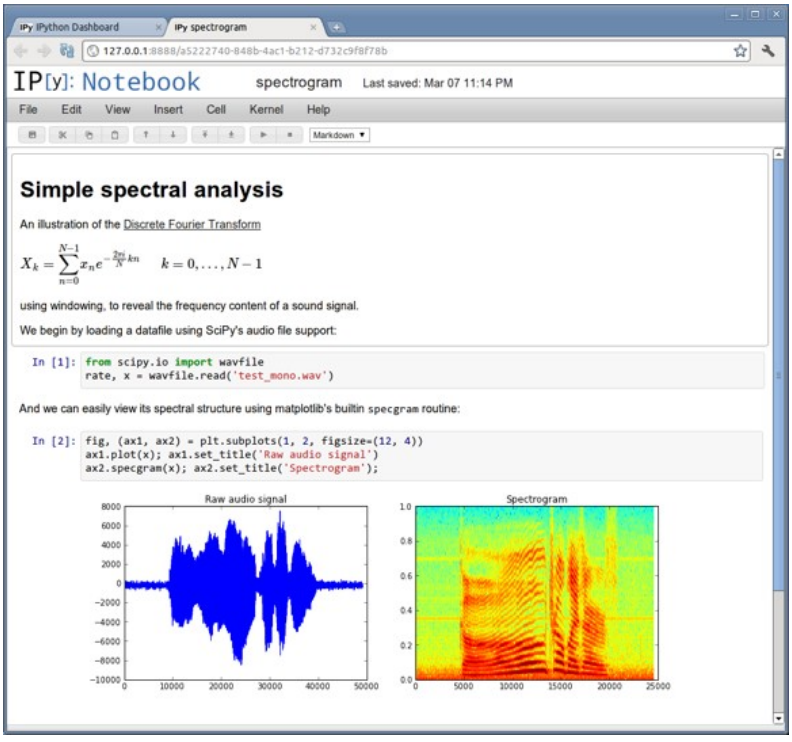
- The REPL as a network protocol
- Kernels
  - execute code
- Clients
  - Read input
  - Present output

Simple abstractions enable rich, sophisticated clients



2011: The IPython Notebook

- Rich web client
- Text & math
- Code
- Results
- Share, reproduce.



Funding

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CONTINUUM ANALYTICS

Microsoft

ENTHOUGHT SCIENTIFIC COMPUTING SOLUTIONS

Google

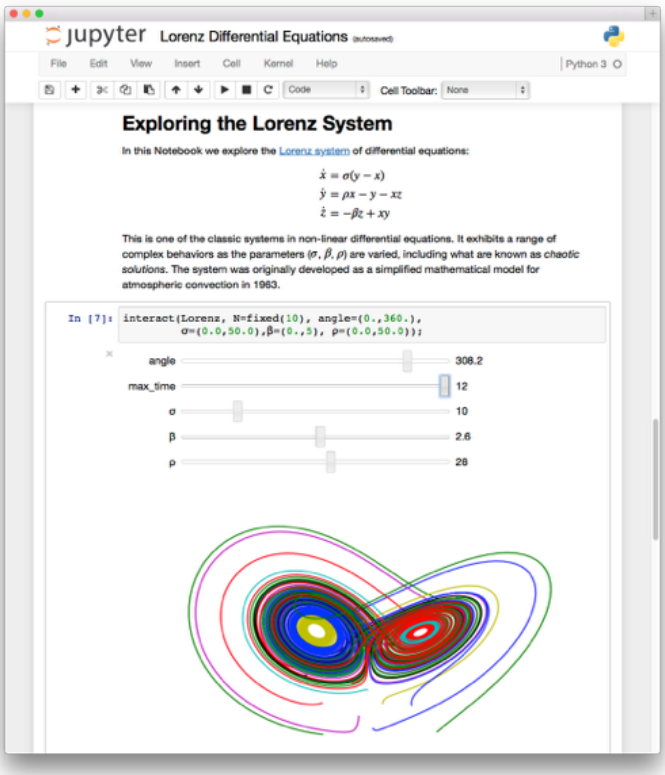
Bloomberg

Why ?

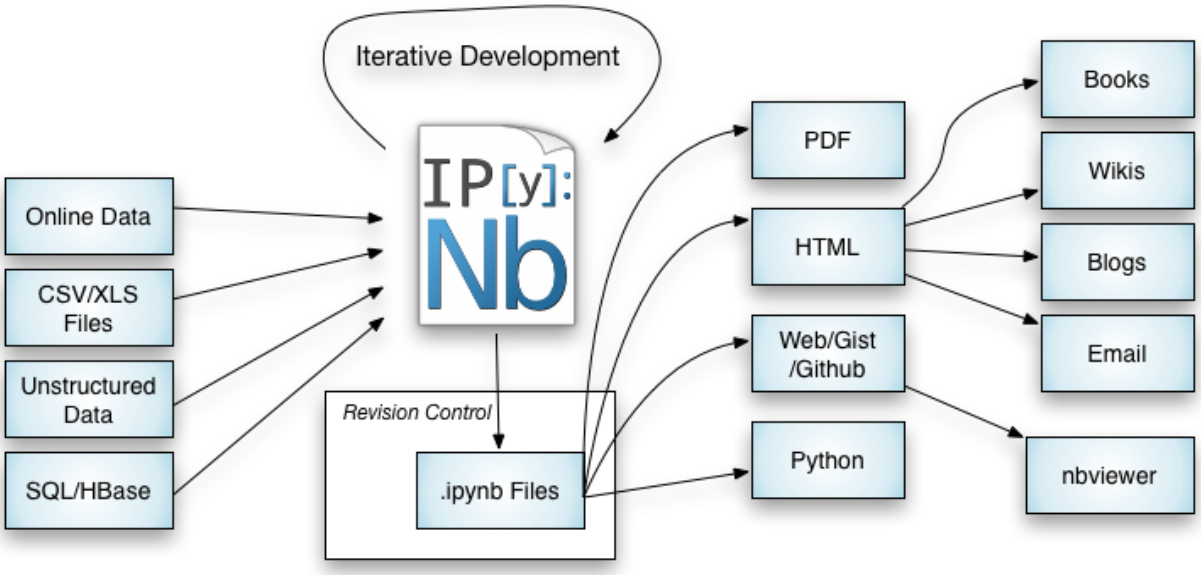
- Jupyter is the tool of choices for Data Scientist
- It is the foundation of Google Colab, AWS Sagemaker etc.
- You don't like the frontend, write a new one for Python get 50+ languages that work out of the box with it. (https://github.com/ipython/ipython/wiki/IPython-kernels-for-other-languages)
- You don't like a language, write your own kernel, get all the IDEs, conversion tools.
- Etc..

Jupyter notebook

- Web Application, that allow code to produce web-rich representation (images, sound, video, math, …)
- The Browser, Server, and kernel(s) can be on separate machines.
- The default application to edit `.ipynb` files.
- `.ipynb` file are JSON based files embeding input and output, so which can be read & converted without a running kernel.



The Notebook Fileformat (`.ipynb`)



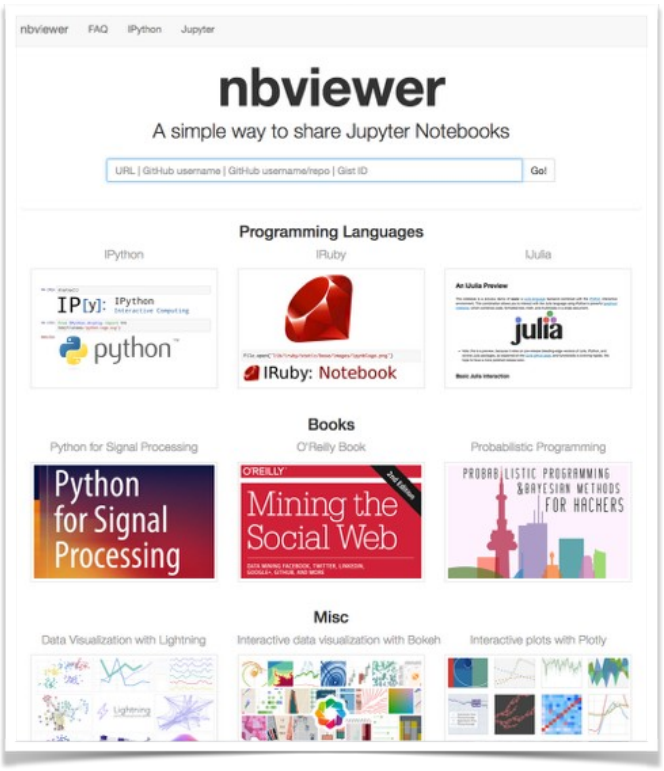
NbViewer

- Zero-install reading of notebooks
  Just share a URL
- nbviewer.org

Under the hood: get raw URL and convert to HTML on the fly.

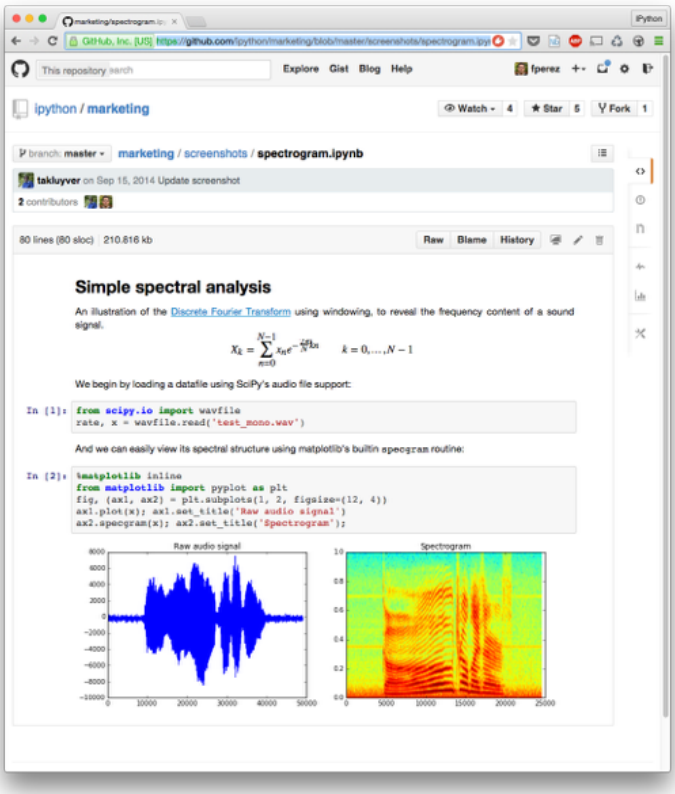
Sharing:

git push, or dropbox sync.



Nbviewer on GitHub

- Since May GitHub renders Notebooks
- Powered by `nbconvert`, the library that deals with
  `.ipynb` -> *
- Over 200,000 notebooks on GitHub



Exercise 2

- Create “Hello World” using Jupyter Notebook
- Issue command print(“Hello World”)

Data Structure

A little more text

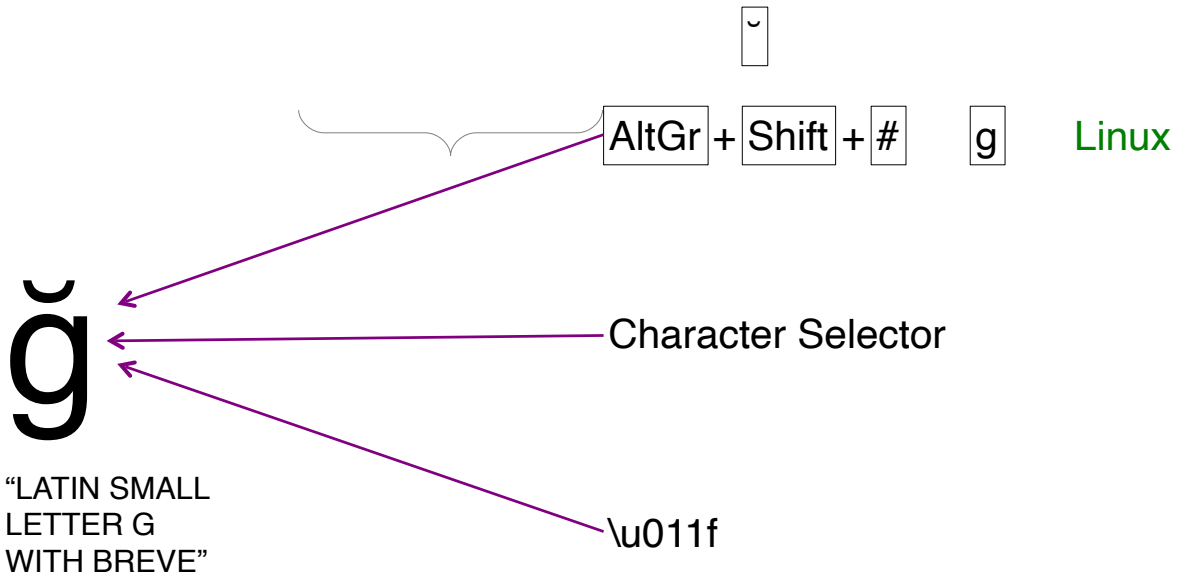
Full “Unicode” support

www.unicode.org/charts/

```
print('ɦəɬlʊ0, ω☺λɲəd!!')
```

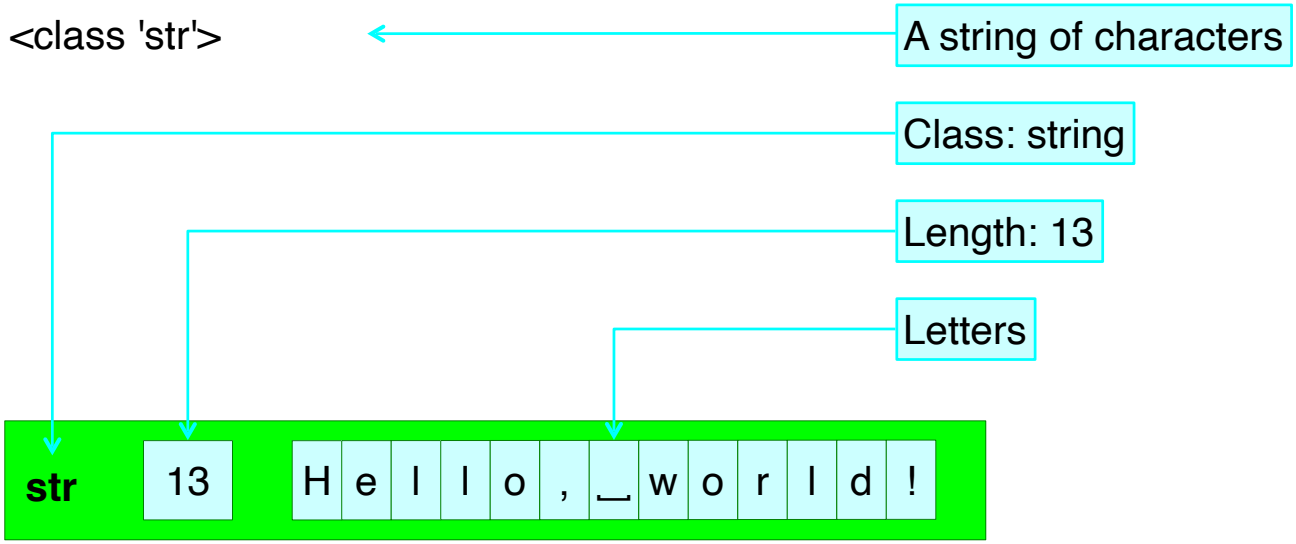
hello2.py

Getting characters

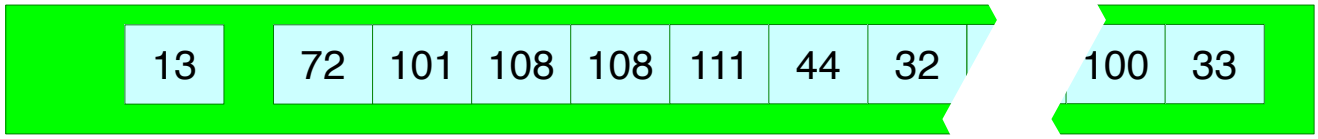


Text: a "string" of characters

```
>>> type('Hello, world!')
<class 'str'>
```



Text: "behind the scenes"




```
>>> '\u011f'
'ğ'
>>> ord('ğ')
287
>>> chr(287)
'ğ'
```

Adding strings together: +

"Concatenation"

```
print('Hello, ' + 'world!')
```

hello3.py

```
>>> 'Hello, ' + 'world!'
'Hello, world!'
>>>
```


Pure concatenation

```
>>> 'Hello,_' + 'world!'
'Hello, world!'
```

```
>>> 'Hello,' + '_world!'
'Hello, world!'
```

Only simple concatenation

```
>>> 'Hello,' + 'world!'
'Hello,world!'
```

No spaces added automatically.

Single & double quotes

```
>>> 'Hello, world!'
'Hello, world!'

>>> "Hello, world!"
'Hello, world!'
```

Single quotes

Single quotes

Double quotes

Single quotes

Python strings: input & output

'Hello, world!'

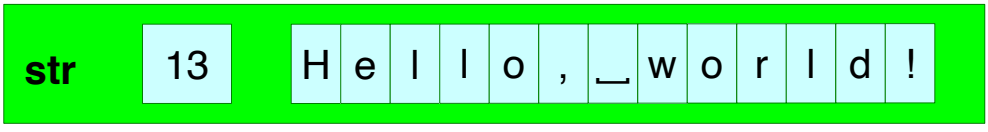
"Hello, world!"

Single or double quotes on input.

Create same string object.

'Hello, world!'

Single quotes on output.



Uses of single & double quotes

```
>>> print('He said "hello" to her.')

He said "hello" to her.
```

```
>>> print("He said 'hello' to her.")

He said 'hello' to her.
```


Why we need different quotes

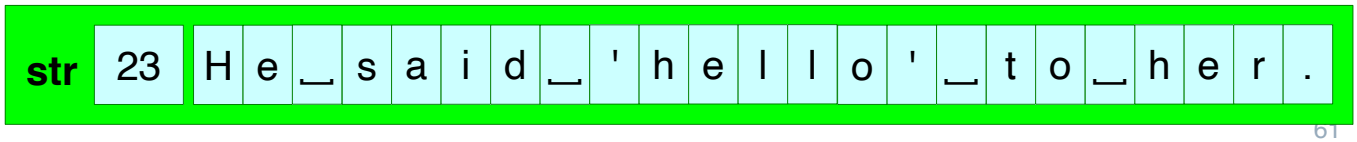
```
>>> print('He said 'hello' to her.')

File "<stdin>", line 1
  print('He said 'hello' to her.')
                   ^
SyntaxError: invalid syntax
```

Adding arbitrary quotes

```
>>> print('He said \'hello\' to her.')

He said 'hello' to her.
```

\' → ' Just an ordinary character.

\" → " "Escaping"



Putting line breaks in text

```
Hello,
world!
```

What we want

```
>>> print('Hello,
world')
```

↵ Try this

```
>>> print('Hello,
File "<stdin>", line 1
  print('Hello,
              ^
SyntaxError: EOL while
scanning string literal
```

↵

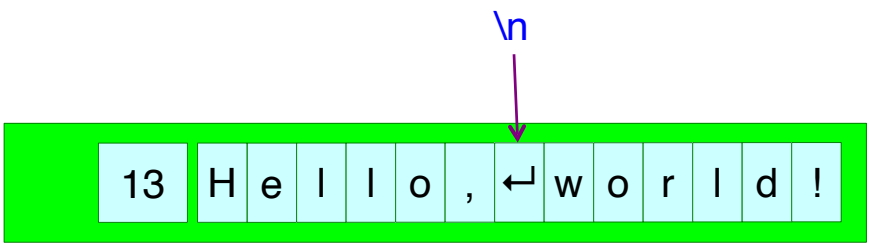
✘

"EOL": End Of Line

Inserting "special" characters

```
>>> print('Hello,\n world!')
Hello,
world!
```

Treated as a new line.



Converted into a *single* character.

```
>>> len ('Hello,\nworld!')
13
```

len() function: gives the length of the object

The backslash

Special → Ordinary

\' → '

\" → "

Ordinary → Special

\n → ↵

\t → →|

\n: unwieldy for long text

```
'SQUIRE TRELAWNEY, Dr. Livesey, and the\n
rest of these gentlemen having asked me\n
to write down the whole particulars\nabou
t Treasure Island, from the\nbeginning to
 the end, keeping nothing\nback but the b
earings of the island,\nand that only bec
ause there is still\ntreasure not yet lif
ted, I take up my\npen in the year of gra
ce 17__ and go\nback to the time when my
father kept\nthe Admiral Benbow inn and t
he brown\nold seaman with the sabre cut f
irst\ntook up his lodging under our roof.'
```

Single line

Special input method for long text

```
'''  SQUIRE TRELAWNEY, Dr. Livesey, and the
rest of these gentlemen having asked me
to write down the whole particulars
about Treasure Island, from the
beginning to the end, keeping nothing
back but the bearings of the island,
and that only because there is still
treasure not yet lifted, I take up my
pen in the year of grace 17__ and go
back to the time when my father kept
the Admiral Benbow inn and the brown
old seaman with the sabre cut first
took up his lodging under our roof.
'''
```

Triple quotes

Multiple lines

Python's "secondary" prompt

```
>>> '''Hello,
...    world'''
```

Python asking for more of the same command.

It's still just text!

```
>>> 'Hello,\nworld!'

'Hello\nworld'
```

Python uses \n to represent line breaks in strings.

```
>>> '''Hello,
...    world!'''

'Hello\nworld'
```

Exactly the same!

Your choice of input quotes:

Four inputs:

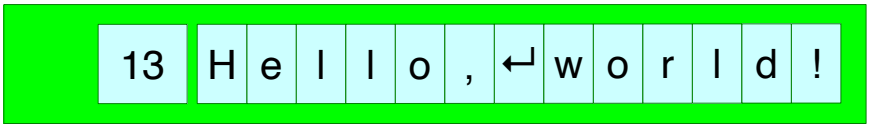
```
'Hello,\nworld!'
```

```
"Hello,\nworld!"
```

```
'''Hello,
world!'''
```

```
"""Hello,
world!"""
```

Same result:



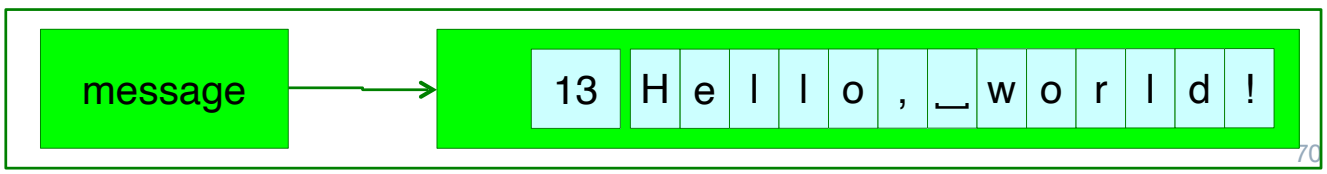
Attaching names to values

"variables"

```
>>> message='Hello, world!'

>>> message

'Hello, world!'

>>> type(message)

<class 'str'>
```

```
message = 'Hello, world!'
print(message)
```

hello3.py

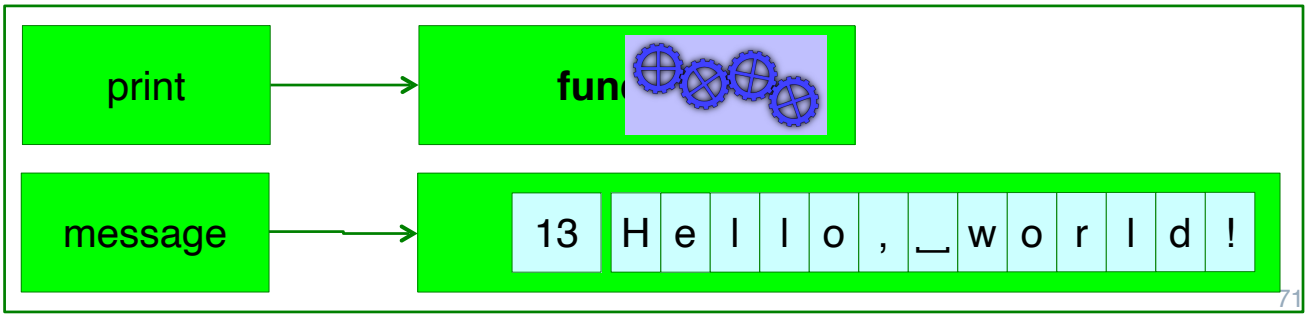


Attaching names to values

```
message = 'Hello, world!'
print(message)
```

hello4.py

```
>>> type(print)

<class 'builtin_function_or_method'>
```



Reading some text into a script

```
message = input('Yes?_')
print(message)
```

input1.py

```
$ python3 input1.py

Yes? Boo!

Boo!
```

input('Yes?_')

message = …

print(message)

Can't read numbers directly!

```
$ python3 input2.py

N? 10
```

```
number = input('N?_')
print(number + 1)
```

input2.py

```
Traceback (most recent call last):
  File "input2.py", line 2, in <module>
    print( number + 1 )
TypeError:
Can't convert 'int' object
to str implicitly
```

string

integer

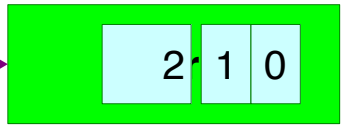
input(): strings only

```
$ python3 input2.py

N? 10
```

```
number = input('N?_')
print(number + 1)
```

input2.py

input('N?_') →



≠

Some more types

```
>>> type('Hello, world!')
<class 'str'>
```

string of characters

```
>>> type(42)
<class 'int'>
```

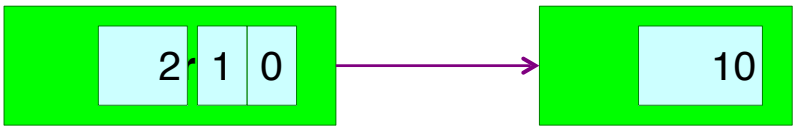
integer

```
>>> type(3.14159)
<class 'float'>
```

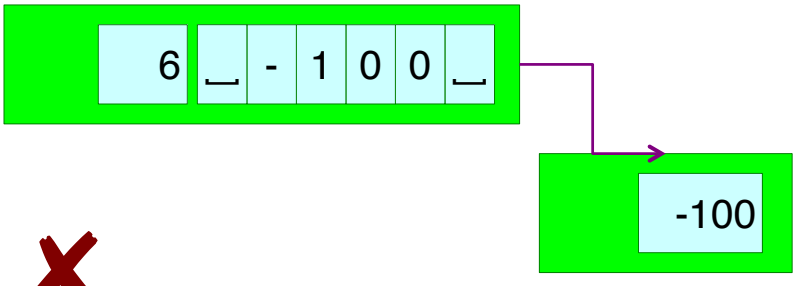
floating point number

Converting text to integers

```
>>> int('10')
10
```




```
>>> int('_-100_')
-100
```




```
>>> int('100-10')
```



```
ValueError:
invalid literal for int() with base 10: '100-10'
```

Converting text to floats

```
>>> float('10.0')
10.0

>>> float('  10.  ')
10.0
```

'10.0' is a string

10.0 is a floating point number

Converting between ints and floats

```
>>> float(10)
10.0

>>> int(10.9)
10

>>> int(-10.9)
-10
```

Truncates fractional part

Converting into text

```
>>> str(10)
'10'
```

integer → string

```
>>> str(10.000)
'10.0'
```

float → string

Converting between types

int()	anything → integer
float()	anything → float
str()	anything → string

Functions named after the type they convert *into*.

Integers

$\mathbb{Z}$ {… -2, -1, 0, 1, 2, 3, 4 …}

Integer addition & subtraction

```
>>> 20+5
25

>>> 20_-_5
15
```

Spaces around the operator don't matter.

"No surprises"

Integer multiplication

There is no "×" on the keyboard.

Use "*" instead

Linux:
AltGr + Shift + ,

```
>>>  20_*_5
100
```

Still no surprises

Integer division

There is no "÷" on the keyboard.

Use "/" instead

Linux:
AltGr + Shift + .

```
>>>  20_/_5
4.0
```

This is a floating point number!

Surprise!

Integer division gives floats !

Fractions → Floats sometimes

Consistency → Floats **always**

```
>>> 20_/_40
0.5

>>> 20_/_30
0.6666666666666666
```


Integer powers

There is no "4^2" on the keyboard.

Use "**" instead

```
>>> 4_**_2
16

>>> 4*_*2
SyntaxError: invalid syntax
```

Spaces *around* the operator don't matter.

Spaces *in* the operator do!

Integer remainders

e.g. Is a number even or odd?

Use "%"

```
>>> 4 % 2
0

>>> 5 % 2
1

>>> -5 % 2
1
```

Remainder is always non-negative

How big can a Python integer be?

```
>>> 2**2
4

>>> 4**2
16

>>> 16**2
256

>>> 256**2
65536

>>> 65536**2
4294967296
```

How big can a Python integer be?

```
>>> 4294967296**2
18446744073709551616

>>> 18446744073709551616**2
340282366920938463463374607431768211456

>>> 340282366920938463463374607431768211456**2
115792089237316195423570985008687907853269846
65640564039457584007913129639936

>>> 115792089237316195423570985008687907853269
98466564056403945758400791312963993 6**2
134078079299425970995740249982058461274793658205
9239337772356144372176403007354697680187429816690342769003185818648605085375388281194656994643364900608 4096
```


How big can a Python integer be?

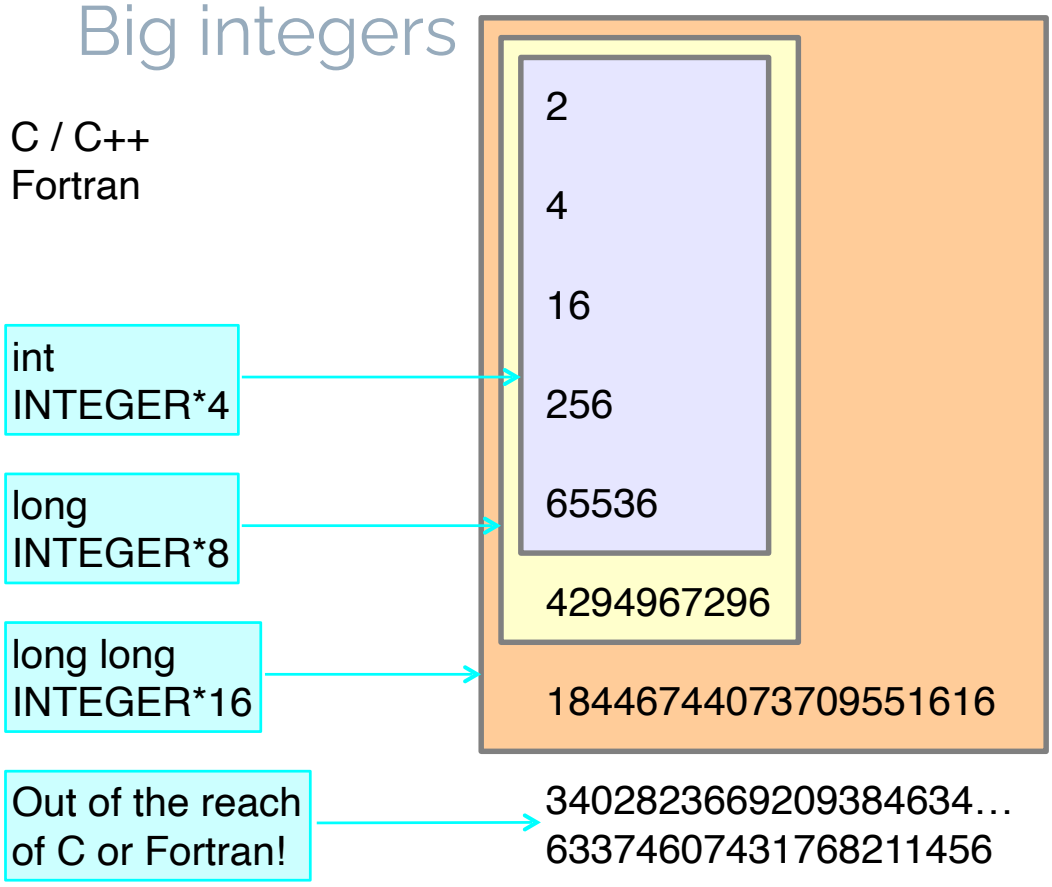
```
104438888141315250669175271071662438257996424904738378038423348328 39
539079715574568488268119349975583408901067144392628379875734381857 93
607263236087851365277945956976543709998340361590134383718314428070 01
185594622637631883939771274567233468434458661749680790870580370407 12
840487401186091144679777835980290066869389768817877859469056301902 60
94059957945343282 … 1554169383555
98852914863182379 … 3490084170616
75093668333850551 … 3796825837188
09183365675122131 … 9567449219461
702380650591324561082573183538008760862210283427019769820231316901 76
780066751954850799216364193702853751247840149071591354599827905133 99
611551794271106831134090584272884279791554849782954 …
906139490598769300212296339568778287894844061600741 …
716423771548163213806310459029161369267083428564407 …
465763473223850267253059899795996090799469201774624 …
925017832907047311943316555080756822184657174637329 …
570024409266169108741483850784119298045229818573389776481031260859 03
001302413467189726673216491511131602920781738033436090243804708340 40
3154190336
```

There is no limit!

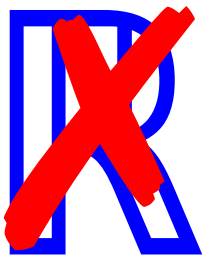
Except for machine memory

Big integers

C / C++
Fortran



Floating point numbers



1.0
0.33333333
3.14159265
2.71828182

Basic operations

```
>>> 20.0 + 5.0
25.0

>>> 20.0 * 5.0
100.0

>>> 20.0 ** 5.0
3200000.0
```

```
>>> 20.0 - 5.0
15.0

>>> 20.0 / 5.0
4.0
```

Equivalent to integer arithmetic

Floating point imprecision

```
>>> 1.0 / 3.0
0.3333333333333333

>>> 10.0 / 3.0
3.3333333333333335
```

If you are relying on this last decimal place, you are doing it wrong!

≈ **17** significant figures

Hidden imprecision

```
>>> 0.1
0.1

>>> 0.1 + 0.1
0.2

>>> 0.1 + 0.1 + 0.1
0.30000000000000004
```

Really: if you are relying on this last decimal place, you are doing it wrong!

How big can a Python float be? — 1

```
>>> 65536.0**2
4294967296.0
```

So far, so good.

```
>>> 4294967296.0**2
1.8446744073709552e+19
```

Switch to "scientific notation"

1.8446744073709552 e+19

1.8446744073709552 $\times 10^{19}$

Floats are not exact

```
>>> 4294967296.0**2
1.8446744073709552e+19
```

Floating point

```
>>> 4294967296**2
18446744073709551616
```

Integer

$1.8446744073709552 \times 10^{19}$ → 18446744073709552000

\- 18446744073709551616

384

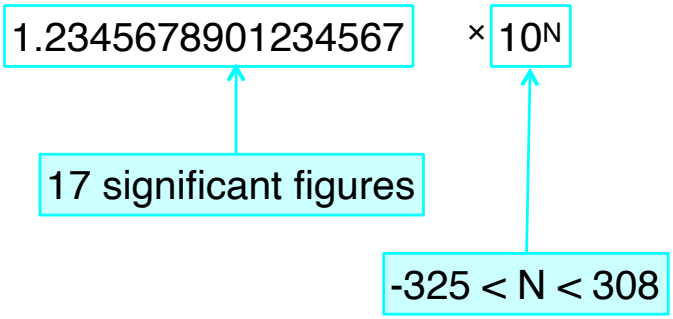
How big can a Python float be? — 2

```
>>> 1.8446744073709552e+19**2
3.402823669209385e+38

>>> 3.402823669209385e+38**2
1.157920892373162e+77

>>> 1.157920892373162e+77**2
1.3407807929942597e+154

>>> 1.3407807929942597e+154**2
OverflowError: (34,
'Numerical result out of range')
```

So far, so good.

Too big!

Floating point limits

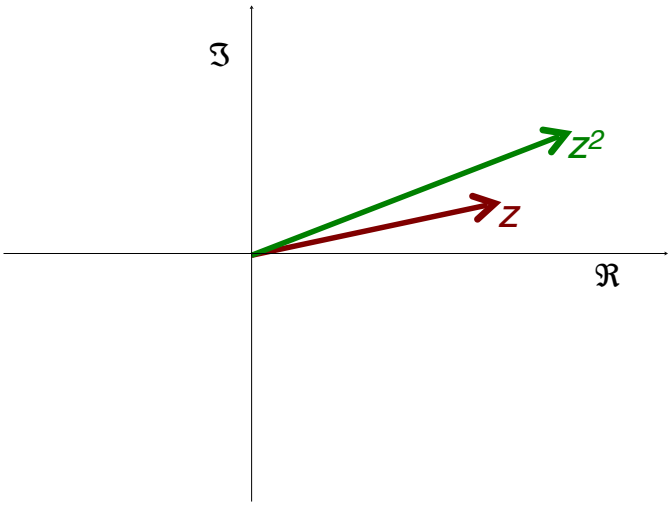


Positive values:

$4.94065645841 \times 10^{-324} < N < 8.98846567431 \times 10^{307}$

Complex numbers

ℂ




```
>>> (1.25+0.5j)**2
(1.3125+1.25j)
```

Comparisons

$5 < 10$ ✔

$5 > 10$ ✘

Comparisons

```
>>>  5 < 10
True
```

Asking the question

✔

```
>>>  5 > 10
False
```

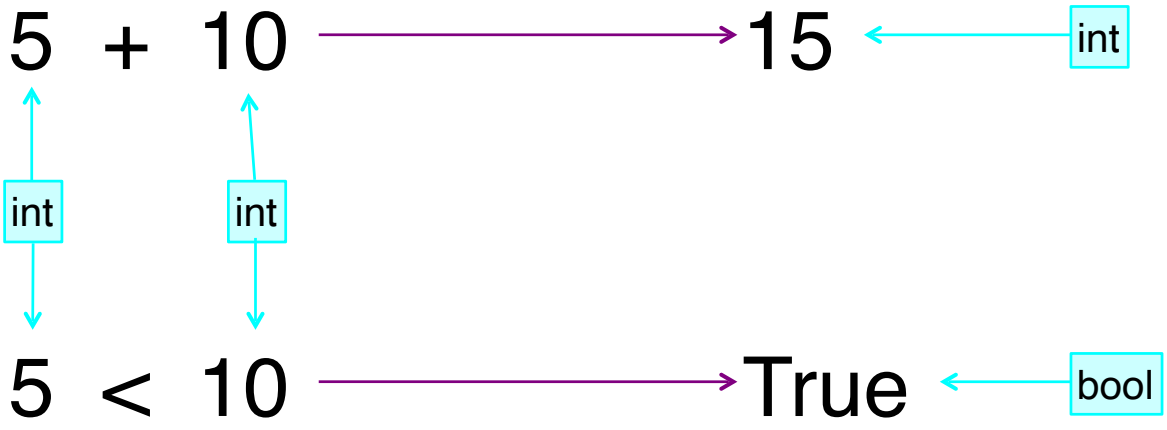
Asking the question

✘

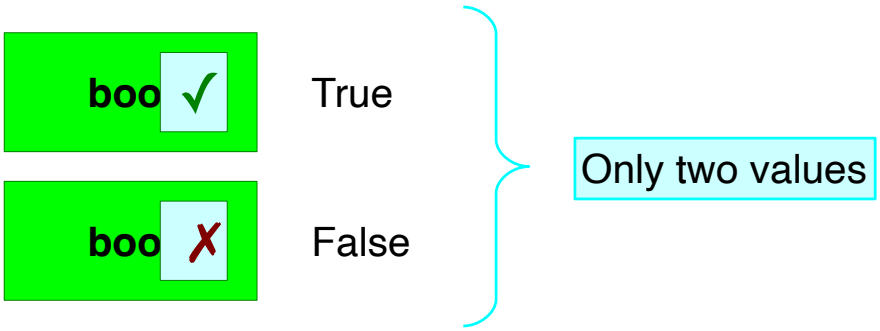
True & False

```
>>>  type(True)
<class 'bool'>
```

"Booleans"



True & False



Six comparisons

Maths	Python
=	==
≠	!=
<	<
>	>
≤	<=
≥	>=

Double equals sign

Equality comparison & assignment

=

name = value

Attach a name to a value.

==

$value_1$ == $value_2$

Compare two values

Textual comparisons

```
>>> 'cat' < 'dog'
True
```

Alphabetic ordering

```
>>> 'Cat' < 'cat'
True
```

Uppercase before lowercase

```
>>> 'Dog' < 'cat'
True
```

All uppercase before lowercase

Ordering text is *complicated*

Python inequalities use Unicode character numbers.

This is over-simplistic for “real” use.

“Collation” is a whole field of computing in itself

Alphabetical order?

German: z < ö

Swedish: ö < z

“Syntactic sugar”

0 < number < 10

0 < number

and

number < 10

```
>>> number = 5
>>> 0 < number < 10
True
```

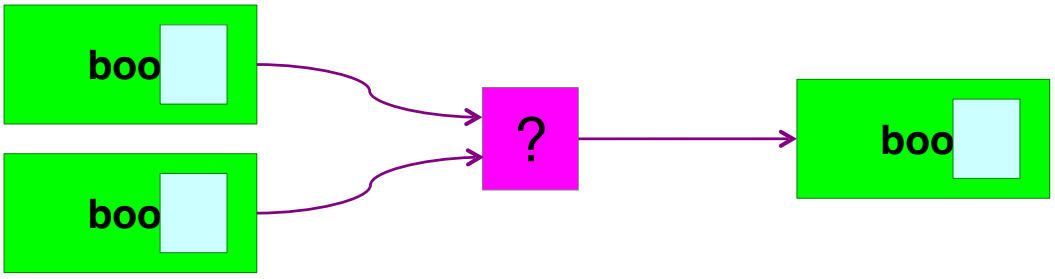

Converting to booleans

float()	Converts to floating point numbers
	<class 'float'>
int()	Converts to integers
	<class 'int'>
str()	Converts to strings
	<class 'str'>
bool()	Converts to booleans
	<class 'bool'>

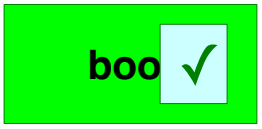
Useful conversions

''	→ False	Empty string
'Fred'	→ True	Non-empty string
0	→ False	Zero
1	→ True	Non-zero
12	→ True	
-1	→ True	

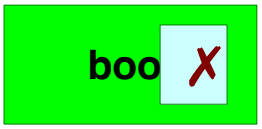
Boolean operations



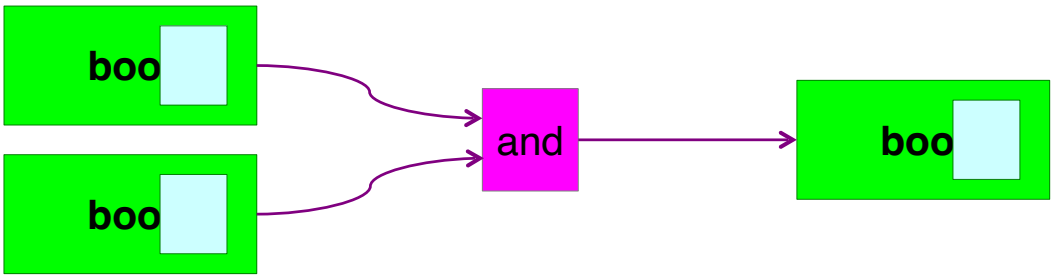
Numbers have +, –, * …



What do booleans have?



Boolean operations — "and"



True	and	True	⟶	True	Both have to be True
True	and	False	⟶	False	
False	and	True	⟶	False	
False	and	False	⟶	False	

Boolean operations — "and"

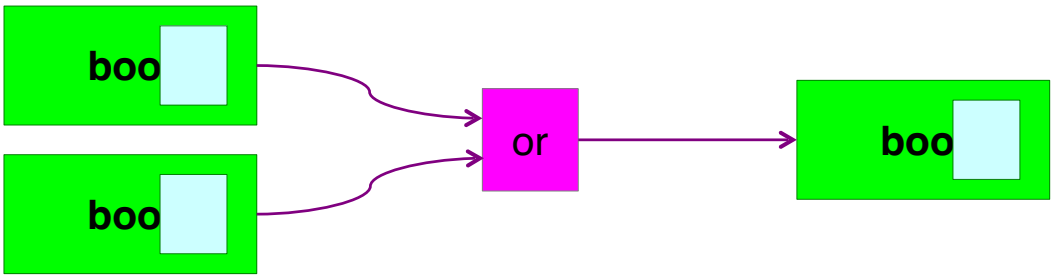
```
>>> 4 < 5 and 6 < 7
True
```

4 < 5 ⟶ True
6 < 7 ⟶ True
and ⟶ True

```
>>> 4 < 5 and 6 > 7
False
```

4 < 5 ⟶ True
6 > 7 ⟶ False
and ⟶ False

Boolean operations — "or"



True or True → True

True or False → True

False or True → True

False or False → False

At least one has to be True

Boolean operations — "or"

```
>>> 4 < 5 or 6 < 7
True
```

4 < 5 → True

6 < 7 → True

(True) or → True

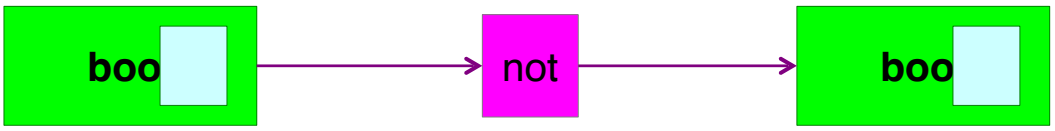
```
>>> 4 < 5 or 6 > 7
True
```

4 < 5 → True

6 > 7 → False

(True) or → True

Boolean operations — "not"



not True ⟶ False

not False ⟶ True

Boolean operations — "not"

>>> **not 6 < 7**

False

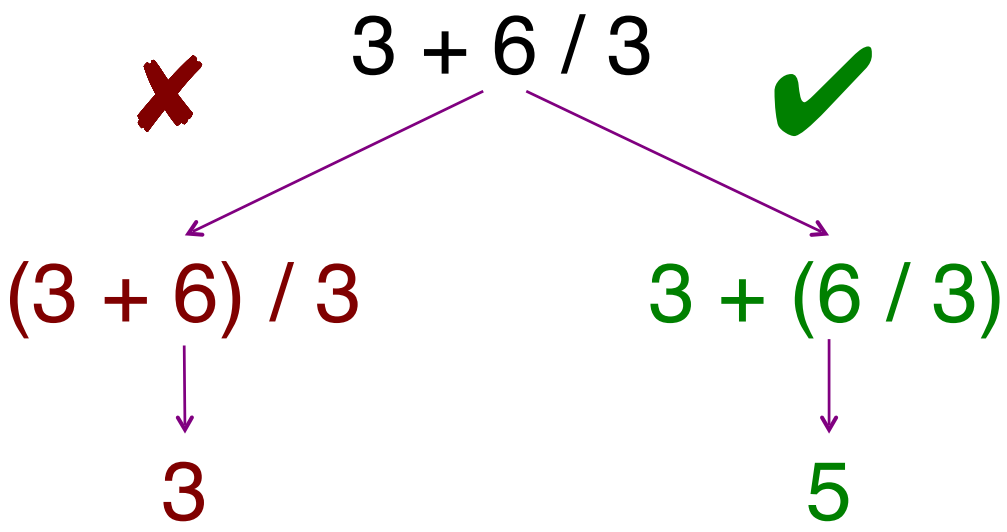
6 < 7 ⟶ True ⟶ not ⟶ False

>>> **not 6 > 7**

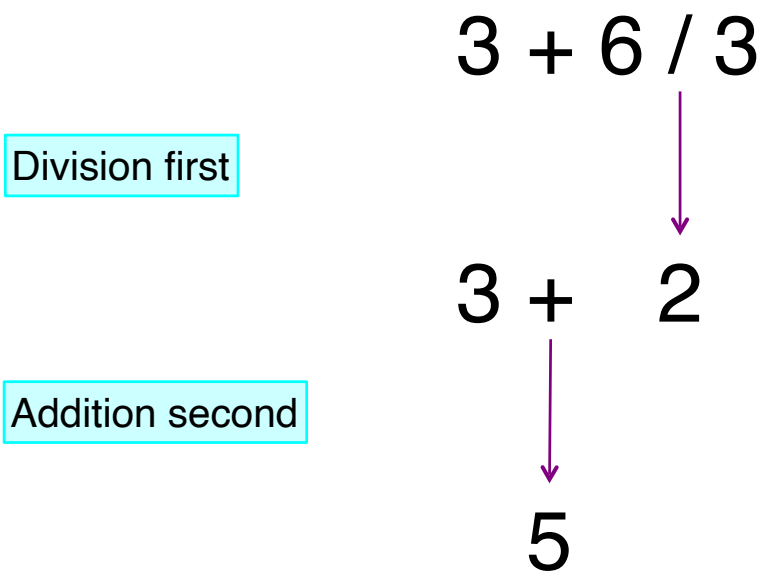
True

6 > 7 ⟶ False ⟶ not ⟶ True

Ambiguity in expressions



Division before addition



"Order of precedence"

First

x**y -x +x x%y x/y x*y x-y x+y

x==y x!=y x>=y x>y x<=y x<y

not x x **and** y x **or** y

Last

Exercise 3

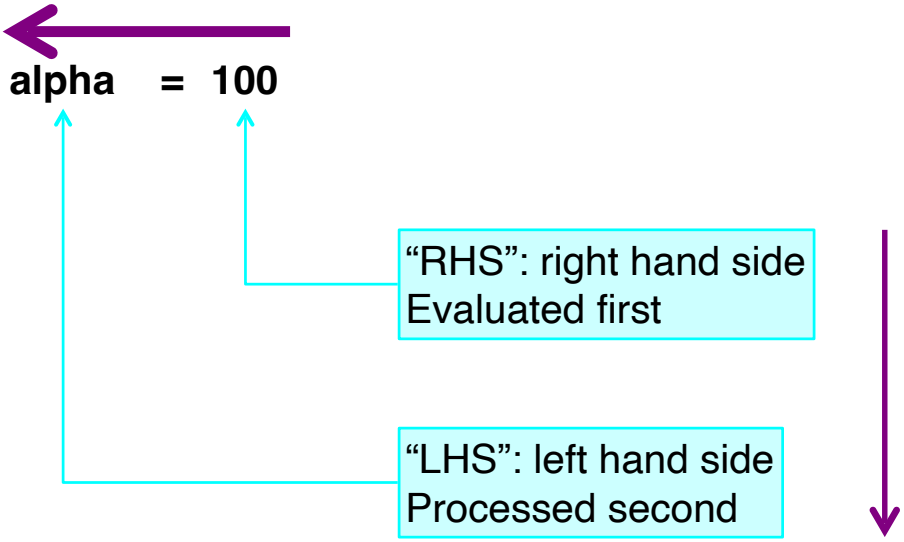
Predict whether these expressions will evaluate to True or False. Then try them.

1. 'sparrow' > 'eagle'

2. 'dog' > 'Cat' or 45 % 3 == 0

3. 60 - 45 / 5 + 10 == 1

Assignment: right to left

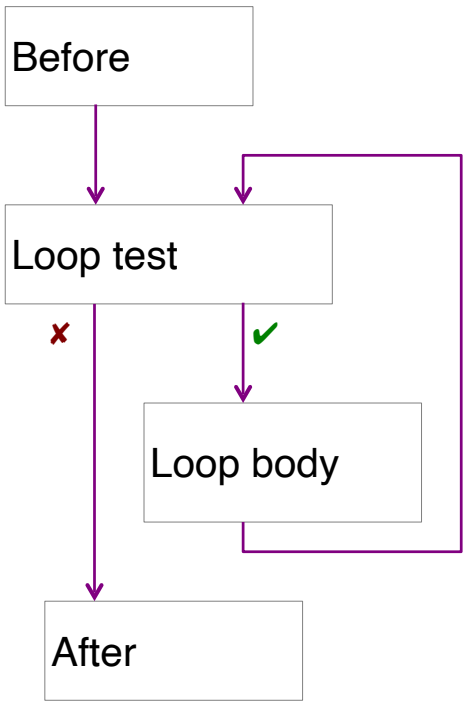


"Syntactic sugar"

thing += 10	is equivalent to	thing = thing + 10
thing -= 10		thing = thing - 10
thing *= 10		thing = thing * 10
thing /= 10		thing = thing / 10
thing **= 10		thing = thing ** 10
thing %= 10		thing = thing % 10

Looping

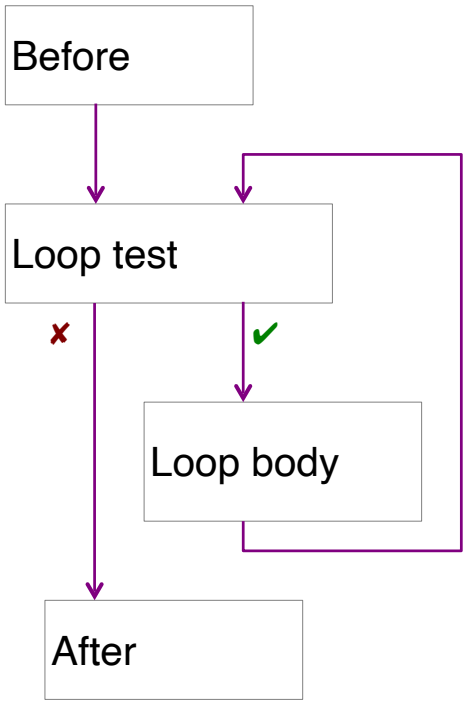
Looping

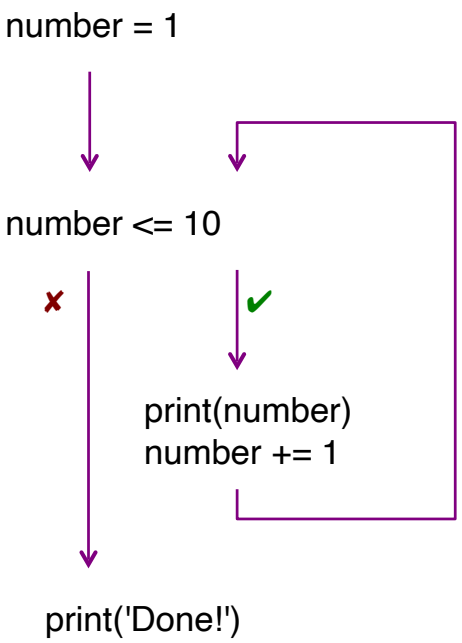


Should the loop run (again)?

What is run each loop?

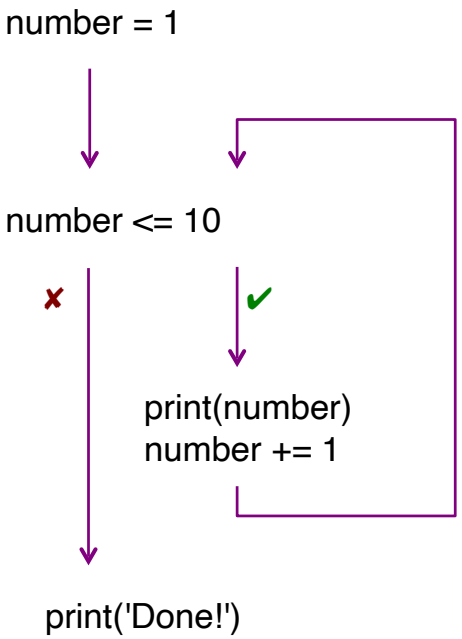
Loop example: Count from 1 to 10





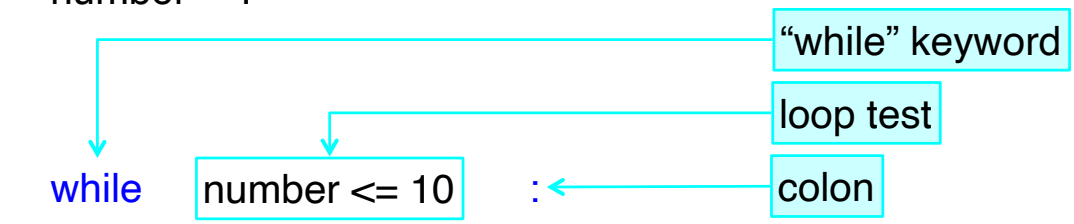
Loop example: Count from 1 to 10

```
number = 1

while     number <= 10      :

    print(number)
    number += 1

print('Done!')
```



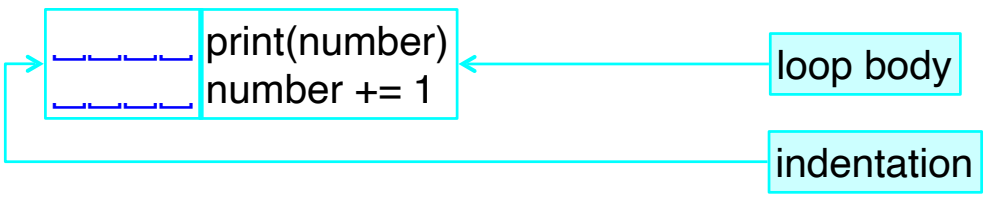
Loop test: Count from 1 to 10

```
number = 1

while number <= 10 :
    print(number)
    number += 1

print('Done!')
```



Loop body: Count from 1 to 10

```
number = 1

while number <= 10 :
    print(number)
    number += 1

print('Done!')
```



Loop example: Count from 1 to 10

```
number = 1

while number <= 10 :

    print(number)
    number += 1


print('Done!')
```

while1.py

```
$ python3 while1.py
1
2
3
4
5
6
7
8
9
10
Done!
$
```


Python's use of indentation

```
number = 1

while number <= 10 :
    print(number)
    number += 1

print('Done!')
```

Four spaces' indentation indicate a "block" of code.

The block forms the repeated lines.

The first unindented line marks the end of the block.

Other languages

Shell

```
while ...
do
    ....
    ....
done
```

do ... done ← Syntax

.... ← Clarity

C

```
while ...
{
    ....
    ....
}
```

{ ... } ← Syntax

.... ← Clarity

Keep looping while … ?

uncertainty > tolerance

```
while uncertainty > tolerance :
    Do stuff.
    ....
    ....
    ....
```

Square root: the loop

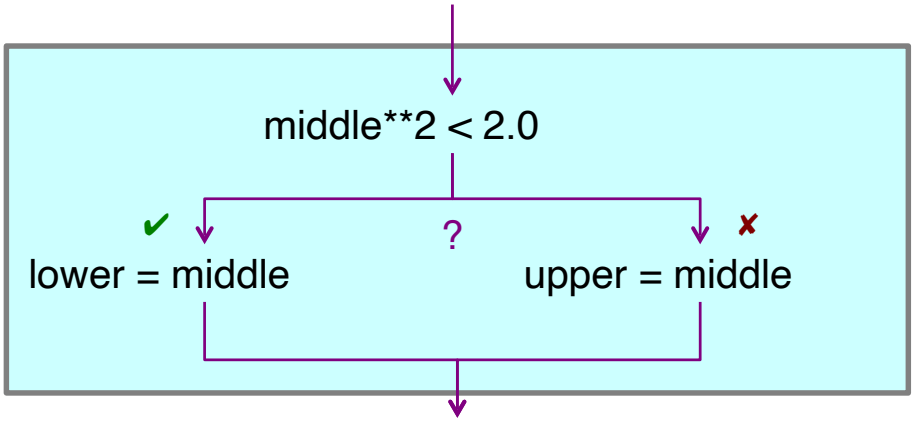
```
tolerance = 1.0e-15
lower = 0.0
upper = 2.0
uncertainty = upper - lower

while uncertainty > tolerance :

    middle = (lower + upper)/2
    ?

    print(lower, upper)
    uncertainty = upper - lower
```

Set up

Loop

Choice

Choosing



Choice

middle**2 < 2.0 → True or False

True → lower = middle

False → upper = middle

Simple example

```
text = input('Number? ')
number = int(text)

if number % 2 == 0:
    print('Even number')
else:
    print('Odd number')

print('That was fun!')
```

ifthenelse1.py

```
$ python3 ifthenelse1.py
Number? 8
Even number
That was fun

$ python3 ifthenelse1.py
Number? 7
Odd number
That was fun
```


Lists

['hydrogen', 'helium', 'lithium', 'beryllium', 'boron', …, 'thorium', 'protactinium' 'uranium']

[-3.141592653589793, -1.5707963267948966, 0.0, 1.5707963267948966, 3.141592653589793]

[2, 3, 5, 7, 11, 13, 17, 19]

What is a list?

hydrogen, helium, lithium, beryllium, …, protactinium, uranium

A *sequence* of values	The names of the elements
Values stored in order	Atomic number order
Individual value identified by position in the sequence	“helium” is the name of the second element

What is a list?

2, 3, 5, 7, 11, 13, 17, 19, 23, 29, 31, 37, 41, 43, 47, 53, 59

A *sequence* of values	The prime numbers less than sixty
Values stored in order	Numerical order
Individual value identified by position in the sequence	7 is the fourth prime

Creating a list in Python

```
>>> primes = [ 2, 3, 5, 7, 11, 13, 17, 19]
```

A literal list

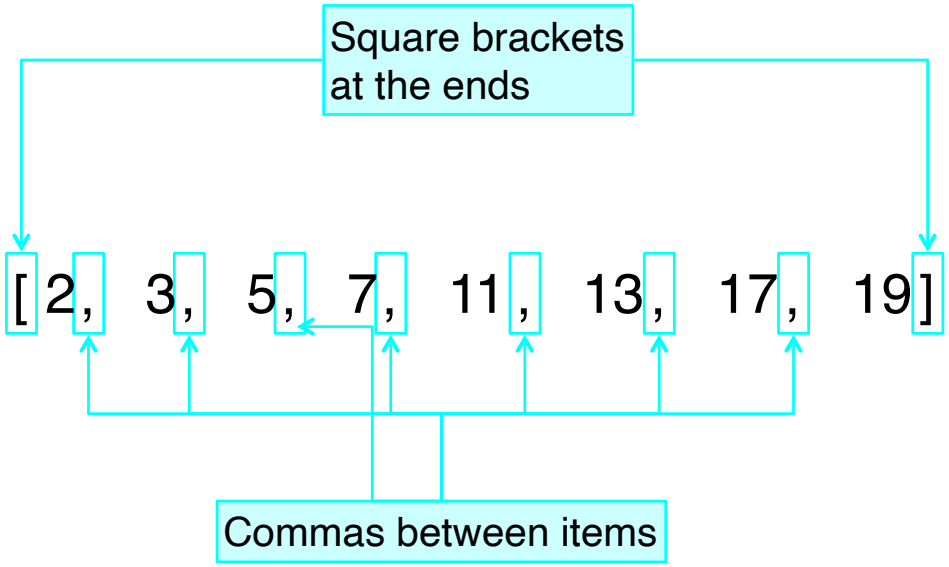
```
>>> primes
[2, 3, 5, 7, 11, 13, 17, 19]
```

The whole list

```
>>> type(primes)
<class 'list'>
```

A Python type

How Python presents lists

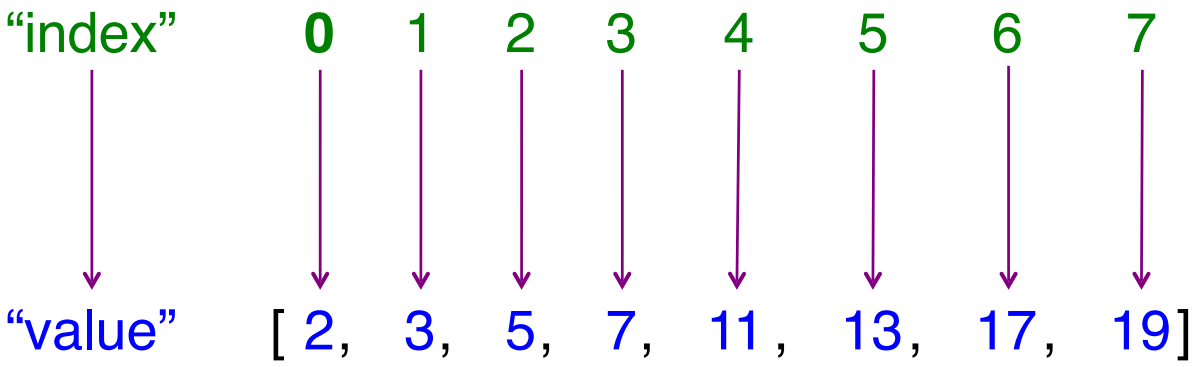


Square brackets

```
primes = [2, 3, 5, 7, 11]
```

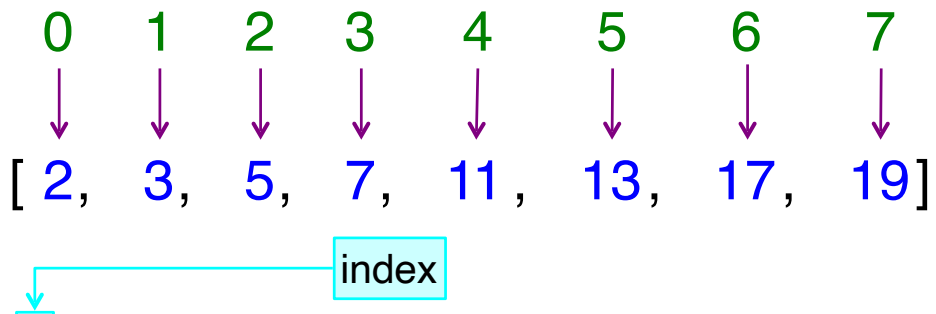
Literal list

Python counts from **zero**



Looking things up in a list

```
>>> primes = [ 2, 3, 5, 7, 11, 13, 17, 19]
```



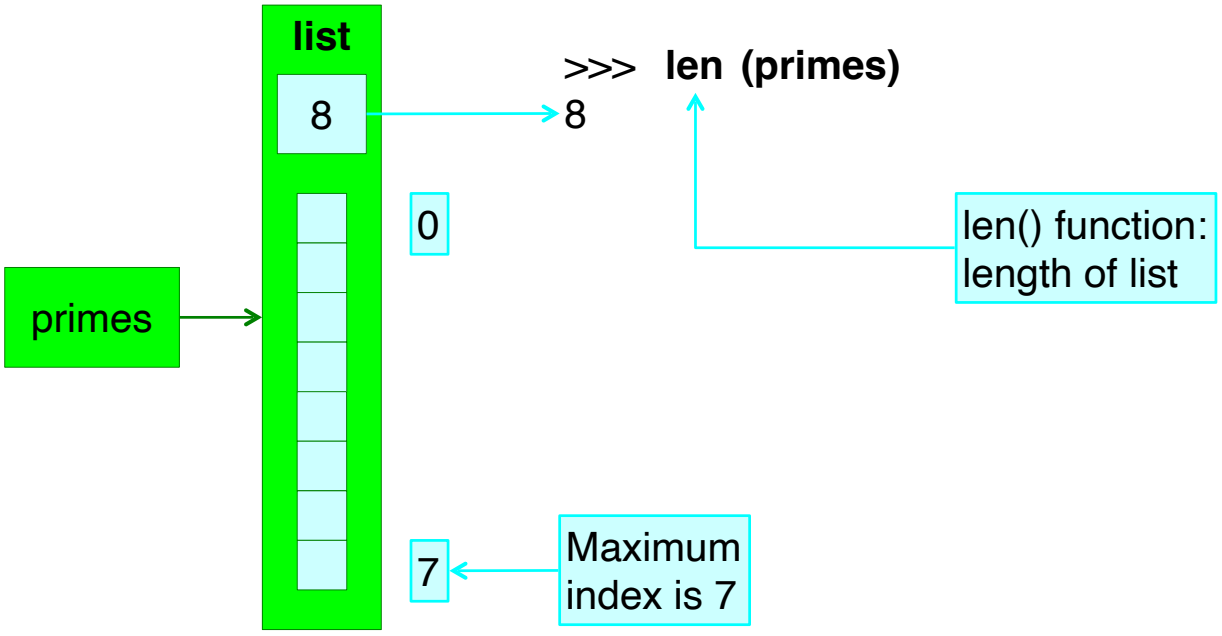
index

```
>>> primes [ 0]
2
```

square brackets

```
>>> primes [ 6]
17
```


Length of a list



Changing a value in a list

```
>>> data = ['alpha', 'beta', 'gamma']
```
The list

```
>>> data[2]
```
Initial value

```
'gamma'
```

```
>>> data[2] = 'G'
```
Change value

```
>>> data[2]
```
Check change

```
'G'
```

```
>>> data
```
Changed list

```
['alpha', 'beta', 'G']
```


Exercise 4

Track what the value of numbers is at each stage of this sequence of instructions.

1 `>>> numbers = [5, 7, 11, 13, 17, 19, 29, 31]`

2 `>>> numbers[1] = 3`

3 `>>> del numbers[3]`

4 `>>> numbers[3] = 37`

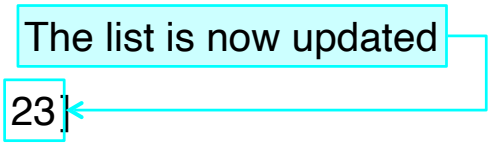
5 `>>> numbers[4] = numbers[5]`

Appending to a list

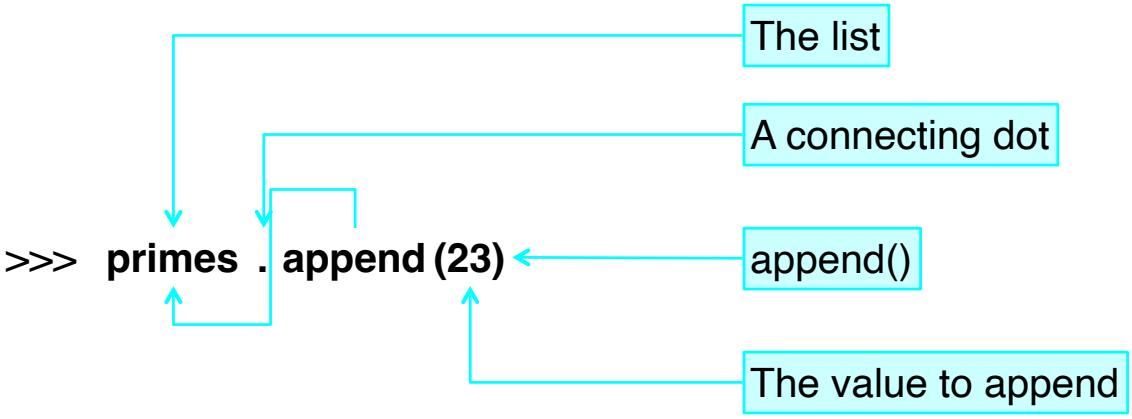
```
>>> primes
[2, 3, 5, 7, 11, 13, 17, 19]
```


```
>>> primes . append (23)
```

```
>>> primes
[2, 3, 5, 7, 11, 13, 17, 19, 23]
```



primes.append() ?



"Methods"

Behaves just like a function

a function that has special access to the object's data.

Using the append() method

```
>>> print(primes)
[2, 3, 5, 7, 11, 13, 17, 19]

>>> primes . append (23)
>>> primes . append (29)
>>> primes . append (31)
>>> primes . append (37)
>>> print(primes)
[2, 3, 5, 7, 11, 13, 17, 19, 23, 29, 31, 37]
```

The function doesn't return any value.

It modifies the list itself.

Other methods on lists: reverse()

```
>>> numbers = [4, 7, 5, 1]

>>> numbers.reverse()

>>> print(numbers)

[1, 5, 7, 4]
```

The function doesn't return any value.

It modifies the list itself.

Other methods on lists: sort()

```
>>> numbers = [4, 7, 5, 1]

>>> numbers.sort()

>>> print(numbers)

[1, 4, 5, 7]
```

The function does not return the sorted list.

It sorts the list itself.

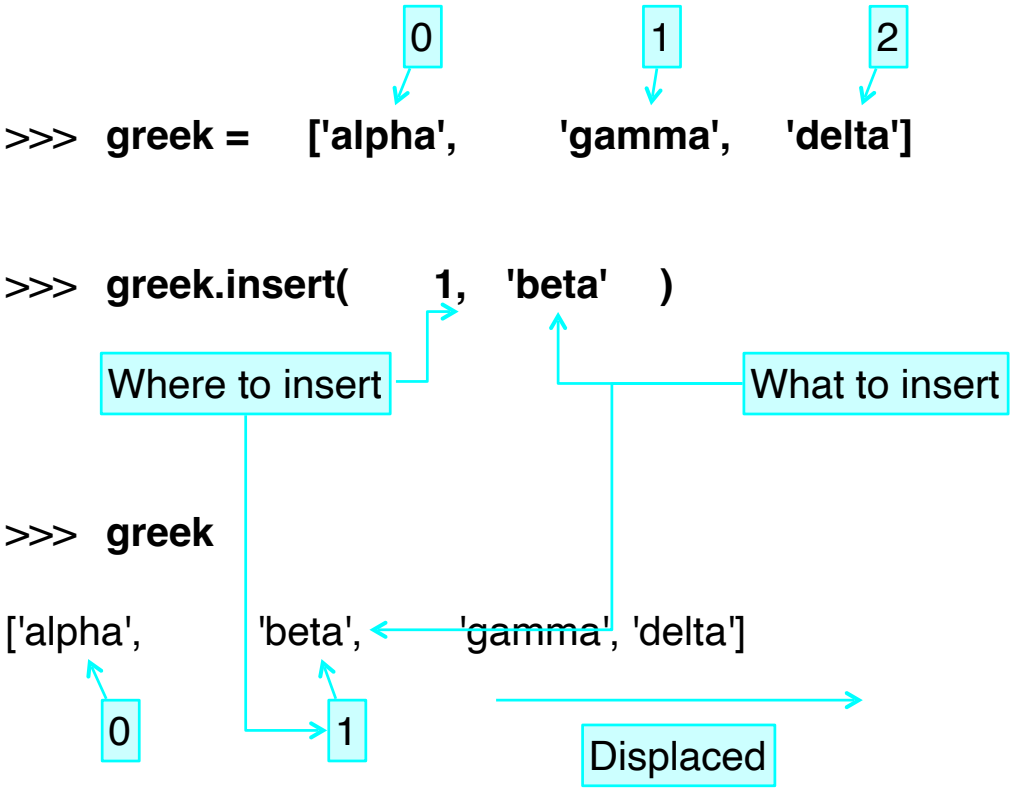
Numerical order.

Other methods on lists: sort()

```
>>> greek = ['alpha', 'beta', 'gamma', 'delta']

>>> greek.sort()

>>> print(greek)
['alpha', 'beta', 'delta', 'gamma']
```

Alphabetical order of the *words*.

Other methods on lists: insert()



Other methods on lists: remove()

```
>>> numbers = [7, 4, 8, 7, 2, 5, 4]
>>> numbers.remove (8)
>>> print(numbers)
[7, 4, 7, 2, 5, 4]
```

Value to remove

c.f. del numbers[2]

Index to remove

Other methods on lists: remove()

```
>>> print(numbers)
[7, 4, 7, 2, 5, 4]
```

There are two instances of 4.

```
>>> numbers.remove (4)
>>> print(numbers)
[7, 7, 2, 5, 4]
```

Only the first instance is removed

What methods are there?

```
>>> help(numbers)

Help on list object:

class list(object)
...
 |  append(...)
 |      L.append(object) -- append object to end
...
```

Pagination: _ next page

B back one page

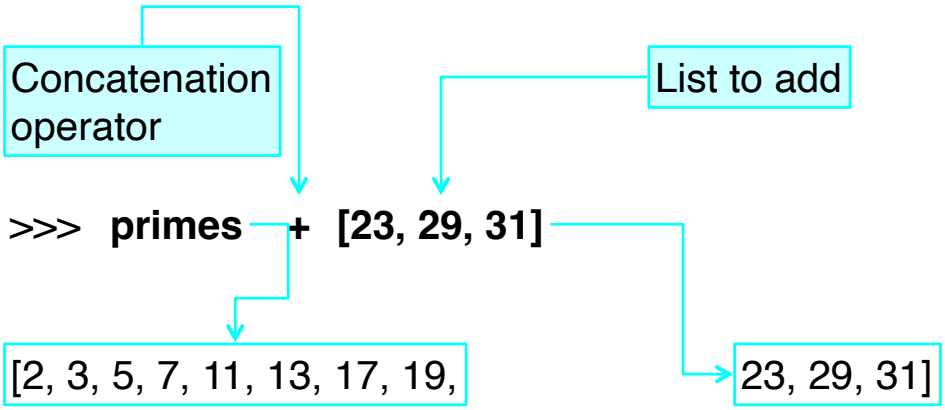
Q quit

Help on a single method

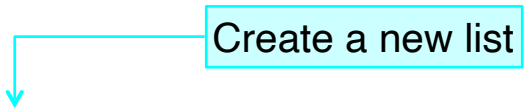
```
>>> help(numbers.append)

Help on built-in function append:

append(...)
    L.append(object) -- append object to end
```

Adding to a list *redux*: "+"

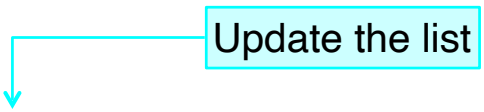
```
>>> primes
[2, 3, 5, 7, 11, 13, 17, 19]
>>> primes + [23, 29, 31]
```



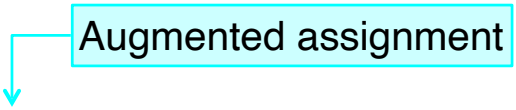
Concatenation




```
>>> newlist = primes + [23, 29, 31]
```




```
>>> primes = primes + [23, 29, 31]
```




```
>>> primes += [23, 29, 31]
```

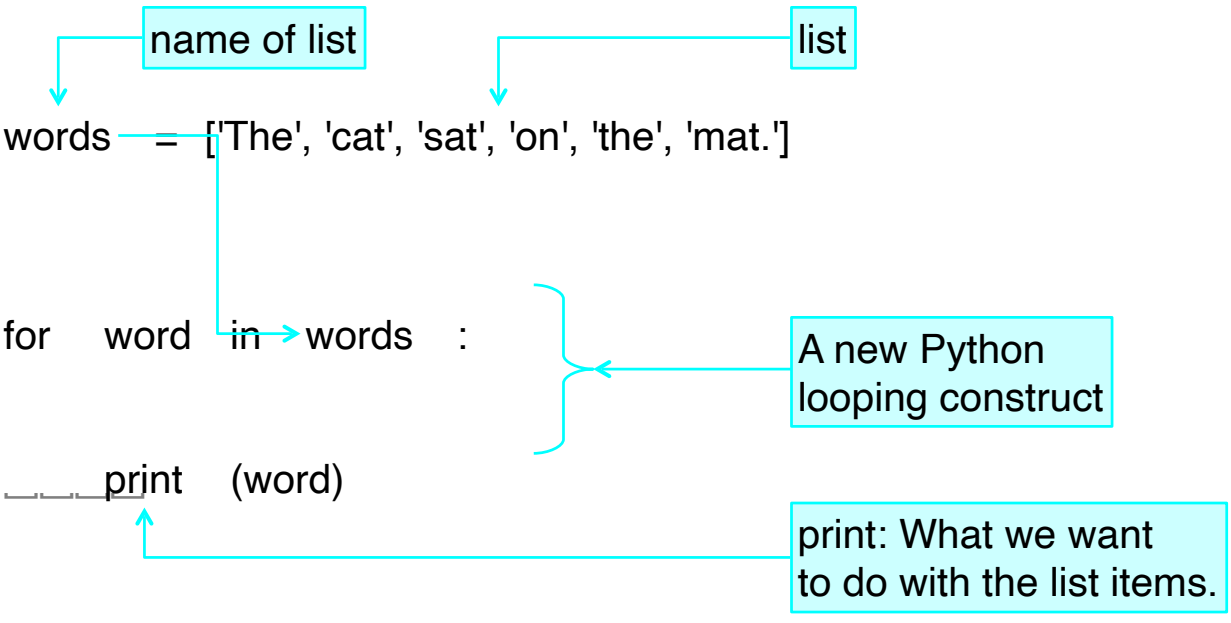
Print a list

Printing each element on a line

['The', 'cat', 'sat', 'on', 'the', 'mat.']

The
cat
sat
on
the
mat.

The "for loop" — 1



The “for loop” — 2

```
words = ['The', 'cat', 'sat', 'on', 'the', 'mat.']

for word in words :
    print (word)
```

keywords

colon followed by an indented block

The “for loop” — 3

```
words = ['The', 'cat', 'sat', 'on', 'the', 'mat.']

for word in words :
    print( word )
```

Defining the **loop variable**

Using the loop variable

Exercise 5

What does this print?

```
numbers = [0, 1, 2, 3, 4, 5]

total = 0
total_so_far = []

for number in numbers:
    total += number
    total_so_far.append(total)

print(total_so_far)
```


List "slices"

```
>>> primes = [2, 3, 5, 7, 11, 13, 17, 19, 23, 29]

>>> primes
[2, 3, 5, 7, 11, 13, 17, 19, 23, 29]
```

The list

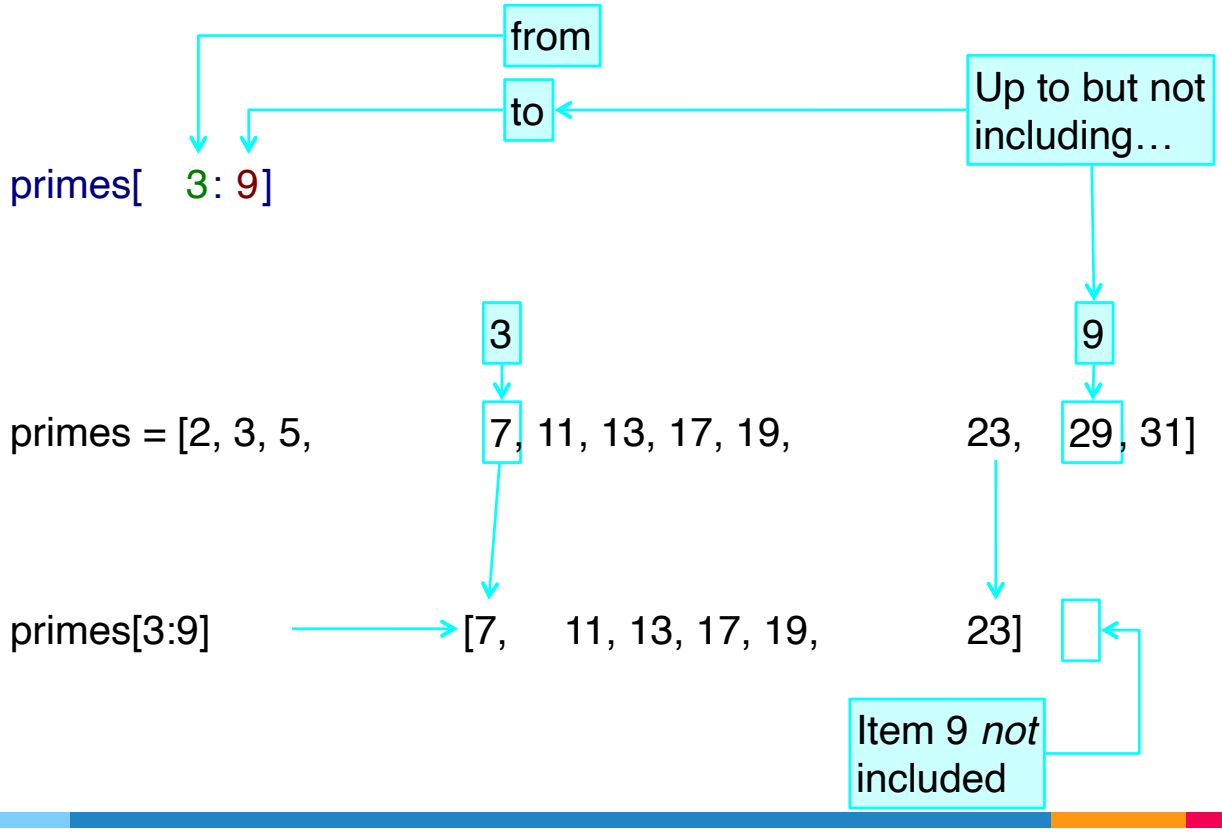
```
>>> primes[3]
7
```

An item

```
>>> primes[3:9]
[7, 11, 13, 17, 19, 23]
```

Part of the list

Slices — 1



Slices — 2

primes [2, 3, 5, 7, 11, 13, 17, 19, 23, 29, 31]

primes[3: 9] [7, 11, 13, 17, 19, 23]

primes[: 9] [2, 3, 5, 7, 11, 13, 17, 19, 23]

primes[3:] [7, 11, 13, 17, 19, 23, 29, 31]

primes[:] [2, 3, 5, 7, 11, 13, 17, 19, 23, 29, 31]

Slices — 3

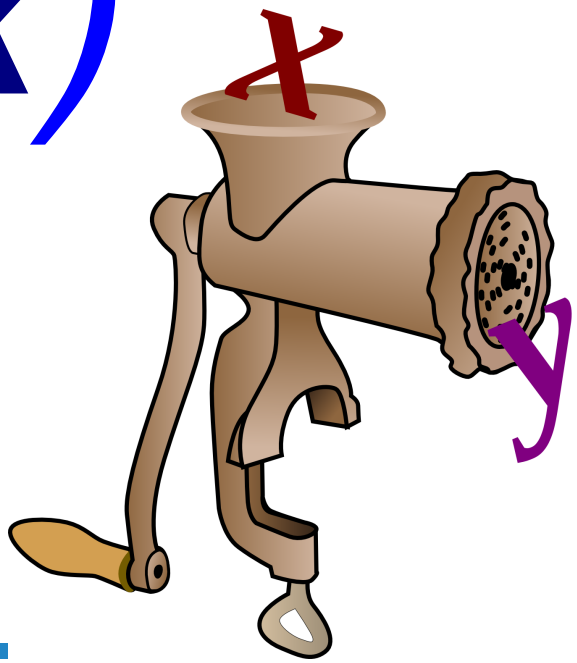
```
primes          [2, 3, 5,     7, 11, 13, 17, 19,        23,   29, 31]
```

```
primes[  3: 9]              [7, 11, 13, 17, 19, 23]
primes[  3: 9: 2]           [7,   13,   19   ]
primes[  3: 9: 3]           [7,      17      ]
```


Function

Functions

$$y = f(x)$$



Functions we have met

input(*prompt*)

len(*thing*)

open(*filename*, *mode*)

print(*line*)

type(*thing*)

ord(*char*)

chr(*number*)

Not that many!

bool(*thing*)

float(*thing*)

int(*thing*)

iter(*list*)

list(*thing*)

range(*from*, *to*, *stride*)

str(*thing*)

"The Python Way":
If it is appropriate to an object, make it a method of that object.

Why write our own functions?

Easier to …

… read

… write

… test

… fix

… improve

… add to

… develop

"Structured programming"

Defining a function

$(y_1, y_2, y_3) = f(x_1, x_2, x_3, x_4, x_5)$

Identify the inputs

Identify the processing

Identify the outputs

A function to define: total()

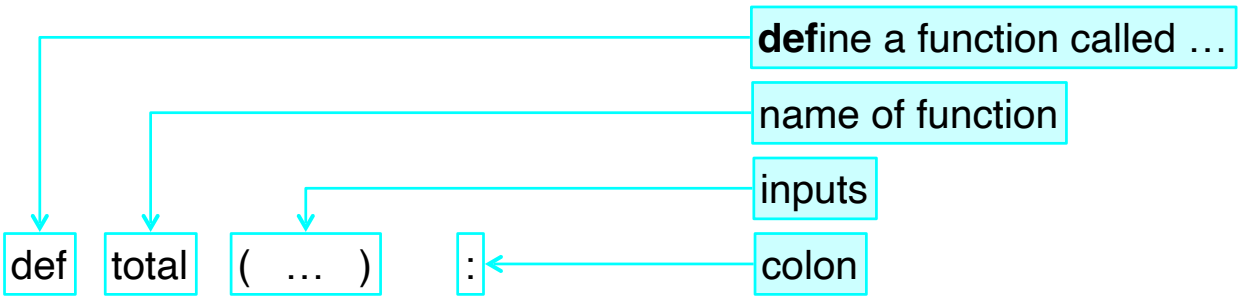
Sum a list

[1, 2, 3] → 6

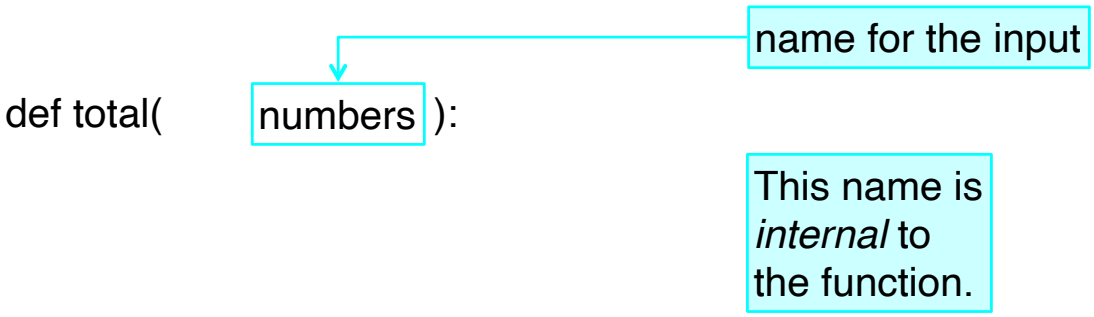
[7, -4, 1, 6, 0] → 10

[ ] → 0 "Edge case"

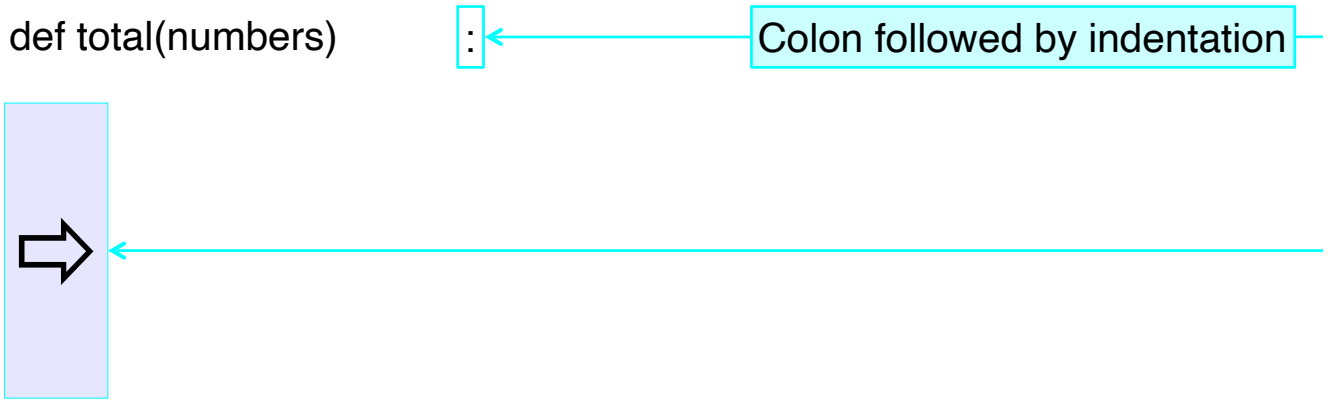
Defining a Python function — 1



Defining a Python function — 2



Defining a Python function — 3



Defining a Python function — 4

```
def total(numbers):
    sum_so_far = 0

    for number in numbers:
        sum_so_far += number
```

"Body" of function

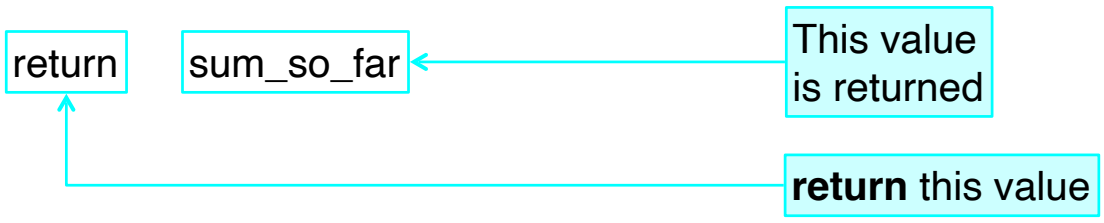
Defining a Python function — 4

```
def total( numbers ):
    sum_so_far = 0

    for number in numbers:
        sum_so_far += number
```

These variables exist *only* within the function's body.

Defining a Python function — 5

```
def total(numbers):

    sum_so_far = 0

    for number in numbers:
        sum_so_far += number
```



Defining a Python function — 6

And that's it!

```
def total(numbers):

    sum_so_far = 0

    for number in numbers:
        sum_so_far += number

    return sum_so_far
```

Defining a Python function — 7

And that's it!

All internal names *internal* → No need to avoid reusing names

All internal names cleaned up → No need for del

Using a Python function — 1

```
def total(numbers):

    sum_so_far = 0

    for number in numbers:
        sum_so_far += number

    return sum_so_far


print(     total(     [1, 2, 3]       ) )
```

The list we want to add up

Using a Python function — 2

```
def total(numbers):

    sum_so_far = 0

    for number in numbers:
        sum_so_far += number

    return sum_so_far


print(    total(    [1, 2, 3]    ) )
```

The function we have just written

Using a Python function — 3

```
def total(numbers):

    sum_so_far = 0

    for number in numbers:
        sum_so_far += number

    return sum_so_far


print(    total(    [1, 2, 3]    ) )
```

Printing out the answer

Exercise 6

- It currently defines and uses a function total() which adds the elements of a list.
- Change it to create a function threetimestotal()
- which multiplies them with 3 for each elements before total them.

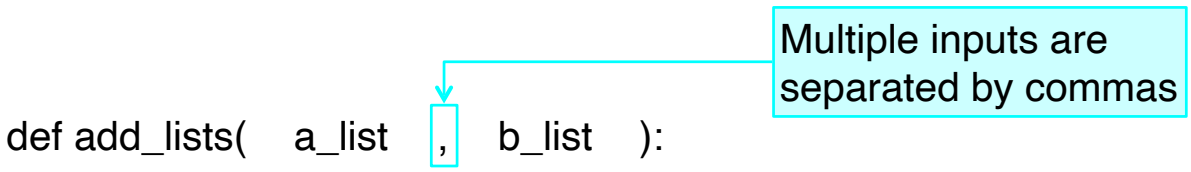
Anonymous (lambda) Functions

- Python has support “anonymous” or “lambda” functions
- It consists of a single statement, the result is the return value
- Use “lambda” keyword.
- They are convenient in data analysis

```
def short_foo(x):
    return x * 2
```

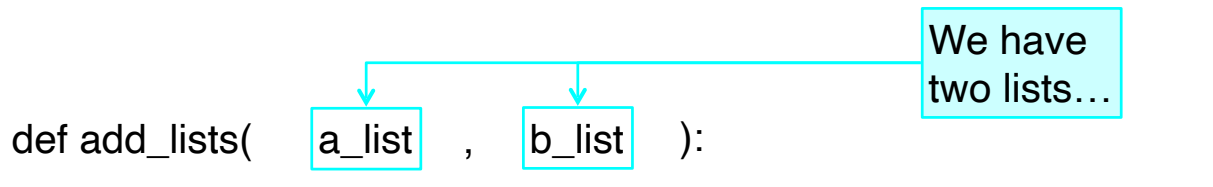
```
lambda_short_foo = lambda x: x *
```

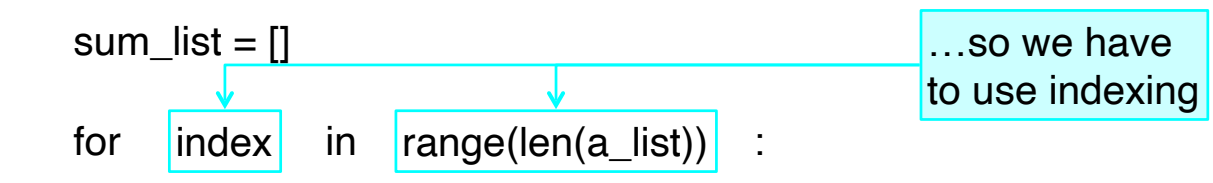
Functions with multiple inputs




```
def add_lists(    a_list    ,    b_list    ):
    sum_list = []
    for    index    in    range(len(a_list)) :
        sum  =  a_list[index]          +  b_list[index]
        sum_list.append(sum)
    return sum_list
```


Functions with multiple inputs

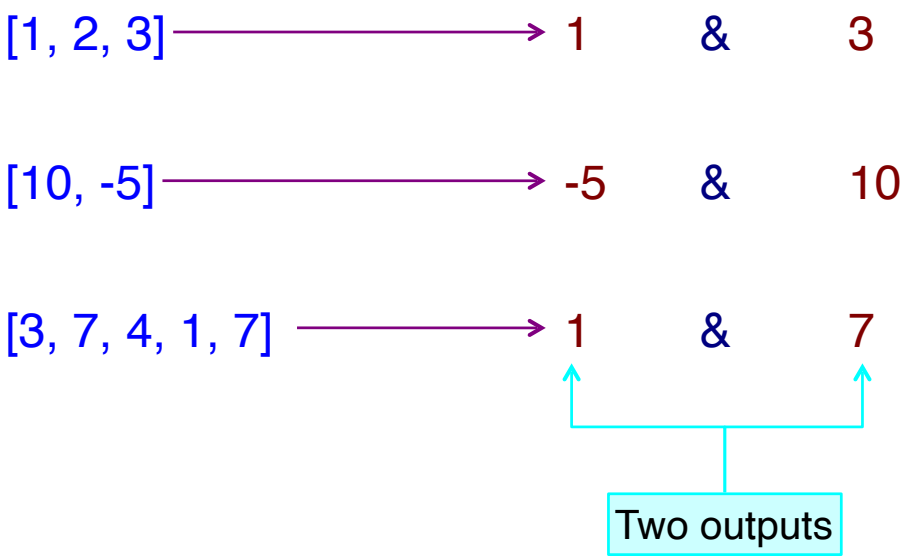





```
def add_lists(    a_list    ,    b_list    ):
    sum_list = []
    for    index    in    range(len(a_list))    :
        sum  =  a_list[index]          +  b_list[index]
        sum_list.append(sum)
    return sum_list
```

Multiple outputs

- Write a function to find minimum *and* maximum value in a list



Finding both

```
def minmax_list(a_list):

    min_so_far = a_list[0]
    max_so_far = a_list[0]

    for   a  in   a_list  :

        if a < min_so_far:
            min_so_far = a

        if a > max_so_far:
            max_so_far = a
```

return *what?* ← This is the real question

Returning both

```
def minmax_list(a_list):

    min_so_far = a_list[0]
    max_so_far = a_list[0]

    for   a  in   a_list    :

        if a < min_so_far:
            min_so_far = a

        if a > max_so_far:
            max_so_far = a

    return    min_so_far, max_so_far
```

A *pair* of values

"Tuples"

e.g. min_value , max_value — Pair

min_value , avg_value , max_value — Triple

Commas

Often written with parentheses:

(min_value , max_value)

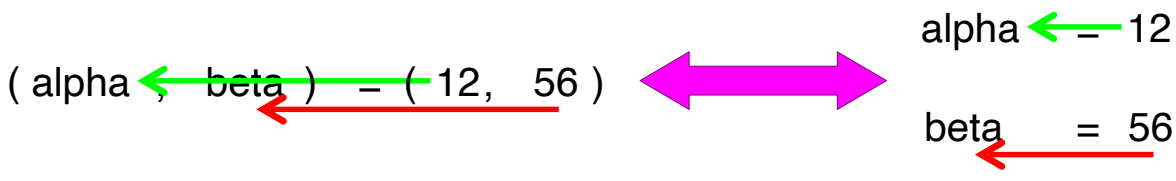
(min_value , avg_value , max_value)

Using tuples to return values

```
def  …                                          In the function definition

     return      min_value     ,   max_value
```

```
                                                Using the function

minimum   ,   maximum    = minmax_list(values)
```


Using tuples to attach names



Swapping values

```
>>> alpha = 12
>>> beta = 56
>>> (alpha, beta) = (beta, alpha)
>>> print(alpha)
56
>>> print(beta)
12
```

Swapping values

Tuples and lists: similarities

```
>>> x = ['alpha','beta']
>>> x[1]
'beta'
```

Indexing

```
>>> len(x)
2
```

Length

```
>>> (a, b) = (1, 2)
>>> a
1
```

Simultaneous asignment

```
>>> y = ('alpha','beta')
>>> y[1]
'beta'
>>> len(y)
2
>>> [c, d] = [1, 2]
>>> c
1
```

Tuples and lists: differences

```
>>> x = ['alpha','beta']

>>> x[1] = 'B'

>>> x
['alpha','B']
```

Lists are *mutable*

```
>>> y = ('alpha','beta')

>>> y[1] = 'B'
TypeError:
'tuple' object does not
support item assignment
```

Tuples are *immutable*

Tuples and lists: philosophy

Lists

Sequential:
Concept of “next item”

Best with all items
of the same type

Serial

[2, 3, 5, 7, 11, 13,
17, 19, 23, 29, 31]

Sequence of prime numbers

Tuples

Simultaneous:
All items “at once”

Safe to have
multiple types

Parallel

('Dowling', 'Bob',
50, 105.0, 'rjd4')

Surname, forename,
age, weight, user id

Reusing functions within a script

```
def square(limit):
    ...

...

squares_a = square(34)

...

five_squares = squares(5)

...

squares_b = squares(56)

...
```

One definition

Multiple uses in the same file

Easy!

Reusing functions between scripts?

```
def squares(limit):
    ...
```

One definition

```
...
squares_a = squares(34)
...
```

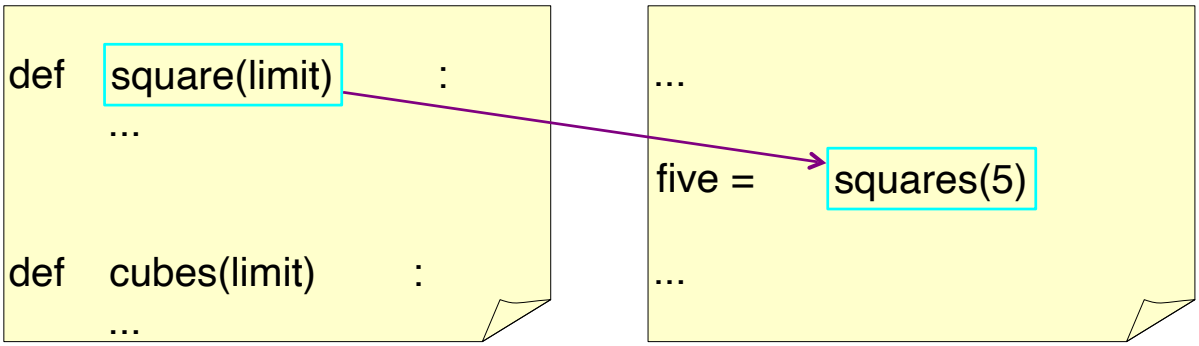
```
...
squares_b = squares(56)
...
```

Multiple uses in multiple files

```
five_squares = squares(5)

...
```

How?

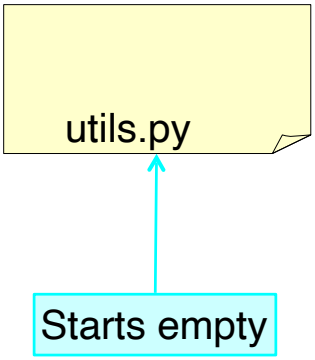
"Modules"



Definition → Use

Module: a container of functions

Modules: a worked example — 1a




```
def squares(limit):
    answer = []
    for n in range(0,limit):
        answer.append(n**2)
    return answer

def total(numbers):
    sum_so_far = 0
    for number in numbers:
        sum_so_far += number
    return sum_so_far

text = input('Number? ')
number = int(text)
squares_n = squares(number)
total_n = total(squares_n)
print(total_n)
```

sum_squares.py

Modules: a worked example — 1b

$ **python3 sum_squares.py**

Number? **5**

30 = 0 + 1 + 4 + 9 + 16

$ **python3 sum_squares.py**

Number? **7**

91 = 0 + 1 + 4 + 9 + 16 + 25 + 36

Modules: a worked example — 2a

```
def squares(limit):
    answer = []
    for n in range(0,limit):
        answer.append(n**2)
    return answer

def total(numbers):
    sum_so_far = 0
    for number in numbers:
        sum_so_far += number
    return sum_so_far
```

utils.py

```
text = input('Number? ')
number = int(text)
squares_n = squares(number)
total_n = total(squares_n)
print(total_n)
```

sum_squares.py

Move the definitions into the other file.

Modules: a worked example — 2b

```
$ python3 sum_squares.py

Number? 5

Traceback (most recent call last):
  File "sum_squares.py", line 4, in <module>
    squares_n = squares(number)
NameError: name 'squares' is not defined
```

Because we have (re)moved its definition.

Modules: a worked example — 3a

```
def squares(limit):
    answer = []
    for n in range(0,limit):
        answer.append(n**2)
    return answer

def total(numbers):
    sum_so_far = 0
    for number in numbers:
        sum_so_far += number
    return sum_so_far
```

utils.py

```
import utils


text = input('Number? ')
number = int(text)
squares_n = squares(number)
total_n = total(squares_n)
print(total_n)
```

sum_squares.py

import utils and *not* import utils.py

import: Make a reference to the other file.

Modules: a worked example — 3b

```
$ python3 sum_squares.py

Number? 5

Traceback (most recent call last):
  File "sum_squares.py", line 4, in <module>
    squares_n = squares(number)
NameError: name 'squares' is not defined
```

Still can't find the function(s).

Modules: a worked example — 4a

squares()

utils.squares()

total()

utils.total()

```
import utils

text = input('Number? ')
number = int(text)
squares_n = utils.squares(number)
total_n = utils.total(squares_n)
print(total_n)
```

sum_squares.py

utils.…: Identify the functions as coming from the module.

Modules: a worked example — 4b

```
$ python3 sum_squares.py
Number? 5
30

$ python3 sum_squares.py
Number? 7
91
```

Working again!

Python Library

The Python philosophy

A small core language …

… plus lots of modules

Example: the “math” module

```
>>> import math
```

Load in the “math” module.

Run the sqrt() function…

```
>>> math. sqrt( 2.0)
```

… from the math module.

```
1.4142135623730951
```

import *module* as *alias*

```
>>> import math
>>> math.sqrt(2.0)
1.4142135623730951

>>> import math as m
>>> msqrt(2.0)
1.4142135623730951
```

Too long to keep typing?

"Alias"

Don't do these

```
>>> from math import sqrt
>>> sqrt(2.0)
1.4142135623730951
```

Much better to track the module.

```
>>> from math import *
>>> sqrt(2.0)
1.4142135623730951
```

What system modules are there?

Python 3.2.3 comes with over 250 modules.

glob	math	argparse	csv
io	cmath	datetime	html
os	random	getpass	json
signal	colorsys	logging	re
subprocess	email	pickle	string
sys	http	sqlite3	unicodedata
tempfile	webbrowser	unittest	xml

Additional downloadable modules

Numerical

numpy

scipy

panda

Graphics

matplotlib

Databases

pyodbc	
psycopg2	PostgreSQL
MySQLdb	MySQL
cx_oracle	Oracle
ibm_db	DB2
pymssql	SQL Server

Help with modules

```
>>> import math

>>> help(math)

NAME
    math

DESCRIPTION
    This module is always available.  It provides
    access to the mathematical functions defined
    by the C standard.

…
```


Help with module functions

```
…

FUNCTIONS

  acos(x)
    Return the arc cosine (measured in
    radians) of x.
…


>>> math.acos(1.0)

0.0
```

Help with module constants

```
…

DATA
    e = 2.718281828459045
    pi = 3.141592653589793
…
```

```
>>> math.pi

3.141592653589793
```


Help for our own modules?

```
def squares(limit):
    answer = []
    for n in range(0,limit):
        answer.append(n**2)
    return answer

def total(numbers):
    sum_so_far = 0
    for number in numbers:
        sum_so_far += number
    return sum_so_far
```

utils.py

Basic help already provided by Python

```
>>> import utils

>>> help(utils)

NAME
  utils

FUNCTIONS
  squares(limit)

  total(numbers)

FILE
  /home/y550/utils.py
```

Adding extra help text

```
"""Some utility functions
from the Python for
Absolute Beginners course
"""

def squares(limit):
    answer = []
    for n in range(0,limit):
        answer.append(n**2)
    return answer

def total(numbers):
    sum_so_far = 0
    for number in numbers:
        sum_so_far += number
    return sum_so_far
```

utils.py

```
>>> import utils

>>> help(utils)

NAME
  utils

DESCRIPTION
  Some utility functions
  from the Python for
  Absolute Beginners course

FUNCTIONS
  squares(limit)

  total(numbers)
```

Fresh start

Adding extra help text to functions

```
"""Some utility functions
from the Python for
Absolute Beginners course
"""

def squares(limit):
    """Returns a list of
    squares from zero to
    limit**2.
    """
    answer = []
    for n in range(0,limit):
        answer.append(n**2)
    return answer
```

utils.py

```
>>> import utils

>>> help(utils)

NAME
  utils

DESCRIPTION
  ...

FUNCTIONS
  squares(limit)
      Returns a list of
      squares from zero to
      limit**2.
```

Fresh start

Adding extra help text to functions

```
"""Some utility functions
from the Python for
Absolute Beginners course
"""

def squares(limit):
    """Returns a list of
    squares from zero to
    limit**2.
    """
    answer = []
    for n in range(0,limit):
        answer.append(n**2)
    return answer
```

utils.py

```
>>> import utils
```

Fresh start

```
>>> help(utils.squares)
```

```
squares(limit)
    Returns a list of
    squares from zero to
    limit**2.
```


NumPy

Without NumPy

```
from math import sin, pi

def sinc(x):
    if x == 0:
        return 1.0
    else:
        pix = pi*x
        return sin(pix)/pix

def step(x):
    if x > 0:
        return 1.0
    elif x < 0:
        return 0.0
    else:
        return 0.5
```

functions.py

```
>>> import functions as f
>>> xval = [x/3.0 for x in
range(-10,10)]
>>> yval1 = [f.sinc(x) for x
in xval]
>>> yval2 = [f.step(x) for x
in xval]
```

Python is a great language but needed a way to operate quickly and cleanly over multi-dimensional arrays.

With NumPy

```
from numpy import sin, pi
from numpy import vectorize
import functions as f

vsinc = vectorize(f.sinc)
def sinc(x):
    pix = pi*x
    val = sin(pix)/pix
    val[x==0] = 1.0
    return val

vstep = vectorize(f.step)
def step(x):
    y = x*0.0
    y[x>0] = 1
    y[x==0] = 0.5
    return y
```

functions2.py

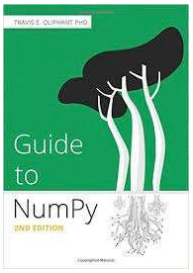
```
>>> import functions2 as f
>>> from numpy import *
>>> x = r_[-10:10]/3.0
>>> y1 = f.sinc(x)
>>> y2 = f.step(x)
```

Offers N-D array, element-by-element functions, and basic random numbers, linear algebra, and FFT capability for Python

http://numpy.org

Fiscally sponsored by NumFOCUS

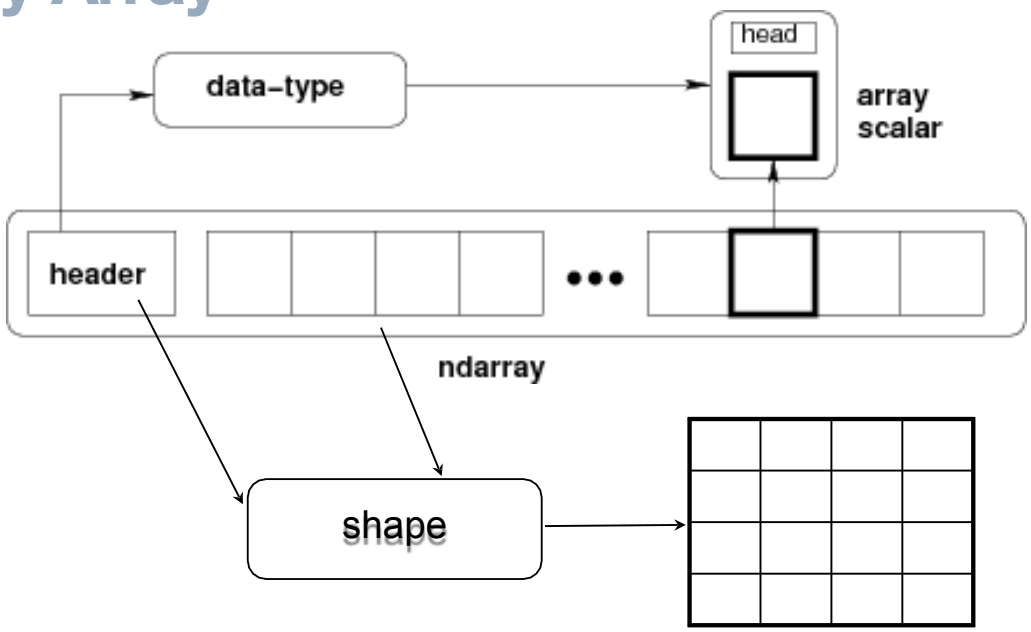
NumPy: an Array Extension of Python



- Data: the array object
  - slicing and shaping
  - data-type map to Bytes
- Fast Math (ufuncs):
  - vectorization
  - broadcasting
  - aggregations

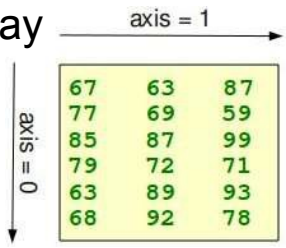
NumPy Array

Key Attributes
- dtype
- shape
- ndim
- strides
- data



NumPy Examples

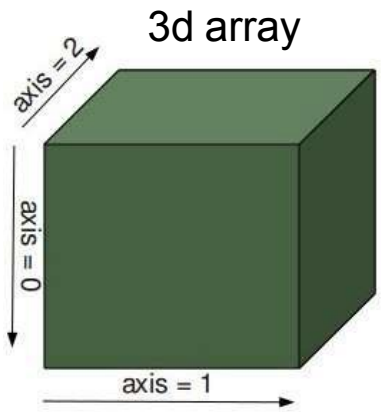
2d array




```
1  import numpy as np
2
3  x = np.array([[67, 63, 87],
4                [77, 69, 59],
5                [85, 87, 89],
6                [79, 72, 71],
7                [63, 89, 93],
8                [68, 92, 78]])
9  print x.sum(axis=0), x.sum(axis=1)
```

[439 472 477]
[217 205 261 222 245 238]

3d array

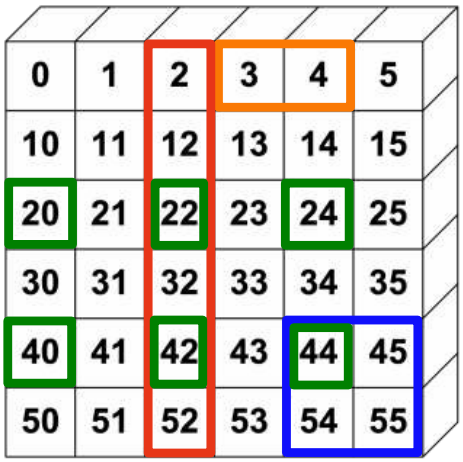



```
12  y = 3*np.random.randn(10,20,30)+10
13  print y.mean(), y.std()
```

9.98330639789 2.96677717122

NumPy Slicing (Selection)

```
>>> a[0,3:5]
array([3, 4])

>>> a[4:,4:]
array([[44, 45],
       [54, 55]])

>>> a[:,2]
array([2,12,22,32,42,52])

>>> a[2::2,::2]
array([[20, 22, 24],
       [40, 42, 44]])
```



SciPy

SciPy

"Distribution of Python Numerical Tools masquerading as a Library"

Name	Description
cluster	KMeans and Vector Quantization
fftpack	Discrete Fourier Transform
integrate	Numerical Integration
interpolate	Interpolation routines
io	Data Input and Output
linalg	Fast Linear algebra
misc	Utilities
ndimage	N-dimensional Image processing

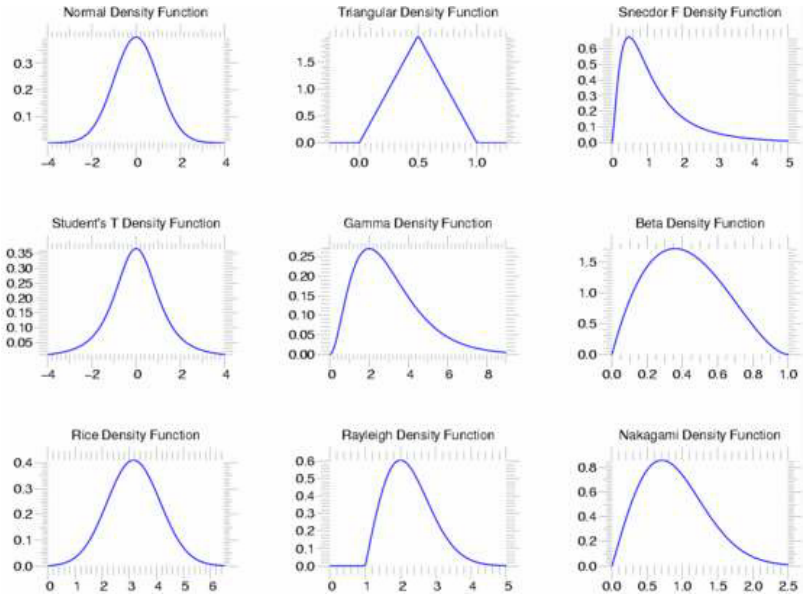
Name	Description
odr	Orthogonal Distance Regression
optimize	Constrained and Unconstrained Optimization
signal	Signal Processing Tools
sparse	Sparse Matrices and Algebra
spatial	Spatial Data Structures and Algorithms
special	Special functions (e.g. Bessel)
stats	Statistical Functions and Distributions

scipy.stats --- Continuous Distributions

94 continuous distributions!

Methods on all Random Variable Objets.

- `pdf`
- `cdf`
- `rvs`
- `ppf`
- `stats`

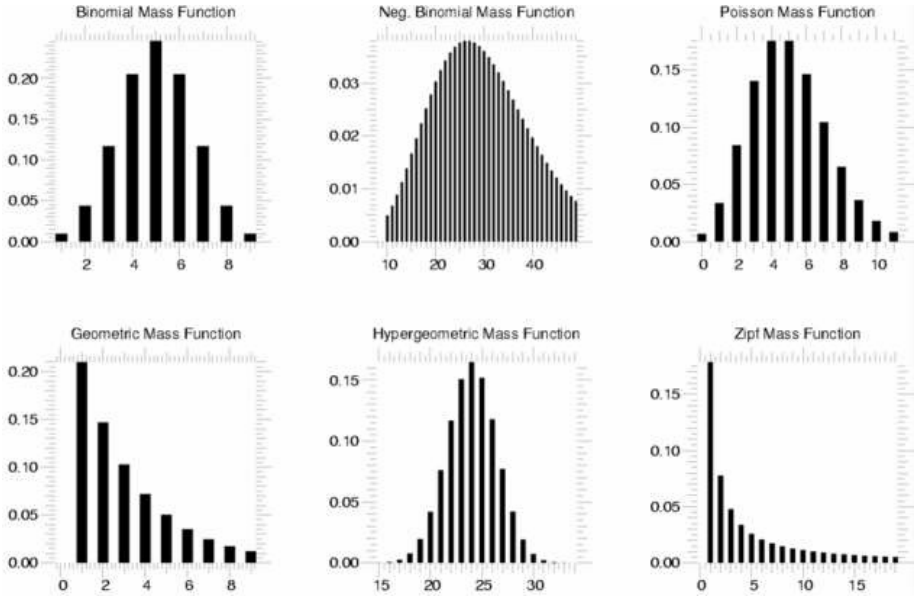


scipy.stats --- Discrete Distributions

13 standard discrete distributions (plus any arbitrary finite RV)

Methods

- `pdf`
- `cdf`
- `rvs`
- `ppf`
- `stats`

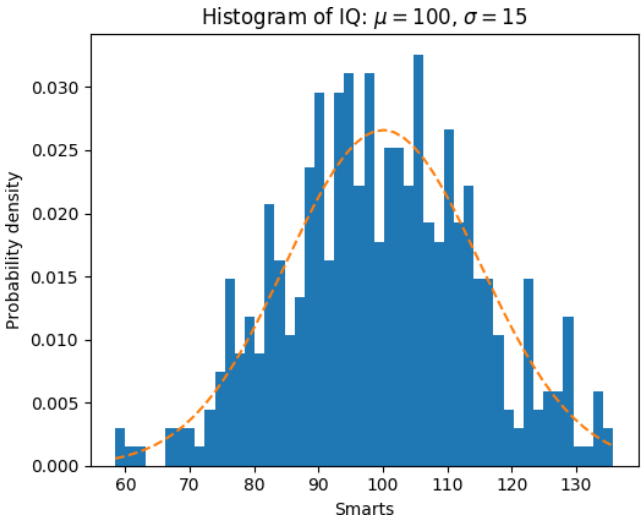


Matplotlib

matplotlib

a powerful plotting engine

```
import numpy as np
import matplotlib.mlab as mlab
import matplotlib.pyplot as plt

np.random.seed(0)

# example data
mu = 100   # mean of distribution
sigma = 15   # standard deviation of distribution
x = mu + sigma * np.random.randn(437)

num_bins = 50

fig, ax = plt.subplots()

# the histogram of the data
n, bins, patches = ax.hist(x, num_bins,  normed=1)

# add a 'best fit' line
y = mlab.normpdf(bins, mu, sigma)
ax.plot(bins, y, '--')
ax.set_xlabel('Smarts')
ax.set_ylabel('Probability density')
ax.set_title(r'Histogram of IQ:  $\mu=100$,
$\sigma=15$')

# Tweak spacing to prevent clipping of ylabel
fig.tight_layout()
plt.show()
```



matplotlib

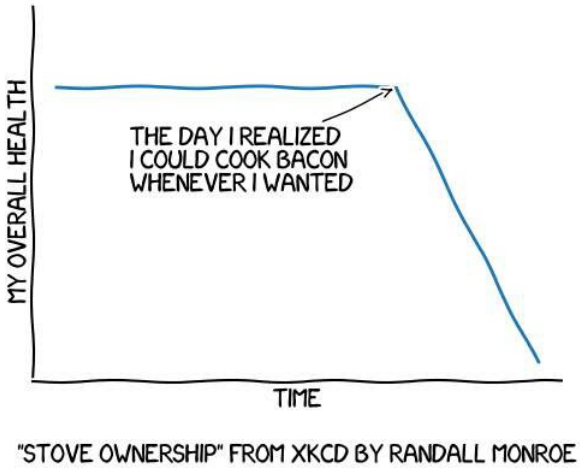
a powerful plotting engine

```
import matplotlib.pyplot as plt
import scipy.misc as misc

im = misc.face()
ax = plt.imshow(im)

plt.title('Racoon Face of size
%d x %d' % im.shape[:2])

plt.savefig('face.png')
```

matplotlib

a powerful plotting engine


```
import matplotlib.pyplot as plt
import numpy as np

with plt.xkcd():
    fig = plt.figure()
    ax = fig.add_axes((0.1, 0.2, 0.8, 0.7))
    ax.spines['right'].set_color('none')
    ax.spines['top'].set_color('none')
    plt.xticks([])
    plt.yticks([])
    ax.set_ylim([-30, 10])
    data = np.ones(100)
    data[70:] -= np.arange(30)

    plt.annotate('THE DAY I REALIZED\nI COULD
COOK BACON\nWHENEVER I WANTED',
        xy=(70, 1),
        arrowprops=dict(arrowstyle='->'),
        xytext=(15, -10))

    plt.plot(data)

    plt.xlabel('time')
    plt.ylabel('my overall health')
    fig.text(0.5, 0.05, '"Stove Ownership" from
xkcd by Randall Monroe',
         ha='center')
```

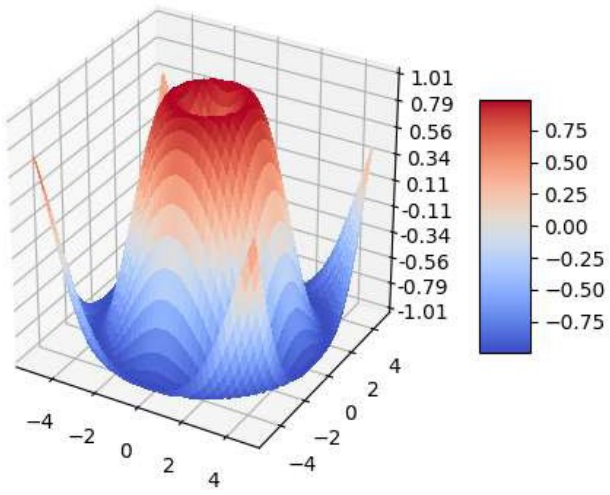


"STOVE OWNERSHIP" FROM XKCD BY RANDALL MONROE

matplotlib

a powerful plotting engine

```
from mpl_toolkits.mplot3d import Axes3D
import matplotlib.pyplot as plt
from matplotlib import cm
from matplotlib.ticker import LinearLocator,
FormatStrFormatter
import numpy as np

fig = plt.figure()
ax = fig.gca(projection='3d')
# Make data.
X = np.arange(-5, 5, 0.25)
Y = np.arange(-5, 5, 0.25)
X, Y = np.meshgrid(X, Y)
R = np.sqrt(X**2 + Y**2)
Z = np.sin(R)
# Plot the surface.
surf = ax.plot_surface(X, Y, Z, cmap=cm.coolwarm,
linewidth=0, antialiased=False)

# Customize the z axis.
ax.set_zlim(-1.01, 1.01)
ax.zaxis.set_major_locator(LinearLocator(10))
ax.zaxis.set_major_formatter(FormatStrFormatter('%
.02f'))

# Add a color bar which maps values to colors.
fig.colorbar(surf, shrink=0.5, aspect=5)
plt.show()
```

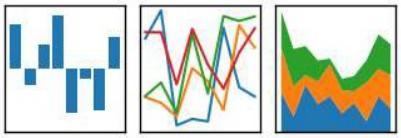


Pandas

Easy Data Wrangling

pandas

$y_{it} = \beta' x_{it} + \mu_i + \epsilon_{it}$

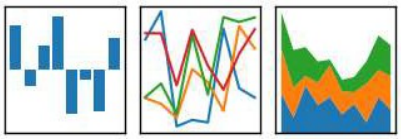


- Adds **indexes and labels** to 1-d and 2-d NumPy arrays (Series and DataFrame)
- Many convenience functions and methods to manipulate messy data-sets including **time-series**.
- Powerful indexing with automatic **data alignment**.
- Easy handling of **missing data**.
- Allows easy j**oining and merging** Data Sets
- **Pivots** and reshaping (split-apply-combine)
- Powerful **group-by** operations with **summarization**
- Builtin visualization using labels and indexes

Easy Data Wrangling

pandas

$y_{it} = \beta' x_{it} + \mu_i + \epsilon_{it}$

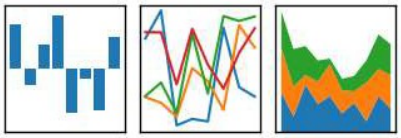


- Series Data Structure
  - built for **1-dimensional** series data
  - homogeneous data
  - Two arrays. One of data and another which is the index that can be a homogeneous array of any type like integers, objects, or date-times.
- DataFrame
  - built for **2-dimensional** collections of tabular data (think Excel sheet)
  - heterogeneous data comprised of multiple Series
  - includes an index column allowing sophisticated selection and alignment

Easy Data Wrangling

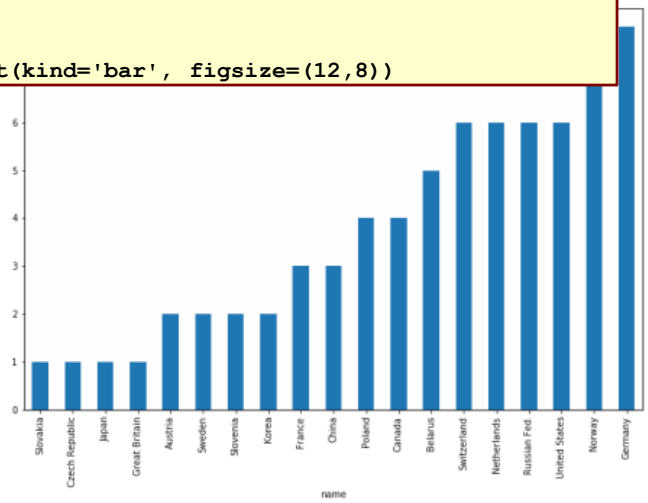
pandas

$y_{it} = \beta' x_{it} + \mu_i + \epsilon_{it}$



```
medals = pd.read_csv('data/medals.csv', index_col='name')
medals.head()
gold = medals['medal'] == 'gold'
won = medals['count'] > 0
medals.loc[gold & won, 'count'].sort_values().plot(kind='bar', figsize=(12,8))
```

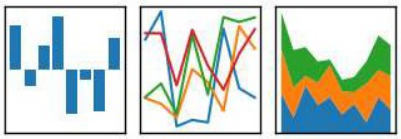
	count	medal	country
name			
Australia	1	bronze	AUS
Australia	2	silver	AUS
Australia	0	gold	AUS
Austria	1	bronze	AUT
Austria	6	silver	AUT



Easy Data Wrangling

pandas

$y_{it} = \beta' x_{it} + \mu_i + \epsilon_{it}$



```
google = pd.read_csv('data/goog.csv', index_col='Date', parse_dates=True)
google.info()
google.head()
google.describe()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 1257 entries, 2010-01-04 to 2014-12-31
Data columns (total 5 columns):
Open      1257 non-null float64
High      1257 non-null float64
Low       1257 non-null float64
Close     1257 non-null float64
Volume    194 non-null float64
dtypes: float64(5)
memory usage: 58.9 KB
```

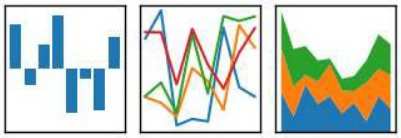
	Open	High	Low	Close	Volume
Date					
2010-01-04	313.16	314.44	311.81	313.06	NaN
2010-01-05	313.28	313.61	310.46	311.68	NaN
2010-01-06	312.62	312.62	302.88	303.83	NaN
2010-01-07	304.40	304.70	296.03	296.75	NaN
2010-01-08	295.70	301.32	294.26	300.71	NaN

	Open	High	Low	Close	Volume
count	1257.000000	1257.000000	1257.000000	1257.000000	1.940000e+02
mean	375.275593	378.450247	372.132474	375.327064	1.937264e+06
std	115.684354	116.288827	114.935742	115.664301	9.842775e+05
min	218.940000	220.920000	216.600000	217.820000	7.040350e+05
25%	285.790000	288.760000	283.060000	285.450000	1.338451e+06
50%	318.330000	320.800000	315.180000	317.260000	1.684634e+06
75%	452.540000	456.020000	449.740000	452.830000	2.164369e+06
max	612.790000	613.830000	608.690000	609.470000	6.795393e+06

Easy Data Wrangling

pandas

$y_{it} = \beta' x_{it} + \mu_i + \epsilon_{it}$



```
df = pd.read_excel("data/pbpython/salesfunnel.xlsx")
df.head()
table = pd.pivot_table(df,
                       index=["Manager","Rep","Product"],
                       values=["Price","Quantity"],
                       aggfunc=[np.sum,np.mean])
```

	Account	Name	Rep	Manager	Product	Quantity	Price	Status
0	714466	Trantow-Barrows	Craig Booker	Debra Henley	CPU	1	30000	presented
1	714466	Trantow-Barrows	Craig Booker	Debra Henley	Software	1	10000	presented
2	714466	Trantow-Barrows	Craig Booker	Debra Henley	Maintenance	2	5000	pending
3	737550	Fritsch, Russel and Anderson	Craig Booker	Debra Henley	CPU	1	35000	declined
4	146832	Kiehn-Spinka	Daniel Hilton	Debra Henley	CPU	2	65000	won

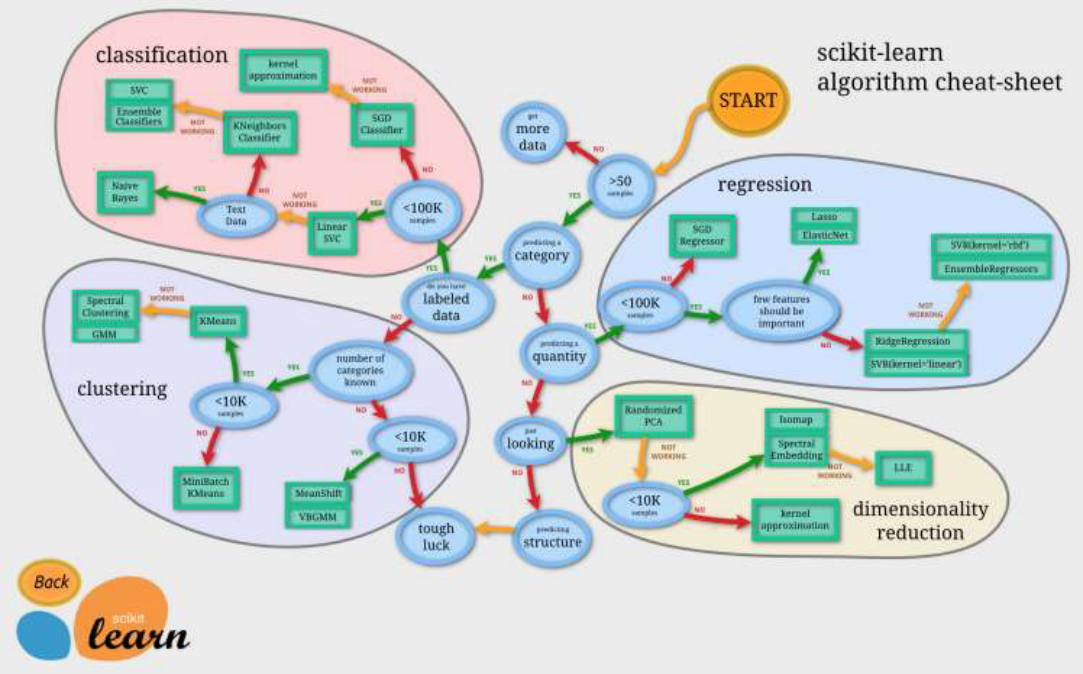
			sum		mean	
			Price	Quantity	Price	Quantity
Manager	Rep	Product				
Debra Henley	Craig Booker	CPU	65000	2	32500.0	1.0
		Maintenance	5000	2	5000.0	2.0
		Software	10000	1	10000.0	1.0
	Daniel Hilton	CPU	105000	4	52500.0	2.0
		Software	10000	1	10000.0	1.0
	John Smith	CPU	35000	1	35000.0	1.0
		Maintenance	5000	2	5000.0	2.0
Fred Anderson	Cedric Moss	CPU	95000	3	47500.0	1.5
		Maintenance	5000	1	5000.0	1.0
		Software	10000	1	10000.0	1.0
	Wendy Yule	CPU	165000	7	82500.0	3.5
		Maintenance	7000	3	7000.0	3.0
		Monitor	5000	2	5000.0	2.0

Scikit-Learn

Machine Learning made easy

- **Supervised Learning** — uses “labeled” data to train a model
  - Regression — predicted variable is continuous
  - Classification — predicted variable is discrete
- **Unsupervised Learning**
  - Clustering — discover categories in the data
  - Density Estimation — determine representation of data
  - Dimensionality Reduction — represent data with fewer variables or feature vectors

- Reinforcement Learning — “goal-oriented” learning (e.g. drive a car)
- **Deep Learning** — neural networks with many layers
- Semi-supervised Learning (use some labeled data for training)



Python Libraries for Data Science

Many popular Python toolboxes/libraries:

- NumPy
- SciPy
- Pandas
- SciKit-Learn

Visualization libraries

- matplotlib
- Seaborn

and many more …

Loading Python Libraries

```
In [ ]: #Import Python Libraries
        import numpy as np
        import scipy as sp
        import pandas as pd
        import matplotlib as mpl
        import seaborn as sns
```

Press `Shift+Enter` to execute the *jupyter* cell

Reading data using pandas

In [ ]:
```
#Read csv file
df = pd.read_csv("Salaries.csv")
```

Note: The above command has many optional arguments to fine-tune the data import process.

There is a number of pandas commands to read other data formats:

```
pd.read_excel('myfile.xlsx',sheet_name='Sheet1', index_col=None,
na_values=['NA'])
pd.read_stata('myfile.dta')
pd.read_sas('myfile.sas7bdat')
pd.read_hdf('myfile.h5','df')
```


Exploring data frames

In [3]:
```
#List first 5 records
df.head()
```

Out[3]:

	rank	discipline	phd	service	sex	salary
0	Prof	B	56	49	Male	186960
1	Prof	A	12	6	Male	93000
2	Prof	A	23	20	Male	110515
3	Prof	A	40	31	Male	131205
4	Prof	B	20	18	Male	104800

Data Frame data types

Pandas Type	Native Python Type	Description
object	string	The most general dtype. Will be assigned to your column if column has mixed types (numbers and strings).
int64	int	Numeric characters. 64 refers to the memory allocated to hold this character.
float64	float	Numeric characters with decimals. If a column contains numbers and NaNs(see below), pandas will default to float64, in case your missing value has a decimal.
datetime64, timedelta[ns]	N/A (but see the datetime module in Python's standard library)	Values meant to hold time data. Look into these for time series experiments.

Data Frame data types

```
In [4]: #Check a particular column type
        df['salary'].dtype
```

```
Out[4]: dtype('int64')
```

```
In [5]: #Check types for all the columns
        df.dtypes
```

```
Out[4]: rank          object
        discipline    object
        phd           int64
        service       int64
        sex           object
        salary        int64
        dtype: object
```

Data Frames attributes

Python objects have *attributes* and *methods*.

df.attribute	description
dtypes	list the types of the columns
columns	list the column names
axes	list the row labels and column names
ndim	number of dimensions
size	number of elements
shape	return a tuple representing the dimensionality
values	numpy representation of the data

Exercises 7

✓Find how many records this data frame has;

✓How many elements are there?

✓What are the column names?

✓What types of columns we have in this data frame?

Data Frames methods

Unlike attributes, python methods have *parenthesis.*
All attributes and methods can be listed with a *dir()* function:
`dir(df)`

df.method()	description
head([n]), tail([n])	first/last n rows
describe()	generate descriptive statistics (for numeric columns only)
max(), min()	return max/min values for all numeric columns
mean(), median()	return mean/median values for all numeric columns
std()	standard deviation
sample([n])	returns a random sample of the data frame
dropna()	drop all the records with missing values

Data Frames Attributes

```
In [10]: #List the column names
         df.columns

Out[10]: Index(['rank', 'discipline', 'phd', 'service', 'sex', 'salary'], dtype='object')

In [11]: #List the row labels and the column names
         df.axes

Out[11]: [RangeIndex(start=0, stop=78, step=1),
          Index(['rank', 'discipline', 'phd', 'service', 'sex', 'salary'], dtype='object')]

In [12]: #Number of dimensions
         df.ndim

Out[12]: 2

In [13]: #Total number of elements in the Data Frame
         df.size

Out[13]: 468

In [14]: #Number of rows and columns
         df.shape

Out[14]: (78, 6)
```

```
In [15]: #Output basic statistics for the numeric columns
         df.describe()
```

Out[15]:

	phd	service	salary
count	78.000000	78.000000	78.000000
mean	19.705128	15.051282	108023.782051
std	12.498425	12.139768	28293.661022
min	1.000000	0.000000	57800.000000
25%	10.250000	5.250000	88612.500000
50%	18.500000	14.500000	104671.000000
75%	27.750000	20.750000	126774.750000
max	56.000000	51.000000	186960.000000

```
In [16]: #Calculate mean for all numeric columns
         df.mean()
```

```
Out[16]: phd            19.705128
         service        15.051282
         salary     108023.782051
         dtype: float64
```


exercises # 8

✓Give the summary for the numeric columns in the dataset

✓Calculate standard deviation for all numeric columns;

✓What are the mean values of the first 50 records in the dataset?

Hint: use head() method to subset the first 50 records and then calculate the mean

```
In [17]: #Calculate the standard deviation (std() method) for all numeric columns
         # <your code goes here>
         df.std()

Out[17]: phd           12.498425
         service       12.139768
         salary     28293.661022
         dtype: float64

In [18]: #Calculate average of the columns in the first 50 rows
         # <your code goes here>
         df.head(50).mean()

Out[18]: phd            21.52
         service        17.60
         salary     113789.14
         dtype: float64
```


Selecting a column in a Data Frame

Method 1: Subset the data frame using column name:

df['sex']

Method 2: Use the column name as an attribute:

df.sex

Note: there is an attribute *rank* for pandas data frames, so to select a column with a name "rank" we should use method 1.

Exercises 8-1

✓Calculate the basic statistics for the *salary* column;

✓Find how many values in the *salary* column (use *count* method);

✓Calculate the average salary;

Data Frames *groupby* method

Using "group by" method we can:

- Split the data into groups based on some criteria
- Calculate statistics (or apply a function) to each group
- Similar to dplyr() function in R

In [ ]:
```
#Group data using rank
df_rank = df.groupby(['rank'])
```

In [ ]:
```
#Calculate mean value for each numeric column per each group
df_rank.mean()
```

rank	phd	service	salary
AssocProf	15.076923	11.307692	91786.230769
AsstProf	5.052632	2.210526	81362.789474
Prof	27.065217	21.413043	123624.804348

Data Frames *groupby* method

Once groupby object is create we can calculate various statistics for each group:

In [ ]:
```
#Calculate mean salary for each professor rank:
df.groupby('rank')[['salary']].mean()
```

rank	salary
AssocProf	91786.230769
AsstProf	81362.789474
Prof	123624.804348

Note: If single brackets are used to specify the column (e.g. salary), then the output is Pandas Series object. When double brackets are used the output is a Data Frame

Data Frames *groupby* method

groupby performance notes:

- no grouping/splitting occurs until it's needed. Creating the *groupby* object only verifies that you have passed a valid mapping
- by default the group keys are sorted during the *groupby* operation. You may want to pass sort=False for potential speedup:

In [ ]:
```
#Calculate mean salary for each professor rank:
df.groupby(['rank'], sort=False)[['salary']].mean()
```

Data Frame: filtering

To subset the data we can apply Boolean indexing. This indexing is commonly known as a filter. For example if we want to subset the rows in which the salary value is greater than $120K:

In [ ]:
```
#Calculate mean salary for each professor rank:
df_sub = df[ df['salary'] > 120000 ]
```

Any Boolean operator can be used to subset the data:
> greater; >= greater or equal;
< less; <= less or equal;
== equal; != not equal;

In [ ]:
```
#Select only those rows that contain female professors:
df_f = df[ df['sex'] == 'Female' ]
```


Data Frames: Slicing

There are a number of ways to subset the Data Frame:

- one or more columns
- one or more rows
- a subset of rows and columns

Rows and columns can be selected by their position or label

Data Frames: Slicing

When selecting one column, it is possible to use single set of brackets, but the resulting object will be a Series (not a DataFrame):

In [ ]:
```
#Select column salary:
df['salary']
```

When we need to select more than one column and/or make the output to be a DataFrame, we should use double brackets:

In [ ]:
```
#Select column salary:
df[['rank','salary']]
```


Data Frames: Selecting rows

If we need to select a range of rows, we can specify the range using ":"

In [ ]:
```
#Select rows by their position:
df[10:20]
```

Notice that the first row has a position 0, and the last value in the range is omitted:
So for 0:10 range the first 10 rows are returned with the positions starting with 0 and ending with 9

Data Frames: method loc

If we need to select a range of rows, using their labels we can use method loc:

In [ ]:
```
#Select rows by their labels:
df_sub.loc[10:20,['rank','sex','salary']]
```

Out[ ]:

	rank	sex	salary
10	Prof	Male	128250
11	Prof	Male	134778
13	Prof	Male	162200
14	Prof	Male	153750
15	Prof	Male	150480
19	Prof	Male	150500

Data Frames: method iloc

If we need to select a range of rows and/or columns, using their positions we can use method iloc:

In [ ]:
```
#Select rows by their labels:
df_sub.iloc[10:20,[0, 3, 4, 5]]
```

Out[ ]:

	rank	service	sex	salary
26	Prof	19	Male	148750
27	Prof	43	Male	155865
29	Prof	20	Male	123683
31	Prof	21	Male	155750
35	Prof	23	Male	126933
36	Prof	45	Male	146856
39	Prof	18	Female	129000
40	Prof	36	Female	137000
44	Prof	19	Female	151768
45	Prof	25	Female	140096

Data Frames: method iloc (summary)

```
df.iloc[0]  # First row of a data frame
df.iloc[i]  #(i+1)th row
df.iloc[-1] # Last row
```

```
df.iloc[:, 0]  # First column
df.iloc[:, -1] # Last column
```

```
df.iloc[0:7]        #First 7 rows
df.iloc[:, 0:2]     #First 2 columns
df.iloc[1:3, 0:2]   #Second through third rows and first 2
columns
df.iloc[[0,5], [1,3]]   #1st and 6th rows and 2nd and 4th columns
```


Data Frames: Sorting

We can sort the data by a value in the column. By default the sorting will occur in ascending order and a new data frame is return.

In [ ]:
```
# Create a new data frame from the original sorted by the column Salary
df_sorted = df.sort_values( by ='service')
df_sorted.head()
```

Out[ ]:

	rank	discipline	phd	service	sex	salary
55	AsstProf	A	2	0	Female	72500
23	AsstProf	A	2	0	Male	85000
43	AsstProf	B	5	0	Female	77000
17	AsstProf	B	4	0	Male	92000
12	AsstProf	B	1	0	Male	88000

Data Frames: Sorting

We can sort the data using 2 or more columns:

In [ ]:
```
df_sorted = df.sort_values( by =['service', 'salary'], ascending = [True, False])
df_sorted.head(10)
```

Out[ ]:

	rank	discipline	phd	service	sex	salary
52	Prof	A	12	0	Female	105000
17	AsstProf	B	4	0	Male	92000
12	AsstProf	B	1	0	Male	88000
23	AsstProf	A	2	0	Male	85000
43	AsstProf	B	5	0	Female	77000
55	AsstProf	A	2	0	Female	72500
57	AsstProf	A	3	1	Female	72500
28	AsstProf	B	7	2	Male	91300
42	AsstProf	B	4	2	Female	80225
68	AsstProf	A	4	2	Female	77500

Missing Values

Missing values are marked as NaN

In [ ]:
```
# Read a dataset with missing values
flights = pd.read_csv("flights.csv")
```

In [ ]:
```
# Select the rows that have at least one missing value
flights[flights.isnull().any(axis=1)].head()
```

Out[ ]:

	year	month	day	dep_time	dep_delay	arr_time	arr_delay	carrier	tailnum	flight	origin	dest	air_time	distance	hour	minute
330	2013	1	1	1807.0	29.0	2251.0	NaN	UA	N31412	1228	EWR	SAN	NaN	2425	18.0	7.0
403	2013	1	1	NaN	NaN	NaN	NaN	AA	N3EHAA	791	LGA	DFW	NaN	1389	NaN	NaN
404	2013	1	1	NaN	NaN	NaN	NaN	AA	N3EVAA	1925	LGA	MIA	NaN	1096	NaN	NaN
855	2013	1	2	2145.0	16.0	NaN	NaN	UA	N12221	1299	EWR	RSW	NaN	1068	21.0	45.0
858	2013	1	2	NaN	NaN	NaN	NaN	AA	NaN	133	JFK	LAX	NaN	2475	NaN	NaN

Missing Values

There are a number of methods to deal with missing values in the data frame:

df.method()	description
dropna()	Drop missing observations
dropna(how='all')	Drop observations where all cells is NA
dropna(axis=1, how='all')	Drop column if all the values are missing
dropna(thresh = 5)	Drop rows that contain less than 5 non-missing values
fillna(0)	Replace missing values with zeros
isnull()	returns True if the value is missing
notnull()	Returns True for non-missing values

Missing Values

- When summing the data, missing values will be treated as zero
- If all values are missing, the sum will be equal to NaN
- cumsum() and cumprod() methods ignore missing values but preserve them in the resulting arrays
- Missing values in GroupBy method are excluded (just like in R)
- Many descriptive statistics methods have *skipna* option to control if missing data should be excluded . This value is set to *True* by default (unlike R)

Handle Missing

```
In [52]: # Remove all the observations with missing values
         flights2 = flights.dropna()

In [53]: # Fill missing values with zeros
         nomiss =flights['dep_delay'].fillna(0)
         nomiss.isnull().any()

Out[53]: False
```


Aggregation Functions in Pandas

Aggregation - computing a summary statistic about each group, i.e.

- compute group sums or means
- compute group sizes/counts

Common aggregation functions:

min, max
count, sum, prod
mean, median, mode, mad
std, var

Aggregation Functions in Pandas

agg() method are useful when multiple statistics are computed per column:

In [ ]:
```
flights[['dep_delay','arr_delay']].agg(['min','mean','max'])
```

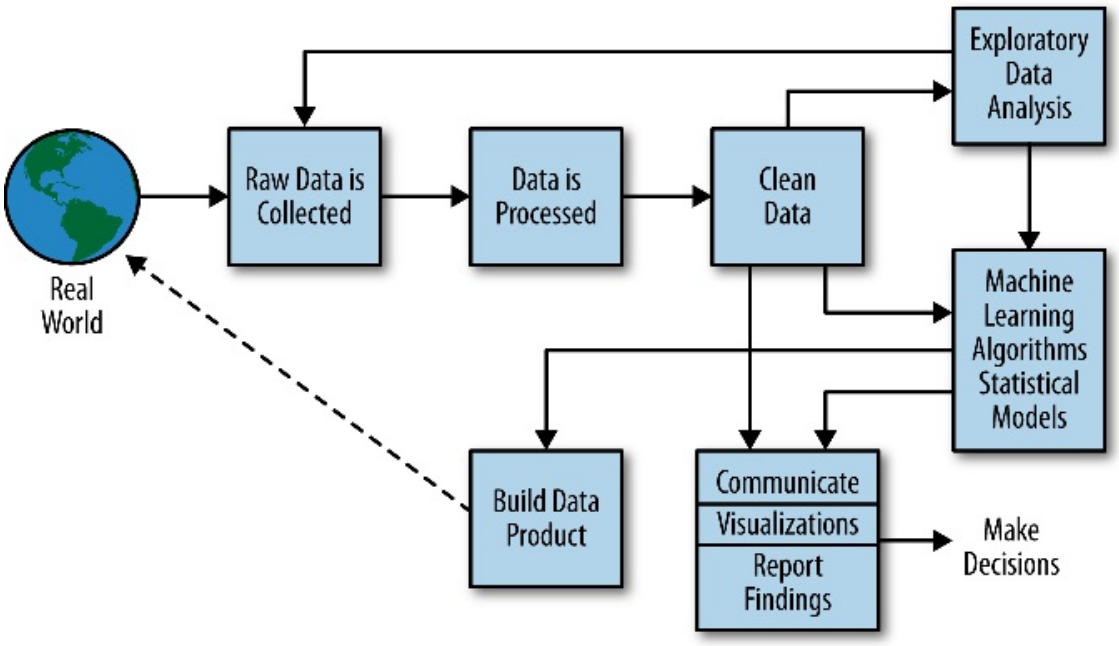
Out[ ]:

	dep_delay	arr_delay
min	-16.000000	-62.000000
mean	9.384302	2.298675
max	351.000000	389.000000

Basic Descriptive Statistics

df.method()	description
describe	Basic statistics (count, mean, std, min, quantiles, max)
min, max	Minimum and maximum values
mean, median, mode	Arithmetic average, median and mode
var, std	Variance and standard deviation
sem	Standard error of mean
skew	Sample skewness
kurt	kurtosis

Data Science Process



Exploratory Data Analysis

Exploratory Data Analysis Concept

EDA is an iterative cycle. You:

- Generate questions about your data.
- Search for answers by visualizing, transforming, and modelling your data.
- Use what you learn to refine your questions and/or generate new questions.

EDA Question

1. What type of variation occurs within my variables?
2. What type of covariation occurs between my variables?

Variation

- **Variation** is the tendency of the values of a variable to change from measurement to measurement.
- Simple Rules

Data Type	EDA Graph
1. Categorical Data	Bar Plot
2. Numerical Data	Histogram

Covariation

- If variation describes the behavior *within* a variable, covariation describes the behavior *between* variables.
- **Covariation** is the tendency for the values of two or more variables to vary together in a related way.

Data Type Between	EDA Graph
1. A Categorical and Numerical Data	Frequency Plot, Box Plot
2. A Numerical and Numerical Data	Scatter Plot
3. A Categorical and Categorical Data	Heatmap

Graphics to explore the data

Seaborn package is built on matplotlib but provides high level interface for drawing attractive statistical graphics, similar to ggplot2 library in R. It specifically targets statistical data visualization

To show graphs within Python notebook include inline directive:

In [ ]:
```
%matplotlib inline
```

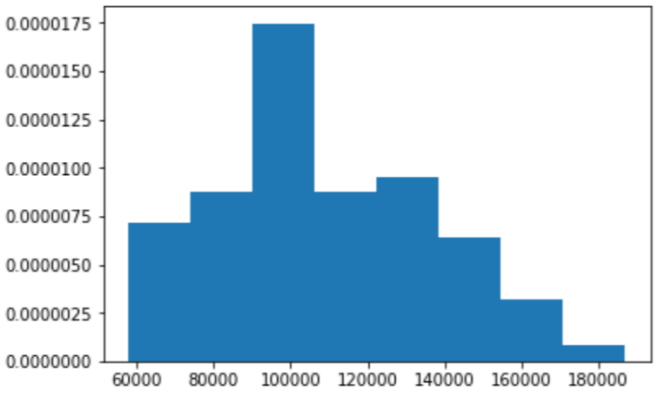

Graphics

	description
distplot	histogram
barplot	estimate of central tendency for a numeric variable
violinplot	similar to boxplot, also shows the probability density of the data
jointplot	Scatterplot
regplot	Regression plot
pairplot	Pairplot
boxplot	boxplot
swarmplot	categorical scatterplot
factorplot	General categorical plot

Histogram using Matplotlib

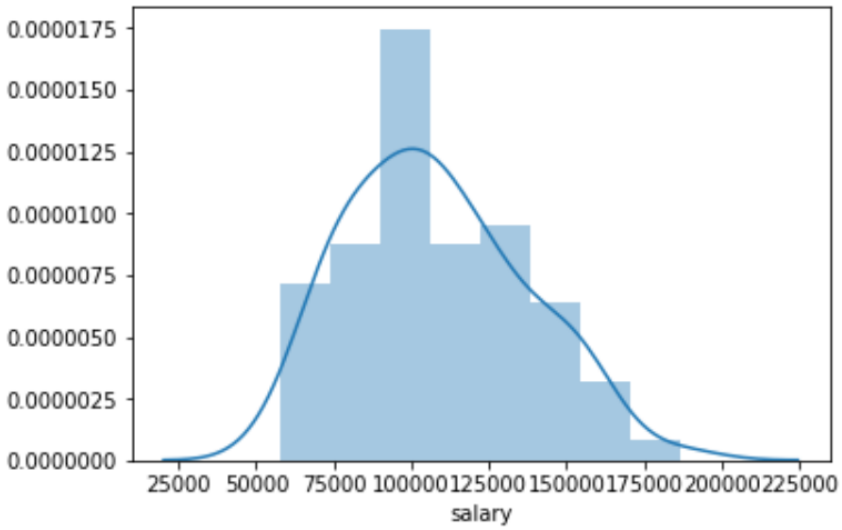
```
In [64]: #Use matplotlib to draw a histogram of a salary data
         plt.hist(df['salary'],bins=8, normed=1)
```

```
Out[64]: (array([  7.14677085e-06,   8.73494215e-06,   1.74698843e-05,
                   8.73494215e-06,   9.52902780e-06,   6.35268520e-06,
                   3.17634260e-06,   7.94085650e-07]),
          array([  57800.,   73945.,   90090.,  106235.,  122380.,  138525.,
                  154670.,  170815.,  186960.]),
          <a list of 8 Patch objects>)
```



Histogram using Seabon

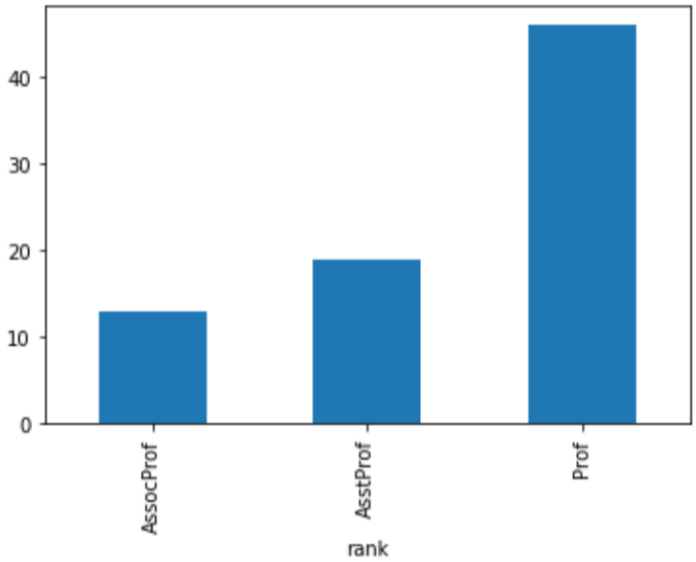
```
In [65]: #Use seaborn package to draw a histogram
         sns.distplot(df['salary']);
```



Barplot using Matplotlib

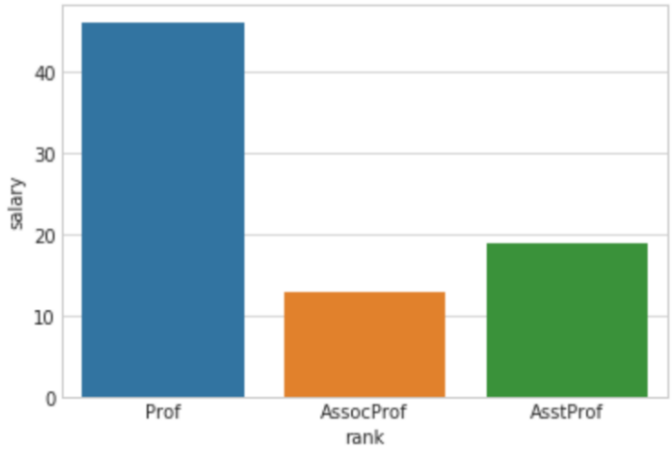
```
In [66]: # Use regular matplotlib function to display a barplot
         df.groupby(['rank'])['salary'].count().plot(kind='bar')
```

```
Out[66]: <matplotlib.axes._subplots.AxesSubplot at 0x7ff58213f860>
```



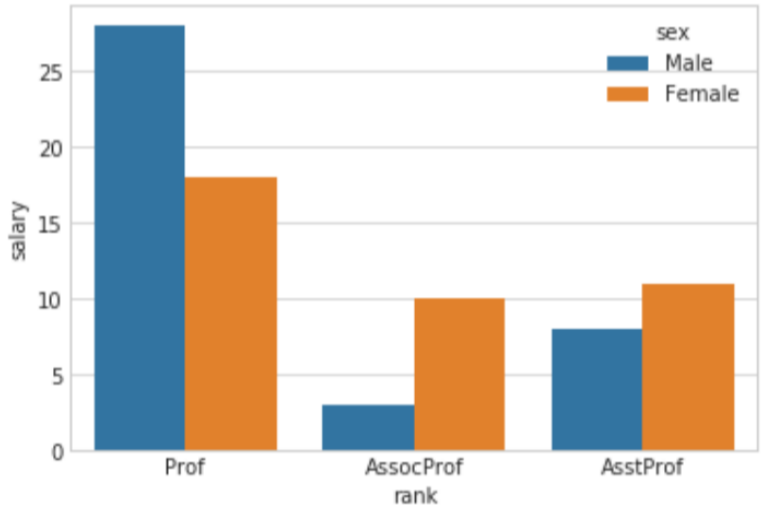
Barplot using Seabon

```
In [67]: # Use seaborn package to display a barplot
         sns.set_style("whitegrid")

         ax = sns.barplot(x='rank',y ='salary', data=df, estimator=len)
```



Multiple Group Barplot

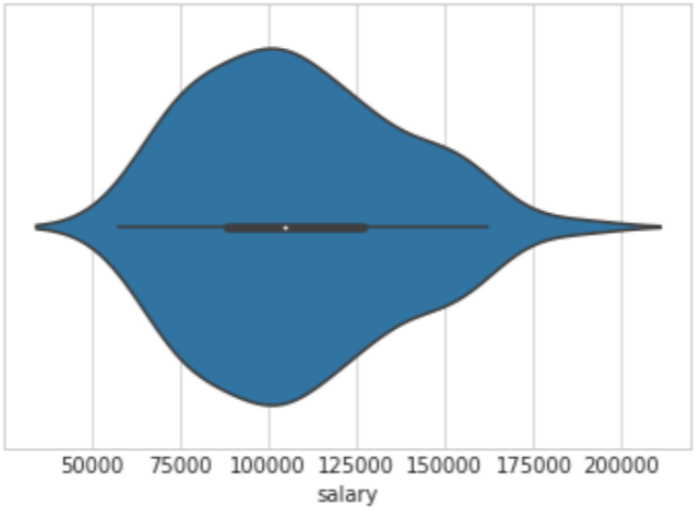
In [68]:
```
# Split into 2 groups:
ax = sns.barplot(x='rank',y ='salary', hue='sex', data=df, estimator=len)
```



Violin Plot

In [69]:
```
#Violinplot
sns.violinplot(x = "salary", data=df)
```

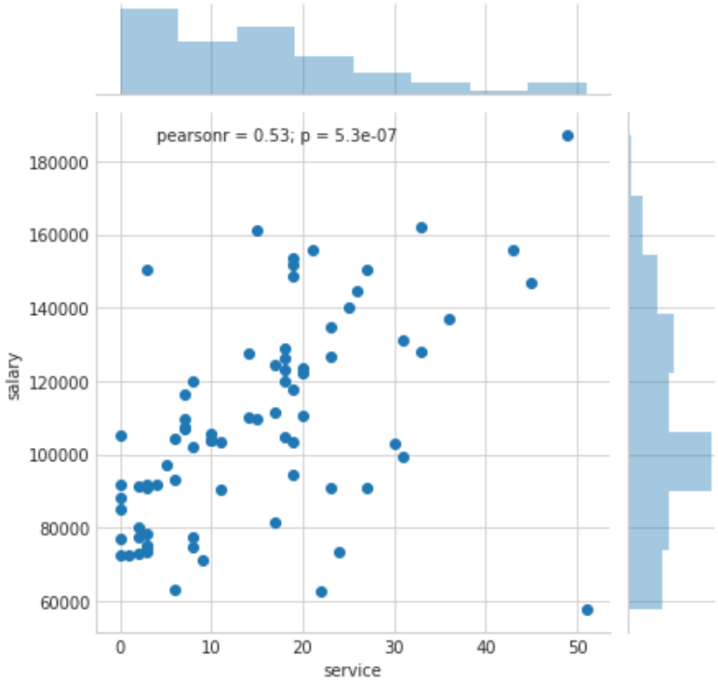
Out[69]: <matplotlib.axes._subplots.AxesSubplot at 0x7ff5819b79e8>



Scatter Plot

In [70]:
```
#Scatterplot in seaborn
sns.jointplot(x='service', y='salary', data=df)
```

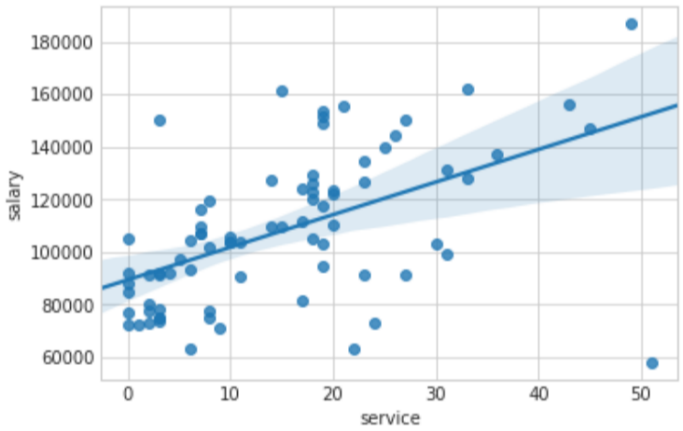
Out[70]: <seaborn.axisgrid.JointGrid at 0x7ff581984550>



Regression Plot

In [71]:
```
#If we are interested in linear regression plot for 2 numeric variables we can use regplot
sns.regplot(x='service', y='salary', data=df)
```

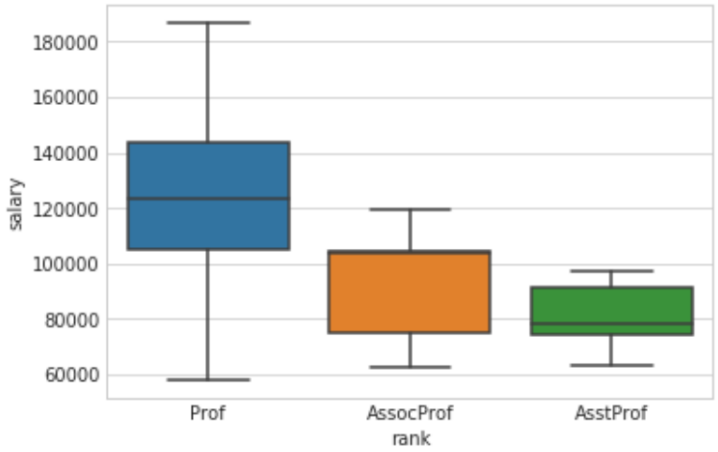
Out[71]: <matplotlib.axes._subplots.AxesSubplot at 0x7ff58184c470>



Box Plot

```
In [72]: # box plot
         sns.boxplot(x='rank',y='salary', data=df)
```

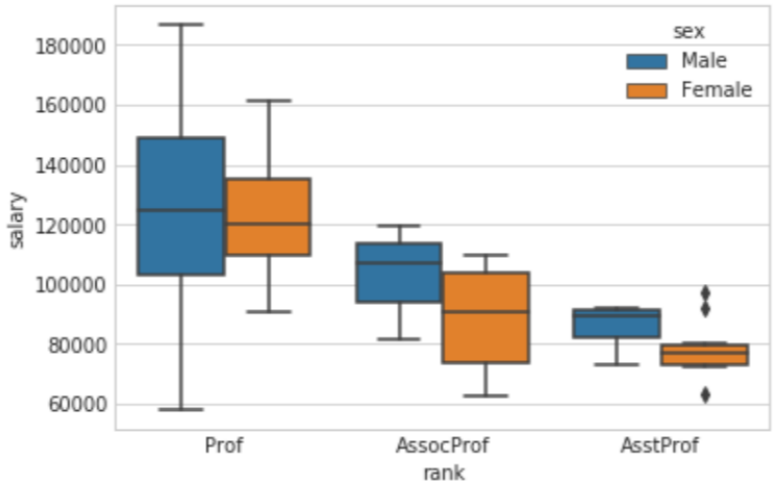
```
Out[72]: <matplotlib.axes._subplots.AxesSubplot at 0x7ff58170de80>
```



Group Box Plot

```
In [73]: # side-by-side box plot
         sns.boxplot(x='rank',y='salary', data=df, hue='sex')
```

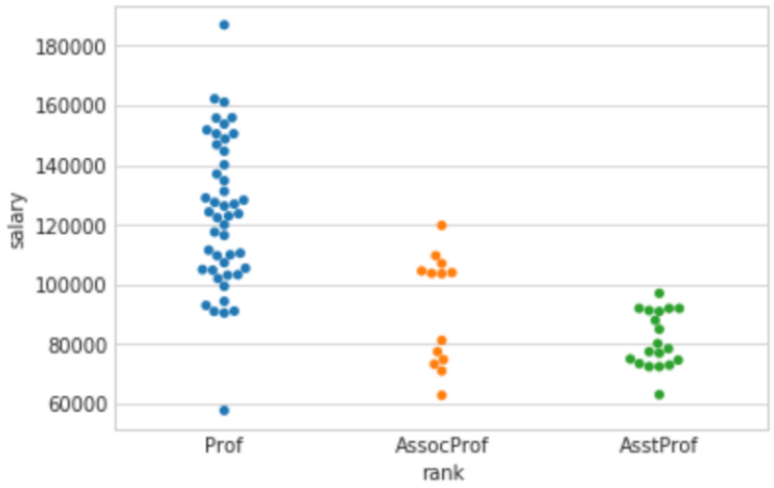
```
Out[73]: <matplotlib.axes._subplots.AxesSubplot at 0x7ff5818edc18>
```



Swam Plot

```
In [74]: # swarm plot
         sns.swarmplot(x='rank',y='salary', data=df)
```

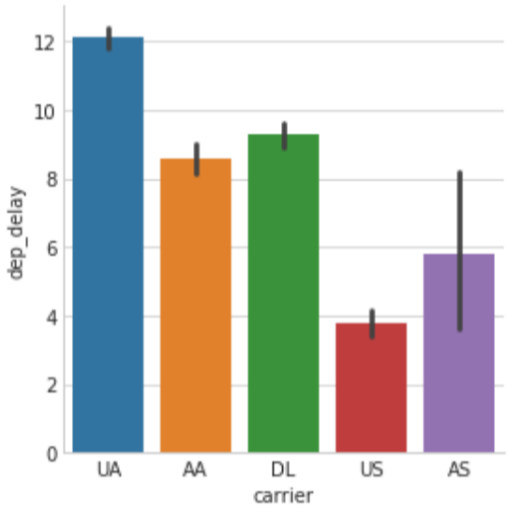
```
Out[74]: <matplotlib.axes._subplots.AxesSubplot at 0x7ff5814f75c0>
```



Factor Plot

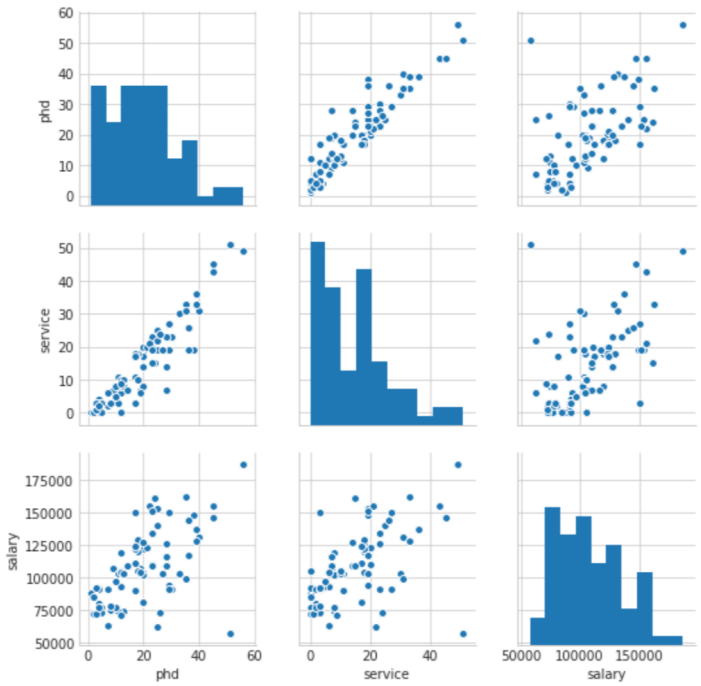
```
In [75]: #factorplot
         sns.factorplot(x='carrier',y='dep_delay', data=flights, kind='bar')
```

```
Out[75]: <seaborn.axisgrid.FacetGrid at 0x7ff58178a198>
```



Pair Plot

```
In [76]: # Pairplot
         sns.pairplot(df)

Out[76]: <seaborn.axisgrid.PairGrid at 0x7ff5822296a0>
```



Exercise 9

1. Explore data using matplotlib and seaborn
2. From “flights” dataset and using seaborn package, please explore the dependency of arrival delay(arr_delay) on departure delay (dep_delay) using scatterplot or regplot.
3. Creat Heatmap chart between carrier and origin.

Statistics

Statistics

- The essential component of Data Science is **Statistics**. It is a method to collect and analyze the numerical data in a large amount to get useful and meaningful insights.
- There are two main categories of Statistics:
  - Descriptive Statistics
  - Inferential Statistics

The Role of Statistical Analysis in Data Science

- **Understanding Data**: Statistical analysis provides the tools for this exploratory data analysis (EDA), allowing for a deeper understanding of the data's characteristics.
- **Informed Decision Making**: By applying statistical methods, data scientists can make evidence-based decisions.
- **Data Cleaning and Preparation**: Statistical techniques are employed to identify outliers, handle missing values, and understand the distribution of data, which are critical steps in preparing a dataset for modeling.

Descriptive Statistics

Descriptive Statistics

- **Descriptive Statistics** helps to organize data and only focuses on the characteristics of data providing parameters.

1. **Measures of Central Tendency**:
   - **Mean (Average)**: The sum of all data values divided by the number of values.
     Formula: $\mu = \frac{\sum_{i=1}^{n} x_i}{n}$
   - **Median**: The middle value in a sorted dataset.
   - **Mode**: The most frequently occurring value(s) in a dataset.
2. **Measures of Dispersion (or Spread)**:
   - **Range**: The difference between the highest and lowest values.
     Formula: $Range = Max - Min$
   - **Variance**: Average of the squared differences from the Mean.
     Formula for population: $\sigma^2 = \frac{\sum_{i=1}^{n}(x_i-\mu)^2}{n}$
     Formula for sample: $s^2 = \frac{\sum_{i=1}^{n}(x_i-\bar{x})^2}{n-1}$
   - **Standard Deviation**: Square root of the variance.
     Formula for population: $\sigma = \sqrt{\sigma^2}$
     Formula for sample: $s = \sqrt{s^2}$
   - **Interquartile Range (IQR)**: The difference between the third quartile (Q3) and the first quartile (Q1). It represents the range within which the middle 50% of the values lie.

Descriptive Statistics

3. **Measures of Shape**:
   - **Skewness**: Measures the asymmetry of the distribution of data around the mean. Positive skewness indicates a distribution that is skewed towards the right, while negative skewness indicates a distribution skewed left.
   - **Kurtosis**: Measures the "tailedness" of the distribution. High kurtosis indicates a distribution with tails that are heavier than a normal distribution, and low kurtosis indicates a distribution with tails that are lighter than a normal distribution.
4. **Measures of Position**:
   - **Quartiles**: Values that divide a dataset into four equal parts. They include Q1 (25th percentile), Q2 (which is the median or 50th percentile), and Q3 (75th percentile).
   - **Percentiles**: Values below which a given percentage of observations fall.
   - **Z-scores**: Measure of how many standard deviations an element is from the mean.
     Formula: $Z = \frac{x-\mu}{\sigma}$
5. **Others**:
   - **Count**: Number of data points.
   - **Minimum and Maximum**: Smallest and largest data values, respectively.
   - **Sum**: Total of all data values.

Inferential Statistics

Inferential Statistics

- **Inferential statistics** allows you to make predictions or inferences about a population based on a sample from that population. It provides the tools to make generalizations beyond the immediate data at hand and helps in hypothesis testing and determining the relationships between variables.

1. **Probability Distributions**:
   - **Normal Distribution**
   - **Binomial Distribution**
   - **Poisson Distribution**
   - **Exponential Distribution**
   - ... and many others.
2. **Sampling Techniques**:
   - **Random Sampling**
   - **Stratified Sampling**
   - **Cluster Sampling**
   - **Systematic Sampling**

Inferential Statistics

3. **Hypothesis Testing**:
   - **Z-test**: For the mean, typically used when population variance is known.
   - **T-test**: For the mean, used when population variance is unknown. Types include:
     - One-sample t-test
     - Two-sample t-test (independent and paired)
   - **Chi-squared test**: For independence in a contingency table.
   - **ANOVA (Analysis of Variance)**: For comparing means across more than two groups.
   - **F-test**: For comparing variances of two samples.
4. **Confidence Intervals**:
   - **For a mean**:
     Formula (for known population variance): $\bar{x} \pm Z\left(\frac{\sigma}{\sqrt{n}}\right)$
     Formula (for unknown population variance): $\bar{x} \pm t\left(\frac{s}{\sqrt{n}}\right)$
   - **For a proportion**:
     Formula: $p \pm Z\sqrt{\frac{p(1-p)}{n}}$
5. **Regression Analysis**:
   - **Linear Regression**: Understand the relationship between two continuous variables.
   - **Logistic Regression**: Predict the probability of a categorical outcome based on predictor variables.
   - **Multiple Regression**: Understand the relationship between multiple predictor variables and a response variable.

Examples of Business Questions

- **Simple (descriptive) Stats**
  - "Who are the most profitable customers?"
- **Hypothesis Testing**
  - "Is there a difference in value to the company of these customers?"
- **Segmentation/Classification**
  - What are the common characteristics of these customers?
- **Prediction**
  - Will this new customer become a profitable customer? If so, how profitable?

Basic statistical Analysis

statsmodel and **scikit-learn** - both have a number of function for statistical analysis

The first one is mostly used for regular analysis using R style formulas, while scikit-learn is more tailored for Machine Learning.

statsmodels:

- linear regressions
- ANOVA tests
- hypothesis testings
- many more ...

scikit-learn:

- kmeans
- support vector machines
- random forests
- many more ...

Hypothesis Testing

- Compare an experimental group and a control group.
- **H_0 : Null Hypothesis**
  - No difference between the groups
- **H_A : Alternative Hypothesis**
  - Statistically significant difference between the groups
- "difference" defined in the terms of some test statistic
  - Different means (e.g. t-test), Different varianes (e.g. F-test)
- Group defined through careful experimental design
  - Randomized, blinded, double-blinded
- Examples
  - "The new ad placement produces more click-throughs"
  - "This treatment produces better outcomes"

More on Hypothesis Testing

- **Null Hypothesis** is given the benefit of the doubt (e.g., innocent until proven guilty).
- **Alternative Hypothesis** directly contradicts the Null Hypothesis
- "**Step 1**: State the hypotheses."
- "**Step 2**: Set the criteria for a decision."
- "**Step 3**: Compute the test statistic."
- "**Step 4**: Make a decision."

p Value

- A **p value** is the probability of obtaining a sample outcome, given that the value stated in the null hypothesis is true.
- In many cases: when the p value is less than 5% ($p < .05$), we reject the null hypothesis
  - Note this means that 1 out of 20 times we incorrectly reject the null hypothesis

Reason to Reject Ho

Illustration: Let say, we **assume** that average age in the US is 50 years (H0=50).

If in fact this is the true (unknown) population mean, it is unlikely that we get a sample mean of 20.

So, if we have a sample that produces an average of 20, then we **reject** that the null hypothesis that average age is 50. (note that we are rejecting our assumption or claim).

(would we get 20 if the true population mean was 50?

NO.That is why we reject 50)

How Is the Test done?

We use the distribution of a Test Statistic, such as Z or t as the criteria.

A. Rejection Region Method:

- Divide the distribution into rejection and non-rejection regions
- Defines the unlikely values of the sample statistic if the null hypothesis is true, the critical value(s)
- Defines rejection region of the sampling distribution Rejection region(s) is designated by α, (level of significance)

Typical values are .01, .05, or .10

α is selected by the researcher at the beginning

α provides the critical value(s) of the test

Non-rejection region

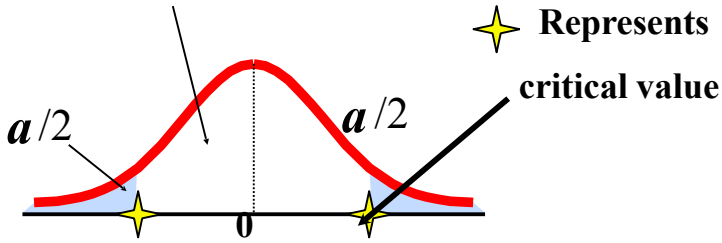
Rejection Region or Critical Value Approach:

Level of significance = α

$H_0: \mu = 12$

$H_1: \mu \neq 12$

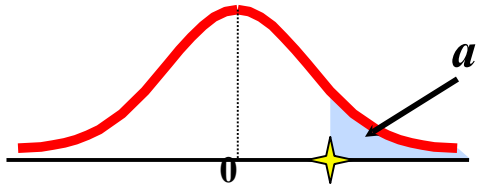
Two-tail test



$H_0: \mu \leq 12$

$H_1: \mu > 12$

Upper-tail test

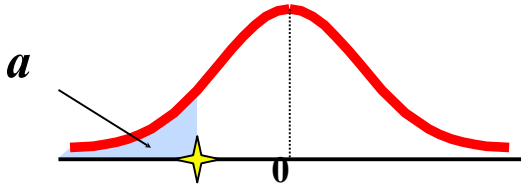


Rejection region is shaded

$H_0: \mu \geq 12$

$H_1: \mu < 12$

Lower-tail test



P-Value Approach –

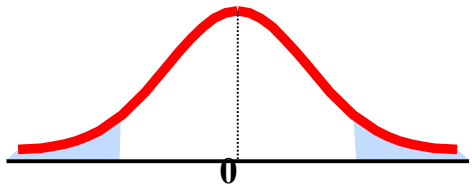
P-value=Max. Probability of (Type I Error), calculated from the sample.

Given the sample information what is the size of blue are?

$H_0: \mu = 12$

$H_1: \mu \neq 12$

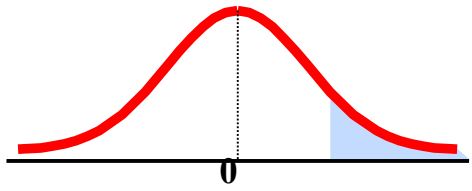
Two-tail test



$H_0: \mu \leq 12$

$H_1: \mu > 12$

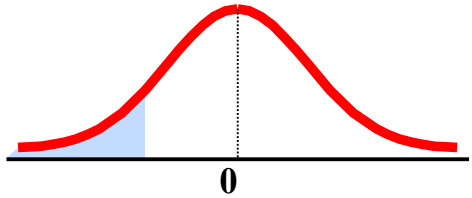
Upper-tail test

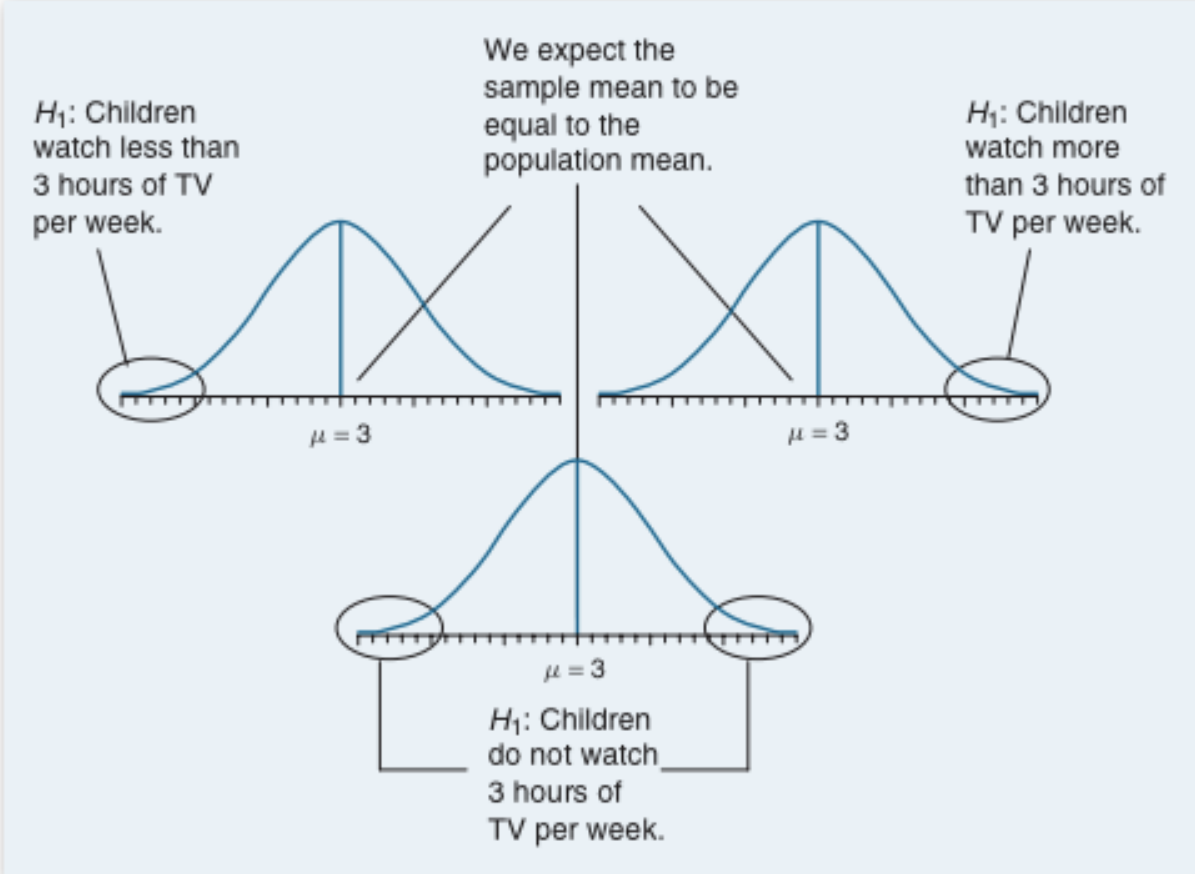


$H_0: \mu \geq 12$

$H_1: \mu < 12$

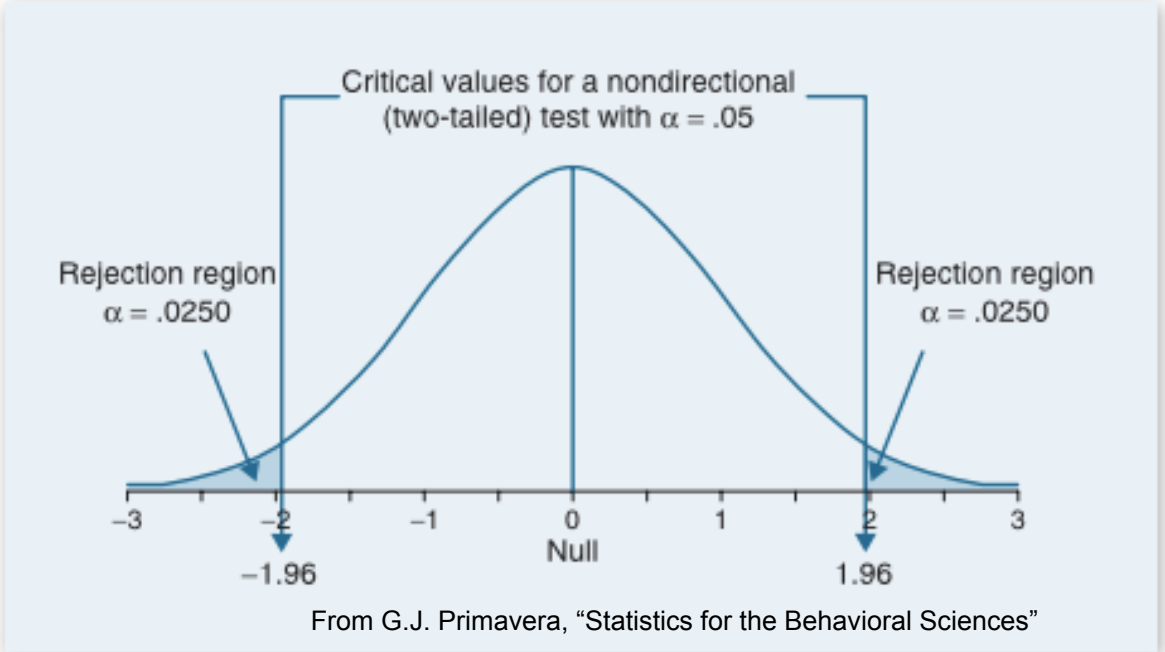
Lower-tail test





From G.J. Primavera, “Statistics for the Behavioral Sciences”

Two-tailed Significance



From G.J. Primavera, “Statistics for the Behavioral Sciences”

When the p value is less than 5% ($p < .05$), we reject the null hypothesis

Hypothesis Testing

		Decision	
		Retain the null	**Reject the null**
Truth in the population	True	CORRECT $1 - \alpha$	TYPE I ERROR α
	False	TYPE II ERROR β	CORRECT $1 - \beta$ POWER

From G.J. Primavera, “Statistics for the Behavioral Sciences”

Hypothesis Testing in Python

Student t-test

For comparing means between 2 group, we can use ttest_ind from Scipy's stats package.

```
In [83]: # Using scipy package:
         from scipy import stats
         df_w = df[ df['sex'] == 'Female']['salary']
         df_m = df[ df['sex'] == 'Male']['salary']
         stats.ttest_ind(df_w, df_m)
```

```
Out[83]: Ttest_indResult(statistic=-2.2486865976699053, pvalue=0.027429778657910103)
```


ANOVA (Analysis of Variance)

For comparing Means more than 2 group, we can use stats package from Scipy

stats.f_oneway(data_group1, data_group2, data_group3, data_groupN)

```
In [5]: from scipy import stats
        stats.f_oneway(df['salary'][df['rank'] == 'Prof'],
                       df['salary'][df['rank'] == 'AsstProf'],
                       df['salary'][df['rank'] == 'AssocProf'])
```

```
Out[5]: F_onewayResult(statistic=31.47638426157928, pvalue=1.1882466669224665e-10)
```

Assumption

- There are 3 assumptions that need to be met for the results of an ANOVA test to be considered accurate. They are:
- Normality
  - Caveat to this is, if group sizes are equal, the F-statistic is robust to violations of normality
- Homogeneity of variance
  - Same caveat as above, if group sizes are equal, the F-statistic is robust to this violation
- Independent observations

Assumption of Normality

- Using Shapiro-Wilk test

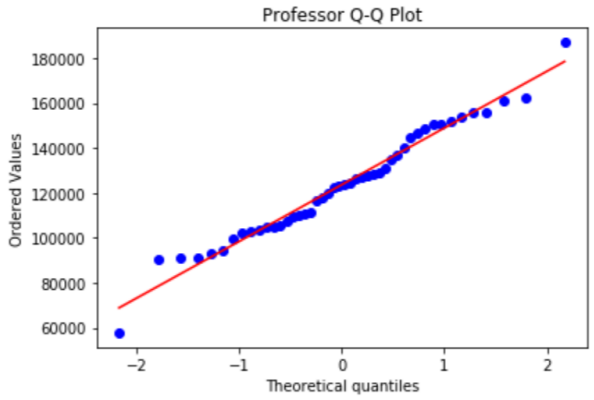
```
In [6]: stats.shapiro(df['salary'][df['rank'] == 'Prof'])
Out[6]: (0.9807326793670654, 0.636059582233429)

In [7]: stats.shapiro(df['salary'][df['rank'] == 'AssocProf'])
Out[7]: (0.8890405893325806, 0.09464861452579498)

In [8]: stats.shapiro(df['salary'][df['rank'] == 'AsstProf'])
Out[8]: (0.9256936311721802, 0.14421962201595306)
```

Assumption of Normality

Using Normal QQ-Plot

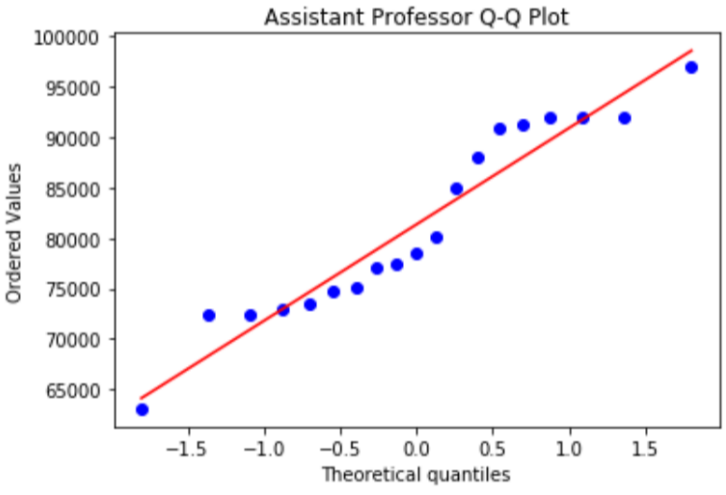
```
In [9]: stats.probplot(df['salary'][df['rank'] == 'Prof'], plot= plt)
        plt.title("Professor Q-Q Plot")
```

```
Out[9]: Text(0.5,1,'Professor Q-Q Plot')
```



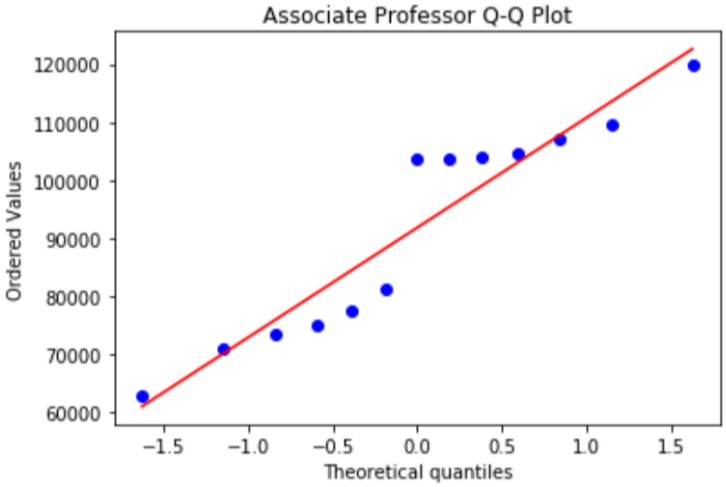

```
In [10]: stats.probplot(df['salary'][df['rank'] == 'AsstProf'], plot= plt)
         plt.title("Assistant Professor Q-Q Plot")
```

```
Out[10]: Text(0.5,1,'Assistant Professor Q-Q Plot')
```



```
In [11]: stats.probplot(df['salary'][df['rank'] == 'AssocProf'], plot= plt)
         plt.title("Associate Professor Q-Q Plot")
```

```
Out[11]: Text(0.5,1,'Associate Professor Q-Q Plot')
```



Assumption of Homogeneity of Variance

- We can use Levene's Test for this

```
In [12]: stats.levene(df['salary'][df['rank'] == 'Prof'],
                      df['salary'][df['rank'] == 'AssocProf'],
                      df['salary'][df['rank'] == 'AsstProf'])
```

```
Out[12]: LeveneResult(statistic=5.455185896137257, pvalue=0.006138855806188982)
```

Exercise 10

Use flights dataset, find out whether they are differences between mean of departure delay between carriers?

Linear Regression

Regression Models

- Relationship between one dependent variable and explanatory variable(s)
- Use equation to set up relationship
  - Numerical Dependent (Response) Variable
  - 1 or More Numerical or Categorical Independent (Explanatory) Variables
- Used Mainly for Prediction & Estimation

Regression Modeling Steps

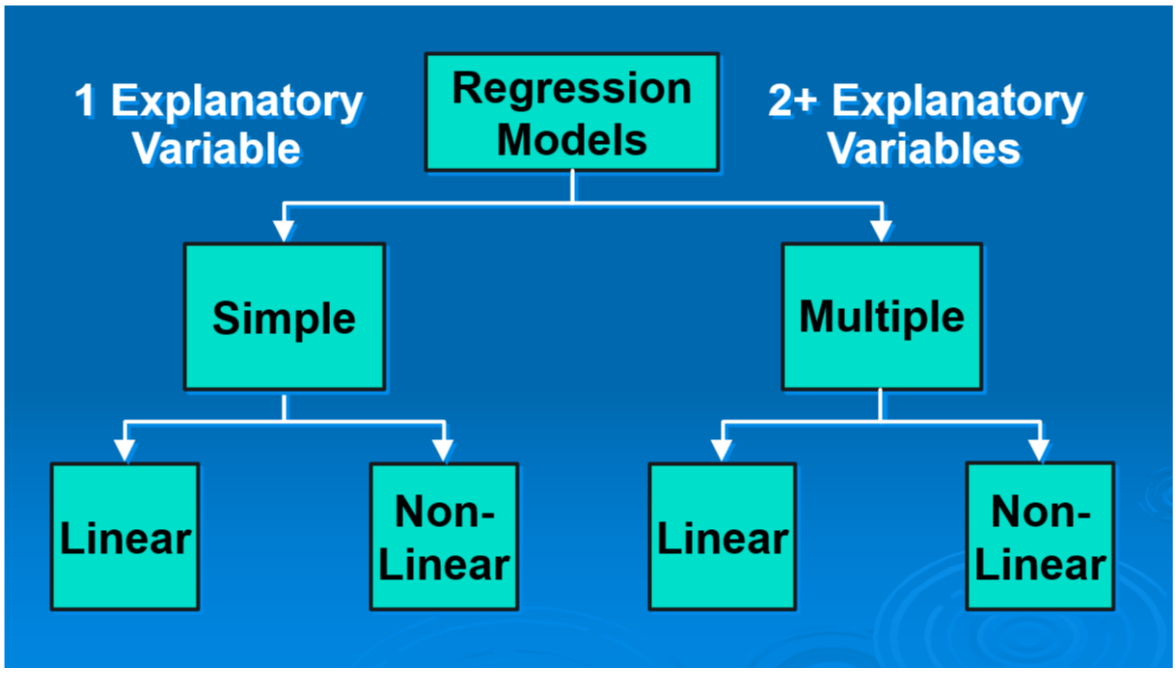
1. Hypothesize Deterministic Component
   - Estimate Unknown Parameters
2. Specify Probability Distribution of Random Error Term
   - Estimate Standard Deviation of Error
3. Evaluate the fitted Model
4. Use Model for Prediction & Estimation

Specifying the deterministic component

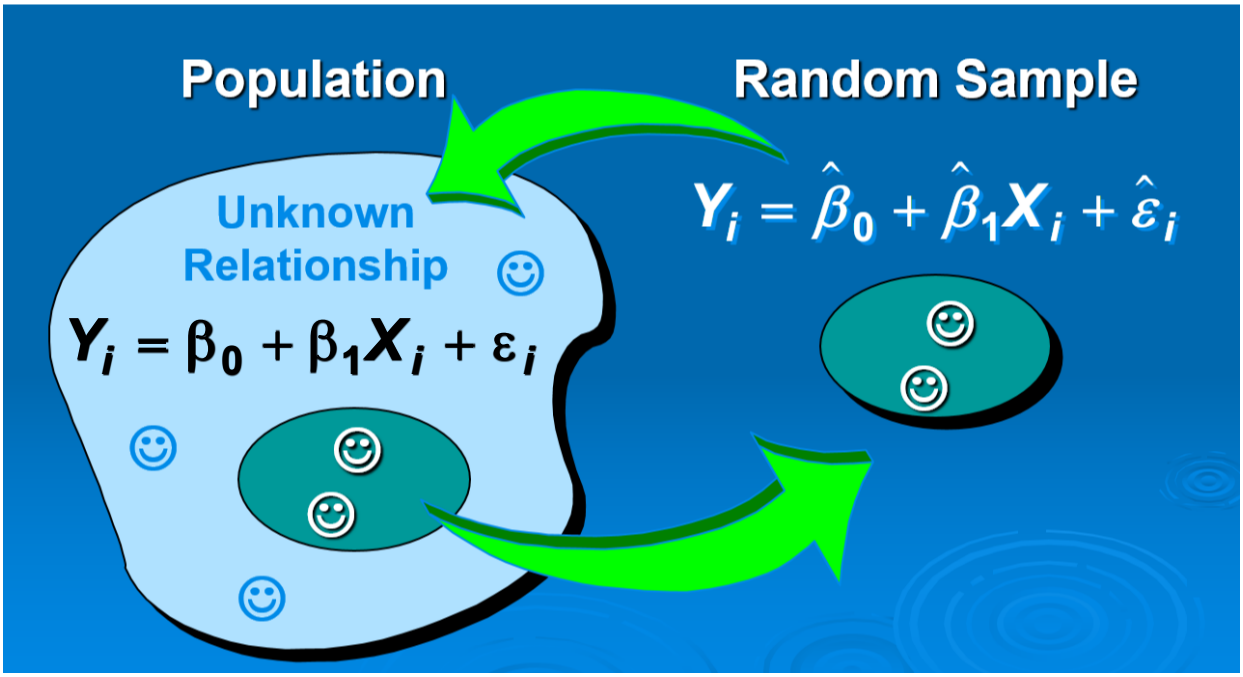
1. Define the dependent variable and independent variable

2. Hypothesize Nature of Relationship
   - Expected Effects (i.e., Coefficients' Signs)
   - Functional Form (Linear or Non-Linear)
   - Interactions

Types of Regression Models



Population & Sample Regression Models



Sample Linear Regression Model

- The model to be estimated from sample data is:

$$Y_i = b_0 + b_1 X_i + e_i$$

Residual (random error from the sample)

- The actual estimated from the sample

Estimated (or predicted) Y value for observation i

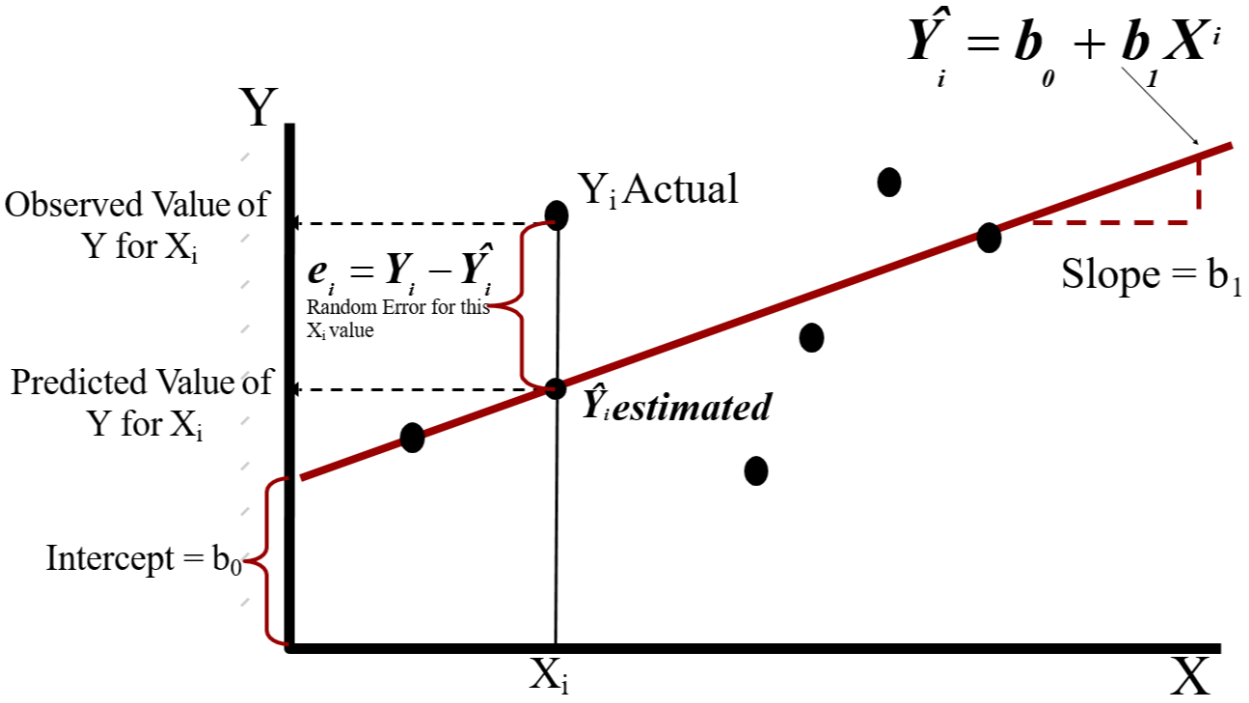
Estimate of the regression intercept

Estimate of the regression slope

Value of X for observation i

$$\hat{Y}_i = b_0 + b_1 X_i$$

– Where $e_i = Y_i \quad \hat{Y}_i$



Liear Regression using Python

Question

Using linear regression to create model that have relationship between services year and salary.

In [78]:
```
# Import Statsmodel functions:
import statsmodels.formula.api as smf
```

In [79]:
```
# create a fitted model
lm = smf.ols(formula='salary ~ service', data=df).fit()

#print model summary
print(lm.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                 salary   R-squared:                       0.283
Model:                            OLS   Adj. R-squared:                  0.274
Method:                 Least Squares   F-statistic:                     30.03
Date:                Fri, 15 Sep 2017   Prob (F-statistic):           5.31e-07
Time:                        14:11:46   Log-Likelihood:                -896.72
No. Observations:                  78   AIC:                             1797.
Df Residuals:                      76   BIC:                             1802.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept   8.935e+04   4365.651     20.468      0.000    8.07e+04     9.8e+04
service     1240.3567    226.341      5.480      0.000     789.560    1691.153
==============================================================================
Omnibus:                       12.741   Durbin-Watson:                   1.630
Prob(Omnibus):                  0.002   Jarque-Bera (JB):               21.944
Skew:                          -0.576   Prob(JB):                     1.72e-05
Kurtosis:                       5.329   Cond. No.                         30.9
==============================================================================
```

In [80]:
```
# print the coefficients
lm.params
```

Out[80]:
```
Intercept    89354.824215
service       1240.356654
dtype: float64
```

In [81]:
```
#using scikit-learn:
from sklearn import linear_model
est = linear_model.LinearRegression(fit_intercept = True)   # create estimator object
est.fit(df[['service']], df[['salary']])

#print result
print("Coef:", est.coef_, "\nIntercept:", est.intercept_)
```

```
Coef: [[ 1240.3566535]]
Intercept: [ 89354.82421525]
```


Workshop 11

- Use flight dataset, find linear regression model for
  - Independent variable: Departure Delay (dep_delay)
  - Dependent variable : Arrival Delay (arr_delay)
- Explain the model

Thanks!

Any questions?

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