

# Welcome!

WRITING EFFICIENT PYTHON CODE



**Logan Thomas**

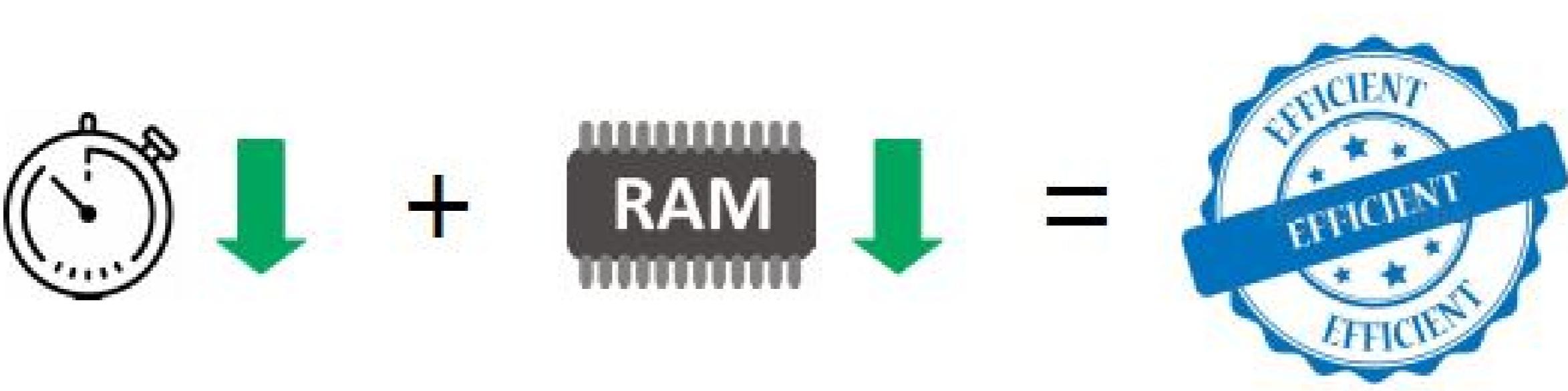
Senior Data Scientist, Protection  
Engineering Consultants

# Course overview

- Your code should be a tool used to gain insights
  - Not something that leaves you waiting for results
- In this course, you will learn:
  - How to write clean, fast, and efficient Python code
  - How to profile your code for bottlenecks
  - How to eliminate bottlenecks and bad design patterns

# Defining efficient

- Writing *efficient* Python code
  - Minimal completion time (*fast runtime*)
  - Minimal resource consumption (*small memory footprint*)



# Defining Pythonic

- Writing efficient *Python* code
  - Focus on readability
  - Using Python's constructs as intended (i.e., *Pythonic*)

```
# Non-Pythonic
doubled_numbers = []

for i in range(len(numbers)):
    doubled_numbers.append(numbers[i] * 2)

# Pythonic
doubled_numbers = [x * 2 for x in numbers]
```

# The Zen of Python by Tim Peters

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.

...

# Things you should know

- Data types typically used in Data Science
  - [Data Types for Data Science](#)
- Writing and using your own functions
  - [Python Data Science Toolbox \(Part 1\)](#)
- Anonymous functions (`lambda` expressions)
  - [Python Data Science Toolbox \(Part 1\)](#)
- Writing and using list comprehensions
  - [Python Data Science Toolbox \(Part 2\)](#)

# Let's get started!

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# Building with built-ins

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# The Python Standard Library

- **Python 3.6 Standard Library**
  - Part of every standard Python installation
- Built-in types
  - `list` , `tuple` , `set` , `dict` , and others
- Built-in functions
  - `print()` , `len()` , `range()` , `round()` , `enumerate()` , `map()` , `zip()` , and others
- Built-in modules
  - `os` , `sys` , `itertools` , `collections` , `math` , and others

# Built-in function: range()

Explicitly typing a list of numbers

```
nums = [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10]
```

## Using `range()` to create the same list

```
# range(start, stop)
nums = range(0, 11)

nums_list = list(nums)
print(nums_list)
```

```
[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10]
```

```
# range(stop)
nums = range(11)

nums_list = list(nums)
print(nums_list)
```

```
[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10]
```

# Built-in function: range()

Using `range()` with a step value

```
even_nums = range(2, 11, 2)

even_nums_list = list(even_nums)
print(even_nums_list)
```

```
[2, 4, 6, 8, 10]
```

# Built-in function: enumerate()

Creates an indexed list of objects

```
letters = ['a', 'b', 'c', 'd']

indexed_letters = enumerate(letters)

indexed_letters_list = list(indexed_letters)

print(indexed_letters_list)
```

```
[(0, 'a'), (1, 'b'), (2, 'c'), (3, 'd')]
```

# Built-in function: enumerate()

Can specify a start value

```
letters = ['a', 'b', 'c', 'd']

indexed_letters2 = enumerate(letters, start=5)

indexed_letters2_list = list(indexed_letters2)
print(indexed_letters2_list)
```

```
[(5, 'a'), (6, 'b'), (7, 'c'), (8, 'd')]
```

# Built-in function: map()

Applies a function over an object

```
nums = [1.5, 2.3, 3.4, 4.6, 5.0]
```

```
rnd_nums = map(round, nums)
```

```
print(list(rnd_nums))
```

```
[2, 2, 3, 5, 5]
```

# Built-in function: map()

map() with lambda (anonymous function)

```
nums = [1, 2, 3, 4, 5]

sqrd_nums = map(lambda x: x ** 2, nums)

print(list(sqrd_nums))
```

```
[1, 4, 9, 16, 25]
```

# Let's start building with built-ins!

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# The power of NumPy arrays

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# NumPy array overview

- Alternative to Python lists

```
nums_list = list(range(5))
```

```
[0, 1, 2, 3, 4]
```

```
import numpy as np
```

```
nums_np = np.array(range(5))
```

```
array([0, 1, 2, 3, 4])
```

```
# NumPy array homogeneity  
nums_np_ints = np.array([1, 2, 3])
```

```
array([1, 2, 3])
```

```
nums_np_ints.dtype
```

```
dtype('int64')
```

```
nums_np_floats = np.array([1, 2.5, 3])
```

```
array([1. , 2.5, 3. ])
```

```
nums_np_floats.dtype
```

```
dtype('float64')
```

# NumPy array broadcasting

- Python lists don't support broadcasting

```
nums = [-2, -1, 0, 1, 2]  
nums ** 2
```

```
TypeError: unsupported operand type(s) for ** or pow(): 'list' and 'int'
```

- List approach

```
# For loop (inefficient option)
sqrd_nums = []
for num in nums:
    sqrd_nums.append(num ** 2)
print(sqrd_nums)
```

```
[4, 1, 0, 1, 4]
```

```
# List comprehension (better option but not best)
sqrd_nums = [num ** 2 for num in nums]
print(sqrd_nums)
```

```
[4, 1, 0, 1, 4]
```

# NumPy array broadcasting

- NumPy array broadcasting for the win!

```
nums_np = np.array([-2, -1, 0, 1, 2])
nums_np ** 2
```

```
array([4, 1, 0, 1, 4])
```

## Basic 1-D indexing (lists)

```
nums = [-2, -1, 0, 1, 2]  
nums[2]
```

```
0
```

```
nums[-1]
```

```
2
```

```
nums[1:4]
```

```
[-1, 0, 1]
```

## Basic 1-D indexing (arrays)

```
nums_np = np.array(nums)  
nums_np[2]
```

```
0
```

```
nums_np[-1]
```

```
2
```

```
nums_np[1:4]
```

```
array([-1, 0, 1])
```

```
# 2-D list  
nums2 = [ [1, 2, 3],  
          [4, 5, 6] ]
```

```
# 2-D array  
nums2_np = np.array(nums2)
```

- Basic 2-D indexing (lists)

```
nums2[0][1]
```

```
2
```

```
[row[0] for row in nums2]
```

```
[1, 4]
```

- Basic 2-D indexing (arrays)

```
nums2_np[0,1]
```

```
2
```

```
nums2_np[:,0]
```

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

# NumPy array boolean indexing

```
nums = [-2, -1, 0, 1, 2]
nums_np = np.array(nums)
```

- Boolean indexing

```
nums_np > 0
```

```
array([False, False, False, True, True])
```

```
nums_np[nums_np > 0]
```

```
array([1, 2])
```

- No boolean indexing for lists

```
# For loop (inefficient option)
pos = []
for num in nums:
    if num > 0:
        pos.append(num)
print(pos)
```

```
[1, 2]
```

```
# List comprehension (better option but not best)
pos = [num for num in nums if num > 0]
print(pos)
```

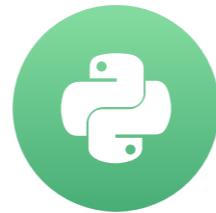
```
[1, 2]
```

**Let's practice with  
powerful NumPy  
arrays!**

**WRITING EFFICIENT PYTHON CODE**

# Examining runtime

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# Why should we time our code?

- Allows us to pick the **optimal** coding approach
- Faster code == more efficient code!

# How can we time our code?

- Calculate runtime with IPython magic command `%timeit`
- **Magic commands:** enhancements on top of normal Python syntax
  - Prefixed by the "%" character
  - Link to docs ([here](#))
  - See all available magic commands with `%lsmagic`

# Using %timeit

Code to be timed

```
import numpy as np  
  
rand_nums = np.random.rand(1000)
```

Timing with `%timeit`

```
%timeit rand_nums = np.random.rand(1000)
```

8.61  $\mu$ s  $\pm$  69.1 ns per loop (mean  $\pm$  std. dev. of 7 runs, 100000 loops each)

# %timeit output

Code to be timed

```
rand_nums = np.random.rand(1000)
```

Timing with %timeit

```
%timeit rand_nums = np.random.rand(1000)
```

```
8.61 µs ± 69.1 ns per loop (mean ± std. dev. of 7 runs, 100000 loops each)
```

# %timeit output

Code to be timed

```
rand_nums = np.random.rand(1000)
```

Timing with %timeit

```
%timeit rand_nums = np.random.rand(1000)
```

```
8.61 µs ± 69.1 ns per loop (mean ± std. dev. of 7 runs, 100000 loops each)
```

# %timeit output

Code to be timed

```
rand_nums = np.random.rand(1000)
```

Timing with %timeit

```
%timeit rand_nums = np.random.rand(1000)
```

```
8.61 µs ± 69.1 ns per loop (mean ± std. dev. of 7 runs, 100000 loops each)
```

# Specifying number of runs/loops

Setting the number of runs ( `-r` ) and/or loops ( `-n` )

```
# Set number of runs to 2 (-r2)
# Set number of loops to 10 (-n10)

%timeit -r2 -n10 rand_nums = np.random.rand(1000)
```

```
16.9 µs ± 5.14 µs per loop (mean ± std. dev. of 2 runs, 10 loops each)
```

# Using %timeit in line magic mode

Line magic( `%timeit` )

```
# Single line of code
```

```
%timeit nums = [x for x in range(10)]
```

```
914 ns ± 7.33 ns per loop (mean ± std. dev. of 7 runs, 1000000 loops each)
```

# Using %timeit in cell magic mode

Cell magic ( `%%timeit` )

```
# Multiple lines of code
```

```
%%timeit
nums = []
for x in range(10):
    nums.append(x)
```

```
1.17 µs ± 3.26 ns per loop (mean ± std. dev. of 7 runs, 1000000 loops each)
```

# Saving output

Saving the output to a variable ( `-o` )

```
times = %timeit -o rand_nums = np.random.rand(1000)
```

```
8.69 µs ± 91.4 ns per loop (mean ± std. dev. of 7 runs, 100000 loops each)
```

times.timings

```
[8.697893059998023e-06,  
 8.651204760008113e-06,  
 8.634270530001232e-06,  
 8.66847825998775e-06,  
 8.619398139999247e-06,  
 8.902550710008654e-06,  
 8.633500570012985e-06]
```

times.best

```
8.619398139999247e-06
```

times.worst

```
8.902550710008654e-06
```

# Comparing times

Python data structures can be created using formal name

```
formal_list = list()  
formal_dict = dict()  
formal_tuple = tuple()
```

Python data structures can be created using literal syntax

```
literal_list = []  
literal_dict = {}  
literal_tuple = ()
```

```
f_time = %timeit -o formal_dict = dict()
```

```
145 ns ± 1.5 ns per loop (mean ± std. dev. of 7 runs, 10000000 loops each)
```

```
l_time = %timeit -o literal_dict = {}
```

```
93.3 ns ± 1.88 ns per loop (mean ± std. dev. of 7 runs, 10000000 loops each)
```

```
diff = (f_time.average - l_time.average) * (10**9)
print('l_time better than f_time by {} ns'.format(diff))
```

```
l_time better than f_time by 51.90819192857814 ns
```

# Comparing times

```
%timeit formal_dict = dict()
```

```
145 ns ± 1.5 ns per loop (mean ± std. dev. of 7 runs, 1000000 loops each)
```

```
%timeit literal_dict = {}
```

```
93.3 ns ± 1.88 ns per loop (mean ± std. dev. of 7 runs, 1000000 loops each)
```

# Off to the races!

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# Code profiling for runtime

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# Code profiling

- Detailed stats on frequency and duration of function calls
- Line-by-line analyses
- Package used: `line_profiler`

```
pip install line_profiler
```

# Code profiling: runtime

```
heroes = ['Batman', 'Superman', 'Wonder Woman']
```

```
hts = np.array([188.0, 191.0, 183.0])
```

```
wts = np.array([ 95.0, 101.0, 74.0])
```

```
def convert_units(heroes, heights, weights):  
  
    new_hts = [ht * 0.39370 for ht in heights]  
    new_wts = [wt * 2.20462 for wt in weights]  
  
    hero_data = {}  
  
    for i,hero in enumerate(heroes):  
        hero_data[hero] = (new_hts[i], new_wts[i])  
  
    return hero_data
```

```
convert_units(heroes, hts, wts)
```

```
{'Batman': (74.0156, 209.4389),  
'Superman': (75.1967, 222.6666),  
'Wonder Woman': (72.0471, 163.1419)}
```

# Code profiling: runtime

```
%timeit convert_units(heroes, hts, wts)
```

```
3 µs ± 32 ns per loop (mean ± std. dev. of 7 runs, 100000 loops each)
```

```
%timeit new_hts = [ht * 0.39370  for ht in hts]
```

```
1.09 µs ± 11 ns per loop (mean ± std. dev. of 7 runs, 1000000 loops each)
```

```
%timeit new_wts = [wt * 2.20462  for wt in wts]
```

```
1.08 µs ± 6.42 ns per loop (mean ± std. dev. of 7 runs, 1000000 loops each)
```

```
%%timeit
hero_data = {}
for i,hero in enumerate(heroes):
    hero_data[hero] = (new_hts[i], new_wts[i])
```

```
634 ns ± 9.29 ns per loop (mean ± std. dev. of 7 runs, 1000000 loops each)
```

# Code profiling: line\_profiler

Using `line_profiler` package

```
%load_ext line_profiler
```

Magic command for line-by-line times

```
%lprun -f
```

# Code profiling: line\_profiler

Using `line_profiler` package

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Magic command for line-by-line times

```
%lprun -f convert_units
```

# Code profiling: line\_profiler

Using `line_profiler` package

```
%load_ext line_profiler
```

Magic command for line-by-line times

```
%lprun -f convert_units convert_units(heroes, hts, wts)
```

# %lprun output

```
%lprun -f convert_units convert_units(heroes, hts, wts)
```

```
Timer unit: 1e-06 s

Total time: 2.6e-05 s
File: <ipython-input-211-2e40813f07a3>
Function: convert_units at line 1

Line #      Hits       Time  Per Hit   % Time  Line Contents
=====
 1           1      13.0     13.0    50.0    def convert_units(heroes, heights, weights):
 2
 3           1      4.0      4.0    15.4        new_hts = [ht * 0.39370 for ht in heights]
 4           1      4.0      4.0    15.4        new_wts = [wt * 2.20462 for wt in weights]
 5
 6           1      1.0      1.0     3.8        hero_data = {}
 7
 8           4      4.0      1.0    15.4        for i,hero in enumerate(heroes):
 9           3      3.0      1.0    11.5            hero_data[hero] = (new_hts[i], new_wts[i])
10
11           1      1.0      1.0     3.8        return hero_data
```

# %lprun output

```
%lprun -f convert_units convert_units(heroes, hts, wts)
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# %lprun output

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# %lprun output

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# %lprun output

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Function: convert\_units at line 1

Line #	Hits	Time	Per Hit	% Time	Line Contents
1					def convert_units(heroes, heights, weights):
2					
3	1	13.0	13.0	50.0	new_hts = [ht * 0.39370 for ht in heights]
4	1	4.0	4.0	15.4	new_wts = [wt * 2.20462 for wt in weights]
5					
6	1	1.0	1.0	3.8	hero_data = {}
7					
8	4	4.0	1.0	15.4	for i,hero in enumerate(heroes):
9	3	3.0	1.0	11.5	hero_data[hero] = (new_hts[i], new_wts[i])
10					
11	1	1.0	1.0	3.8	return hero_data

```
%timeit convert_units convert_units(heroes, hts, wts)
```

3  $\mu$ s  $\pm$  32 ns per loop (mean  $\pm$  std. dev. of 7 runs, 100000 loops each)

```
%lprun -f convert_units convert_units(heroes, hts, wts)
```

```
Timer unit: 1e-06 s

Total time: 2.6e-05 s
File: <ipython-input-211-2e40813f07a3>
Function: convert_units at line 1

Line #      Hits       Time  Per Hit   % Time  Line Contents
=====
1                      def convert_units(heroes, heights, weights):
2
3          1      13.0     13.0    50.0
4          1       4.0      4.0    15.4      new_hts = [ht * 0.39370 for ht in heights]
5
6          1       1.0      1.0     3.8      new_wts = [wt * 2.20462 for wt in weights]
7
8          4       4.0      1.0    15.4      hero_data = {}
9          3       3.0      1.0    11.5      for i,hero in enumerate(heroes):
10
11         1       1.0      1.0     3.8          hero_data[hero] = (new_hts[i], new_wts[i])
12
13
```

**Let's practice your  
new profiling  
powers!**

**WRITING EFFICIENT PYTHON CODE**

# Code profiling for memory usage

WRITING EFFICIENT PYTHON CODE

Logan Thomas

Senior Data Scientist, Protection  
Engineering Consultants



# Quick and dirty approach

```
import sys
```

```
nums_list = [*range(1000)]  
sys.getsizeof(nums_list)
```

```
9112
```

```
import numpy as np
```

```
nums_np = np.array(range(1000))  
sys.getsizeof(nums_np)
```

```
8096
```

# Code profiling: memory

- Detailed stats on memory consumption
- Line-by-line analyses
- Package used: `memory_profiler`

```
pip install memory_profiler
```

- Using `memory_profiler` package

```
%load_ext memory_profiler
```

```
%mprun -f convert_units convert_units(heroes, hts, wts)
```

# Code profiling: memory

- Functions must be imported when using `memory_profiler`
  - `hero_funcs.py`

```
from hero_funcs import convert_units
```

```
%load_ext memory_profiler
```

```
%mprun -f convert_units convert_units(heroes, hts, wts)
```

# %mprun output

```
%mprun -f convert_units convert_units(heroes, hts, wts)
```

Filename: ~/hero\_funcs.py

Line #	Mem usage	Increment	Line Contents
1	103.8 MiB	103.8 MiB	def convert_units(heroes, heights, weights):
2			
3	103.9 MiB	0.0 MiB	new_hts = [ht * 0.39370 for ht in heights]
4	104.1 MiB	0.2 MiB	new_wts = [wt * 2.20462 for wt in weights]
5			
6	104.1 MiB	0.0 MiB	hero_data = {}
7			
8	104.3 MiB	0.0 MiB	for i,hero in enumerate(heroes):
9	104.3 MiB	0.2 MiB	hero_data[hero] = (new_hts[i], new_wts[i])
10			
11	104.3 MiB	0.0 MiB	return hero_data

# %mprun output

```
%mprun -f convert_units convert_units(heroes, hts, wts)
```

Filename: ~/hero\_funcs.py

Line #	Mem usage	Increment	Line Contents
1	103.8 MiB	103.8 MiB	def convert_units(heroes, heights, weights):
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# %mprun output

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```

Filename: ~/hero\_funcs.py

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10			
11	104.3 MiB	0.0 MiB	return hero_data

# %mprun output

```
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# %mprun output

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# %mprun output

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10			
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# %mprun output caveats

```
%mprun -f convert_units convert_units(heroes, hts, wts)
```

Filename: ~/hero\_funcs.py

Line #	Mem usage	Increment	Line Contents
1	103.8 MiB	103.8 MiB	def convert_units(heroes, heights, weights):
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10			
11	104.3 MiB	0.0 MiB	return hero_data

# %mprun output caveats

Data used in this example is a random sample of 35,000 heroes.

(not original 480 superheroes dataset)

```
%mprun -f convert_units convert_units(heroes, hts, wts)
```

Filename: ~/hero\_funcs.py

Line #	Mem usage	Increment	Line Contents
1	103.8 MiB	103.8 MiB	def convert_units(heroes, heights, weights):
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9	104.3 MiB	0.2 MiB	hero_data[hero] = (new_hts[i], new_wts[i])
10			
11	104.3 MiB	0.0 MiB	return hero_data

# %mprun output caveats

Small memory allocations could result in `0.0 MiB` output.

(using original 480 superheroes dataset)

```
%mprun -f convert_units convert_units(heroes, hts, wts)
```

Filename: ~/hero\_funcs.py

Line #	Mem usage	Increment	Line Contents
1	98.7 MiB	98.7 MiB	def convert_units(heroes, heights, weights):
2			
3	98.7 MiB	0.0 MiB	new_hts = [ht * 0.39370 for ht in heights]
4	98.7 MiB	0.0 MiB	new_wts = [wt * 2.20462 for wt in weights]
5			
6	98.7 MiB	0.0 MiB	hero_data = {}
7			
8	98.7 MiB	0.0 MiB	for i,hero in enumerate(heroes):
9	98.7 MiB	0.0 MiB	hero_data[hero] = (new_hts[i], new_wts[i])
10			
11	98.7 MiB	0.0 MiB	return hero_data

# %mprun output caveats

- Inspects memory by querying the operating system
- Results may differ between platforms and runs
  - Can still observe how each line of code compares to others based on memory consumption

# Let's practice!

WRITING EFFICIENT PYTHON CODE

# Efficiently combining, counting, and iterating

WRITING EFFICIENT PYTHON CODE

Logan Thomas

Senior Data Scientist, Protection  
Engineering Consultants



# Pokémon Overview

- Trainers (collect Pokémon)

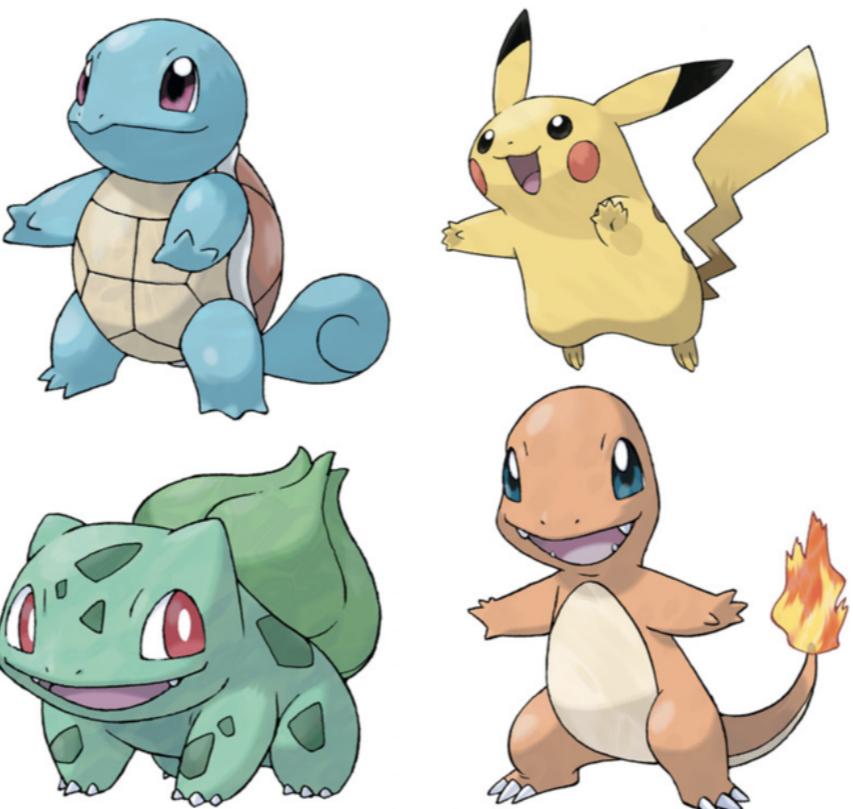


# Pokémon Overview

- Pokémon (fictional animal characters)



*Trainer*



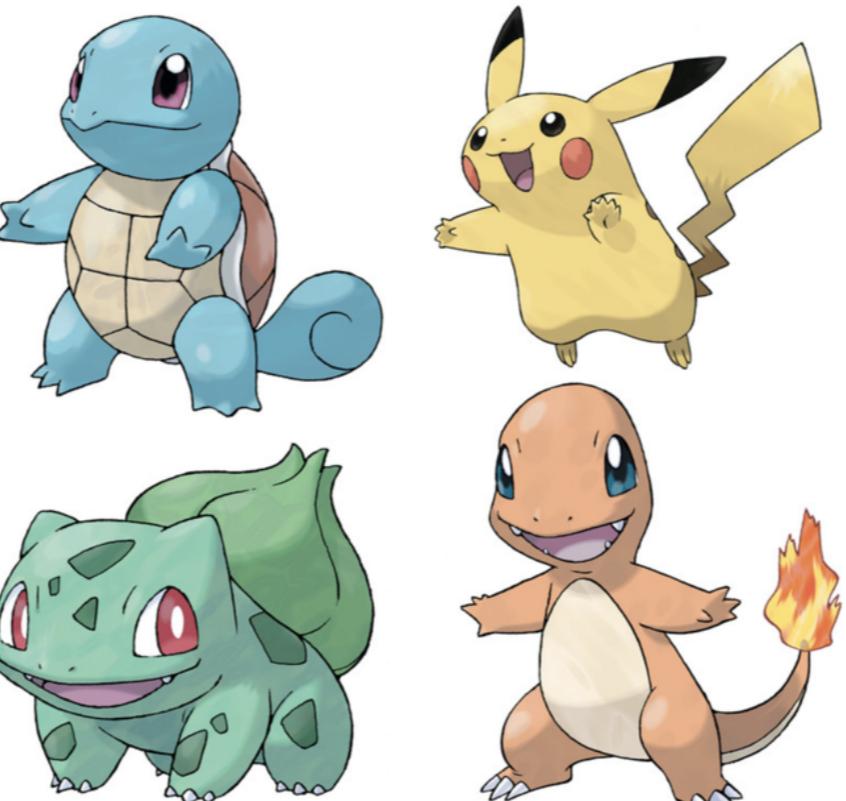
*Pokémon*

# Pokémon Overview

- Pokédex (stores captured Pokémon)



*Trainer*



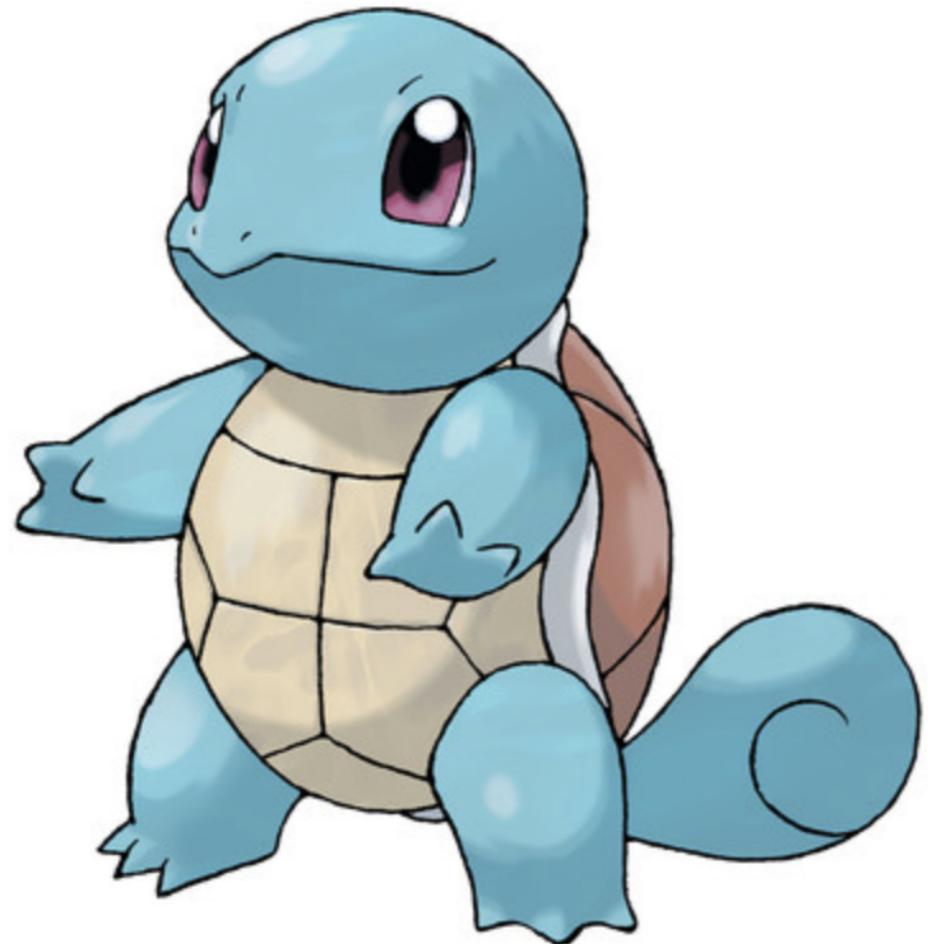
*Pokémon*



*Pokédex*

# Pokémon Description

Squirtle is a [Water](#) type Pokémon introduced in Generation 1. It is known as the 'Tiny Turtle Pokémon'.



## Pokédex data

National № **007**

Type **WATER**

Legendary **False**

## Base stats

HP **44** A horizontal orange bar representing Squirtle's HP stat, which is 44.

Attack **48** A horizontal orange bar representing Squirtle's Attack stat, which is 48.

Defense **65** A horizontal yellow bar representing Squirtle's Defense stat, which is 65.

Sp. Atk **50** A horizontal orange bar representing Squirtle's Special Attack stat, which is 50.

Sp. Def **64** A horizontal yellow bar representing Squirtle's Special Defense stat, which is 64.

Speed **43** A horizontal orange bar representing Squirtle's Speed stat, which is 43.

Total **314**

# Pokémon Description

Squirtle is a Water type Pokémon introduced in Generation 1. It is known as the 'Tiny Turtle Pokémon'.



## Pokédex data

National № 007

Type WATER

Legendary False

## Base stats

HP 44

Attack 48

Defense 65

Sp. Atk 50

Sp. Def 64

Speed 43

Total 314

# Pokémon Description

Squirtle is a Water type Pokémon introduced in Generation 1. It is known as the 'Tiny Turtle Pokémon'.



## Pokédex data

National № 007

Type WATER

Legendary False

## Base stats

HP 44

Attack 48

Defense 65

Sp. Atk 50

Sp. Def 64

Speed 43

Total 314

# Pokémon Description

Squirtle is a Water type Pokémon introduced in Generation 1. It is known as the 'Tiny Turtle Pokémon'.



## Pokédex data

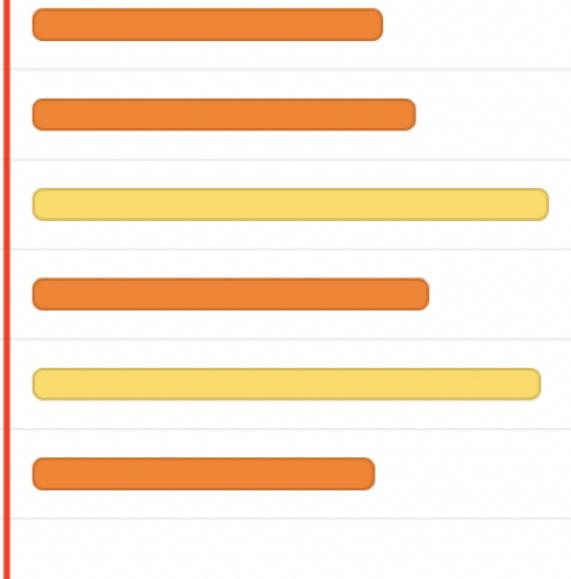
National № 007

Type WATER

Legendary False

## Base stats

HP	44
Attack	48
Defense	65
Sp. Atk	50
Sp. Def	64
Speed	43
Total	314



# Combining objects

```
names = ['Bulbasaur', 'Charmander', 'Squirtle']  
hps = [45, 39, 44]
```

```
combined = []  
  
for i, pokemon in enumerate(names):  
    combined.append((pokemon, hps[i]))  
  
print(combined)
```

```
[('Bulbasaur', 45), ('Charmander', 39), ('Squirtle', 44)]
```

# Combining objects with zip

```
names = ['Bulbasaur', 'Charmander', 'Squirtle']  
hps = [45, 39, 44]
```

```
combined_zip = zip(names, hps)  
print(type(combined_zip))
```

```
<class 'zip'>
```

```
combined_zip_list = [*combined_zip]  
  
print(combined_zip_list)
```

```
[('Bulbasaur', 45), ('Charmander', 39), ('Squirtle', 44)]
```

# The collections module

- Part of Python's Standard Library (built-in module)
- Specialized container datatypes
  - Alternatives to general purpose dict, list, set, and tuple
- Notable:
  - `namedtuple` : tuple subclasses with named fields
  - `deque` : list-like container with fast appends and pops
  - `Counter` : dict for counting hashable objects
  - `OrderedDict` : dict that retains order of entries
  - `defaultdict` : dict that calls a factory function to supply missing values

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  - `Counter` : dict for counting hashable objects
  - `OrderedDict` : dict that retains order of entries
  - `defaultdict` : dict that calls a factory function to supply missing values

# Counting with loop

```
# Each Pokémon's type (720 total)
poke_types = ['Grass', 'Dark', 'Fire', 'Fire', ...]

type_counts = {}

for poke_type in poke_types:
    if poke_type not in type_counts:
        type_counts[poke_type] = 1
    else:
        type_counts[poke_type] += 1

print(type_counts)
```

```
{'Rock': 41, 'Dragon': 25, 'Ghost': 20, 'Ice': 23, 'Poison': 28, 'Grass': 64,
'Flying': 2, 'Electric': 40, 'Fairy': 17, 'Steel': 21, 'Psychic': 46, 'Bug': 65,
'Dark': 28, 'Fighting': 25, 'Ground': 30, 'Fire': 48, 'Normal': 92, 'Water': 105}
```

# `collections.Counter()`

```
# Each Pokémon's type (720 total)
poke_types = ['Grass', 'Dark', 'Fire', 'Fire', ...]

from collections import Counter

type_counts = Counter(poke_types)

print(type_counts)
```

```
Counter({'Water': 105, 'Normal': 92, 'Bug': 65, 'Grass': 64, 'Fire': 48,
         'Psychic': 46, 'Rock': 41, 'Electric': 40, 'Ground': 30,
         'Poison': 28, 'Dark': 28, 'Dragon': 25, 'Fighting': 25, 'Ice': 23,
         'Steel': 21, 'Ghost': 20, 'Fairy': 17, 'Flying': 2})
```

# The itertools module

- Part of Python's Standard Library (built-in module)
- Functional tools for creating and using iterators
- Notable:
  - Infinite iterators: `count` , `cycle` , `repeat`
  - Finite iterators: `accumulate` , `chain` , `zip_longest` ,etc.
  - Combination generators: `product` , `permutations` , `combinations`

# The itertools module

- Part of Python's Standard Library (built-in module)
- Functional tools for creating and using iterators
- Notable:
  - Infinite iterators: `count` , `cycle` , `repeat`
  - Finite iterators: `accumulate` , `chain` , `zip_longest` , etc.
  - Combination generators: `product` , `permutations` , `combinations`

# Combinations with loop

```
poke_types = ['Bug', 'Fire', 'Ghost', 'Grass', 'Water']
combos = []

for x in poke_types:
    for y in poke_types:
        if x == y:
            continue
        if ((x,y) not in combos) & ((y,x) not in combos):
            combos.append((x,y))

print(combos)
```

```
[('Bug', 'Fire'), ('Bug', 'Ghost'), ('Bug', 'Grass'), ('Bug', 'Water'),
 ('Fire', 'Ghost'), ('Fire', 'Grass'), ('Fire', 'Water'),
 ('Ghost', 'Grass'), ('Ghost', 'Water'), ('Grass', 'Water')]
```

# itertools.combinations()

```
poke_types = ['Bug', 'Fire', 'Ghost', 'Grass', 'Water']
from itertools import combinations
combos_obj = combinations(poke_types, 2)
print(type(combos_obj))
```

```
<class 'itertools.combinations'>
```

```
combos = [*combos_obj]
print(combos)
```

```
[('Bug', 'Fire'), ('Bug', 'Ghost'), ('Bug', 'Grass'), ('Bug', 'Water'),
 ('Fire', 'Ghost'), ('Fire', 'Grass'), ('Fire', 'Water'),
 ('Ghost', 'Grass'), ('Ghost', 'Water'), ('Grass', 'Water')]
```

# Let's practice!

WRITING EFFICIENT PYTHON CODE

# Set theory

WRITING EFFICIENT PYTHON CODE



Logan Thomas

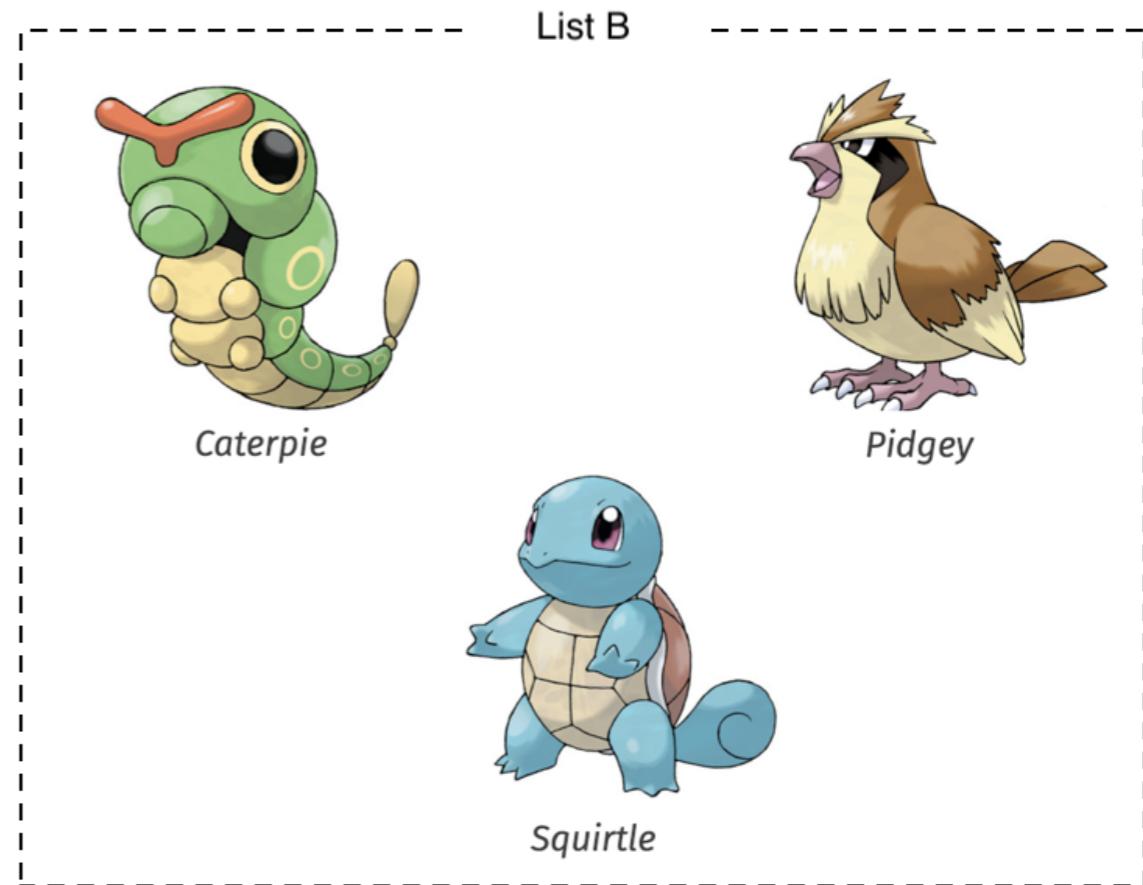
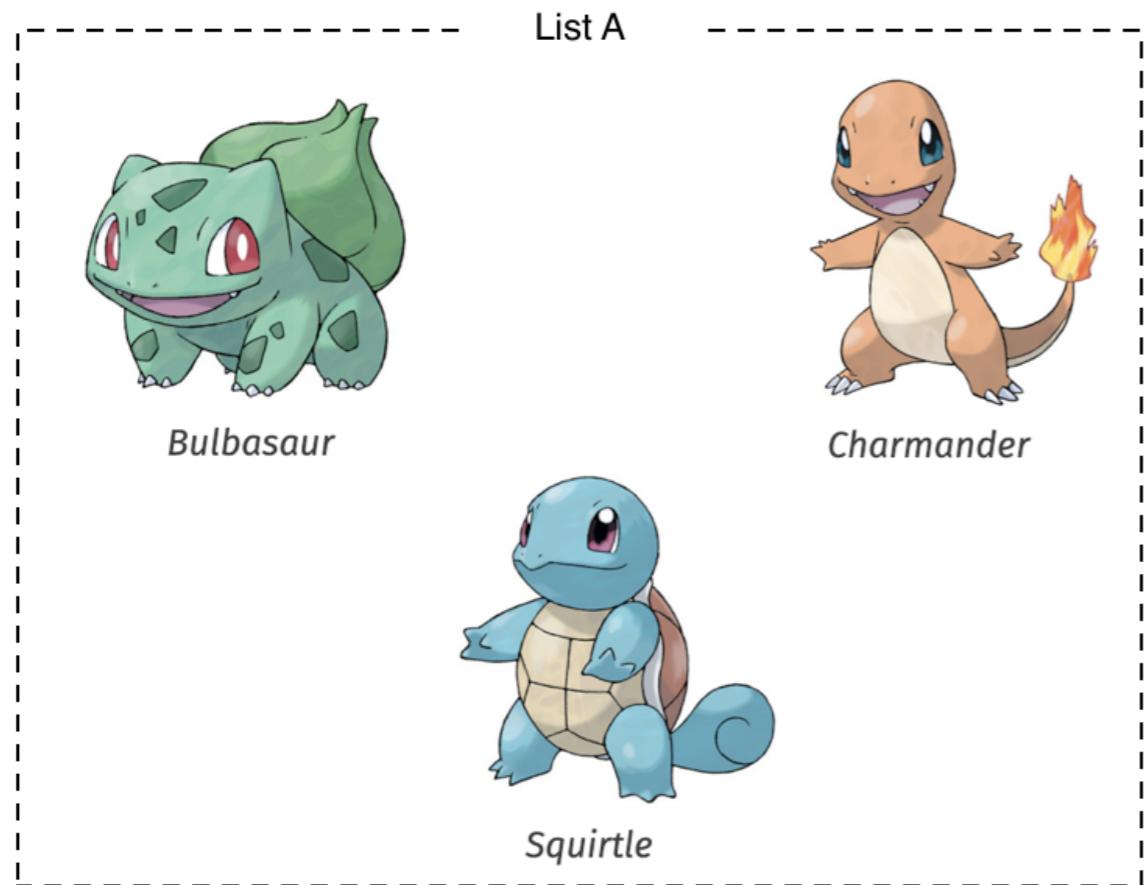
Senior Data Scientist, Protection  
Engineering Consultants

# Set theory

- Branch of Mathematics applied to collections of objects
  - i.e., sets
- Python has built-in set datatype with accompanying methods:
  - intersection() : all elements that are in both sets
  - difference() : all elements in one set but not the other
  - symmetric\_difference() : all elements in exactly one set
  - union() : all elements that are in either set
- Fast membership testing
  - Check if a value exists in a sequence or not
  - Using the in operator

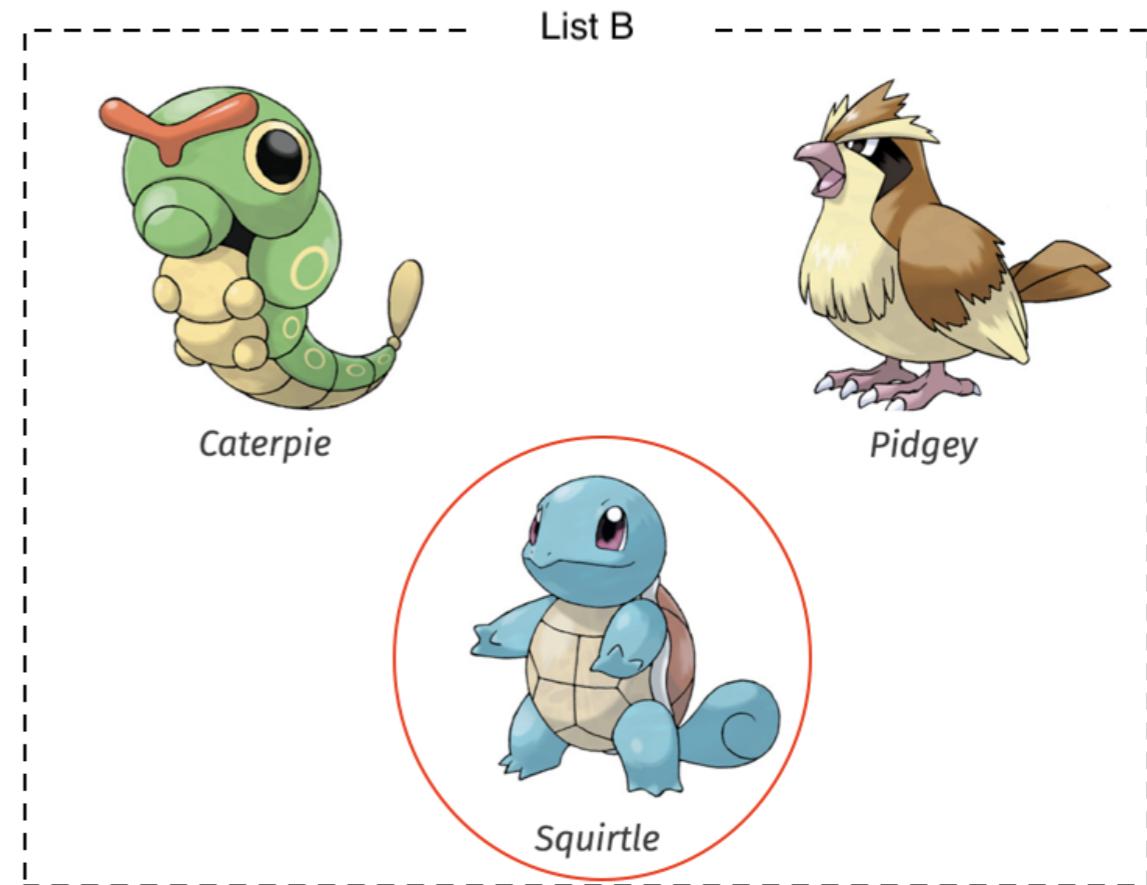
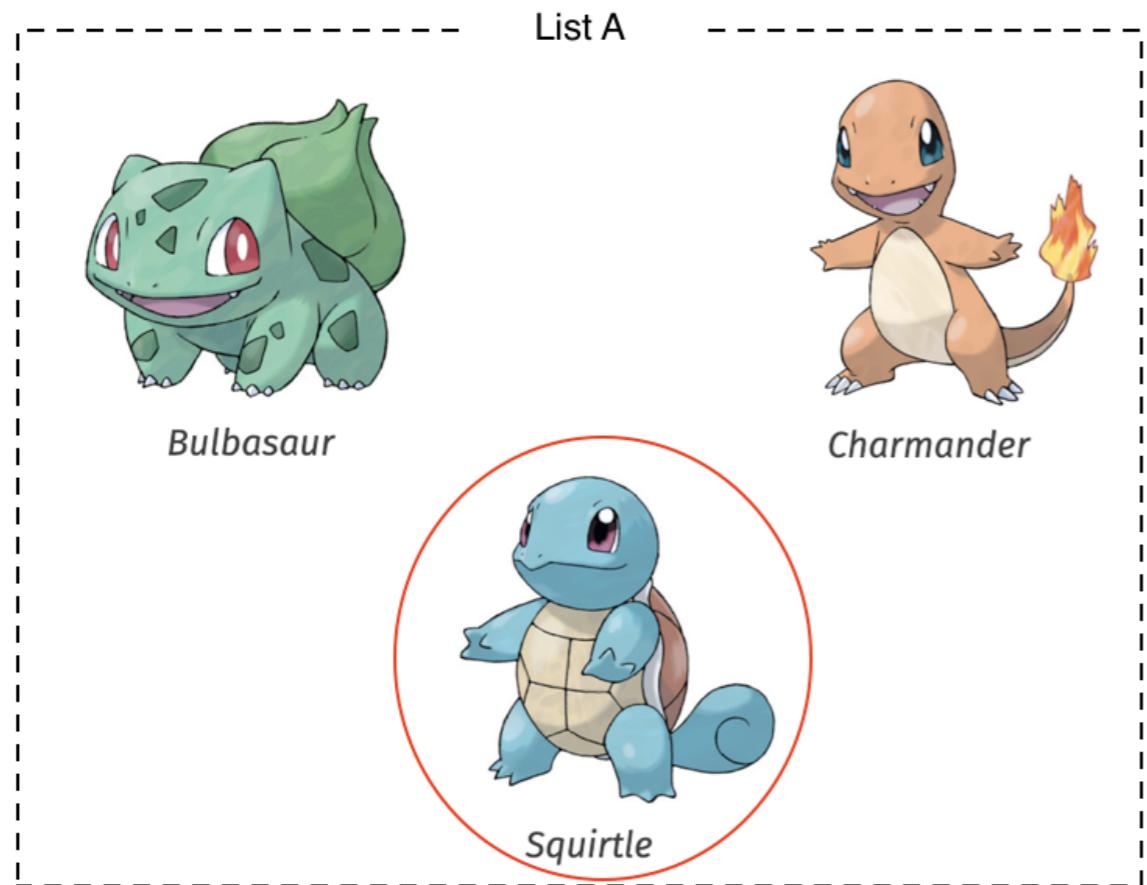
# Comparing objects with loops

```
list_a = ['Bulbasaur', 'Charmander', 'Squirtle']  
list_b = ['Caterpie', 'Pidgey', 'Squirtle']
```



# Comparing objects with loops

```
list_a = ['Bulbasaur', 'Charmander', 'Squirtle']  
list_b = ['Caterpie', 'Pidgey', 'Squirtle']
```



```
list_a = ['Bulbasaur', 'Charmander', 'Squirtle']
list_b = ['Caterpie', 'Pidgey', 'Squirtle']
```

```
in_common = []

for pokemon_a in list_a:
    for pokemon_b in list_b:
        if pokemon_a == pokemon_b:
            in_common.append(pokemon_a)

print(in_common)
```

```
['Squirtle']
```

```
list_a = ['Bulbasaur', 'Charmander', 'Squirtle']
list_b = ['Caterpie', 'Pidgey', 'Squirtle']
```

```
set_a = set(list_a)
print(set_a)
```

```
{'Bulbasaur', 'Charmander', 'Squirtle'}
```

```
set_b = set(list_b)
print(set_b)
```

```
{'Caterpie', 'Pidgey', 'Squirtle'}
```

```
set_a.intersection(set_b)
```

```
{'Squirtle'}
```

# Efficiency gained with set theory

```
%%timeit  
in_common = []  
  
for pokemon_a in list_a:  
    for pokemon_b in list_b:  
        if pokemon_a == pokemon_b:  
            in_common.append(pokemon_a)
```

601 ns ± 17.1 ns per loop (mean ± std. dev. of 7 runs, 1000000 loops each)

```
%timeit in_common = set_a.intersection(set_b)
```

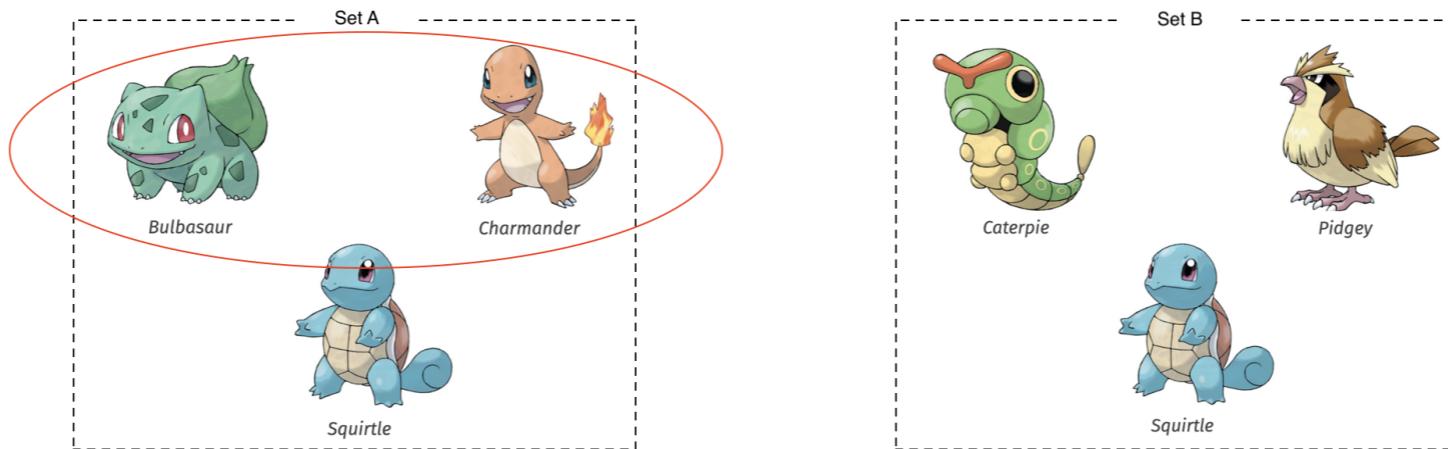
137 ns ± 3.01 ns per loop (mean ± std. dev. of 7 runs, 1000000 loops each)

# Set method: difference

```
set_a = {'Bulbasaur', 'Charmander', 'Squirtle'}  
set_b = {'Caterpie', 'Pidgey', 'Squirtle'}
```

```
set_a.difference(set_b)
```

```
{'Bulbasaur', 'Charmander'}
```

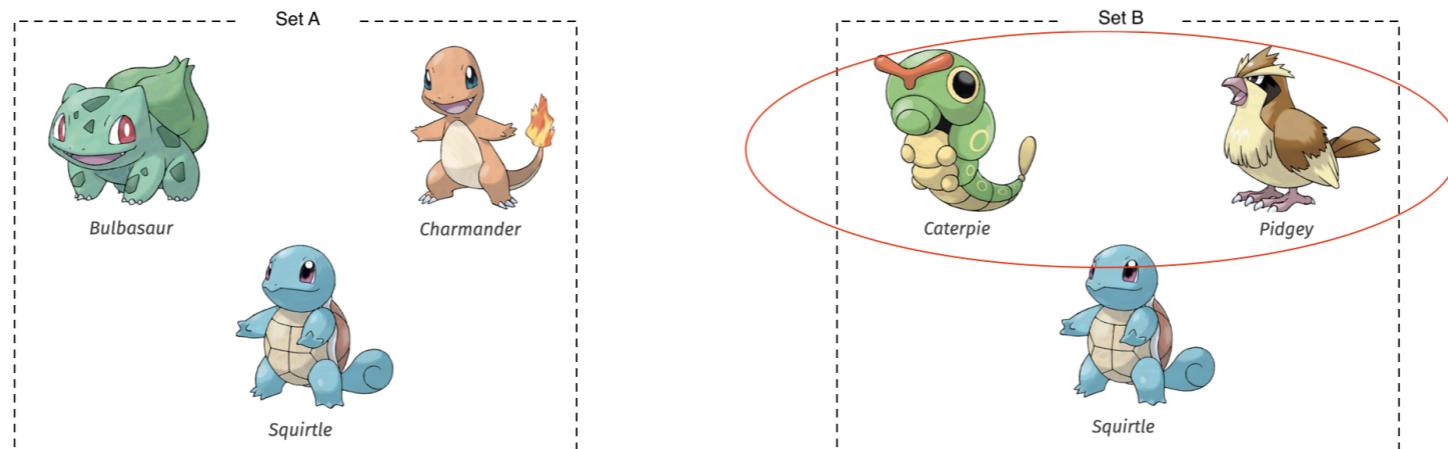


# Set method: difference

```
set_a = {'Bulbasaur', 'Charmander', 'Squirtle'}  
set_b = {'Caterpie', 'Pidgey', 'Squirtle'}
```

```
set_b.difference(set_a)
```

```
{'Caterpie', 'Pidgey'}
```

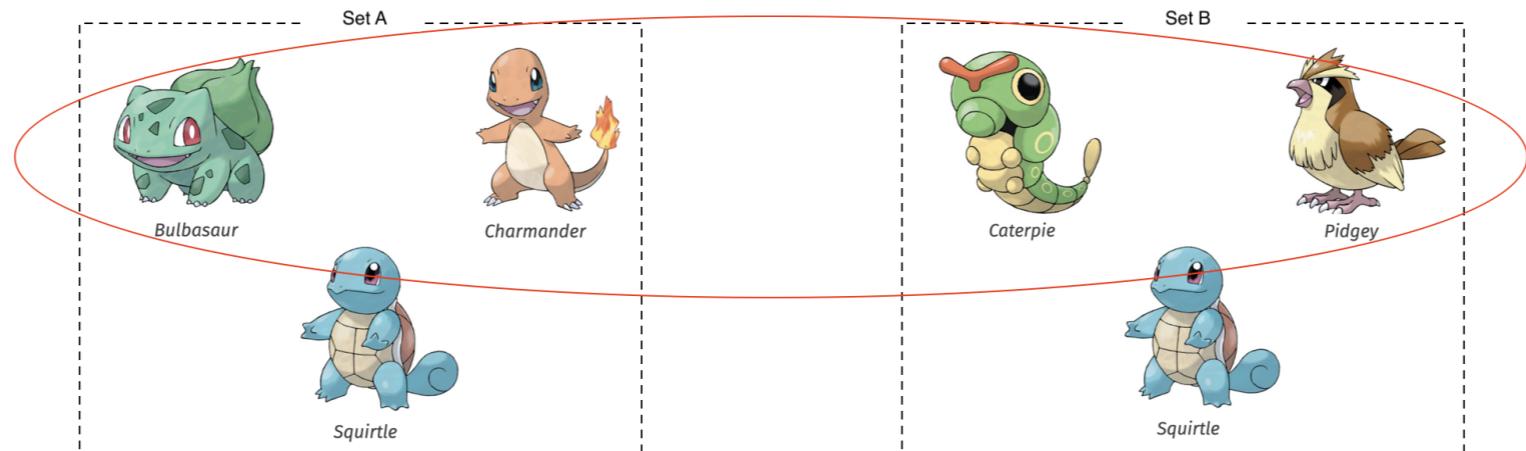


# Set method: symmetric difference

```
set_a = {'Bulbasaur', 'Charmander', 'Squirtle'}  
set_b = {'Caterpie', 'Pidgey', 'Squirtle'}
```

```
set_a.symmetric_difference(set_b)
```

```
{'Bulbasaur', 'Caterpie', 'Charmander', 'Pidgey'}
```

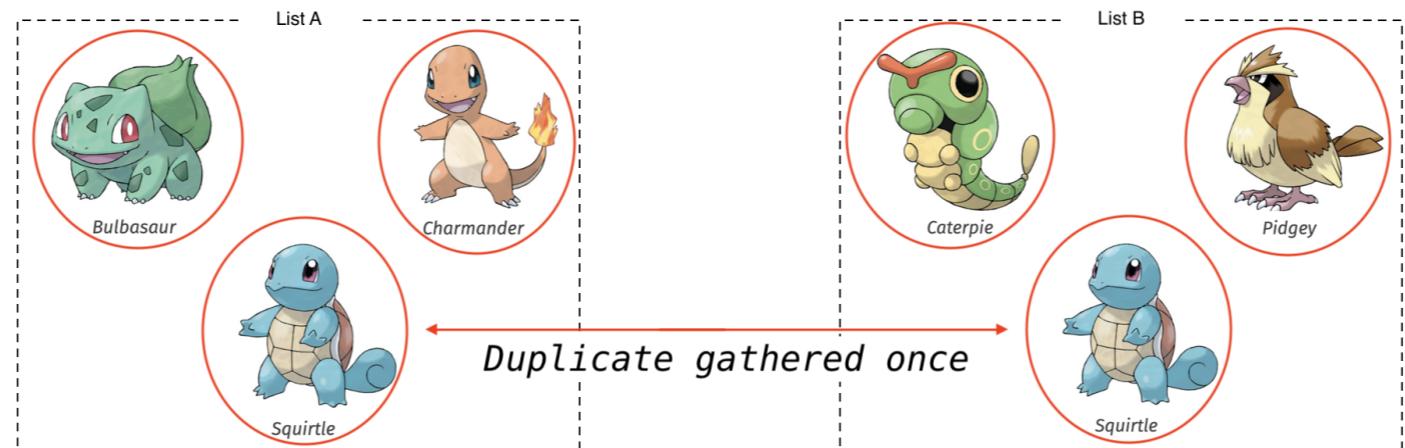


# Set method: union

```
set_a = {'Bulbasaur', 'Charmander', 'Squirtle'}  
set_b = {'Caterpie', 'Pidgey', 'Squirtle'}
```

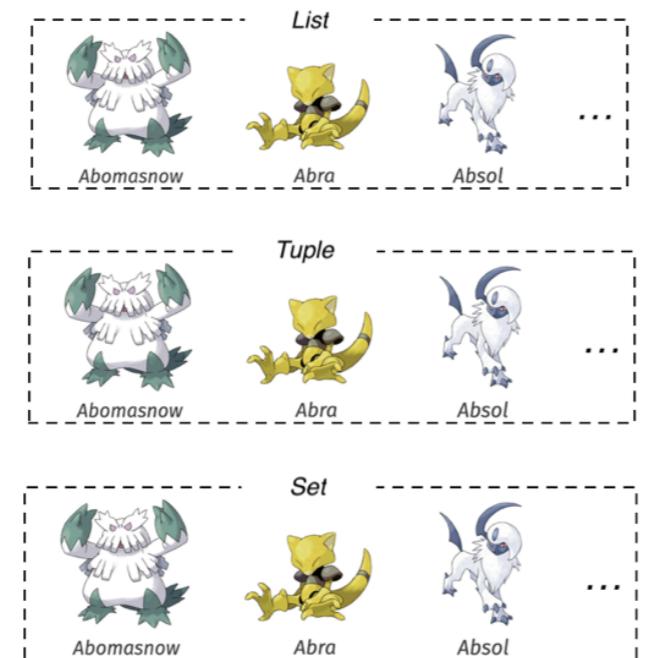
```
set_a.union(set_b)
```

```
{'Bulbasaur', 'Caterpie', 'Charmander', 'Pidgey', 'Squirtle'}
```



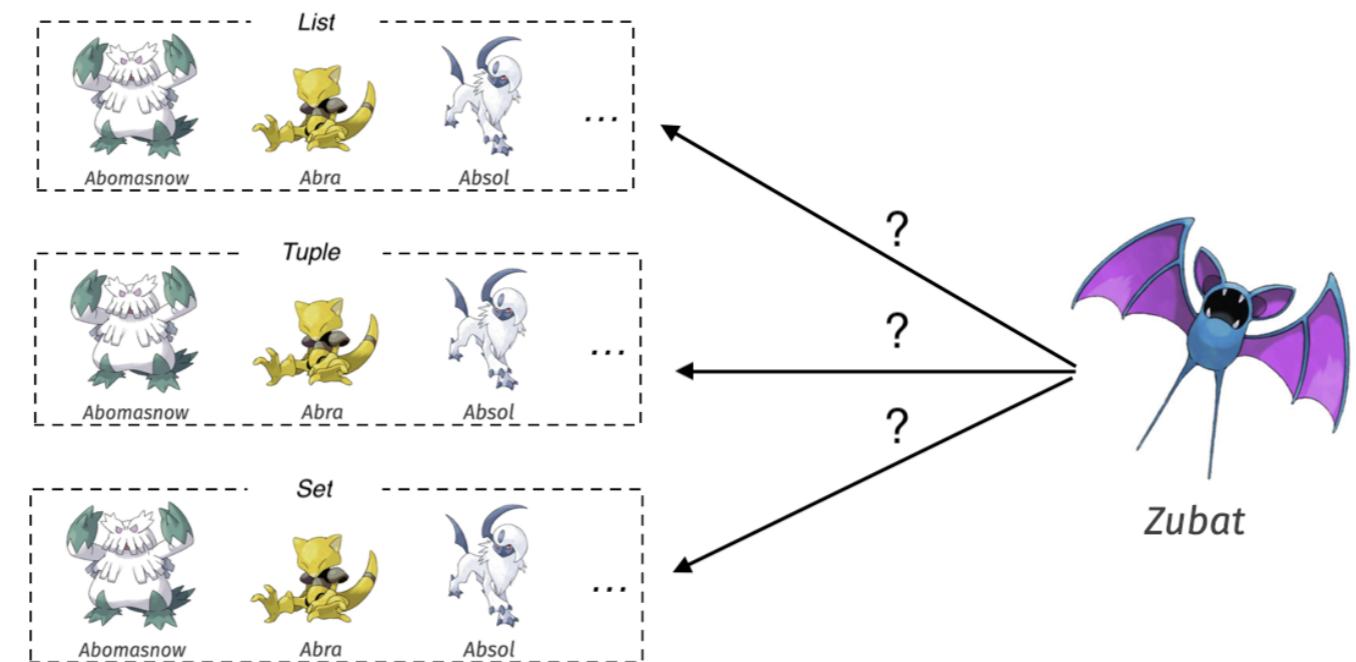
# Membership testing with sets

```
# The same 720 total Pokémon in each data structure  
names_list = ['Abomasnow', 'Abra', 'Absol', ...]  
names_tuple = ('Abomasnow', 'Abra', 'Absol', ...)  
names_set = {'Abomasnow', 'Abra', 'Absol', ...}
```



# Membership testing with sets

```
# The same 720 total Pokémon in each data structure  
names_list = ['Abomasnow', 'Abra', 'Absol', ...]  
names_tuple = ('Abomasnow', 'Abra', 'Absol', ...)  
names_set = {'Abomasnow', 'Abra', 'Absol', ...}
```



```
names_list = ['Abomasnow', 'Abra', 'Absol', ...]  
names_tuple = ('Abomasnow', 'Abra', 'Absol', ...)  
names_set = {'Abomasnow', 'Abra', 'Absol', ...}
```

```
%timeit 'Zubat' in names_list
```

```
7.63 µs ± 211 ns per loop (mean ± std. dev. of 7 runs, 100000 loops each)
```

```
%timeit 'Zubat' in names_tuple
```

```
7.6 µs ± 394 ns per loop (mean ± std. dev. of 7 runs, 100000 loops each)
```

```
%timeit 'Zubat' in names_set
```

```
37.5 ns ± 1.37 ns per loop (mean ± std. dev. of 7 runs, 1000000 loops each)
```

# Uniques with sets

```
# 720 Pokémon primary types corresponding to each Pokémon  
primary_types = ['Grass', 'Psychic', 'Dark', 'Bug', ...]
```

```
unique_types = []  
  
for prim_type in primary_types:  
    if prim_type not in unique_types:  
        unique_types.append(prim_type)  
  
print(unique_types)
```

```
['Grass', 'Psychic', 'Dark', 'Bug', 'Steel', 'Rock', 'Normal',  
'Water', 'Dragon', 'Electric', 'Poison', 'Fire', 'Fairy', 'Ice',  
'Ground', 'Ghost', 'Fighting', 'Flying']
```

# Uniques with sets

```
# 720 Pokémon primary types corresponding to each Pokémon  
primary_types = ['Grass', 'Psychic', 'Dark', 'Bug', ...]  
  
unique_types_set = set(primary_types)  
  
print(unique_types_set)
```

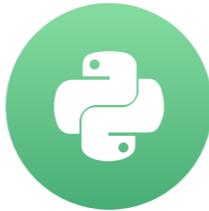
```
{'Grass', 'Psychic', 'Dark', 'Bug', 'Steel', 'Rock', 'Normal',  
'Water', 'Dragon', 'Electric', 'Poison', 'Fire', 'Fairy', 'Ice',  
'Ground', 'Ghost', 'Fighting', 'Flying'}
```

# Let's practice set theory!

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# Eliminating loops

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# Looping in Python

- Looping patterns:
  - `for` loop: iterate over sequence piece-by-piece
  - `while` loop: repeat loop as long as condition is met
  - "nested" loops: use one loop inside another loop
  - Costly!

# Benefits of eliminating loops

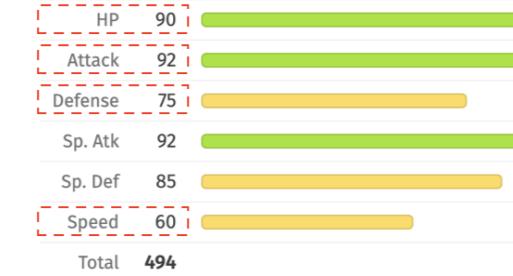
- Fewer lines of code
- Better code readability
  - "Flat is better than nested"
- Efficiency gains

# Eliminating loops with built-ins

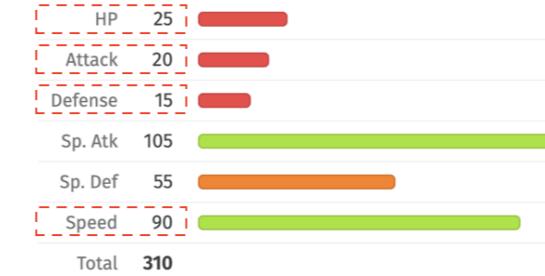
```
# List of HP, Attack, Defense, Speed
poke_stats = [
    [90, 92, 75, 60],
    [25, 20, 15, 90],
    [65, 130, 60, 75],
    ...
]
```



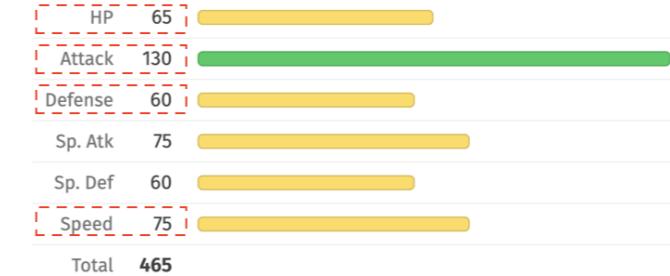
**Base stats**



**Base stats**



**Base stats**



```
# List of HP, Attack, Defense, Speed
poke_stats = [
    [90, 92, 75, 60],
    [25, 20, 15, 90],
    [65, 130, 60, 75],
    ...
]

# For loop approach
totals = []
for row in poke_stats:
    totals.append(sum(row))

# List comprehension
totals_comp = [sum(row) for row in poke_stats]

# Built-in map() function
totals_map = [*map(sum, poke_stats)]
```

```
%%timeit  
totals = []  
for row in poke_stats:  
    totals.append(sum(row))
```

```
140 µs ± 1.94 µs per loop (mean ± std. dev. of 7 runs, 10000 loops each)
```

```
%timeit totals_comp = [sum(row) for row in poke_stats]
```

```
114 µs ± 3.55 µs per loop (mean ± std. dev. of 7 runs, 10000 loops each)
```

```
%timeit totals_map = [*map(sum, poke_stats)]
```

```
95 µs ± 2.94 µs per loop (mean ± std. dev. of 7 runs, 10000 loops each)
```

# Eliminating loops with built-in modules

```
poke_types = ['Bug', 'Fire', 'Ghost', 'Grass', 'Water']
```

```
# Nested for loop approach
combos = []
for x in poke_types:
    for y in poke_types:
        if x == y:
            continue
        if ((x,y) not in combos) & ((y,x) not in combos):
            combos.append((x,y))
```

```
# Built-in module approach
from itertools import combinations
combos2 = [*combinations(poke_types, 2)]
```

# Eliminate loops with NumPy

```
# Array of HP, Attack, Defense, Speed
import numpy as np

poke_stats = np.array([
    [90, 92, 75, 60],
    [25, 20, 15, 90],
    [65, 130, 60, 75],
    ...
])
```

# Eliminate loops with NumPy

```
avgs = []
for row in poke_stats:
    avg = np.mean(row)
    avgs.append(avg)

print(avgs)
```

```
[79.25, 37.5, 82.5, ...]
```

```
avgs_np = poke_stats.mean(axis=1)
print(avgs_np)
```

```
[ 79.25  37.5   82.5   ...]
```

# Eliminate loops with NumPy

```
%timeit avgs = poke_stats.mean(axis=1)
```

```
23.1 µs ± 235 ns per loop (mean ± std. dev. of 7 runs, 10000 loops each)
```

```
%%timeit  
avgs = []  
for row in poke_stats:  
    avg = np.mean(row)  
    avgs.append(avg)
```

```
5.54 ms ± 224 µs per loop (mean ± std. dev. of 7 runs, 100 loops each)
```

# Let's practice!

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# Writing better loops

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# Lesson caveat

- Some of the following loops can be eliminated with techniques covered in previous lessons.
- Examples in this lesson are used for **demonstrative** purposes.



**Warning:** *For demonstration purposes only*

# Writing better loops

- Understand what is being done with each loop iteration
- Move one-time calculations outside (above) the loop
- Use holistic conversions outside (below) the loop
- Anything that is done **once** should be outside the loop

# Moving calculations above a loop

```
import numpy as np

names = ['Absol', 'Aron', 'Jynx', 'Natu', 'Onix']
attacks = np.array([130, 70, 50, 50, 45])

for pokemon, attack in zip(names, attacks):
    total_attack_avg = attacks.mean()
    if attack > total_attack_avg:
        print(
            "{}'s attack: {} > average: {}!"
            .format(pokemon, attack, total_attack_avg)
        )
```

```
Absol's attack: 130 > average: 69.0!
Aron's attack: 70 > average: 69.0!
```

```
import numpy as np

names = ['Absol', 'Aron', 'Jynx', 'Natu', 'Onix']
attacks = np.array([130, 70, 50, 50, 45])
# Calculate total average once (outside the loop)
total_attack_avg = attacks.mean()

for pokemon, attack in zip(names, attacks):

    if attack > total_attack_avg:
        print(
            "{}'s attack: {} > average: {}!"
            .format(pokemon, attack, total_attack_avg)
        )
```

```
Absol's attack: 130 > average: 69.0!
Aron's attack: 70 > average: 69.0!
```

# Moving calculations above a loop

```
%%timeit
for pokemon, attack in zip(names, attacks):
    total_attack_avg = attacks.mean()

    if attack > total_attack_avg:
        print(
            "{}'s attack: {} > average: {}!".format(pokemon, attack, total_attack_avg)
        )
```

74.9  $\mu$ s  $\pm$  3.42  $\mu$ s per loop (mean  $\pm$  std. dev. of 7 runs, 10000 loops each)

# Moving calculations above a loop

```
%%timeit
# Calculate total average once (outside the loop)
total_attack_avg = attacks.mean()

for pokemon, attack in zip(names, attacks):

    if attack > total_attack_avg:
        print(
            "{}'s attack: {} > average: {}!"
            .format(pokemon, attack, total_attack_avg)
        )
```

```
37.5 µs ± 281 ns per loop (mean ± std. dev. of 7 runs, 10000 loops each)
```

# Using holistic conversions

```
names = ['Pikachu', 'Squirtle', 'Articuno', ...]
legend_status = [False, False, True, ...]
generations = [1, 1, 1, ...]

poke_data = []
for poke_tuple in zip(names, legend_status, generations):
    poke_list = list(poke_tuple)
    poke_data.append(poke_list)

print(poke_data)
```

```
[['Pikachu', False, 1], ['Squirtle', False, 1], ['Articuno', True, 1], ...]
```

# Using holistic conversions

```
names = ['Pikachu', 'Squirtle', 'Articuno', ...]
legend_status = [False, False, True, ...]
generations = [1, 1, 1, ...]

poke_data_tuples = []
for poke_tuple in zip(names, legend_status, generations):
    poke_data_tuples.append(poke_tuple)

poke_data = [*map(list, poke_data_tuples)]
print(poke_data)
```

```
[['Pikachu', False, 1], ['Squirtle', False, 1], ['Articuno', True, 1], ...]
```

```
%%timeit
poke_data = []
for poke_tuple in zip(names, legend_status, generations):
    poke_list = list(poke_tuple)
    poke_data.append(poke_list)
```

```
261 µs ± 23.2 µs per loop (mean ± std. dev. of 7 runs, 1000 loops each)
```

```
%%timeit
poke_data_tuples = []
for poke_tuple in zip(names, legend_status, generations):
    poke_data_tuples.append(poke_tuple)

poke_data = [*map(list, poke_data_tuples)]
```

```
224 µs ± 1.67 µs per loop (mean ± std. dev. of 7 runs, 1000 loops each)
```

# Time for some practice!

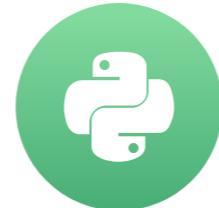
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# Intro to pandas DataFrame iteration

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# pandas recap

- See pandas overview in [Intermediate Python for Data Science](#)
- Library used for data analysis
- Main data structure is the DataFrame
  - Tabular data with labeled rows and columns
  - Built on top of the NumPy array structure
- Chapter Objective:
  - Best practice for iterating over a pandas DataFrame

# Baseball stats

```
import pandas as pd\n\nbaseball_df = pd.read_csv('baseball_stats.csv')\nprint(baseball_df.head())
```

	Team	League	Year	RS	RA	W	G	Playoffs
0	ARI	NL	2012	734	688	81	162	0
1	ATL	NL	2012	700	600	94	162	1
2	BAL	AL	2012	712	705	93	162	1
3	BOS	AL	2012	734	806	69	162	0
4	CHC	NL	2012	613	759	61	162	0

# Baseball stats

Team

- 0 ARI
- 1 ATL
- 2 BAL
- 3 BOS
- 4 CHC



*Arizona Diamondbacks (ARI)*



*Atlanta Braves (ATL)*



*Baltimore Orioles (BAL)*



*Boston Red Sox (BOS)*



*Chicago Cubs (CHC)*

# Baseball stats

	Team	League	Year	RS	RA	W	G	Playoffs
0	ARI	NL	2012	734	688	81	162	0
1	ATL	NL	2012	700	600	94	162	1
2	BAL	AL	2012	712	705	93	162	1
3	BOS	AL	2012	734	806	69	162	0
4	CHC	NL	2012	613	759	61	162	0

# Calculating win percentage

```
import numpy as np

def calc_win_perc(wins, games_played):

    win_perc = wins / games_played

    return np.round(win_perc, 2)
```

```
win_perc = calc_win_perc(50, 100)
print(win_perc)
```

0.5

# Adding win percentage to DataFrame

```
win_perc_list = []

for i in range(len(baseball_df)):
    row = baseball_df.iloc[i]

    wins = row['W']
    games_played = row['G']

    win_perc = calc_win_perc(wins, games_played)

    win_perc_list.append(win_perc)

baseball_df['WP'] = win_perc_list
```

# Adding win percentage to DataFrame

```
print(baseball_df.head())
```

	Team	League	Year	RS	RA	W	G	Playoffs	WP
0	ARI	NL	2012	734	688	81	162	0	0.50
1	ATL	NL	2012	700	600	94	162	1	0.58
2	BAL	AL	2012	712	705	93	162	1	0.57
3	BOS	AL	2012	734	806	69	162	0	0.43
4	CHC	NL	2012	613	759	61	162	0	0.38

# Iterating with .iloc

```
%%timeit
win_perc_list = []

for i in range(len(baseball_df)):
    row = baseball_df.iloc[i]

    wins = row['W']
    games_played = row['G']

    win_perc = calc_win_perc(wins, games_played)
    win_perc_list.append(win_perc)

baseball_df['WP'] = win_perc_list
```

183 ms ± 1.73 ms per loop (mean ± std. dev. of 7 runs, 10 loops each)

# Iterating with .iterrows()

```
win_perc_list = []

for i, row in baseball_df.iterrows():

    wins = row['W']
    games_played = row['G']

    win_perc = calc_win_perc(wins, games_played)

    win_perc_list.append(win_perc)

baseball_df['WP'] = win_perc_list
```

# Iterating with .iterrows()

```
%%timeit
win_perc_list = []

for i, row in baseball_df.iterrows():

    wins = row['W']
    games_played = row['G']

    win_perc = calc_win_perc(wins, games_played)
    win_perc_list.append(win_perc)

baseball_df['WP'] = win_perc_list
```

95.3 ms ± 3.57 ms per loop (mean ± std. dev. of 7 runs, 10 loops each)

# Practice DataFrame iterating with .iterrows()

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# Another iterator method: `.itertuples()`

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# Team wins data

```
print(team_wins_df)
```

```
   Team  Year     W
0    ARI  2012    81
1    ATL  2012    94
2    BAL  2012    93
3    BOS  2012    69
4    CHC  2012    61
...

```

```
for row_tuple in team_wins_df.iterrows():
    print(row_tuple)
    print(type(row_tuple[1]))
```

```
(0, Team      ARI
Year      2012
W        81
Name: 0, dtype: object)
<class 'pandas.core.series.Series'>

(1, Team      ATL
Year      2012
W        94
Name: 1, dtype: object)
<class 'pandas.core.series.Series'>
...
```

# Iterating with .itertuples()

```
for row_namedtuple in team_wins_df.itertuples():
    print(row_namedtuple)
```

```
Pandas(Index=0, Team='ARI', Year=2012, W=81)
Pandas(Index=1, Team='ATL', Year=2012, W=94)
...

```

```
print(row_namedtuple.Index)
```

```
1
```

```
print(row_namedtuple.Team)
```

```
ATL
```

# Comparing methods

```
%%timeit
for row_tuple in team_wins_df.iterrows():
    print(row_tuple)
```

527 ms ± 41.1 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)

```
%%timeit
for row_namedtuple in team_wins_df.itertuples():
    print(row_namedtuple)
```

7.48 ms ± 243 µs per loop (mean ± std. dev. of 7 runs, 100 loops each)

```
for row_tuple in team_wins_df.iterrows():
    print(row_tuple[1]['Team'])
```

ARI  
ATL  
...

```
for row_namedtuple in team_wins_df.itertuples():
    print(row_namedtuple['Team'])
```

TypeError: tuple indices must be integers or slices, not str

```
for row_namedtuple in team_wins_df.itertuples():
    print(row_namedtuple.Team)
```

ARI  
ATL  
...

# Let's keep iterating!

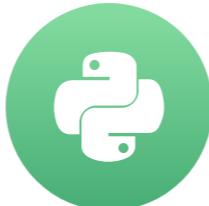
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# pandas alternative to looping

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```
print(baseball_df.head())
```

	Team	League	Year	RS	RA	W	G	Playoffs
0	ARI	NL	2012	734	688	81	162	0
1	ATL	NL	2012	700	600	94	162	1
2	BAL	AL	2012	712	705	93	162	1
3	BOS	AL	2012	734	806	69	162	0
4	CHC	NL	2012	613	759	61	162	0

```
def calc_run_diff(runs_scored, runs_allowed):  
  
    run_diff = runs_scored - runs_allowed  
  
    return run_diff
```

# Run differentials with a loop

```
run_diffs_iterrows = []

for i, row in baseball_df.iterrows():
    run_diff = calc_run_diff(row['RS'], row['RA'])
    run_diffs_iterrows.append(run_diff)

baseball_df['RD'] = run_diffs_iterrows
print(baseball_df)
```

	Team	League	Year	RS	RA	W	G	Playoffs	RD
0	ARI	NL	2012	734	688	81	162	0	46
1	ATL	NL	2012	700	600	94	162	1	100
2	BAL	AL	2012	712	705	93	162	1	7
...									

# pandas .apply() method

- Takes a function and applies it to a DataFrame
  - Must specify an axis to apply ( 0 for columns; 1 for rows)
- Can be used with anonymous functions ( lambda functions)
- Example:

```
baseball_df.apply(  
    lambda row: calc_run_diff(row['RS'], row['RA']),  
    axis=1  
)
```

# Run differentials with .apply()

```
run_diffs_apply = baseball_df.apply(  
    lambda row: calc_run_diff(row['RS'], row['RA']),  
    axis=1)  
  
baseball_df['RD'] = run_diffs_apply  
  
print(baseball_df)
```

	Team	League	Year	RS	RA	W	G	Playoffs	RD
0	ARI	NL	2012	734	688	81	162	0	46
1	ATL	NL	2012	700	600	94	162	1	100
2	BAL	AL	2012	712	705	93	162	1	7
...									

# Comparing approaches

```
%%timeit  
run_diffs_iterrows = []  
  
for i, row in baseball_df.iterrows():  
    run_diff = calc_run_diff(row['RS'], row['RA'])  
    run_diffs_iterrows.append(run_diff)  
  
baseball_df['RD'] = run_diffs_iterrows
```

86.8 ms ± 3 ms per loop (mean ± std. dev. of 7 runs, 10 loops each)

# Comparing approaches

```
%%timeit  
  
run_diffs_apply = baseball_df.apply(  
    lambda row: calc_run_diff(row['RS'], row['RA']),  
    axis=1)  
  
baseball_df['RD'] = run_diffs_apply
```

30.1 ms ± 1.75 ms per loop (mean ± std. dev. of 7 runs, 10 loops each)

**Let's practice using  
pandas .apply()  
method!**

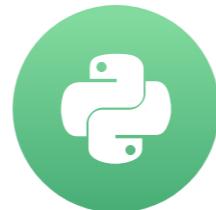
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# Optimal pandas iterating

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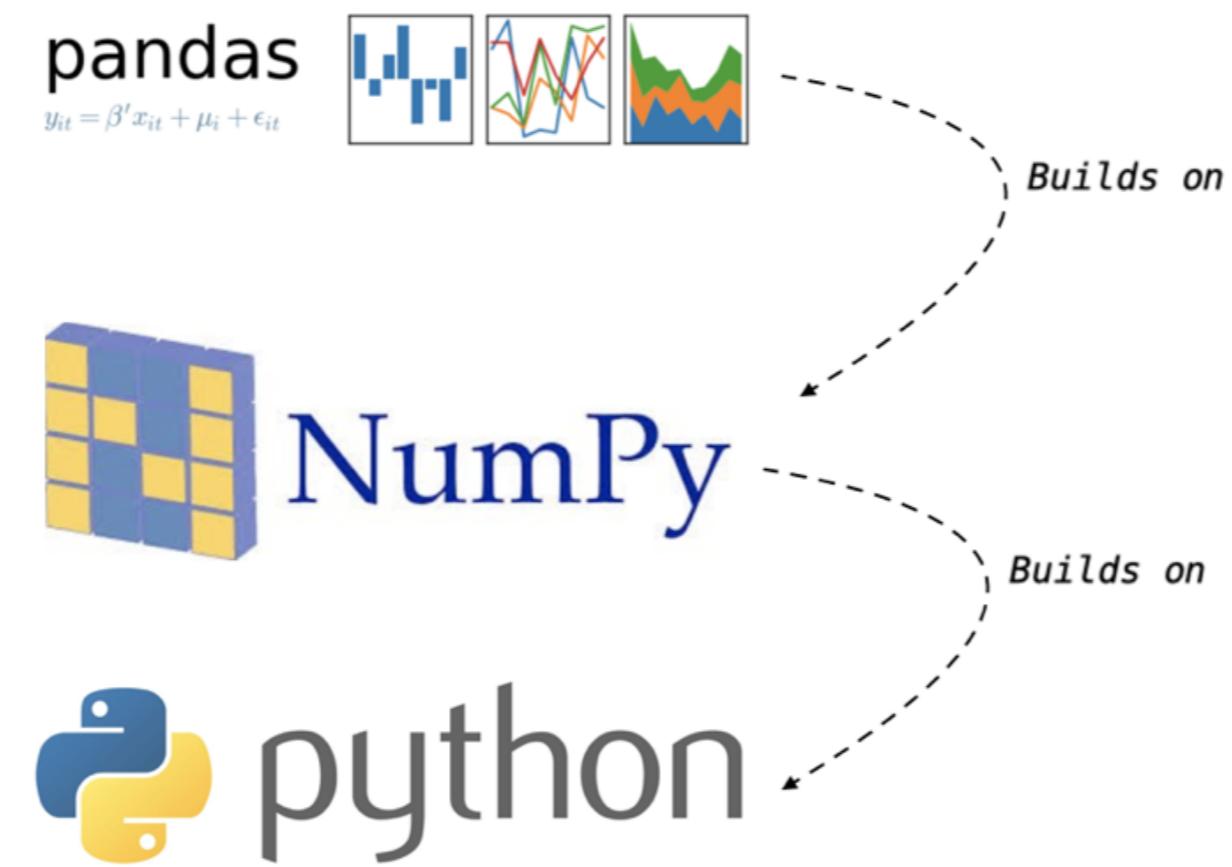
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# pandas internals

- Eliminating loops applies to using pandas as well
- pandas is built on NumPy
  - Take advantage of NumPy array efficiencies



```
print(baseball_df)
```

	Team	League	Year	RS	RA	W	G	Playoffs
0	ARI	NL	2012	734	688	81	162	0
1	ATL	NL	2012	700	600	94	162	1
2	BAL	AL	2012	712	705	93	162	1
...								

```
wins_np = baseball_df['W'].values  
print(type(wins_np))
```

```
<class 'numpy.ndarray'>
```

```
print(wins_np)
```

```
[ 81  94  93 ...]
```

# Power of vectorization

- Broadcasting (vectorizing) is extremely efficient!

```
baseball_df[ 'RS' ].values - baseball_df[ 'RA' ].values
```

```
array([ 46, 100, 7, ..., 188, 110, -117])
```

# Run differentials with arrays

```
run_diffs_np = baseball_df['RS'].values - baseball_df['RA'].values  
baseball_df['RD'] = run_diffs_np  
print(baseball_df)
```

	Team	League	Year	RS	RA	W	G	Playoffs	RD
0	ARI	NL	2012	734	688	81	162	0	46
1	ATL	NL	2012	700	600	94	162	1	100
2	BAL	AL	2012	712	705	93	162	1	7
3	BOS	AL	2012	734	806	69	162	0	-72
4	CHC	NL	2012	613	759	61	162	0	-146
...									

# Comparing approaches

```
%%timeit  
run_diffs_np = baseball_df['RS'].values - baseball_df['RA'].values  
  
baseball_df['RD'] = run_diffs_np
```

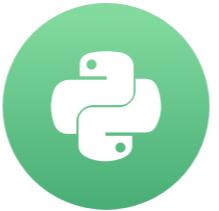
124  $\mu$ s  $\pm$  1.47  $\mu$ s per loop (mean  $\pm$  std. dev. of 7 runs, 10000 loops each)

**Let's put our skills  
into practice!**

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# Congratulations!

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# What you have learned

- The definition of **efficient** and **Pythonic** code
- How to use Python's powerful built-in library
- The advantages of NumPy arrays
- Some handy magic commands to profile code
- How to deploy efficient solutions with `zip()`, `itertools`, `collections`, and set theory
- The cost of looping and how to eliminate loops
- Best practices for iterating with pandas DataFrames

# Well done!

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