Speed Up Your Data Processing: Parallel and Asynchronous Programming in Python

Presented by:
Ong Chin Hwee (@ongchinhwee)

20 March 2020 FOSSASIA Summit 2020, Singapore

About me

Ong Chin Hwee 王敬惠

- Data Engineer @ ST Engineering
- Background in aerospace engineering + computational modelling
- Contributor to pandas 1.0 release
- Mentor team at BigDataX





A typical data science workflow

- 1. Extract raw data
- 2. Process data
- 3. Train model
- 4. Deploy model

Bottlenecks in a data science project

- Lack of data / Poor quality data
- Data processing
 - The 80/20 data science dilemma
 - In reality, it's closer to 90/10

Data Processing in Python

- For loops in Python
 - Run on the interpreter, not compiled
 - Slow compared with C

```
a_list = []
for i in range(100):
    a_list.append(i*i)
```

Data Processing in Python

- List comprehensions
 - Slightly faster than for loops
 - No need to call append function at each iteration

```
a_list = [i*i for i in range(100)]
```

Challenges with Data Processing

Pandas

- Optimized for in-memory analytics using DataFrames
- Performance + out-of-memory issues when dealing with large datasets (> 1 GB)

```
import pandas as pd
import numpy as np
df = pd.DataFrame(list(range(100)))
df.apply(np.square)
```

Challenges with Data Processing

"Why not just use a Spark cluster?"

<u>Communication overhead</u>: Distributed computing involves communicating between (independent) machines across a network!

"Small Big Data"(*): Data too big to fit in memory, but not large enough to justify using a Spark cluster.

(*) Credits to Itamar Turner-Trauring (@itamarst) for this term

What is parallel processing?

Let's imagine I work at a cafe which sells toast.

Task 1: Toast 100 slices of bread

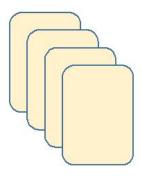
Assumptions:

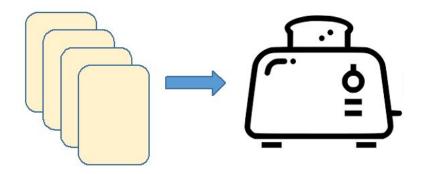
- 1. I'm using single-slice toasters. (Yes, they actually exist.)
- 2. Each slice of toast takes 2 minutes to make.
- 3. No overhead time.



Image taken from:

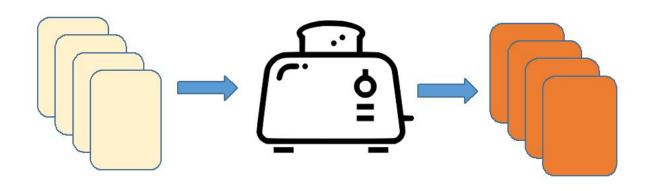
https://www.mitsubishielectric.co.jp/home/breadoven/product/to-st1-t/feature/index.html





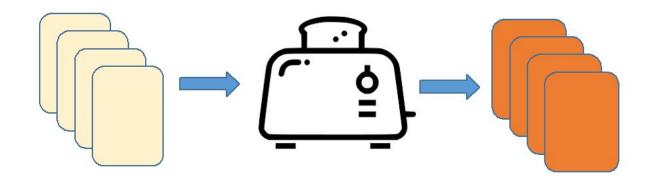
Processor/Worker:

Toaster

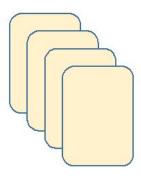


= 25 bread slices

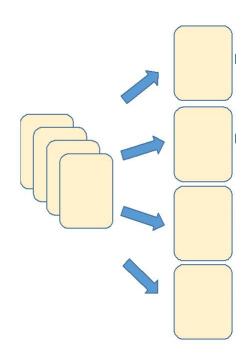
<u>Processor/Worker</u>: Toaster = 25 toasts

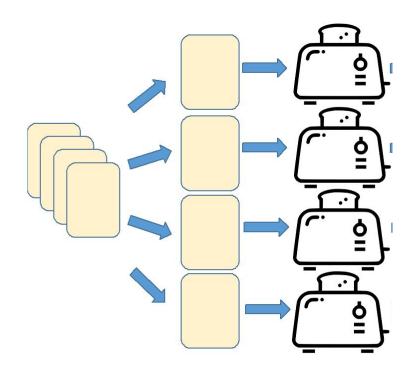


Execution Time = 100 toasts × 2 minutes/toast = 200 minutes



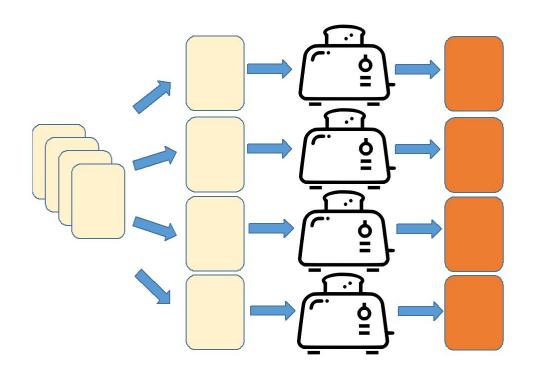
= 25 bread slices





Processor (Core):

Toaster



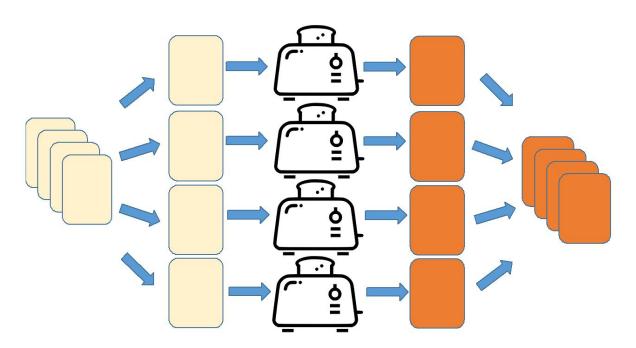
Processor (Core):

Toaster

Task is executed using a **pool** of **4 toaster subprocesses**.

Each toasting subprocess runs <u>in</u> <u>parallel</u> and <u>independently</u> from each other.

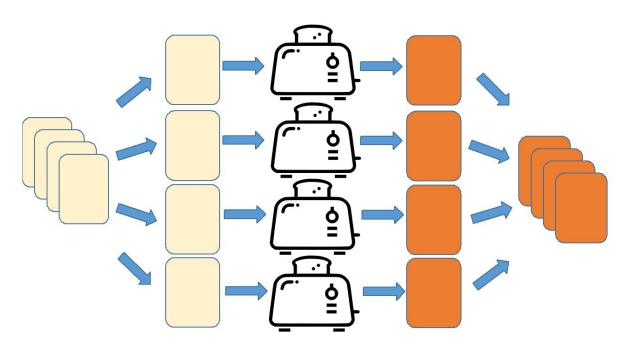
@ongchinhwee



Processor (Core):

Toaster

Output of each toasting process is **consolidated** and **returned** as an overall output (which may or may not be ordered).



Execution Time

= 100 toasts × 2 minutes/toast ÷

4 toasters

= 50 minutes

Speedup = 4 times

Synchronous vs Asynchronous Execution

What do you mean by "Asynchronous"?

Task 2: Brew gourmet coffee

Assumptions:

- 1. I can do other stuff while making coffee.
- 2. One coffee maker to make one cup of coffee.
- 3. Each cup of coffee takes 5 minutes to make.



Synchronous Execution



Task 2: Brew a cup of coffee on

coffee machine

Duration: 5 minutes

Synchronous Execution

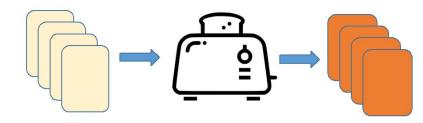


Task 1: Toast a slice of bread on single-slice toaster <u>after</u>
Task 2 is completed
Duration: 2 minutes

Task 2: Brew a cup of coffee on

coffee machine

Duration: 5 minutes



Synchronous Execution

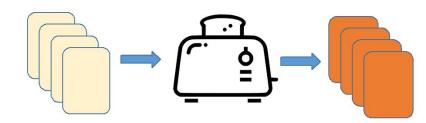


Task 1: Toast a slice of bread on single-slice toaster <u>after</u>
Task 2 is completed
Duration: 2 minutes

Task 2: Brew a cup of coffee on

coffee machine

Duration: 5 minutes



Output: 1 toast + 1 coffee

Total Execution Time = 5 minutes + 2 minutes = **7 minutes**

@ongchinhwee

Asynchronous Execution

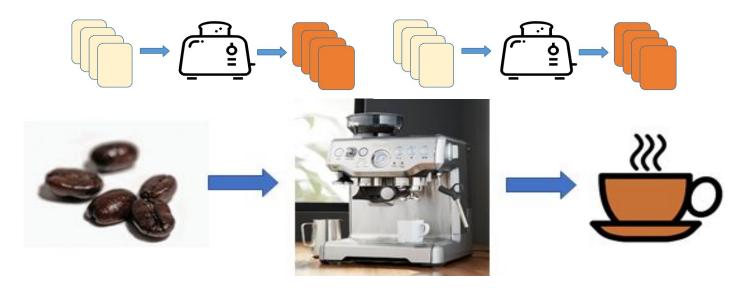
While brewing coffee:



Make some toasts:



Asynchronous Execution



Output: **2 toasts + 1 coffee** (1 more toast!) **Total Execution Time = 5 minutes**

@ongchinhwee

When is it a good idea to go for parallelism?

(or, "Is it a good idea to simply buy a 256-core processor and parallelize all your codes?")

Practical Considerations

- Is your code already optimized?
 - Sometimes, you might need to rethink your approach.
 - Example: Use list comprehensions or map functions instead of for-loops for array iterations.

Practical Considerations

- Is your code already optimized?
- Problem architecture
 - Nature of problem limits how successful parallelization can be.
 - If your problem consists of processes which depend on each others' outputs, maybe not. (Task + Data independence)

Practical Considerations

- Is your code already optimized?
- Problem architecture
- Overhead in parallelism
 - There will always be parts of the work that cannot be parallelized. \rightarrow **Amdahl's Law**
 - Extra time required for coding and debugging (parallelism vs sequential code) → <u>Increased complexity</u>
 - System overhead including communication overhead

Amdahl's Law and Parallelism

Amdahl's Law states that the <u>theoretical speedup</u> is defined by the fraction of code p that can be parallelized:

$$S = \frac{1}{(1-p) + \frac{p}{N}}$$

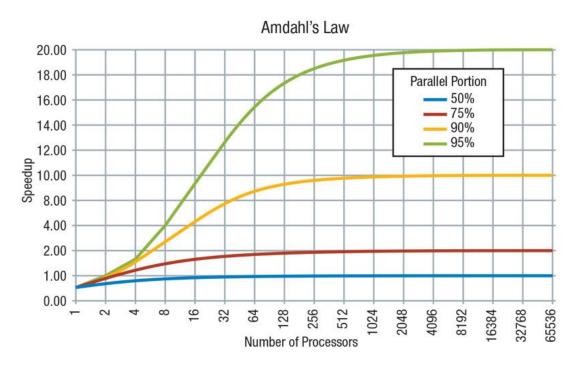
S: Theoretical speedup (theoretical latency)

p: Fraction of the code that can be parallelized

N: Number of processors (cores)

Amdahl's Law and Parallelism

If there are **no parallel parts** (*p* = 0): **Speedup = 0**

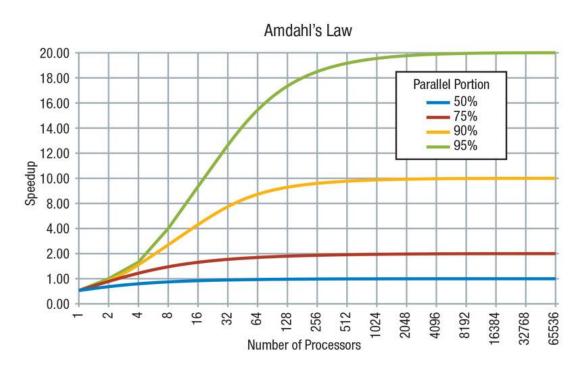


@ongchinhwee

Amdahl's Law and Parallelism

If there are **no parallel parts** (*p* = 0): **Speedup = 0**

If all parts are parallel (p = 1): Speedup = $N \rightarrow \infty$



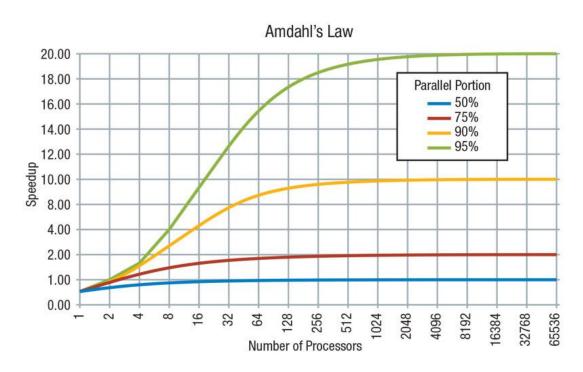
@ongchinhwee

Amdahl's Law and Parallelism

If there are **no parallel parts** (*p* = 0): **Speedup = 0**

If all parts are parallel (p = 1): Speedup = $N \rightarrow \infty$

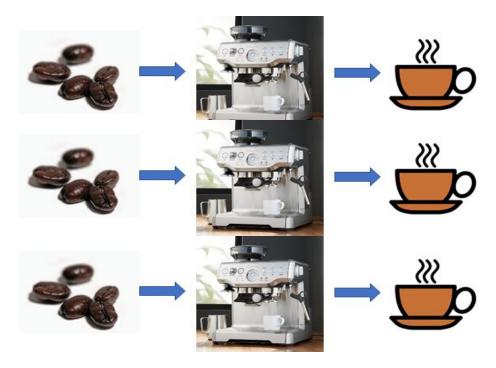
Speedup is <u>limited</u> by fraction of the work that is not parallelizable - will not improve <u>even with infinite</u> number of processors



Multiprocessing vs Multithreading

Multiprocessing:

System allows executing multiple processes at the same time using multiple processors



Multiprocessing vs Multithreading

Multiprocessing:

System allows executing multiple processes at the same time using multiple processors

Multithreading:

System executes <u>multiple</u>
<u>threads</u> of sub-processes at
the same time within a
<u>single processor</u>

Multiprocessing vs Multithreading

Multiprocessing:

System allows executing multiple processes at the same time using multiple processors

Better for processing large volumes of data

Multithreading:

System executes <u>multiple</u>
threads of sub-processes at
the same time within a
single-processor

Best suited for I/O or blocking operations

Some Considerations

Data processing tends to be **more compute-intensive**

- → Switching between threads become increasingly inefficient
- → Global Interpreter Lock (GIL) in Python does not allow parallel thread execution

Did some pythonic developer just say





How to do Parallel + Asynchronous in Python?

Parallel + Asynchronous Programming in Python

concurrent.futures module

- High-level API for launching <u>asynchronous (async)</u>
 <u>parallel tasks</u>
- Introduced in Python 3.2 as an abstraction layer over multiprocessing module
- Two modes of execution:
 - ThreadPoolExecutor() for async multithreading
 - ProcessPoolExecutor() for async multiprocessing

ProcessPoolExecutor vs ThreadPoolExecutor

From the Python Standard Library documentation:

For *ProcessPoolExecutor*, this method chops iterables into a number of chunks which it submits to the pool as separate tasks. The (approximate) size of these chunks can be specified by setting chunksize to a positive integer. For very long iterables, using a large value for chunksize can significantly improve performance compared to the default size of 1. With *ThreadPoolExecutor*, chunksize has no effect.

ProcessPoolExecutor vs ThreadPoolExecutor

ProcessPoolExecutor:

System allows executing multiple processes asynchronously using multiple processors

Uses multiprocessing module - side-steps GIL

ThreadPoolExecutor:

System executes <u>multiple</u> threads of sub-processes asynchronously within a single processor

Subject to GIL - not truly "concurrent"

submit() in concurrent.futures

Executor.submit() takes as input:

- 1. The function (callable) that you would like to run, and
- 2. <u>Input arguments (*args, **kwargs)</u> for that function;

and returns a <u>futures object</u> that <u>represents the execution of</u> the function.

map() in concurrent.futures

Similar to map(), **Executor.map()** takes as input:

- 1. The <u>function (callable)</u> that you would like to run, and
- 2. A <u>list (iterable)</u> where each element of the list is a single input to that function;

and returns an <u>iterator</u> that <u>yields</u> the results of the function being applied to every element of the list.

Case: Network I/O Operations

Dataset: Data.gov.sg Realtime Weather Readings (https://data.gov.sg/dataset/realtime-weather-readings)

API Endpoint URL: https://api.data.gov.sg/v1/environment/

Response: JSON format

Initialize Python modules

```
import numpy as np
import requests
import json
import sys
import time
import datetime
from tgdm import trange, tgdm
from time import sleep
from retrying import retry
import threading
```

Initialize API request task

```
@retry(wait_exponential_multiplier=1000, wait_exponential_max=10000)
def get_airtemp_data_from_date(date):
    print('{}: running {}'.format(threading.current_thread().name,
        date))
    # for daily API request
    url =
"https://api.data.gov.sg/v1/environment/air-temperature?date="\
        + str(date)
    JSONContent = requests.get(url).json()
    content = json.dumps(JSONContent, sort_keys=True)
    sleep(1)
                                                  threading module to
    print('{}: done with {}'.format(
                                                  monitor thread
       threading.current_thread().name, date))
                                                  execution
    return content
                                                           @ongchinhwee
```

Initialize Submission List

Using List Comprehensions

```
start_cpu_time = time.clock()

data_np = [get_airtemp_data_from_date(str(date)) for date in
tqdm(date_range)]

end_cpu_time = time.clock()
print(end_cpu_time - start_cpu_time)
```

Using List Comprehensions

Using ThreadPoolExecutor

```
from concurrent.futures import ThreadPoolExecutor, as_completed
start_cpu_time = time.clock()
with ThreadPoolExecutor() as executor:
    future = {executor.submit(get_airtemp_data_from_date, date):date
        for date in tqdm(date_range)}
resultarray_np = [x.result() for x in as_completed(future)]
end_cpu_time = time.clock()
total_tpe_time = end_cpu_time - start_cpu_time
sys.stdout.write('Using ThreadPoolExecutor: {} seconds.\n'.format(
    total_tpe_time))
                                                           @ongchinhwee
```

Using ThreadPoolExecutor

```
from concurrent.futures import ThreadPoolExecutor, as_completed
                                    ThreadPoolExecutor (40 threads):
start_cpu_time = time.clock()
                                    46.83 seconds (~20.9 times faster)
with ThreadPoolExecutor() as executor:
    future = {executor.submit(get_airtemp_data_from_date, date):date
        for date in tqdm(date_range)}
resultarray_np = [x.result() for x in as_completed(future)]
end_cpu_time = time.clock()
total_tpe_time = end_cpu_time - start_cpu_time
sys.stdout.write('Using ThreadPoolExecutor: {} seconds.\n'.format(
    total_tpe_time))
                                                            @ongchinhwee
```

Case: Image Processing

Dataset: Chest X-Ray Images (Pneumonia) (https://www.kaggle.com/paultimothymooney/chest-xray-pneumonia)

Size: 1.15GB of x-ray image files with normal and pneumonia (viral or bacterial) cases

Data Quality: Images in the dataset are of **different dimensions**

Initialize Python modules

```
import numpy as np
from PIL import Image
import os
import sys
import time
```

Initialize image resize process

```
def image_resize(filepath):
  '''Resize and reshape image'''
 sys.stdout.write('{}: running {}\n'.format(os.getpid(), filepath))
  im = Image.open(filepath)
                                               os.getpid()to
 resized_im = np.array(im.resize((64,64)))
                                               monitor process
  sys.stdout.write('{}: done with
                                               execution
{}\n'.format(os.getpid(),filepath))
  return resized im
```

Initialize File List in Directory

Using map()

```
start_cpu_time = time.clock()
result = map(image_resize, train_normal)
output = np.array([x for x in result])
end_cpu_time = time.clock()
total_tpe_time = end_cpu_time - start_cpu_time
sys.stdout.write('Map completed in {}
seconds.\n'.format(total_tpe_time))
```

Using map()

```
start_cpu_time = time.clock()

result = map(image_resize, train_normal)

output = np.array([x for x in result])

end_cpu_time = time.clock()
total_tpe_time = end_cpu_time - start_cpu_time
sys.stdout.write('Map completed in {}
```

seconds.\n'.format(total_tpe_time))

Using List Comprehensions

```
start_cpu_time = time.clock()
listcomp_output = np.array([image_resize(x) for x in
train_normall)
end_cpu_time = time.clock()
total_tpe_time = end_cpu_time - start_cpu_time
sys.stdout.write('List comprehension completed in {}
seconds.\n'.format(
    total_tpe_time))
```

Using List Comprehensions

```
start_cpu_time = time.clock()
```

List Comprehensions: **29.71 seconds**

```
listcomp_output = np.array([image_resize(x) for x in
train_normal])
```

```
end_cpu_time = time.clock()
total_tpe_time = end_cpu_time - start_cpu_time
sys.stdout.write('List comprehension completed in {}
seconds.\n'.format(
    total_tpe_time))
```

Using ProcessPoolExecutor

total_tpe_time))

```
from concurrent.futures import ProcessPoolExecutor
start_cpu_time = time.clock()
with ProcessPoolExecutor() as executor:
   future = executor.map(image_resize, train_normal)
array_np = np.array([x for x in future])
end_cpu_time = time.clock()
total_tpe_time = end_cpu_time - start_cpu_time
sys.stdout.write('ProcessPoolExecutor completed in {}
seconds.\n'.format(
```

Using ProcessPoolExecutor

```
from concurrent.futures import ProcessPoolExecutor
                                          ProcessPoolExecutor (8 cores):
start_cpu_time = time.clock()
                                          6.98 seconds (~4.3 times faster)
with ProcessPoolExecutor() as executor:
    future = executor.map(image_resize, train_normal)
array_np = np.array([x for x in future])
end_cpu_time = time.clock()
total_tpe_time = end_cpu_time - start_cpu_time
sys.stdout.write('ProcessPoolExecutor completed in {}
seconds.\n'.format(
    total_tpe_time))
```

Key Takeaways

Not all processes should be parallelized

- Parallel processes come with overheads
 - Amdahl's Law on parallelism
 - System overhead including communication overhead
 - If the <u>cost of rewriting your code for parallelization</u>
 <u>outweighs</u> the time savings from parallelizing your code,
 consider <u>other ways of optimizing your code</u> instead.

References

Official Python documentation on concurrent.futures (https://docs.python.org/3/library/concurrent.futures.html)

Source code for ThreadPoolExecutor (https://github.com/python/cpython/blob/3.8/Lib/concurrent/futures/thread.py)

Source code for ProcessPoolExecutor (https://github.com/python/cpython/blob/3.8/Lib/concurrent/futures/thread.py)

Reach out to me!

: ongchinhwee

: @ongchinhwee

: hweecat

: https://ongchinhwee.me

And check out my slides on:

hweecat/talk_parallel-async-python