Speed Up Your Data Processing

Parallel and Asynchronous Programming in Data Science

By: Chin Hwee Ong (@ongchinhwee)

PyCon Taiwan 2020
6 September 2020

About me

Ong Chin Hwee 王敬惠

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

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A typical data science workflow

1. Extract raw data
2. Process data
3. Train model
4. Evaluate and 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

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Data Processing in Python

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

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

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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)]
```

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Challenges with Data Processing

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

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

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Challenges with Data Processing

- **“Why not just use a Spark cluster?”**

  Communication overhead: 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.

  (*) Inspired by “The Small Big Data Manifesto”. Itamar Turner-Trauring (@itamarst) gave a great talk about Small Big Data at PyCon 2020.

What is parallel processing?

Let’s imagine I work at a *kopi tiam* (咖啡店).

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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

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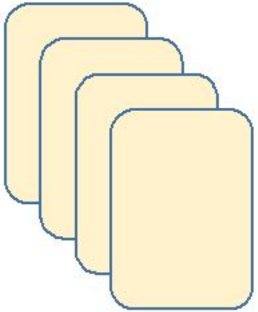
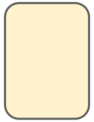
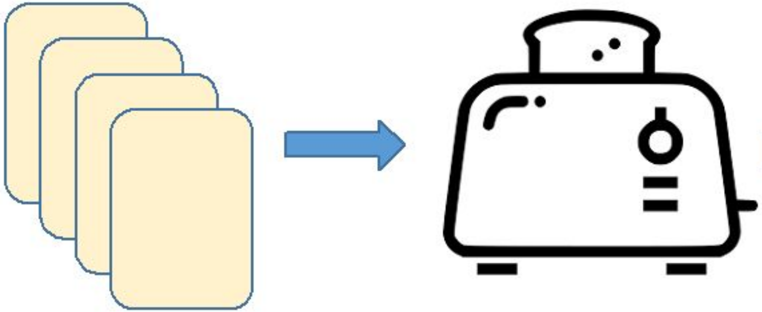
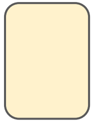
Sequential Processing



 = 25 bread slices

Sequential Processing



 = 25 bread slices

<u>Processor/Worker</u>:
Toaster

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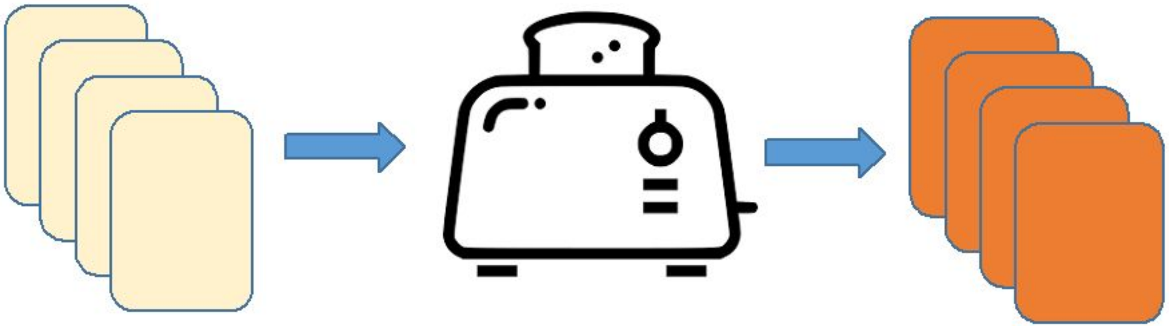
Sequential Processing



= 25 bread slices

<u>Processor/Worker</u>:
Toaster

= 25 toasts

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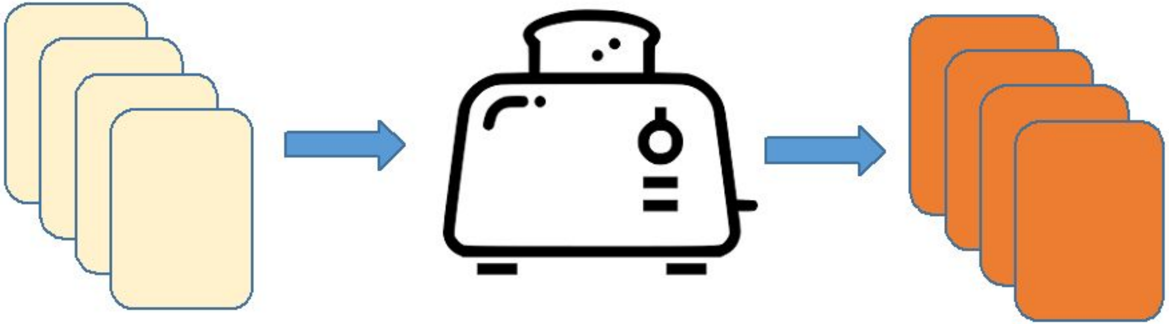
Sequential Processing



Execution Time = 100 toasts × 2 minutes/toast

= **<u>200 minutes</u>**

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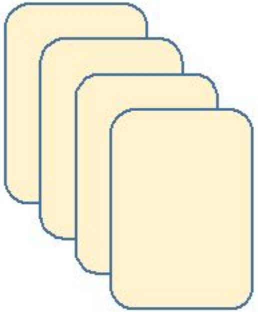
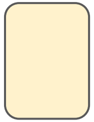
Parallel Processing




= 25 bread slices

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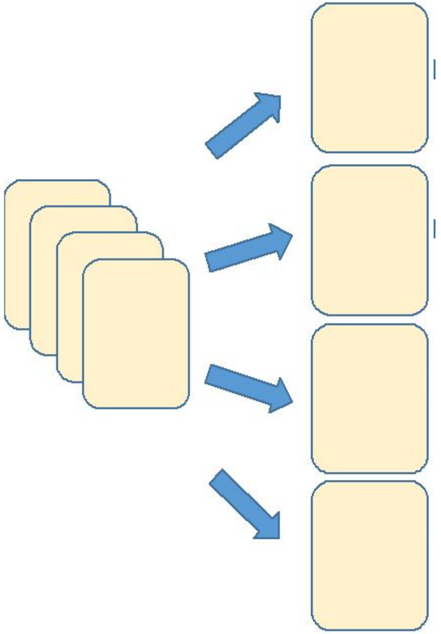
Parallel Processing



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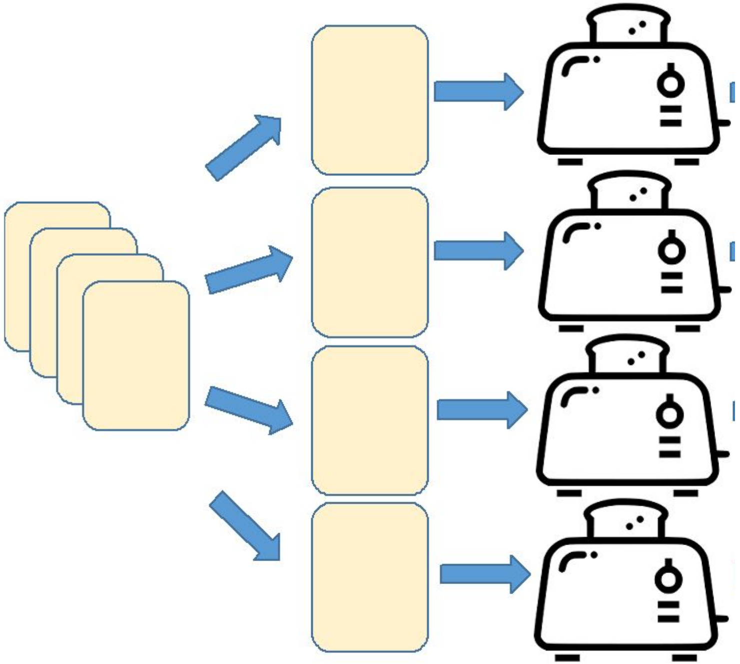
Parallel Processing



<u>Processor (Core)</u>:
Toaster

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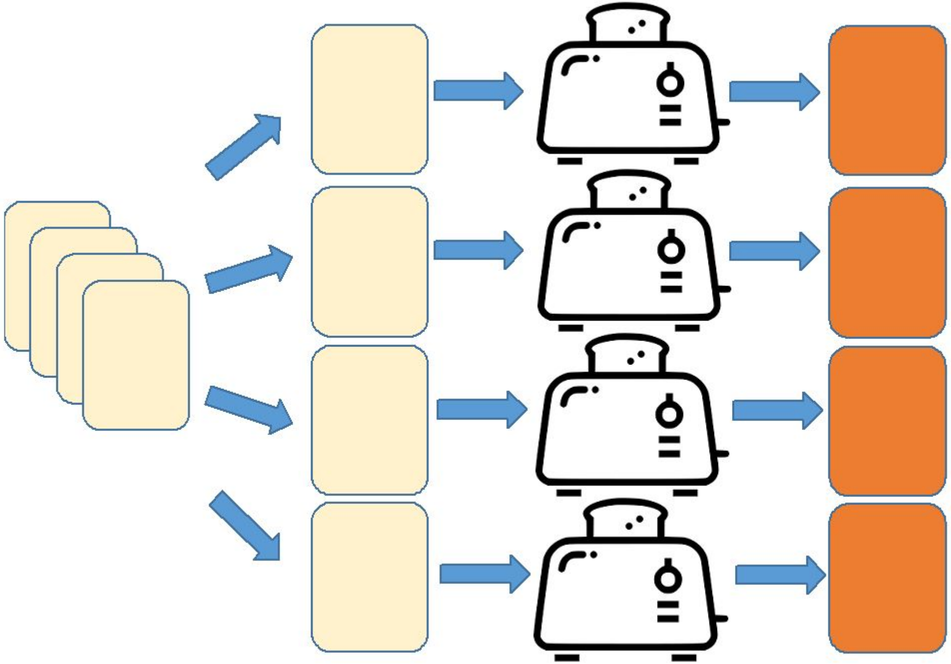
Parallel Processing



<u>Processor (Core)</u>:
Toaster

Task is executed using a **<u>pool</u>** of **<u>4 toaster subprocesses</u>**.

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

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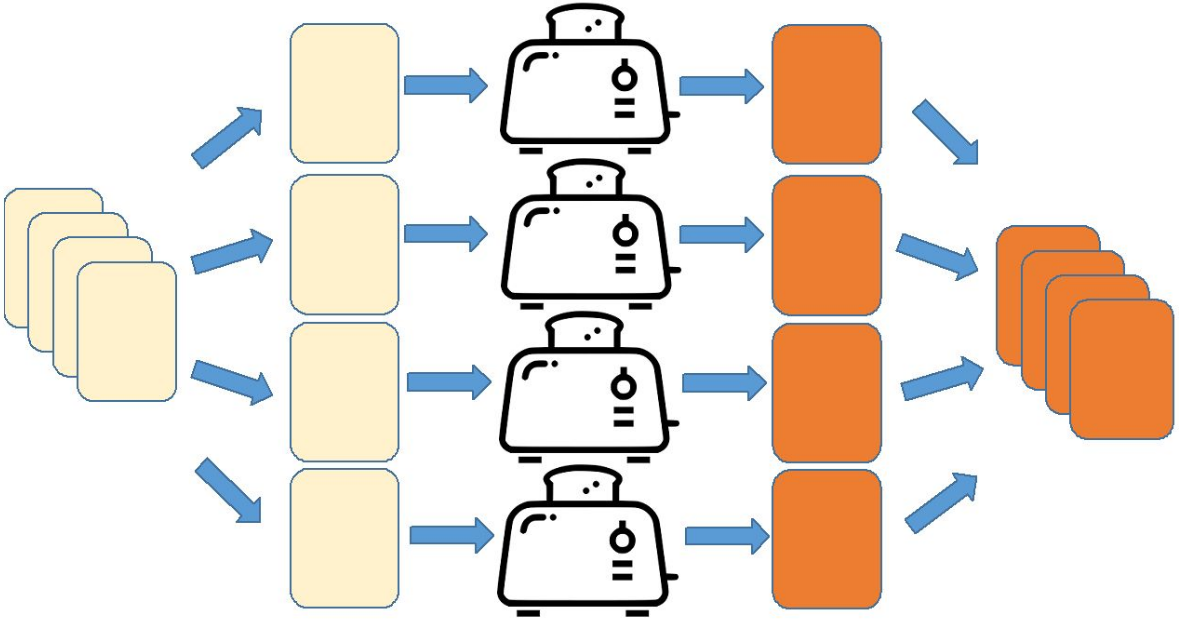
Parallel Processing



<u>Processor (Core)</u>:
Toaster

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

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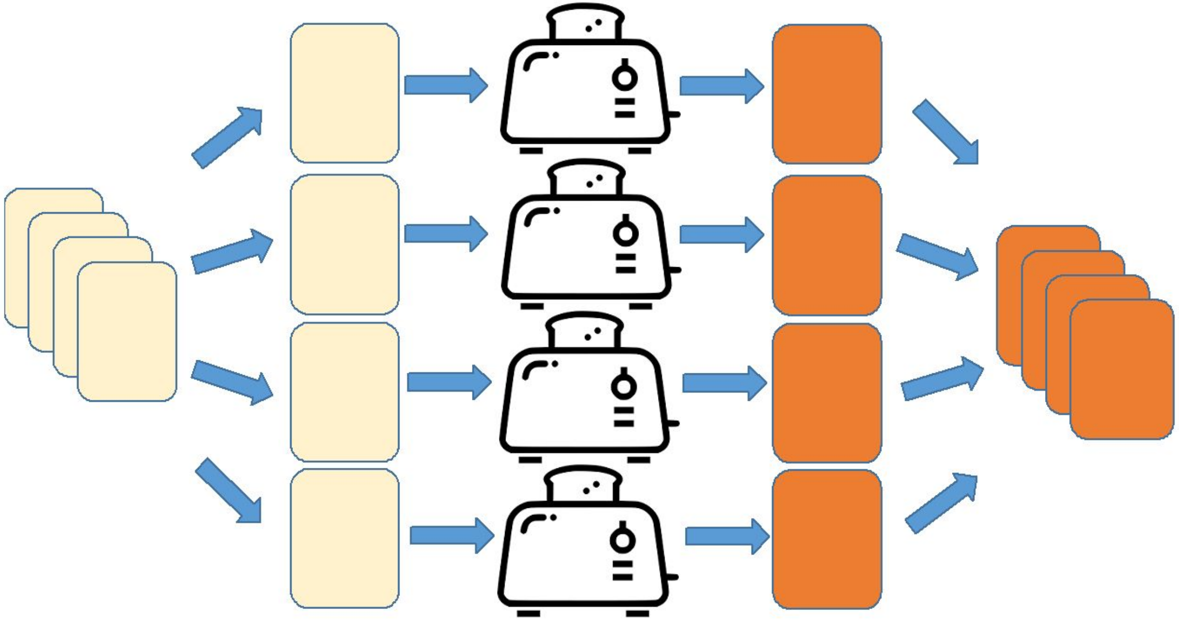
Parallel Processing



Execution Time
= 100 toasts × 2 minutes/toast ÷ 4 toasters
= **<u>50 minutes</u>**

Speedup
= **<u>4 times</u>**

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Synchronous vs Asynchronous Execution

What do you mean by “Asynchronous”?

Task 2: Brew 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.

Image taken from: https://mothership.sg/2020/08/kopimatic-machine/

Synchronous Execution

Task 2: Brew a cup of coffee on coffee machine
Duration: 5 minutes

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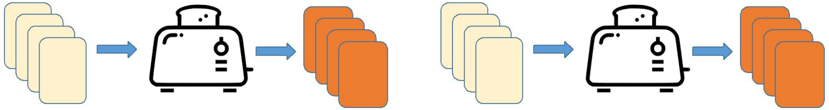
Synchronous Execution

Task 1: Toast two slices of bread on single-slice toaster after Task 2 is completed
Duration: 4 minutes



Task 2: Brew a cup of coffee on coffee machine
Duration: 5 minutes

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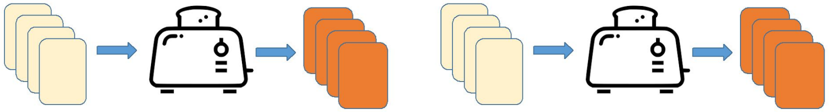
Synchronous Execution

Task 1: Toast two slices of bread on single-slice toaster after Task 2 is completed
Duration: 4 minutes



Task 2: Brew a cup of coffee on coffee machine
Duration: 5 minutes

Output: **2 toasts + 1 coffee**
Total Execution Time = 5 minutes + 4 minutes = **9 minutes**

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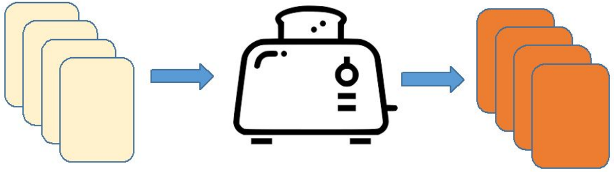
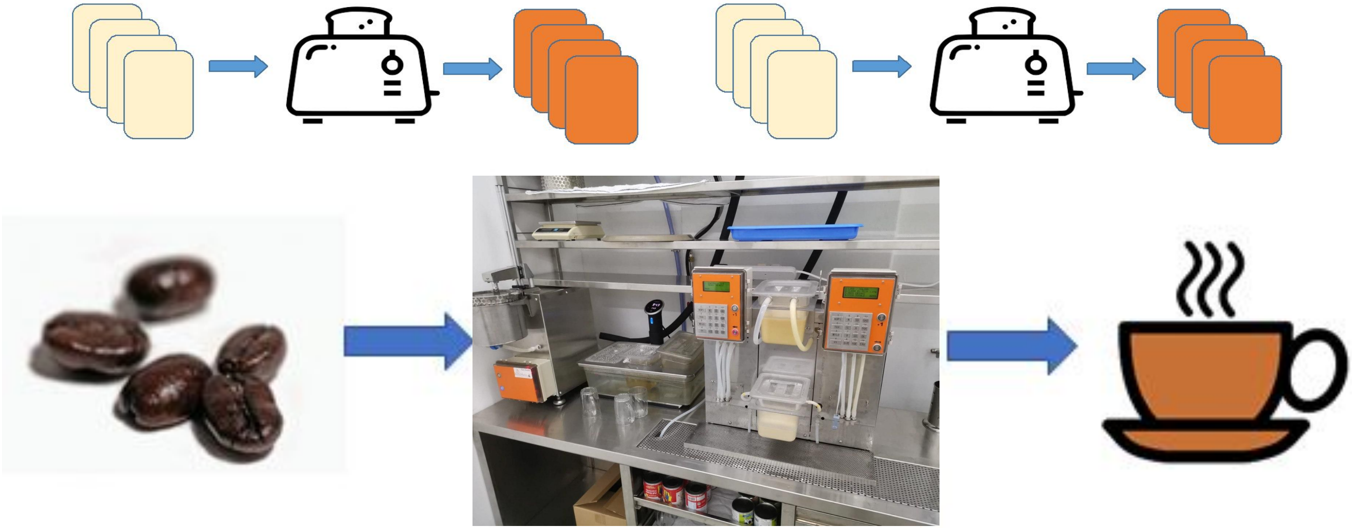
Asynchronous Execution

<u>While</u> brewing coffee:

Make some toasts:



Asynchronous Execution



Output: **2 toasts + 1 coffee**
Total Execution Time = 5 minutes

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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?”)

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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 **(Data dependency)** and/or intermediate results **(Task dependency)**, maybe not.

Practical Considerations

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

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Amdahl's Law and Parallelism

Amdahl's Law states that the theoretical speedup 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)

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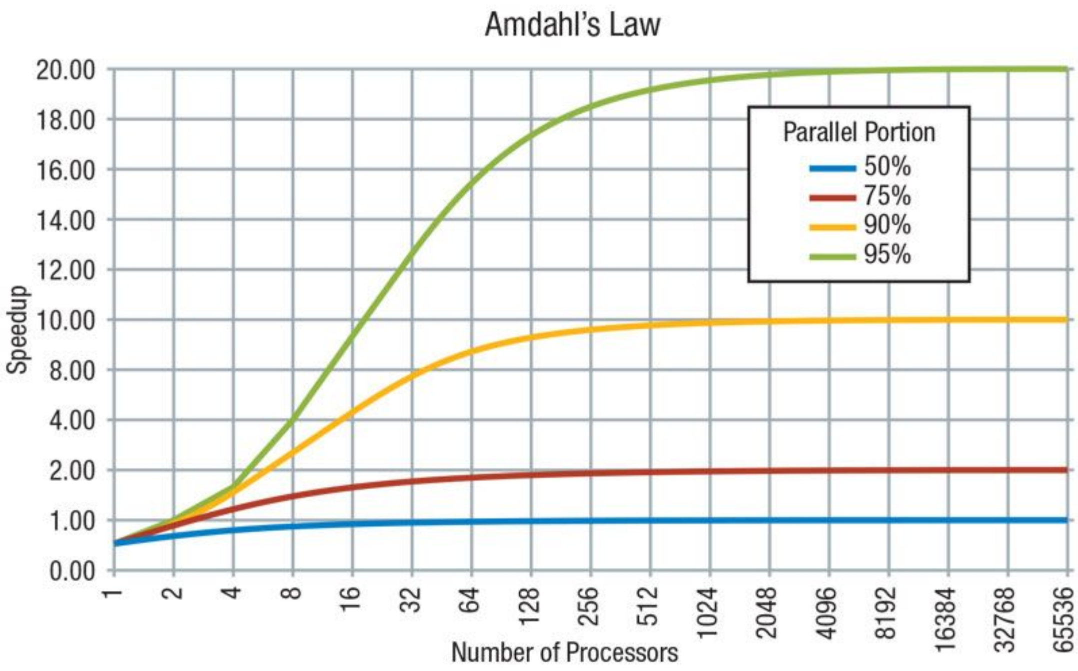
Amdahl's Law and Parallelism

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



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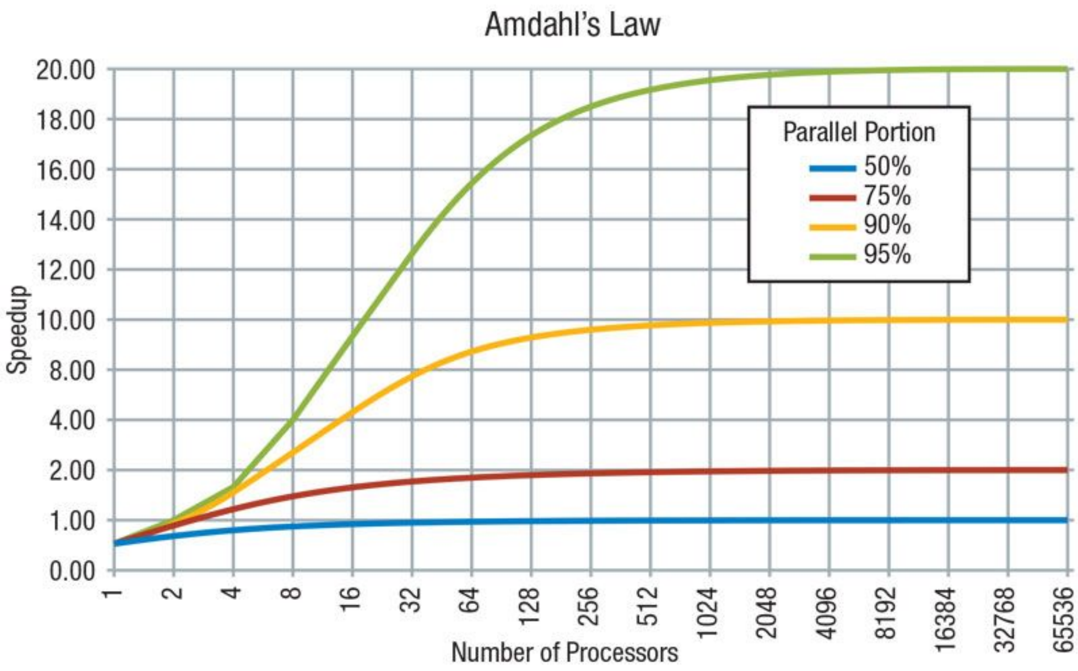
Amdahl’s Law and Parallelism

If there are **no parallel parts** (*p* = 0): **<u>Speedup = 0</u>**

If **all parts are parallel** (*p* = 1): **<u>Speedup = N → ∞</u>**



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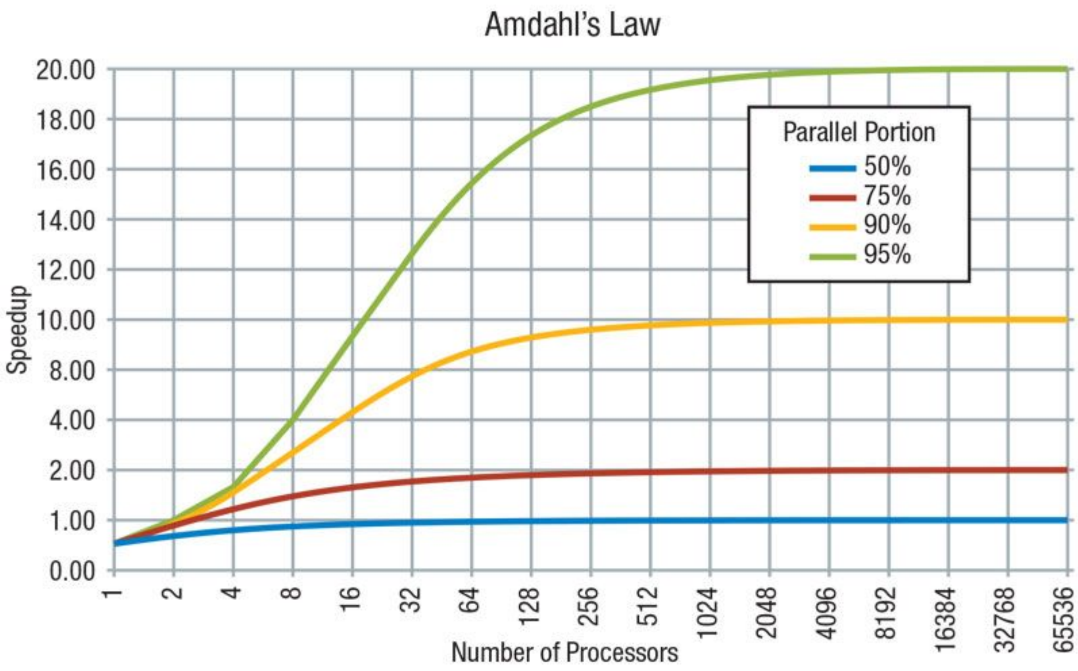
Amdahl’s Law and Parallelism

If there are **no parallel parts** (*p* = 0): **<u>Speedup = 0</u>**

If **all parts are parallel** (*p* = 1): **<u>Speedup = N → ∞</u>**

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



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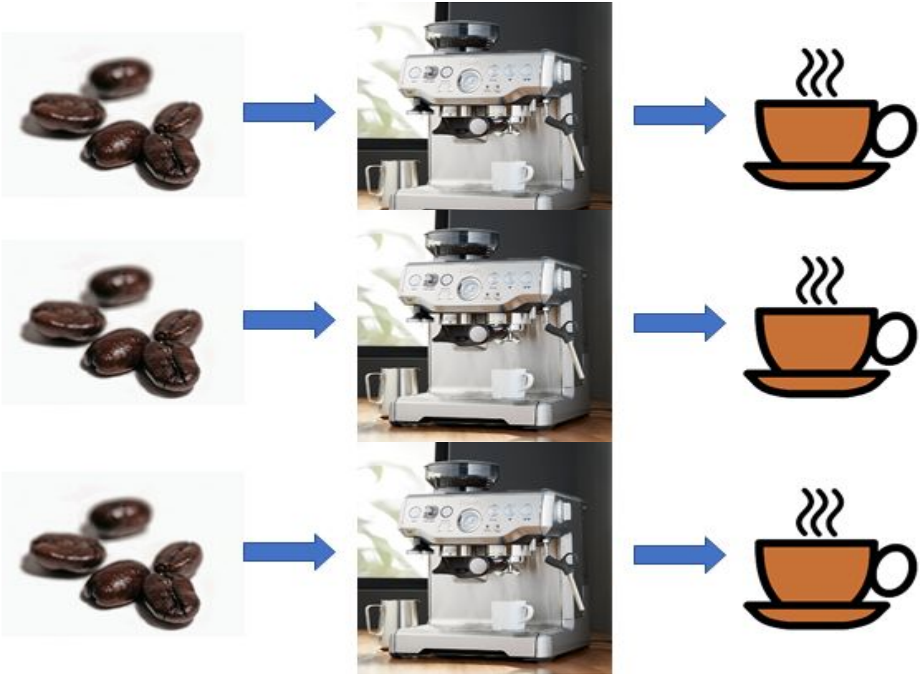
Multiprocessing vs Multithreading

Multiprocessing:

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



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Multiprocessing vs Multithreading

Multiprocessing:

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

Multithreading:

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

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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 multiple threads of sub-processes at the same time within a single processor

Best suited for **I/O or blocking operations**

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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

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How to do Parallel + Asynchronous in Python?

(for data processing workflows (**))

(**) Common machine-learning libraries (e.g. scikit-learn, Tensorflow) already have their own implementation of multiprocessing

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Parallel + Asynchronous Programming in Python

concurrent.futures module

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

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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.

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ProcessPoolExecutor vs ThreadPoolExecutor

ProcessPoolExecutor:

System allows executing multiple processes asynchronously using multiple processors

Uses `multiprocessing` module - side-steps GIL

ThreadPoolExecutor:

System executes multiple threads of sub-processes asynchronously within a single processor

Subject to GIL - not truly "concurrent"

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submit() in concurrent.futures

Executor.submit() takes as input:

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

and returns a futures object that **represents the execution of the function**.

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map() in concurrent.futures

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

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

and returns an iterator that **yields** the results of the function being applied to every element of the list.

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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 tqdm import trange, tqdm
from time import sleep
from retrying import retry

import threading
```

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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)
    print('{}: done with {}'.format(
        threading.current_thread().name, date))
    return content
```

threading module to monitor thread execution

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Initialize Submission List

```
date_range = np.array(sorted(
    [datetime.datetime.strftime(
        datetime.datetime.now() - datetime.timedelta(i)
 ,'%Y-%m-%d') for i in trange(100)]))
```

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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)
```

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Using List Comprehensions

List Comprehensions:
977.88 seconds (~ 16.3mins)

```
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 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))
```

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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
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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))
```

ThreadPoolExecutor (40 threads):
46.83 seconds (~20.9 times faster)

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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**

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Initialize Python modules

```
import numpy as np
from PIL import Image

import os
import sys
import time
```

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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)
  resized_im = np.array(im.resize((64,64)))
  sys.stdout.write('{}: done with
{}\n'.format(os.getpid(),filepath))
  return resized_im
```

os.getpid() to monitor process execution

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Initialize File List in Directory

```
DIR = './chest_xray/train/NORMAL/'

train_normal = [DIR + name for name in os.listdir(DIR)
    if os.path.isfile(os.path.join(DIR, name))]
```

No. of images in 'train/NORMAL': **1431**

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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))
```

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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))
```

map():
29.48 seconds

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Using List Comprehensions

```
start_cpu_time = time.clock()

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))
```

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Using List Comprehensions

List Comprehensions:
29.71 seconds

```
start_cpu_time = time.clock()

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))
```

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Using ProcessPoolExecutor

```
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(
    total_tpe_time))
```

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Using ProcessPoolExecutor

```
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(
    total_tpe_time))
```

ProcessPoolExecutor (**8 cores**):
6.98 seconds (**~4.3 times faster**)

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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 cost of rewriting your code for parallelization outweighs the time savings from parallelizing your code, consider **other ways of optimizing your code** instead.

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Reach out to me!

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: hweecat

: https://ongchinhwee.me

And check out my slides on:

hweecat/talk_parallel-async-python