How to Make Your Data Processing Faster -

Parallel Processing and JIT in Data Science

Presented by:
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Women Who Code Connect Asia, Singapore

About me

- Current role: Data Engineer at ST Engineering
- Background in aerospace engineering and computational modelling
- Experience working on aerospace-related projects in collaboration with academia and industry partners
- Find me if you would like to chat about Industry 4.0 and flight + travel!

Scope of Talk

I will talk about:

1. Bottlenecks in a data science project
2. What is parallel processing?
3. When should you go for parallelism?
4. Parallel processing in data science
5. JIT in data science

A typical data science workflow

1. Define problem objective
2. Data collection and pipeline
3. Data parsing/preprocessing and Exploratory Data Analysis (EDA)
4. Feature engineering
5. Model training
6. Model evaluation
7. Visualization and Reporting
8. Model deployment

What do you think are some of the bottlenecks in a data science project?

Bottlenecks in a data science project

- Lack of data / Poor quality data
- Data Preprocessing
  - The 80/20 data science dilemma
    - In reality, it’s closer to 90/10
- The organization itself

Bottlenecks in a data science project

- Data Preprocessing
  - Pandas faces low performance and long runtime issues when dealing with large datasets (> 1 GB)

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Bottlenecks in a data science project

- Data Preprocessing
  - Pandas faces low performance and long runtime issues when dealing with large datasets (> 1 GB)
  - Slow loops in Python
    - Loops are run on the interpreter, not compiled (unlike loops in C)
  - Not every data science team has extremely large volumes of data to justify using a Spark cluster

What is parallel processing?

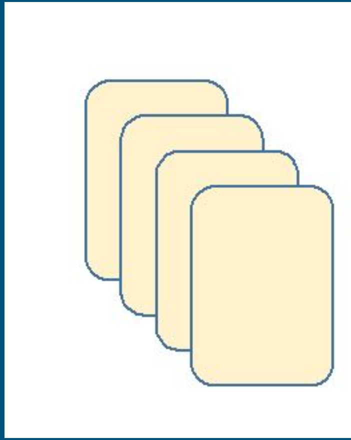
Let's imagine I own a bakery cafe.

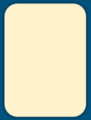
Task 1: Toast 100 slices of bread

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.

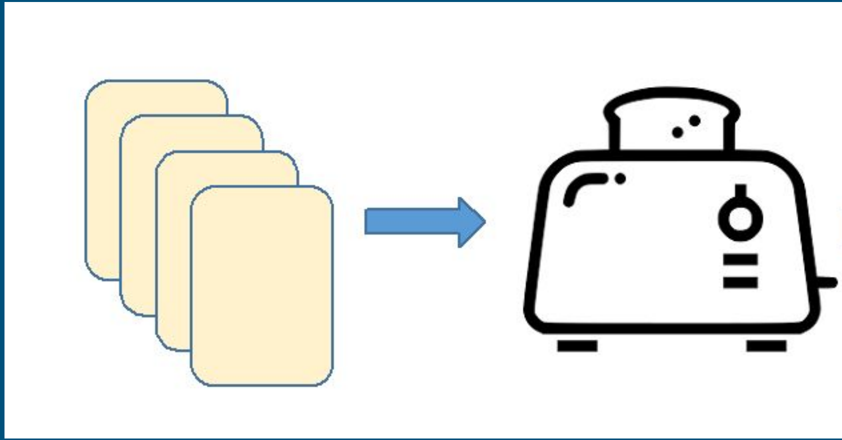
Image taken from: https://www.mitsubishielectric.co.jp/home/breadoven/product/to-st1-t/feature/index.html

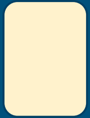
Sequential Processing



 = 25 bread slices

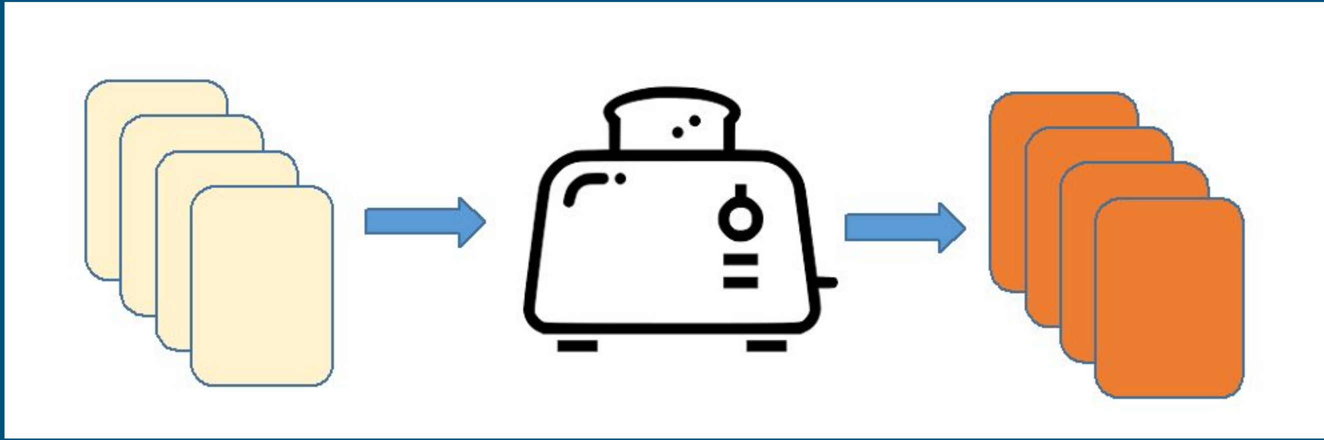
Sequential Processing

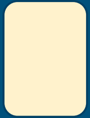


 = 25 bread slices

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

Sequential Processing

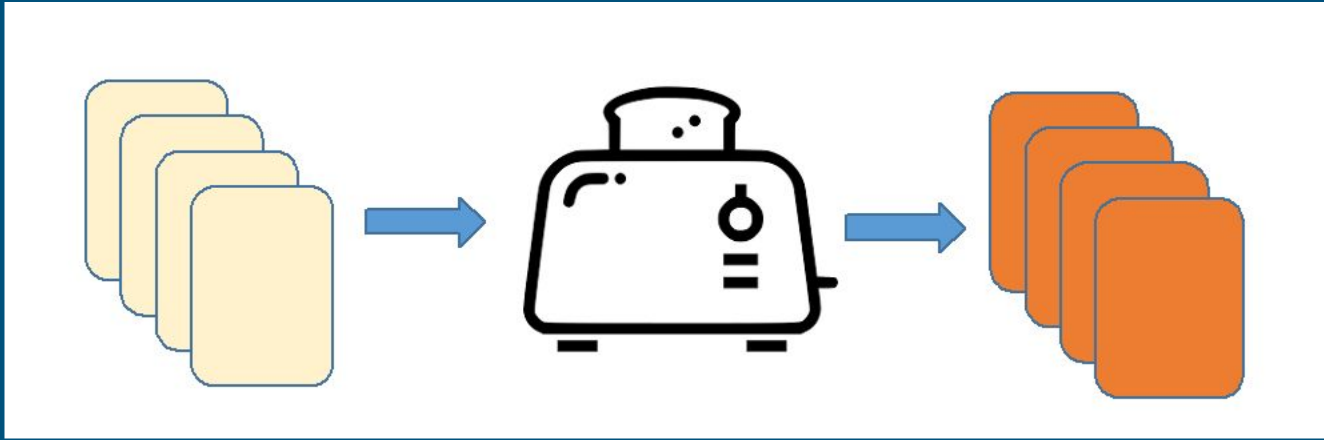


 = 25 bread slices

Processor/Worker:
Toaster

 = 25 toasts

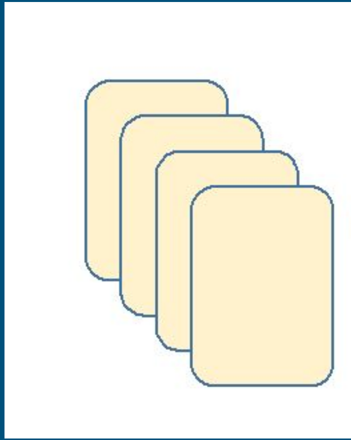
Sequential Processing

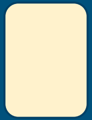


Execution Time = 100 toasts × 2 minutes/toast

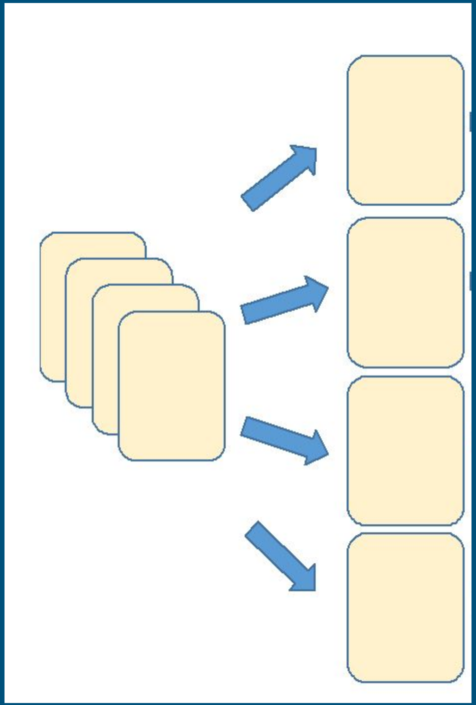
= **<u>200 minutes</u>**

Parallel Processing

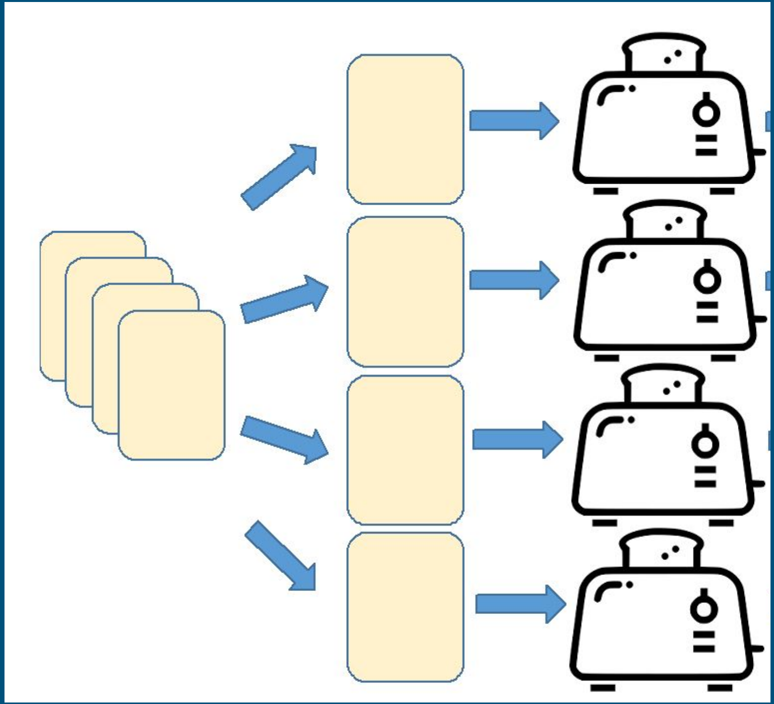


 = 25 bread slices

Parallel Processing

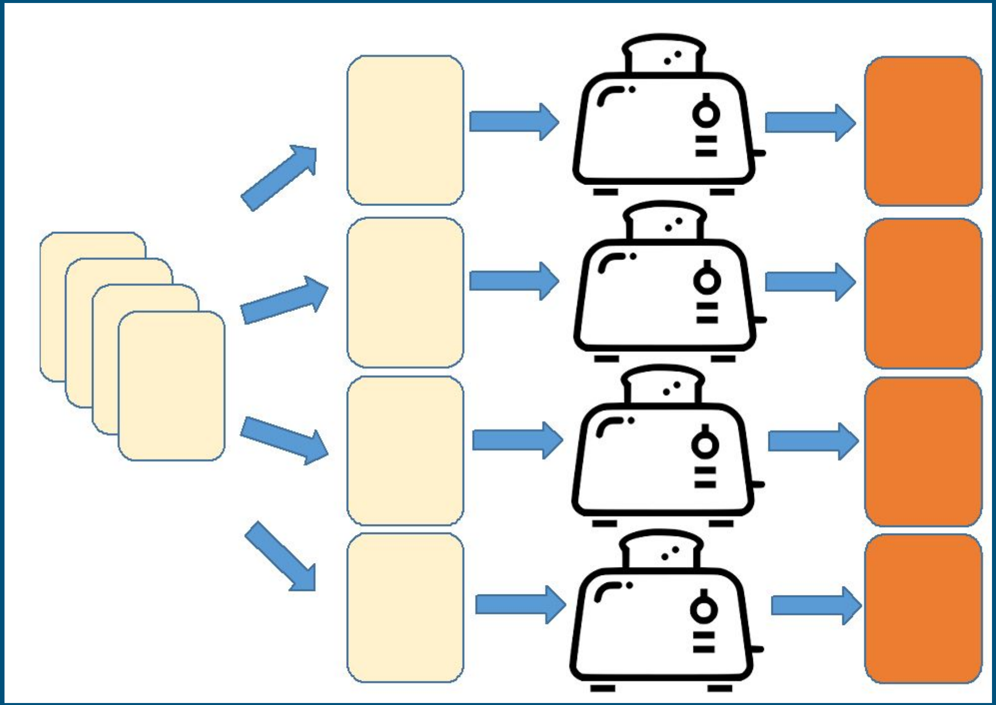


Parallel Processing



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

Parallel Processing

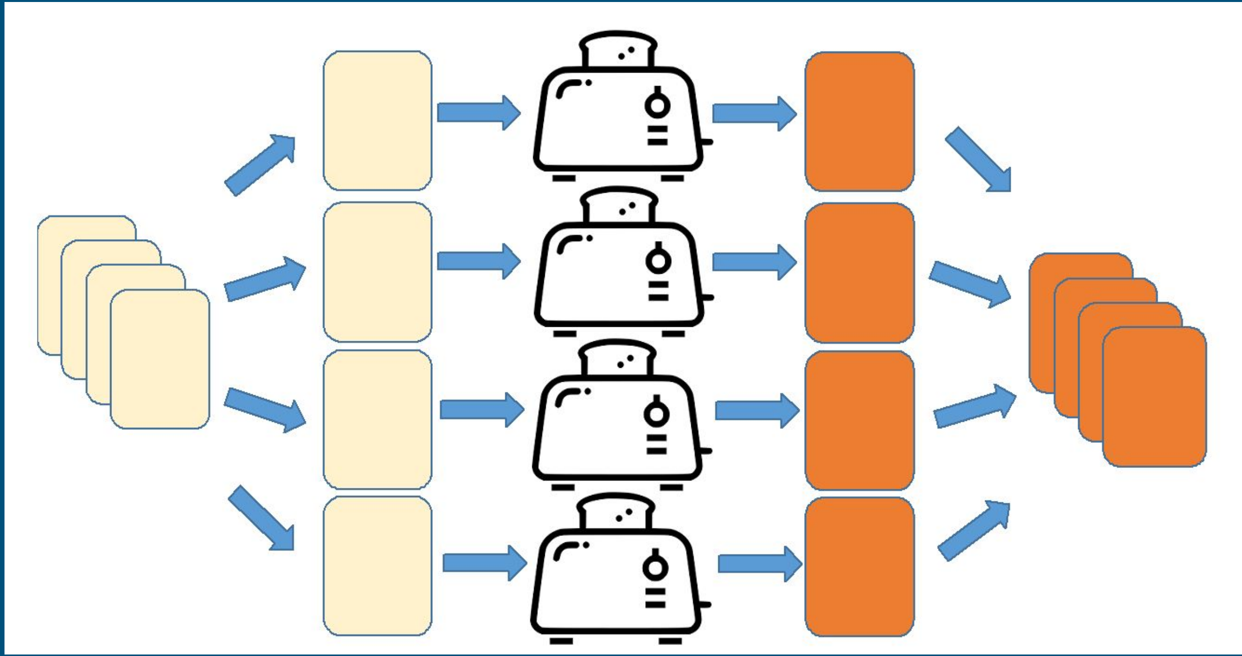


Processor (Core): Toaster

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

Each toasting subprocess runs **in parallel** and **independently** from each other.

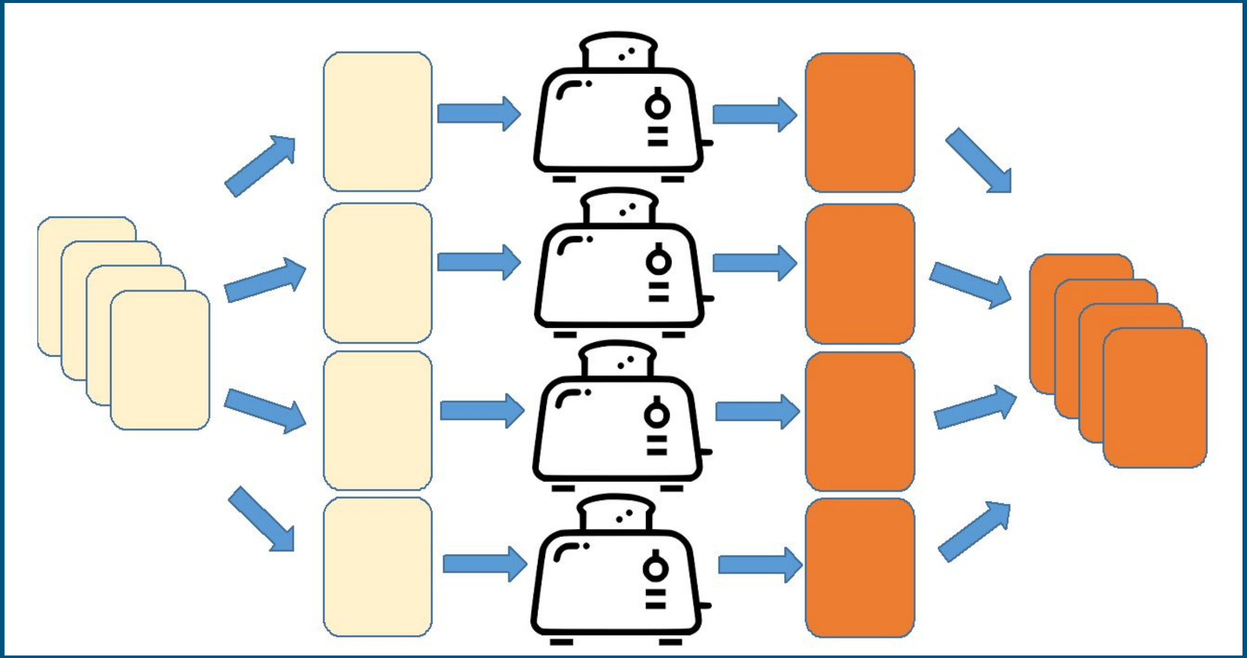
Parallel Processing



Processor (Core): Toaster

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

Parallel Processing



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

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

Synchronous vs Asynchronous Execution

What do you mean by “Asynchronous”?

Let’s get some ideas from the Kopi.JS folks.

(since they do async programming more than the data folks)

Ong Chin Hwee

@ongchinhwee

A question to the #javascript #nodejs folks: How would you explain async/await and promises to a layman who is new to async programming - using coffee? The coffee part is partly inspired by @kopi_js in Singapore. ☕

11:29 · 30 Aug 19 · Hootsuite Inc.

me: One kopi pls

(promise)
Uncle: Ok, take this number and sit down, send to you when ready
me: [sits down, surfs twitter]
uncle: [walks over] order #23, here you go

(async/await)
uncle: Ok [makes kopi]
me: [wait in place, surfs twitter]
uncle: [kopi done] Here you go

(Credits to: @sheldytox)

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(Credits to: @sheldytox)

Another scenario, you wake up and order coffee via a delivery app. Do you wait by the phone for the coffee to arrive or do you go and do other things (while "awaiting" for the coffee to arrive)?

(Credits to: @yingkh_tweets)

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://www.crateandbarrel.com/breville-barista-espresso-machine/s267619

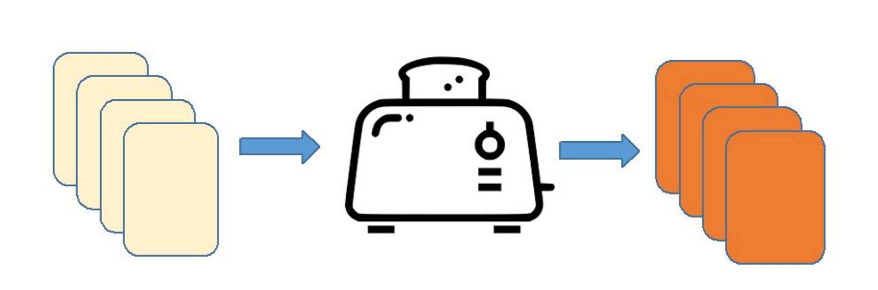
Synchronous Execution

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

Synchronous Execution

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

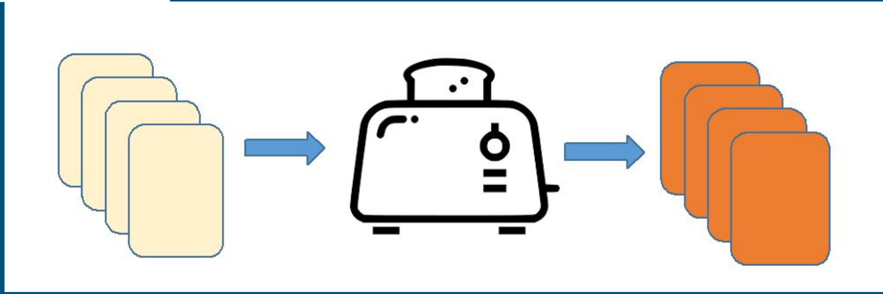
Process 2: Brew a cup of coffee on coffee machine
Duration: 5 minutes



Synchronous Execution

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

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

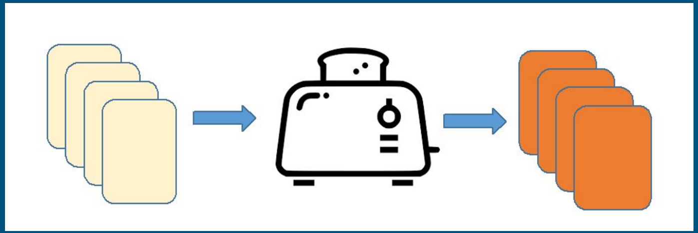


Output: <u>**1 toast + 1 coffee**</u>
Total Execution Time = 5 minutes + 2 minutes = <u>**7 minutes**</u>

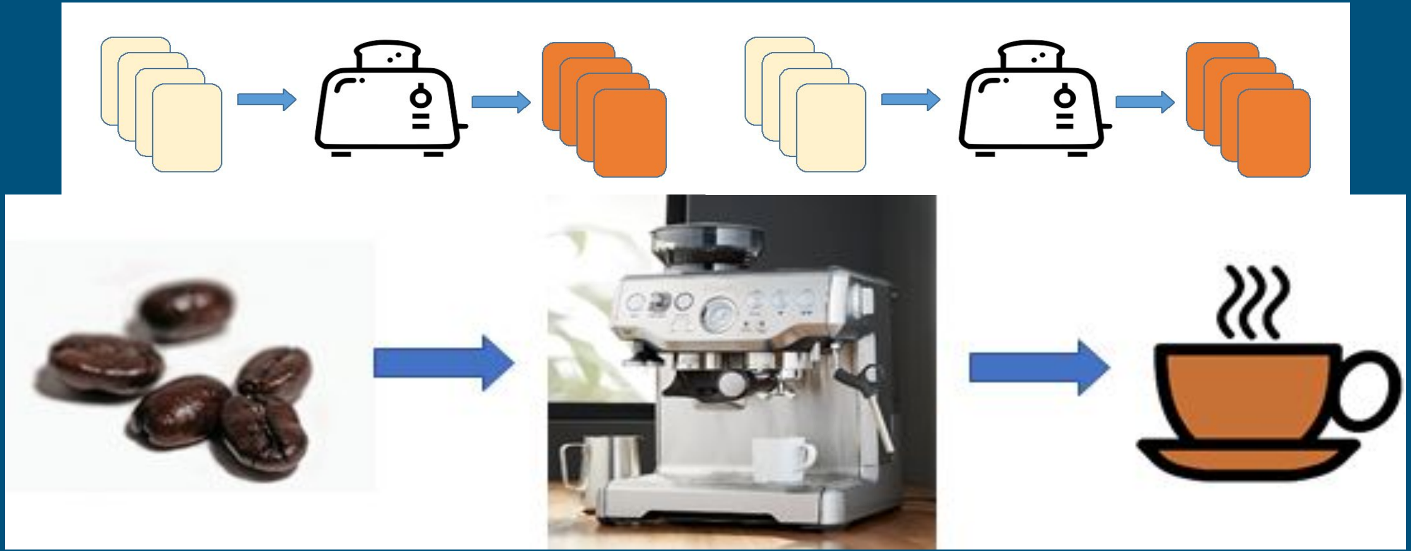
Asynchronous Execution

While brewing coffee:

Make some toasts:



Asynchronous Execution



Output: **<u>2 toasts + 1 coffee</u>** (1 more toast!)

Total Execution Time = **<u>5 minutes</u>**

When is it a good idea to go for parallelism?

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?
  - Sometimes, you might need to rethink your approach.
- 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.

Practical Considerations

- Is your code already optimized?
    - Sometimes, you might need to rethink your approach.
- Problem architecture
    - Nature of problem limits how successful parallelization can be.
- 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)

Amdahl's Law and Parallelism

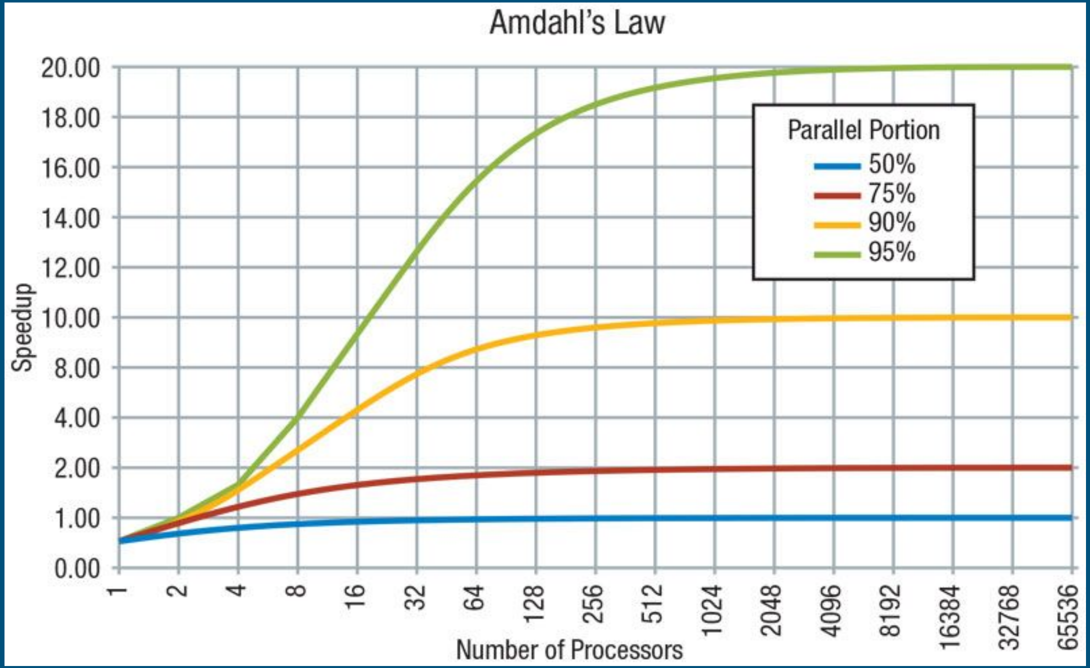
Amdahl's Law states that the theoretical speedup is defined by the fraction of code ***p*** that can be parallelized:

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

S: Theoretical speedup (theoretical latency)
p: Fraction of the code that can be parallelized
N: Number of processors (cores)

Amdahl's Law and Parallelism

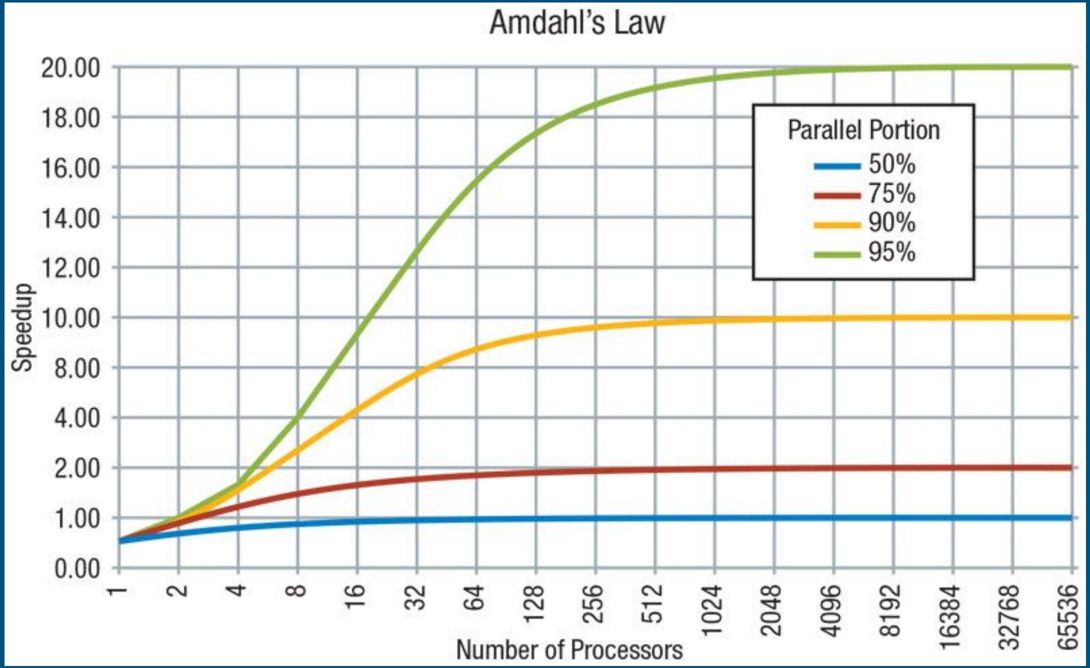
If there are **no parallel parts** (*p* = 0): **<u>Speedup = 0</u>**



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>**

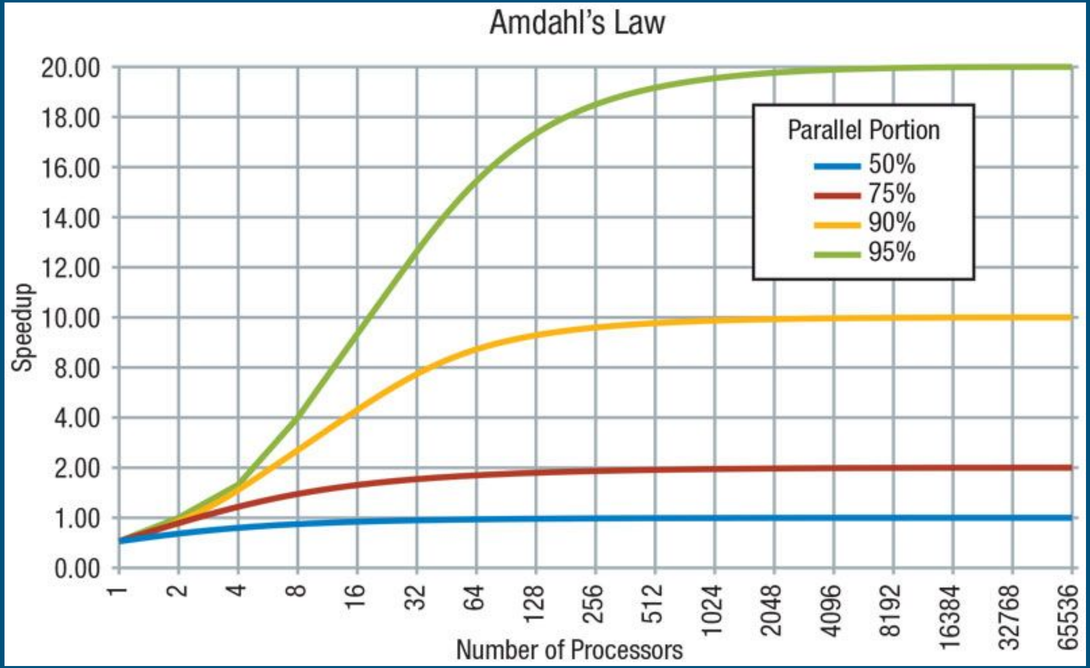


Amdahl’s Law and Parallelism

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

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

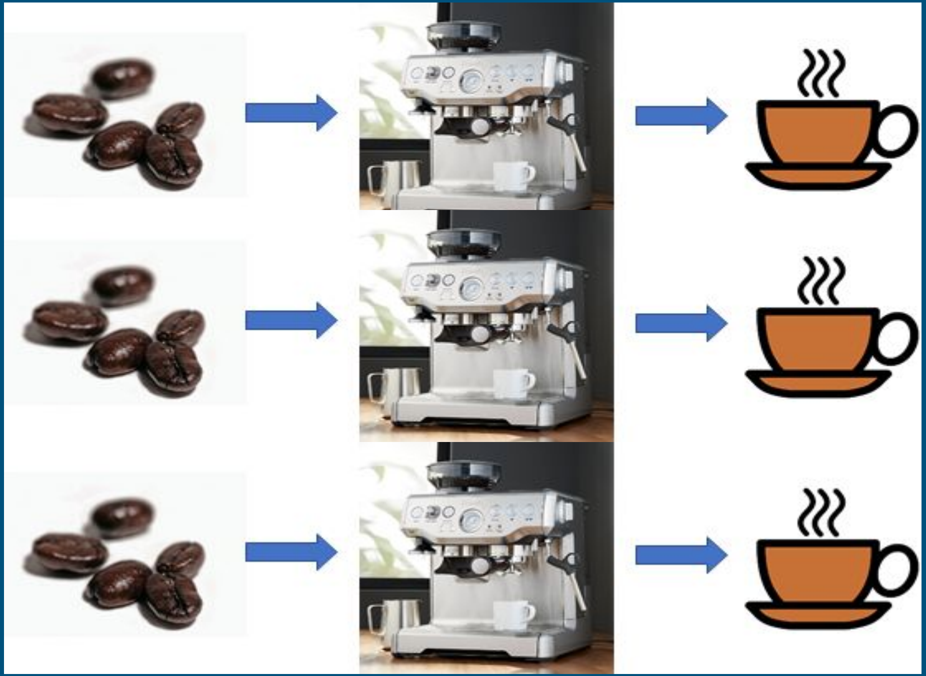
Speedup is limited by **fraction of the work that is not parallelizable** - will not improve **even with infinite number of processors**



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

Multiprocessing vs Multithreading

Multiprocessing:

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

Better option 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 operations**

Parallel Processing in Data Science

Parallel Processing in Data Science

Python is the most widely-used programming language in data science

Distributed processing is one of the core concepts of Apache Spark

Apache Spark is available in Python as **PySpark**

Parallel Processing in Data Science

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

→ Switching between threads become <u>increasingly inefficient</u>

→ **Global Interpreter Lock (GIL)** in Python <u>does not allow parallel thread execution</u>

How to do Parallel Processing in Python?

Parallel Processing in Python

concurrent.futures module

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

Recap: map()

map() takes as input:

1. The function 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.

map() in concurrent.futures

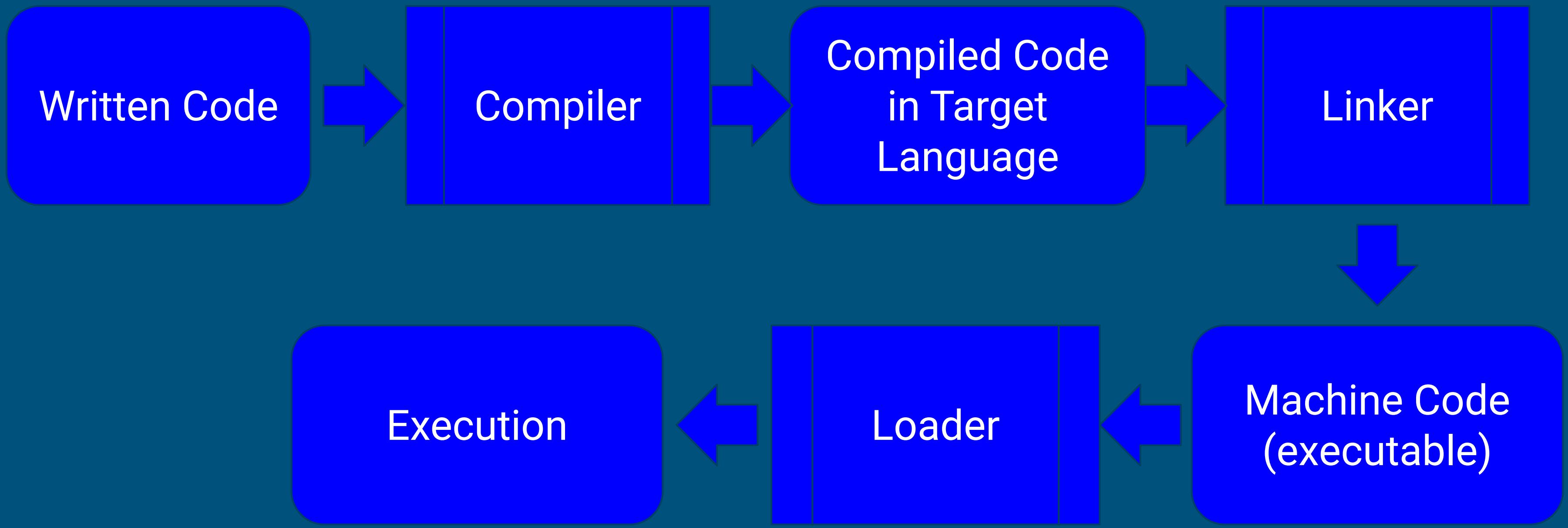
Similarly, **executor.map()** takes as input:

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

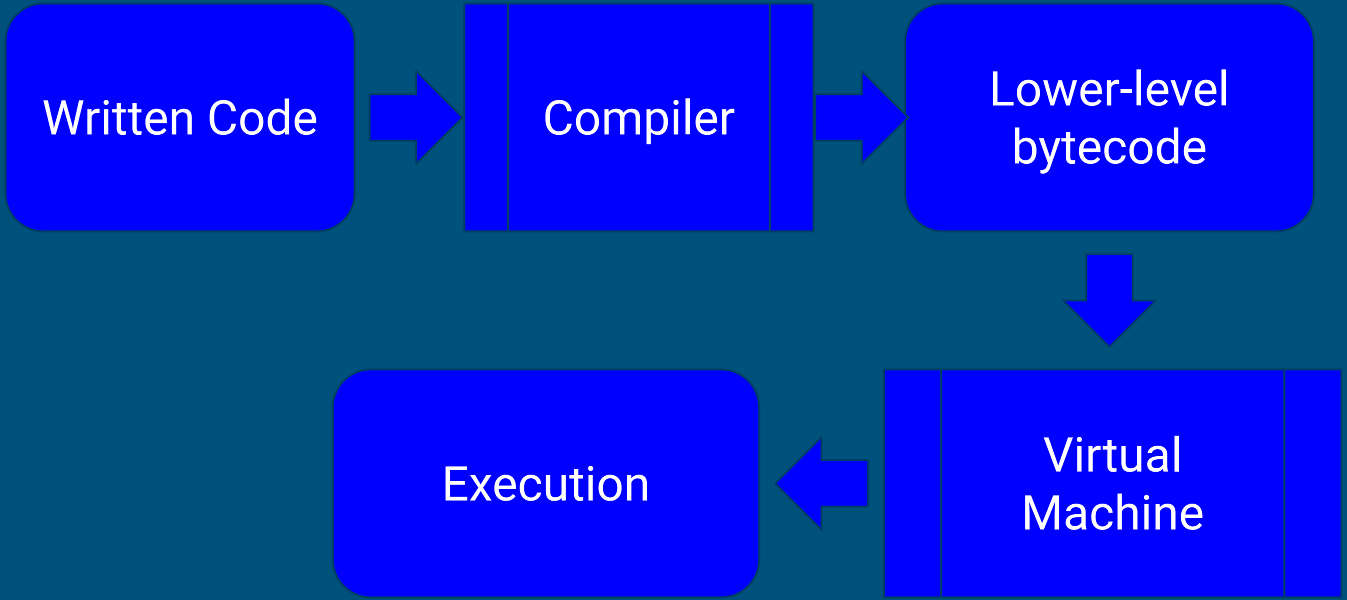
and returns an iterator that **yields** the results of the function being applied to every element of the list.

“Okay, I tried using parallel processing but my processing code in Python is still slow. What else can I do?”

Compiled vs Interpreted Languages



Compiled vs **Interpreted** Languages



JIT Compilation

Just-In-Time (JIT) compilation

- Converts source code into **native machine code** at runtime
- Is the reason why Java runs on a Virtual Machine (JVM) yet has **comparable performance** to compiled languages (C/C++ etc., Go)

JIT Compilation in Data Science

JIT Compilation in Data Science

numba module

- **Just-in-Time (JIT) compiler** for Python that converts Python functions into <u>machine code</u>
- Can be used by simply applying **a decorator (a wrapper)** around functions to instruct numba to compile them
- Two modes of execution:
  - *njit* for no-Python mode (JIT only)
  - *jit* for object mode (JIT + Python interpreter)

Practical Implementation

Case: Image Processing

Dataset: Shopee National Data Science Challenge (https://www.kaggle.com/c/ndsc-advanced)

Size: **77.6GB** of image files

Data Quality: Images in the dataset are of **different formats** (some are RGB while others are RGBA) and **different dimensions**

Without Parallelism

```
import sys
import time

N = 35000 # size of dataset to be processed
start = 0
batch_size = 1000
partition = int(np.ceil(N/step))
partition_count = 0
imagearray_list = [None] * partition

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

Without Parallelism

```
while start < N:

	end = start + batch_size
	if end > N:
		end = N

	imagearray_list[partition_count] = 
[arraypartition_calc(image) for image in range(start, end)]

	start += batch_size
	partition_count += 1
```

Without Parallelism

```
while start < N:

      end = start + batch_size
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Without Parallelism

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while start < N:

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[arraypartition_calc(image) for image in range(start, end)]

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      partition_count += 1
```

Execution Speed:
3300 images after 7 hours
= 471.43 images/hr

With Parallelism and JIT compilation

```
from PIL import Image
from numba import jit

@jit
def image_proc(index):
      '''Convert + resize image'''
      im = Image.open(define_imagepath(index))
      im = im.convert("RGB")
      im_resized = np.array(im.resize((64,64)))

      return im_resized
```

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     return im_resized
```

Note: I can't use no-Python mode (@njit) as PIL codes can't seem to be compiled into machine code

With Parallelism and JIT compilation

```
@jit
def arraypartition_calc(start, batch_size):
    '''Process images in partition/batch'''
    end = start + batch_size
    if end > N:
        end = N

    partition_list = [image_proc(image) for image
in range(start, end)]

    return partition_list
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With Parallelism and JIT compilation

```
N = 35000
start = 0
batch_size = 1000
partition, mod = divmod(N, batch_size)

if mod:
    partition_index = [i * batch_size for i in range(start //
batch_size, partition + 1)]
else:
    partition_index = [i * batch_size for i in range(start //
batch_size, partition)]
```

With Parallelism and JIT compilation

```
import sys
import time
from concurrent.futures import ProcessPoolExecutor

start_cpu_time = time.clock()
start_wall_time = time.time()

with ProcessPoolExecutor() as executor:
      future = executor.map(arraypartition_calc, partition_index)

imgarray_np = np.array([x for x in future])
```

With Parallelism and JIT compilation

Execution Speed:
35000 images after 3.6 hours
= 9722.22 images/hr

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import sys
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With Parallelism and JIT compilation

Execution Speed:
35000 images after 3.6 hours
= 9722.22 images/hr

No. of cores: 2
Speedup: 19.4 times

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Extract results from iterator (similar to generator)

Key Takeaways

Parallel Processing in Data Science

- Not all processes should be parallelized
  - **Amdahl's Law** on parallelism
  - Extra time required for coding and debugging (parallelism vs sequential code)
  - If the cost of rewriting your code for parallelization outweighs the time savings from parallelizing your code (especially if your process only takes a few hours), maybe you should consider **other ways of optimizing your code** instead.

JIT compilation in Data Science

- **Just-in-Time (JIT) compilation**
  - converts source code from non-compiled languages into **native machine code** at runtime
  - may not work for some functions/modules - these are still run on the interpreter
  - **significantly enhances** speedups provided by parallelization

References

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

Built-in Functions - Python 3.7.4 Documentation
(https://docs.python.org/3/library/functions.html#map)

5-minute Guide to Numba
(http://numba.pydata.org/numba-doc/latest/user/5minguide.html)

Contact

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