

Parallel Programming

ภาษาที่ใช้, lib ที่ใช้, compiler อะไรก็ได้
เลือกนำเสนอสอน parallelism ที่ใช้ใน algorithm
เช่น มี GPU ก็ควรเขียน code ที่รองรับ GPU
หรือ multi-core ควรเขียน code แบบ thread programming
หรือ cluster เขียน code แบบ multi-processor

Parallel Programming Models

- Parallel programming allows programmers to express parallelism in the algorithm that can match with the underlying parallel architecture.
- Parallel programming models
 - **Vectorization** ใช้ประโยชน์จาก vector computing ที่ใช้คำสั่งเฉพาะ: vector operation
 - Usually based on compiler optimization dev ไม่ค่อยยุ่งยาก อันเป็น low level ที่ compiler จัดการใน
 - **Thread programming**
 - Threads communicate via shared memory
 - Run on single computer อาจเป็น multi-core, multi-processor ก็ได้ แต่อยู่บนเครื่องเดียว
 - **Multi-process programming** สิ่งที่ต้องระวัง ไม่ให้ share memory ร่วมกัน
 - Processes communicate via message passing สื่อสารด้วยการส่ง message ผ่าน process
 - Run on single computer or cluster of computers
 - **High-level parallel programming**
 - E.g. parallel libraries, compiler directives, functional programming
 - Implicit parallelism บอกเผื่อว่าทำงานแบบ parallelism
 - Implemented with low-level libraries
 - Explicit parallelism ต้องระบุว่าจะรันที่ thread ที่ process สื่อสารกันอย่างไร (Detail การสร้าง subtask)

Getting System Information in Python

```
!pip install -q psutil
!pip install -q py-cpuinfo
import platform
import psutil
import cpuinfo

print('platform      : ', platform.platform())
print('cpu model      : ', cpuinfo.get_cpu_info()['brand_raw'])
print('physical cpu    : ', psutil.cpu_count(logical=False))
print('logical cpu      : ', psutil.cpu_count(logical=True))
print('virtual memory   : ', psutil.virtual_memory())
```

notebook

```
platform      : Windows-11-10.0.22631-SP0
cpu model     : AMD Ryzen 7 6800HS Creator Edition
physical cpu  : 8 cores }
logical cpu   : 16      } การเขียน code ต้องใช้จำนวน thread > logical cpu (16) เพราะหากน้อยกว่า 16 โหนดมันจะไม่ (ปกติ: จำนวน thread จะมากกว่าหรือเท่ากับจำนวน core)
virtual memory : svmem(total=14702026752, available=5497176064, percent=62.6, used=9204850688, free=5497176064)
```

server

```
platform      : Linux-4.19.0-18-amd64-x86_64-with-glibc2.35
cpu model     : Intel(R) Xeon(R) Gold 6248R CPU @ 3.00GHz
physical cpu   : 48
logical cpu    : 96 } 2x
virtual memory : svmem(total=405303078912, available=197320822784, percent=51.3, used=202437398528, free=39546245120,
588412416, buffers=5755064320, cached=157564370944, shared=4242927616, slab=8781287424)
```

Google Colab

```
platform      : Linux-6.1.58+-x86_64-with-glibc2.35
cpu model     : Intel(R) Xeon(R) CPU @ 2.00GHz
physical cpu   : 1
logical cpu    : 2
virtual memory : svmem(total=13609451520, available=12530159616, percent=7.9, used=786333696, free=10113830912,
```

Kaggle

```
platform      : Linux-5.15.133+-x86_64-with-debian-bullseye-sid
cpu model     : Intel(R) Xeon(R) CPU @ 2.20GHz
physical cpu   : 2
logical cpu    : 4
virtual memory : svmem(total=33669914624, available=32371695616, percent=3.9, used=820023296, free=31915687936,
```

Getting GPU Information in Python

```
import torch
import tensorflow as tf
import subprocess

def check_gpu_info():
    """Checks for GPU availability and prints information if found.

    # Check with PyTorch
    if torch.cuda.is_available():
        gpu_index = 0 # Adjust if you have multiple GPUs
        device = torch.device(gpu_index)
        print("GPU Found (PyTorch):")
        print(f" - Device Name: {torch.cuda.get_device_name(gpu_index)}")
        print(f" - Compute Capability: {torch.cuda.get_device_capability(gpu_index)}")
        return

    # Check with TensorFlow
    if tf.test.gpu_device_name():
        print("GPU Found (TensorFlow):")
        # TensorFlow might provide more detailed information (if you need it)
        # Explore the tf.test.gpu_device_name() output
        print(tf.test.gpu_device_name())
        return

    # System-level Check (nvidia-smi)
    try:
        info = subprocess.check_output('nvidia-smi', stderr=subprocess.STDOUT).decode()
        print("GPU Found (nvidia-smi):")
        print(info) # Print the full output from nvidia-smi
        return
    except Exception:
        pass

    # No GPU found
    print("No GPU detected.")

check_gpu_info()
```

```
GPU Found (PyTorch):
 - Device Name: Tesla T4
 - Device Properties: _CudaDeviceProperties(name='Tesla T4', major=7, minor=5, total_memory=15102MB, multi_processor_count=40)
```

Measure execution time in Python

```
import time
start = time.process_time()
sum(range(100000000))
end = time.process_time()
print(end - start, "seconds")
```

2.578125 seconds

```
import datetime
start = datetime.datetime.now()
sum(range(100000000))
end = datetime.datetime.now()
print(end - start, "h:mm:ss")
```

0:00:02.180773 h:mm:ss

```
%time sum(range(100000000))
```

CPU times: total: 2.34 s

Wall time: 2.35 s *พื้ที่มองเห็น (import time)*

4999999950000000

จำนวนแบบทศนิยม เลื่อนตำแหน่ง มักจะเป็นตัวส่งที่เสร็จภายในเสี้ยววินาที

```
%timeit sum(range(100000000))
```

2.13 s \pm 46.2 ms per loop (mean \pm std. dev. of 7 runs, 1 loop each)

ทำ 1 รอบ

```
%timeit -r 1 sum(range(100000000))
sum(range(100000000))
```

%timeit -r 1 คือจับเวลาแบบ block 1 code (หลายบรรทัด)

4.31 s \pm 0 ns per loop (mean \pm std. dev. of 1 run, 1 loop each)

In Jupyter Notebook

Multithreading in Python

Windows thread } runs multi-core program
Pthread

- Multithreading in Python does **not exploit multicore/multiprocessor**, due to Global Interpreter Lock (GIL). So, threads run concurrently but not in parallel. Probably good for threads with I/O.

```
import threading
import time
```

Python เป็น multi-thread ได้ แต่ thread หนึ่งๆ ไม่ได้ทำงานแบบ Parallelism แต่สลับไปมาทำงานกัน
กับ I/O

```
def thread(tid):
    for i in range(5):
        print("thread ", tid, " iteration ", i)
        time.sleep(1)
```

```
t1 = threading.Thread(target=thread, args=(1,))
t2 = threading.Thread(target=thread, args=(2,))
```

create thread

```
# Will execute both threads concurrently
t1.start()
t2.start()
```

2 thread สลับกันทำงาน สามารถทำกันได้

```
# Joins threads back to the parent process, which is this program
t1.join()
t2.join()
```

} ทำงานเสร็จ ดึงตัวงานที่ไว้ใน memory

```
thread 1 iteration 0
thread 2 iteration 0
thread thread 2 iteration 1
1 iteration 1
thread thread 1 iteration 2
2 iteration 2
thread 1 iteration 3
thread 2 iteration 3
thread thread 1 iteration 4
2 iteration 4
```

concurrency

→ output ของ thread 1 ที่ถูกประมวลผล output thread 2

Multithreading in Python

- Multithreading in Python does not exploit multicore/multiprocessor, due to Global Interpreter Lock (GIL). So, threads run concurrently but not in parallel. Probably good for threads with I/O.

```
import threading
```

```
def calc_partial_pi(rank, nthreads, nsteps, dx, partial_pi):
```

```
    partial_pi[rank] = 0.0
```

```
    for i in range(rank, nsteps, nthreads):
```

```
        x = (i + 0.5) * dx
```

```
        partial_pi[rank] += 4.0 / (1.0 + x * x) ←
```

```
    partial_pi[rank] *= dx
```

Partial results are stored in shared memory.

```
nsteps = 10000000
```

```
dx = 1.0 / nsteps
```

```
nthreads = 10 ←
```

```
partial_pi = np.zeros(nthreads)
```

Try changing *nthreads* and measure execution time.

```
inputs = [(rank, nthreads, nsteps, dx, partial_pi) for rank in range(nthreads)]
```

```
threads = [threading.Thread(target=calc_partial_pi, args=inp) for inp in inputs]
```

```
for t in threads:
```

```
    t.start()
```

```
for t in threads:
```

```
    t.join()
```

```
pi = partial_pi.sum()
```

Vectorization and multithreading in Numpy

- Numpy array is faster than Python list due to more efficient memory access.
- Numpy implements many functions using C libraries, with vectorization and multithreading, so they can run in parallel.
- Numpy element-wise multiply is not multithreaded, but dot product is multithreaded.

```
import random
import numpy as np
```

```
## element-wise multiplication of Python lists
xs = [random.random() for i in range(10000000)]
ys = [random.random() for i in range(10000000)]
%timeit [x*y for x, y in zip(xs, ys)]
```

$XS : [1, 2, 3, 4]$
 $YS : [5, 6, 7, 8]^x$
 $z : [5, 12, 21, 32]$

1.54 s ± 312 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)

```
## element-wise multiplication of Numpy arrays (vectorized)
np_xs = np.random.rand(10000000)
np_ys = np.random.rand(10000000)
%timeit np.multiply(np_xs, np_ys)
```

1 thread

40.8 ms ± 2.19 ms per loop (mean ± std. dev. of 7 runs, 10 loops each)

```
## dot product of Numpy arrays (vectorized and threaded)
np_xs = np.random.rand(10000000)
np_ys = np.random.rand(10000000)
%timeit np.dot(np_xs, np_ys)
```

numpy technique
dot product is multi thread and optimized

8.77 ms ± 343 µs per loop (mean ± std. dev. of 7 runs, 100 loops each)

Dot product runs more operations than element-wise multiply, but faster due to multithreading.

Matrix Multiplication in Python

```
def matrix_multiplication(A, B, result):  
    for i in range(result.shape[0]):  
        for j in range(result.shape[1]):  
            temp = 0.  
            for k in range(A.shape[1]):  
                temp += A[i, k] * B[k, j]  
            result[i, j] = temp
```

```
C = np.empty([100, 100], np.float32)  
%timeit matrix_multiplication(A, B, C)
```

```
1 loop, best of 3: 471 ms per loop
```

- Try larger matrices

Matrix Multiplication with Numpy

```
A = np.random.rand(100, 100)
B = np.random.rand(100, 100)
%timeit C = np.dot(A, B)
```

$$\begin{matrix} \begin{bmatrix} 100 \times 100 \end{bmatrix} & \cdot & \begin{bmatrix} 100 \times 100 \end{bmatrix} \\ A & & B \end{matrix}$$

The slowest run took 5.89 times longer than the fastest.
10000 loops, best of 3: 136 μ s per loop

```
A = np.random.rand(1000, 1000)
B = np.random.rand(1000, 1000)
%timeit C = np.dot(A, B)
```

$$\begin{matrix} \begin{bmatrix} 1000 \times 1000 \end{bmatrix} & \cdot & \begin{bmatrix} 1000 \times 1000 \end{bmatrix} \\ A & & B \end{matrix}$$

10 loops, best of 3: 49.8 ms per loop

Numba

- Numba translates Python functions to optimized machine code at runtime. (Just In Time Compilation) *convert code python into parallel code*
- It offers options for parallelizing Python code for CPUs and GPUs, often with only minor code changes (e.g. compiler directives).

for Python CPU / GPU

```
def matrix_multiplication(A, B, result):
    for i in range(result.shape[0]):
        for k in range(A.shape[1]):
            for j in range(result.shape[1]):
                result[i, j] += A[i, k] * B[k, j]
```

```
!pip install -q numba
from numba import jit
```

jit = Just in time

```
@jit
def matrix_multiplication_numba(A, B, result):
    for i in range(result.shape[0]):
        for k in range(A.shape[1]):
            for j in range(result.shape[1]):
                result[i, j] += A[i, k] * B[k, j]
```

} code python ที่เราเขียนไว้ก่อนหน้านี้
แต่ครอบด้วย numba annotate

```
A = np.random.rand(1000, 1000)
B = np.random.rand(1000, 1000)
```

```
C = np.empty([1000, 1000], float)
%timeit matrix_multiplication(A, B, C)
```

14min 39s ± 9.62 s per loop (mean ± std. dev. of 7 runs, 1 loop each)

```
## matrix multiplication with Numpy
%timeit C = np.dot(A, B)
```

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

very fast

```
## matrix multiplication with Numba
C = np.empty([1000, 1000], float)
%timeit matrix_multiplication_numba(A, B, C)
```

370 ms ± 16.2 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)

Multiprocessing in Python

Multiprocessing in Python can exploit multicore/multiprocessor.

```
import multiprocessing as mp
import numpy as np
```

```
def dotprod(a, b, q):
    q.put(np.dot(a, b))
```

```
nprocs = 10 10 processes
size = 10000000
```

```
a = np.random.rand(size)
```

```
b = np.random.rand(size)
```

```
q = mp.Queue() เก็บผลลัพธ์ของแต่ละ process
procs = [] list ของ process object
```

```
for i in range(nprocs):
    start = int(i*size/nprocs)
    end = int((i+1)*size/nprocs - 1)
    procs.append(mp.Process(target=dotprod, args=(a[start:end], b[start:end], q)))
```

```
# will execute both in parallel
```

```
for p in procs:
    p.start()
```

```
# Joins process back to the parent process, which is this program
```

```
for p in procs:
    p.join()
```

```
c = [q.get() for p in procs]
print(sum(c))
```

ถ้ามีหลาย core เติเรอ python เพื่อสร้างหลาย process แทน
เพราะ python ไม่ได้สร้าง multi-thread