Parallel Processing in Python

DS 5110/CS 5501: Big Data Systems

Spring 2024

Lecture 3

Yue Cheng

UNIVERSITY of VIRGINIA

Some material taken/derived from:

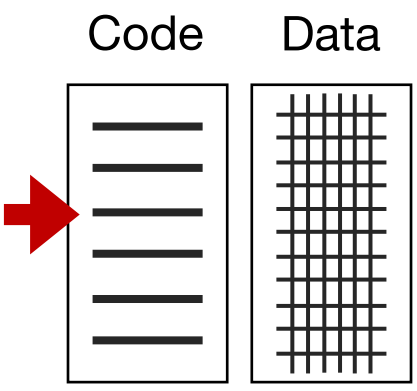
- Wisconsin CS 320 by Tyler Caraza-Harter.

Learning objectives

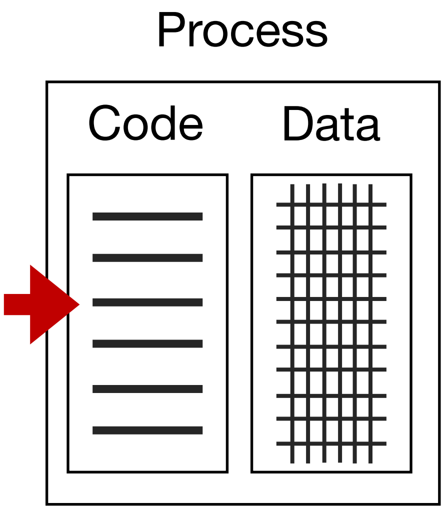
- Describe the execution model of
  - process-level parallelism
  - thread-level parallelism
  - task-level parallelism
- Know how to measure the speedup metric
- Understand the difference of strong scaling vs. weak scaling

Outline

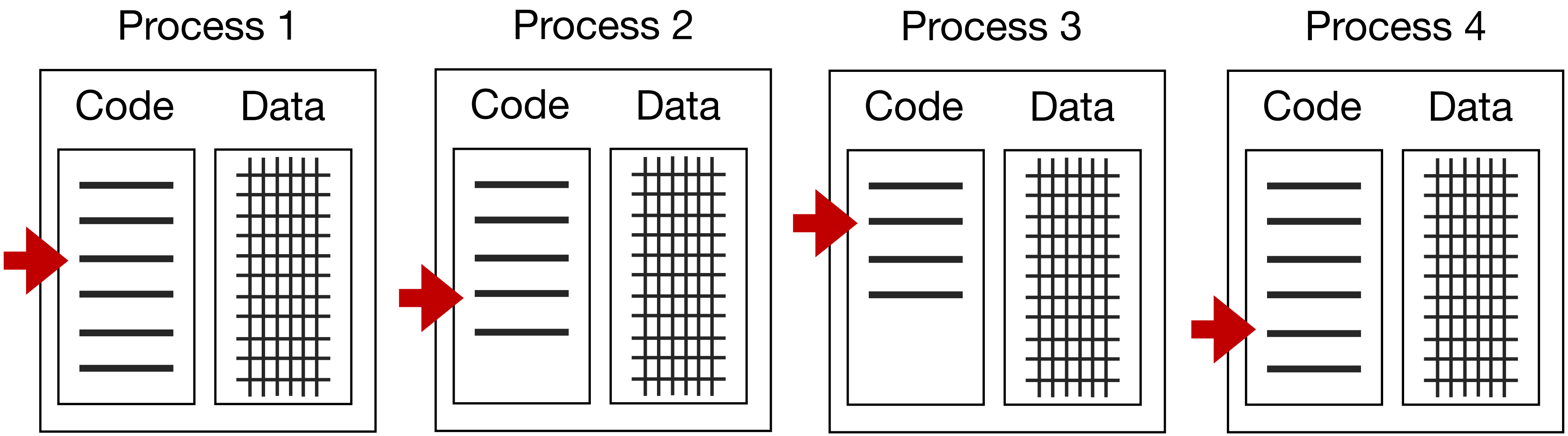
- Motivation
- Three parallel execution models
- Demo
- Measuring speedup metric
- Task parallelism in Dask
- Demo

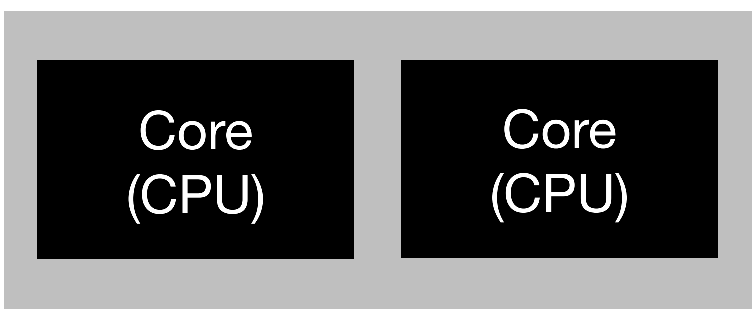


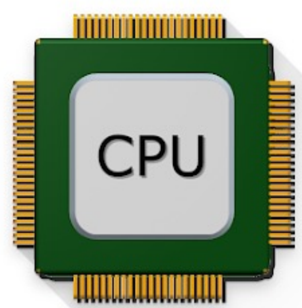
Instruction pointer
(also called “program counter”)



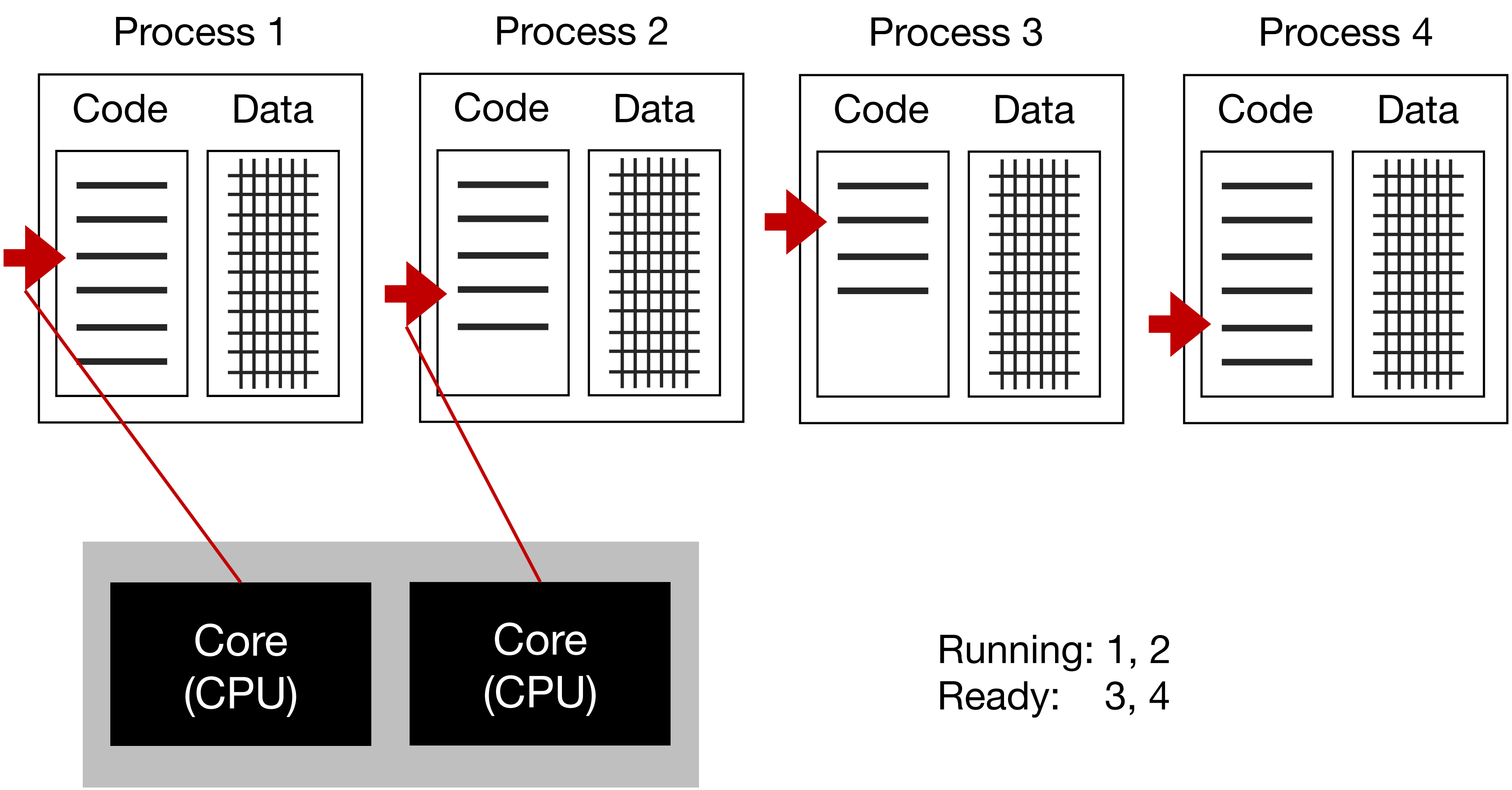
Instruction pointer belongs to a thread within the process





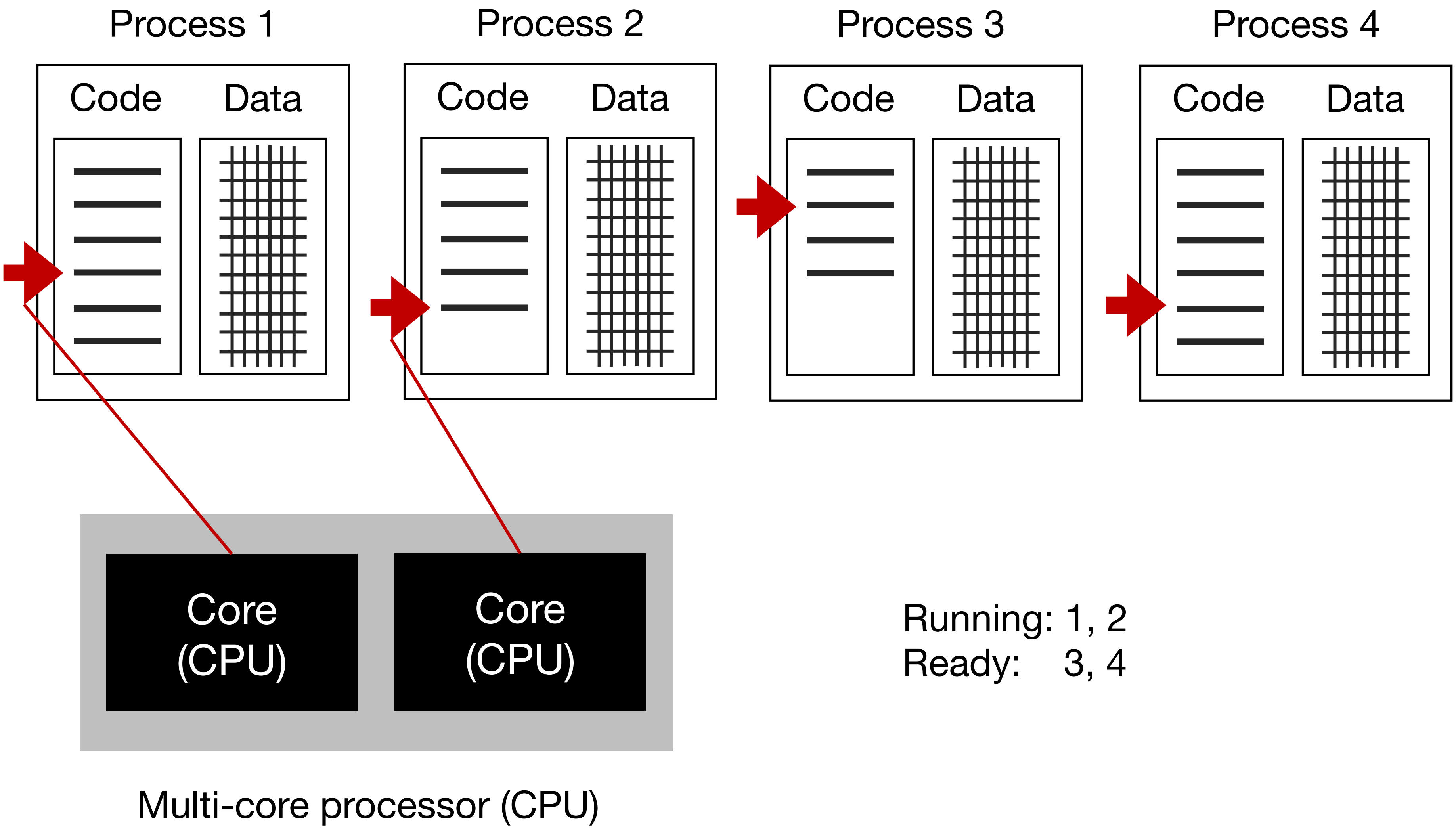


Multi-core processor (CPU)

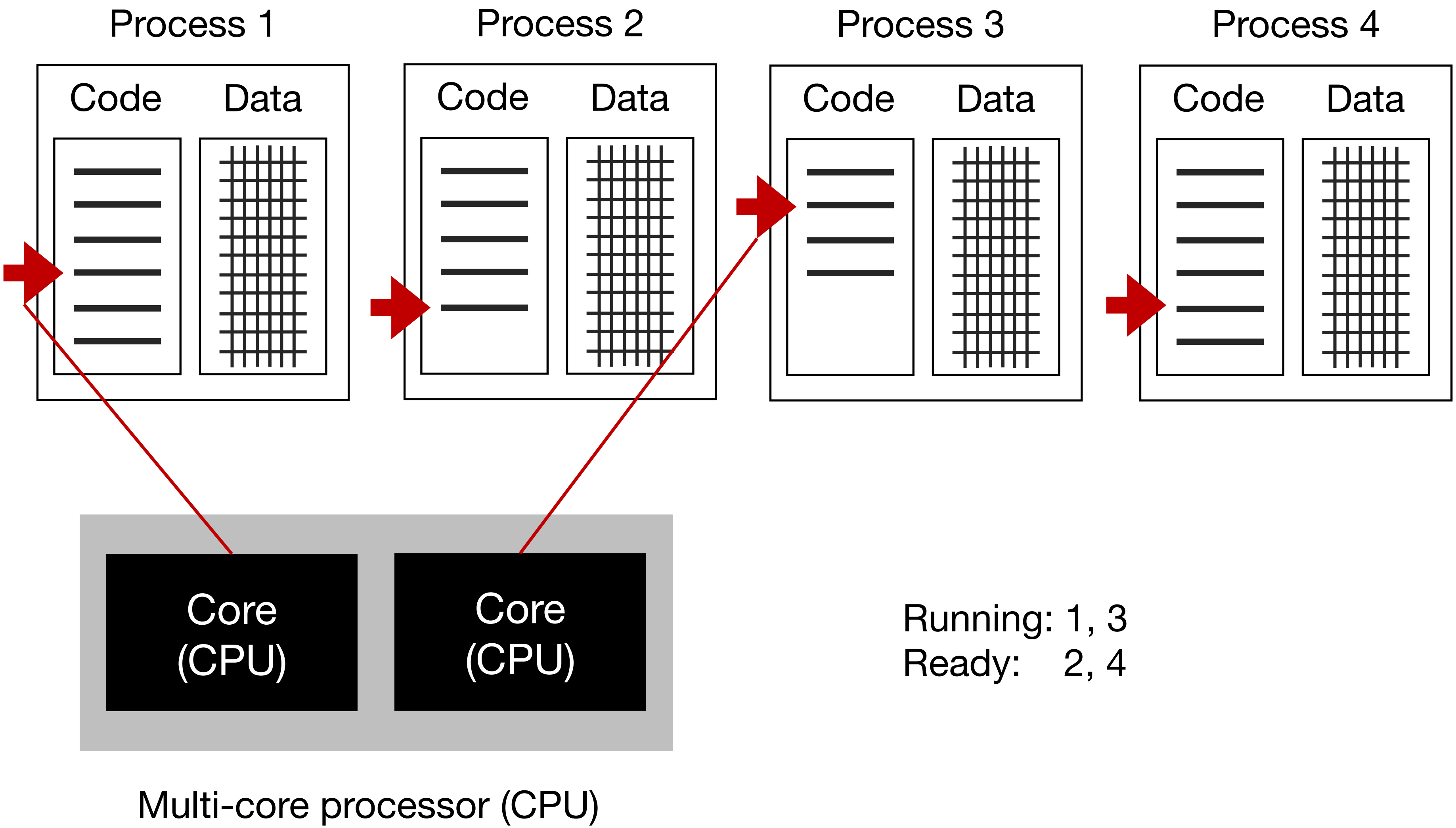


Multi-core processor (CPU)

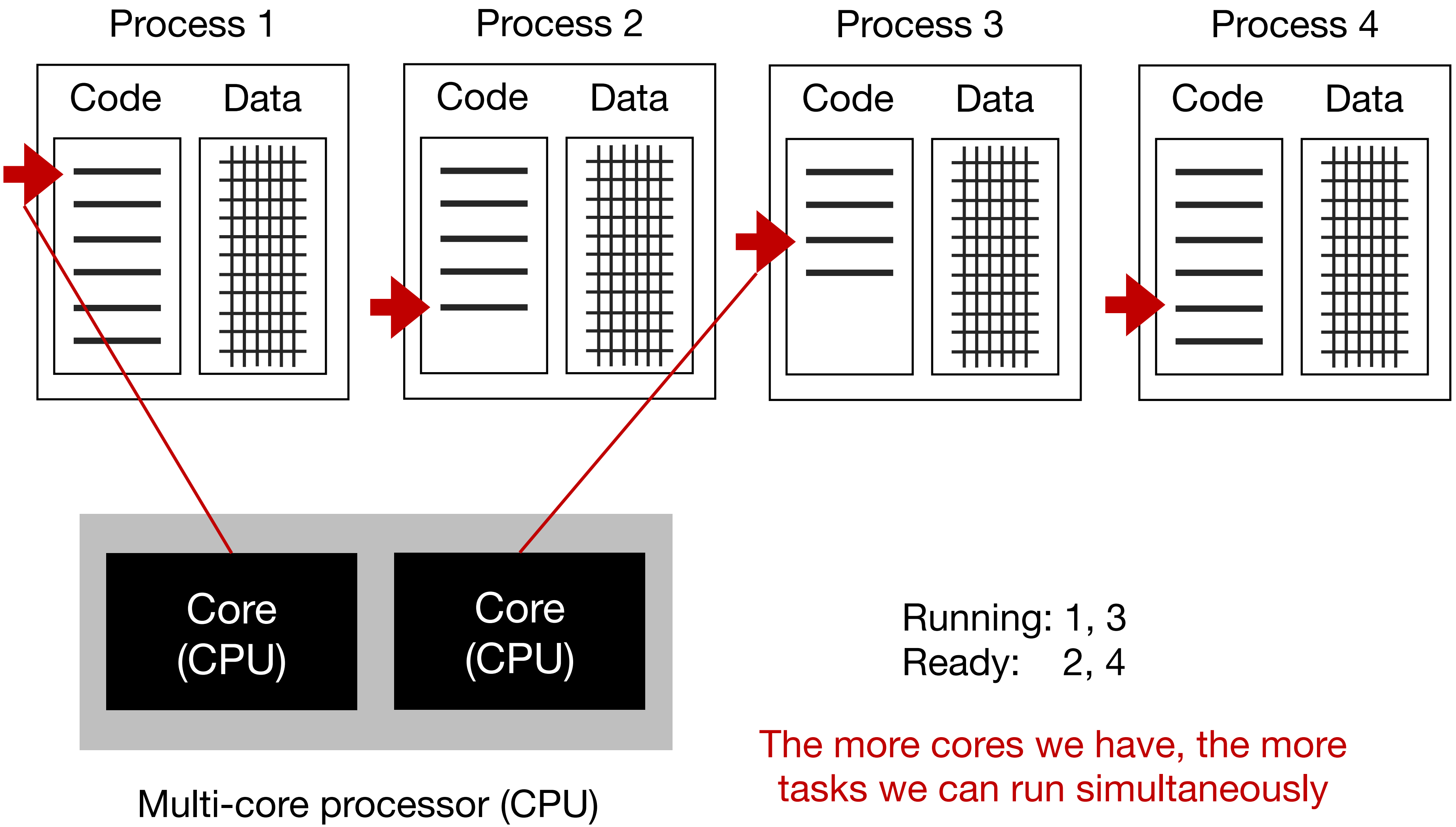
Running: 1, 2
Ready: 3, 4



Running: 1, 2
Ready: 3, 4



Running: 1, 3
Ready: 2, 4



Running: 1, 3
Ready: 2, 4

The more cores we have, the more tasks we can run simultaneously

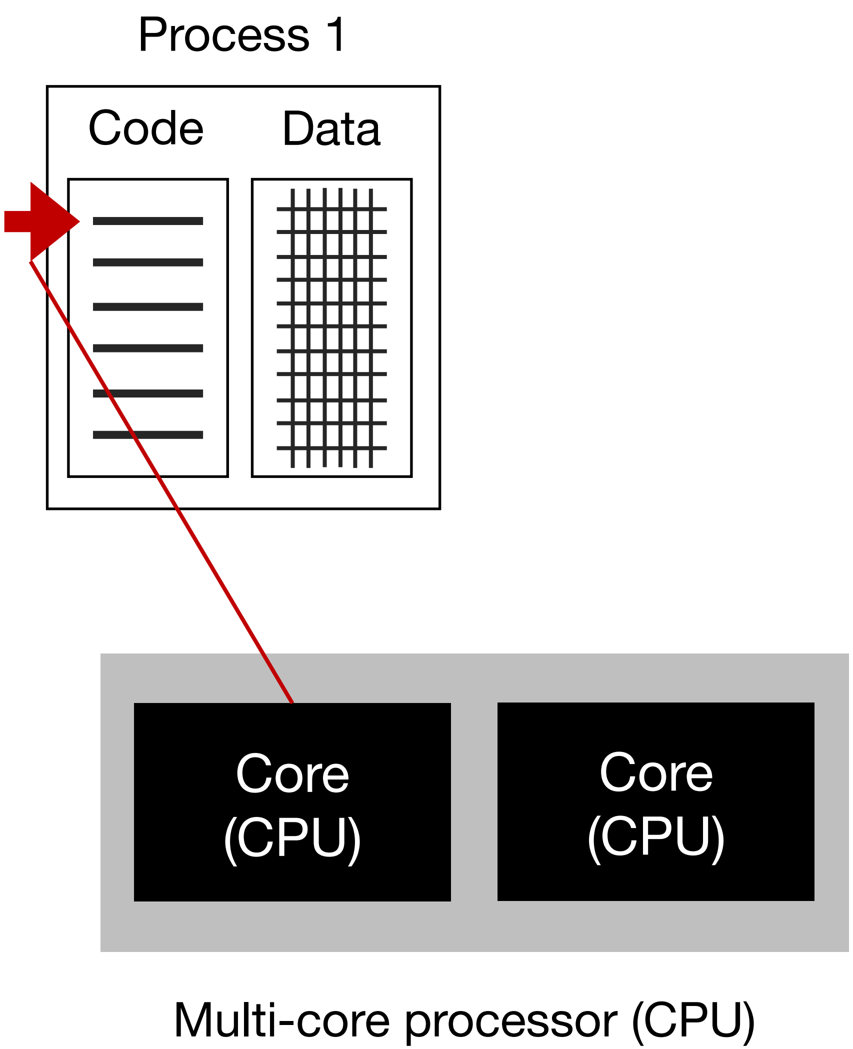
Parallel execution models

- Process-level parallelism
- Thread-level parallelism
- Task-level parallelism

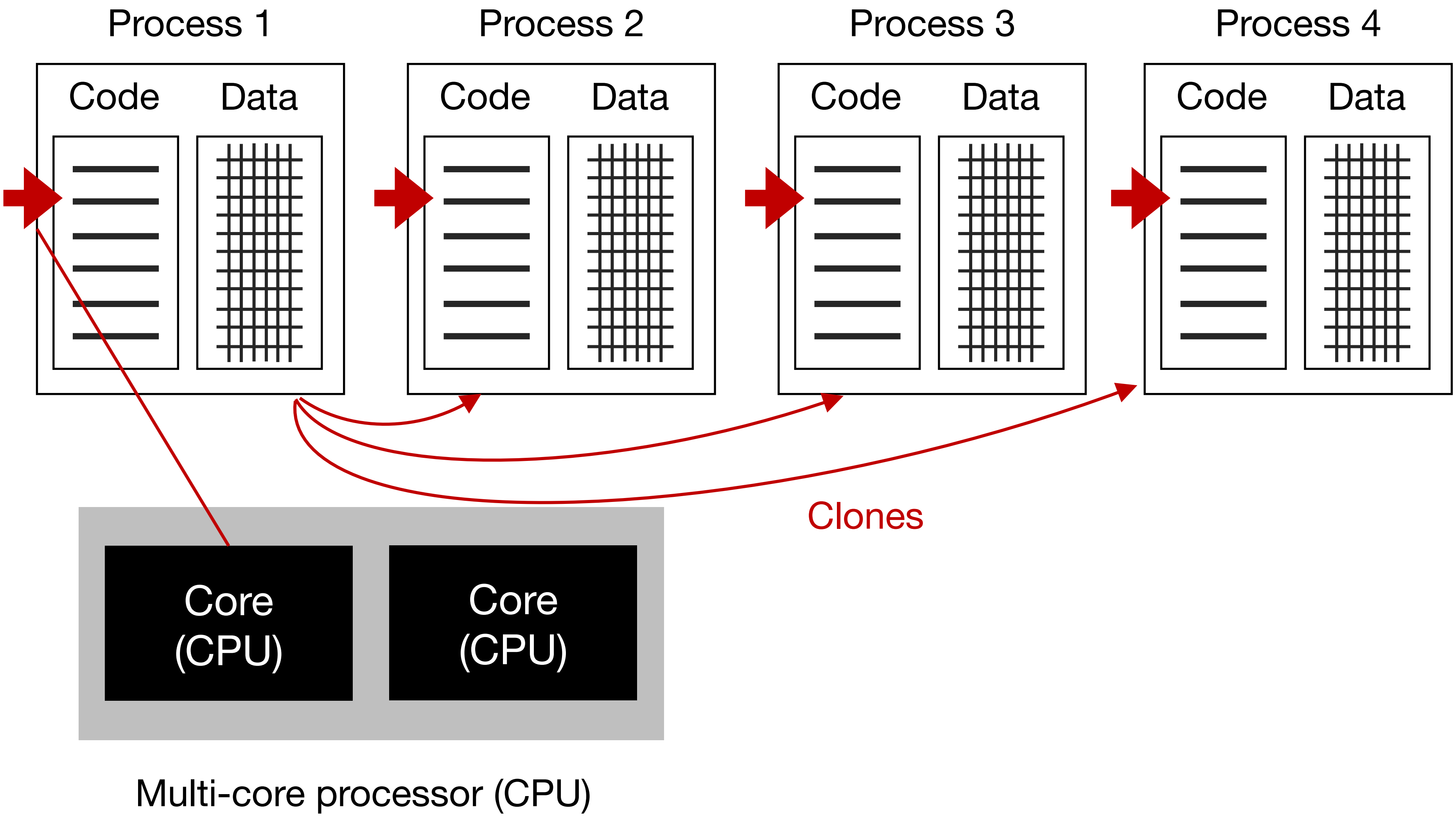
Parallel execution models

- **Process-level parallelism**
- Thread-level parallelism
- Task-level parallelism

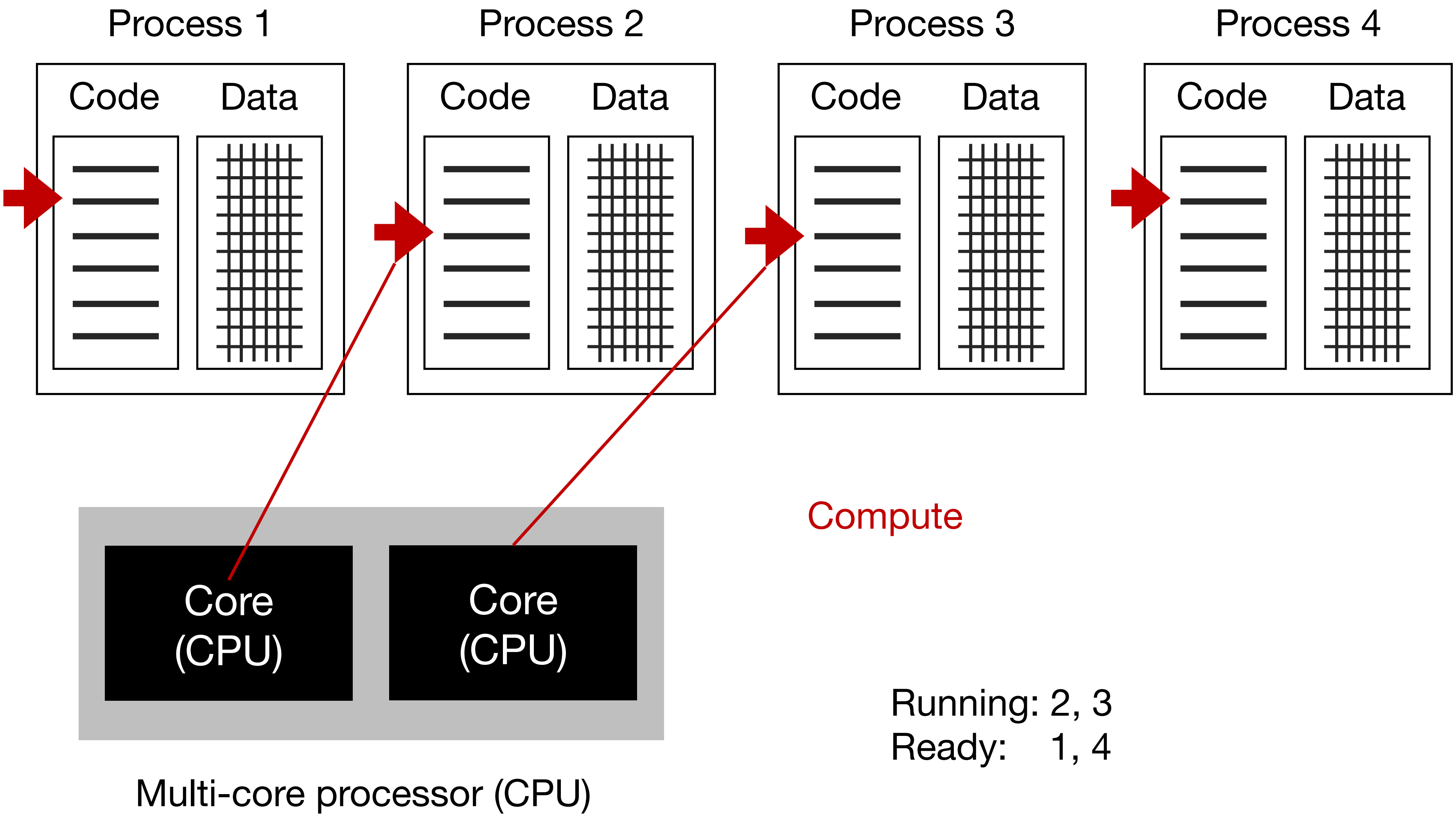
Process-level parallelism



Process-level parallelism

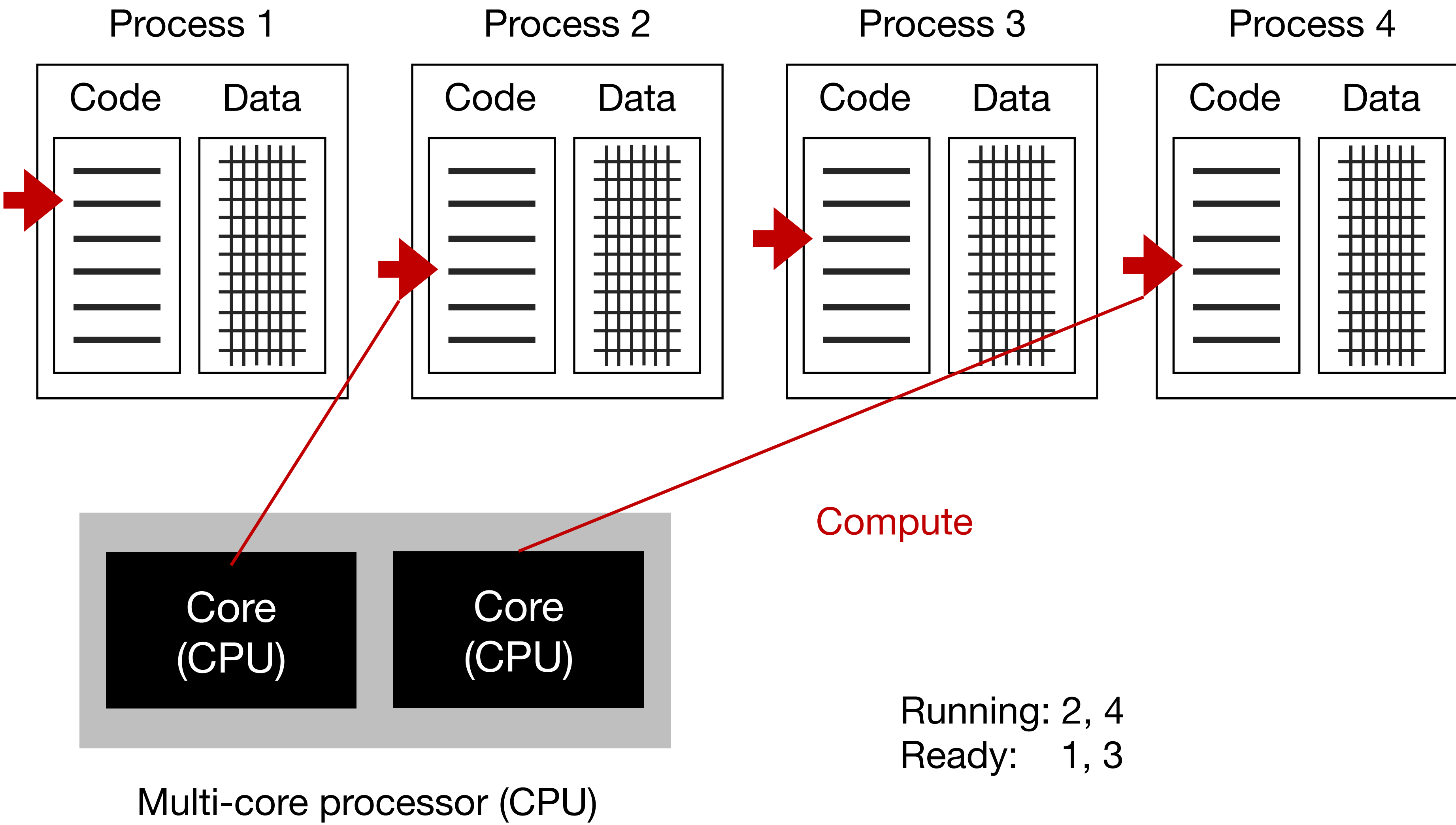


Process-level parallelism



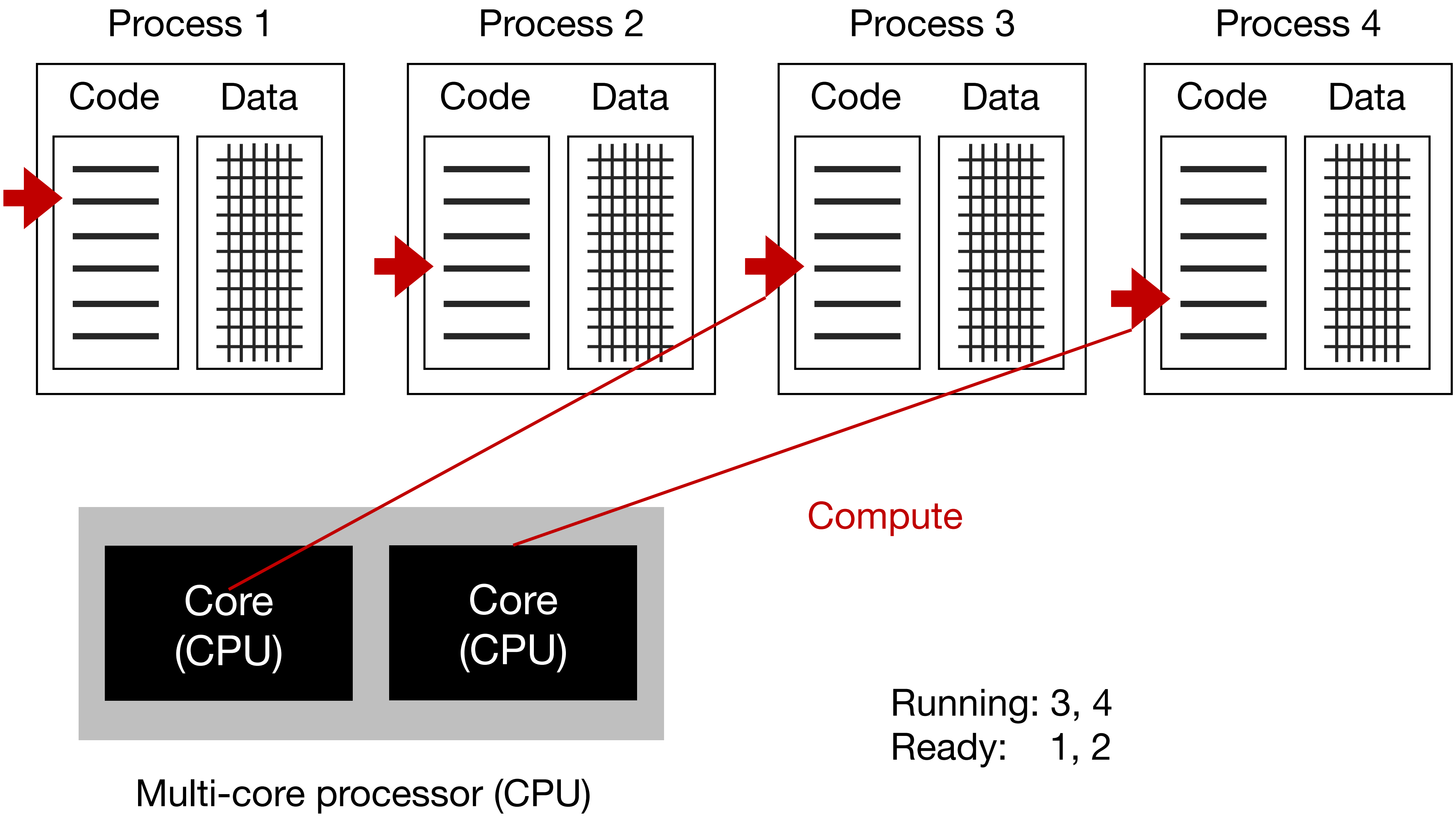
Running: 2, 3
Ready: 1, 4

Process-level parallelism

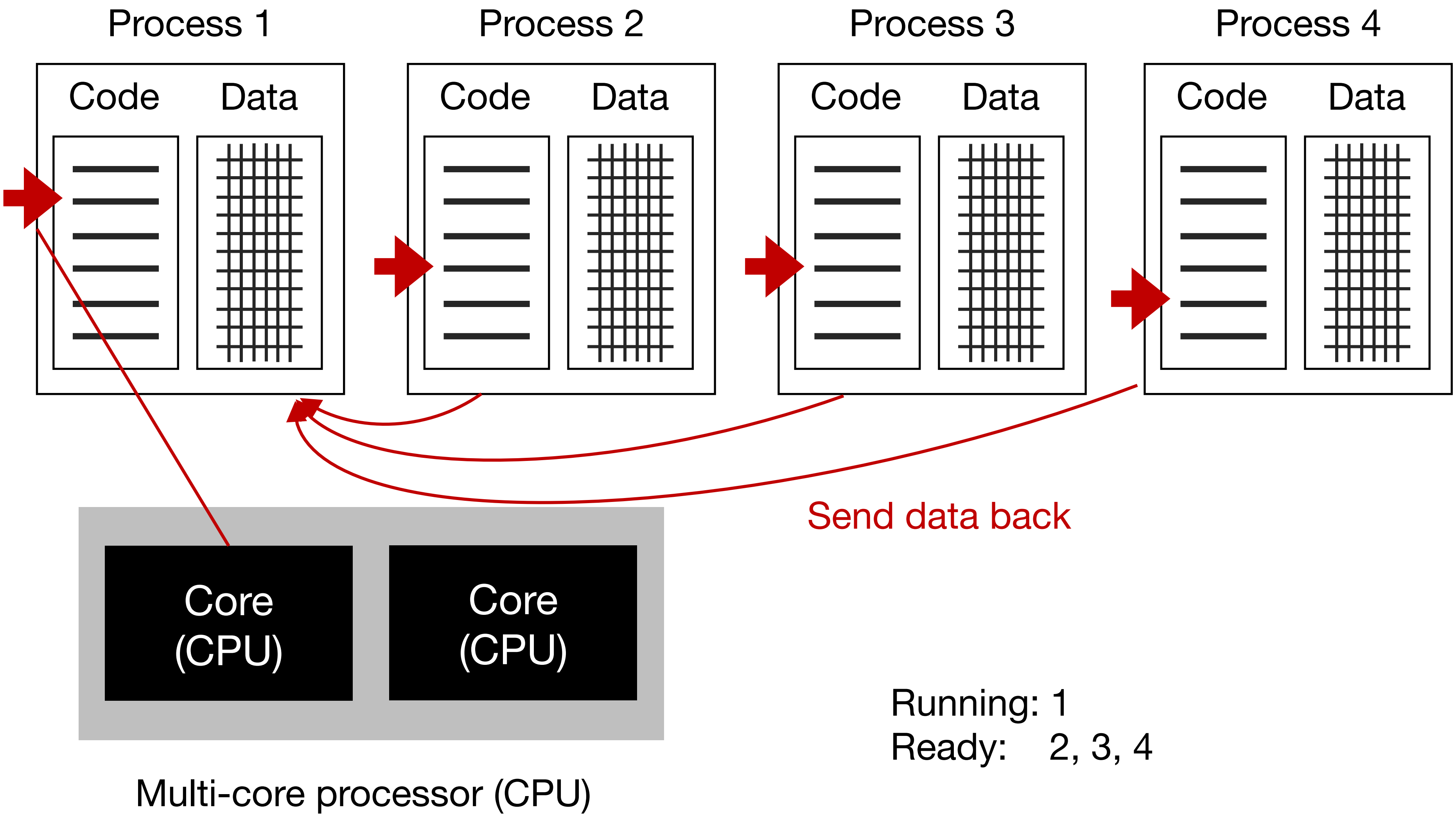


Running: 2, 4
Ready: 1, 3

Process-level parallelism

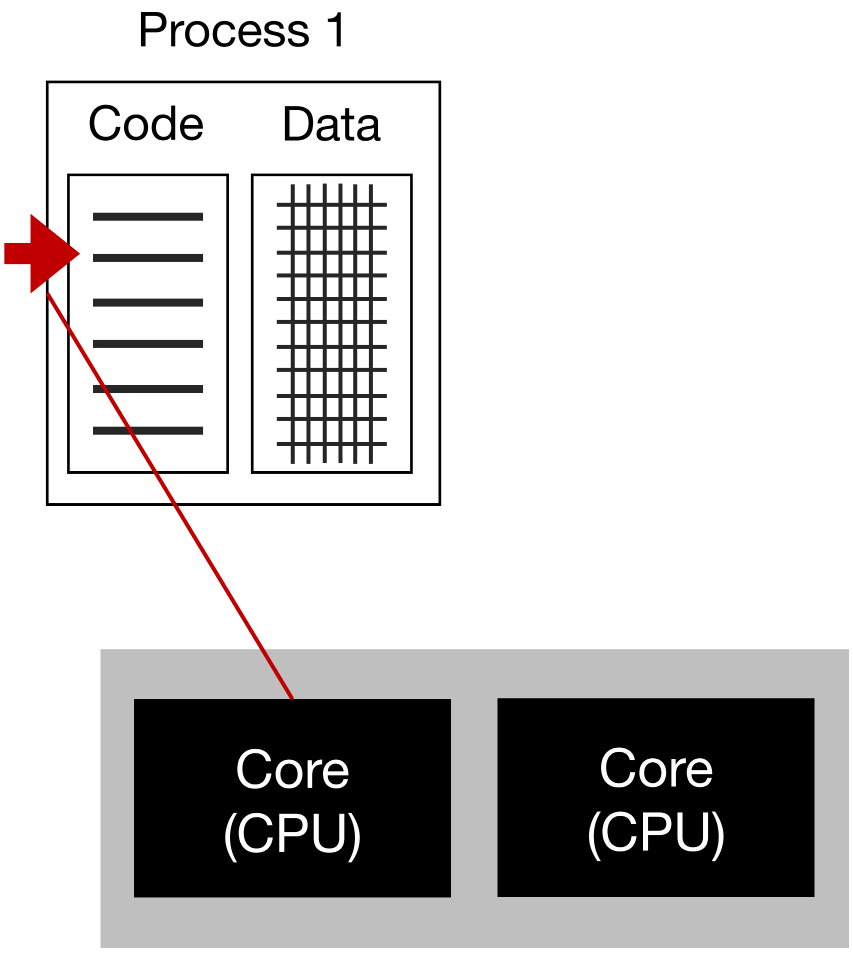


Process-level parallelism



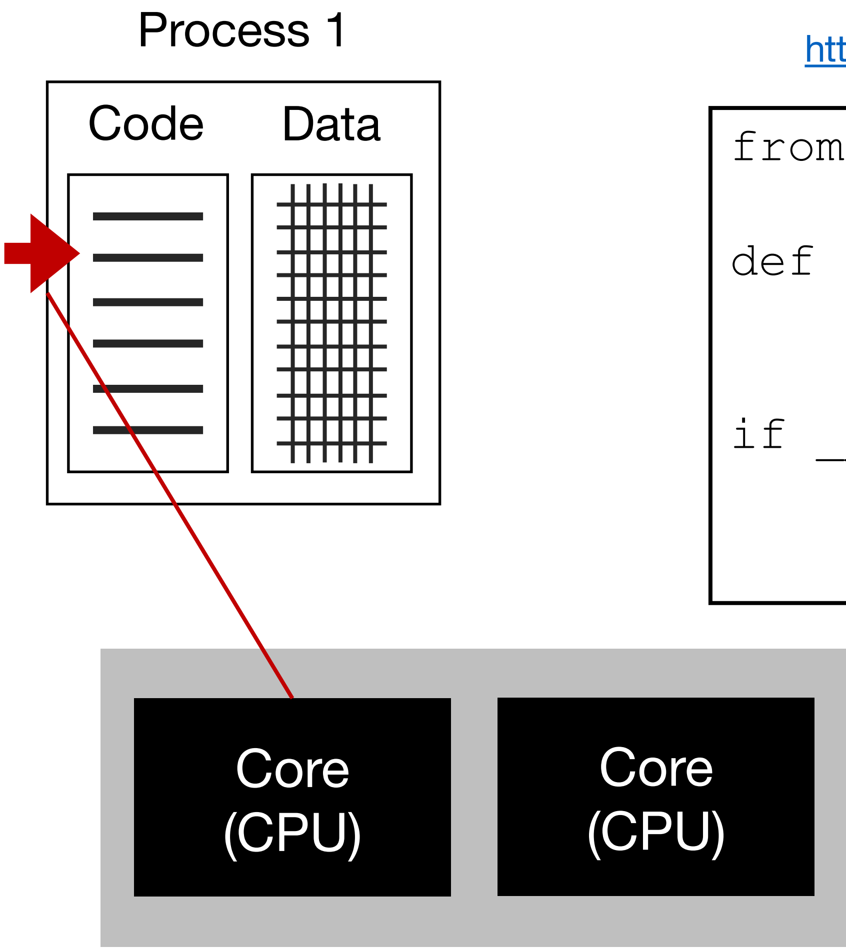
Running: 1
Ready: 2, 3, 4

Process-level parallelism



Multi-core processor (CPU)

Process-level parallelism in Python



Multi-core processor (CPU)

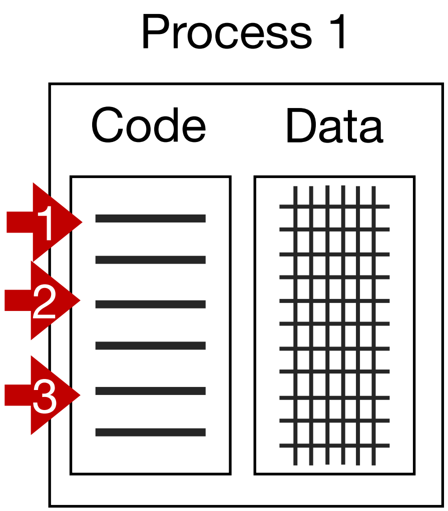
https://docs.python.org/3/library/multiprocessing.html

```
from multiprocessing import Pool

def f(x):
     return x*x

if __name__ == '__main__':
     with Pool(3) as p:
          print(p.map(f, [1,2,3]))
```

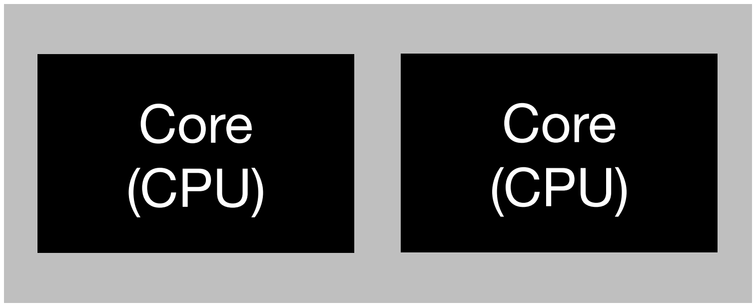
Parallel execution models

- Process-level parallelism
- **Thread-level parallelism**
- Task-level parallelism

Thread-level parallelism

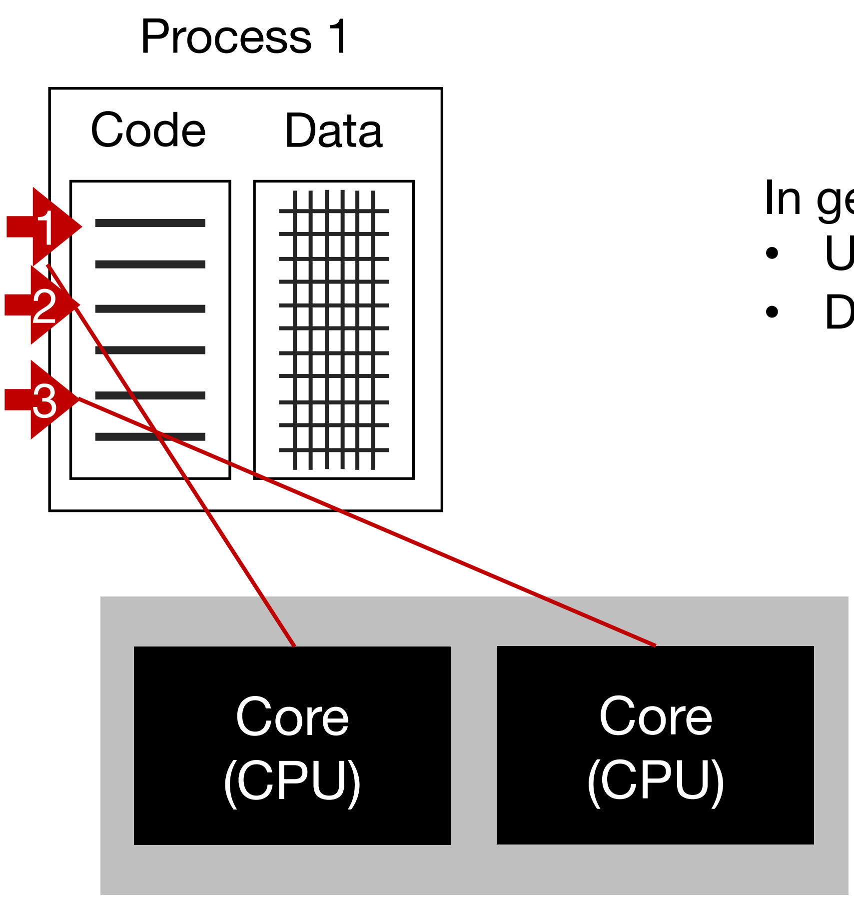


Threads give us multiple instruction pointers in a process, allowing us to execute multiple parts of the code at the same time!



Multi-core processor (CPU)

Thread-level parallelism



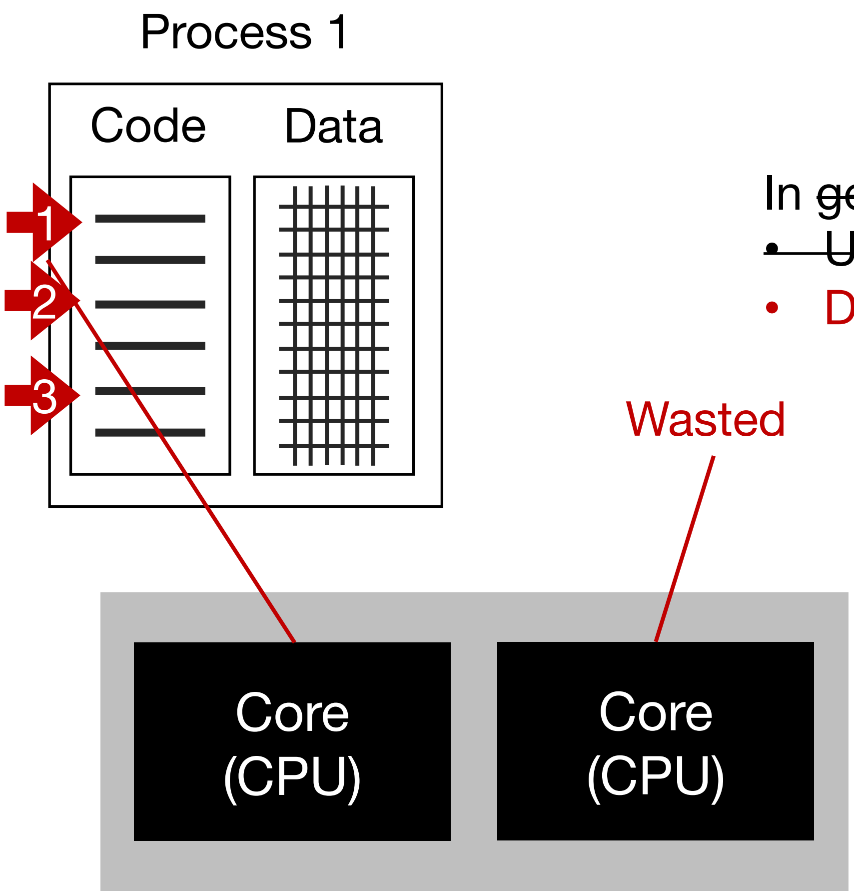
Multi-core processor (CPU)

In general, threads help:

- Use multiple cores
- Do useful work when threads are blocking

Running: 1, 3
Ready: 2

Thread-level parallelism in Python



Multi-core processor (CPU)

In ~~general~~ Python, threads help:

- ~~Use multiple cores~~ (b/c of the GIL)
- Do useful work when threads are blocking

https://wiki.python.org/moin/GlobalInterpreterLock

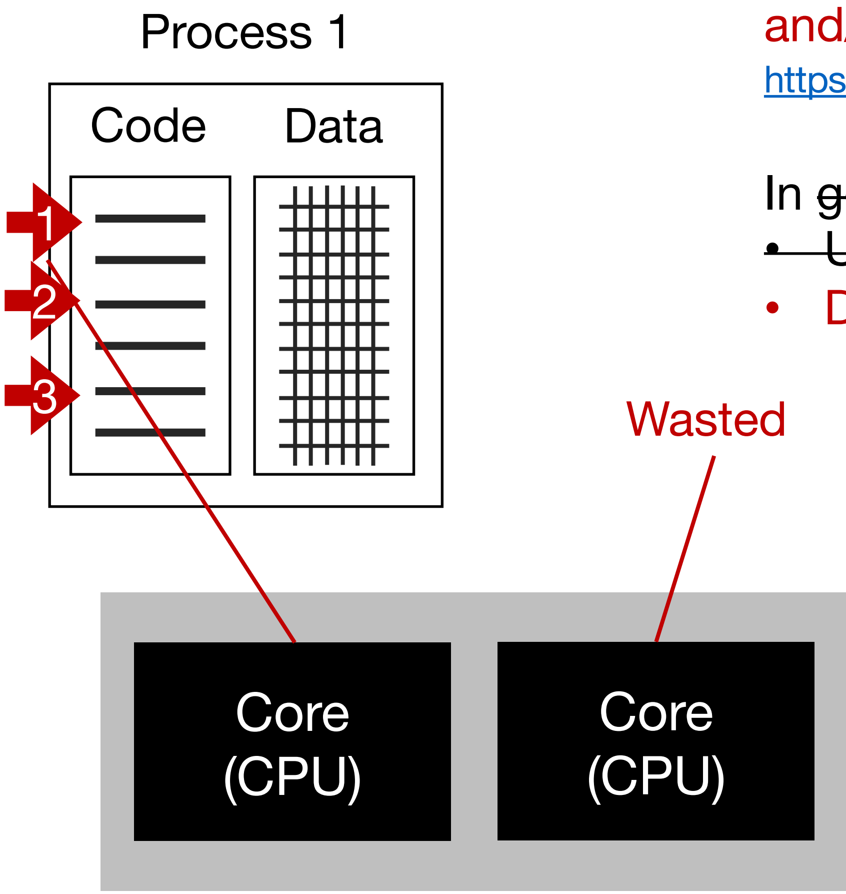
Running: 1
Ready: 3
Blocked: 2

Thread-level parallelism in Python

Recommendation: Don't use threads unless you learn a lot on asynchronous processing and/or coroutines
https://docs.python.org/3/library/asyncio-task.html

In ~~general~~ Python, threads help:
- ~~Use multiple cores~~ (b/c of the GIL)
- Do useful work when threads are blocking

https://wiki.python.org/moin/GlobalInterpreterLock



Multi-core processor (CPU)

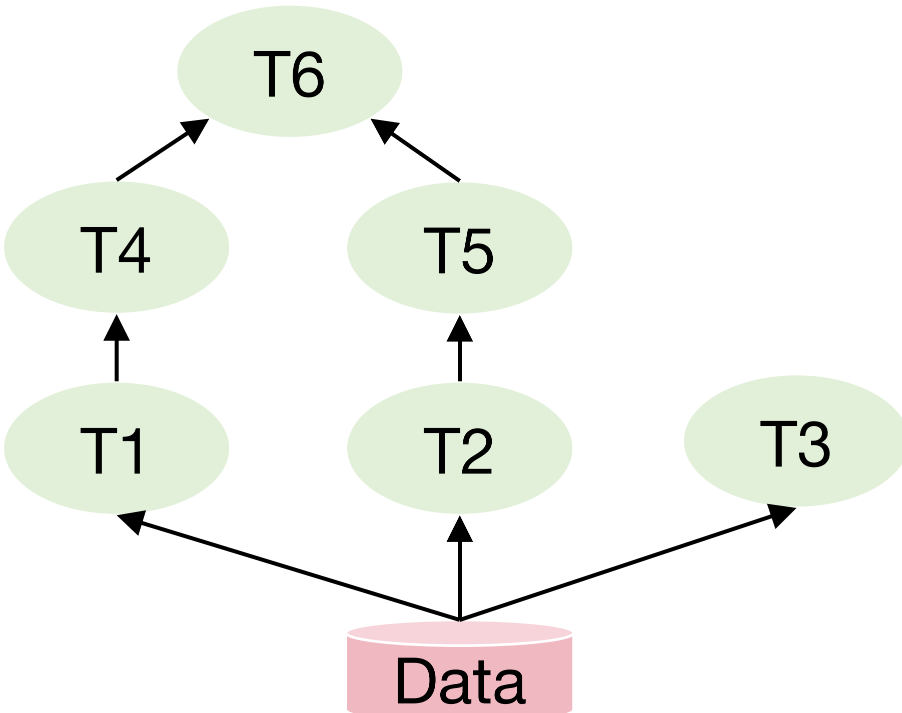
Running: 1
Ready: 3
Blocked: 2

Demo …

Parallel execution models

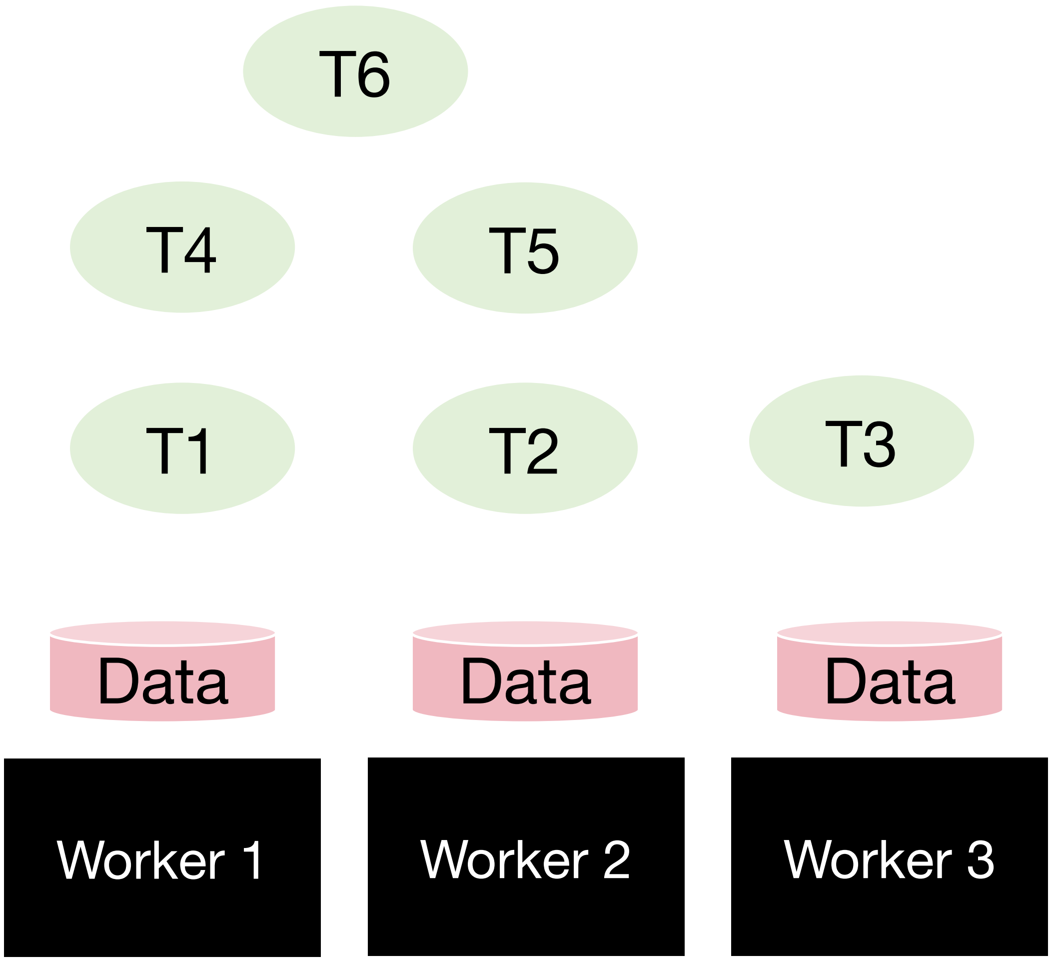
- Process-level parallelism
- Thread-level parallelism
- **Task-level parallelism**

Task-level parallelism



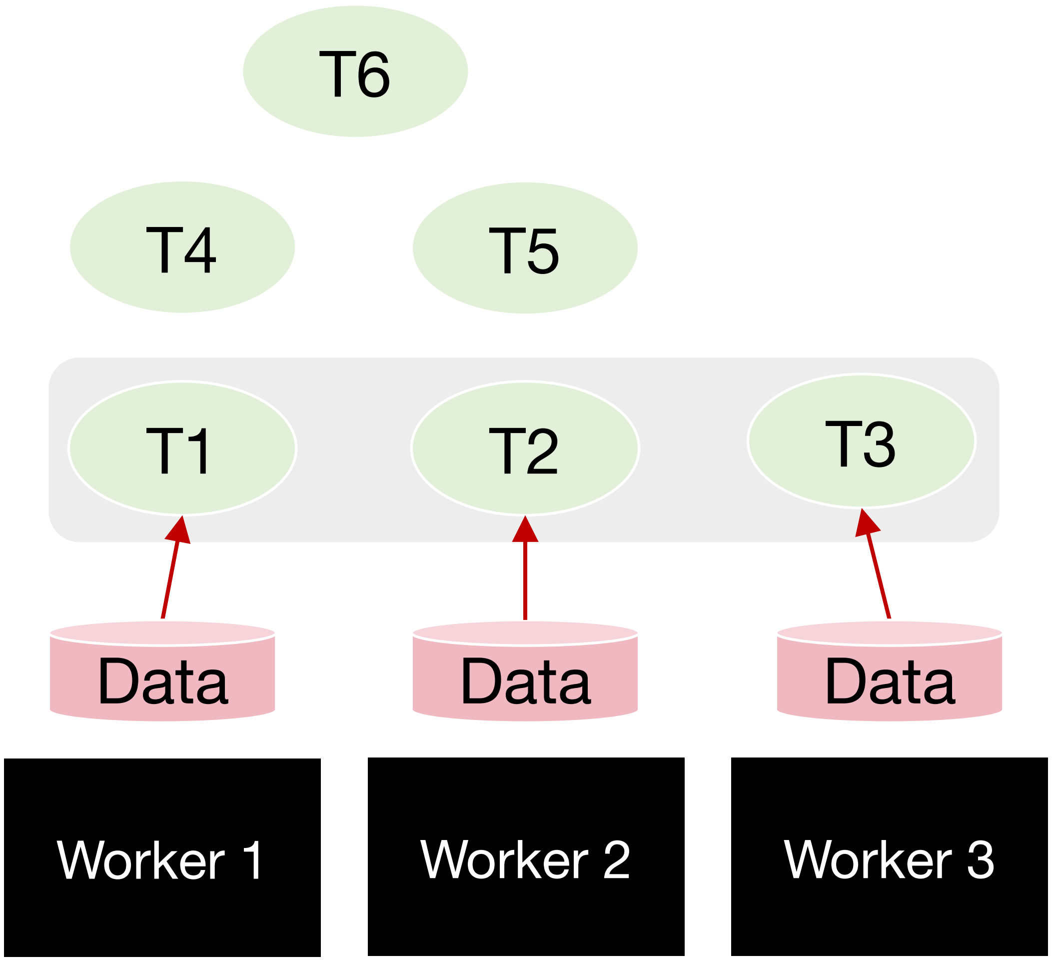
Task DAG
(Directed Acyclic Graph)

Task-level parallelism



S1: Copy whole dataset to all workers

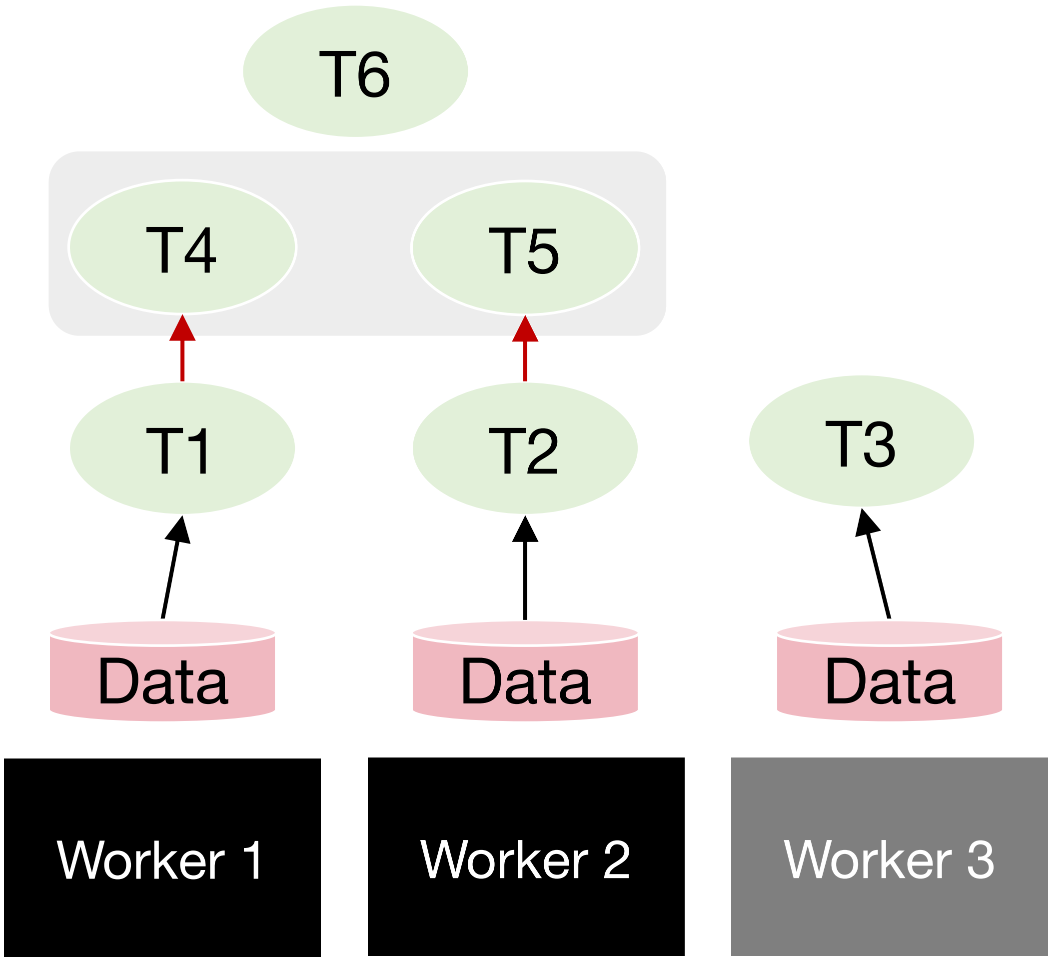
Task-level parallelism



S2: Schedule T1 to W1, T2 to W2, T3 to W3

S1: Copy whole dataset to all workers

Task-level parallelism

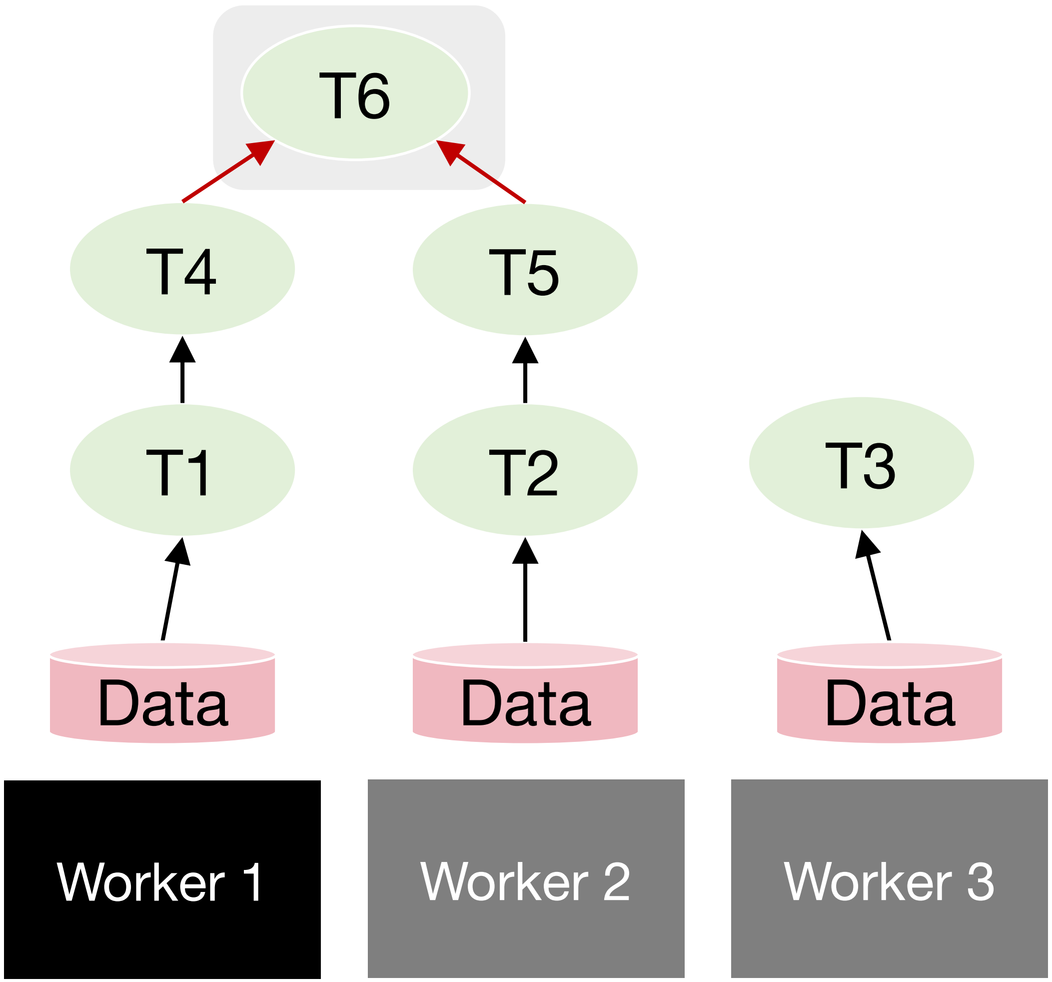


S3: Run T4 after T1 on W1, run T5 after T2 on W2; after T3, W3 is idle

S2: Schedule T1 to W1, T2 to W2, T3 to W3

S1: Copy whole dataset to all workers

Task-level parallelism



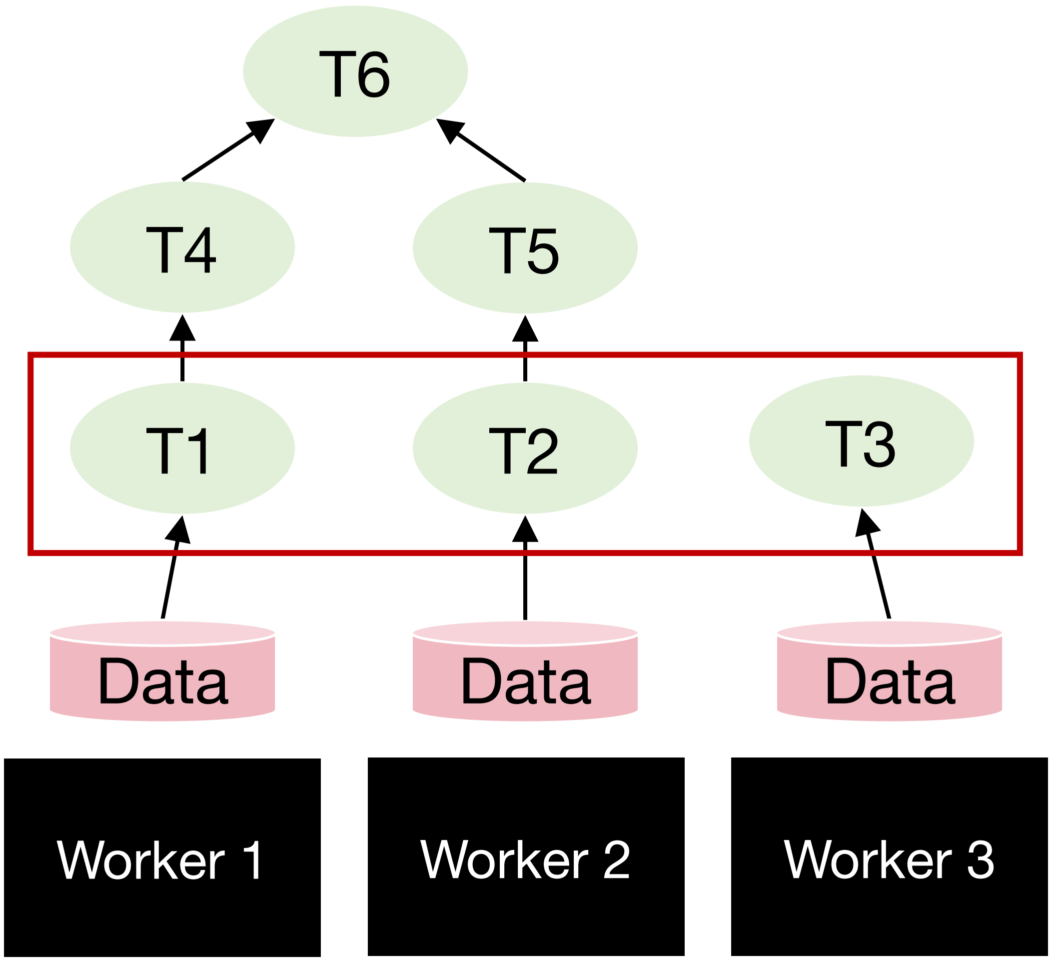
S4: After T4 and T5 ends, run T6 on W1; after T5, W2 is idle

S3: Run T4 after T1 on W1, run T5 after T2 on W2; after T3, W3 is idle

S2: Schedule T1 to W1, T2 to W2, T3 to W3

S1: Copy whole dataset to all workers

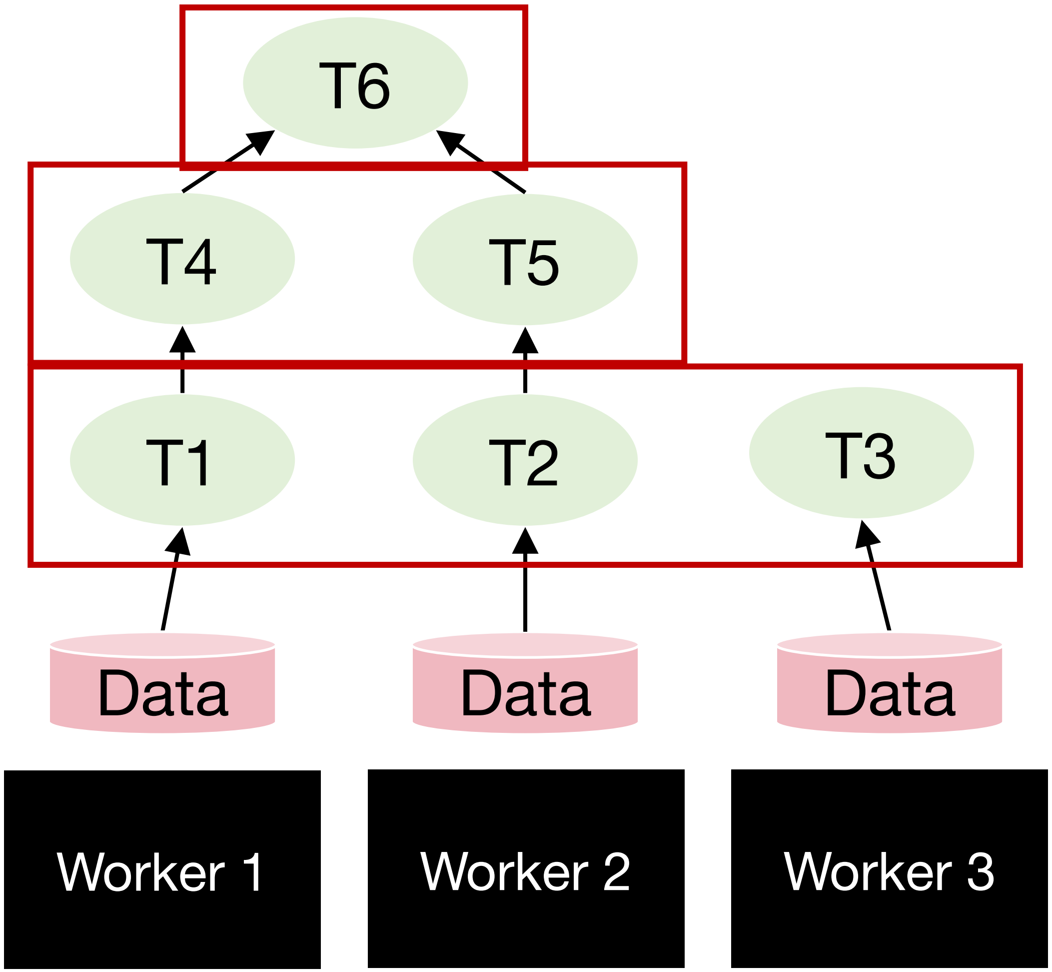
Task-level parallelism



Degree of parallelism is the largest amount of parallelism possible in the DAG:

- How many tasks can be run in parallel at most

Task-level parallelism



Observations:

Resource wastage on idle workers

Overtime degree of parallelism drops!

Degree of parallelism is the largest amount of parallelism possible in the DAG:

- How many tasks can be run in parallel at most

Quantify benefit of parallelism: Speedup

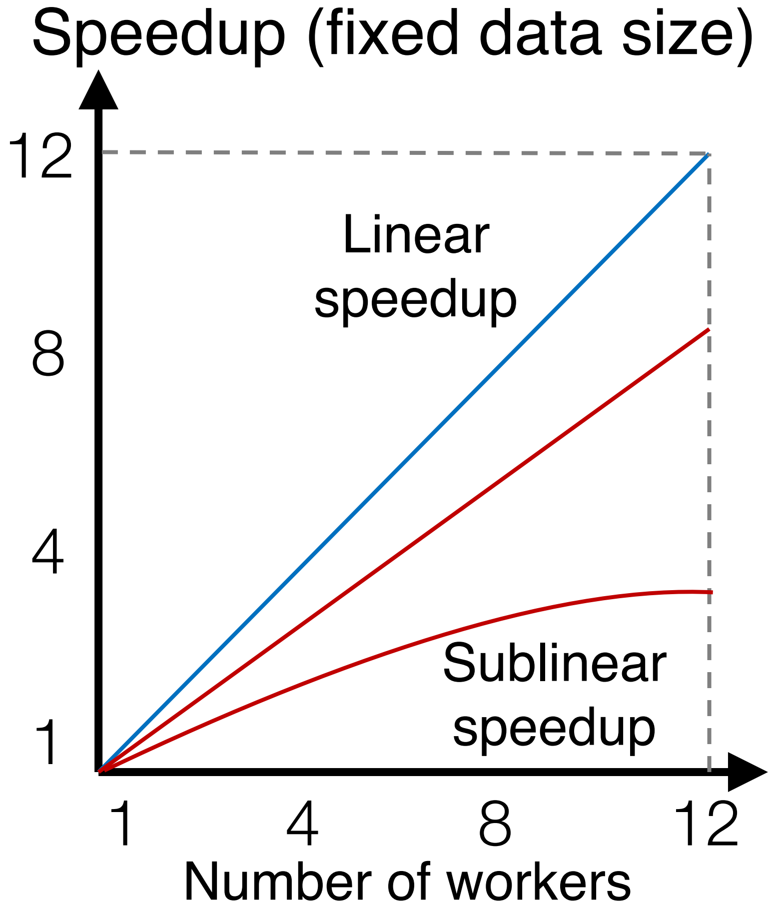
$$\textbf{Speedup} = \frac{\text{Completion time given 1 worker}}{\text{Completion time given N worker}}$$

Quantify benefit of parallelism: Speedup

$$\textbf{Speedup} = \frac{\text{Completion time given 1 worker}}{\text{Completion time given N worker}}$$

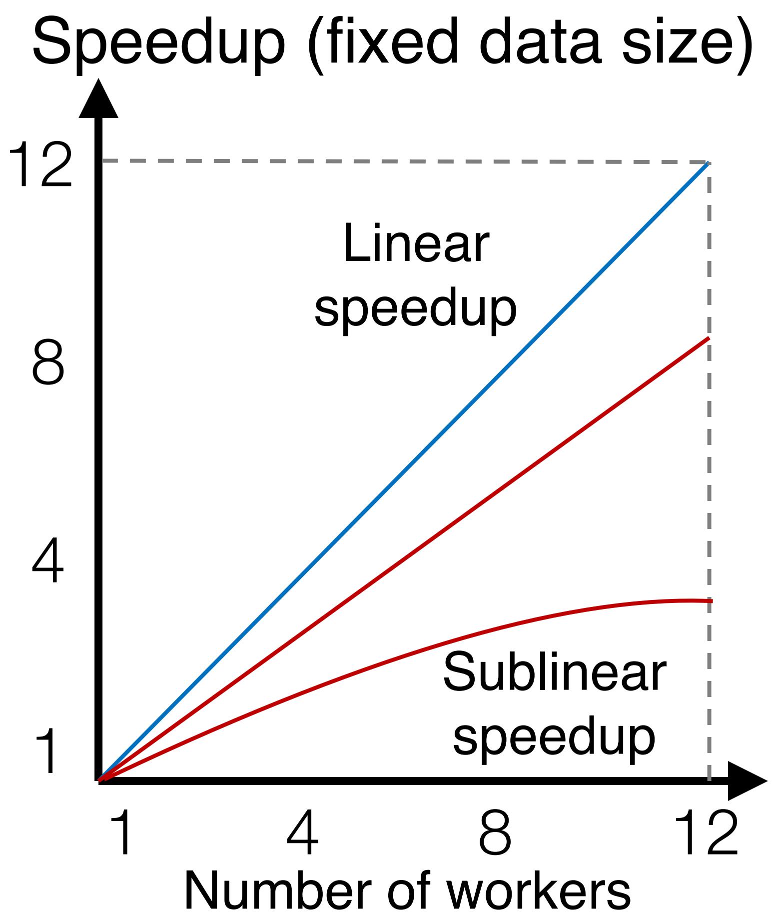
Q: Given N workers, can we get a speedup of N?

Quantify speedup

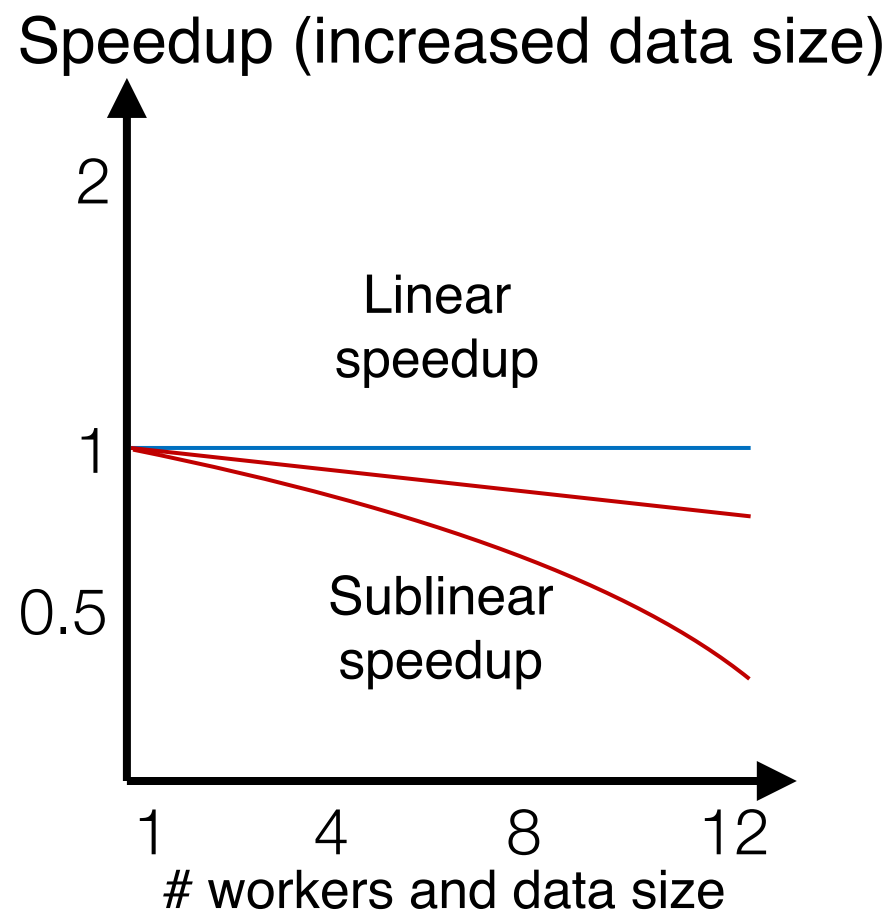


Strong scaling

Quantify speedup

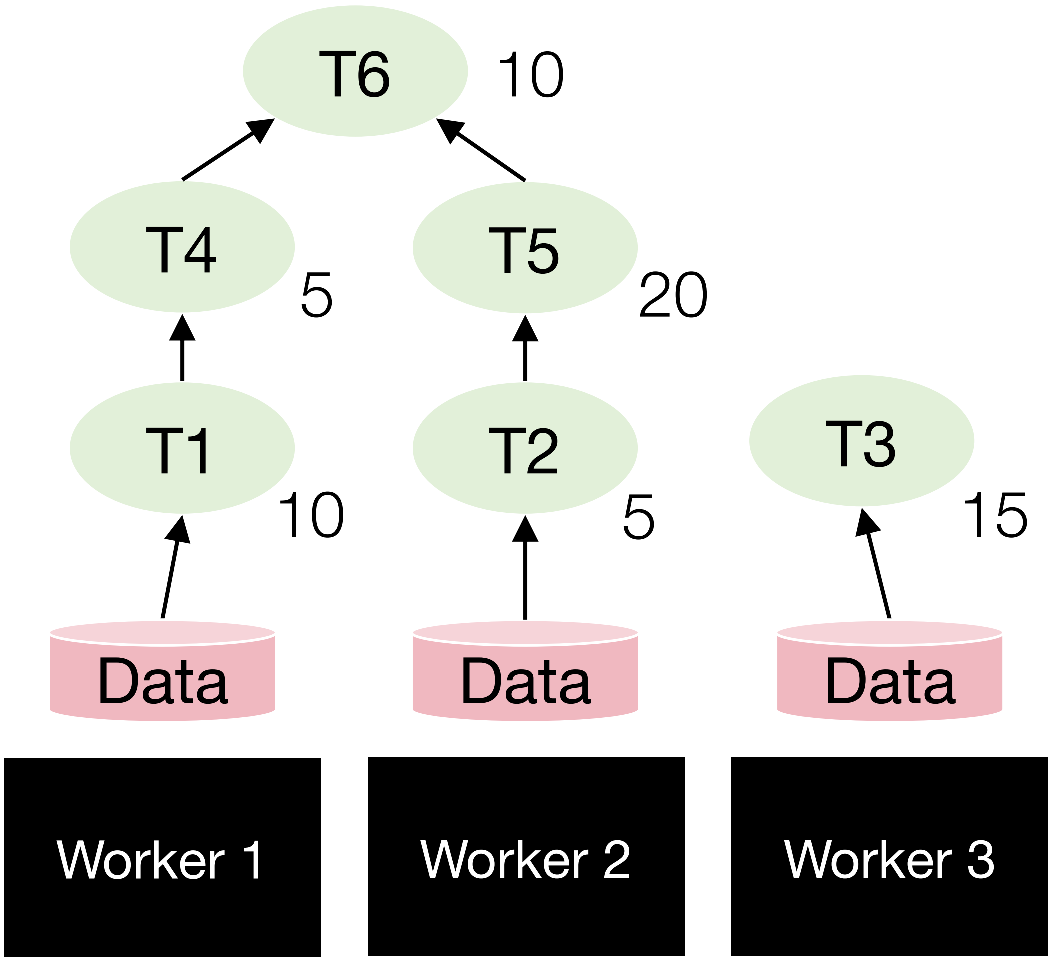


Strong scaling



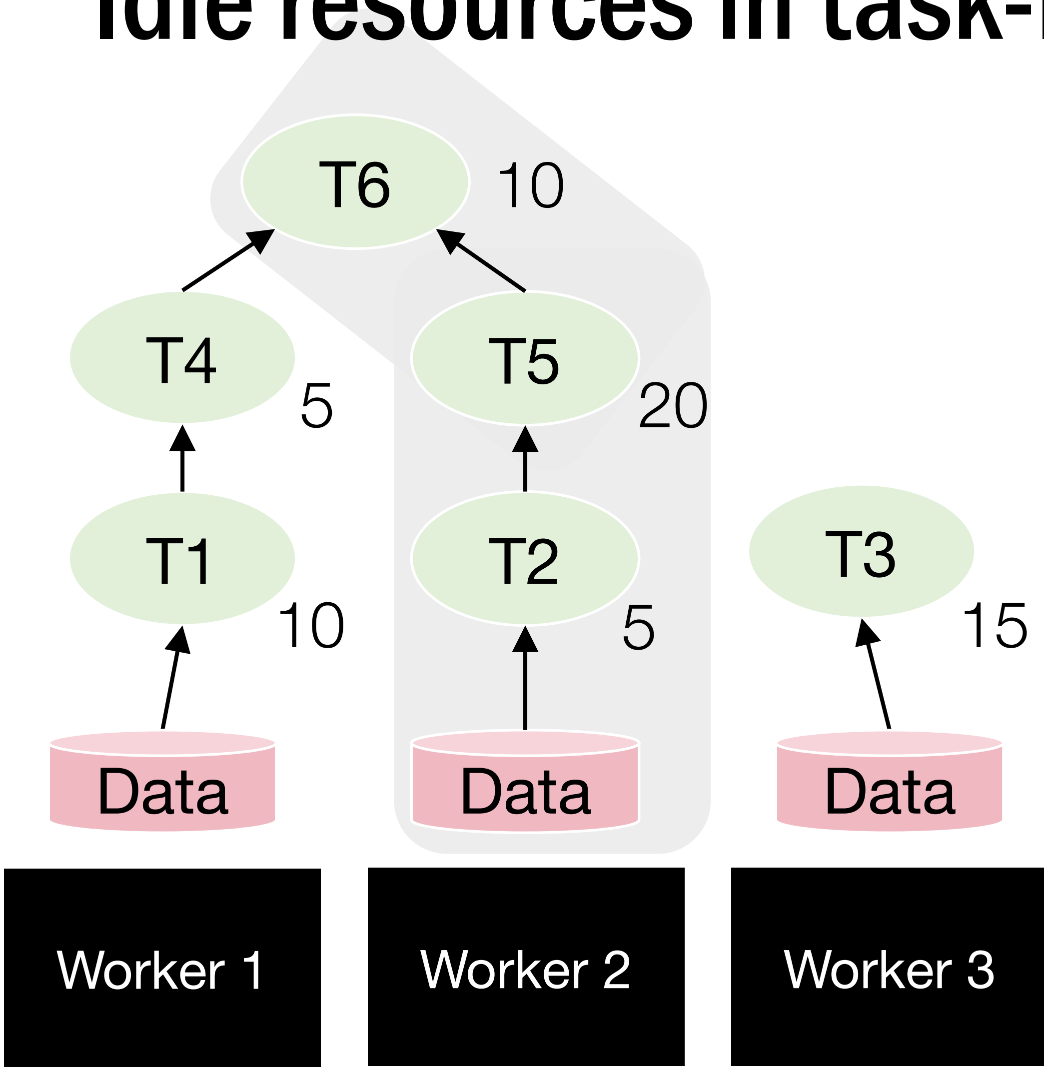
Weak scaling

Idle resources in task-level parallelism



Task completion time varies

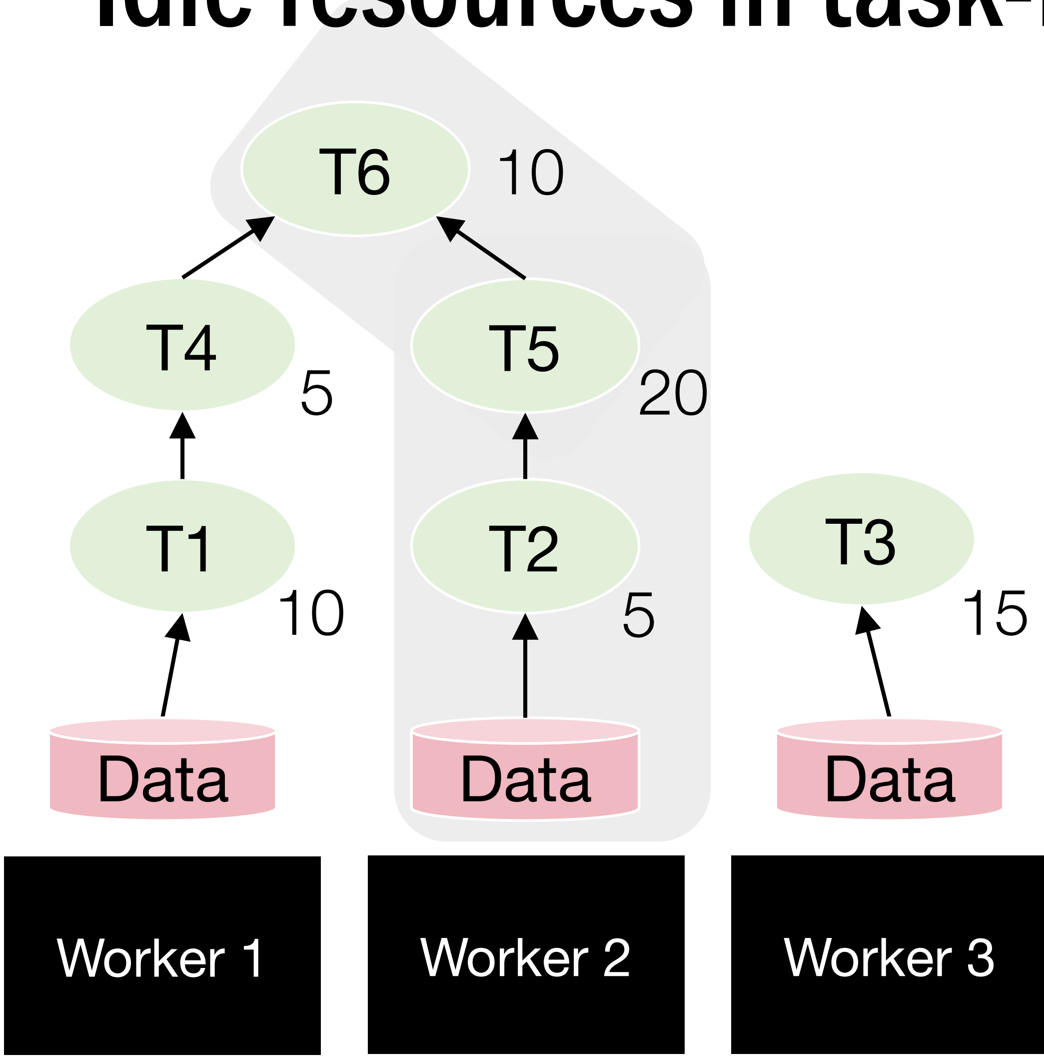
Idle resources in task-level parallelism



Task completion time varies

- Job completion time is always bounded by the **longest path** in the DAG

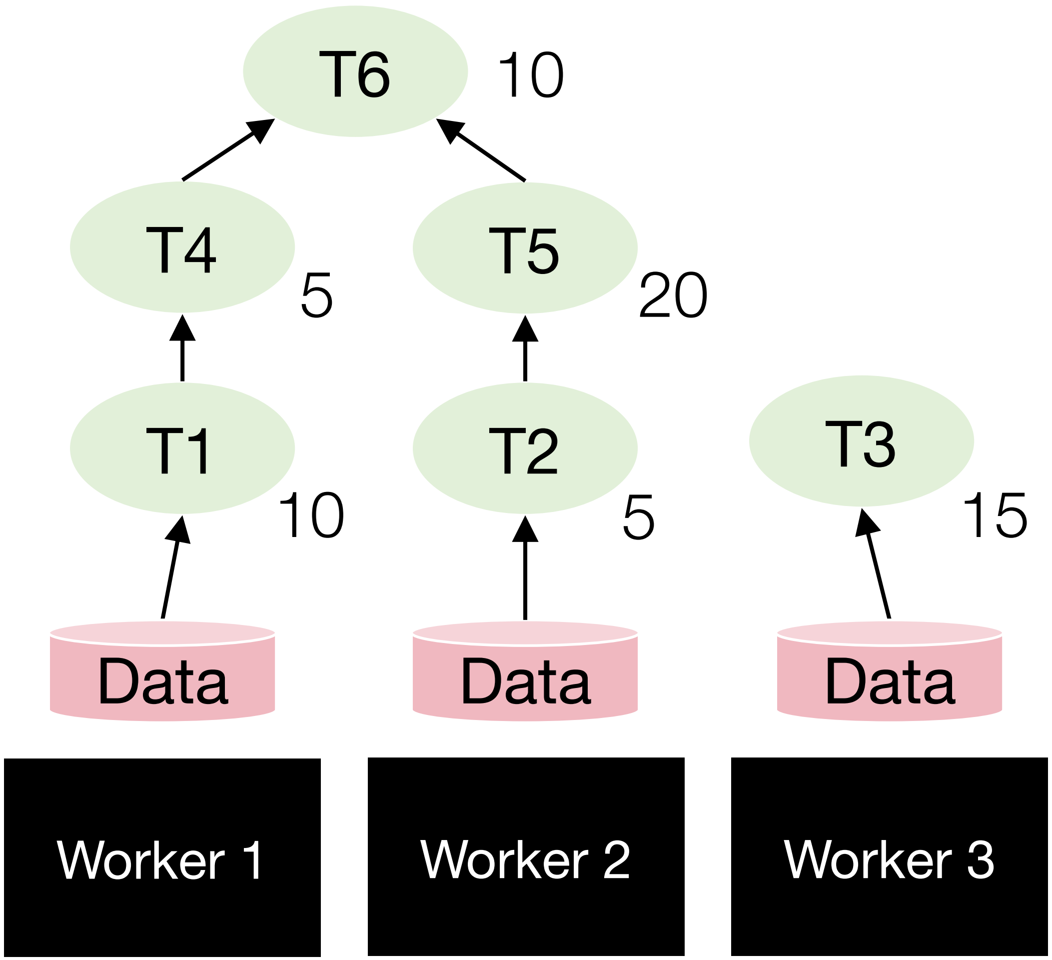
Idle resources in task-level parallelism



Task completion time varies

- Job completion time is always bounded by the **longest path** in the DAG
- **Potential optimization:** The scheduler can elastically release a worker if it knows the worker will be idle till the end
  - Can **save $ cost** in cloud

Idle resources in task-level parallelism

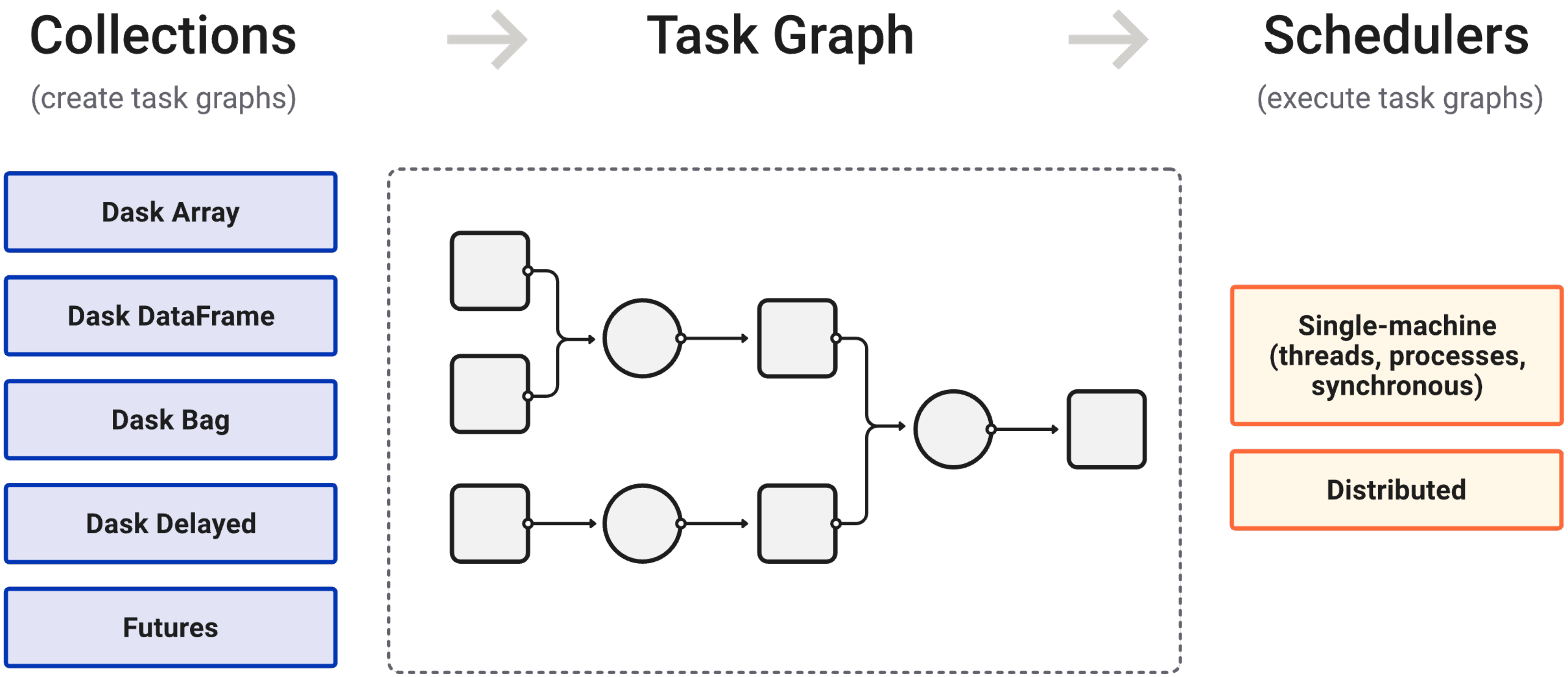


Q: What's the job completion time with 1 worker?

Q: What's the job completion time with 3 worker?

Q: What's the speedup?

Task parallelism in Dask



* https://docs.dask.org/en/stable/
* https://docs.dask.org/en/stable/scheduling.html

Dask's task graph and workflow

```
import dask
import dask.array as da
x = da.random.normal(size=1_000_000, chunks=100_000)
```

Dask's task graph and workflow

```
import dask
import dask.array as da
x = da.random.normal(size=1_000_000, chunks=100_000)
```

```
data = x.compute()
```

Lazy evaluation: Dask computation can be triggered manually, e.g., `.compute()`

- only when the result is needed

Dask's task graph and workflow

```
import dask
import dask.array as da
x = da.random.normal(size=1_000_000, chunks=100_000)
```

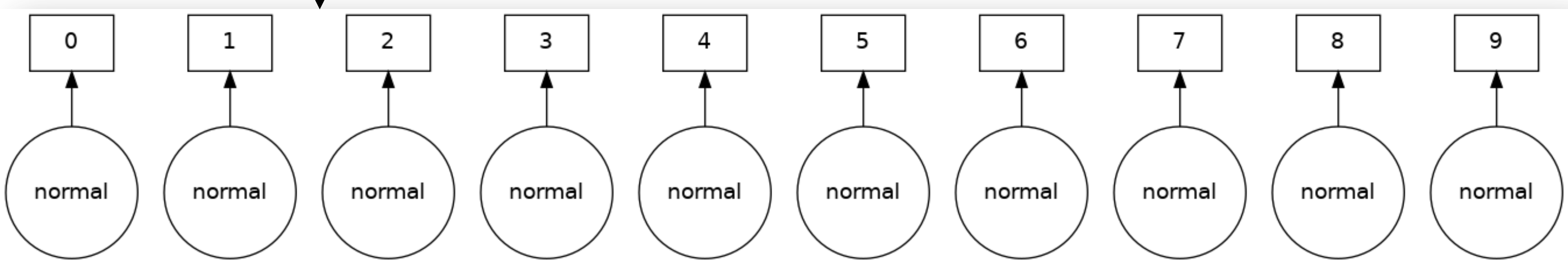
```
data = x.compute()
```

Lazy evaluation: Dask computation can be triggered manually, e.g., `.compute()`

- only when the result is needed

```
dask.visualize(x)
```

Draw the task graph using `.visualize()`



Dask task graph

Demo ...