Parallel Algorithms and Programming

Performance and Challenges

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In this lecture

- Measuring performance of parallel programs
  - Beyond execution time

- Challenges of parallel programming
  - 100% efficiency is not always achievable

References

- The lecture notes of F. Desprez
- The lecture notes of K. Fatahalian
  - CS149: Parallel Computing @Standford
  - 15418: Parallel Computer Architecture and Programming @CMU
- The teaching material of the eduWRENCH project
  - Pedagogic modules

Performance of parallel programs

Execution time of non-interactive programs

Non-interactive programs

- We consider programs whose main purpose is not to interact with a user
  - It implies that the execution time does not depend on the user activity
  - Simplify reasoning about performance

Execution time

- **Work**: The amount of computation to be executed by a program
- **Compute speed**: The amount of work that can be executed by the hardware per unit of time

$$Execution\ time = \frac{Work}{Compute\ Speed}$$

How to measure Work and Compute Speed?

Measuring the Work (FLOP)

Multiple possible ways of measuring the work

- Application specific (can be high level)
    - Number of images to process
    - Number of items to sort
    - etc.
- At the level of instructions
    - Number of instructions to execute
    - Problems:
        - All instructions do not have the same cost
        - Not all instructions are *useful* (for the final result)

Floating-point operations (FLOP)

- Most compute-intensive programs are manipulating floating point numbers
- The FLOP represent the *useful* work

Measuring the compute speed (FLOPS)

Floating-point operation per seconds (FLOP/s or FLOPS)

- Can be used to evaluate the capacity of the hardware
    - Defines the peak performance of a computing system

Back to the execution time

- A program requires executing 1 TFlop
- A system can execute 10 GFlop/s
- We can estimate its execution time:

$$Execution\ time = \frac{1 \times 10^{12}}{10 \times 10^{9}} = 100s$$

Other usage of FLOPS

- FLOPS can also be used to evaluate the efficiency of an algorithm on a given hardware
    - Through measurements + comparison with the theoretical value

CPI (Cycles per instruction)

Definition:

$$CPI = \frac{execution\ time}{total\ number\ of\ instructions}$$

- Another metric that can give an idea of how well a program is behaving on a given hardware:
  - Measures how often a processor stalls
  - For instance, can indicate a bad use of the caches

Question:

- Is it possible to achieve $CPI < 1$ on one processor core?

Performance of parallel programs

- The execution time measures the absolute performance
  - Does not tell us if a parallel program is good

- Other metrics need to be introduced
  - Speedup
  - Efficiency
  - Scalability

Speedup

Speedup

For a sequential execution time T_s, and a parallel execution time T_p:

$$Speedup = \frac{T_s}{T_p}$$

- When executing on N computing resources, we would like that the speedup to be N
    - This is in general not going to be the case

Question: Can the speedup be more than N?

- **Super-linear speedup**
- May happen in different cases:
    - Less instruction executed in the parallel version of the code (search)
    - Better usage of the cache/memory/storage hierarchy

Amdahl's law

```
The speedup of parallel code is limited by the sequential part of the
code
```

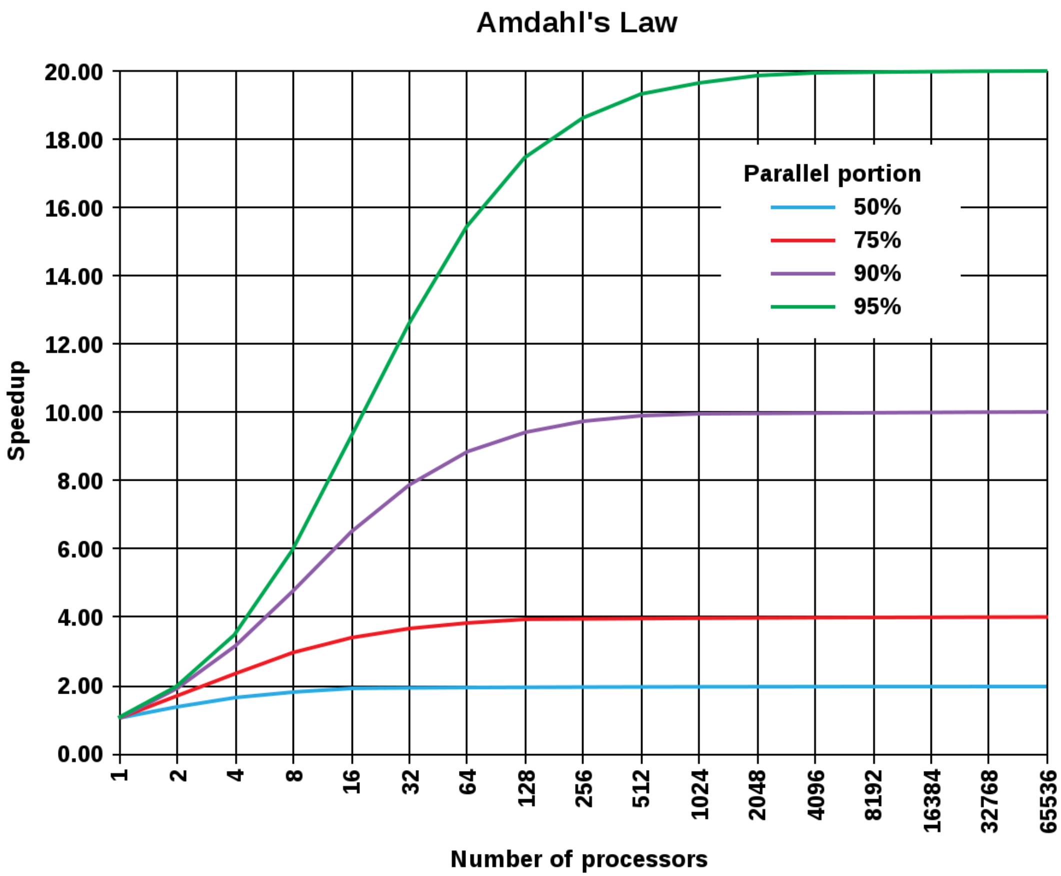
- In a program where a fraction P of the code is parallel, the maximum speedup is:

$$Speedup_{max} = \frac{1}{1-P} = \frac{1}{S}$$

- For a program running on N computing resources, with S being the serial fraction:

$$Speedup(N) = \frac{1}{\frac{P}{N} + S}$$

Amdahl's law



Credit: Daniels220 at English Wikipedia

Efficiency

- The efficiency measures how efficiently the computing resources are used.
- For a program running on N computing resources:

$$Efficiency(N) = \frac{Speedup(N)}{N}$$

- Ideally an efficiency of 100% would be achieved

Scalability

```
*Scalability* measures the evolution of the efficiency when
the number of processors used increases.

*Strong scaling*: Compute a problem N times **faster** using N
computing resources

*Weak scaling*: Compute a problem N times **bigger** in the same
amount of time using N computing resources
```

What limits strong scaling ?

- Amdahl's law
- Achieving strong scaling implies minimizing the serial work

What limits weak scaling ?

- Achieving weak scaling implies ensuring that the amount of serial work and the amount of communication remains constant when the problem size increases

Some comments about scalability and speedup

- Speedup should be computed based on the most efficient sequential algorithm
    - A parallel algorithm might not perform well sequentially

- The algorithm that performance the best at small scale is not necessary the one that scales best
    - An algorithm that has a synchronization/communication that increases linearly with the number of computing resources: $10 \times N$
    - Another algorithm that has a synchronization/communication that increases linearly: $2 \times N^2$

- At the end the most important is the absolute performance
    - A very slow algorithm that scales well is not interesting

Challenges for the Performance of parallel programs

Idle time

- We saw that in general, a parallel efficiency of 100% is not achievable
    - One of the main reason is **Idle time**

- Reasons for idle time:
    - Load imbalance
    - Management of I/Os
    - Task dependencies

Load imbalance

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Load imbalance describes a situation where the work is not equally
distributed among the processing units
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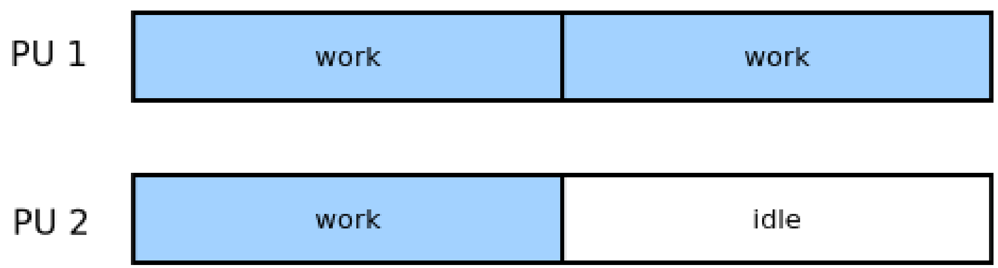


- In this situation, the efficiency can be computed as a function of the idle time:

$$Efficiency(N) = 1 - \frac{\frac{\sum idle\ times}{N}}{execution\ time}$$

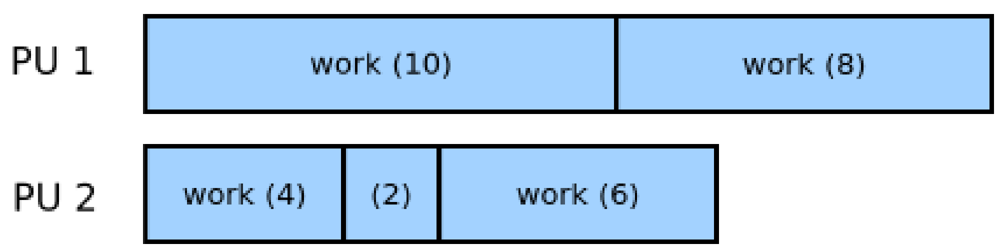
Load imbalance

Case of *identical* tasks

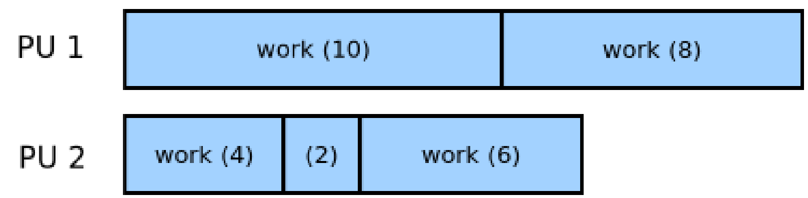
- Load imbalance can appear when the number of tasks to execute is not a multiple of the number of processing units
    - Example: 2 PUs -- 3 tasks
    - See example on the previous slide
- Here identical = takes same amount of time to execute

Case of *non-identical* tasks

- In practice, it happens often that not all tasks take the same amount of time to execute
    - In this case, load imbalance is almost unavoidable



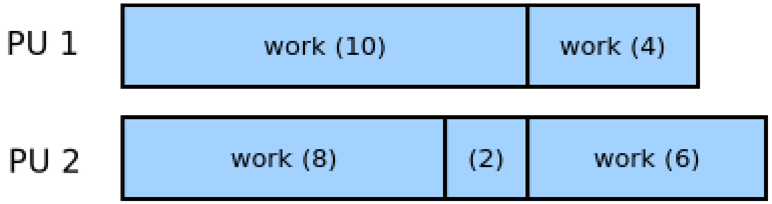
Exercises on load imbalance



- Compute the parallel efficiency in this scenario

$$Efficiency = 1 - \frac{\frac{6}{2}}{18} = 1 - 0.166 = 0.83$$

- Can we assign the tasks differently to the processing units to achieve a better efficiency?



$$Efficiency = 1 - \frac{\frac{2}{2}}{18} = 0.9375$$

More on load imbalance

- When the number of tasks is small, it is possible to compute the optimal solution
  - Assumes that you are able to accurately evaluate the time to execute each task
- When the number of big, it becomes too costly to try computing the optimal solutions

- Alternative solutions to static scheduling can be implemented:
  - Dynamic scheduling
    - The PUs get new tasks when they are idle
  - Work stealing
    - The PUs *steal* tasks from busy PUs when they are idle

Dealing with I/Os

- Tasks might need to perform I/O operations to the storage system
    - Read input data
    - Write results

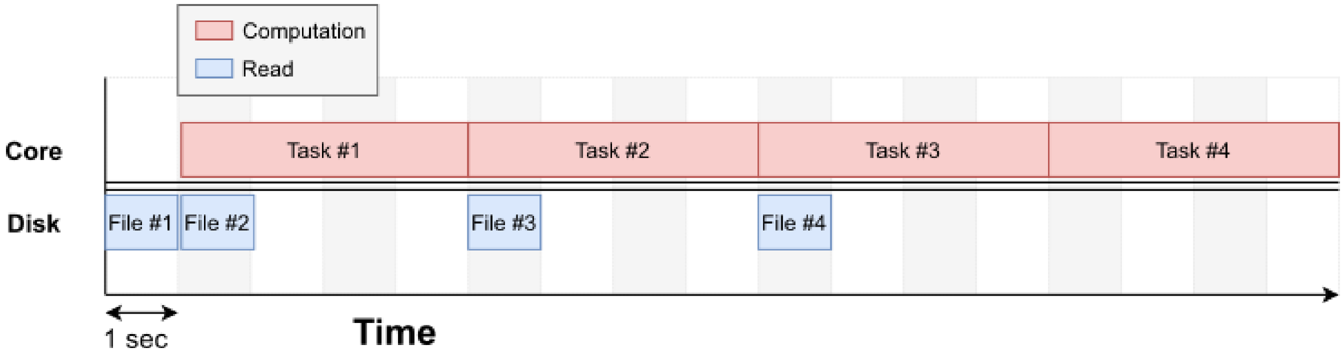
- Operating systems (together with the hardware) implement a set of mechanisms to limit the impact of I/O operations on performance
    - Interrupts
    - DMA engine for data transfers
- Assuming that I/O time is less than compute time, it can make I/O almost *invisible* with a sequential program

Dealing with I/Os

Example

- A 4-task parallel program
    - Each task read a 10-MB file before starting computing
        - Takes 1 second on the target platform
    - Each task performs 400 GFlop of computation
        - A core can perform 100 GFlops
        - 4 seconds per task

Execution with a single core

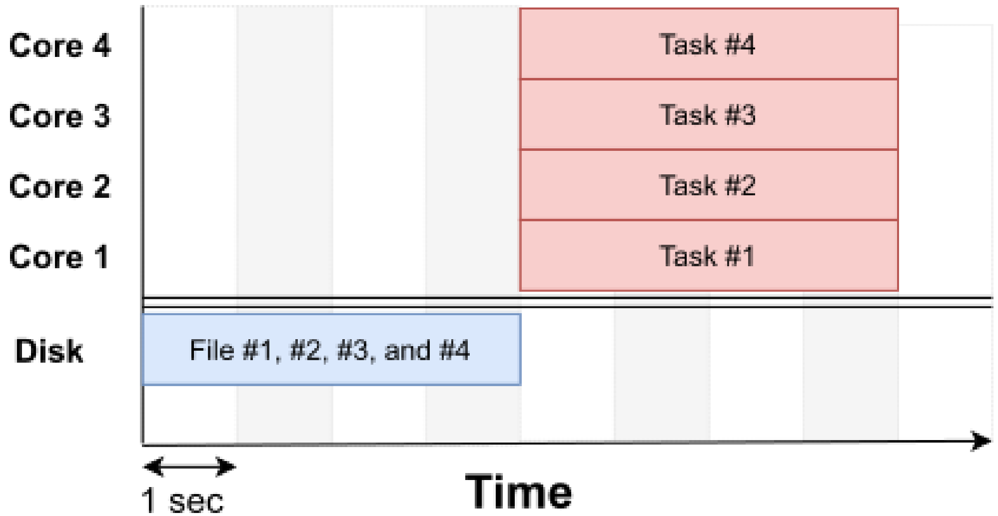


Credits: figure from eduWRENCH

Dealing with I/Os

What happens if we use multiple cores ?

- Execution on a 4-core processor
- Worst-case scenario:
  - We do all reads before starting processing



Speedup and efficiency

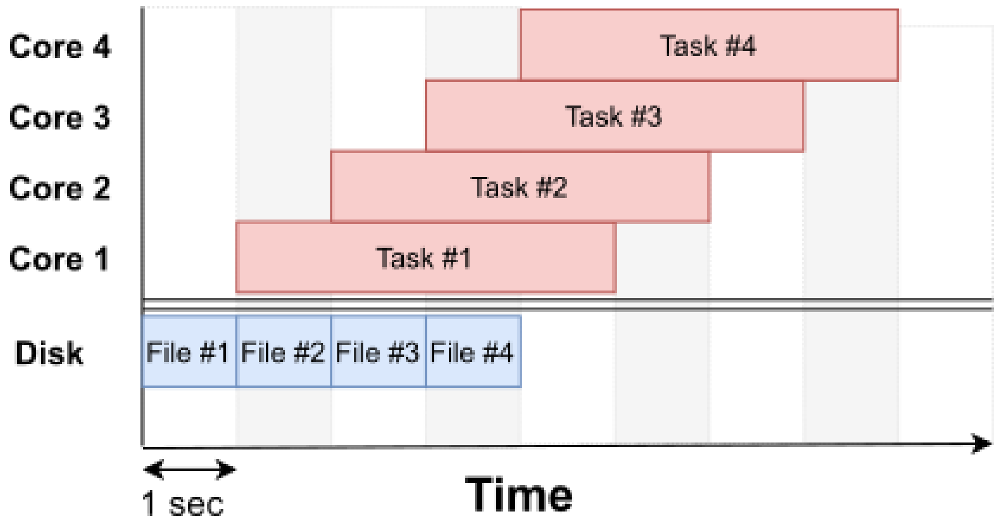
$Speedup = 17/8 = 2.125$

$Efficiency = 0.53$

Dealing with I/Os

What happens if we use multiple cores ?

- To improve performance we can still try to overlap I/O operations and computations



There is no performance improvement compared to the previous solution

Credits: figure from eduWRENCH

Exercise about I/Os

- A parallel program consists of 2 tasks:
  - Task 1 reads 20 MB of input, computes 500 Gflop, writes back 100 MB of output
  - Task 2 reads 100 MB of input, computes for 500 Gflop, writes back 100 MB of output
- We execute this program on a computer with two cores that compute at 100 Gflop/sec and with a disk with 100 MB/sec read and write bandwidth.

Is it better to run Task 1 or Task 2 first?

- Running Task 1 first allows starting computing earlier
- T1 first -- Exec time = 7.2 s
- T2 first -- Exec time = 8 s

Task dependencies

- Until now, we have assumed that tasks can be executed in any order
  - It is not always the case

Definitions

```
There is a dependency between task A and task B, if B cannot starts
executing until A is done
```

- The typical reason for having task dependencies is that Task B needs the output of task A

DAG of tasks

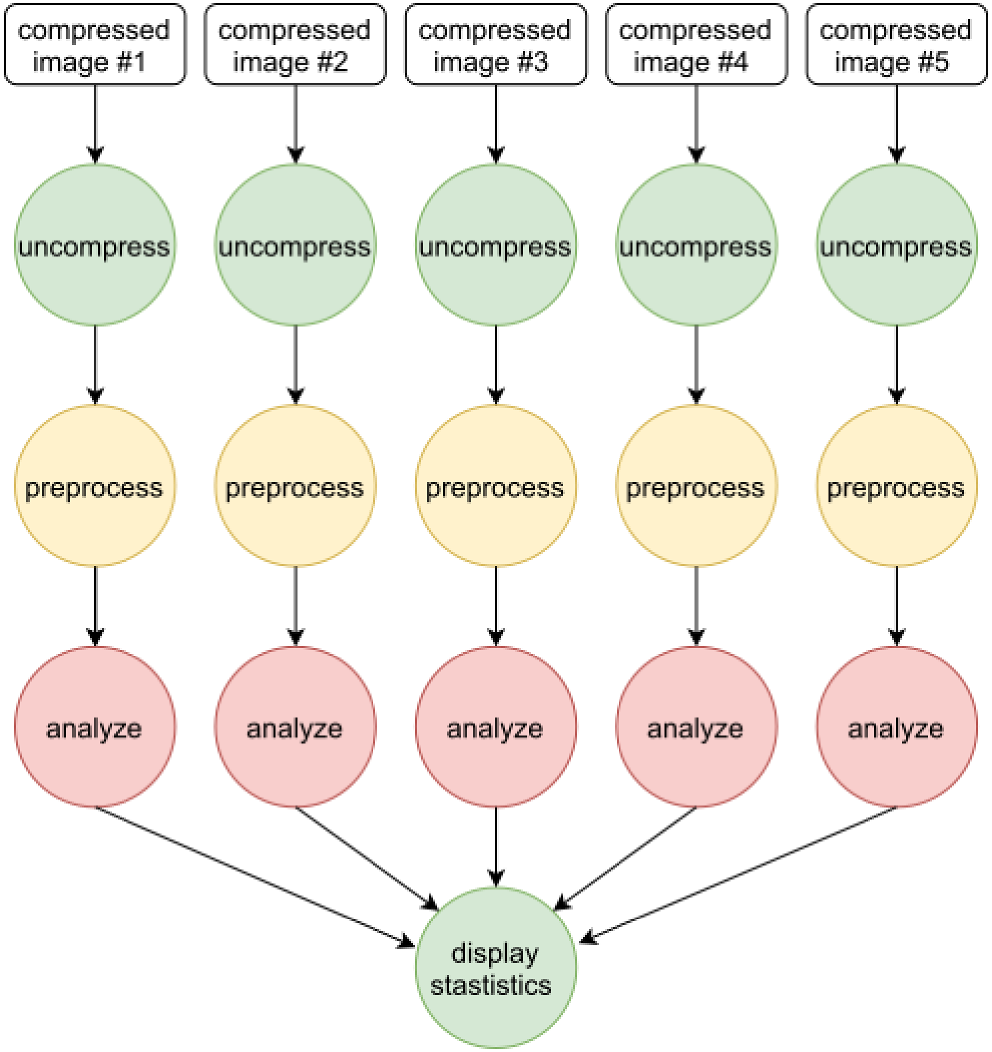
- It can be convenient to represent dependencies between graphs using a **Directed Acyclic Graph**
  - Vertices are tasks
  - Edges are dependencies

Example of DAG

- Program that counts the number of car objects in a set of compressed street images.
- It includes the following steps:
    - Each image needs to be uncompressed
    - Each image is pre-processed to remove noise
    - Each image is analyzed to find cars
    - Car count statistics are displayed

Example of DAG

DAG assuming 5 images



Some concepts related to DAGs

DAG level

- A task is on level `n` of the DAG if the longest path from the entry task(s) to this task is of length `n`
  - The entry tasks are the tasks that do not depend on any other tasks
  - The path length is measured in number of traversed vertices

Maximum level width

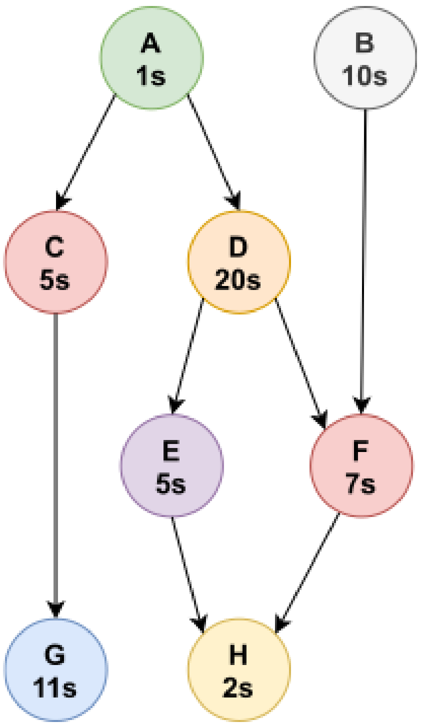
- The maximum number of tasks in one DAG level
  - Helps determining the maximum number of PUs to use
- If the maximum level width is 4
  - Using 4 PUs should provide a speedup compared to using 3 PUs
  - It does not necessarily implies that 5 PUs would not improve performance
    - We do not have to wait for all tasks from one level to terminate before starting the tasks from the next level

Some concepts related to DAGs

Critical path

- The longest path in the DAG from the entry task(s) to the exit task(s)
  - The path length is measured in task duration, including the entry and the exit task(s)
- Allows evaluating the maximum performance that can be obtained
  - No matter the number of PUs, the program cannot execute faster than the length of the critical path

Exercise about DAGs



- Task level of each task:
  - Level 1: A, B
  - Level 2: C, D
  - Level 3: E, F, G
  - Level 4: H
- Maximum width:
  - Level 3 has 3 tasks
- Critical path:
  - A - D - F - H
  - 1 + 20 + 7 + 2 = 30s

Credits: figure from eduWRENCH

Conclusion

Take-away points

Several metrics to measure the performance of parallel programs

- Execution time
- Speedup
- Efficiency
- Scalability

Amdahl's law implies that infinite scalability is impossible

Problems that impair performance/scalability

- Load imbalance
- I/O operations
- Task dependencies