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

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

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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:

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- 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?
  - Remember ILP

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?

-

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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
```

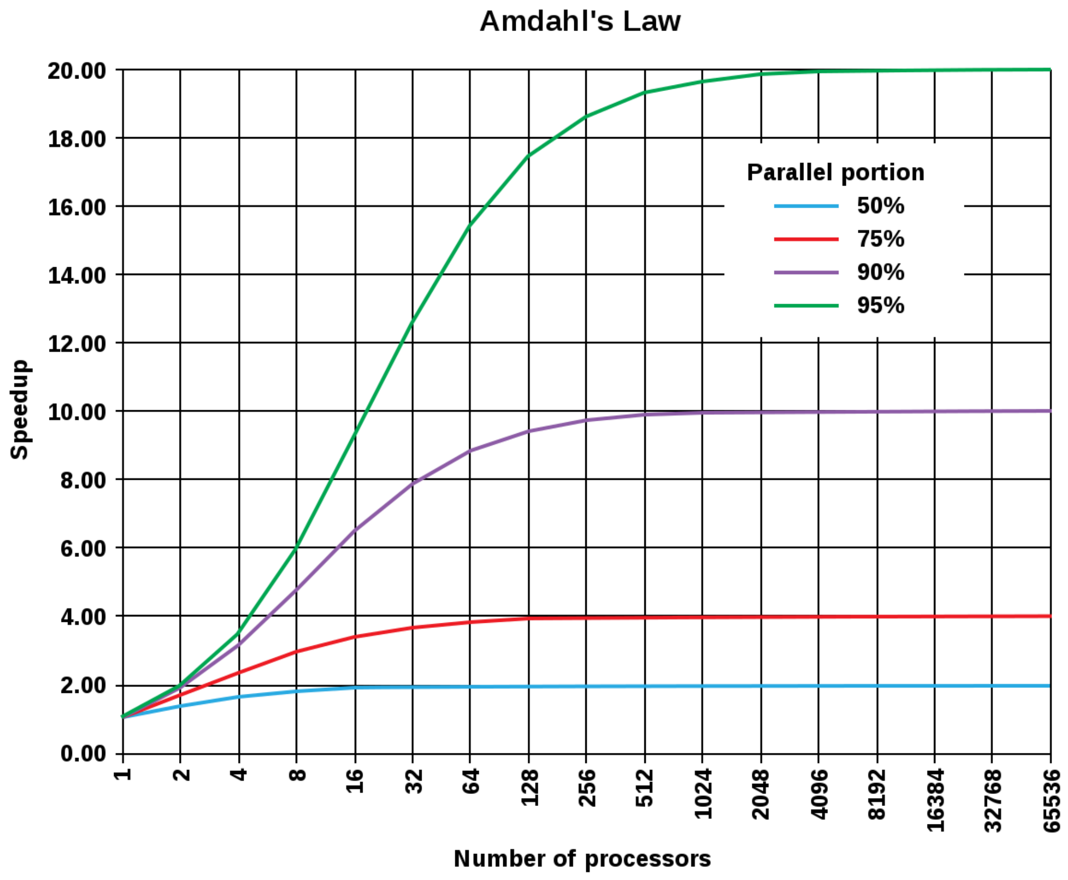
- For a program running on N computing resources, where a fraction `P` of the code is parallel and `S = 1-P` is the serial fraction:

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

- Hence, the maximum speedup is:

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

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 ?

What limits weak scaling ?

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

What limits weak scaling ?

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What limits strong scaling ?

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

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

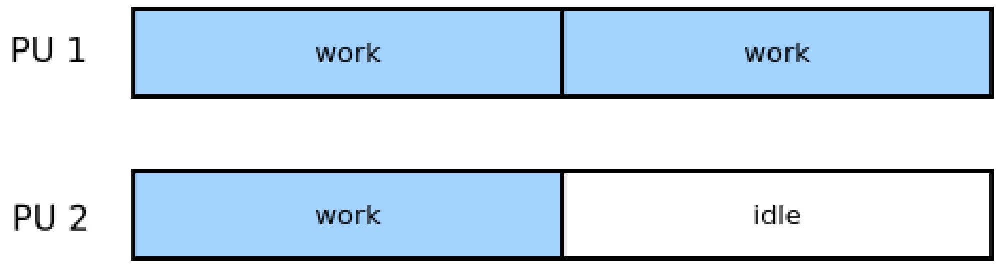
Idle time

- 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

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



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

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

- Explanation:
  - We compute the average idle time per processing unit
  - We compute a ratio to the total execution time

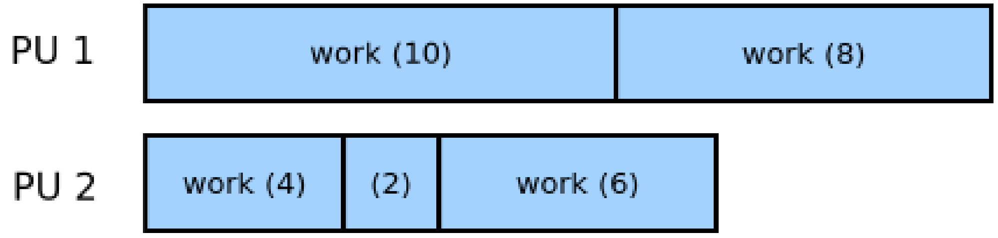
Load imbalance

Case of *identical* tasks

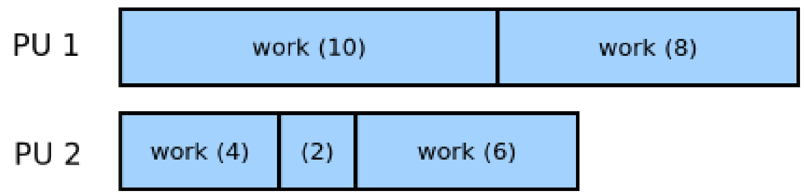
- Load imbalance can appear when the number of tasks to execute is not a multiple of the number of processing units
    - Example: 2 PUs -- 3 tasks
    - See example on the previous slide
- Here identical = takes same amount of time to execute

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

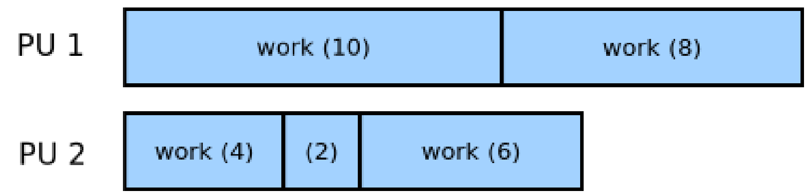


Exercises on load imbalance



- Compute the parallel efficiency in this scenario
- Can we assign the tasks differently to the processing units to achieve a better efficiency?

Exercises on load imbalance



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

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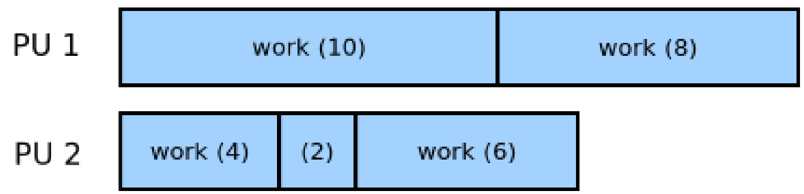
Exercises on load imbalance



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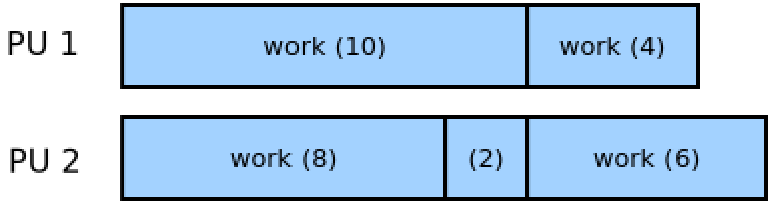

$$Efficiency = 1 - \frac{\frac{2}{2}}{16} = 0.9375$$

More on load imbalance

- When the number of tasks is small, it is possible to compute the optimal solution
    - Assuming that we 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
    - The idea is to overlap I/O operations and computation
        - 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

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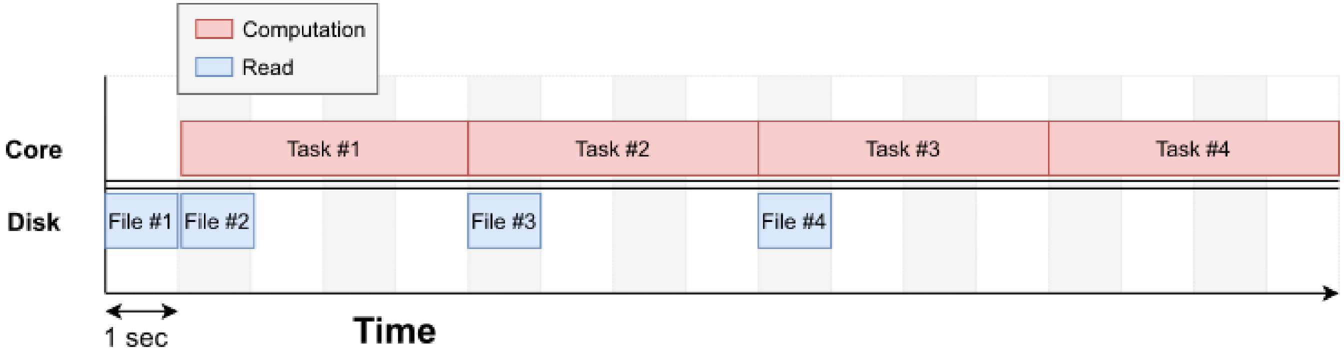

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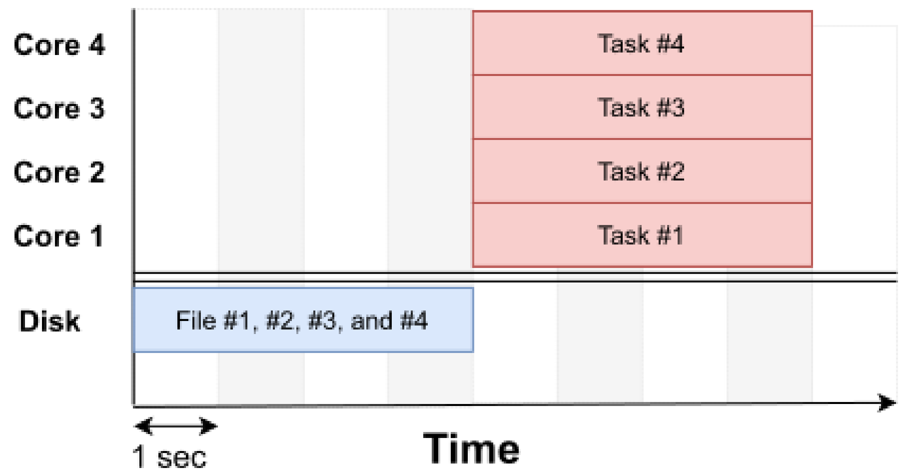
Dealing with I/Os

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

Note that here computing the efficiency based on idle time would give a different result. This is because the sequential execution was already including idle time.

Dealing with I/Os

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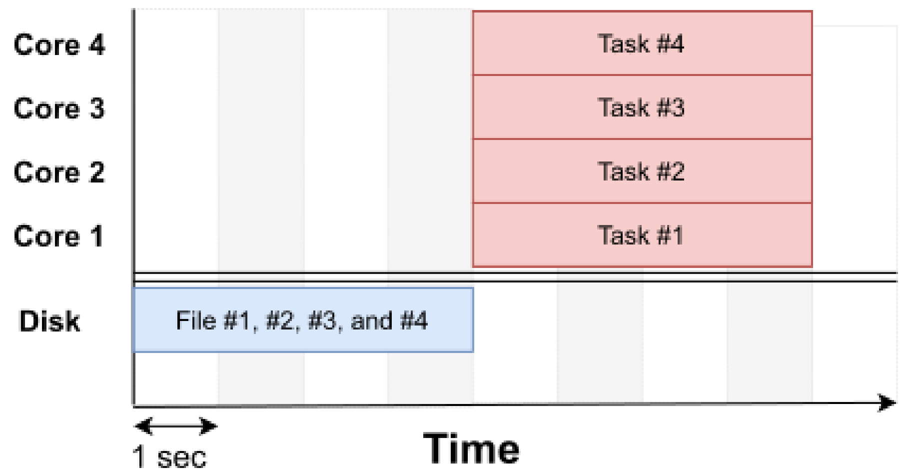

Speedup and efficiency

$$Speedup = 17/8 = 2.125$$

$$Efficiency == \frac{2.125}{4} = 0.53$$

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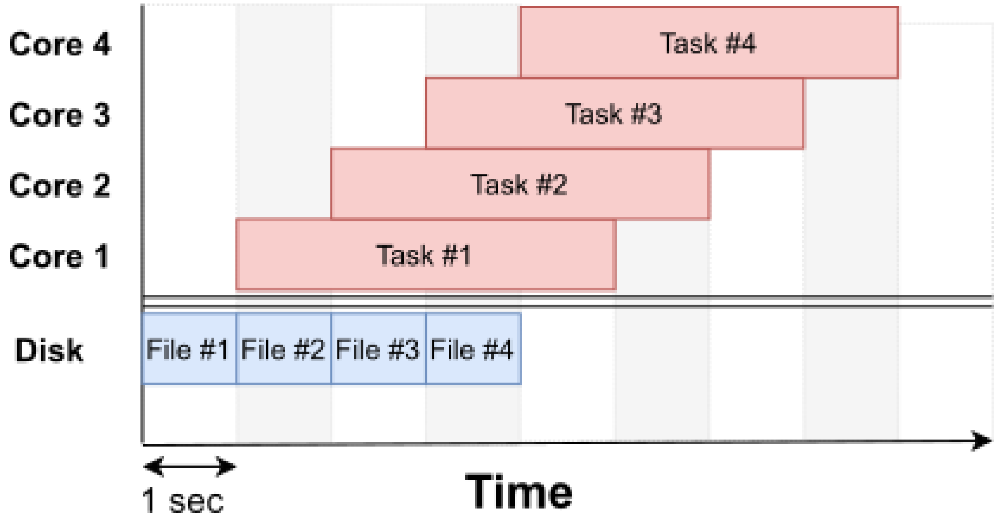
Dealing with I/Os

What happens if we use multiple cores ?

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



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Dealing with I/Os

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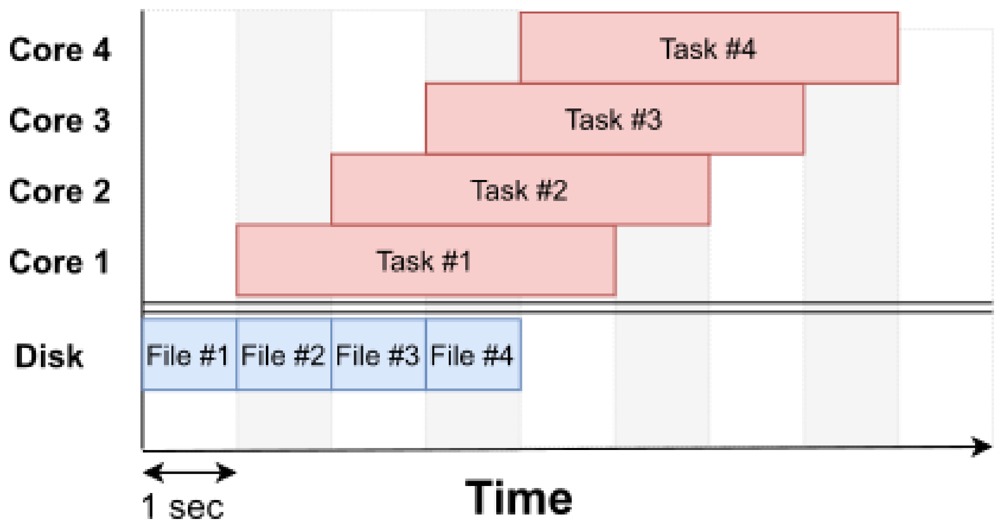

There is no performance improvement compared to the previous solution

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?

Exercise about I/Os

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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

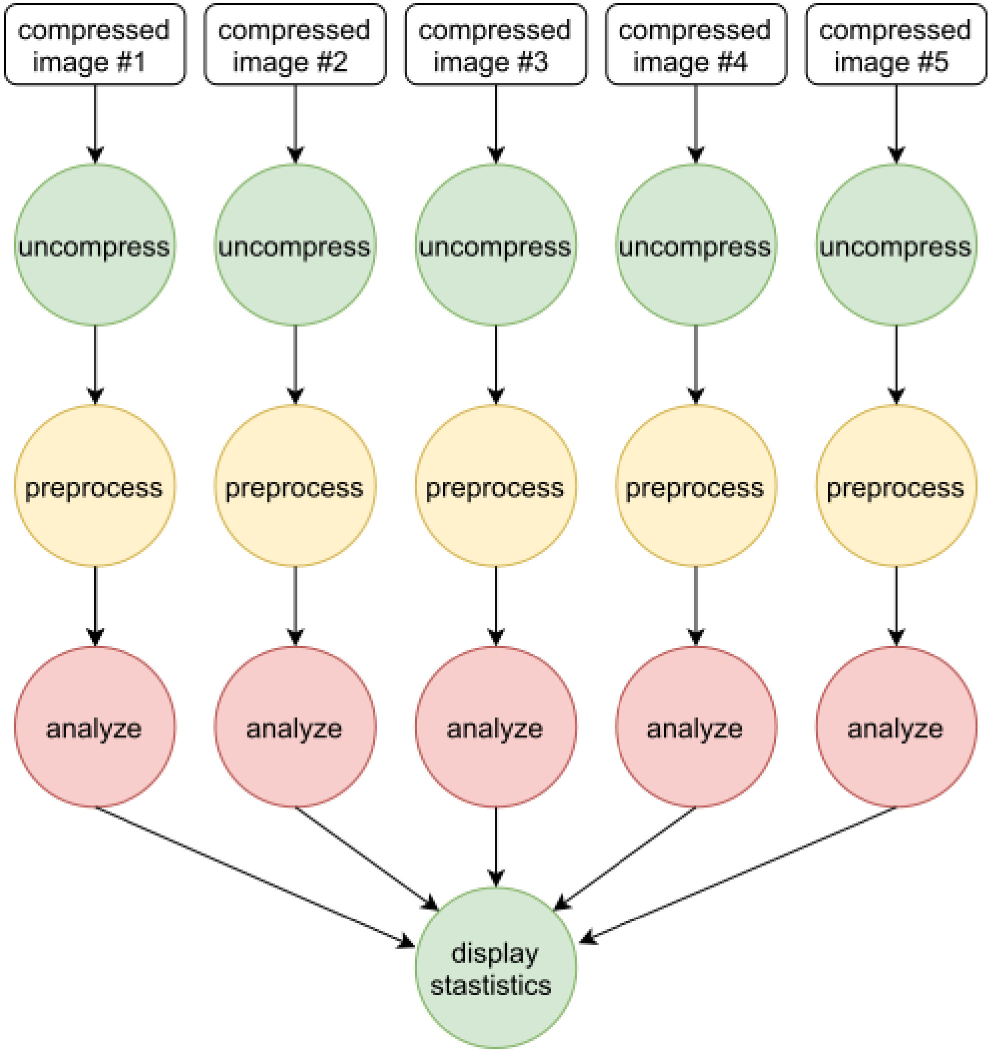
- It can be convenient to represent dependencies between tasks using a **Directed Acyclic Graph**
  - Vertices are tasks
  - Edges are dependencies

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 level width of a DAG 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

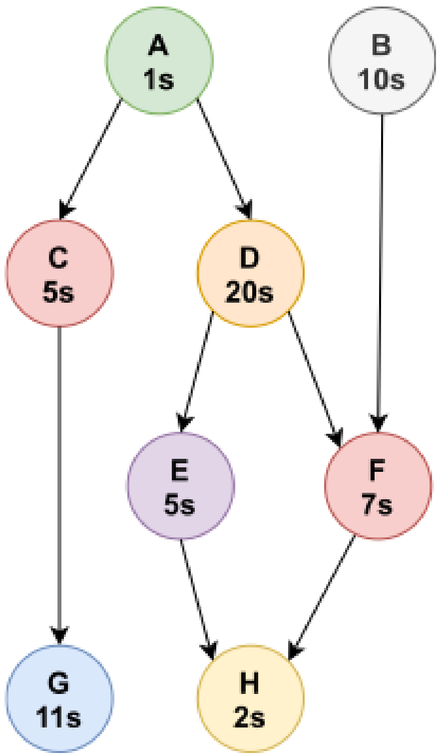
Some concepts related to DAGs

Critical path

```
The critical path is *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

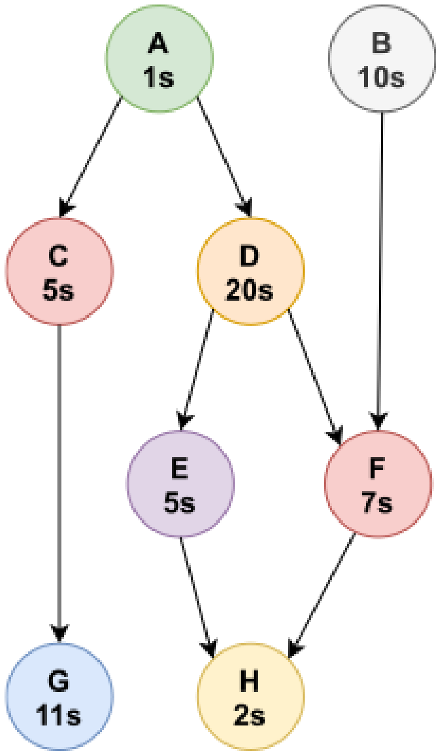
Exercise about DAGs



- Task level of each task:
- Maximum width:
- Critical path:

Credits: figure from eduWRENCH

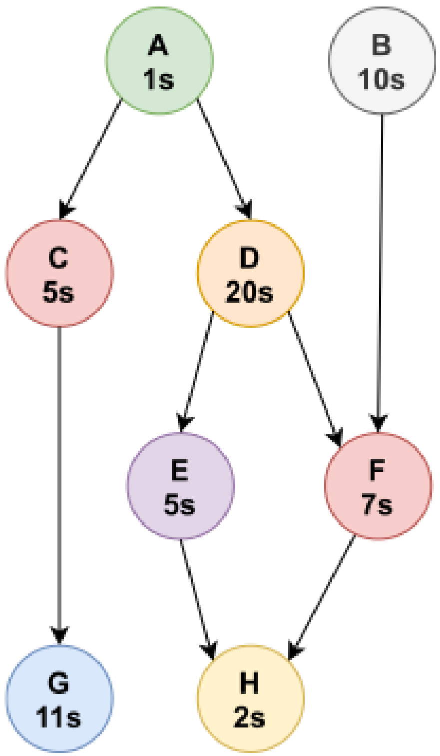
Exercise about DAGs



- Task level of each task:
  - Level 0: A, B
  - Level 1: C, D
  - Level 2: E, F, G
  - Level 3: H
- Maximum width:
- Critical path:

Credits: figure from eduWRENCH

Exercise about DAGs



- Task level of each task:
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  - Level 2 has 3 tasks
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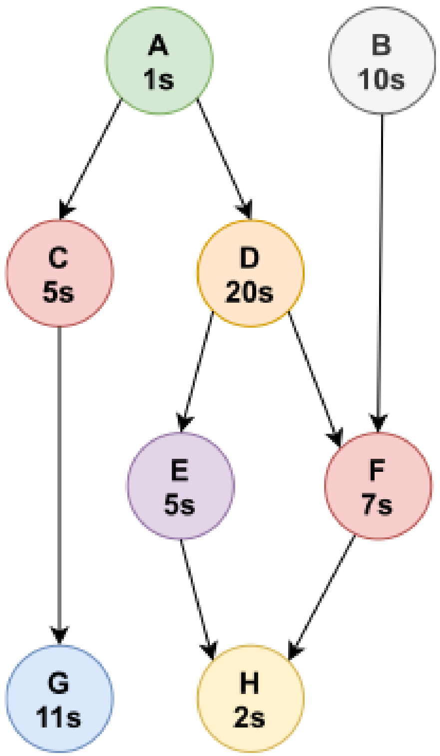
Exercise about DAGs



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  - Level 0: A, B
  - Level 1: C, D
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- Maximum width:
  - Level 2 has 3 tasks
- Critical path:
  - A - D - F - H
  - 1 + 20 + 7 + 2 = 30s

Credits: figure from eduWRENCH

Chosing which task to run

- Choose a task that is ready to run
  - All parents tasks are finished
  - **What if multiple tasks are ready to run?**

Multiple strategies are possible

Chosing which task to run

- Choose a task that is ready to run
    - All parents tasks are finished
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Multiple strategies are possible

- Task on the critical path first (in general a good strategy)
- Task with the largest work first
- task with the smallest work first

No strategy is always best

Other constraint on the execution of tasks: Memory

- Each task comsumes memory space
  - Load input data
  - Write output data

- Comsuming more memory that the total physical memory space is not recommended
  - Induces swapping memory pages from/to disk
  - **Very slow**, to be avoided

Memory constraints should be taken into account when scheduling tasks

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