# Introduction to Parallel Computing

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# Instructor Notes

- An analogy of picking apples is used to relate different types of parallelism and begin thinking about the best way to tackle a problem
- The decomposition slides build on this and are relevant to GPU computing since we split up tasks into kernels and decompose kernels into threads
- The topics then shift to parallel computing hardware and software models that progress into how these models combine on the GPU

# Topics

- Introduction to types of parallelism
- Task and data decomposition
- Parallel computing
  - Software models
  - Hardware architectures
- Challenges with using parallelism

# Parallelism

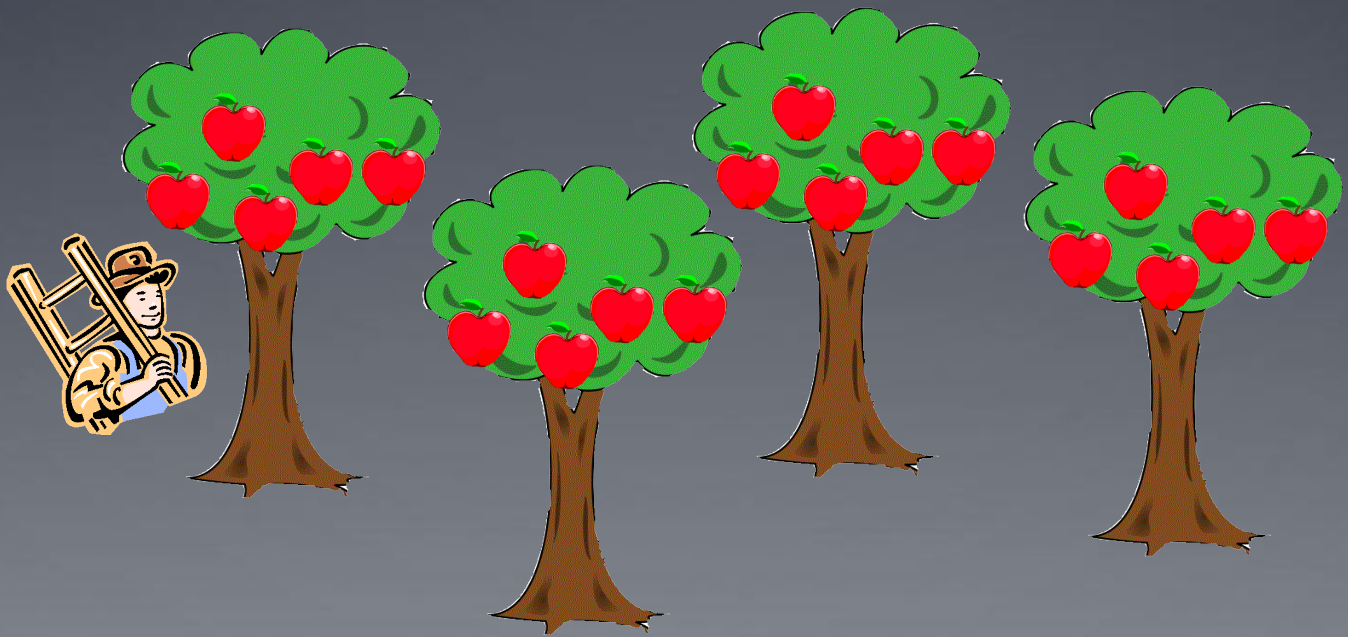
- *Parallelism* describes the potential to complete multiple parts of a problem at the same time
- In order to exploit parallelism, we have to have the physical resources (i.e. hardware) to work on more than one thing at a time
- There are different types of parallelism that are important for GPU computing:
  - *Task parallelism* – the ability to execute different tasks within a problem at the same time
  - *Data parallelism* – the ability to execute parts of the same task (i.e. different data) at the same time

# Parallelism

- As an analogy, think about a farmer who hires workers to pick apples from an orchard of trees
  - The workers that do the apple picking are the (hardware) processing elements
  - The trees are the tasks to be executed
  - The apples are the data to be operated on

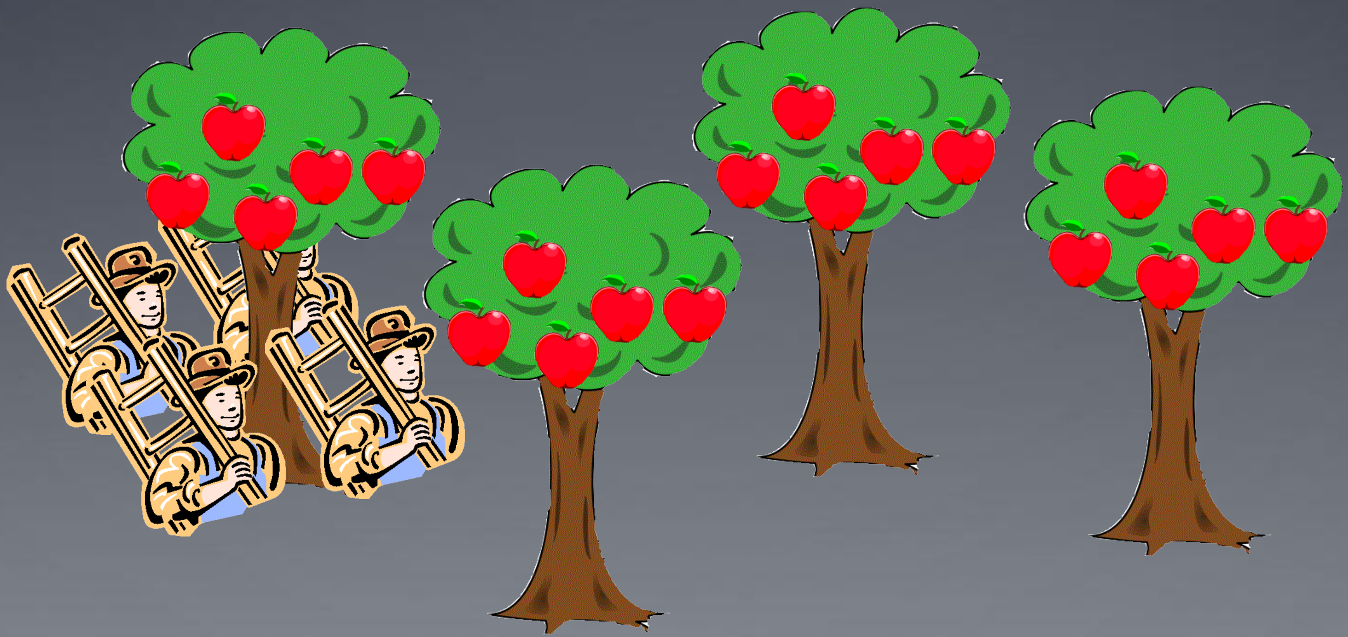
# Parallelism

- The *serial* approach would be to have one worker pick all of the apples from each tree
  - After one tree is completely picked, the worker moves on to the next tree and completes it as well



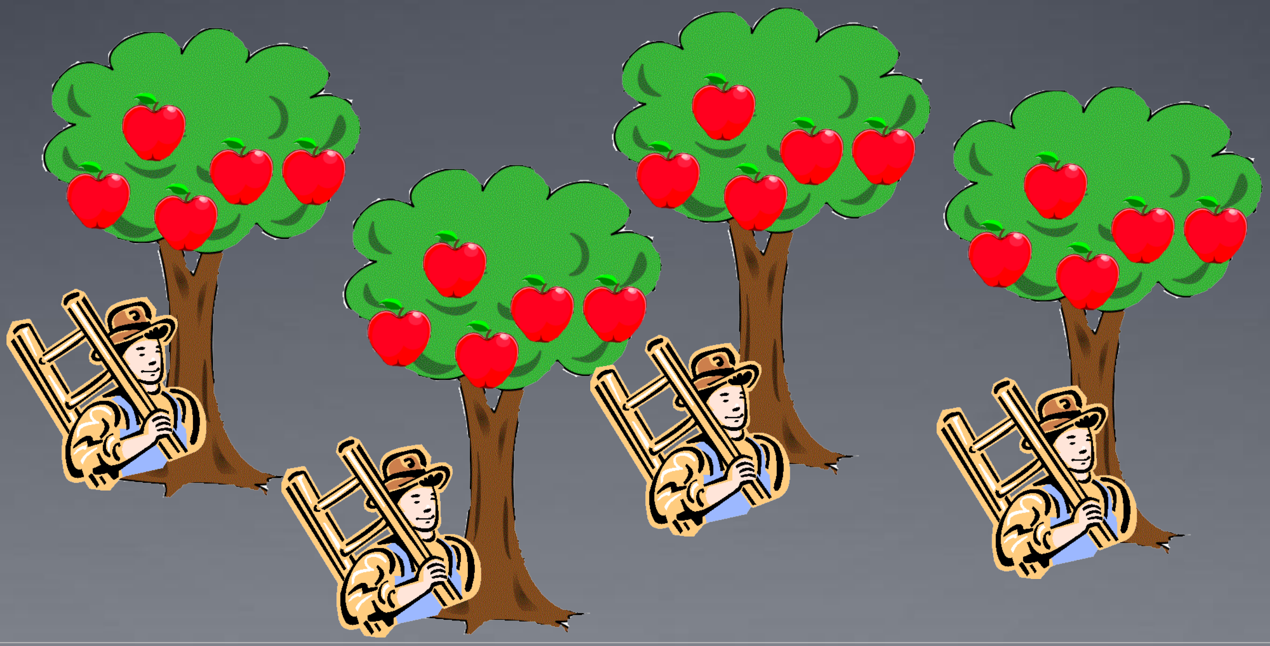
# Parallelism

- If the farmer hired more workers, he could have many workers picking apples from the same tree
  - This represents data parallel hardware, and would allow each task to be completed quicker
    - How many workers should there be per tree?
    - What if some trees have few apples, while others have many?



# Parallelism

- An alternative would be to have each worker pick apples from a different tree
  - This represents task parallelism, and although each task takes the same time as in the serial version, many are accomplished in parallel
  - What if there are only a few densely populated trees?

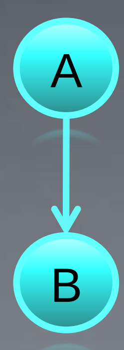


# Decomposition

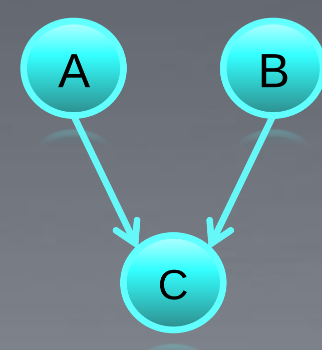
- For non-trivial problems, it helps to have more formal concepts for determining parallelism
- When we think about how to parallelize a program we use the concepts of decomposition:
  - *Task decomposition*: dividing the algorithm into individual tasks (don't focus on data)
    - In the previous example the goal is to pick apples from trees, so clearing a tree would be a task
  - *Data decomposition*: dividing a data set into discrete chunks that can be operated on in parallel
    - In the previous example we can pick a different apple from the tree until it is cleared, so apples are the unit of data

# Task Decomposition

- Task decomposition reduces an algorithm to functionally independent parts
- Tasks may have dependencies on other tasks
  - If the input of task B is dependent on the output of task A, then task B is dependent on task A
  - Tasks that don't have dependencies (or whose dependencies are completed) can be executed at any time to achieve parallelism
  - *Task dependency graphs* are used to describe the relationship between tasks




B is dependent on A

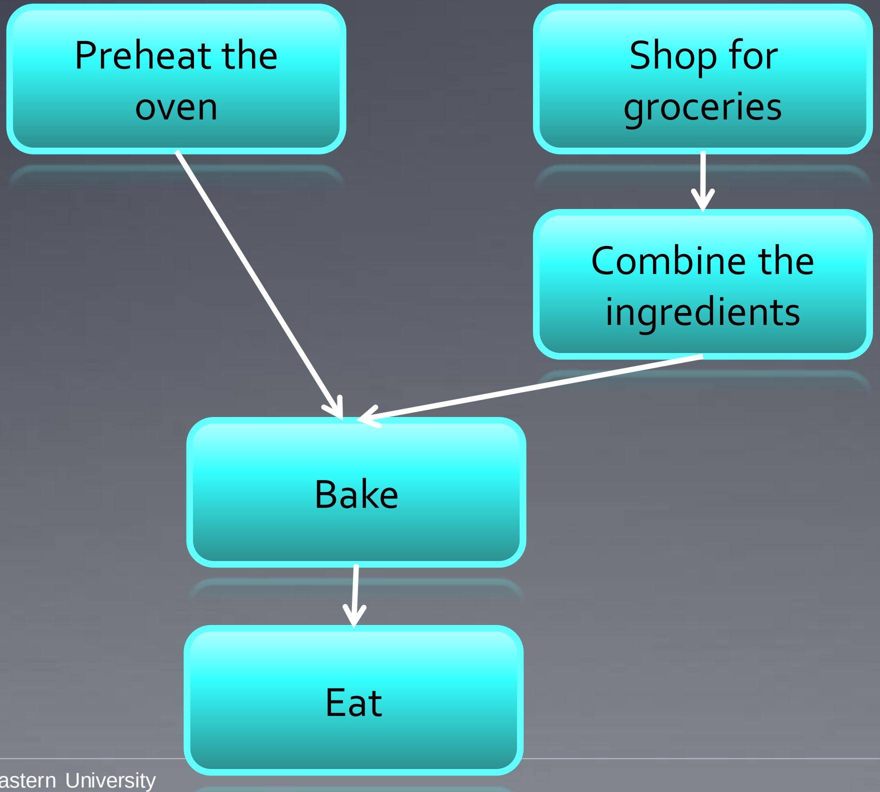



A and B are independent of each other

C is dependent on A and B

# Task Dependency Graphs

- We can create a simple task dependency graph for baking cookies
  - Any tasks that are not connected via the graph can be executed in parallel (such as preheating the oven and shopping for groceries)



# Output Data Decomposition

- For most scientific and engineering applications, data is decomposed based on the output data
  - Each output pixel of an image convolution is obtained by applying a filter to a region of input pixels
  - Each output element of a matrix multiplication is obtained by multiplying a row by a column of the input matrices
- This technique is valid any time the algorithm is based on one-to-one or many-to-one functions

# Input Data Decomposition

- Input data decomposition is similar, except that it makes sense when the algorithm is a one-to-many function
  - A histogram is created by placing each input datum into one of a fixed number of bins
  - A search function may take a string as input and look for the occurrence of various substrings
- For these types of applications, each thread creates a “partial count” of the output, and synchronization, atomic operations, or another task are required to compute the final result

# Parallel Computing

- The choice of how to decompose a problem is based solely on the algorithm
- However, when actually implementing a parallel algorithm, both hardware and software considerations must be taken into account

# Parallel Computing

- There are both hardware and software approaches to parallelism
- Much of the 1990s was spent on getting CPUs to *automatically* take advantage of Instruction Level Parallelism (ILP)
  - Multiple instructions (without dependencies) are issued and executed in parallel
  - Automatic hardware parallelization will not be considered for the remainder of the lecture
- Higher-level parallelism (e.g. threading) cannot be done automatically, so software constructs are required for programmers to tell the hardware where parallelism exists
  - When parallel programming, the programmer must choose a programming model and parallel hardware that are suited for the problem

# Parallel Hardware

- Hardware is generally better suited for some types of parallelism more than others

| Hardware type | Examples | Parallelism |
|---|---|---|
| Multi-core superscalar processors | Phenom II CPU | Task |
| Vector or SIMD processors | SSE units (x86 CPUs) | Data |
| Multi-core SIMD processors | Radeon 5870 GPU | Data |

- Currently, GPUs are comprised of many independent "processors" that have SIMD processing elements
  - One task is run at a time on the GPU*
  - *Loop strip mining* (next slide) is used to split a data parallel task between independent processors
  - Every instruction must be data parallel to take full advantage of the GPU's SIMD hardware
    - SIMD hardware is discussed later in the lecture

*if multiple tasks are run concurrently, no inter-communication is possible

# Loop Strip Mining

- *Loop strip mining* is a loop-transformation technique that partitions the iterations of a loop so that multiple iterations can be:
  - executed at the same time (vector/SIMD units),
  - split between different processing units (multi-core CPUs),
  - or both (GPUs)
- An example with loop strip mining is shown in the following slides

# Parallel Software – SPMD

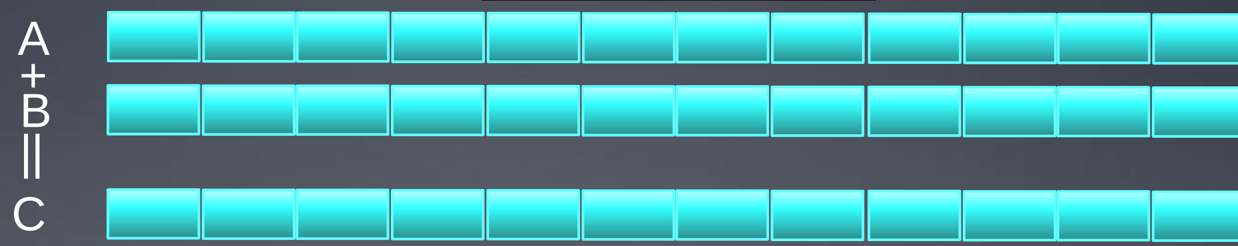
- GPU programs are called *kernels*, and are written using the Single Program Multiple Data (SPMD) programming model
  - SPMD executes multiple instances of the same program independently, where each program works on a different portion of the data
- For data-parallel scientific and engineering applications, combining SPMD with loop strip mining is a very common parallel programming technique
  - Message Passing Interface (MPI) is used to run SPMD on a distributed cluster
  - POSIX threads (pthreads) are used to run SPMD on a shared-memory system
  - Kernels run SPMD within a GPU

# Parallel Software – SPMD

- Consider the following vector addition example

```
for( i = 0:11 ) {
   C[ i ] = A[ i ] + B[ i ]
}
```

Serial program:
one program completes
the entire task




- Combining SPMD with loop strip mining allows multiple copies of the same program execute on different data in parallel

```
for( i = 0:3 ) {
   C[ i ] = A[ i ] + B[ i ]
}
```

```
for( i = 4:7 ) {
   C[ i ] = A[ i ] + B[ i ]
}
```

```
for( i = 8:11 ) {
   C[ i ] = A[ i ] + B[ i ]
}
```

SPMD program:
multiple copies of the
same program run on
different chunks of the
data

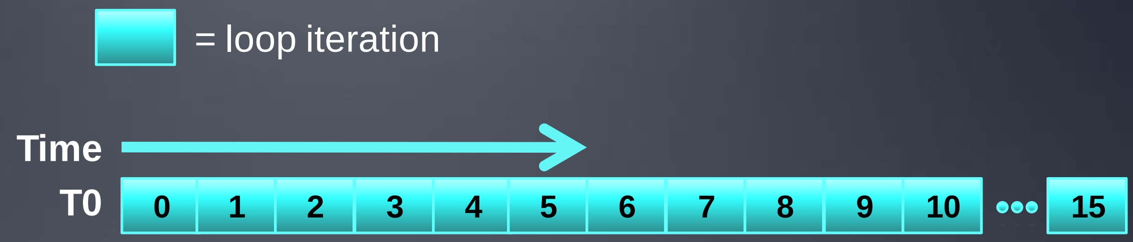
# Parallel Software – SPMD

- In the vector addition example, each chunk of data could be executed as an independent thread
- On modern CPUs, the overhead of creating threads is so high that the chunks need to be large
  - In practice, usually a few threads (about as many as the number of CPU cores) and each is given a large amount of work to do
- For GPU programming, there is low overhead for thread creation, so we can create one thread per loop iteration

# Parallel Software – SPMD

## Single-threaded (CPU)

```
// there are N elements
for(i = 0; i < N; i++)
  C[i] = A[i] + B[i]
```

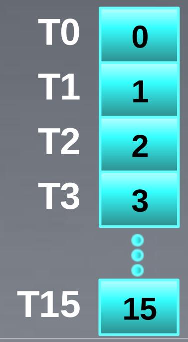



## Multi-threaded (CPU)

```
// tid is the thread id
// P is the number of cores
for(i = 0; i < tid*N/P; i++)
  C[i] = A[i] + B[i]
```


## Massively Multi-threaded (GPU)

```
// tid is the thread id
C[tid] = A[tid] + B[tid]
```

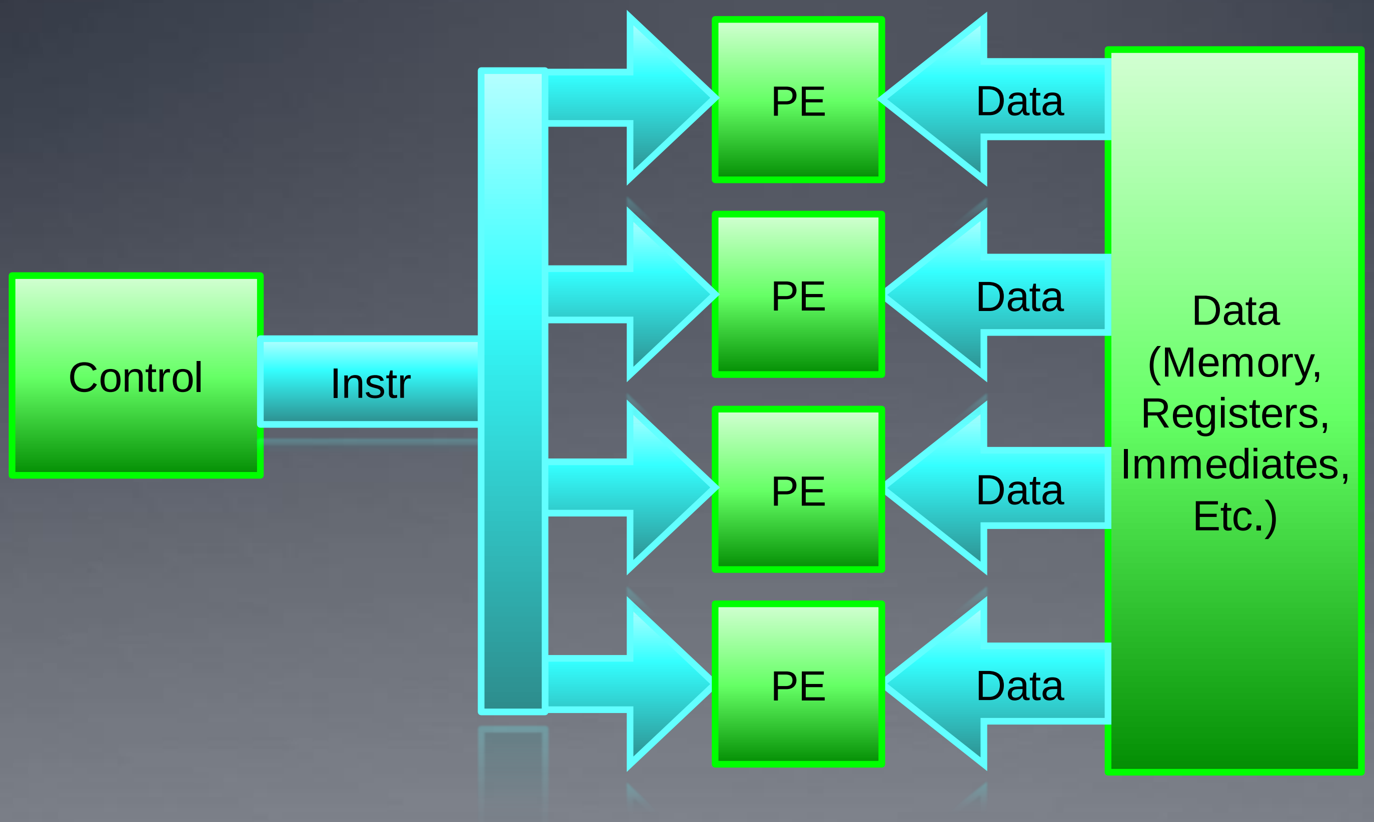


# Parallel Hardware – SIMD

- Each processing element of a Single Instruction Multiple Data (SIMD) processor executes the same instruction with different data at the same time
  - A single instruction is issued to be executed simultaneously on many ALU units
  - We say that the number of ALU units is the *width* of the SIMD unit
- SIMD processors are efficient for data parallel algorithms
  - They reduce the amount of control flow and instruction hardware in favor of ALU hardware

# Parallel Hardware – SIMD

- A SIMD hardware unit

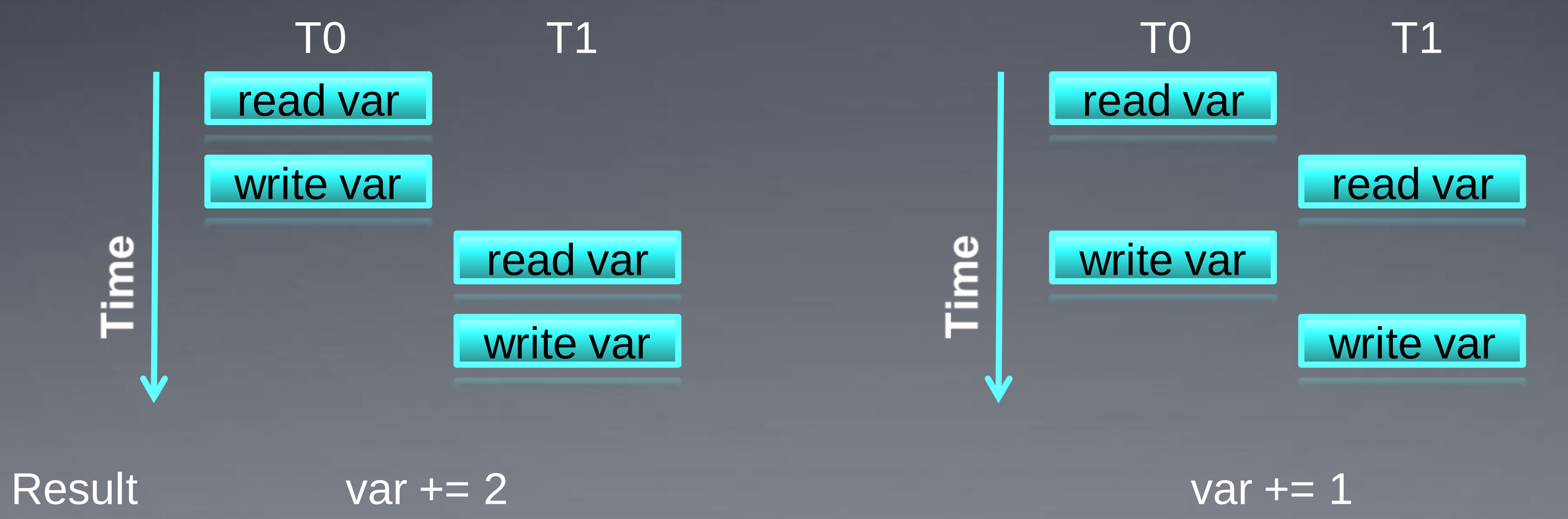


# Parallel Hardware – SIMD

- In the vector addition example, a SIMD unit with a width of four could execute four iterations of the loop at once
- Relating to the apple-picking example, a worker picking apples with both hands would be analogous to a SIMD unit of width 2
- All current GPUs are based on SIMD hardware
  - The GPU hardware implicitly maps each SPMD thread to a SIMD "core"
    - The programmer does not need to consider the SIMD hardware for correctness, just for performance
  - This model of running threads on SIMD hardware is referred to as Single Instruction Multiple Threads (SIMT)

# Challenges of Parallelization

- *Concurrency* is the simultaneous execution of instructions from multiple programs or threads
  - We must ensure that the execution order of concurrent threads does not affect the correctness of the result
- The classic example illustrating the problem with shared-memory concurrency is two threads trying to increment the same variable (2 possible outcomes shown here)
  - When the outcome of an operation depends on the order in which instructions are executed, it's called a *race condition*



# Challenges of Parallelization

- On CPUs, hardware-supported atomic operations are used to enable concurrency
  - Atomic operations allow data to be read and written without intervention from another thread
- Some GPUs support system-wide atomic operations, but with a large performance trade-off
  - Usually code that requires global synchronization is not well suited for GPUs (or should be restructured)
  - Any problem that is decomposed using input data partitioning (i.e., requires results to be combined at the end) will likely need to be restructured to execute well on a GPU

# Summary

- Choosing appropriate parallel hardware and software models is highly dependent on the problem we are trying to solve
  - Problems that fit the output data decomposition model are usually mapped fairly easily to data-parallel hardware
- Naively, OpenCL's parallel programming model is easy because it is simplified SPMD programming
  - We can often map iterations of a for-loop directly to OpenCL threads
  - However, we will see that obtaining high performance requires thorough understanding of hardware (incorporating hardware parallelism + memory subsystem), and complicates the programming model