

Fundamentals of Parallelism

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• Learning objectives:

- Learn about communication patterns
- Learn about reordering algorithms
- Learn about handling dependencies
- Learn about work distribution

Parallel computing is about breaking up a problem into smaller tasks and having multiple processors working together to solve a problem

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This requires communication, and in parallel computing this is done via memory

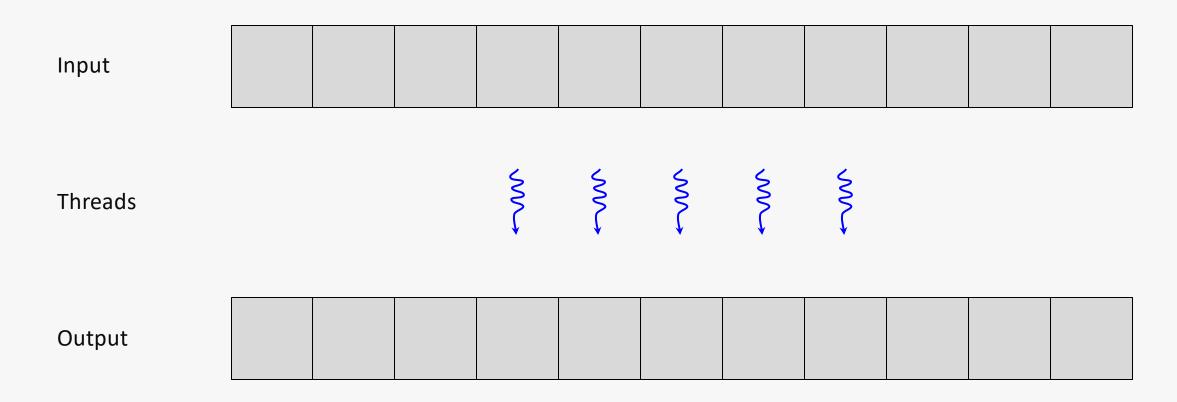
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Memory

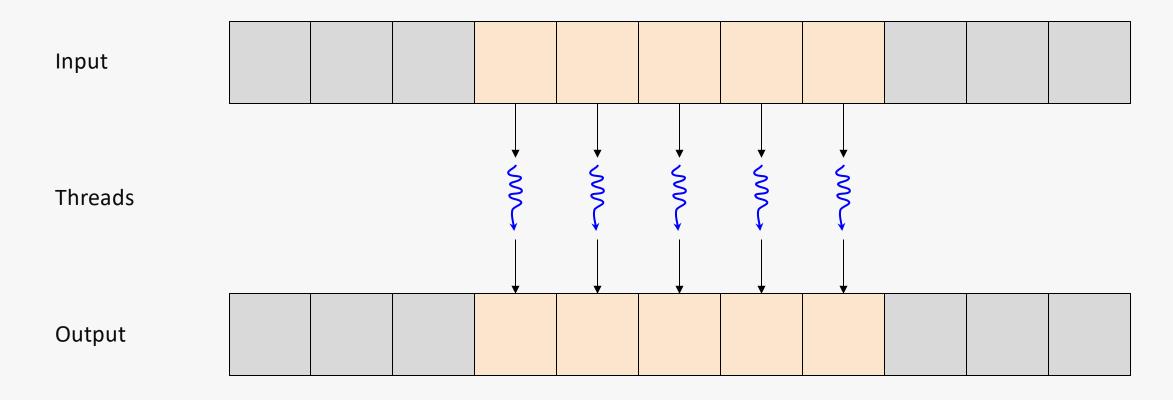


Communication patterns are used to describe the relationship between threads and the data they read from and write to



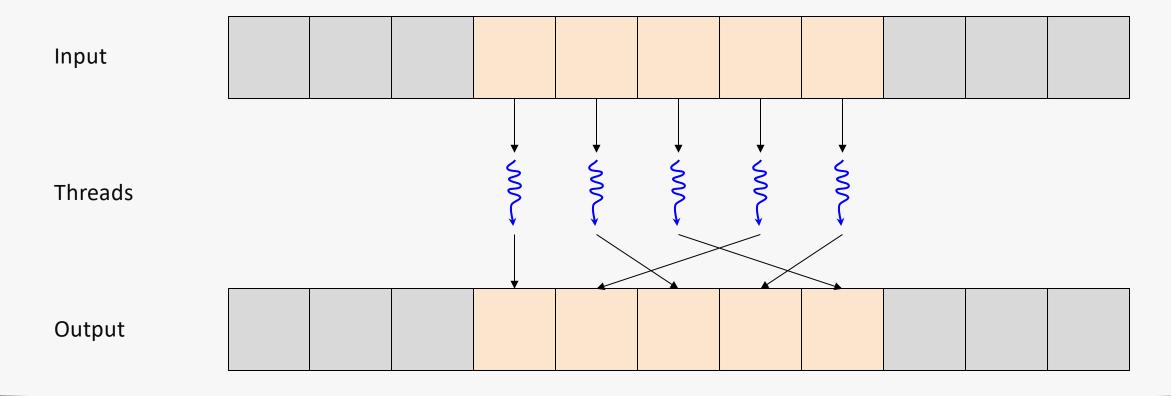
Map pattern

A map pattern is any operation in which each element of the input range maps to the same element of the output range.



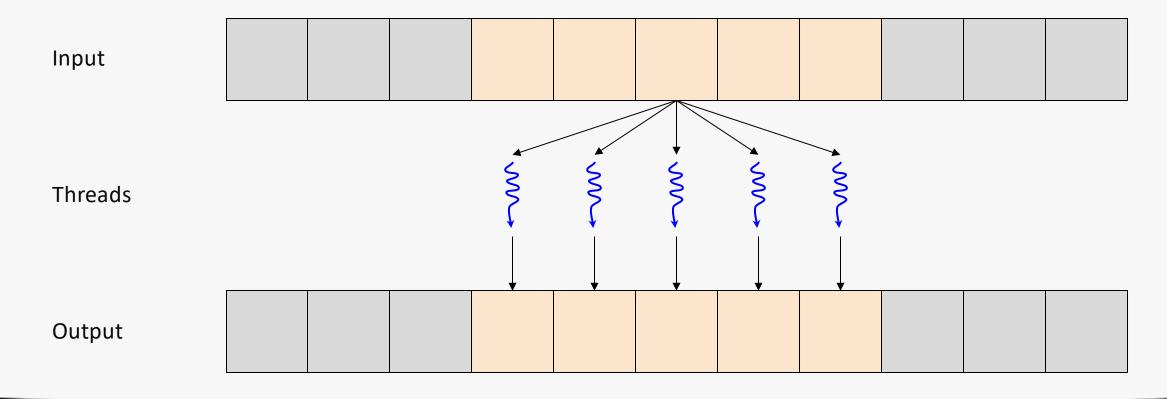
Transpose pattern

A transpose pattern is any operation in which each element of the input range maps to a different element of the output range.



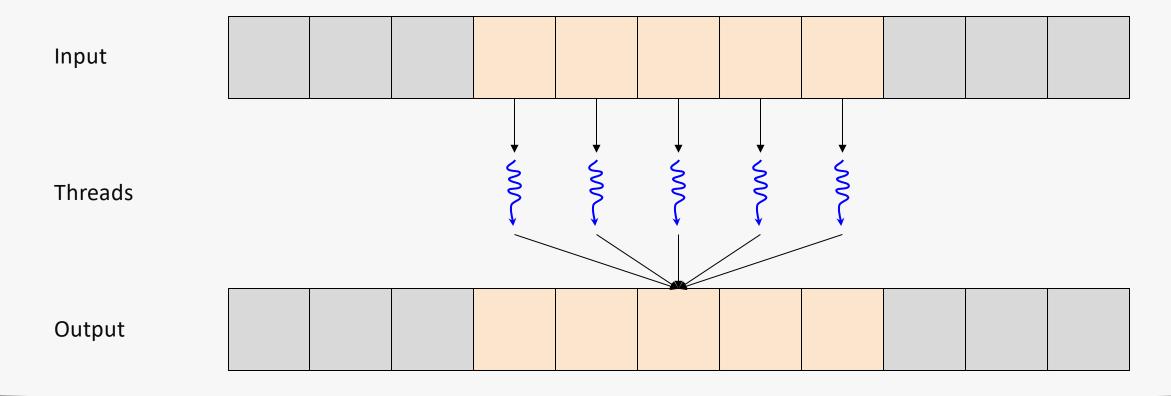
Scatter pattern

A scatter pattern is any operation in which a single element of the input range maps to multiple elements of the output range.



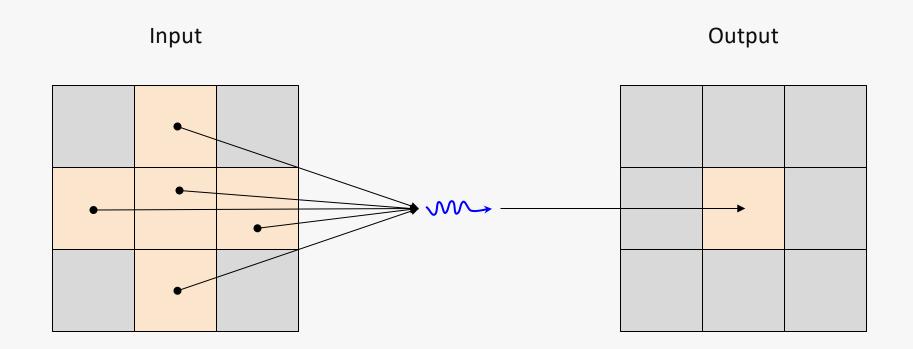
Gather pattern

A gather pattern is any operation in which multiple elements of the input range maps to a single element of the output range.



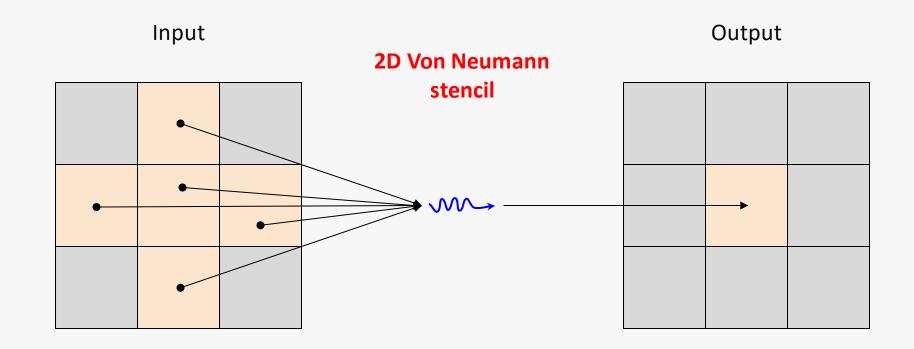
Stencil pattern

A stencil pattern is a special case of the gather pattern where elements are arranged a multi-dimensional space in which a grouping of elements of the input range maps to a single element of the output range.



Stencil pattern

A stencil pattern is a special case of the gather pattern where elements are arranged a multi-dimensional space in which a grouping of elements of the input range maps to a single element of the output range.



```
void foo(int *in, int *out, int index) {
  out[index] = pi * in[128 - index];
}
```

Map

Transpose

Stencil

Gather

Scatter

```
void foo(int *in, int *out, int index) {
   out[index] = pi * in[128 - index];
}
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Map

Transpose

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void foo(int *in, int *out, int index) {
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Map

Transpose

Scatter

Gather

```
void foo(int *in, int *out, int index) {
  out[index] = pi * in[index];
}
```

Map

Transpose

Scatter

Gather

```
void foo(int *in, int *out, int index) {
   if(index % 2) {
      out[index] = (in[index] + in[index - 1] + in[index + 1]) / 3;
}
```

Map

Transpose

Scatter

Gather

```
void foo(int *in, int *out, int index) {
   if(index % 2) {
      out[index] = (in[index] + in[index - 1] + in[index + 1]) / 3;
}
```

Map

Transpose

Scatter

Gather

```
void foo(int *in, int *out, int index) {
   if(index % 2) {
      out[index - 1] = in[index] / 2;
      out[index + 1] = in[index] / 2;
}
```

Map

Transpose

Scatter

Gather

```
void foo(int *in, int *out, int index) {
   if(index % 2) {
      out[index - 1] = in[index] / 2;
      out[index + 1] = in[index] / 2;
}
```

Map

Transpose

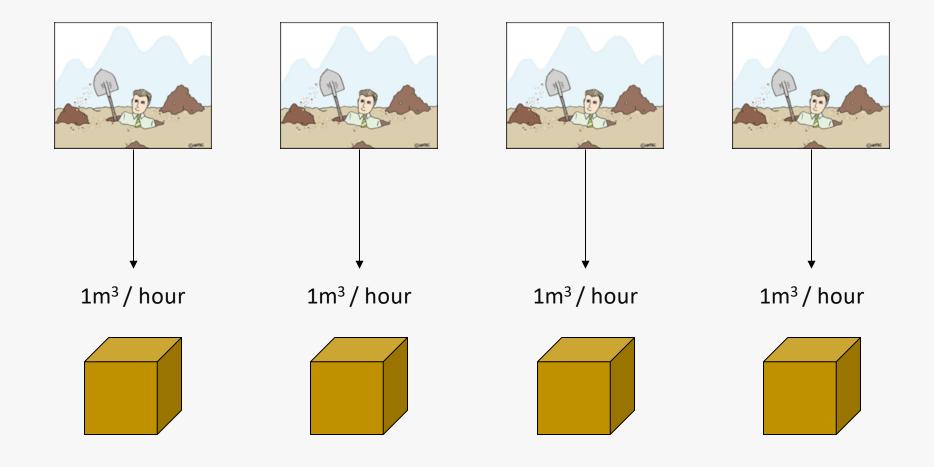
Scatter

Gather

Let's go back to the holes analogy...



Say you now have four diggers...



Say you want a hole with a 4m² surface area

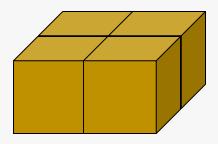




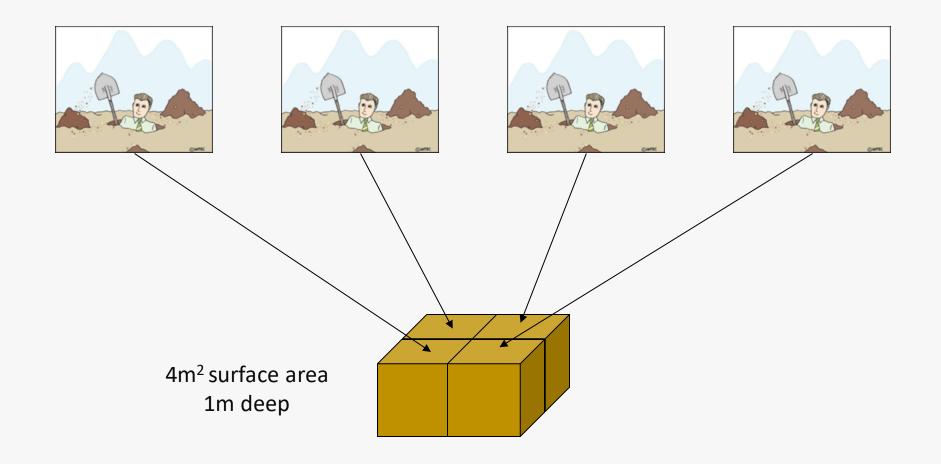




4m² surface area 1m deep



Each digger digs a part each



Say you want a hole with a 36m² surface area

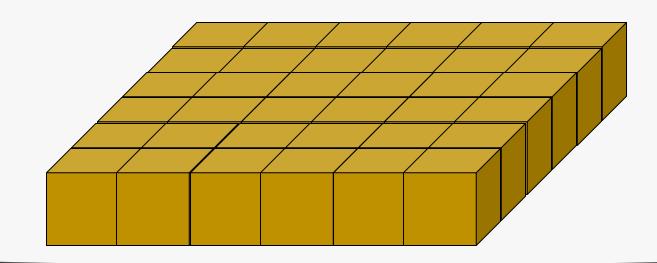




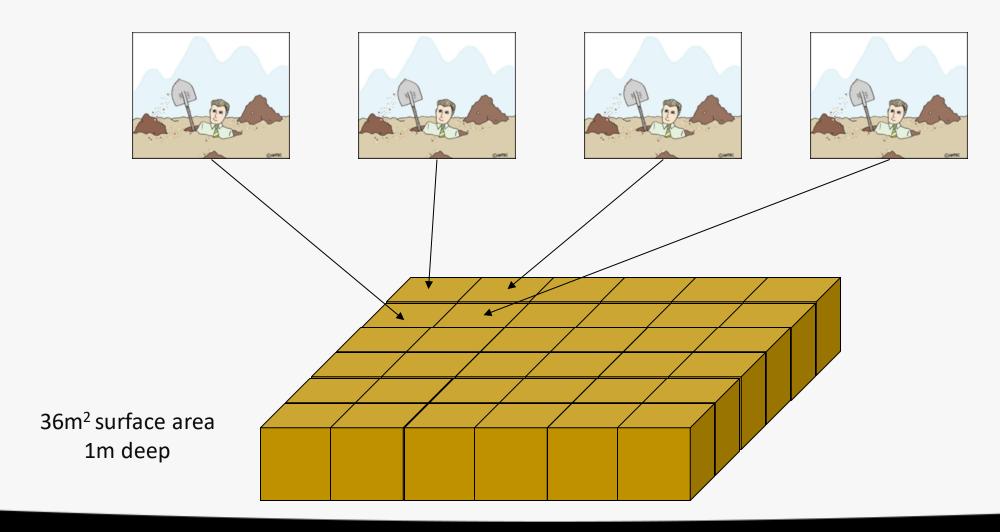




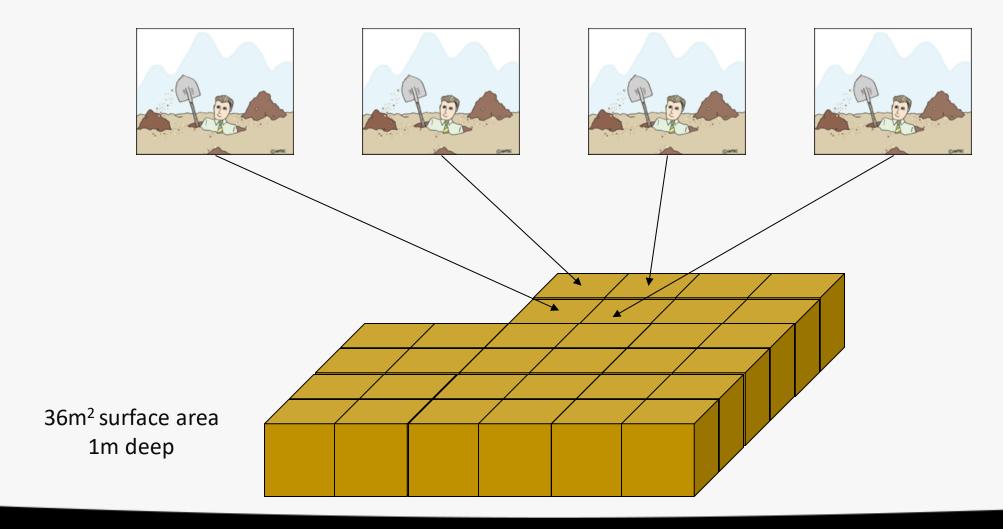
36m² surface area 1m deep



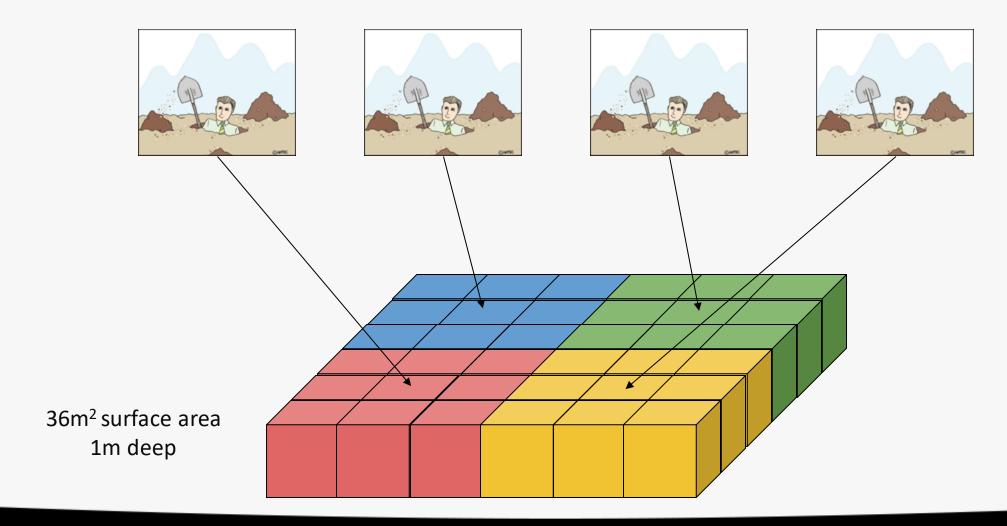
You can share the work between the diggers



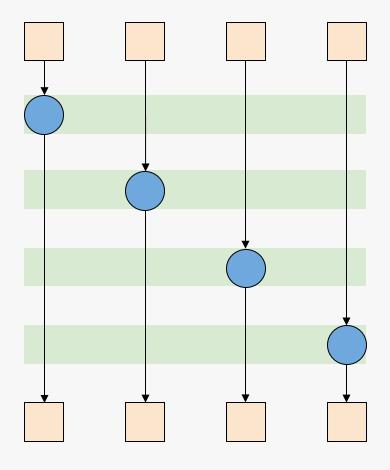
You can share the work between the diggers

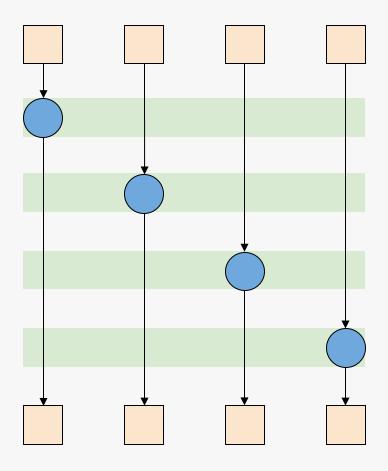


You can distribute work across the diggers

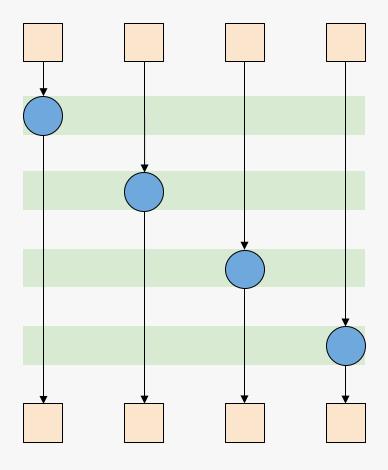


This applies to a transform algorithm

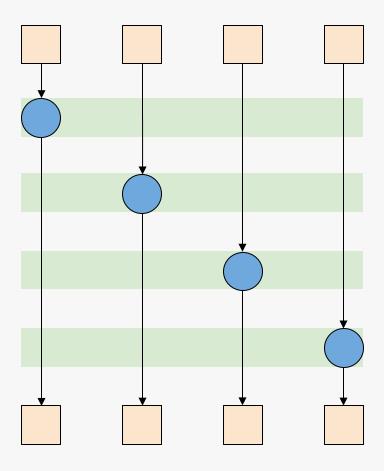




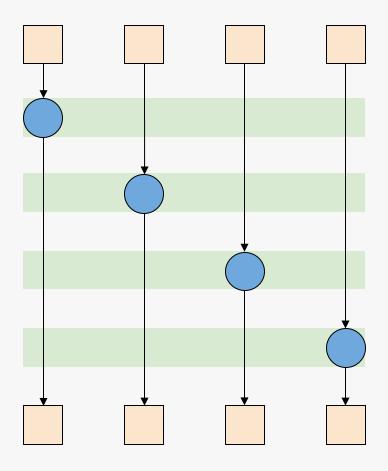
4 elements



4 elements | 4 Operations

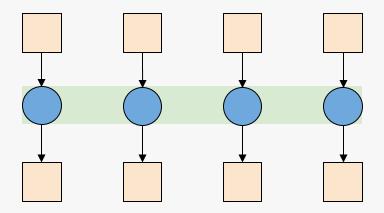


4 elements | 4 Operations | 4 steps



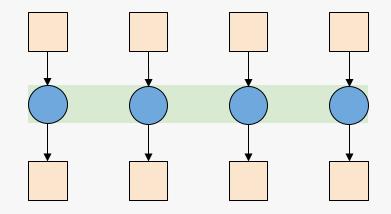
4 elements | 4 Operations | 4 steps | 1 operations / step

Now let's look at a parallel transform...



4 elements | 4 Operations | 1 step | 4 operations / step

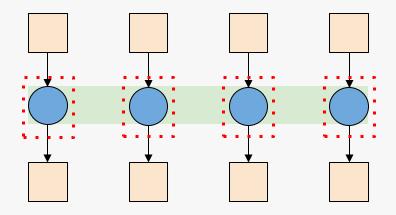
Now let's look at a parallel transform...



Brent's theorem

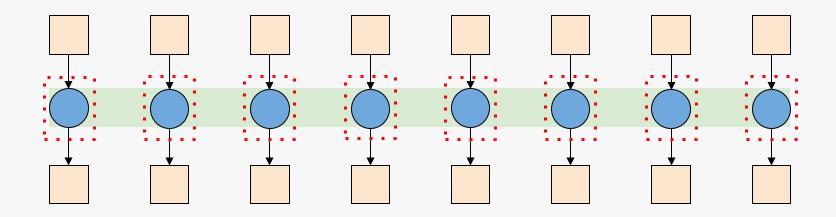
4 elements | 4 Operations | 1 step | 4 operations / step

In order to do this you need parallel workers



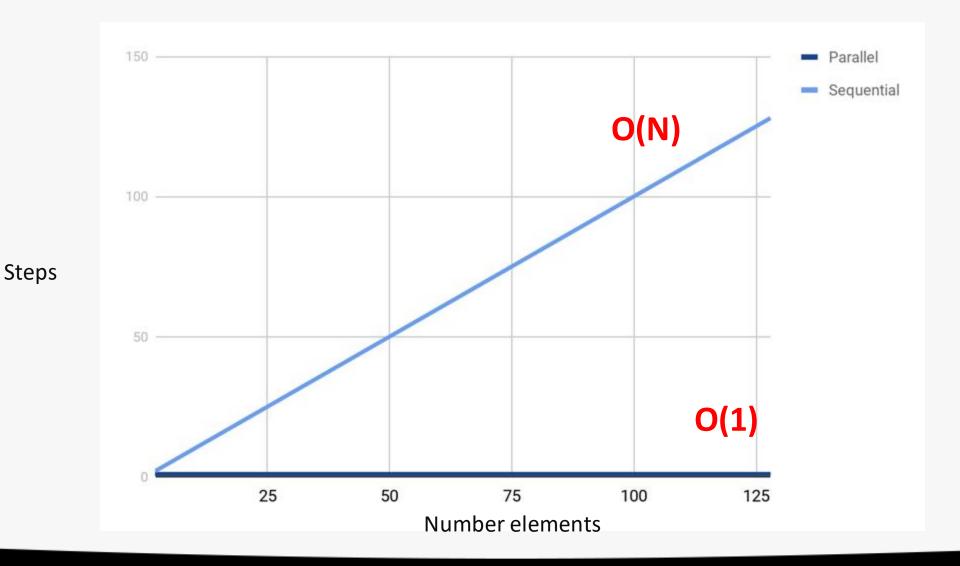
4 elements | 4 Operations | 4 workers | 1 steps | 4 operations / step

Now let's scale this up...

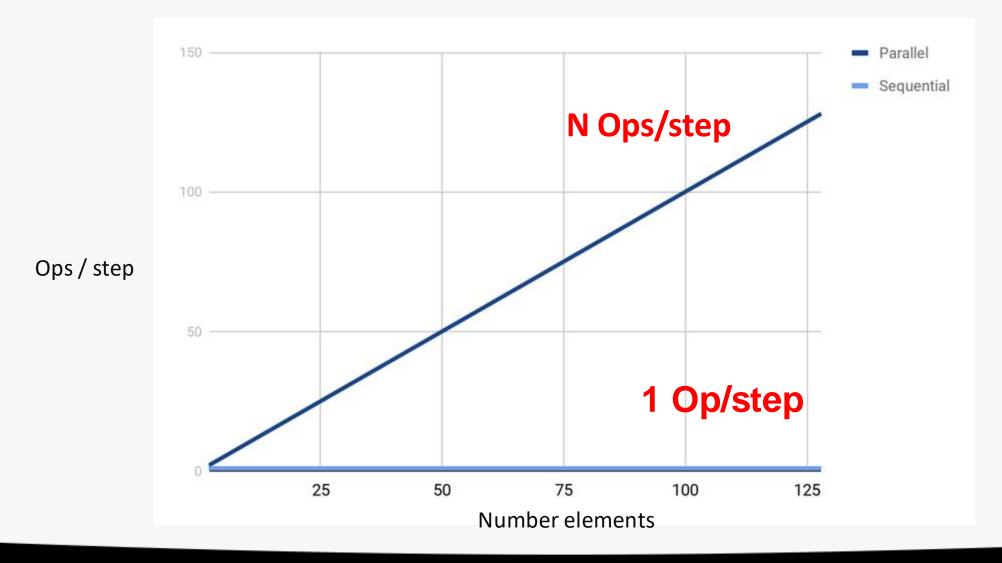


8 elements | 8 Operations | 8 workers | 1 step | 8 operations / step

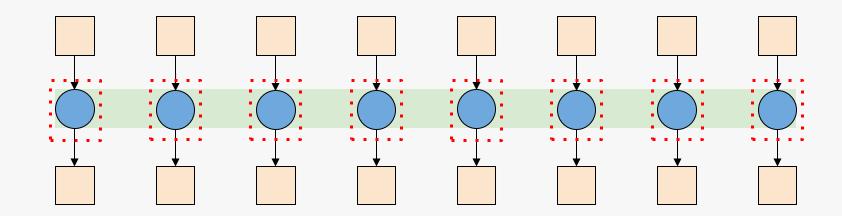
Step complexity of transform



Theoretical operations per step

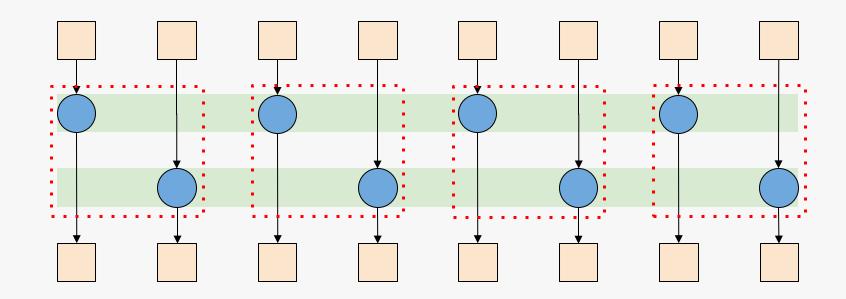


What happens if you only have 4 workers?



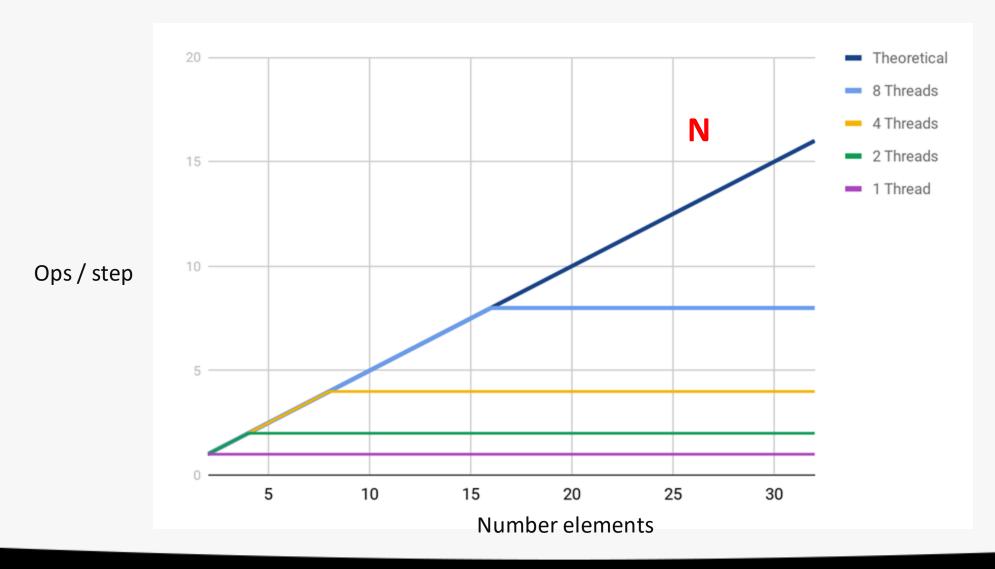
8 elements | 8 Operations | 8 workers | 1 step | 8 operations / step

You have to batch work together



8 elements | 8 Operations | 4 workers | 2 steps | 4 operations / step

Actual operations per step



Maximizing throughput

The theoretical operations / step is always limited by the available workers

Maximising the actual operations / step will provide optimal throughout

You will most often have a much larger number of operations to perform than available workers

How you perform this batching may differ depending on the architecture you are executing on

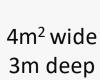
Say you want to dig a hole 3m deep

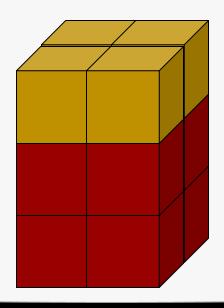




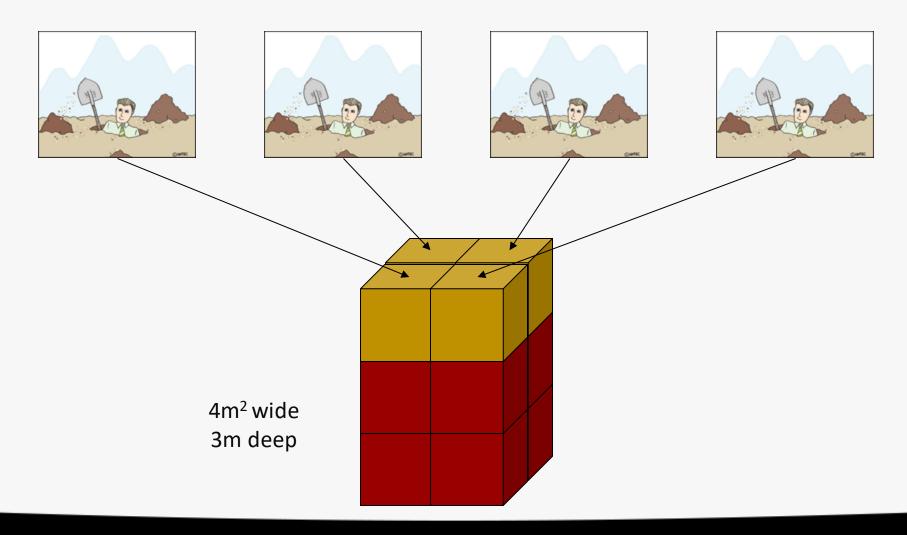




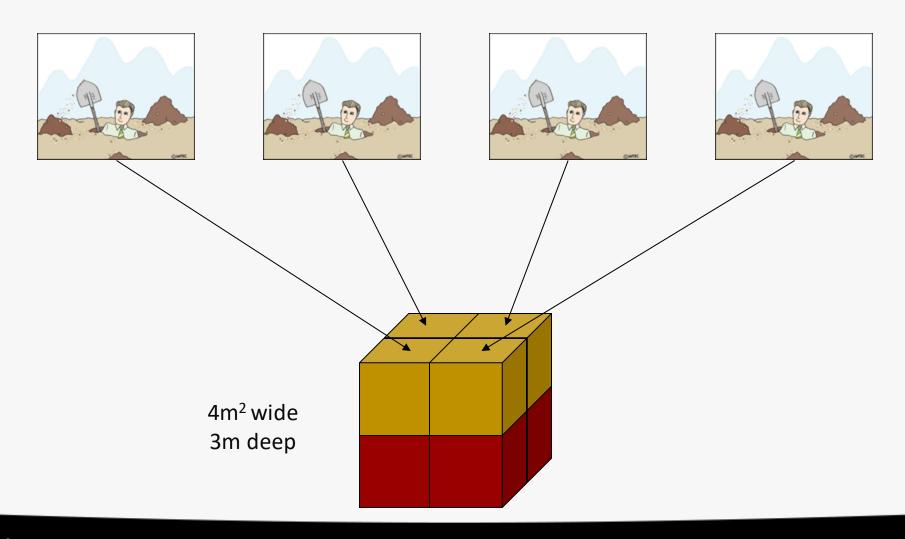




All four diggers have work to do



All four diggers have work to do



Now say the hole is 8m² wide

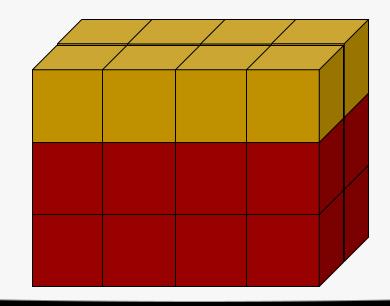




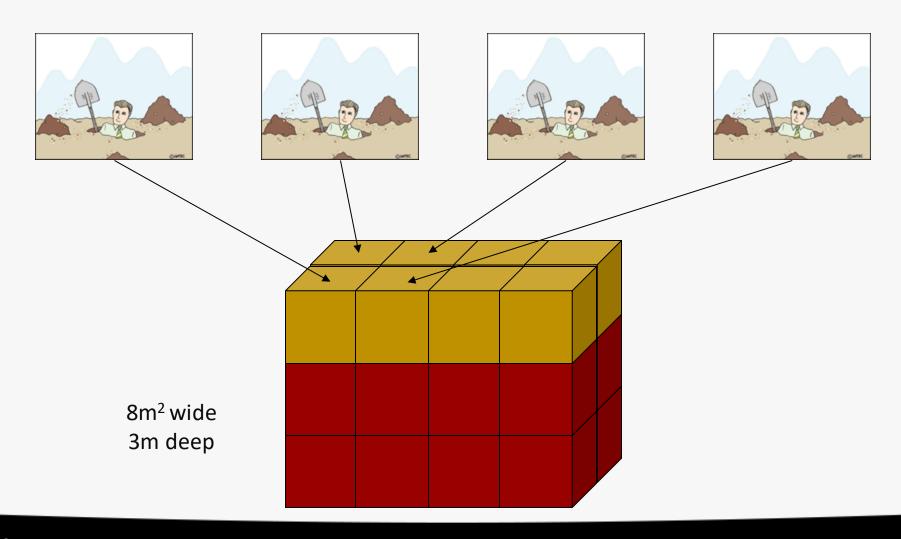




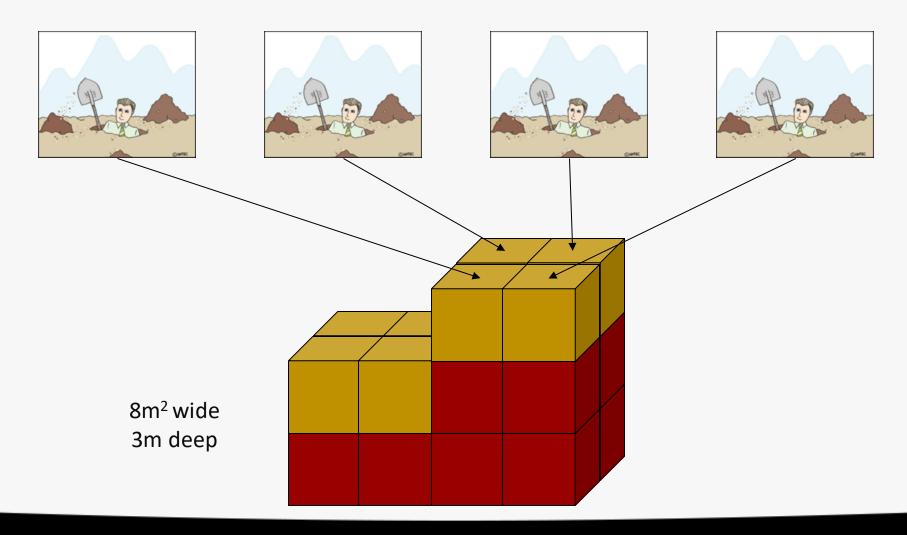
8m² wide 3m deep



Again can share the work



Again can share the work



Now say the hole 2m² wide

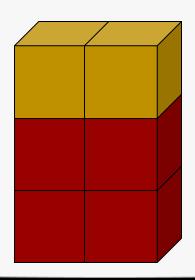




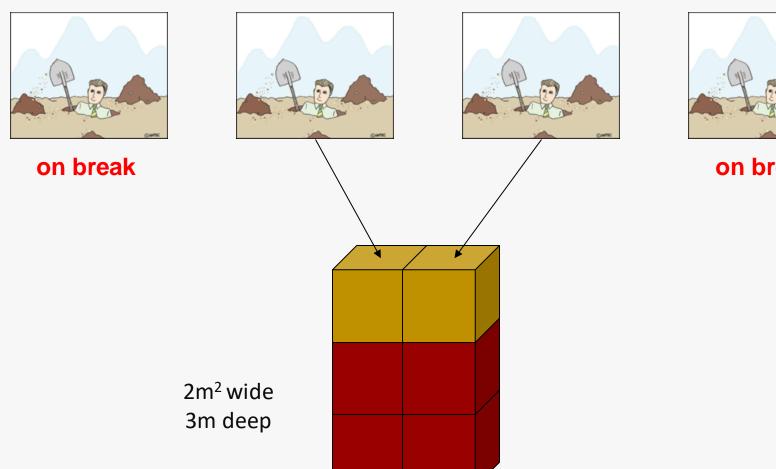




2m² wide 3m deep

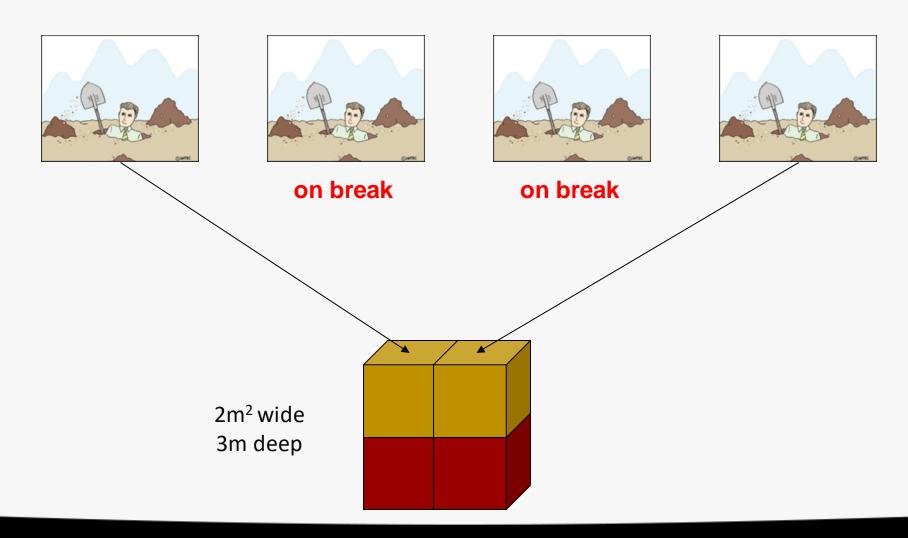


Now you have diggers with no work to do

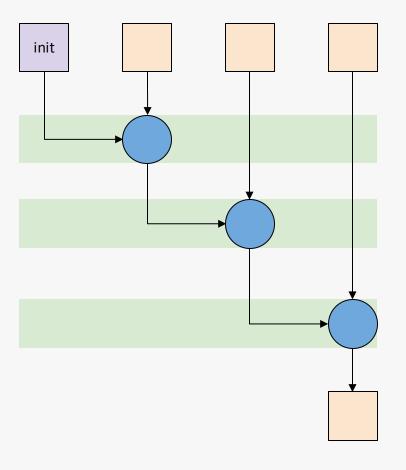


on break

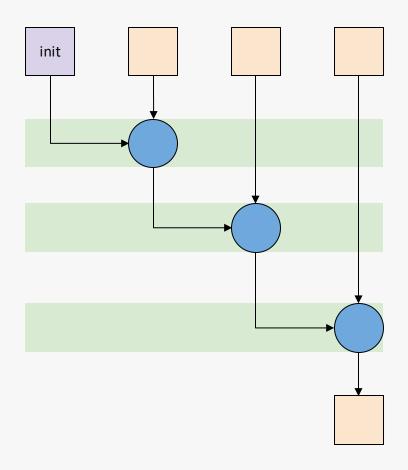
Now you have diggers with no work to do



This applies to a reduction algorithm

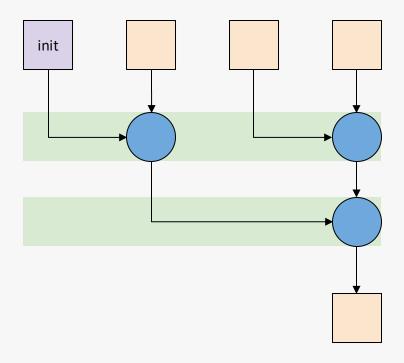


Let's look at a serial reduction...



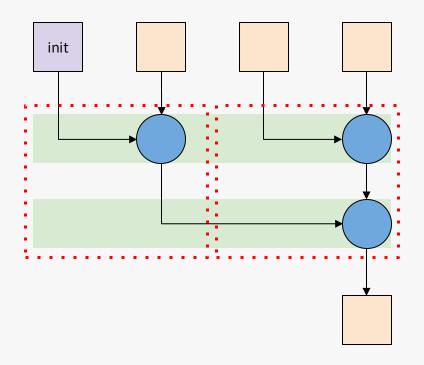
3 elements | 3 Operations | 3 steps | 1 operations / step

Now let's look at a parallel reduction...



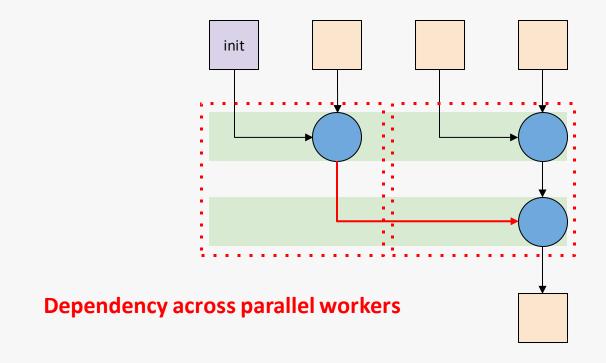
3 elements | 3 Operations | 2 steps | 1.5 operations / step

Let's try to distribute this work



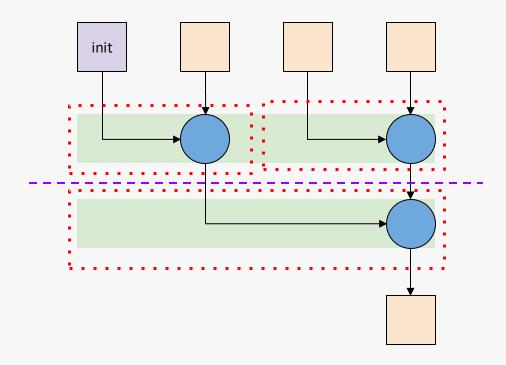
3 elements | 3 Operations | 2 workers | 2 steps | 1.5 operations / step

This creates a dependency between workers



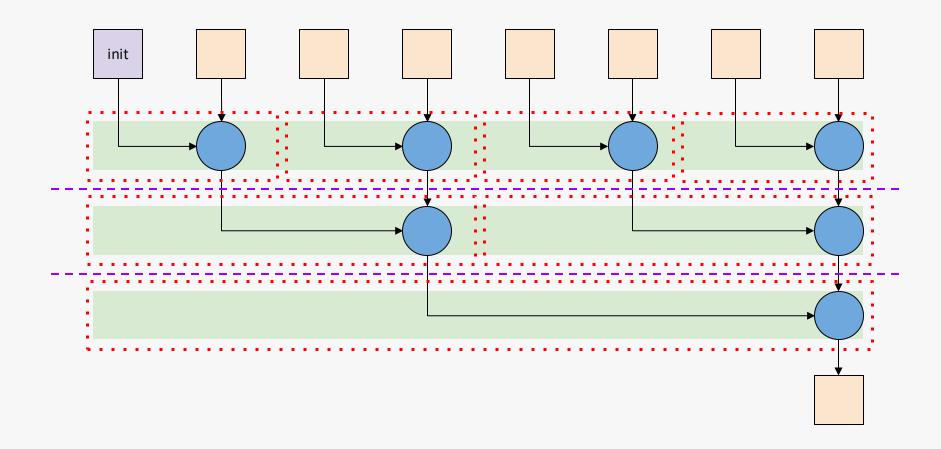
3 elements | 3 Operations | 2 workers | 2 steps | 1.5 operations / step

This creates a dependency between workers



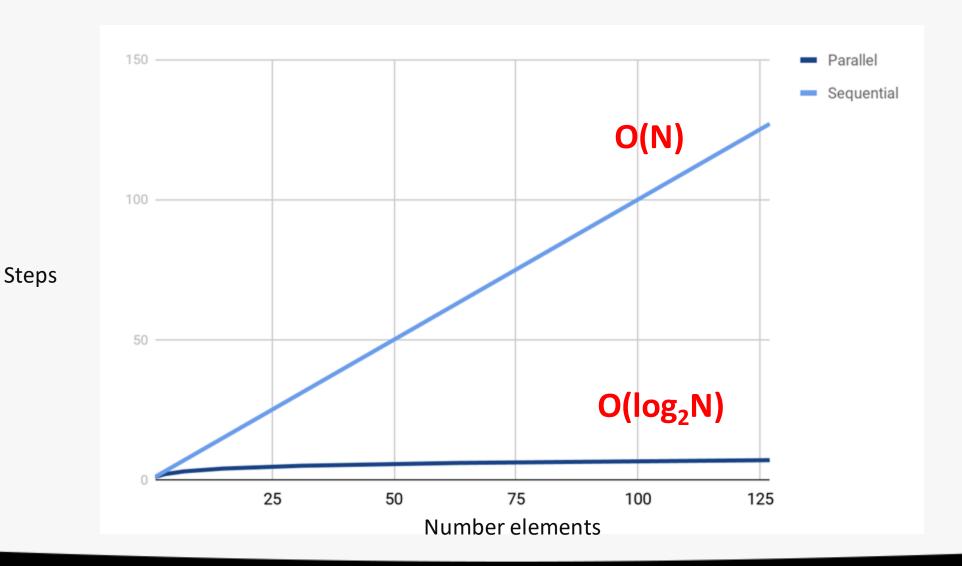
3 elements | 3 Operations | 2 workers | 2 steps | 1.5 operations / step

Now let's scale this up for 4 workers



7 elements | 7 Operations | 4 workers | 3 steps | 2.3 operations / step

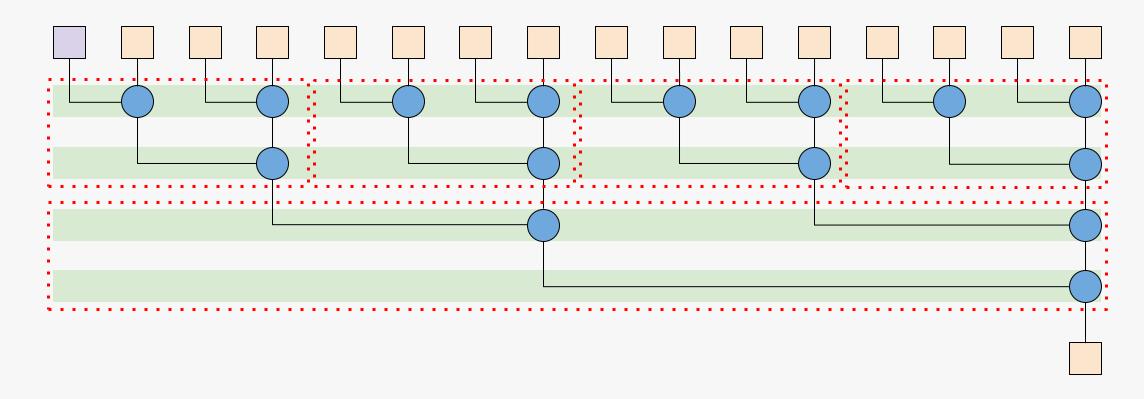
Step complexity of reduce



Theoretical operations per step

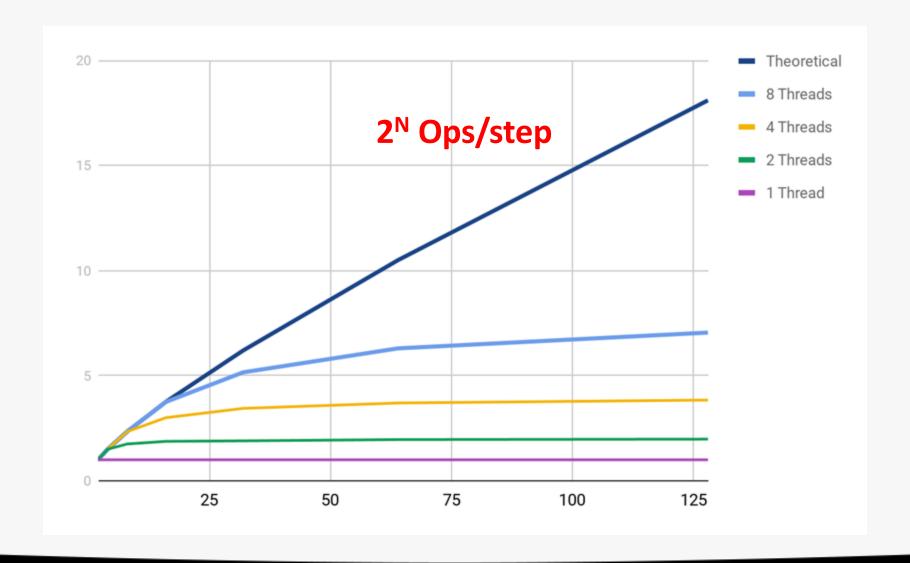


Now let's scale this up for 4 workers



15 elements | 15 operations | 4 workers | 4 steps | 3.8 operations / step

Actual operations per step



Handling dependencies

You should structure your algorithm to distribute dependencies

You should avoid dependencies across workers in the same step

When you have dependencies between operations this creates dependencies between workers

These dependencies often have different implications depending on the architecture you are executing on

Key takeaways

Designing your algorithm to maximize the operations per step will improve throughput and utilization of the hardware

Designing your algorithm to distribute dependencies between operations will reduce increase operations per step and improve throughput

How you batch work together on workers and how you handle dependencies will vary depending on the architecture you are executing on



Questions?