Understanding Parallelism & Concurrency

(informal introduction)

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Why Parallelism?

- **Parallelism and Partitioning are foundations of big data solutions.**
  - MapReduce is based on parallelism and partitioning data
  - Hadoop is based on parallelism and partitioning data
  - Spark is based on parallelism and partitioning data
  - Snowflake is based on parallelism and partitioning data

- **The concept of parallel computing is based on**
  - dividing a large problem into smaller ones, and
  - each of them is carried out by one single processor individually.

Parallelism Example: array addition

```
// a: a[0], a[1], …, a[n-1]
// b: b[0], b[1], …, b[n-1]
for (i = 0; i < n; i++) {
    c[i] = a[i] + b[i];
}
```

```
c[0] = a[0] + b[0]
c[1] = a[1] + b[1]
c[2] = a[2] + b[2]
…
c[n-1] = a[n-1] + b[n-1]
```

Sequential:

n steps

one processor

Parallel:

one step

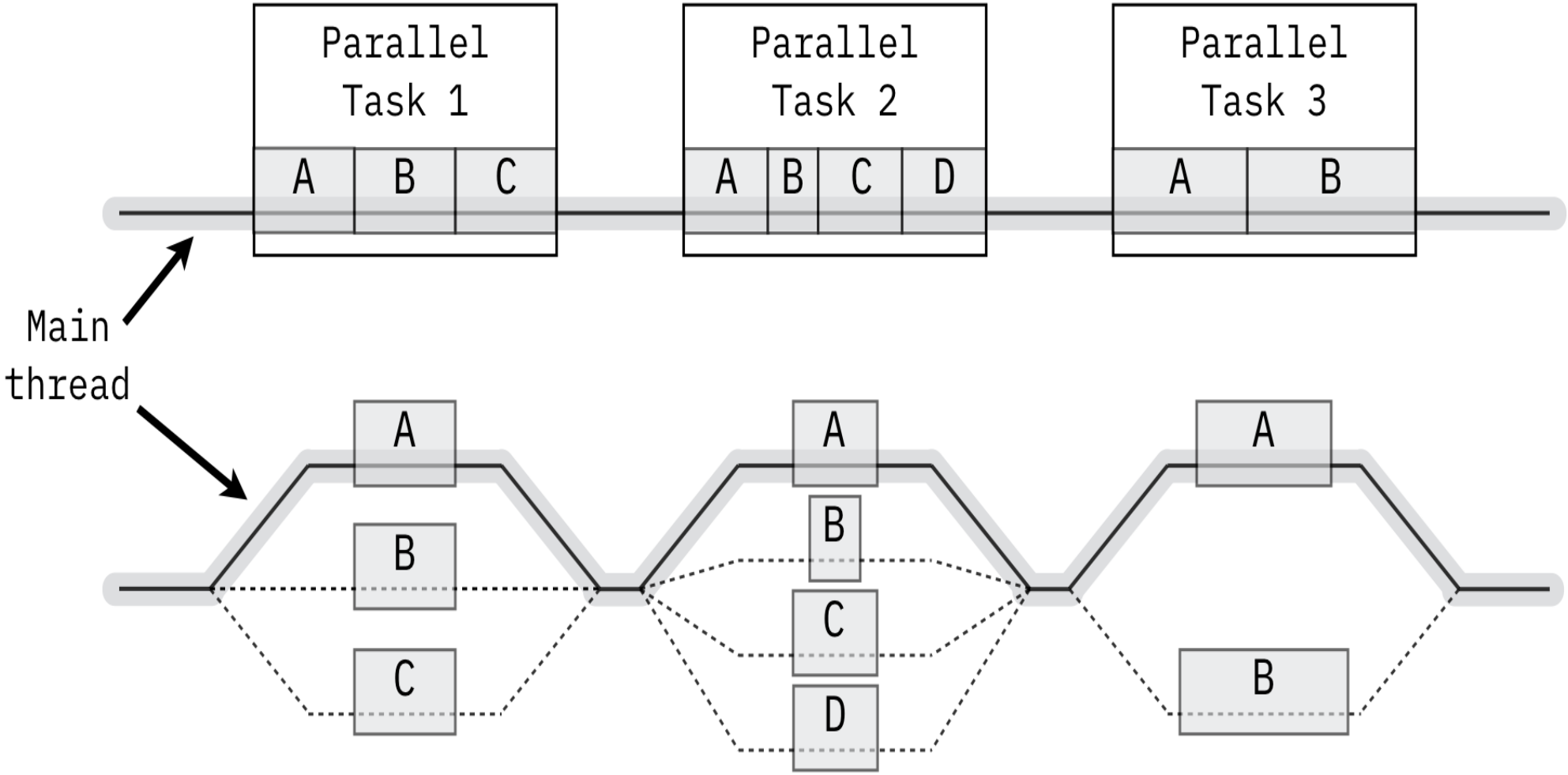
n processors

Concurrency & Parallelism (informal definition):

Some definitions:

- The fact of two or more events or circumstances happening or existing at the same time.
- The ability to execute more than one program or task simultaneously.
- Example: "a high level of concurrency is crucial to good performance in a multiuser database system"
  - Multiple reads at a time
  - Multiple writes at a time

Concurrency & Parallelism (informal definition):

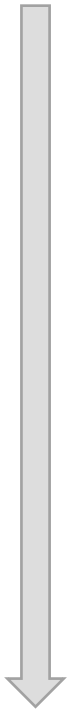


Concurrency & Parallelism

Task A = { A1, A2, A3, A4}, Task B = {B1, B2, B3}, Task C = {C1, C2}

Execute Tasks A and B and C (in sequential order):

1. A1
2. A2
3. A3
4. A4
5. B1
6. B2
7. B3
8. C1
9. C2



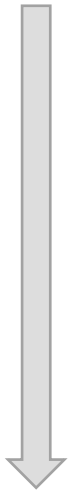
Concurrency & Parallelism

Task A = { A1, A2, A3, A4} Task B = {B1, B2, B3}, Task C = {C1, C2}

Assume that Tasks (A, B, and C) are independent of each other

Execute Tasks A, B, C: (concurrently)

1. A1 B1 C1 (3 tasks running concurrently)
2. A2 B2 C2 (3 tasks running concurrently)
3. A3 B3 (2 tasks running concurrently)
4. A4 (1 task running)



Concurrency & Parallelism: Maximum Parallelism

Task A = { A1, A2, A3, A4}

Task B = {B1, B2, B3},

Task C = {C1, C2}

If there is NO dependency between any tasks:

Then run all of these 9 tasks concurrently:

```
A1, A2, A3, A4, B1, B2, B3, C1, C2
```

Parallelism

Parallelism is basically a type of computation in which many tasks/computations/operations are carried out in parallel.

Sequential Tasks:

Task-1: 20 minutes

Task-2: 20 minutes

Task-3: 25 minutes

Task-4: 25 minutes

==========

Total Elapsed time: 90 minutes

(assuming that there is no dependencies between tasks)

Parallel Tasks:

Task-1, Task-2, Task-3, Task-4

==========

Total Elapsed time: 25 minutes

→ Therefore, Parallelism improves execution time.

Parallelism

What if {Task-3 and Task-4} depends on output of {Task-1 and Task-2}

4 Sequential Tasks:

Iteration-1: **Task-1** : 20 minutes

Iteration-2: **Task-2** : 20 minutes

Iteration-3: **Task-3**: 25 minutes

Iteration-4: **Task-4** : 25 minutes

==========

Total Elapsed time: 90 minutes

(assuming that there is no dependencies between tasks)

Dependencies can be bottlenecks!!!

4 Parallel Tasks:

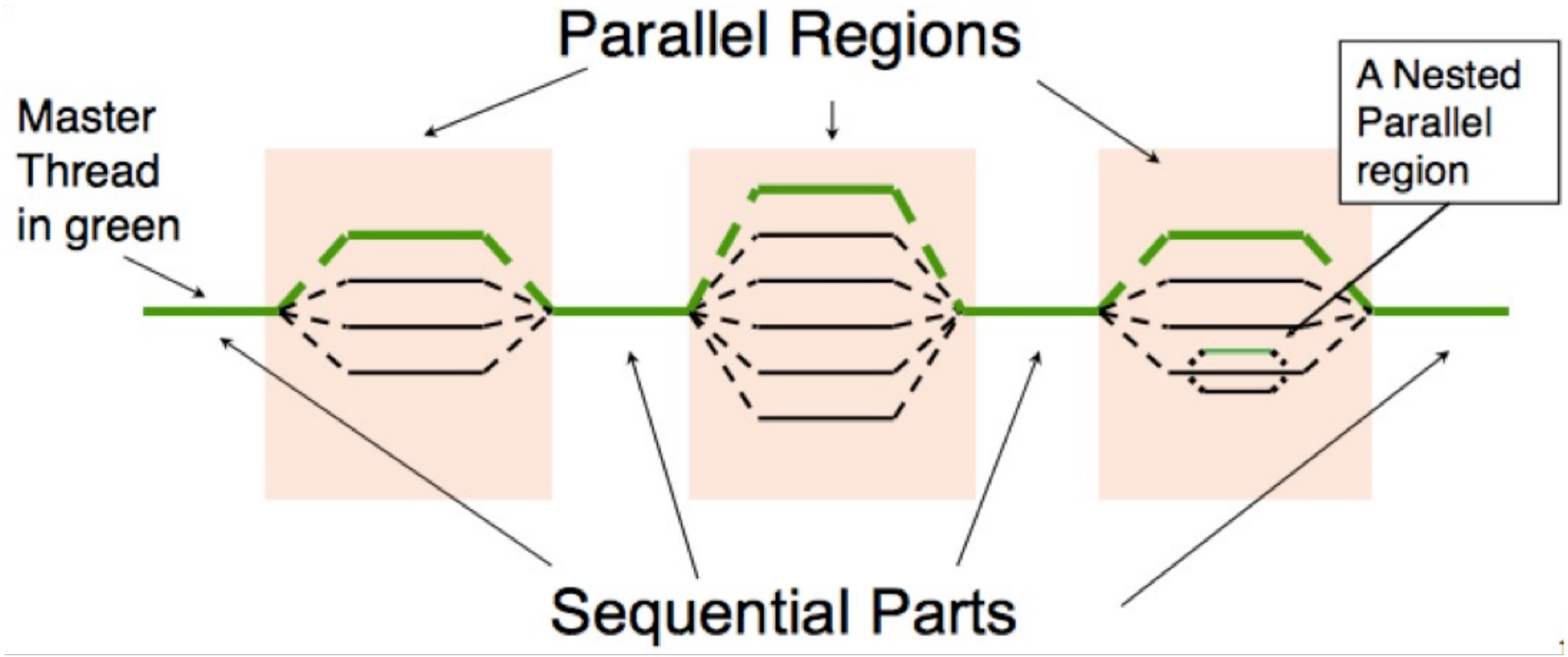
Iteration-1: **Task-1**, **Task-2** (duration: 20 mins)

Iteration-2: **Task-3**, **Task-4** (duration: 25 mins)

==========

Total Elapsed time: 45 minutes

Parallelism



Birthday Example

- Alex wants to throw a big birthday party.
- He has a list of 1000 items to buy from a Safeway (grocery store).
- Items to buy:
    - item-1: ice-cream
    - item-2: chips
    - item-3: oranges
    - item-4: cup cakes
    - …
    - item-1000: grapes
- How long will it take for Alex to buy all these 1000 items
    - assuming that he is the only person in grocery store?

What is our Data?

ID	Item to buy
1	ice-cream
2	chips
3	oranges
4	Cup-cakes
…	…
1000	grapes

Birthday Example …

- How long will it take for Alex to buy all these 1000 items?
  - assuming that he is the only person in grocery store
- It is estimated that on average he needs 14 seconds to find the item and put in the shopping cart.
- Therefore, he will spend

```
1000 x 14 = 14,000 seconds = 234 minutes
```

BUT, Alex is busy and can not spend **234 minutes** for shopping.

What to do?

Processing Data? One Executor: Alex
Buy item-1, then item-2, …, then item-1000, …
All is done in sequence: No Parallelism yet.

ID	Item to buy
1	ice-cream
2	chips
3	oranges
4	Cup-cakes
…	…
1000	grapes

Birthday Example …

But, Alex is busy and can not spend 234 minutes for shopping.

What to do?

- **Alex calls 10 of his friends (F1, F2, …, F10):**
  - they will do shopping and deliver to Alex.
- **Therefore, Each friend will buy 100 items**
- **Total time elapsed to buy all items:**

  `100 x 14 = 1400 seconds = 24 minutes`
- **THIS IS a BIG IMPROVEMENT: 234 minutes reduced to 24 minutes**
- **Alex is still not satisfied with this plan.**

Processing Data? 10 parallel executors

Each executor operates in parallel & independently

Executor-1: F1

ID	Item to buy
1	ice-cream
2	chips
3	oranges
4	Cup-cakes
…	…
100	grapes

Executor-1: F2

ID	Item to buy
101	…
102	…
103	…
104	…
…	…
200	grapes

…

Executor-10: F-10

ID	Item to buy
901	…
902	…
903	…
904	…
…	…
1000	grapes

Birthday Example …

But, Alex is busy and can not spend 24 minutes for shopping.

What to do?

- Alex calls 100 of his friends (F1, F2, …, F100):

  they will do shopping and deliver to Alex.
- Therefore, Each friend will buy 10 items
- Total time elapsed to buy all items:

  `10 x 14 = 140 seconds = about 3 minutes`
- THIS IS a BIG IMPROVEMENT: **234 minutes** reduced to **3 minutes**
- **Alex is still not satisfied with this plan.**

Processing Data? 100 parallel executors

Each executor operates in parallel & independently

Executor-1: F1

ID	Item to buy
1	ice-cream
2	chips
3	oranges
4	Cup-cakes
…	…
10	…

Executor-2: F2

ID	Item to buy
11	…
12	…
13	…
14	…
…	…
20	…

• • •

Executor-100: F-100

ID	Item to buy
991	…
992	…
993	…
994	…
…	…
1000	grapes

Birthday Example …

But, Alex is busy and can not even spend 3 minutes for shopping.

What to do?

- **Alex calls 1000 of his friends (F1, F2, …, F1000):**
  - they will do shopping and deliver to Alex.
- **Therefore, Each friend will buy 1 single item**
- **Total time elapsed to buy all items:**

  `1 x 14 = 14 seconds`
- **THIS IS a HUGE IMPROVEMENT:**

  `234 minutes` reduced to `14 seconds`
- **Alex is satisfied with this plan.**

Processing Data? 1000 parallel executors

Each executor operates in parallel & independently

Executor-1: F1

ID	Item to buy
1	ice-cream

Executor-2: F2

ID	Item to buy
2	chips

...

Executor-1000: F-1000

ID	Item to buy
1000	grapes

How do we write parallel programs?

- **Task parallelism**
  - Partition various tasks carried out solving the problem among the cores.

- **Data parallelism**
  - Partition the data used in solving the problem among the cores.
  - Each core carries out similar operations on it's part of the data.

Data parallelism

- Let your data has 200,000,000,000 data points
- Partition your data into 100,000 chunks:
  - Number of partitions: **100,000**
  - Number of records per partition: **2000,000**
  - **100,000 x 2000,000 =** 200,000,000,000
- Assume you want to execute map(function) on (a transformation function) each record and create a new record
- With these partitioning in place, The fastest way to execute map(function) will be to have **100,000** mappers (mappers are transformations, which execute in parallel)
- What happens if we have only 1000 mappers?

Data parallelism

- What happens if we have only 1000 mappers?
- First, we assign 1000 of these partitions to 1000 mappers (**each mapper gets a single partition, which has 2,000,000 records**)
- Once a mapper completes its task, we assign another partition to that mapper
- This iteration continues until we exhaust all 100,000 partitions
- **At most 1000 mappers are executing at a single point of time.**
- **The more mappers we have:**

  The more we execute faster

Parallelism requires Coordination

- Executors usually need to coordinate their work.
- Communication – one or more Executors send their current partial results to another core.
- Load balancing – share the work evenly among the Executors so that one is not heavily loaded.
- Synchronization – because each Executors works at its own pace, make sure Executors do not get too far ahead of the rest.

NOTE: If you use Spark or MapReduce, then all of these are done automagically for you!!!

Partitioner: partition data into chunks

- **A partitioner partitions the input into chunks.**
- **If input has 200,000,000,000 records and we partition this input into 200,000 chunks, then we have:**
  - Number of partitions: 200,000
  - Size of each partition: 1000,000 records
  - 200,000,000,000 = 200,000 x 1000,000

- **Typically, a chunk (1000,000 records) becomes a unit of parallelism.**

Chunk = Partition

Benefits of Parallel Computing

- **Parallel computing models the real world.** The world around us isn't serial and sequential: many things happen at the same time
- **Saves time.** Serial/sequential computing forces fast processors to do things inefficiently.
- **Saves money.** By saving time, parallel computing makes things cheaper and faster
- **Solve more complex or larger problems** be partitioning them into smaller problems
- **Solve Larger Problems in a short point of time.**

References

- **Introduction to Parallel Computing**
  - https://www.geeksforgeeks.org/introduction-to-parallel-computing/

- **Introduction: Parallelism = Opportunities + Challenges**
  - https://courses.cs.washington.edu/courses/csep524/07sp/poppChaper1.pdf