CORK INSTITUTE OF TECHNOLOGY
INSTITIÚID TEICNEOLAÍOCHTA CHORCAÍ

Big Data Processing

L26: Module Wrap Up

24 Ideas from 24 Lectures

Dr. Ignacio Castineiras
Department of Computer Science

Outline

Let’s summarise the main ideas presented in our module Big Data Processing.

Outline

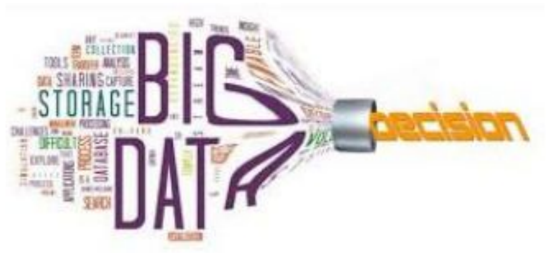
Idea 1:

A View for Artificial Intelligence

Idea 1: A View for Artificial Intelligence

Artificial Intelligence:

Big Data



+

Machine Learning

+

Combinatorial Optimisation

Idea 1: A View for Artificial Intelligence

Example Project:
Google HashCode'18 Self-driving rides

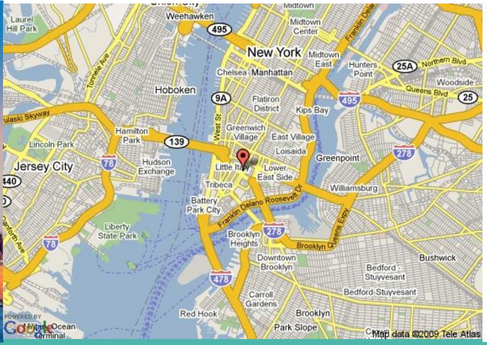
Google
Hash Code
Team up to solve an engineering problem from Google
Are you up for the challenge?

Idea 1: A View for Artificial Intelligence

Example Project:

Google HashCode'18 Self-driving rides

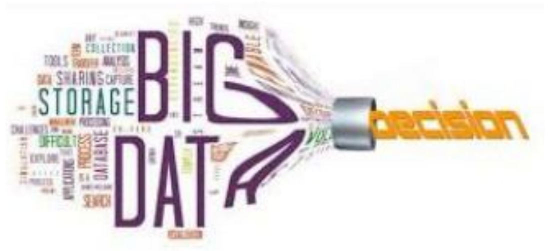
Google
Hash Code
Team up to solve an engineering problem from Google
Are you up for the challenge?



Idea 1: A View for Artificial Intelligence

Role of Big Data:
Put your hands into tons of data, to analyse what has happened and what is happening...

Big Data



+

Machine Learning

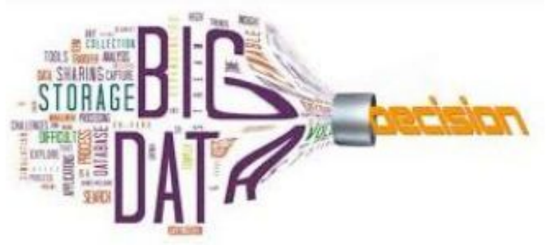
+

Combinatorial Optimisation

Idea 1: A View for Artificial Intelligence

Role of Big Data:
Put your hands into tons of data, to analyse what has happened and what is happening…

Big
Data

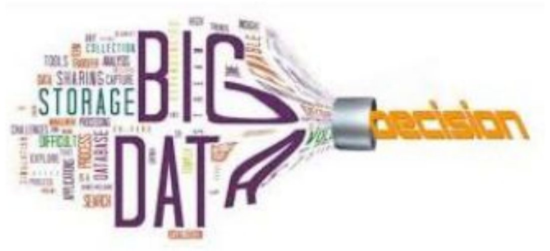


HOW'S THE BIG DATA PROJECT COMING ALONG, HOSKINS?
© D.Fletcher for CloudTweaks.com

Idea 1: A View for Artificial Intelligence

Role of Machine Learning:
...based on what has happened and is happening, build models to predict what will happen...

Big Data



+

Machine Learning

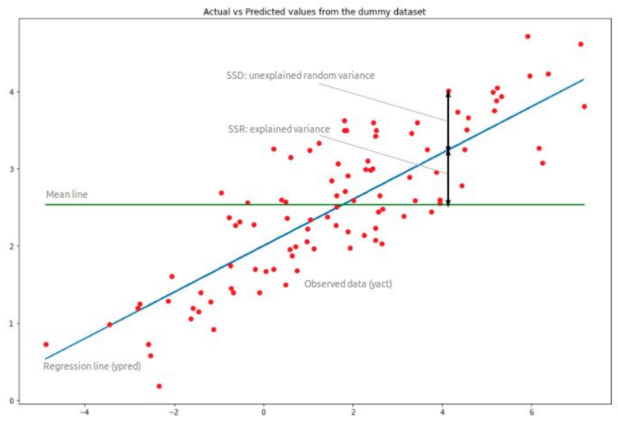
+

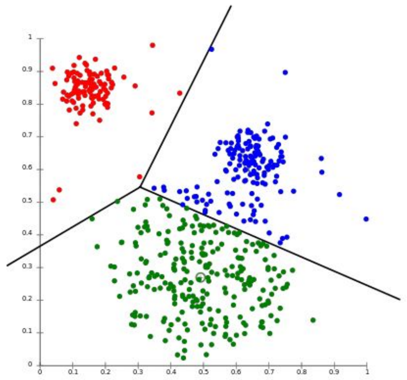
Combinatorial Optimisation

Idea 1: A View for Artificial Intelligence

Role of Machine Learning:
...based on what has happened and is happening,
build models to predict what will happen...

Machine Learning

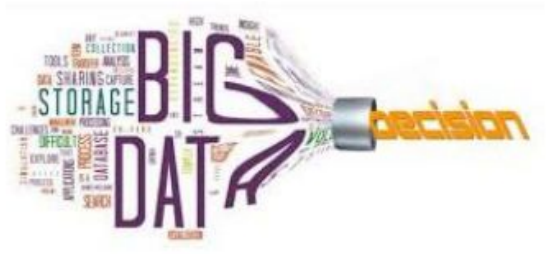




Idea 1: A View for Artificial Intelligence

Role of Combiantorial Optimisation:
...based on what we predict it will happen,
make decisions to achieve an optimal performance.

Big Data



+

Machine Learning

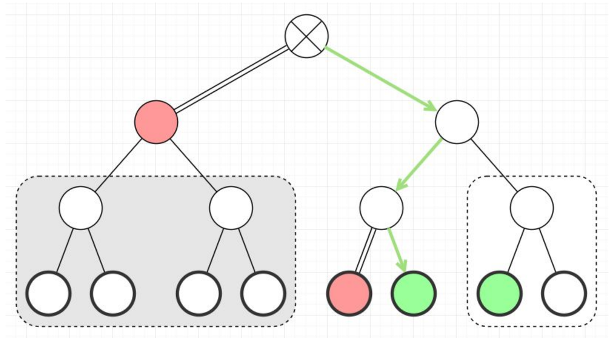
+

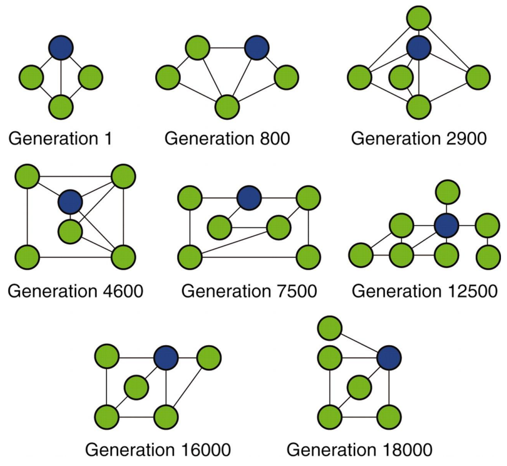
Combinatorial Optimisation

Idea 1: A View for Artificial Intelligence

Role of Combiantorial Optimisation:
…based on what we predict it will happen,
make decisions to achieve an optimal performance.

Combinatorial Optimisation





Outline

Idea 2:

A View for Big Data Processing

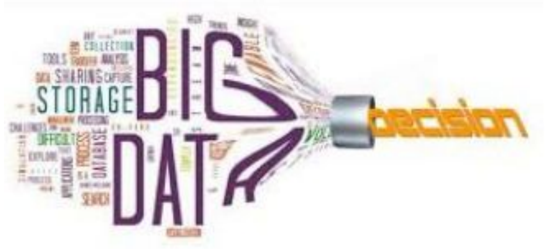
Idea 2: A View for Big Data Processing

Based on our view of Artificial Intelligence…

Big Data

Machine Learning

Combinatorial Optimisation



+

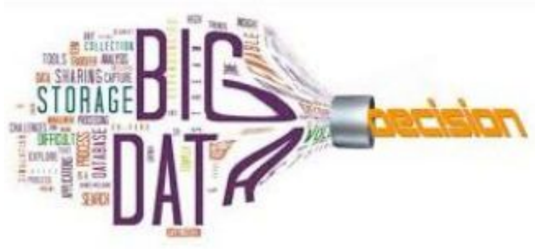
+

Idea 2: A View for Big Data Processing

Based on our view of Artificial Intelligence…

Studying Big Data Processing is crucial,
as it will be the start of the journey
for whatever problem you take!

Big Data



+

Machine Learning

+

Combinatorial Optimisation

Outline

Idea 3:

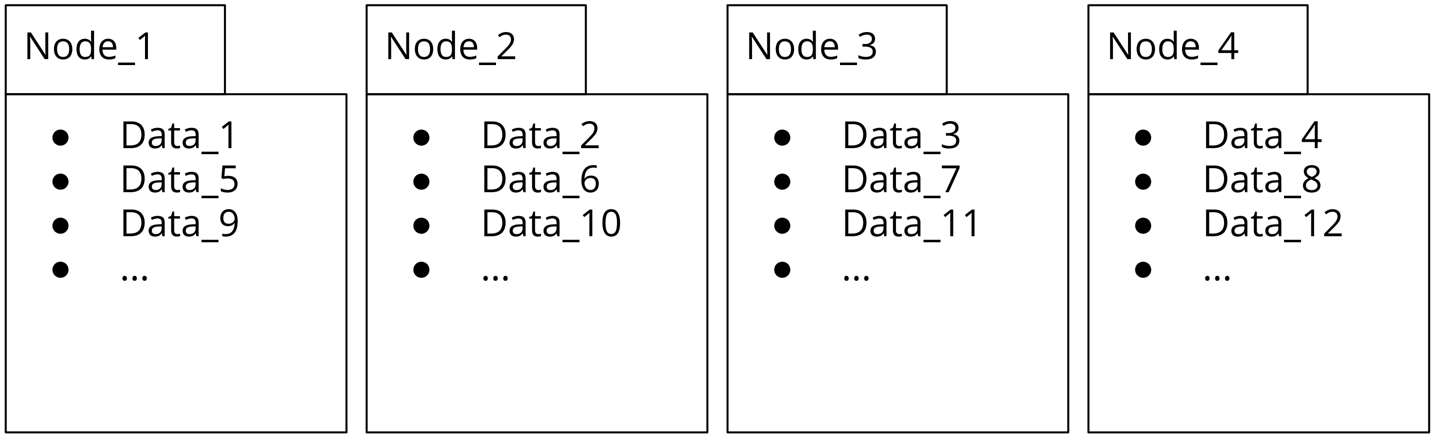
For Big Data to be Processed
Big Data Must be Previously Stored

Idea 3: Big Data Storage

Big Data must be
efficiently organised
when it is stored
for its further processing.

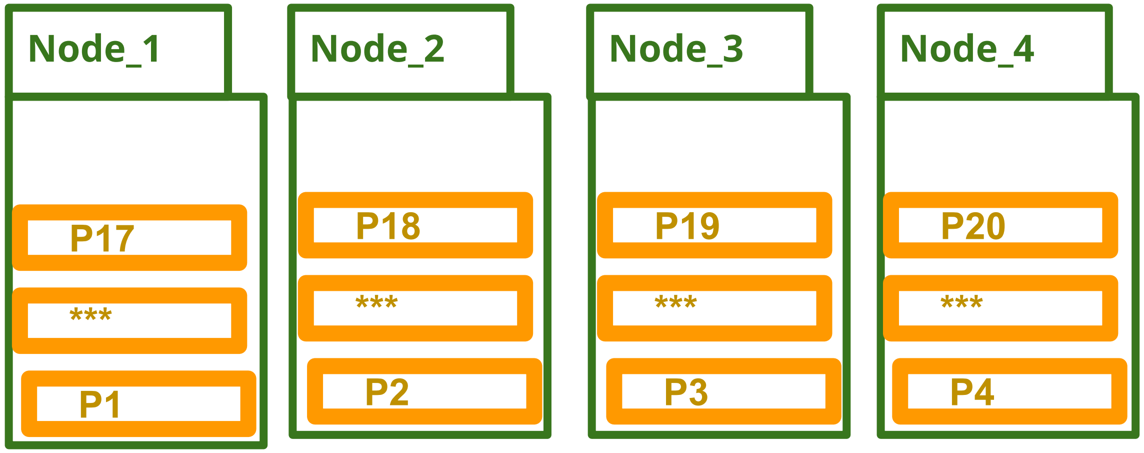
Idea 3: Big Data Storage

Data is organised and distributed among the nodes according to certain **policies** (e.g., split, migrate and auto-scale).



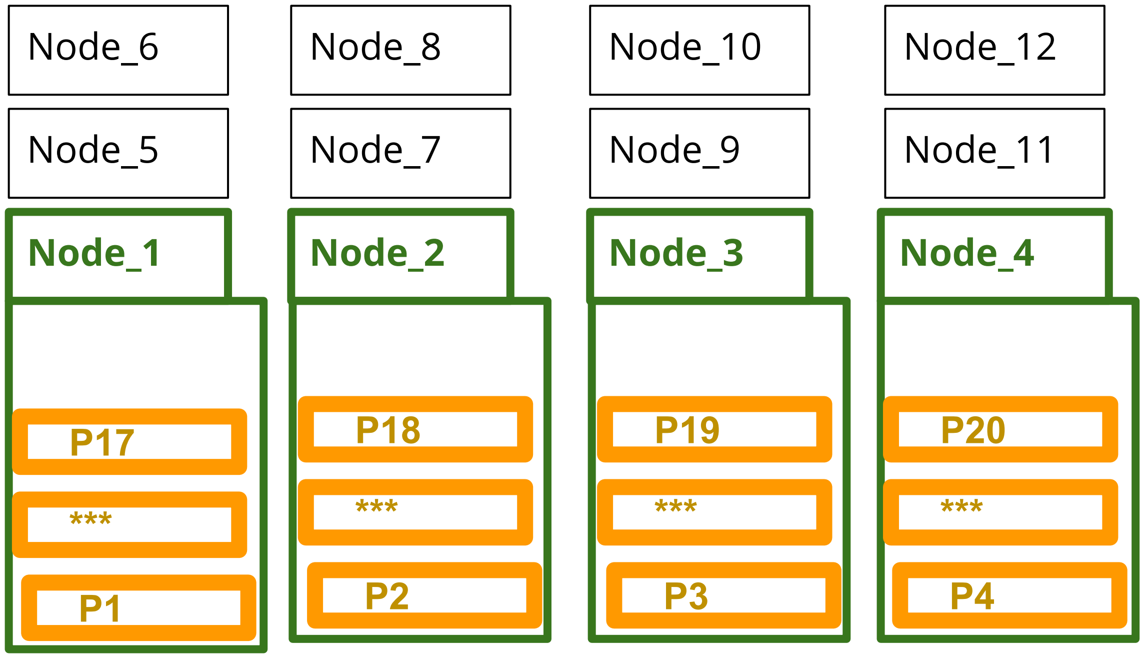
Idea 3: Big Data Storage

Data items are amalgamated among partitions.



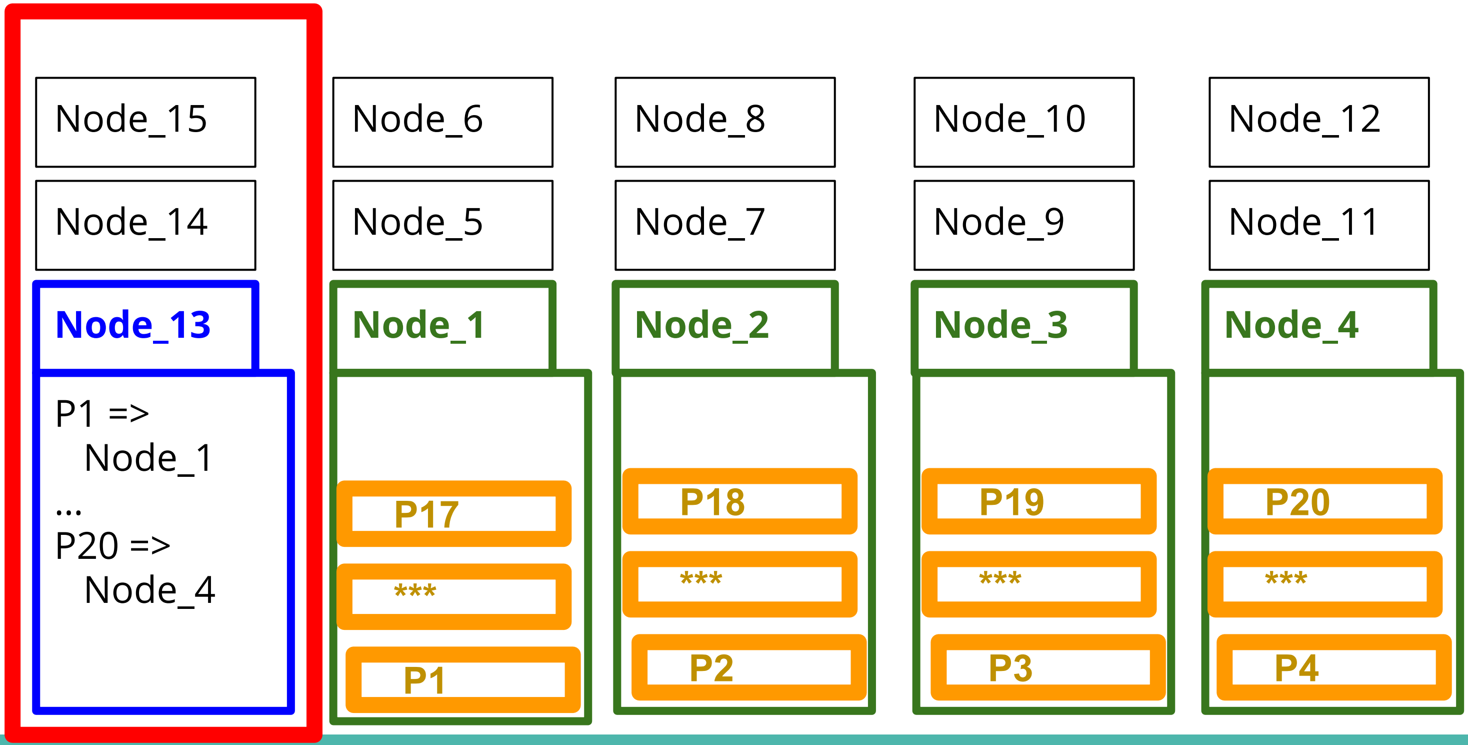
Idea 3: Big Data Storage

Data partitions are replicated for fault tolerance purposes.



Idea 3: Big Data Storage

Data is easily accessible via a centralised table of contents mapping each data item to the node hosting it.



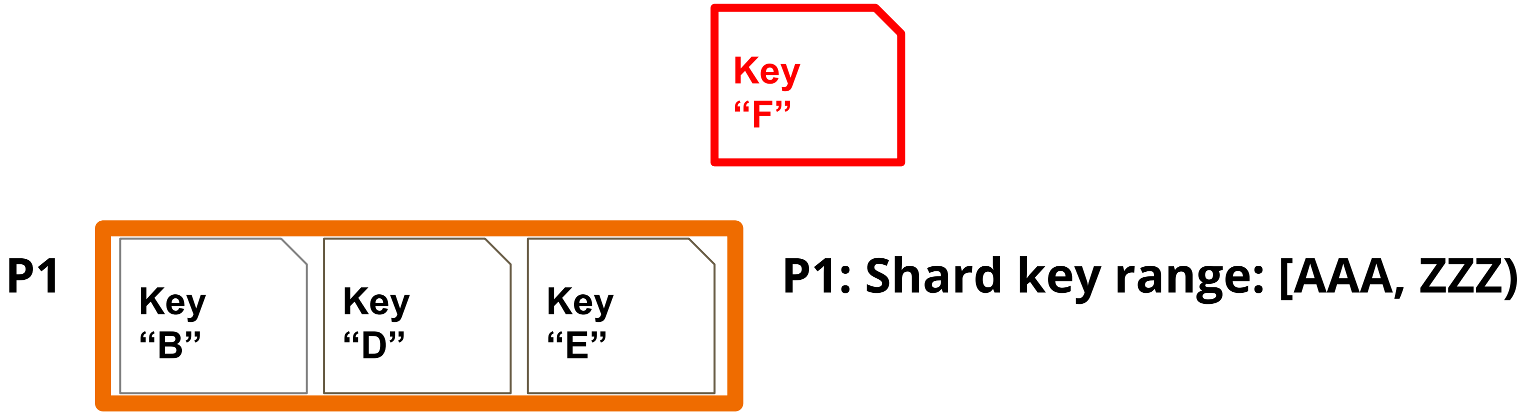
Outline

Idea 4:

Implementing split, migrate and auto-scale policies is not complex.

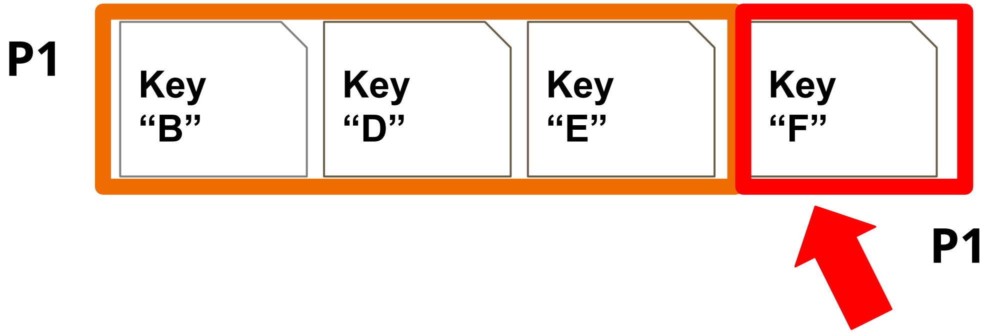
Idea 4: Implementing Split, Migrate and Auto-Scale

Split



Idea 4: Implementing Split, Migrate and Auto-Scale

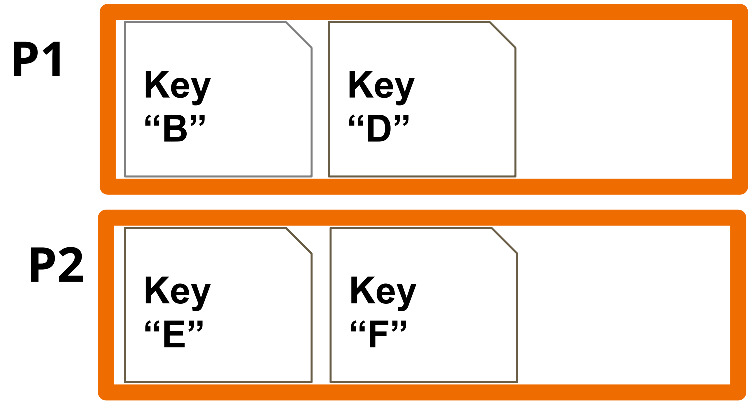
Split



P1: Shard key range: [AAA, ZZZ)

Idea 4: Implementing Split, Migrate and Auto-Scale

Split

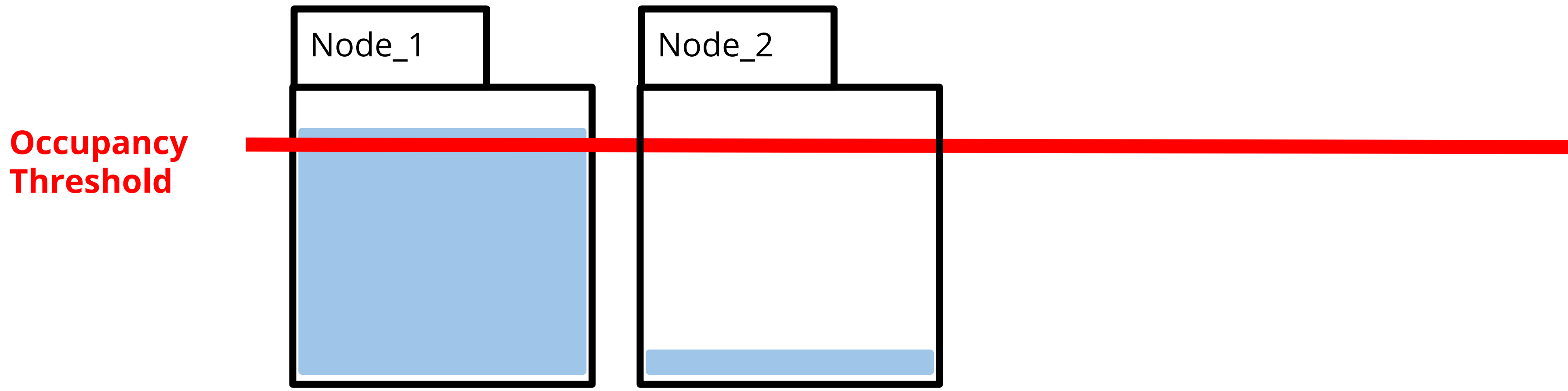


P1: Shard key range: [AAA, E)

P2: Shard key range: [E, ZZZ)

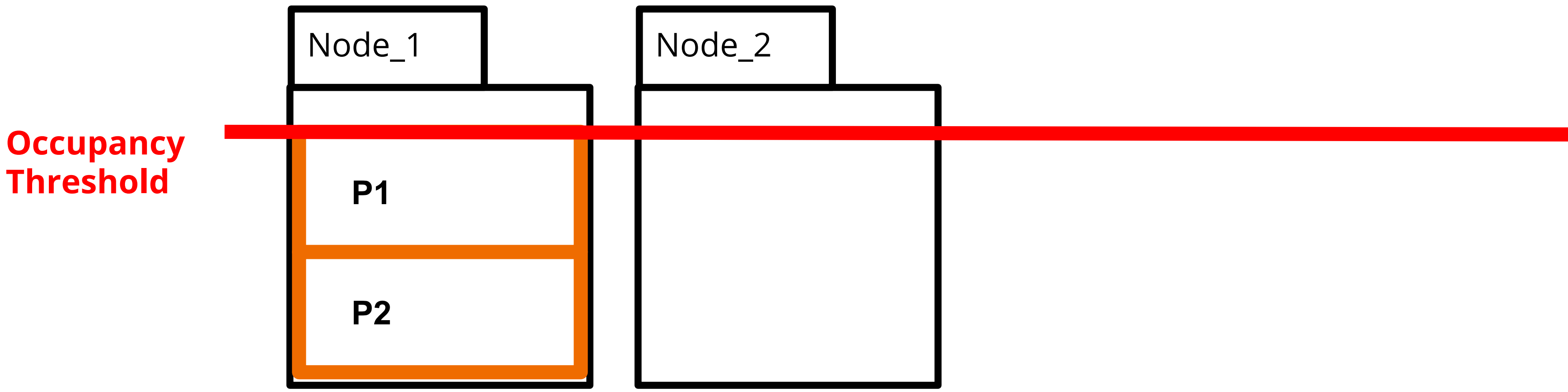
Idea 4: Implementing Split, Migrate and Auto-Scale

Migration.



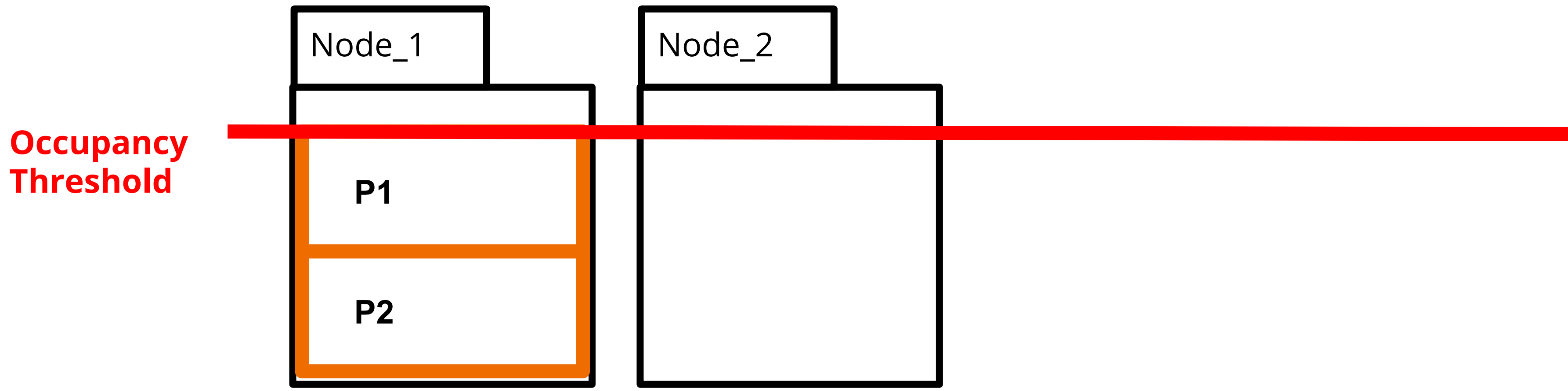
Idea 4: Implementing Split, Migrate and Auto-Scale

Migration.



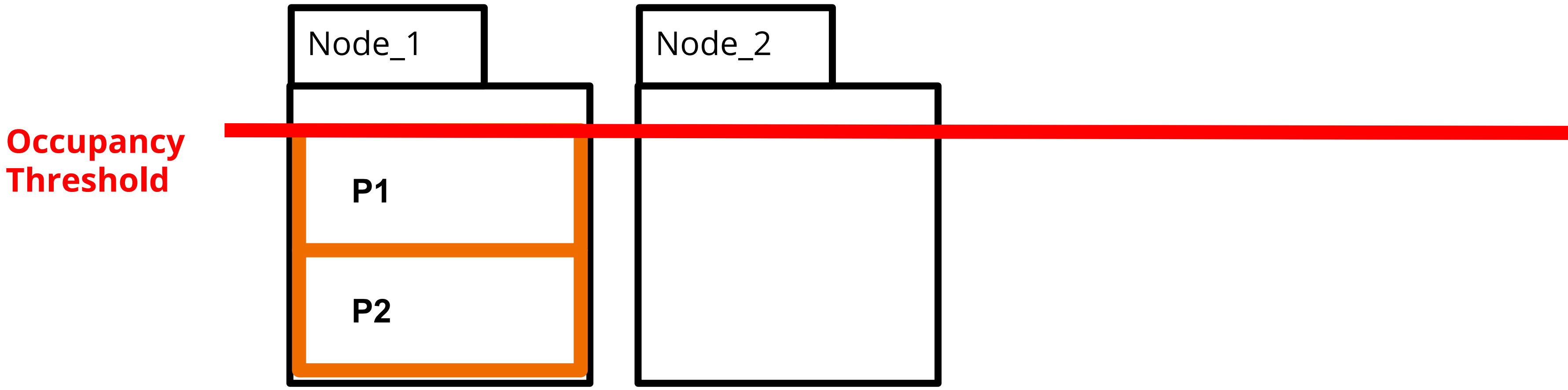
Idea 4: Implementing Split, Migrate and Auto-Scale

Migration.



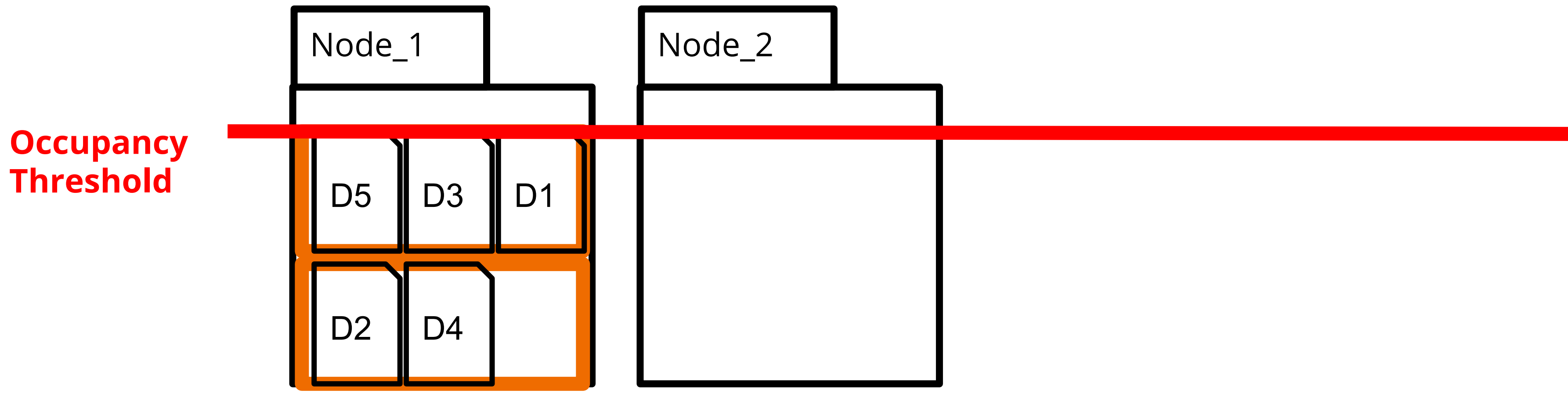
Idea 4: Implementing Split, Migrate and Auto-Scale

Migration.



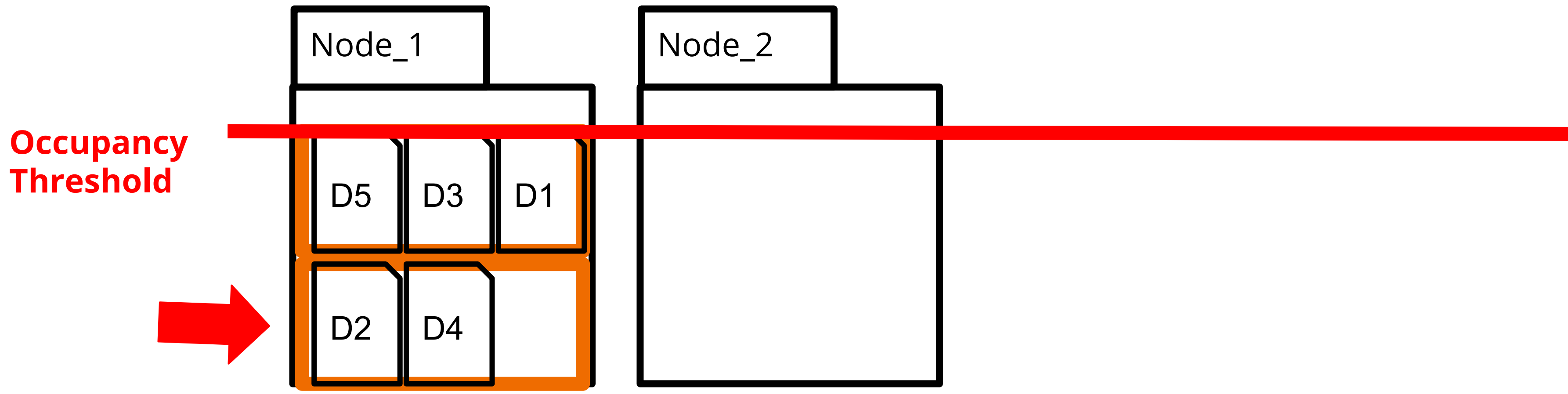
Idea 4: Implementing Split, Migrate and Auto-Scale

Migration.



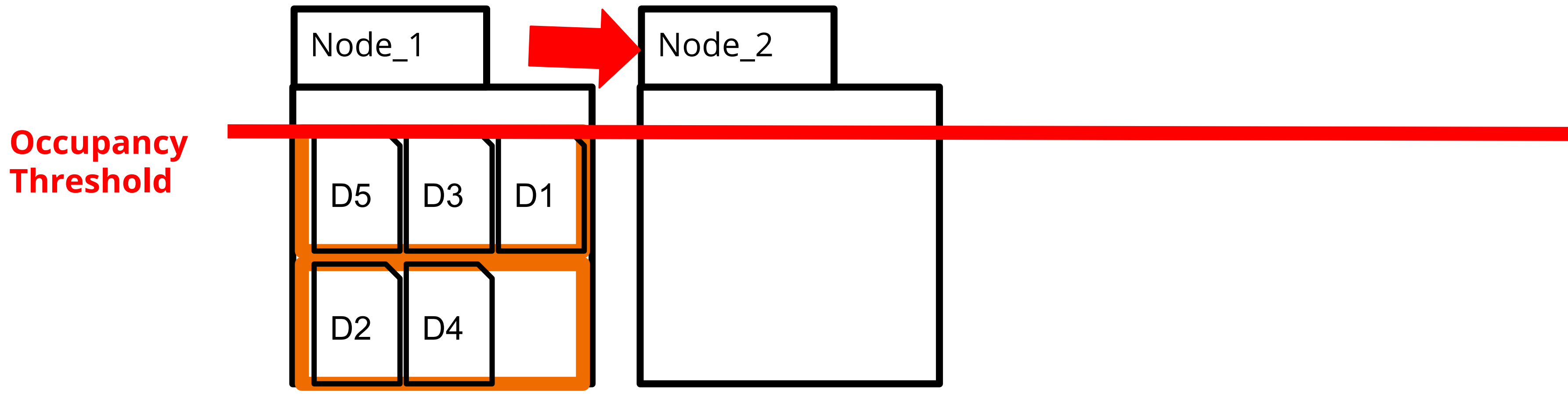
Idea 4: Implementing Split, Migrate and Auto-Scale

Migration.



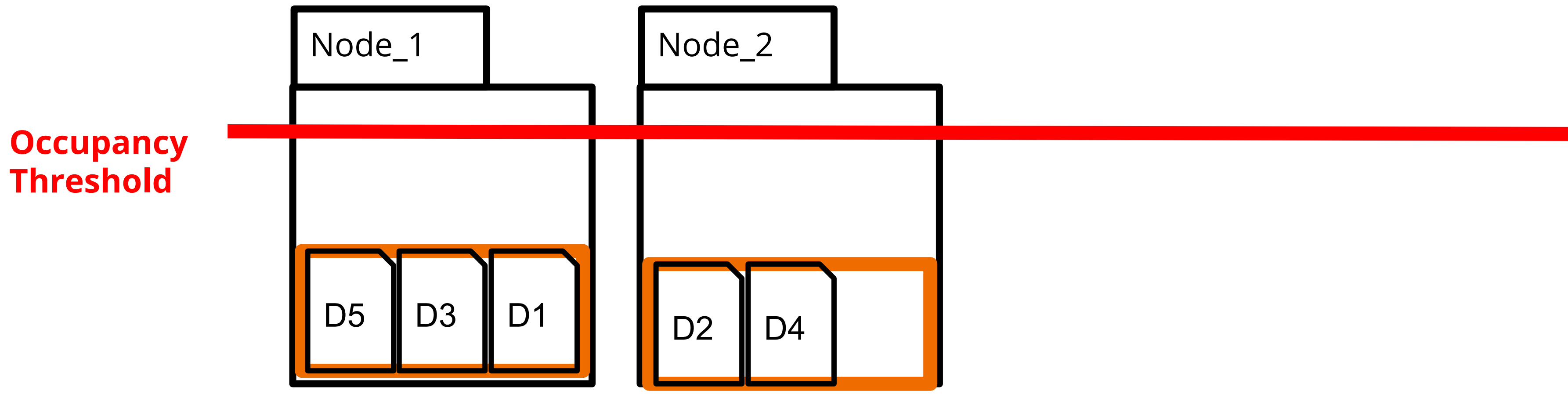
Idea 4: Implementing Split, Migrate and Auto-Scale

Migration.



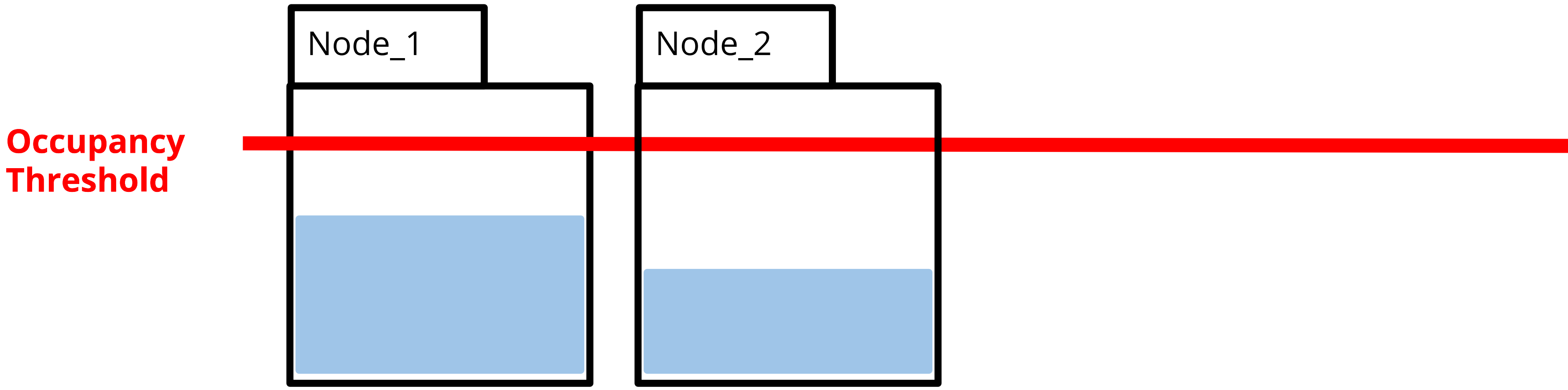
Idea 4: Implementing Split, Migrate and Auto-Scale

Migration.



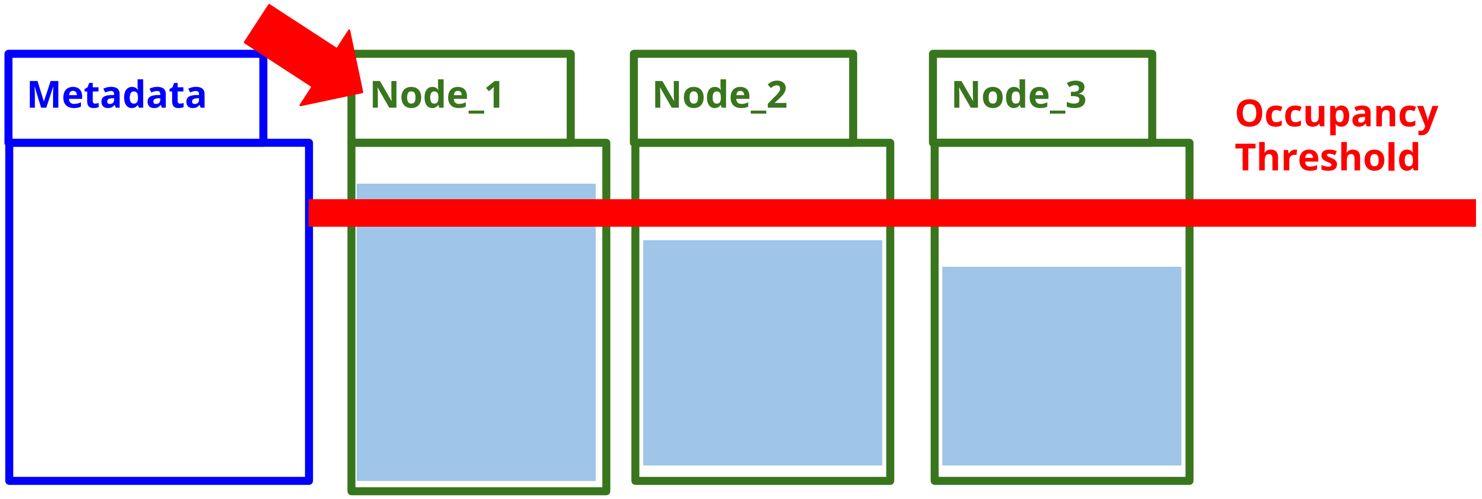
Idea 4: Implementing Split, Migrate and Auto-Scale

Migration.



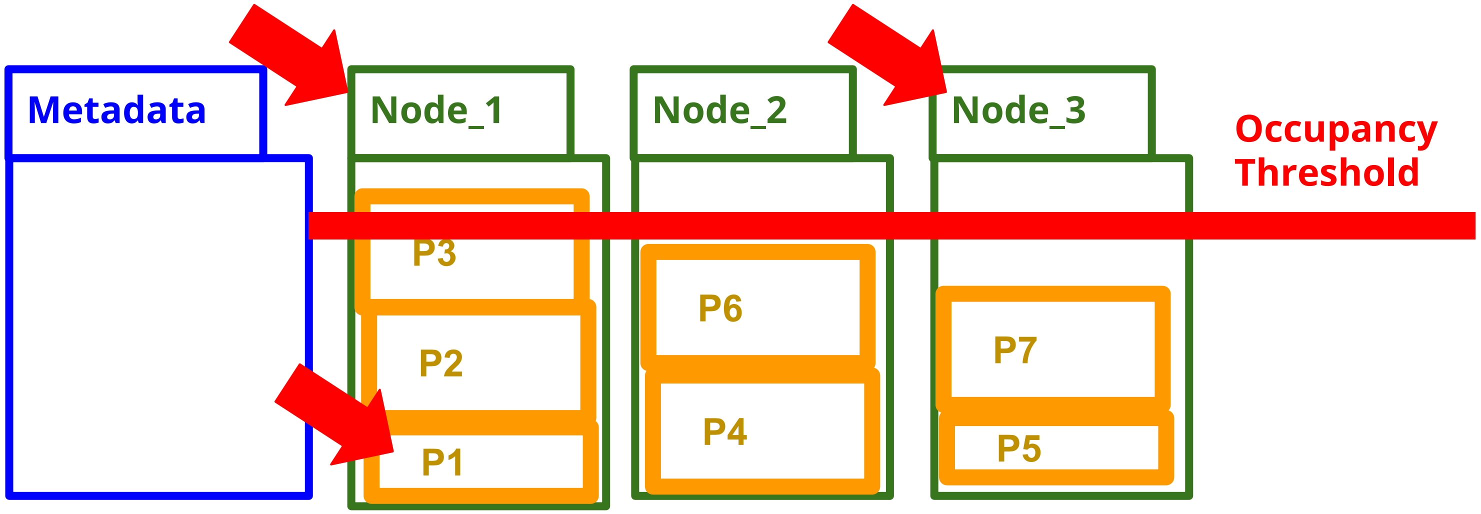
Idea 4: Implementing Split, Migrate and Auto-Scale

Auto-scale:



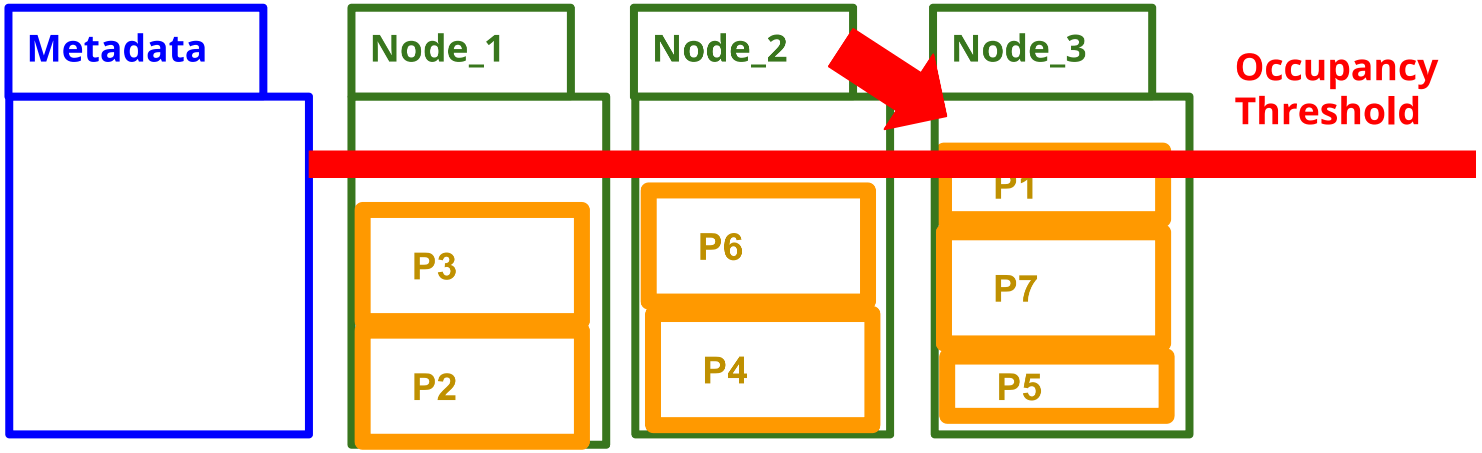
Idea 4: Implementing Split, Migrate and Auto-Scale

Auto-scale:



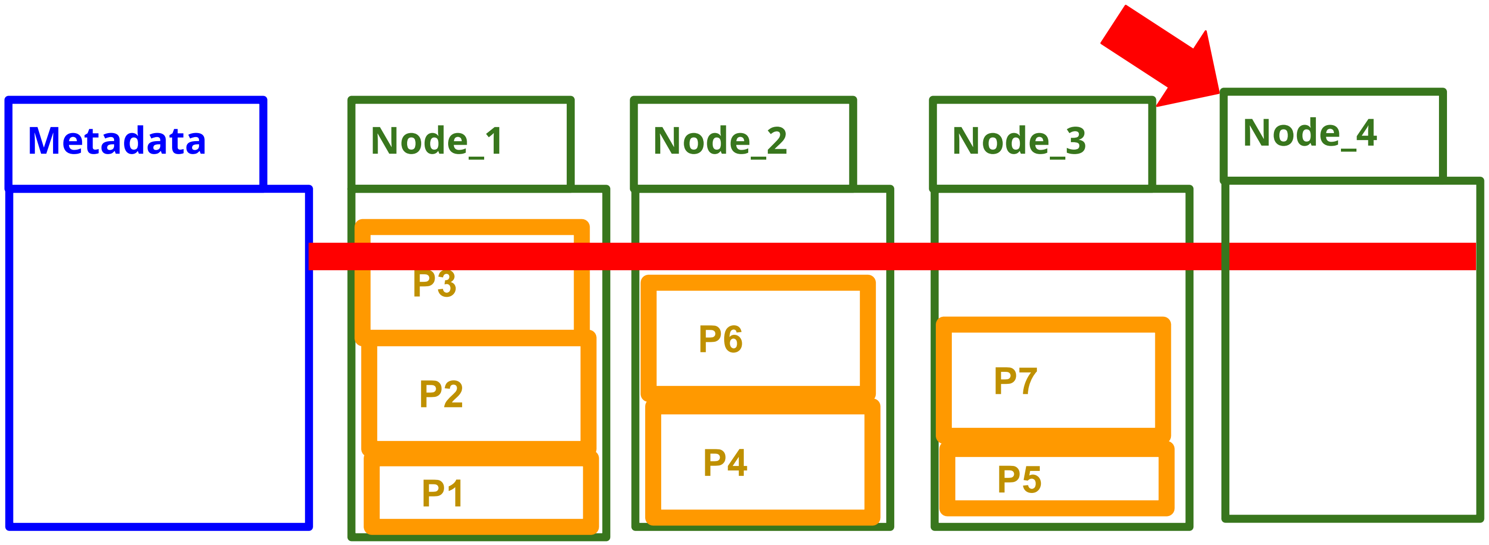
Idea 4: Implementing Split, Migrate and Auto-Scale

Auto-scale:



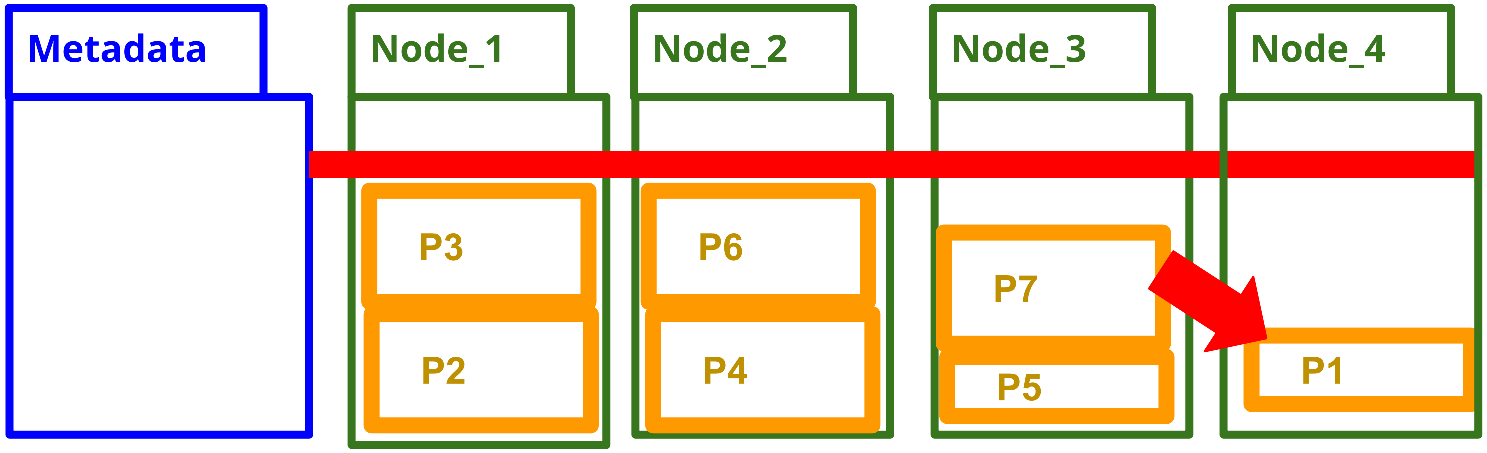
Idea 4: Implementing Split, Migrate and Auto-Scale

Auto-scale:



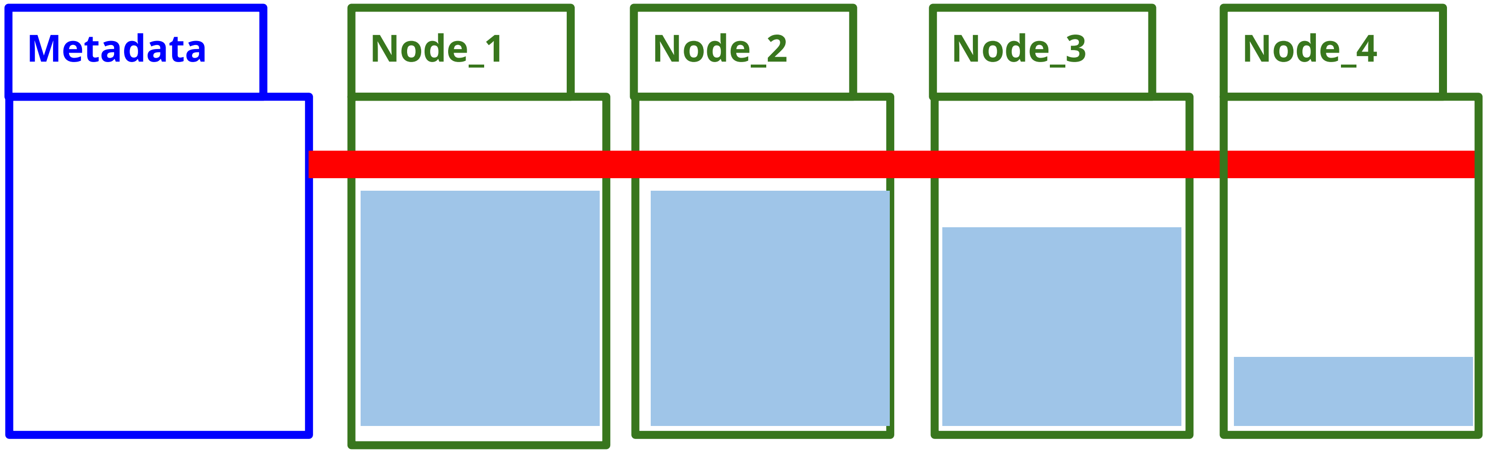
Idea 4: Implementing Split, Migrate and Auto-Scale

Auto-scale:



Idea 4: Implementing Split, Migrate and Auto-Scale

Auto-scale:



Outline

Idea 5:

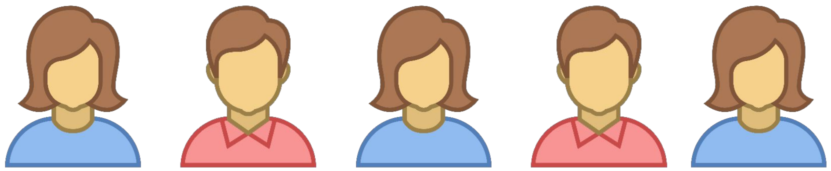
A View for Interesting Problems

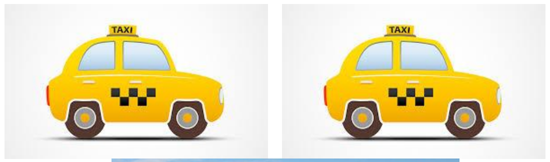
Idea 5: A View for Interesting Problems

Interesting problems
might involve a *complex* formulation…

Google HashCode'18 Self-driving rides

Google
Hash Code
Team up to solve an engineering problem from Google
Are you up for the challenge?





Idea 5: A View for Interesting Problems

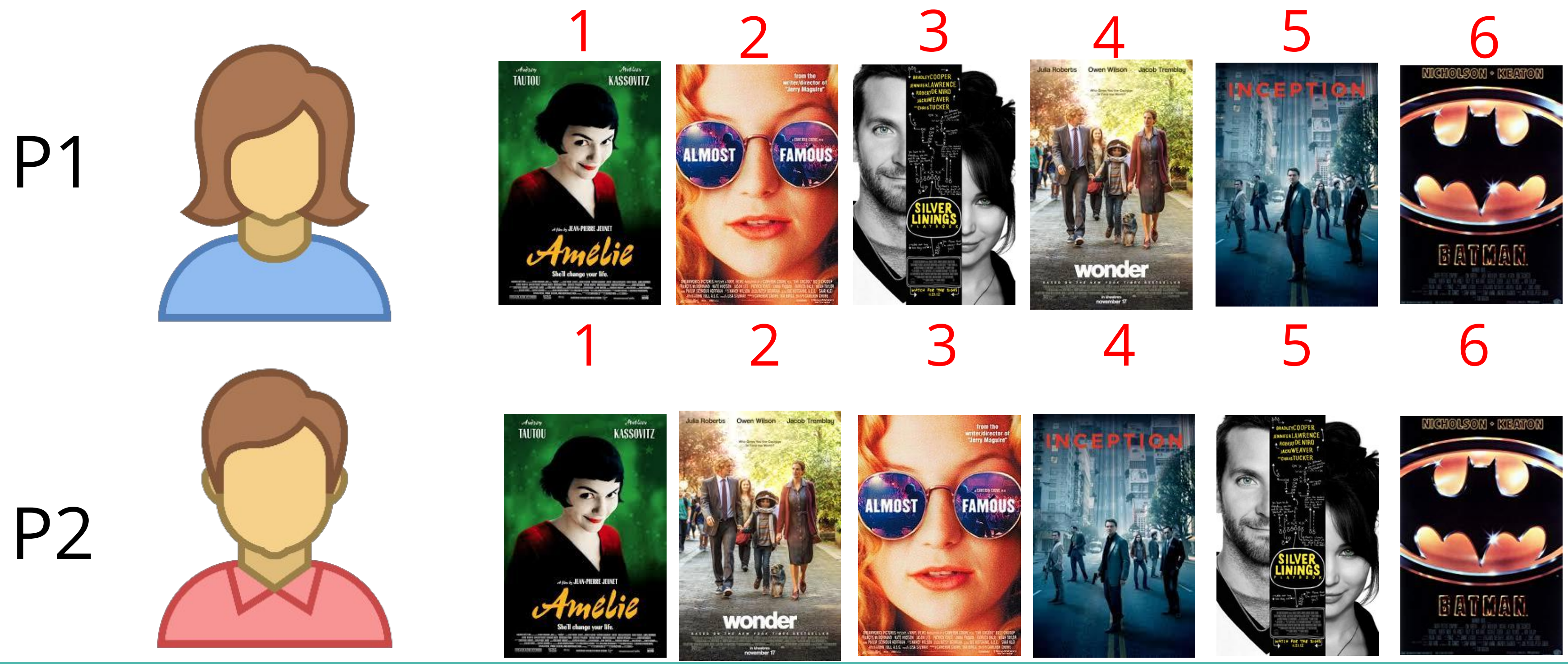
Interesting problems
...might involve a *simple* formulation

List Inversions

	1	2	3	4	5	6
A	1	3	5	2	4	6

Idea 5: A View for Interesting Problems

Interesting problems
…might involve a *simple* formulation



Idea 5: A View for Interesting Problems

But, whether simple or complex formulated, interesting problems are <u>truly</u> interesting…

Idea 5: A View for Interesting Problems

But, whether simple or complex formulated, interesting problems are truly interesting…

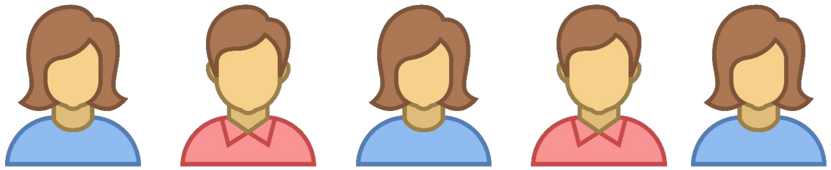
at scale! *(when computational challenging)*

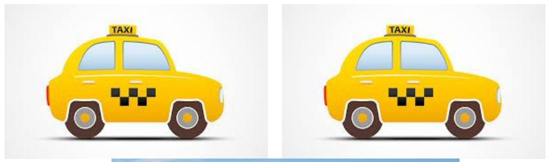
Idea 5: A View for Interesting Problems

But, whether simple or complex formulated, interesting problems are truly interesting…

Google HashCode'18
Self-driving rides

Google
Hash Code
Team up to solve an engineering problem from Google
Are you up for the challenge?



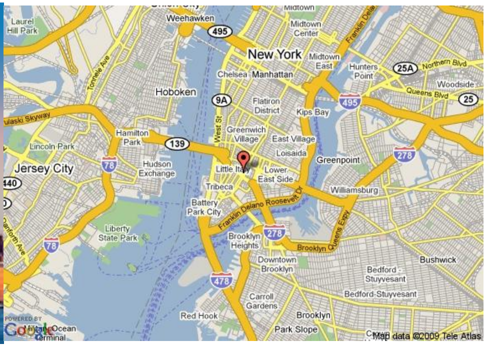


Idea 5: A View for Interesting Problems

But, whether simple or complex formulated, interesting problems are <u>truly</u> interesting...
at scale! ***(when computational challenging)***

Google HashCode'18
Self-driving rides

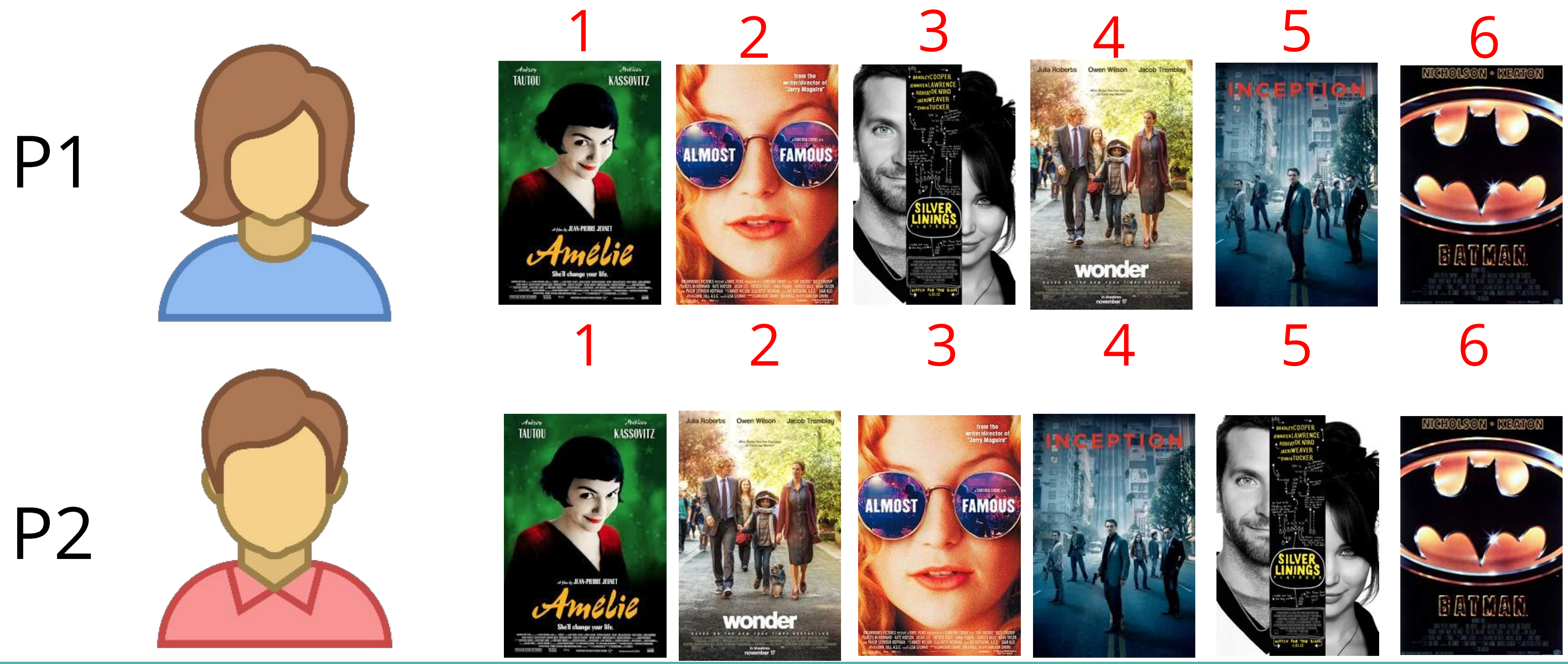
Google
Hash Code
Team up to solve an engineering problem from Google
Are you up for the challenge?



Idea 5: A View for Interesting Problems

But, whether simple or complex formulated, interesting problems are truly interesting...

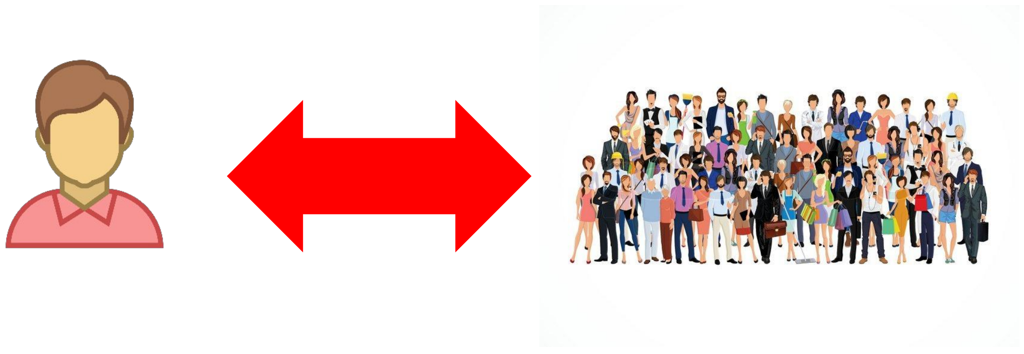
List Inversions



Idea 5: A View for Interesting Problems

But, whether simple or complex formulated, interesting problems are <u>truly</u> interesting…
at scale! *(when computational challenging)*

List Inversions



	1	2	3	4	…	n
A1	1	3	5	2	..	6

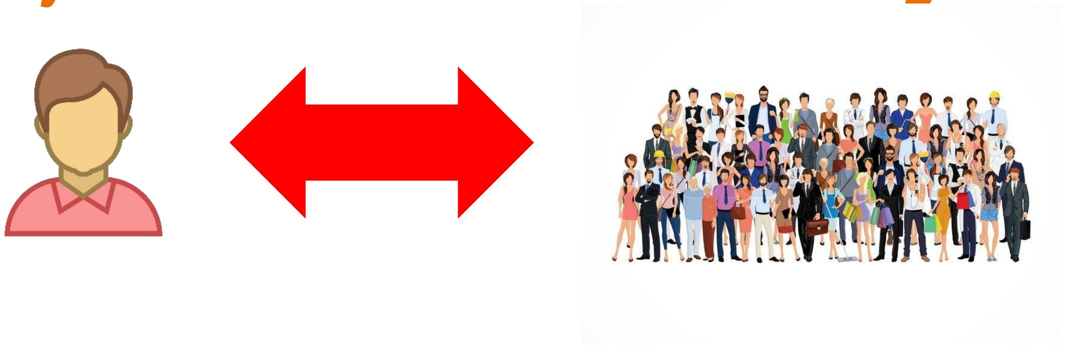
	1	2	3	4	…	n
Ak	5	9	4	1	..	2

Outline

Idea 6:

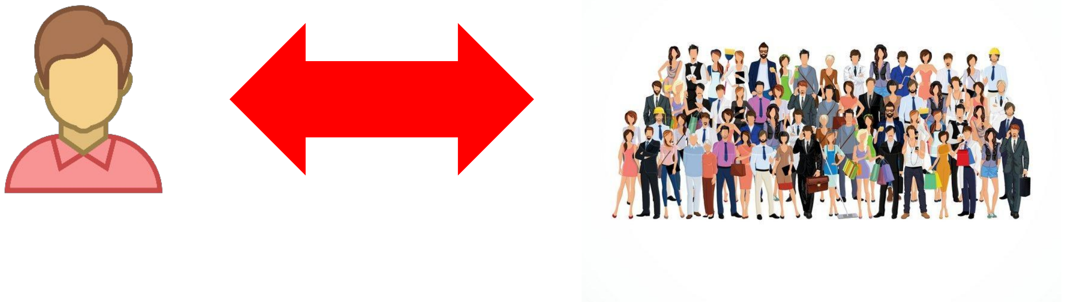
Scalability Tackled Via Distributed Programming

Idea 6: Scalability Tackled Via Distributed Programming



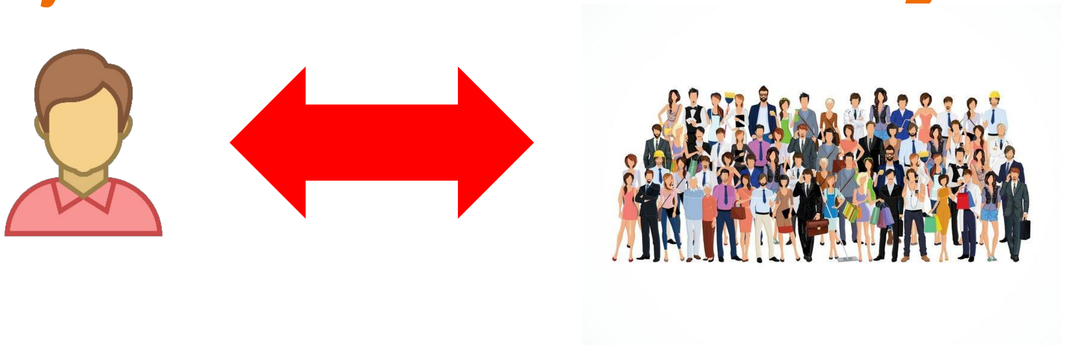
The problem workload can be balanced among multiple cores.

Idea 6: Scalability Tackled Via Distributed Programming



The problem workload can be balanced among multiple cores.

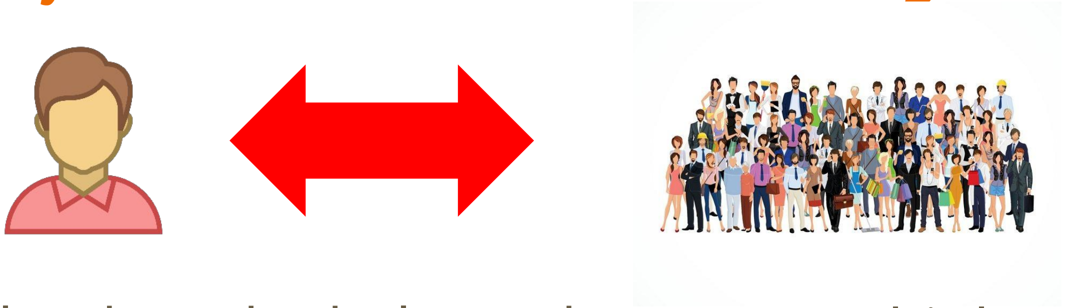
Idea 6: Scalability Tackled Via Distributed Programming



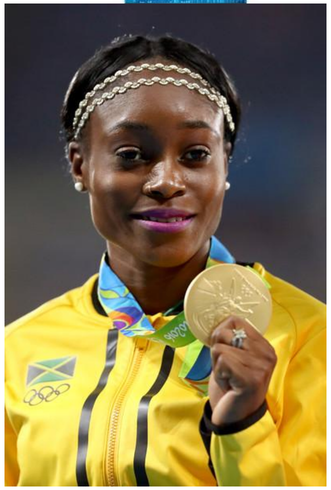
The problem workload can be balanced among multiple cores.

Shaunae Miller (400m)

Idea 6: Scalability Tackled Via Distributed Programming

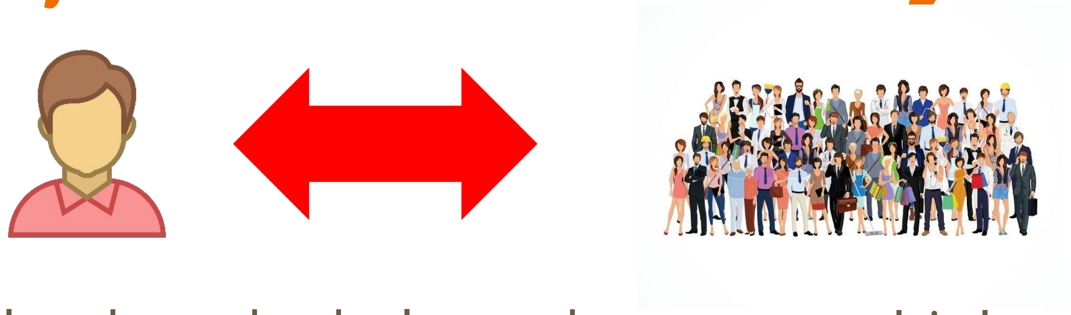


The problem workload can be balanced among multiple cores.



Elaine Thompson (100m) Tori Bowie (100m) Shelly-Ann Fraser-Pryce (100m) Marie-Josee Ta Lou (100m)

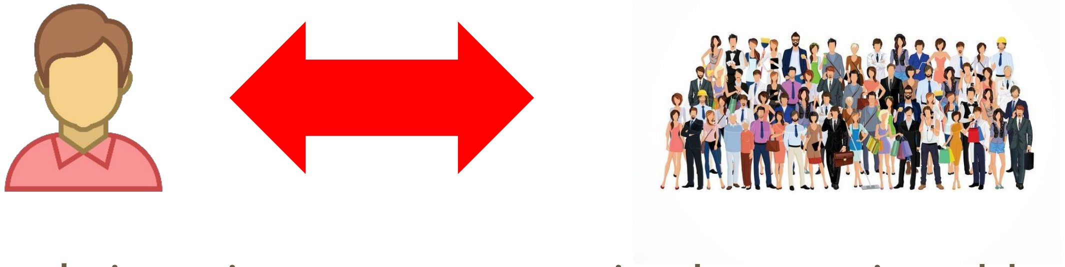
Idea 6: Scalability Tackled Via Distributed Programming



The problem workload can be balanced among multiple cores.

- **TOTAL COMPUTATION TIME:** Same in both approaches.
- **TOTAL ELAPSED TIME:** Distributed approach is ¼ of classical single-thread sequential approach.

Idea 6: Scalability Tackled Via Distributed Programming



The elapsed time improvement is determined by the number of cores (size of the cluster)

Outline

Idea 7:

Distributed Programming
Centralised Coordination

Idea 7: Distributed Programming Centralised Coordination

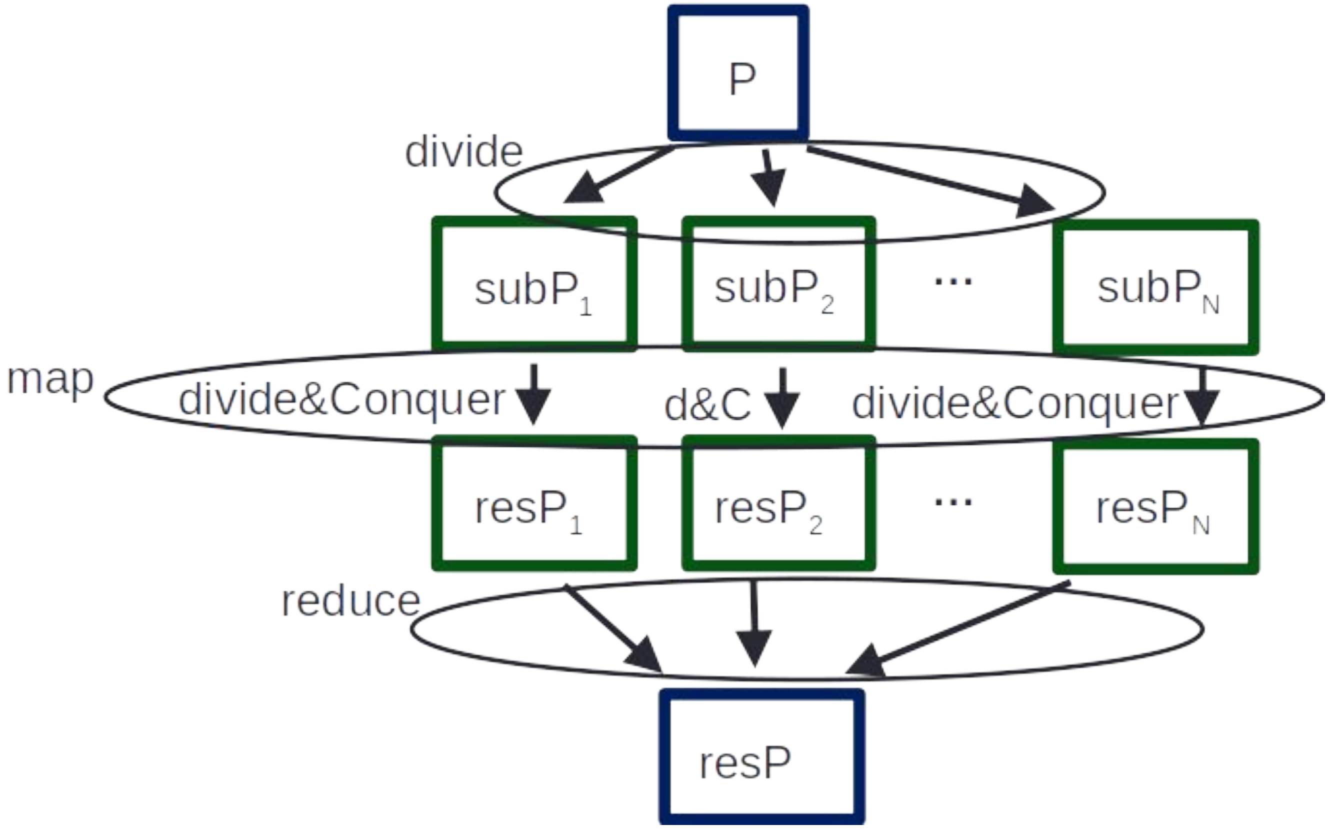
Passing from sequential to distributed mode requires the use of a meta-algorithm, in charge of controlling the distributed execution.

Meta-algorithm core coordinating that the job is done

Working cores actually doing the job

Idea 7: Distributed Programming Centralised Coordination

This meta-algorithm follows the **divide-map-reduce** approach of the classical Divide and Conquer programming paradigm!

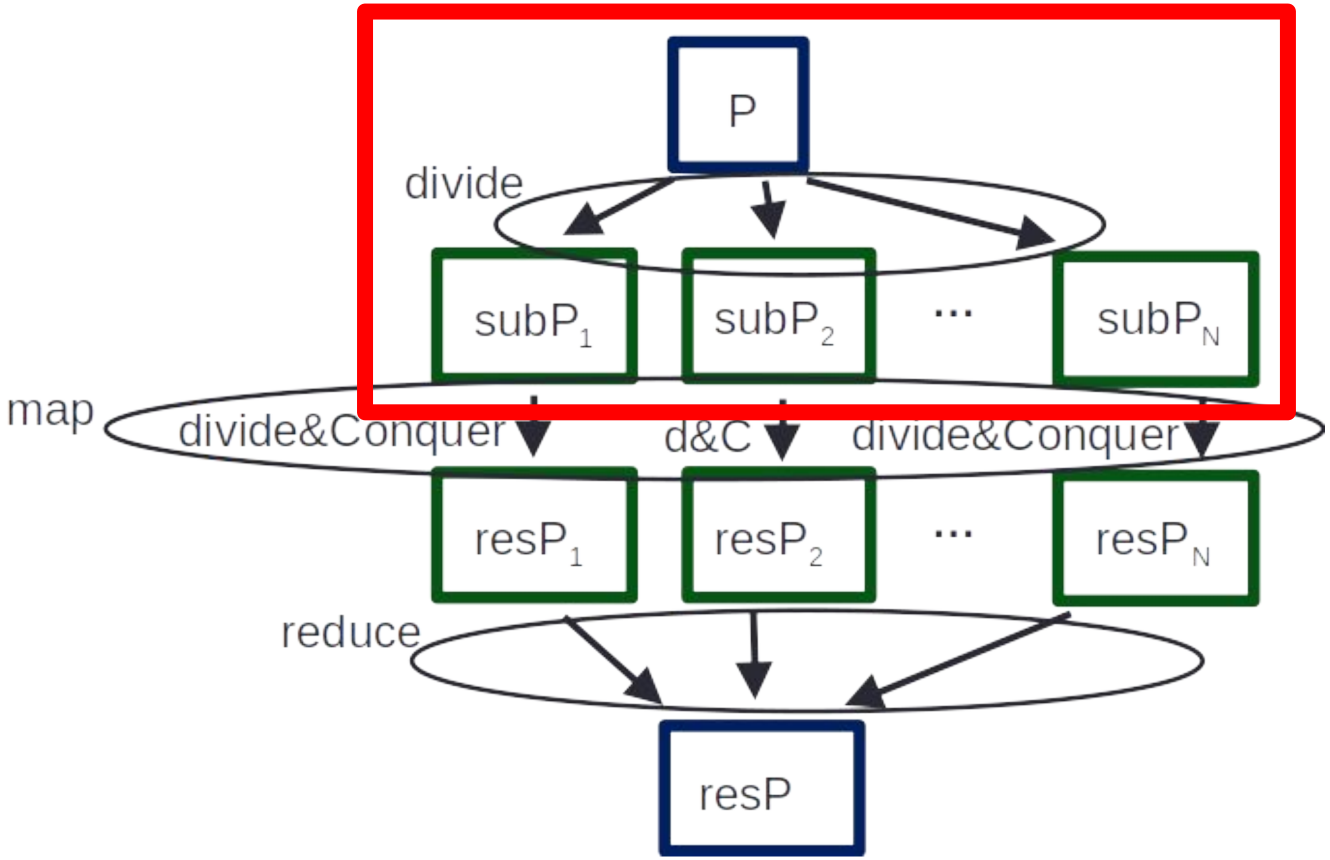


Idea 7: Distributed Programming Centralised Coordination

This meta-algorithm follows the **divide-map-reduce** approach of the classical Divide and Conquer programming paradigm!

1. **DIVIDE STAGE.**

It divides the original problem by splitting it into *n* sub-parts, to be assigned to the working cores.

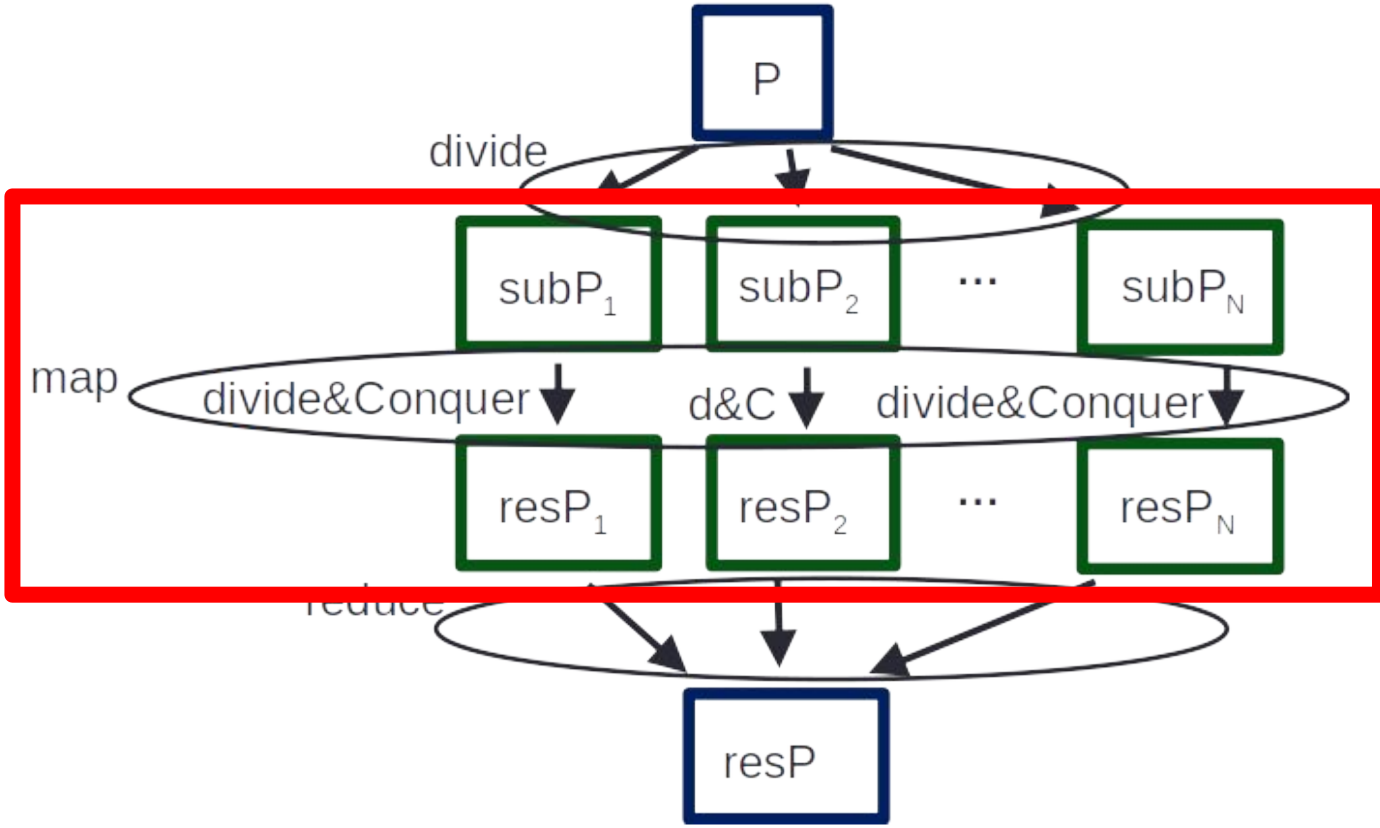


Idea 7: Distributed Programming Centralised Coordination

This meta-algorithm follows the **divide-map-reduce** approach of the classical Divide and Conquer programming paradigm!

2. **MAP STAGE**

Each working core solves its sub-part separately.

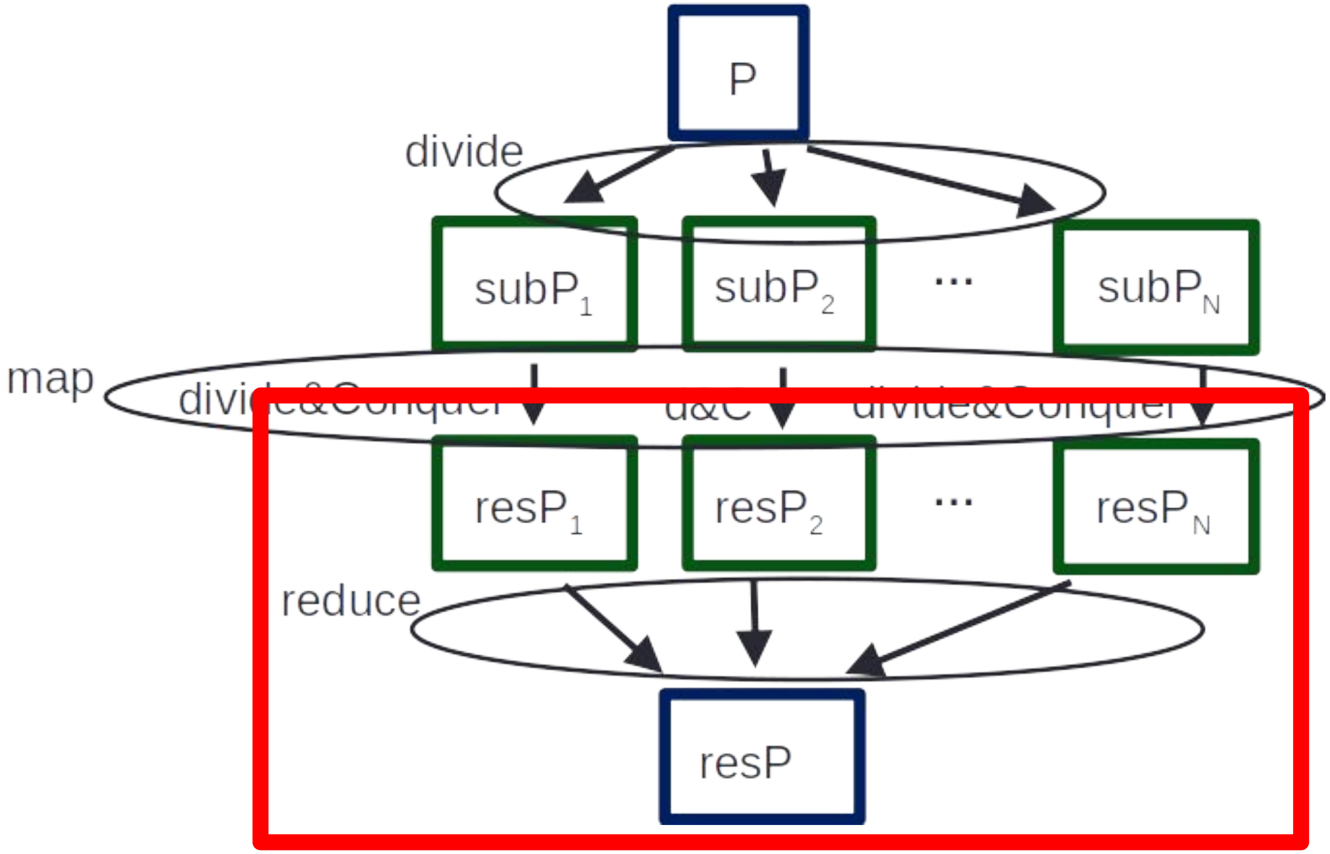


Idea 7: Distributed Programming Centralised Coordination

This meta-algorithm follows the **divide-map-reduce** approach of the classical Divide and Conquer programming paradigm!

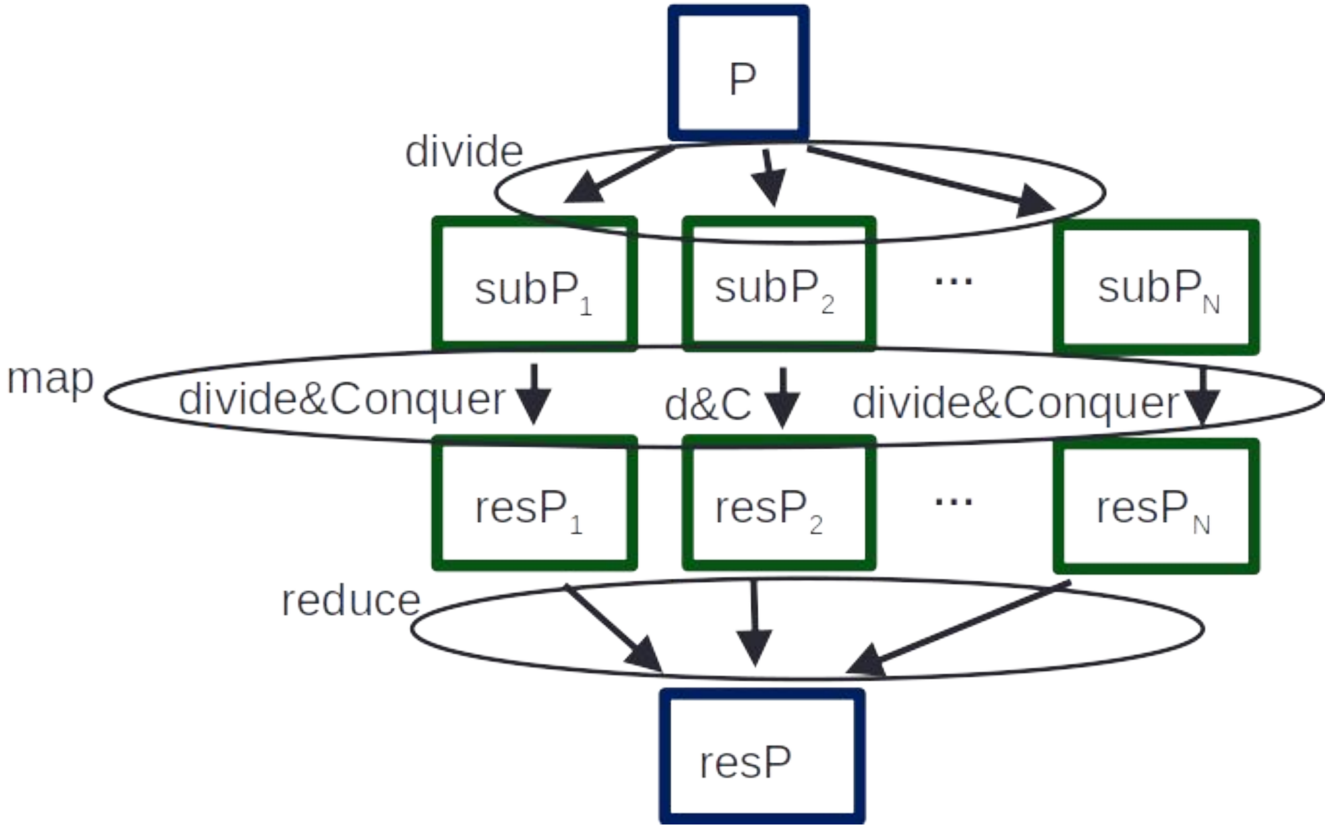
3. DIVIDE STAGE

The sub-part solutions found by the working cores are combined *(this additional combination work is also done by working cores)* so as to get the solution to the original problem.



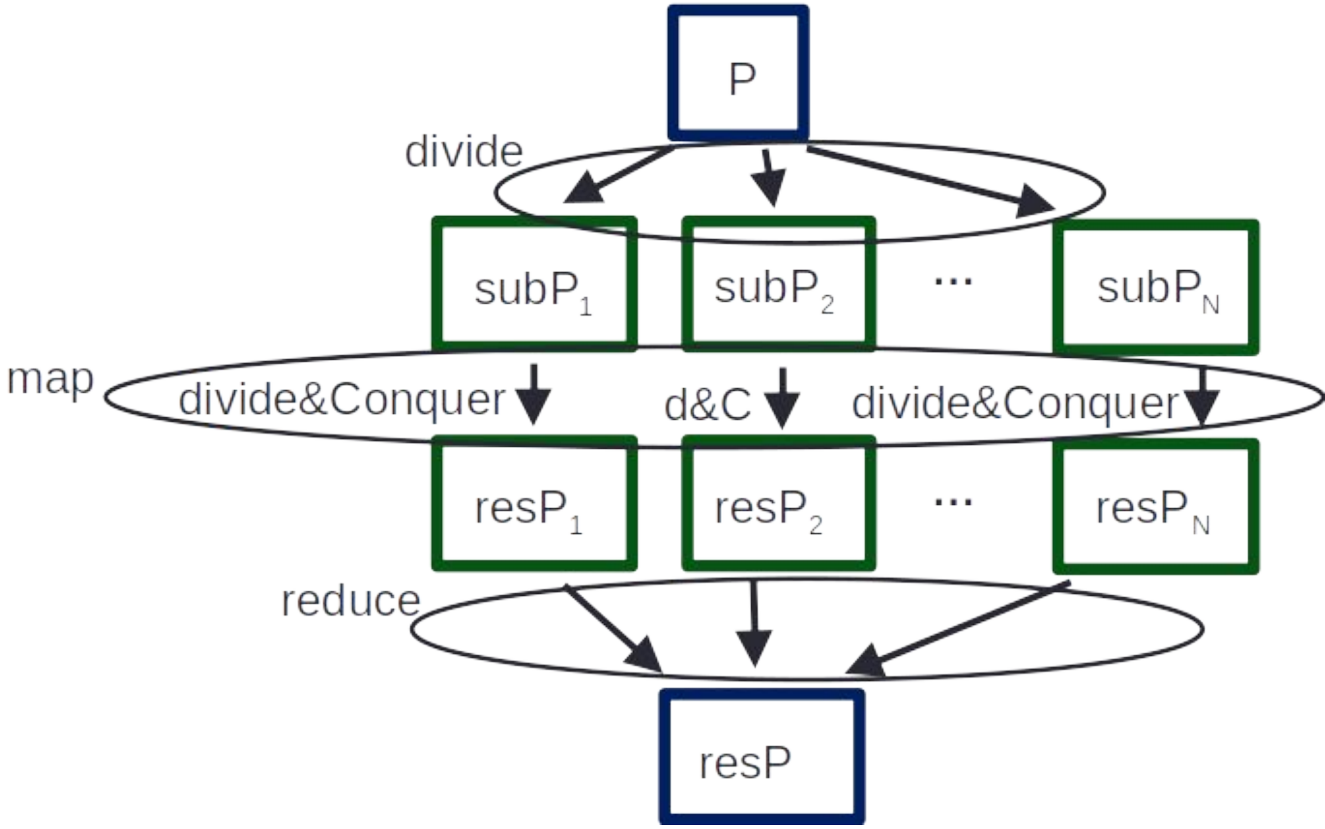
Idea 7: Distributed Programming Centralised Coordination

Now, programming this meta-algorithm is difficult.



Idea 7: Distributed Programming Centralised Coordination

Moreover, the meta-algorithm is problem domain-specific
(it might not necessarily be reusable for a different problem).



Outline

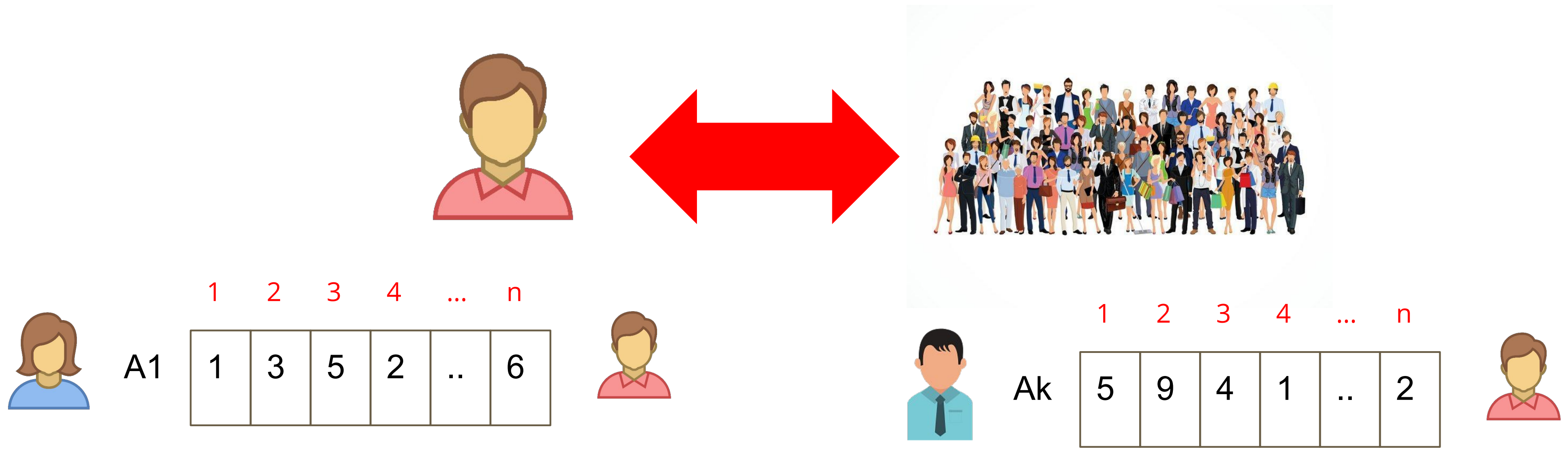
Idea 8:

Scalability Tackled Via
A More Efficient Algorithm

Idea 8: Scalability Tackled Via A More Efficient Algorithm

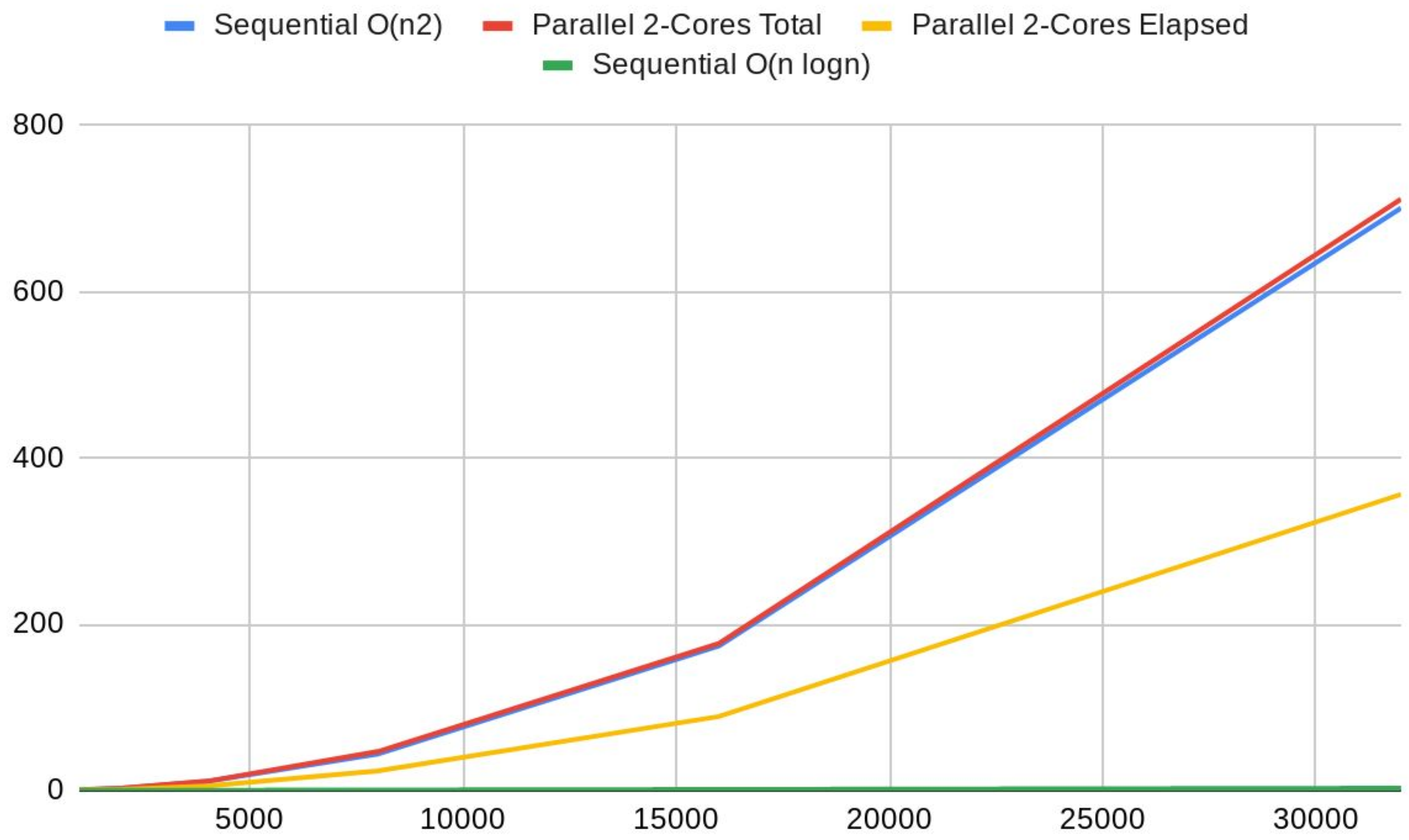
As computer scientists we always have to challenge our algorithms:
Can we do better?

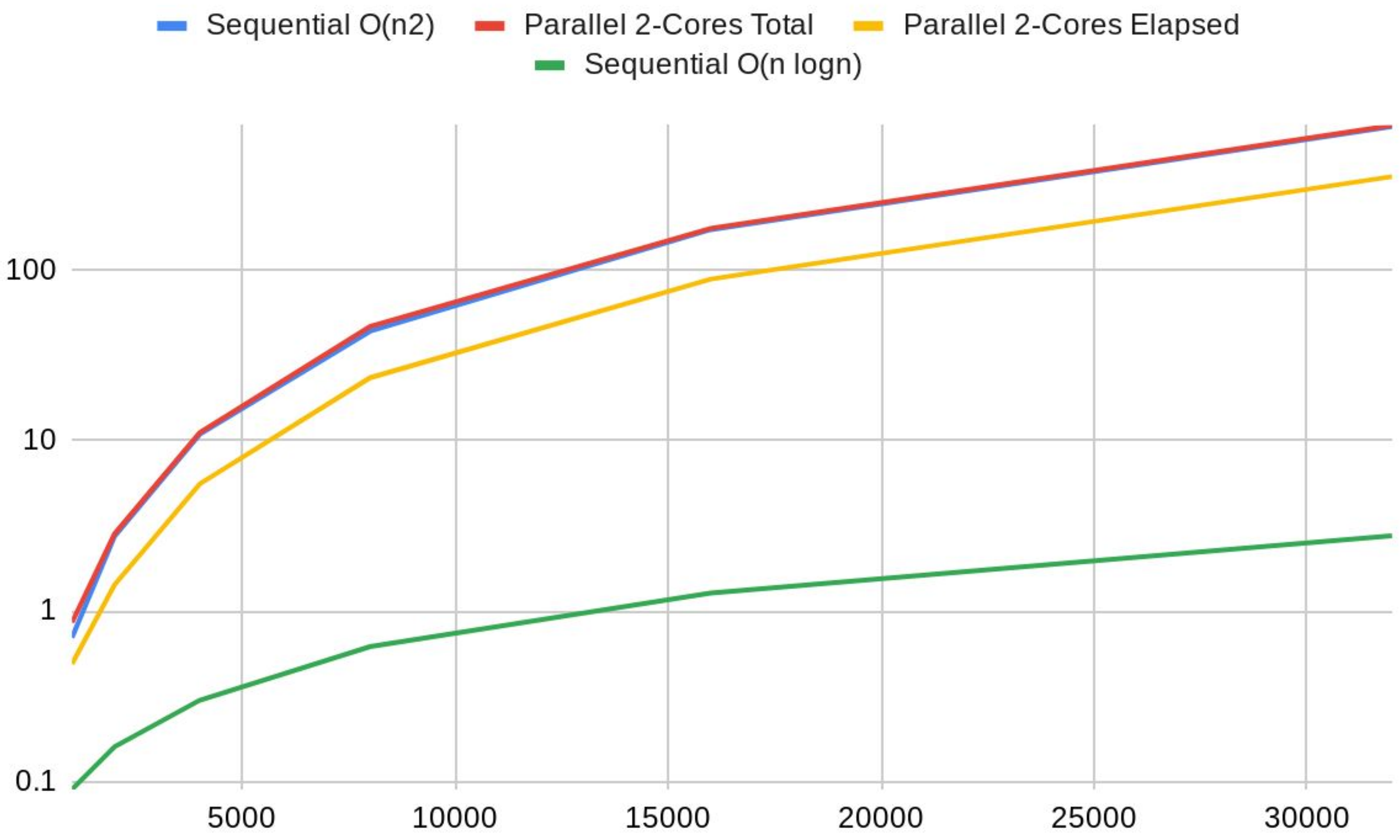
Idea 8: Scalability Tackled Via A More Efficient Algorithm



When evaluating our List Inversions problem ***at scale****...*

- Our MergeSort-based algorithm with complexity O(n log n) improved the sequential one with O(n^2) by orders of magnitude.


Sequential O(n2)
Parallel 2-Cores Total
Parallel 2-Cores Elapsed
Sequential O(n logn)
800
600
400
200
0
5000
10000
15000
20000
25000
30000



These are the results in logarithmic scale, as it is the only way to see the green line

Idea 8: Scalability Tackled Via A More Efficient Algorithm

The performance of one core using the O(n log n) algorithm was comparable to the performance of hundreds of cores working together using the O(n^2) algorithm.

O(n log n)

O(n^2)

Idea 8: Scalability Tackled Via A More Efficient Algorithm

So, all in all...
Yes! Distributed Programming is indeed the way to tackle Big Data Processing problems.

Idea 8: Scalability Tackled Via A More Efficient Algorithm

So, all in all...
Yes! Distributed Programming is indeed the way to tackle Big Data Processing problems.

However, we still must challenge our algorithms for them to be as efficient as possible.

Idea 8: Scalability Tackled Via A More Efficient Algorithm

So, all in all...
Yes! Distributed Programming is indeed the way to tackle
Big Data Processing problems.

However, we still must challenge our algorithms
for them to be as efficient as possible.

In many cases,
the performance improvement we get from these better algorithms
outperforms the improvement achieved by parallelization itself.

Outline

Idea 9:

Distributed Programming with Apache Spark

Idea 9: Distributed Programming with Apache Spark

In this module we have used
Apache Spark!

The state-of-the-art technology
for Big Data Processing
(based on distributed programming)

Idea 9: Distributed Programming with Apache Spark

Apache Spark is an

- open-source
- distributed
- general-purpose
- cluster-computing framework.

Idea 9: Distributed Programming with Apache Spark

Apache Spark is an

- open-source
- distributed
- general-purpose
- cluster-computing framework.

It has been designed to fit 3 purposes:

Be easy to use.

Be fast.

Be general.

Idea 9: Distributed Programming with Apache Spark

Spark itself is written in Scala, and runs on the Java Virtual Machine (JVM).

Spark offers simple APIs the proper Scala, and also in Java, Python and R.

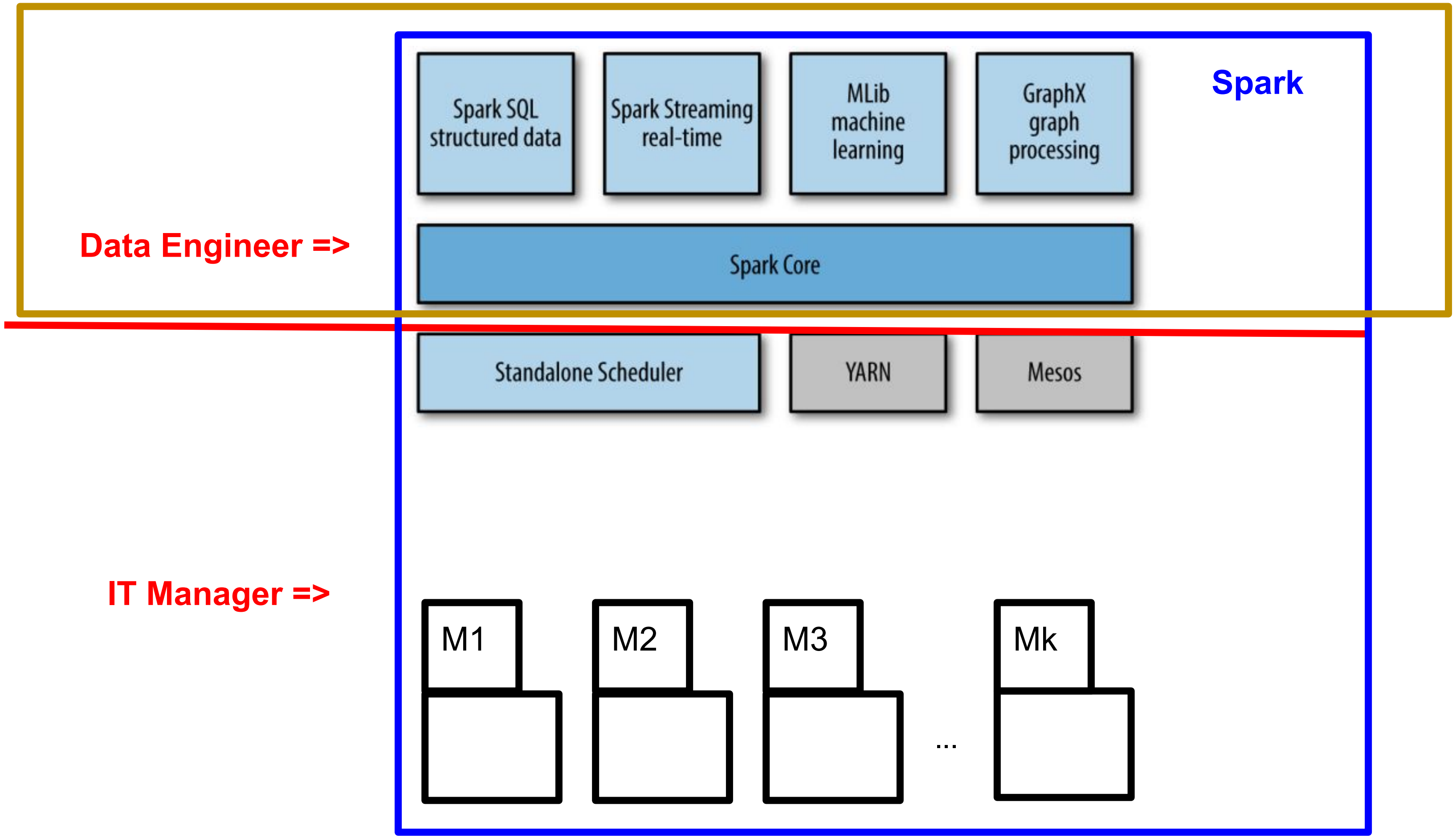
Idea 9: Distributed Programming with Apache Spark

Spark itself is written in Scala, and runs on the Java Virtual Machine (JVM).

Spark offers simple APIs the proper Scala, and also in Java, Python and R.
In our module we have focused mainly in Python (and sometimes in Scala).

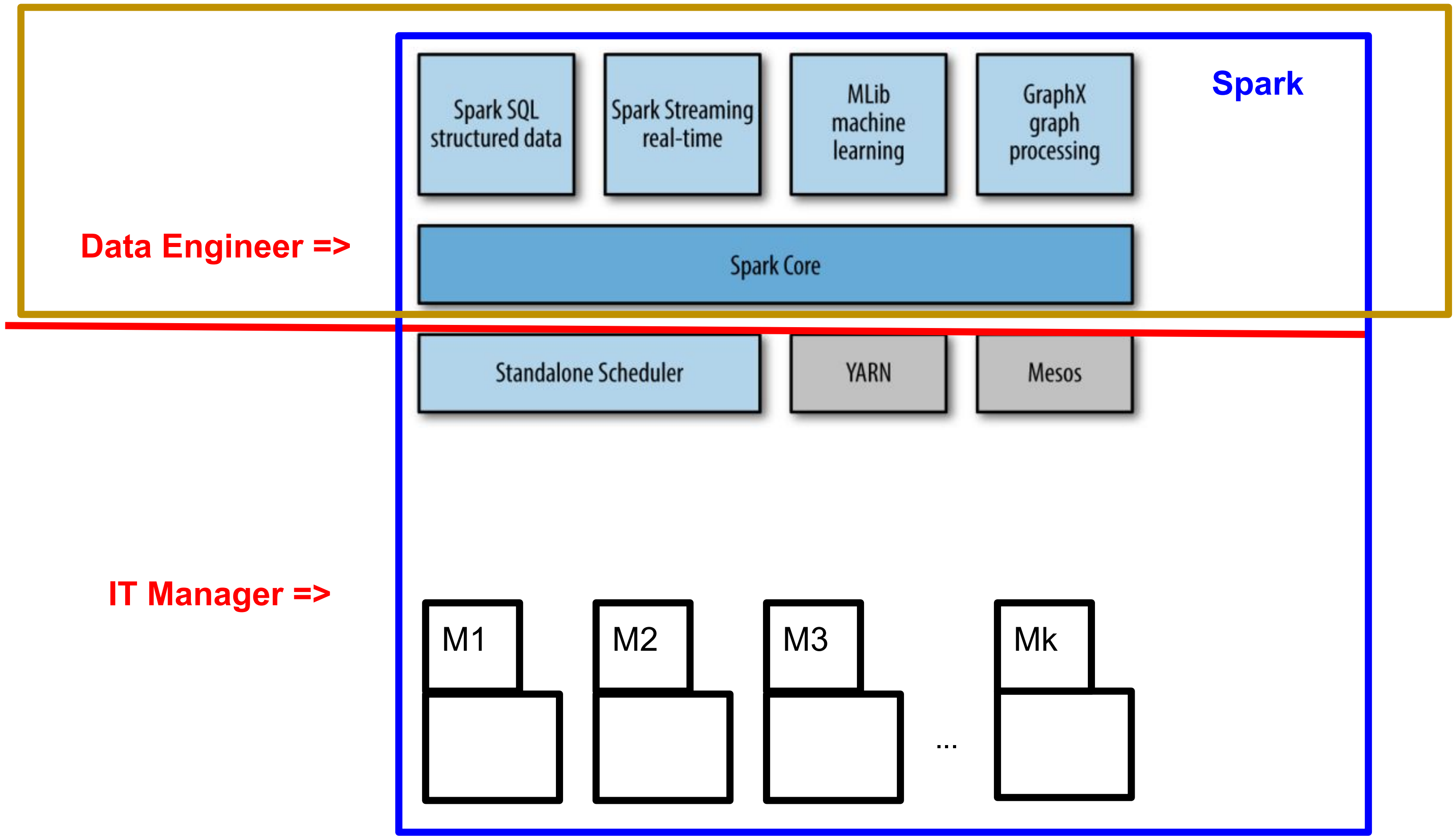
Idea 9: Distributed Programming with Apache Spark

We have focused in the role of Data Engineer,
who uses Spark on top of a *"ready"* cluster.



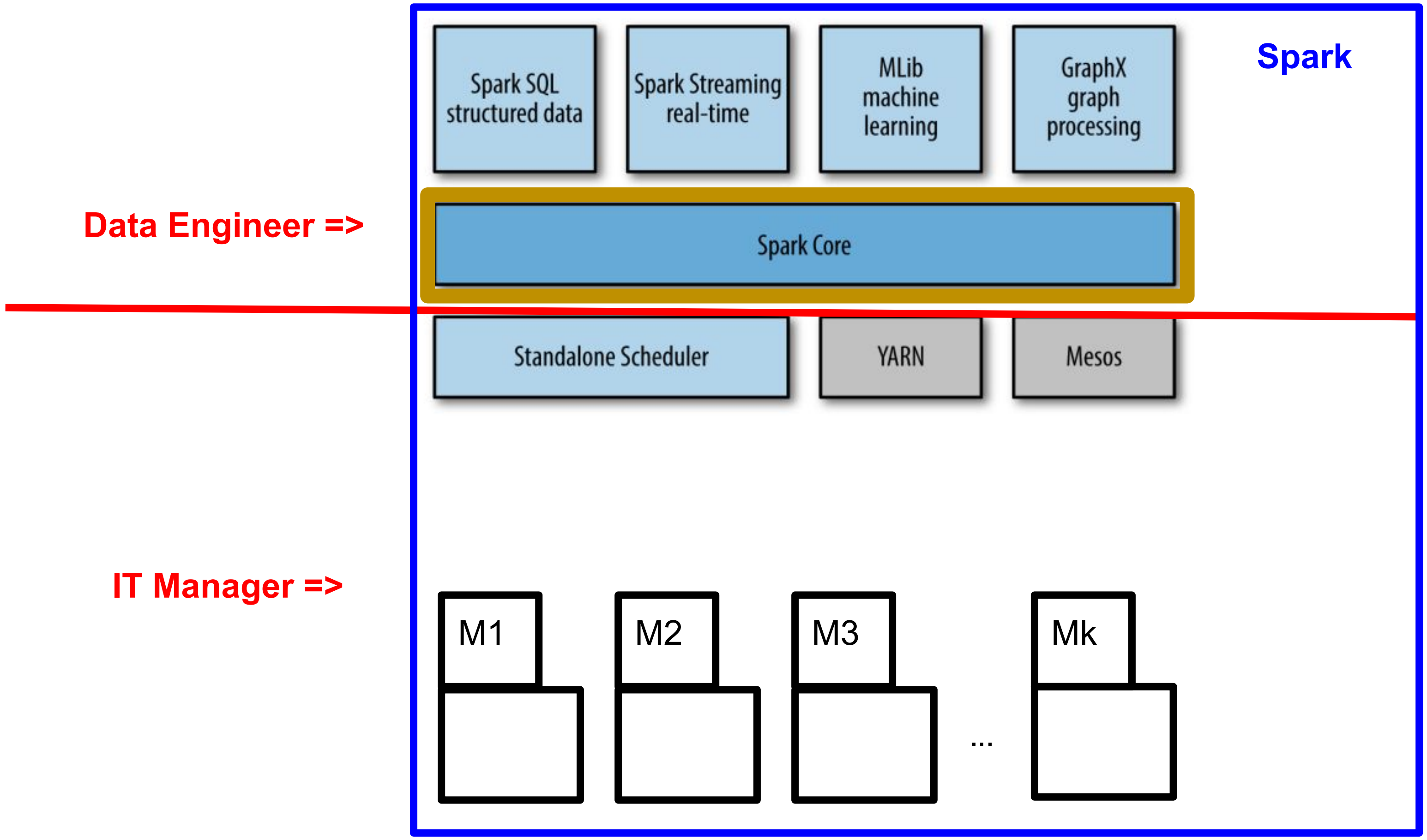
Idea 9: Distributed Programming with Apache Spark

Among the different components for the Data Engineer role, we have focus on:



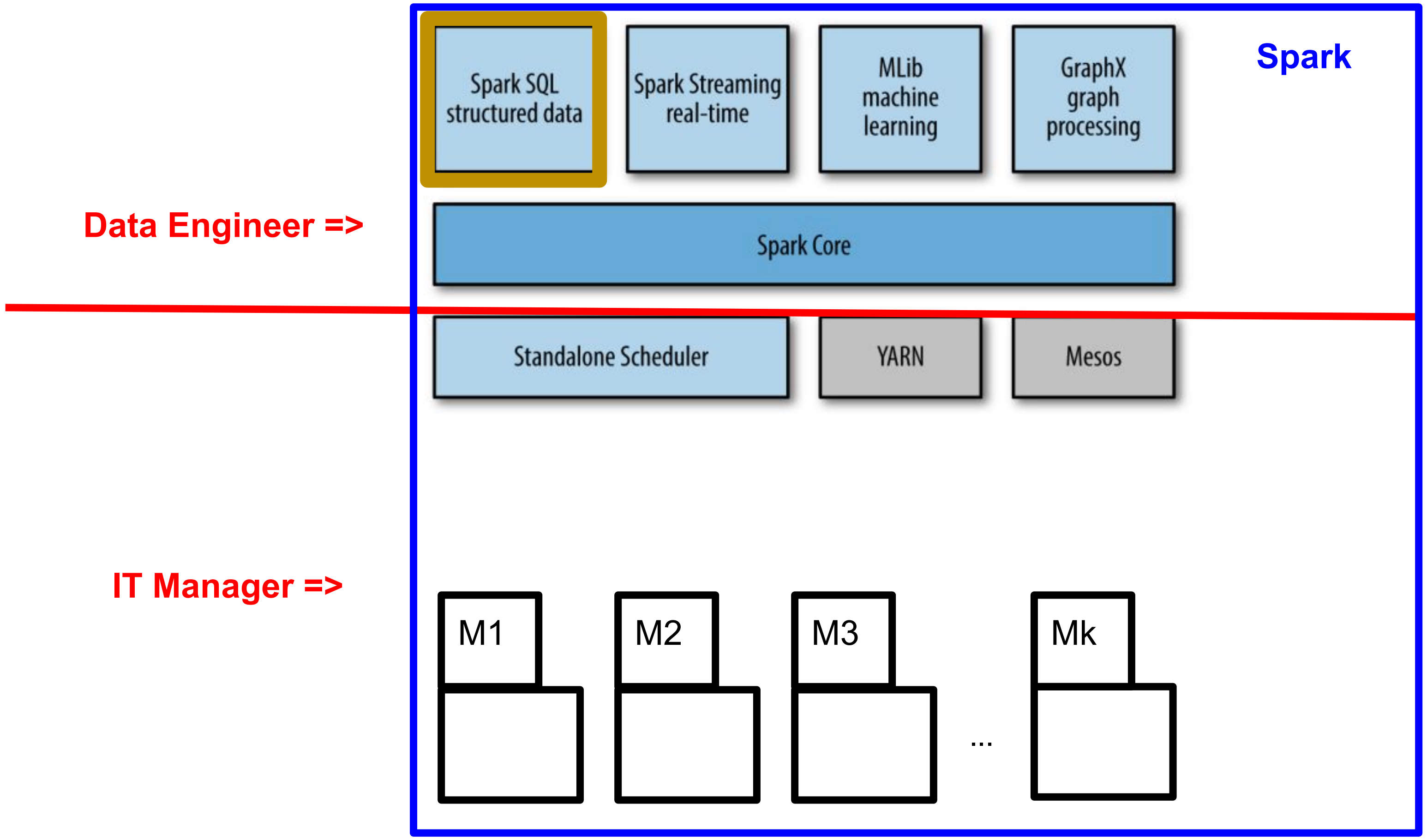
Idea 9: Distributed Programming with Apache Spark

Among the different components for the Data Engineer role, we have focus on:
Spark Core



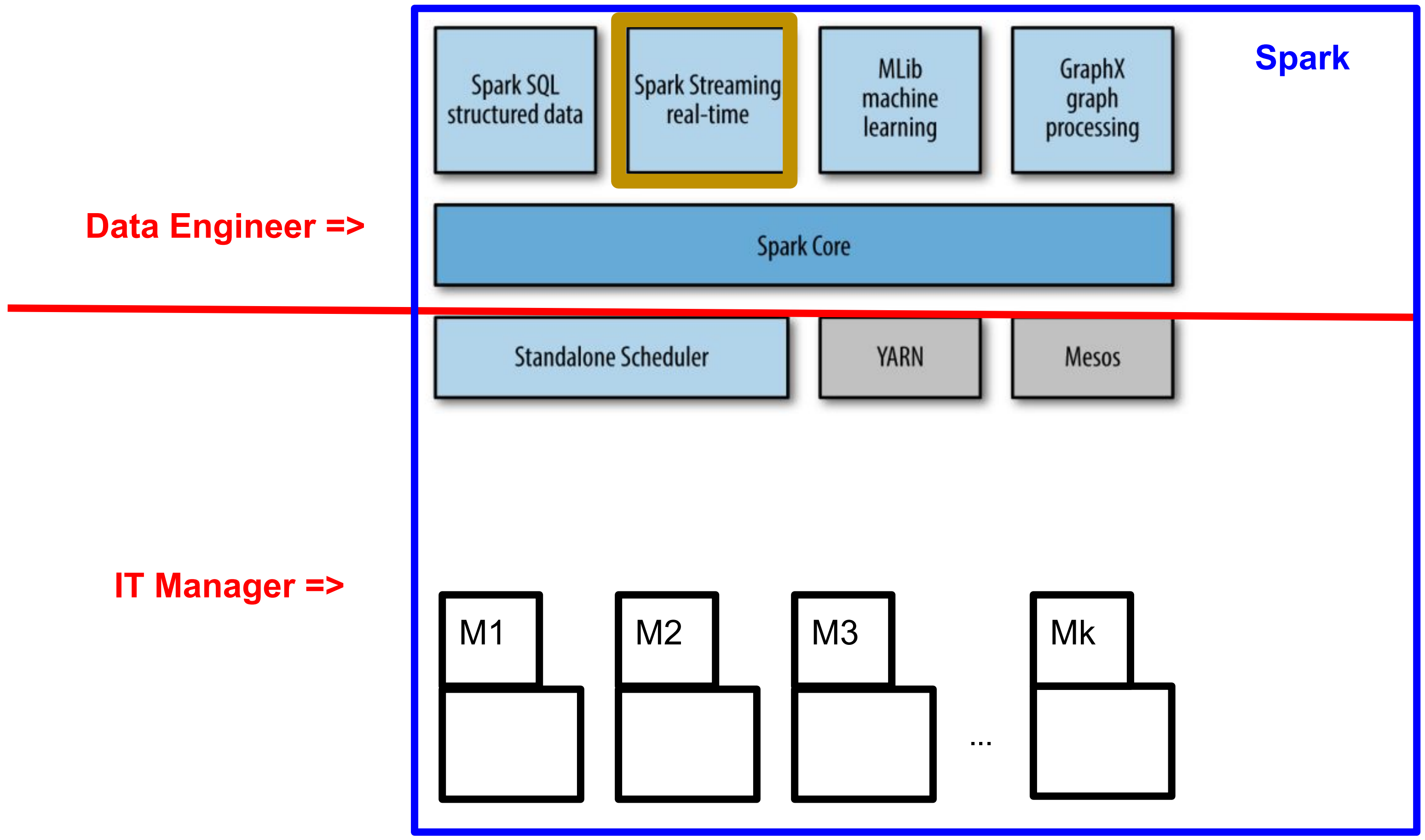
Idea 9: Distributed Programming with Apache Spark

Among the different components for the Data Engineer role, we have focus on:
Spark SQL



Idea 9: Distributed Programming with Apache Spark

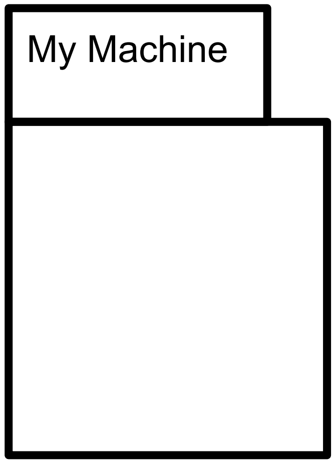
Among the different components for the Data Engineer role, we have focus on:
The two libraries for extending Spark with streaming capabilities



Idea 9: Distributed Programming with Apache Spark

For running Spark applications we have used:

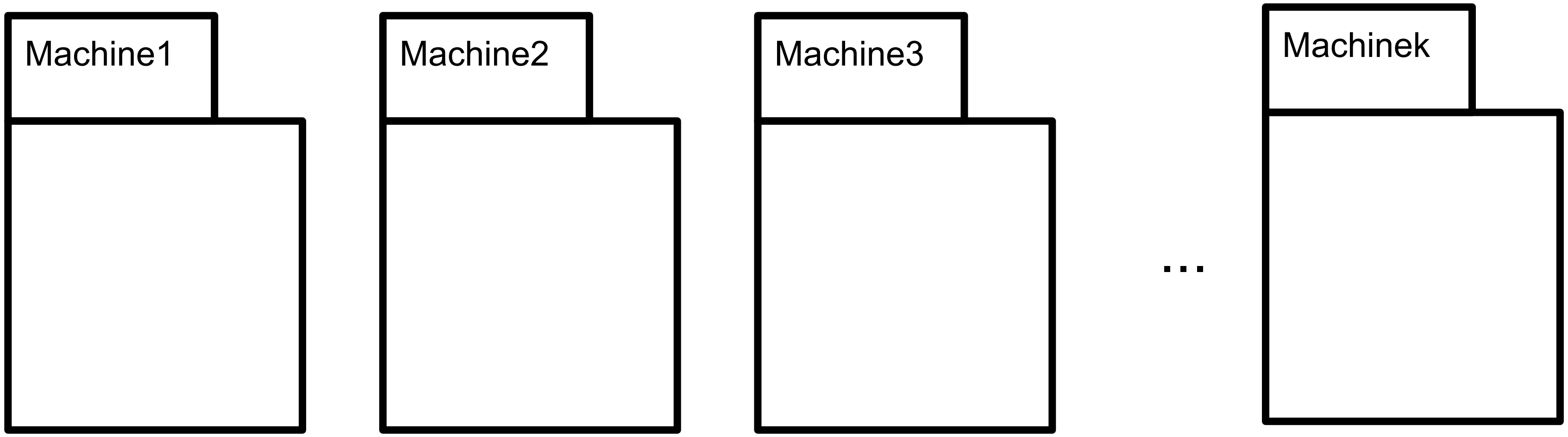
1. Local Mode (using our own local machine)



Idea 9: Distributed Programming with Apache Spark

For running Spark applications we have used:

1. Local Mode (using our own local machine).
2. Databricks: An online cluster-based platform.



Outline

Idea 10:

Databricks - Big Data Made Simple

Idea 10: Databricks - Big Data Made Simple

databricks

- Databricks is a spin-off company leveraging Spark as a **cloud-based** big data processing tool https://databricks.com/

Idea 10: Databricks - Big Data Made Simple

databricks

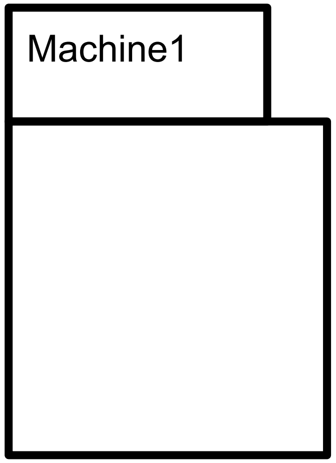
- Databricks is a spin-off company leveraging Spark as a **cloud-based** big data processing tool https://databricks.com/

- It abstracts the IT management tasks by allowing to set up and configure a cluster with just a few clicks.
  It provides an easy interface for performing Data Engineering tasks (such as import, edit and running Spark applications) on top of the cluster being created.

Idea 10: Databricks - Big Data Made Simple

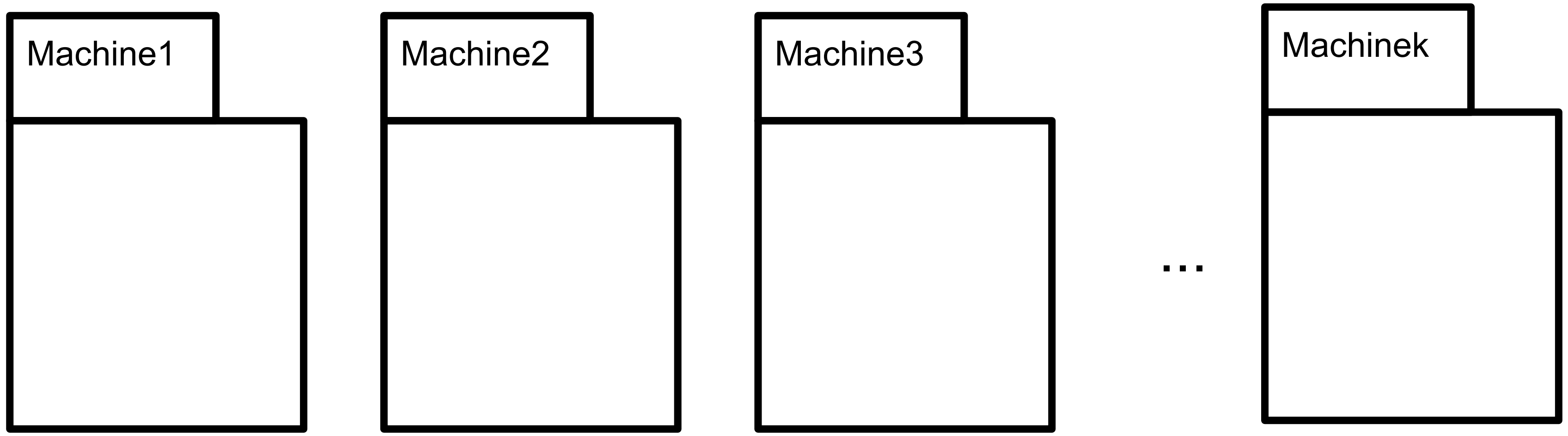
databricks

- The Databricks Community Edition is free to use. It provides us with an equivalent to **local mode** Spark configuration:
  - 1 physical machine with
    - 2 cores and
  - 8GB of memory storage.



Idea 10: Databricks - Big Data Made Simple

- If needed, the Databricks Enterprise Edition would allow us to rent a cluster in a price-per-usage basis, and configure it to target the Business Unit specific needs.



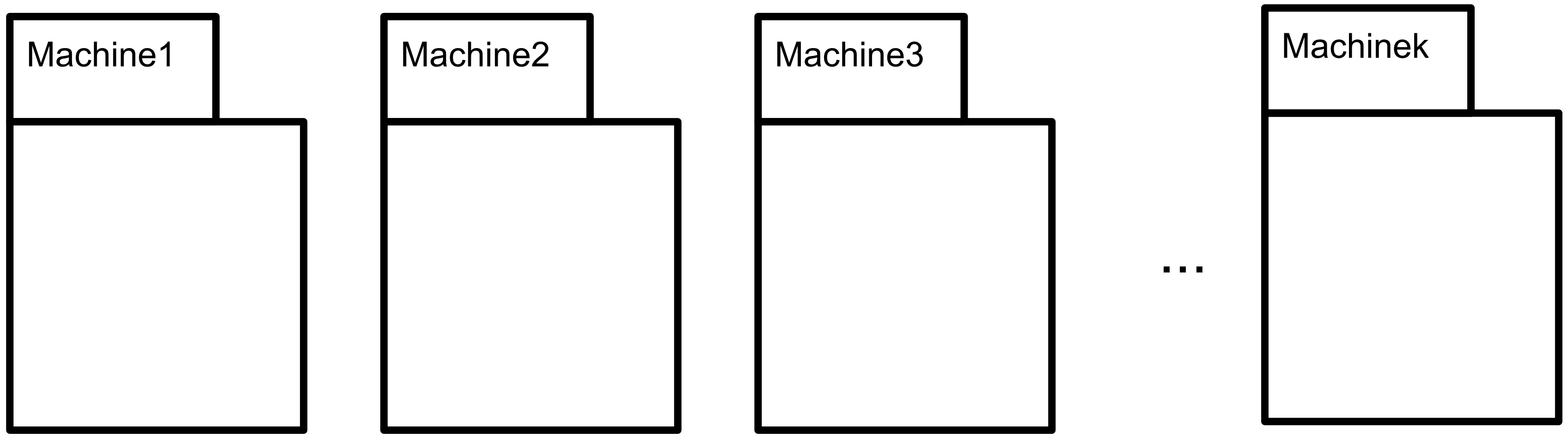
Outline

Idea 11:

Spark Recipe
Set of Ingredients

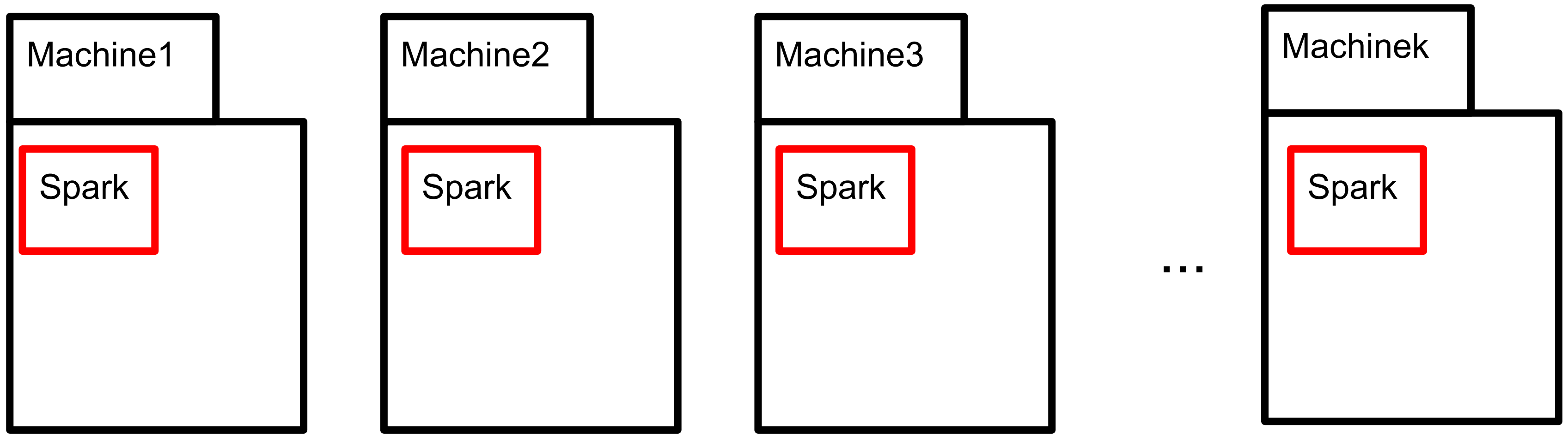
Idea 11: Spark Recipe - Set of Ingredients

1. We need a **cluster of computers**, connected among them so as to support the distributed computation.



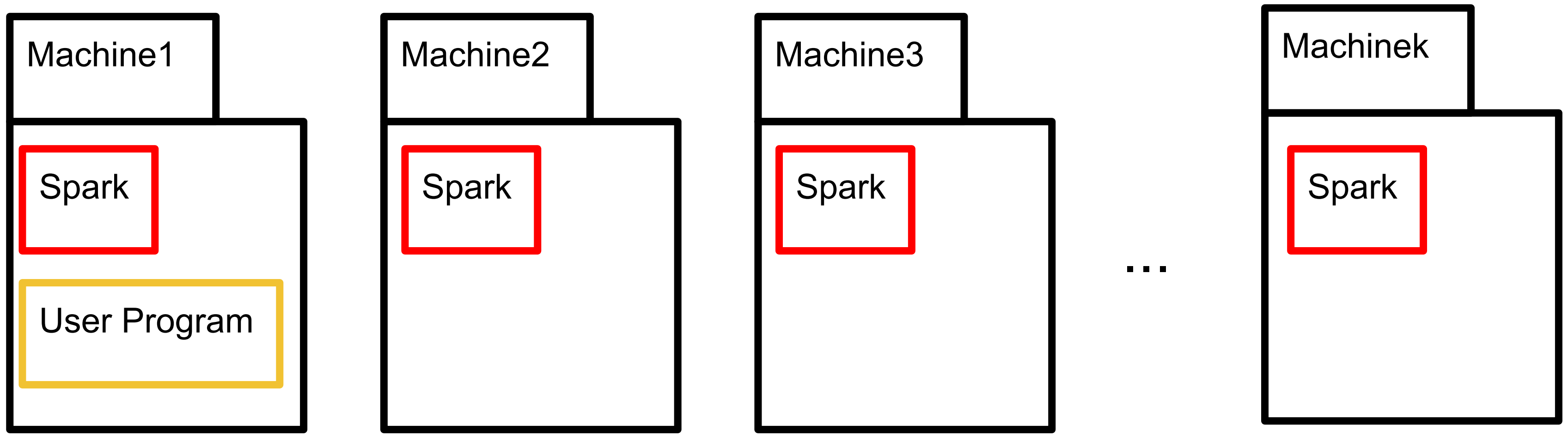
Idea 11: Spark Recipe - Set of Ingredients

2. These computers need **Spark** to be installed on them, to proceed with the desired computation.



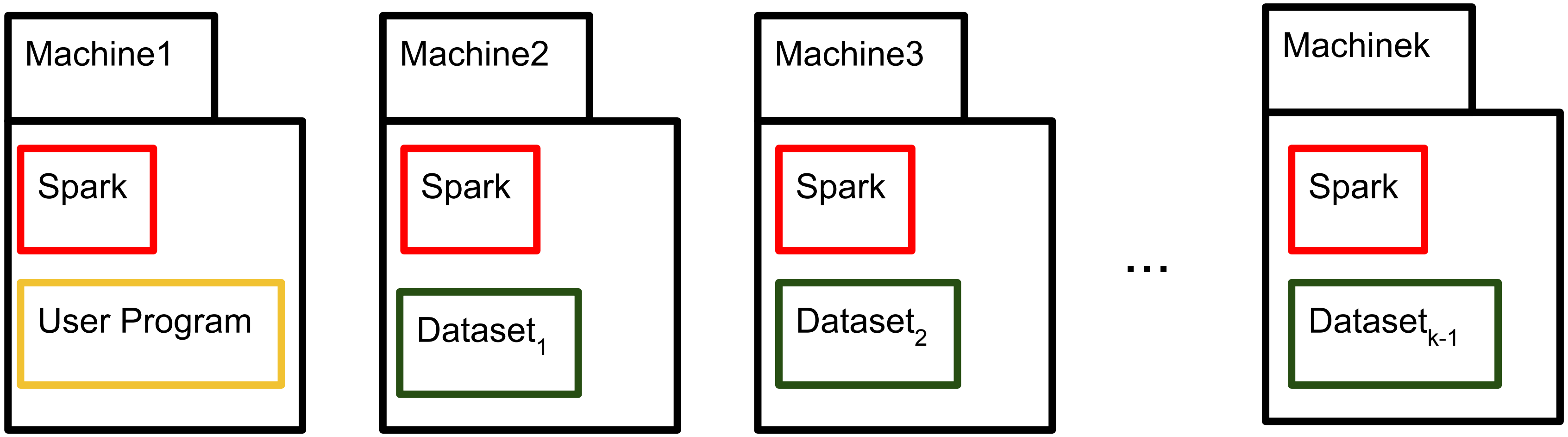
Idea 11: Spark Recipe - Set of Ingredients

3. We need a **user program**,
stating the desired data analysis to be performed.



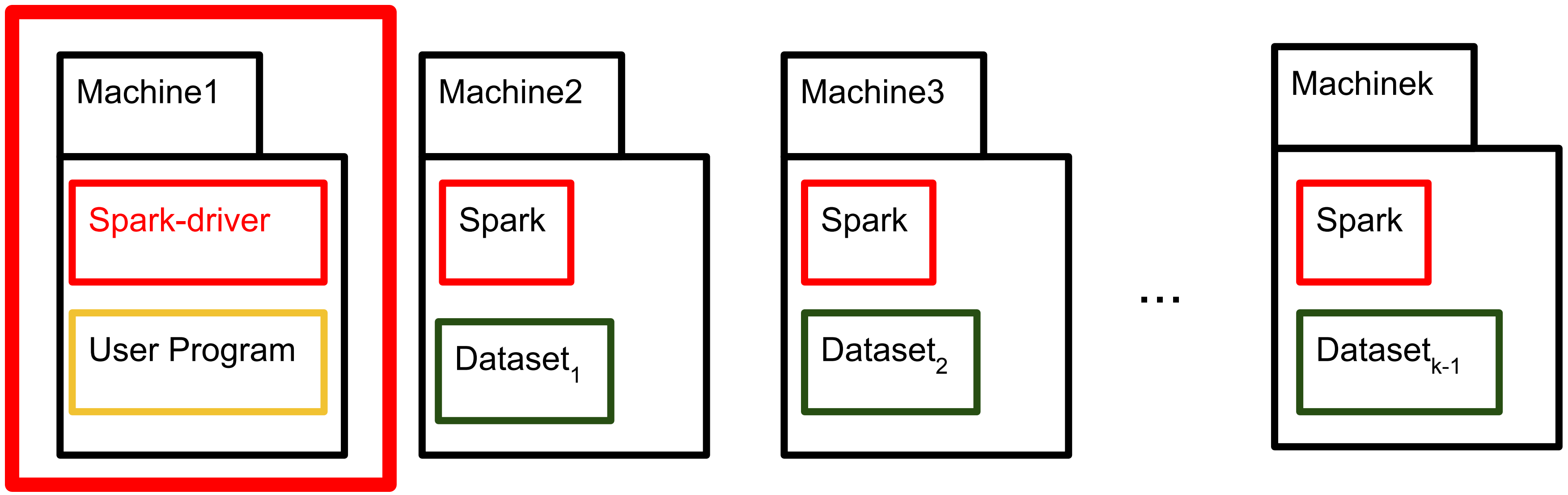
Idea 11: Spark Recipe - Set of Ingredients

4. We need a **dataset**, possibly split among the cluster:
   dataset = dataset_1 + dataset_2 + … + dataset_{k-1}



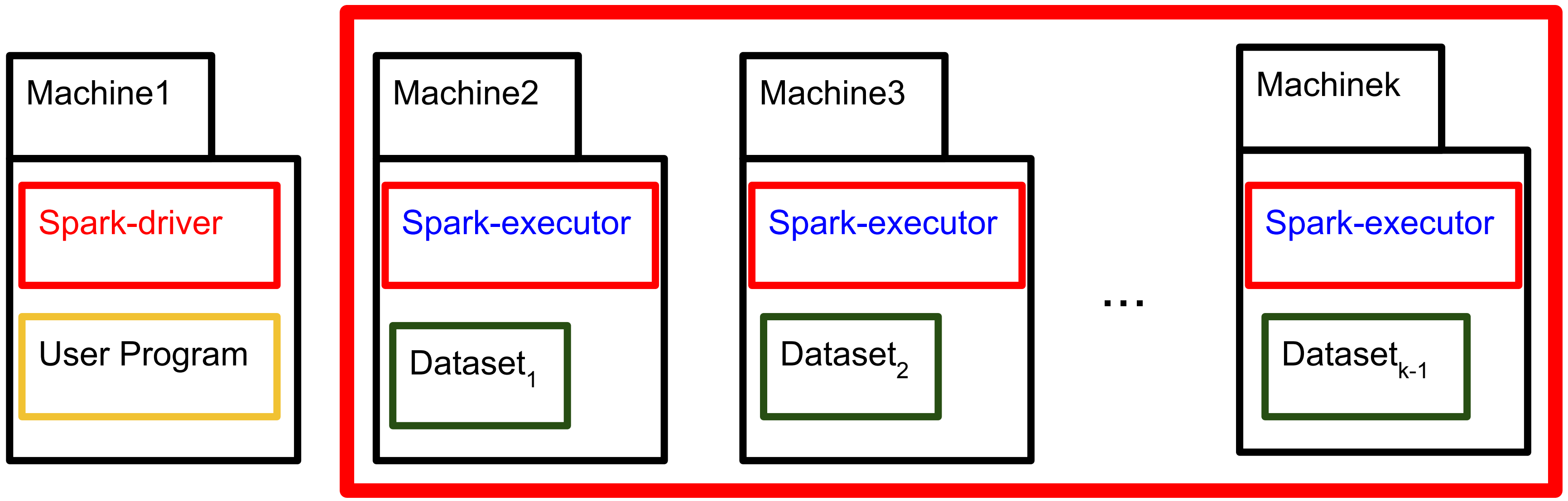
Idea 11: Spark Recipe - Set of Ingredients

5. One core in the cluster (e.g., a core of Machine 1) runs the **Spark Driver** JVM process.



Idea 11: Spark Recipe - Set of Ingredients

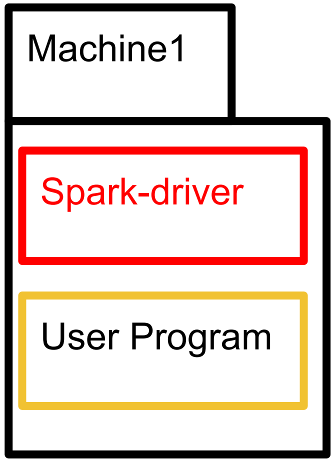
5. Remaining cores in the cluster run a **Spark Executor** JVM process.



Idea 11: Spark Recipe - Set of Ingredients

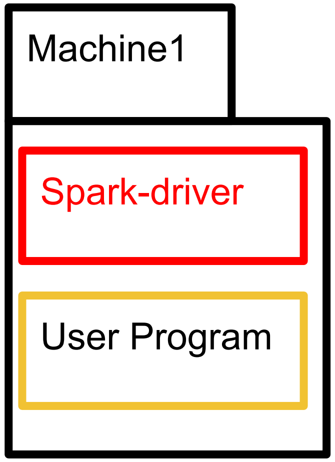
5. The **Spark Driver** JVM process plays the role of the meta-algorithm, or distributed programming centralised coordinator.

Meta-algorithm core coordinating that the job is done



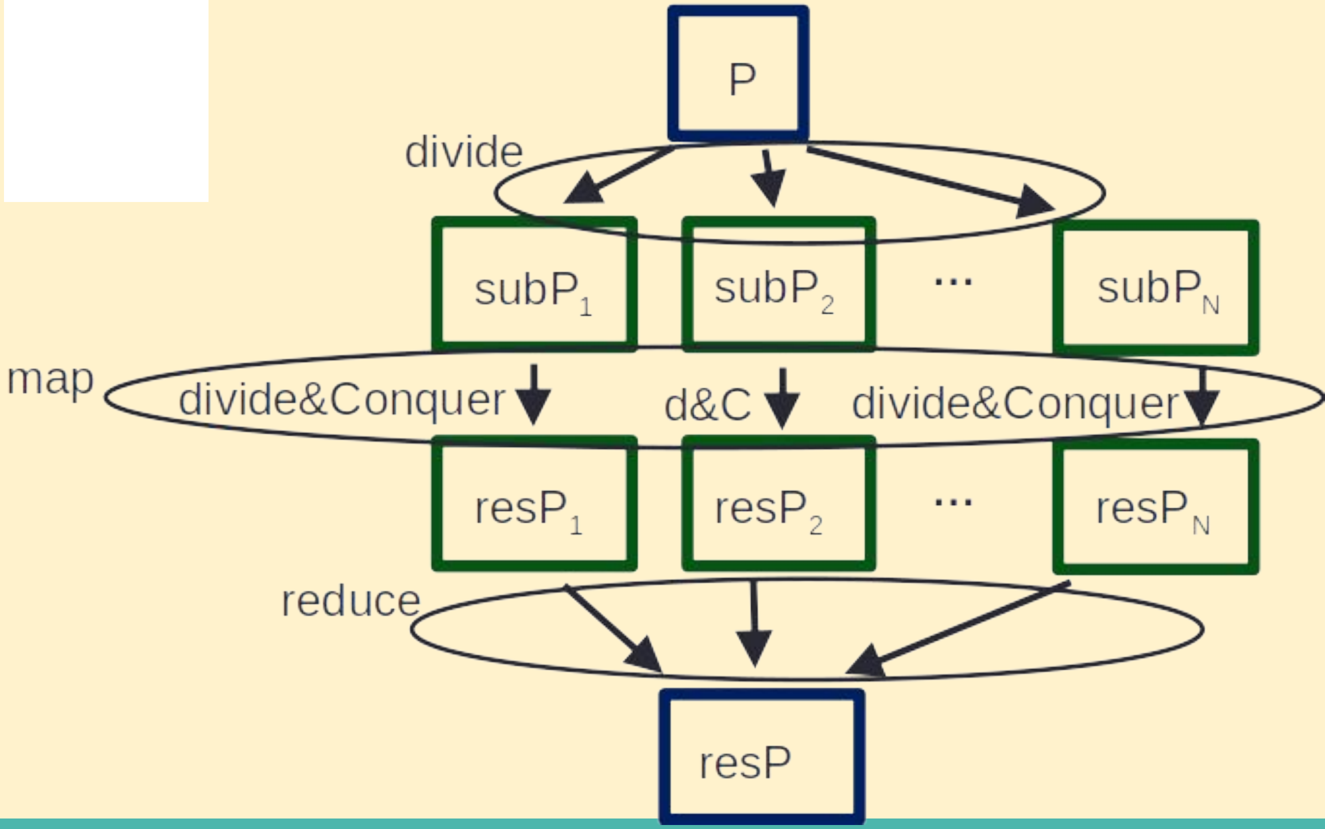
Idea 11: Spark Recipe - Set of Ingredients

5. This is really nice, as the **Spark Driver** takes care of the 2 difficulties mentioned beforehand for distributed programming:



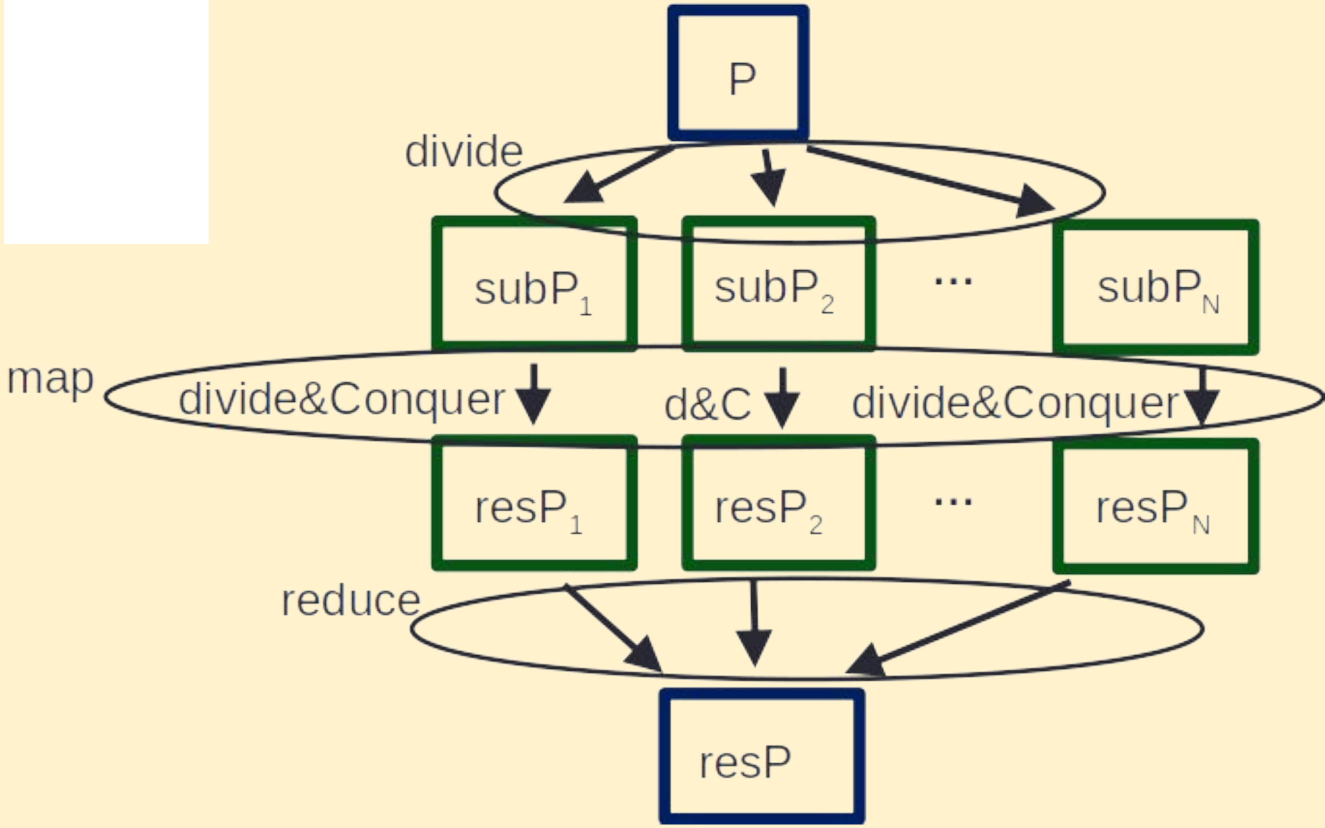
Idea 11: Spark Recipe - Set of Ingredients

Programming the meta-algorithm is difficult.



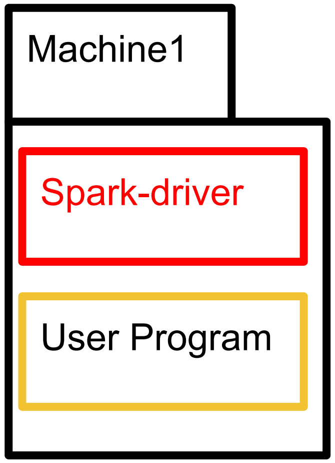
Idea 11: Spark Recipe - Set of Ingredients

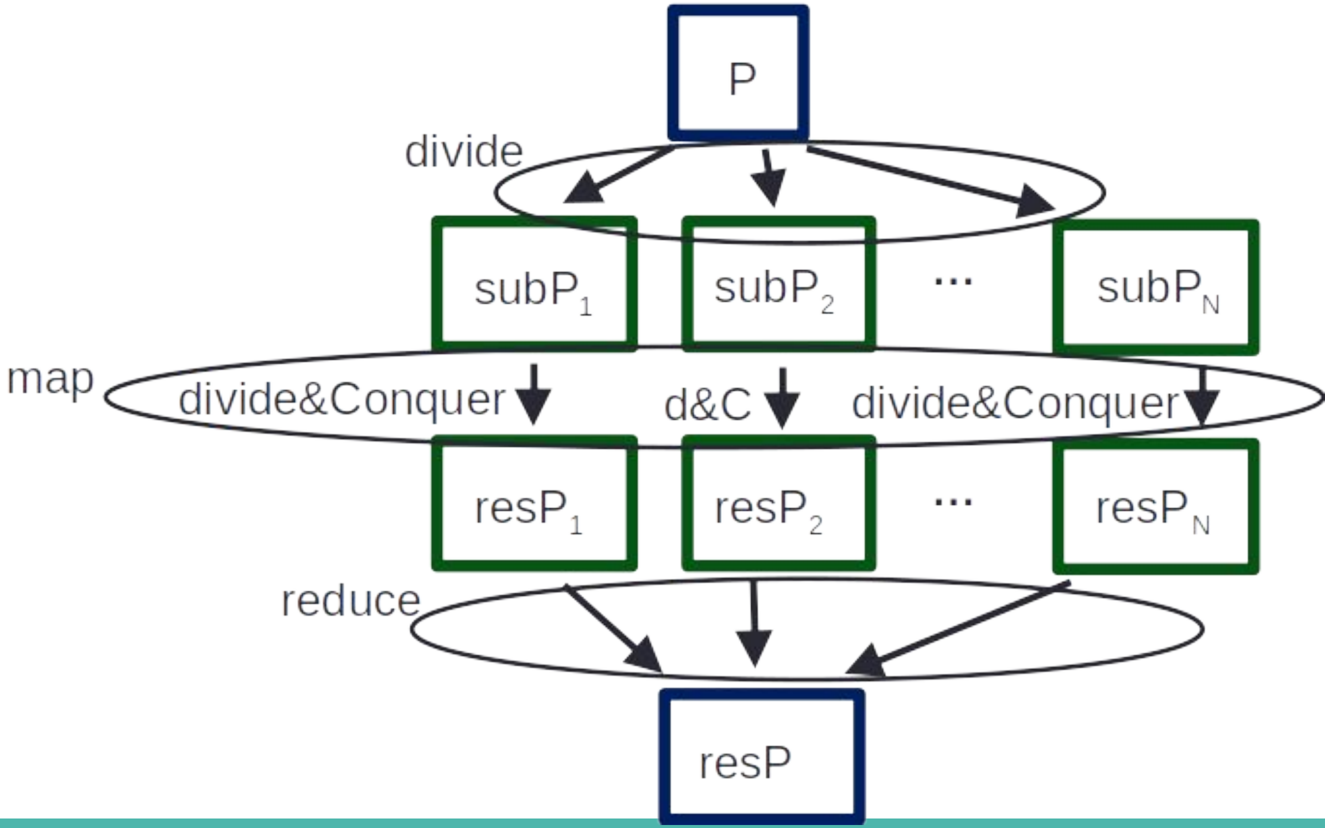
Moreover, the meta-algorithm is problem domain-specific (it might not necessarily be reusable for a different problem).



Idea 11: Spark Recipe - Set of Ingredients

Now with Spark, the **Spark driver** makes this meta-algorithm (and its adaptation to the problem being tackled) transparent to the user.

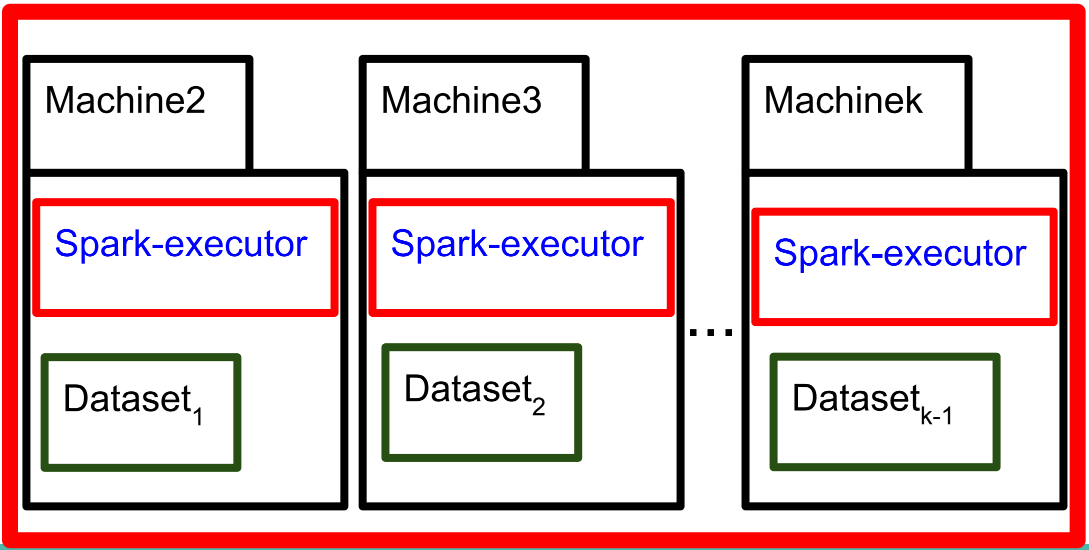




Idea 11: Spark Recipe - Set of Ingredients

5. The **Spark Executor** JVM processes play the role of the working cores, accomplishing the tasks requested by the **Spark Driver**.

Working cores actually doing the job

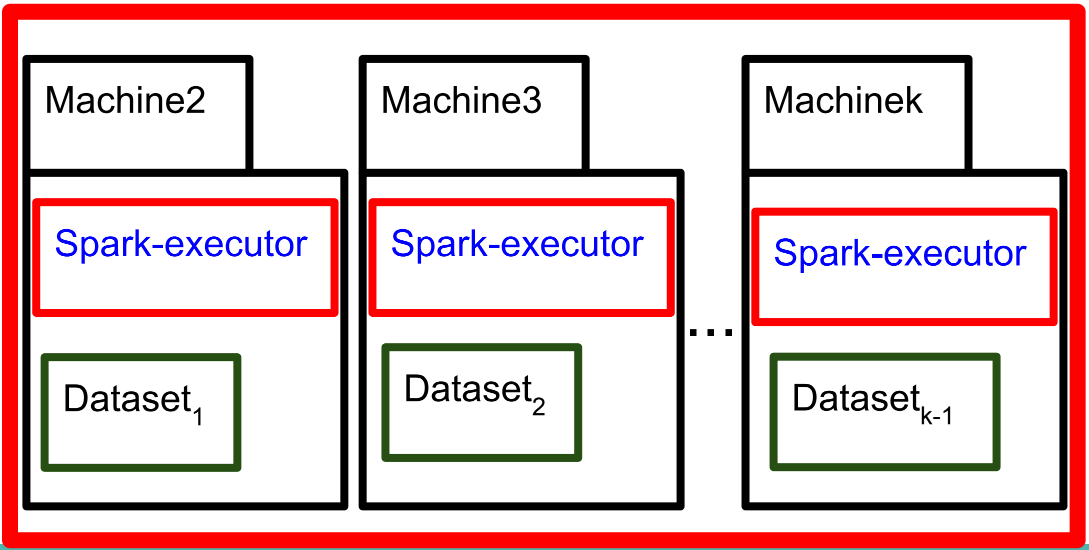


Idea 11: Spark Recipe - Set of Ingredients

5. The **Spark Executor** JVM processes play the role of the working cores, accomplishing the tasks requested by the **Spark Driver**.

This job is all about:

- Using their CPU to compute new data.
- Using their RAM and disk memory to store the computed data.



Outline

Idea 12:

Spark Core is
the Home of RDDs

Idea 12: Spark Core is the Home of RDDs

The main **data abstraction** of Spark Core
are the well-known **Resilient Distributed Datasets (RDDs)**.

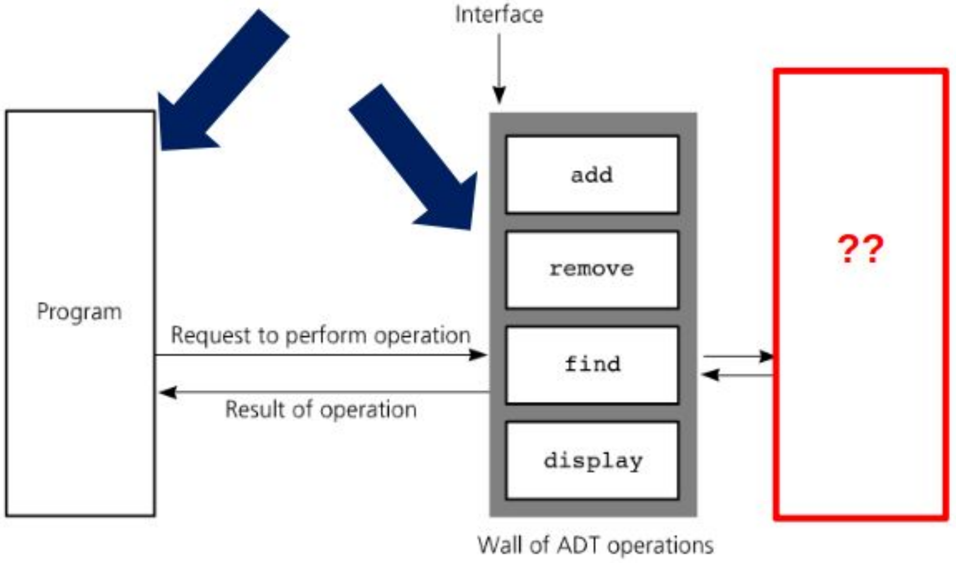
An RDD is nothing but an Abstract Data Type (ADT).

Idea 12: Spark Core is the Home of RDDs

- The **ADT public side** puts on the feet of the data user.
  To do so, it has to sort out 2 main questions:

  1. **What** defines or specifies the type of data being offered?
  2. **What** are the operations that can be performed with this data? Specify each of them.

  - However, the public side does not need to worry about internal representation and implementation of the data.

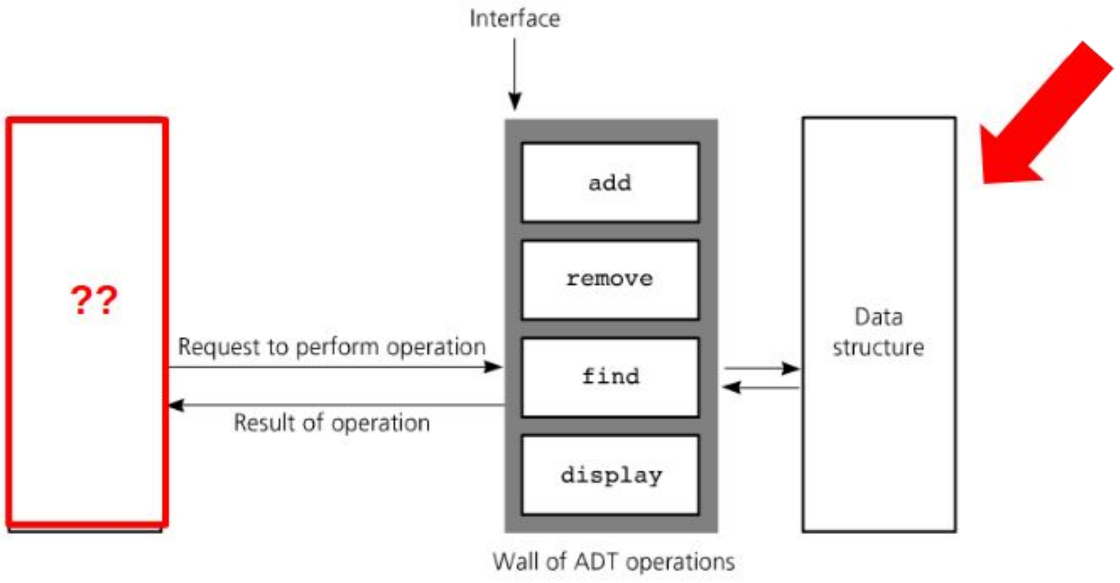


Idea 12: Spark Core is the Home of RDDs

- The **ADT private side** puts on the feet of the data developer.
  To do so, it has to sort out another 2 main questions:

  3. **How** is the data internally represented?
     Specify the concrete data structures used to layout the data.
  4. **How** is each operation internally implemented?

  - However, the private side does not need to worry about the future user of the data.



Outline

Idea 13:

Public Side of RDDs

Idea 13: Public Side of RDDs

Let's go with the ADT public side:

1. **What** defines or specifies the type of data being offered?

Idea 13: Public Side of RDDs

Let's go with the ADT public side:

1. <u>**What** defines or specifies the type of data being offered?</u>

- An RDD defines or specifies an...
  1. **indivisible** (logically presented as an atomic variable)
  2. **generic,** but **statically-typed** (available for any data type T you want, as long as it sticks to T for all its element)
  3. **lazily-evaluated** (only computed if required, and as much as required)
  4. **non-mutable** (cannot change type nor value)

<u>**...collection of elements**</u>.

Idea 13: Public Side of RDDs

Let's go with the ADT public side:

1. **What** defines or specifies the type of data being offered?

- An RDD defines or specifies an...
  1. **indivisible** (logically presented as an atomic variable)
  2. **generic,** but **statically-typed** (available for any data type T you want, as long as it sticks to T for all its element)
  3. **lazily-evaluated** (only computed if required, and as much as required)
  4. **non-mutable** (cannot change type nor value)

  ...collection of elements.

You can think of it as:
- A kind of list, in the sense that elements can be repeated.
- A kind of set, in the sense that elements have no particular default order.

Idea 13: Public Side of RDDs

Let’s go with the ADT public side:

2. **What** are the operations that can be performed with this data? Specify each of them.

Idea 13: Public Side of RDDs

Let’s go with the ADT public side:

2. **What** are the operations that can be performed with this data? Specify each of them.

- An RDD offers an extense API, with plenty of **operations**:

Idea 13: Public Side of RDDs

Let's go with the ADT public side:

2. **What** are the operations that can be performed with this data? Specify each of them.

- An RDD offers an extense API, with plenty of **operations**:
  1. **Creator**: They create a new RDD from an existing collection or dataset.

Idea 13: Public Side of RDDs

Let’s go with the ADT public side:

2. **What** are the operations that can be performed with this data? Specify each of them.

- An RDD offers an extense API, with plenty of **operations**:
  1. **Creator**: They create a new RDD from an existing collection or dataset.
  2. **Mutator**: These operations are called **Transformations**. They take one or more RDDs and produce a new RDD.

Idea 13: Public Side of RDDs

Let’s go with the ADT public side:

2. **What** are the operations that can be performed with this data? Specify each of them.

- An RDD offers an extense API, with plenty of **operations**:
  1. **Creator**: They create a new RDD from an existing collection or dataset.
  2. **Mutator**: These operations are called **Transformations**. They take one or more RDDs and produce a new RDD.
  3. **Persistent**: They keep an RDD permanently stored until the Spark program finishes.

Idea 13: Public Side of RDDs

Let's go with the ADT public side:

2. **What** are the operations that can be performed with this data? Specify each of them.

- An RDD offers an extense API, with plenty of **operations**:
  1. **Creator**: They create a new RDD from an existing collection or dataset.
  2. **Mutator**: These operations are called **Transformations**.
     They take one or more RDDs and produce a new RDD.
  3. **Persistent**: They keep an RDD permanently stored until the Spark program finishes.
  4. **Observer**: These operations are called **Actions**.
     They return some property/info from an RDD without modifying it.

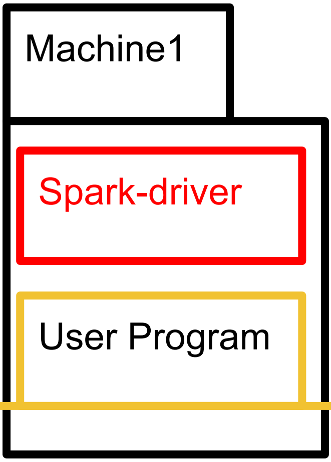
Outline

Idea 14:

Spark Core User Program Life-cycle

Idea 14: Spark Core User Program Life-Cycle

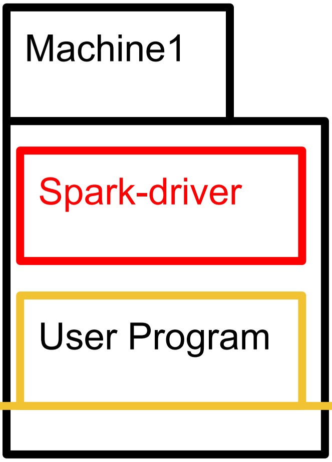
- The prefix number 1, 2, 3 and 4 in these operations is not casual: They determine the structure of a Spark typical user program!



1. **Creator**: They create a new RDD from an existing collection or dataset.
2. **Mutator**: These operations are called **Transformations**. They take one or more RDDs and produce a new RDD.
3. **Persistent**: They keep an RDD permanently stored until the Spark program finishes.
4. **Observer**: These operations are called **Actions**. They return some property/info from an RDD without modifying it.

Idea 14: Spark Core User Program Life-Cycle

- The prefix number 1, 2, 3 and 4 in these operations is not casual: They determine the structure of a Spark typical user program!



Typical Spark User Program:

1. Create some input RDDs from external data.
2. Transform them to define new RDDs using transformations.
3. Persist any intermediate RDDs that will need to be reused.
4. Launch actions to kick off a distributed computation.

Idea 14: Spark Core User Program Life-Cycle

- The prefix number 1, 2, 3 and 4 in these operations is not casual: They determine the structure of a Spark typical user program!

1. Creation:

```
inputRDD = sc.parallelize( [ 1, 2, 3, 4, 5] )
```

2. Transformations:

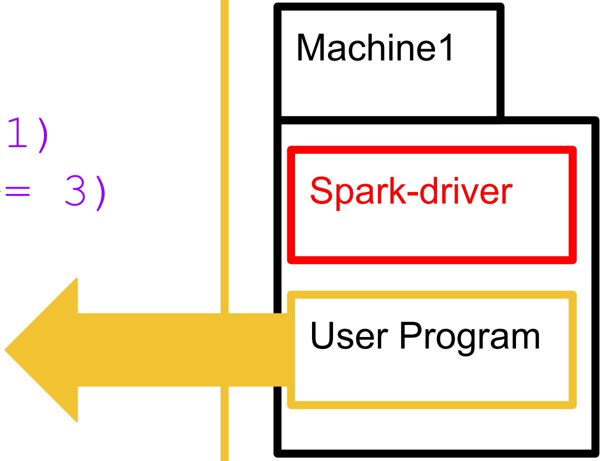
```
mappedRDD = inputRDD.map(lambda x: x + 1)
solRDD = mappedRDD.filter(lambda x: x >= 3)
```

3. Persistence:

```
solRDD.persist( )
```

4. Actions:

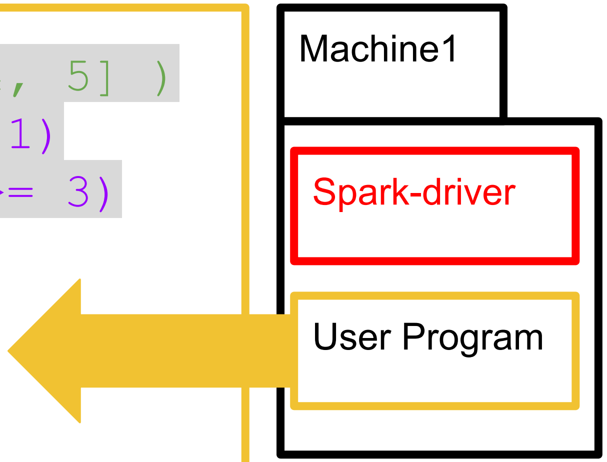
```
resVAL = filterRDD.count( )
solRDD.saveAsTextFile()
print(resVAL)
```



Idea 14: Spark Core User Program Life-Cycle

- The prefix number 1, 2, 3 and 4 in these operations is not casual: They determine the structure of a Spark typical user program!

```
inputRDD = sc.parallelize( [ 1, 2, 3, 4, 5] )
mappedRDD = inputRDD.map(lambda x: x + 1)
solRDD = mappedRDD.filter(lambda x: x >= 3)
solRDD.persist( )
resVAL = filterRDD.count( )
solRDD.saveAsTextFile()
print(resVAL)
```



Outline

Idea 15:

Functional Programming Flavour of RDD Operations

Idea 15: Functional Programming Flavour of RDD Operations

RDD operations support the following Functional Programming (FP) features:

Idea 15: Functional Programming Flavour of RDD Operations

RDD operations support the following Functional Programming (FP) features:

1. **Polymorphism.**
   - Functions support parametric input/output arguments.

Idea 15: Functional Programming Flavour of RDD Operations

RDD operations support the following Functional Programming (FP) features:

1. **Polymorphism.**
    - Functions support parametric input/output arguments.

2. **Higher-order functions.**
    - Functions support receiving functions as arguments, and/or returning a function as a result.

Idea 15: Functional Programming Flavour of RDD Operations

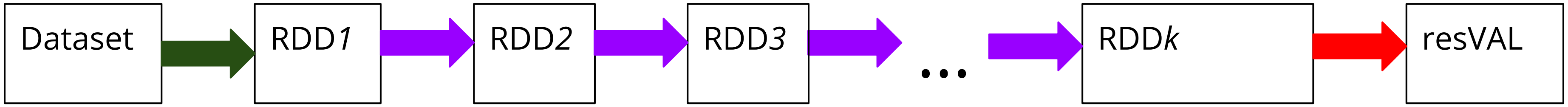
RDD operations support the following Functional Programming (FP) features:

1. **Polymorphism.**
    - Functions support parametric input/output arguments.
2. **Higher-order functions.**
    - Functions support receiving functions as arguments, and/or returning a function as a result.
3. **Partial application.**
    - Functions support fixing a number of its arguments, leading to another function of smaller arity.

Idea 15: Functional Programming Flavour of RDD Operations

All in all, a Spark Core program life-cycle is based in the RDD ops:

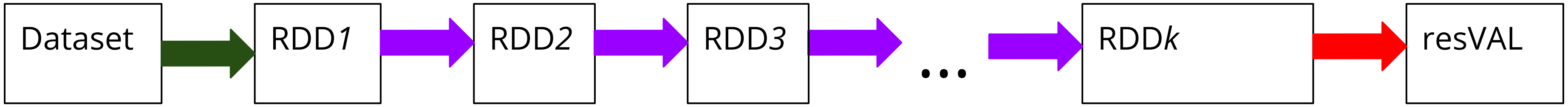
A very small set of FP primitives,
each of them supporting the application of very general functions.



Idea 15: Functional Programming Flavour of RDD Operations

<u>All in all, a Spark Core program life-cycle is based in the RDD ops:</u>

A very small set of FP primitives,
each of them supporting the application of very general functions.



```
newRDD = inputRDD.map( f ) with any f: a -> b

resVAL = inputRDD.reduce( f ) with any f: a -> a -> a

resVAL = inputRDD.aggregate( accum, f1, f2 )
          With any accum:: b, f1: b -> a -> b, f2: b -> b -> b

newRDD = inputRDD.reduceByKey( f ) with any f: a -> a

newRDD = inputRDD.combineByKey( f1, f2, f3 )
      with any f1: a -> b, f2: b -> a -> b and f3: b -> b -> b
```

Outline

Idea 16:

RDDs are Lazily Evaluated

Idea 16: RDDs are Lazily Evaluated

Creation, **Transformation** and **Persist** operations are lazy!

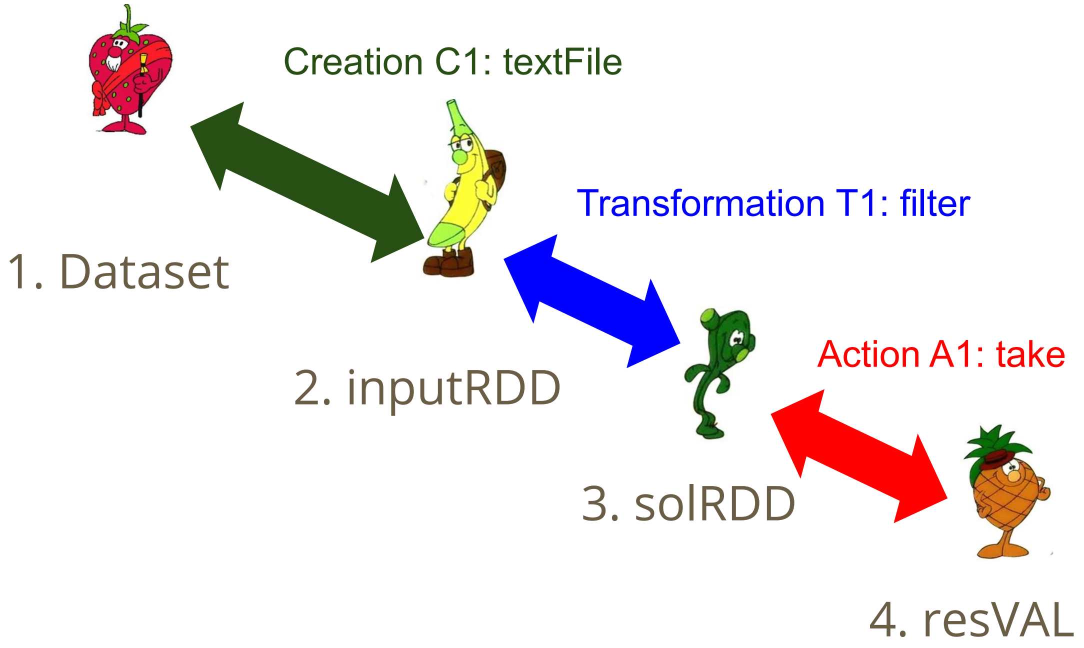
Idea 16: RDDs are Lazily Evaluated

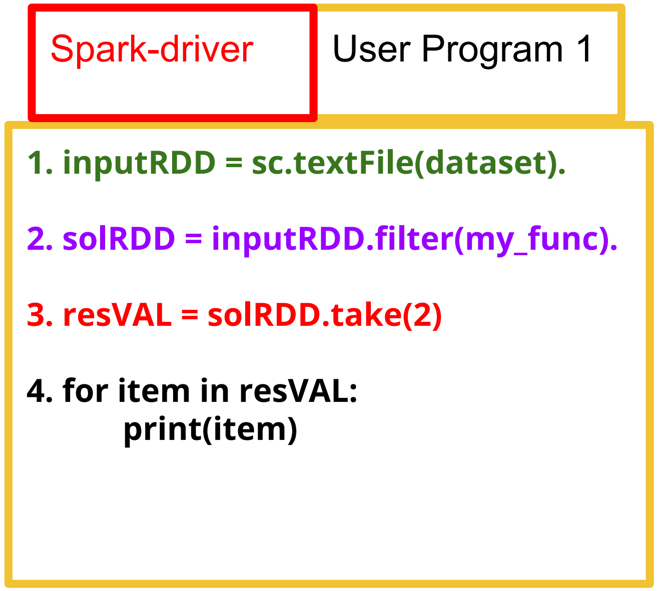
They only start working when an **Action** takes place!

Idea 16: RDDs are Lazily Evaluated

Idea 16: RDDs are Lazily Evaluated

Moreover, when it's time for these operations to work, they only compute as much data as it is absolutely required.

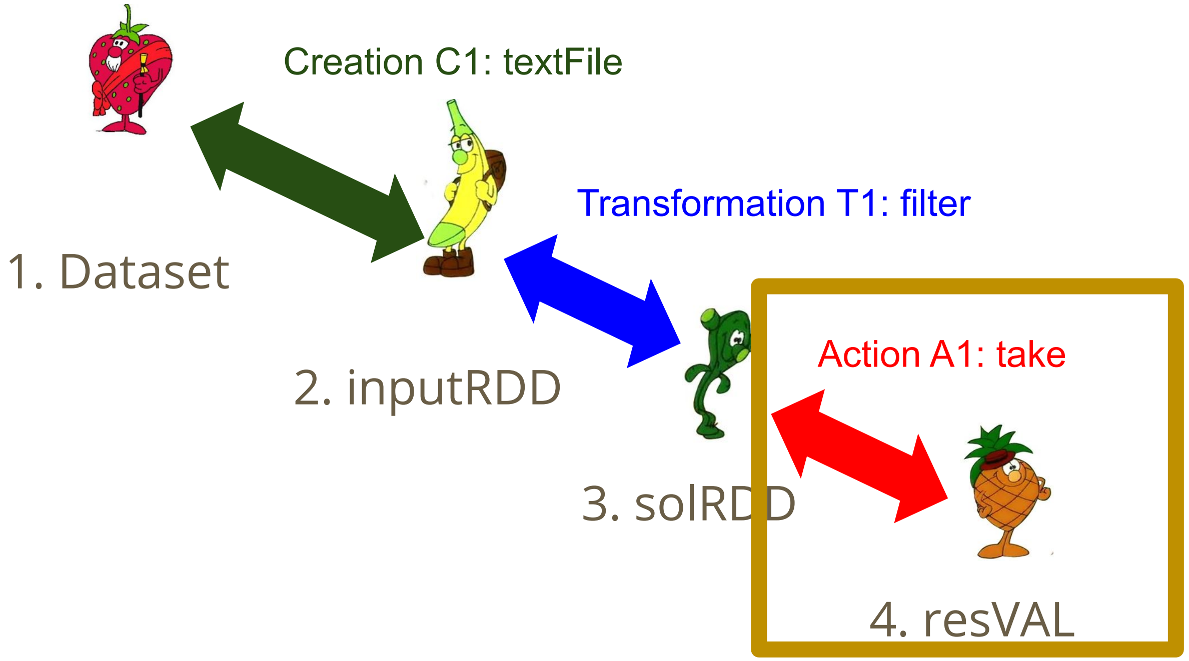




```
1. inputRDD = sc.textFile(dataset).

2. solRDD = inputRDD.filter(my_func).

3. resVAL = solRDD.take(2)

4. for item in resVAL:
        print(item)
```

Idea 16: RDDs are Lazily Evaluated

Specifically, the **Spark driver** process focuses on the **action** operation triggering the computation…

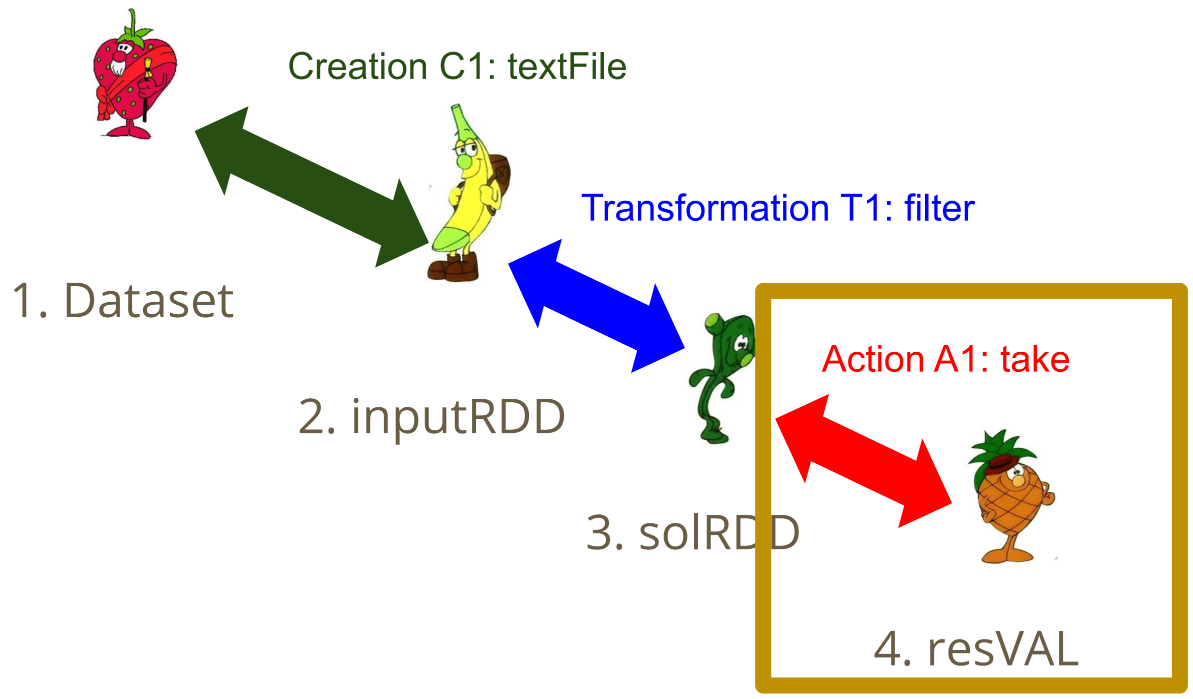


Spark-driver | User Program 1

```
1. inputRDD = sc.textFile(dataset).

2. solRDD = inputRDD.filter(my_func).

3. resVAL = solRDD.take(2)

4. for item in resVAL:
        print(item)
```

Idea 16: RDDs are Lazily Evaluated

Specifically, the **Spark driver** process focuses on the **action** operation triggering the computation…
…to start tracing backwards from it, so as to reason what is the minimum amount of data that must be computed.

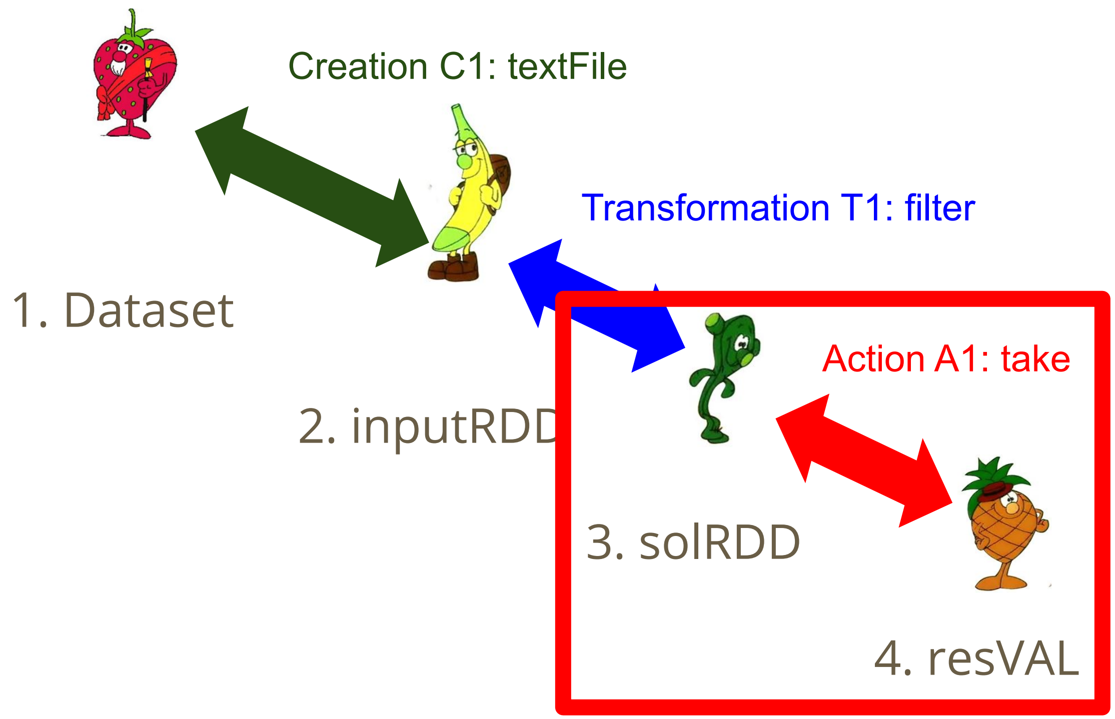


Spark-driver | User Program 1

```
1. inputRDD = sc.textFile(dataset).

2. solRDD = inputRDD.filter(my_func).

3. resVAL = solRDD.take(2)

4. for item in resVAL:
        print(item)
```

Idea 16: RDDs are Lazily Evaluated

What is the minimum data we have to compute?

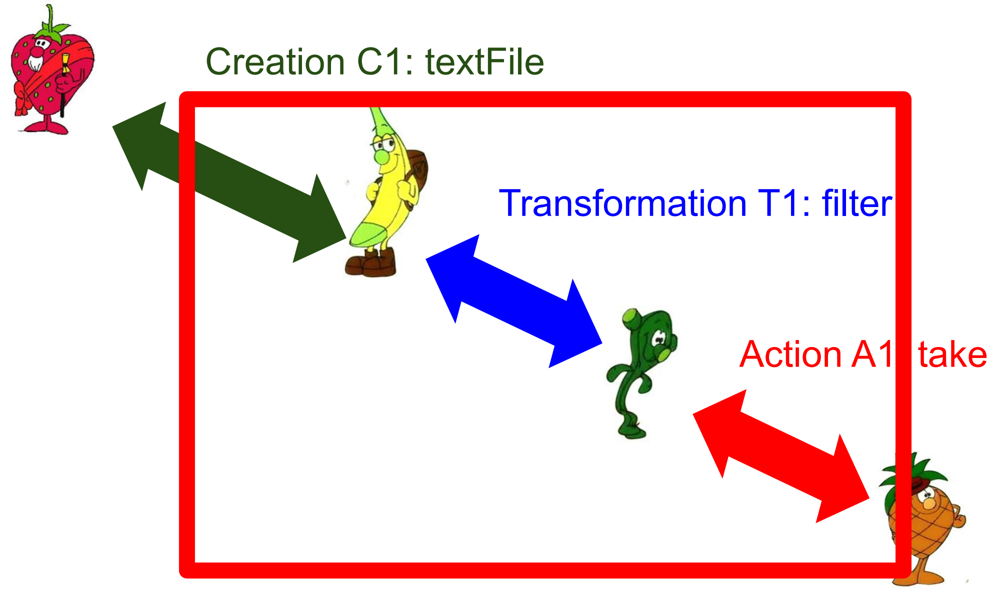


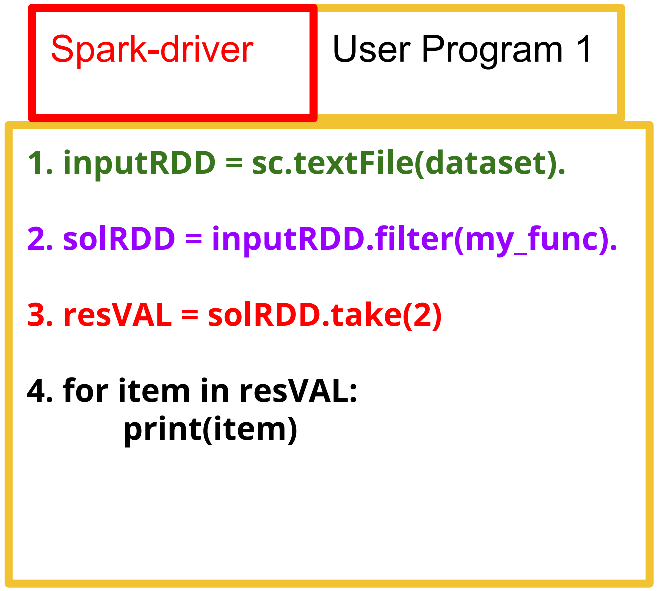
Spark-driver	User Program 1

```
1. inputRDD = sc.textFile(dataset).

2. solRDD = inputRDD.filter(my_func).

3. resVAL = solRDD.take(2)

4. for item in resVAL:
       print(item)
```

Idea 16: RDDs are Lazily Evaluated

What is the minimum data we have to compute?





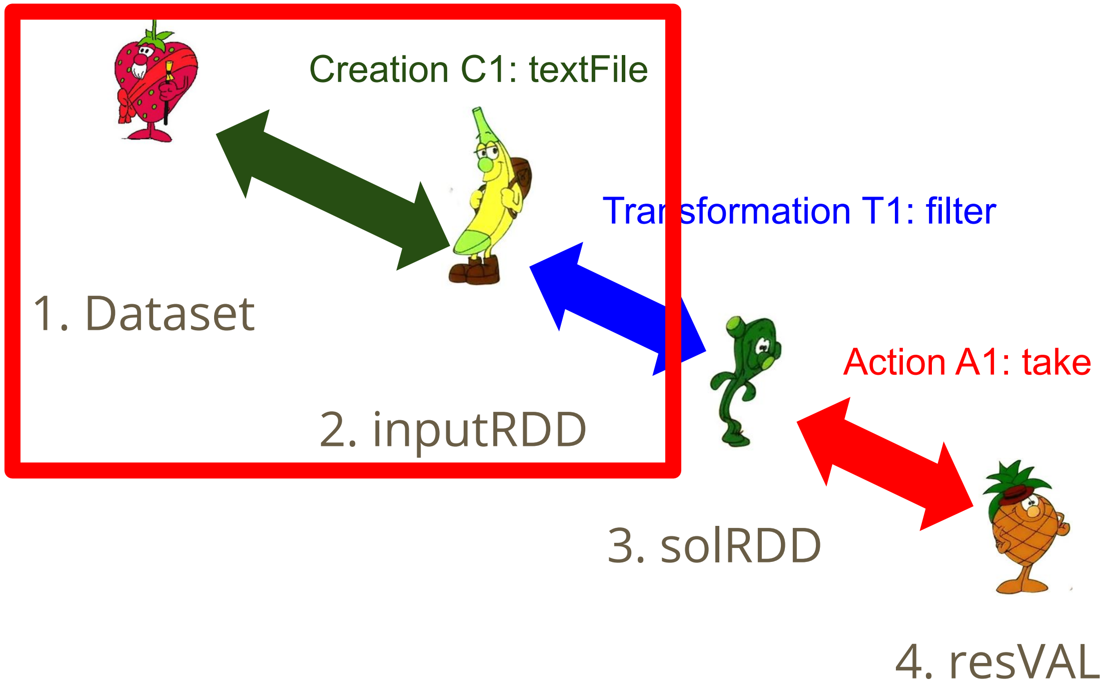
```
1. inputRDD = sc.textFile(dataset).

2. solRDD = inputRDD.filter(my_func).

3. resVAL = solRDD.take(2)

4. for item in resVAL:
        print(item)
```

1. Dataset

2. inputRDD

Idea 16: RDDs are Lazily Evaluated

What is the minimum data we have to compute?



Spark-driver | User Program 1

```
1. inputRDD = sc.textFile(dataset).

2. solRDD = inputRDD.filter(my_func).

3. resVAL = solRDD.take(2)

4. for item in resVAL:
        print(item)
```

Outline

Idea 17:

Spark SQL
A Higher-Level API

Idea 17: Spark SQL - A Higher Level API

In the same way Spark Core makes possible *functional Spark* via the ADT Resilient Distributed Datasets (RDD)...

...Spark SQL makes possible *structured Spark* via the ADTs DataFrame (DF).

Idea 17: Spark SQL - A Higher Level API

Let’s go with the DataFrame ADT public side:

1. **What** defines or specifies the type of data being offered?

Idea 17: Spark SQL - A Higher Level API

Let's go with the DataFrame ADT public side:

1. **What** defines or specifies the type of data being offered?

- A DataFrame defines or specifies an...
  1. **indivisible** (logically presented as an atomic variable)
  2. **structured,** in the sense of having a fixed number of fields, each of them of a concrete data type T.
  3. **lazily-evaluated** (only computed if required, and as much as required)
  4. **non-mutable** (cannot change type nor value)

...collection of elements.

Idea 17: Spark SQL - A Higher Level API

Let's go with the DataFrame ADT public side:

1. <u>**What** defines or specifies the type of data being offered?</u>

- A DataFrame defines or specifies an...
  1. **indivisible** (logically presented as an atomic variable)
  2. **structured,** in the sense of having a fixed number of fields, each of them of a concrete data type T.
  3. **lazily-evaluated** (only computed if required, and as much as required)
  4. **non-mutable** (cannot change type nor value)

<u>**...collection of elements**</u>.

You can think of it as:
- A table in a relational database, in the sense that each Row follows the schema.
- A collection in a NoSQL document oriented database, in the sense that the content of the collection is distributed.

Idea 17: Spark SQL - A Higher Level API

Let’s go with the DataFrame/Dataset ADT public side:

2. **What** are the operations that can be performed with this data? Specify each of them.

Idea 17: Spark SQL - A Higher Level API

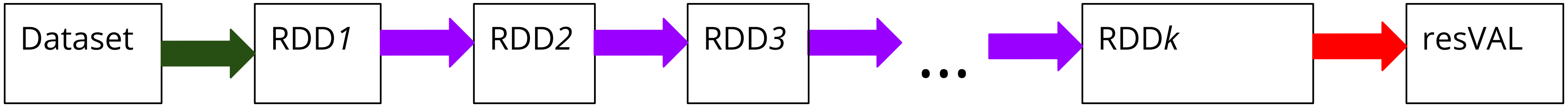
Let's go with the DataFrame/Dataset ADT public side:

2. **What** are the operations that can be performed with this data? Specify each of them.

- DataFrames provide a Catalog of Domain Specific Language (DSL) operators, which can be classified into **Creation**, **Transformation**, **Persistance** and **Actions**, as it was the case for the Spark Core RDD-based primitives.

Idea 17: Spark SQL - A Higher Level API

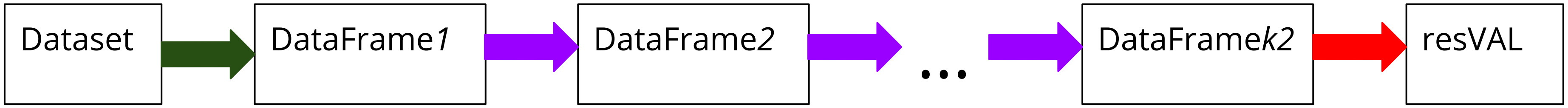
But, whereas RDDs provided a small set of primitives,
each of them supporting the application of very general functions...



```
newRDD = inputRDD.map( f ) with any f: a -> b

resVAL = inputRDD.reduce( f ) with any f: a -> a -> a

resVAL = inputRDD.aggregate( accum, f1, f2 )
          With any accum:: b, f1: b -> a -> b, f2: b -> b -> b

newRDD = inputRDD.reduceByKey( f ) with any f: a -> a

newRDD = inputRDD.combineByKey( f1, f2, f3 )
      with any f1: a -> b, f2: b -> a -> b and f3: b -> b -> b
```

Idea 17: Spark SQL - A Higher Level API

Now, DFs provide an extensive set of DSL operators,
each of them very restrictive in what expressions they accept.



Idea 17: Spark SQL - A Higher Level API

- These operators represent the most common patterns present in a data analysis. Moreover, each new version of Spark includes new DSL operators.

- If something cannot be expressed, DFs allow to revert back to RDDs, as well as to provide your own User-Defined Expression (at the price of Spark not being able to reason internally with it).

Idea 17: Spark SQL - A Higher Level API

- These operators represent the most common patterns present in a data analysis. Moreover, each new version of Spark includes new DSL operators.

- If something cannot be expressed, DFs allow to revert back to RDDs, as well as to provide your own User-Defined Expression (at the price of Spark not being able to reason internally with it).

- These DSL operators are indeed very restrictive with their inner expressions, so that Spark can understand/reason with/perform a semantic analysis of them.

Outline

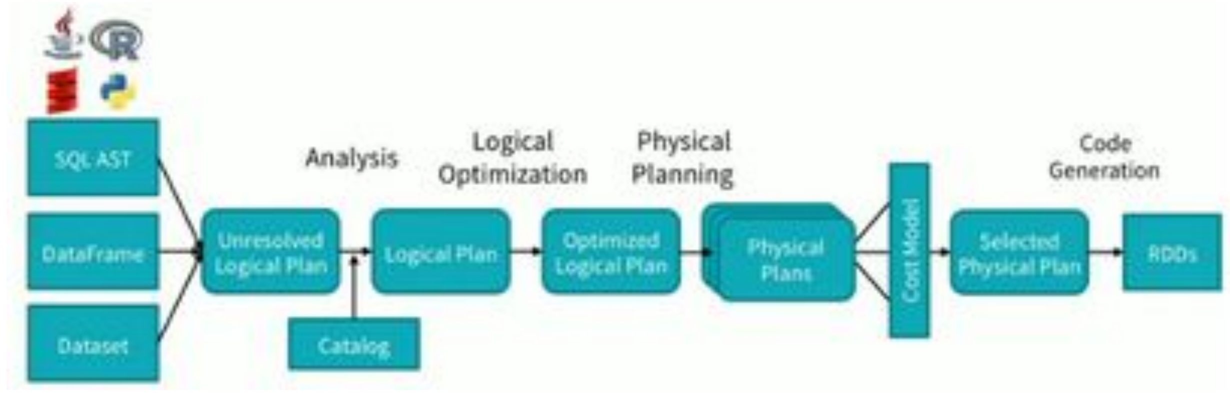
Idea 18:

Translation from Spark SQL to Spark Core

Idea 18: Translation from Spark SQL to Spark Core

For a Spark DF-based program to be executed, it has to be firstly translated into an equivalent Spark Core RDD-based program.

$$\begin{tikzcd}
\boxed{\text{Dataset}} \arrow[r] & \boxed{\text{DataFrame}\mathit{1}} \arrow[r] & \boxed{\text{DataFrame}\mathit{2}} \arrow[r] & \dots \arrow[r] & \boxed{\text{DataFrame}\mathit{k1}} \arrow[r] & \boxed{\text{resVAL}}
\end{tikzcd}$$



$$\begin{tikzcd}
\boxed{\text{Dataset}} \arrow[r] & \boxed{\text{RDD}\mathit{1}} \arrow[r] & \boxed{\text{RDD}\mathit{2}} \arrow[r] & \boxed{\text{RDD}\mathit{3}} \arrow[r] & \dots \arrow[r] & \boxed{\text{RDD}\mathit{k2}} \arrow[r] & \boxed{\text{resVAL}}
\end{tikzcd}$$

Idea 18: Translation from Spark SQL to Spark Core

This translation process includes the following stages:

1. Logical Query Plan.
2. Optimised Logical Query Plan.
3. Code Generation.

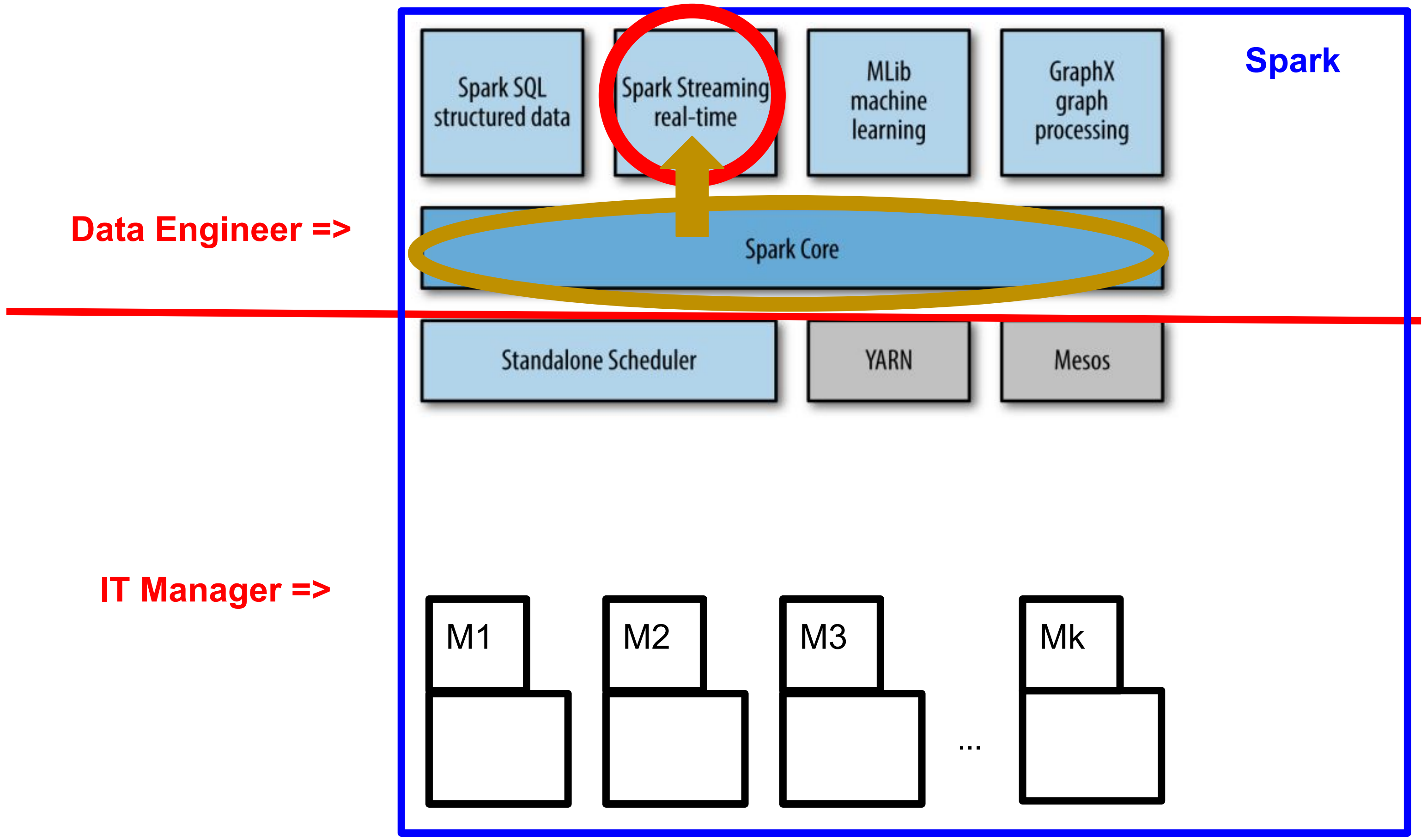
Outline

Idea 19:

Extending Spark Core
with Streaming Functionality

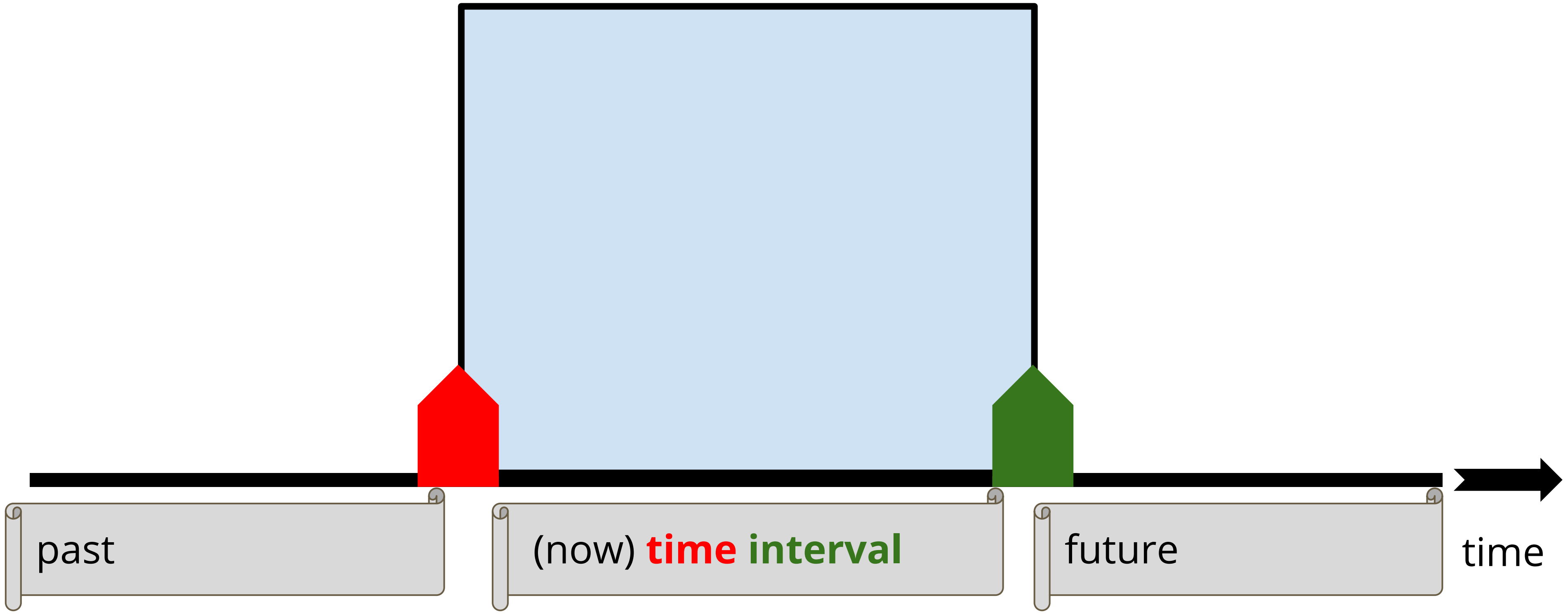
Idea 19: Extending Spark Core with Streaming Functionality

We have seen that Spark Core functionality can be extended to work in a Streaming fashion.



Idea 19: Extending Spark Core with Streaming Functionality

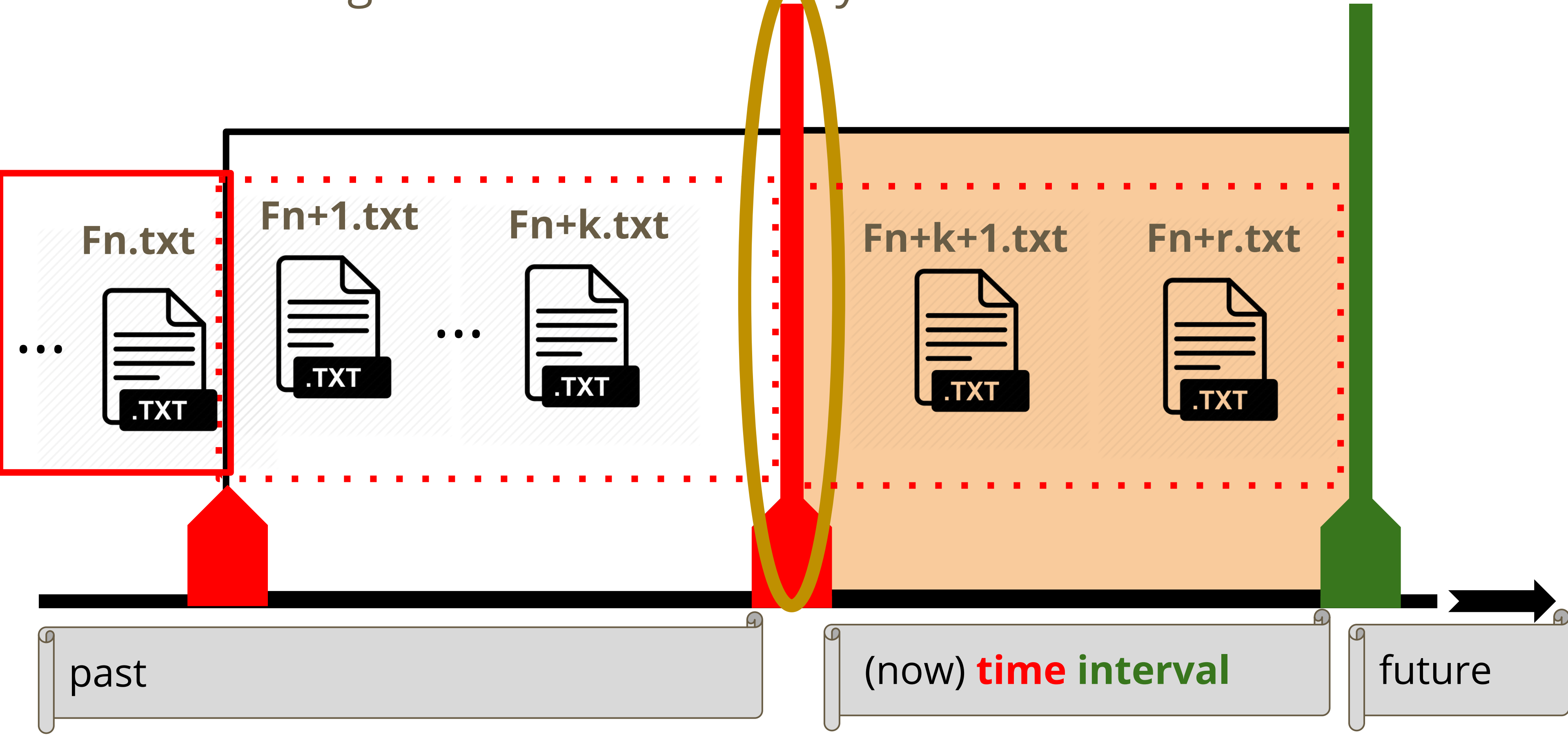
For it we need the notion of **time interval**...



Setting Up the Context

For it we need the notion of **time interval**...

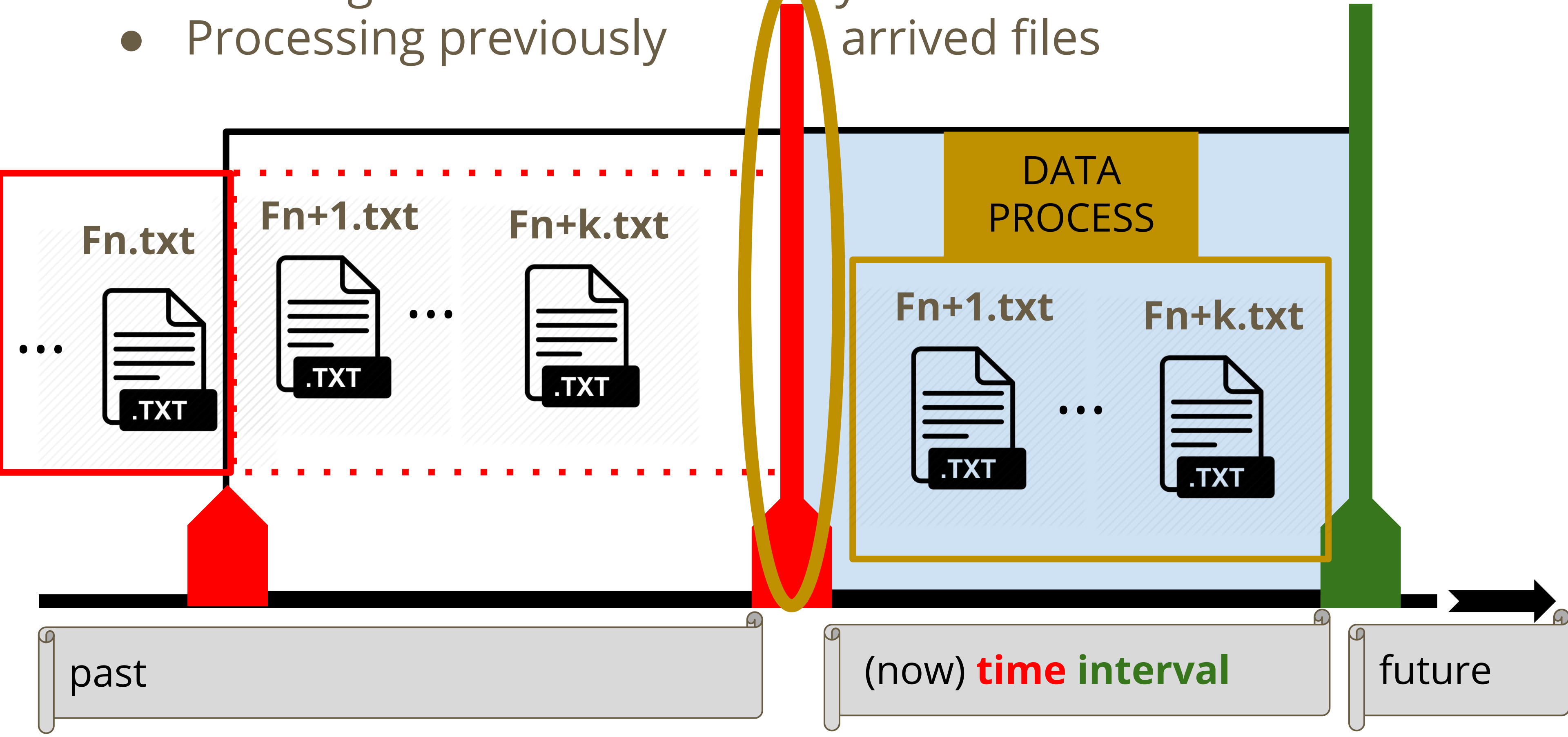
- Allowing new files from our dynamic dataset to arrive!



Setting Up the Context

For it we need the notion of **time interval**...

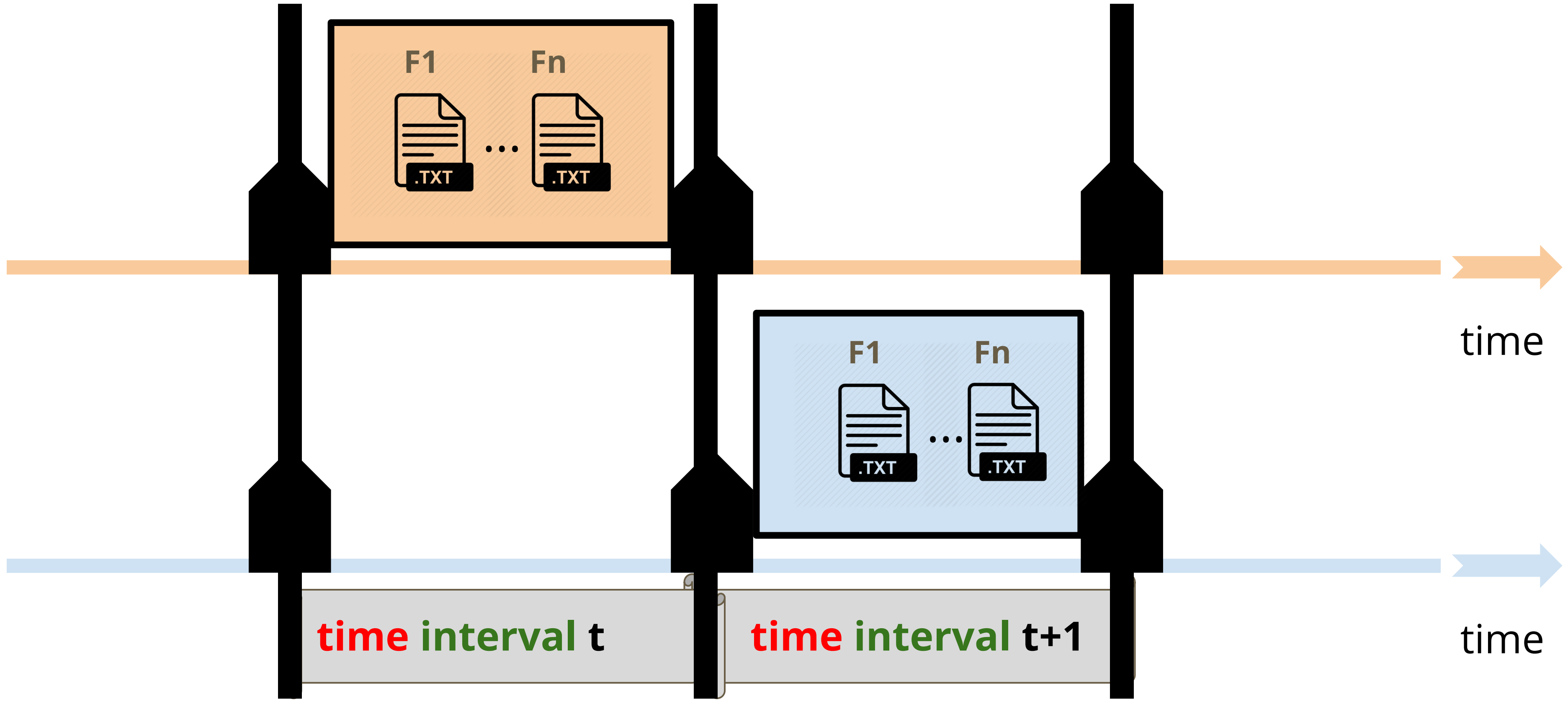
- Allowing new files from our dynamic dataset to arrive!
- Processing previously arrived files



Idea 19: Extending Spark Core with Streaming Functionality

For it we need the notion of **time interval**…

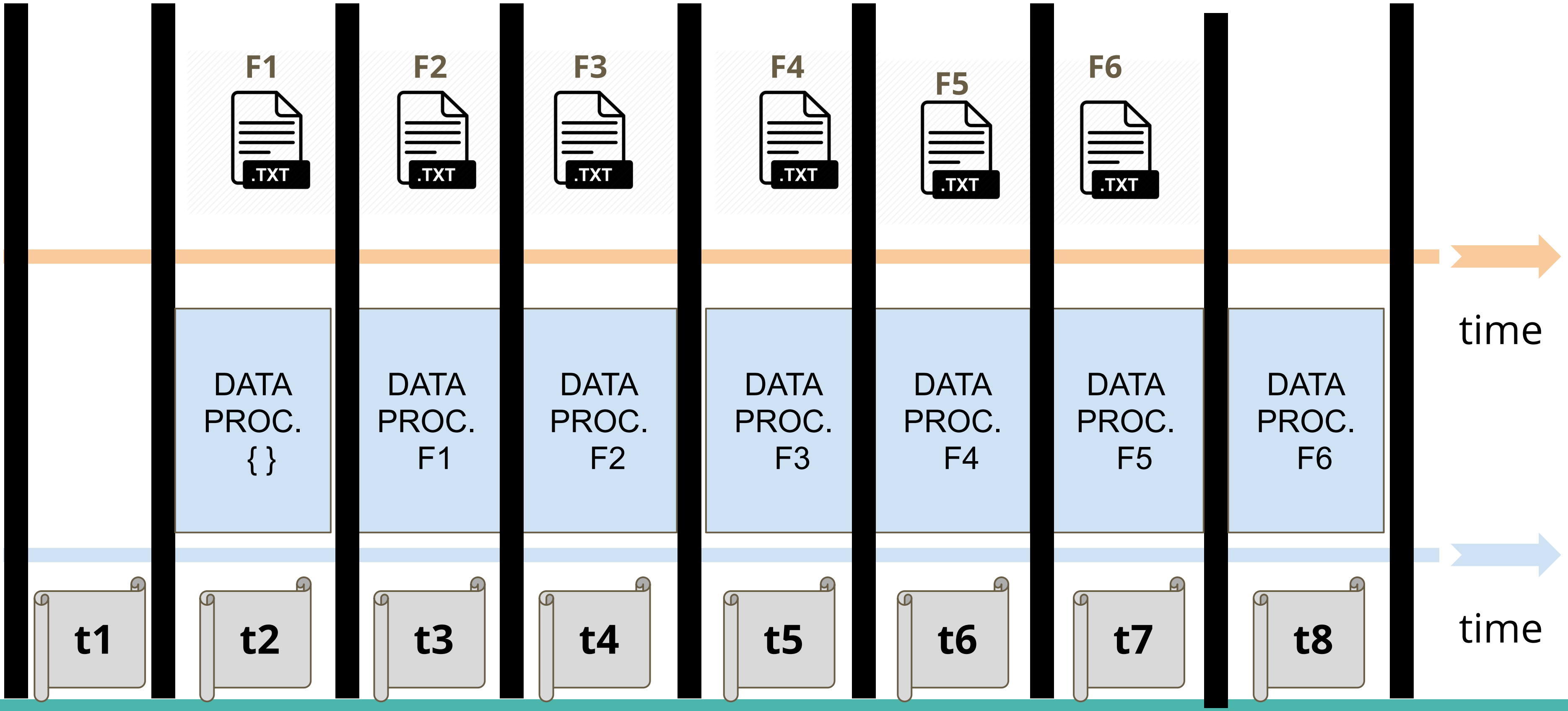
- ➢ In a process that is repeated over and over.



Idea 19: Extending Spark Core with Streaming Functionality

For it we need the notion of **time interval**...

➢ In a process that is repeated over and over.



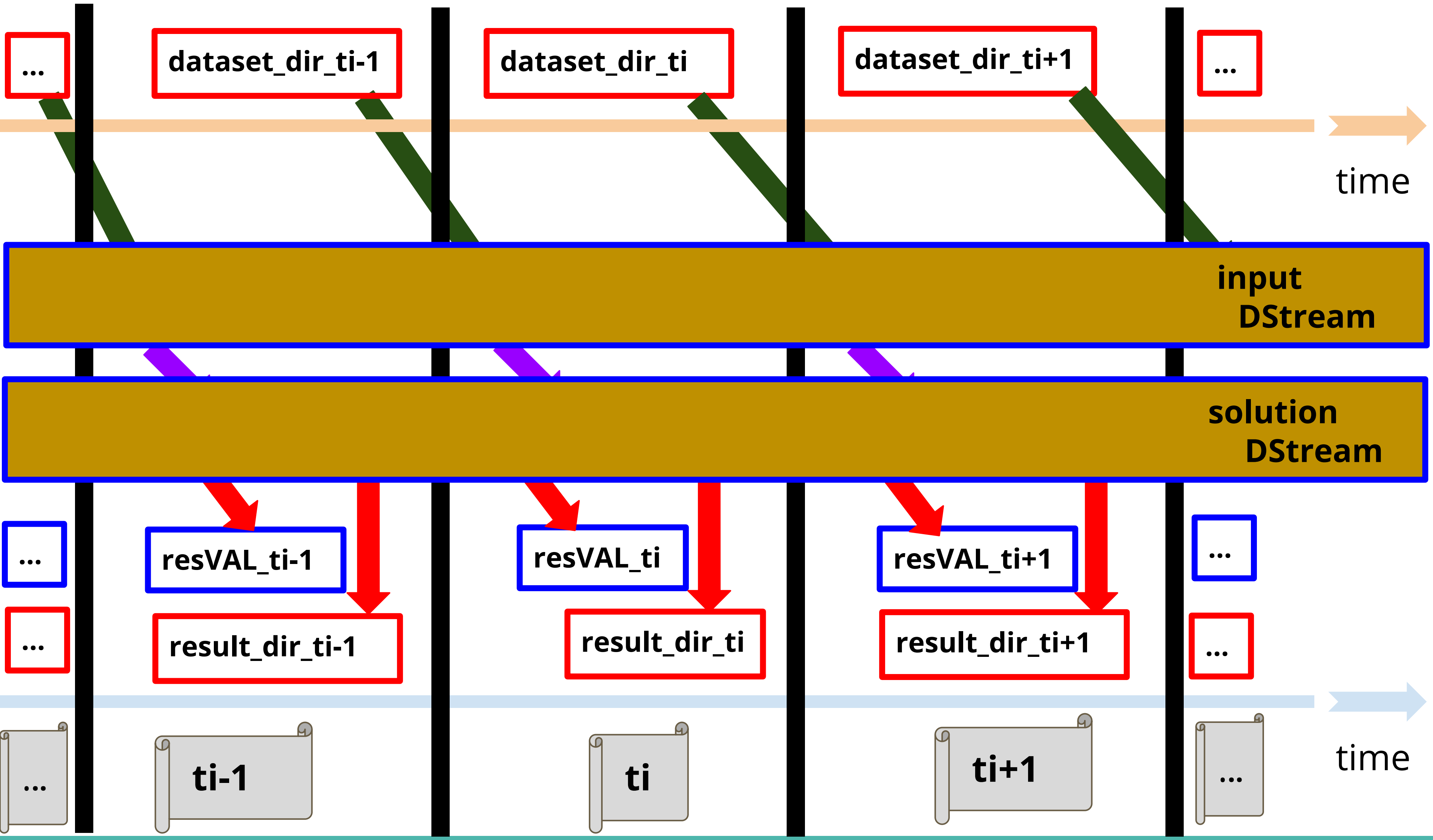
Idea 19: Extending Spark Core with Streaming Functionality

The data abstraction of Spark Streaming is a **DStream**, which can be seen as a **train** where each **wagon** represents the underlying **RDD** being processed during a concrete **time interval**.

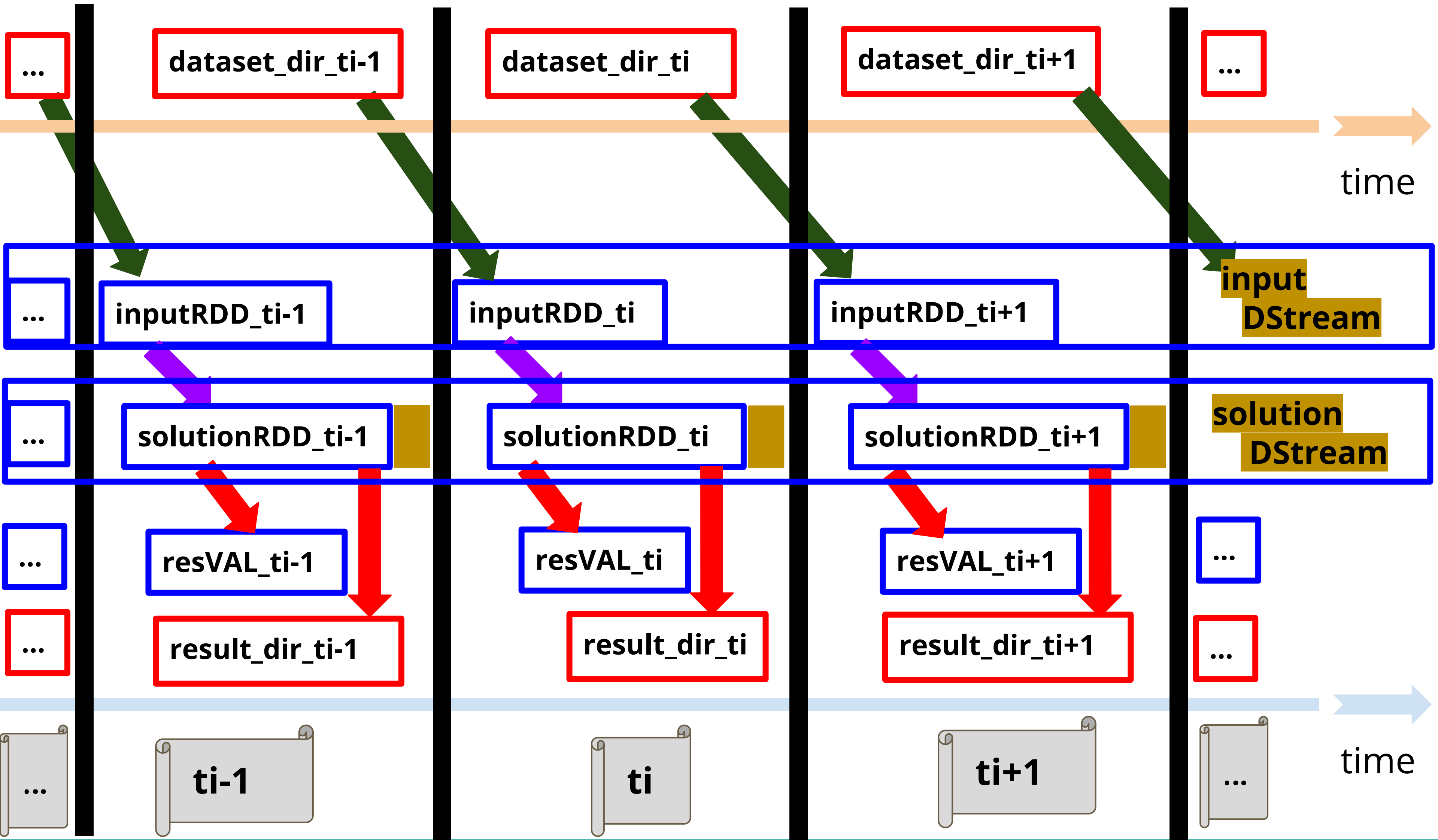
...

...

Idea 19: Extending Spark Core with Streaming Functionality

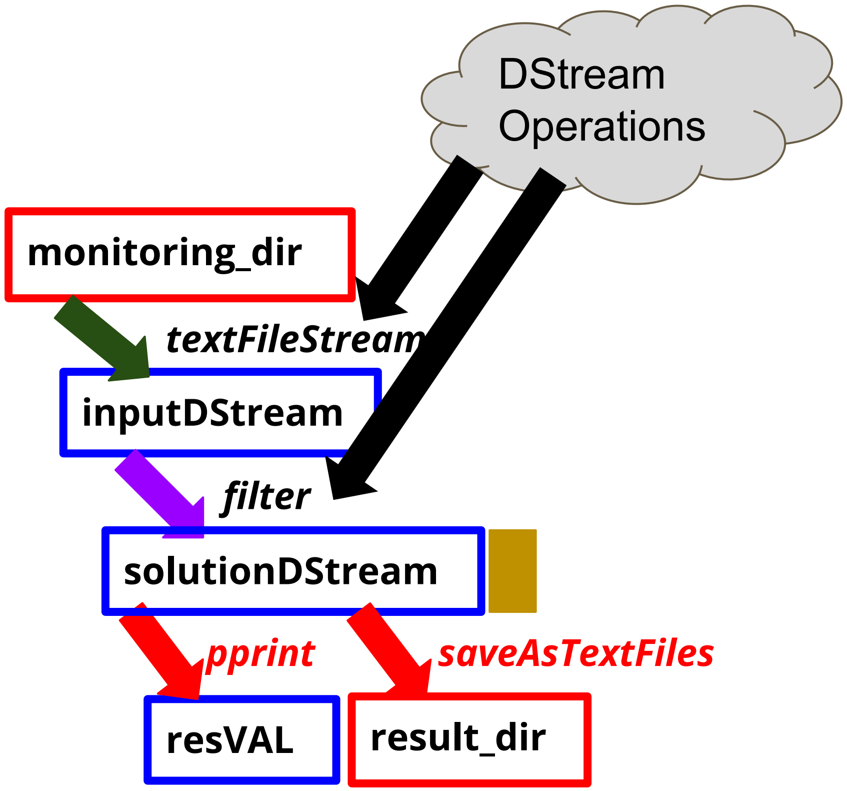


Idea 19: Extending Spark Core with Streaming Functionality

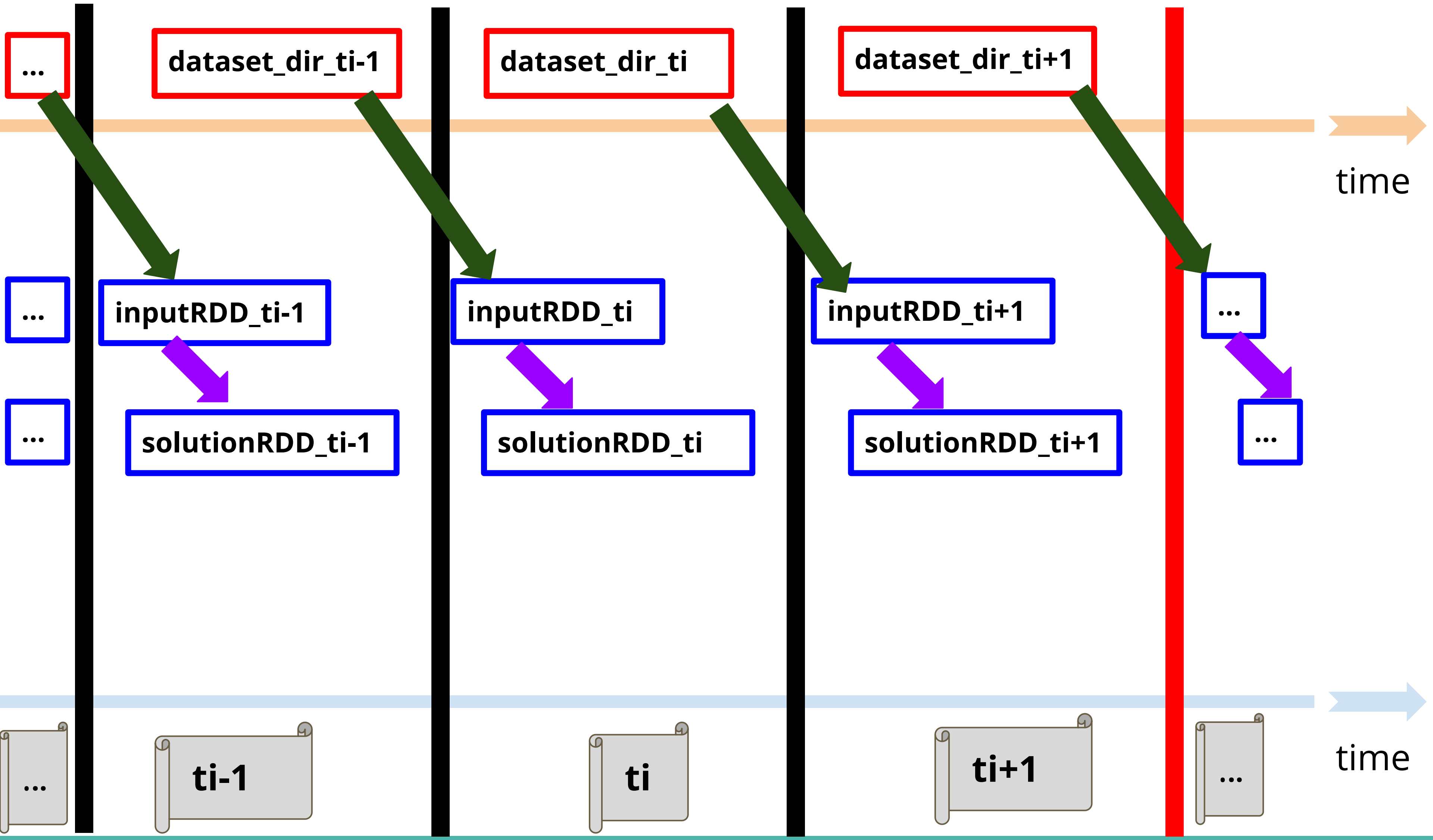


Idea 19: Extending Spark Core with Streaming Functionality

Regular **DStream** operations are applied to the underlying **RDDs** over time.



Idea 19: Extending Spark Core with Streaming Functionality



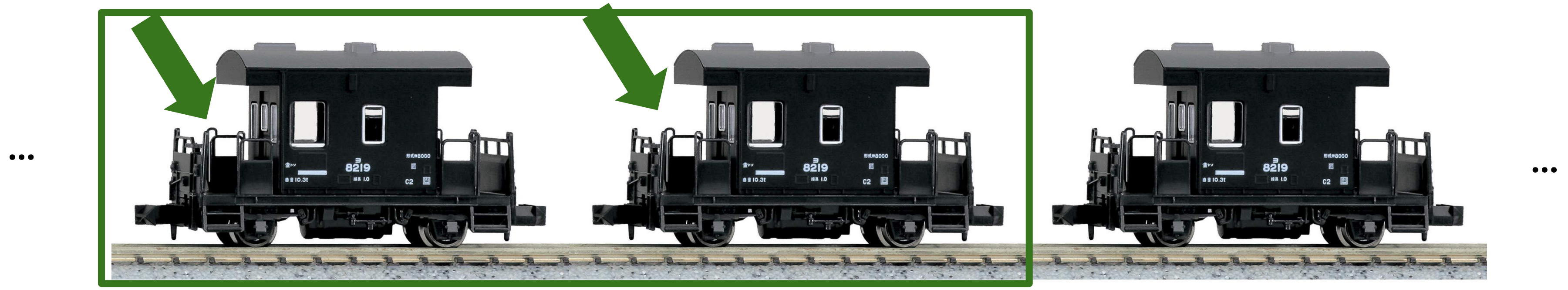
Outline

Idea 20:

On Altering Classical Time Period Reasoning Pattern

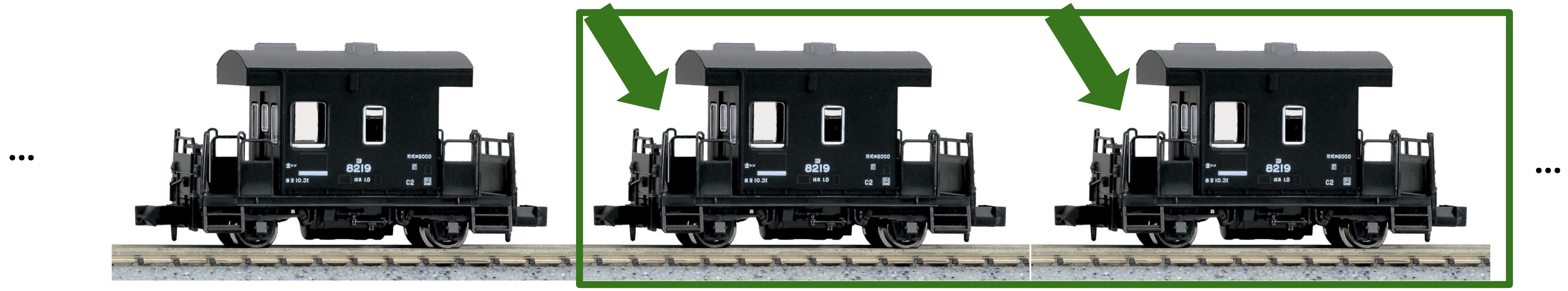
Idea 20: On Altering Classical Time Period Reasoning Pattern

Window-based Operations can be used to group **wagons** together.



Idea 20: On Altering Classical Time Period Reasoning Pattern

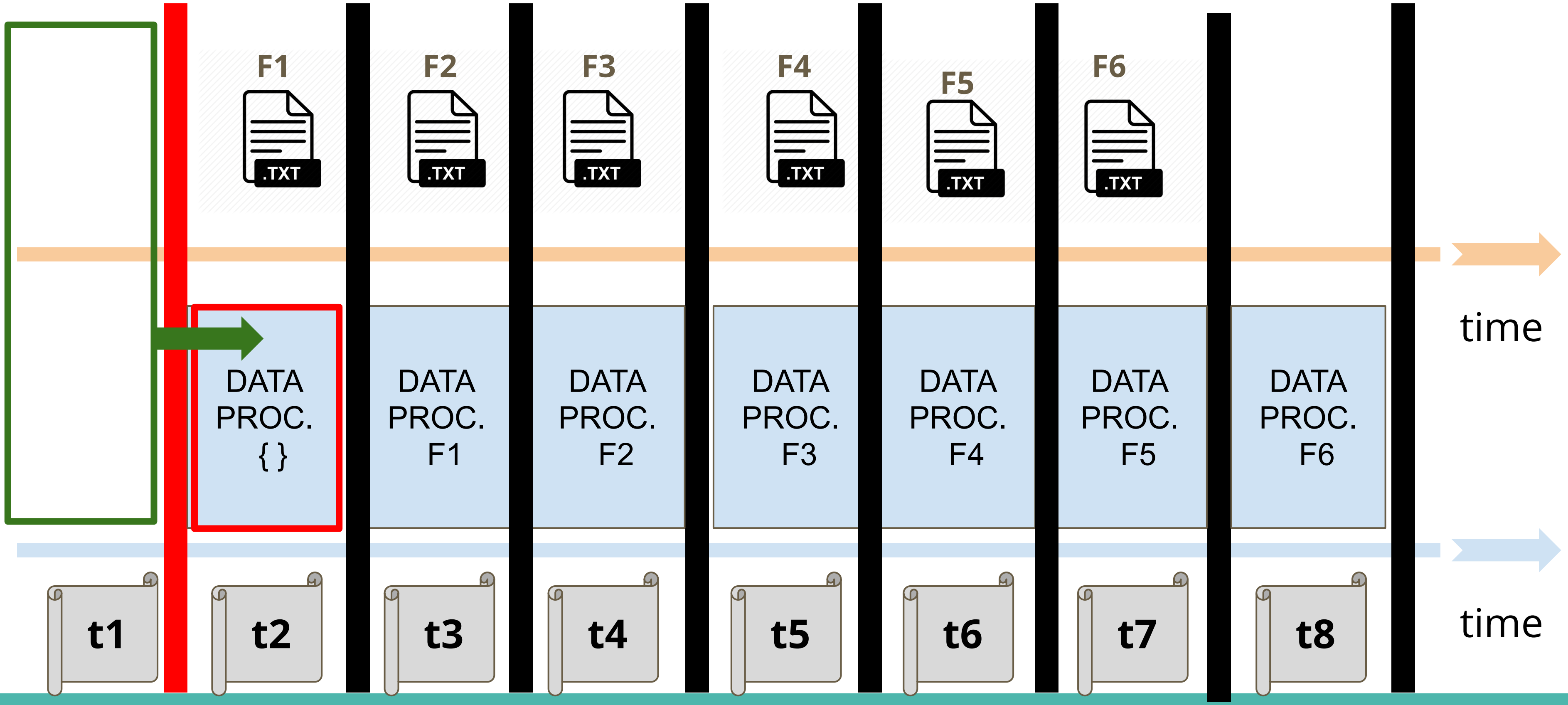
Window-based Operations can be used to group **wagons** together.



Idea 20: On Altering Classical Time Period Reasoning Pattern

Window-based Operations can be used to group wagons together.

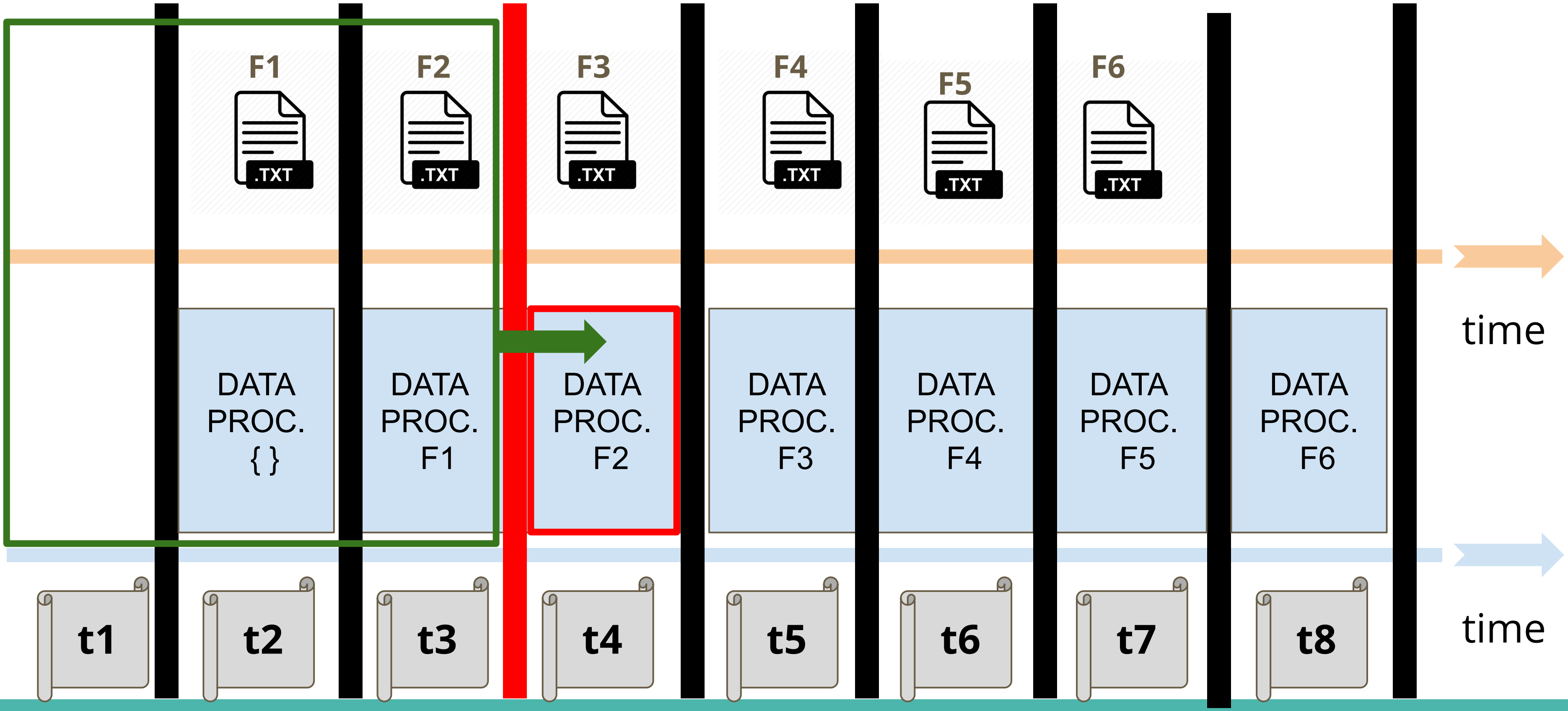
Sliding Duration = 2 and **Window Duration = 3**
we create the following windows at the following times



Idea 20: On Altering Classical Time Period Reasoning Pattern

Window-based Operations can be used to group wagons together.

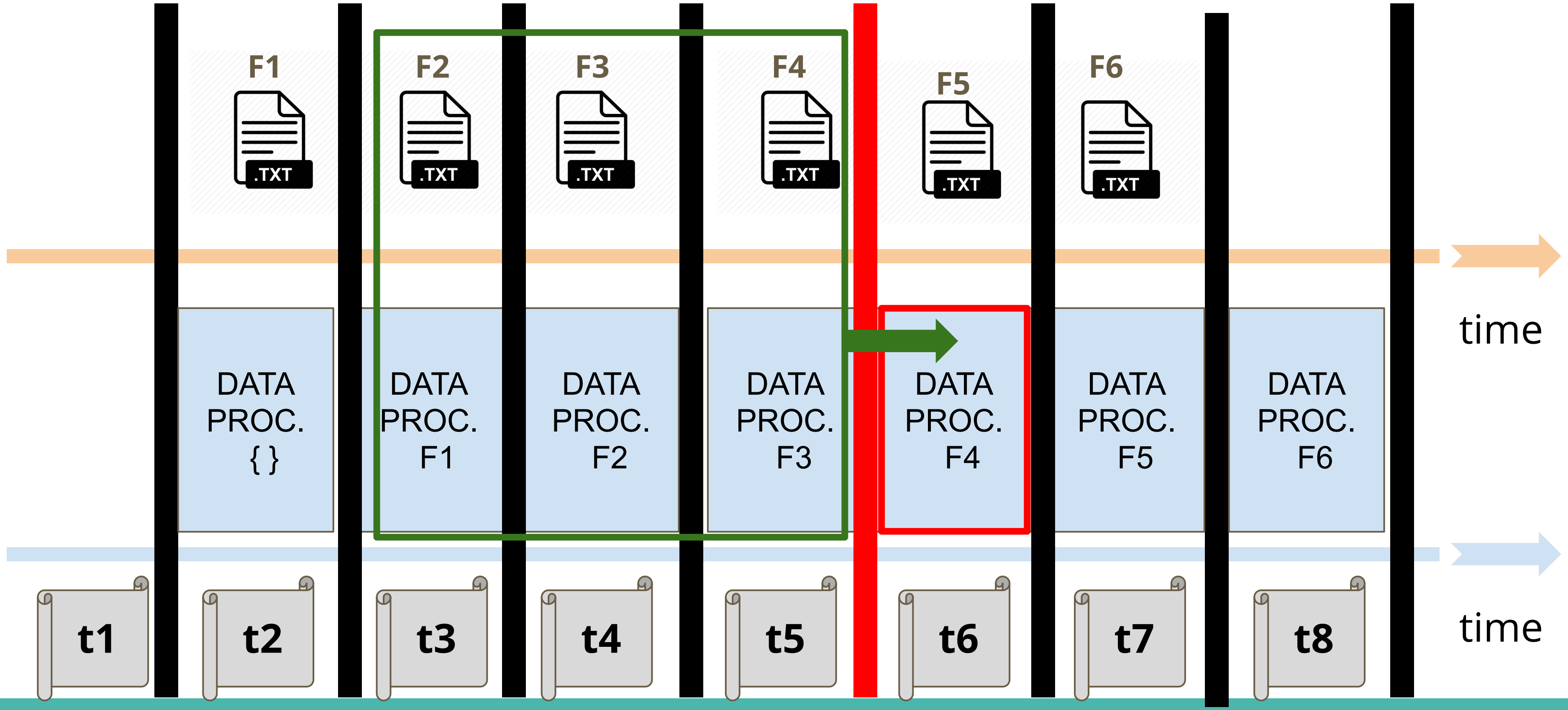
Sliding Duration = 2 and **Window Duration = 3**
we create the following windows at the following times



Idea 20: On Altering Classical Time Period Reasoning Pattern

Window-based Operations can be used to group wagons together.

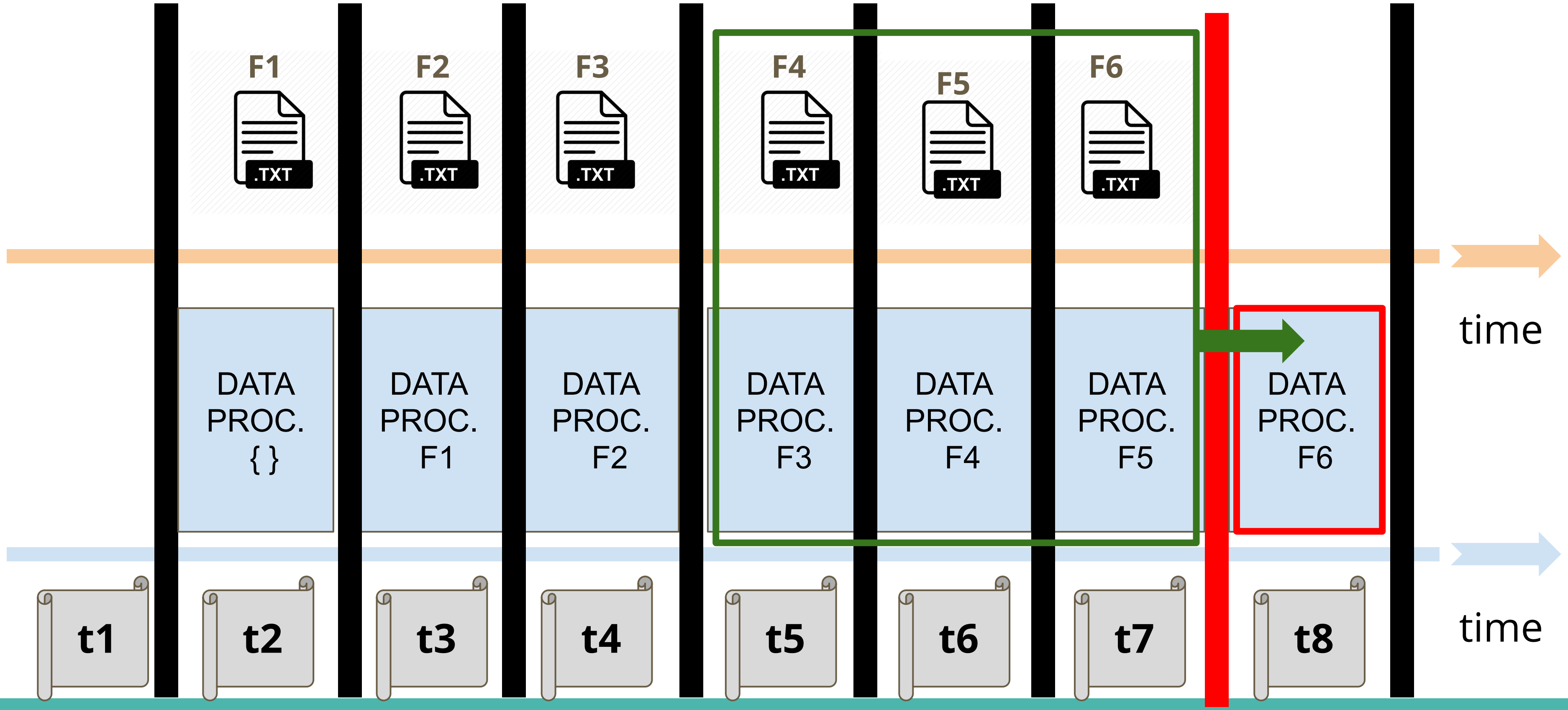
Sliding Duration = 2 and **Window Duration = 3**
we create the following windows at the following times



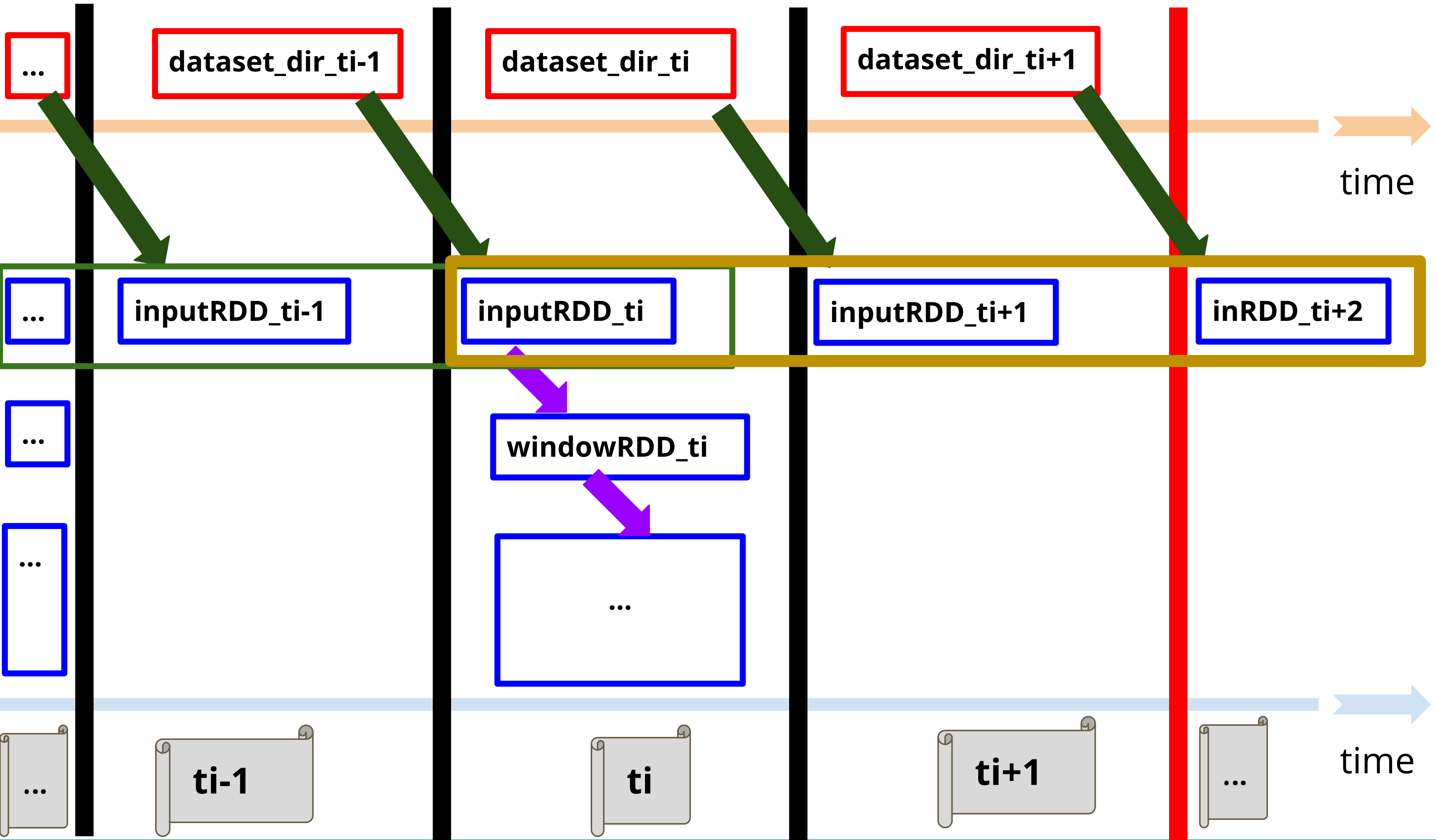
Idea 20: On Altering Classical Time Period Reasoning Pattern

Window-based Operations can be used to group wagons together.

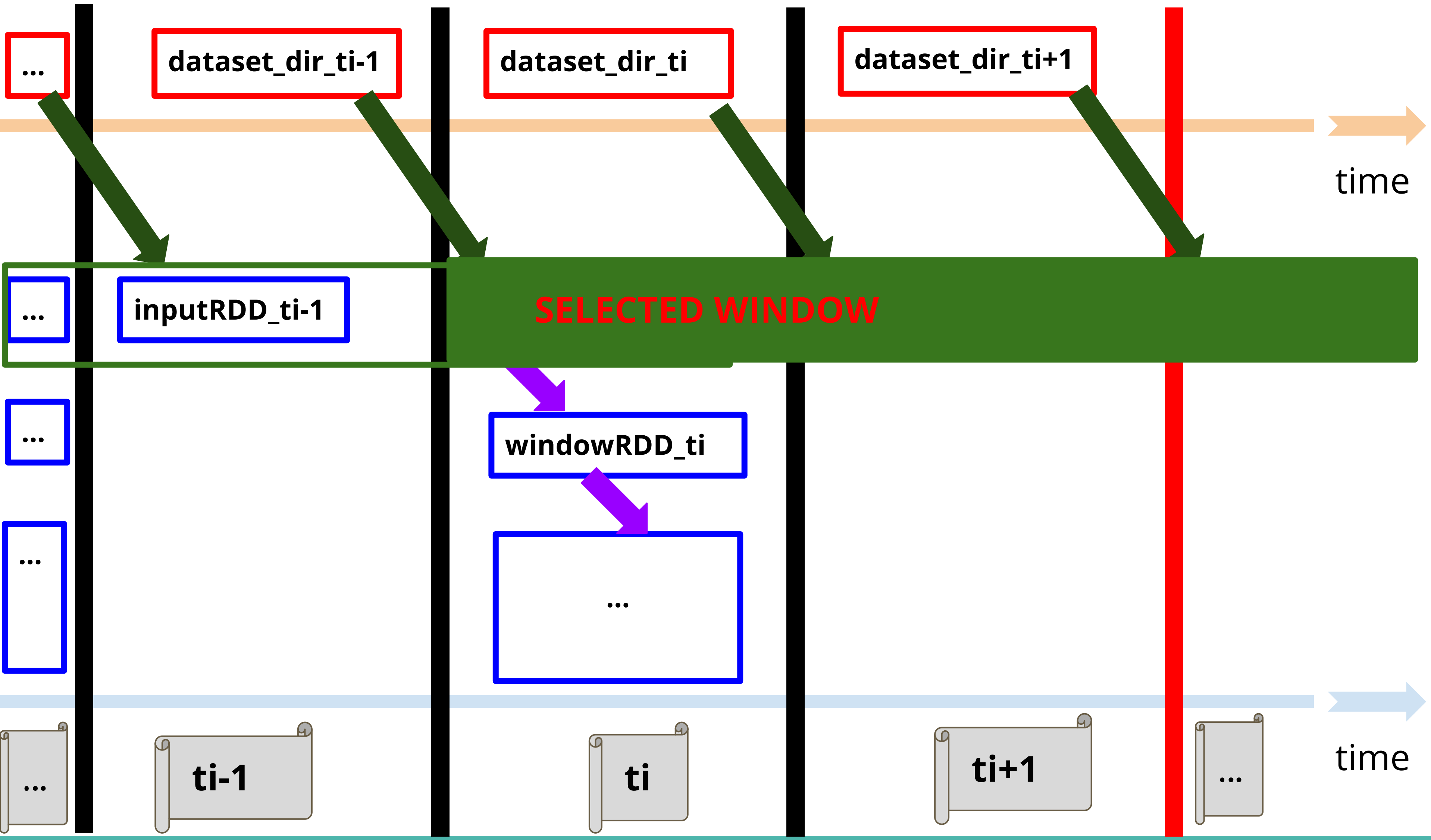
Sliding Duration = 2 and **Window Duration = 3**
we create the following windows at the following times



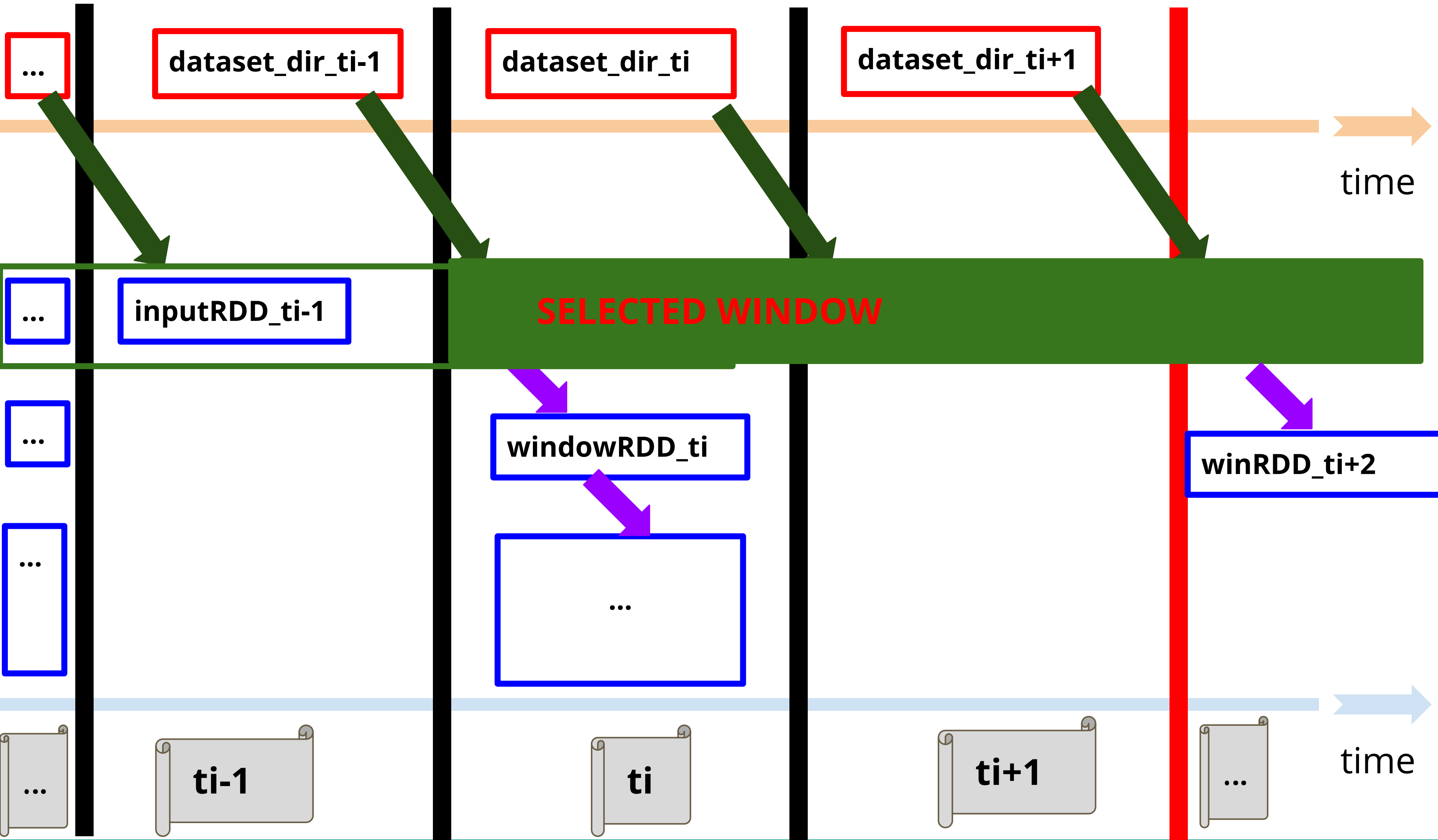
Idea 20: On Altering Classical Time Period Reasoning Pattern



Idea 20: On Altering Classical Time Period Reasoning Pattern

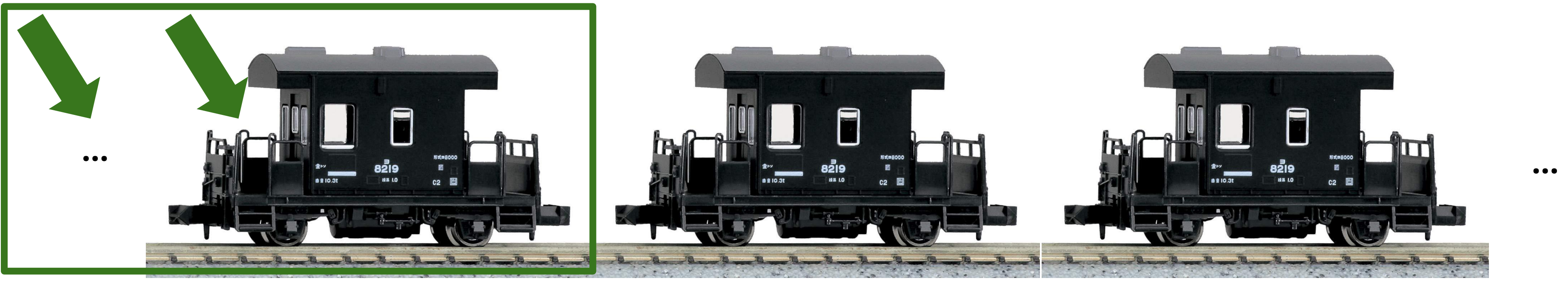


Idea 20: On Altering Classical Time Period Reasoning Pattern



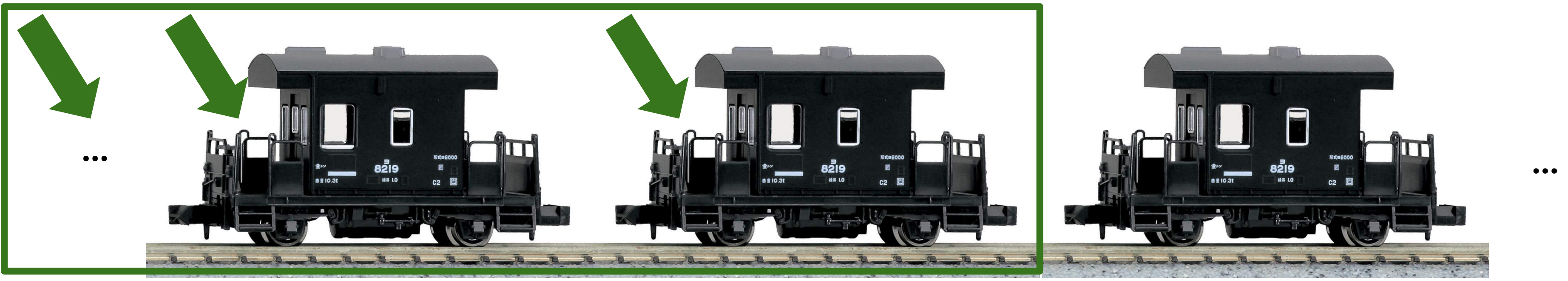
Idea 20: On Altering Classical Time Period Reasoning Pattern

Update-based operations aggregate results for all the **wagons** processed so far.

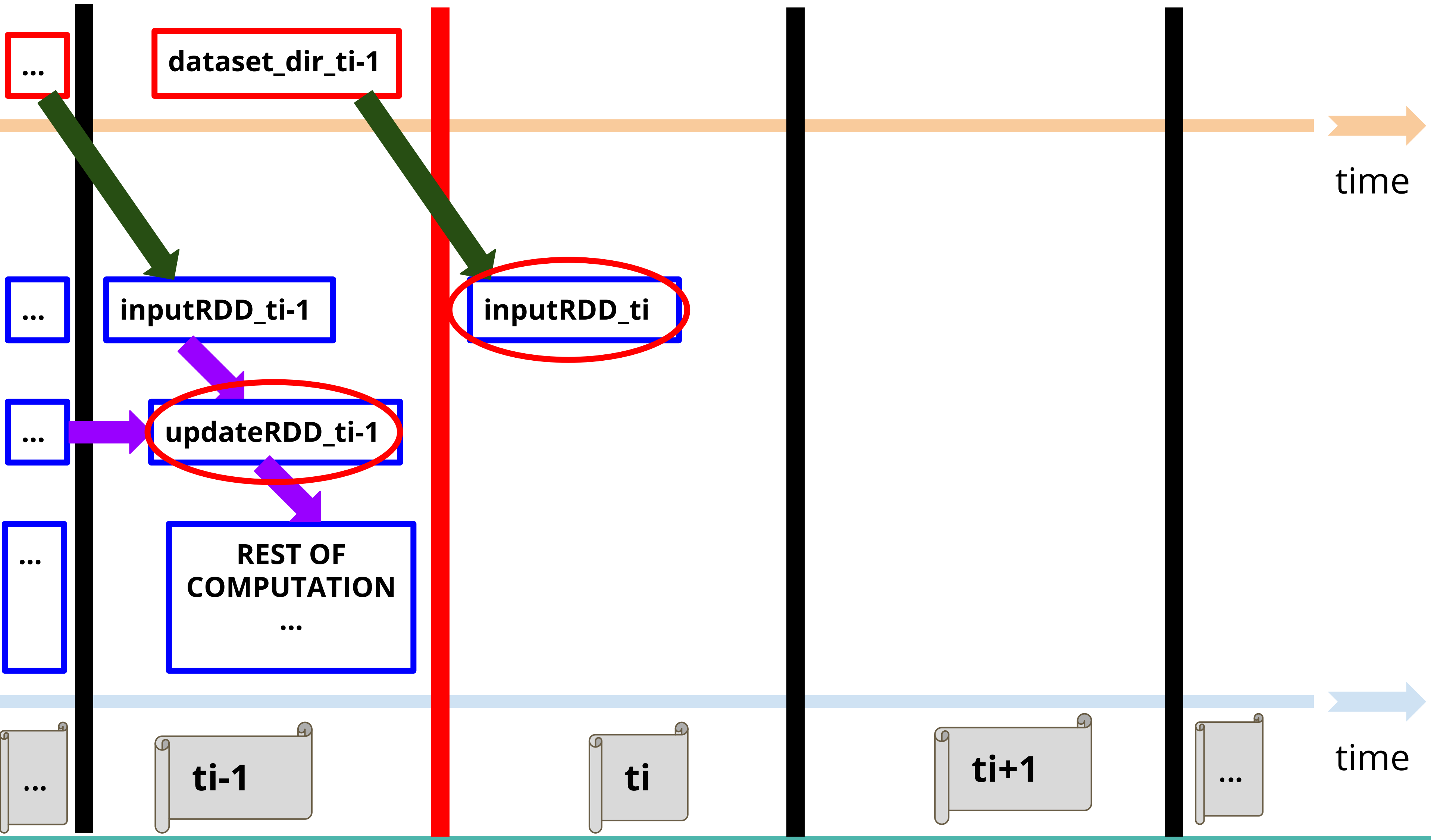


Idea 20: On Altering Classical Time Period Reasoning Pattern

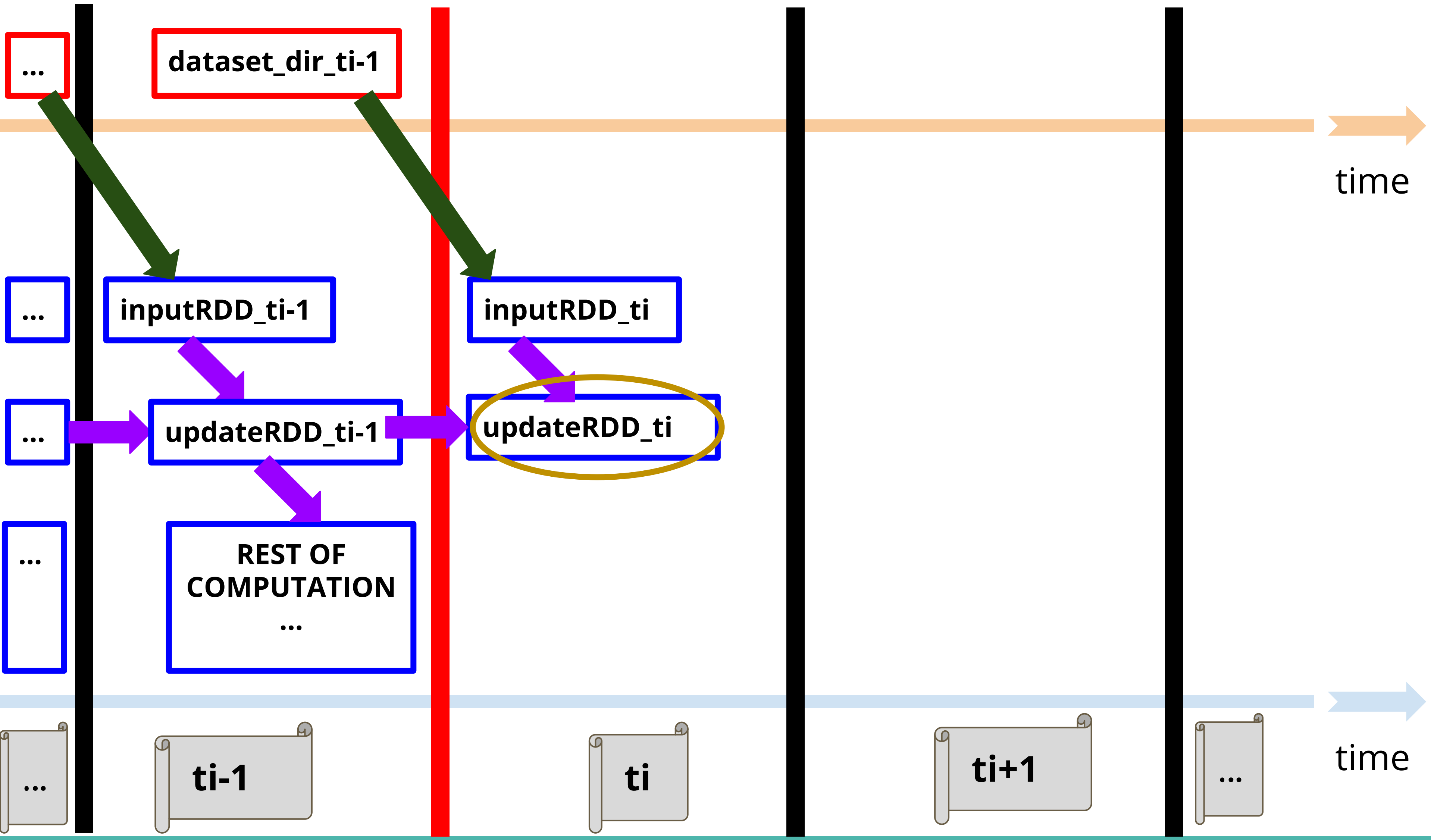
Update-based operations aggregate results for all the **wagons** processed so far.



Idea 20: On Altering Classical Time Period Reasoning Pattern

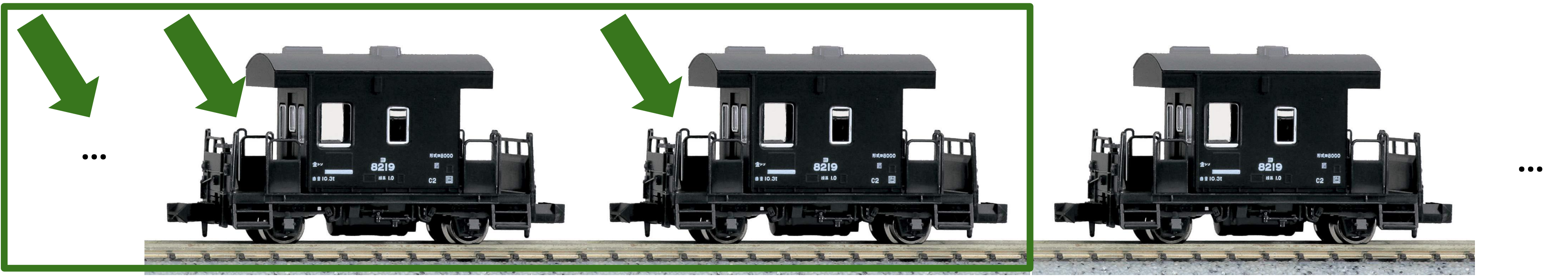


Idea 20: On Altering Classical Time Period Reasoning Pattern



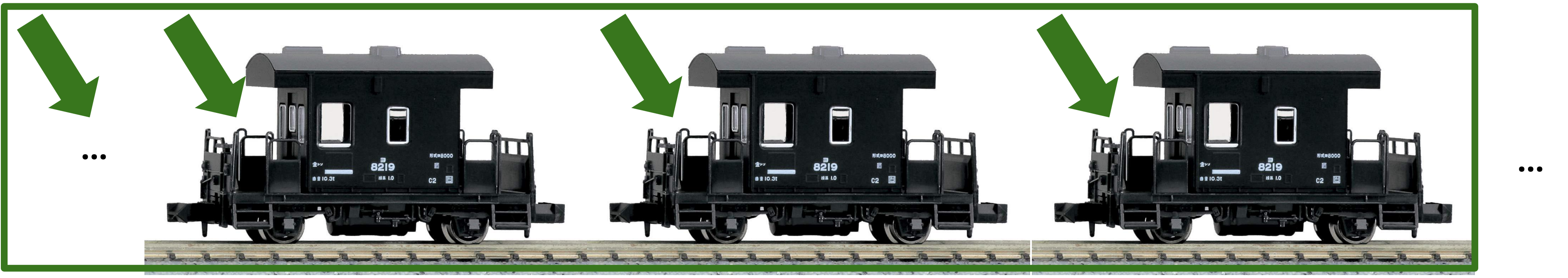
Idea 20: On Altering Classical Time Period Reasoning Pattern

Update-based operations aggregate results for all the **wagons** processed so far.

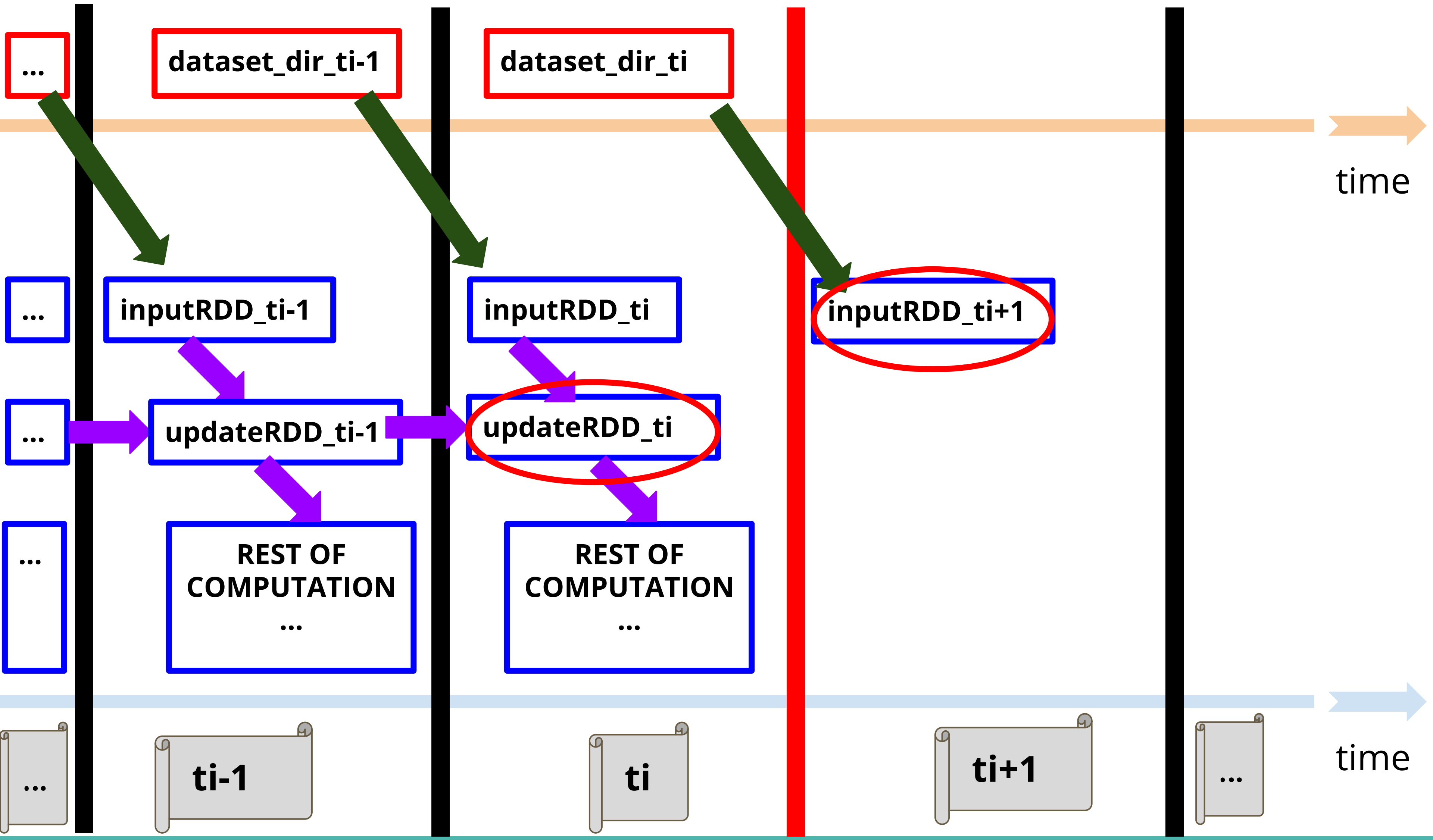


Idea 20: On Altering Classical Time Period Reasoning Pattern

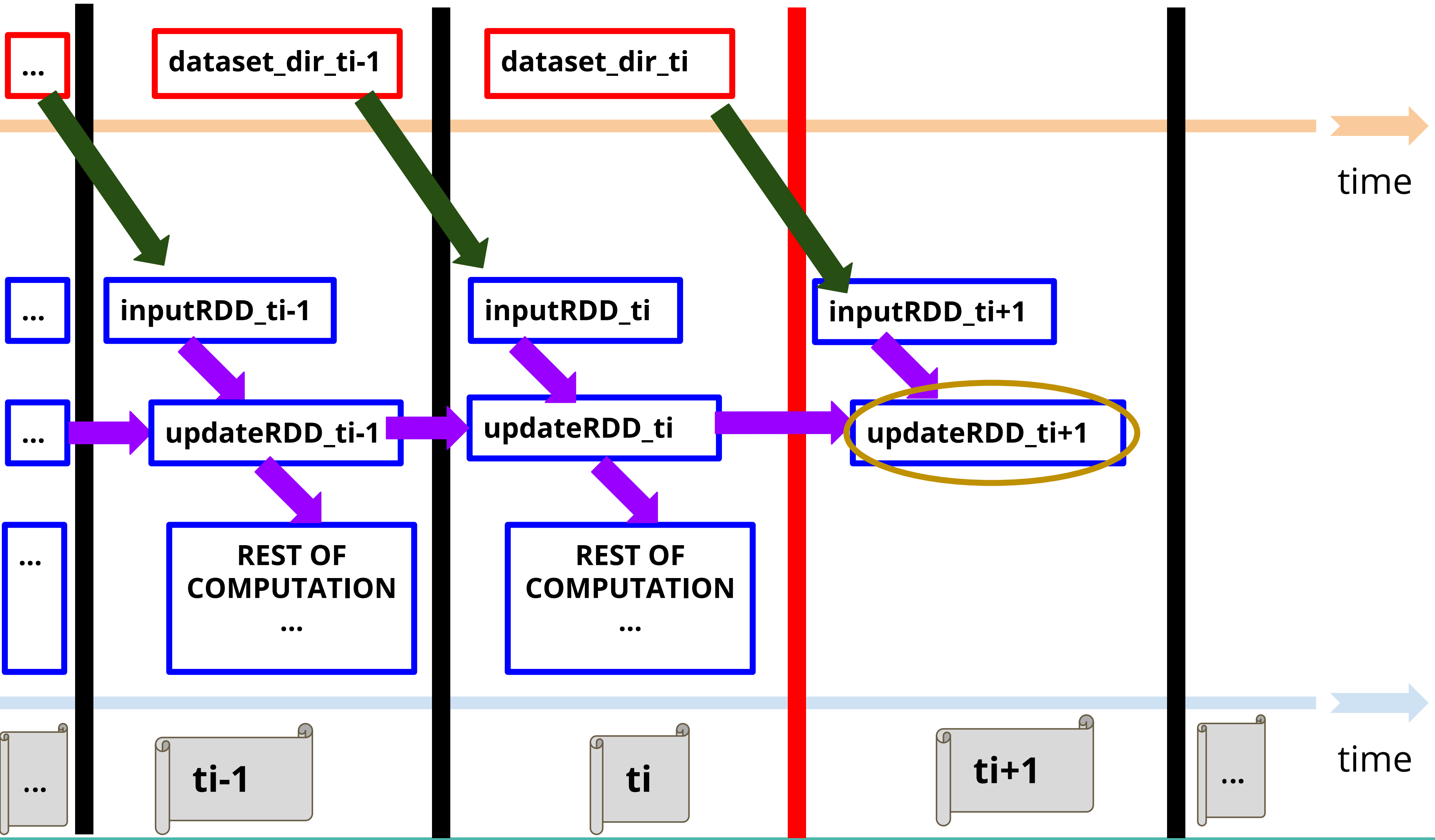
Update-based operations aggregate results for all the **wagons** processed so far.



Idea 20: On Altering Classical Time Period Reasoning Pattern



Idea 20: On Altering Classical Time Period Reasoning Pattern

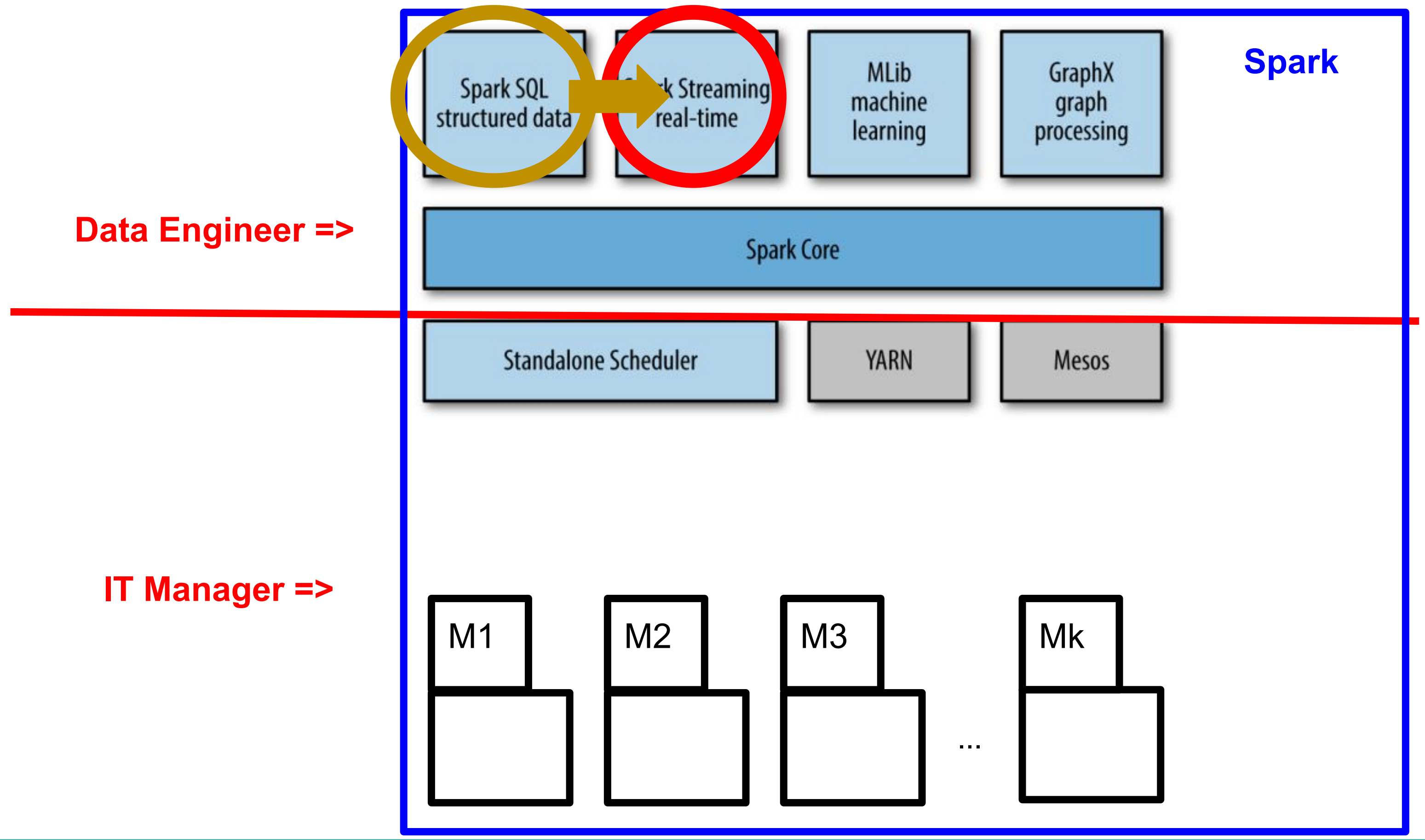


Outline

Idea 21:

Extending Spark SQL
with Streaming Functionality

Idea 21: Extending Spark SQL with Streaming Functionality



Idea 21: Extending Spark SQL with Streaming Functionality

The same behaviour of **DStream** applies to Streaming DataFrames (**SDF**)!

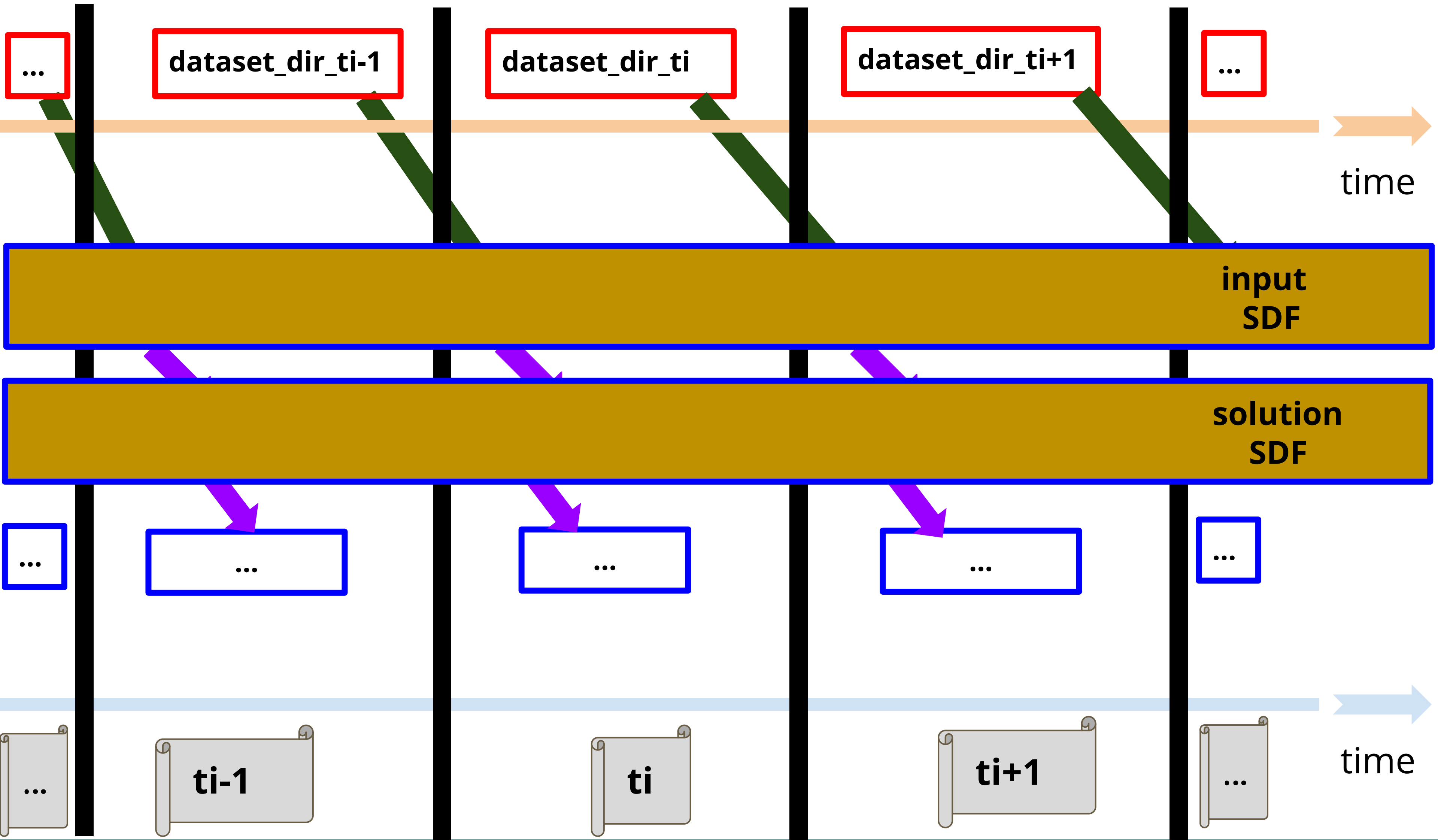
Idea 21: Extending Spark SQL with Streaming Functionality

A **Streaming DataFrame (SDF)** also represents an amalgamation of **DataFrames (DF)** over time.

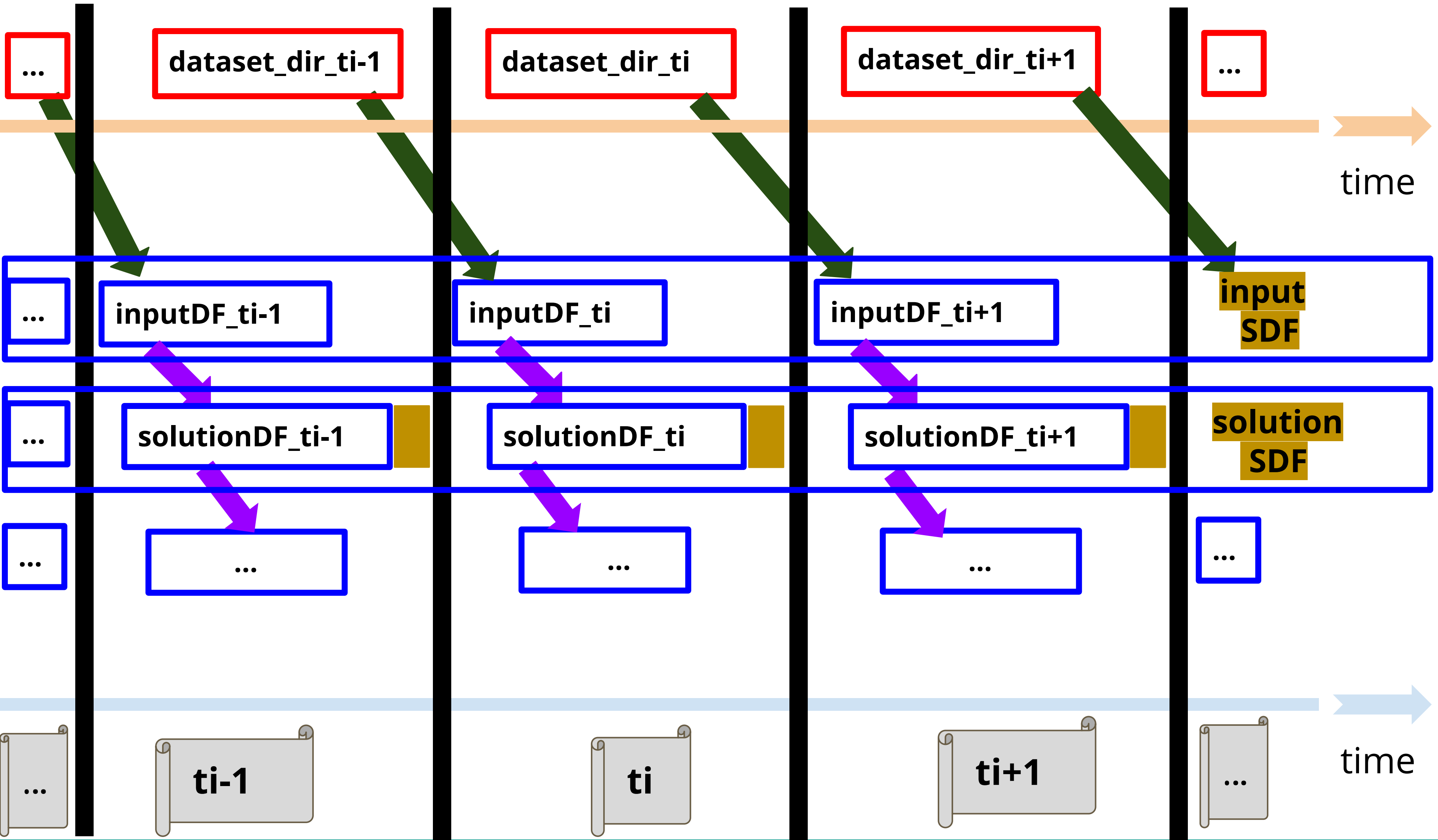
…

…

Idea 21: Extending Spark SQL with Streaming Functionality

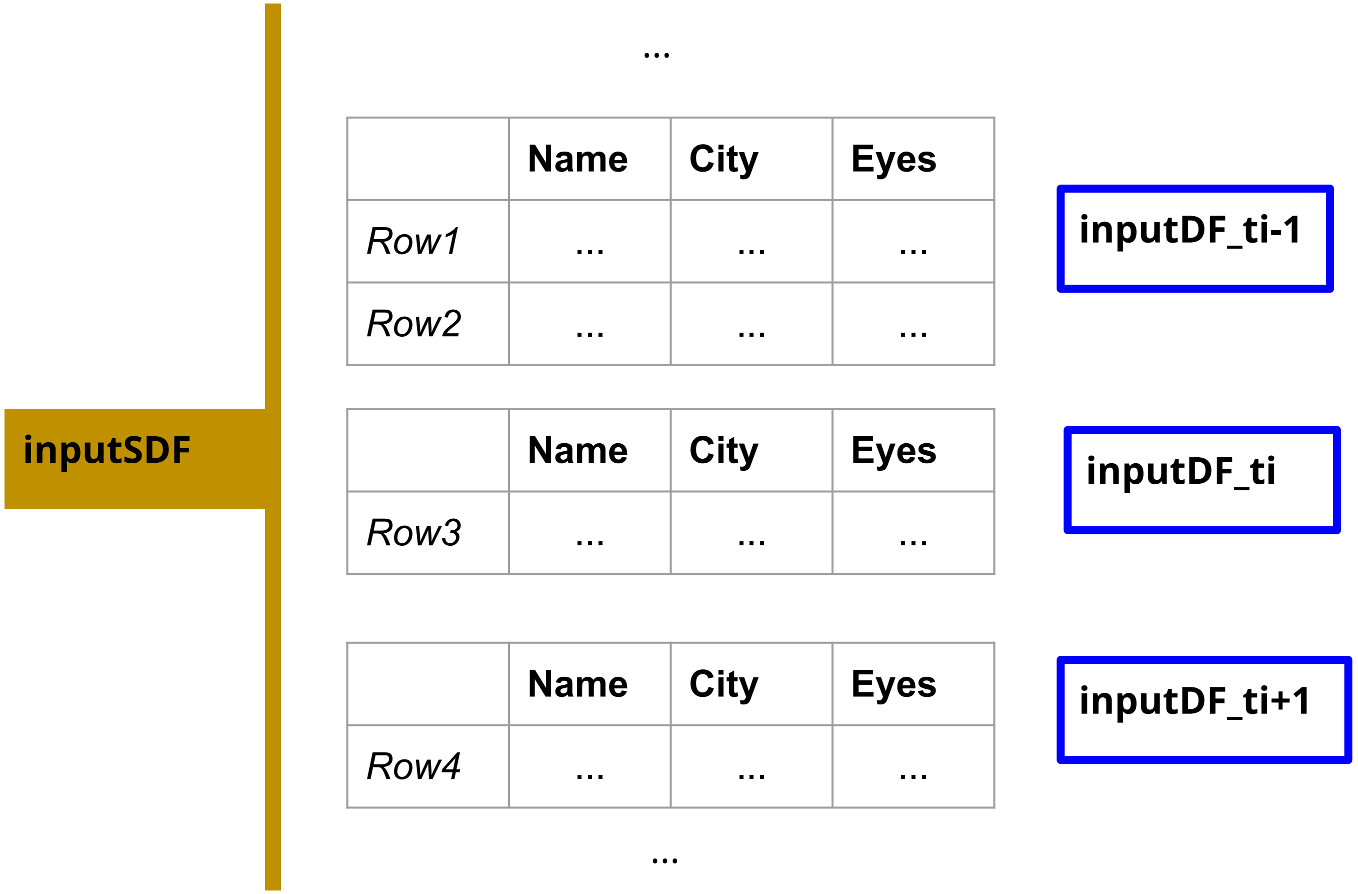


Idea 21: Extending Spark SQL with Streaming Functionality



Idea 21: Extending Spark SQL with Streaming Functionality

The SDF can also be visualised as an Unbound table, which keeps receiving Rows over time.



	Name	City	Eyes
Row1	...	...	...
Row2	...	...	...

	Name	City	Eyes
Row3	...	...	...

	Name	City	Eyes
Row4	...	...	...

Idea 21: Extending Spark SQL with Streaming Functionality

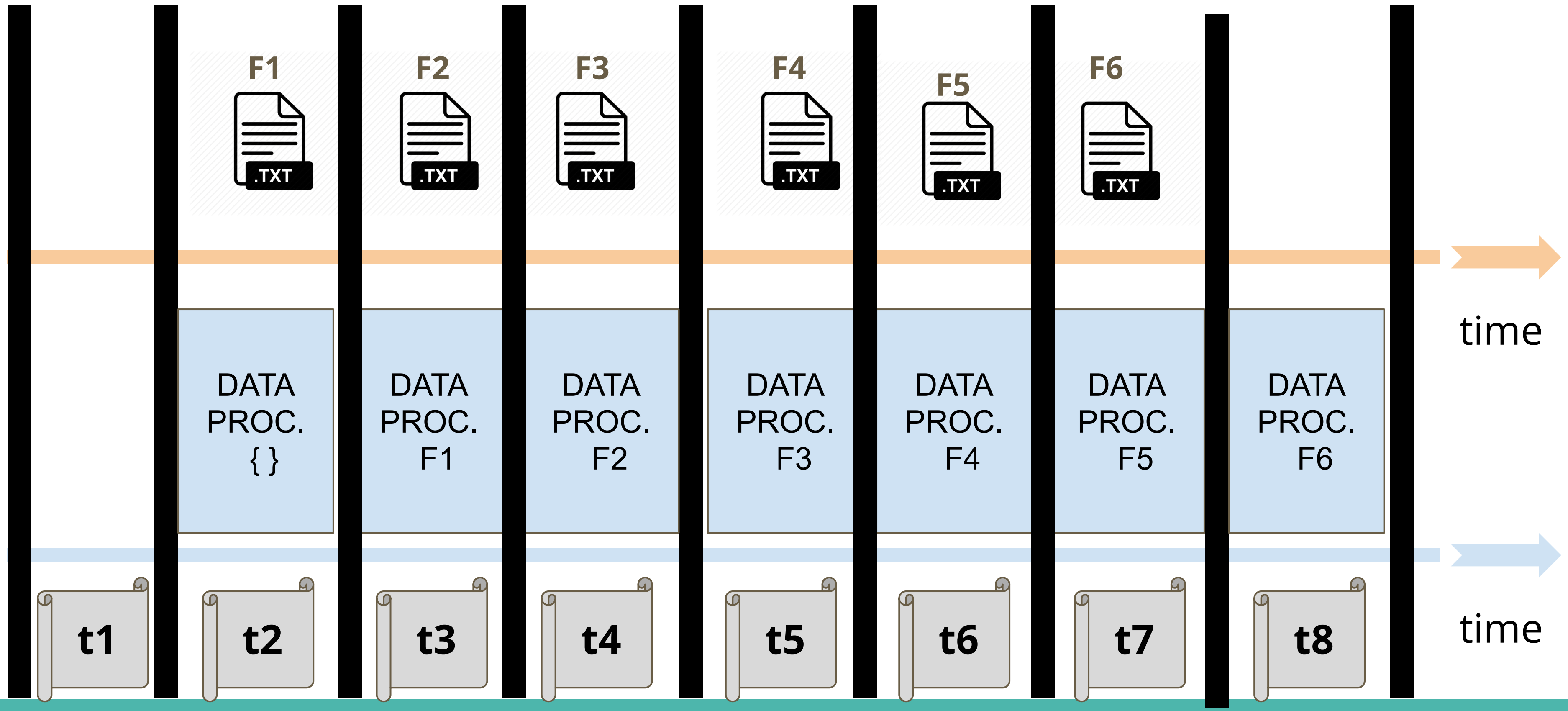
In any case, whether you use:

1. An horizontal viewing based on a train of wagons (DFs)
2. A vertical viewing based on an unbound data structure of Rows

the behaviour of **DStream** and **SDF** is equivalent!

Idea 21: Extending Spark SQL with Streaming Functionality

Our regular working mode is called Append Mode.

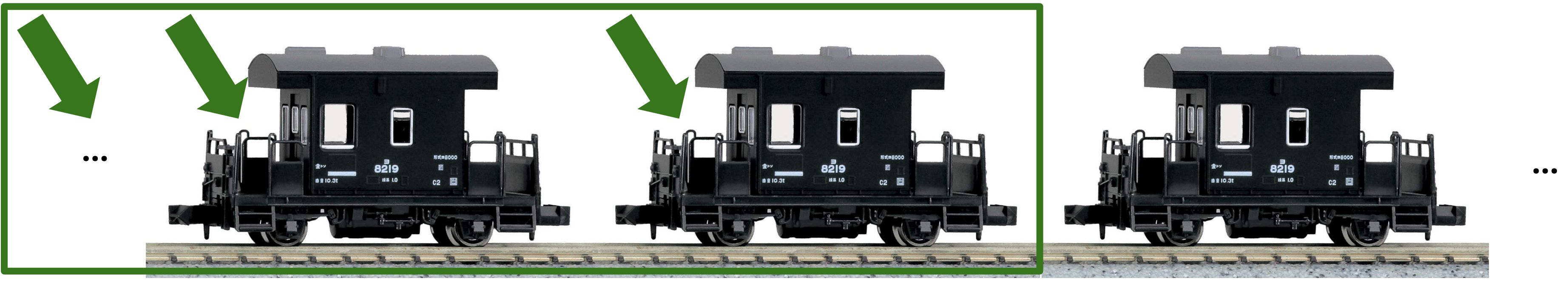


Idea 21: Extending Spark SQL with Streaming Functionality

Our update-based operations lead to Complete Mode.

Idea 21: Extending Spark SQL with Streaming Functionality

Our update-based operations lead to Complete Mode.



Idea 21: Extending Spark SQL with Streaming Functionality

Our update-based operations lead to Complete Mode.

Idea 21: Extending Spark SQL with Streaming Functionality

- Both Append and Complete Mode support reasoning over windows.

Idea 21: Extending Spark SQL with Streaming Functionality

- Both Append and Complete Mode support reasoning over windows.

- As a difference, in Structured Spark Streaming, we have to choose on whether:
  - Print the results by the screen (Console Sink mode).
  - Save the results to our file system (File Sink Output).

Outline

Idea 22:

Spark Structured Streaming
Limited Functionality

Idea 22: Spark Structured Streaming Limited Functionality

We have seen that we can apply some of the functionality of **Spark Streaming** to **Spark Structured Streaming** as well.

However, there are quite some differences and limitations making Spark Structured Streaming not as appealing as it should be.

Outline

Idea 23:

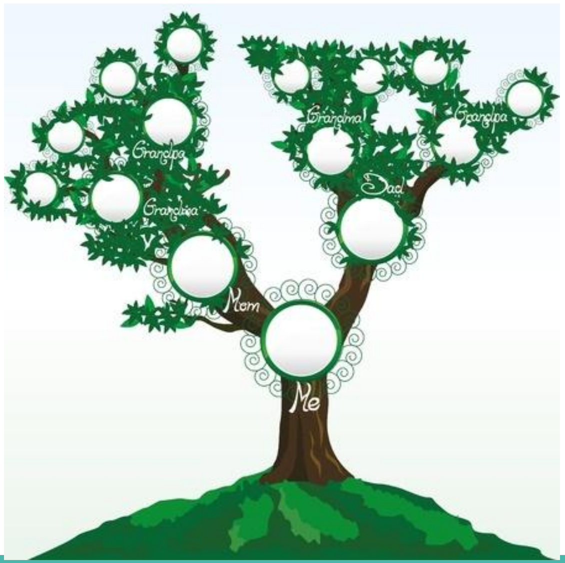
Private Side of RDDs

Idea 23: Private Side of RDDs

Let's go with the ADT private side:

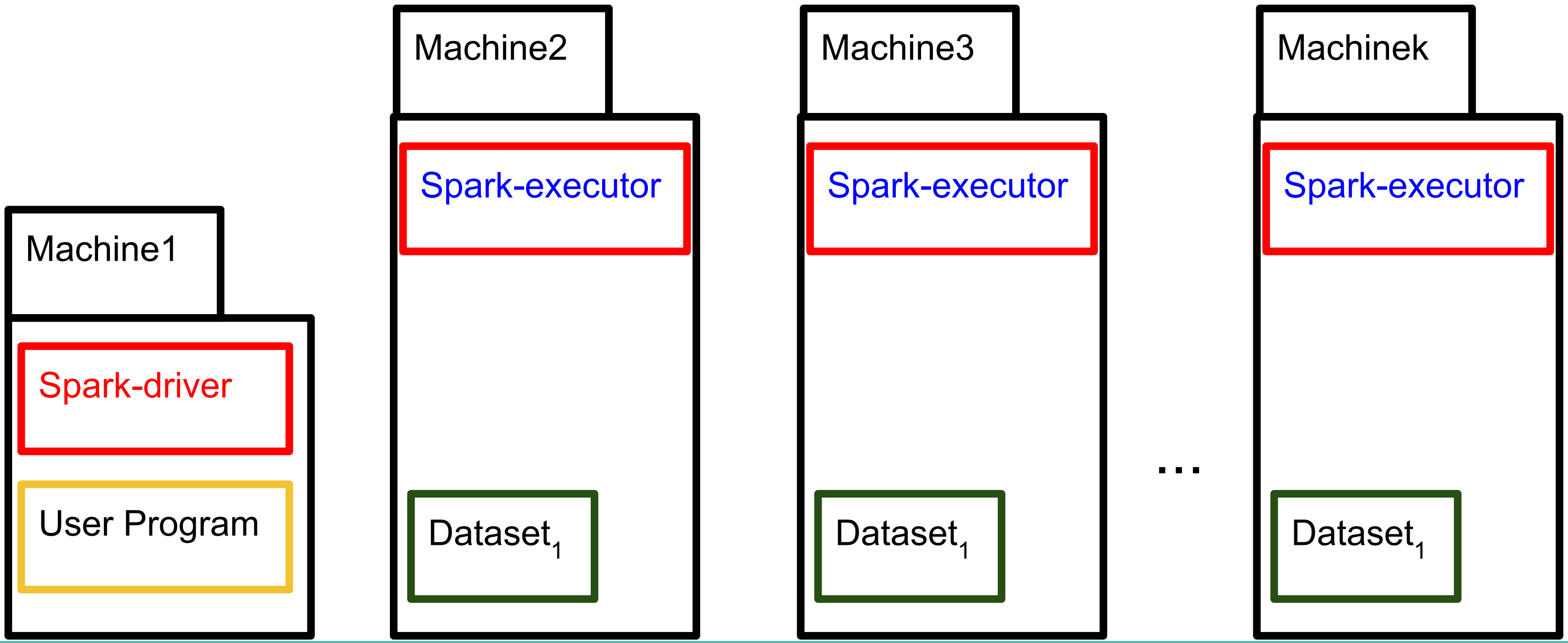
3. **How** is the data internally represented?
   Specify the concrete data structures used to layout the data.

- An RDD is internally represented via...
  1. A set of **partitions**
  2. Enriched with **lineage** metadata for their re-computation.



Idea 23: Private Side of RDDs

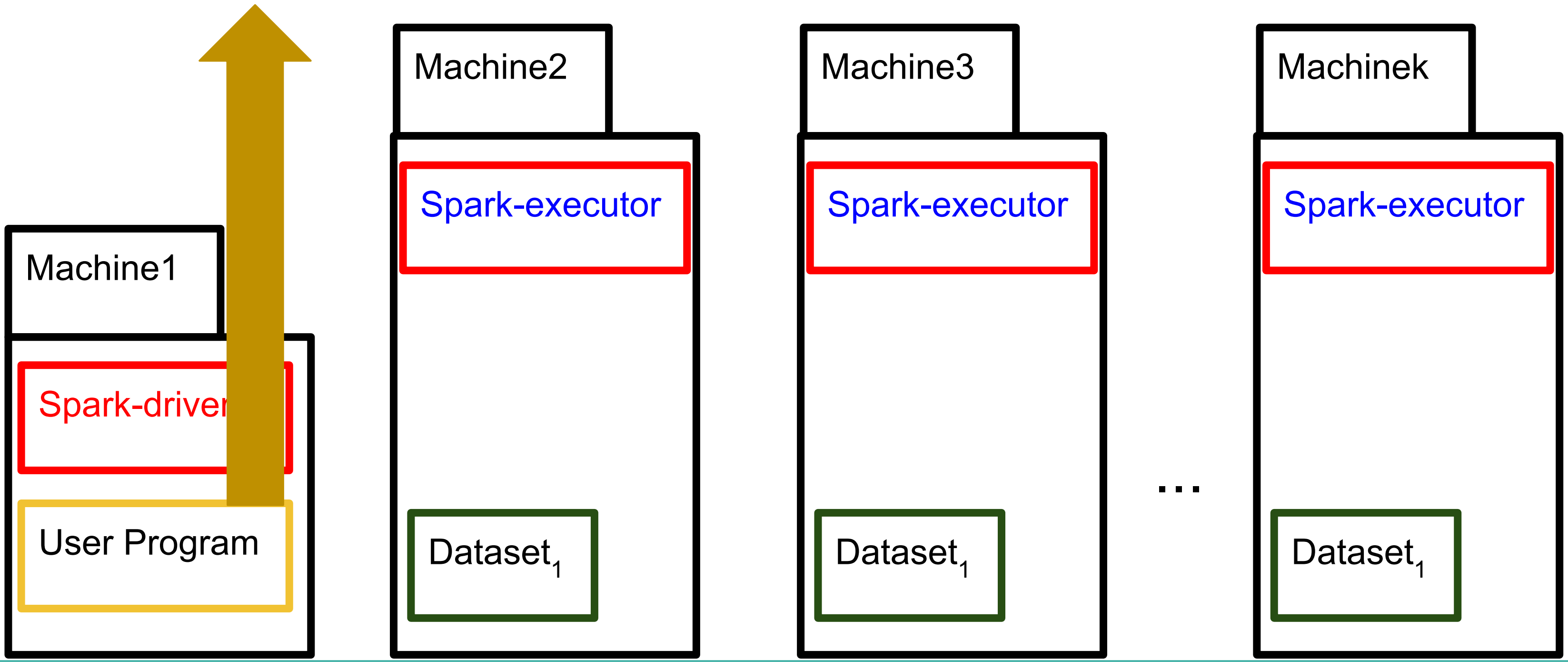
- Partitions allow to distribute an RDD over the machines of the cluster.



Idea 23: Private Side of RDDs

- Partitions allow to distribute an RDD over the machines of the cluster.

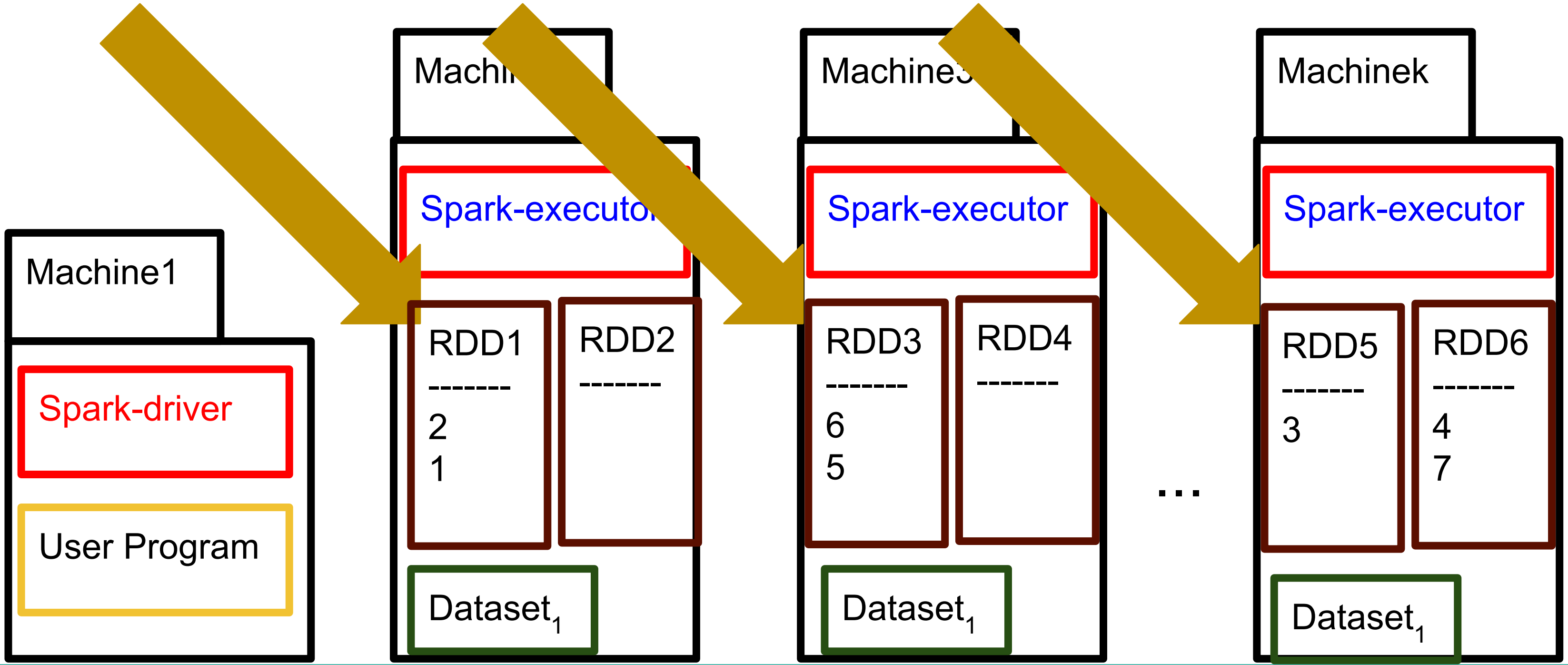
```
inputRDD  = sc.parallelize( [ 1, 2, 3, 4, 5, 6, 7 ] )
```



Idea 23: Private Side of RDDs

- Partitions allow to distribute an RDD over the machines of the cluster.

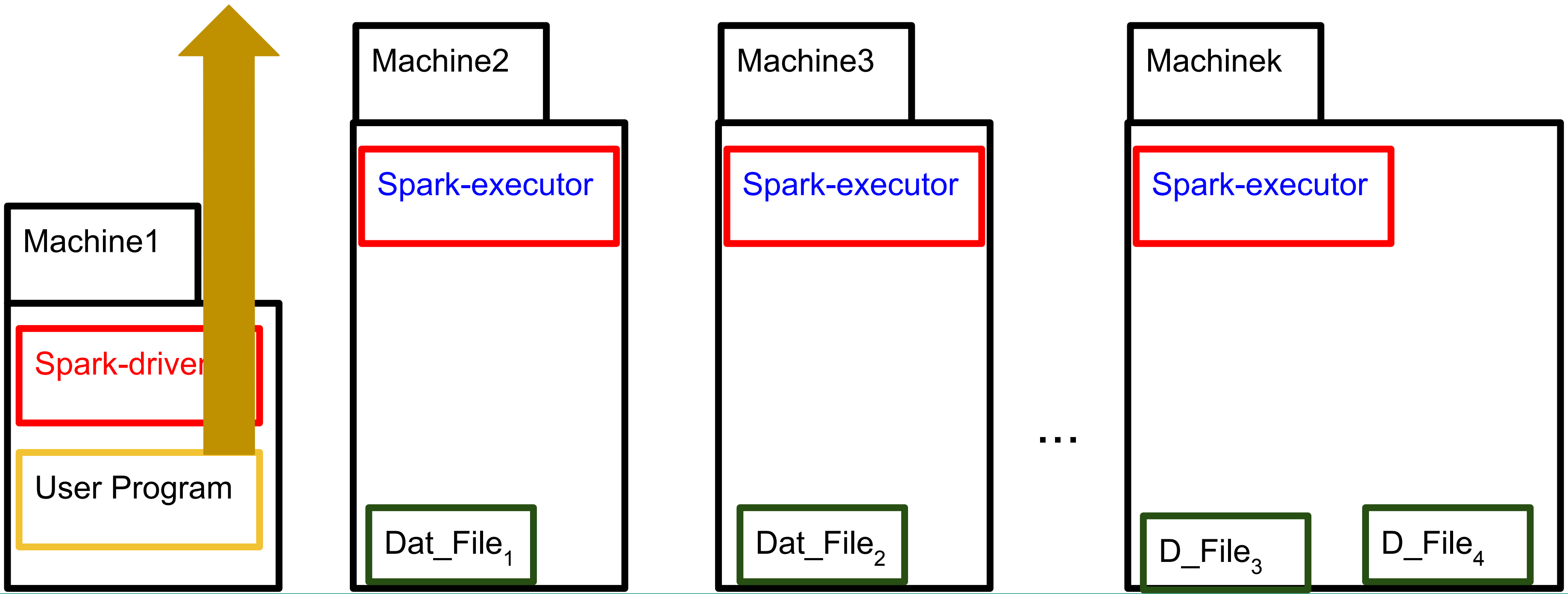
```
inputRDD  = sc.parallelize( [ 1, 2, 3, 4, 5, 6, 7 ] )
```



Idea 23: Private Side of RDDs

- Partitions allow to distribute an RDD over the machines of the cluster.

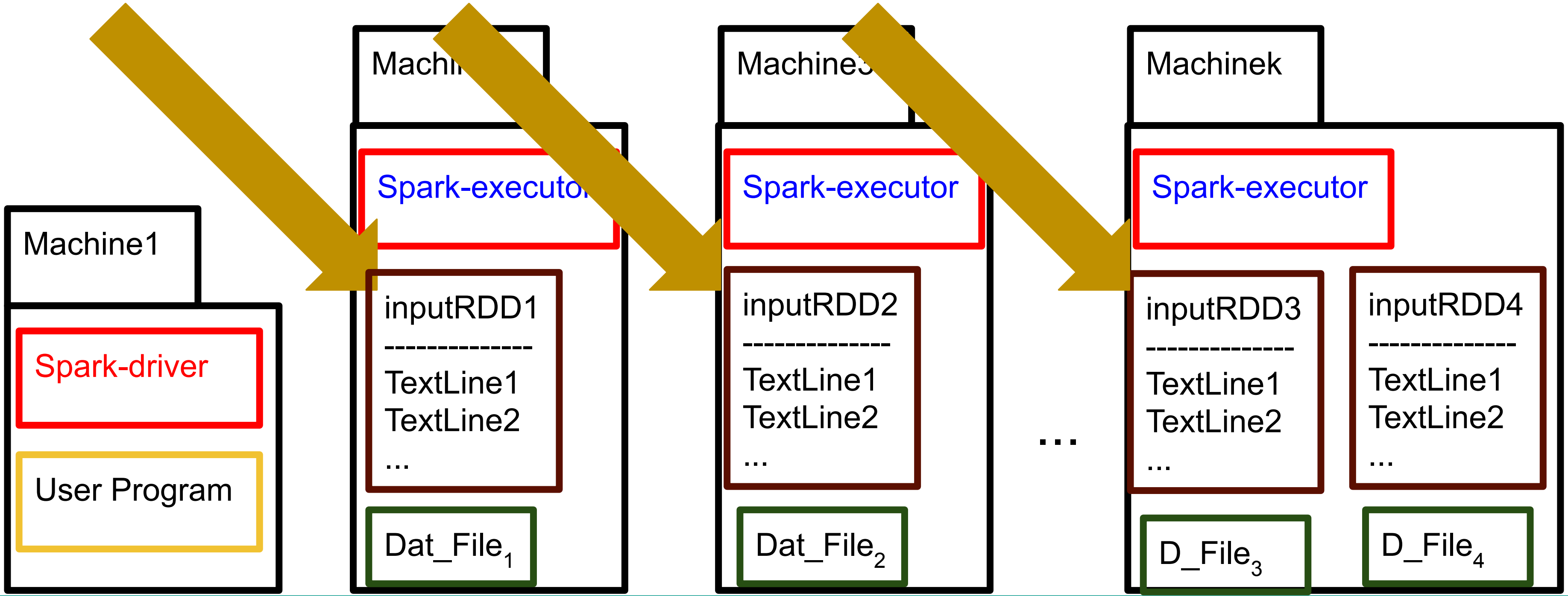
```
inputRDD  = sc.textFile( my_dataset )
```



Idea 23: Private Side of RDDs

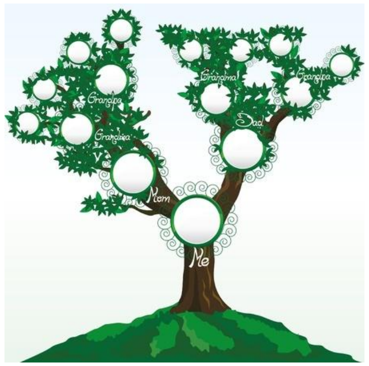
- Partitions allow to distribute an RDD over the machines of the cluster.

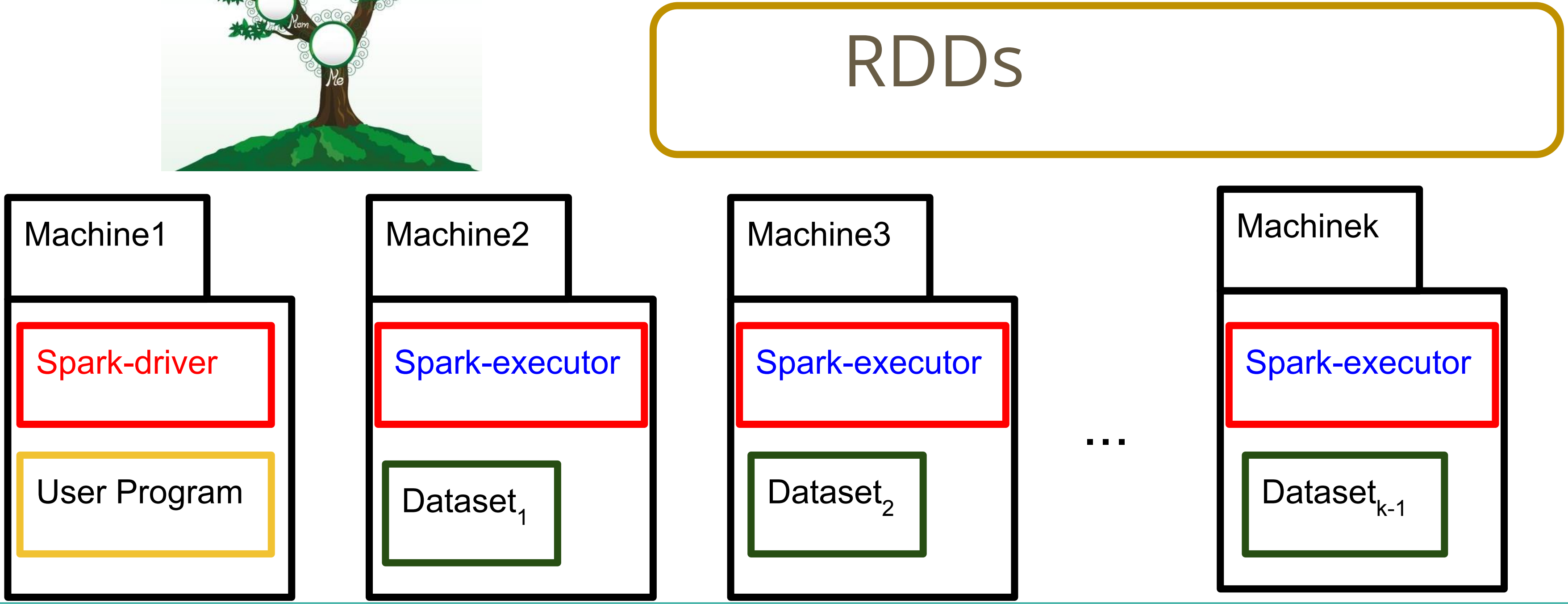
```
inputRDD  = sc.textFile( my_dataset )
```



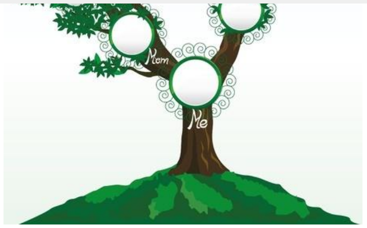
Idea 23: Private Side of RDDs

- Lineage allows us to (re-)computate partitions based on their dependencies. This is crucial for lazy evaluation and fault tolerance.



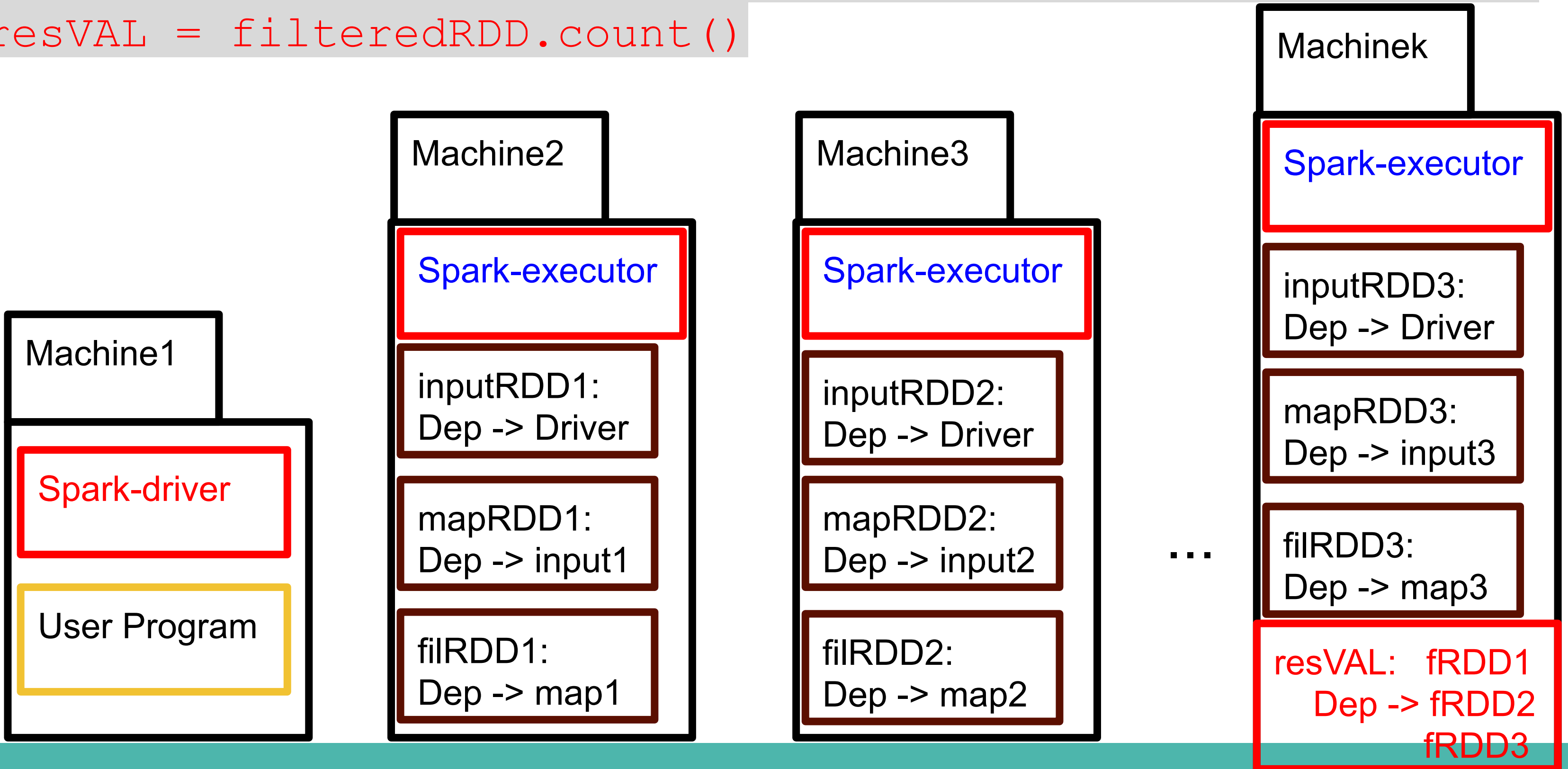


Idea 23: Private Side of RDDs

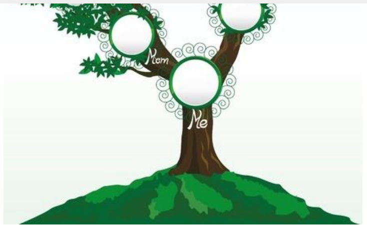


When an **action** takes place, computation is triggered by tracing this lineage backwards.

```
inputRDD  = sc.parallelize( [ 1, 2, 3, 4, 5 ] )
mappedRDD  = inputRDD.map( lambda elem : elem + 1 )
filteredRDD  = mappedRDD.filter( lambda elem : elem > 3 )
resVAL = filteredRDD.count()
```

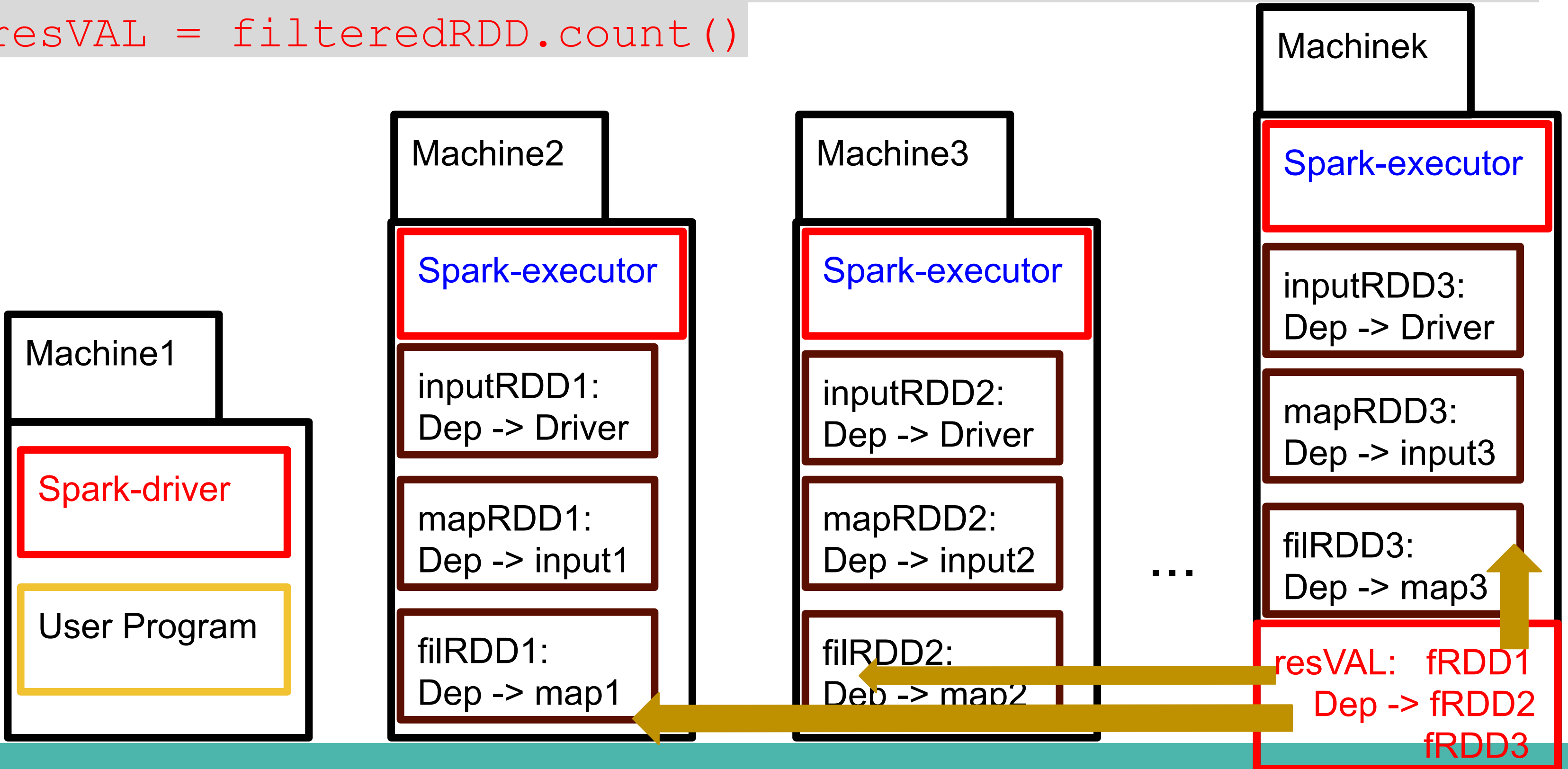


Idea 23: Private Side of RDDs



Who do I depend on?

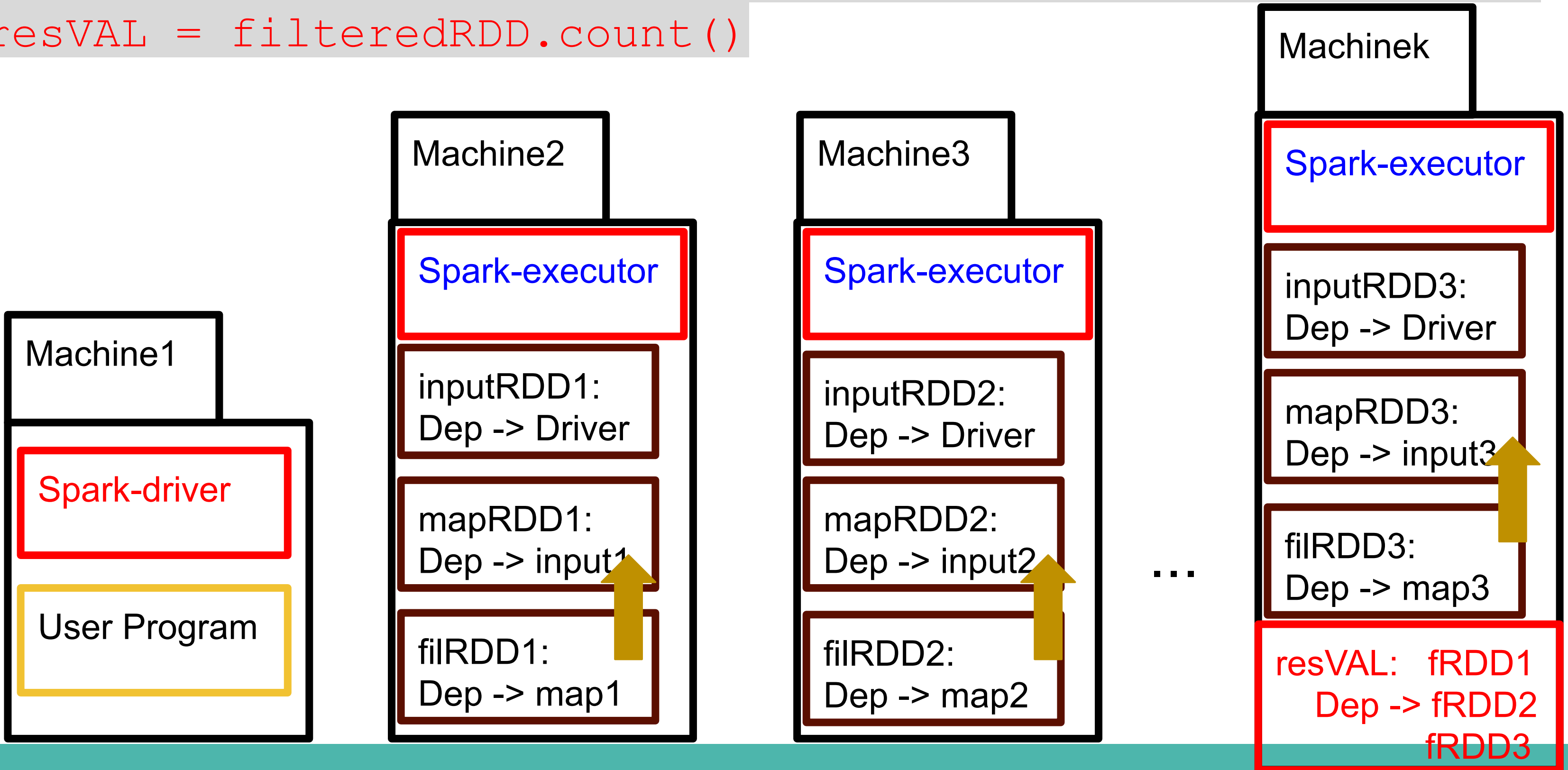
```
inputRDD  = sc.parallelize( [ 1, 2, 3, 4, 5 ] )
mappedRDD  = inputRDD.map( lambda elem : elem + 1 )
filteredRDD  = mappedRDD.filter( lambda elem : elem > 3 )
resVAL = filteredRDD.count()
```



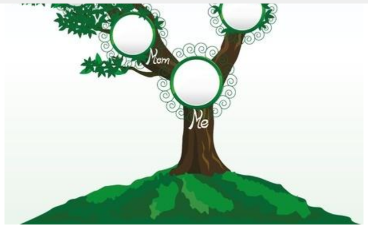
Idea 23: Private Side of RDDs

And, likewise, who do these RDD partitions depend on?

```
inputRDD  = sc.parallelize( [ 1, 2, 3, 4, 5 ] )
mappedRDD  = inputRDD.map( lambda elem : elem + 1 )
filteredRDD  = mappedRDD.filter( lambda elem : elem > 3 )
resVAL = filteredRDD.count()
```

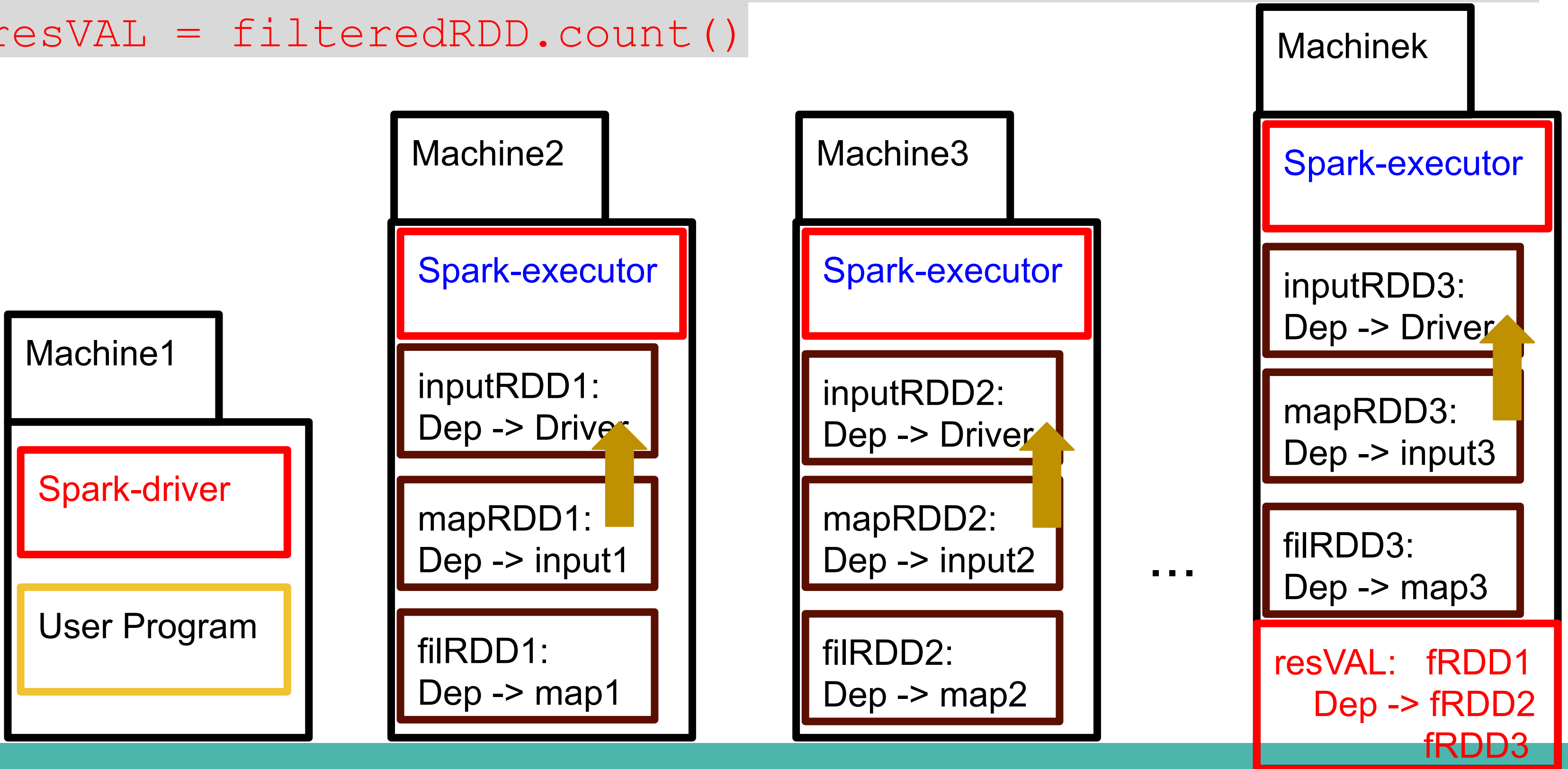


Idea 23: Private Side of RDDs



And so on and so on…

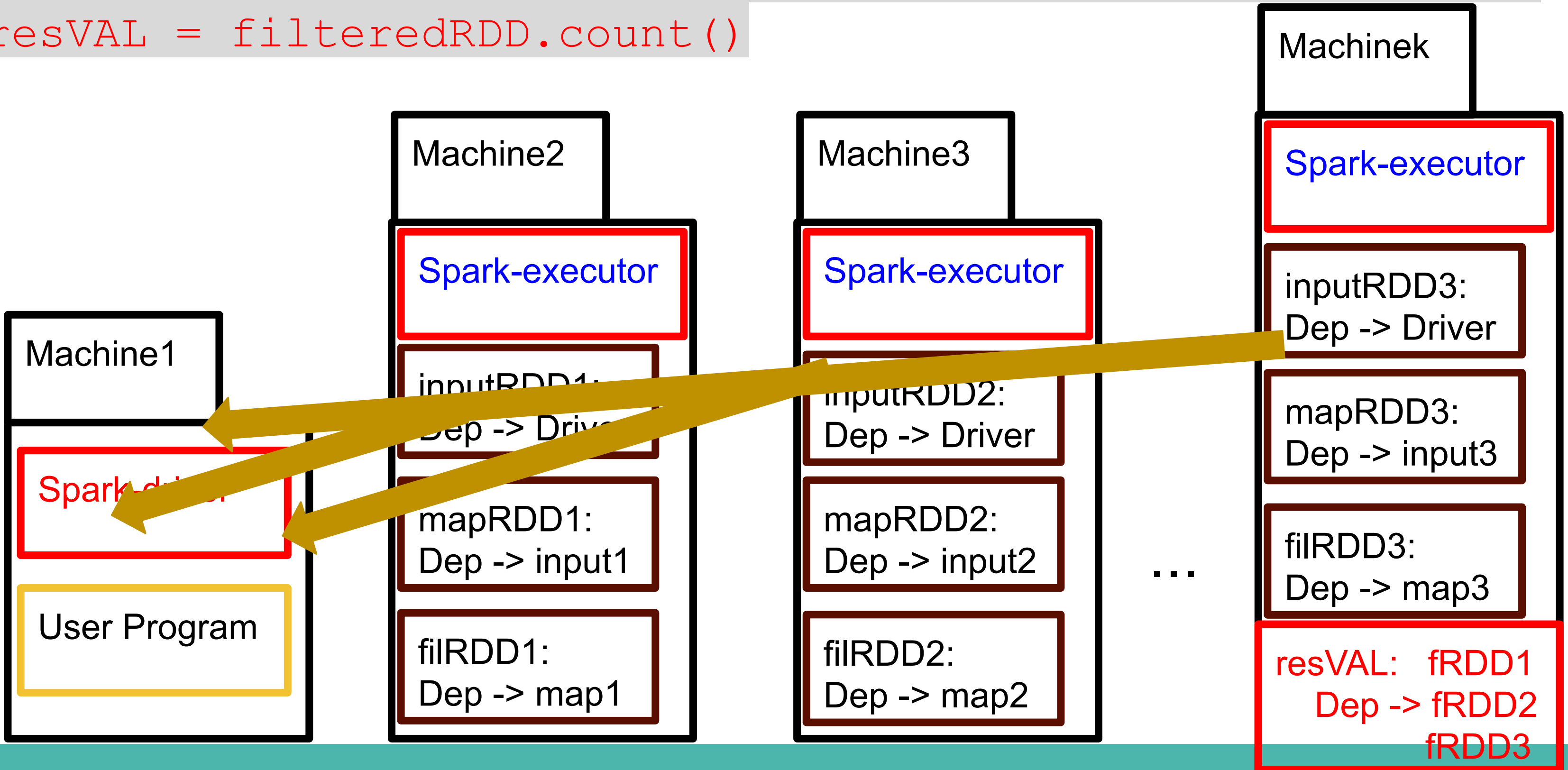
```
inputRDD  = sc.parallelize( [ 1, 2, 3, 4, 5 ] )
mappedRDD  = inputRDD.map( lambda elem : elem + 1 )
filteredRDD  = mappedRDD.filter( lambda elem : elem > 3 )
resVAL = filteredRDD.count()
```



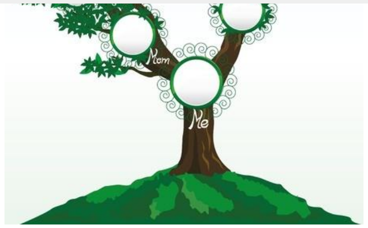
Idea 23: Private Side of RDDs

And so on and so on…

```
inputRDD    = sc.parallelize( [ 1, 2, 3, 4, 5 ] )
mappedRDD   = inputRDD.map( lambda elem : elem + 1 )
filteredRDD  = mappedRDD.filter( lambda elem : elem > 3 )
resVAL = filteredRDD.count()
```

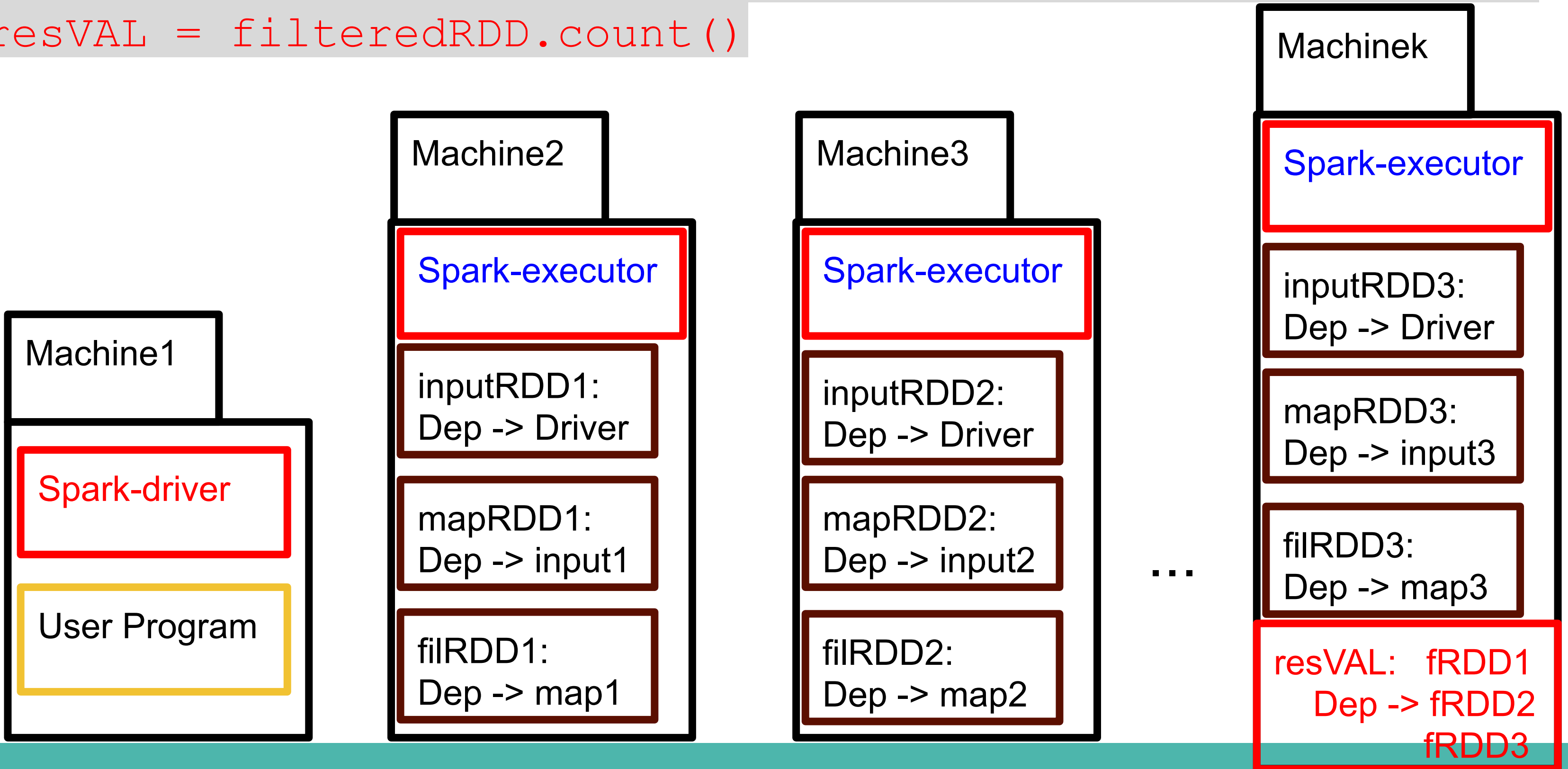


Idea 23: Private Side of RDDs

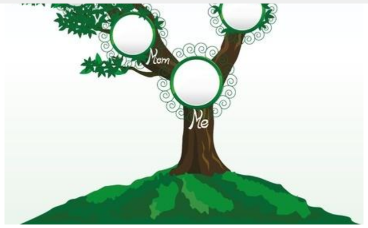


And now that I know the full lineage, computation can start lazily.

```
inputRDD  = sc.parallelize( [ 1, 2, 3, 4, 5 ] )
mappedRDD  = inputRDD.map( lambda elem : elem + 1 )
filteredRDD  = mappedRDD.filter( lambda elem : elem > 3 )
resVAL = filteredRDD.count()
```

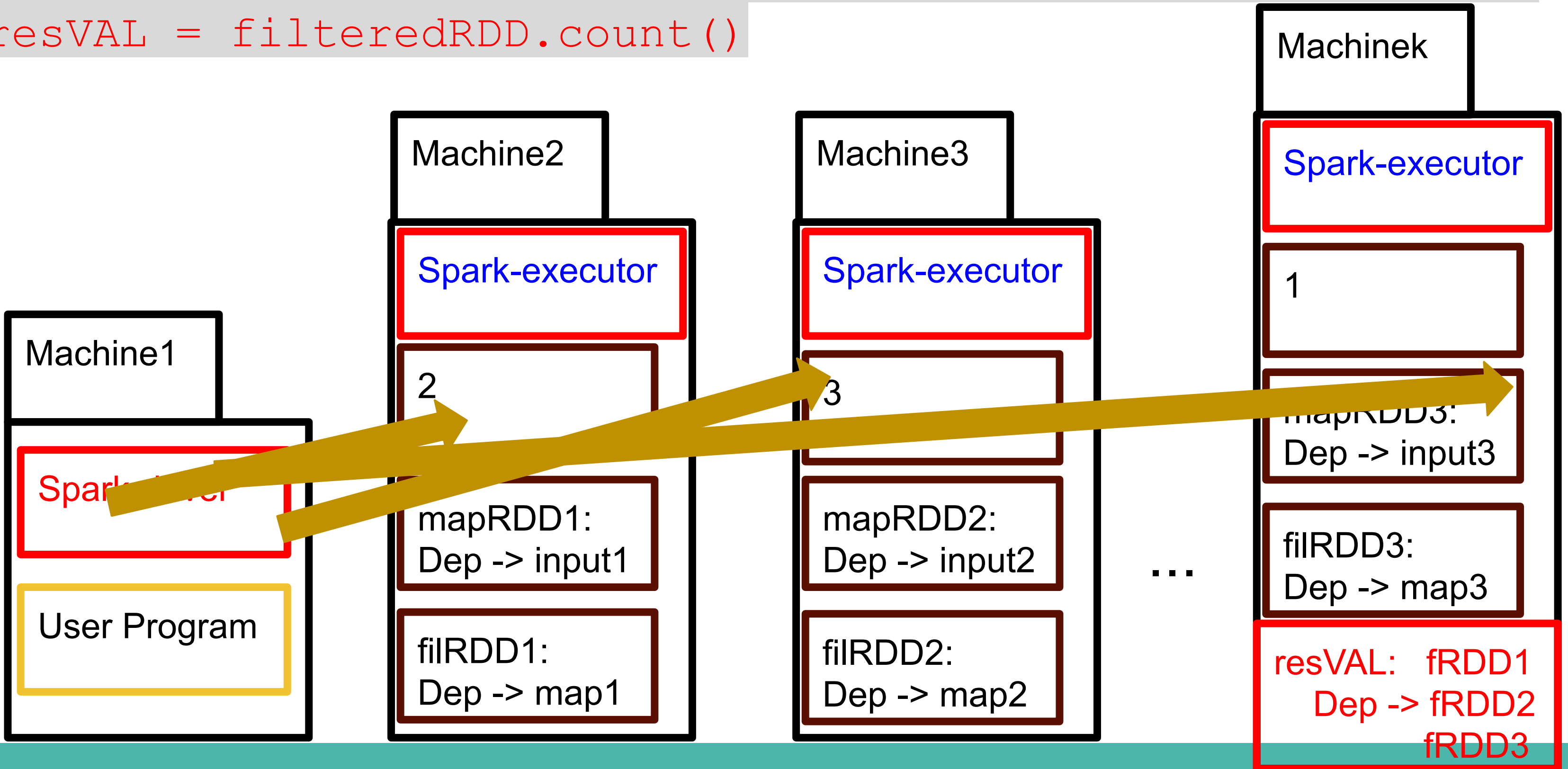


Idea 23: Private Side of RDDs



In this case, going forward!

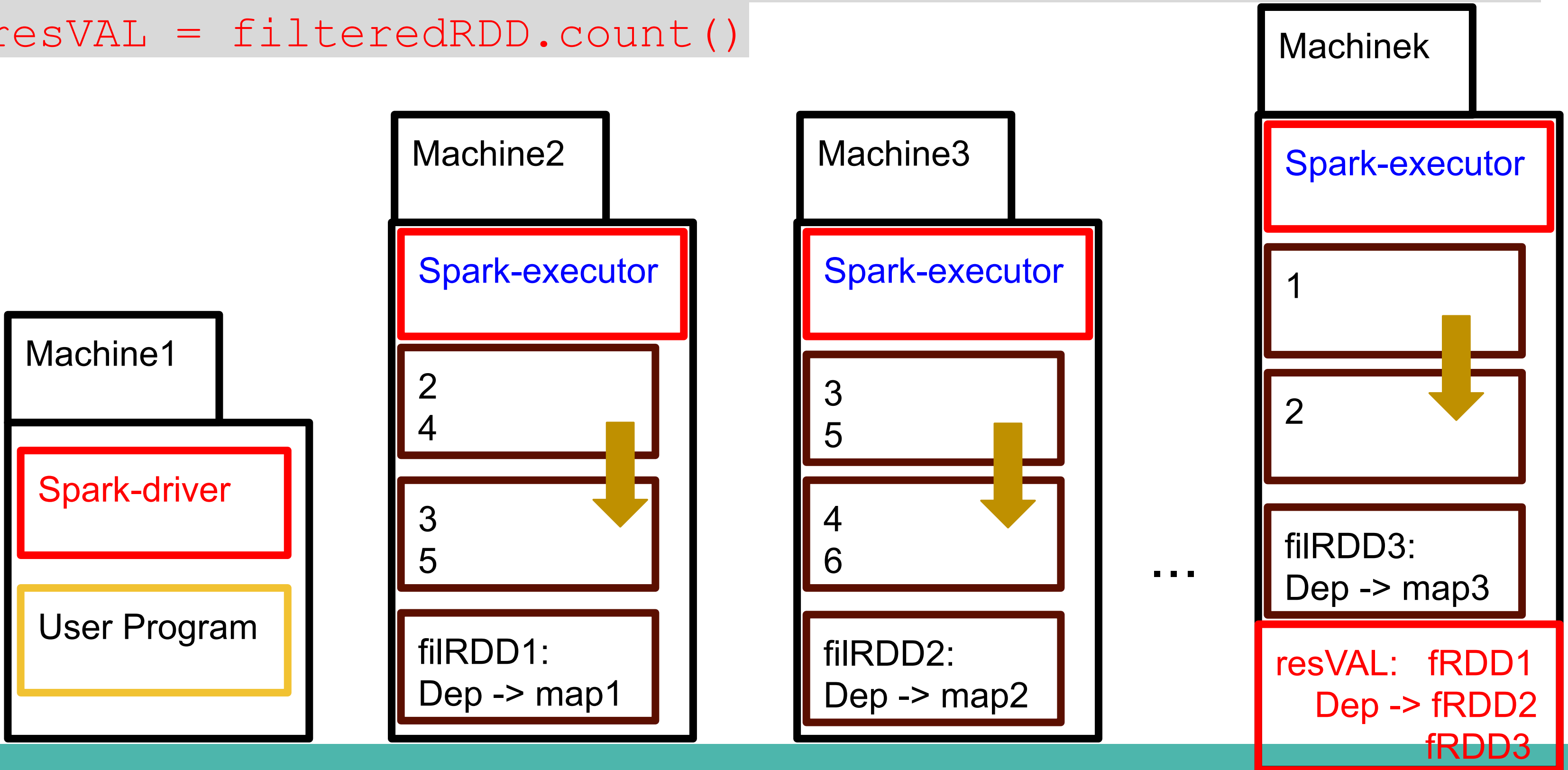
```
inputRDD   = sc.parallelize( [ 1, 2, 3, 4, 5 ] )
mappedRDD  = inputRDD.map( lambda elem : elem + 1 )
filteredRDD  = mappedRDD.filter( lambda elem : elem > 3 )
resVAL = filteredRDD.count()
```



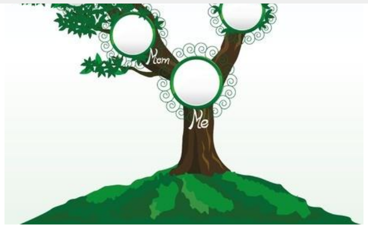
Idea 23: Private Side of RDDs

In this case, going forward!

```
inputRDD   = sc.parallelize( [ 1, 2, 3, 4, 5 ] )
mappedRDD  = inputRDD.map( lambda elem : elem + 1 )
filteredRDD  = mappedRDD.filter( lambda elem : elem > 3 )
resVAL = filteredRDD.count()
```

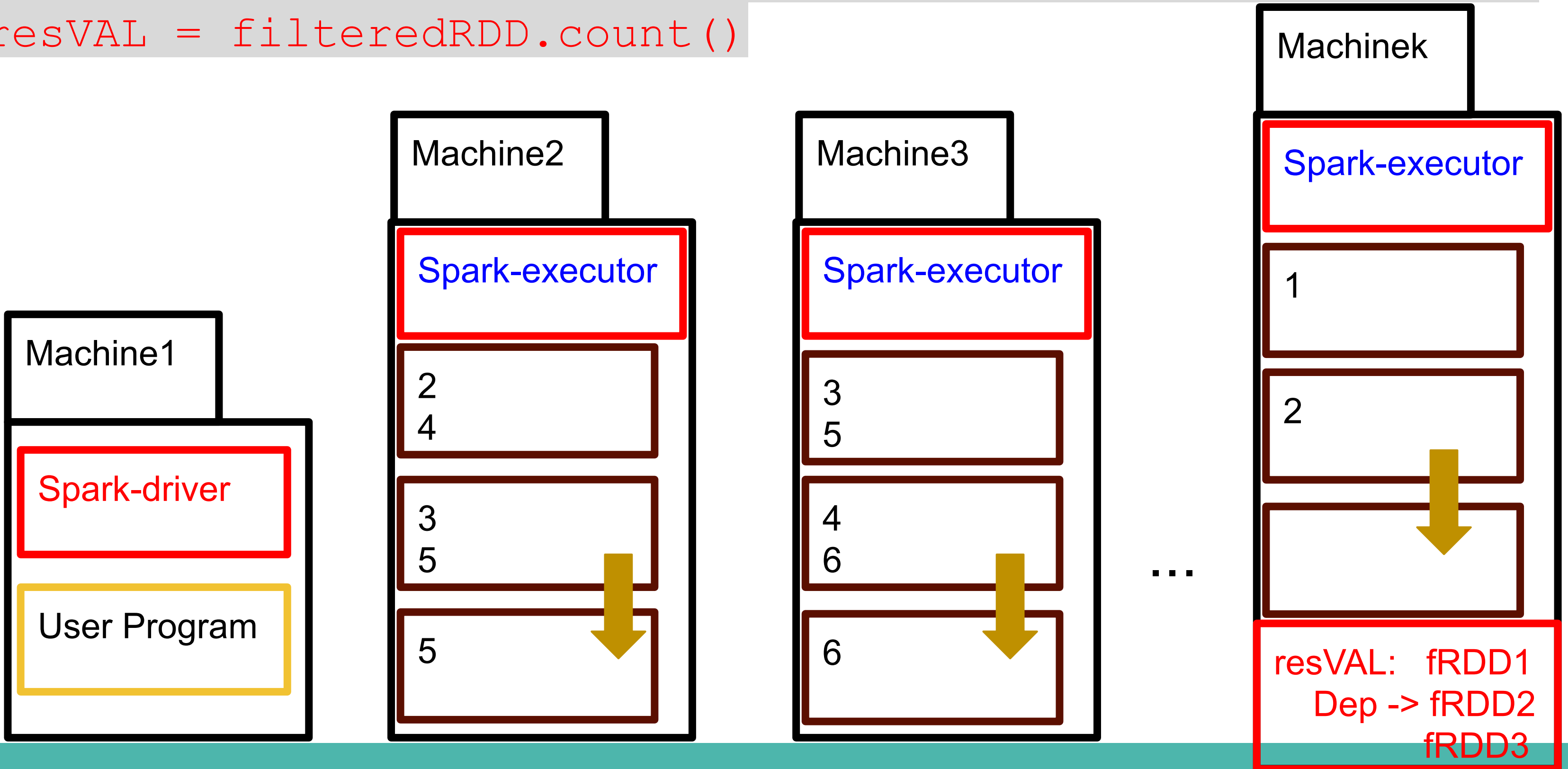


Idea 23: Private Side of RDDs

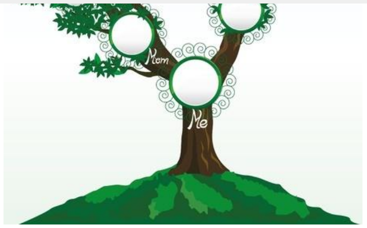


In this case, going forward!

```
inputRDD   = sc.parallelize( [ 1, 2, 3, 4, 5 ] )
mappedRDD  = inputRDD.map( lambda elem : elem + 1 )
filteredRDD  = mappedRDD.filter( lambda elem : elem > 3 )
resVAL = filteredRDD.count()
```

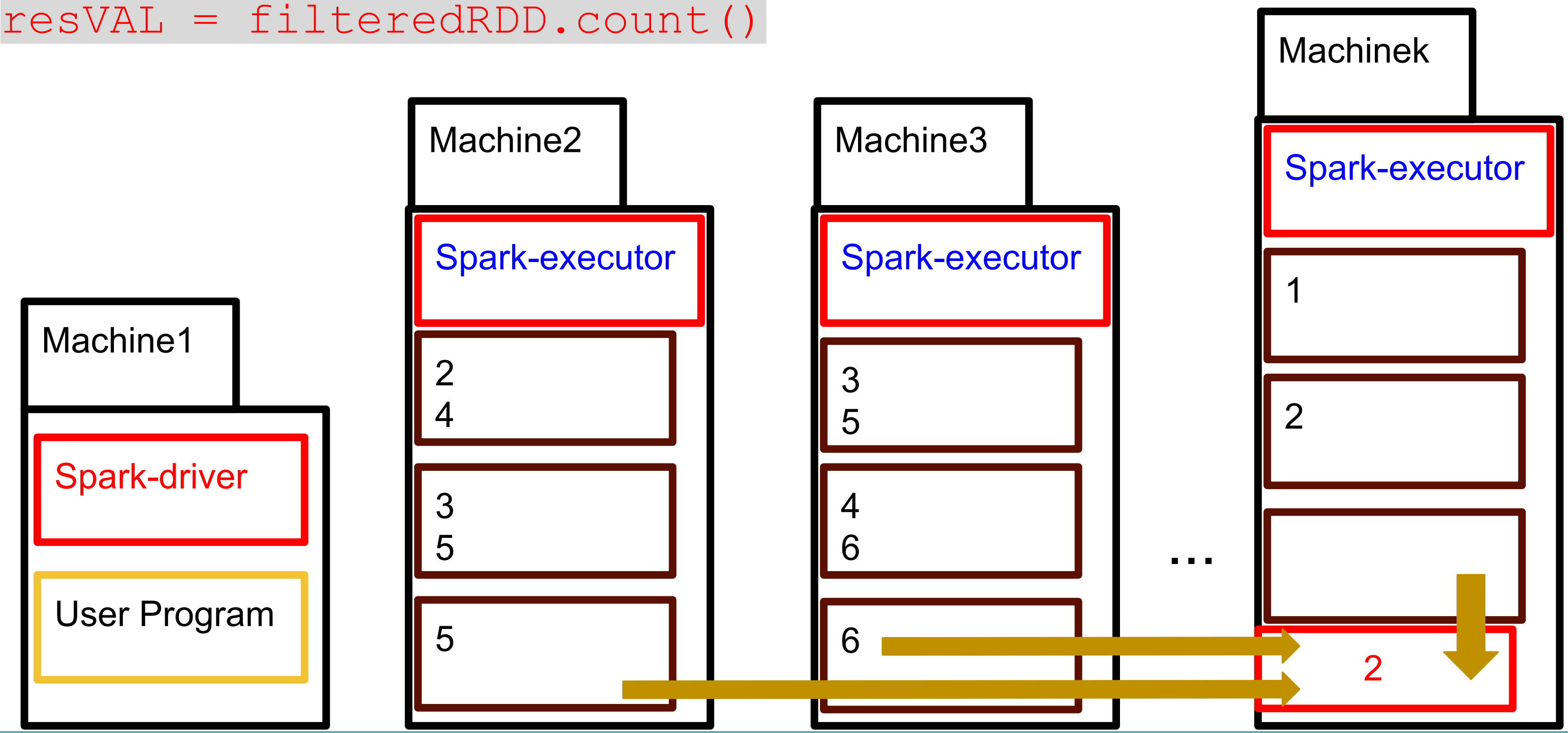


Idea 23: Private Side of RDDs



In this case, going forward!

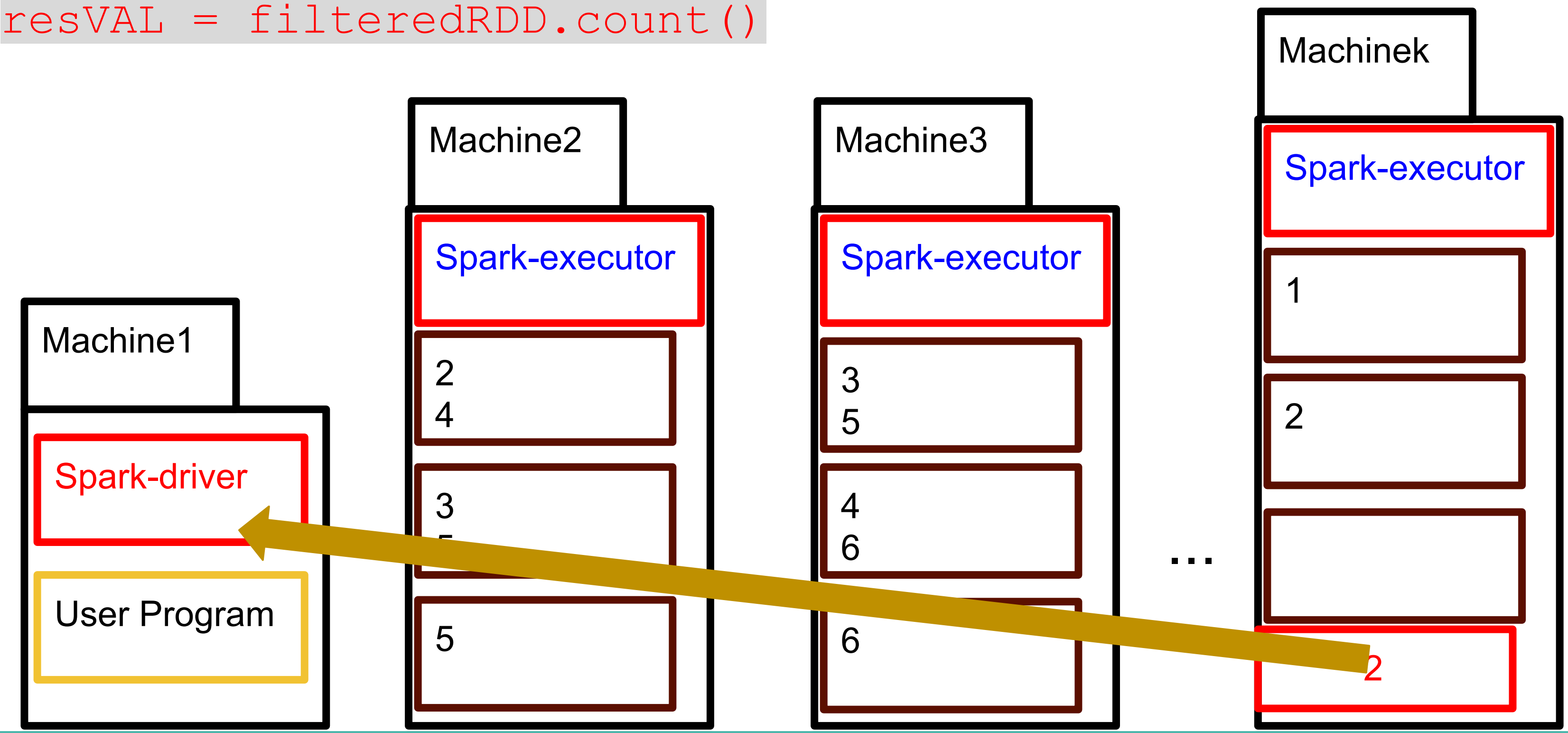
```
inputRDD   = sc.parallelize( [ 1, 2, 3, 4, 5 ] )
mappedRDD  = inputRDD.map( lambda elem : elem + 1 )
filteredRDD  = mappedRDD.filter( lambda elem : elem > 3 )
resVAL = filteredRDD.count()
```



Idea 23: Private Side of RDDs

In this case, going forward!

```
inputRDD   = sc.parallelize( [ 1, 2, 3, 4, 5 ] )
mappedRDD  = inputRDD.map( lambda elem : elem + 1 )
filteredRDD  = mappedRDD.filter( lambda elem : elem > 3 )
resVAL = filteredRDD.count()
```



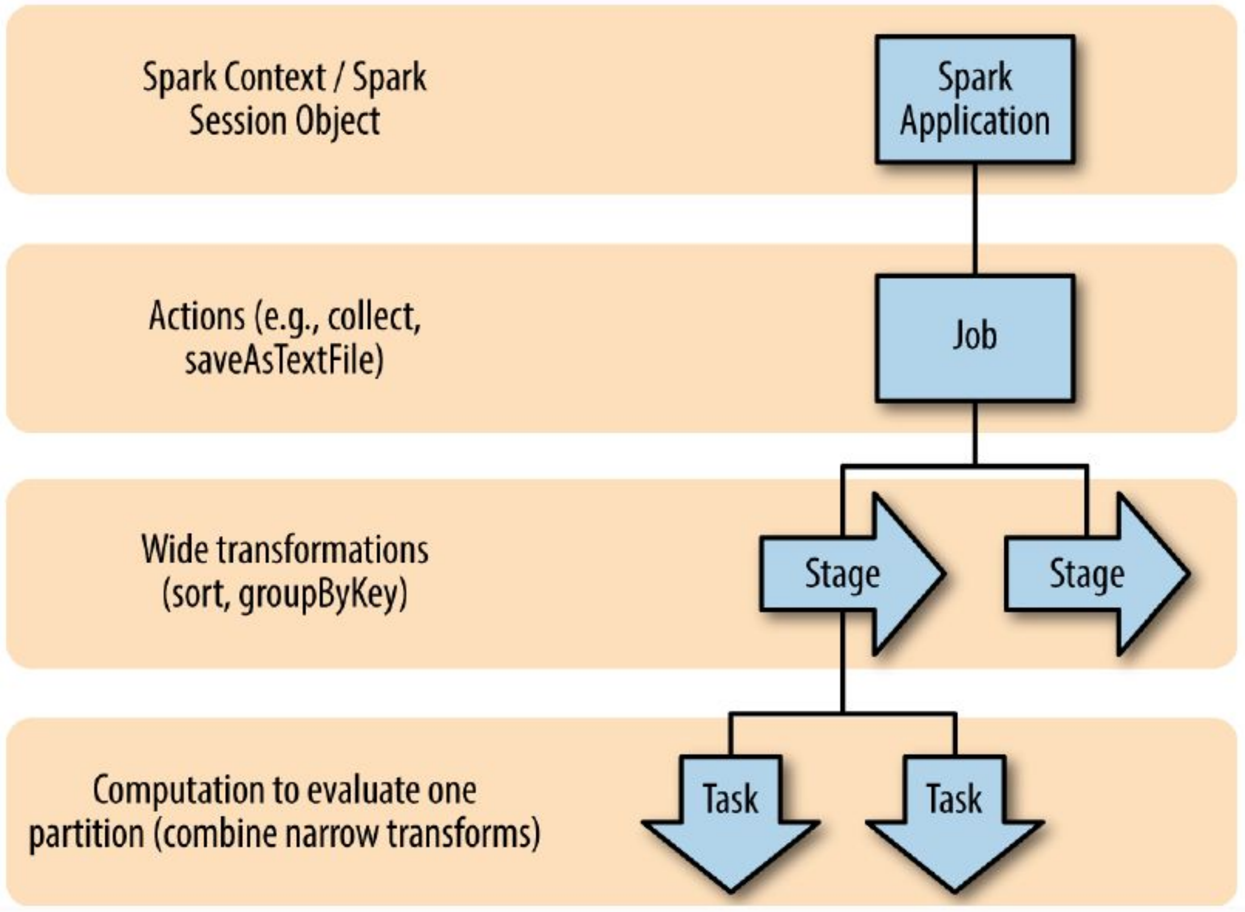
Outline

Idea 24:

Execution of a Spark User program

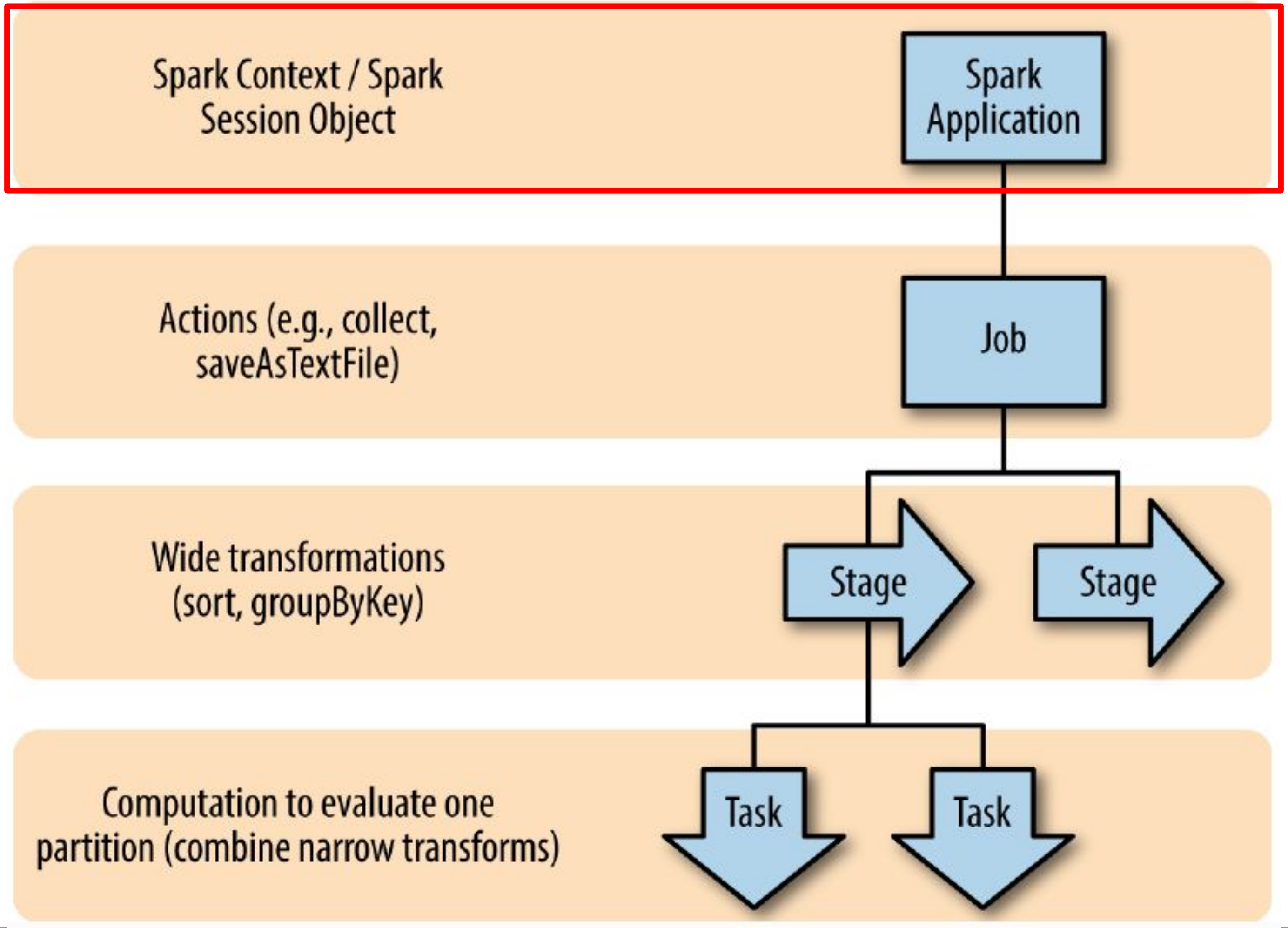
Idea 24: Execution of a Spark User Program

There are 4 concepts we must be familiar with in order to understand the execution of a Spark user program: **Application, Job, Stage and Task.**

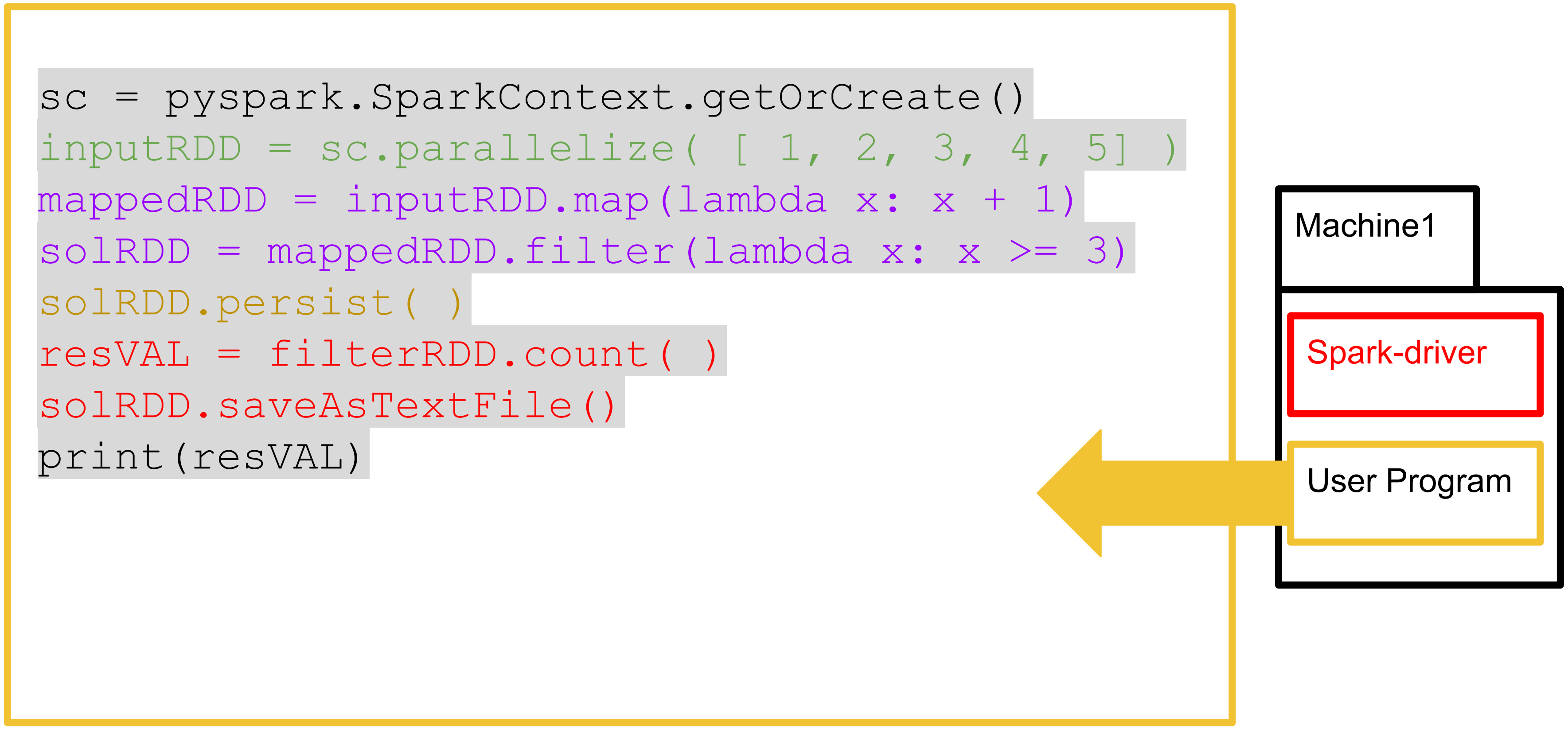

Spark Context / Spark Session Object
Spark Application
Actions (e.g., collect, saveAsTextFile)
Job
Wide transformations (sort, groupByKey)
Stage
Stage
Computation to evaluate one partition (combine narrow transforms)
Task
Task

Idea 24: Execution of a Spark User Program

A Spark Application corresponds to a Spark User program.


Spark Context / Spark Session Object
Spark Application
Actions (e.g., collect, saveAsTextFile)
Job
Wide transformations (sort, groupByKey)
Stage
Stage
Computation to evaluate one partition (combine narrow transforms)
Task
Task

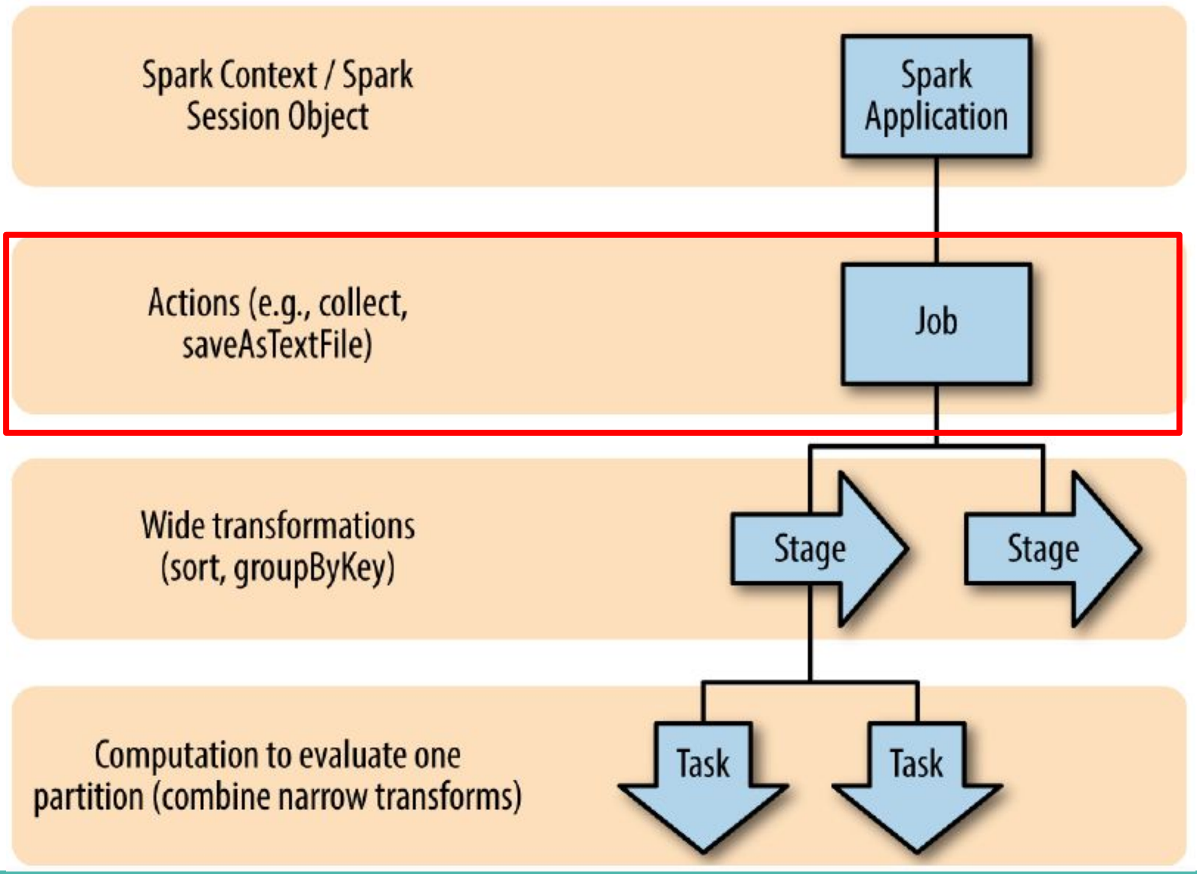
Idea 24: Execution of a Spark User Program



```
sc = pyspark.SparkContext.getOrCreate()
inputRDD = sc.parallelize( [ 1, 2, 3, 4, 5] )
mappedRDD = inputRDD.map(lambda x: x + 1)
solRDD = mappedRDD.filter(lambda x: x >= 3)
solRDD.persist( )
resVAL = filterRDD.count( )
solRDD.saveAsTextFile()
print(resVAL)
```

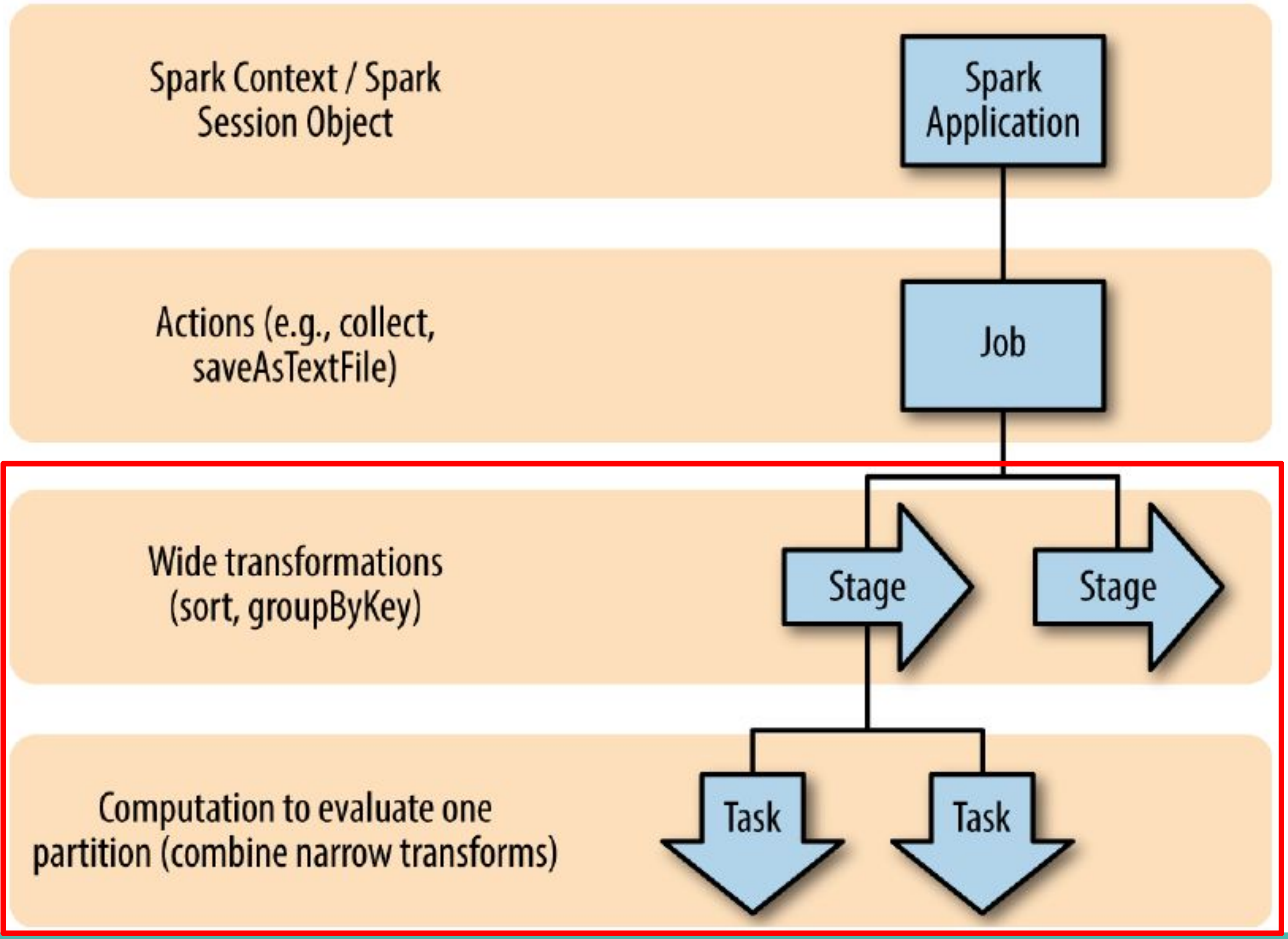
Idea 24: Execution of a Spark User Program

A Spark Job corresponds to one **action** operation in the user program. Thus, given a user program, it leads to as many jobs as actions it contains.


Spark Context / Spark Session Object
Spark Application
Actions (e.g., collect, saveAsTextFile)
Job
Wide transformations (sort, groupByKey)
Stage
Stage
Computation to evaluate one partition (combine narrow transforms)
Task
Task

Idea 24: Execution of a Spark User Program

Stages and Tasks depend on the type of transformations used by the job.

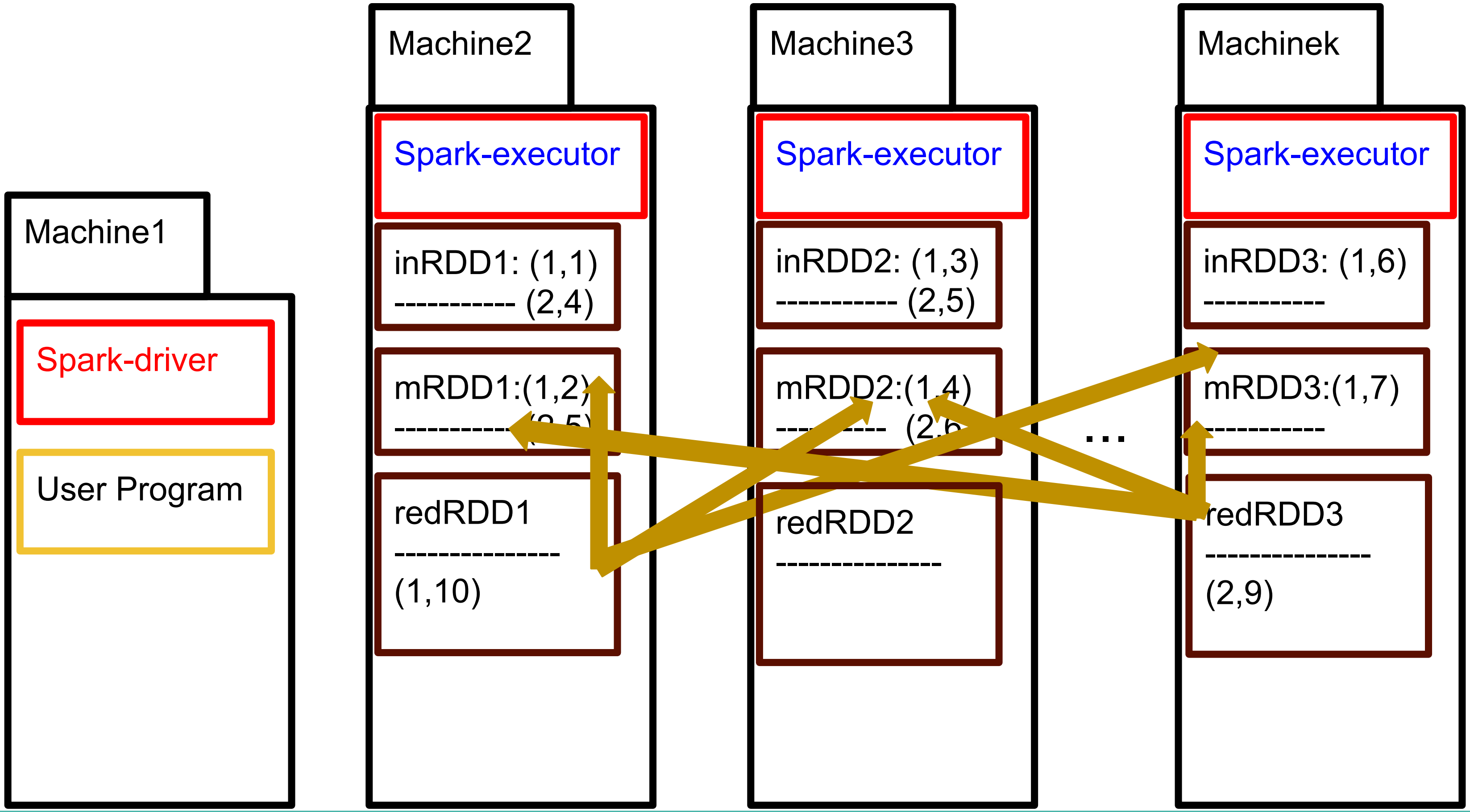

Spark Context / Spark Session Object
Spark Application
Actions (e.g., collect, saveAsTextFile)
Job
Wide transformations (sort, groupByKey)
Stage
Stage
Computation to evaluate one partition (combine narrow transforms)
Task
Task

Idea 24: Execution of a Spark User Program

- Wide transformations require data to be shuffled over the network.

```
inputRDD  = sc.parallelize([(1,1), (2,4), (1,3), (2,5), (1,6)])
mapRDD = inputRDD.map( lambda elem : elem[1] + 1 )
redRDD = mapRDD.reduceByKey( lambda x, y: x + y )
solRDD = mapRDD.filter( lambda elem : elem[1] > 9 )
```

Idea 24: Execution of a Spark User Program



Idea 24: Execution of a Spark User Program

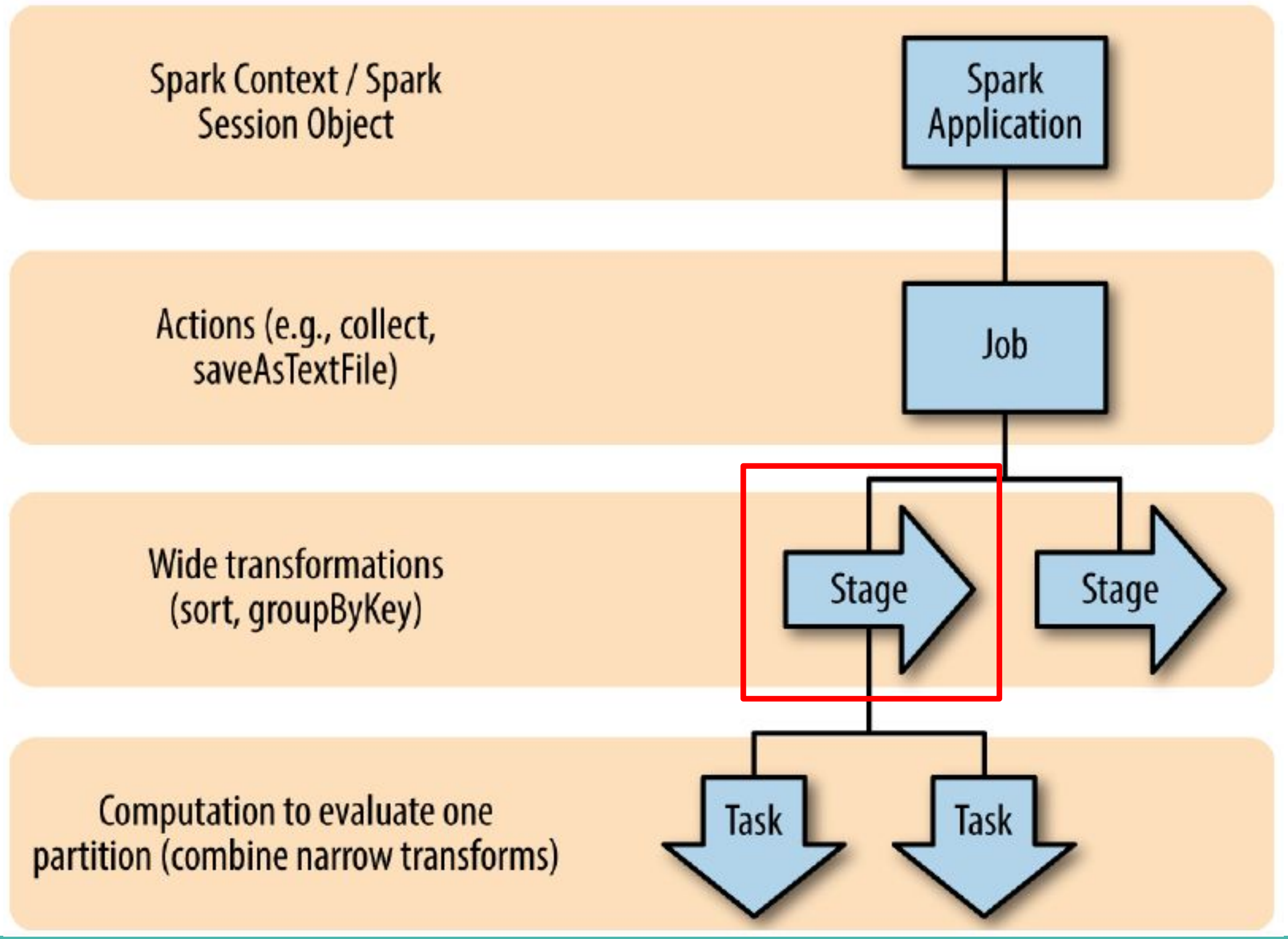
- Wide transformations require data to be shuffled over the network.

```
inputRDD  = sc.parallelize([(1,1), (2,4), (1,3), (2,5), (1,6)])
mapRDD = inputRDD.map( lambda elem : elem[1] + 1 )
redRDD = mapRDD.reduceByKey( lambda x, y: x + y )
solRDD = mapRDD.filter( lambda elem : elem[1] > 9 )
```

- Thus, for it to happen, all partitions must by fully computed, creating dependencies among partitions.

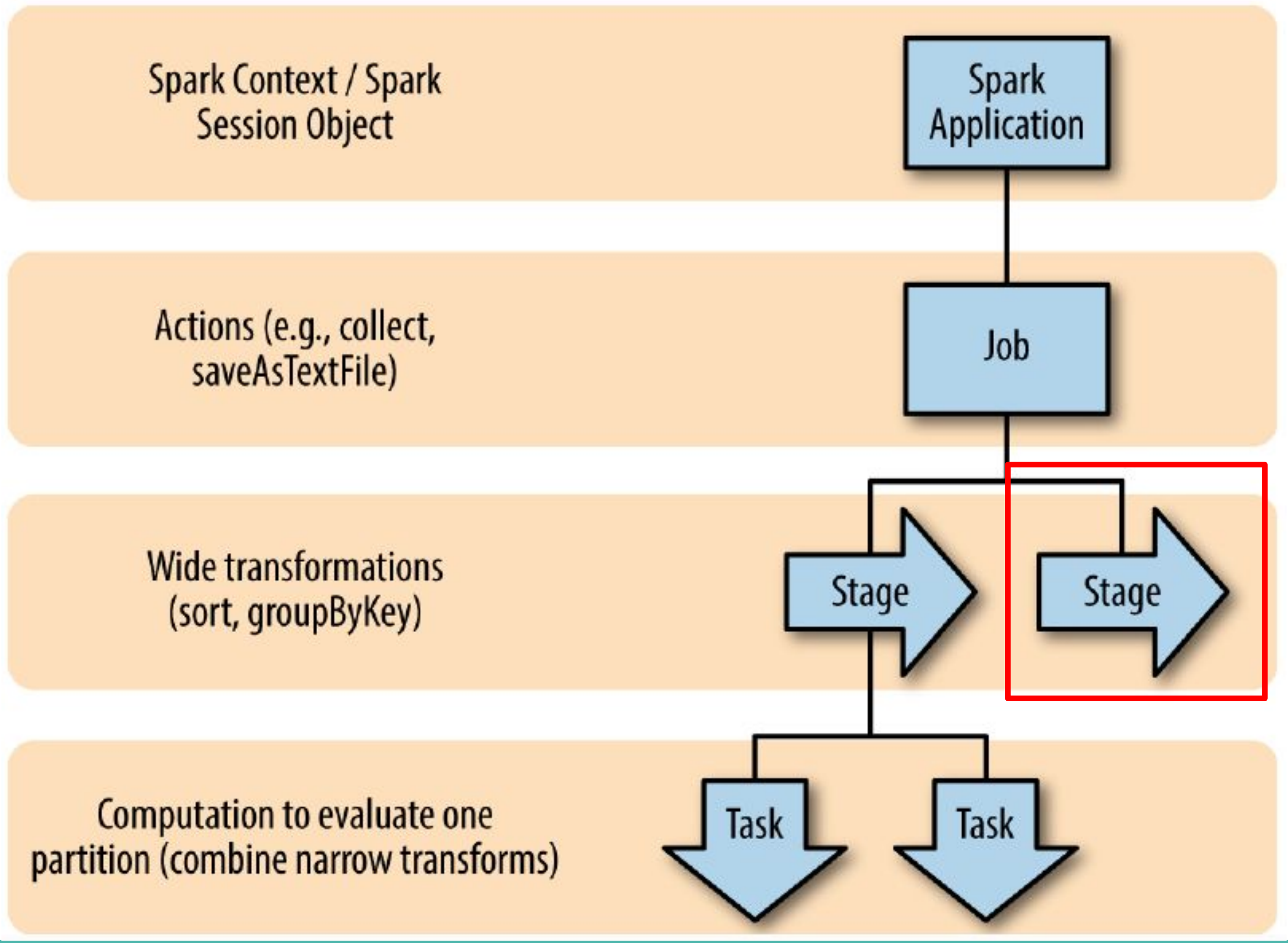
Idea 24: Execution of a Spark User Program

That's why stages are to be scheduled in sequential order.


Spark Context / Spark Session Object
Spark Application
Actions (e.g., collect, saveAsTextFile)
Job
Wide transformations (sort, groupByKey)
Stage
Stage
Computation to evaluate one partition (combine narrow transforms)
Task
Task

Idea 24: Execution of a Spark User Program

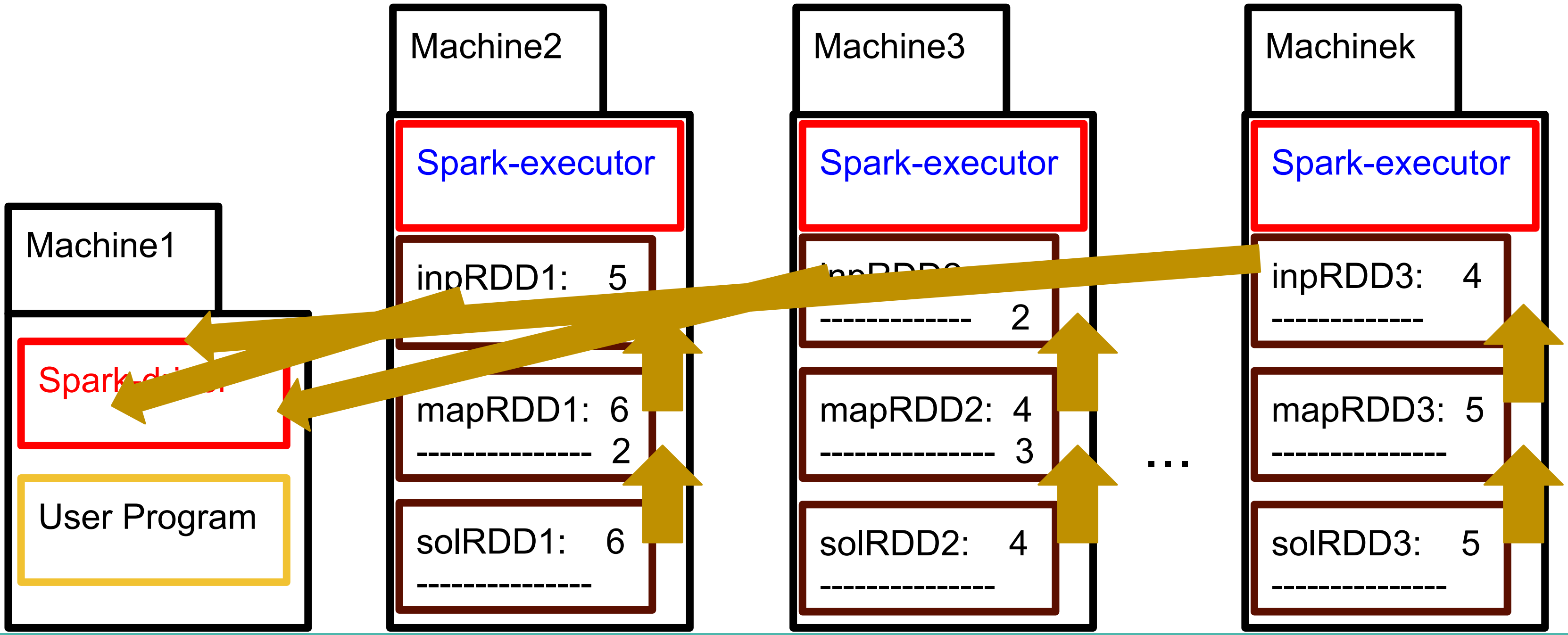
That's why stages are to be scheduled in sequential order.


Spark Context / Spark Session Object
Spark Application
Actions (e.g., collect, saveAsTextFile)
Job
Wide transformations (sort, groupByKey)
Stage
Stage
Computation to evaluate one partition (combine narrow transforms)
Task
Task

Idea 24: Execution of a Spark User Program

- Within a stage, all narrow operations can be chained and executed on each partition separately, without any dependency among partitions.

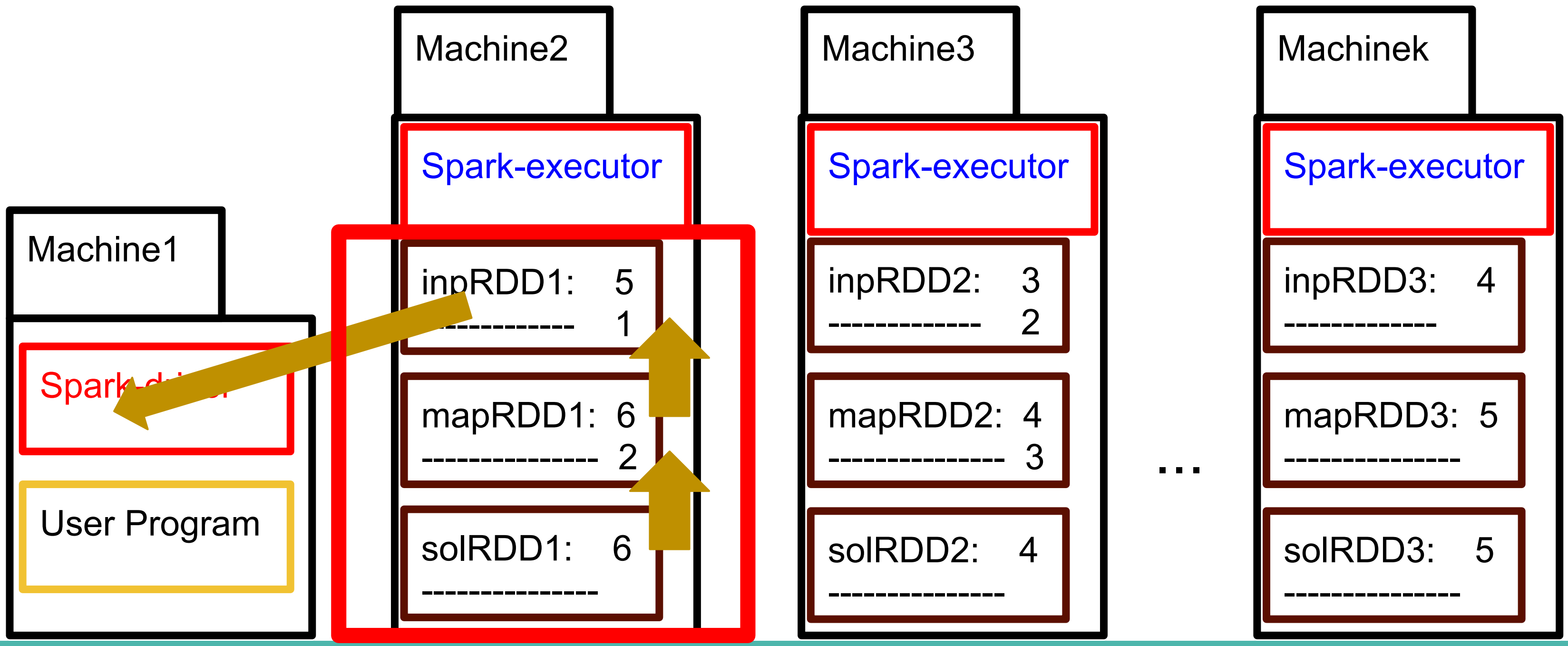
```
inputRDD  = sc.parallelize( [ 1, 2, 3, 4, 5 ] )
mapRDD = inputRDD.map( lambda elem : elem + 1 )
solRDD = mapRDD.filter( lambda elem : elem > 3 )
```



Idea 24: Execution of a Spark User Program

- Within a stage, all narrow operations can be chained and execution on each partition separately, without any dependency among partitions.

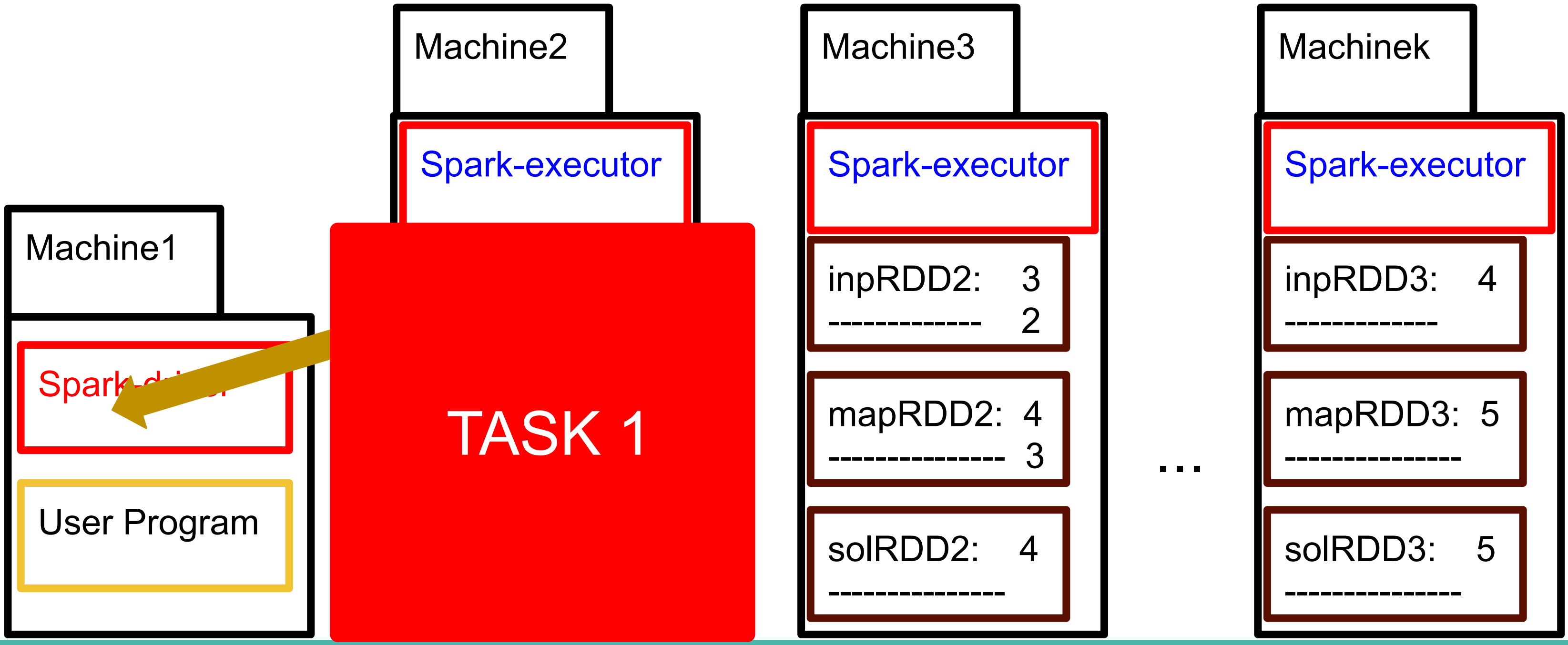
```
inputRDD  = sc.parallelize( [ 1, 2, 3, 4, 5 ] )
mapRDD = inputRDD.map( lambda elem : elem + 1 )
solRDD = mapRDD.filter( lambda elem : elem > 3 )
```



Idea 24: Execution of a Spark User Program

- Within a stage, all narrow operations can be chained and execution on each partition separately, without any dependency among partitions.

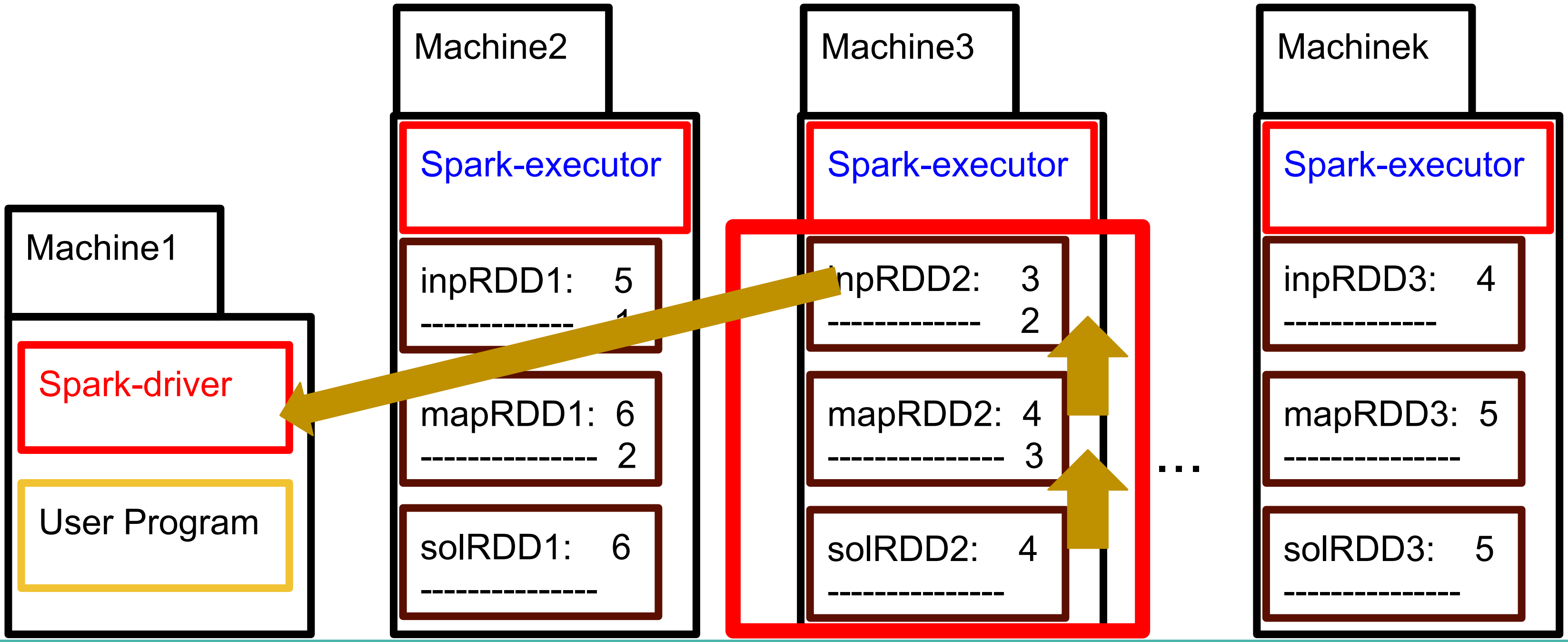
```
inputRDD  = sc.parallelize( [ 1, 2, 3, 4, 5 ] )
mapRDD = inputRDD.map( lambda elem : elem + 1 )
solRDD = mapRDD.filter( lambda elem : elem > 3 )
```



Idea 24: Execution of a Spark User Program

- Within a stage, all narrow operations can be chained and execution on each partition separately, without any dependency among partitions.

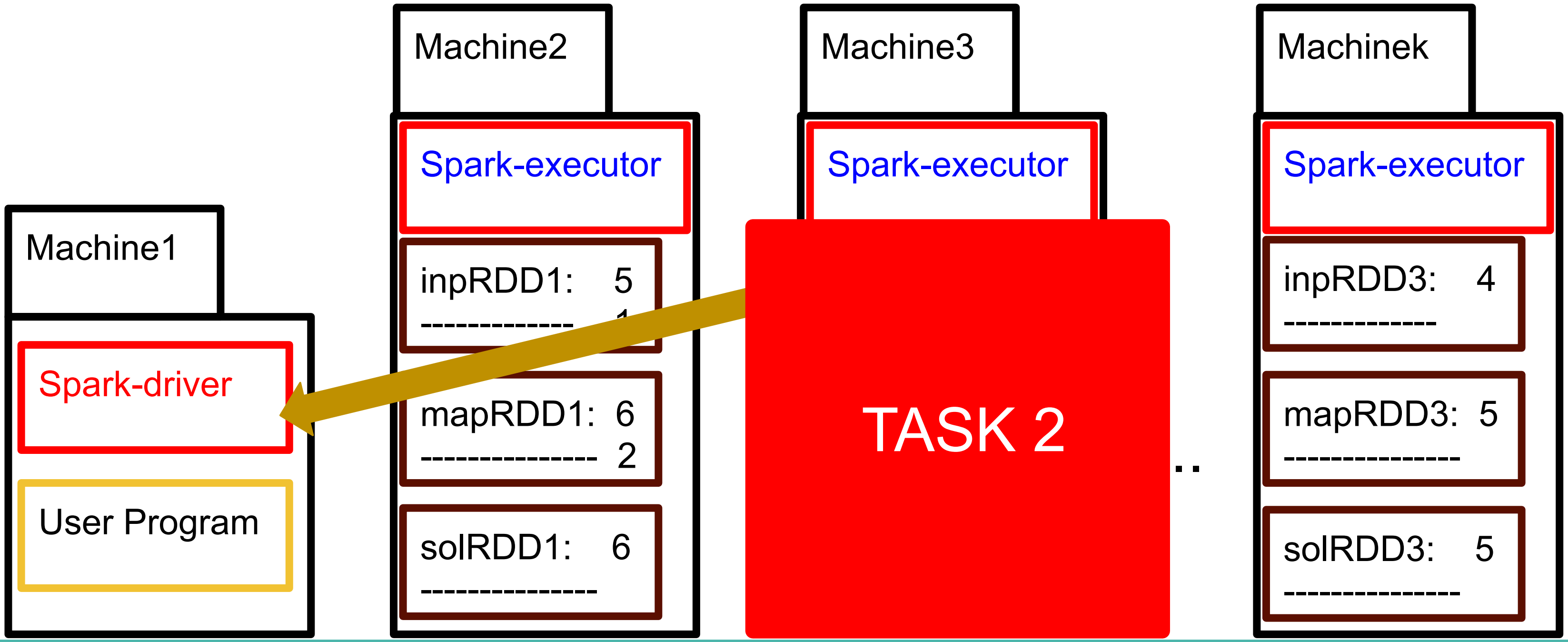
```
inputRDD  = sc.parallelize( [ 1, 2, 3, 4, 5 ] )
mapRDD = inputRDD.map( lambda elem : elem + 1 )
solRDD = mapRDD.filter( lambda elem : elem > 3 )
```



Idea 24: Execution of a Spark User Program

- Within a stage, all narrow operations can be chained and execution on each partition separately, without any dependency among partitions.

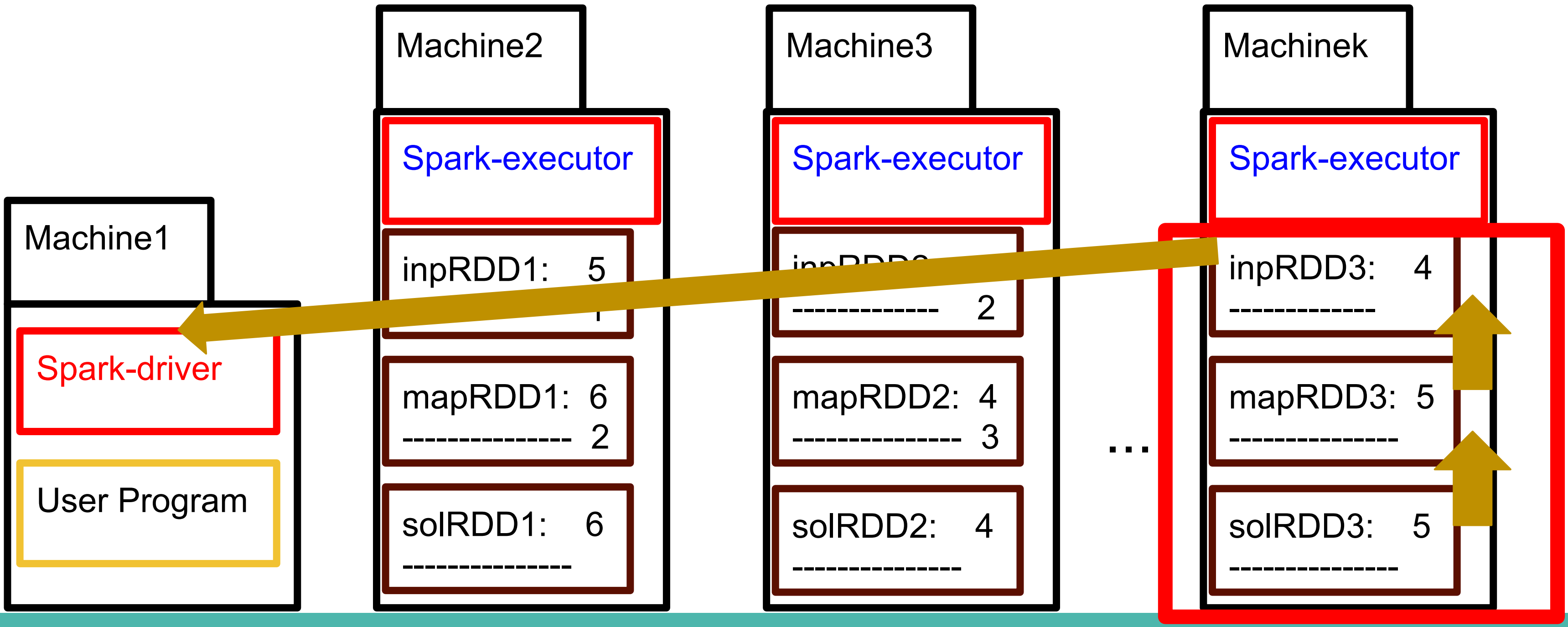
```
inputRDD  = sc.parallelize( [ 1, 2, 3, 4, 5 ] )
mapRDD = inputRDD.map( lambda elem : elem + 1 )
solRDD = mapRDD.filter( lambda elem : elem > 3 )
```



Idea 24: Execution of a Spark User Program

- Within a stage, all narrow operations can be chained and execution on each partition separately, without any dependency among partitions.

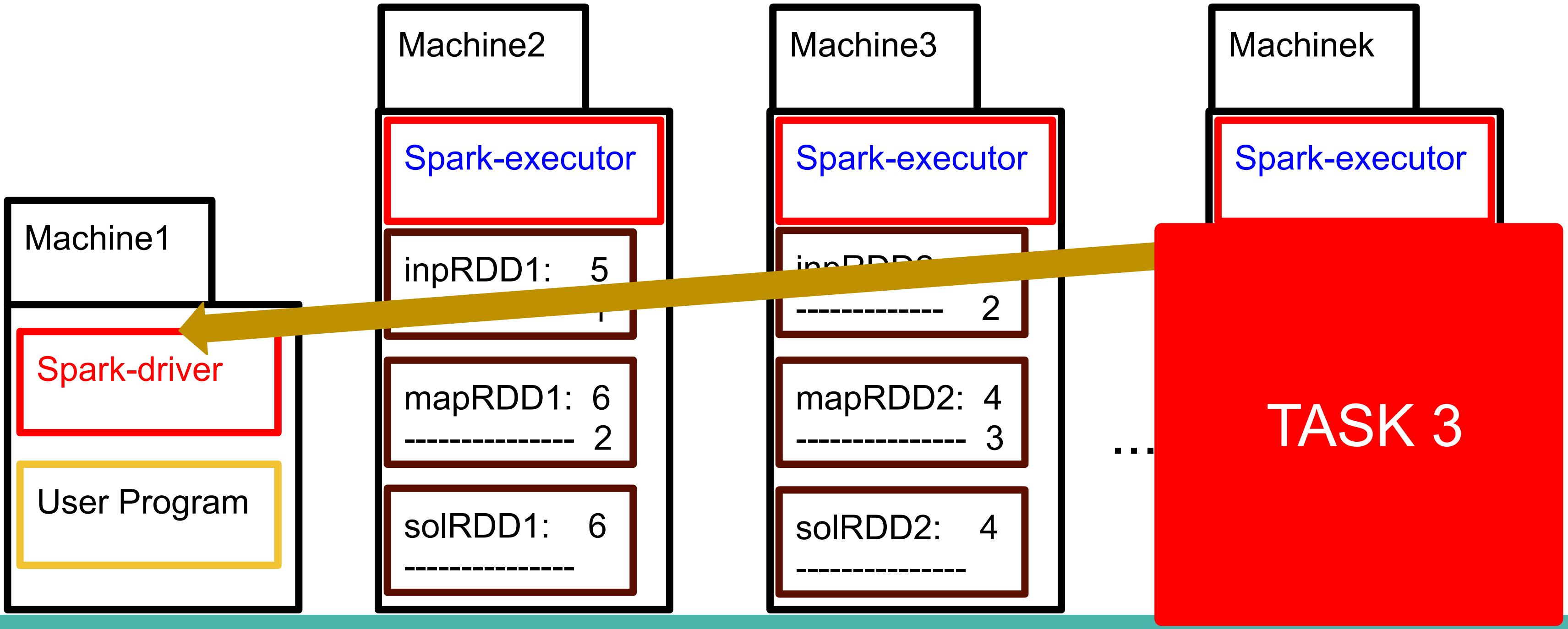
```
inputRDD  = sc.parallelize( [ 1, 2, 3, 4, 5 ] )
mapRDD = inputRDD.map( lambda elem : elem + 1 )
solRDD = mapRDD.filter( lambda elem : elem > 3 )
```



Idea 24: Execution of a Spark User Program

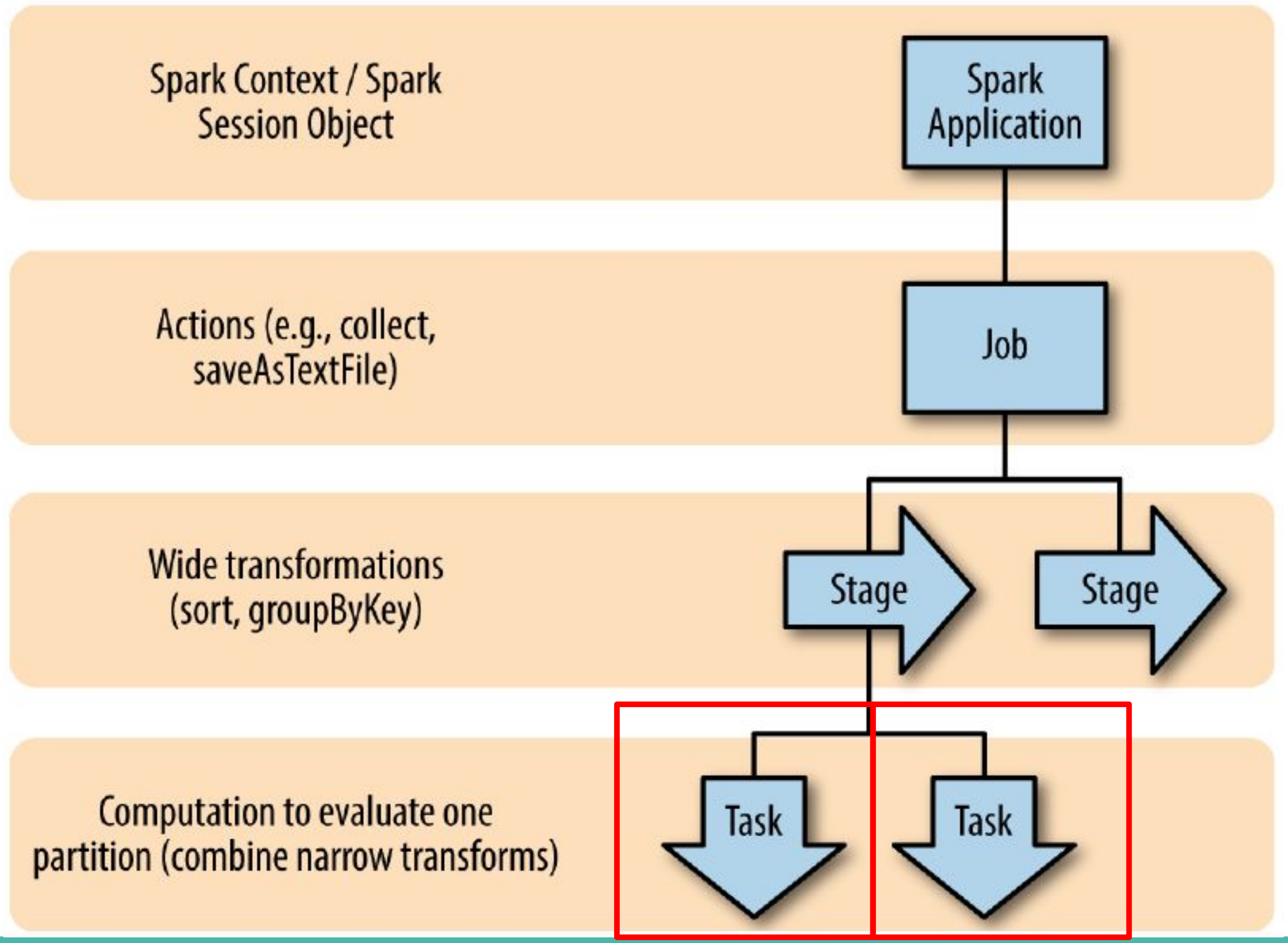
- Within a stage, all narrow operations can be chained and execution on each partition separately, without any dependency among partitions.

```
inputRDD  = sc.parallelize( [ 1, 2, 3, 4, 5 ] )
mapRDD = inputRDD.map( lambda elem : elem + 1 )
solRDD = mapRDD.filter( lambda elem : elem > 3 )
```



Idea 24: Execution of a Spark User Program

That’s why within a stage, tasks can run in parallel.


Spark Context / Spark Session Object
Spark Application
Actions (e.g., collect, saveAsTextFile)
Job
Wide transformations (sort, groupByKey)
Stage
Stage
Computation to evaluate one partition (combine narrow transforms)
Task
Task

Outline

We have summarised the main ideas presented in our module Big Data Processing.

Outline

Let’s finish now with a final synthesis.

Outline

Let’s finish now with a final synthesis.

If we were define our module
Big Data Processing
in just one slide,
what would we say?

Outline

Big Data Processing (COMP9062)

Big Data processing is the first stage of each AI problem's journey.

In this module we have taught the theory behind Big Data Processing and its application using the state-of-the-art technology Apache Spark.

Thank you so much for your attention,

I hope you have enjoyed it :)