NYU | Center for Data Science

Week 05.1: Spark and RDDs

DS-GA 1004: Big Data

Map-Reduce... too low-level?

- Map-Reduce is great for one-time jobs with simple dependencies
- What if you want interactive or iterative procedures?
  - **Data exploration**
  - **Complex queries** with multiple joins and aggregations
  - **Optimization** and machine learning

Imagine doing gradient descent with MR

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And we don't even care about the previous iterations after they're done...

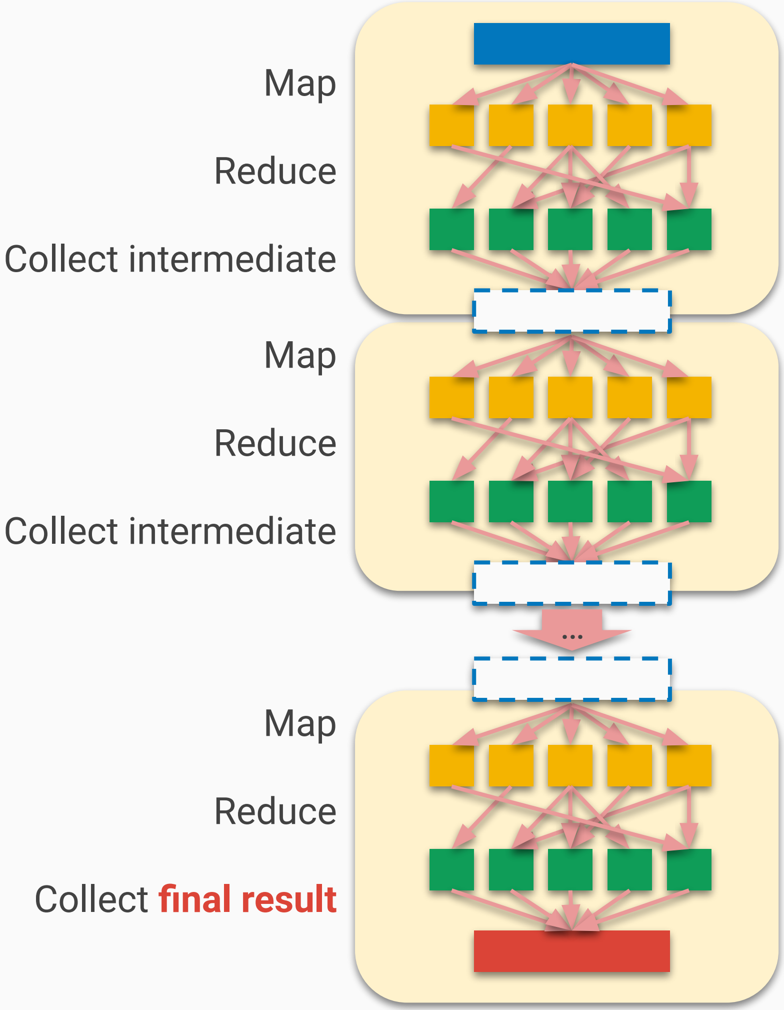
Reducer can't start until all mappers have finished
⇒ high latency

Complex pipelines

Some computations can be decomposed into a sequence of MR jobs

But this isn’t always the easiest or most natural way to do it!

What if you want to rapidly iterate?

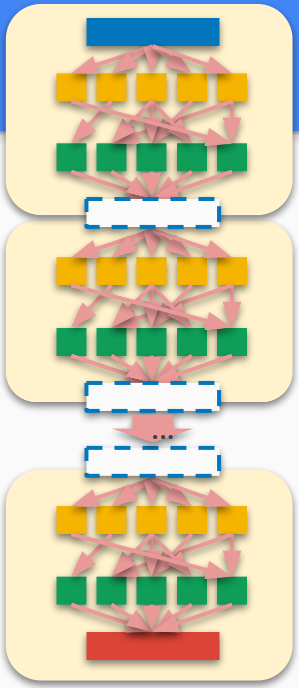


Resilient distributed datasets (RDDs)

[Zaharia et al., 2012]

Reusing data

- Complex computations usually have many **intermediate steps**
- Map-Reduce paradigm favors the following pattern:
  - Compute each step
  - Store intermediate results
  - Move on to the next step
- This can be **wasteful** and **awkward** to implement



Resilient distributed datasets (RDDs)

- RDD:
  - **Data source**
  - Lineage graph of **transformations** to apply to **data**
  - + interfaces for data **partitioning** and **iteration**

- Think of this as **deferred computation**
  - Nothing is **computed** until you ask for it
  - Nothing is **saved** until you say so
  - This makes optimization possible

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Some notation:

RDD[T] denotes an RDD with data of type T, e.g.

- RDD[String]
- RDD[Tuple(String, Float)]

RDD example: log processing

Spark code

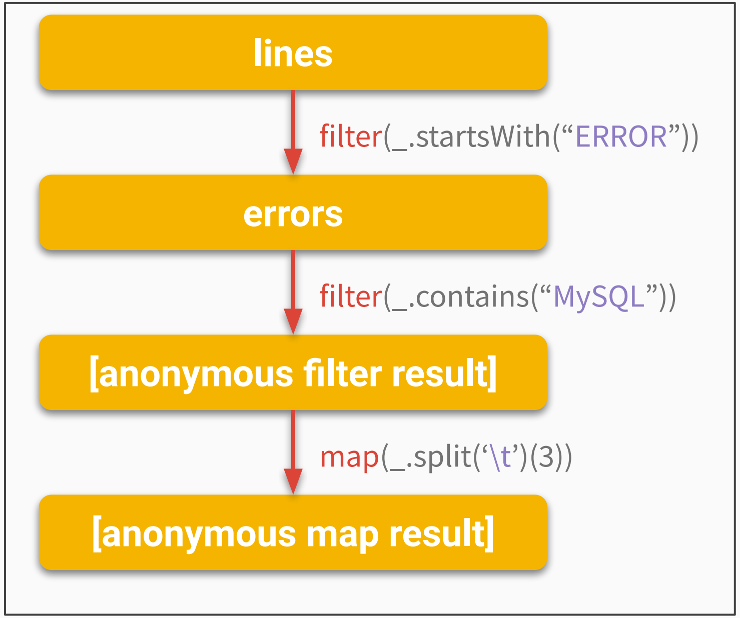
```
lines = spark.textFile("hdfs://...")

errors = lines.filter(_.startsWith("ERROR"))

errors.filter(_.contains("MySQL"))
      .map(_.split('\t')(3))
      .collect()
```

Legend:
Data **RDD** **Transformation** **Action**

Lineage graph



Adapted from [Zaharia et al., 2012]

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No computation happens until you take an **action!**

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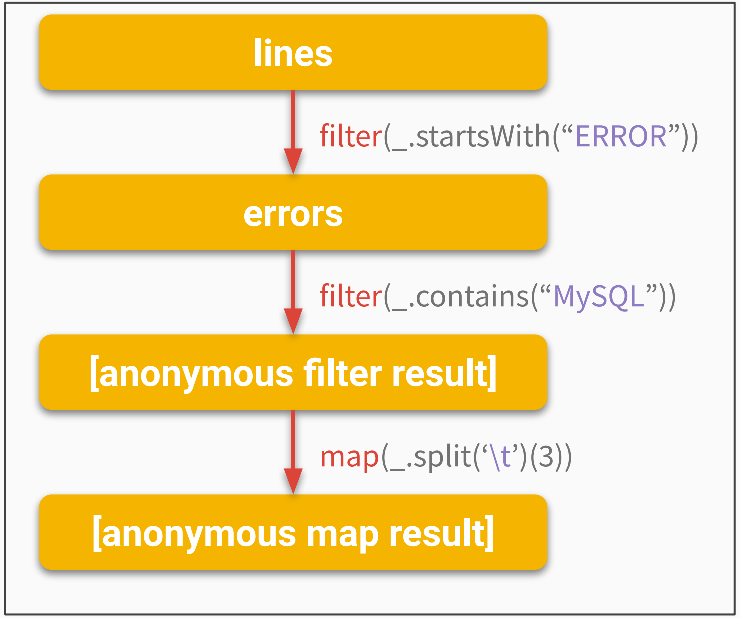

Adapted from [Zaharia et al., 2012]

Transformations

Transformations turn one or more RDDs into a new RDD

Transformations are cheap to construct because they don't actually do the computation

Building an RDD is like **writing** (not ***running***) a map-reduce script or a SQL query

- Examples:
  - **map**(**function** T → U) ⇒ RDD[T] → RDD[U]
  - **filter**(**function** T → **Boolean**) ⇒ RDD[T] → RDD[T]
  - **union**() ⇒ (RDD[T], RDD[T]) → RDD[T]

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Actions

Actions are what execute computation defined by an RDD

Results of actions are not RDDs

- Examples:
  - **count**() ⇒ RDD[T] → Integer
  - **collect**() ⇒ RDD[T] → Sequence[T]
  - **reduce**(**function** (T, T) → T) ⇒ RDD[T] → T
  - **save**(**path**) ⇒ Save RDD to file system or HDFS

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Work backwards from actions

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1. **collect**() depends on **map**()
2. **map**() depends on **filter**(MySQL)
3. **filter**(MySQL) depends on **filter**(ERROR)
4. **filter**(ERROR) depends on **lines**

Work backwards from actions

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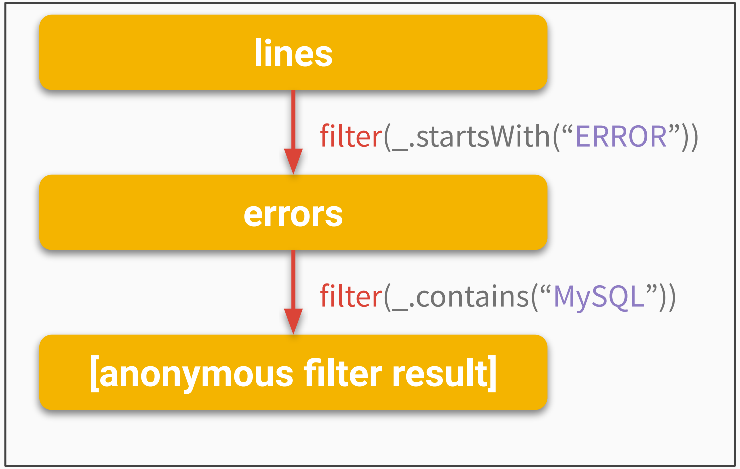
Any previously computed RDDs can be **cached** and reused!

Any lost / corrupted RDDs can be rebuilt from scratch by tracing the **lineage**!

1. **collect**() depends on **map**()
2. **map**() depends on **filter**(MySQL)
3. **filter**(MySQL) depends on **filter**(ERROR)
4. **filter**(ERROR) depends on **lines**

Pipelines

- Lineages can be **pipelined**
- We don't need to wait for all of **lines** to finish to build **errors**
- **No need for intermediate storage like in Map-Reduce**



lines	errors	[anonymous filter]
Status OK Status OK ERROR: Rampaging T-Rex Status OK ERROR: MySQL failure Status OK ERROR: Utahraptor ate my lunch		

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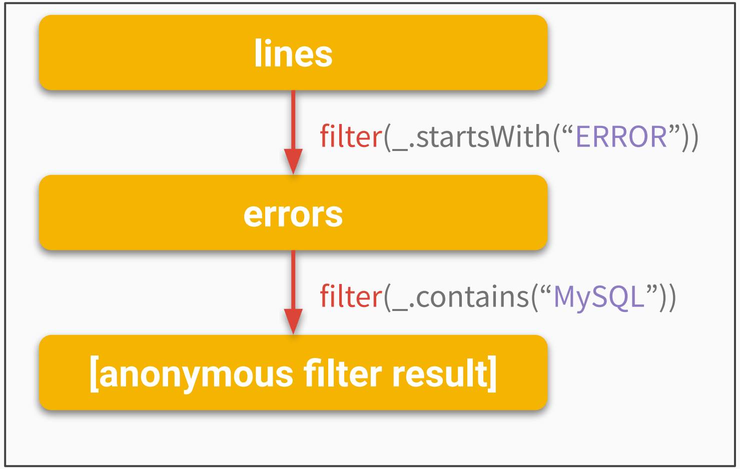

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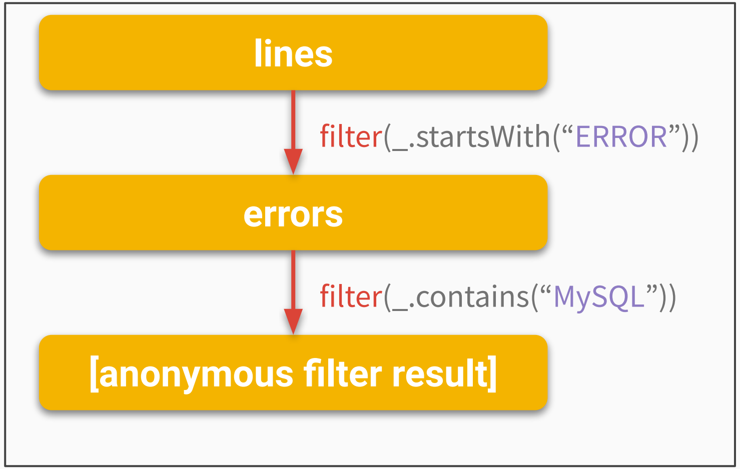

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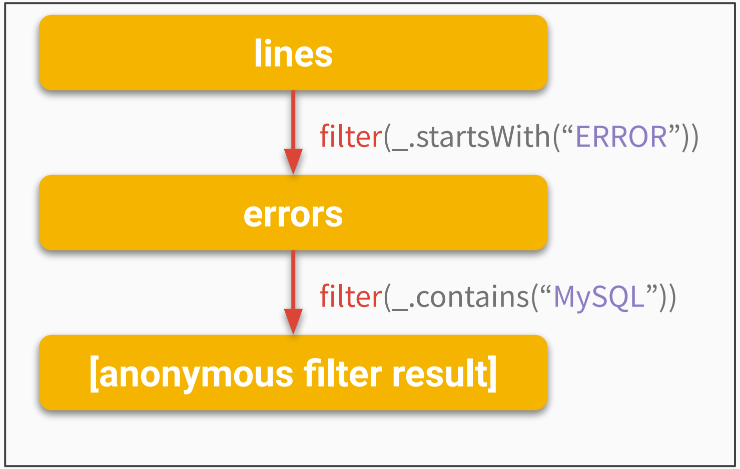

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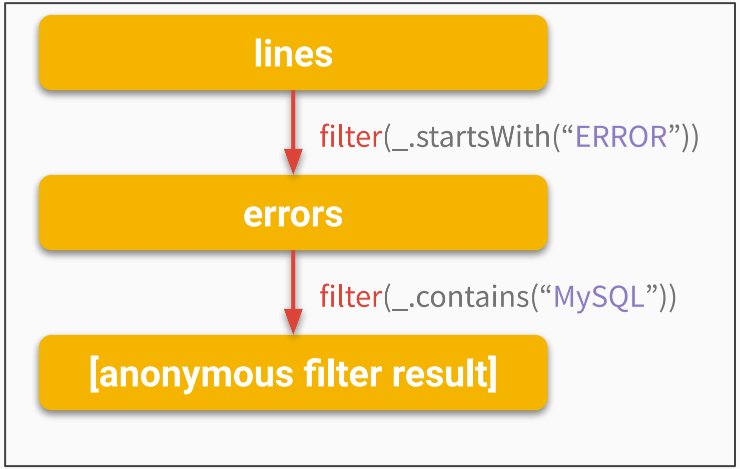

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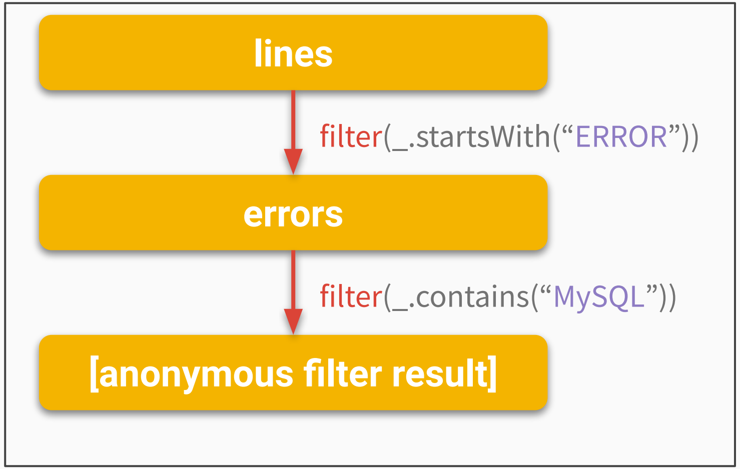

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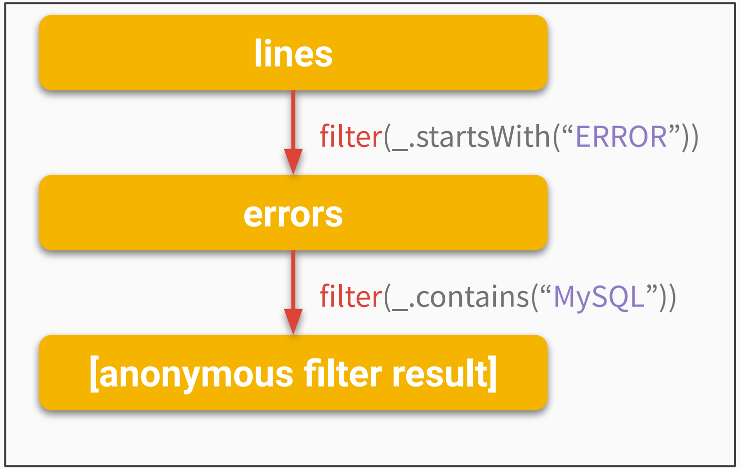

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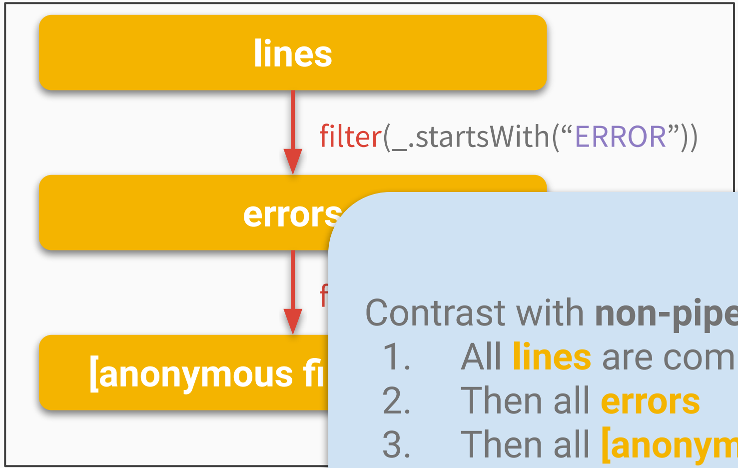

Contrast with **non-pipelined** implementation:

1. All lines are computed
2. Then all errors
3. Then all [anonymous filter]

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The RDD interface

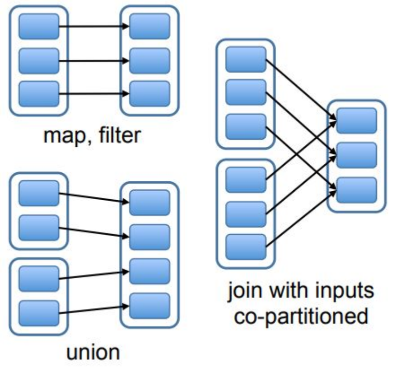
- **partitions**() → Returns a list of *Partitions* (analogous to **splits** in map-reduce)
- **preferredLocations**(*p*) → (HDFS) Nodes where partition *p* can be found
- **dependencies**() → Get the dependencies for this RDD
- **iterator**(*p*, *parentIters*) → Get elements of partition *p*, given iterators for parent partitions
- **partitioner**() → Get metadata about how the RDD is partitioned (e.g., is it a hash or range?)

Narrow and wide dependencies

Narrow dependencies

Partition of parent RDD goes to at most 1 partition of child RDDs

- Low communication
- Localized
- Easy to pipeline
- Easy failure recovery



Figures adapted from [Zaharia et al., 2012]

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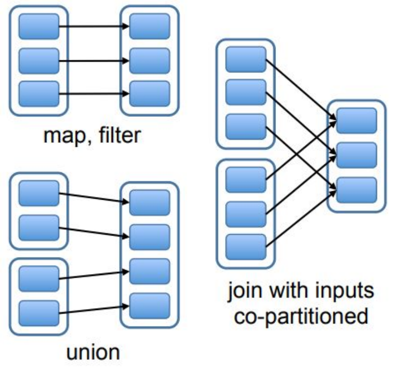
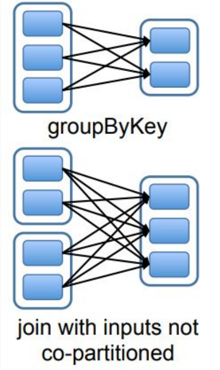


Wide dependencies

Partition of parent RDD goes to multiple child RDD partitions

- High communication
- High latency
- Difficult to pipeline
- Difficult to recover



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RDDs

- Resilient Distributed Datasets (RDDs) and the fundamental data structure of Spark
- Spark uses deferred computation to more efficiently construct complex analyses
    - Transformations and actions!
- RDD partitions are analogous to map-reduce splits, and allow parallel execution