# cloudera®



Chapter 15



# **Course Chapters**

1	Introduction	Course Introduction
2 3	Introduction to Hadoop and the Hadoop Ecosystem Hadoop Architecture and HDFS	Introduction to Hadoop
4 5 6 7 8	Importing Relational Data with Apache Sqoop Introduction to Impala and Hive Modeling and Managing Data with Impala and Hive Data Formats Data File Partitioning	Importing and Modeling Structured Data
9	Capturing Data with Apache Flume	Ingesting Streaming Data
10 11 12 13 14 <b>15</b> 16 17	Spark Basics Working with RDDs in Spark Aggregating Data with Pair RDDs Writing and Deploying Spark Applications Parallel Processing in Spark Spark RDD Persistence Common Patterns in Spark Data Processing Spark SQL and DataFrames	Distributed Data Processing with Spark
18	Conclusion	Course Conclusion



# **Spark RDD Persistence**

## In this chapter you will learn

- How Spark uses an RDD's lineage in operations
- How to persist RDDs to improve performance

# **Chapter Topics**

## **Spark RDD Persistence**

**Distributed Data Processing** with Spark

- RDD Lineage
- RDD Persistence Overview
- Distributed Persistence
- Conclusion
- Homework: Persist an RDD

# Lineage Example (1)

Each transformation operation creates a new child RDD

File: purplecow.txt

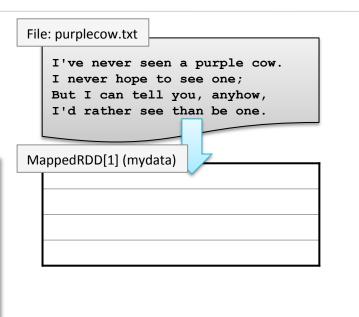
I've never seen a purple cow. I never hope to see one; But I can tell you, anyhow, I'd rather see than be one.



# Lineage Example (2)

Each transformation operation creates a new child RDD

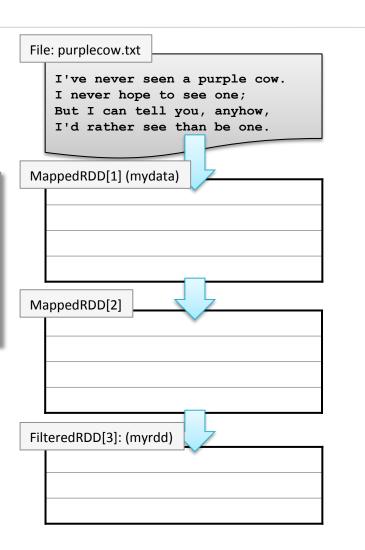
> mydata = sc.textFile("purplecow.txt")



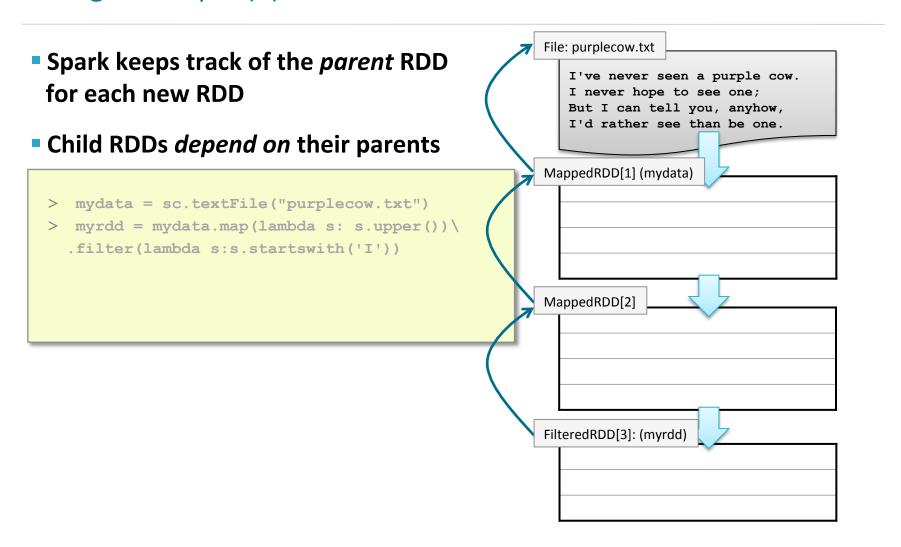
# Lineage Example (3)

Each transformation operation creates a new child RDD

```
> mydata = sc.textFile("purplecow.txt")
> myrdd = mydata.map(lambda s: s.upper()) \
  .filter(lambda s:s.startswith('I'))
```



## Lineage Example (4)





# Lineage Example (5)

File: purplecow.txt • Action operations execute the I've never seen a purple cow. parent transformations I never hope to see one; But I can tell you, anyhow, I'd rather see than be one. MappedRDD[1] (mydata) I've never seen a purple cow. > mydata = sc.textFile("purplecow.txt") I never hope to see one; > myrdd = mydata.map(lambda s: s.upper())\ But I can tell you, anyhow, .filter(lambda s:s.startswith('I')) I'd rather see than be one. > myrdd.count() MappedRDD[2] I'VE NEVER SEEN A PURPLE COW. I NEVER HOPE TO SEE ONE; BUT I CAN TELL YOU, ANYHOW, I'D RATHER SEE THAN BE ONE. FilteredRDD[3]: (myrdd) I'VE NEVER SEEN A PURPLE COW. I NEVER HOPE TO SEE ONE; I'D RATHER SEE THAN BE ONE.



## Lineage Example (6)

File: purplecow.txt Each action re-executes the lineage I've never seen a purple cow. transformations starting with the I never hope to see one; But I can tell you, anyhow, base I'd rather see than be one. - By default MappedRDD[1] (mydata) > mydata = sc.textFile("purplecow.txt") > myrdd = mydata.map(lambda s: s.upper())\ .filter(lambda s:s.startswith('I')) > myrdd.count() MappedRDD[2] myrdd.count() FilteredRDD[3]: (myrdd)

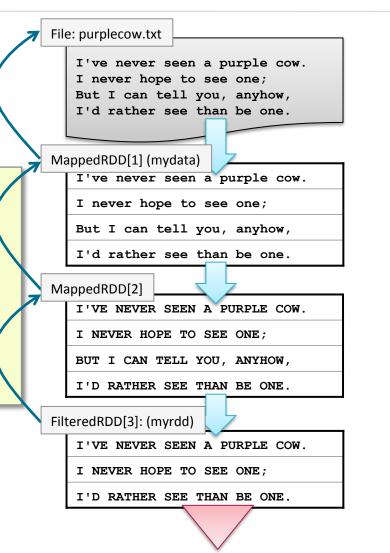


# Lineage Example (7)

Each action re-executes the lineage transformations starting with the base

By default

```
> mydata = sc.textFile("purplecow.txt")
> myrdd = mydata.map(lambda s: s.upper())\
  .filter(lambda s:s.startswith('I'))
> myrdd.count()
  myrdd.count()
```



# **Chapter Topics**

## **Spark RDD Persistence**

**Distributed Data Processing** with Spark

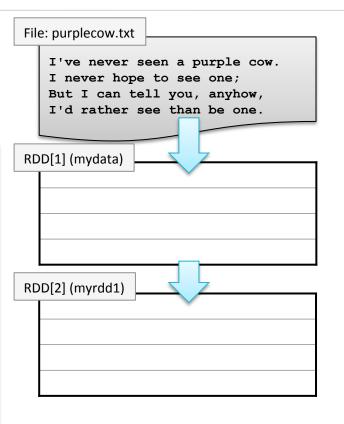
- RDD Lineage
- RDD Persistence Overview
- Distributed Persistence
- Conclusion
- Homework: Persist an RDD

Persisting an RDD saves the data (by default in memory)

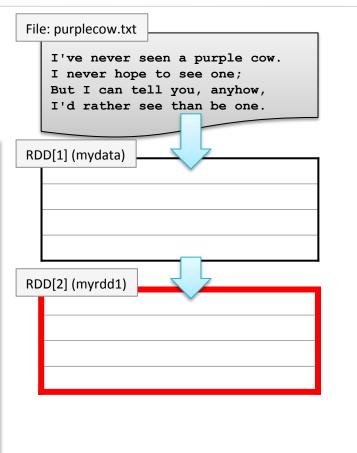
File: purplecow.txt

I've never seen a purple cow. I never hope to see one; But I can tell you, anyhow, I'd rather see than be one.

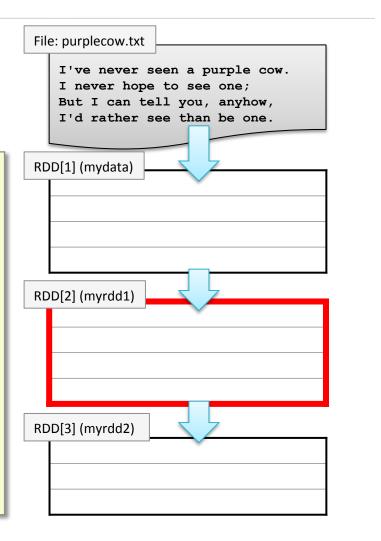
```
> mydata = sc.textFile("purplecow.txt")
> myrdd1 = mydata.map(lambda s:
  s.upper())
```



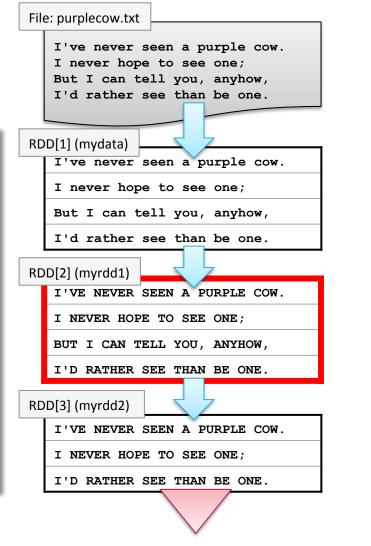
```
> mydata = sc.textFile("purplecow.txt")
> myrdd1 = mydata.map(lambda s:
  s.upper())
> myrdd1.persist()
```



```
> mydata = sc.textFile("purplecow.txt")
> myrdd1 = mydata.map(lambda s:
  s.upper())
> myrdd1.persist()
> myrdd2 = myrdd1.filter(lambda \
  s:s.startswith('I'))
```

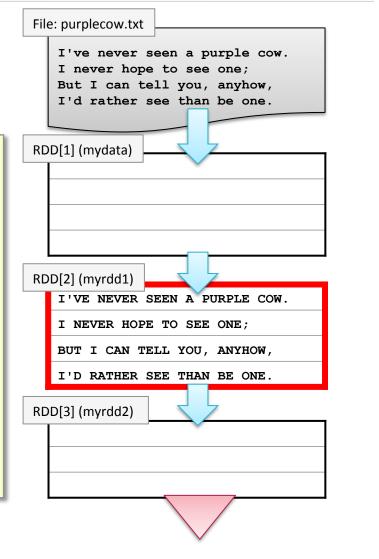


```
> mydata = sc.textFile("purplecow.txt")
> myrdd1 = mydata.map(lambda s:
  s.upper())
> myrdd1.persist()
> myrdd2 = myrdd1.filter(lambda \
  s:s.startswith('I'))
> myrdd2.count()
```



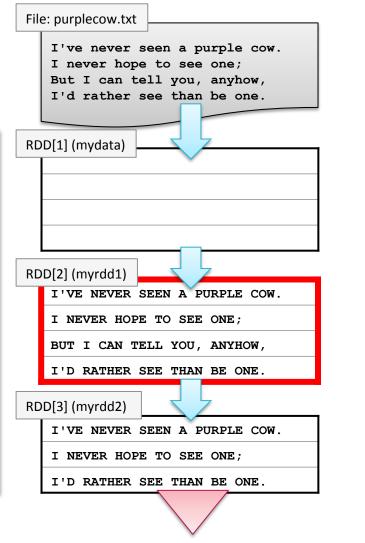
## Subsequent operations use saved data

```
> mydata = sc.textFile("purplecow.txt")
> myrdd1 = mydata.map(lambda s:
  s.upper())
> myrdd1.persist()
> myrdd2 = myrdd1.filter(lambda \
  s:s.startswith('I'))
> myrdd2.count()
> myrdd2.count()
```



## Subsequent operations use saved data

```
> my data =
  sc.textFile("purplecow.txt")
> myrdd1 = mydata.map(lambda s:
  s.upper())
> myrdd1.persist()
> myrdd2 = myrdd1.filter(lambda \
  s:s.startswith('I'))
> myrdd2.count()
> myrdd2.count()
3
```



## **Memory Persistence**

#### In-memory persistence is a *suggestion* to Spark

- If not enough memory is available, persisted partitions will be cleared from memory
  - Least recently used partitions cleared first
- Transformations will be re-executed using the lineage when needed

# **Chapter Topics**

## **Spark RDD Persistence**

**Distributed Data Processing** with Spark

- RDD Lineage
- RDD Persistence Overview
- Distributed Persistence
- Conclusion
- Homework: Persist an RDD

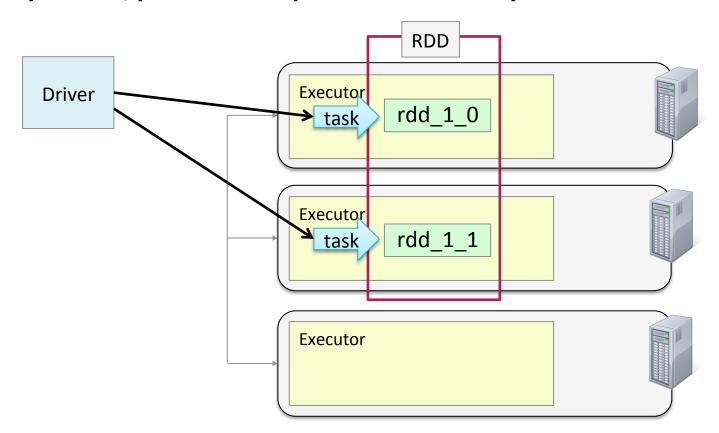
#### Persistence and Fault-Tolerance

#### RDD = Resilient Distributed Dataset

- Resiliency is a product of tracking lineage
- RDDs can always be recomputed from their base if needed

## **Distributed Persistence**

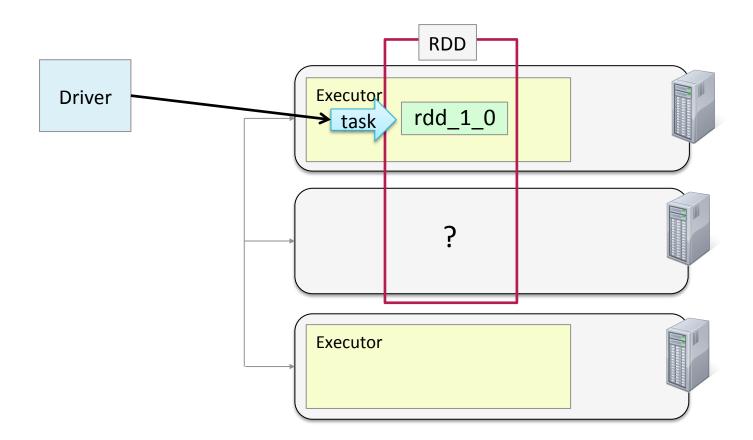
- RDD partitions are distributed across a cluster
- By default, partitions are persisted in memory in Executor JVMs





# RDD Fault-Tolerance (1)

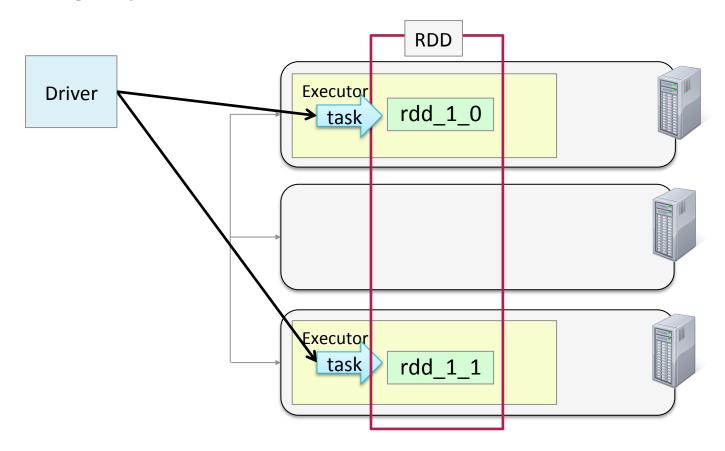
What happens if a partition persisted in memory becomes unavailable?





# RDD Fault-Tolerance (2)

- The driver starts a new task to recompute the partition on a different node
- Lineage is preserved, data is never lost





#### Persistence Levels

- By default, the persist method stores data in memory only
  - The cache method is a synonym for default (memory) persist
- The persist method offers other options called Storage Levels
- Storage Levels let you control
  - Storage location
  - Format in memory
  - Partition replication

## Persistence Levels: Storage Location

- Storage location where is the data stored?
  - MEMORY ONLY (default) same as cache
  - MEMORY AND DISK Store partitions on disk if they do not fit in memory
    - Called spilling
  - **DISK ONLY** Store all partitions on disk

Python

- > from pyspark import StorageLevel
- > myrdd.persist(StorageLevel.DISK ONLY)

Scala

- > import org.apache.spark.storage.StorageLevel
- myrdd.persist(StorageLevel.DISK ONLY)

# Persistence Levels: Memory Format

- Serialization you can choose to serialize the data in memory
  - MEMORY ONLY SER and MEMORY\_AND\_DISK\_SER
  - Much more space efficient
  - Less time efficient
    - If using Java or Scala, choose a fast serialization library (e.g. Kryo)

## Persistence Levels: Partition Replication

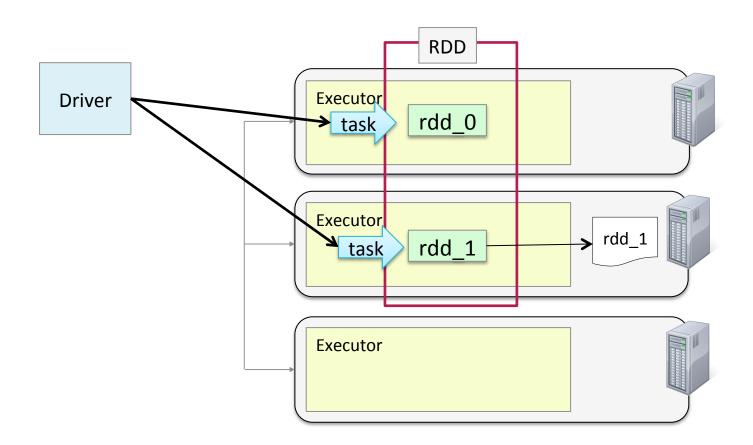
- Replication store partitions on two nodes
  - -MEMORY ONLY 2
  - -MEMORY AND DISK 2
  - -DISK ONLY 2
  - -MEMORY\_AND\_DISK\_SER\_2
  - -DISK\_ONLY 2
  - You can also define custom storage levels

## **Changing Persistence Options**

- To stop persisting and remove from memory and disk
  - -rdd.unpersist()
- To change an RDD to a different persistence level
  - Unpersist first

## **Disk Persistence**

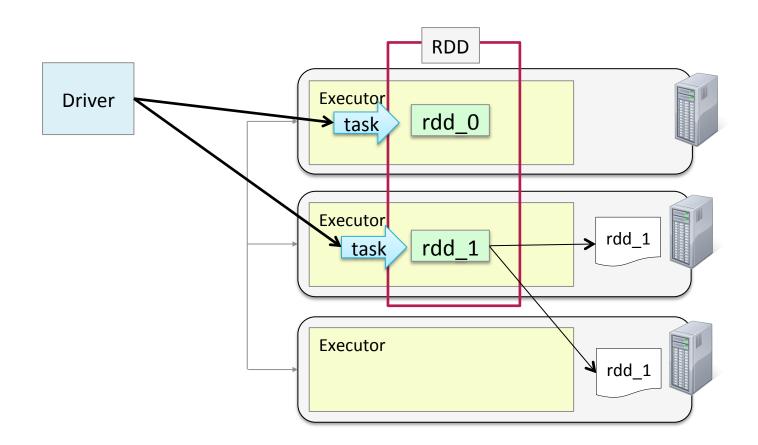
## Disk-persisted partitions are stored in local files





# Disk Persistence with Replication (1)

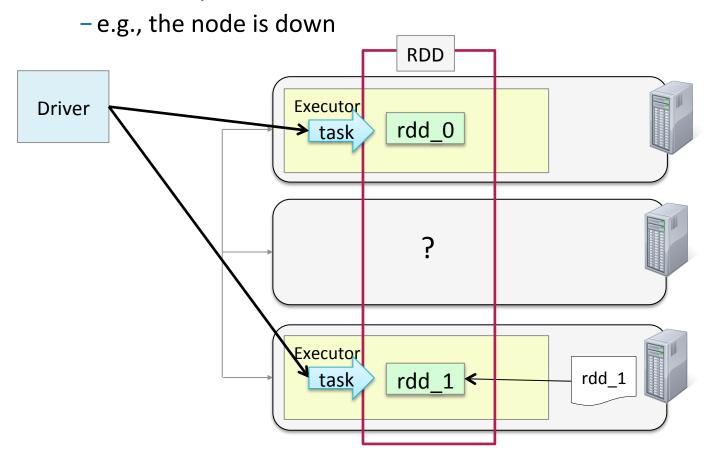
Persistence replication makes recomputation less likely to be necessary





# Disk Persistence with Replication (2)

- Replicated data on disk will be used to recreate the partition if possible
  - Will be recomputed if the data is unavailable





#### When and Where to Persist

#### When should you persist a dataset?

- When a dataset is likely to be re-used
  - e.g., iterative algorithms, machine learning

#### How to choose a persistence level

- Memory only when possible, best performance
  - Save space by saving as serialized objects in memory if necessary
- Disk choose when recomputation is more expensive than disk read
  - e.g., expensive functions or filtering large datasets
- Replication choose when recomputation is more expensive than memory

# **Chapter Topics**

## **Spark RDD Persistence**

**Distributed Data Processing** with Spark

- RDD Lineage
- RDD Persistence Overview
- Distributed Persistence
- Conclusion
- Homework: Persist an RDD

#### **Essential Points**

- Spark keeps track of each RDD's lineage
  - Provides fault tolerance
- By default, every RDD operation executes the entire lineage
- If an RDD will be used multiple times, persist it to avoid re-computation
- Persistence options
  - Location memory only, memory and disk, disk only
  - Format in-memory data can be serialized to save memory (but at the cost of performance)
  - Replication saves data on multiple nodes in case a node goes down, for job recovery without recomputation

# **Chapter Topics**

## **Spark RDD Persistence**

**Distributed Data Processing** with Spark

- RDD Lineage
- RDD Persistence Overview
- Distributed Persistence
- Conclusion
- Homework: Persist an RDD

#### Homework: Persist an RDD

- In this homework assignment you will
  - Persist an RDD before reusing it
  - Use the Spark Application UI to see how an RDD is persisted
- Please refer to the Homework description