Unified Big Data Analytics Pipeline

连城 lian@databricks.com

What is Spark

- A fast and general engine for large-scale data processing
- An open source implementation of Resilient Distributed Datasets (RDD)
- Has an advanced DAG execution engine that supports cyclic data flow and *in-memory* computing

Why Spark

- Fast
  - Run machine learning like iterative programs up to 100x faster than Hadoop MapReduce in memory or 10x faster on disk
  - Run HiveQL compatible queries 100x faster than Hive (with Shark / Spark SQL)

Why Spark

- Compatibility
  - Compatible with most popular storage systems on top of HDFS
  - New users needn’t suffer ETL to deploy Spark

Why Spark

- Easy to use
  - Fluent Scala / Java / Python API
  - Interactive shell
  - 2-5x less code (than Hadoop MapReduce)

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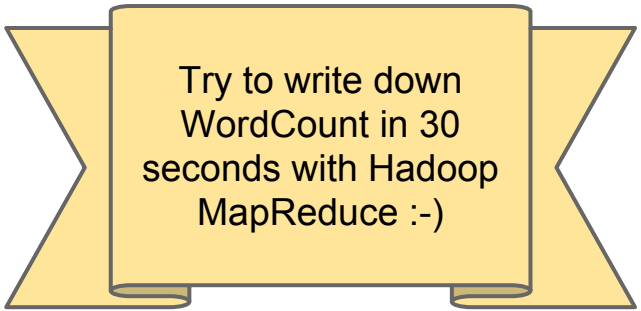
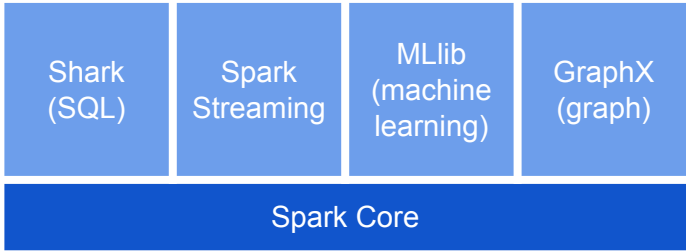
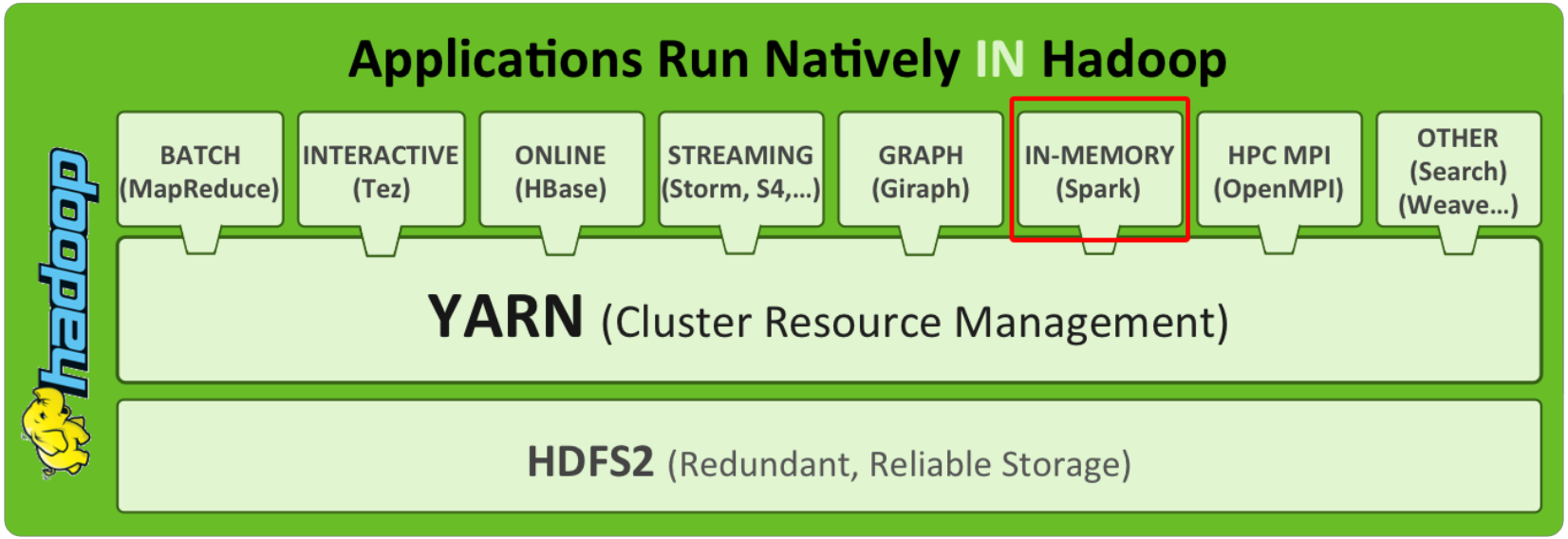


Why Spark

- Unified big data analytics pipeline for
  - Batch / interactive (Spark Core vs MR / Tez)
  - SQL (Shark / Spark SQL vs Hive)
  - Streaming (Spark Streaming vs Storm)
  - Machine learning (MLlib vs Mahout)
  - Graph (GraphX vs Giraph)



The Hadoop Family

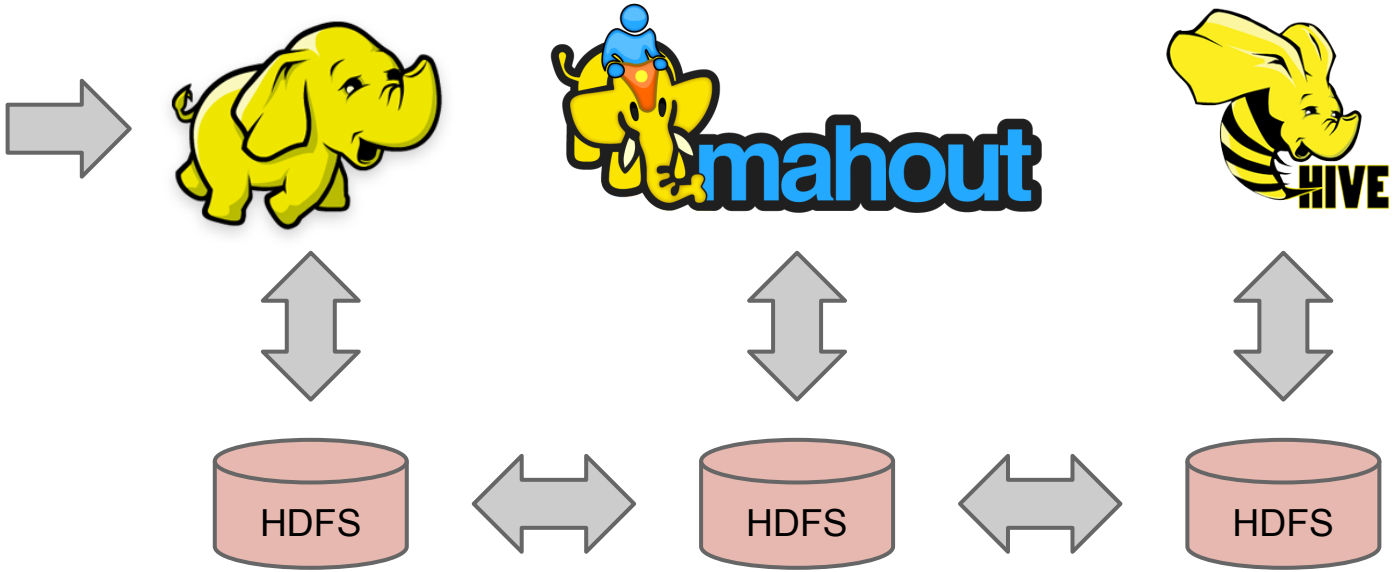


The Hadoop Family

General Batching	Specialized systems			
	Streaming	Iterative	Ad-hoc / SQL	Graph
MapReduce	Storm	Mahout	Pig	Giraph
	S4		Hive	
	Samza		Drill	
			Impala	

Big Data Analytics Pipeline Today

Using separate frameworks



Big Data Analytics Pipeline Today

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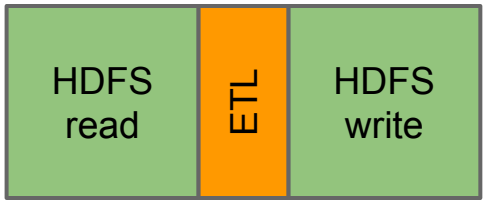

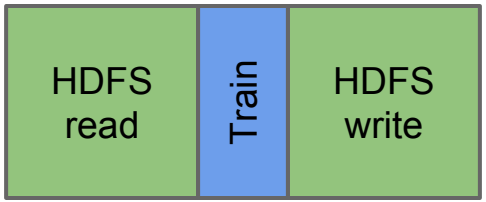

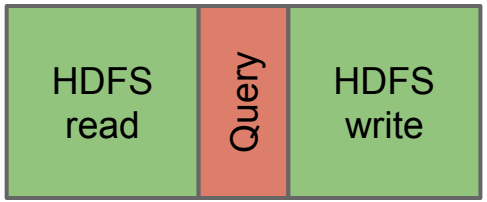

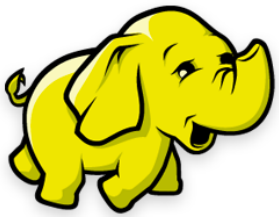

Big Data Analytics Pipeline Today

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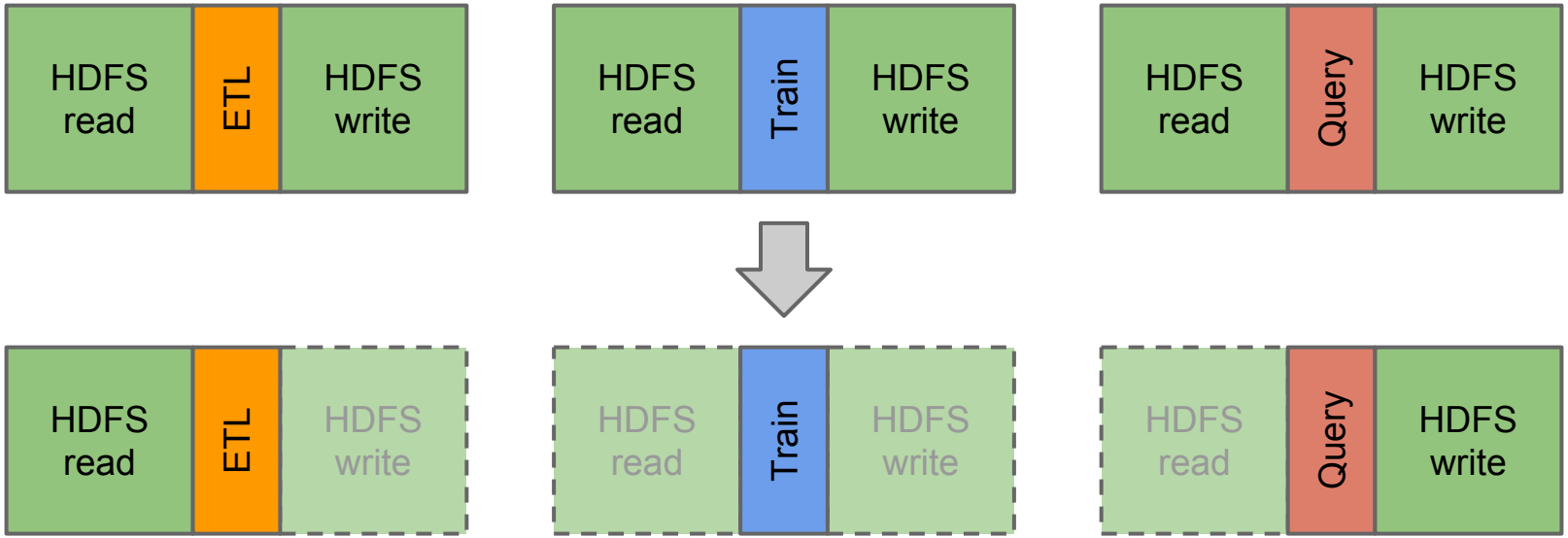

Big Data Analytics Pipeline Today

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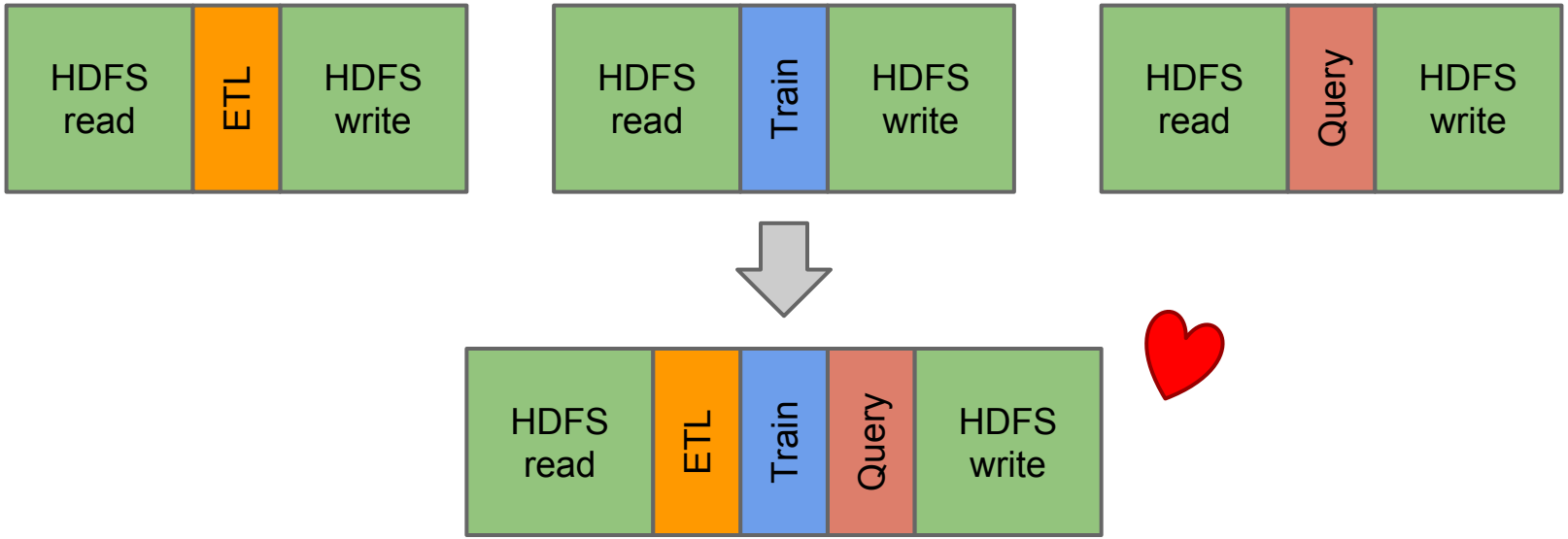

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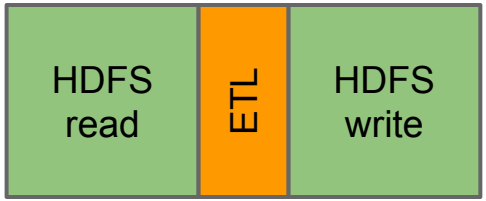
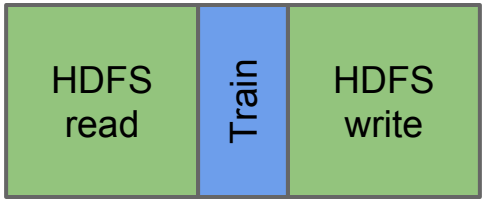
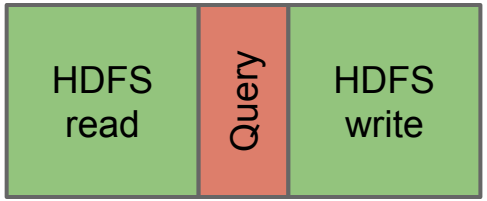
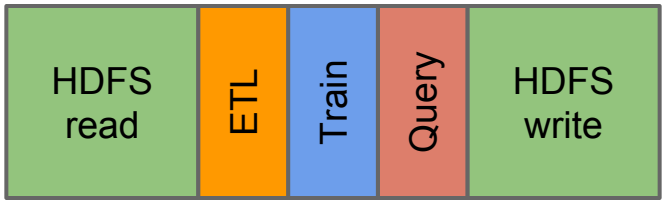






How?




Ahhh!!!
DATA HAS
GRAVITY

Resilient Distributed Datasets

- RDDs
  - are *read-only*, *partitioned* collections of records
  - can be cached *in-memory* and are *locality aware*
  - can only be created through *deterministic operations* on either (1) *data in stable storage*, or (2) *other RDDs*

Resilient Distributed Datasets

- Core data sharing abstraction in Spark
- Computation can be represented by lazily evaluated RDD lineage DAG(s)

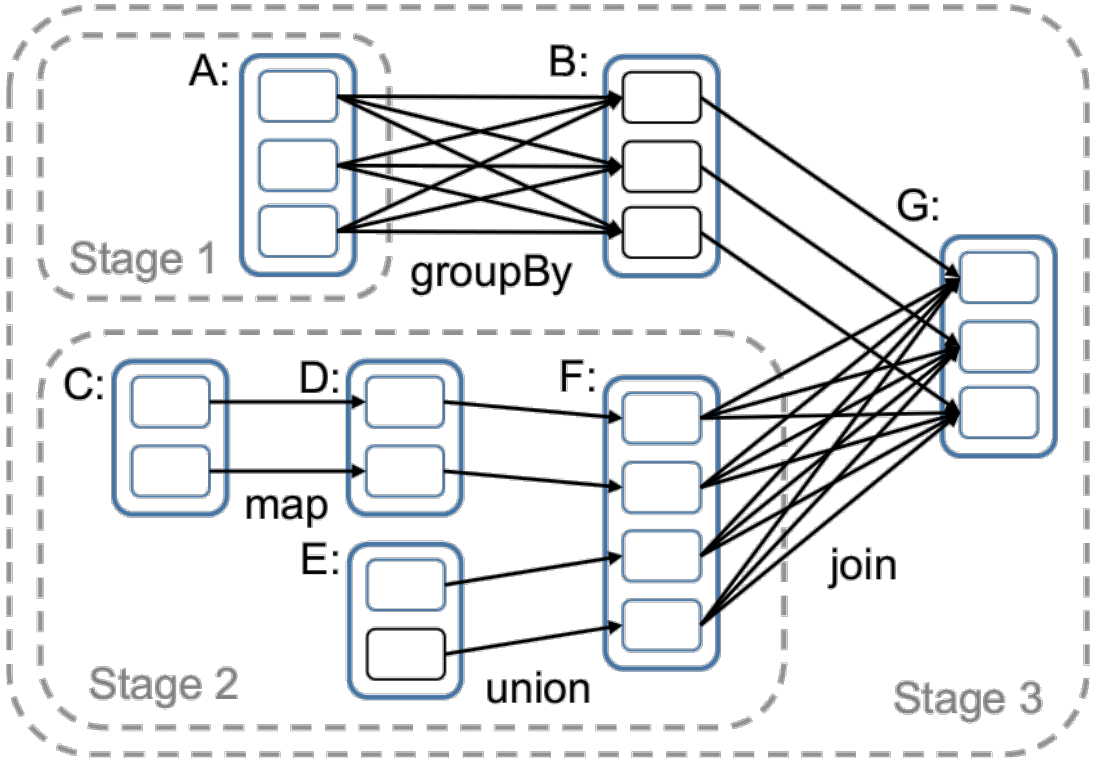
Resilient Distributed Datasets

- An RDD
  - is a read-only, partitioned, locality aware distributed collection of records
  - either points to a stable data source, or
  - is created through deterministic transformations on some other RDD(s)

Resilient Distributed Datasets

- Coarse grained
  - Applies the same operation on many records
- Fault tolerant
  - Failed tasks can be recovered in parallel with the help of the lineage DAG

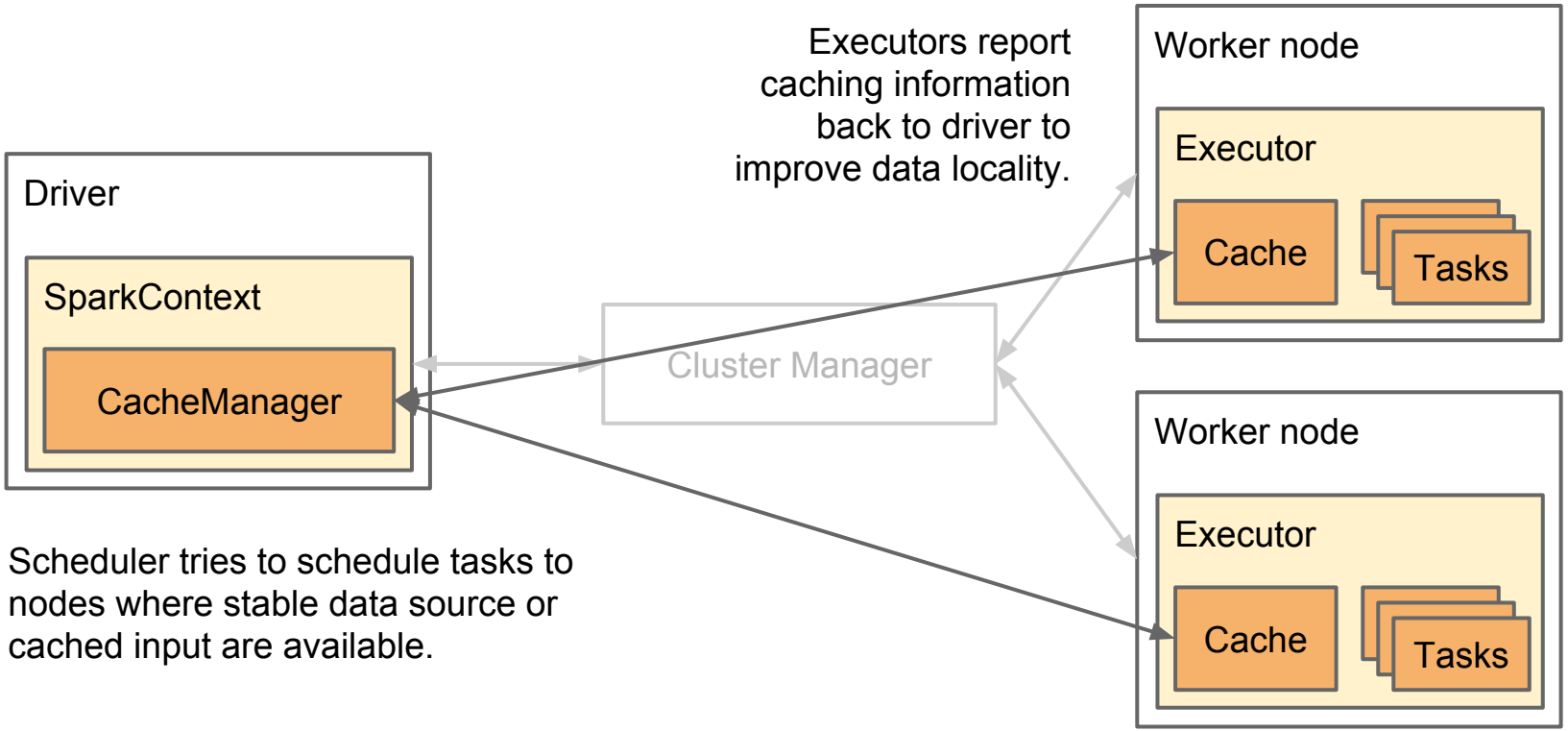
Resilient Distributed Datasets



Data Sharing in Spark

- Frequently accessed RDDs can be materialized and cached in memory
  - Cached RDD can also be replicated for fault tolerance
- Spark scheduler takes cached data locality into account

Data Sharing in Spark



Data Sharing in Spark

- As a consequence, intermediate results are
  - either cached *in memory*, or
  - written to local file system as shuffle map output and waiting to be fetched by reducer tasks (similar to MapReduce)
- Enables in-memory data sharing, avoids unnecessary HDFS I/O

Generality of RDDs

- From an expressiveness point of view
  - The coarse grained nature is not a big limitation since many parallel programs naturally *apply the same operation to many records*, making them easy to express
  - In fact, RDDs can emulate *any* distributed system, and will do so *efficiently* in many cases unless the system is sensitive to network latency

Generality of RDDs

- From system perspective
  - RDDs gave applications control over the most common bottleneck resources in cluster applications (i.e., network and storage I/O)
  - Makes it possible to express the same optimizations that specialized systems have and achieve similar performance

Limitations of RDDs

- Not suitable for
  - Latency (millisecond scale)
  - Communication patterns beyond all-to-all
  - Asynchrony
  - Fine-grained updates

Analytics Models Built over RDDs

MR / Dataflow

```
spark
  .textFile("hdfs://...")
  .flatMap(_ split " ")
  .map(_ -> 1)
  .reduceByKey(_ + _)
  .collectAsMap()
```

Streaming

```
val streaming = new StreamingContext(
  spark, Seconds(1))
streaming.socketTextStream(host, port)
  .flatMap(_ split " ")
  .map(_ -> 1)
  .reduceByKey(_ + _)
  .print()
streaming.start()
```

Analytics Models Built over RDDs

SQL

```
val hiveContext = new HiveContext(spark)
import hiveContext._
val children = hiveql(
  """SELECT name, age FROM people
    |WHERE age < 13
  """.striMargin).map {
    case Row(name: String, age: Int) =>
      name -> age
  }.foreach(println)
```

Machine Learning

```
val points = spark.textFile("hdfs://...")
  .map(_.split.map(_.toDouble)).splitAt(1)
  .map { case (Array(label), features) =>
    LabeledPoint(label, features)
  }
val model = KMeans.train(points)
```

Mixing Different Analytics Models

MapReduce & SQL

```
// ETL with Spark Core
case class Person(name: String, age: Int)
val people = spark.textFile("hdfs://people.txt").map { line =>
  val Array(name, age) = line.split(",")
  Person(name, age.trim.toInt)
}.registerAsTable("people")
// Query with Spark SQL
val teenagers = sql("SELECT name FROM people WHERE age >= 13 AND age <= 19")
teenagers.collect().foreach(println)
```

Mixing Different Analytics Models

SQL & iterative computation (machine learning)

```
// ETL with Spark SQL & Spark Core
val trainingData = sql("""SELECT e.action, u.age, u.latitude, u.longitude
                          |FROM Users u JOIN Events e ON u.userId = e.userId
                        """.stripMargin).map {
  case Row(_, age: Double, latitude: Double, longitude: Double) =>
    val features = Array(age, latitude, longitude)
    LabeledPoint(age, features)
}
// Training with MLlib
val model = new LogisticRegressionWithSGD().run(trainingData)
```

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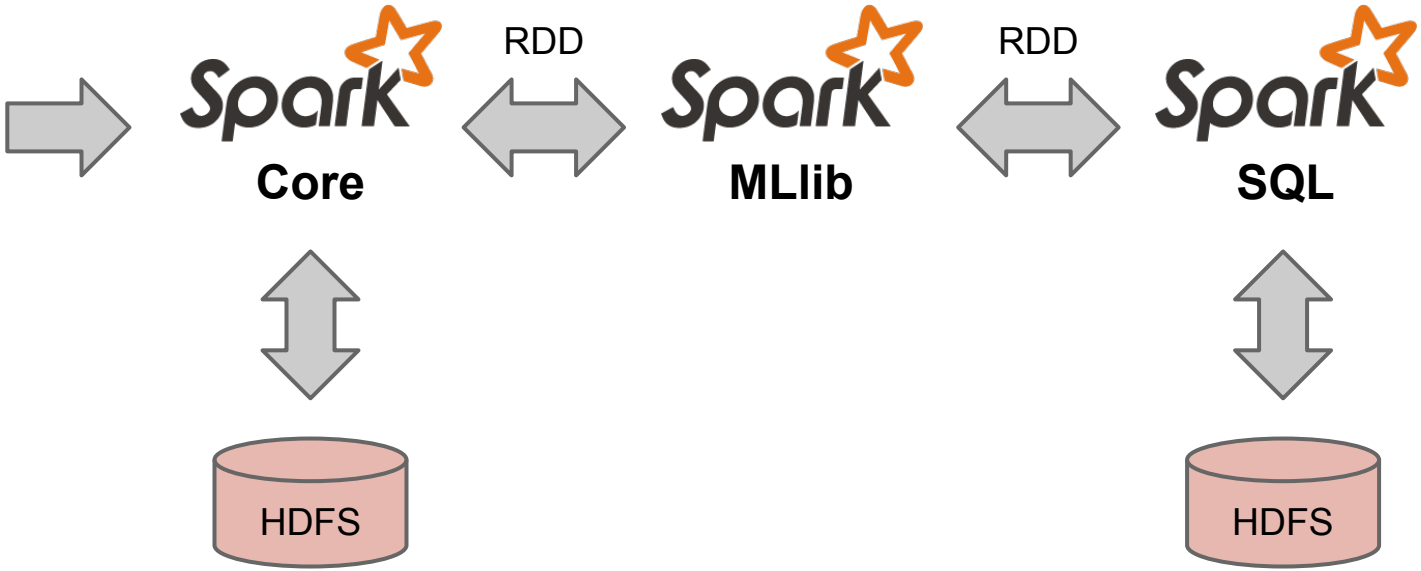

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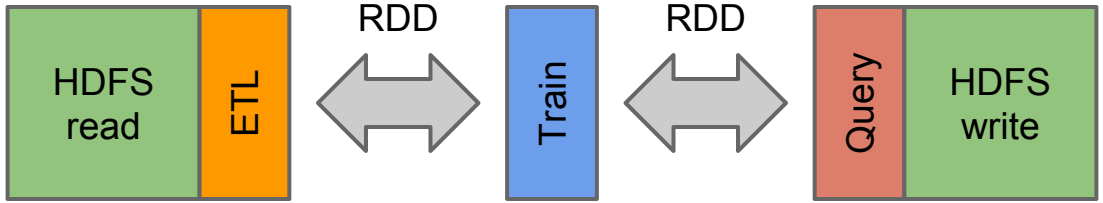

Spark Core

Spark MLlib

Spark SQL

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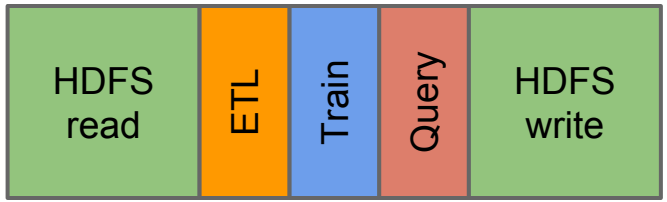

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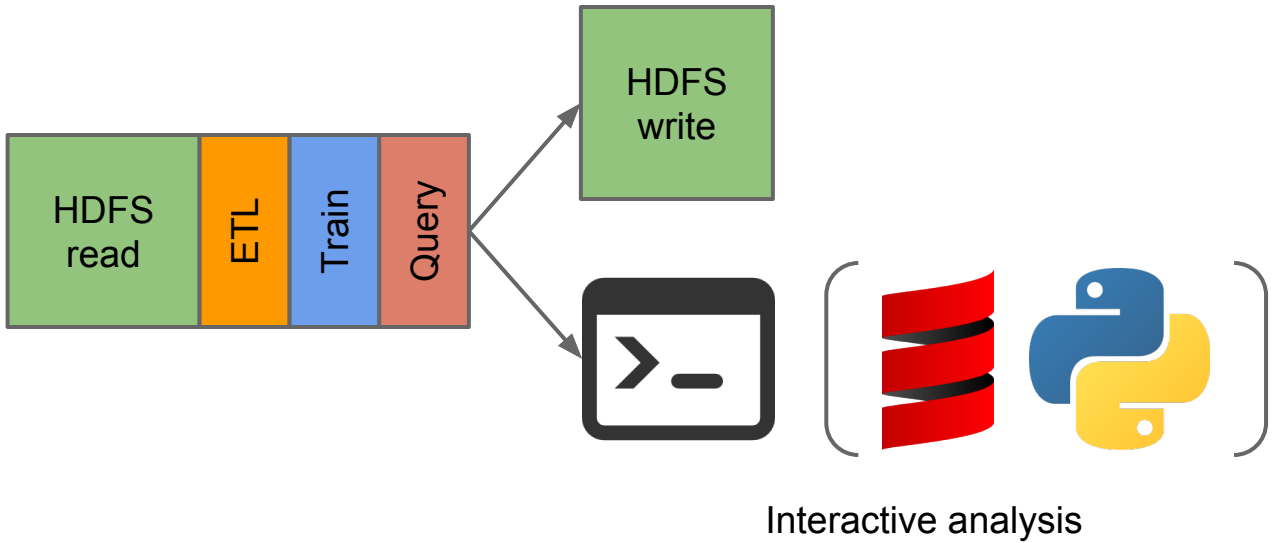
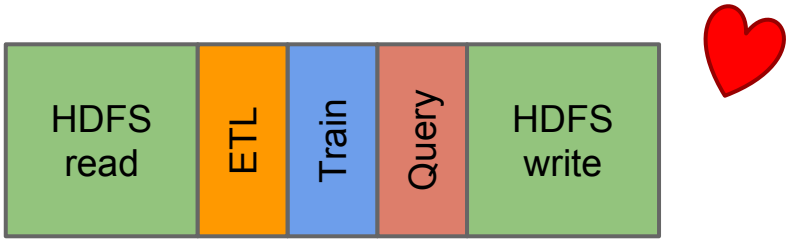


Unified Big Data Analytics Pipeline

- Unified in-memory data sharing abstraction
- Efficient runtime brings significant performance boost and enables interactive analysis
- “One stack to rule them all”



Thanks!

Q&A