Spark

Lecture 6

Recap

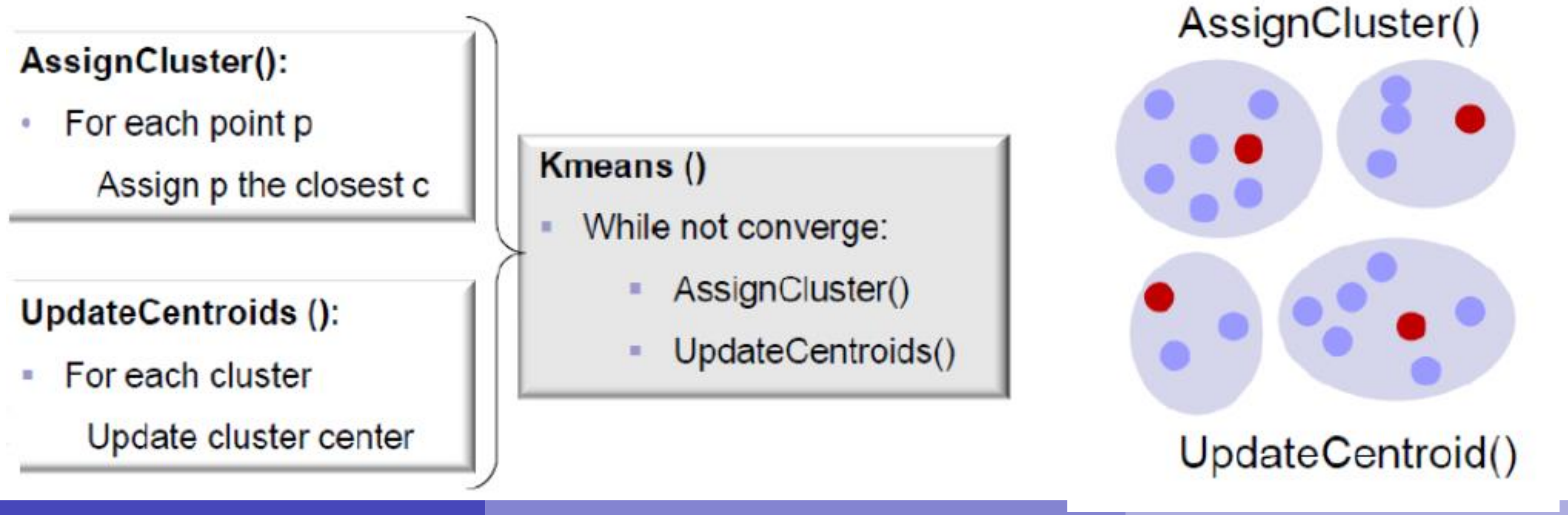
- MapReduce introduced by Google
  - Simple programming model for building distributed applications that process vast amounts of data
  - Runtime for executing jobs on large clusters in a reliable, fault-tolerant manner

- Hadoop makes MapReduce broadly available
  - HDFS becomes central data repository
  - Becomes Defacto standard for batch processing

- Stonebraker & Dewitt: Mapreduce a major step backwards

New applications, new workloads

- Iterative computations
  - Ex: More and more people aiming to get insights from data
  - Apache Mahout becomes popular framework for ML over Hadoop
- How would we implement K-Means with MapReduce?
- Traditional k-means



K-means MapReduce algorithm

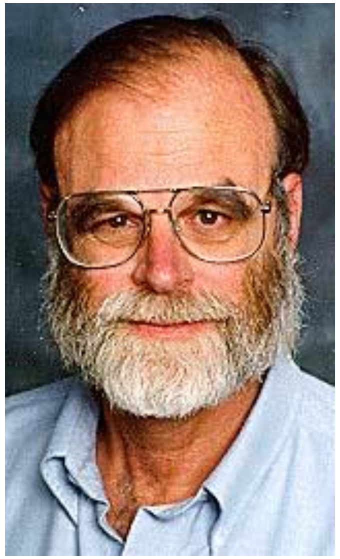
- Configure: A single file containing cluster centers
- **Mapper**
  - Input: Input data points
  - Compute: Distance of a point from each centroid to identify a cluster
  - Output: (cluster id, data id)
- **Reducer**
  - Input: (cluster id, data id)
  - Compute: New cluster centroid based on data points assigned
  - Output: (cluster id, cluster centroid)
- **Driver**
  - Each iteration produces new cluster centroids
  - Run multiple iteration jobs using mapper + reducer until convergence: *<u>High overhead leading to poor performance</u>*

MapReduce & Iterative Computations

- MapReduce is built for batch processing
  - Entirely disk based: Input and output sit on HDFS
- Let us look at **k-means algorithm, 1 iteration**
  - HDFS Read
  - **Map**(Assign sample to closest centroid)
  - NETWORK Shuffle
  - **Reduce**(Compute new centroids)
  - HDFS Write
- Each iteration reads and writes data from disk-based HDFS
  - To understand why this is bad, let us look at the memory hierarchy

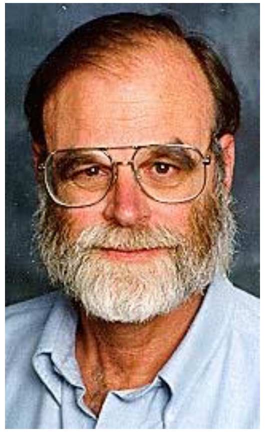
Understanding Memory Hierarchy: How Far Away is the Data?

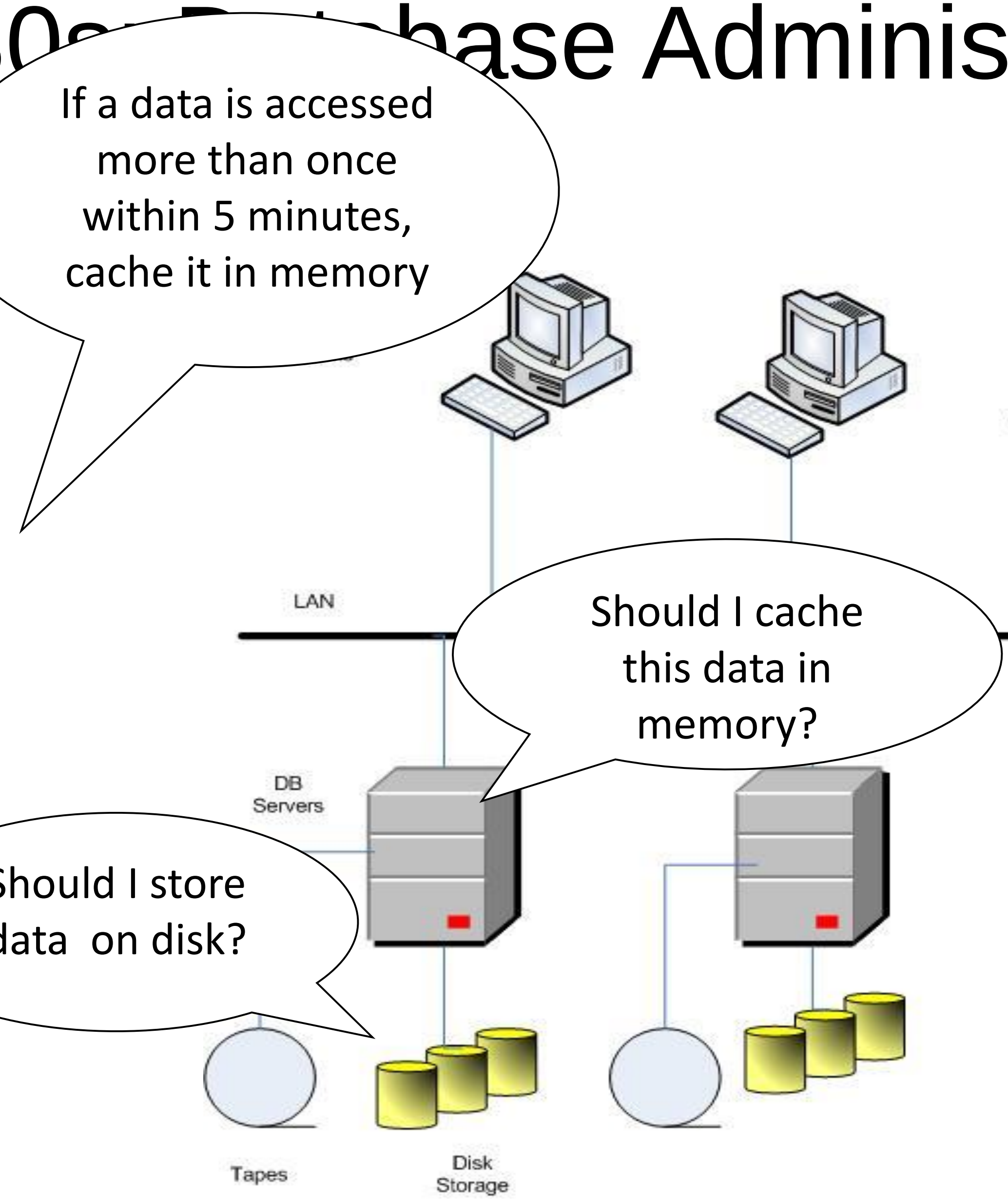
10^9	Tape	Andromeda	2,000 Years
10^6	Disk	Pluto	2 Years
100	Memory	St. Tropez	1.5 hr
10	On Board Cache	This Building	10 min
1	Registers	This Room	1 min

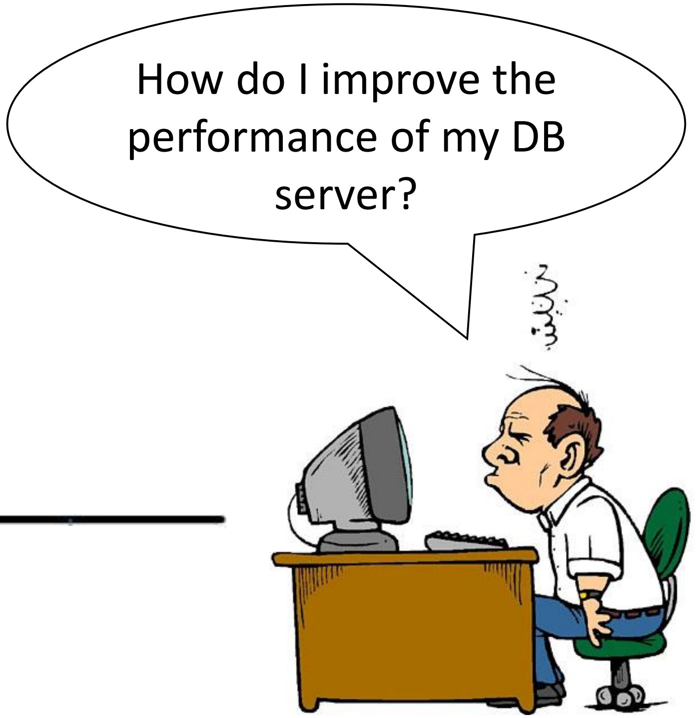


Jim Gray

1980s: Database Administrators Dilemma







Tandem Computers: Price/performance

- Tandem disk: **$1k/access**
  - cost: $15k for 180MB
  - performance: 15 accesses / second
- Tandem CPU + supporting hardware: **$1k/access**
  - Cost: $15,000
- Cost of accessing data from disk: **$2k/access**

- Memory cost: $5k for 1MB => **$5/KB**

Five-minute rule

- Cost of accessing data from disk: **$2k/access,** Memory cost: **$5/KB**
- If we keep 1KB in memory, assuming we have 1 access/sec
  - We save $2k of disk i/o by paying $5 for memory
- If we have 1 access every 10 secs => 0.1 access/sec
  - We save $200 of disk i/o by paying $5 for memory

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- Break even point : 1 access every 400 secs

400 seconds ~ 5 minutes

Five-minute rule: then and now

Page size (4KB)	1987	Now
RAM-HDD	5 mins	5 hours

- RAM-HDD break-even 60x higher due to drop in DRAM price
  - Take away: Never ever go to disk!
- See "Five minute rule" CACM paper for more details
  - https://cacm.acm.org/magazines/2019/11/240388-the-five-minute-rule-30-years-later-and-its-impact-on-the-storage-hierarchy/fulltext

MapReduce/Hadoop and memory hierarchy

- Hadoop misaligned with five-minute rule
  - All data is stored in disk
  - Does not cache data in memory even if workload can fit
- Hadoop unfit for new classes of workloads
  - Interactive and iterative applications are bottlenecked by disk
- MapReduce was also too simple a computational model
  - Algorithm design with just map and reduce functions is non trivial

Hadoop: Fractured ecosystem

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

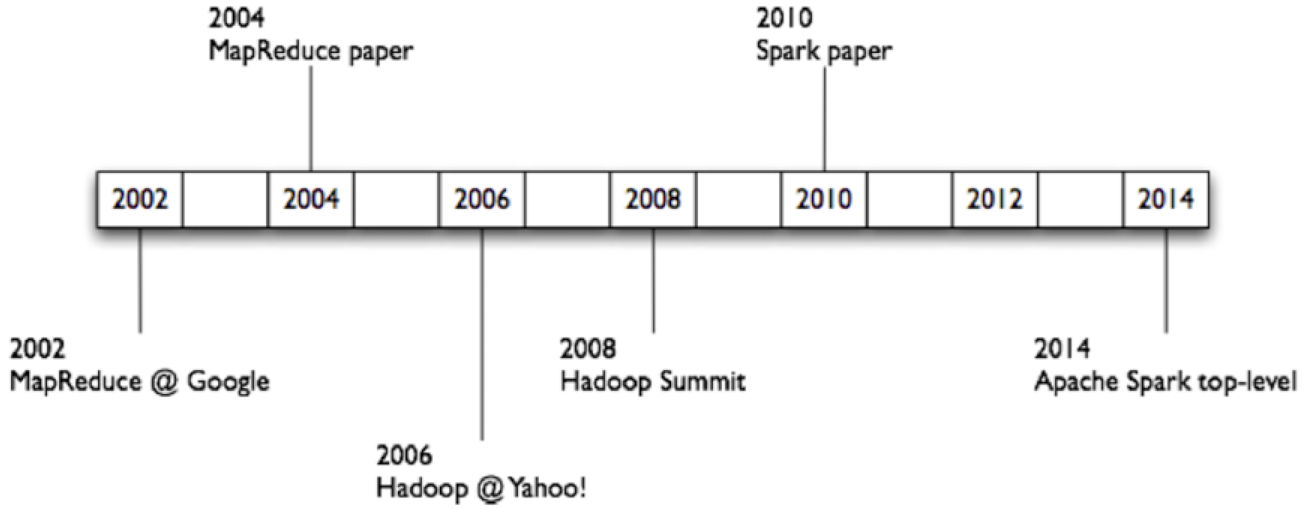
- Specialized systems emerged with no unified vision
  - Diverse APIs, sparse modules, high operational costs
  - MapReduce runtime replaced with more optimized ones

Lighting a Spark

Flexible, in-memory data processing framework written in Scala

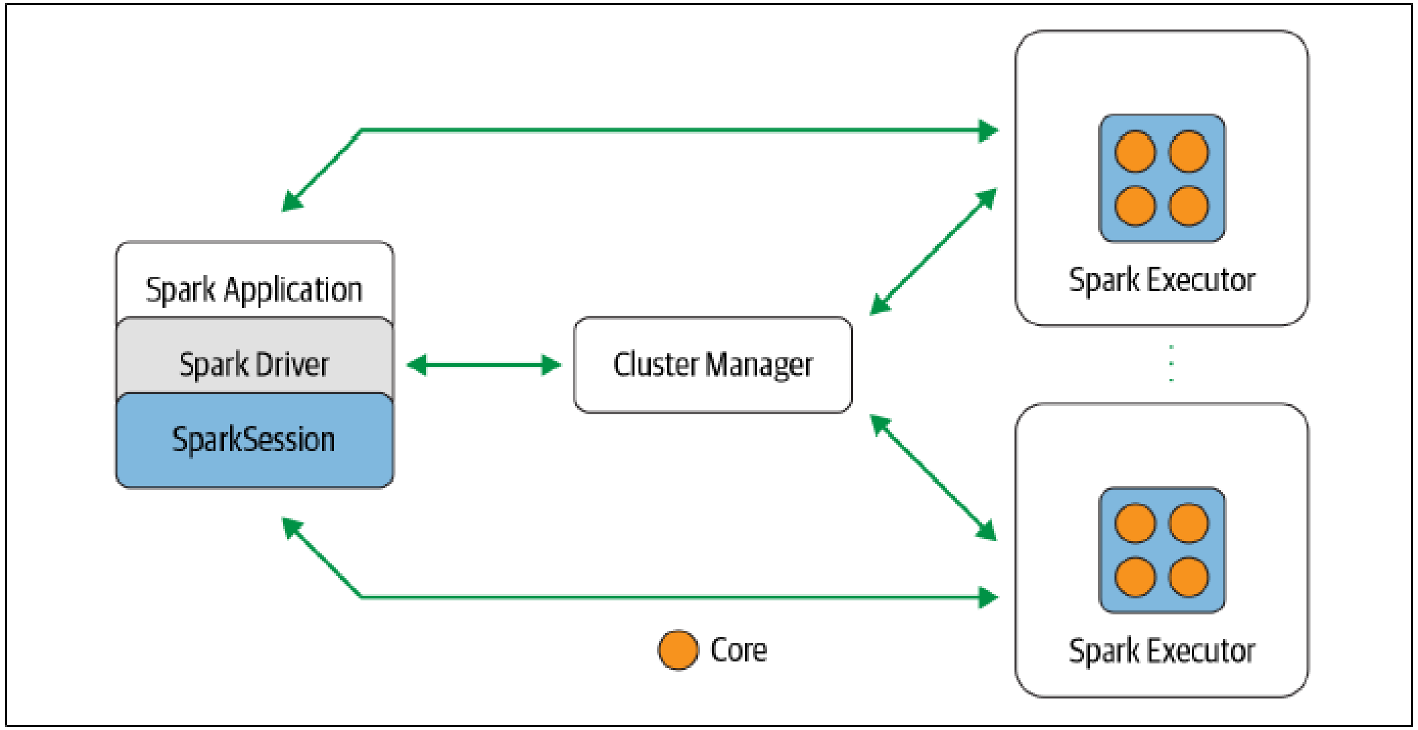
Central Ideas

- Exploit memory by caching data to enable fast data sharing
- Generalize the two-stage computational model of mapreduce to a Directed Acyclic Graph-based one that can support a richer API



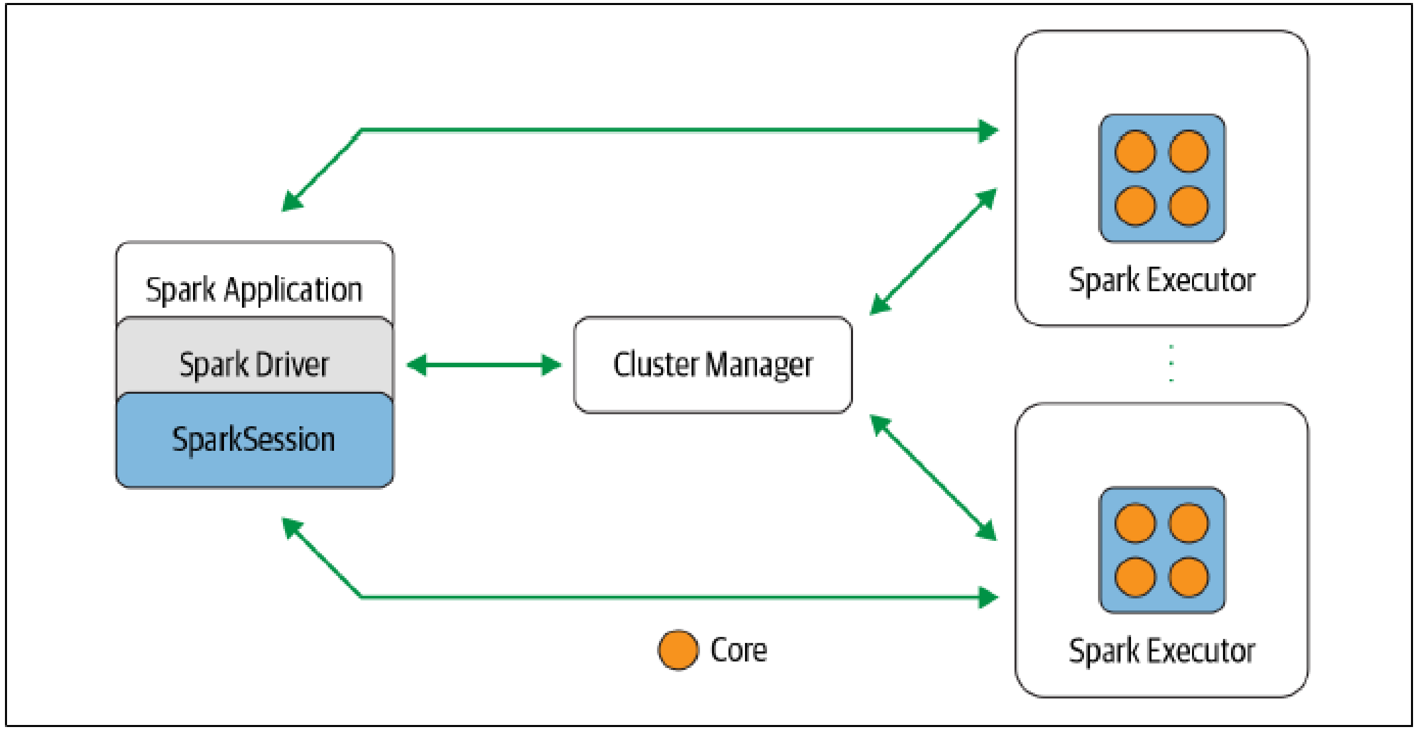
Spark Distributed Architecture

- Spark Application
  - User program built on Spark
  - Contains the Spark driver
- Spark Driver
  - Transforms all the Spark operations into DAG computations
  - Communicates with the cluster manager & requests resources (CPU, memory, etc.) for Spark executors
  - Schedules computations
  - Instantiates SparkSession



Spark Distributed Architecture

- SparkSession
  - A unified conduit to all Spark operations and data
- Cluster Manager
  - Responsible for managing and allocating resources
  - 4 supported: Standalone, YARN, Mesos, Kubernetes
- Executor
  - Responsible for executing tasks
  - Usually one per node, but depends on deployment mode



RDD: Need for a new abstraction

- Need an efficient way to share data stored in memory
- Traditional way: Distributed shared memory abstraction
  - General purpose, extends single-node shared memory to a cluster
  - Applications can make fine-grained updates to any data in memory
  - Can be used to build very efficient applications
- Problem: Fault tolerance
  - Need to replicate data across nodes or log updates which is 10-100x slower than memory write
  - Too expensive for data-intensive apps
- Goal: In-memory abstraction that provides fault-tolerance and efficiency

Resilient Distributed Dataset

RDD (Resilient Distributed Dataset): Restricted form of DSM

- An immutable, partitioned collection of objects
- Can only be built through coarse-grained deterministic transformations

- **RDD are data structures that:**
  - Either point to a direct data source (e.g. HDFS)
  - Apply some transformations to its parent RDD(s) to generate new data elements

RDD

- An abstraction that encapsulates 3 things
  - Dependencies, Partitions, Compute function
- Dependencies
  - Instruct Spark how an RDD is constructed
  - To reproduce results, Spark can recreate an RDD from these dependencies and replicate operations on it => resiliency
- Partitions
  - Split the work to parallelize computation on partitions across executors
  - Exploit data locality
- Compute function: Partition -> Iterator[t]
  - A function that produces an iterator for data stored in RDD

RDD: Example

- Query: Find average age for each name
  - aggregate all the ages for each name
  - group by name
  - average the ages

```python
# In Python
# Create an RDD of tuples (name, age)
dataRDD = sc.parallelize([("Brooke", 20), ("Denny", 31), ("Jules", 30),
  ("TD", 35), ("Brooke", 25)])
# Use map and reduceByKey transformations with their lambda
# expressions to aggregate and then compute average

agesRDD = (dataRDD
  .map(lambda x: (x[0], (x[1], 1)))
  .reduceByKey(lambda x, y: (x[0] + y[0], x[1] + y[1]))
  .map(lambda x: (x[0], x[1][0]/x[1][1])))
```

RDD Transformations

- Set of operations that define how to transform an RDD
  - Examples: map(), filter(), select(), join(), orderby(), …
- As in relational algebra, the application of a transformation to an RDD yields a new RDD
  - RDD are immutable
- Transformations are lazily evaluated
  - Computation that performs the transformation is not performed immediately

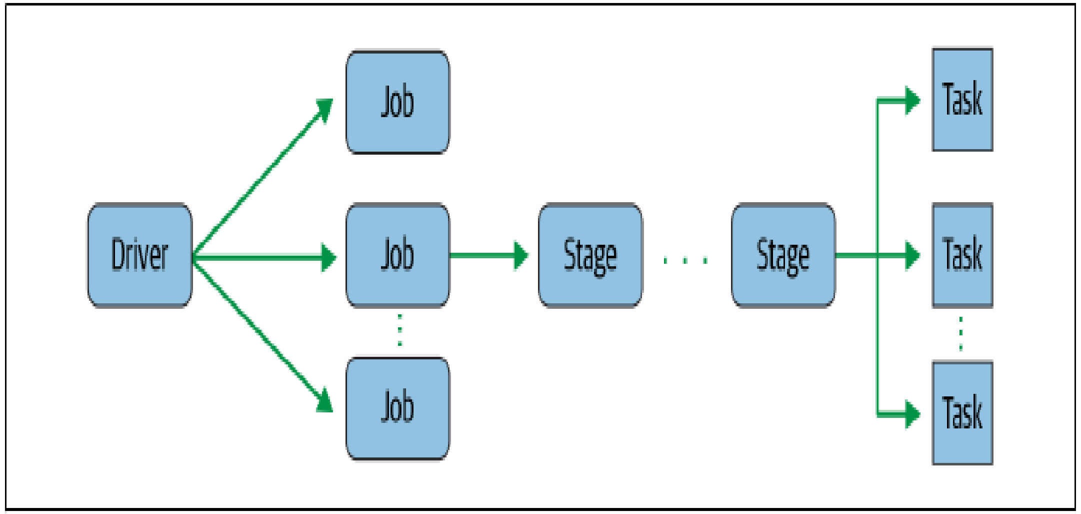
RDD Actions

- Actions trigger computation of the chain of transformations
- Some actions only store data to an external data source (e.g. HDFS)
  - Ex: show(), take(), count(), collect(), ..
- Others fetch data from the RDD (and its transformation chain) upon which the action is applied, and convey it to the driver
  - count() – return the number of elements
  - take(*n*) – return an array of the first *n* elements
  - collect()– return an array of all elements
  - …

RDD & Lazy Execution Demo

Spark Execution

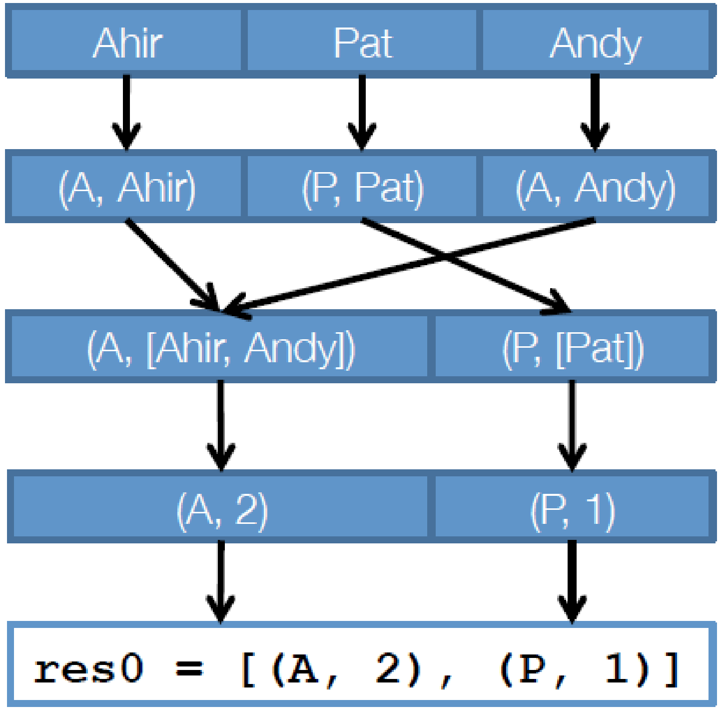
- Spark Driver
  - Converts your Spark application into one or more Spark jobs
  - Transforms each job into a DAG – execution plan
- Job broke into stages
  - Stages are created based on what operations can be performed in parallel
  - Dictate data transfer among Spark executors.
- Stages composed of tasks
  - Task - a unit of execution
  - Maps to a single core
  - Maps to 1 partition of data



Spark DAG execution: An Example

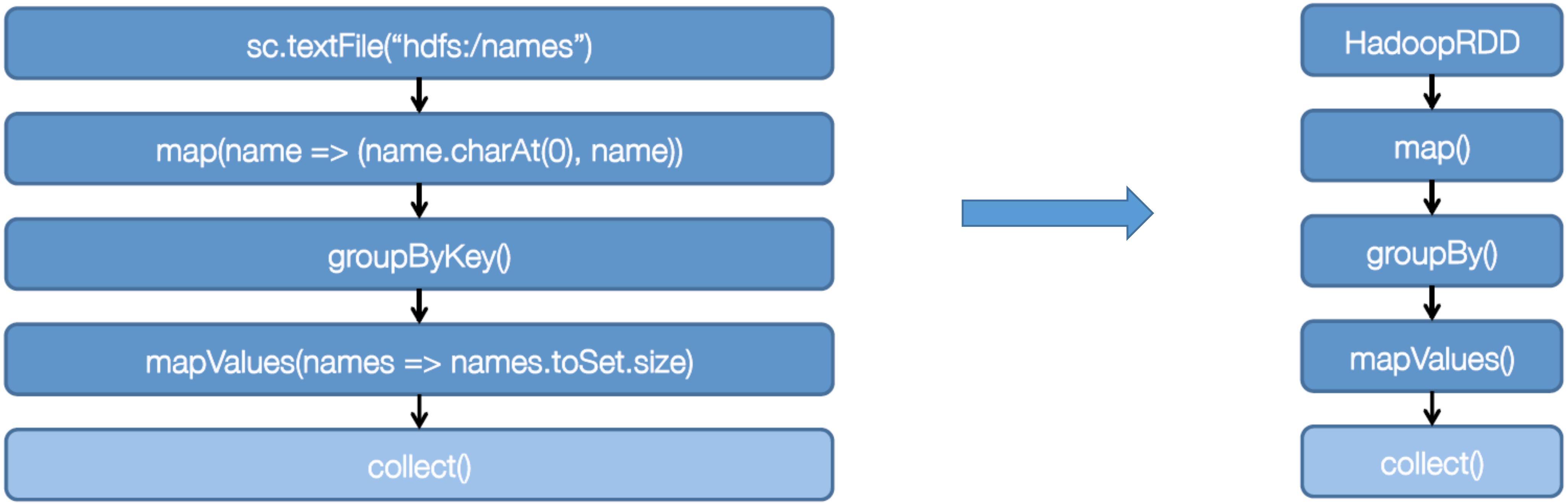
- Goal: Find the number of distinct names per first letter

```
sc.textFile("hdfs:/names")
   .map(name => (name.charAt(0), name))
   .groupByKey()
   .mapValues(names => names.toSet.size)
   .collect()
```



Spark Execution (1)

1. Create a DAG of RDDs to represent computation



Spark Execution (2)

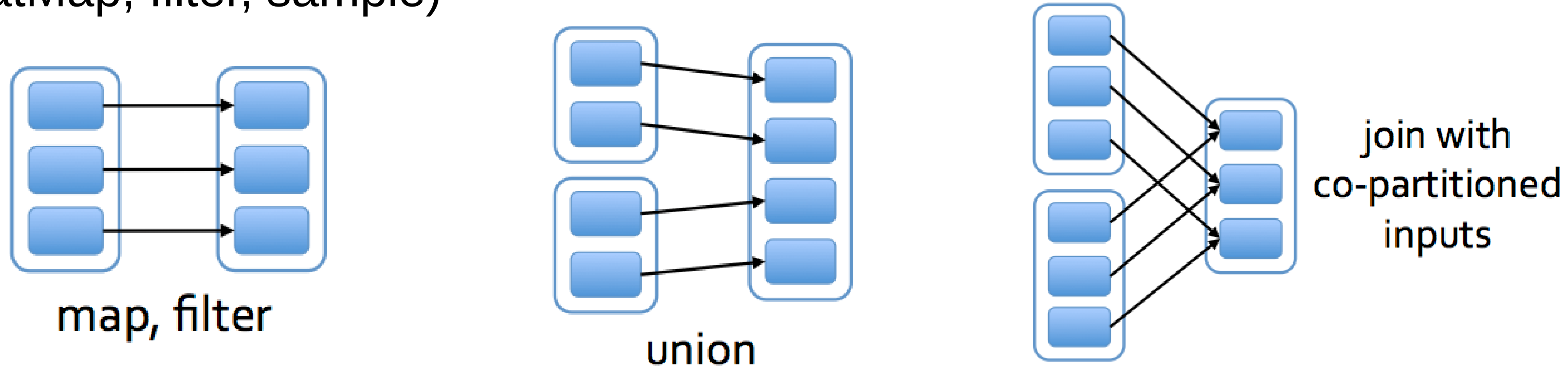
1. Create a DAG of RDDs to represent computation
2. Create logical execution plan for the DAG
   - Split DAG into “stages” based on dependencies
   - Pipeline as much as possible

RDD: Data Set vs Partition Views

Much like in Hadoop MapReduce, each RDD is stored physically in multiple nodes as input partitions

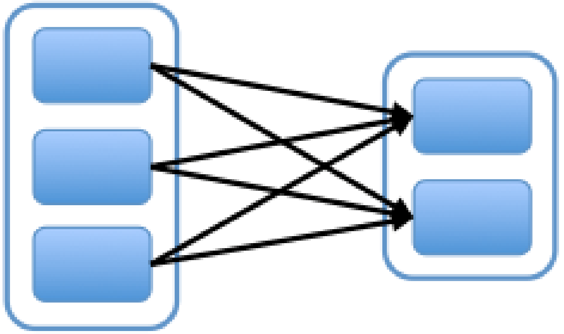
A word about dependencies (1)

- Dependencies determine the need to shuffle data
  - Two types: Narrow and wide
- Narrow dependencies
  - Each partition of the parent RDD is used by at most one partition of the child RDD
  - Task can be executed locally and we don't have to shuffle. (E.g. map, flatMap, filter, sample)

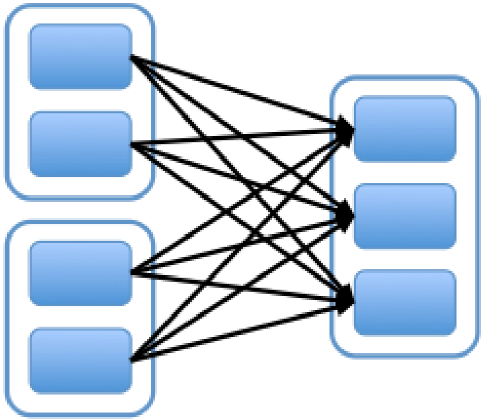


A word about dependencies (2)

- Wide dependencies
  - Multiple child partitions may depend on one partition of the parent RDD
  - We have to shuffle data (E.g. sortByKey, reduceByKey, groupByKey, cogroupByKey, join, cartesian)



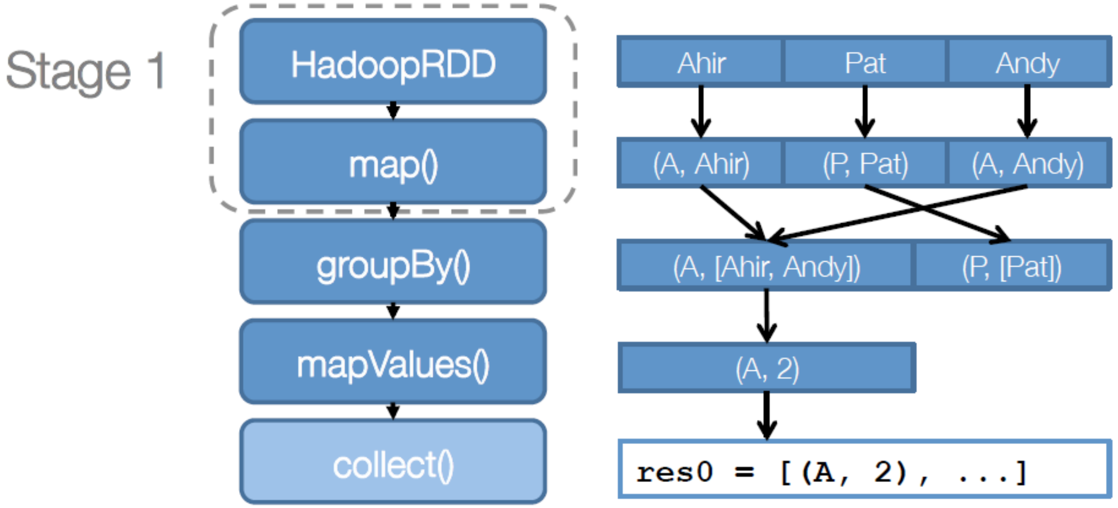
groupByKey

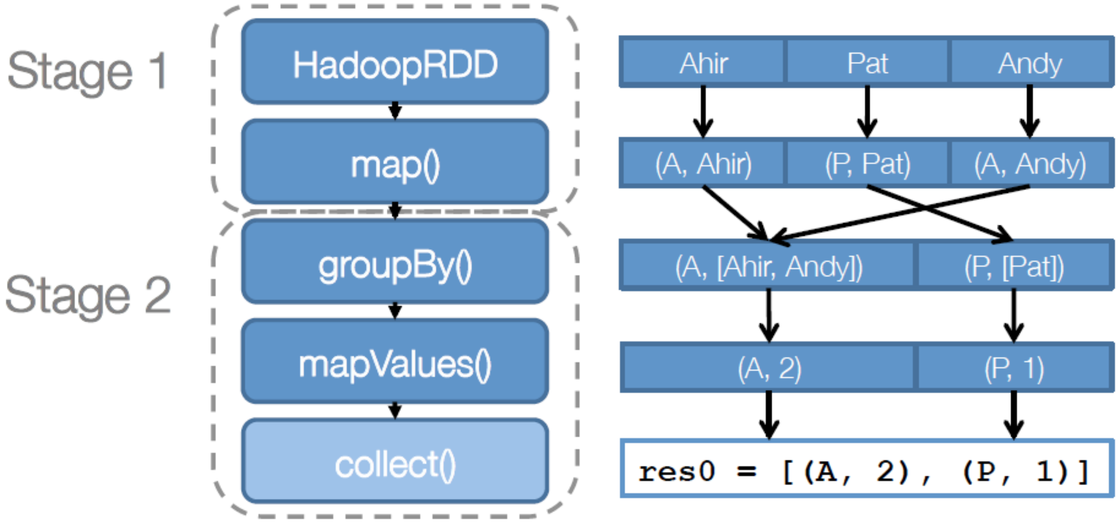


join with inputs not co-partitioned

How does Spark execute this job?

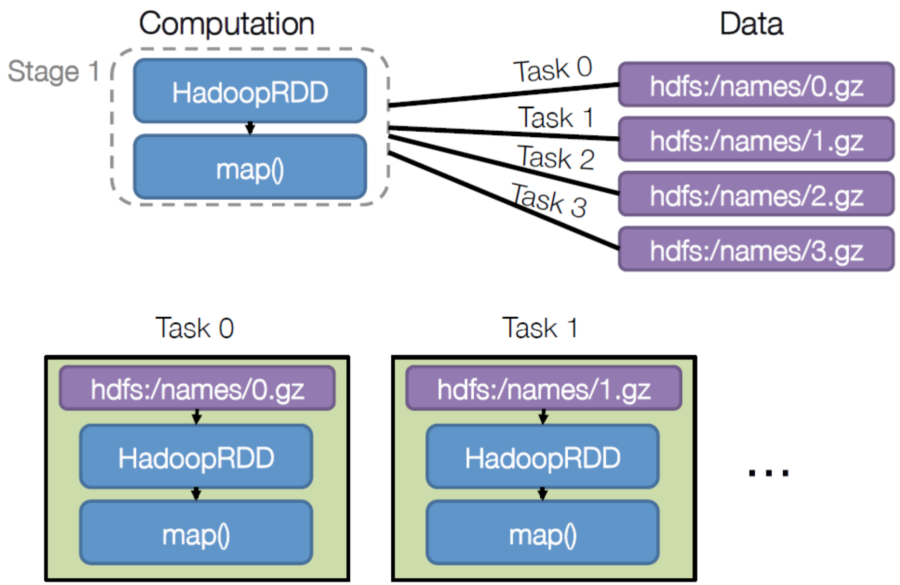
1. Create a DAG of RDDs to represent computation
2. Create logical execution plan for the DAG
   - Pipeline as much as possible
   - Split DAG into “stages” based on need to shuffle data





Spark Execution (3)

1. Create a DAG of RDDs to represent computation
2. Create logical execution plan for the DAG
3. Split each stage into tasks and execute tasks stage by stage
    - Task = Data + Computation
    - In this example, all tasks from stage 1 would be executed together first



Spark Execution (3)

1. Create a DAG of RDDs to represent computation
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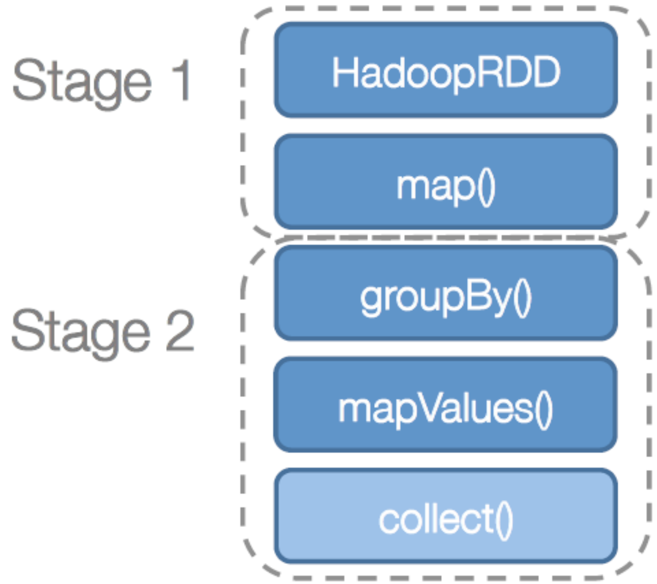
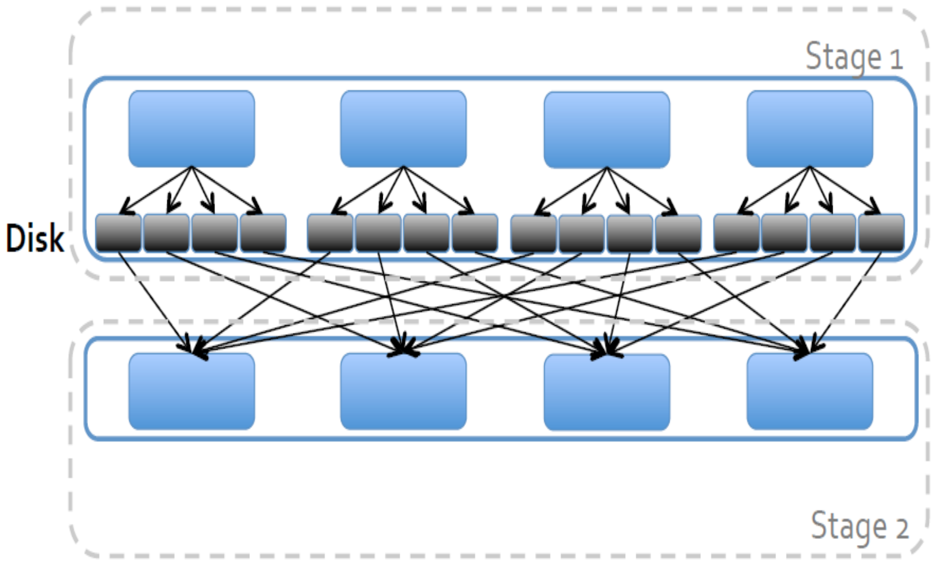
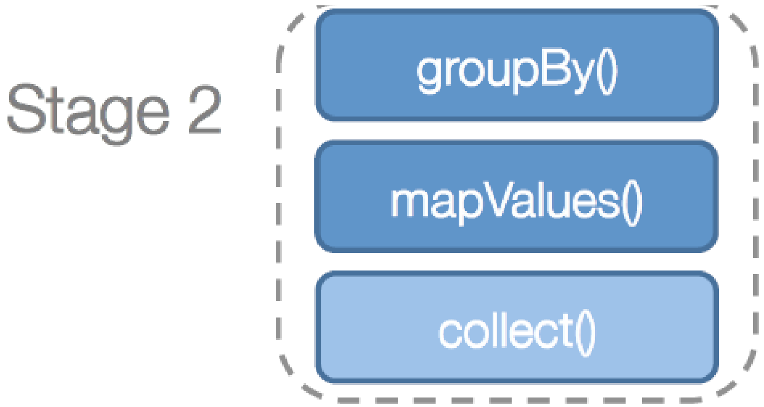
    - In this example, all tasks from stage 1 would be executed together first
    - After stage 1, pull-based shuffle occurs (intermediates written to files and pulled)





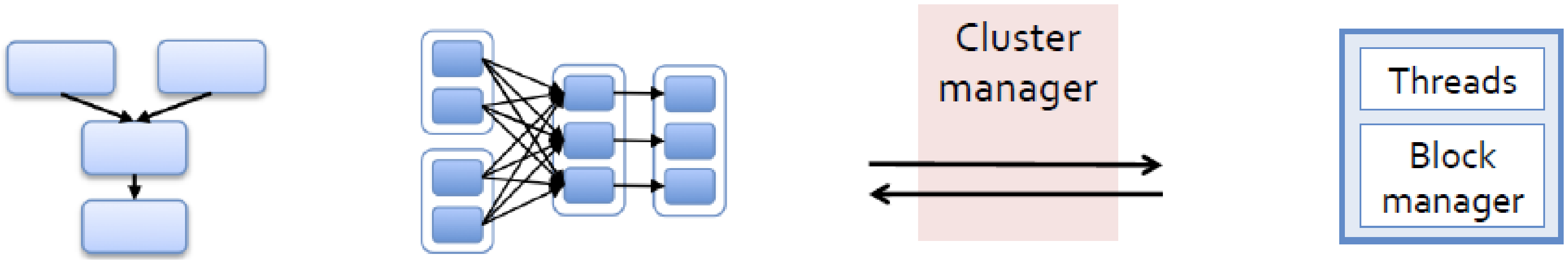
Spark Execution (3)

1. Create a DAG of RDDs to represent computation
2. Create logical execution plan for the DAG
3. Split each stage into tasks and execute tasks stage by stage
   - In this example, all tasks from stage 1 would be executed together first
   - After stage 1, pull-based shuffle occurs (intermediates written to files and pulled)
   - Now, tasks from stage 2 are executed (operators pipelined in each task)



Putting it all together

RDD Objects	DAG Scheduler	Task Scheduler	Worker



RDD Objects	DAG Scheduler	Task Scheduler	Worker
`rdd1.join(rdd2) .groupBy(...) .filter(...)`	Split the DAG into *stages* of *tasks*	Launch tasks via Master	Execute tasks
Build the operator DAG	Submit each stage and its tasks as ready	Retry failed and straggler tasks	Store and serve blocks

RDD to Structured API

- Spark can support interactive workloads
  - But working with RDD is procedural
- SQL as a high-level programming language
  - Offers expressiveness, succinctness
  - Enables compatibility with existing tools, e.g. Business Intelligence using JDBC
  - Large pool of engineers proficient in SQL

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  .map(lambda x: (x[0], x[1][0]/x[1][1])))
```

```sql
SELECT name, avg(age)
FROM people
GROUP BY name
```

DataFrame: Schema

- **General idea borrowed from Python Pandas**
  - Tabular data with an API
- **Schema to the rescue**
  - A distributed collection of rows organized into named, typed columns
  - Basic types and Structured/Complex types supported

Data type	Value assigned in Python	API to instantiate
ByteType	int	DataTypes.ByteType
ShortType	int	DataTypes.ShortType
IntegerType	int	DataTypes.IntegerType
LongType	int	DataTypes.LongType
FloatType	float	DataTypes.FloatType
DoubleType	float	DataTypes.DoubleType
StringType	str	DataTypes.StringType
BooleanType	bool	DataTypes.BooleanType
DecimalType	decimal.Decimal	DecimalType

Data type	Value assigned in Python	API to instantiate
BinaryType	bytearray	BinaryType()
TimestampType	datetime.datetime	TimestampType()
DateType	datetime.date	DateType()
ArrayType	List, tuple, or array	ArrayType(dataType, [nullable])
MapType	dict	MapType(keyType, valueType, [nullable])
StructType	List or tuple	StructType([fields])
StructField	A value type corresponding to the type of this field	StructField(name, dataType, [nullable])

DataFrame: Schema

- **General idea borrowed from Python Pandas**
  - Tabular data with an API

- **Schema to the rescue**
  - A distributed collection of rows organized into named, typed columns
  - Basic types and Structured/Complex types supported
  - Schema defines column names and associated types
  - 3 ways to get schema definition (demo)
    - (i) Define with struct type, (ii) define with DDL, (iii) auto infer
  - Columns and Rows are objects with APIs

APIs

- DataSource API
  - Enables you to read/write data from/to a DataFrame from myriad data sources in formats such as JSON, CSV, Parquet, Text, Avro, ORC, etc.
- Tranformations and Actions
  - Relational Projections: done with select() method
  - Relational Selection: done with filter() or where() method
  - Aggregations: groupBy, orderBy, count, …
  - Descriptive stats: min, max, sum, avg
- Demo
  - time taken to infer schema vs predeclare
  - Transformations, actions

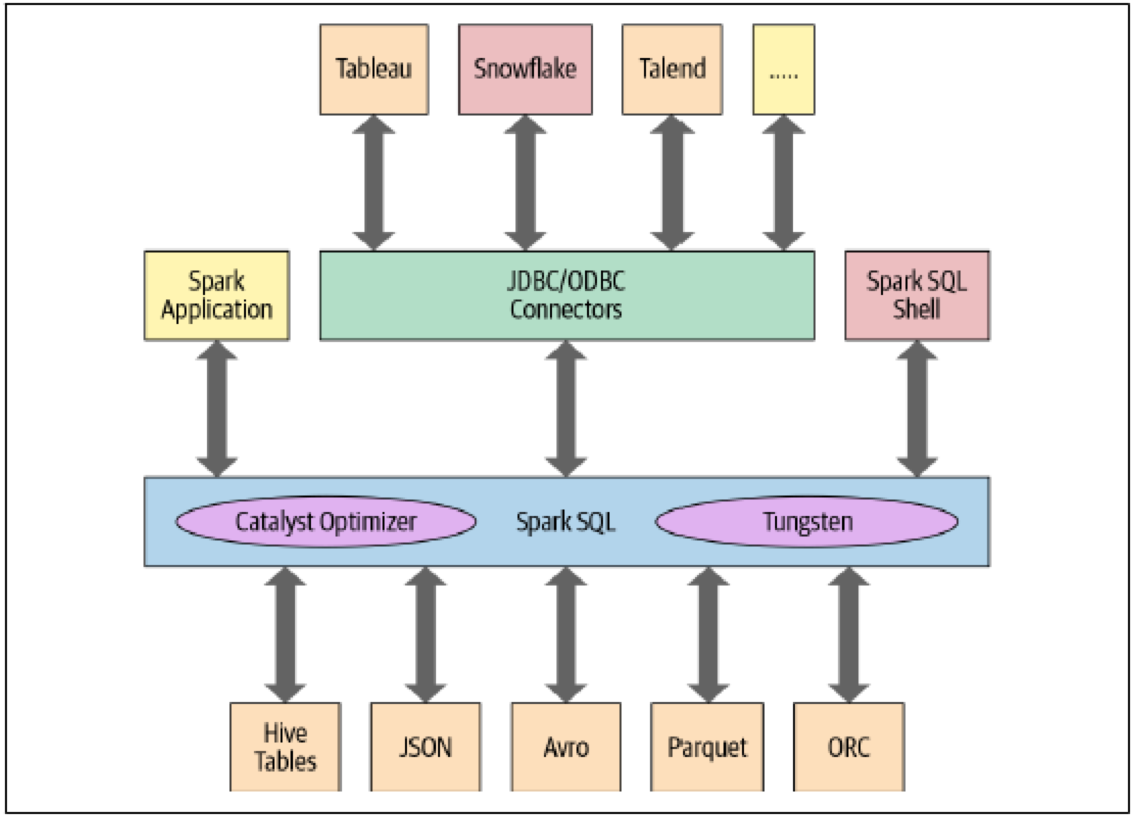
RDD vs DF

- Use RDD when
  - Want to precisely instruct Spark *how to do* a query
  - Can forgo the code optimization, efficient space utilization, and performance benefits available with DataFrames and Datasets!
  - You can get rdd from df: df.rdd

- Basically, save yourself some time and use DF

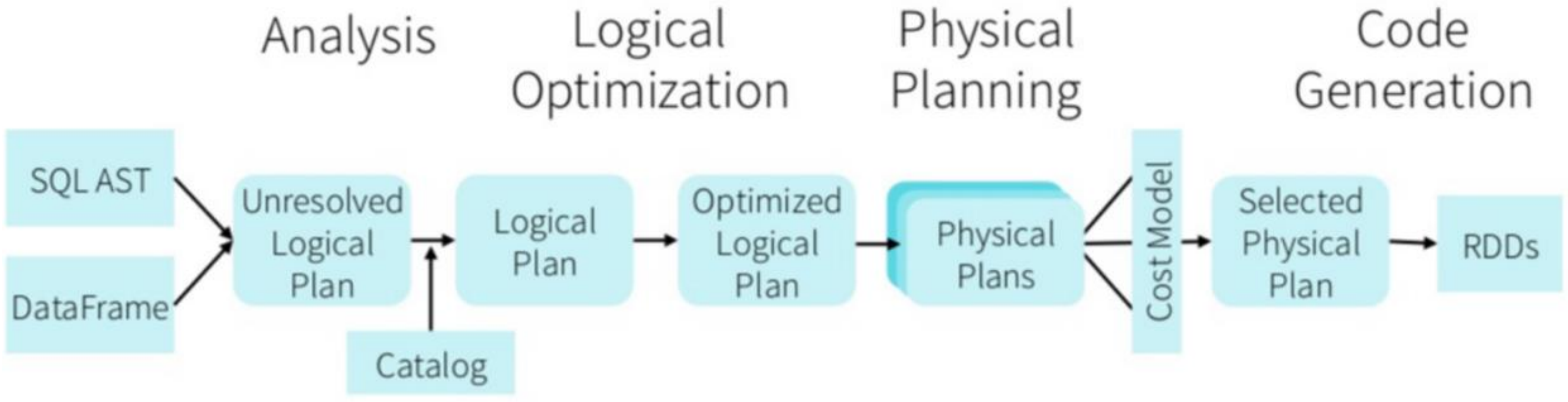
SparkSQL engine

- The substrate on which structured APIs are built
- Core components
  - Catalyst and Tungsten



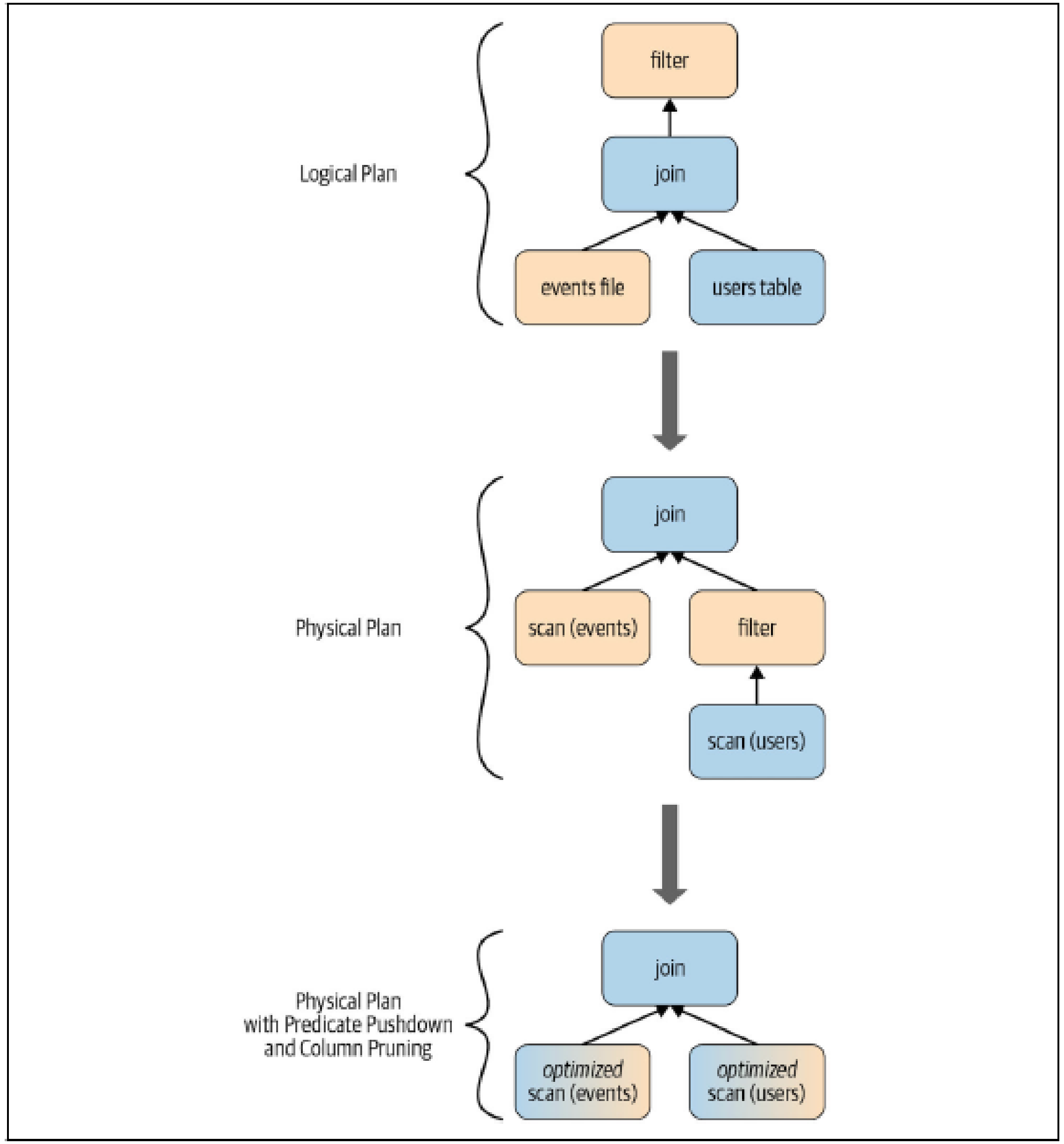
Catalyst Optimizer

- **Reminiscent of traditional database systems**
  - Analysis: SQL to Plan Abstract Syntax Tree
  - Logical & physical optimization: Use cost-based optimization to pick optimal plan



Catalyst Example

```scala
// In Scala
// Users DataFrame read from a Parquet table
val usersDF  = ...
// Events DataFrame read from a Parquet table
val eventsDF = ...
// Join two DataFrames
val joinedDF = users
  .join(events, users("id") === events("uid"))
  .filter(events("date") > "2015-01-01")
```



Tungesten & Code Generation

- Take optimized physical plan and do “Full stage code generation”
  - collapses the whole query into a single function
  - getting rid of virtual function calls
  - employing CPU registers for intermediate data

- Demo of Catalyst and Tungsten

Spark & Caching

- DataFrame.cache()
  - store as many of the partitions read in memory across Spark executors as memory
- Dataframe.persist(StorageLevel)
  - Control how your data is cached
- Unpersist
  - Remove any cached data
- Cache/persist are hints
  - DataFrame is not fully cached until yo
- Demo of caching perf

StorageLevel	Description
MEMORY_ONLY	Data is stored directly as objects and stored only in memory.
MEMORY_ONLY_SER	Data is serialized as compact byte array representation and stored only in memory. To use it, it has to be deserialized at a cost.
MEMORY_AND_DISK	Data is stored directly as objects in memory, but if there's insufficient memory the rest is serialized and stored on disk.
DISK_ONLY	Data is serialized and stored on disk.
OFF_HEAP	Data is stored off-heap. Off-heap memory is used in Spark for storage and query execution; see "Configuring Spark executors' memory and the shuffle service" on page 178.
MEMORY_AND_DISK_SER	Like MEMORY_AND_DISK, but data is serialized when stored in memory. (Data is always serialized when stored on disk.)

Spark & RDBMS: Summary

- Spark: unified analytics engine
  - Quickly adopted RDBMS concepts to optimize SQL analytics
  - Other libraries developed for machine learning (Mlib), graph analytics(GraphX),…
  - RDD: an underlying abstraction that supports several libraries

- DBMSs have also evolved
  - Disk-based to in-memory to NVM
  - One-size-fits-all “OldSQL” DBMS to customized “NewSQL” engines
    - column stores for Business Intelligence
    - highly parallel transaction engines for OLTP
    - Array databases for scientific applications
    - …
  - NewSQL still king for structured data management