Distributed Systems

22. Spark

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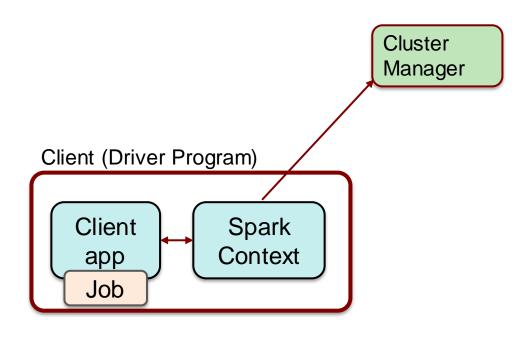
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Apache Spark

- Goal: generalize MapReduce
 - Similar shard-and-gather approach to MapReduce
 - Add fast data sharing & general DAGs (graphs)
- Generic data storage interfaces
 - Storage agnostic: use HDFS, Cassandra database, whatever
 - Resilient Distributed Data (RDD) sets
 - An RDD is a chunk of data that gets processed a large collection of stuff
 - In-memory caching
- More general functional programming model
 - Transformations and actions
 - In Map-Reduce, transformation = map, action = reduce

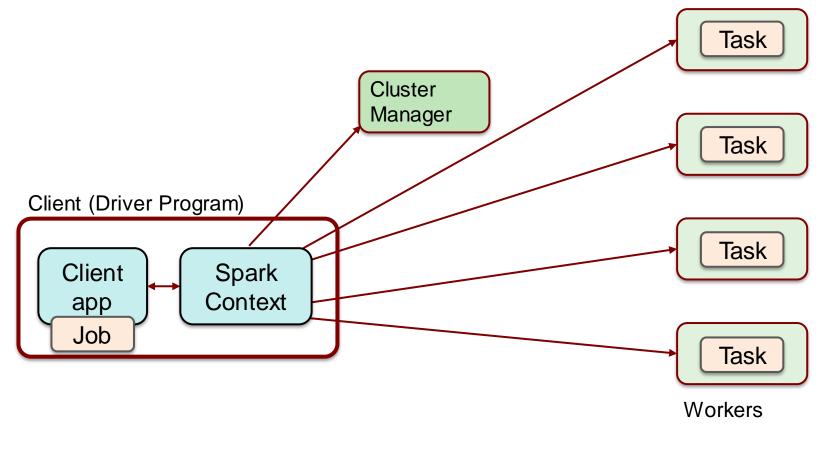
High-level view

- Job = bunch of transformations & actions on RDDs
- Cluster manager: Allocates worker nodes



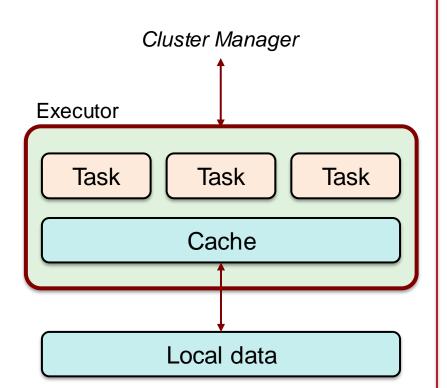
High-level view

- Driver breaks the job into tasks
- Sends tasks to worker nodes where the data lives



Worker node

- One or more executors
 - JVM process
 - Talks with cluster manager
 - Receives tasks
 - JVM code (e.g., compiled Java, Clojure, Scala, Jruby, ...)
 - Task = transformation or action
 - Data to be processed (RDD)
 - · Local to the node
 - Cache
 - Stores frequently-used data in memory
 - Key to high performance



Data & RDDs

- Data organized into RDDs:
 - Big data: partition it across lots of computers
- How are RDDs created?
 - 1. Create from any file stored in HDFS or other storage supported in Hadoop (Amazon S3, HDFS, HBase, Cassandra, etc.)
 - Created externally (e.g., event stream, text files, database)
 - Example:
 - Query a database & make query the results an RDD
 - Any Hadoop InputFormat, such as a list of files or a directory
 - 2. Streaming sources (via Spark Streaming)
 - Fault-tolerant stream with a sliding window
 - 3. An RDD can be the output of a Spark transformation function
 - Example, filter out data, select key-value pairs

Properties of RDDs

Main Properties

- Immutable
 - You cannot change it only create new RDDs
 - The framework will eventually collect unused RDDs
- Partitioned parts of an RDD go to different servers
 - Default partitioning function = hash(key) mod server_count

Optional Properties

- Typed: they're not BLOBs
 - Embedded data structure e.g., key-value set
- Ordered
 - Elements in an RDD can be sorted

Operations on RDDs

Two types of operations on RDDs

Transformations

- Lazy not computed immediately
- Transformed RDD is recomputed when an action is run on it
 - Work backwards:
 - What RDDs do you need to apply to get an action?
 - What RDDs do you need to apply to get the input to this RDD?
- RDD can be persisted into memory or disk storage

Actions

- Finalizing operations
 - Reduce, count, grab samples, write to file

Spark Transformations

Transformation	Description
map(func)	Pass each element through a function <i>func</i>
filter(func)	Select elements of the source on which <i>func</i> returns true
flatmap(func)	Each input item can be mapped to 0 or more output items
sample (withReplacement, fraction, seed)	Sample a <i>fraction</i> fraction of the data, with or without replacement, using a given random number generator seed
union(otherdataset)	Union of the elements in the source data set and otherdataset
distinct([numtasks])	The distinct elements of the source dataset

Spark Transformations

Transformation	Description
groupByKey([numtasks])	When called on a dataset of (K, V) pairs, returns a dataset of (K, seq[V]) pairs
reduceByKey(func, [numtasks])	Aggregate the values for each key using the given <i>reduce</i> function
sortByKey([ascending], [numtasks])	Sort keys in ascending or descending order
join (otherDataset, [numtasks])	Combines two datasets, (K, V) and (K, W) into (K, (V, W))
cogroup(otherDataset, [numtasks])	Given (K, V) and (K, W), returns (K, Seq[V], Seq[W])
cartesian (other Dataset)	For two datasets of types T and U, returns a dataset of (T, U) pairs

Spark Actions

Action	Description
reduce (func)	Aggregate elements of the dataset using <i>func</i> .
collect(func, [numtasks])	Return all elements of the dataset as an array
count()	Return the number of elements in the dataset
first()	Return the first element of the dataset
take (n)	Return an array with the first <i>n</i> elements of the dataset
takeSample(withReplacement, fraction, seed)	Return an array with a random sample of <i>num</i> elements of the dataset

Spark Actions

Action	Description
saveAsTextFile(path)	Write dataset elements as a text file
saveAsSequenceFile(path)	Write dataset elements as a Hadoop SequenceFile
countByKey ()	For (K, V) RDDs, return a map of (K, Int) pairs with the count of each key
foreach(func)	Run <i>func</i> on each element of the dataset

Data Storage

- Spark does not care how source data is stored
 - RDD connector determines that
 - E.g., read RDDs from tables in a Cassandra DB; write new RDDs to Cassandra tables

- RDD Fault tolerance
 - RDDs track the sequence of transformations used to create them
 - Enables recomputing of lost data
 - Go back to the previous RDD and apply the transforms again

Example: processing logs

- Transform (creates new RDDs)
 - Grab error message from a log
 - Grab only ERROR messages & extract the source of error
- Actions : Count mysql & php errors

```
// base RDD
val lines = sc.textFile("hdfs://...")
// transformed RDDs
val errors = lines.filter(_.startsWith("ERROR"))
val messages = errors.map(_.split("\t")).map(r => r(1))
messages.cache()
// action 1
messages.filter(_.contains("mysql")).count()
// action 2
messages.filter(_.contains("php")).count()
```

Spark Streaming

- Map-Reduce & Pregel expect static data
- Spark Streaming enables processing live data streams
 - Same programming operations
 - Input data is chunked into batches
 - Programmer specifies time interval

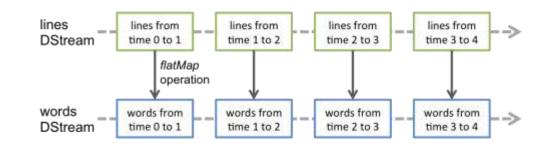


Spark Streaming: DStreams

- Discretized Stream = DStream
 - Continuous stream of data (from source or a transformation)
 - Appears as a continuous series of RDDs, each for a time interval



- Each operation on a DStream translates to operations on the RDDs



- Join operations allow combining multiple streams

Spark Summary

- Supports streaming
 - Handle continuous data streams via Spark Streaming
- Fast
 - Often up to 10x faster on disk and 100x faster in memory than MapReduce
 - General execution graph model
 - No need to have "useless" phases just to fit into the model
 - In-memory storage for RDDs
- Fault tolerant: RDDs can be regenerated
 - You know what the input data set was, what transformations were applied to it, and what output it creates

The end