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Resilient Distributed Datasets: A Fault-Tolerant Abstraction for In-Memory Cluster Computing

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Principal Motivation

- MapReduce/Dryad built around acyclic flow of data
- Inefficient at handling iterative computation & data reuse
  - Machine Learning Algorithms
  - Interactive data mining tools
- Propose a solution for a class of applications that require
  - Working sets of data
  - scalability and fault tolerance

Resilient Distributed Datasets

Key Idea

- Leverage distributed memory
- Improve upon specialised frameworks e.g. Haloop, Pregel, etc.

What are RDDs?

- Read-only collection objects
- Partitioned across several nodes
- Reconstructible incase of node failure
- Enables in-memory computation

Resilient Distributed Datasets

Representation of RDDs

- set of partitions
- set of dependencies — lineage
- function to compute RDD from parent RDDs
- metadata on partitioning scheme & data placement

Lineage

- Recompute elements of a partition
- Iterate over parent partitions; use the function in RDD

RDDs: Types of Dependencies

Narrow Dependencies

- One-to-one mapping of partitions between parent & child
- Pipelined execution on cluster nodes
- Involve map operation

Wide Dependencies

- Many-to-one mapping between parent & child
- Require data from all parent partitions and shuffle-like operation
- Involve join operation

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Key Differences[1]

Aspect	*RDDs*	*Dist. Shared Mem.*
Reads	*Coarse or fine grained*	*Fine-grained*
Writes	*Coarse-grained; immutable consistency*	*Fine-grained*
Behaviour if not enough RAM	*Similar to existing data flow systems*	*Poor performance*
Fault Recovery	*Fine grained & low-overhead using lineage*	*Requires checkpoints & rollbacks*

Resilient Distributed Datasets

Computational Factors

- Cost of storage
- Disk I/O overhead
- Probability of node failure
- Cost of recomputing a partition

Limitations

- Inefficient for asynchronous fine-grained updates
- E.g. incremental web crawler, storage system for a webApp,etc.

Spark: Cluster Computing Framework

Introduction

- Implemented in Scala
- Built on top of Mesos (cluster operating system)
  - Enables resource sharing with Hadoop MPI
- RDD implementation
  - HDFS file objects
  - partition-to-block size mapping

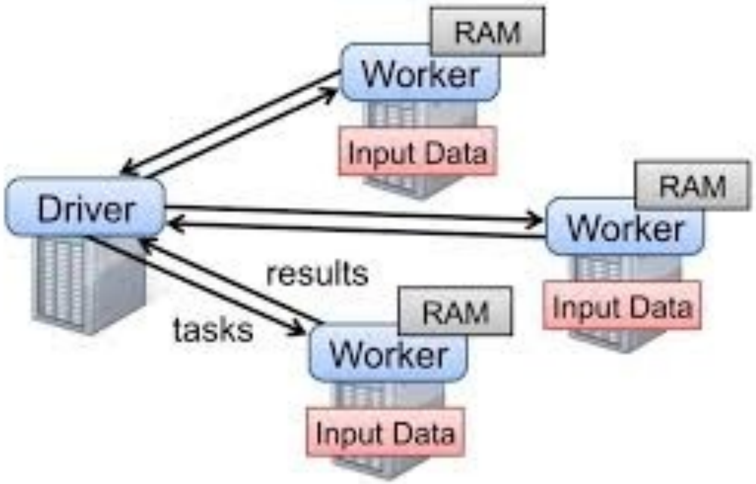
Spark: RDD representation

Types of RDD constructs

- File in a shared file system e.g. HDFS
- Scala collection object e.g. an array
- Transforming an existing RDD using flatMap()
- Change persistence of an existing RDD
  - Cache action: dataset is kept in memory
  - Save action: dataset is written to the file system

Spark: Dataflow

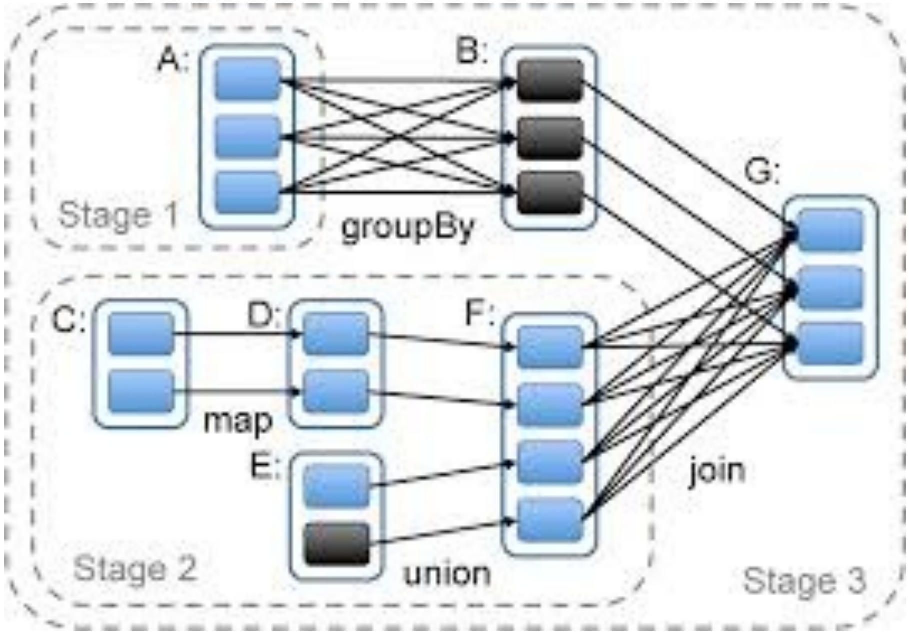
- Driver program implements control flow
- Parallel programming abstractions
  - RDDs
  - parallel operations
- Types of parallel operations
  - reduce
  - collect
  - foreach



Spark: Dataflow

Job Scheduling

- RDD lineage graph examined
- DAG of stages is built
- Characteristics of a stage
  - as many narrow dependencies
- Wide dependencies require shuffle operation
- Tasks assigned on data locality



Spark: Limitations

- Scheduler failures not tolerated
  - re-run the task till stage’s parents available
  - else, replicate RDD lineage graph to compute partition
- Checkpointing API application/user dependent
  - Replicate Flag to persist

Spark: Assessment

Datasets

- User written applications
- ML algorithms: K-means & logistical regression
- 1 TB dataset for interactive queries

Benchmarks

- Hadoop: 0.20.2 stable release
- HadoopBinMem
  - converts input data to binary format
  - reduces over-head

Spark: Assessment

ML Algorithms

- Spark outperforms hadoop by 20x
- Avoided repeated I/O and deserialisation cost

Interactive query dataset

- Spark performed with the response time of 5.5-7s
- Dependent on the page rank implementation

User Applications

- Analytics report execution improved by 40x
- Other apps scale and perform well

RDDs: Conclusion

- Showed better performance
- Express cluster programming models
- Capture optimisations
  - keeping specific data in-memory
  - partitioning to minimize communication
  - recover from failures efficiently
- Promising paradigm in cluster computing