Resilient Distributed Datasets

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15799b Talk

Why not MapReduce

- Provide fault-tolerance, but:

- Hard to reuse intermediate results across multiple computations
  - stable storage for sharing data across jobs

- Hard to support interactive ad-hoc queries

Why not Other In-Memory Storage

- Examples: Piccolo
  - Apply fine-grained updates to shared states

- Efficient, but:
- Hard to provide fault-tolerance
  - need replication or checkpointing

Resilient Distributed Datasets (RDDs)

- Restricted form of distributed shared memory
  - read-only, partitioned collection of records
  - can only be built through coarse-grained deterministic transformations
    - data in stable storage
    - transformations from other RDDs.
- Express computation by
  - defining RDDs

Fault Recovery

- Efficient fault recovery using lineage
  - log one operation to apply to many elements (lineage)
  - recompute lost partitions on failure

Example

```
lines = spark.textFile("hdfs://...")
errors = lines.filter(_.startsWith("ERROR"))
hdfs_errors = errors.filter(_.contains(“HDFS"))
```

Advantages of the RDD Model

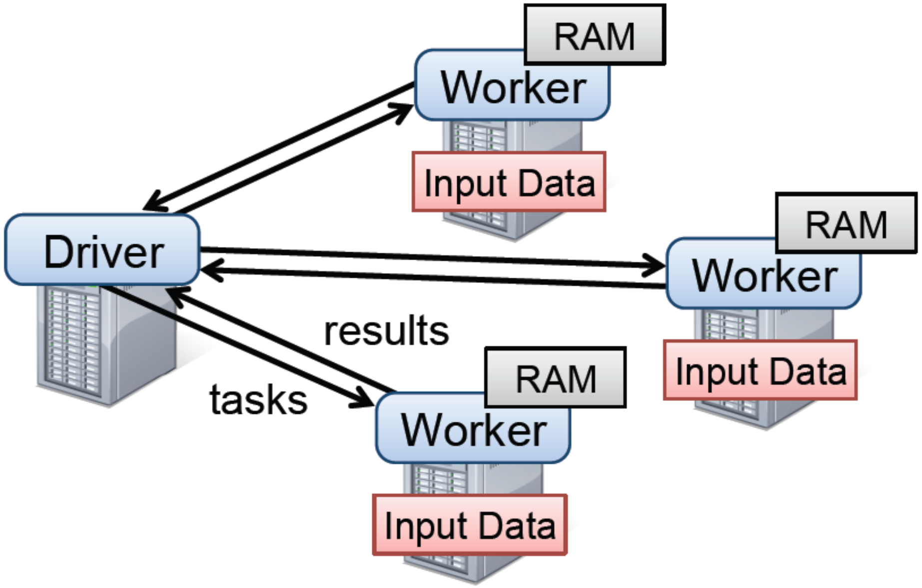
- Efficient fault recovery
  - fine-grained and low-overhead using lineage
- Immutable nature can mitigate stragglers
  - backup tasks to mitigate stragglers
- Graceful degradation when RAM is not enough

Spark

- Implementation of the RDD abstraction
  - Scala interface
- Two components
  - Driver
  - Workers

Spark Runtime

- Driver
  - defines and invokes actions on RDDs
  - tracks the RDDs' lineage
- Workers
  - store RDD partitions
  - perform RDD transformations



Supported RDD Operations

- Transformations
  - map (f: T->U)
  - filter (f: T->Bool)
  - join()
  - ... (and lots of others)
- Actions
  - count()
  - save()
  - ... (and lots of others)

Representing RDDs

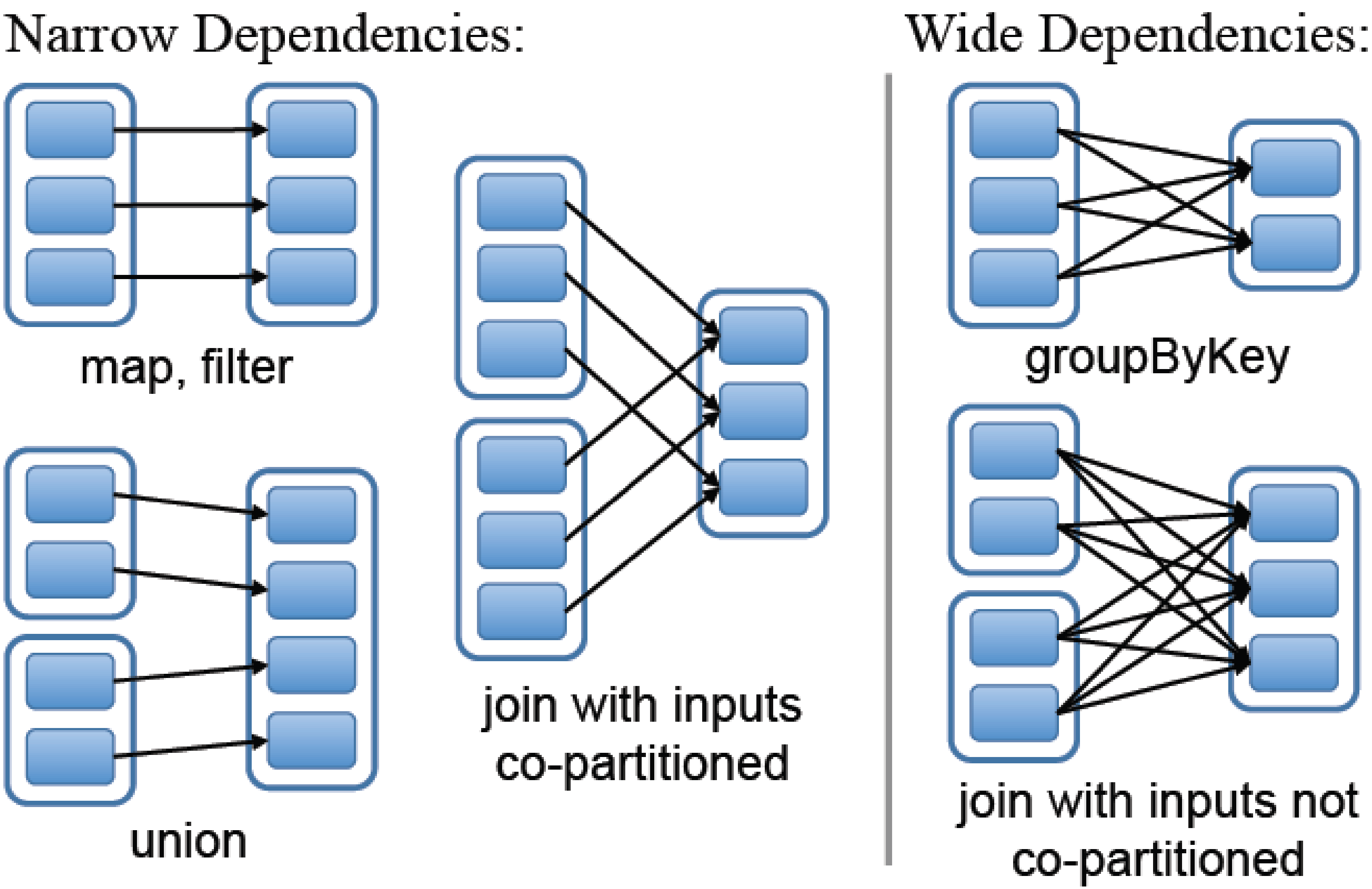
- A graph-based representation for RDDs

- Pieces of information for each RDD
  – a set of partitions
  – a set of dependencies on parent RDDs
  – a function for computing it from its parents
  – metadata about its partitioning scheme and data placement

RDD Dependencies

- Narrow dependencies
  - each partition of the parent RDD is used by at most one partition of the child RDD
- Wide dependencies
  - multiple child partitions may depend on it

RDD Dependencies



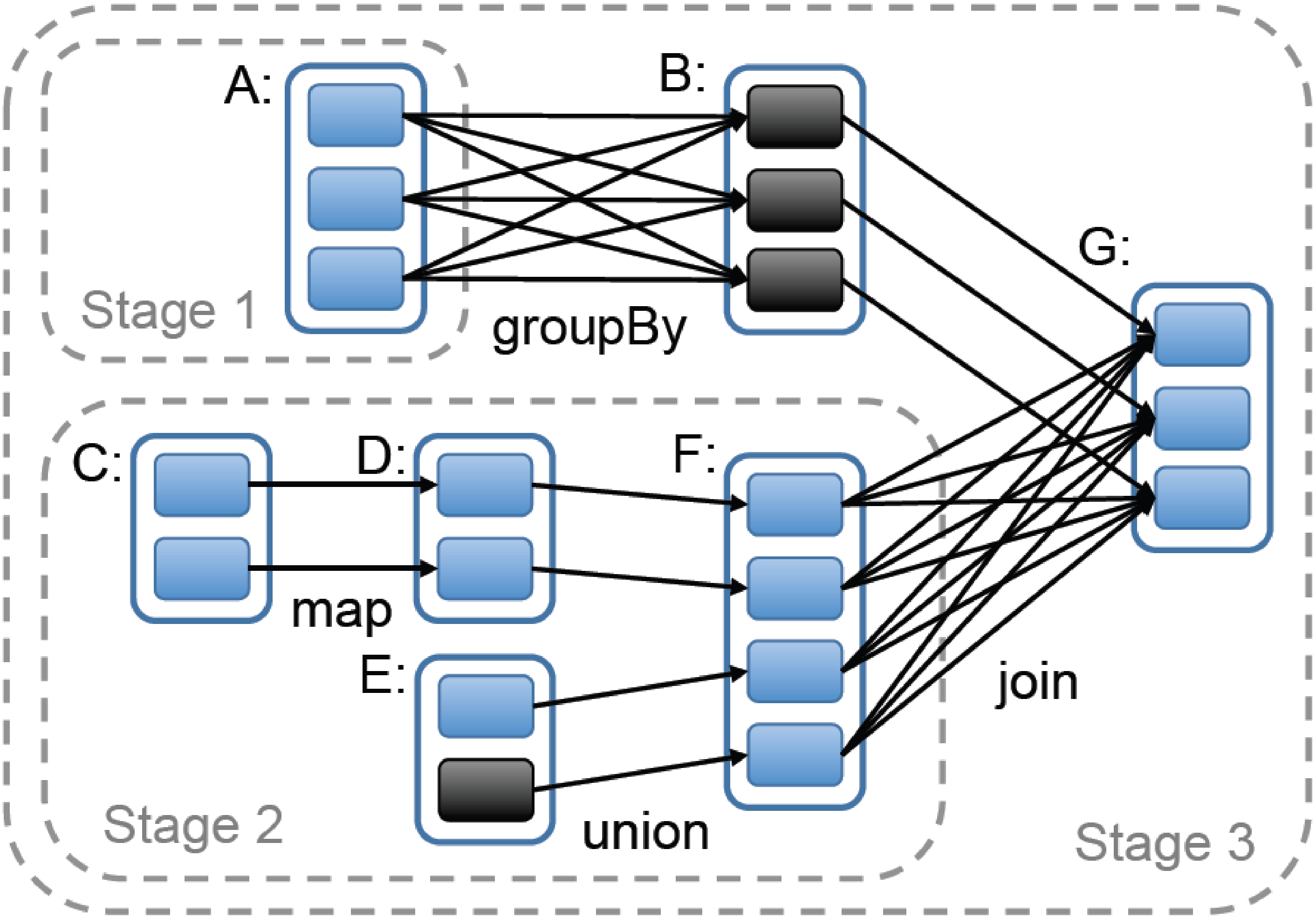
RDD Dependencies

- Narrow dependencies
  - allow for pipelined execution on one cluster node
  - easy fault recovery
- Wide dependencies
  - require data from all parent partitions to be available and to be shuffled across the nodes
  - a single failed node might cause a complete re-execution.

Job Scheduling

- To execute an action on an RDD
  - scheduler decide the stages from the RDD's lineage graph
  - each stage contains as many pipelined transformations with narrow dependencies as possible

Job Scheduling



Memory Management

- Three options for persistent RDDs
  - in-memory storage as deserialized Java objects
  - in-memory storage as serialized data
  - on-disk storage
- LRU eviction policy at the level of RDDs
  - when there's not enough memory, evict a partition from the least recently accessed RDD

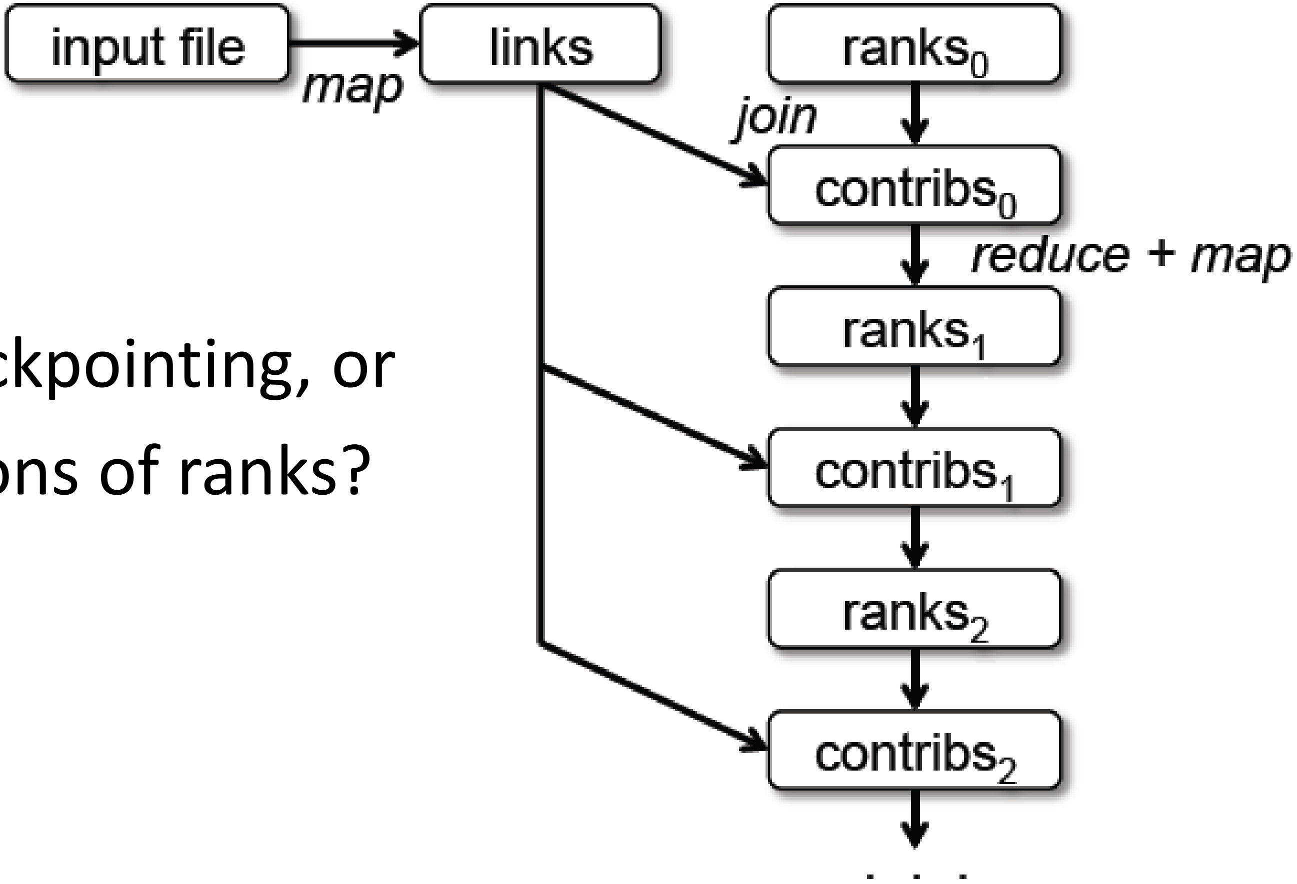
Checkpointing

- Checkpoint RDDs to prevent long lineage chains during fault recovery

- Simpler to checkpoint than shared memory
  - Read-only nature of RDDs

Discussions

Checkpointing or Versioning?



- Frequent checkpointing, or Keep all versions of ranks?