Spark

In-Memory Cluster Computing for Iterative and Interactive Applications

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Background

Commodity clusters have become an important computing platform for a variety of applications

» **In industry:** search, machine translation, ad targeting, …

» **In research:** bioinformatics, NLP, climate simulation, …

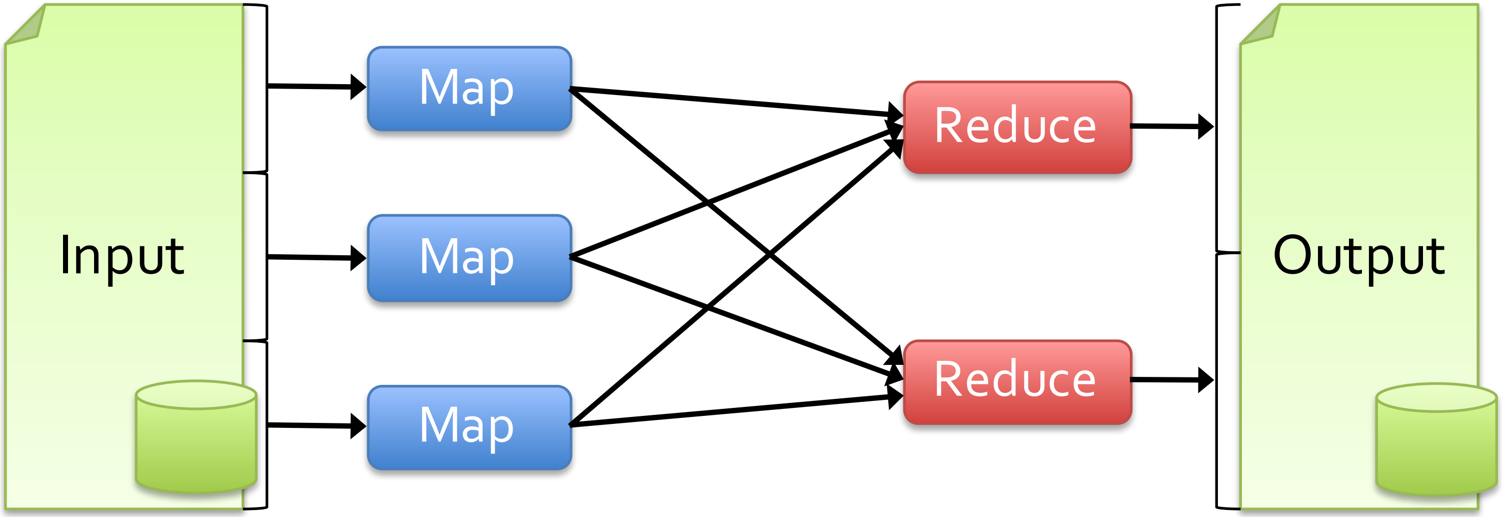
High-level cluster programming models like MapReduce power many of these apps

Theme of this work: provide similarly powerful abstractions for a broader class of applications

Motivation

Current popular programming models for clusters transform data flowing from stable storage to stable storage

E.g., MapReduce:



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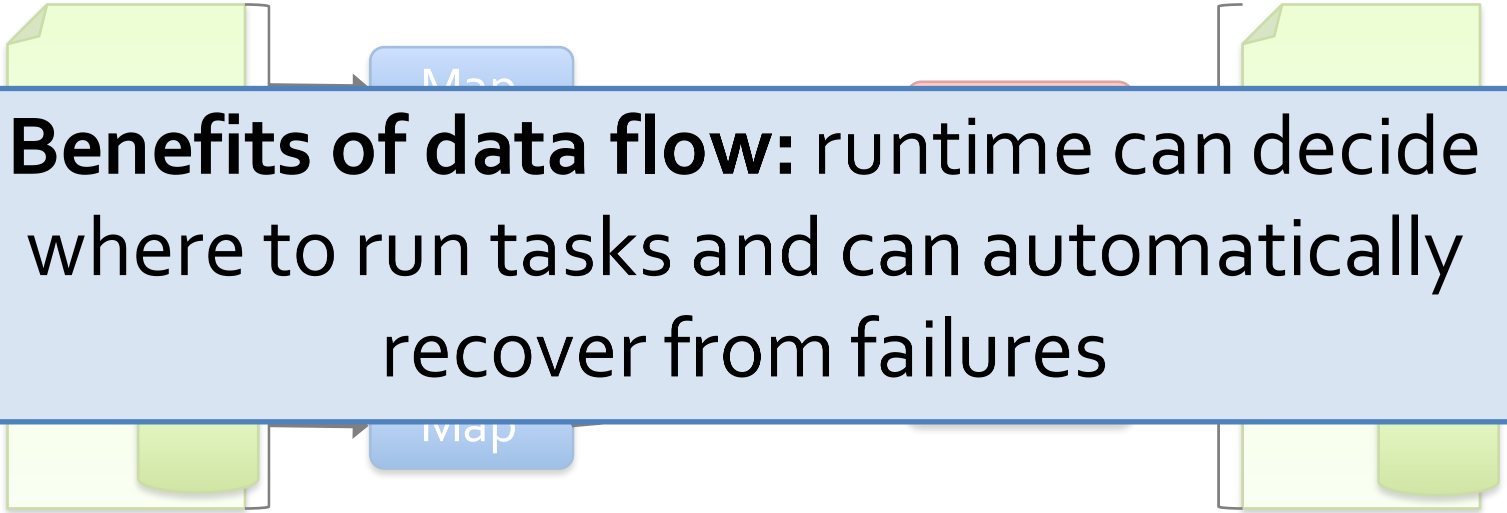


Benefits of data flow: runtime can decide where to run tasks and can automatically recover from failures

Motivation

Acyclic data flow is a powerful abstraction, but is not efficient for applications that repeatedly reuse a *working set* of data:

» **Iterative** algorithms (many in machine learning)

» **Interactive** data mining tools (R, Excel, Python)

Spark makes working sets a first-class concept to efficiently support these apps

Spark Goal

Provide distributed memory abstractions for clusters to support apps with working sets

Retain the attractive properties of MapReduce:

- » Fault tolerance (for crashes & stragglers)
- » Data locality
- » Scalability

Solution: augment data flow model with "resilient distributed datasets" (RDDs)

Generality of RDDs

We conjecture that Spark's combination of data flow with RDDs unifies many proposed cluster programming models

» *General data flow models:* MapReduce, Dryad, SQL

» *Specialized models for stateful apps:* Pregel (BSP), HaLoop (iterative MR), Continuous Bulk Processing

Instead of specialized APIs for one type of app, give user first-class control of distrib. datasets

Outline

Spark programming model

Example applications

Implementation

Demo

Future work

Programming Model

Resilient distributed datasets (RDDs)

- » Immutable collections partitioned across cluster that can be rebuilt if a partition is lost
- » Created by transforming data in stable storage using data flow operators (map, filter, group-by, …)
- » Can be *cached* across parallel operations

Parallel operations on RDDs

- » Reduce, collect, count, save, …

Restricted shared variables

- » Accumulators, broadcast variables

Example: Log Mining

Load error messages from a log into memory, then interactively search for various patterns

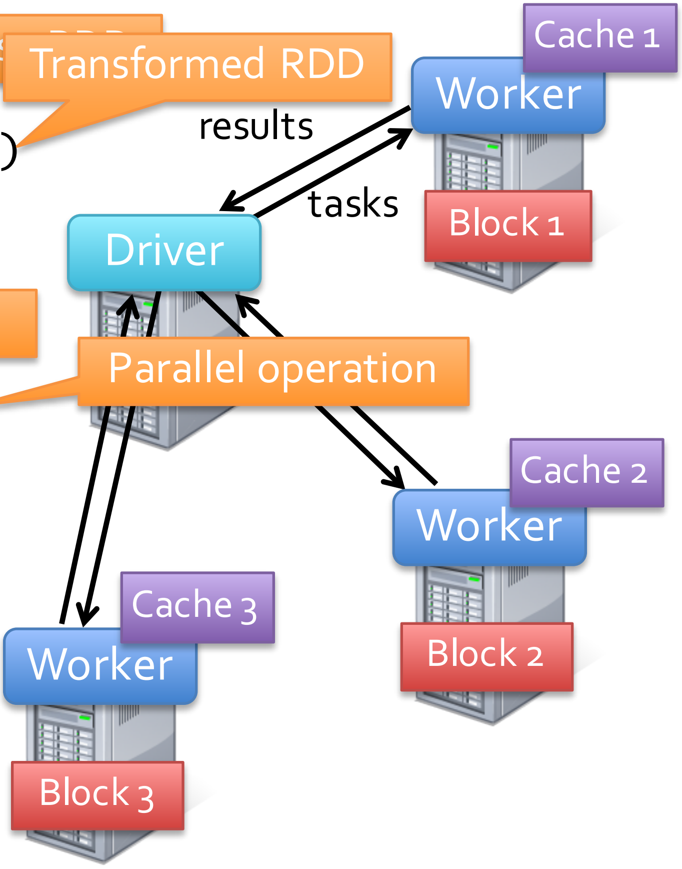
```
lines = spark.textFile(“hdfs://...”)
errors = lines.filter(_.startsWith(“ERROR”))
messages = errors.map(_.split(‘\t’)(2))
cachedMsgs = messages.cache()

cachedMsgs.filter(_.contains(“foo”)).count
cachedMsgs.filter(_.contains(“bar”)).count
. . .
```

Bas

Transformed RDD

Cached RDD

Parallel operation



Result: full-text search of Wikipedia in <1 sec (vs 20 sec for on-disk data)

RDDs in More Detail

An RDD is an immutable, partitioned, logical collection of records

- » Need not be materialized, but rather contains information to rebuild a dataset from stable storage

Partitioning can be based on a key in each record (using hash or range partitioning)

Built using bulk transformations on other RDDs

Can be cached for future reuse

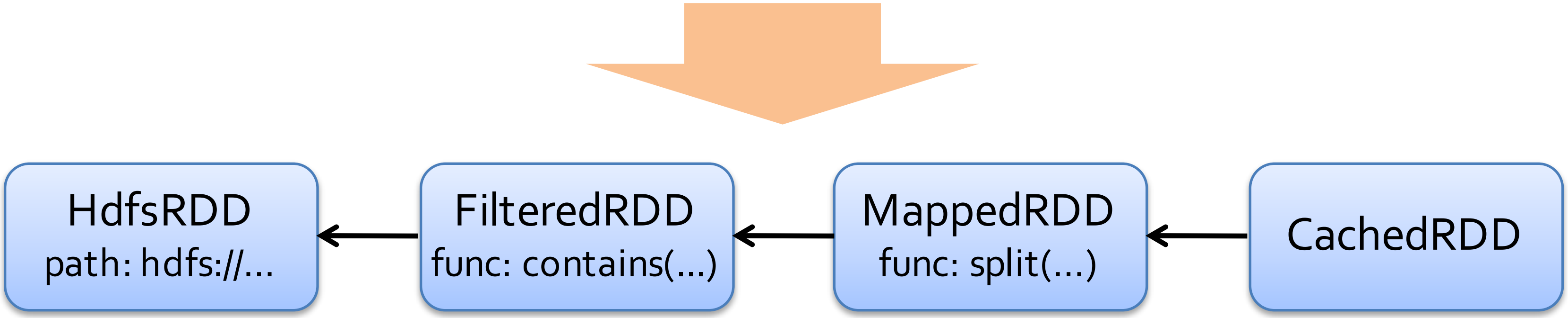
RDD Operations

Transformations (define a new RDD)	**Parallel operations** (return a result to driver)
map	reduce
filter	collect
sample	count
union	save
groupByKey	lookupKey
reduceByKey	…
join	
cache	
…	

RDD Fault Tolerance

RDDs maintain *lineage* information that can be used to reconstruct lost partitions

Ex:
```
cachedMsgs = textFile(...).filter(_.contains(“error”))
                          .map(_.split(‘\t’)(2))
                          .cache()
```



HdfsRDD
path: hdfs://…

FilteredRDD
func: contains(...)

MappedRDD
func: split(…)

CachedRDD

Benefits of RDD Model

Consistency is easy due to immutability

Inexpensive fault tolerance (log lineage rather than replicating/checkpointing data)

Locality-aware scheduling of tasks on partitions

Despite being restricted, model seems applicable to a broad variety of applications

RDDs vs Distributed Shared Memory

Concern	RDDs	Distr. Shared Mem.
Reads	Fine-grained	Fine-grained
Writes	Bulk transformations	Fine-grained
Consistency	Trivial (immutable)	Up to app / runtime
Fault recovery	Fine-grained and low-overhead using lineage	Requires checkpoints and program rollback
Straggler mitigation	Possible using speculative execution	Difficult
Work placement	Automatic based on data locality	Up to app (but runtime aims for transparency)

Related Work

DryadLINQ

- Language-integrated API with SQL-like operations on lazy datasets
- Cannot have a dataset persist *across* queries

Relational databases

- Lineage/provenance, logical logging, materialized views

Piccolo

- Parallel programs with shared distributed tables; similar to distributed shared memory

Iterative MapReduce (Twister and HaLoop)

- Cannot define multiple distributed datasets, run different map/reduce pairs on them, or query data interactively

RAMCloud

- Allows random read/write to all cells, requiring logging much like distributed shared memory systems

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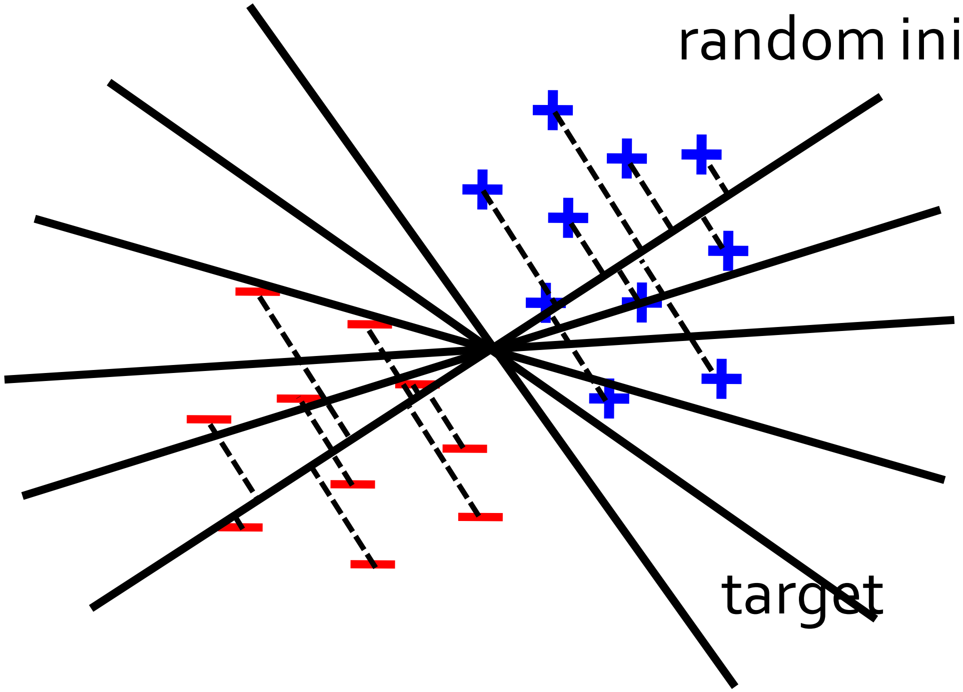
Example: Logistic Regression

Goal: find best line separating two sets of points



Logistic Regression Code

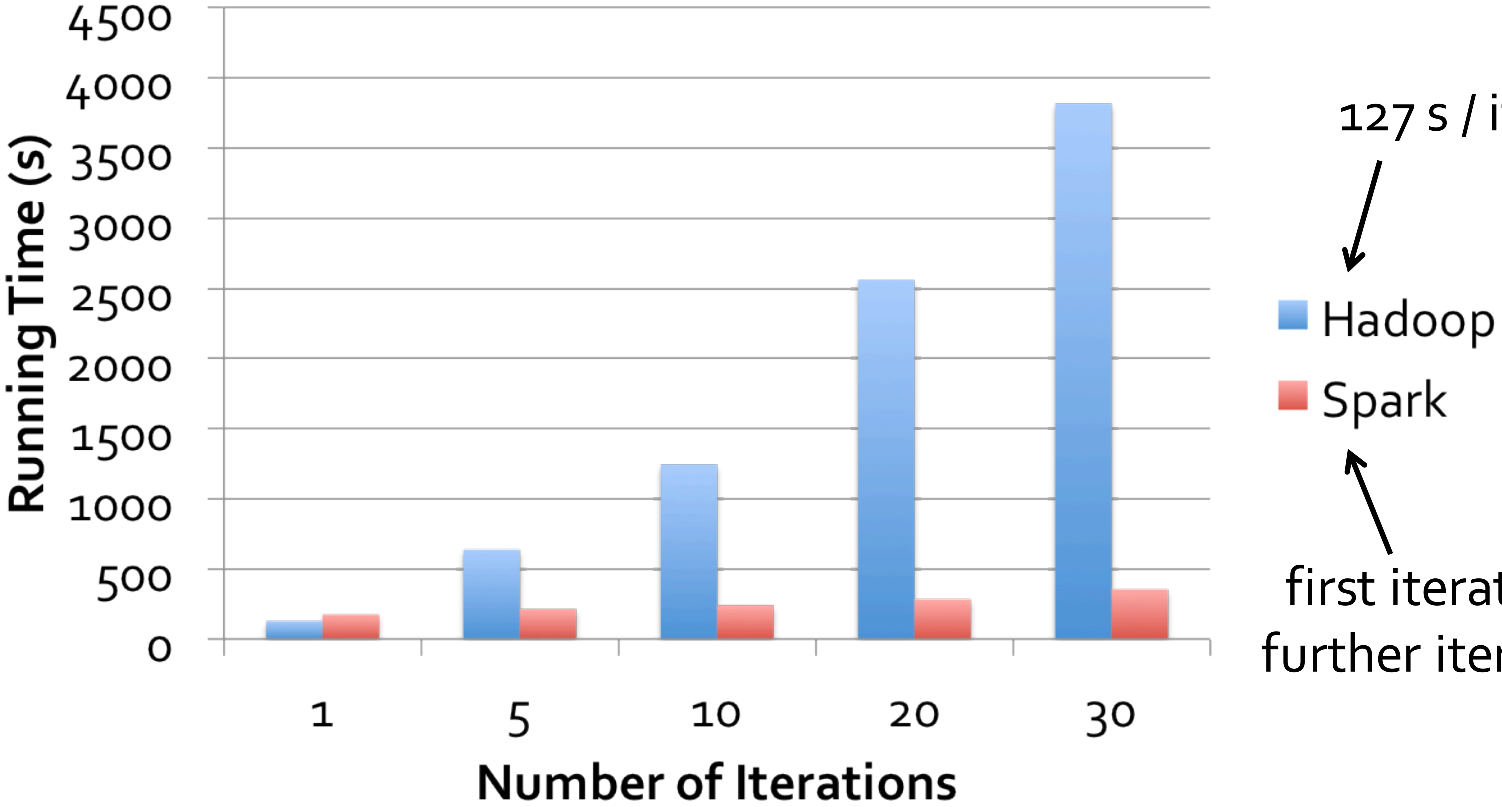
```
val data = spark.textFile(...).map(readPoint).cache()

var w = Vector.random(D)

for (i <- 1 to ITERATIONS) {
  val gradient = data.map(p =>
    (1 / (1 + exp(-p.y*(w dot p.x))) - 1) * p.y * p.x
  ).reduce(_ + _)
  w -= gradient
}

println("Final w: " + w)
```

Logistic Regression Performance



127 s / iteration

first iteration 174 s
further iterations 6 s

Example: MapReduce

MapReduce data flow can be expressed using RDD transformations

```
res = data.flatMap(rec => myMapFunc(rec))
          .groupByKey()
          .map((key, vals) => myReduceFunc(key, vals))
```

Or with combiners:

```
res = data.flatMap(rec => myMapFunc(rec))
          .reduceByKey(myCombiner)
          .map((key, val) => myReduceFunc(key, val))
```

Word Count in Spark

```
val lines = spark.textFile(“hdfs://...”)

val counts = lines.flatMap(_.split(“\\s”))
                  .reduceByKey(_ + _)

counts.save(“hdfs://...”)
```

Example: Pregel

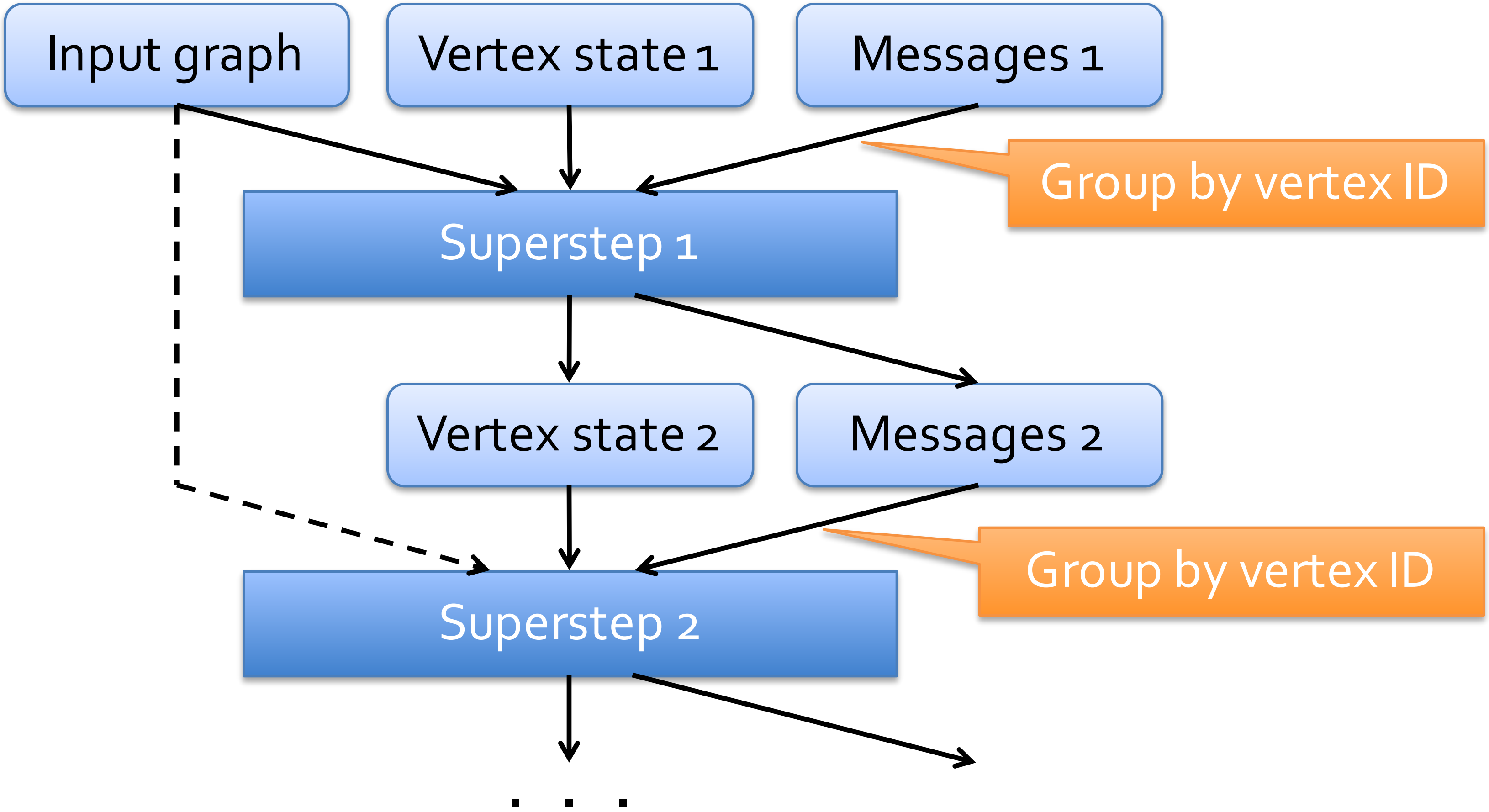
Graph processing framework from Google that implements Bulk Synchronous Parallel model

Vertices in the graph have state

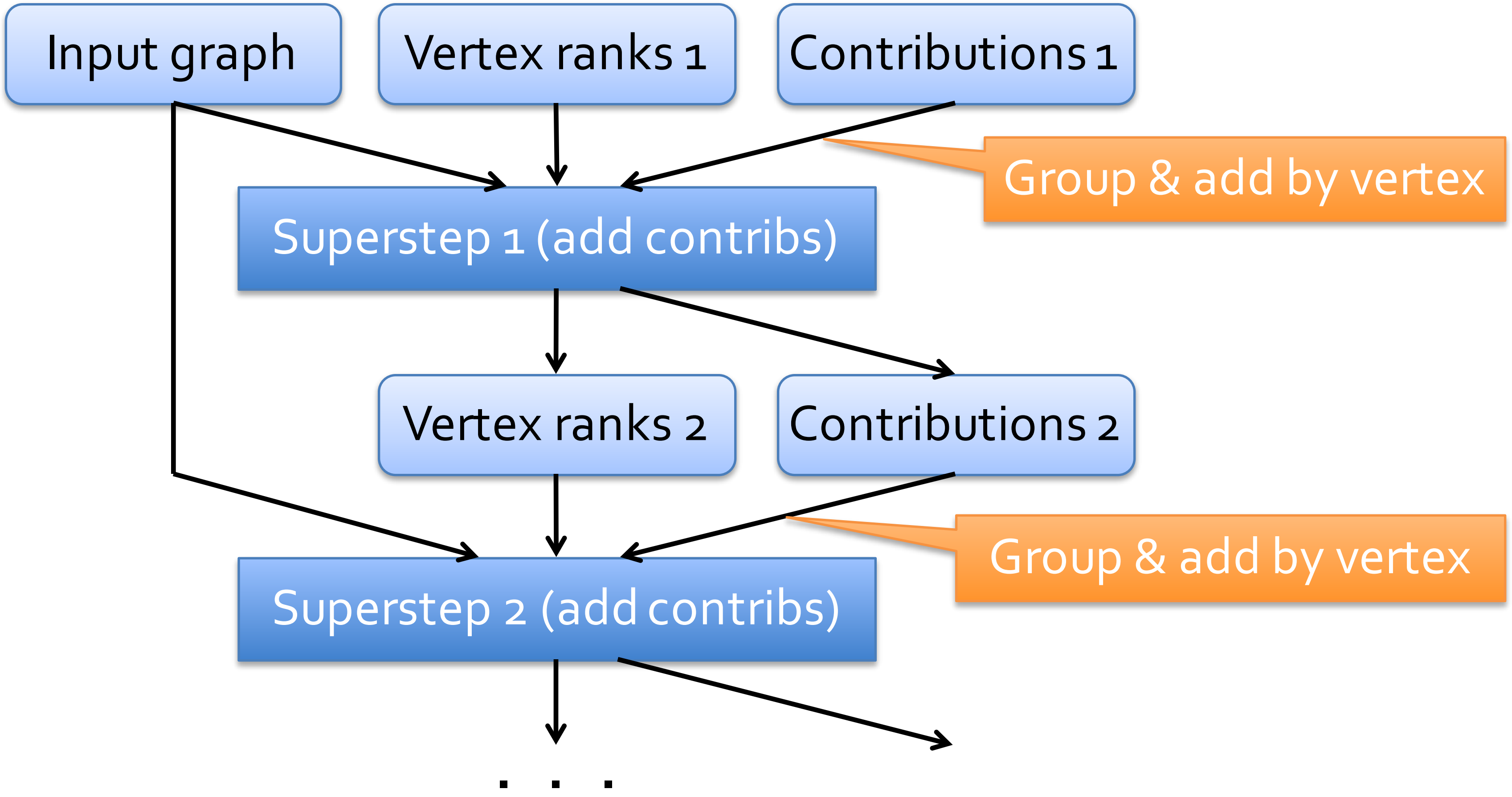
At each superstep, each node can update its state and send messages to nodes in future step

Good fit for PageRank, shortest paths, …

Pregel Data Flow



PageRank in Pregel



Input graph

Vertex ranks 1

Contributions 1

Group & add by vertex

Superstep 1 (add contribs)

Vertex ranks 2

Contributions 2

Group & add by vertex

Superstep 2 (add contribs)

. . .

Pregel in Spark

Separate RDDs for immutable graph state and for vertex states and messages at each iteration

Use groupByKey to perform each step

Cache the resulting vertex and message RDDs

Optimization: co-partition input graph and vertex state RDDs to reduce communication

Other Spark Applications

Twitter spam classification (Justin Ma)

EM alg. for traffic prediction (Mobile Millennium)

K-means clustering

Alternating Least Squares matrix factorization

In-memory OLAP aggregation on Hive data

SQL on Spark (future work)

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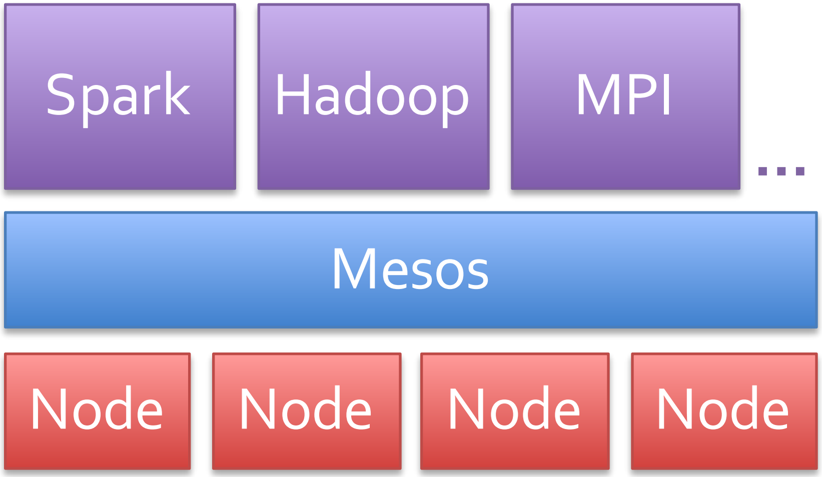
Overview

Spark runs on the Mesos cluster manager [NSDI 11], letting it share resources with Hadoop & other apps



Can read from any Hadoop input source (e.g. HDFS)

~6000 lines of Scala code thanks to building on Mesos

Language Integration

Scala closures are Serializable Java objects

- » Serialize on driver, load & run on workers

Not quite enough

- » Nested closures may reference entire outer scope
- » May pull in non-Serializable variables not used inside
- » Solution: bytecode analysis + reflection

Shared variables implemented using custom serialized form (e.g. broadcast variable contains pointer to BitTorrent tracker)

Interactive Spark

Modified Scala interpreter to allow Spark to be used interactively from the command line

Required two changes:

- » Modified wrapper code generation so that each “line” typed has references to objects for its dependencies
- » Place generated classes in distributed filesystem

Enables in-memory exploration of big data

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Future Work

Further extend RDD capabilities

- » Control over storage layout (e.g. column-oriented)
- » Additional caching options (e.g. on disk, replicated)

Leverage lineage for debugging

- » Replay any task, rebuild any intermediate RDD

Adaptive checkpointing of RDDs

Higher-level analytics tools built on top of Spark

Conclusion

By making distributed datasets a first-class primitive, Spark provides a simple, efficient programming model for stateful data analytics

RDDs provide:

- » Lineage info for fault recovery and debugging
- » Adjustable in-memory caching
- » Locality-aware parallel operations

We plan to make Spark the basis of a suite of batch and interactive data analysis tools

RDD Internal API

Set of partitions

Preferred locations for each partition

Optional partitioning scheme (hash or range)

Storage strategy (lazy or cached)

Parent RDDs (forming a lineage DAG)