Distributed Systems

15-440 / 15-640
Fall 2017

Spark and Distributed ML
Topics Today

Motivation

Going beyond Map/Reduce

In-memory computation (Spark)

Data sharing and fault tolerance

Distributed programming model

Distributed Machine Learning

The scalability challenge
Distributed Data Processing

Map/Reduce (Hadoop) Framework:

Simplified data analysis on large, unreliable clusters
Highly expressive and scalable
Limitations of Map/Reduce I

Fault-tolerance: store input/output after every step on disk

While throughput scales with #servers, latency gets worse

Does not work for interactive data exploration
Limitations of Map/Reduce II

Expressiveness relies on iterating Map/Reduce steps

Iteration steps are small, but there are many

⇒ 90% spent on I/O to disks and over network
⇒ 10% spent on computing (using the CPUs)

Does not work for distributed machine learning
Limitations of Map/Reduce III

M/R abstraction not expressive enough

Explosion of specialized analytics systems

- Streaming analytics:
  - STORM
  - kafka

- Iterative ML algorithms:
  - GraphLab

- Graph/social data:
  - Giraph
  - Google Dremel

Learn all of them? Share data between them?
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Towards a New Unified Framework

Berkeley Extensions to M/R framework (⇒ Apache Spark)

1. In-memory computation and data-sharing
   - 10-100x faster than disks or network
   - Key problem: fault tolerance

2. Unified computation abstraction
   - Power of iterations (“local work + message passing”)
   - Key problem: ease-of-use and generality
In-memory computation and data-sharing

How to build **fault-tolerance** and **efficient** system?

**Traditional fault-tolerance approaches**

- Fine-grained update interface (databases, KV-stores, ..)
- Requires replicating data or logs across nodes

⇒ Expensive (10-100x slowdown)
Approach 1: RamCloud

Replicate in-memory objects 3x, on disks
Parallelize disk reads to speed-up recovery


Involves disks, again! 🧐
Approach 2: RDDs and Lineage

Resilient Distributed Datasets

- Limit update interface to coarse-grained operations
  - Map, group-by, filter, sample, ...

- Efficient fault recovery using lineage
  - Data is partitioned and each operation is applied to every partition
  - Individual operations are cheap
  - Recompute lost partitions on failure

Apache Spark Deployment

Master server ("driver")
- Lineage and scheduling

Cluster manager (not part of Spark)
- Resource allocation
- Mesos, YARN, K8S

Worker nodes
- Executors isolate concurrent tasks
- Caches persist RDDs

https://spark.apache.org/docs/latest/cluster-overview.html
RDD Operations in Spark

1) Transformations: create new RDD from existing one
   - Map, filter, sample, groupByKey, sortByKey, union, join, cross

2) Actions: return value to caller
   - Count, sum, reduce, save, collect

3) Persist RDD to memory

⇒ Transformations are lazy: evaluation triggered by Action

```scala
def main() {
  val lines = spark.textFile("hdfs://...")
  val lineLengths = lines.map(s => s.length)
  val totalLength = lineLengths.reduce((a, b) => a + b)
  lineLengths.persist()
}
```
Example 1: Log Mining

Parse error messages from logs, filter, and query interactively.

```scala
lines = spark.textFile("hdfs://...")
errors = lines.filter(_.startsWith("ERROR"))
messages = errors.map(_.split(\t')(2))
cachedMsgs = messages.persist()
cachedMsgs.filter(_.contains("foo"))\n.. cachedMsgs.filter(_.contains("bar"))\n```

Recall: fault recovery via lineage.

Full-text search of Wikipedia in <1 sec (vs 20 sec for on-disk data).
Example 2: Regression Algorithms

Find a line (plane) that separates some data points

```scala
var w = Vector.random(D-1)
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
}
```
RDD Consistency and Fault Recovery

RDDs are immutable datasets

- Deterministic functions of input
  - recreate any RDD any time
  - how to incorporate randomness?
- Simplifies consistency (caching, sharing, ..)
- Still need periodic RDD checkpoints

Design implications?

- High overhead: copying data (no mutate-in-place)
- Needs lots of memory (might not be able to run your workload)
Towards a New Unified Framework

Berkeley Extensions to M/R framework (⇒ Apache Spark)

1. In-memory computation and data-sharing
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   - Key problem: fault tolerance

2. New computation abstraction
   - Power of iterations ("local work + message passing")
   - Key problem: accessible and unified framework
BSP computation abstraction

- Surprising power of iterations
  - (e.g., iterative Map/Reduce)
- Explained by theory of bulk synchronous parallel (BSP) model

Theorem (Leslie Valiant, 1990):
“Any distributed system can be emulated as local work + message passing” (=BSP).

Spark implements BSP approximately
Spark Pipeline and Scheduler

Support for directed graphs of RDD operations

Automatic pipelining of functions within a stage

Partitioning/Cache-aware scheduling to minimizes shuffles

- cached data partition
Spark as a Uniform Framework

Pregel on Spark (Bagel)
⇒ “200 lines of Spark code”

Iterative MapReduce
⇒ “200 lines of Spark code”

Hive on Spark (Shark)
⇒ “5000 lines of code”

ML-lib and other distributed ML implementations
Limitations of Spark

Spark is not a good fit for (examples):

- Applications with fine-grained updates to shared state
- Storage for web applications
- Incremental web crawlers
- Data sets that don’t fit into memory
- If cannot be expressed as batch-analytics, i.e., apply same function uniformly over dataset
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The scalability challenge
Machine Learning

The ML hype

Enabled by huge leap in parallelization

Often: fast enough to build a powerful machine, lots of GPUs
Is There a Case for Distributed ML?

Some ML systems drive significant revenue

Some ML systems benefit from humongous amount of data

Some ML systems outscale even powerful machines (GPUs et al)

Ads make one case for Distributed Machine Learning.

From: Li et al., Scaling Distributed Machine Learning with the Parameter Server, OSDI 2014.
Behind the Scenes of Machine Learning

... we find a model and an iterative algorithm

ML in a box

Challenge 1: lots of data

Challenge 2: lots of parameters

From: Eric Xing, Strategies & Principles for Distributed Machine Learning, Allen AI, 2016
Scaling Out Distributed Machine Learning

Often data/models fits into just a few nodes

Scale out for **performance**

Best case: 100x speedup from 1000 machines

\[
\arg\max(\theta) = \Phi(\{x_i, y_i\}; \theta) + \Omega(\theta)
\]

data

parameters

solved via iterative convergent algorithm

\[
\theta^{t+1} = g(\theta^t, F(\theta^t(\Phi)))
\]

parallelize this

\[
\text{Iterations / Sec}
\]

\[
\text{Machine Count}
\]

ideal speedup

good speedup

pathetic speedup

Best case: 100x speedup from 1000 machines
Challenge of Communication Overhead

Communication overhead scales badly

e.g., for Netflix-like recommender systems

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Solution: apply P2P ideas

- BitTorrent-like protocol
- Modified for datacenters:
  - 4MB blocks
  - full collaboration (no tit-for-tat)
  - no integrity checks (SHA1 is expensive)

Challenge of Synchronization Overhead

BSP model:
- No computation during barrier
- No communication during computation

Fundamental limitation in BSP model
Constantly waiting for stragglers

Do we need a new programming model?
Relaxing BSP Consistency

Exploit robustness of ML convergence

We can accept slightly stale state

How can we incorporate stale state into the BSP model?

From: Eric Xing, Strategies & Principles for Distributed Machine Learning, Allen AI, 2016
Opposite Extreme: No Synchronization

What if we fully remove BSP’s synchronization barriers?

Asynchronous mode:
- no communication, or
- communication at any time

No correctness guarantee:
Iterative algorithms won’t converge
Bounded-delay BSP for Distributed ML

Bound stale state by N steps:

\[ \Rightarrow N\text{-bounded delay BSP} \]

From: Li et al, Scaling Distributed Machine Learning with the Parameter Server, OSDI 2014

what happens here?
Many Challenges Remain

Trade-Off:  
Stale state -> throughput (iter / sec)

Misleading design decisions:  
Higher throughput, but less progress / iteration

Many open challenges (e.g., automatic model partitioning)

General distributed ML systems  
⇒ Very active field
Summary: Spark and Distributed ML

Spark and in-memory computing

- **Motivation:** overcome disk i/o bottleneck
- **Challenges:** fault tolerance and generality/expressiveness
- **Key ideas:** RDDs, the BSP model, P2P architecture

Distributed Machine Learning

- **Distributed variants highly complex and not always faster!**
- **Challenges:** communication overhead and stragglers
- **Key ideas:** P2P+selective communication, bounded-delay BSP