Three Generations of Tools/Paradigms Realizing Machine Learning Algorithms

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Agenda

• Introduction
  • Hadoop Suitability – iterative and real-time applications
• Three generations of realizations – machine learning (ML) algorithms
• Third generation tools
  • Spark
  • comparison of graph processing paradigms
  • ML algorithm in Storm-Kafka – manufacturing use case
• Benchmarking Big-data analytics
Introduction: Hadoop Adoption Status

• Enterprise level – slowly becoming mainstream
  • Experimental – lot of big companies have their own Hadoop clusters including Sears, Walmart, Disney, AT&T etc.

• Business use case
  • Extract, Transform, Load ETL/ELT/data refinement
    • Pentaho, Datameer SMEs in this space.
    • Big-players – Informatica, Splunk (log analytics company) and IBM

• Industry-wise adoption
  • Financial investment/trading – quite high, just as for any new tech.
  • Banking Financial – slower.
  • Telecom, Retail – cautious.
Introduction: Hadoop Adoption Future

• Hindrances/Hurdles towards Hadoop adoption
  • Single cluster – Hadoop YARN is the way forward.
  • Lack of ODBC connectivity

• Hadoop suitability
  • Mainly for embarrassingly parallel problems
  • Not suitable if data splits need to communicate or data splits are inter-related.
  • Map-Reduce for iterative computations
  • Hadoop not currently well suited – no long lived MR job nor in-memory data structures for persisting/caching data across MR iterations.
Suitability of Map-Reduce for Machine Learning

- Origin in functional programming languages (Lisp and ML)
- Built for embarrassingly parallel computations
  - Map: \((k_1, v_1) \rightarrow \text{list}(k_2, v_2)\)
  - Reduce: \(\text{list}(k_2, \text{list}(v_2)) \rightarrow \text{list}(v_2)\).
- Algorithms which can be expressed in Statistical Query Model in summation form – highly suitable for MR [CC06] – suitable for Hadoop MR.
- Different categorization of ML algorithms
  - Algorithms which need a single execution of an MR model
  - Algorithms which need sequential execution of fixed no. of MR models.
  - Algorithms where 1 iteration is a single execution of MR model.
  - Algorithms where 1 iteration itself needs multiple MR model executions.

What about Iterative Algorithms?

- What are iterative algorithms?
  - Those that need communication among the computing entities
  - Examples – neural networks, PageRank algorithms, network traffic analysis

- Conjugate gradient descent
  - Commonly used to solve systems of linear equations
  - [CB09] tried implementing CG on dense matrices
  - DAXPY – Multiplies vector x by constant a and adds y.
  - DDOT – Dot product of 2 vectors
  - MatVec – Multiply matrix by vector, produce a vector.
  - 1 MR per primitive – 6 MRs per CG iteration, hundreds of MRs per CG computation, leading to 10 of GBs of communication even for small matrices.

- Other iterative algorithms – fast fourier transform, block tridiagonal

Further exploration: Iterative Algorithms

- [SN12] explores CG kind of iterative algorithms on MR
- Compare Hadoop MR with Twister MR ([http://iterativemapreduce.org](http://iterativemapreduce.org))
  - It took 220 seconds on a 16 node cluster to solve system with 24 unknowns, while for 8000 unknowns – took almost 2 hours.
  - MR tasks for each iteration – computation is too little, overhead of setup of MR tasks and communication is too high.
    - Data is reloaded from HDFS for each MR iteration.
    - Surprising that Hadoop does not have support for long running MR tasks
- Other alternative MR frameworks?
  - Spark [MZ10] – introduces resilient distributed datasets (RDD) – RDD can be cached in memory and reused across iterations.
- Beyond MR – Apache Hama ([http://hama.apache.org](http://hama.apache.org)) – BSP paradigm

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[YB10] Yingyi Bu, Bill Howe, Magdalena Balazinska, Michael D. Ernst. *HaLoop: Efficient Iterative Data Processing on Large Clusters* InVLDB’10: The 36th International Conference on Very Large Data Bases, Singapore, 24-30 September, 2010

Data processing: Alternatives to Map-Reduce

- **R language**
  - Good for statistical algorithms
  - Does not scale well – single threaded, single node execution.
  - Inherently good for iterative computations – shared array architecture.

- **Way forward**
  - R-Hadoop integration – or R-Hive integration
  - R extensions to support distributed execution.
    - [SV12] is an effort to provide R runtime for scalable execution on cluster.
    - Revolution Analytics is an interesting startup in this area.
  - Apache HAMA ([http://hama.apache.org](http://hama.apache.org)) is another alternative
    - Based on Bulk Synchronous Parallel (BSP) model – inherently good for iterative algorithms – can do Conjugate gradient, non-linear SVMs – hard in Hadoop MR.

Three Generation of Realization – ML Algos.

• First Generation
  • SAS, SPSS, Informatica etc.
  • Deep analytics – large collection of serial ML algorithms
  • Logistic regression, kernel Support Vector Machines (SVMs), Principal Component Analysis (PCA), Conjugate Gradient (CG) Descent etc.
  • Vertical scaling – increase computation/memory power of node.
Three Generation of Realization – ML Algos.

- **Second Generation**
  - Mahout, RapidMiner, Pentaho
  - Works over Hadoop Map-Reduce (MR) – can potentially scale to large data sets
  - Shallow analytics may only be possible on Big-data
  - Small number of algorithms only available – including linear regression, linear SVMs, Stochastic gradient descent, collaborative filtering, k-means clustering etc.
Three Generation of Realization – ML Algos.

• Third Generation
  • Spark, HaLoop, Twister MR, Apache Hama, Apache Giraph, GraphLab, Pregel, Piccolo
  • Deep analytics on Big-data?
  • Possible – many more algorithms can be realized in parallel
  • Kernel SVMs, Logistic Regression, CG etc.
  • Motivated by iterative processing + social networks (power law graphs)
  • Realize ML algorithms in real-time – use Kafka-Storm integrated environment.
Paradigms for Processing Large Graphs in Parallel

- Pregel [GM10] – Computation engine from Google for processing graphs
  - Implementation of Bulk Synchronous Parallel (BSP) – paradigm from traditional parallel programming
  - User defined compute() for each vertex at each super-step S.
  - Edges – messages between vertices.
  - Parallelism – Vertex compute functions run in parallel
  - Compute-communicate-barrier – each iteration.

- Similar open source alternatives – Apache Giraph, Golden orb, Stanford GPS

- Pregel is good at graph parallel abstraction, ensures deterministic computation, easy to reason with, but
  - user must architect movement of data
  - curse of slow job (barrier synchronization can be slowed by slow jobs – sequential dependencies in the graph).
  - Cannot prioritize/target computation where it is needed most – not adaptive

Piccolo: Another Graph Processing Abstraction

- Piccolo [RP10] – provides asynchronous graph processing abstraction.
  - Application programs comprise
    - control functions – executed on a single machine (master)
      - Create kernels, shared tables, perform global synchronization.
    - Kernel functions – executed on slaves in parallel.
  - Table operations include get, put, update, flush, get_iterator.
  - User defined accumulation functions for concurrent access to table entries.
  - User defined table partition.
- Does not ensure serializable program execution.
  - May be required for some ML algorithms, including dynamic Alternating Least Squares (ALS) and Gibbs sampling.

GraphLab: Ideal Engine for Processing Natural Graphs [YL12]

- Goals – targeted at machine learning.
  - Model graph dependencies, be asynchronous, iterative, dynamic.
- Data associated with edges (weights, for instance) and vertices (user profile data, current interests etc.).
- Update functions – lives on each vertex
  - Transforms data in scope of vertex.
  - Can choose to trigger neighbours (for example only if Rank changes drastically)
  - Run asynchronously till convergence – no global barrier.
- Consistency is important in ML algorithms (some do not even converge when there are inconsistent updates – collaborative filtering).
  - GraphLab – provides varying level of consistency. Parallelism VS consistency.
  - Implemented several algorithms, including ALS, K-means, SVM, Belief propagation, matrix factorization, Gibbs sampling, SVD, CoEM etc.
  - Co-EM (Expectation Maximization) algorithm 15x faster than Hadoop MR – on distributed GraphLab, only 0.3% of Hadoop execution time.

GraphLab 2: PowerGraph – Modeling Natural Graphs [1]

- GraphLab could not scale to Altavista web graph 2002, 1.4B vertices, 6.7B edges.
  - Most graph parallel abstractions assume small neighbourhoods – low degree vertices
  - But natural graphs (LinkedIn, Facebook, Twitter) – power law graphs.
  - Hard to partition power law graphs, high degree vertices limit parallelism.

- GraphLab provides new way of partitioning power law graphs
  - Edges are tied to machines, vertices (esp. high degree ones) span machines
  - Execution split into 3 phases:
    - Gather, apply and scatter.
  - Triangle counting on Twitter graph
    - Hadoop MR took 423 minutes on 1536 machines
    - GraphLab 2 took 1.5 minutes on 1024 cores (64 machines)

<table>
<thead>
<tr>
<th>Graph Paradigm</th>
<th>Computation (Synchronous or Asynchronous)</th>
<th>Determinism and Effects</th>
<th>Efficiency VS Asynchrony</th>
<th>Efficiency of Processing Power Law Graphs.</th>
</tr>
</thead>
<tbody>
<tr>
<td>GraphLab1</td>
<td>Asynchronous</td>
<td>Deterministic – serializable computation.</td>
<td>Uses inefficient locking protocols</td>
<td>Inefficient – Locking protocol is unfair to high degree vertices</td>
</tr>
<tr>
<td>Piccolo</td>
<td>Asynchronous</td>
<td>Non-deterministic – non-serializable computation.</td>
<td>Efficient, but may lead to incorrectness.</td>
<td>May be efficient.</td>
</tr>
<tr>
<td>GraphLab2 (PowerGraph)</td>
<td>Asynchronous</td>
<td>Deterministic – serializable computation.</td>
<td>Uses parallel locking for efficient, serializable and asynchronous computations.</td>
<td>Efficient – parallel locking and other optimizations for processing natural graphs.</td>
</tr>
</tbody>
</table>
Spark: Third Generation ML Tool

- Two parallel programming abstractions [MZ10]
  - Resilient distributed data sets (RDDs)
    - Read-only collection of objects partitioned across a cluster
    - Can be rebuilt if partition is lost.
  - Parallel operation on RDDs
    - User can pass a function – first class entities in Scala.
    - Foreach, reduce, collect
  - Programmer can build RDDs from
    1. a file in HDFS
    2. Parallelizing Scala collection - divide into slices.
    3. Transform existing RDD - Specify flatmap operations such as Map, Filter
    4. Change persistence of RDD Cache or a save action – saves to HDFS.
- Shared variables
  - Broadcast variables, accumulators

Some Spark(ling) examples

Scala code (serial)

```
var count = 0
for (i <- 1 to 100000)
  { val x = Math.random * 2 - 1
    val y = Math.random * 2 - 1
    if (x*x + y*y < 1) count += 1 }
println("Pi is roughly " + 4 * count / 100000.0)
```

Sample random point on unit circle – count how many are inside them (roughly about PI/4). Hence, you get approximate value for PI.

Based on the PS/PC = AS/AC=4/PI, so PI = 4 * (PC/PS).
Spark code (parallel)

```scala
val spark = new SparkContext(<Mesos master>)
var count = spark.accumulator(0)
for (i <- spark.parallelize(1 to 100000, 12))
  { val x = Math.random * 2 - 1 val
    y = Math.random * 2 - 1
    if (x*x + y*y < 1) count += 1 }
println("Pi is roughly "+ 4 * count / 100000.0)
```

Notable points:
1. Spark context created – talks to Mesos master.
2. Count becomes shared variable – accumulator.
3. For loop is an RDD – breaks scala range object (1 to 100000) into 12 slices.
4. Parallelize method invokes foreach method of RDD.

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1 Mesos is an Apache incubated clustering system – [http://mesosproject.org](http://mesosproject.org)
Logistic Regression in Spark: Serial Code

// Read data file and convert it into Point objects
val lines = scala.io.Source.fromFile("data.txt").getLines()
val points = lines.map(x => parsePoint(x))

// Run logistic regression
var w = Vector.random(D)
for (i <- 1 to ITERATIONS) {
  val gradient = Vector.zeros(D)
  for (p <- points) {
    val scale = (1/(1+Math.exp(-p.y*(w dot p.x))))-1)*p.y
    gradient += scale * p.x
  }
  w -= gradient
}
println("Result: " + w)
Logistic Regression in Spark

// Read data file and transform it into Point objects
val spark = new SparkContext(<Mesos master>)
val lines = spark.hdfsTextFile("hdfs://.../data.txt")
val points = lines.map(x => parsePoint(x)).cache()

// Run logistic regression
var w = Vector.random(D)
for (i <- 1 to ITERATIONS) {
  val gradient = spark.accumulator(Vector.zeros(D))
  for (p <- points) {
    val scale = (1/(1+Math.exp(-p.y*(w dot p.x)))-1)*p.y
    gradient += scale * p.x
  }
  w = gradient.value
}
println("Result: " + w)
We Implement Big Data Architecture of Fast Classification System [Patent Pending: 1143/CHE/2013 with Indian PTO]
Benchmarking Big-data

- Efforts made to benchmark NoSQL databases
  - Yahoo Cloud Serving Benchmark
    - Workloads – insert, read, update, scan
  - BigBench
  - Good big-data querying systems/NoSQLs.
- Data analytics pipeline
  - End-to-end data consumption from ingestion to analysis
- Metrics for scoring
Benchmarking Big-data Analytics

• Batch analytics or real-time analytics
• Performance/scalability VS accuracy
  • Increasing data volume – time taken
• Throughput VS accuracy
  • Increasing velocity – time taken
• Data munging time
• Machine learning algorithm time
  • Training/Testing
Thank You!

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Backup slides
Real-time Analytics for Big-Data

• Interesting technologies in this space.
  • Google Dremel – incremental processing
    • Open source version led by MapR – Apache Drill
  • Real time analytics Database from Metamarkets – Druid.
  • Apache S4 from Yahoo – distributed stream computing platform.
  • Storm + Kafka + Trident – can be used for highly scalable stream processing + simple aggregation/summarization.

Interesting Startups in this space.
  • Hstreaming, Truviso (acquired by Cisco), Mixpanel (mobile analytics)
  • Space Time Insight – $14M funding for geospatial and visual analytics software in real-time Big-data space.

Visualization + analytics at speed of thought
  • Self-service data science – no need of data scientist
  • Integration of visualization + big-data + Artificial intelligence + social + analytics
  • Interesting startups in this space – Tableau, Cliktech, Edgespring.
Video Analytics

• Retail – product pilferage. Nearly 30% loss and 50% of pilferage by employees themselves.
  • Need to analyze few hundred hours of surveillance videos
  • Useful in a no. of security applications

• Approach.
  • Video meta-data extraction, storing in NoSQL DB.
  • Video object identification
    • Parallelized image comparison algorithm
  • All sequences/frames identifying occurrences of a given object in video files.
    • Parallelized algorithm over Hadoop MR.
Video Analytics: State of Art

- Video Analytics – focus mainly on
  - Object identification
  - Indexing/Annotating – creating meta-data on video.

Tools available

- OpenTLD a.k.a Predator (https://github.com/zk00006/OpenTLD)
  - Object identification/detection via custom made algorithms
  - Uses Matlab – can work with Octave.

- OpenCV (Computer Vision project from Intel – http://opencv.org)
  - Open source image processing – segmentation, object identification, motion tracking etc.
  - Uses Machine Learning algorithms including decision trees, random forests, expectation maximization, SVMs etc.
  - Can be re-written to work over Hadoop – works on CUDA as of now.

- EMC – presented Hadoop MR based algorithms to speed up video analytics.
- H-Streaming – start-up claims to have MR based video analytics.
Spanner: State of the Art Distributed Database

- Spanner from Google [CJC12] – focus on maintaining cross data centre replicated data.
  - 2 research contributions.
    - Externally consistent reads & writes (Linearizable)
      - Transaction $T_1$’s timestamp < $T_2$’s if $T_1$ commits earlier than $T_2$
    - Globally consistent reads across the database at any timestamp
  - Key idea is the TrueTime API – exposes clock uncertainty
    - Guarantees on Spanner’s timestamp depends on bounds on uncertainty provided by the implementation.
    - Implementation – uses GPS and atomic clocks based elaborate clock synchronization protocols to minimize uncertainty.
    - Uses Paxos algorithm [LL98] within each Data centre at Tablet level.
    - Directory/bucket – set of contiguous keys

[CJC12] Corbett, James C; Dean, Jeffrey; Epstein, Michael; Fikes, Andrew; Frost, Christopher; Furman, JJ; Ghemawat, Sanjay; Gubarev, Andrey et al., "Spanner: Google’s Globally-Distributed Database", Proceedings of Usenix Conference on Operating System Design and Implementation (OSDI) 2012 (Google).