Berkeley Data Analytics Stack (BDAS) Overview

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amplab UC BERKELEY

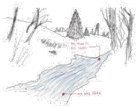
What is Big Data used For?

- Reports, e.g.,
  - Track business processes, transactions
- Diagnosis, e.g.,
  - Why is user engagement dropping?
  - Why is the system slow?
  - Detect spam, worms, viruses, DDoS attacks
- Decisions, e.g.,
  - Decide what feature to add
  - Decide what ad to show
  - Block worms, viruses, …

Data is only as useful as the decisions it enables

Data Processing Goals

- **Low latency (interactive) queries on historical data:** enable faster decisions
  - –E.g., identify why a site is slow and fix it

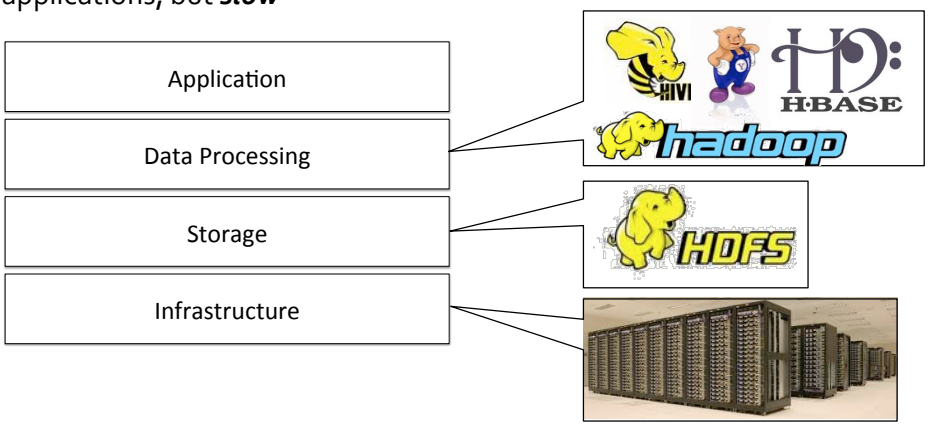


- **Low latency queries on live data (streaming):** enable decisions on real-time data
  - –E.g., detect & block worms in real-time (a worm may infect **1mil** hosts in **1.3sec**)

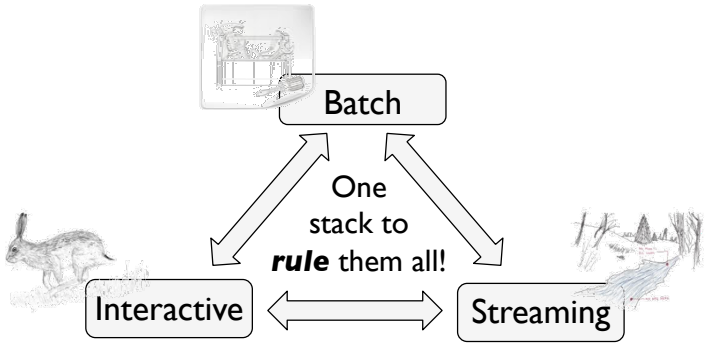
- **Sophisticated data processing:** enable "better" decisions
  - –E.g., anomaly detection, trend analysis

Today's Open Analytics Stack…

- ..mostly focused on large on-disk datasets: great for sophisticated ***batch*** applications, but ***slow***



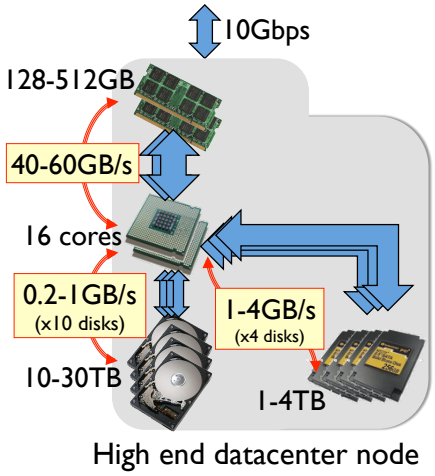
Goals



- ***Easy*** to combine ***batch***, ***streaming***, and ***interactive*** computations
- ***Easy*** to develop ***sophisticated*** algorithms
- ***Compatible*** with existing open source ecosystem (Hadoop/HDFS)

Our Approach: Support Interactive and Streaming Comp.

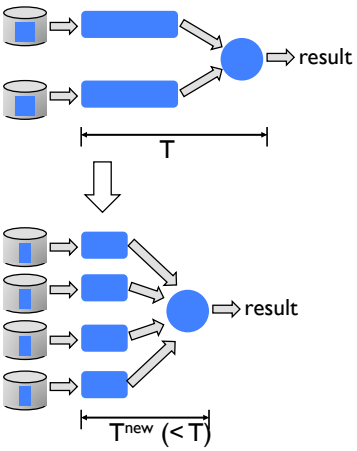
- Aggressive use of ***memory***
- Why?
  1. Memory transfer rates >> disk or even SSDs
     - Gap is growing especially w.r.t. disk
  2. Many datasets already fit into memory
     - The inputs of over 90% of jobs in Facebook, Yahoo!, and Bing clusters fit into memory
     - E.g., 1TB = 1 billion records @ 1 KB each
  3. Memory density (still) grows with Moore's law
     - RAM/SSD hybrid memories at horizon



High end datacenter node

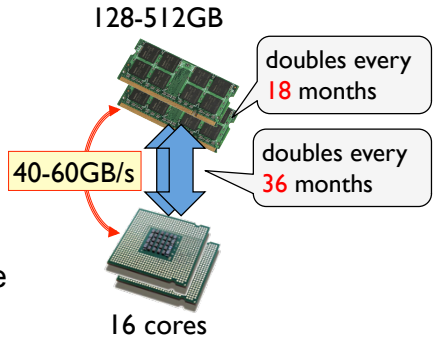
Our Approach: Support Interactive and Streaming Comp.

- Increase ***parallelism***
- Why?
  - –Reduce work per node → improve latency
- Techniques:
  - –Low latency parallel scheduler that achieve high locality
  - –Optimized parallel communication patterns (e.g., shuffle, broadcast)
  - –Efficient recovery from failures and straggler mitigation



Our Approach: Support Interactive and Streaming Comp.

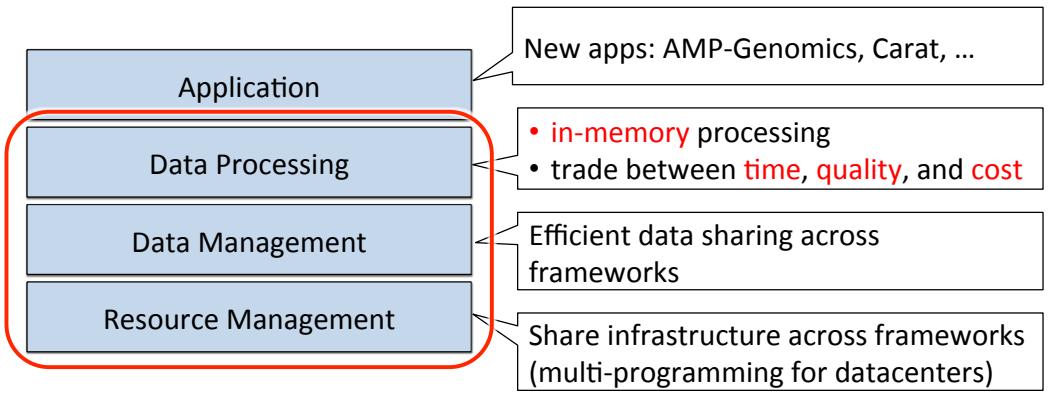
- Trade between result ***accuracy*** and ***response times***
- Why?
  - –In-memory processing does not guarantee interactive query processing
    - •E.g., ~10's sec just to scan 512 GB RAM!
    - •Gap between memory capacity and transfer rate increasing
- Challenges:
  - –accurately estimate error and running time for…
  - –… arbitrary computations



Our Approach

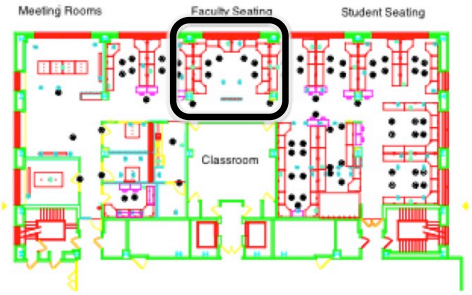
- ***Easy*** to combine ***batch***, ***streaming***, and ***interactive*** computations
  - –Single execution model that ***supports*** all computation models
- ***Easy*** to develop ***sophisticated*** algorithms
  - –Powerful Python and Scala shells
  - –High level abstractions for graph based, and ML algorithms
- ***Compatible*** with existing open source ecosystem (Hadoop/HDFS)
  - –Interoperate with existing storage and input formats (e.g., HDFS, Hive, Flume, ..)
  - –Support existing execution models (e.g., Hive, GraphLab)

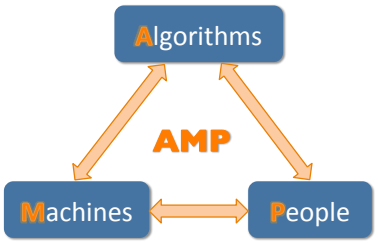
Berkeley Data Analytics Stack (BDAS)



The Berkeley AMPLab

- "Launched" January 2011: 6 Year Plan
  - 8 CS Faculty
  - ~40 students
  - 3 software engineers
- Organized for collaboration:





The Berkeley AMPLab

- Funding:
  - DARPA ata, NSF Expedition Grant
  - Industrial, founding sponsors
  - 18 other sponsors, including

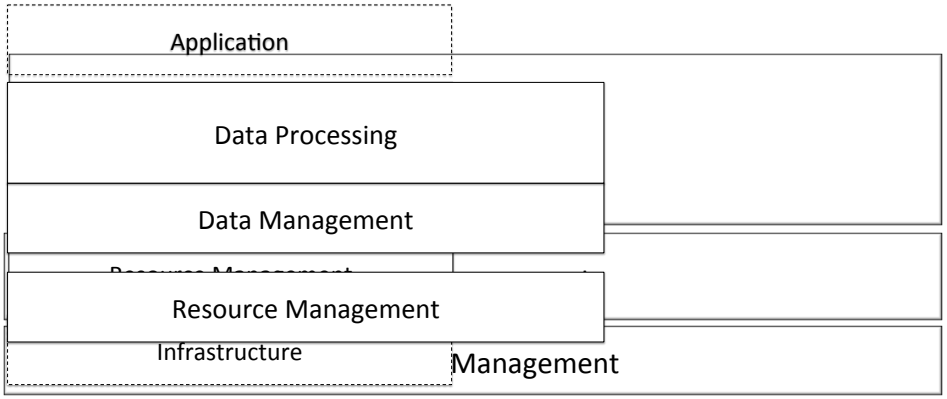
amazon.com web services, Google, SAP

Microsoft, cisco, intel, ORACLE, YAHOO!, facebook, GE imagination at work, cloudera, Hortonworks

Goal: next Generation of open source analytics stack for industry & academia:

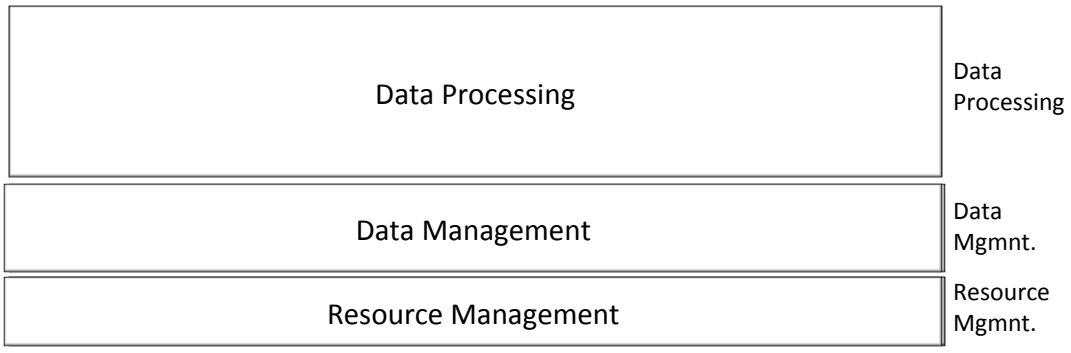
- **Berkeley Data Analytics Stack (BDAS)**

Berkeley Data Analytics Stack (BDAS)



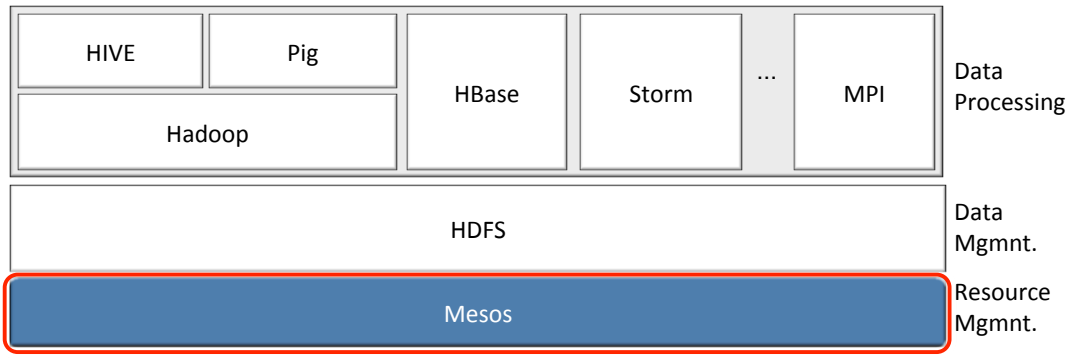
Berkeley Data Analytics Stack (BDAS)

- Existing stack components….



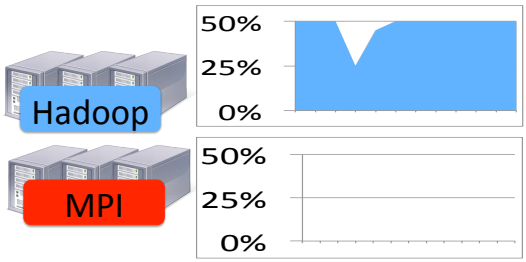
Mesos [Released, v0.9]

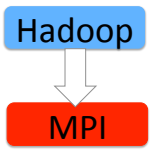
- Management platform that allows multiple framework to share cluster
- Compatible with existing open analytics stack
- Deployed in production at Twitter on 3,500+ servers



One Framework Per Cluster Challenges

- Inefficient resource usage
  - –E.g., Hadoop cannot use available resources from MPI's cluster
  - –No opportunity for stat. multiplexing
- Hard to share data
  - –Copy or access remotely, expensive
- Hard to cooperate
  - –E.g., Not easy for MPI to use data generated by Hadoop

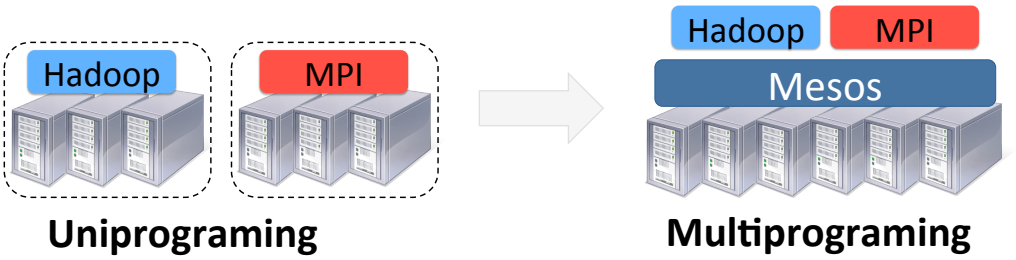




Need to run multiple frameworks on same cluster

Solution: Mesos

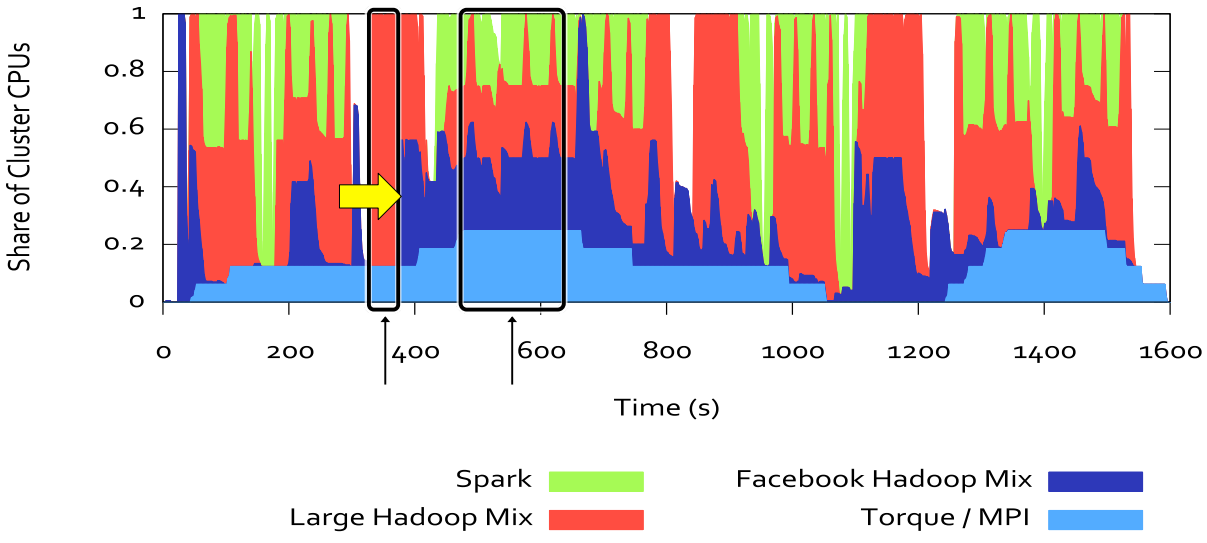
- Common resource sharing layer
  - –abstracts ("virtualizes") resources to frameworks
  - –enable diverse frameworks to share cluster



Uniprograming **Multiprograming**

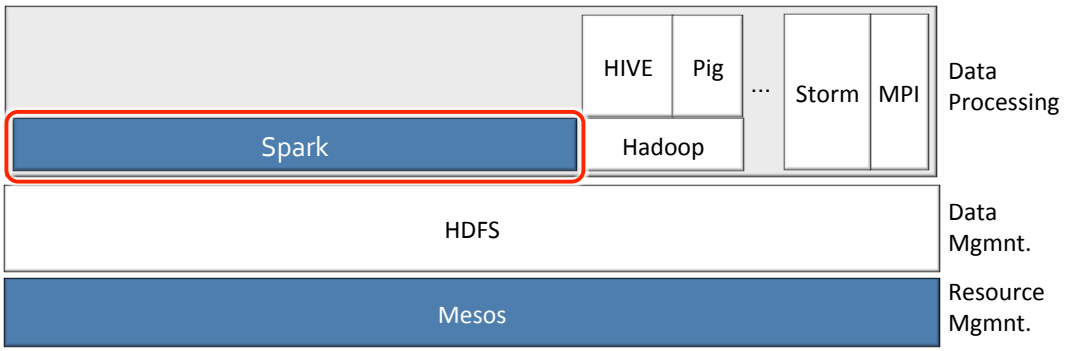
Dynamic Resource Sharing

- 100 node cluster



Spark [Release, v0.7]

- In-memory framework for **interactive** and **iterative** computations
  - Resilient Distributed Dataset **(RDD)**: fault-tolerance, in-memory storage abstraction
- Scala interface, Java and Python APIs

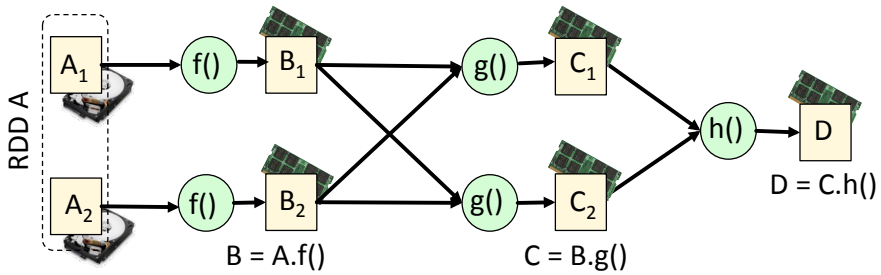


Our Solution

- **Resilient Distributed Data Sets (RDD)**
  - Partitioned collection of records
  - Immutable
  - Can be created only through deterministic operations from other RDDs
- Handle of each RDD stores its **lineage**:
  - Lineage: sequence of operations that created the RDD
- Recovery: use lineage information to rebuild RDD

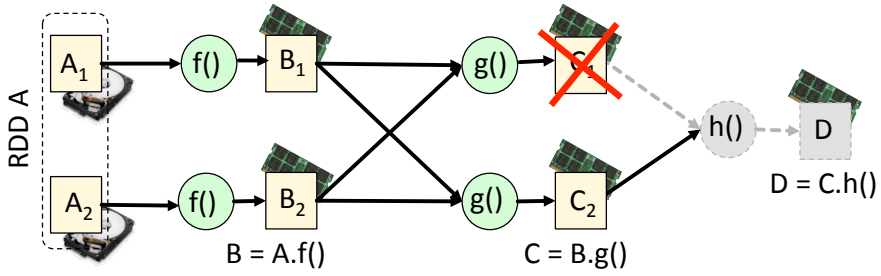
RDD Example

- Two-partition RDD A={A_1, A_2} stored on disk
  1) Apply f() and cache → RDD B
  2) Shuffle, and apply g() → RDD C
  3) Aggregate using h() → D



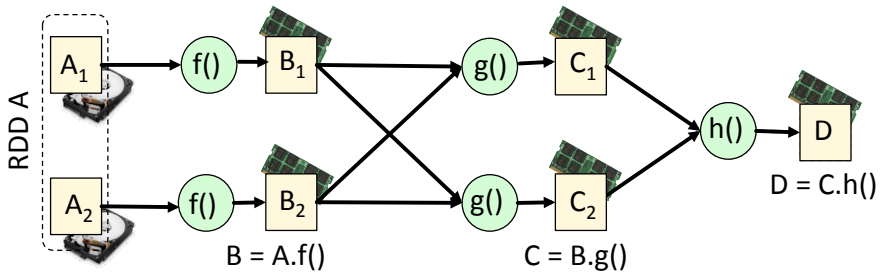
RDD Example

- C_1 lost due to node failure before h() is computed

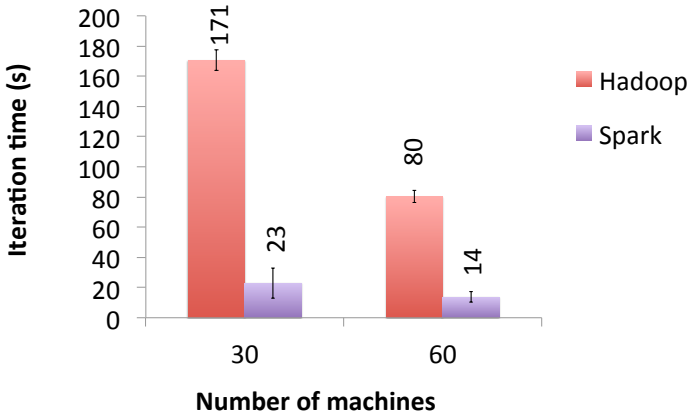


RDD Example

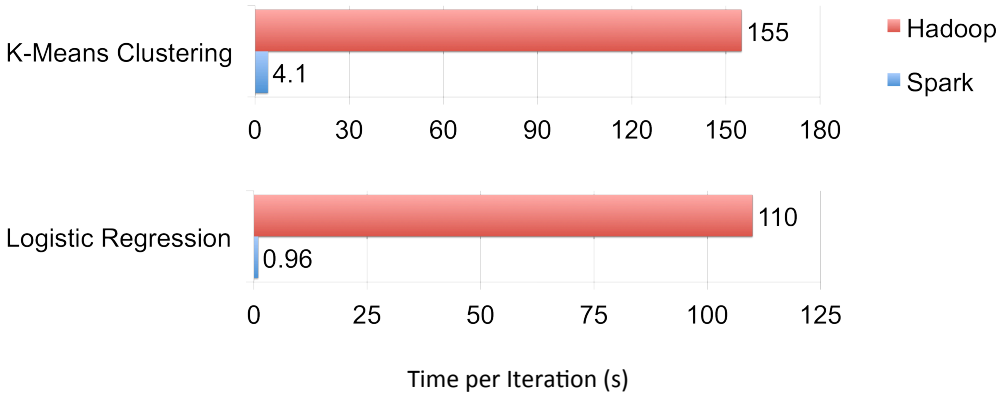
- C_1 lost due to node failure before h() is computed
- Reconstruct C_1, eventually, on a different node



PageRank Performance



Other Iterative Algorithms



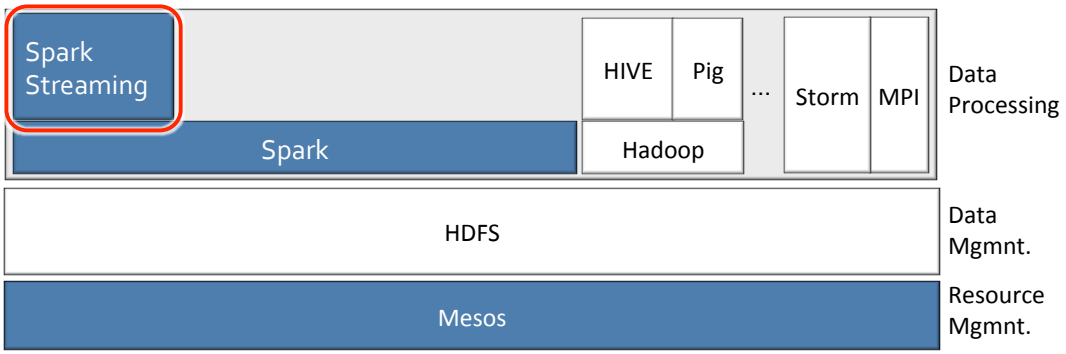
Spark Community

- 3000 people attended online training in August
- 500+ meetup members
- 14 companies contributing

spark-project.org

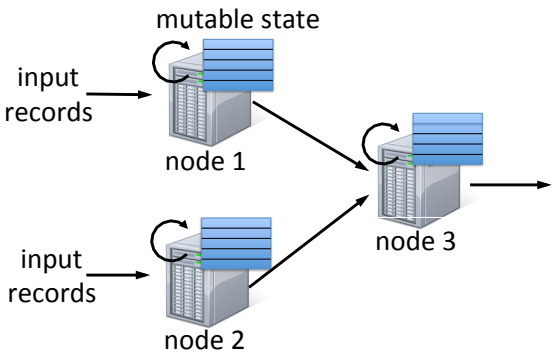
Spark Streaming [Alpha Release]

- Large scale streaming computation
- Ensure exactly one semantics
- Integrated with Spark → unifies ***batch***, ***interactive***, and ***streaming*** computations!



Existing Streaming Systems

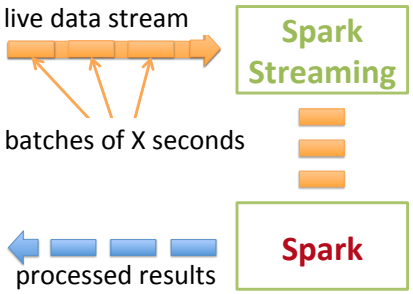
- Traditional streaming systems have a event-driven **record-at-a-time** processing model
  - –Each node has mutable state
  - –For each record, update state & send new records
- State is lost if node dies!
- Making stateful stream processing be fault-tolerant is challenging



Spark: Discretized Stream Processing

Run a streaming computation as a **series of very small, deterministic batch jobs**

- Chop up the live stream into batches of X seconds
- Spark treats each batch of data as RDDs and processes them using RDD operations
- Finally, the processed results of the RDD operations are returned in batches



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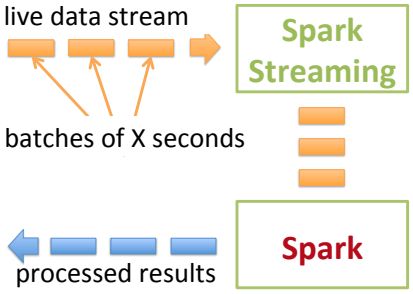
Spark: Discretized Stream Processing

Run a streaming computation as a **series of very small, deterministic batch jobs**

- Batch sizes as low as ½ second, latency ~ 1 sec
- Potential for combining batch processing and streaming processing in the same system



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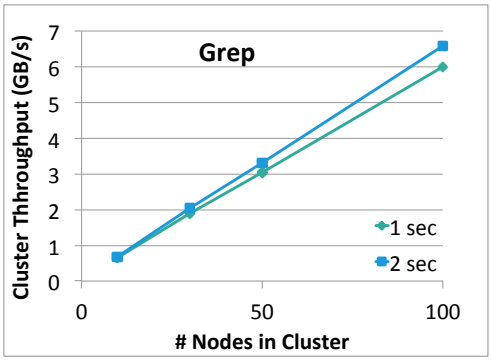
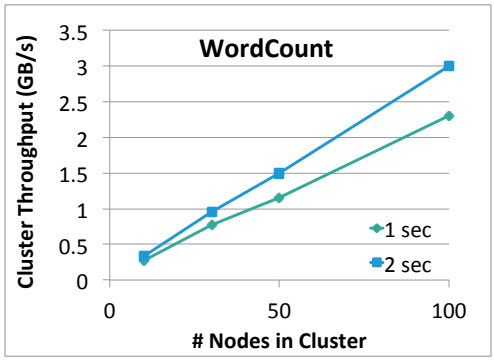
Performance

Can process **6 GB/sec (60M records/sec**) of data on 100 nodes at **sub-second** latency

– Tested with 100 streams of data on 100 EC2 instances with 4 cores each

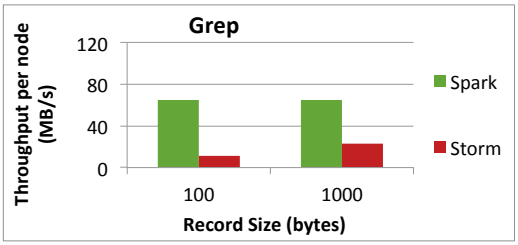


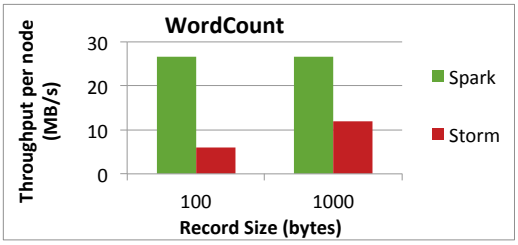


Comparison with Storm and S4

Higher throughput than Storm

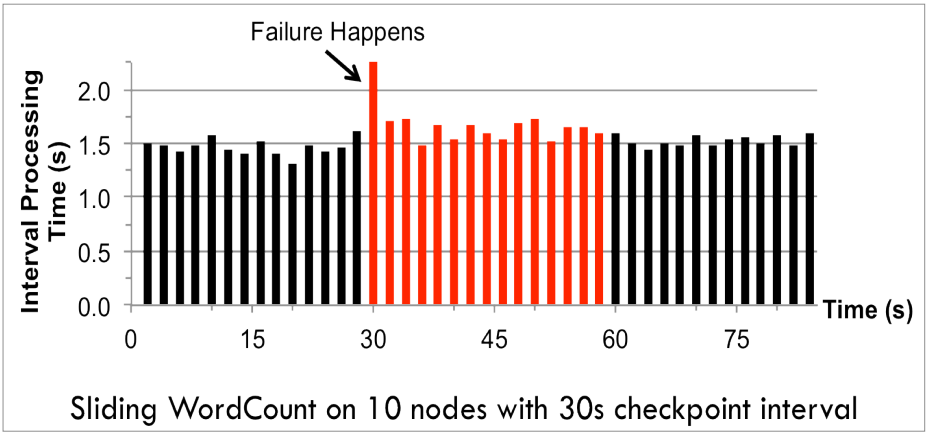
- Spark Streaming: **670k** records/ second/node
- Storm: **115k** records/second/node
- Apache S4: 7.5k records/second/node





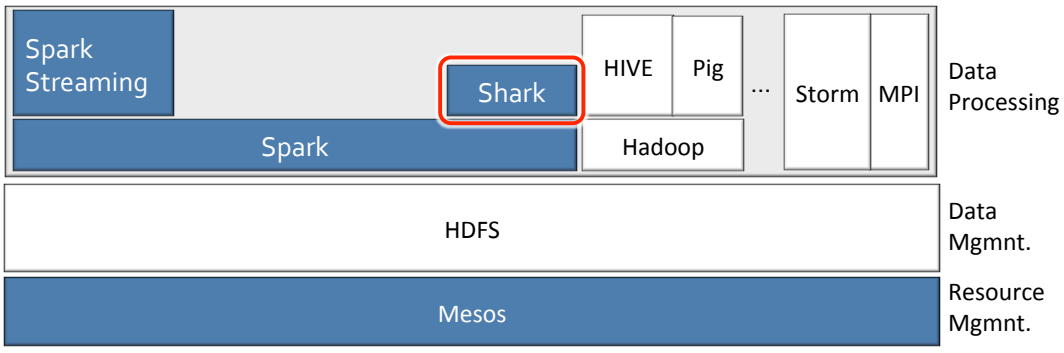
Fast Fault Recovery

Recovers from faults/stragglers within **1 sec**

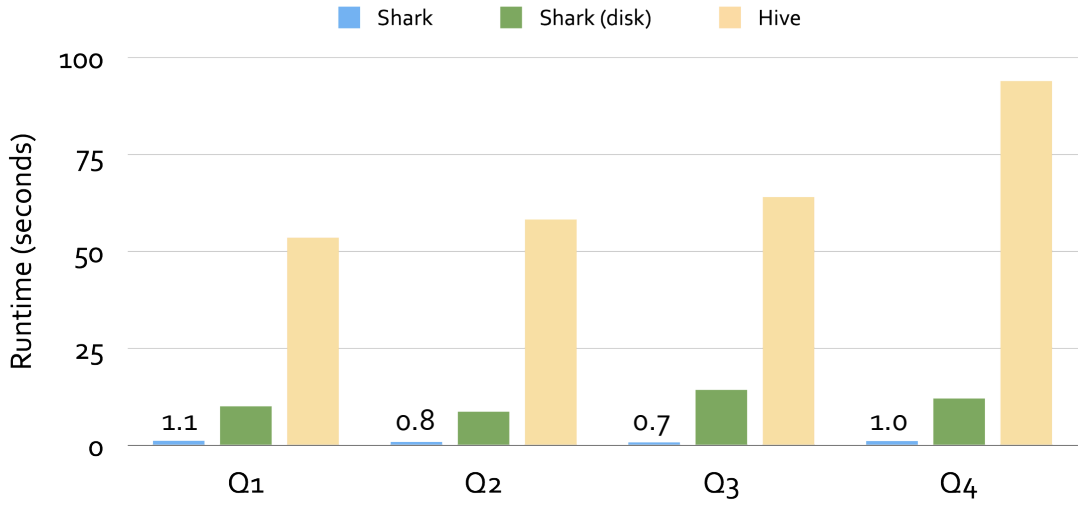


Shark [Release, v0.2]

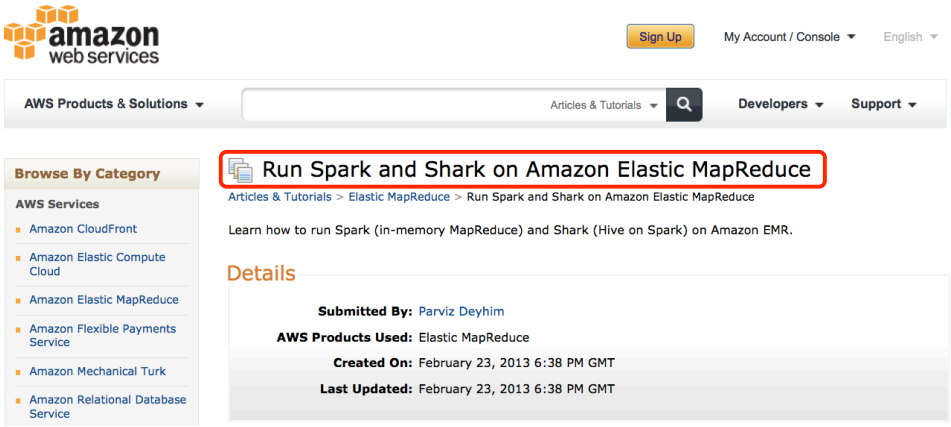
- HIVE over Spark: SQL-like interface (supports Hive 0.9)
  - –up to 100x faster for in-memory data, and 5-10x for disk
- In tests on hundreds node cluster at YAHOO!



Conviva Warehouse Queries (1.7 TB)

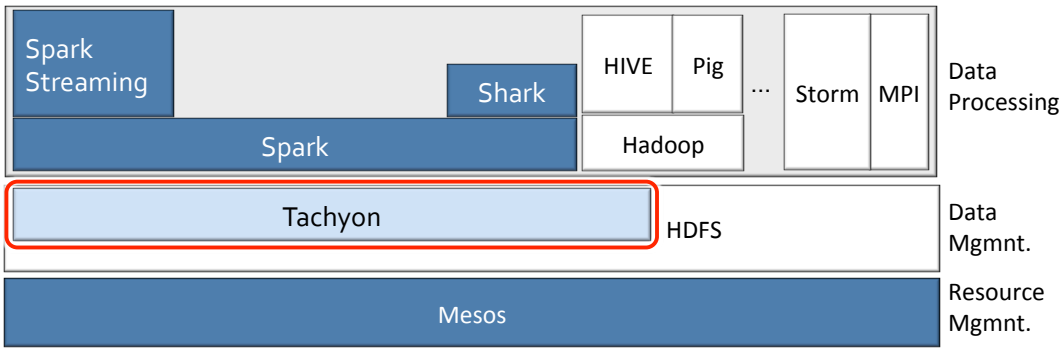


Spark & Shark available now on EMR!



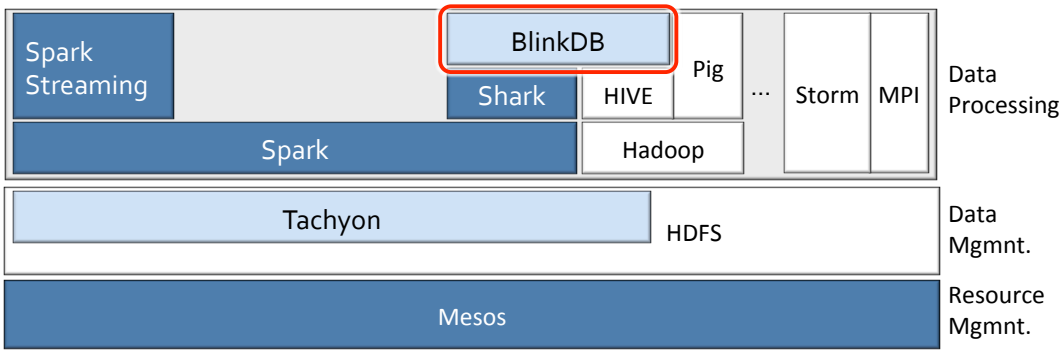
Tachyon [Alpha Release, this Spring]

- High-throughput, fault-tolerant in-memory storage
- Interface compatible to HDFS
- Support for Spark and Hadoop



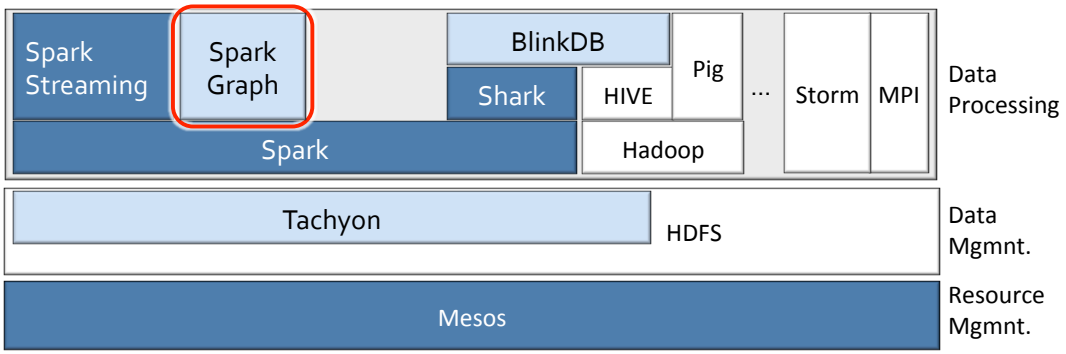
BlinkDB [Alpha Release, this Spring]

- Large scale approximate query engine
- Allow users to specify **error** or **time** bounds
- Preliminary prototype starting being tested at Facebook



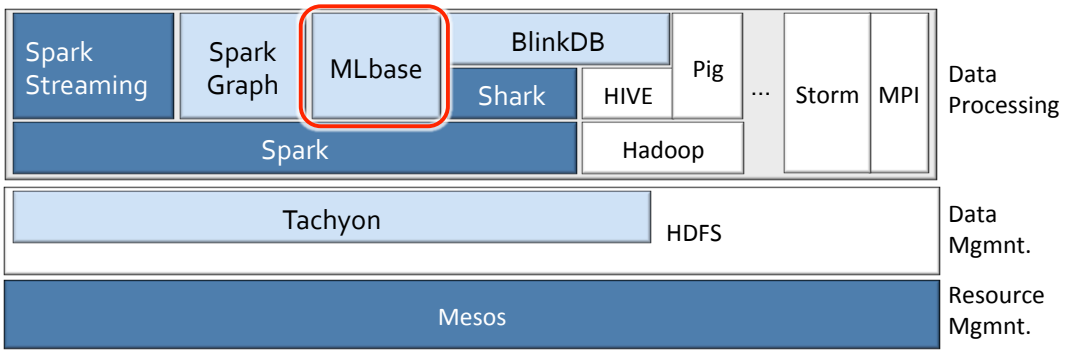
SparkGraph [Alpha Release, this Spring]

- **GraphLab API** and **Toolkits** on top of Spark
- Fault tolerance by leveraging Spark



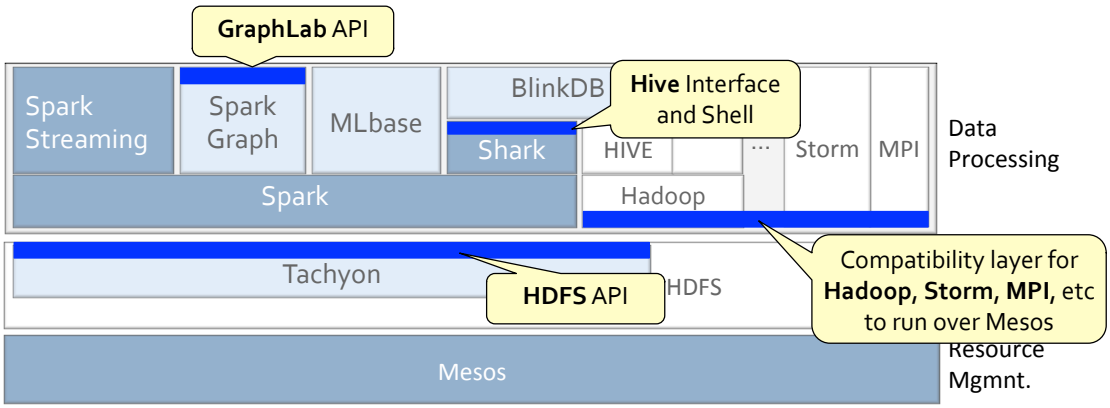
MLbase [In development]

- Declarative approach to ML
- Develop scalable ML algorithms
- Make ML accessible to non-experts



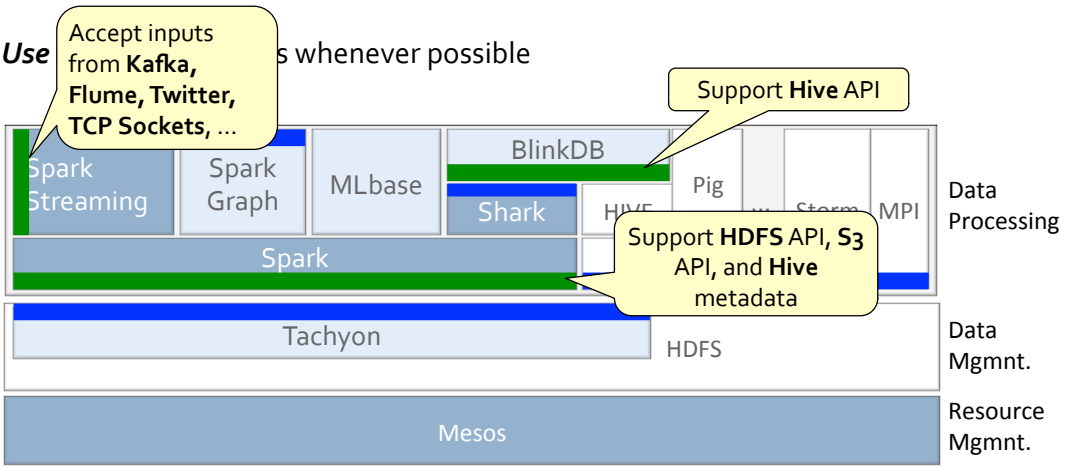
Compatible with Open Source Ecosystem

• ***Support*** existing interfaces whenever possible



Compatible with Open Source Ecosystem

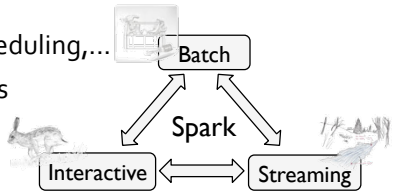
• ***Use*** s whenever possible



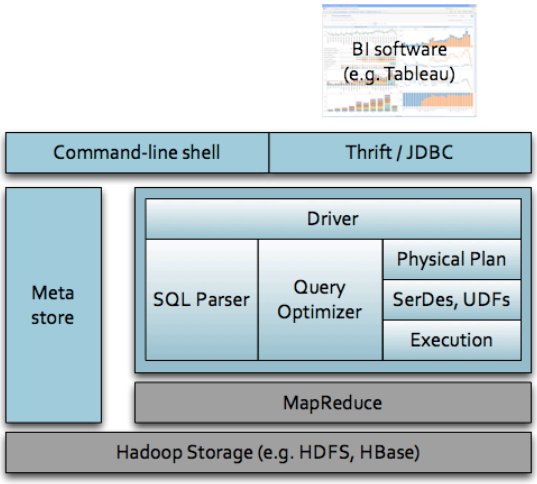
Summary

Holistic approach to address next generation of Big Data challenges!

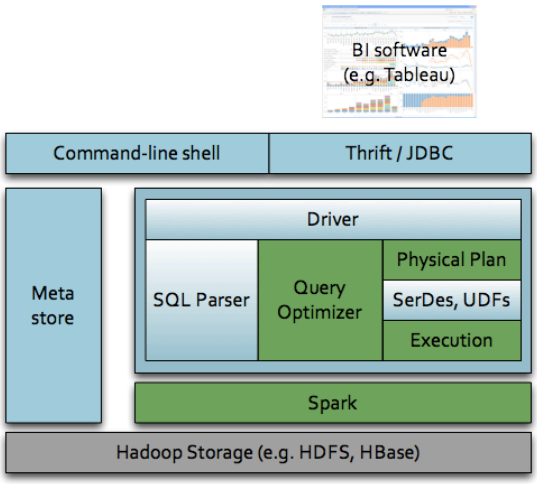
- Support ***interactive*** and ***streaming*** computations
  - –In-memory, fault-tolerant storage abstraction, low-latency scheduling,…
- ***Easy*** to combine ***batch***, ***streaming***, and ***interactive*** computations
  - –Spark execution engine supports all comp. models
- ***Easy*** to develop ***sophisticated*** algorithms
  - –Scala interface, APIs for Java, Python, Hive QL, …
  - –New frameworks targeted to graph based and ML algorithms
- ***Compatible*** with existing open source ecosystem
- ***Open source*** (Apache/BSD) and fully committed to release ***high quality*** software
  - –Three-person software engineering team lead by Matt Massie (creator of Ganglia, 5th Cloudera engineer)



Thanks!



Hive Architecture



Shark Architecture