

Berkeley Data Analytics Stack: Experience and Lesson Learned

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UC Berkeley, Databricks, Conviva



Research Philosophy

Follow real problems Focus on novel usage scenarios Build real systems » Be paranoid about simplicity » Very hard to build complex systems in academia Push for adoption » Develop communities » Train users

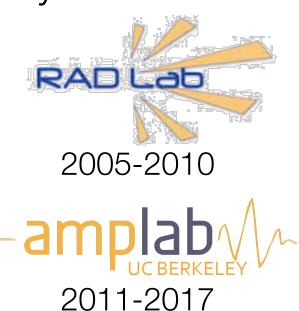
Disclaimer: By no means only way to do research!

A Short History

2006: Start research in cluster computing » Improve MapReduce scheduler (e.g., Fair Scheduler)

2009: Start building a Data Analytics Stack

- » Spring 2009: Mesos
- » Summer 2009: Spark
- »2010: Shark
- »2011: SparkStreaming
- »2012: Tachyon
- »2013: MLlib,



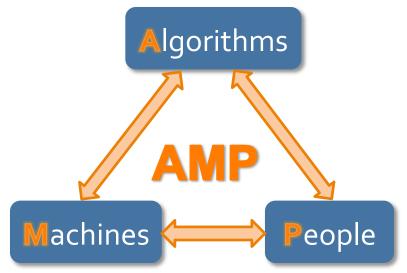
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The Berkeley AMPLab

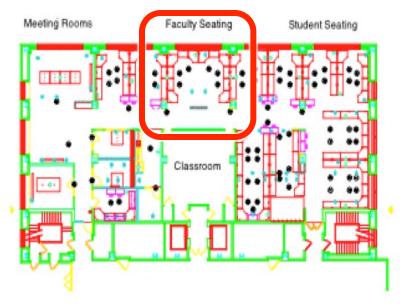
January 2011 – 2017 » 8 faculty

- » > 60 students
- » 3 software engineer team

Organized for collaboration



AMPCamp3 (November, 2014)





3 day retreats (twice a year)

220 campers (100+ companies)

The Berkeley AMPLab

Governmental and industrial funding:



Goal: Next generation of open source data analytics stack for industry & academia: Berkeley Data Analytics Stack (BDAS)

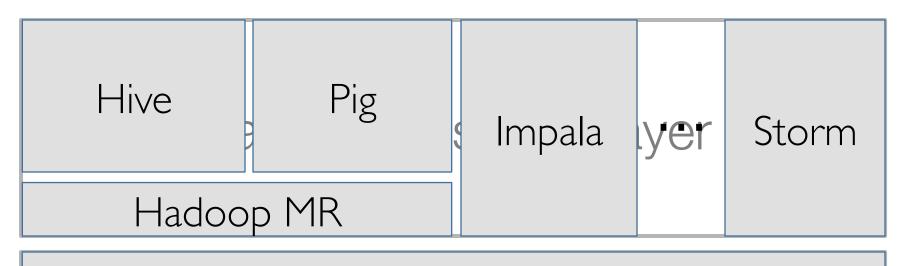
Data Processing Stack

Data Processing Layer

Resource Management Layer

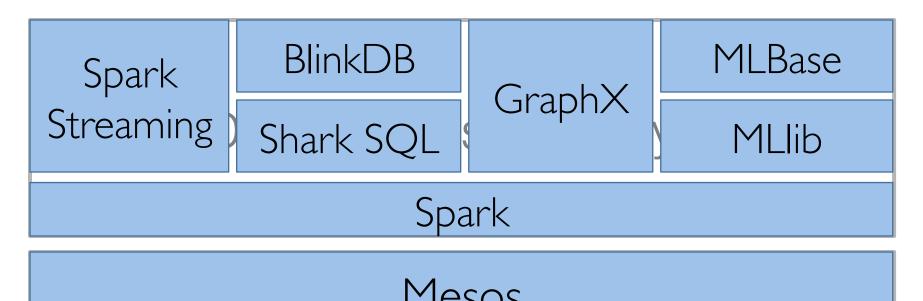
Storage Layer

Hadoop Stack

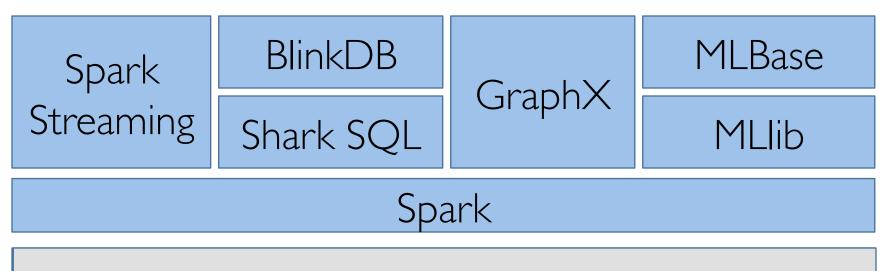


Hadoop Yarn

BDAS Stack

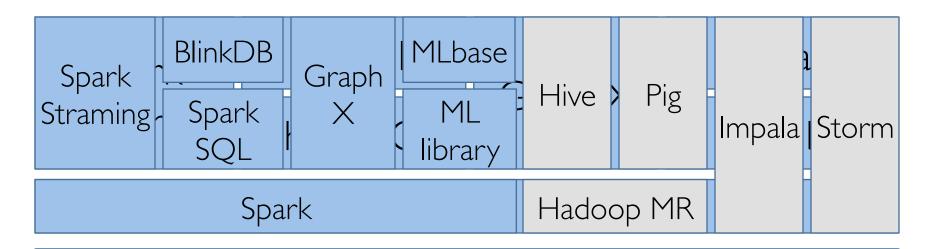


How do BDAS & Hadoop fit together?



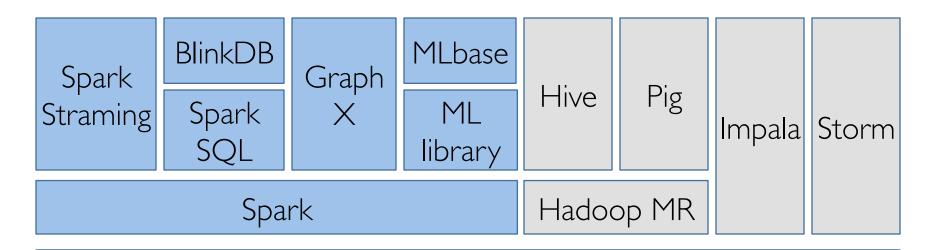
Hadoop Yarn

How do BDAS & Hadoop fit together?



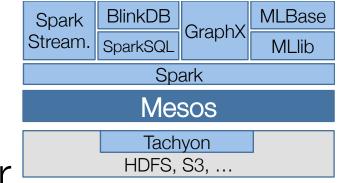
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Hadoop Yarn
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How do BDAS & Hadoop fit together?



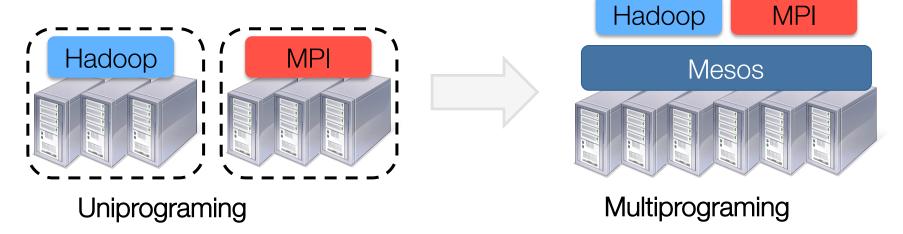
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Hadoop Yarn
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Apache Mesos



Problem: per-framework cluster » Inefficient resource usage » Hard to experiment, upgrade » Hard to share data

Solution: common resource sharing layer » Abstracts ("virtualizes") resources to frameworks » Enable diverse frameworks to share cluster



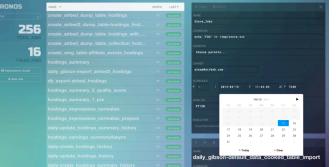
Apache Mesos

Open Source: 2010 (first release: 10,000 LoC)

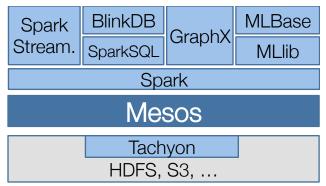
Apache Project: 2012

Used in production at Twitter for past 2.5 years » +10,000 machines » +500 engineers using it

Third party Mesos schedulers » AirBnB's Chronos » Twitter's Aurora



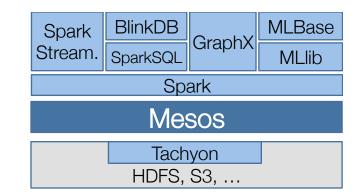
Mesospehere: startup to commercialize Mesos

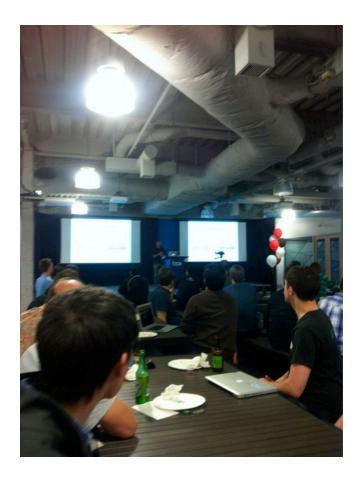


Mesos Meetups

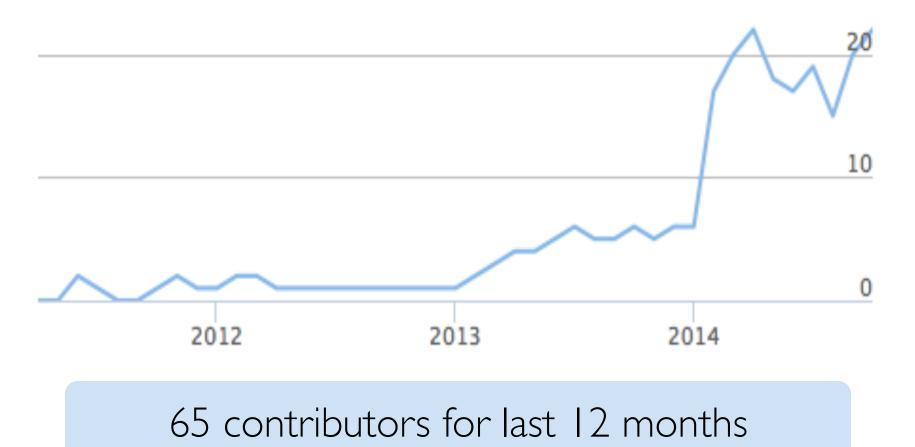
Sept 2012: started Bay Area Spark Meetup »Now +800 members

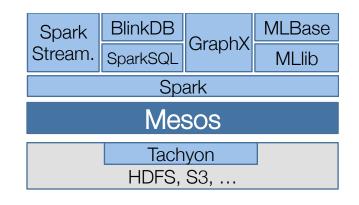
Other user groups: »+700 members » New York, Atlanta, Seattle, Los Angeles, Paris (France), Amsterdam (Netherlands), London (UK)













HubSpot

Selected Users

airbnb

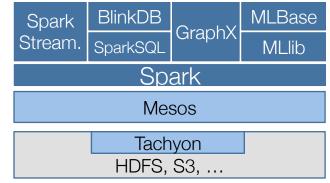
Atlassian

NETFLIX





Apache Spark



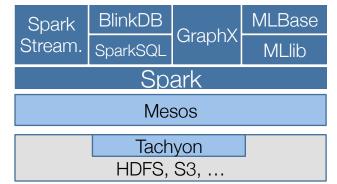
Problem: Need to support workloads beyond batch (MapReduce)

» Interactive, streaming, iterative (ML), graph processing

Motivating use cases:

» Iterative computations (ML researchers in RADLab)
» Interactive queries (Conviva, Facebook)

Apache Spark



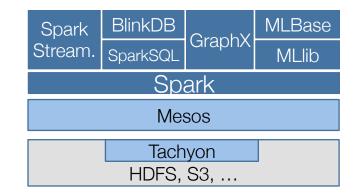
Distributed Execution Engine » Fault-tolerant, efficient in-memory storage » Low-latency large-scale task scheduler » Powerful prog. model and APIs: Python, Java, Scala

Fast: up to 100x faster than Hadoop MR » Can run sub-second jobs on hundreds of nodes

Easy to use: 2-5x less code than Hadoop MR

General: support interactive & iterative apps

Apache Spark



Open Source: end of 2010 (<3,000 LoC, Scala)

Apache Project: 2013

Over time has grown to include key components (everyone being motivated by Spark use in prod.) » Shark (2010) → SparkSLQ (2014) » SparkStreaming (2011) » MLlib (2013)

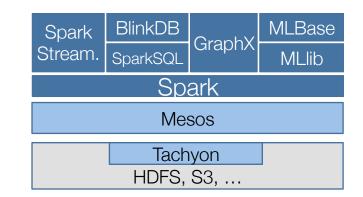
» GraphX (2014)

On its way to become the platform of choice for developing Big Data applications

Spark Meetups

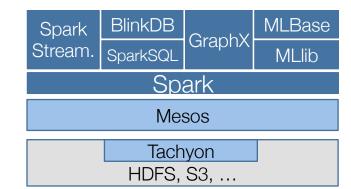
Jan 2012: started Bay Area Spark Meetup »+3100 members

Now » 33 cities » 13 countries





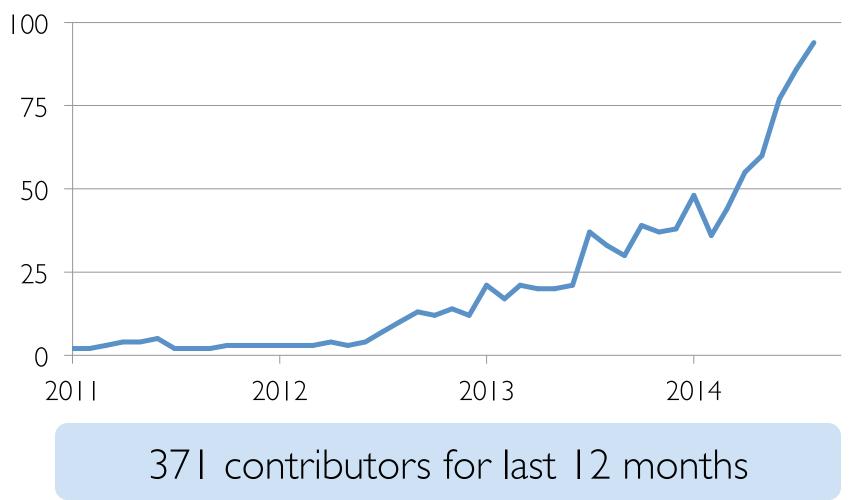
Meetups Around the World



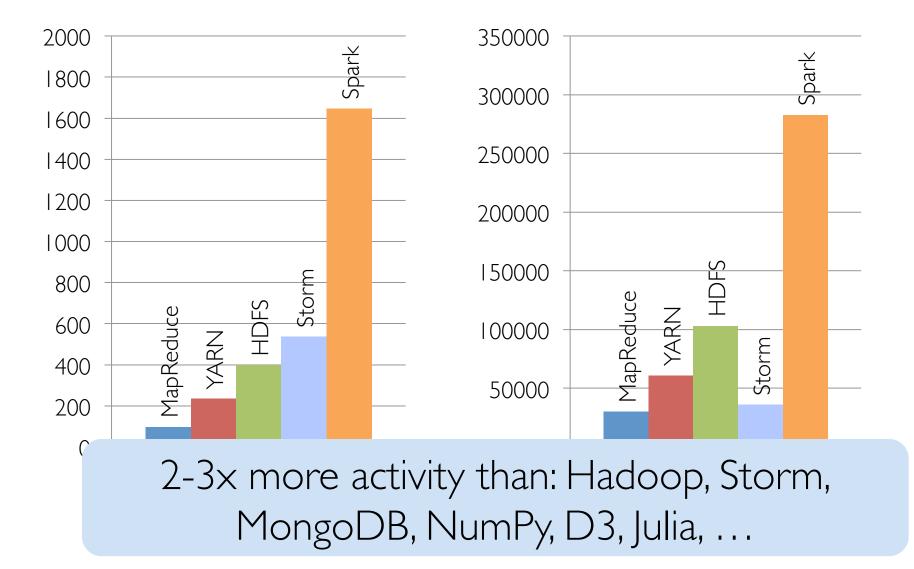


Groups	Members	Interested	Cities	Countries
40	10,900	795	33	13

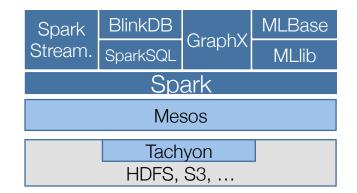




Compared to Other Projects



Wide Adoption

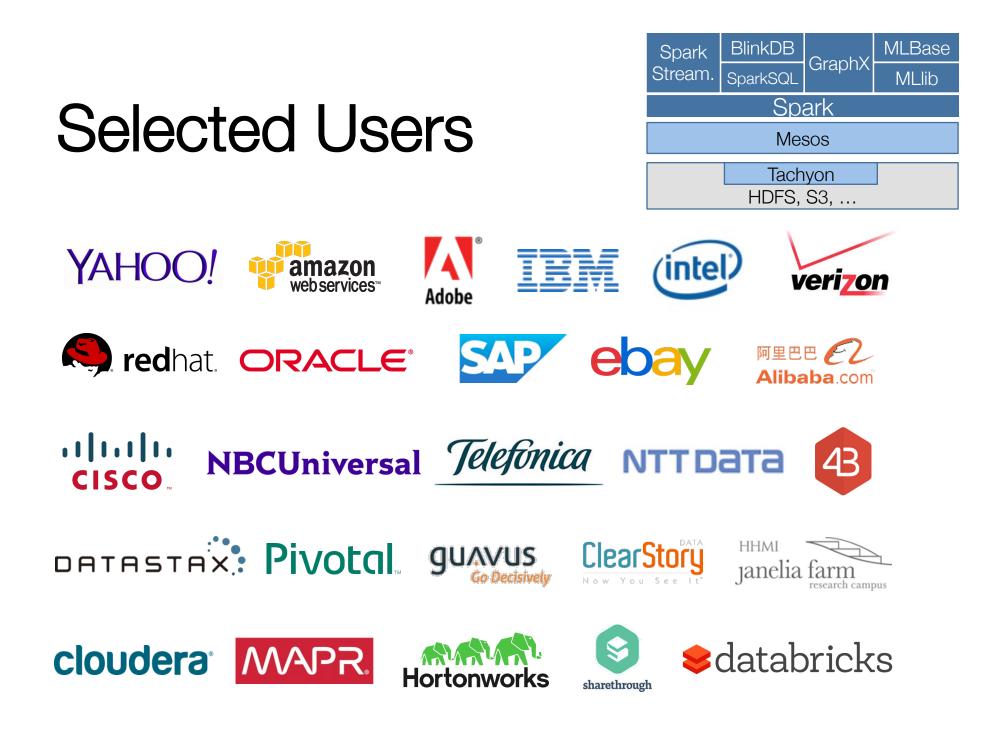


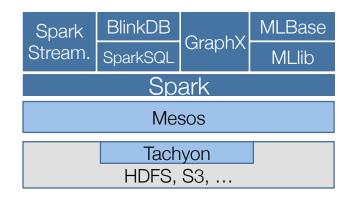
All major Hadoop distributions include Spark



Beyond Hadoop









Events

December 2013 Talks from 22 organizations

450 attendees



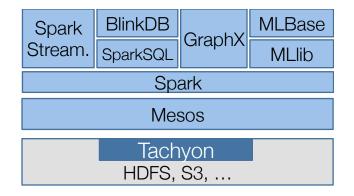
June 2014

Talks from 50 organizations

1100 attendees

spark-summit.org

Tachyon

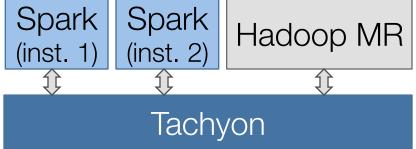


Problem:

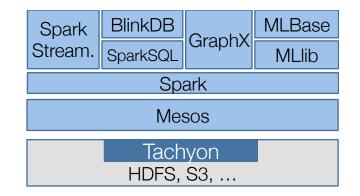
» Different Spark contexts cannot share in-mem data

Solution:

- » Flexible API, including HDFS API
- » Allow multiple frameworks (including Hadoop) to share in-memory data

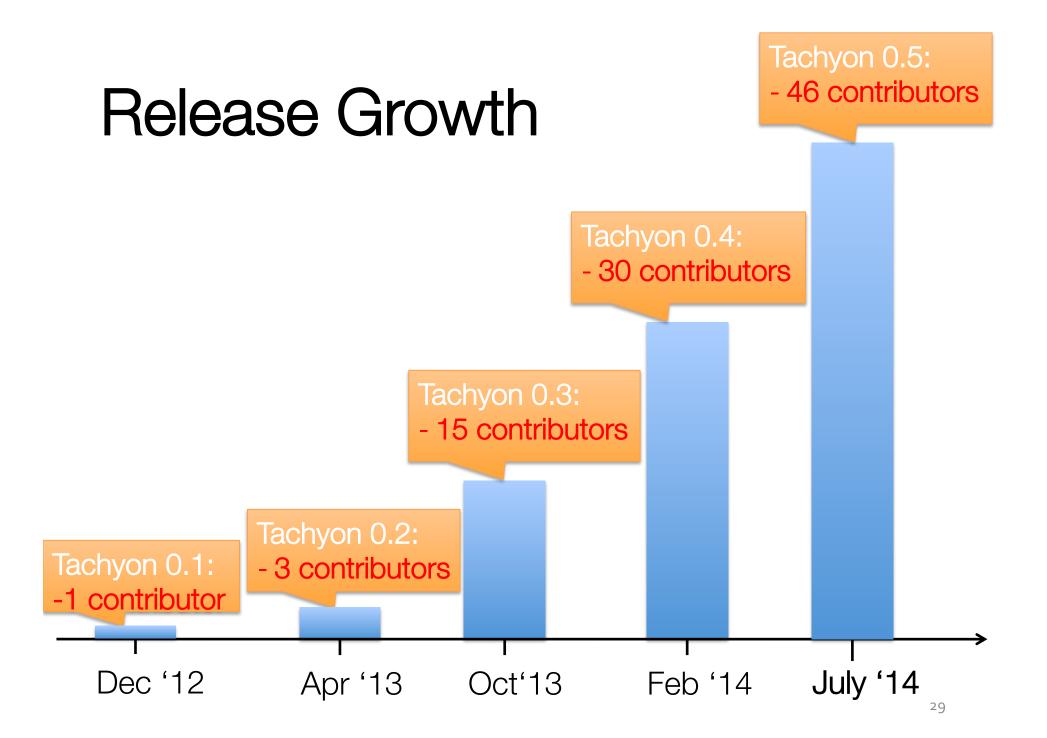


Tachyon



Open Source: Dec 2012 (<10,000 LoC)

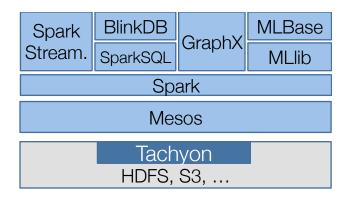
Becoming narrow waist for storage in Big Data space



Spark	BlinkDB	Crophy	MLBase			
Stream.	SparkSQL	GraphX	MLlib			
Spark						
Mesos						
Tachyon						
	HDFS,	S3,	_			

Open Community

- Berkeley Contributors
- Non-Berkeley Contributors
 (20+ companies)



Selected Users









Pivotal...





ClearStory



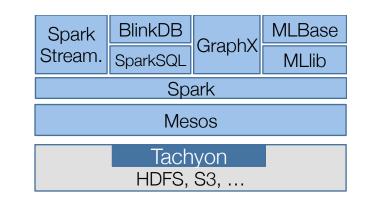
Q Palantir

Multiple File System Choices







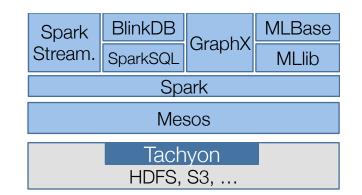








Reaching TippingPointPivotalThe Future ArchiteIn-memory Data EUsing Tachyon and



The Future Architecture of a Data Lake: In-memory Data Exchange Platform Using Tachyon and Apache Spark

OCTOBER 14, 2014 | NEWS | BY PAUL M. DAVIS



Pivotal and EMC are betting on Spark cousin Tachyon as inmemory file system

by Derrick Harris OCT. 14, 2014 - 11:47 AM PDT



Pivotal bets on Tachyon as next inmemory file system



Pivotal Expands on Data Lake Vision with Embrace of Project Tachyon

Oct 14, 2014

Training: Integral Part of Success

Aug 2012: AMP Camp training workshop » 150 in-person, 3000 online » Now a regular event (Strata NY, training +450 people)



Not Only Industrial Impact...

10s of papers at top conferences »SOSP, SIGCOMM, SIGMOD, NIPS, VLDB, OSDI, NSDI, ...

6 Best Paper Awards » SIGCOMM, NSDI, EuroSys (2), ICML, ICDE

Great crop of students »Last two years: MIT (3), Stanford (1), MSR, ...

Open new research directions » Resource allocation / microeconomy (DRF) » Machine learning (Bootstrap Diagnosis)

And Even Saving Lives!

Scalable Nucleotide Alignment (SNAP) » 3x-10x faster than state of art with same accuracy

ADAM Pipeline » In use at the Broad Institute, Duke, Harvard, USCS » 10x-50x faster than state of art



Already saving lives!

» See "SNAP Helps Discover Infection" AMPLab blog 6/4/14 and M. Wilson, ..., & C. Chiu, "Actionable Diagnosis of Neruoleptospirosis by Next-Generation Sequencing," New England Journal of Medicine, 6/4/14

Research Philosophy

Follow real problems Focus on novel usage scenarios Build real systems » Be paranoid about simplicity » Very hard to build complex systems in academia Push for adoption » Develop communities » Train users

Two Types of Research Proj.

New systems

» Inspired from people using ours/existing systems
» E.g., Spark, Shark/SparkSQL, MLlib,
SparkStreaming, Tachyon, ...

New algorithms, techniques, optimizations »Workload traces from large clusters (e.g., Facebook, Conviva)

» E.g., LATE, Sparrow, PACMan, Scarlett, ...

Challenge: Public Clouds

Hugely convenient and powerful »E.g., we won Terabyte sort benchmark this year using 206 AWS instances

- 3x faster, 10x fewer machines than last year (Yahoo!)
- »Whatever you deploy on AWS/Azure/GC can be used by anyone
 - Large pool of users (beyond academia)
 - Easy to train
- » Large public data sets already available http://aws.amazon.com/datasets/

Why Use Experimental Testbeds?

Control and visibility

» Bare-metal servers

• Some clouds do provide this: Rackspace, DigitalOcean » SDN networks, RDMAs, ...

Re-configurability, heterogeneity

Free!

Enable end-to-end / cross-layer optimizations

What about Data and Apps?

Ideally, unique data not found on other clouds

Example:

- » Fine grained logs/traces of cloud usage (public clouds cannot provide this)
- » Scientific data (?)

Applications

- »Ability to run existing systems/apps (need to maintain them!)
- » New education apps (?)

Conclusions

Have right expectations, key to success!

Be aware that:

- » Public clouds cover a big range of needs for system research
- » Insights for new use cases unlikely to come from these testbeds

Focus on what is unique:

 » Cross-layer optimization exploiting access to network (SDN, RDMA), storage, bare-bone servers
» Make available unique data sets (e.g., fine grained logs)