

Berkeley Data Analytics Stack (BDAS)

Ion Stoica

UC Berkeley / Databricks / Conviva



YAHOO!



facebook

Microsoft



ORACLE

SAMSUNG



ERICSSON



vmware

ClearStory
Now You See It

cloudera



Hortonworks

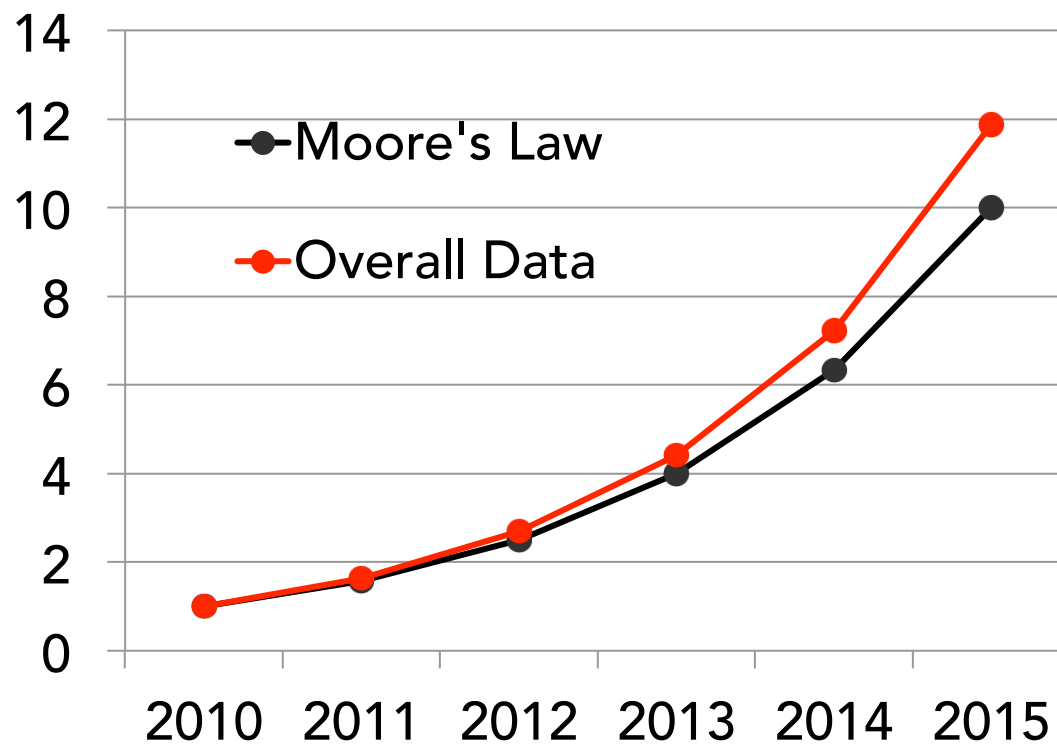
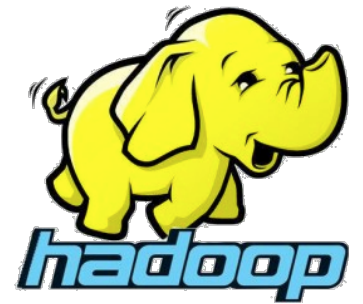
splunk

wanDISCO

Data is Everywhere

Easier and cheaper than ever to collect

Data grows faster than Moore's law



(IDC report*)

The New Gold Rush

Everyone wants to extract value from data

» Big companies & startups alike



Huge potential

» Already demonstrated by Google, Facebook, ...

But, untapped by most companies

» “We have lots of data but no one is looking at it!”

Extracting Value from Data Hard

Data is massive, unstructured, and dirty

Questions are complex

Processing, analysis tools still in their “infancy”

Need tools that are

- » Faster
- » More sophisticated
- » Easier to use

Turning Data into Value

Insights, diagnosis, e.g.,

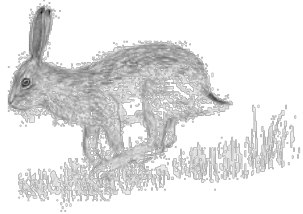
- » Why is user engagement dropping?
- » Why is the system slow?
- » Detect spam, DDoS attacks

Decisions, e.g.,

- » Decide what feature to add to a product
- » Personalized medical treatment
- » Decide when to change an aircraft engine part
- » Decide what ads to show

Data only as useful as the decisions it enables

What do We Need?



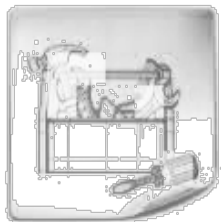
Interactive queries: enable faster decisions

» E.g., identify why a site is slow and fix it



Queries on streaming data: enable decisions on real-time data

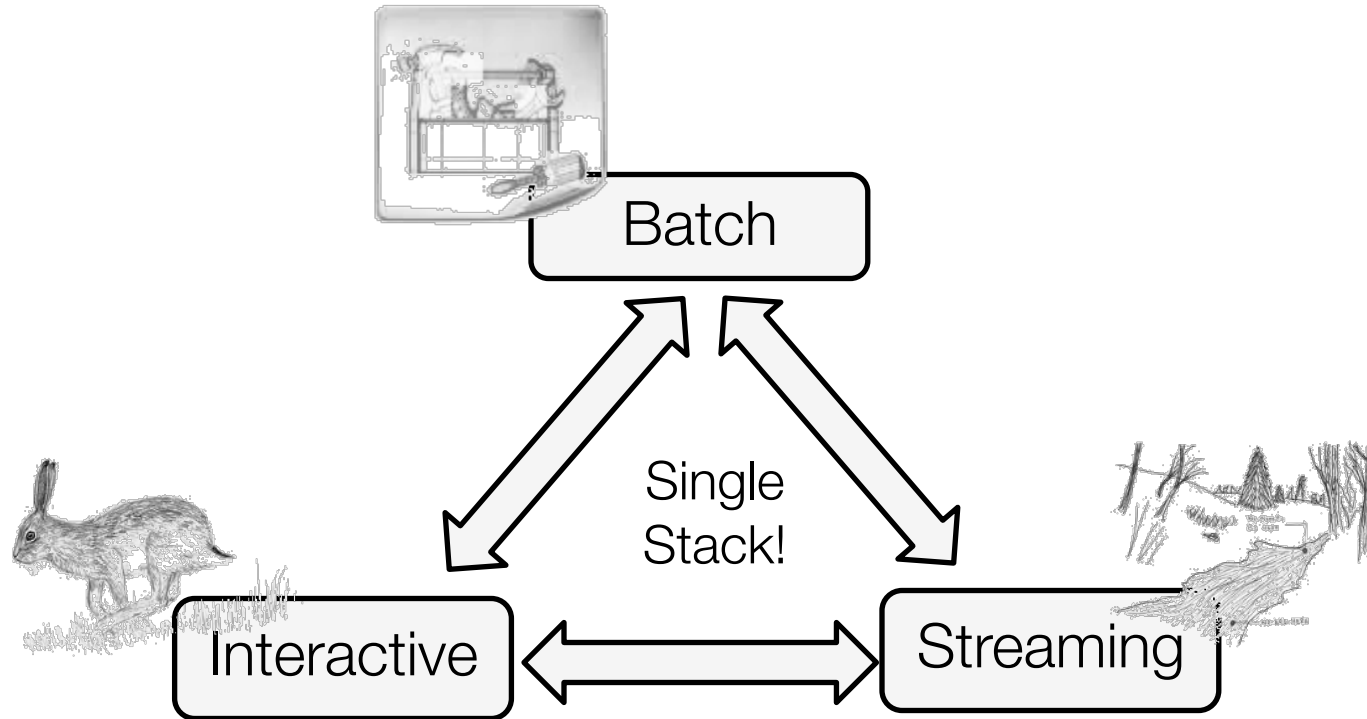
» E.g., fraud detection, detect DDoS attacks



Sophisticated data processing: enable “better” decisions

» E.g., anomaly detection, trend analysis

Our Goal



Support *batch*, *streaming*, and *interactive* computations...
... in a unified framework

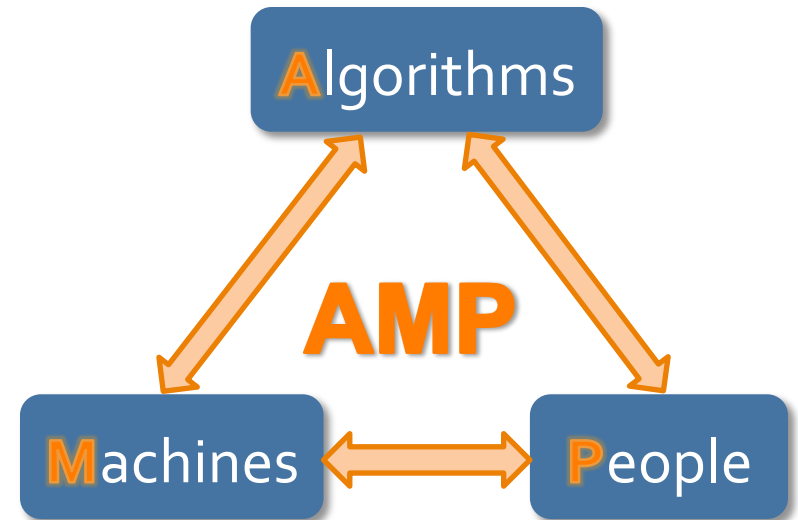
Easy to develop *sophisticated* algorithms (e.g., graph, ML algos)

The Berkeley AMPLab

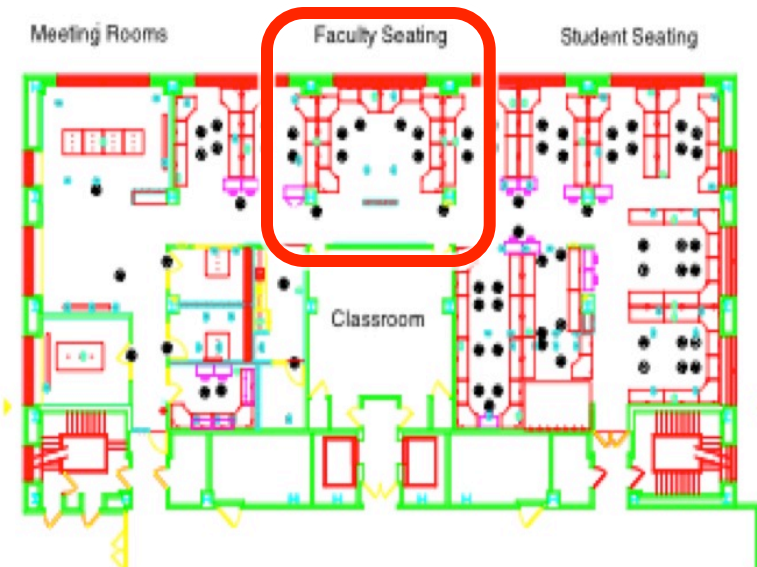
January 2011 – 2017

- » 8 faculty
- » > 40 students and postdocs
- » 3 software engineer team

Organized for collaboration



AMPCamp3
(August, 2013)



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)

BDAG Cluster (Feb 2010)

Enable multiple frameworks to share same cluster resources (e.g., Hadoop, Storm, Spark) (2009)

Scale to thousands of servers (e.g., Twitter)

Third party schedulers, e.g., Chronos, Aurora

Mesos

HDFS, S3, ...



Releases



Research Projects



3rd party

BDAS Stack (Feb, 2013)

Data Processing Layer

Spark

Distributed Execution Engine (2009)

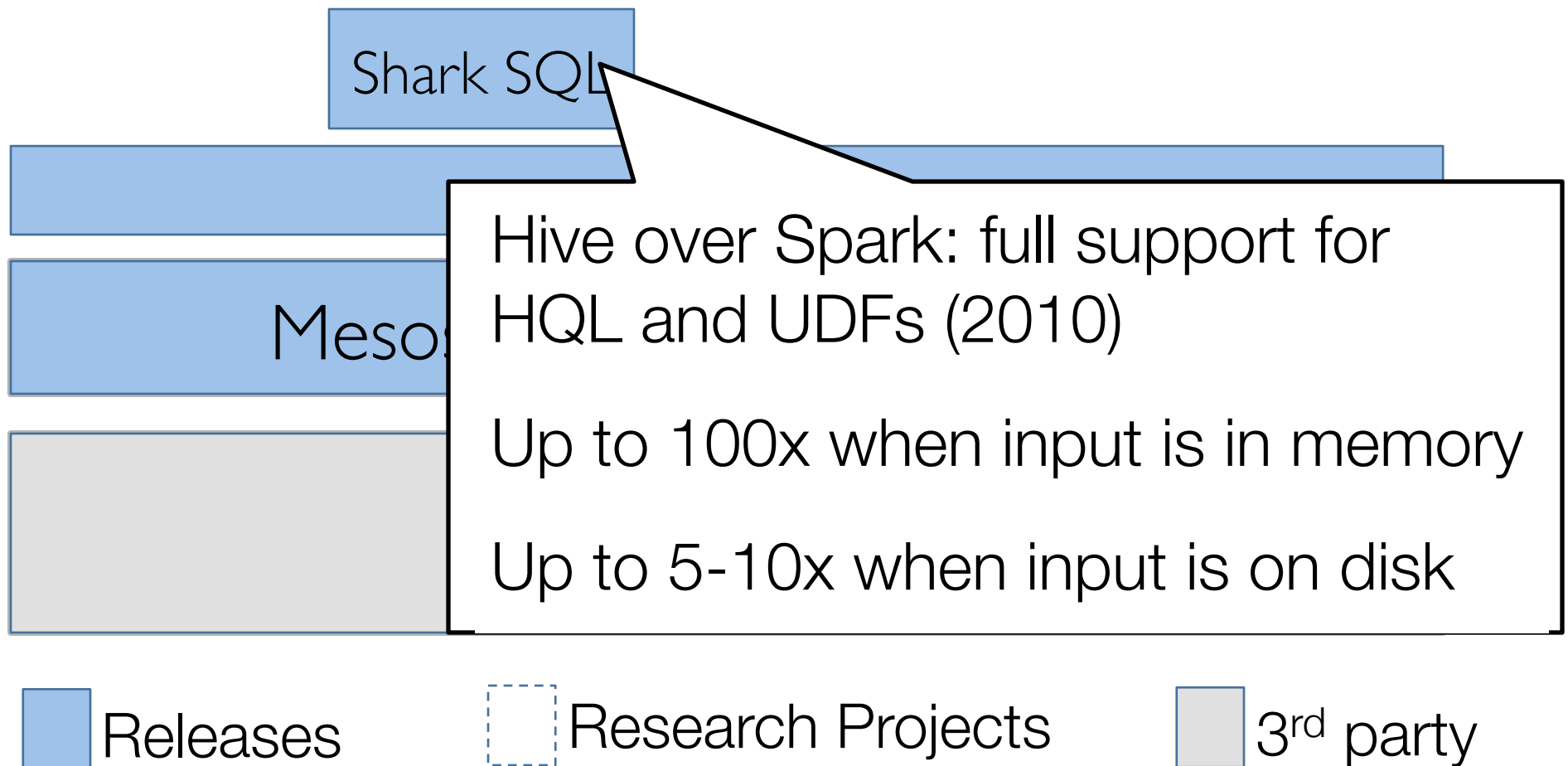
- » Fault-tolerant, in-memory storage
- » Powerful APIs (Scala, Python, Java)

Fast: up to 100x faster than HadoopMR

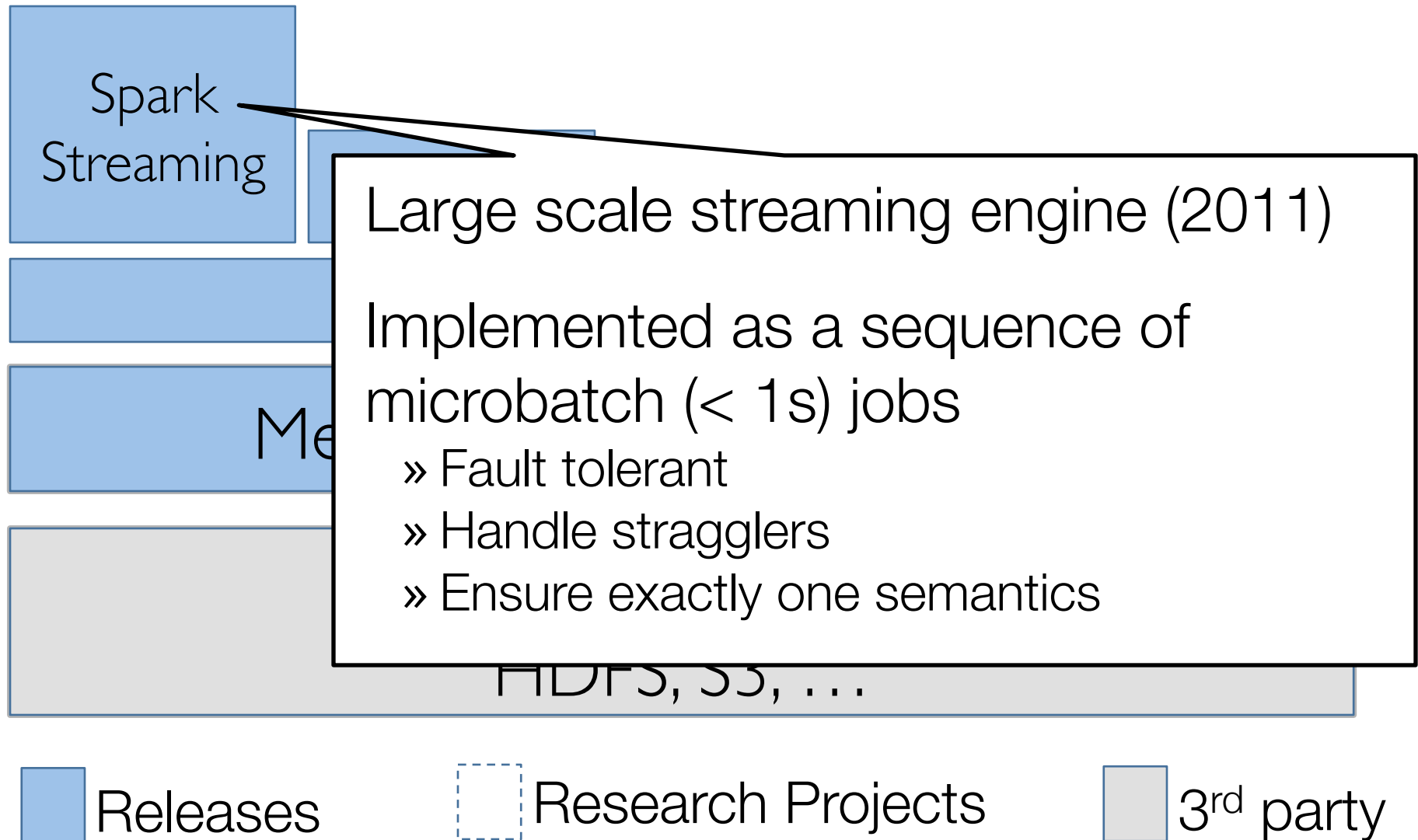
Easy to use: 2-5x less code than HadoopMR

General: support interactive & iterative apps

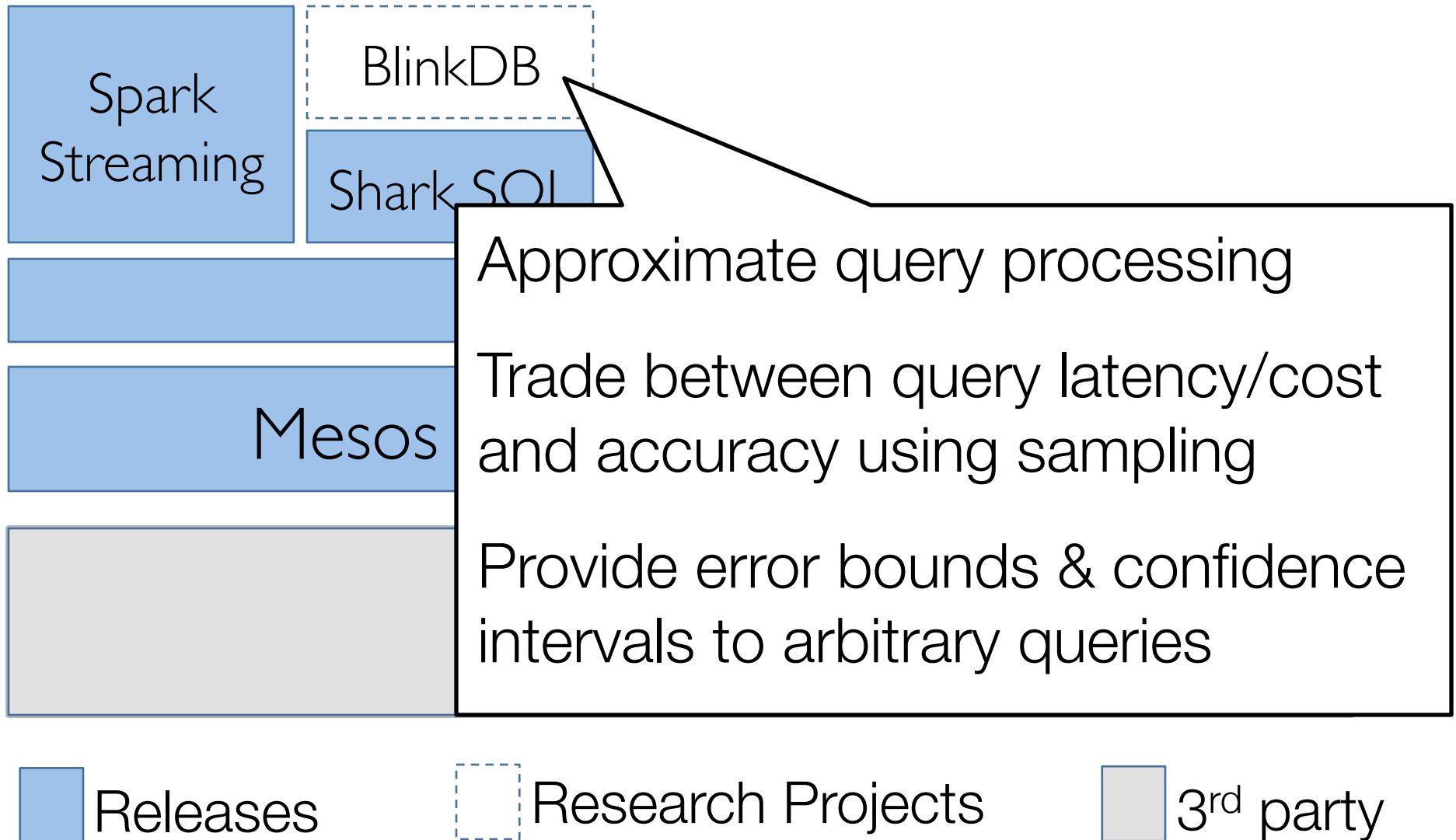
BDAS Stack (Feb, 2013)



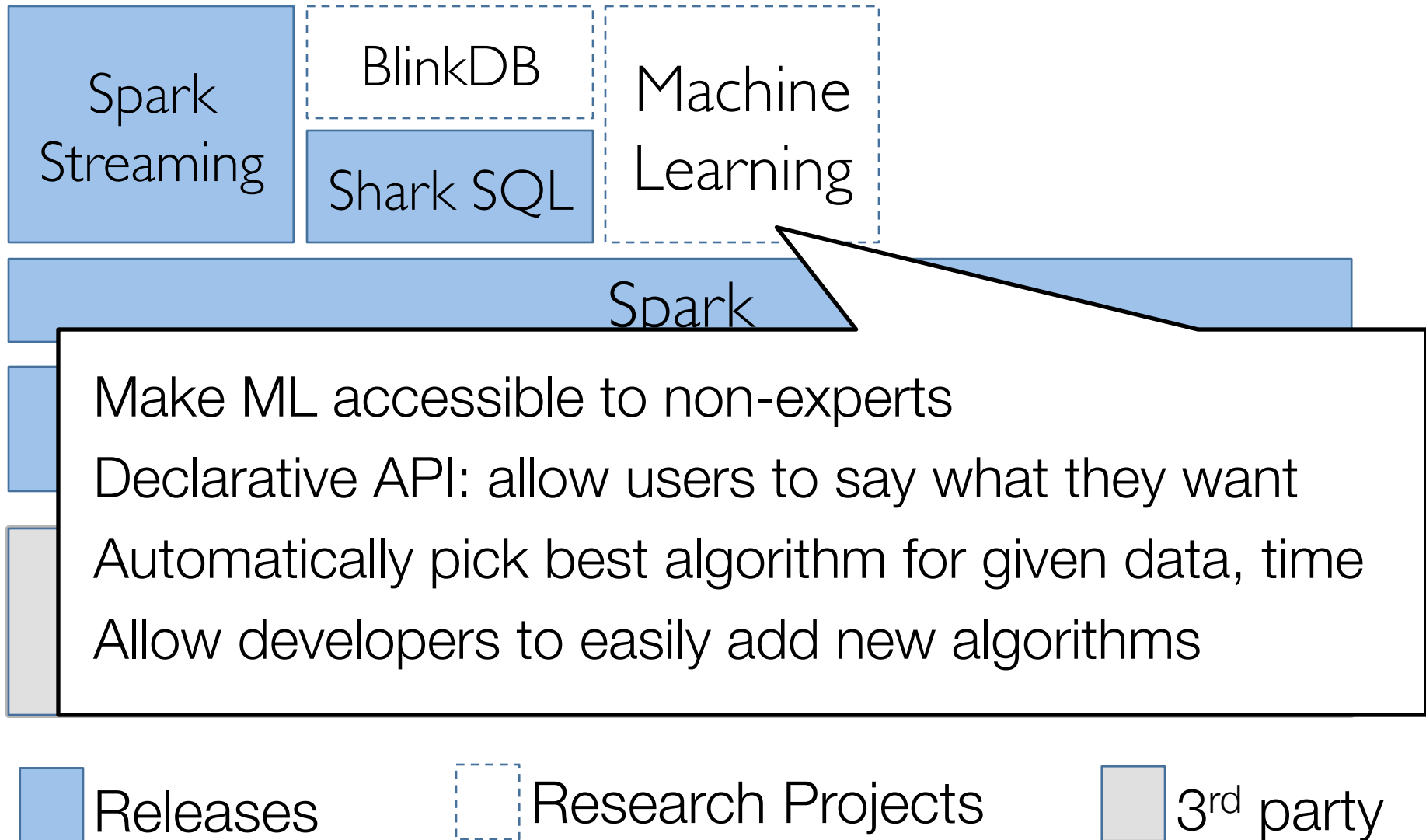
BDAS Stack (Feb, 2013)



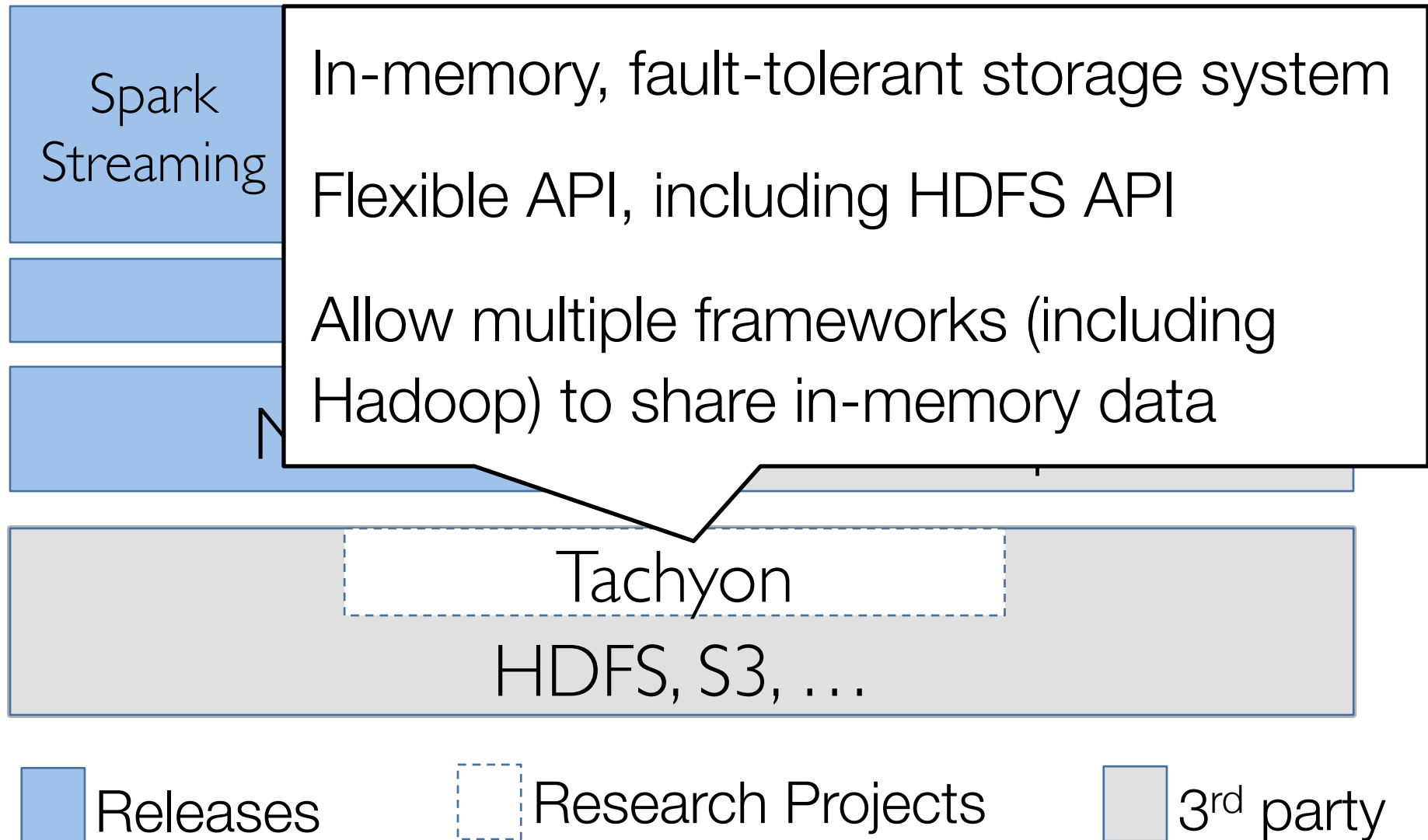
BDAS Stack (Feb, 2013)



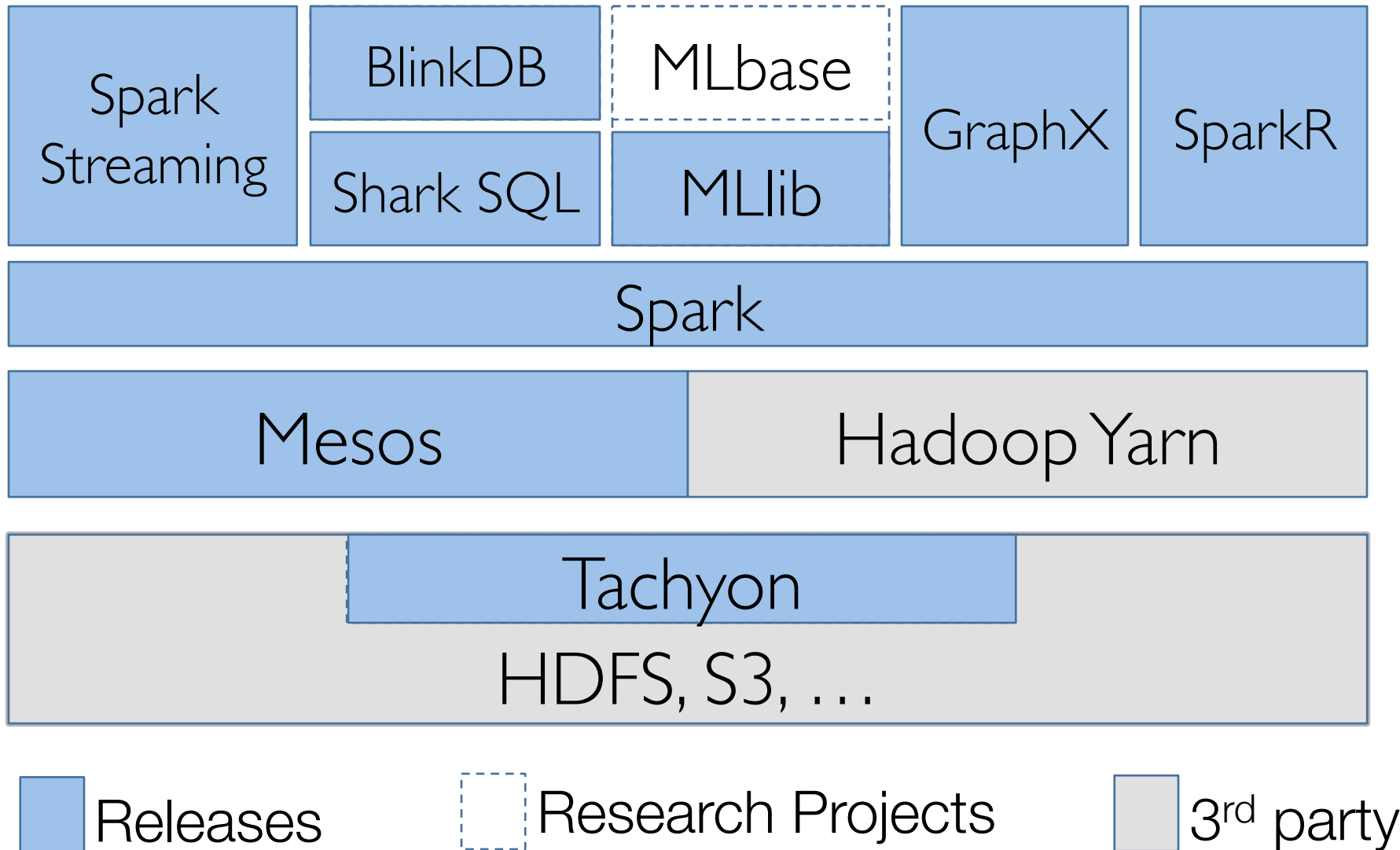
BDAS Stack (Feb, 2013)



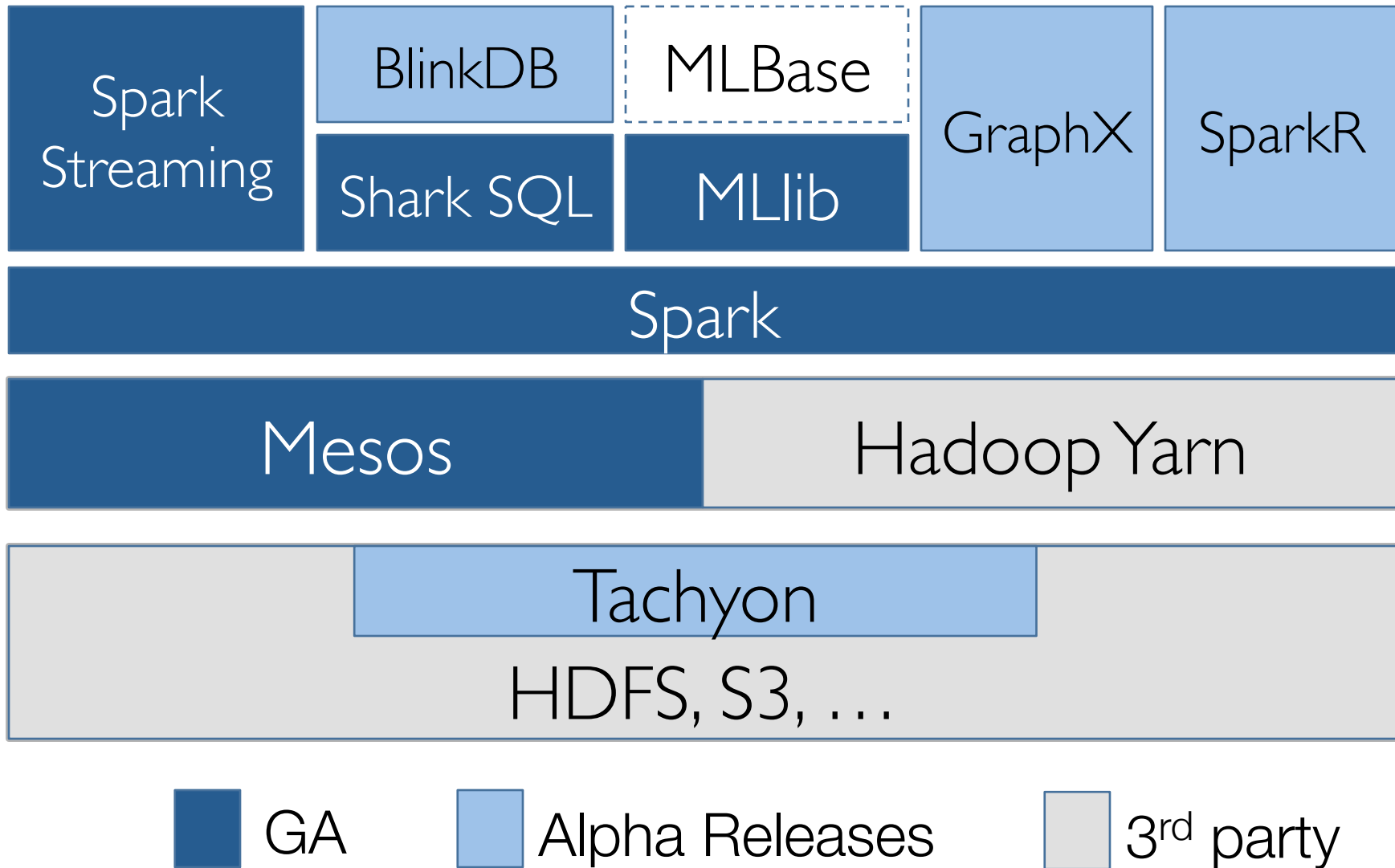
BDAS Stack (Feb, 2013)



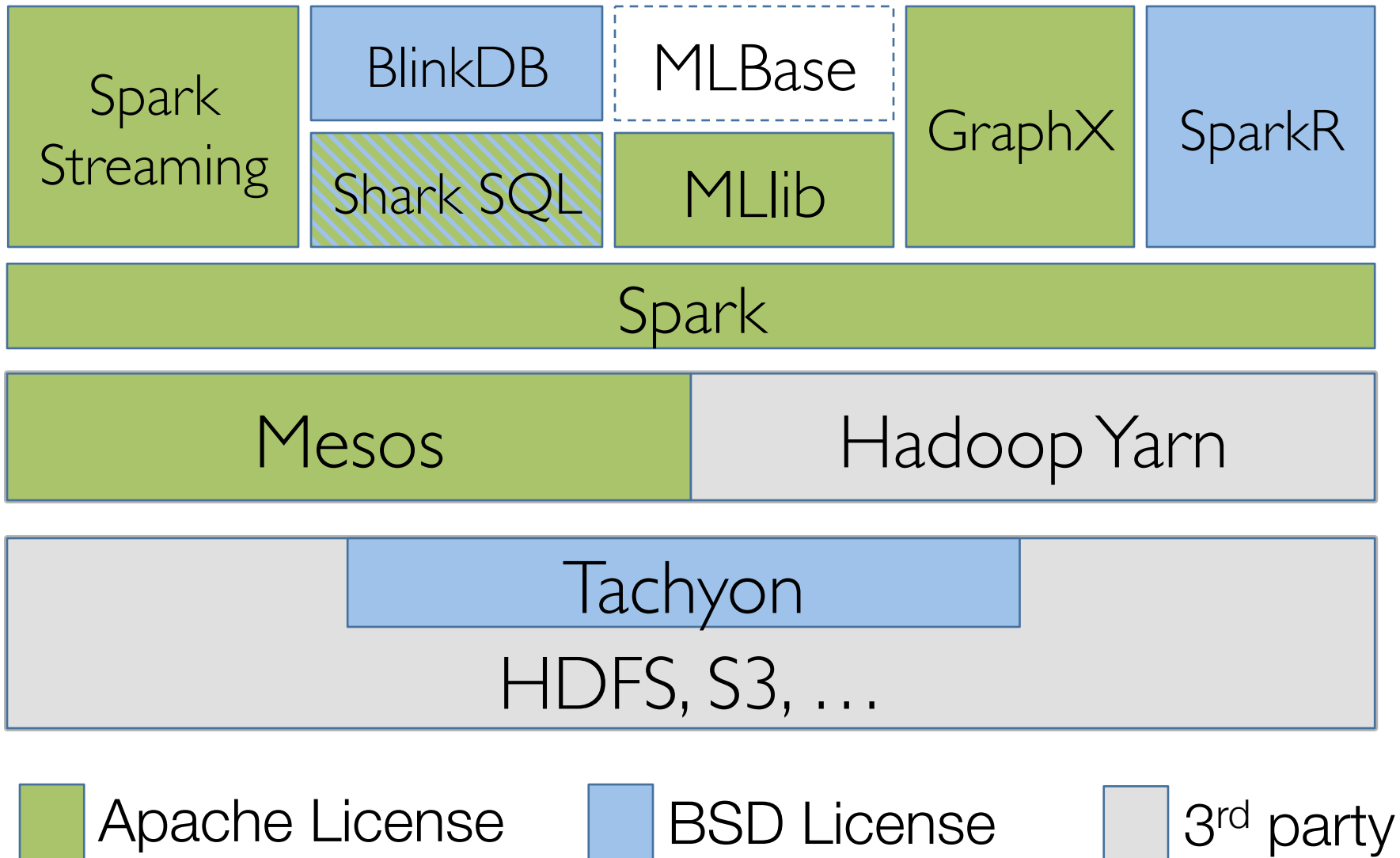
BDAS Stack (Feb, 201⁴)



BDAS Stack (Feb, 2014)



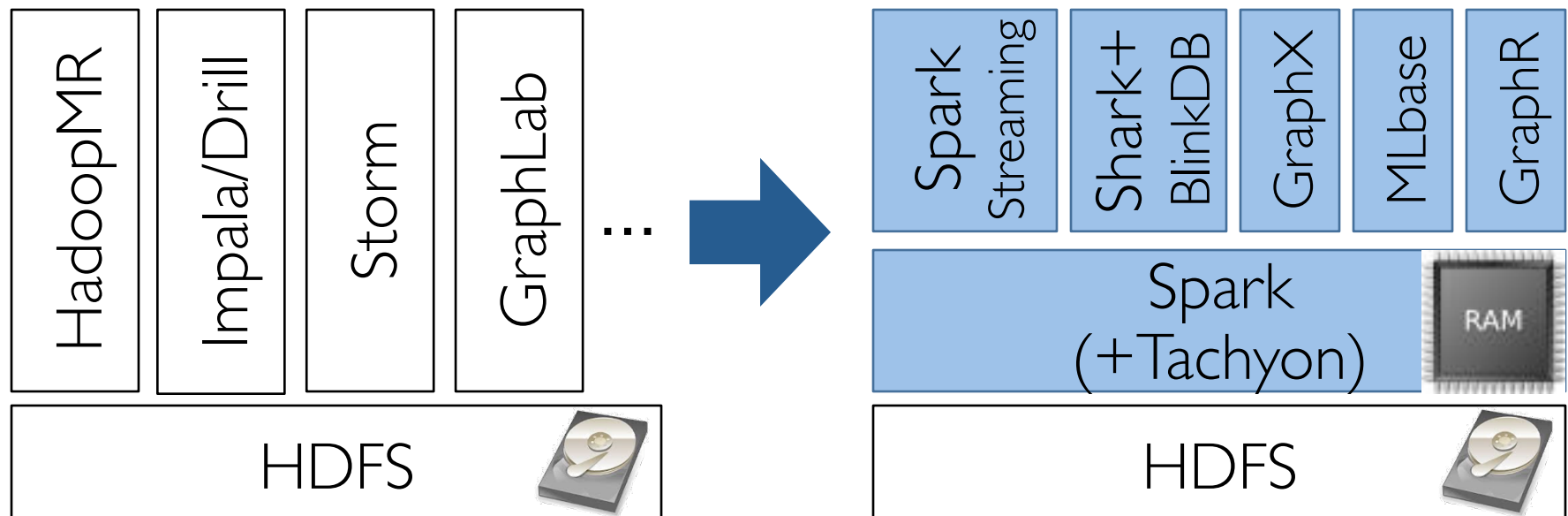
BDAS Stack (Feb, 2014)



Unification: One Size Fits Many!

Using Spark & Tachyon BDAS **unifies**

- » Batch
- » Streaming
- » Interactive
- » Iterative (e.g., graph and ML algorithms)



Unification Examples

Real-time and historical data analysis

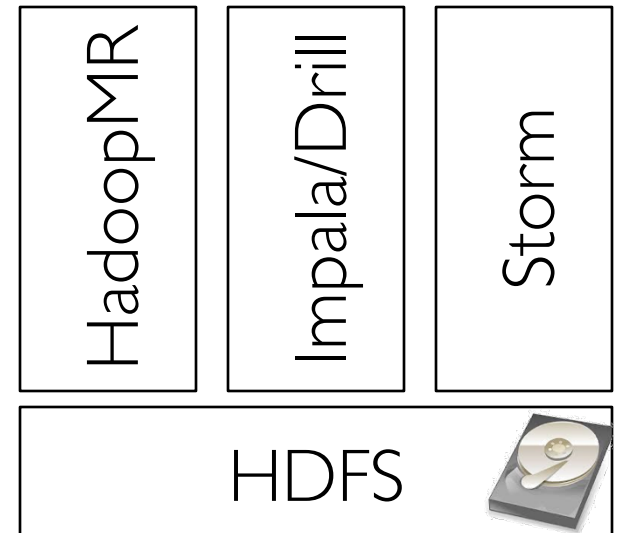
Streaming and machine-learning

Graph processing and ETLs

Unify Real-time and Historical Analytics

Today: separate stacks

- » Historical analysis (Hadoop, Hive)
- » Streaming (Storm)
- » Interactive queries (Impala)



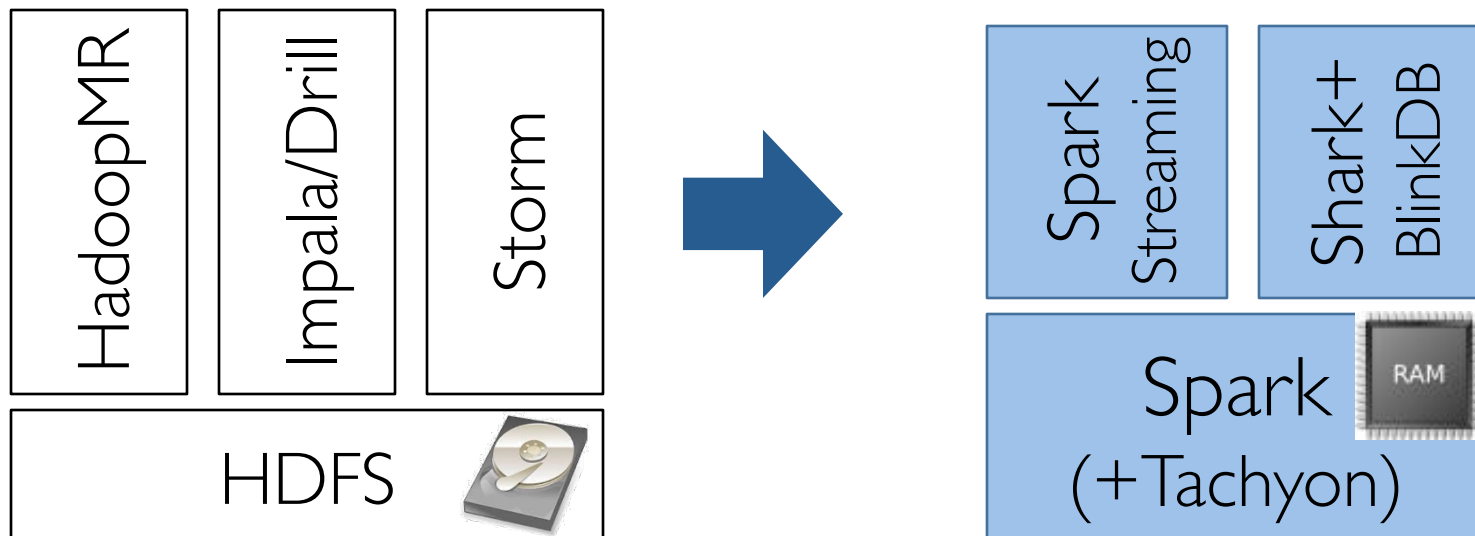
Disadvantages:

- » Hard to maintain and operate
- » Hard to integrate: cannot support interactive ad-hoc queries on streaming data

Unify Real-time and Historical Analytics

Spark (+ Streaming, Shark): single stack

- » Easier to build and maintain
- » Cheaper to operate
- » Interactive queries on streaming data: faster decisions
- » Simplify development



Unify Real-time and Historical Analytics

Batch and streaming codes virtually the same

» Easy to develop and maintain consistency

```
// count words from a file (batch)  
val file = sc.textFile("hdfs://.../pagecounts-*.gz")  
val words = file.flatMap(line => line.split(" "))  
val wordCounts = words.map(x => (x, 1)).reduceByKey(_ + _)  
wordCounts.print()
```

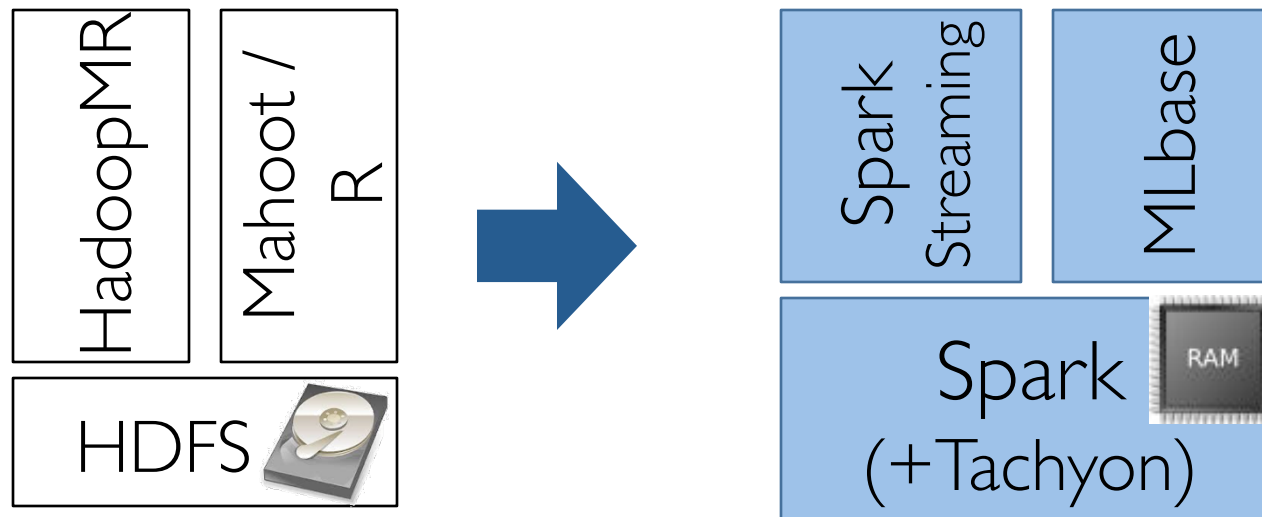
```
// count words from a network stream, every 10s (streaming)  
val ssc = new StreamingContext(args(0), "NetCount", Seconds(10), ..)  
val lines = ssc.socketTextStream("localhost", 3456)  
val words = lines.flatMap(_.split(" "))  
val wordCounts = words.map(x => (x, 1)).reduceByKey(_ + _)  
wordCounts.print()  
ssc.start()
```


Unify Streaming and ML

Today: ML done mostly off-line

Spark (+ Streaming, MLbase): Real-time diagnosis & decisions

- » Fraud detection
- » Early notification of service degradation and failures



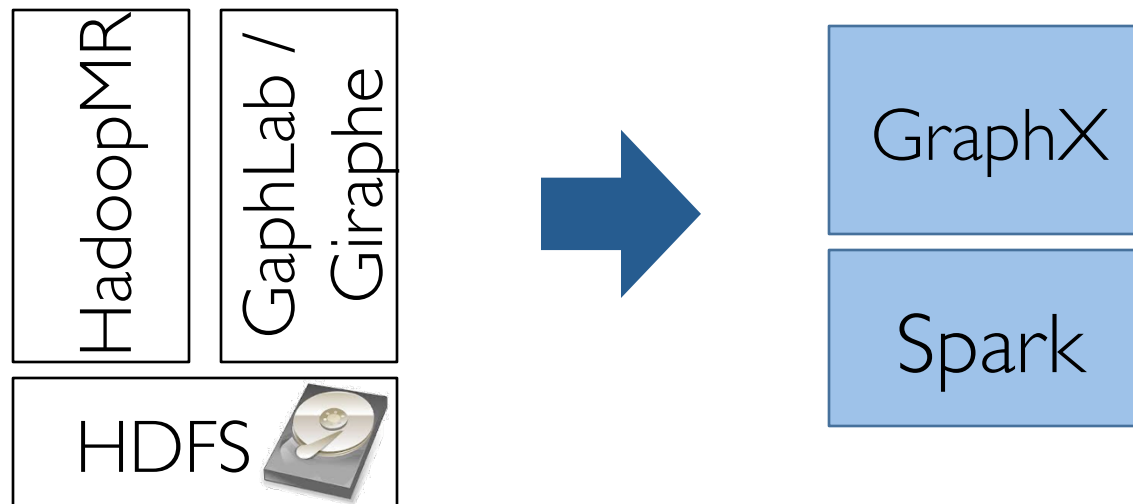
Unify Graph Processing and ETL

Today: Graph-parallel systems (Pregel, GraphLab)

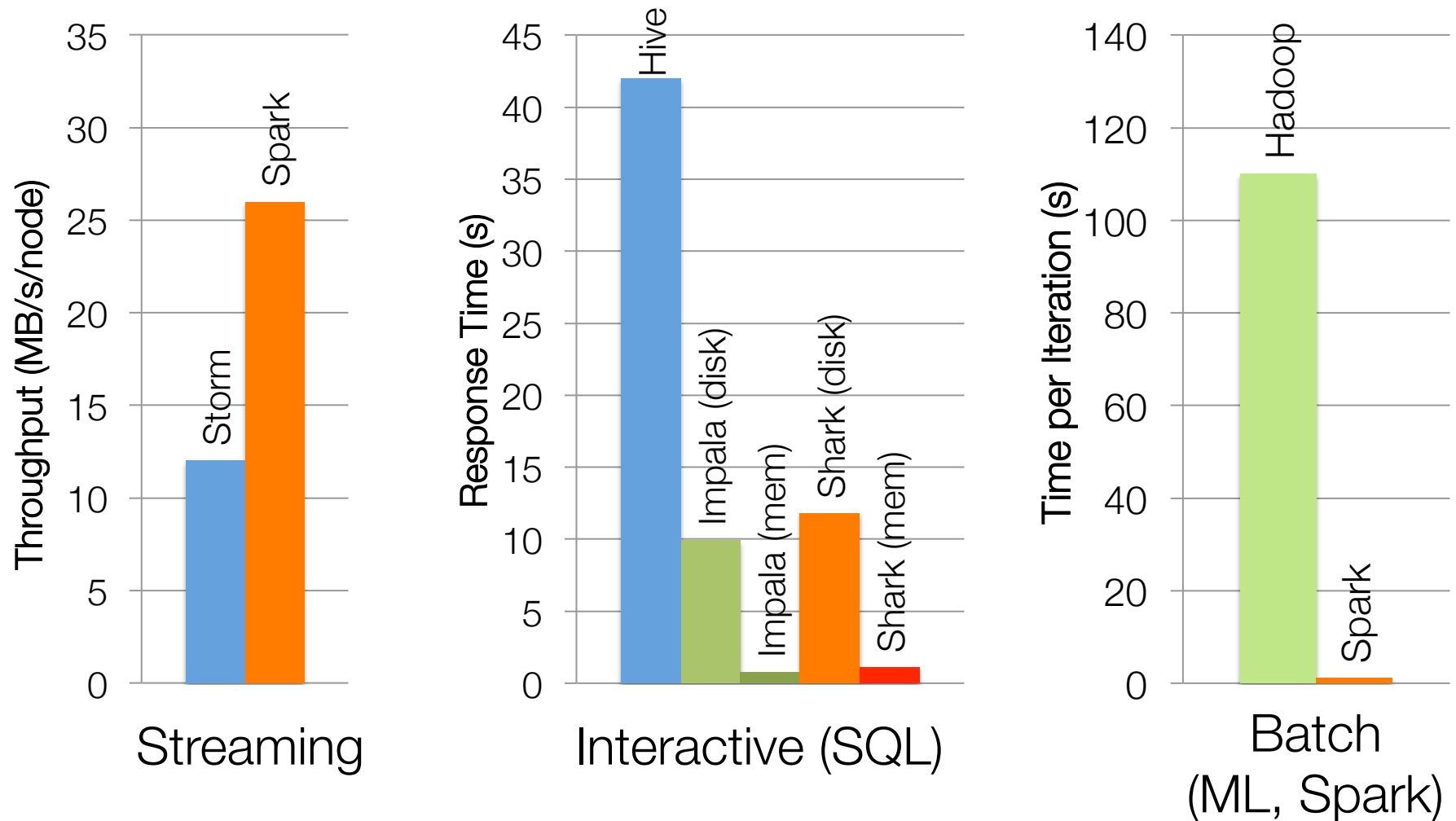
- » Fast and scalable, but...
- » ... inefficient for graph creation, post-processing

Spark (+ GraphX): unifies graph processing & ETL

- » Faster to get social network insights



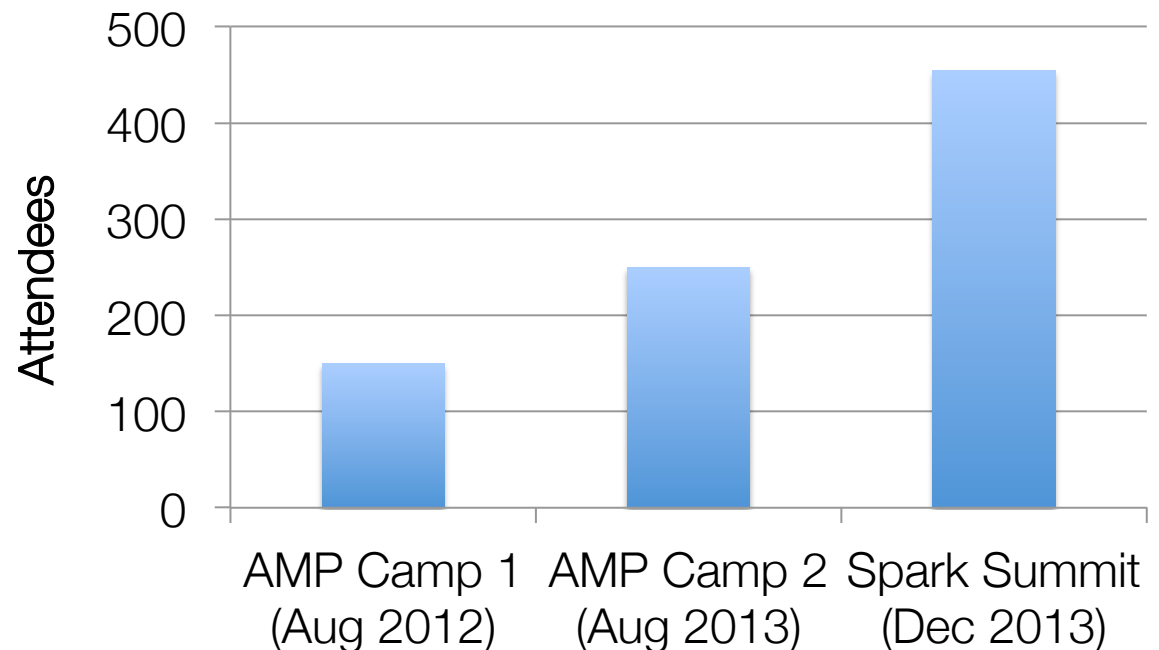
Not Only General, but Fast!



Gaining Rapid Traction

1,500+ Spark meetup users

30+ companies and over 100+ users
contributing code



Cloudera Partnership

Integrate Spark (including SparkStreaming, MLlib) with Cloudera Manager

Spark will become part of CDH

Enterprise class support and professional services available for Spark



Summary

BDAS: address next Big Data challenges

Unify batch, interactive, and streaming computations

Easy to develop sophisticated applications

» Support graph & ML algorithms, approximate queries

Witnessed significant adoption

» 30+ companies, 100+ individuals contributing code

Exciting ongoing work

» MLbase, GraphX, BlinkDB, ...

