photo: Half Dome in morning light, from Little Yosemite Valley campground. You're looking at several thousand vertical feet of rock!

Dean Wampler

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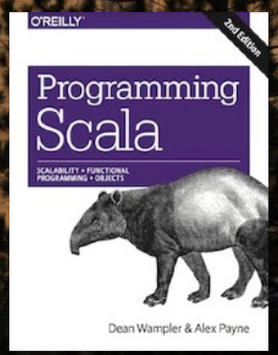
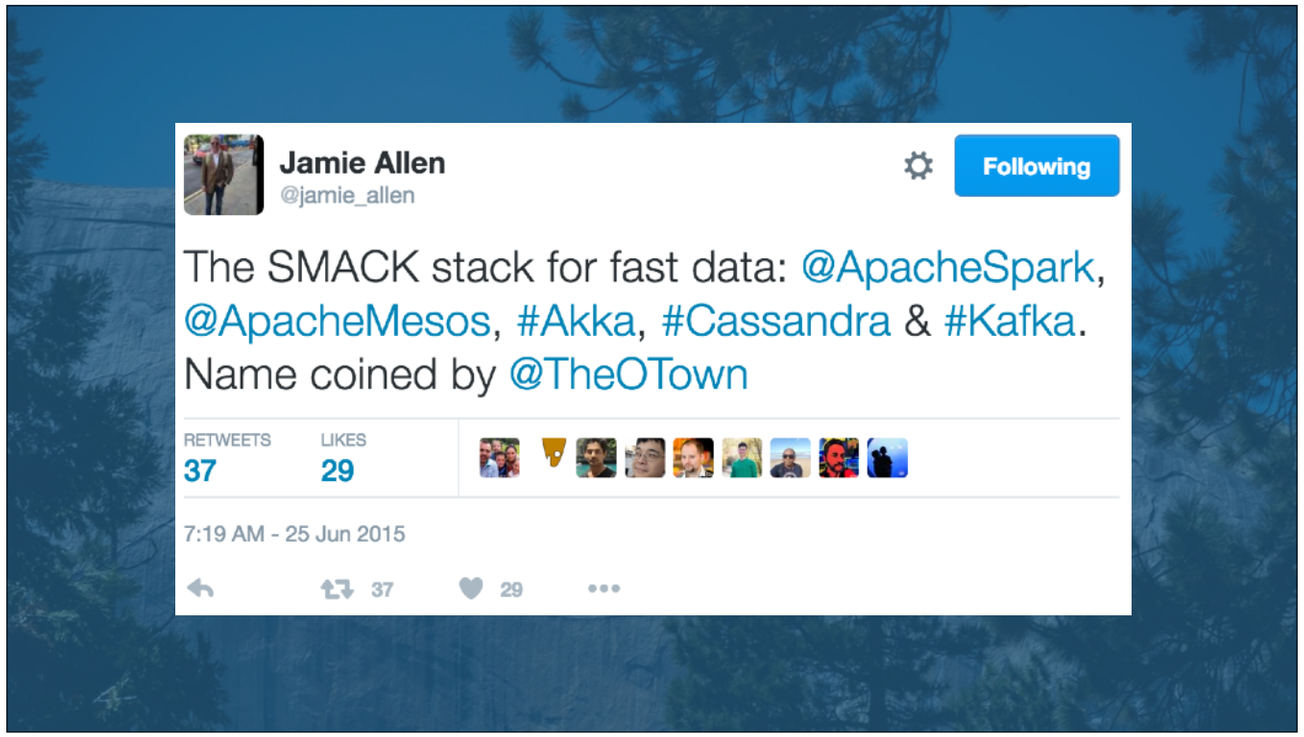
polyglotprogramming.com/talks
@deanwampler



Programming Scala book: http://shop.oreilly.com/product/0636920033073.do
Fast Data Architectures report: http://bit.ly/lightbend-fast-data
All my talks, including this one are at http://polyglotprogramming.com/talks.


About the acronym...
SMACK



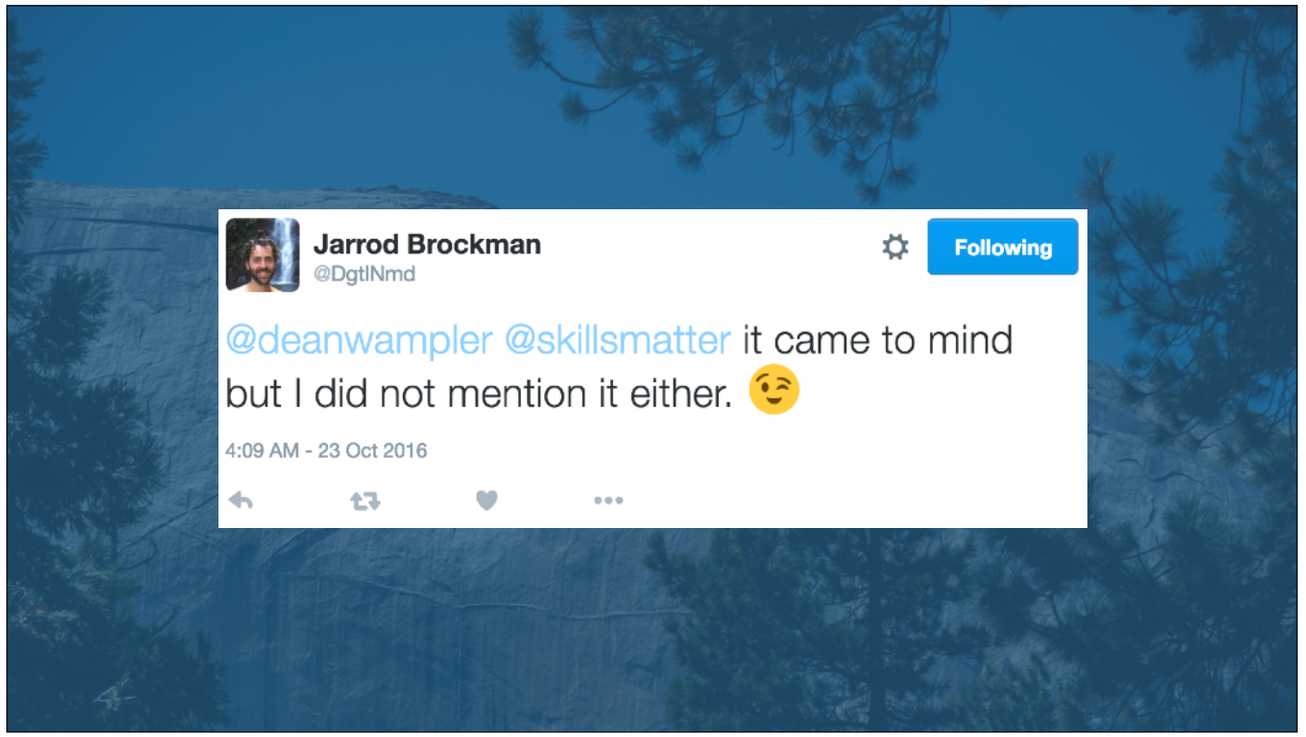
Apparently coined by Oliver White, in the Lightbend Marketing team. Jamie's tweet is the first mention of it.

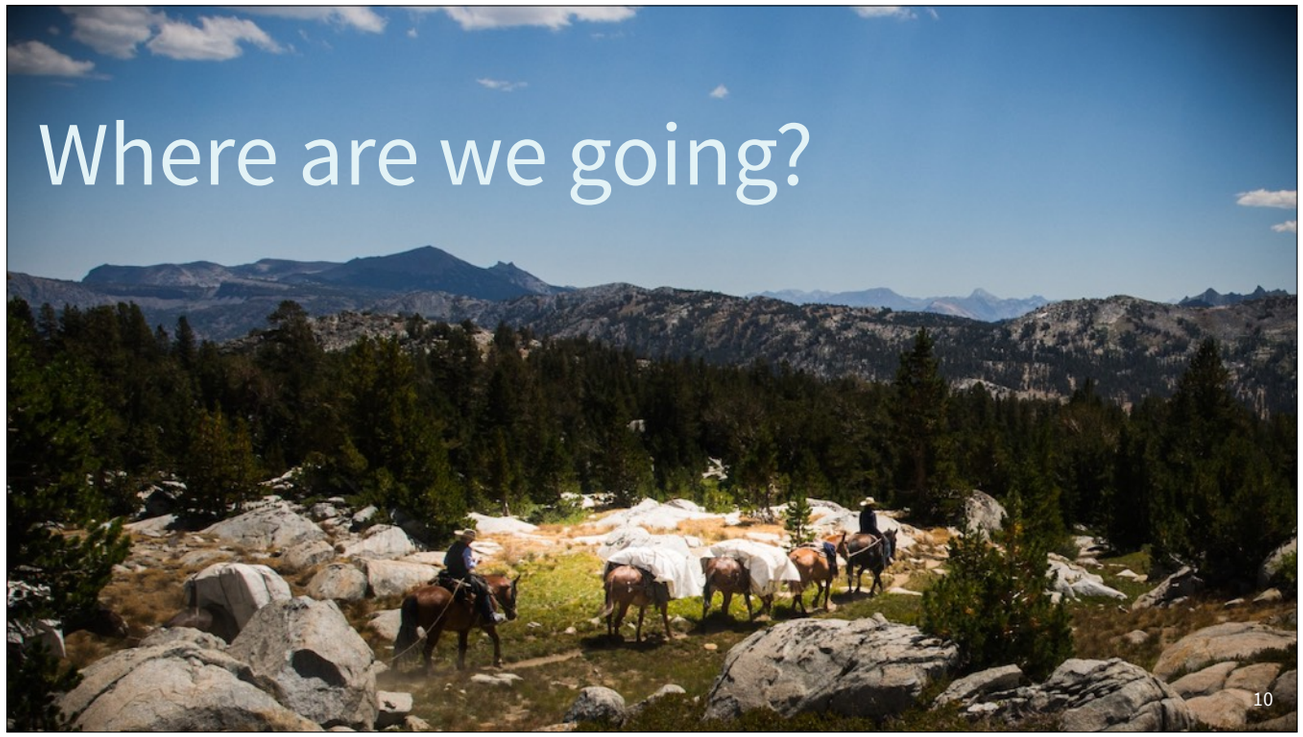
Yesterday, I retweeted this reminder of today's talk...

To which Jarrod Brockman replied this gif. Click this link to see it.
https://twitter.com/DgtlNmd/status/790113697545027584

Here’s a screen capture after one smack...

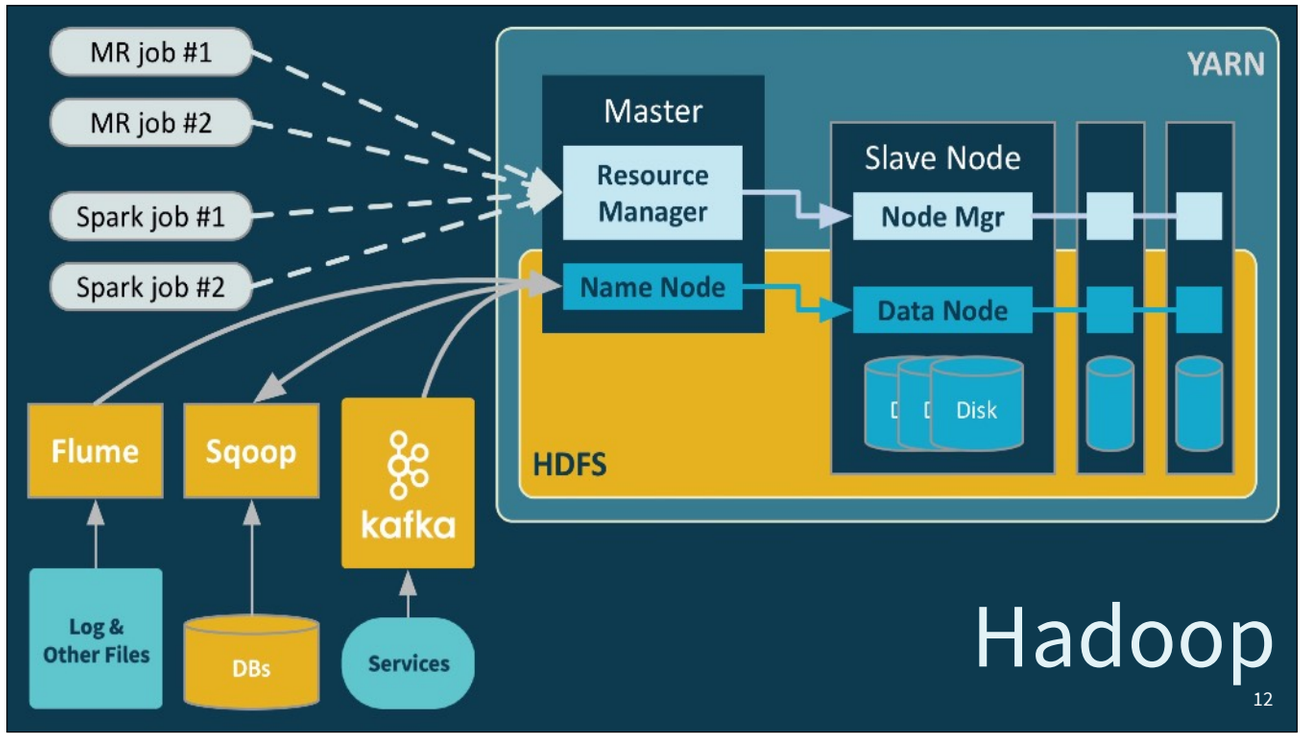

Dean Wampler
@deanwampler
@DgtlNmd @skillsmatter Not to mention the association with Heroin, but I didn't mention it…
3:55 AM - 23 Oct 2016
City of London, London


Jarrod Brockman
@DgtlNmd
Following
@deanwampler @skillsmatter it came to mind but I did not mention it either.
4:09 AM - 23 Oct 2016



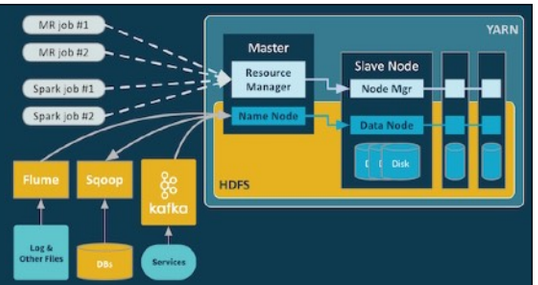
Let’s start with two areas of change right now for architectures: data-centric systems and general-purpose systems.
photo: Pack train below Donahue Pass, Ansel Adams Wilderness

Starting with data-centric systems, the Big Data world is now fairly mature.
photo: Climbing to Donahue Pass, Ansel Adams Wilderness



Hadoop is the dominant, general purpose architecture for big data systems. NoSQL Databases are more specialized big data systems, which we won't consider further.
Three major components: 1) a distributed filesystem (storage), 2) a processing engine (MapReduce and Spark, with jobs and constituent tasks run by services in light blue, 3) and YARN, the service that manages resources and schedules jobs.

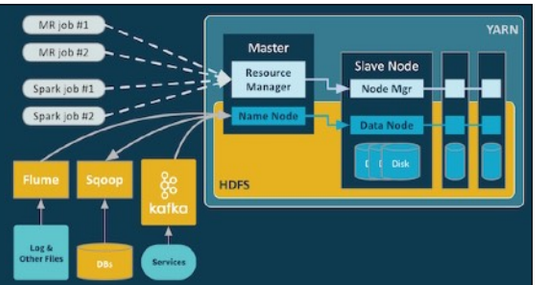
Hadoop



- Very large data sets (HDFS)
- Batch jobs: “Table scans”
- Job durations: minutes to hours
- Latencies: minutes to hours

Table scans, i.e., we tend to scan most of the files we’ve written or a large subset, vs. CRUD operations.

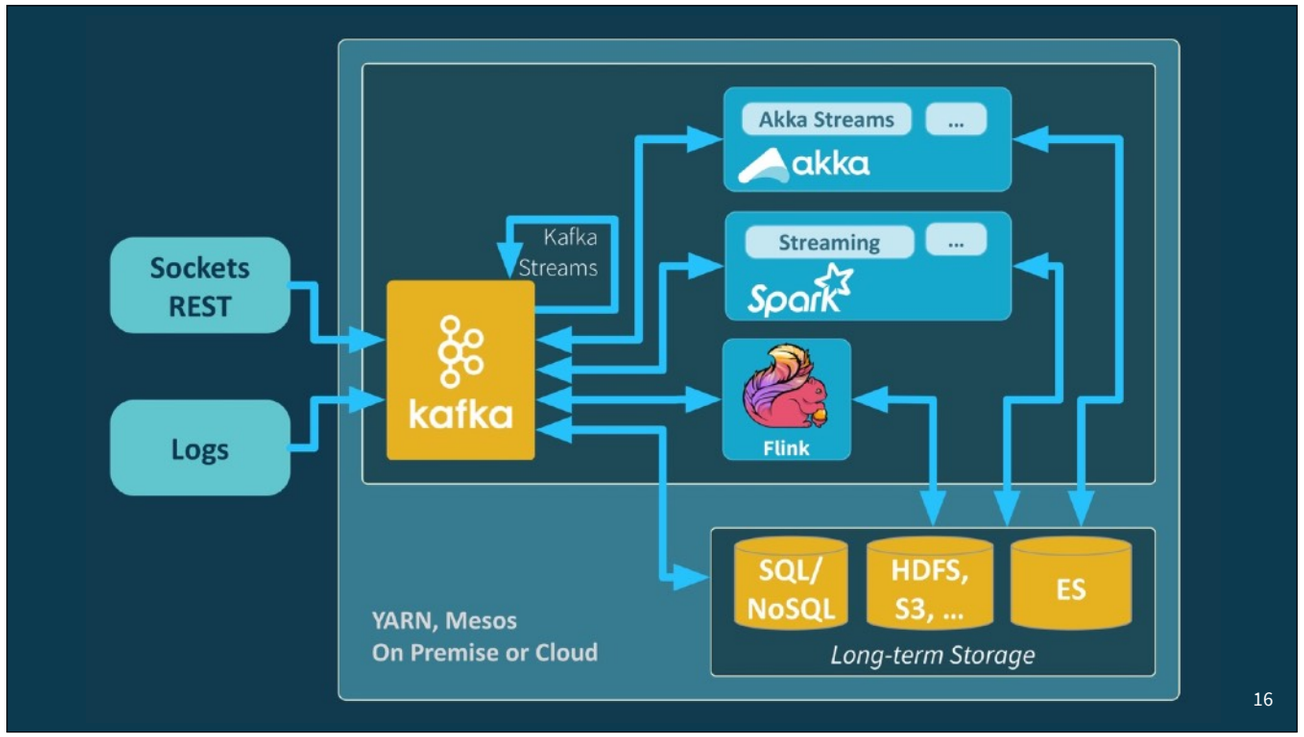
YARN



- Resources are *dynamic*
  - CPU cores & memory
- Global, top-down scheduler
  - Best for “compute” jobs

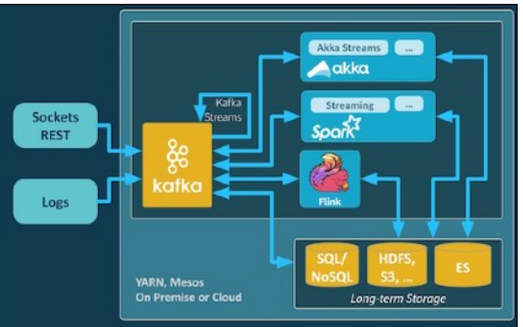
We’ll compare with Mesos. YARN doesn’t yet manage disk space and network ports, but they are being considered. Scheduling is primarily a global concern and uses the Fair Scheduler, Capacity Scheduler, etc. It’s ill-suited to manage things that aren’t like MapReduce or Spark. It can’t even manage HDFS resources, although attempts are being made to address this limitation: http://hortonworks.com/blog/evolving-apache-hadoop-yarn-provide-resource-workload-management-services/

This is the new directory for data-centric systems.
photo: Lyell Creek below Donahue Pass, Yosemite National Park



A partial set of possible, sometimes competing streaming engines. The SMACK stack “mentions” Spark, Mesos, Akka, Cassandra, and Kafka. We’ll talk about the elements here in more detail later, but notice a few are the same from the Hadoop diagram, including HDFS, Spark, and YARN.
The major components are 1) storage (Kafka, for durability and temp. storage of inflight data, HDFS, databases, and Elastic Search), 2) streaming compute engines (Akka, Spark, and Flink, plus many more not shown), and 3) a resource manager & scheduling system (YARN, as before, but also Mesos and cloud services).

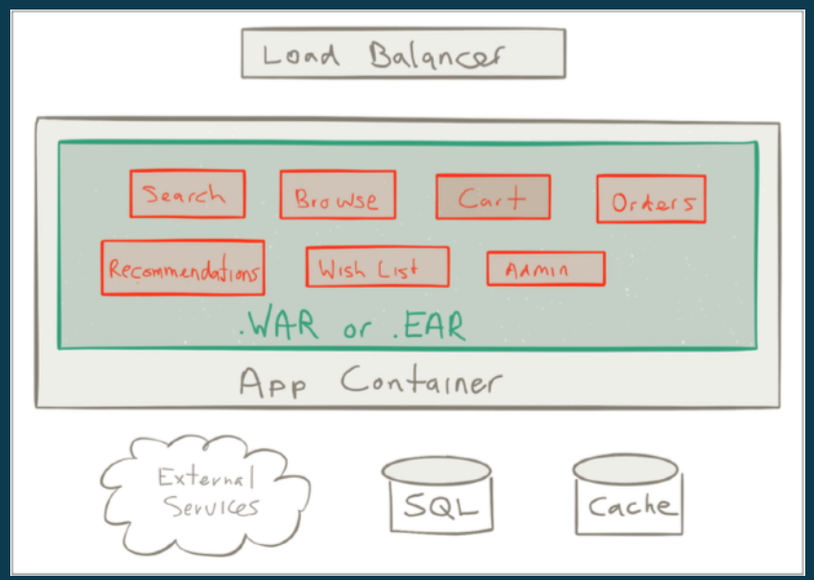
Streaming

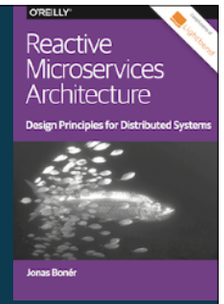


- Never ending sequences (Kafka)
- Incremental processing
- Job durations: forever!
- Latencies: µsecs - seconds

Data “sets” are sequences that could go forever. Instead of being rooted in file system storage (although that’s still present...), a message queue/data bus, especially Kafka is the core. In streaming, they are processed within seconds, in “real-time” event systems possibly down to microseconds. These jobs could run forever, although in practice they are often replaced with updated jobs (or they crash and have to be restarted...)

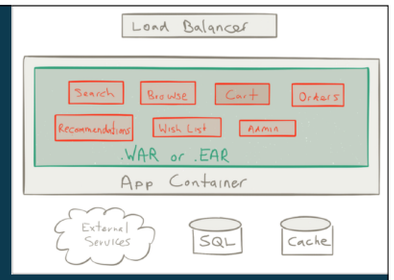
Apart from data-centric systems, we have also been implementing general services for a while. We have been writing big, complex services, a.k.a. monoliths. I'll admit these literal monoliths ("single upright stones") are particularly pretty, though.
photo: Half Dome, Mt. Broderick, Liberty Cap, Nevada Falls. Yosemite National Park





A classic, JEE approach for “macroscopic” services (monoliths). App Containers are too heavyweight to run one per microservice. So, you have a lot of concerns and dependencies in one place. Also, it’s a synchronous model, so throughput and other benefits of asynchrony are not natural outcomes.
Drawing by Kevin Webber in Reactive Microservices Architecture, Jonas Bonér, O’Reilly Media, 2016

Monoliths

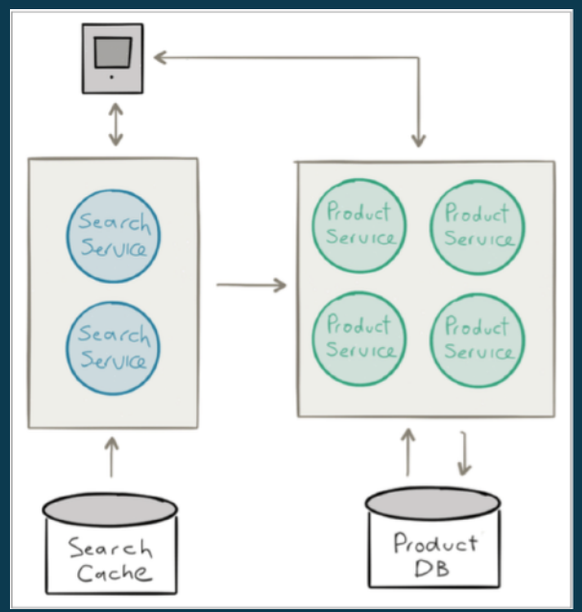


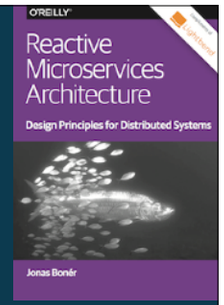
- Tangled responsibilities
- Difficult, infrequent deployments
- Durations: months to years
- Latencies: µsecs to seconds

Monoliths mean fewer things to manage and intraprocess function calls are faster than interprocess communications (the picoseconds), but they tend to become bloated with tangled dependencies, making them fragile and difficult to engineer. Hence, deployments are often “big bang” and too painful to do frequently.

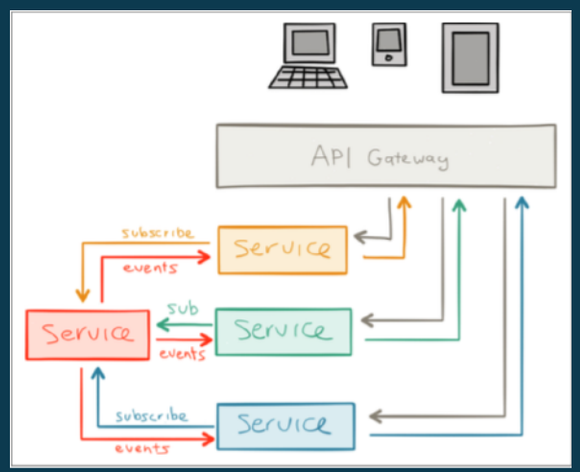
Smaller rocks...
photo: Mt. Lyell and boulders just North of Donahue Pass.

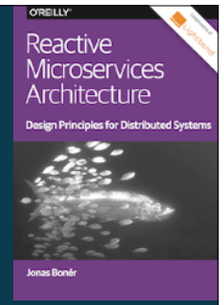
https://twitter.com/alexcrdean/status/790494111396691968





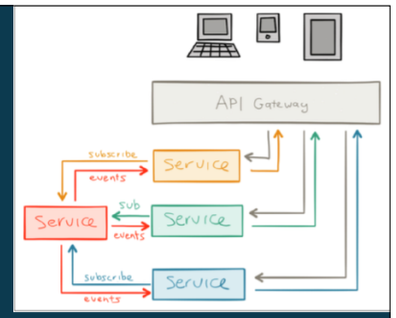
Microservices try to do one thing and do it well. They must manage their own data, because a shared data store is a monolith in disguise.
Drawing by Kevin Webber in Reactive Microservices Architecture, Jonas Bonér, O'Reilly Media, 2016





It’s also common to provide a uniform API abstraction to clients which hides the independent APIs of the underlying sources and also provides a level of indirection, so it’s easier to swap out instances of these services.
Drawing by Kevin Webber in Reactive Microservices Architecture, Jonas Bonér, O’Reilly Media, 2016

Microservices

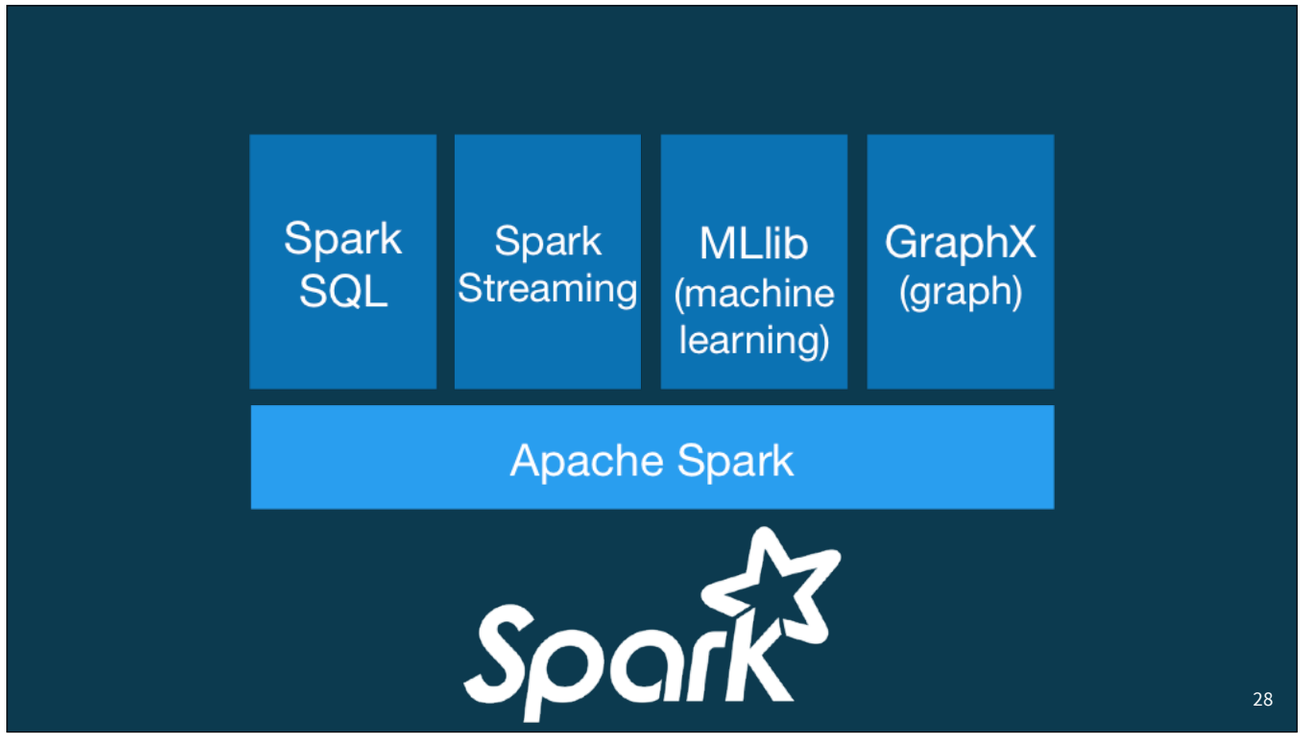


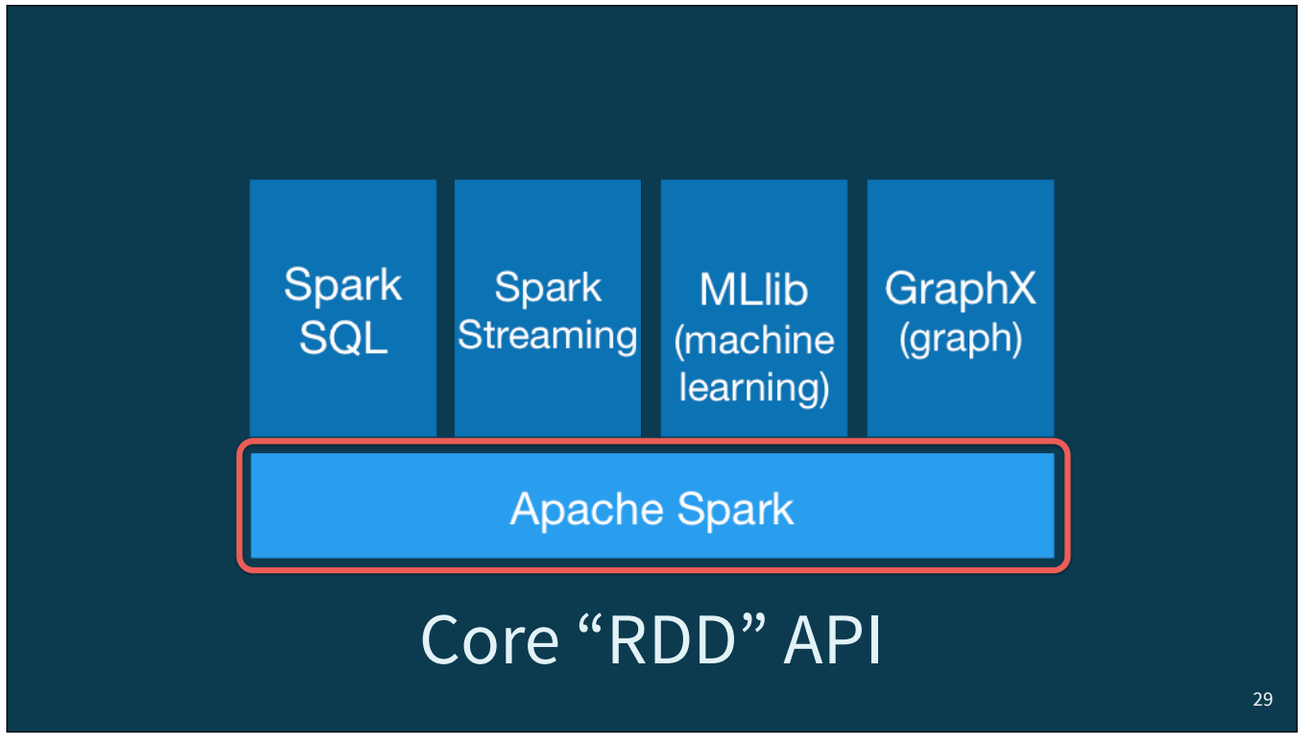
- Each does one thing
- Embrace Conway's Law
- Message driven & asynchronous
- Durations: minutes! to forever
- Latencies: higher than func. calls

They might be smaller in memory and CPU footnote, but only as a side effect of their focus on doing one thing. They communicate with each other through messages and should be asynchronous to maximize throughput, although this isn't always best. Because they do one thing and have a very clear boundary and interfaces to other services, it's easy to organize their development into teams, essentially a Reverse Conway's Law. This makes it easier to evolve and deploy them independently of other microservices, too. Very smaller "dockerized" services might last just a few minutes, but could run a very long time. A big drawback of microservices is the longer communication latency of calls between them compared to function calls in the same process.

Actually, they are (R to L) Tressider Peak, Columbia Finger, Cathedral Peak, Echo Peaks, and Matthes Crest, Yosemite National Park

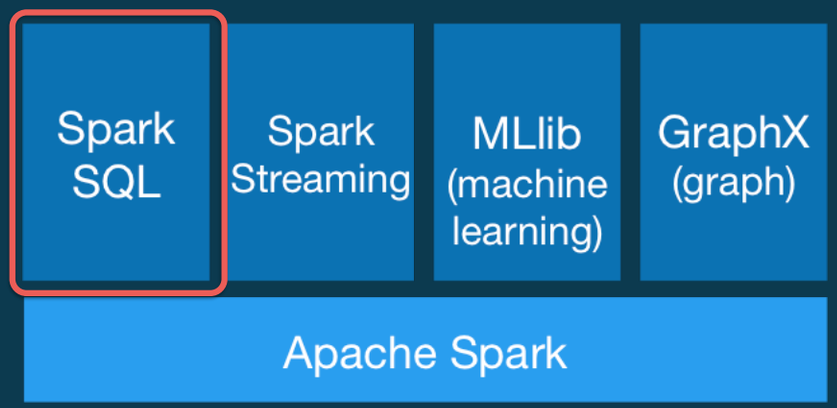
To replace Hadoop, we need the same kinds of components that it provides. Spark, the “S” provides the compute component for batch and streaming.
Photo: Upper Cathedral Lake with Tressider Peak on the left, Yosemite National Park (Spark)


Spark SQL
Spark Streaming
MLlib (machine learning)
GraphX (graph)
Apache Spark
Spark

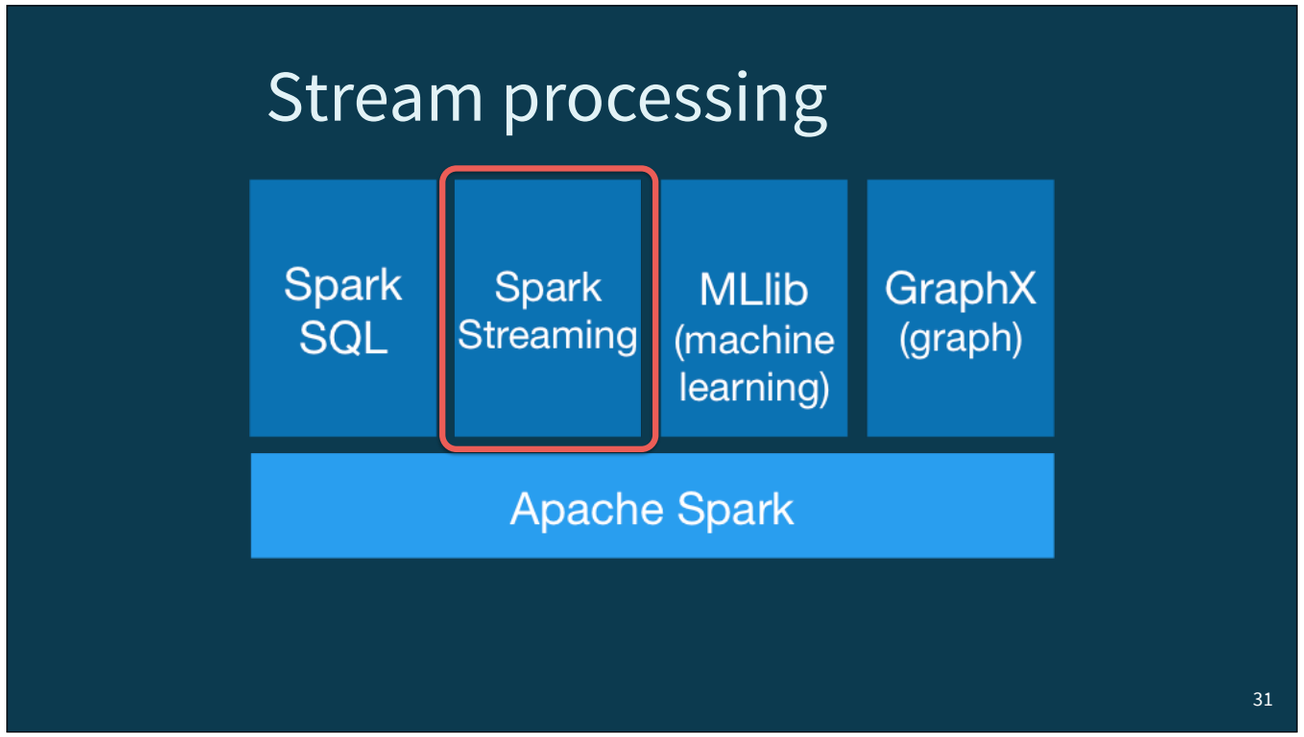


Resilient Distributed Dataset API, the original, batch-mode API and still the core.

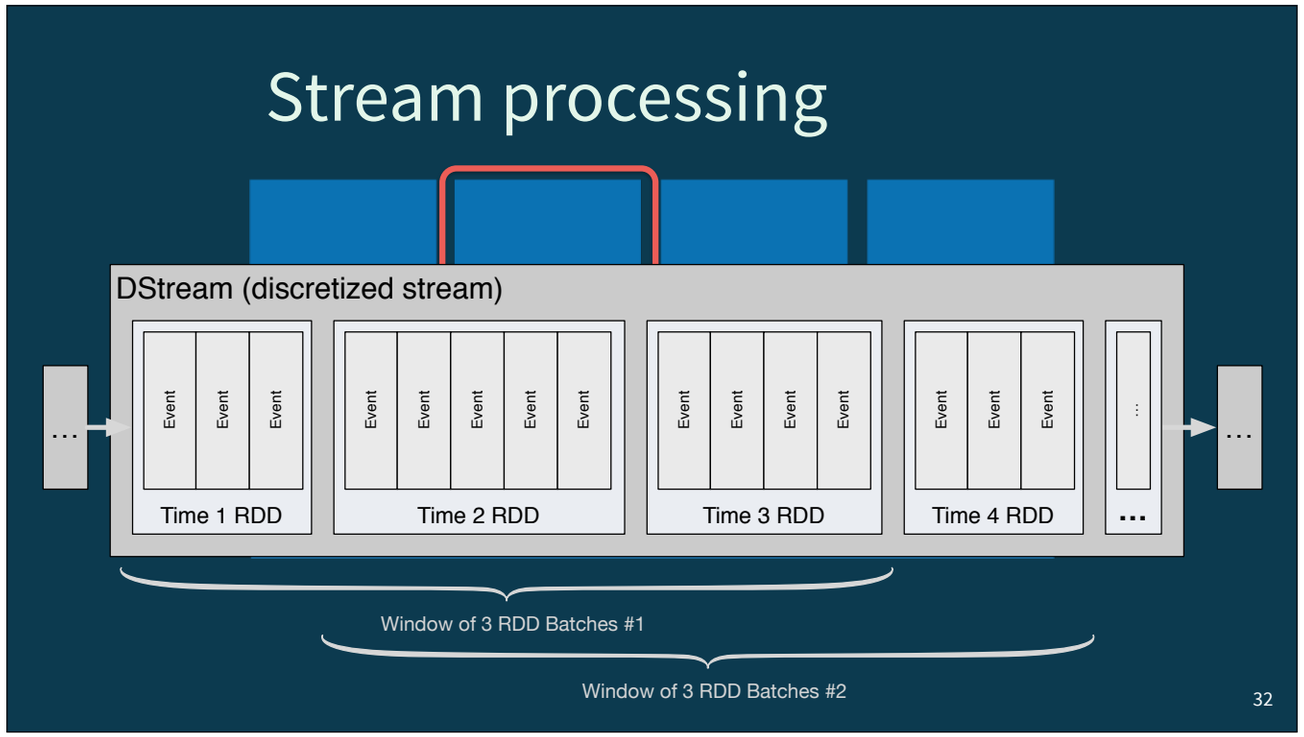
Highly-optimized SQL



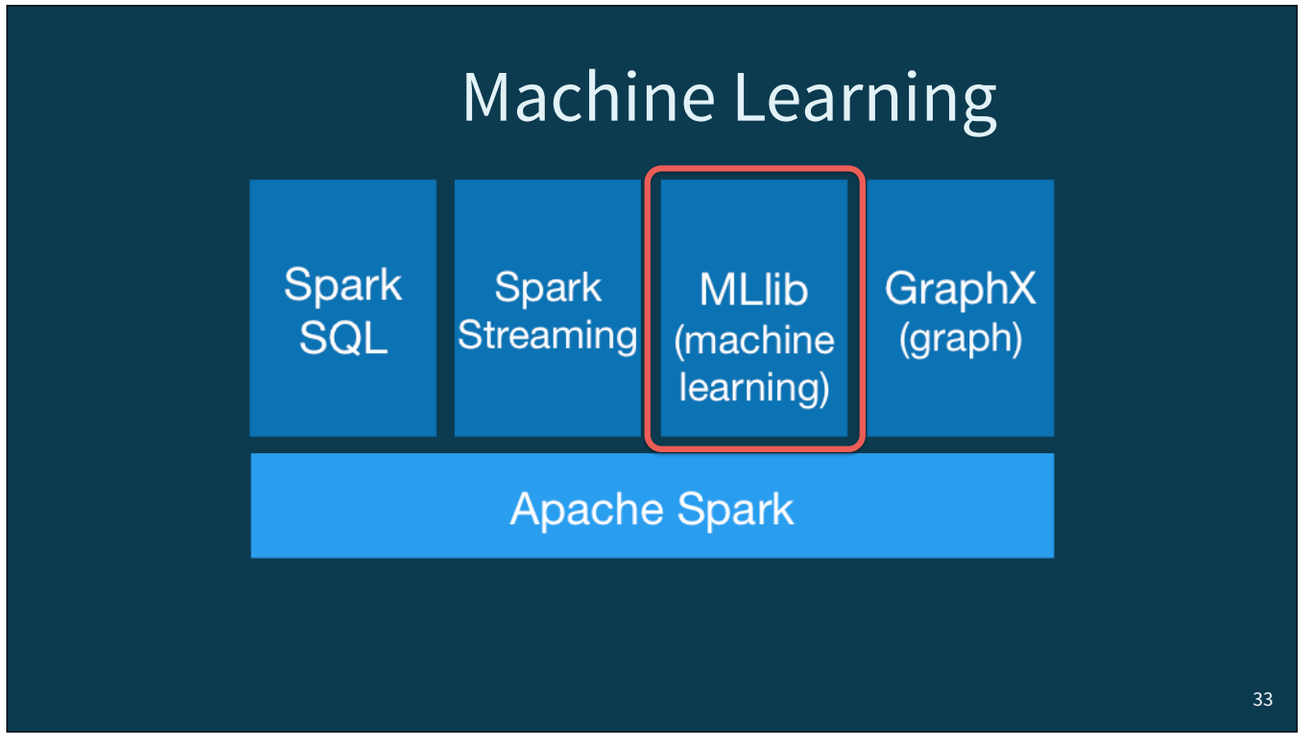
The “DataFrame” API provides SQL queries and a SQL-like domain-specific language (DSL). This API is aggressive optimized, including custom encoding of records in memory and code generation for queries.



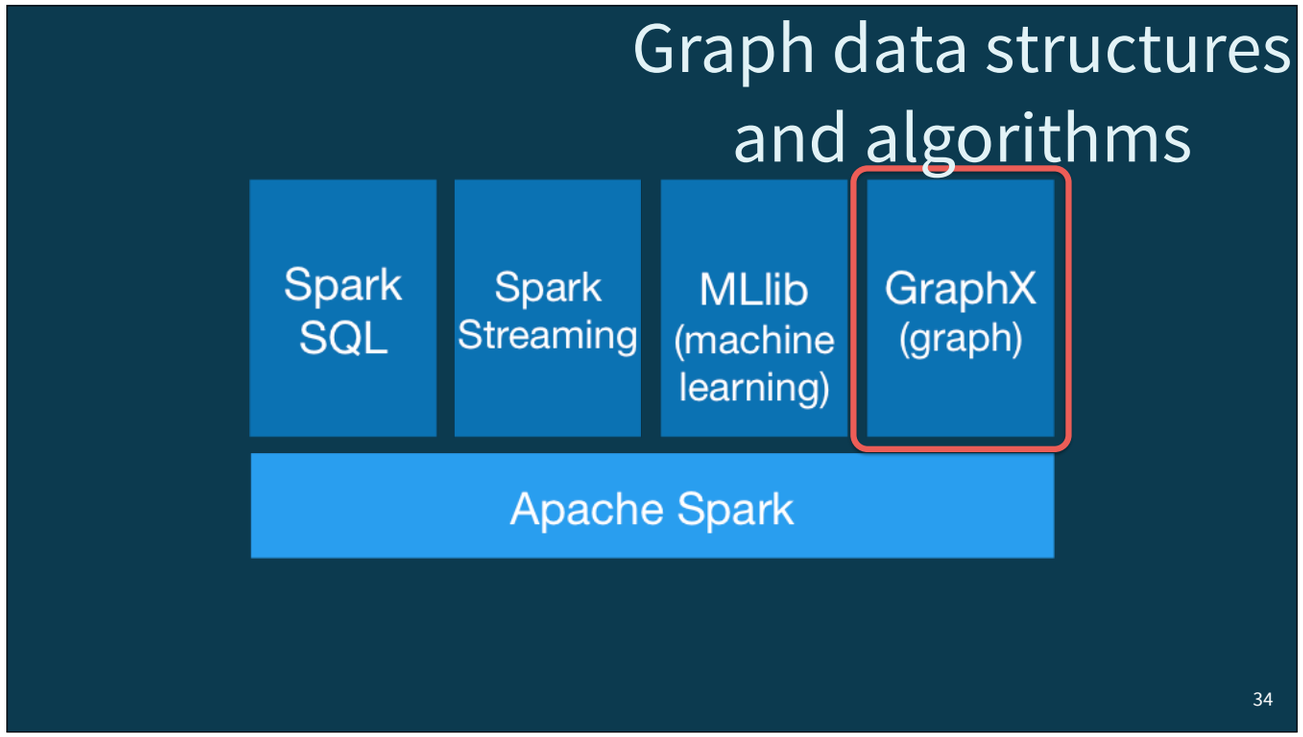
When streaming started getting popular, the Spark community realized that batch-mode Spark is efficient enough that it could be adapted to streaming using a “mini-batch model, with latencies (batch interval durations) down to ~0.5 seconds or so.



A fixed time interval is used and the events captured in each interval are put into an RDD and then processed using the RDD API and extensions, such as window functions as indicated. Spark Streaming is now evolving towards a more pure streaming model with lower latency.



For completeness, there is a built-in ML library, but also lots of third-party integrations.



There is also a graph library.

SMACK is just an reference architecture; what about other streaming engines?
photo: Fairview Dome(?), West of Tuolumne Meadows, Yosemite National Park.

Streaming Tradeoffs

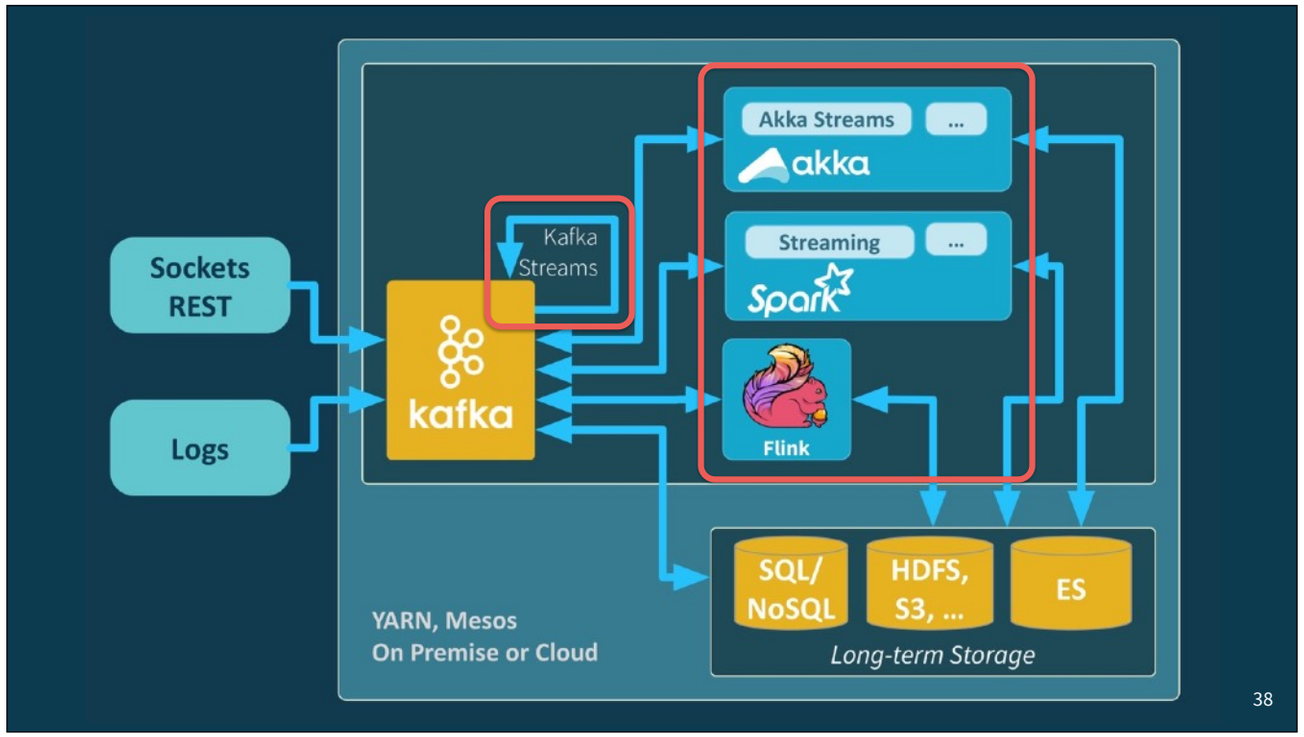
- Low latency? How low?
- High volume? How high?

Some tasks require a few microseconds are less, while others can tolerate more latency, especially if it allows the job to do more sophisticated or expensive things, like train machine learning models iteratively, write to databases, etc.
At high volumes, you might have to pick a very scalable tool with amortized excellent performance per event, but not when processing low volumes (e.g., due to the infrastructure it uses to support high volumes). Alternatively, a tool with excellent per-event performance might not scale well.

Streaming Tradeoffs

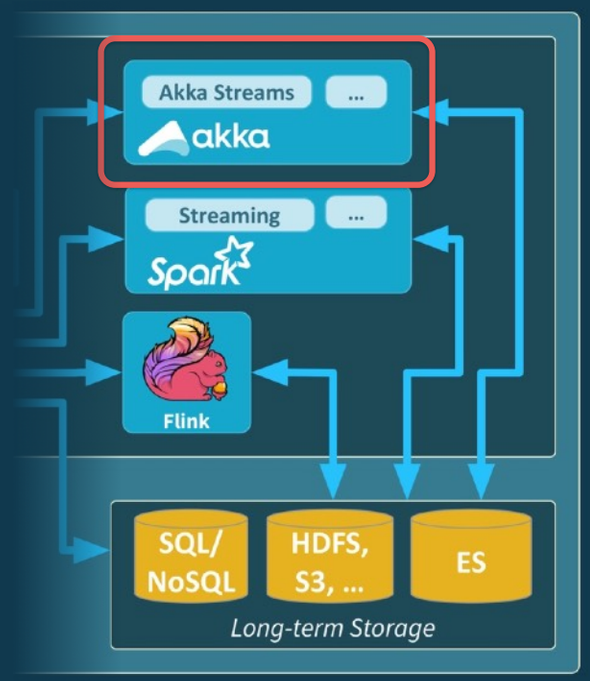
- Which kinds of data processing, analytics are required?
- How?
  - Bulk processing of records?
  - Individual processing of events?

Are you doing complex event processing (CEP)? Aggregations? ETL? Others?
CEP is (usually) best done with a tool that processes each event individually, whereas other kinds of data can be processed “en masse” and it’s more efficient to do so, (like joins and group-bys).



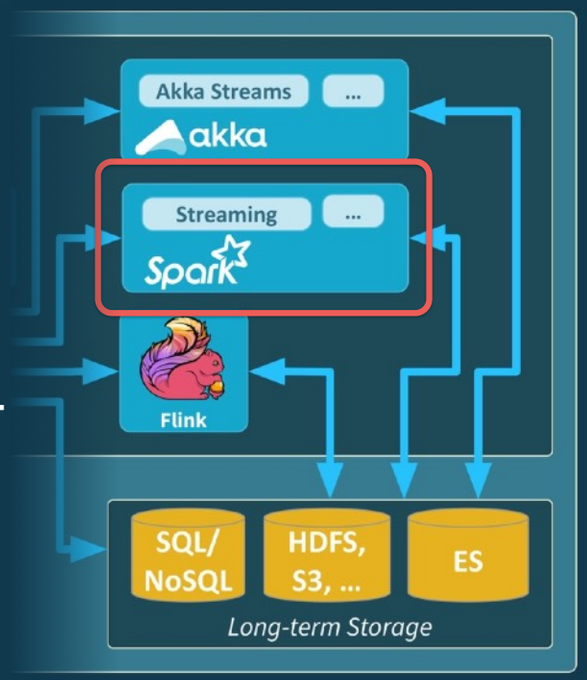
I showed four of dozens(?) of possibilities, Akka, Spark, and Flink. I picked these three because they offer interesting choices in these tradeoffs...

- Low latency
- Low volume
- Complex flows
- Per Event



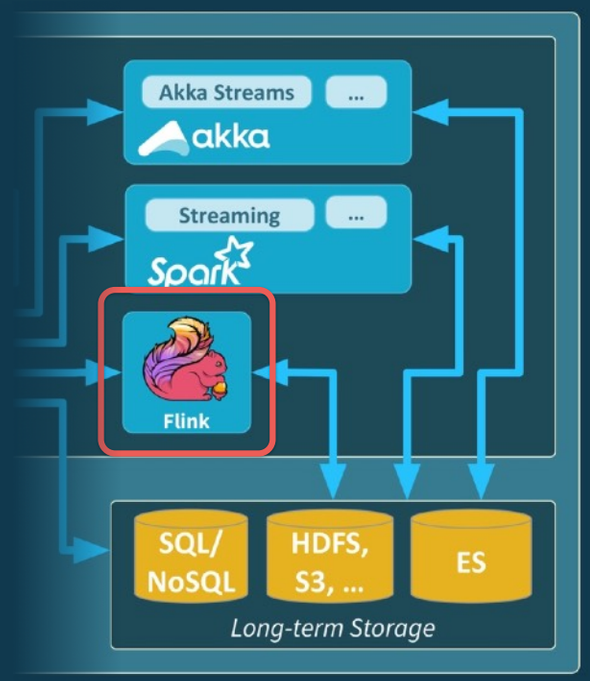
Akka is very low latency, optimized for excellent performance per event instead of high volume processing. You can do arbitrarily complex processing, including a sophisticated “flow graph” model. It is ideal for per-event processing.

- Med. latency
- High volume
- Data flows, SQL
- En masse

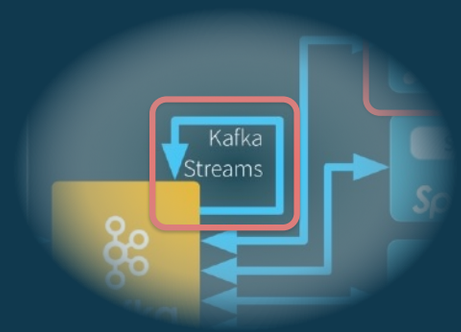


Spark has medium latency (~0.5 seconds and up), optimized for excellent, scalable performance at high volumes. The model is either data flows (think sequential processing nodes) or SQL queries. It is not designed for per-event processing, but “en masse” processing of records.

- Low latency
- High volume
- Data flows, correctness
- En masse



Flink contrasts mostly with Spark. It has low instead of medium latency, both with excellent, scalable performance at high volumes. The model is also primarily data flow oriented (SQL is coming), but it also supports very sophisticated correctness semantics, such has for handling windows of events, processing by event time (not system arrival time), handling late-arriving data, etc.



- Low latency
- Med. volume

- ETL, “tables”
- Data flow / Per Event

Kafka Streaming is focused on reading data in Kafka topics, processing it, and writing the results to new topics. It’s ideal for many common scenarios, such as ETL, but also supports running aggregations including the last seen values for keys (like DB tables work). Using the API, you write data flow code, but the implementation is more like a per-event processor.

R to L: Tressider Peak, Columbia Finger, Cathedral Peak, Echo Peaks, and Matthes Crest, Yosemite National Park

photo: Columbia Finger, Yosemite National Park (Mesos)

Mesos

- Treats your cluster like a large set of resources

While you can’t ignore real resource boundaries and perf. characteristics, like network overhead, for many cases, treating your cluster like a giant machine is a nice simplification, especially for app writers.

Mesos: Analogous to YARN

- Resources are *dynamic*
  - CPU cores & memory
  - but also network, disk, ...

If you know Hadoop/YARN, start there. Mesos. Mesos manages resource, including some that YARN doesn't (yet) manage.

Mesos: Analogous to YARN

- Each application *framework* provides its own scheduler
- Resources are offered
  - They can be refused

YARN has to hard-code knowledge about how any application will need and use resources. This centralization makes it impossible to plug in arbitrary, new apps with very different needs. Mesos delegates this app-specific knowledge to the app. Instead, it naively offers available resources to each running app (a framework in Mesos terms). The app's scheduler decides whether or not to accept any or all of the offered resources. If it doesn't, then Mesos will offer them to another framework. If it does, then the framework tells Mesos how to start the process that will use the resources. This makes Mesos far more flexible than YARN; it can not only run HDFS and databases, which YARN can't, it can even run YARN itself (See https://myriad.apache.org/)https://myriad.apache.org/
There are other advantages, see my Spark on Mesos talk: https://deanwampler.github.io/polyglotprogramming/papers/SparkOnMesos.pdf

http://mesos.berkeley.edu/mesos_tech_report.pdf

Mesos: A Platform for Fine-Grained Resource Sharing in the Data Center

Benjamin Hindman, Andy Konwinski, Matei Zaharia,
Ali Ghodsi, Anthony D. Joseph, Randy Katz, Scott Shenker, Ion Stoica
University of California, Berkeley

Thursday 30th September, 2010, 12:57

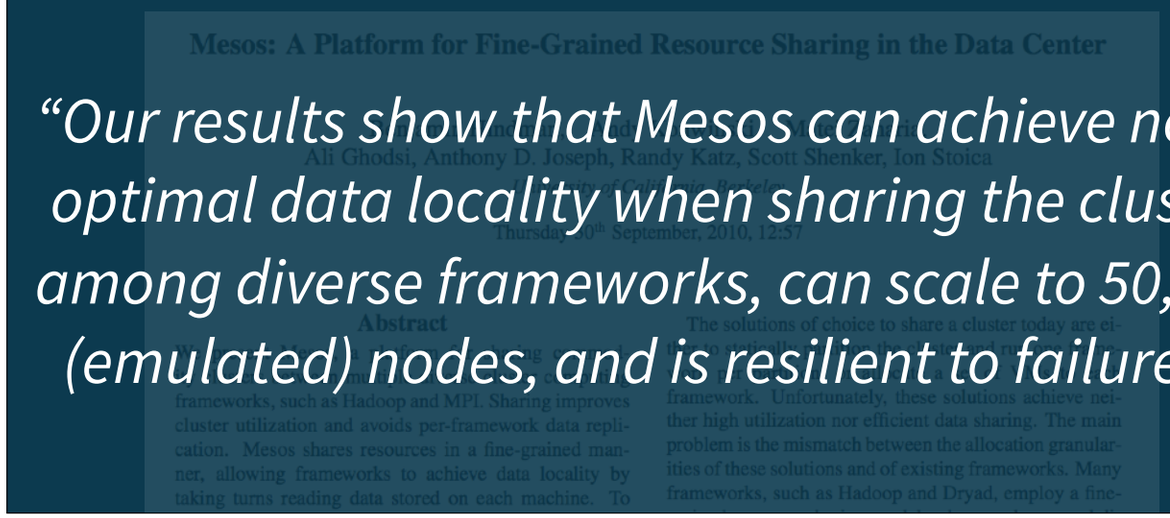
Abstract

We present Mesos, a platform for sharing commodity clusters between multiple diverse cluster computing frameworks, such as Hadoop and MPI. Sharing improves cluster utilization and avoids per-framework data replication. Mesos shares resources in a fine-grained manner, allowing frameworks to achieve data locality by taking turns reading data stored on each machine. To

The solutions of choice to share a cluster today are either to statically partition the cluster and run one framework per partition, or allocate a set of VMs to each framework. Unfortunately, these solutions achieve neither high utilization nor efficient data sharing. The main problem is the mismatch between the allocation granularities of these solutions and of existing frameworks. Many frameworks, such as Hadoop and Dryad, employ a fine-

The Mesos research paper. Ben lead the development as a Berkeley grad student. Matei was a fellow grad student who created Spark...

http://mesos.berkeley.edu/mesos_tech_report.pdf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"Our results show that Mesos can achieve near-optimal data locality when sharing the cluster among diverse frameworks, can scale to 50,000 (emulated) nodes, and is resilient to failures."

It works very well in practice. As its use in industry has grown, it has been refined and extended.

http://mesos.berkeley.edu/mesos_tech_report.pdf


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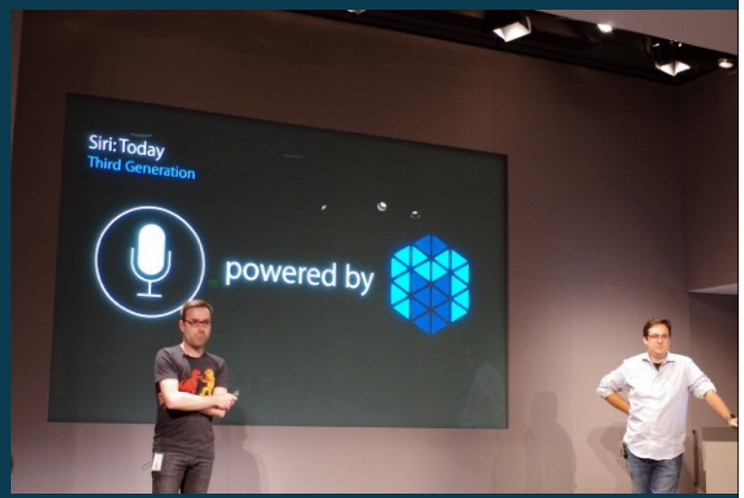
*"To validate our hypothesis ..., we have also built a new framework on top of Mesos called **Spark**..."*

Funny enough, even though Spark is better known and more popular now, it started as a subproject of Mesos...

Adoption

- Twitter
- Apple's Siri
- Airbnb
- Verizon
- CERN, ...



All of Siri runs on it now.


Other
Clustering
Platforms?

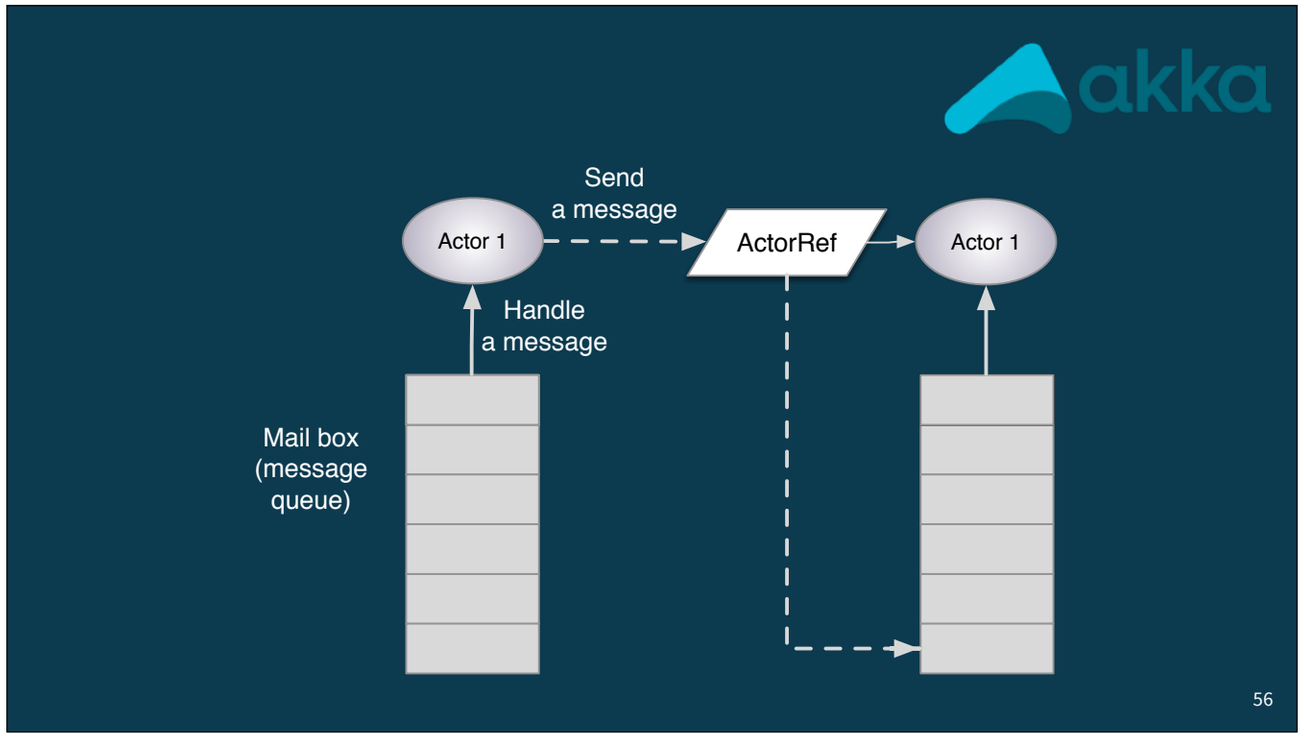
Clouds?

- Compelling, but it's also common to use Mesos on top of clouds:
  - Virtual cluster of resources
  - Uniform deployment, management on-premise & cloud

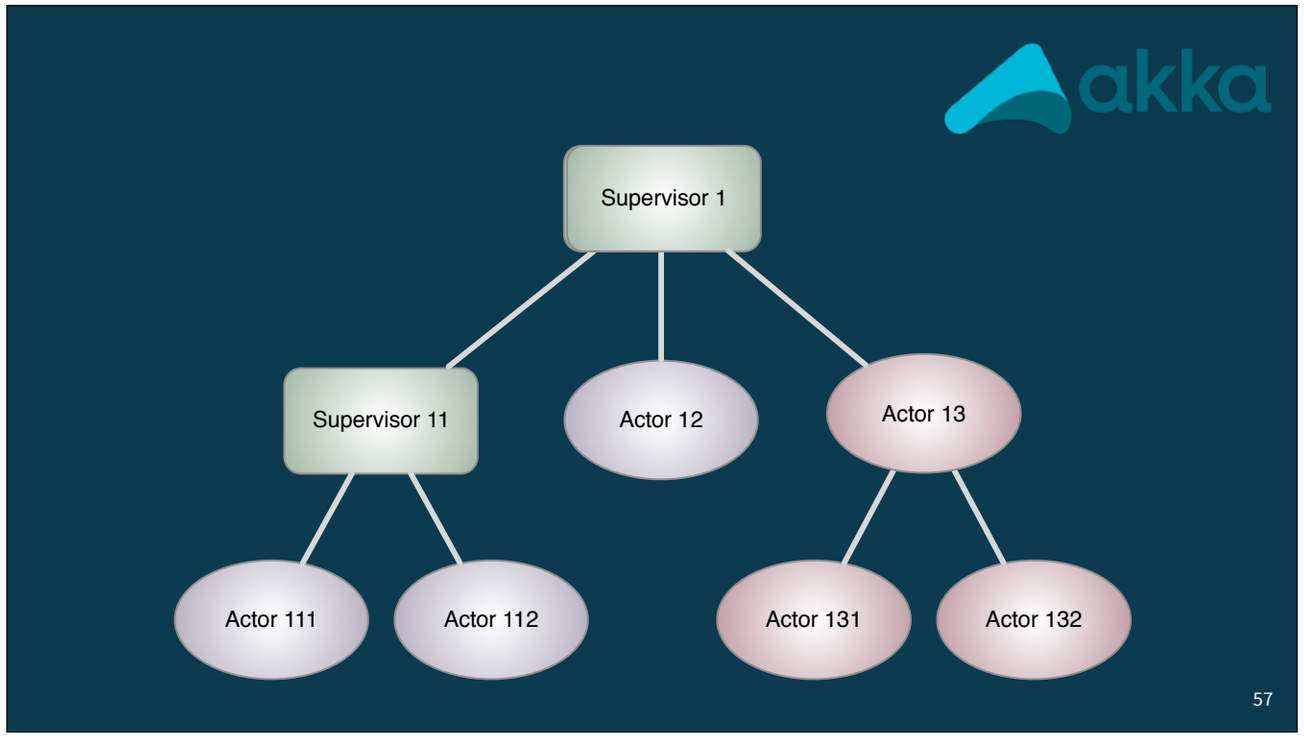
Will Clouds make Mesos unnecessary? Maybe, but there is cost advantages to spin up long-running virtual instances, then manage them as a cluster of resources using Mesos. Also, for hybrid on-premise and cloud environments, uniformity is useful for everything above the server level.

R to L: Tressider Peak, Columbia Finger, Cathedral Peak, Echo Peaks, and Matthes Crest, Yosemite National Park

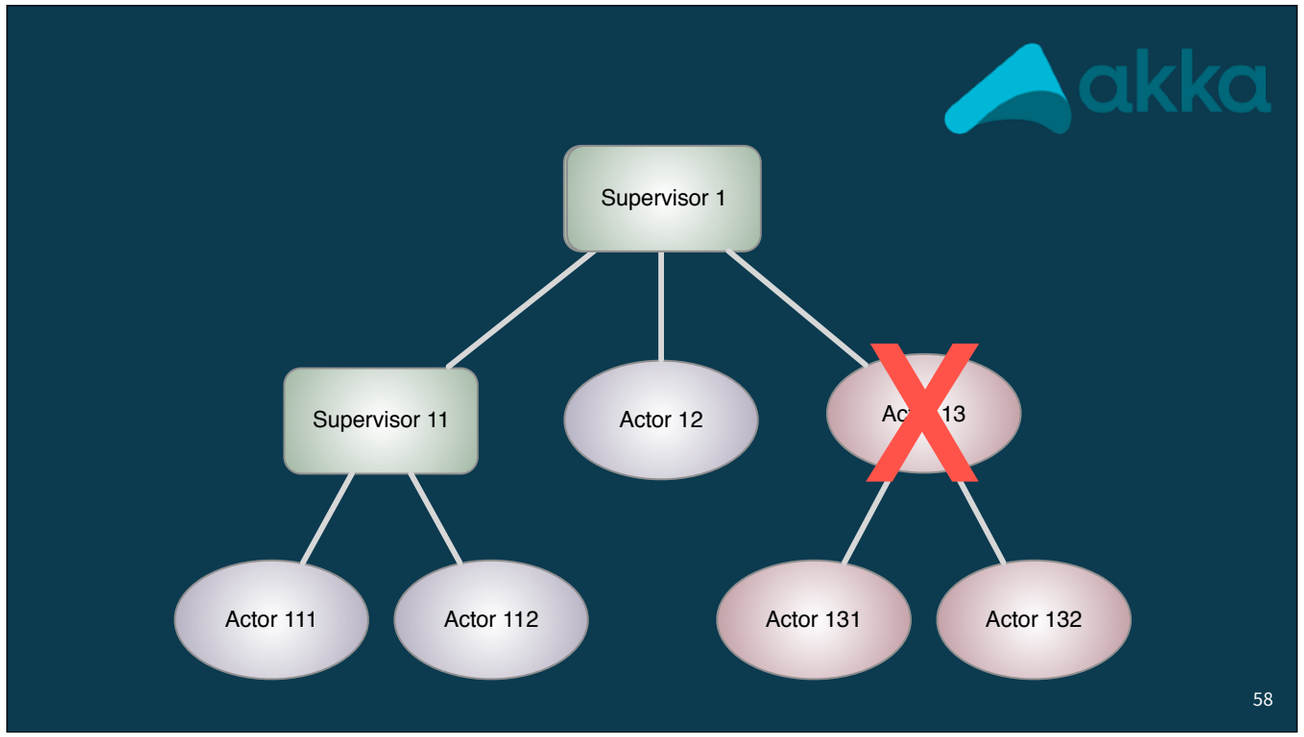
Akka is a set of tools for building resilient, distributed, concurrent apps on the JVM.
for photo: Cathedral Peak, Yosemite National Park (Akka)



At the lowest level, you program to an Actor model, autonomous agents where your code inside them is guaranteed thread safe. Actors send messages to each other to send information and invoke actions asynchronously.
There is also the higher level Akka Streams API we discussed previously.



One of the most powerful features for resiliency is that supervision of your domain actors is a separate concern (special-purpose actors), which manage the lifecycles of domain actors, triggering recovery when failure happens.



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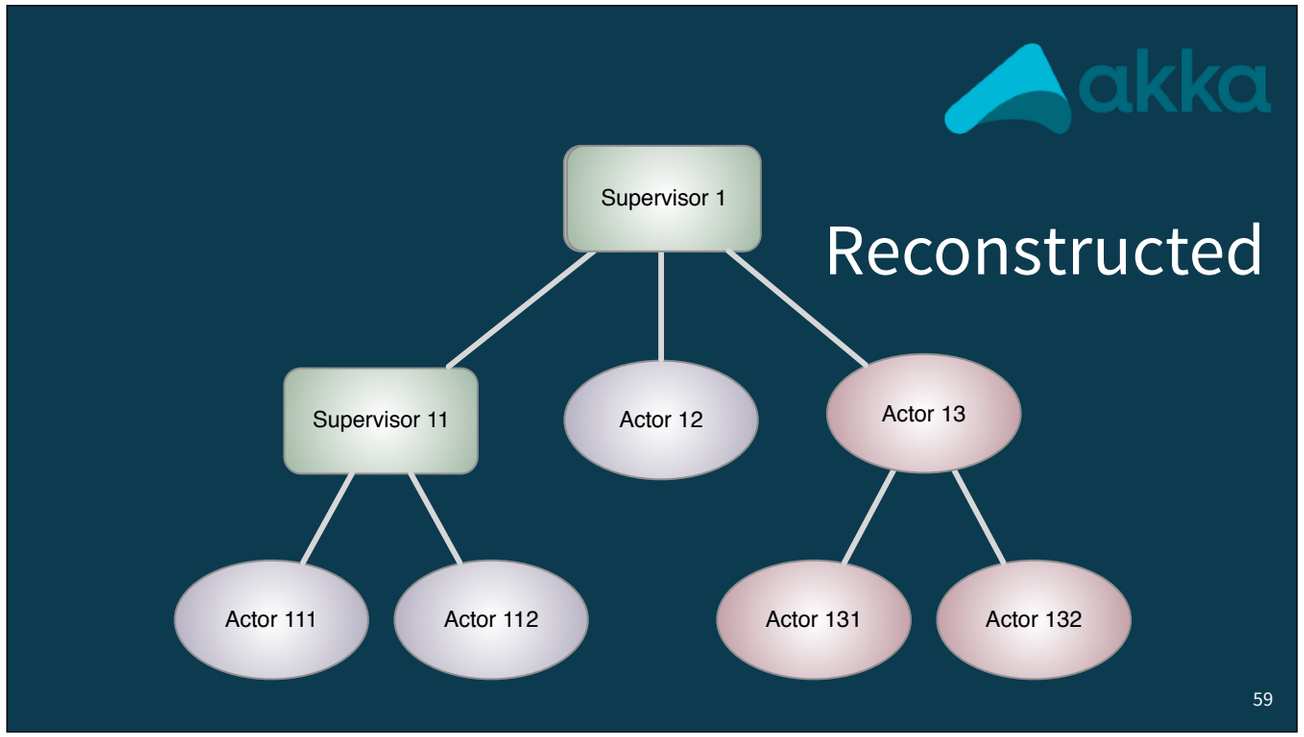

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Distributed Apps

- High performance
  - ~50M msgs/sec on a laptop
- Elastic and decentralized
- Modules for clustering, CQRS, HTTP, ...

Other benefits.

Lightbend Reactive Platform

- Akka is one piece of SMACK. If you add the rest of RP, you get:

SMRCK

If you throw in the rest of our stuff, you get the SMRCK (“smirk”) stack...

I’ll be here all week folks. You’ve been a great audience! Don’t forget to tip your waitress!

photo: Cathedral Peak... or is it the Eye of Sauron??!!

Yes, but it must be *Reactive*

- Is it message driven?
- Is it scalable up and down?
- Is it resilient against failure?
- Is it always responsive?

See http://www.reactivemanifesto.org/

R to L: Tressider Peak, Columbia Finger, Cathedral Peak, Echo Peaks, and Matthes Crest, Yosemite National Park

photo: The really beautiful Echo Peaks, Yosemite National Park (Cassandra)

Distributed Databases

- Cassandra is in SMACK (SMRCK?) because it's so widely used.
- Spark + Cassandra + Kafka is *very* common in streaming systems.

The second bullet is based on surveys that Lightbend and other organizations have done.
I won't discuss the advantages of Cassandra further, as this is already a long talk and you may already be familiar with it or other NoSQL databases.

Other Databases, File Systems?

- Scalable? distribution with partitioning
- Resilient? distribution, replication, availability (CAP) better

Lots of other databases could be used instead of (or along side of Cassandra). Even a distributed file system might be all your need. What about traditional relational (SQL) databases?? NoSQL databases that embrace availability (CAP theorem) will remain available a higher % of time in the face of failure, but note that many exports are concerned that eventual consistency is very hard to do correct, so some organizations are actually choosing consistency instead! TCO is generally lower for NoSQL, too.

Other Databases/file systems?

- Cost? NoSQL *has been* cheaper

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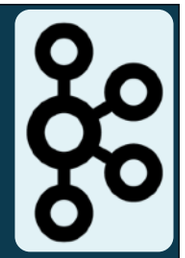
R to L: Tressider Peak, Columbia Finger, Cathedral Peak, Echo Peaks, and Matthes Crest, Yosemite National Park

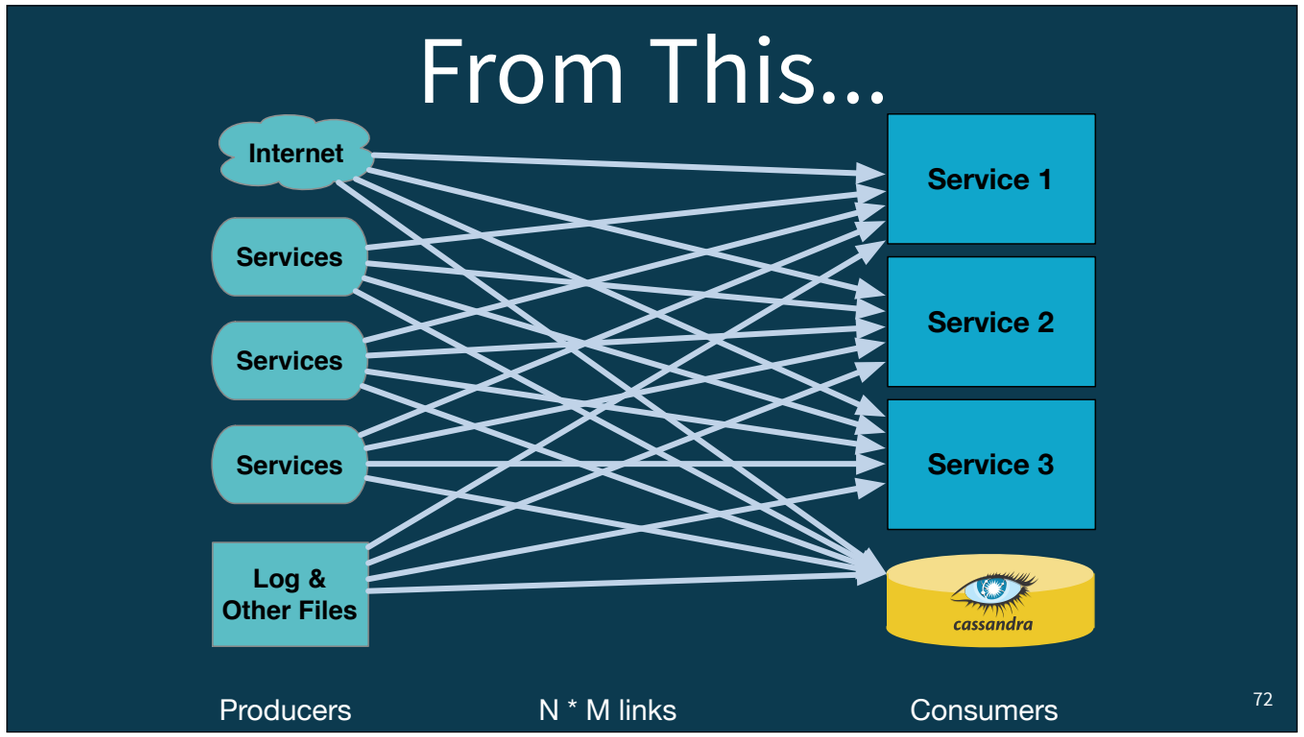
photo: The dramatic Matthes Crest, Yosemite National Park (Kafka)

“Message Bus”

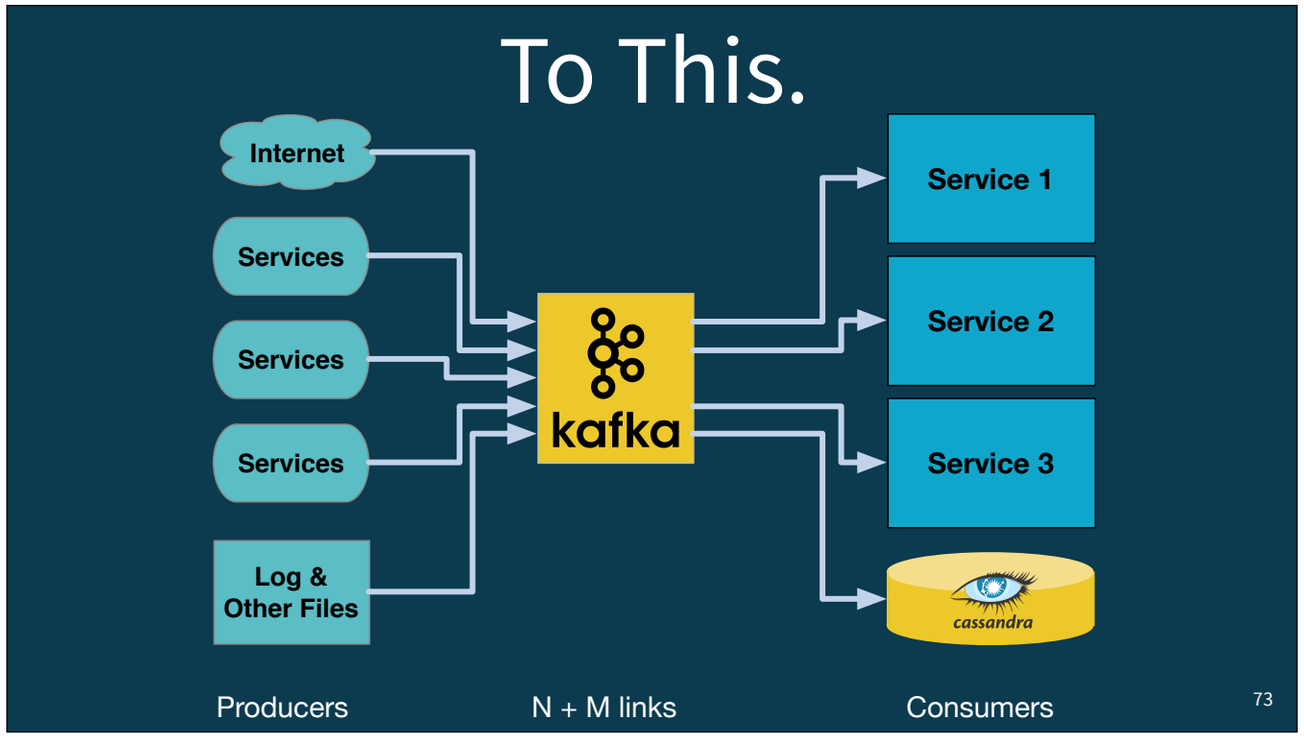


- Pub/Sub model
  - Organized by topic
- Short term, resilient storage
- Massive scalability
  - 1.2+T messages/day at Linkedin

Kafka is “so hot right now” because it’s an excellent tool to glue all the pieces together in the stack. It’s the distributed, highly scalable and reliable message bus between other services, providing intuitive pub/sub semantics, resiliency through on-disk temporary storage (default: 7 days), with optional replication for further resiliency and partitioning for even more scalability.



As an architect tool, Kafka fixes the flaw of having direct point-to-point connections (up to N*M). This is both messy to manage and fragile. If Service1 drops, for instance, all the connections to it are broken, affecting the producers and losing service.



By routing messages through Kafka, you reduce the connections to N+M, allow 1+ producers and 1+ consumers per topic, and provide much greater resiliency. Should Service 1 go down (or need to be upgraded), the messages in the topic will remain there until a replacement comes up.

photo: The dramatic Matthes Crest, Yosemite National Park

Kinesis, Message Queues, ...

- AWS Kinesis
- Traditional message queues: ZeroMQ, RabbitMQ, ...

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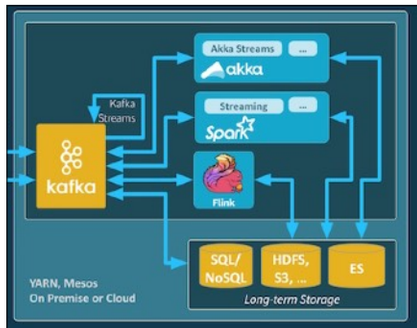
Kinesis, Message Queues, ...

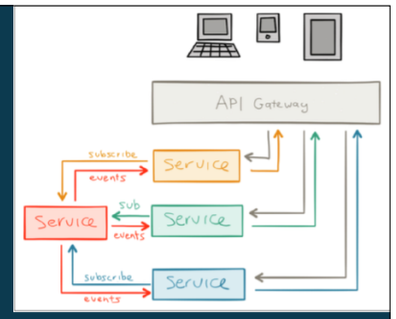
- Evaluate the differences:
  - Scalability & resiliency
  - Pub/Sub semantics different
  - E.g., Kafka readers don’t consume the message!

Be sure that the alternative scale as much as you need them to scale.
Study the pub/sub semantics carefully. For most message queues, reading a message consumes it. That simplifies the implementation, but it complicates writing many applications that need to see the whole stream. Every reader of a Kafka topic will see all the messages. Kafka manages the offsets into the topics for each reader.

photo: First light on Banner Peak from 1000 Island Lake.

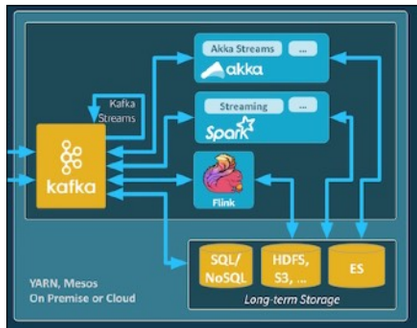


Synergies



- Each (stream|µservice):
  - does one thing
  - has unending (data|messages)

A data stream, in this case a single application written on top of Kafka, Spark, etc. does one calculation (ideally). So does a microservice. Similarly, both process data that keeps coming indefinitely.



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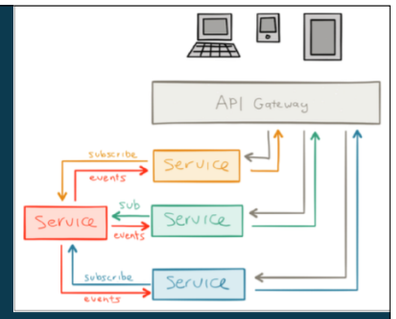
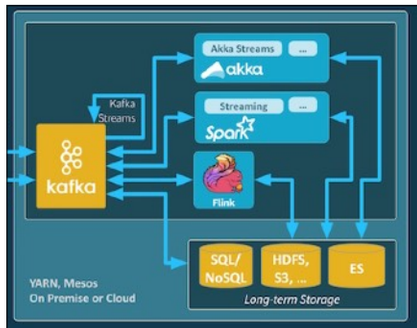
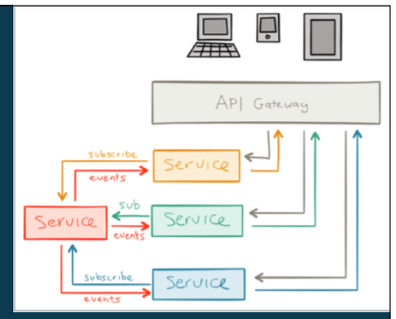


- Each (stream|μservice):
  - encourages asynchrony
  - offers never-ending service

Both require asynchronous behavior for maximal resource utilization and to avoid blocking.
Both need to run potentially forever.



Thesis



- These architectures will converge:
  - Similar design problems
  - Data becomes dominate problem

So, both face similar design problems, encouraging similar solutions. Also, small applications, if successful, grow bigger and eventually, data management becomes the dominant concern. Hence, I argue that the convergence will happen over time.

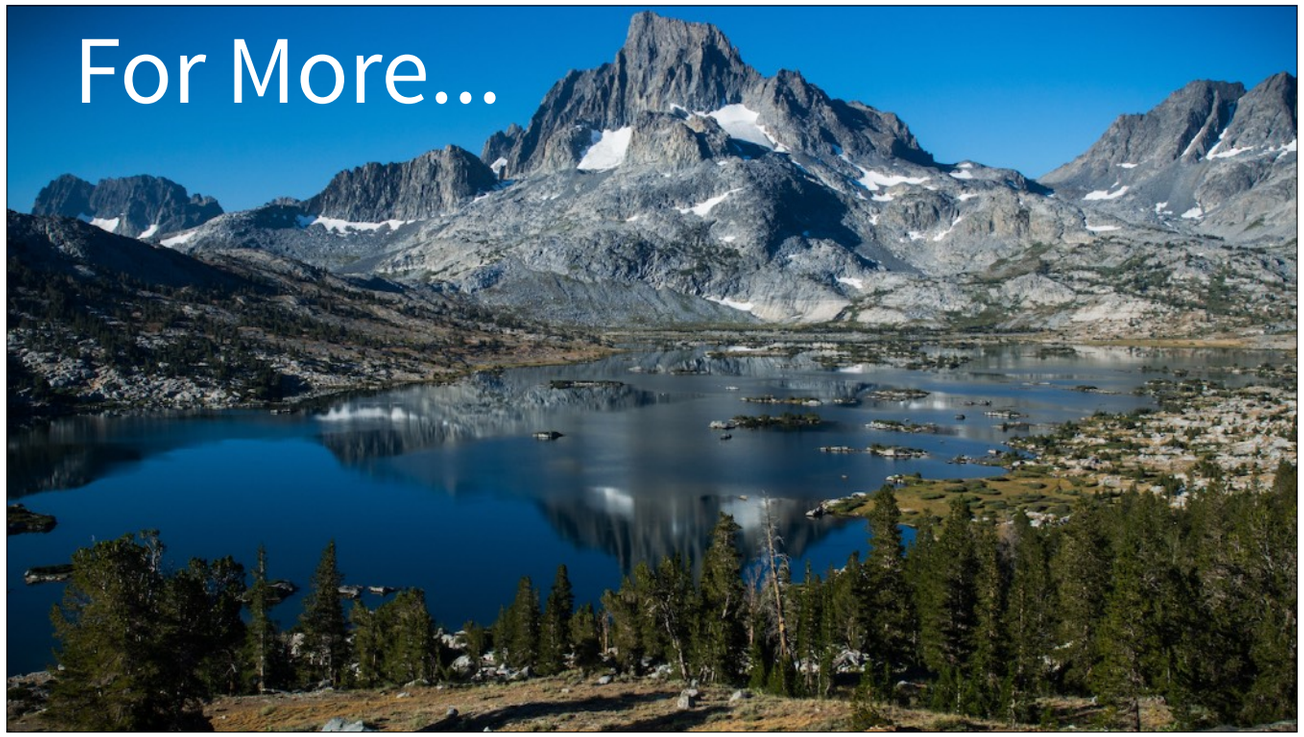
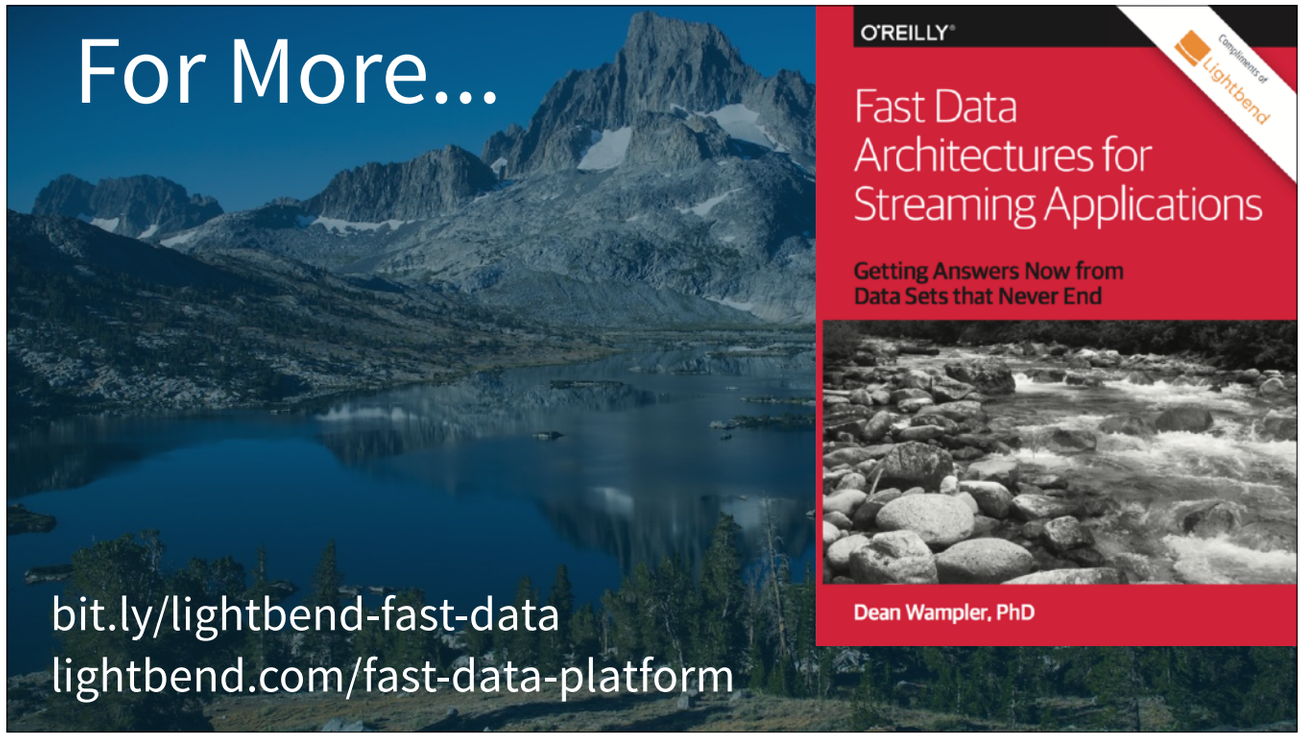


photo: Banner Peak reflected in 1000 Island Lake, Ansel Adams Wilderness

Jonas Bonér's book on architectures for Reactive Microservices



First link is to this report I wrote, published by O'Reilly.
Second link is to learn more about what Lightbend is doing to help teams build fast-data, streaming architectures.

photo: Morning Light and reflections in 1000 Island Lake of Banner and Davis Peaks, Ansel Adams Wilderness