Building Kafka-based Microservices with Akka Streams and Kafka Streams

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Boris Lublinsky and Dean Wampler, Lightbend

boris.lublinsky@lightbend.com

Outline

- Overview of streaming architectures
  - Kafka, Spark, Flink, Akka Streams, Kafka Streams
- Running example: Serving machine learning models
- Streaming in a microservice context
  - Akka Streams
  - Kafka Streams
- Wrap up

But first, introductions…

Why Streaming?

“We live as streams, but we have a tendency to think in batch. Batch might be faster (simpler), but the reality is streams”

— Fabio Yamada, Kafka Mailing List

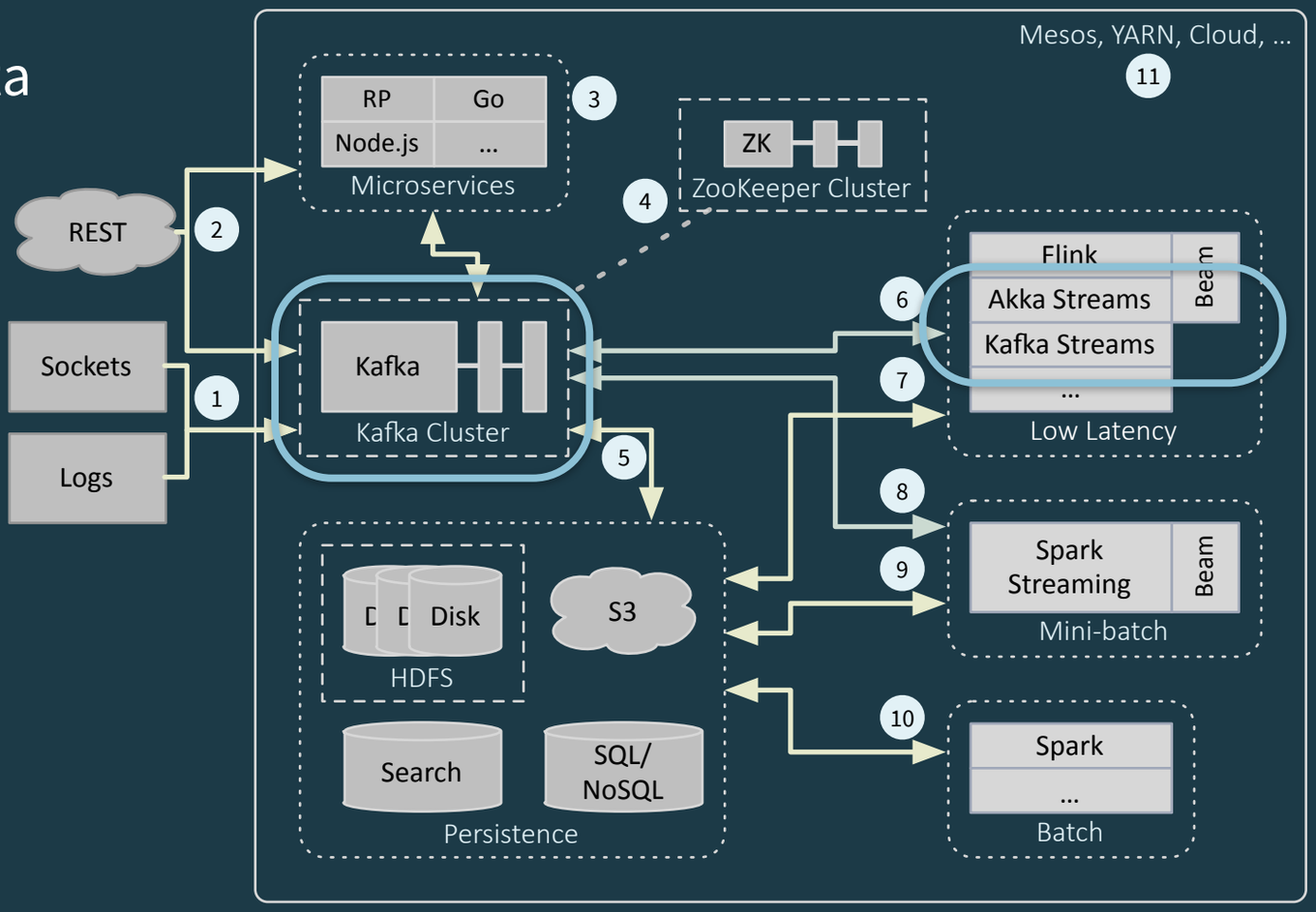
About Streaming Architectures

Why Kafka, Spark, Flink, Akka Streams, and Kafka Streams?

- Dean wrote this report describing the whole fast data landscape.
- bit.ly/lightbend-fast-data
- Previous talks (“Stream All the Things!”) and webinars (such as this one, https://info.lightbend.com/webinar-moving-from-big-data-to-fast-data-heres-how-to-pick-the-right-streaming-engine-recording.html) have covered the whole architecture. This session dives into the next level of detail, using Akka Streams and Kafka Streams to build Kafka-based microservices

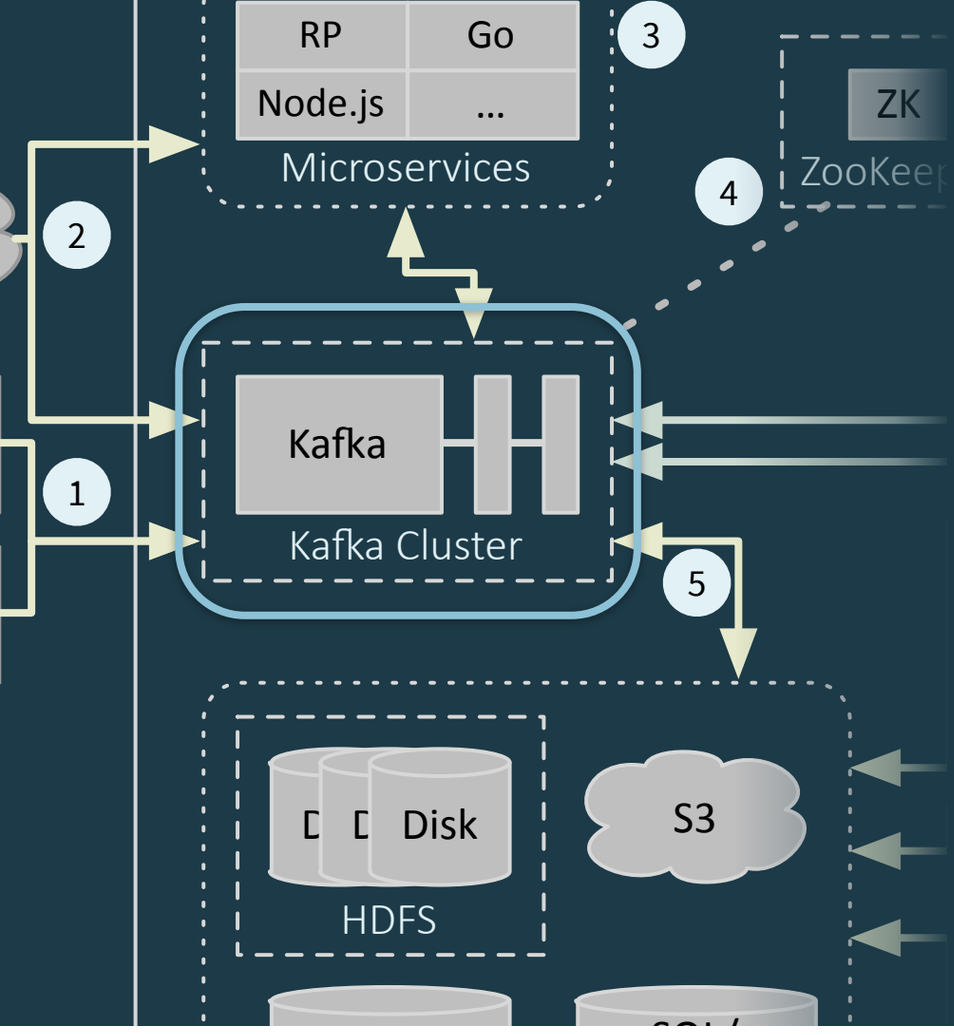
Today's focus:

- Kafka - the data backplane
- Akka Streams and Kafka Streams - streaming microservices



Kafka is the data backplane for high-volume data streams, which are organized by topics. Kafka has high scalability and resiliency, so it's an excellent integration tool between data producers and consumers.

Why Kafka?


RP
Go
Node.js
...
Microservices
3
ZK
ZooKeep
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Kafka
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Kafka Cluster
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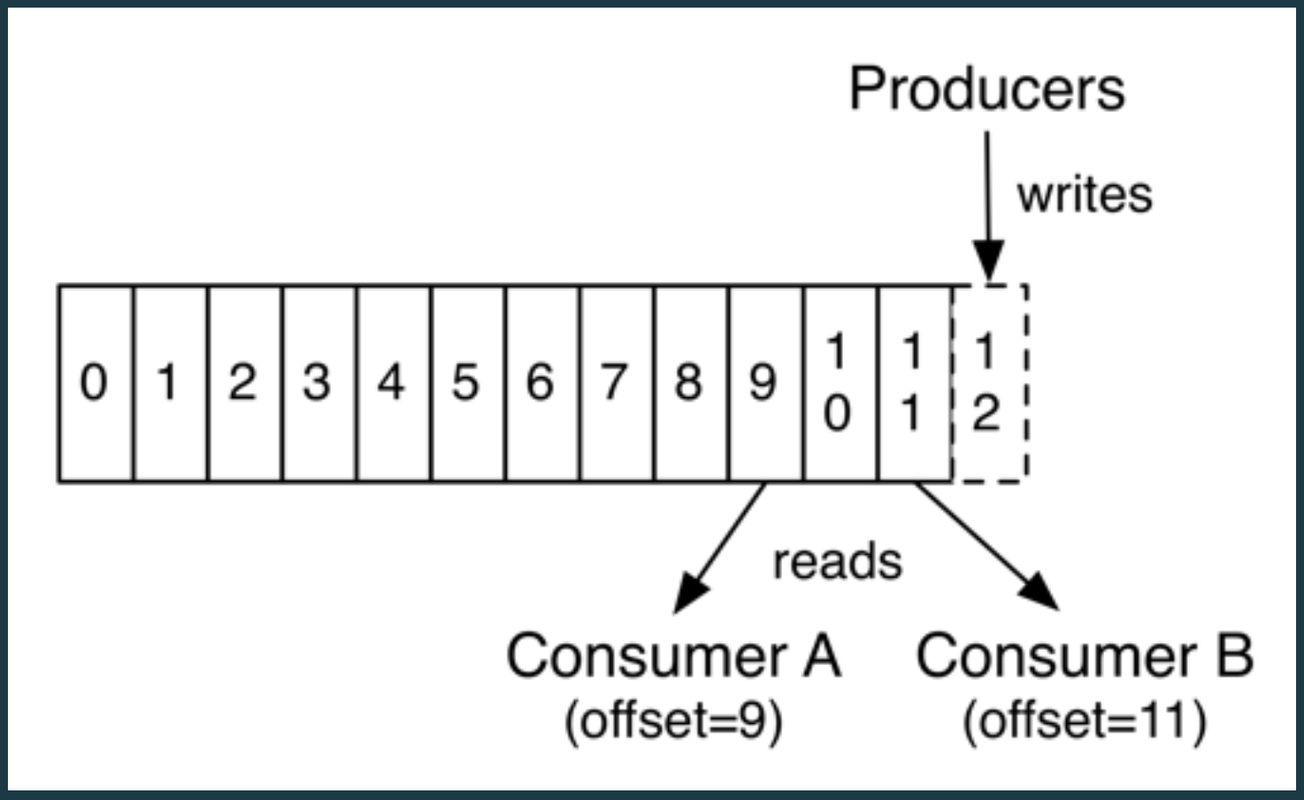
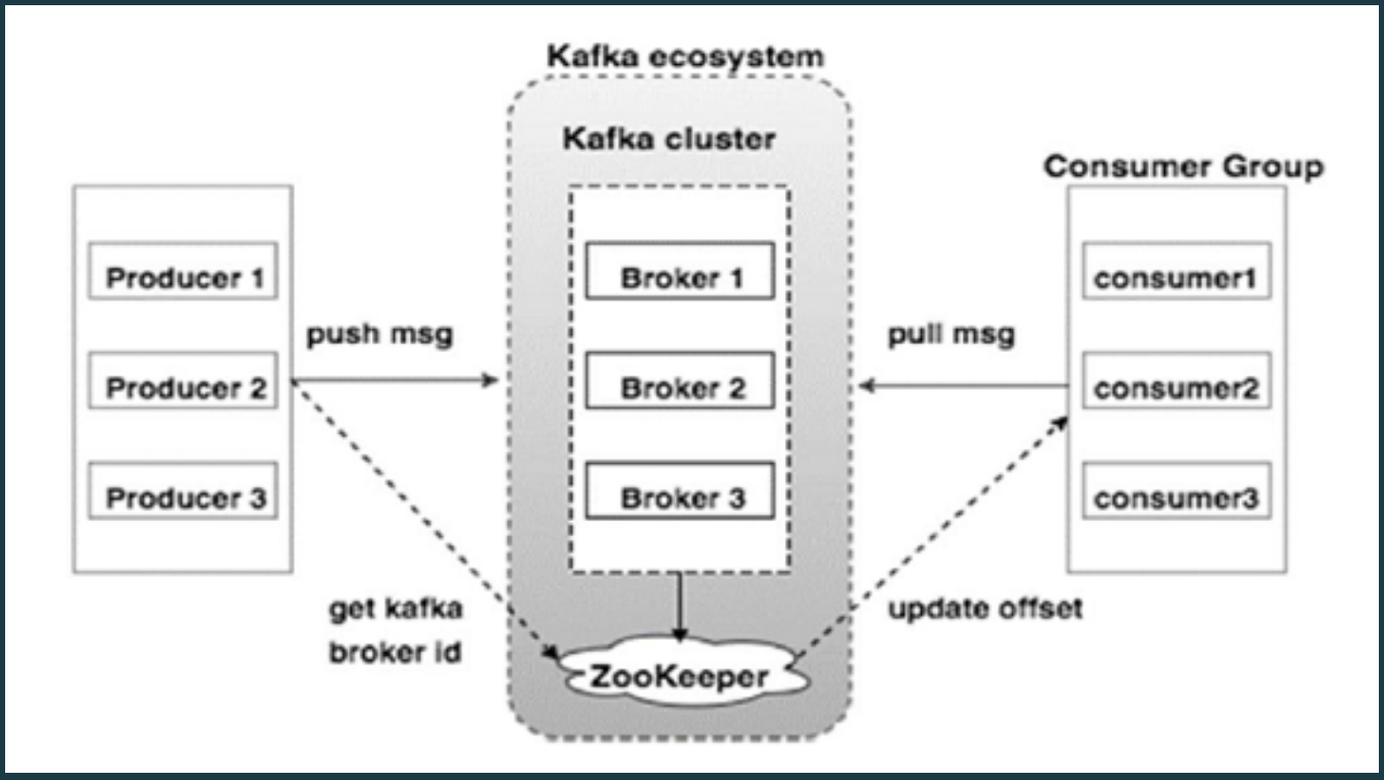
Disk
S3
HDFS



Kafka is a distributed log, storing messages sequentially. Producers always write to the end of the log, consumers can read on the log offset that they want to read from (earliest, latest, …)
Kafka can be used as either a queue or pub sub
The main differences are:
1. Log is persistent where queue is ephemeral (reads pop elements)
2. Traditional message brokers manage consumer offsets, while log systems allow users to manage offsets themselves

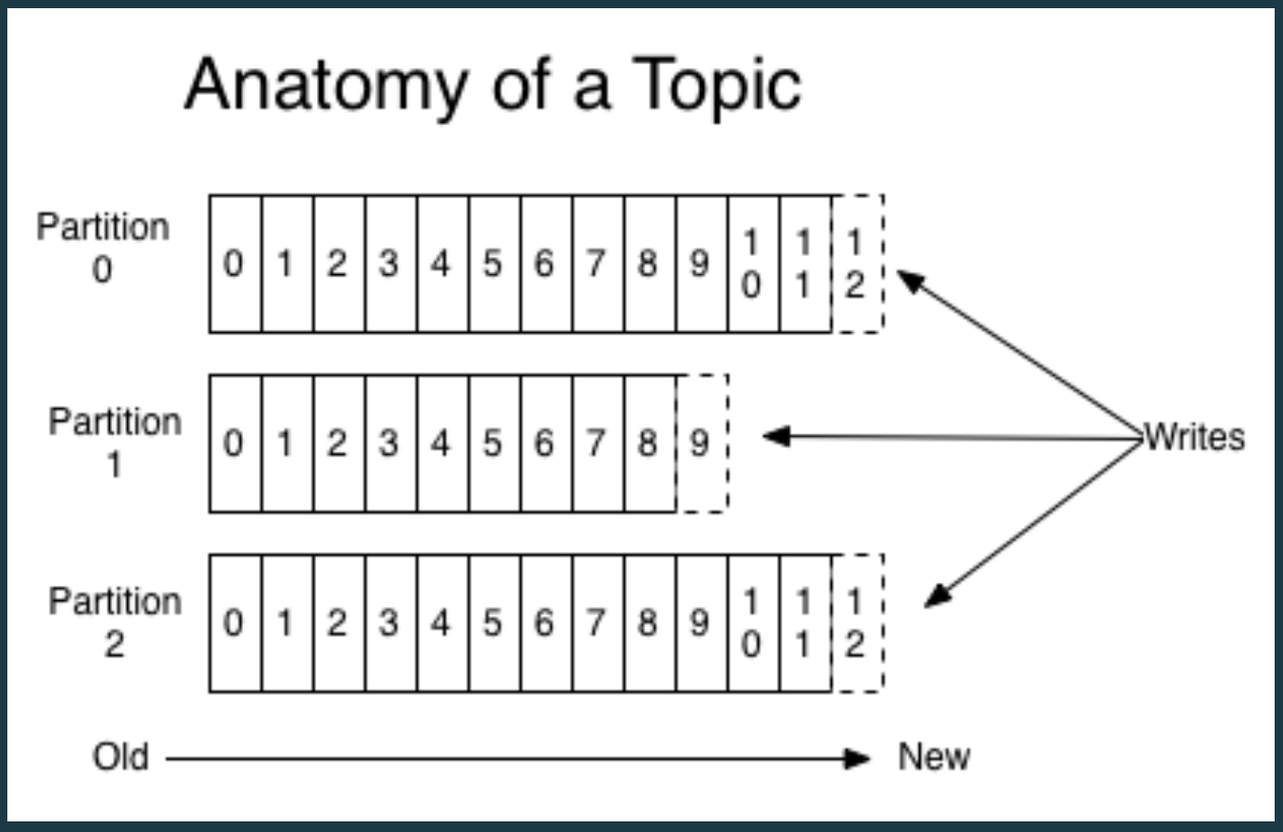
Alternatives to Kafka include Pravega (EMC) and Distributed Log/ Pulsar (Apache)



Kafka cluster typically consists of multiple brokers to maintain load balance.

One Kafka broker instance can handle hundreds of thousands of reads and writes per second and each broker can handle TB (based on the disk size and network performance) of messages without performance impact. Kafka broker leader election can be done by ZooKeeper.

A Topic and Its Partitions



Kafka data is organized by topic

A topic can be comprised of multiple partitions.

A partition is a physical data storage artifact. Data in a partition can be replicated across multiple brokers. Data in a partition is guaranteed to be sequential.

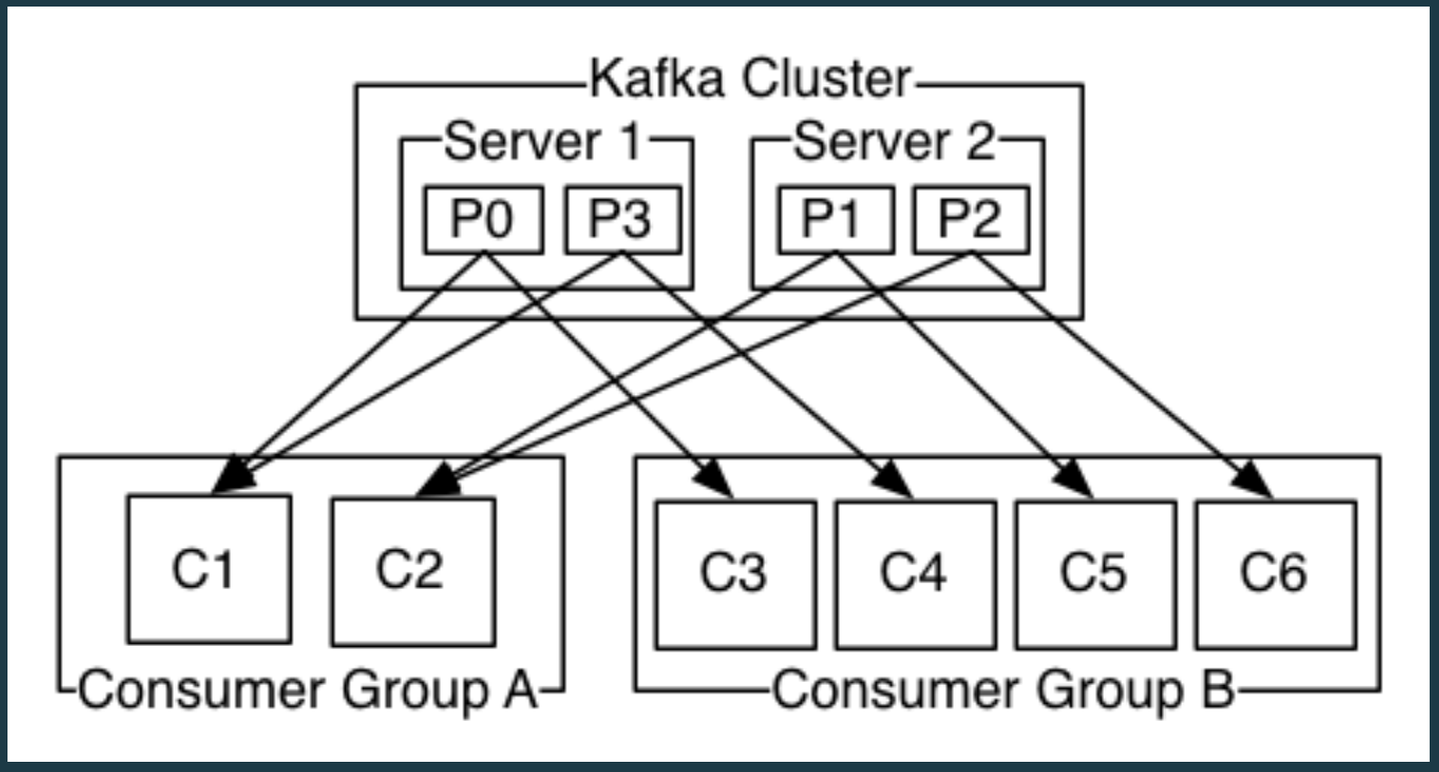
So, a topic is a logical aggregation of partitions. A topic doesn't provide any sequential guarantee (except a one-partition topic, where it's "accidental").

Partitioning is an important scalability mechanism - individual consumers can read dedicated partitions.

Partitioning mechanisms - round-robin, key (hash) based, custom.

Consider the sequential property when designing partitioning.

Consumer Groups



Consumers label themselves with a consumer group name, and each record published to a topic is delivered to one consumer instance within each subscribing consumer group (compare to queue semantics in traditional messaging). Consumer instances can be in separate processes or on separate machines.

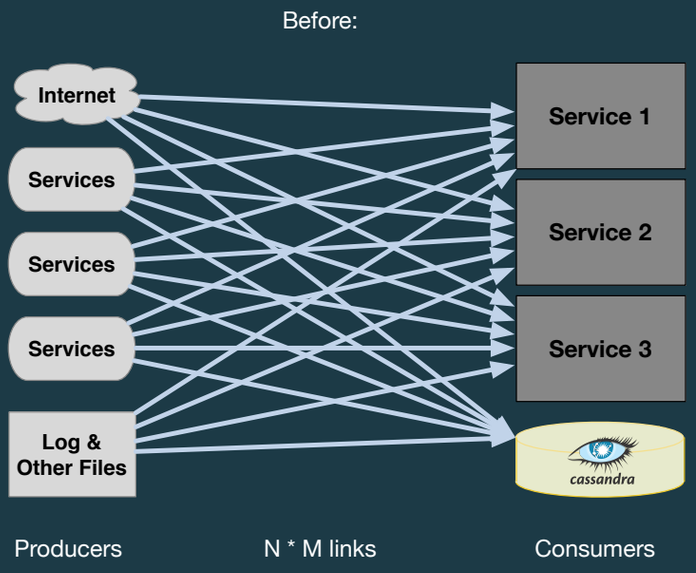
Kafka Producers and Consumers

Code time

1. Project overview
2. Explore and run the *client* project
   - Creates in-memory (“embedded”) Kafka instance and our topics
   - Pumps data into them

We’ll walk through the whole project, to get the lay of the land, then look at the client piece. The embedded Kafka approach is suitable for non-production scenarios only, like learning ;)

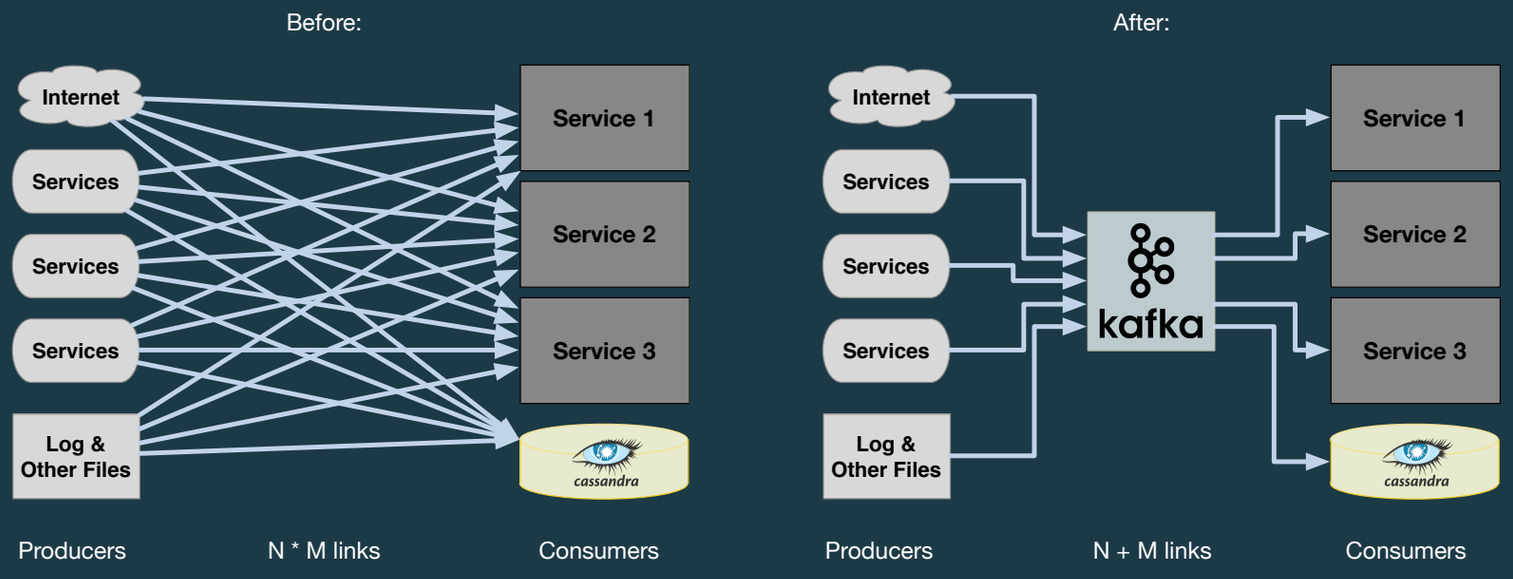
Architecture Benefits of Kafka



We’re arguing that you should use Kafka as the data backplane in your architectures. Why?

First, point to point spaghetti integration quickly becomes unmanageable as the amount of services grows

Architecture Benefits of Kafka

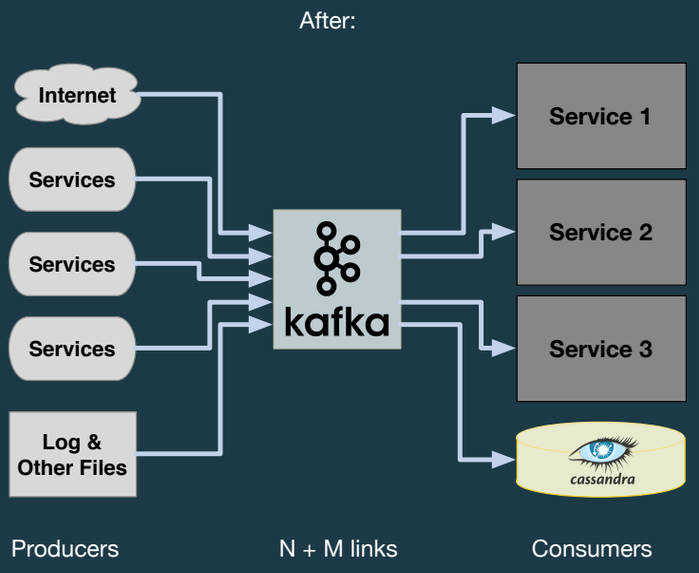


Kafka can simplify the situation by providing a single backbone which is used by all services (there are of coarse topics, but they are more logical then physical connections). Additionally Kafka persistence provides robustness when a service crashes (data is captured safely, waiting for the service to be restarted) - see also temporal decoupling, and provide the simplicity of one “API” for communicating between services.

Architecture Benefits of Kafka

Kafka:

- Simplify dependencies between services
    - Improved data consistency
- Minimize data transmissions
- Reduce data loss when a service crashes

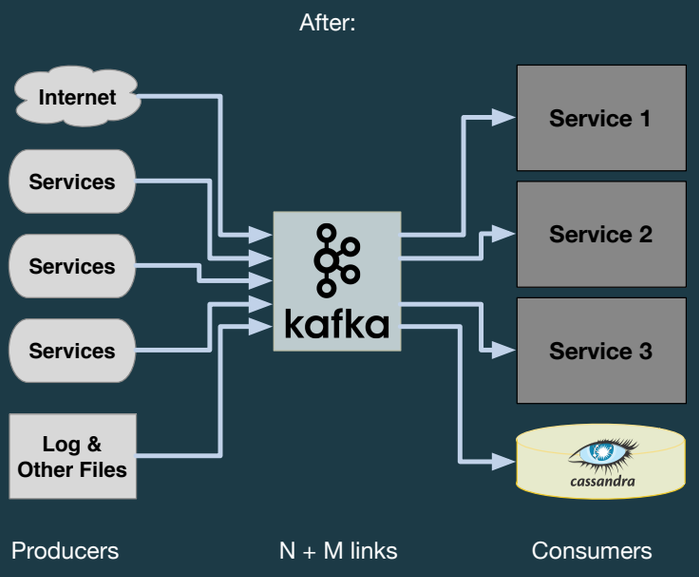


Kafka can significantly improve decoupling (no service specific endpoints, temporal decoupling), It minimize the amount of data send over network, each producer writes data to Kafka, instead of writing it to multiple consumers. This also improves data consistency - the same data is consumed by all consumers. Extensibility is greatly simplified - adding new consumers does not require any changes to producers, and provide the simplicity of one “API” for communicating between services.

Architecture Benefits of Kafka

Kafka:

- M producers, N consumers
    - Improved extensibility
- Simplicity of one “API” for communication



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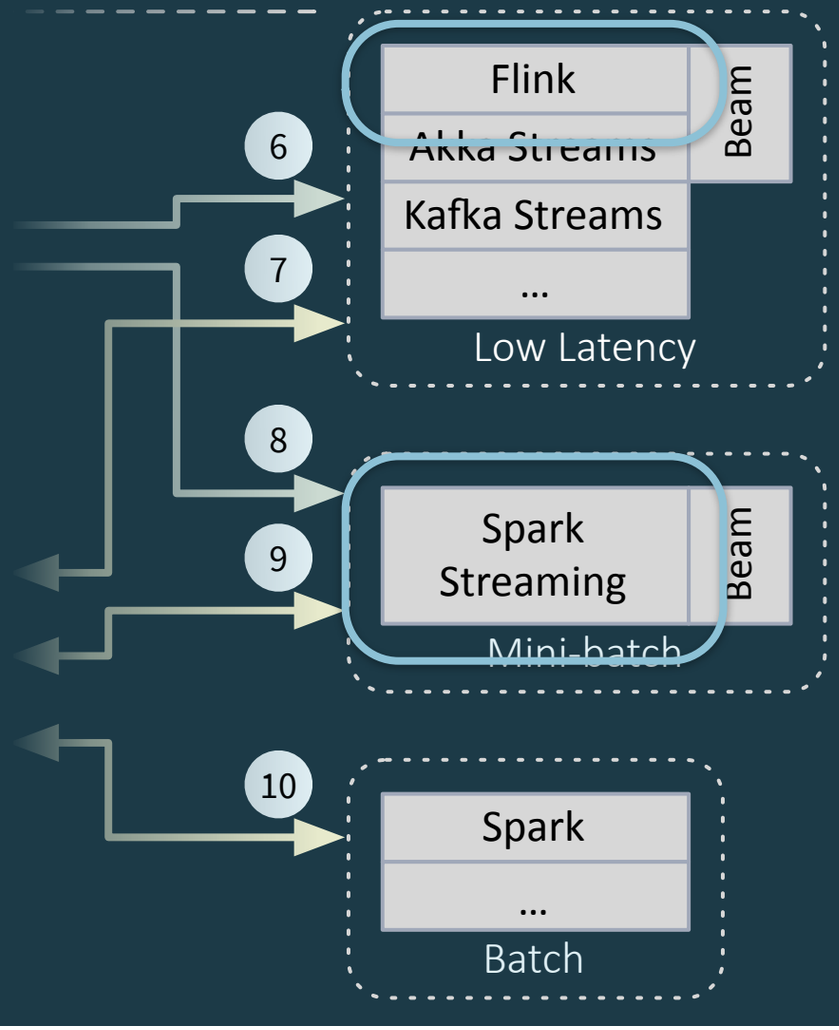
Streaming Architectures

Two options:

- Stream processing engines
- Streaming libraries

Streaming Engines:

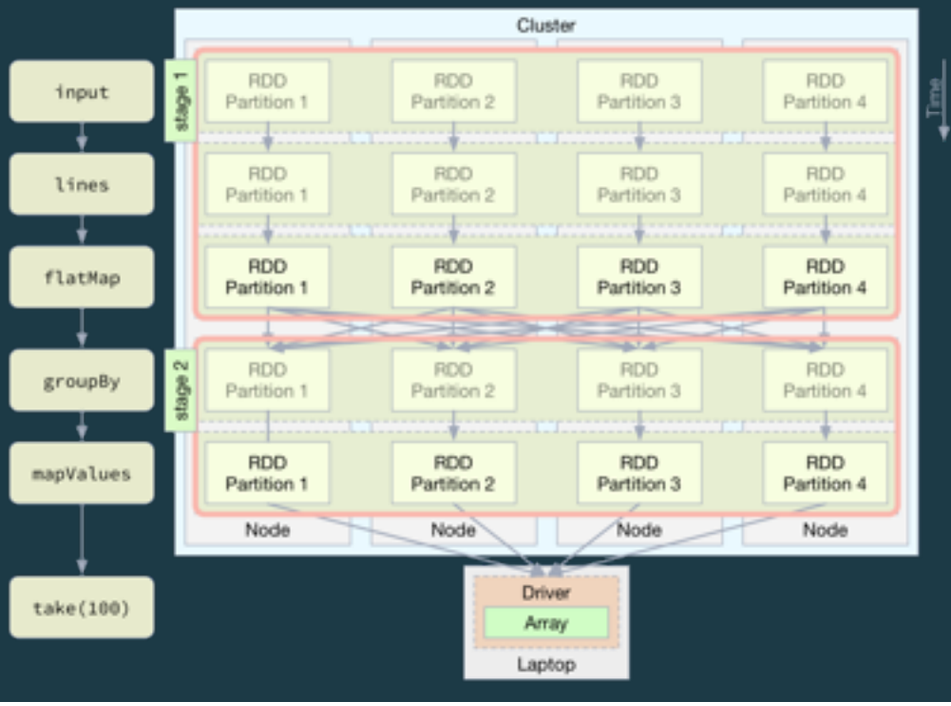
Spark, Flink - services to which you submit work. Large scale, automatic data partitioning.



They support highly scalable jobs, where they manage all the issues of scheduling processes, etc. You submit jobs to run to these running daemons. They handle scalability, failover, load balancing, etc. for you.

Streaming Engines:

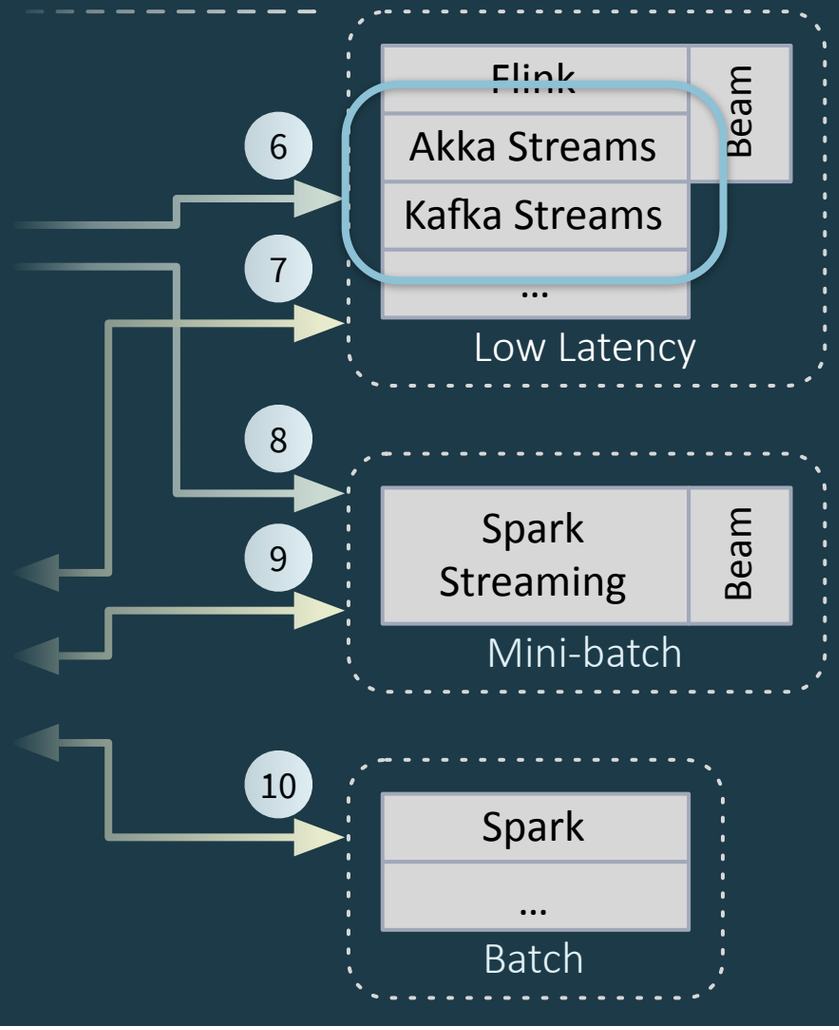
Spark, Flink - services to which you submit work. Large scale, automatic data partitioning.



You have to write jobs, using their APIs, that conform to their programming model. But if you do, Spark and Flink do a great deal of work under the hood for you!

Streaming Libraries:

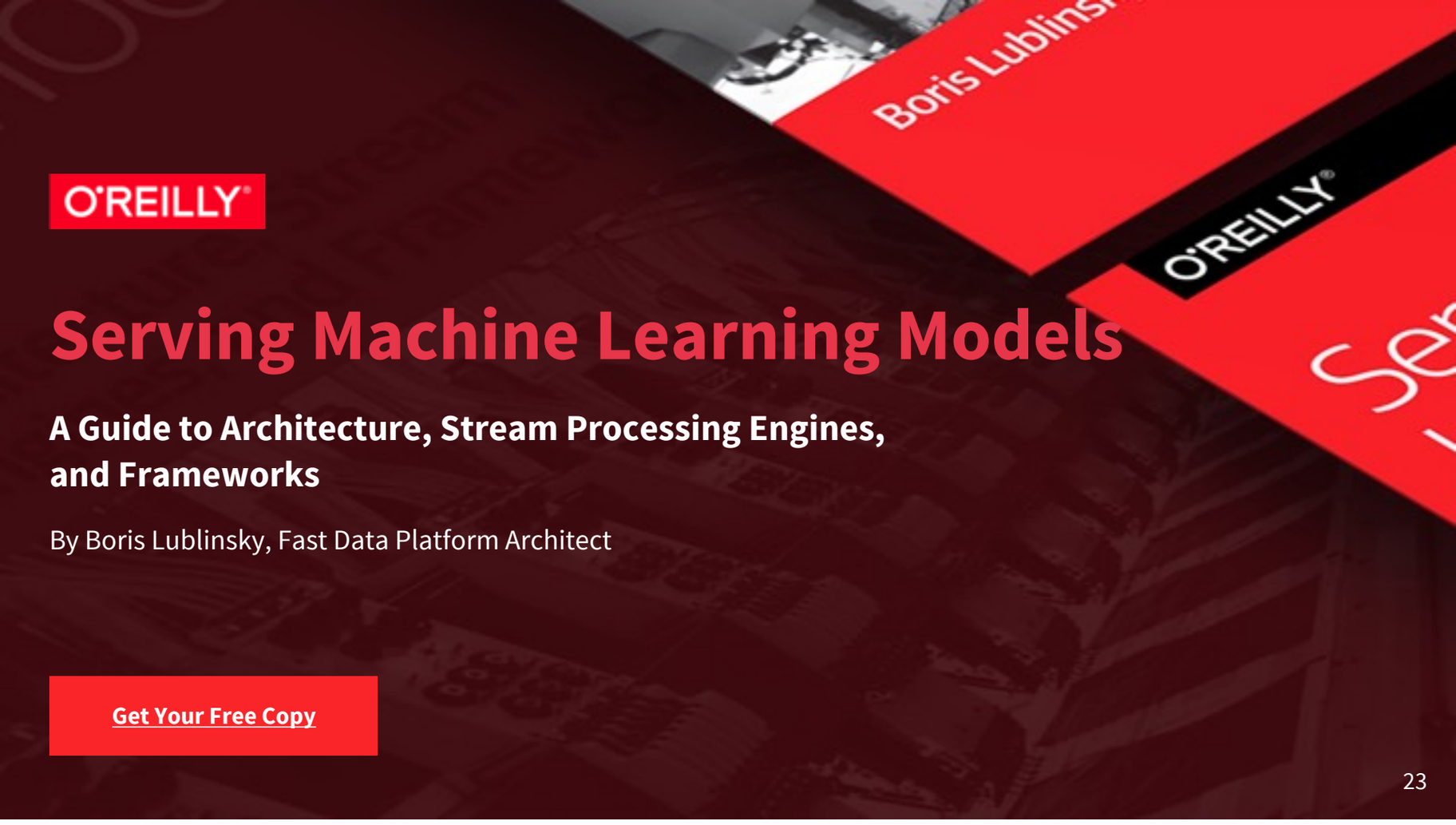
Akka Streams, Kafka Streams - libraries for “data-centric micro services”. Smaller scale, but great flexibility.



Much more flexible deployment and configuration options, compared to Spark and Flink, but more effort is required by you to run them. They are “just libraries”, so there is a lot of flexibility and interoperation capabilities.

Machine Learning and Model Serving: A Quick Introduction

We'll return to more details about AS and KS as we get into implementation details.



Our concrete examples are based on the content of this report by Boris, on different techniques for serving ML models in a streaming context.

ML Is Simple

Get a lot of data
Sprinkle some magic
And be happy with results

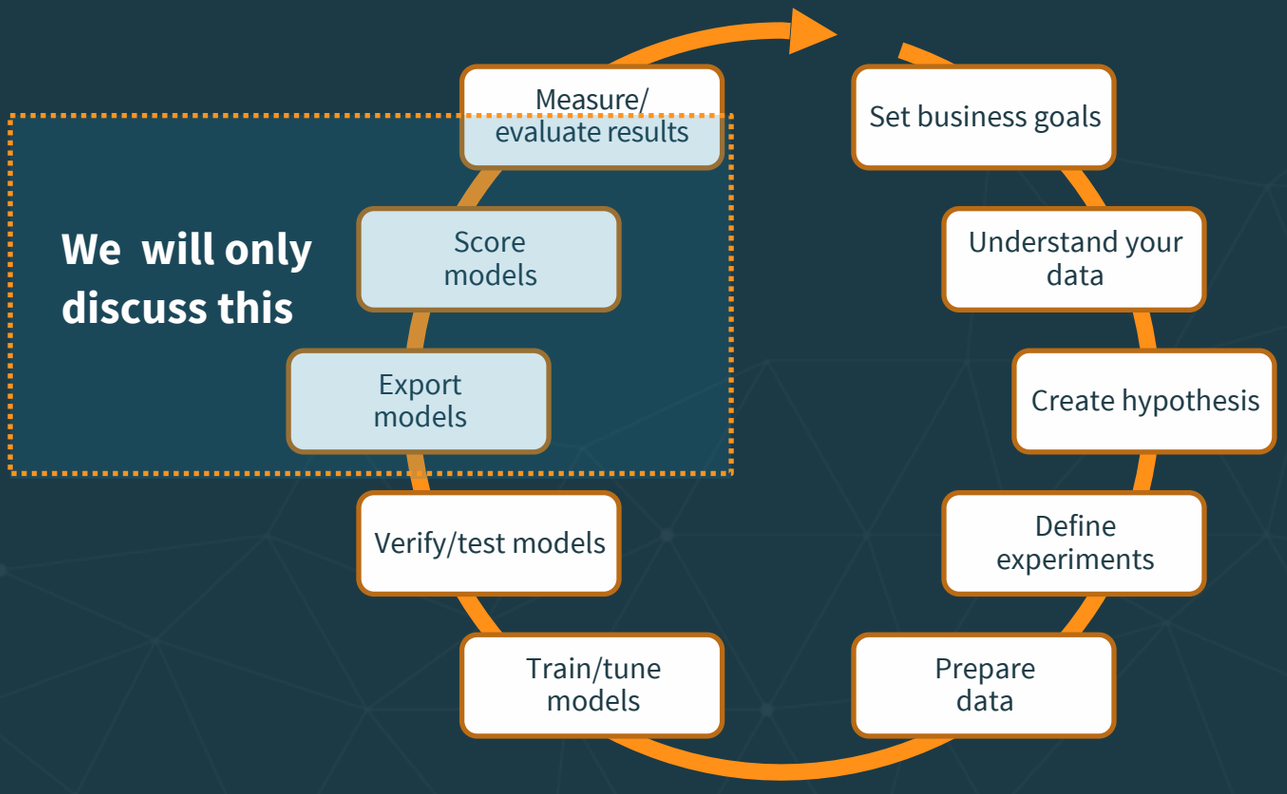
Maybe Not

Not only the climb is steep, but you are not sure which peak to climb
Court of the Patriarchs at Zion National park

Even If There Are Instructions

Not only the climb is steep, but you are not sure which peak to climb Court of the Patriarchs at Zion National park

The Reality


We will only discuss this
Measure/ evaluate results
Score models
Export models
Verify/test models
Train/tune models
Set business goals
Understand your data
Create hypothesis
Define experiments
Prepare data

What Is The Model?

A model is a function transforming inputs to outputs - $y = f(x)$

for example:

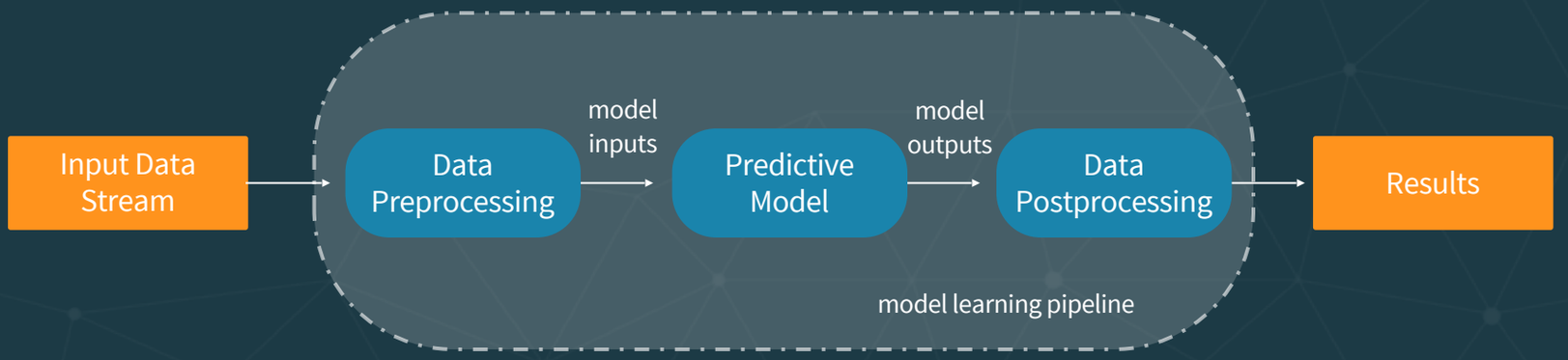
Linear regression: $y = a_c + a_1 * x1 + \ldots + a_n * x_n$

Neural network: $f(x) = K(\sum_i w_i g_i(x))$

Such a definition of the model allows for an easy implementation of model's composition. From the implementation point of view it is just function composition

Model Learning Pipeline

UC Berkeley AMPLab introduced machine learning pipelines as a graph defining the complete chain of data transformation.



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UC Berkeley AMPLab introduced machine learning pipelines as a graph defining the complete chain of data transformation
The advantage of such approach
It captures the whole processing pipeline including data preparation transformations, machine learning itself and any required post processing of the ML results.
Although a single predictive model is shown on this picture, in reality several models can be chained to gather or composed in any other way. See PMML documentation for description of different model composition approaches.
Definition of the complete model allows for optimization of the data processing.
Definition of the complete model allows for optimization of the data processing.
This notion of machine learning pipelines has been adopted by many

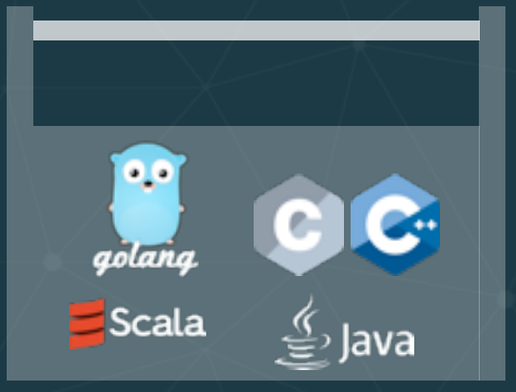
Traditional Approach to Model Serving

- Model is code
- This code has to be saved and then somehow imported into model serving

Why is this problematic?

Impedance Mismatch

Continually expanding Data Scientist toolbox



Defined Software Engineer toolbox

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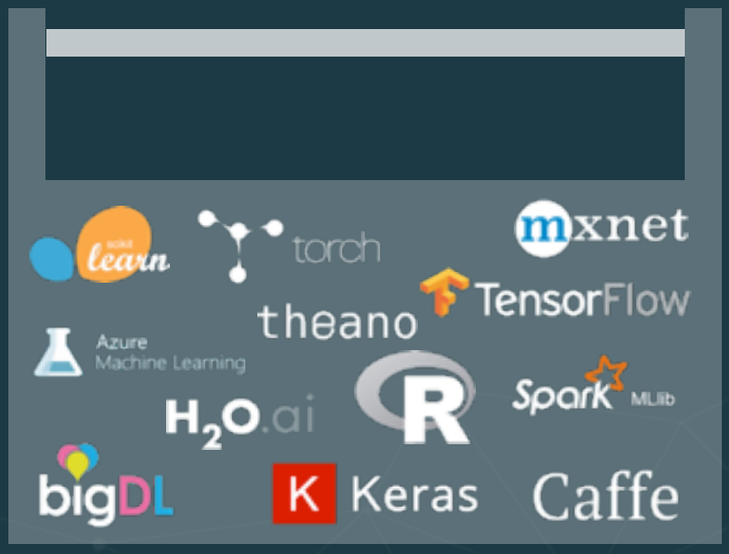
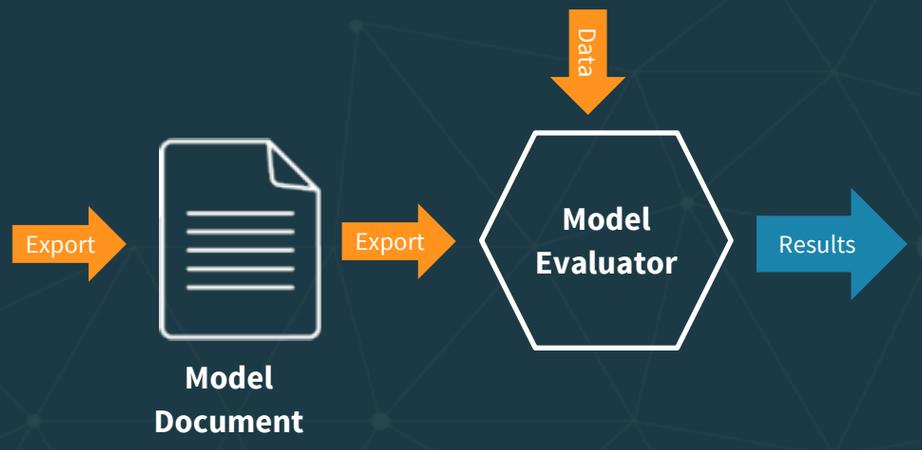
In his talk at the last Flink Forward, Ted Dunning discussed the fact that with multiple tools available to Data scientists, they tend to use different tools for solving different problems and as a result they are not very keen on tools standardization. This creates a problem for software engineers trying to use “proprietary” model serving tools supporting specific machine learning technologies. As data scientists evaluate and introduce new technologies for machine learning, software engineers are forced to introduce new software packages supporting model scoring for these additional technologies.

Alternative - Model As Data





Standards PMML Predictive Model Markup Language

Portable Format for Analytics **(PFA)**

TensorFlow

In order to overcome these differences, Data Mining Group have introduced 2 standards - Predictive Model Markup Language (PMML) and Portable Format for Analytics (PFA), both suited for description of the models that need to be served. Introduction of these models led to creation of several software products dedicated to “generic” model serving, for example Openscoring, Open data group, etc.
Another de facto standard for machine learning is Tensorflow, which is widely used for both machine learning and model serving. Although it is a proprietary format, it is used so widely that it becomes a standard
The result of this standardization is creation of the open source projects, supporting these formats - JPMML and Hadrian which are gaining more and more adoption for building model serving implementations, for example ING, R implementation, SparkML support, Flink support, etc. Tensorflow also released Tensorflow java APIs, which are used in a Flink TensorFlow

Exporting Model As Data With PMML

There are already a lot of export options

Spark MLlib https://github.com/jpmml/jpmml-sparkml

scikit learn https://github.com/jpmml/jpmml-sklearn

R https://github.com/jpmml/jpmml-r

TensorFlow https://github.com/jpmml/jpmml-tensorflow

Evaluating PMML Model

There are also a few PMML evaluators

https://github.com/jpmml/jpmml-evaluator

https://github.com/opendatagroup/augustus

Exporting Model As Data With Tensorflow

- Tensorflow execution is based on Tensors and Graphs
- Tensors are defined as multilinear functions which consist of various vector variables
- A computational graph is a series of Tensorflow operations arranged into graph of nodes
- Tensorflow supports exporting graphs in the form of binary protocol buffers
- There are two different export format - optimized graph and a new format - saved model

Evaluating Tensorflow Model

- Tensorflow is implemented in C++ with a Python interface.
- In order to simplify Tensorflow usage from Java, in 2017 Google introduced Tensorflow Java API.
- Tensorflow Java API supports importing an exported model and allows to use it for scoring.

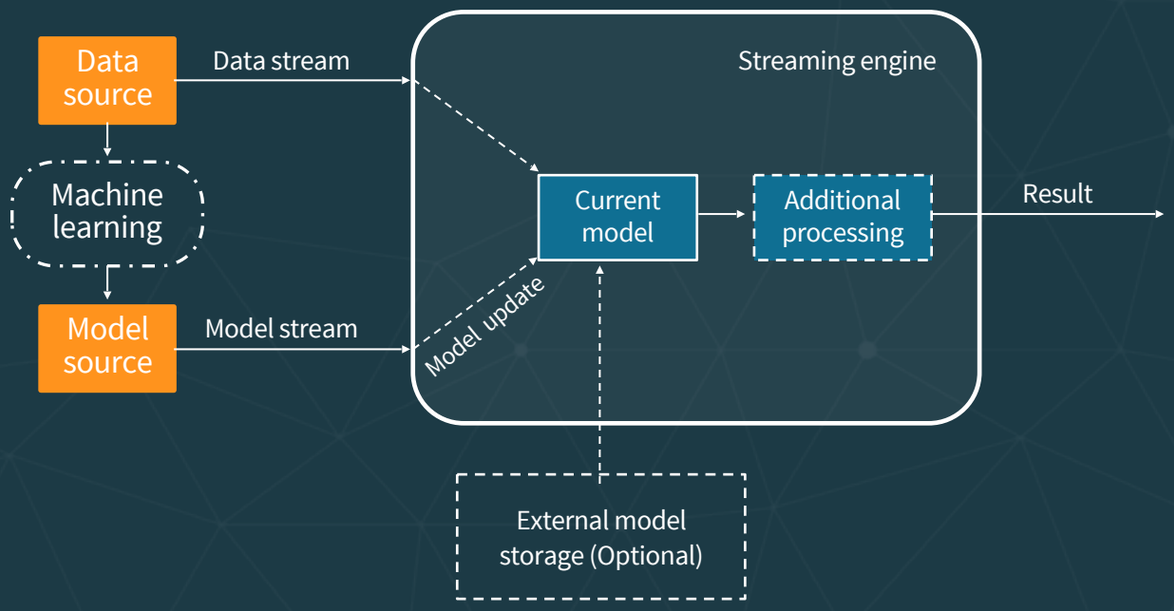
We have a previously-trained TF model on the included “Wine Records” data. We’ll import that model to do scoring.

Additional Considerations – Model Lifecycle

- Models tend to change
- Update frequencies vary greatly – from hourly to quarterly/yearly
- Model version tracking
- Model release practices
- Model update process

The Solution

A streaming system allowing to update models without interruption of execution (dynamically controlled stream).



The majority of machine learning implementations are based on running model serving as a REST service, which might not be appropriate for high-volume data processing or streaming systems, since they require recoding/restarting systems for model updates. For example, Flink TensorFlow or Flink JPPML.

Model Representation (Protobufs)

```
// On the wire
syntax = “proto3”;
// Description of the trained model.
message ModelDescriptor {
  string name = 1;    // Model name
  string description = 2;    // Human readable
  string dataType = 3;  // Data type for which this model is applied.
  enum ModelType {    // Model type
     TENSORFLOW  = 0;
     TENSORFLOWSAVED = 2;
     PMML = 2;
  };
  ModelType modeltype = 4;
  oneof MessageContent {
     // Byte array containing the model
     bytes data = 5;
     string location = 6;
  }
}
```


You need a neutral representation format that can be shared between different tools and over the wire. Protobufs (from Google) is one of the popular options. Recall that this is the format used for model export by TensorFlow. Here is an example.

Model Representation (Scala)

```
trait Model {
  def score(input : Any) : Any
  def cleanup() : Unit
  def toBytes() : Array[Byte]
  def getType : Long
}

def ModelFactoryl {
  def create(input : ModelDescriptor) : Model
  def restore(bytes : Array[Byte]) : Model
}
```


Corresponding Scala code that can be generated from the description.

Side Note: Monitoring

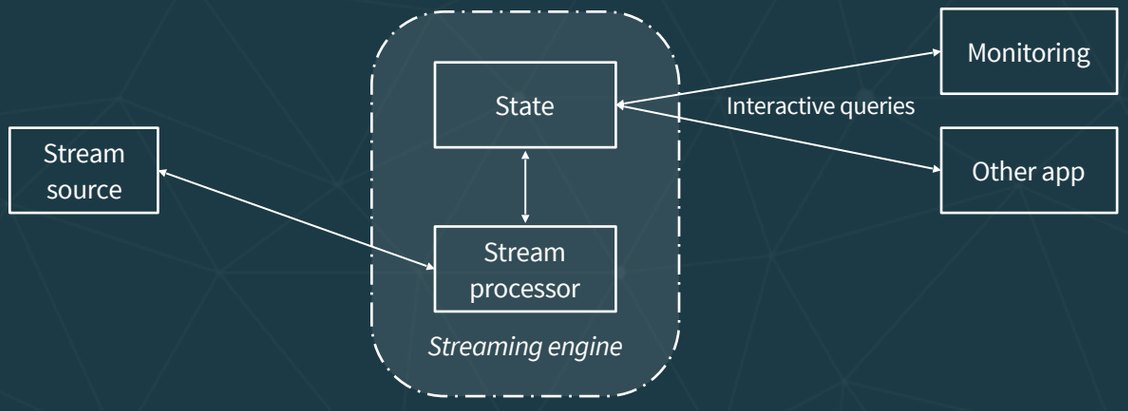
Model monitoring should provide information about usage, behavior, performance and lifecycle of the deployed models

```
case class ModelToServeStats(
name: String,                                  //  Model name
    description: String,                       // Model descriptor
    modelType: ModelDescriptor.ModelType,    // Model type
    since : Long,                              // Start time of model usage
    var usage : Long = 0,                      // Number of servings
    var duration : Double = 0.0,               // Time spent on serving
    var min : Long = Long.MaxValue,     // Min serving time
    var max : Long = Long.MinValue     // Max serving time
)
```

Queryable State

Queryable state: ad hoc query of the state in the stream. Different than the normal data flow.

Treats the stream processing layer as a lightweight embedded *database. Directly query the current state* of a stream processing application. No need to materialize that state to a database, etc. first.

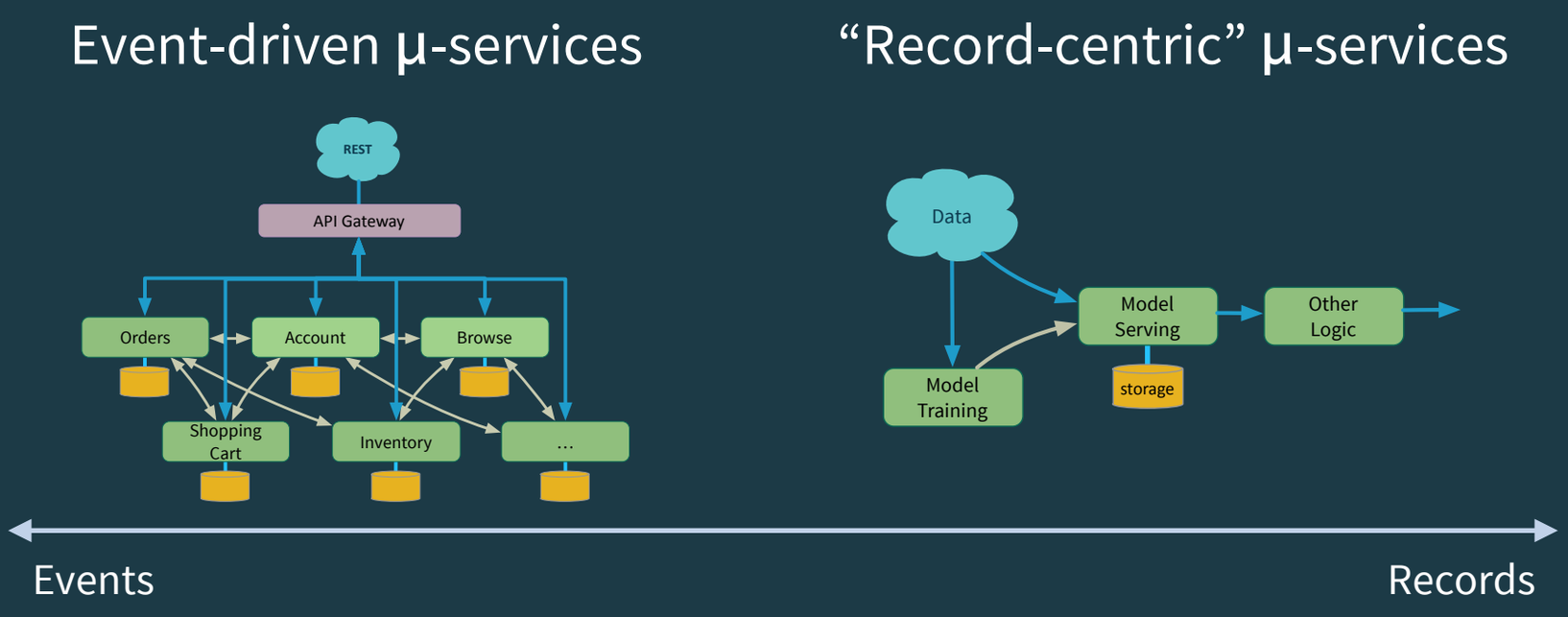


Kafka Streams and Flink have built-in support for this and its being added to Spark Streaming. We'll show how to use other Akka features to provide the same ability in a straightforward way for Akka Streams.

Microservice All the Things!

https://twitter.com/shanselman/status/967703711492423682

A Spectrum of



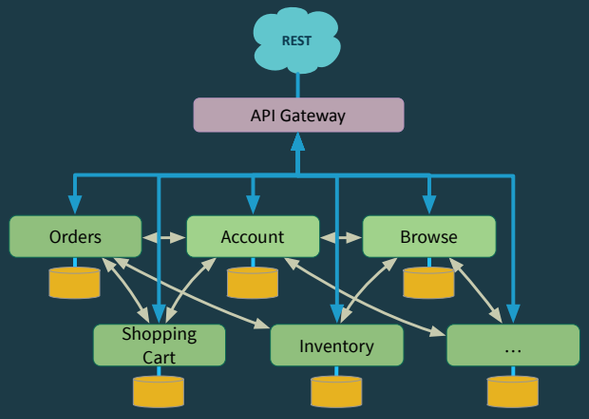
By event-driven microservices, I mean that each individual datum is treated as a specific event that triggers some activity, like steps in a shopping session. Each event requires individual handling, routing, responses, etc. REST, CQRS, and Event Sourcing are ideal for this.

Records are uniform (for a given stream), they typically represent instantiations of the same information type, for example time series; we can process them individually or as a group, for efficiency.

It’s a spectrum because we might take those events and also route them through a data pipeline, like computing statistics or scoring against a machine learning model (as here), perhaps for fraud detection, recommendations, etc.

A Spectrum of

Event-driven μ-services



Akka emerged from the left-hand side of the spectrum, the world of highly *Reactive* microservices.

Akka Streams pushes to the right, more data-centric.

Events

Records

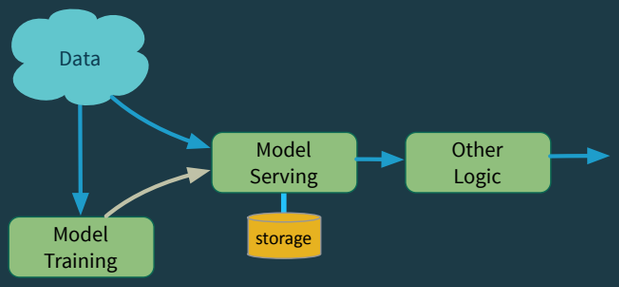
I think it's useful to reflect on the history of these toolkits, because their capabilities reflect their histories. Akka Actors emerged in the world of building *Reactive* microservices, those requiring high resiliency, scalability, responsiveness, CEP, and must be event driven. Akka is extremely lightweight and supports extreme parallelism, including across a cluster. However, the Akka Streams API is effectively a dataflow API, so it nicely supports many streaming data scenarios, allowing Akka to cover more of the spectrum than before.

A Spectrum of

Emerged from the right-hand side.

Kafka Streams pushes to the left, supporting many event-

“Record-centric” μ-services

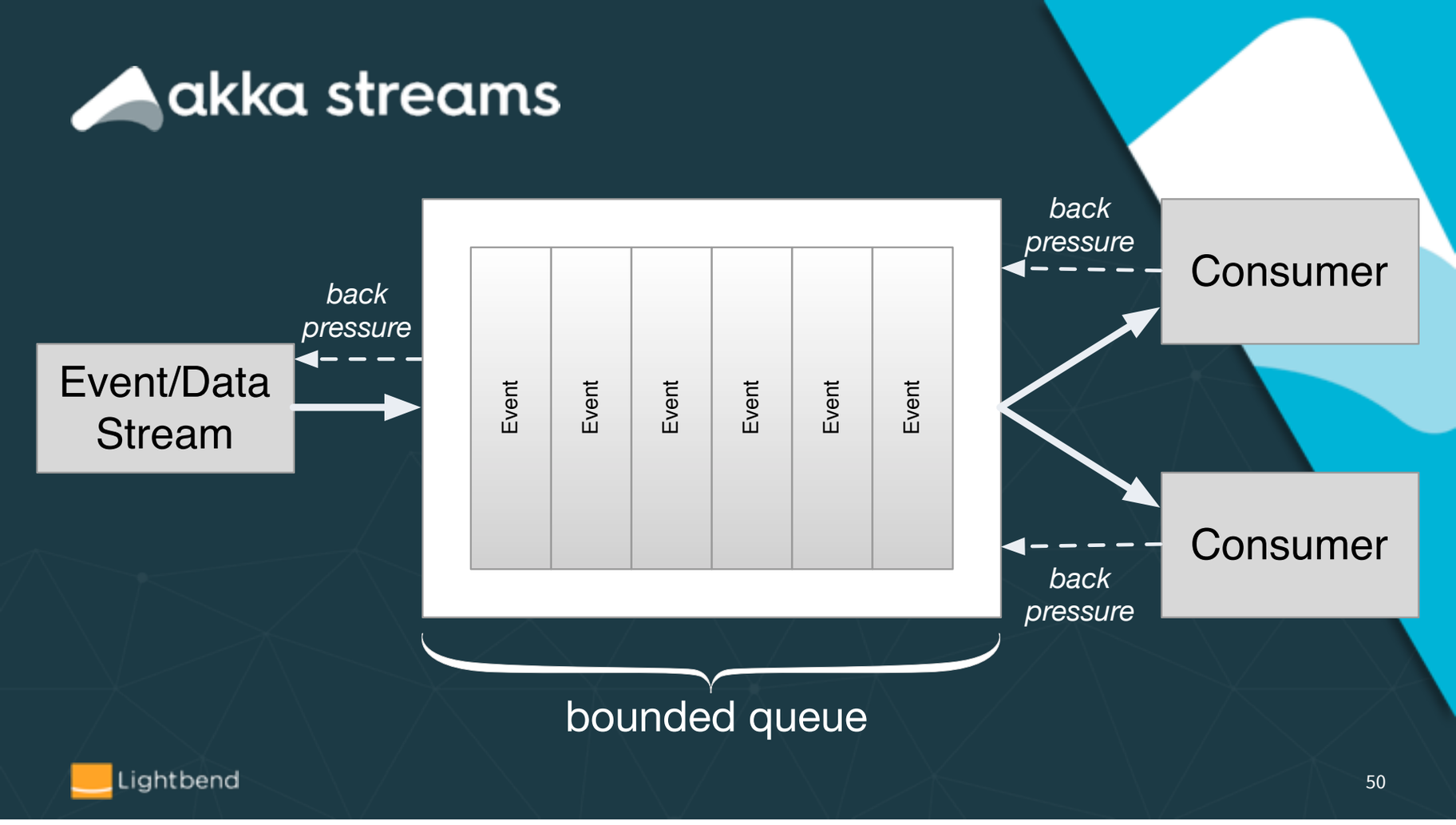


Kafka reflects the heritage of moving and managing streams of data, first at LinkedIn. But from the beginning it has been used for event-driven microservices, where the “stream” contained events, rather than records. Kafka Streams fits squarely in the record-processing world, where you define dataflows for processing and even SQL. It can also be used for event processing scenarios.

Akka Streams

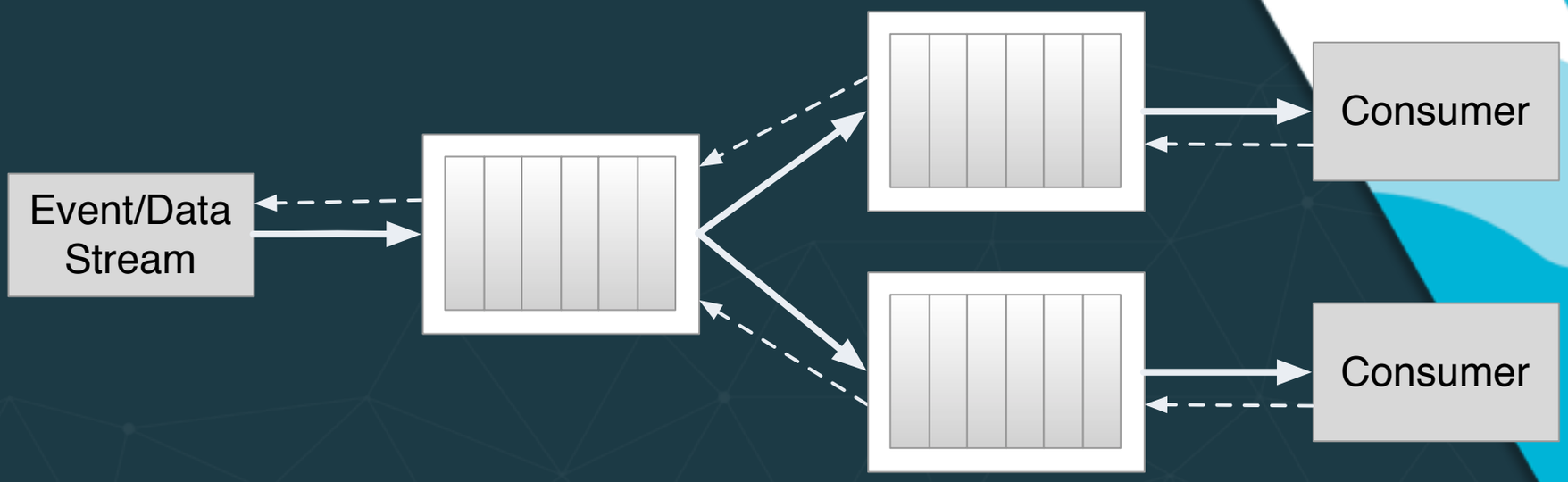
- A *library*
- Implements Reactive Streams.
  - http://www.reactive-streams.org/
  - *Back pressure* for flow control

See this website for details on why *back pressure* is an important concept for reliable flow control, especially if you don't use something like Kafka as your "near-infinite" buffer between services.



Bounded queues are the only sensible option (even Kafka topic partitions are bounded by disk sizes), but to prevent having to drop input when it's full, consumers signal to producers to limit flow. Most implementations use a push model when flow is fine and switch to a pull model when flow control is needed.

akka streams



… and they compose

Lightbend

And they compose so you get end-to-end back pressure.

- Part of the Akka ecosystem
  - Akka Actors, Akka Cluster, Akka HTTP, Akka Persistence, …
  - Alpakka - rich connection library
    - like Camel, but implements Reactive Streams
  - Commercial support from Lightbend

Rich, mature tools for the full spectrum of microservice development.

- A very simple example to get the “gist”…

```
import akka.stream._
import akka.stream.scaladsl._
import akka.NotUsed
import akka.actor.ActorSystem
import scala.concurrent._
import scala.concurrent.duration._

implicit val system = ActorSystem("QuickStart")
implicit val materializer = ActorMaterializer()

val source: Source[Int, NotUsed] = Source(1 to 10)
val factorials = source.scan(BigInt(1)) ( (acc, next) => acc * next )
factorials.runWith(Sink.foreach(println))
```


This example is in akkaStreamsModelServer/simple-akka-streams-example.sc

```
import akka.stream._
import akka.stream.scaladsl._
import akka.NotUsed
import akka.actor.ActorSystem
import scala.concurrent._
import scala.concurrent.duration._
```

Imports!

```
implicit val system = ActorSystem("QuickStart")
implicit val materializer = ActorMaterializer()

val source: Source[Int, NotUsed] = Source(1 to 10)
val factorials = source.scan(BigInt(1)) ( (acc, next) => acc * next )
factorials.runWith(Sink.foreach(println))
```

```
import akka.stream._
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val source: Source[Int, NotUsed] = Source(1 to 10)
val factorials = source.scan(BigInt(1)) ( (acc, next) => acc * next )
factorials.runWith(Sink.foreach(println))
```

Initialize and specify now the stream is “materialized”

```
import akka.stream._
import akka.stream.scaladsl._
import akka.NotUsed
import akka.actor.ActorSystem
import scala.concurrent._
import scala.concurrent.duration._

implicit val system = ActorSystem("QuickStart")
implicit val materializer = ActorMaterializer()

val source: Source[Int, NotUsed] = Source(1 to 10)
val factorials = source.scan(BigInt(1))((acc, next) => acc * next)
factorials.runWith(Sink.foreach(println))
```

Create a Source of Ints. Second type represents a hook used for “materialization” - not used here

```
import akka.stream._
import akka.stream.scaladsl._
import akka.NotUsed
import akka.actor.ActorSystem
import scala.concurrent._
import scala.concurrent.duration._

implicit val system = ActorSystem("QuickStart")
implicit val materializer = ActorMaterializer()

val source: Source[Int, NotUsed] = Source(1 to 10)
val factorials = source.scan(BigInt(1)) ( (acc, next) => acc * next )
factorials.runWith(Sink.foreach(println))
```

Scan the Source and compute factorials, with a seed of 1, of type BigInt

```
import akka.stream._
import akka.stream.scaladsl._
import akka.NotUsed
import akka.actor.ActorSystem
import scala.concurrent._
import scala.concurrent.duration._

implicit val system = ActorSystem("QuickStart")
implicit val materializer = ActorMaterializer()

val source: Source[Int, NotUsed] = Source(1 to 10)
val factorials = source.scan(BigInt(1))((acc, next) => acc * next)
factorials.runWith(Sink.foreach(println))
```

Output to a Sink, and run it

```
import akka.stream._
import akka.stream.scaladsl._
import akka.NotUsed
import akka.actor.ActorSystem
import scala.concurrent._
import scala.concurrent.duration._

implicit val system = ActorSystem("QuickStart")
implicit val materializer = ActorMaterializer()

val so[Source]e[Int, No[Flow]urce(1 to[Sink] next )
val fa
facto
```

A source, flow, and sink constitute a graph

The core concepts are sources and sinks, connected by flows. There is the notion of a Graph for more complex dataflows, but we won't discuss them further

- This example is included in the project:
  - akkaStreamsModelServer/simple-akka-streams-example.sc
- To run it (showing the different prompt!):

```
$ sbt
sbt:akkaKafkaTutorial> project akkaStreamsModelServer
sbt:akkaStreamsModelServer> console
scala> :load akkaStreamsModelServer/simple-akka-streams-example.sc
```


The ".sc" extension is used so that the compiler doesn't attempt to compile this Scala "script". Using ".sc" is an informal convention for such files.
We used yellow to indicate the prompts (3 different shells!)

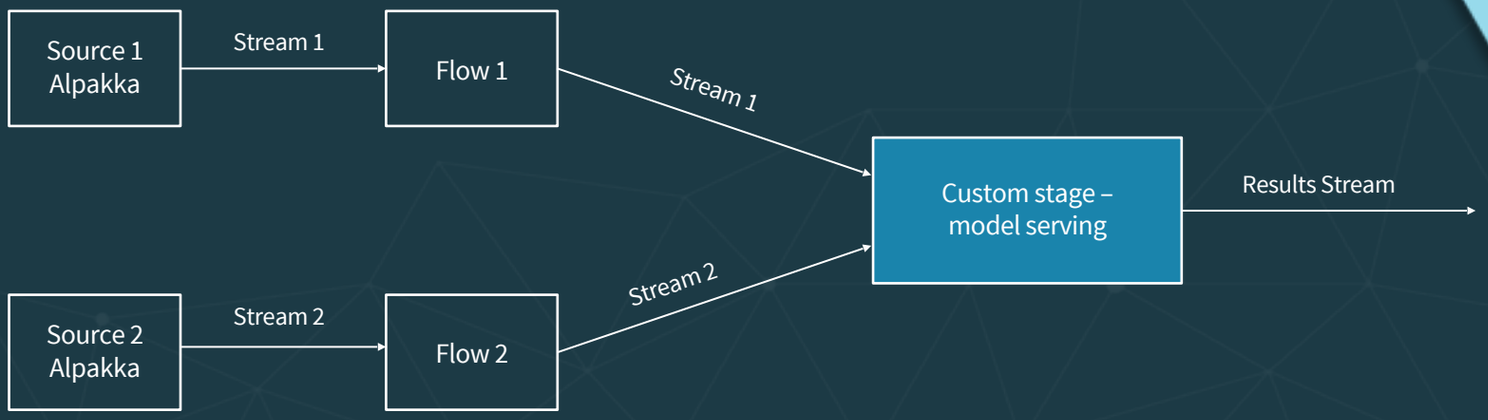
Implementations

- How do we integrate model serving (or any other new capability) into an Akka Streams app? We'll look at two approaches:
  - Implement a *Custom Stage*. Once implemented, you use it like any other "step" in the Akka Streams app.
  - Make asynchronous calls to Akka Actors to do anything you want...

We provide two implementations.

Using Custom Stage

Create a custom stage, a fully type-safe way to encapsulate new functionality. Like adding a new "operator".

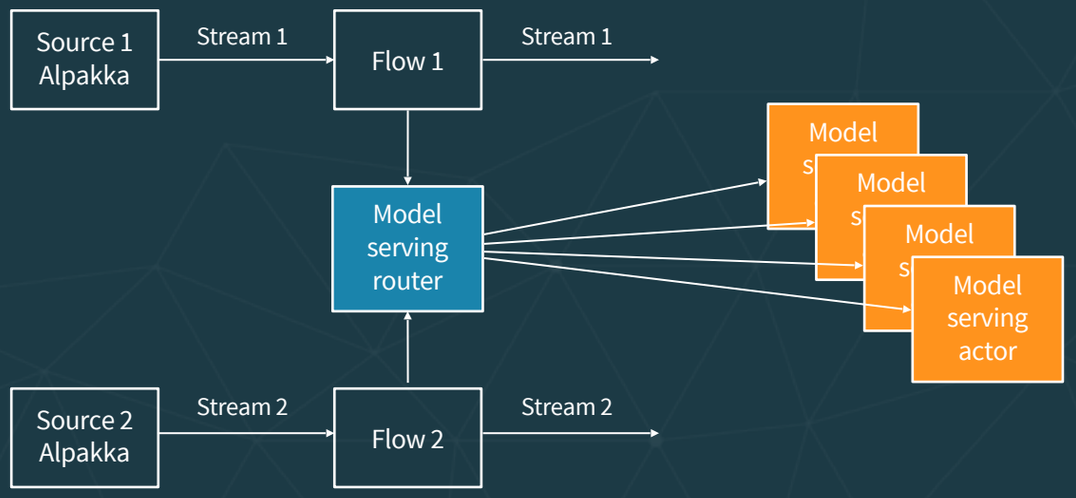


Lightbend

Custom stage is an elegant implementation but doesn't scale well to a large number of models. Although a stage can contain a hash map of models, all of the execution will be happening at the same place

Using Akka Actors

Use a router actor to forward requests to the actor(s) responsible for processing requests for a specific model type. Clone for scalability!!



Lightbend

We here create a routing layer: an actor that will implement model serving for specific model (based on key) and route messages appropriately. This way our system will serve models in parallel.

Akka Streams Example

Code time

1. Run the *client* project (if not already running)
2. Explore and run *akkaStreamsModelServer* project
    1. Use the `c` or `custom` (or default) command-line argument for the *custom stage*
    2. Use the `a` or `actor` command-line argument for the *actor model server*
    3. Use `-h` or `–help` for help

Custom stage is an elegant implementation but not scale well to a large number of models. Although a stage can contain a hash map of models, all of the execution will be happening at the same place

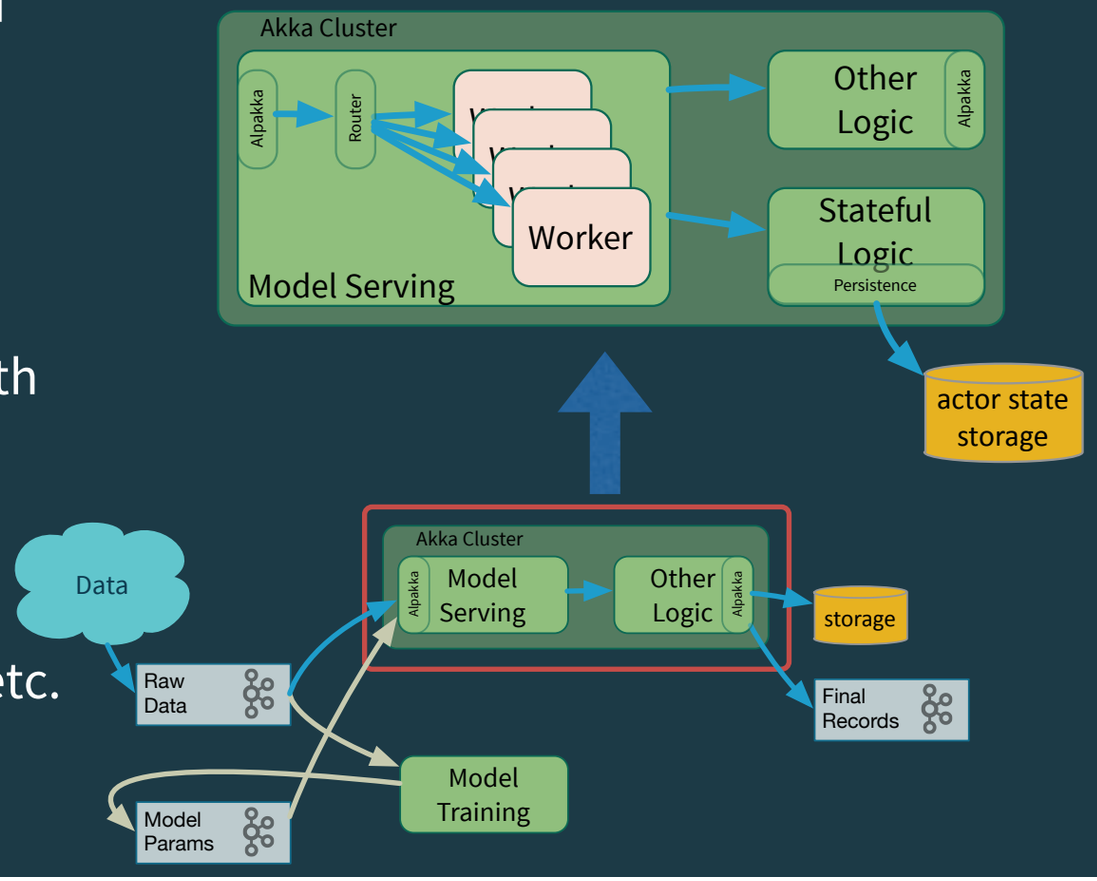
Exercises!

- We've prepared some exercises. We'll return to them after discussing Kafka Streams.

- To find them, search for "// Exercise".

Other Production Concerns

- Scale scoring with workers and routers, across a cluster
- Persist actor state with Akka Persistence
- Connect to *almost* anything with Alpakka
- *Lightbend Enterprise Suite*
  - for production monitoring, etc.

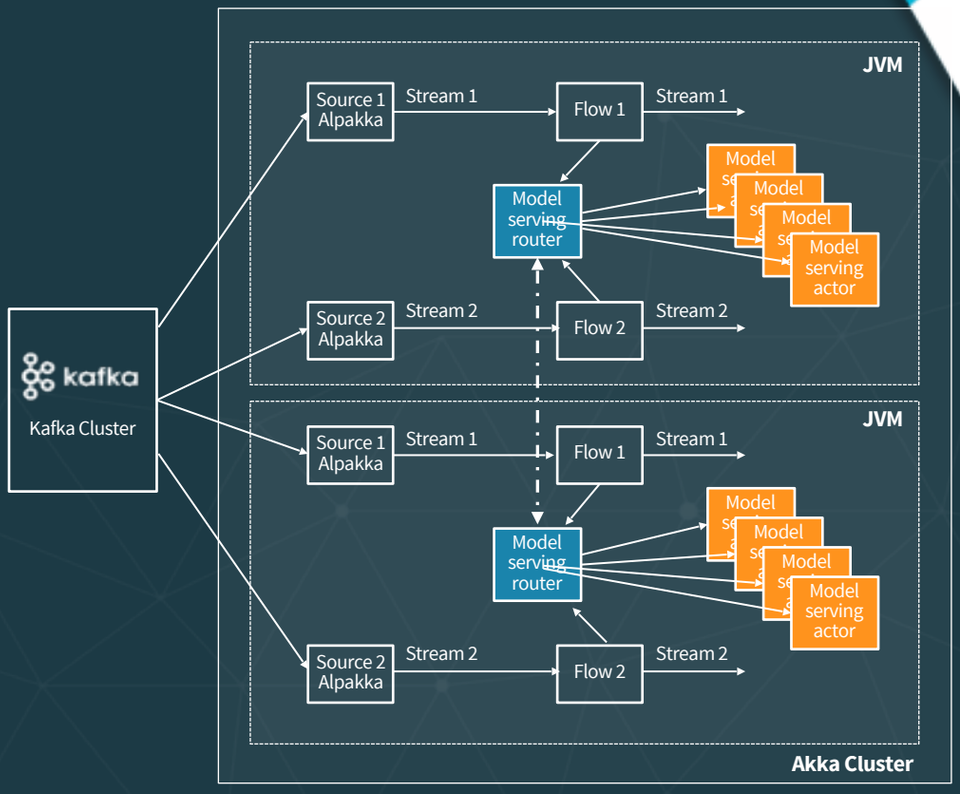


Here's our streaming microservice example adapted for Akka Streams. We'll still use Kafka topics in some places and assume we're using the same implementation for the "Model Training" microservice. Alpakka provides the interface to Kafka, DBs, file systems, etc. We're showing two microservices as before, but this time running in Akka Cluster, with direct messaging between them. We'll explore this a bit more after looking at the example code.

Using Akka Cluster

Two levels of scalability:

- Kafka partitioned topic allow to scale listeners according to the amount of partitions.
- Akka cluster sharing allows to split model serving actors across clusters.



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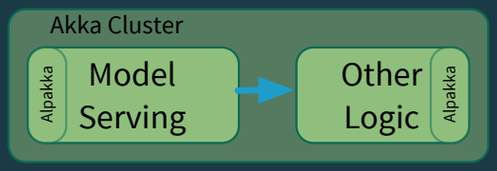
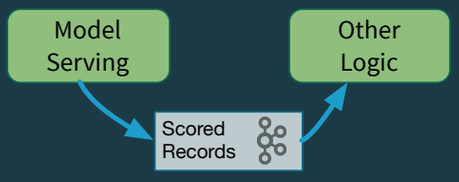
A great article http://michalplachta.com/2016/01/23/scalability-using-sharding-from-akka-cluster/ goes into a lot of details on both implementation and testing

Go Direct or Through Kafka?



vs.



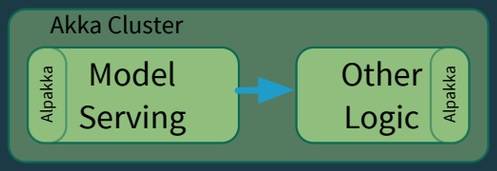
?

- Extremely low latency
- Minimal I/O and memory overhead
- No marshaling overhead (maybe…)

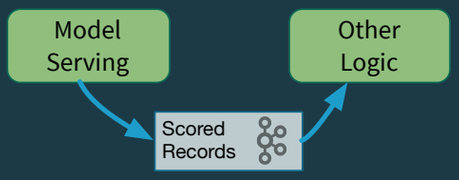
- Higher latency (including queue depth)
- Higher I/O and processing (marshaling) overhead
- Better potential reusability

Design choice: When is it better to use direct actor-to-actor (or service-to-service) messaging vs. going through a Kafka topic?

Go Direct or Through Kafka?



vs.



?

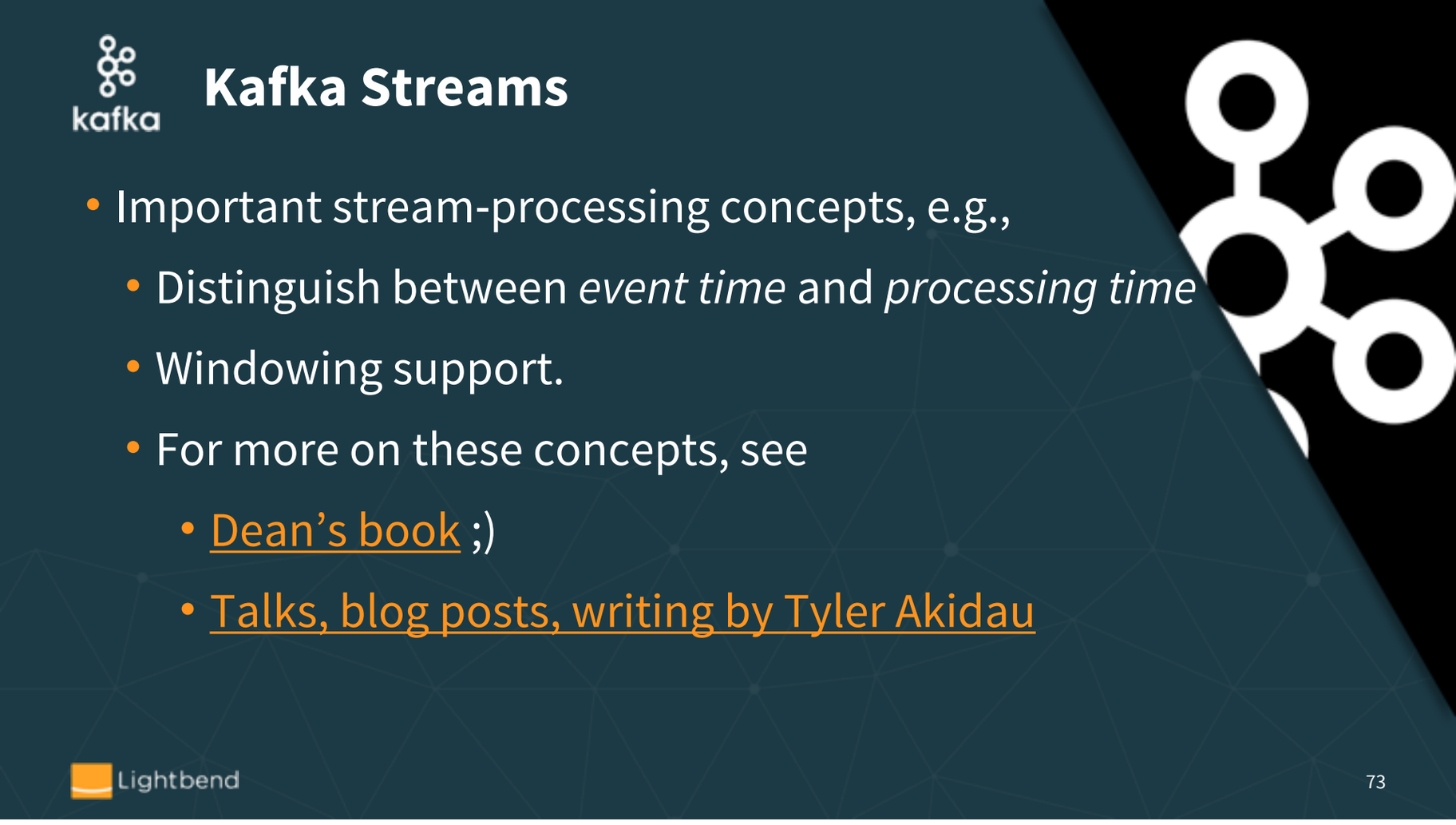
- *Reactive Streams* back pressure
- Direct coupling between sender and receiver, but indirectly through an ActorRef

- Very deep buffer (partition limited by disk size)
- Strong decoupling - M producers, N consumers, completely disconnected

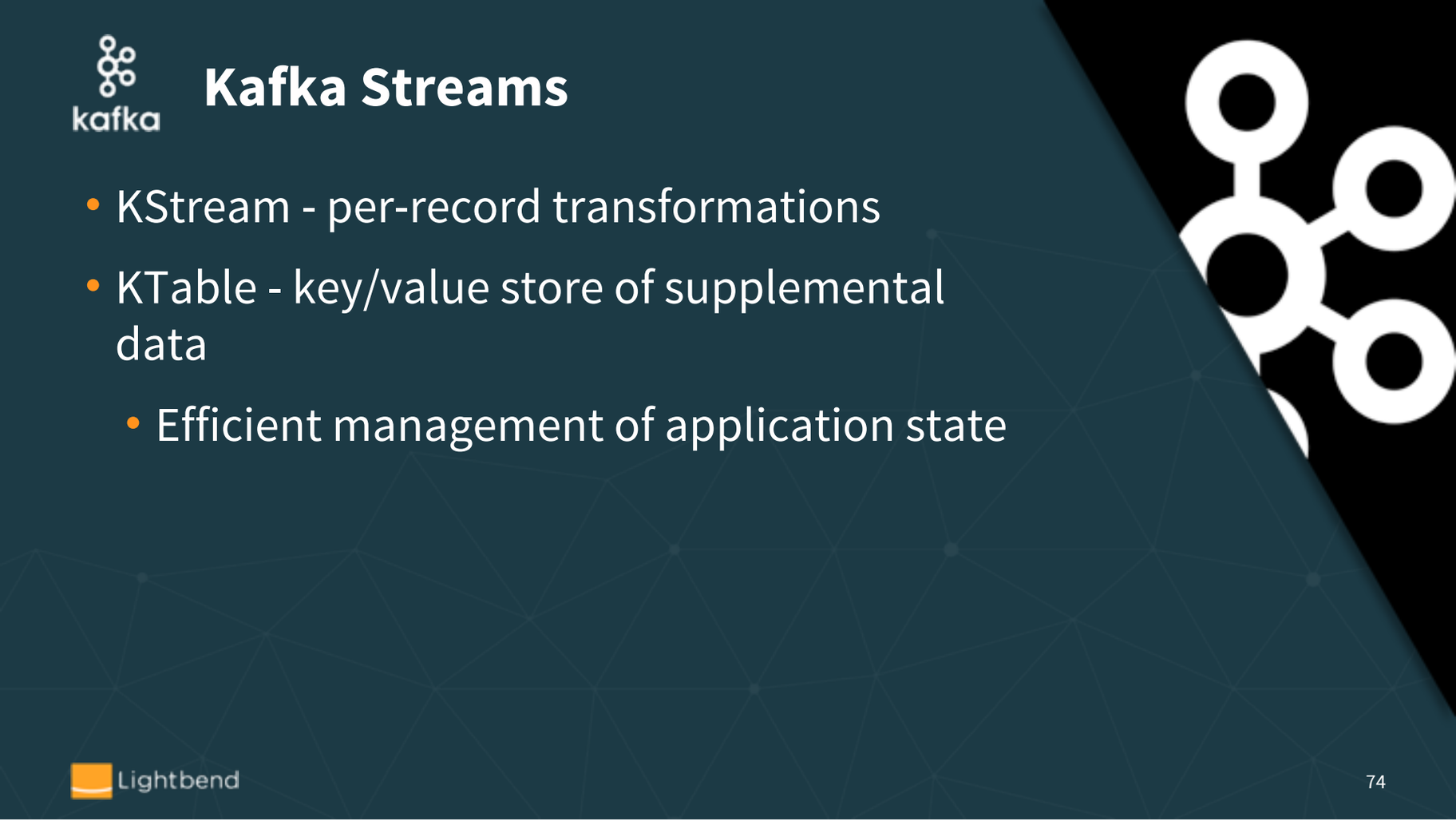
Design choice: When is it better to use direct actor-to-actor (or service-to-service) messaging vs. going through a Kafka topic?

Kafka Streams

Same sample use case, now with Kafka Streams



There's a maturing body of thought about what streaming semantics should be, too much to discuss here. Dean's book provides the next level of details. See Tyler's work (from the Google Apache Beam team) for deep dives.



There is a duality between streams and tables. Tables are the latest state snapshot, while streams record the history of state evolution. A common way to implement databases is to use an event (or change) log, then update the state from the log.

Kafka Streams

- Low overhead
- Read from and write to Kafka topics, memory
  - Could use Kafka Connect for other sources and sinks
- Load balance and scale based on partitioning of topics
- Built-in support for Queryable State

Kafka Streams

- Two types of APIs:
  - Process Topology
    - Compare to Apache Storm
  - DSL based on collection transformations
    - Compare to Spark, Flink, Scala collections.

Kafka Streams

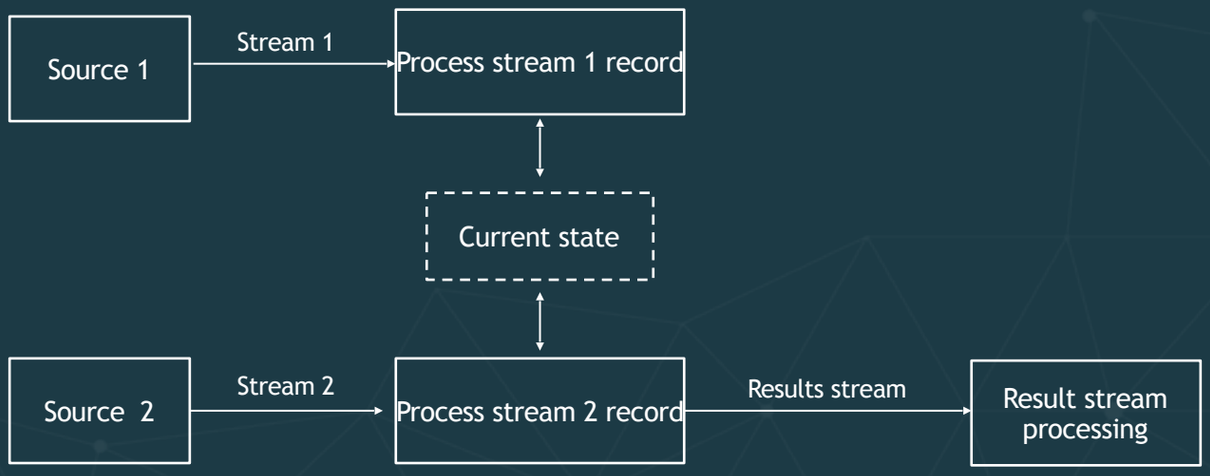
- Provides a Java API
- Lightbend donated a Scala API to Apache Kafka
  - https://github.com/apache/kafka/tree/trunk/streams/streams-scala
  - See also our convenience tools for distributed, queryable state: https://github.com/lightbend/kafka-streams-query
- SQL - yes, but requires a specialized application (i.e., not a library like in Spark or Flink)

The kafka-streams-query uses a KS API to find all the partitions across a cluster for a given topic, query their state, and aggregate the results, behind a web service. Otherwise, you have to query the partitions individually yourself.

Kafka Streams

- Ideally suited for:
  - ETL -> KStreams
  - State -> KTable
  - Joins, including Stream and Table joins
  - “Effectively once” semantics
- Commercial support from Confluent, Lightbend, and others

Model Serving With Kafka Streams



State Store Options We'll Explore

- "Naive", in memory store (no durability!)
  - Also uses the KS Processor Topology API
- Built-in key/value store provided by Kafka Streams
  - Uses the KS DSL
- Custom store
  - Also uses the DSL

We provide three example implementations, using three different ways of storing state. "Naive" - because in-memory state is lost if the process crashes; a restart can't pick up where the previous instance left off.

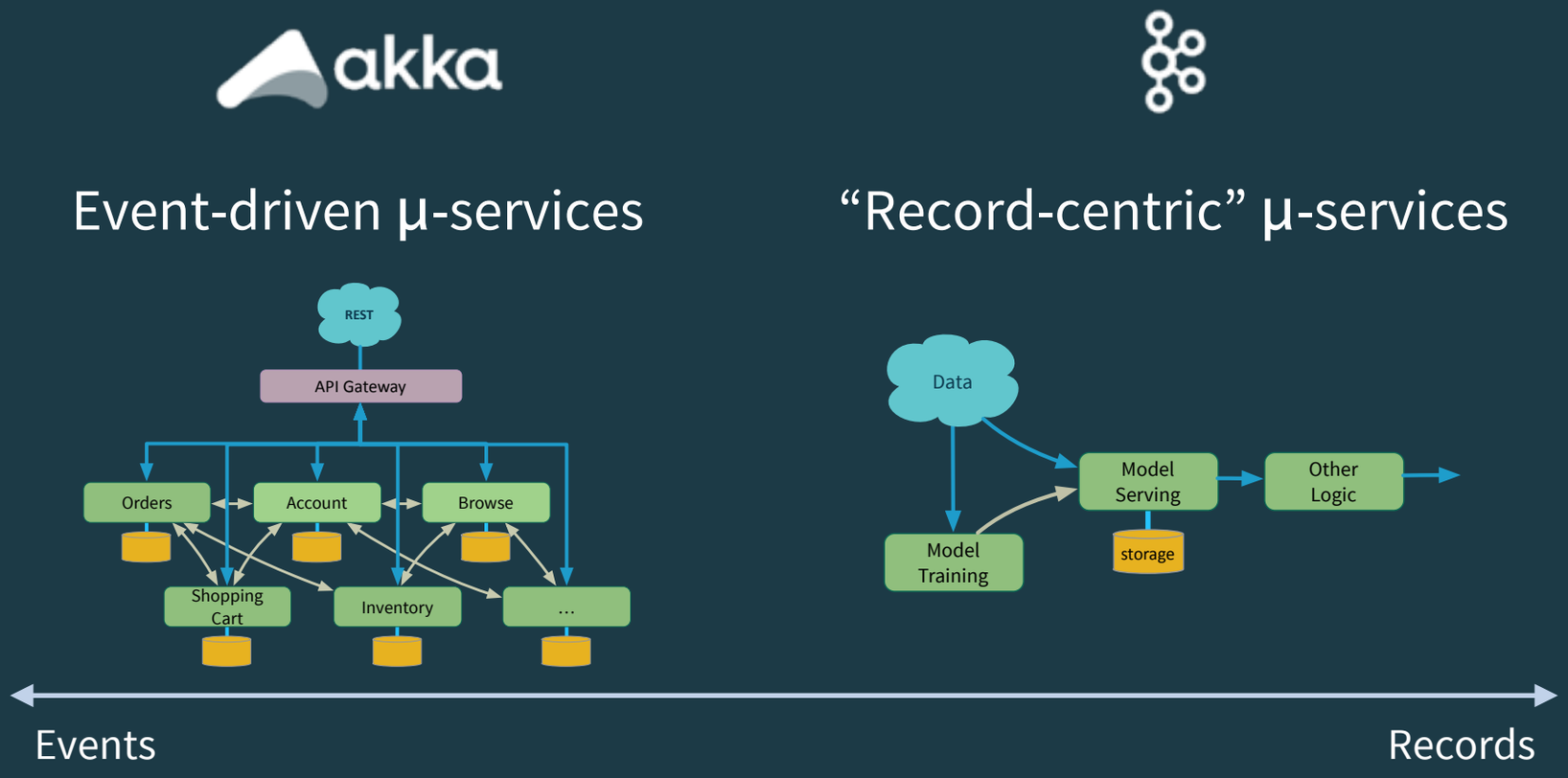
Model Serving With Kafka Streams

Code time

1. Run the *client* project (if not already running)
2. Explore and run *kafkaStreamsModelServer* project
    1. Use the `c` or `custom` (or default) command-line argument for the *custom state store*
    2. Use the `s` or `standard` command-line argument for the KS built-in *standard store*
    3. Use the `m` or `memory` command-line argument for the *in-memory store*
    4. Use `-h` or `--help` for help

Wrapping Up

To Wrap Up



Akka Streams is a great choice if you are building full-spectrum microservices and you need lots of flexibility in your app architectures, connecting to different kinds of data sources and sinks, etc.

Kafka Streams is a great choice if your use cases fit nicely in it’s “sweet spot”, you want SQL access, and you don’t need to full flexibility of something like Akka.

Of course, you can use both! They are “just libraries”.

In Our Remaining Time

1. Explore the code we didn't discuss (there is a lot ;)
    1. Study the different model serving techniques
    2. Study the "model" subproject
    3. Look at how the following are implemented
        1. queryable state
        2. embedded web servers
        3. use of Akka Persistence
        4. model serialization
2. …

In Our Remaining Time

1. …
2. Try the exercises - search for “// Exercise” in the code
3. Ask us for help on anything…
4. Visit lightbend.com/fast-data-platform
5. Profit!!

Thanks for coming

Questions?

- Executive Briefing: What you need to know about fast data (Dean)
  - 14:55–15:35 Wednesday, 23 May 2018, Capital Suite 17
- AMA, Streaming Applications and Architectures (Boris and Dean)
  - 14:05–14:45 Thursday, 24 May 2018, Capital Suite 14

And don’t miss:

- Kafka in jail: Running Kafka in container-orchestrated

lightbend.com/products/fast-data-platform

Thank you! Please check out the other Strata San Jose sessions by Boris, Dean, and our colleagues Sean, Gerard, and Emre. Check out our Fast Data Platform for commercial options for building and running microservices with Kafka, Akka Streams, and Kafka Streams.