Building Kafka-based Microservices with Akka Streams and Kafka Streams

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Lightbend

This Tutorial:

Either clone this or download the latest release

github.com/lightbend/
kafka-with-akka-streams-kafka-streams-tutorial

These slides are in the “presentation” folder

Let’s do introductions while you do this…

Outline

- Quick 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

Overview of Streaming Technologies

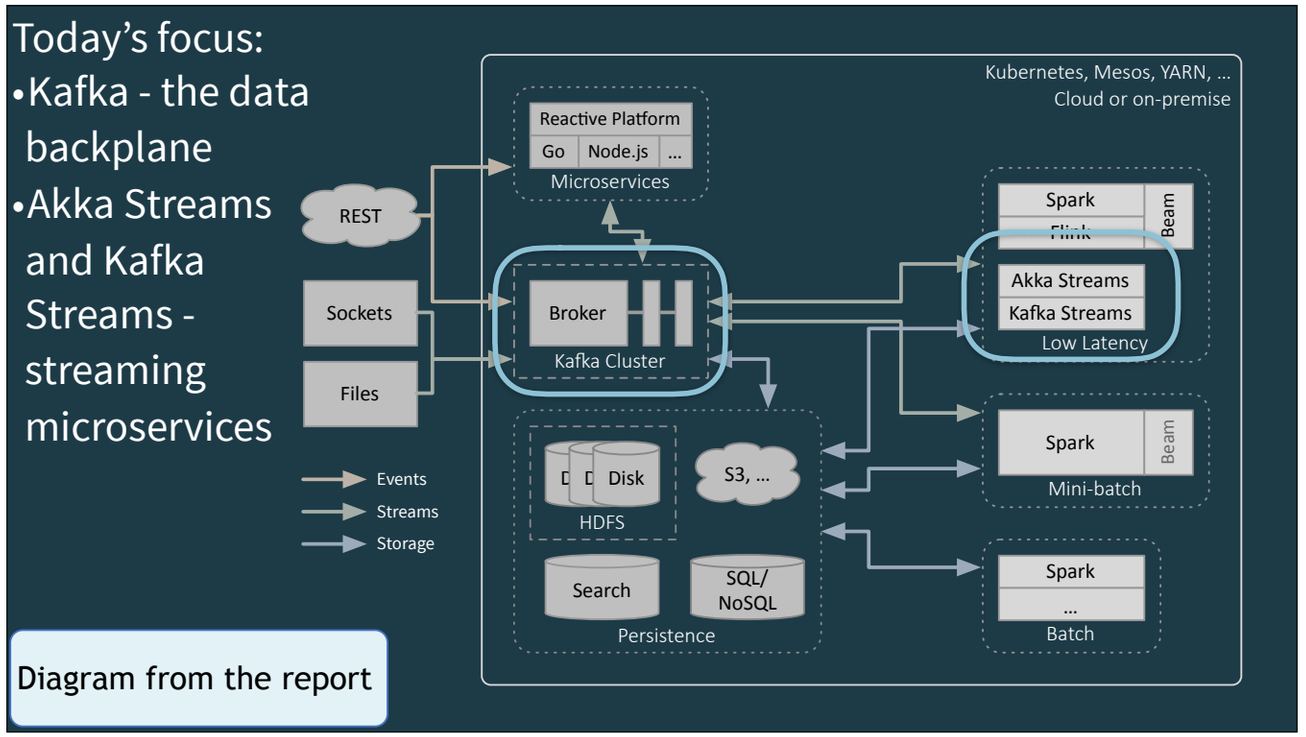
Why Kafka, Spark, Flink, Akka Streams, and Kafka Streams?

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”

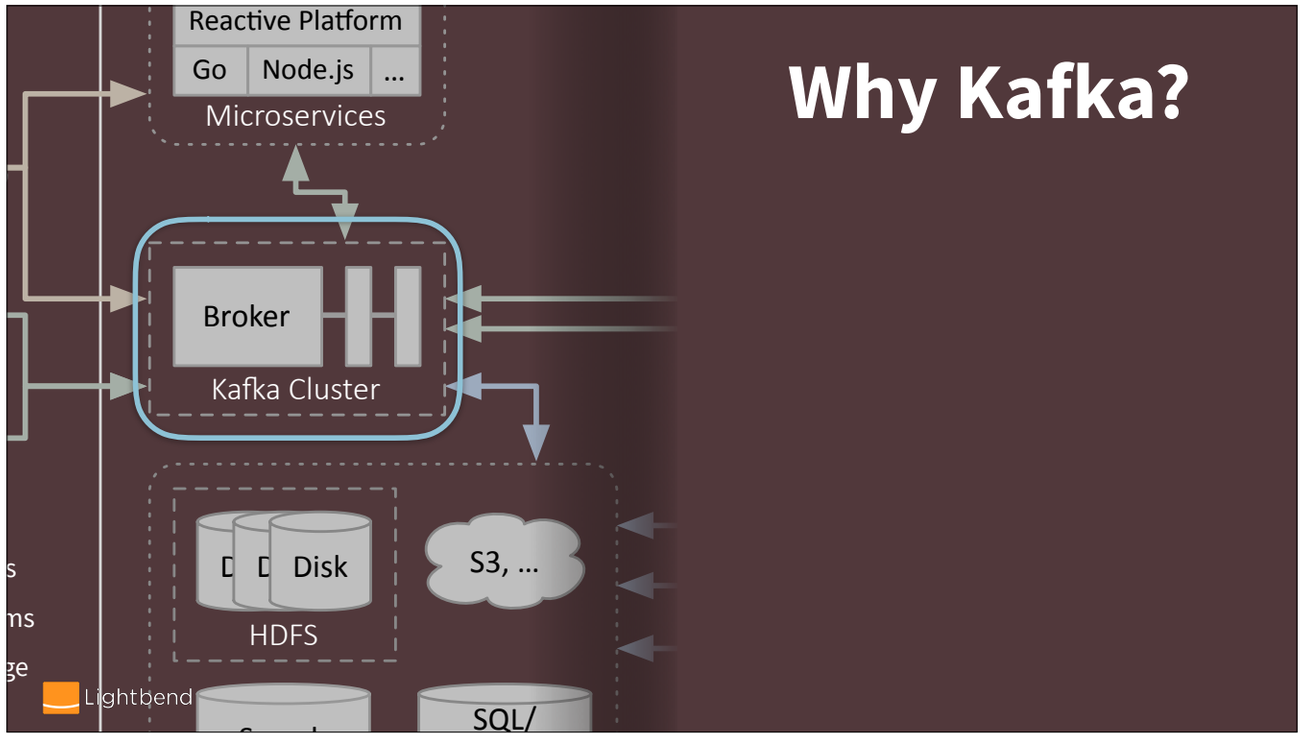
— Fabio Yamada, Kafka Mailing List

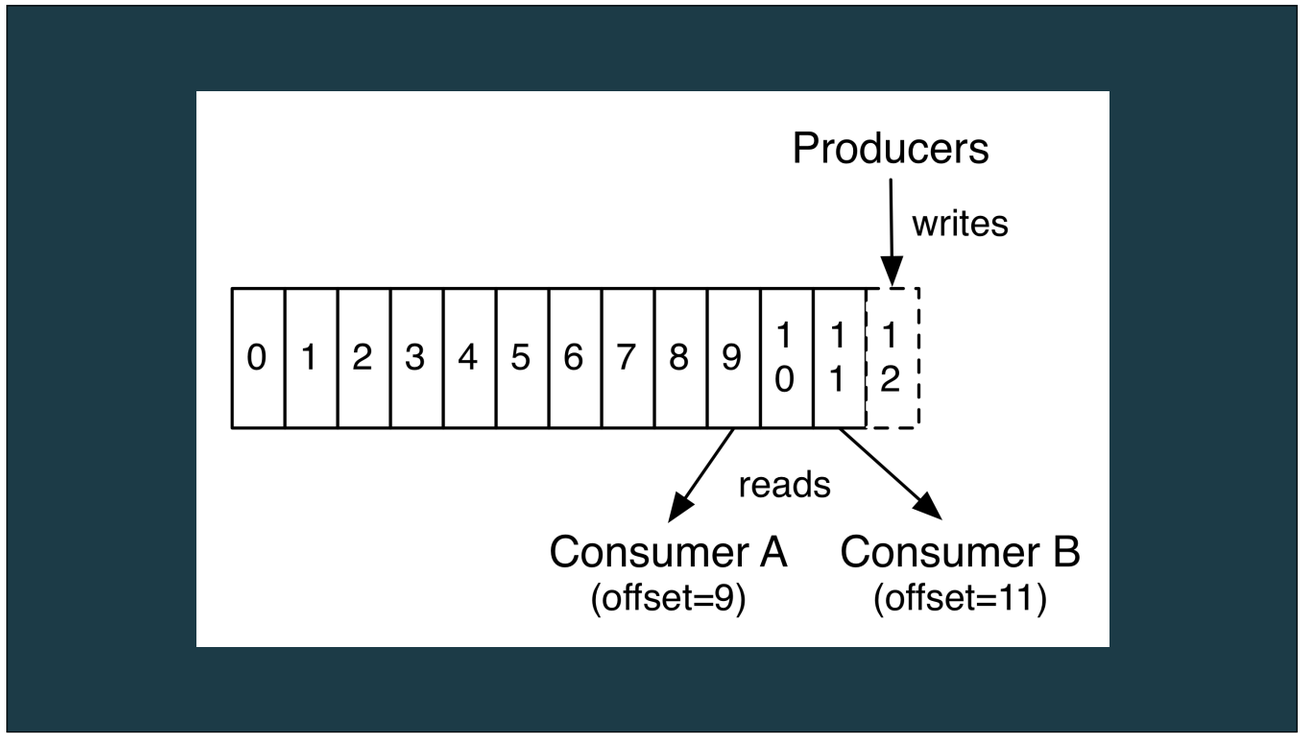
- Dean wrote this report describing the whole fast data landscape.
- bit.ly/lightbend-fast-data
- Previous talks (“Stream All the Things!”) and webinars (such as this one, https://info.lightbend.com/webinar-moving-from-big-data-to-fast-data-heres-how-to-pick-the-right-streaming-engine-recording.html) 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



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.

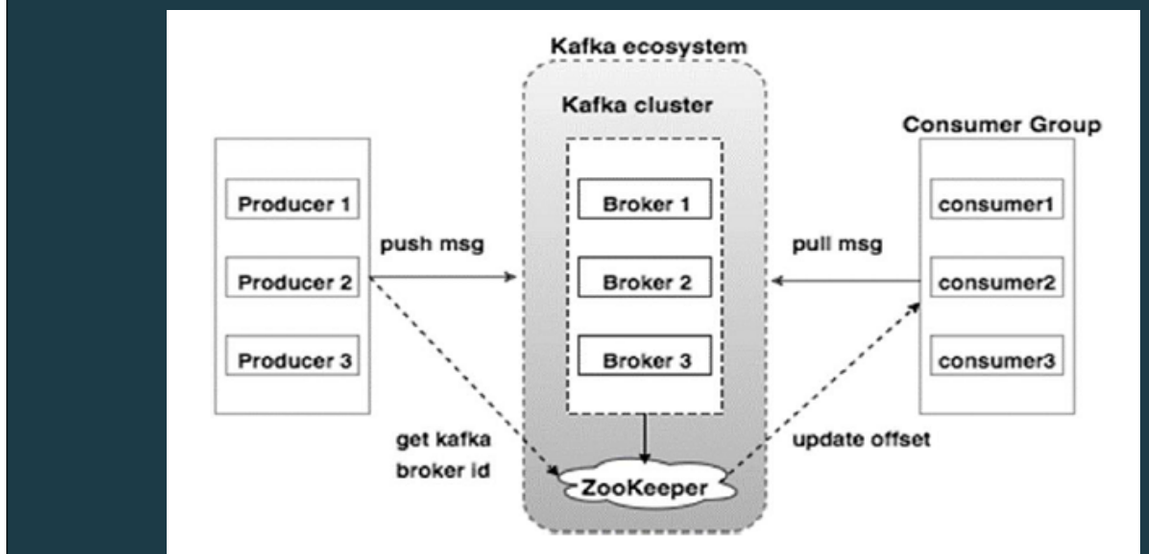
Why Kafka?


Reactive Platform
Go
Node.js
...
Microservices
Broker
Kafka Cluster
Disk
HDFS
S3, ...
SQL/
Lightbend



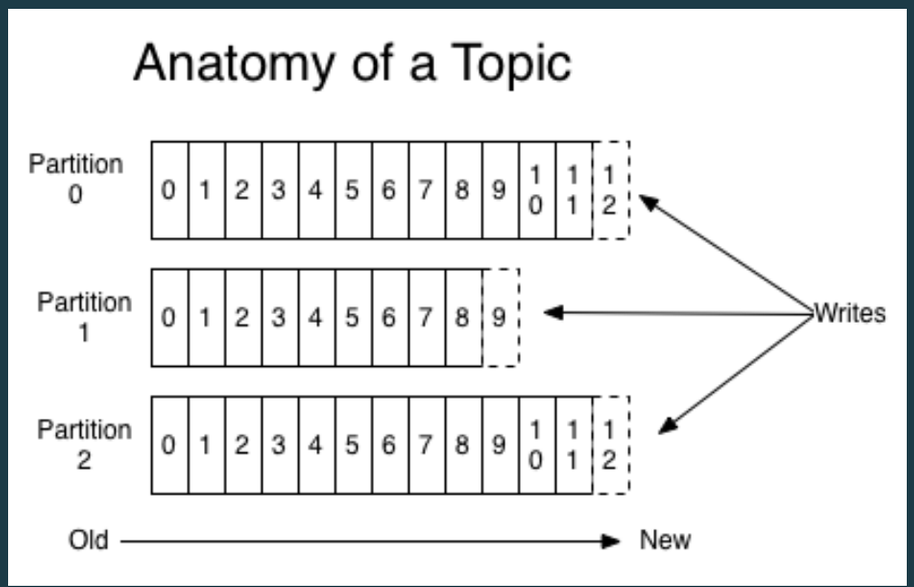
Kafka is a distributed log, storing messages sequentially. Producers always write to the end of the log, consumers can read on the log offset that they want to read from (earliest, latest, …)
Kafka can be used as either a queue or pub sub
The main differences are:
1. Log is persistent where queue is 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)

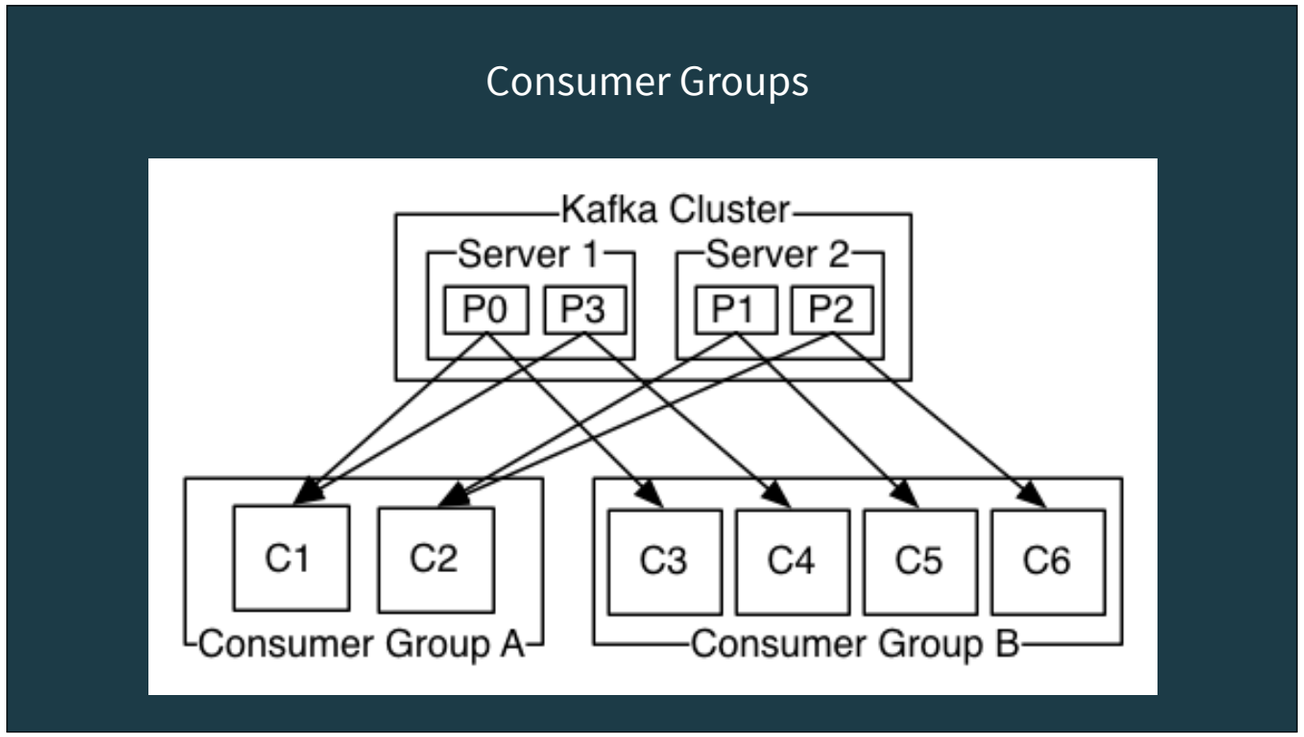


Kafka cluster typically consists of multiple brokers to maintain load balance.
One Kafka broker instance can handle hundreds of thousands of reads and writes per second and each broker can handle TB (based on the disk size and network performance) of messages without performance impact. Kafka broker 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.



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.

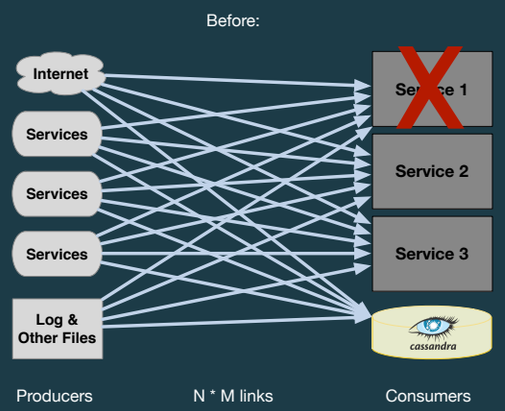
Kafka Producers and Consumers

Code time

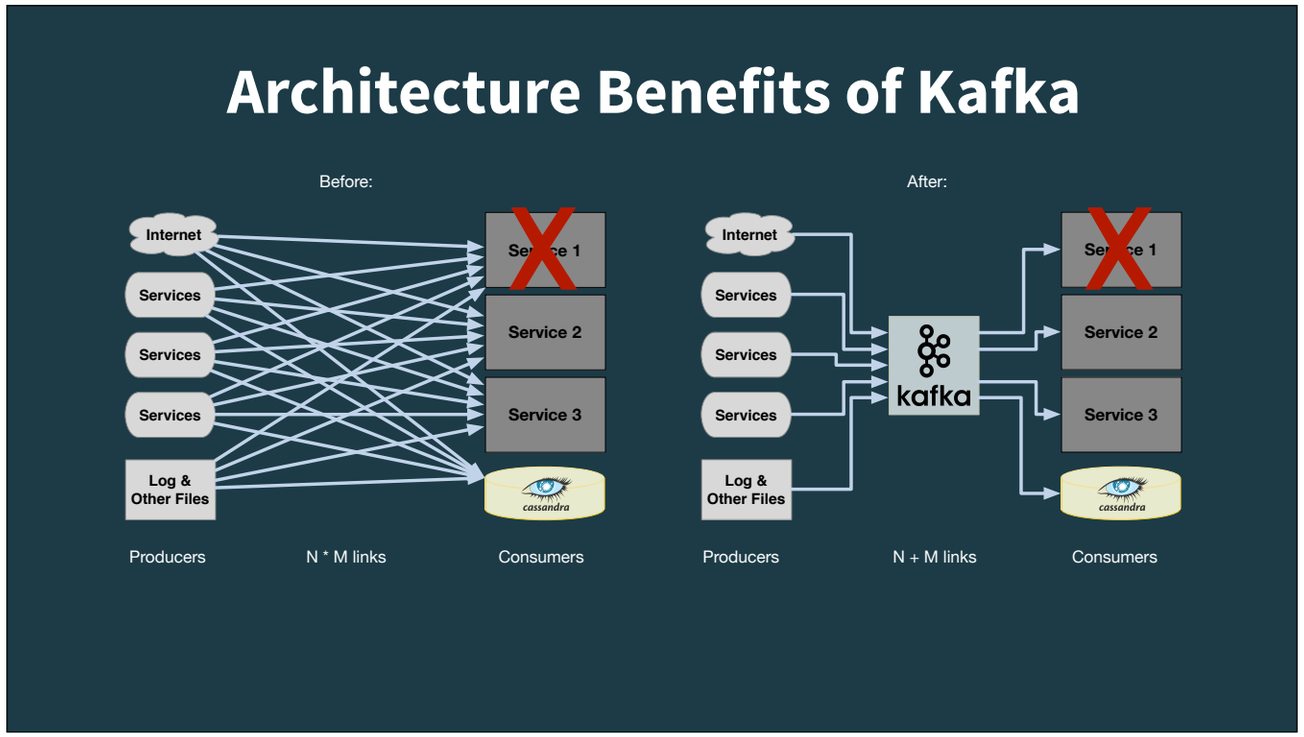
1. Project overview
   - Look at *client*, *data*, *model*, *configuration*, and *protobufs* folders and subprojects.
2. Explore and run the *client* project
   - Creates in-memory (“embedded”) Kafka instance and our Kafka topics
   - Pumps data into them

We’ll walk through the whole project, to get the lay of the land, then look at the subprojects listed. We’ll deep dive into the actual Akka Streams and Kafka Streams subprojects later. 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

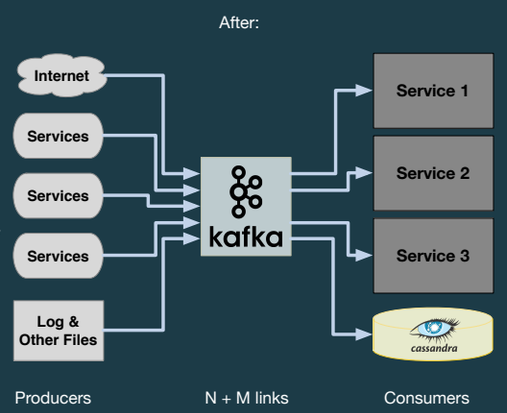


Kafka can simplify the situation by providing a single backbone which is used by all services (there are of coarse topics, but they are more logical then physical connections). Additionally Kafka persistence provides robustness when a service crashes (data is captured safely, waiting for the service 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

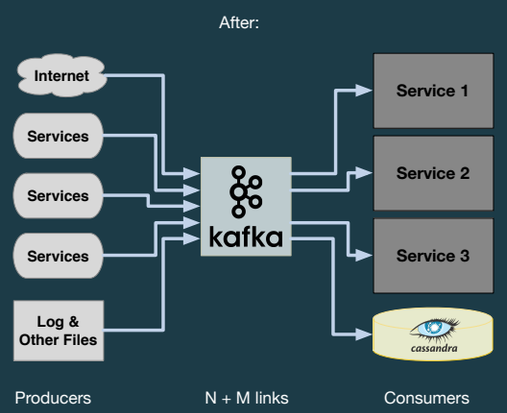


Kafka can significantly improve decoupling (no service specific endpoints, temporal decoupling), It minimize the amount of data send over network, each producer writes data to Kafka, instead of writing it to multiple consumers. This also improves data consistency - the same data is consumed by all consumers. 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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Kafka message size considerations

- Should I use Kafka for all messages?
  - Optimal performance: messages size ~ few KB.
  - Larger messages put heavy load on brokers and is very inefficient.
  - It is inefficient on producers and consumers as well.

Kafka perf tips from Manoj Khangaonkar on the Kafka mailing list.

Kafka message size considerations

- What if my messages are very large?
  - Use *messaging by reference*
    - Store a message in S3, HDFS, etc.
    - Send the *reference* to the location as a Kafka message

Kafka perf tips from Manoj Khangaonkar on the Kafka mailing list.

Message compatibility for Kafka

- Is it okay if messages have different **schemas**?
  - If so, handled at run time (“dynamic typing”) or design time (“static typing”)?
- How is message type determined?
  - Registry or repository?
  - Embedding in Kafka headers?

Keep track of message schema (ID) used for generated code in both consumer and producer. Consumer might additionally have a list of “compatible schema IDs” Once the message is received, check the schema ID published by the producer and decide whether it can be used. If ID is unknown, out message into DLQ

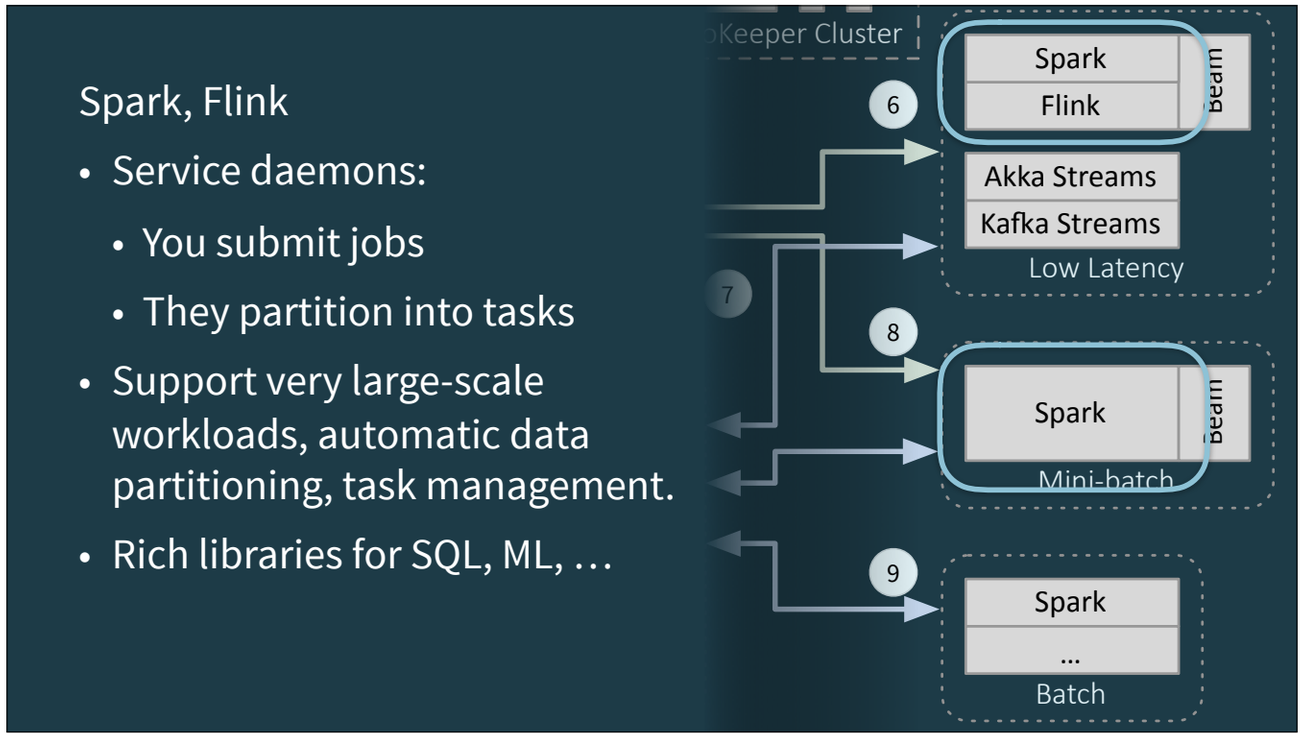
Message versioning

- What happens if a Producer needs to create a new message version that's incompatible with previous versions?
  - Topic versioning similar to endpoint versioning used by services.
  - Should you start new services instead?

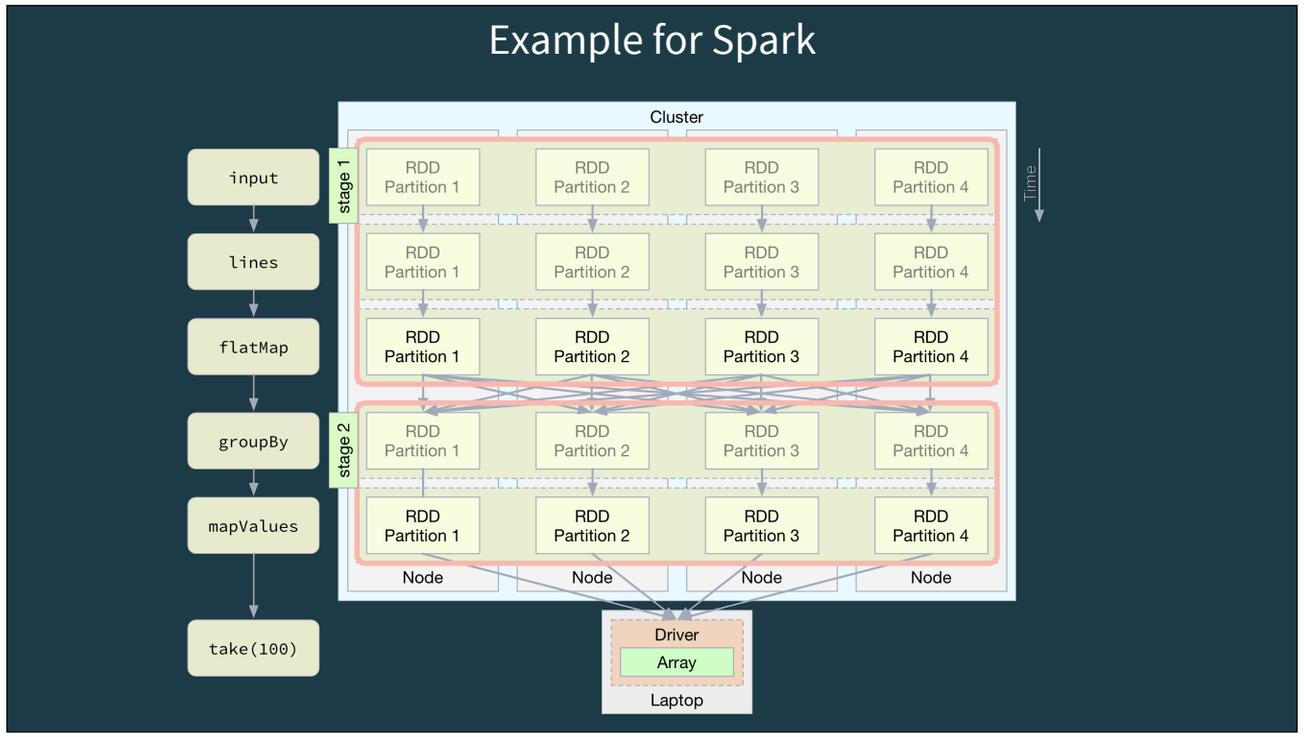
Streaming Architectures

Two approaches:

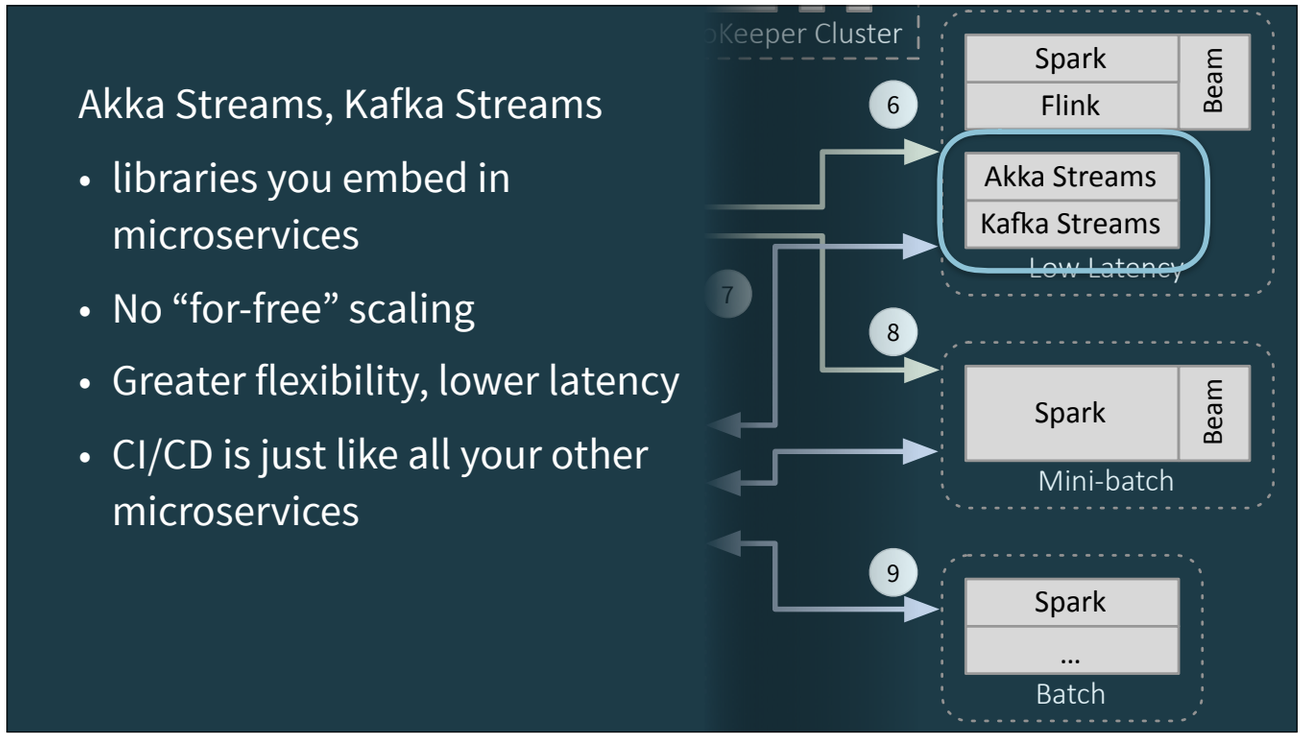
- Stream processing “engines”
  - Spark, Flink, Beam, …
- Streaming libraries
  - Akka Streams, Kafka Streams, …



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.

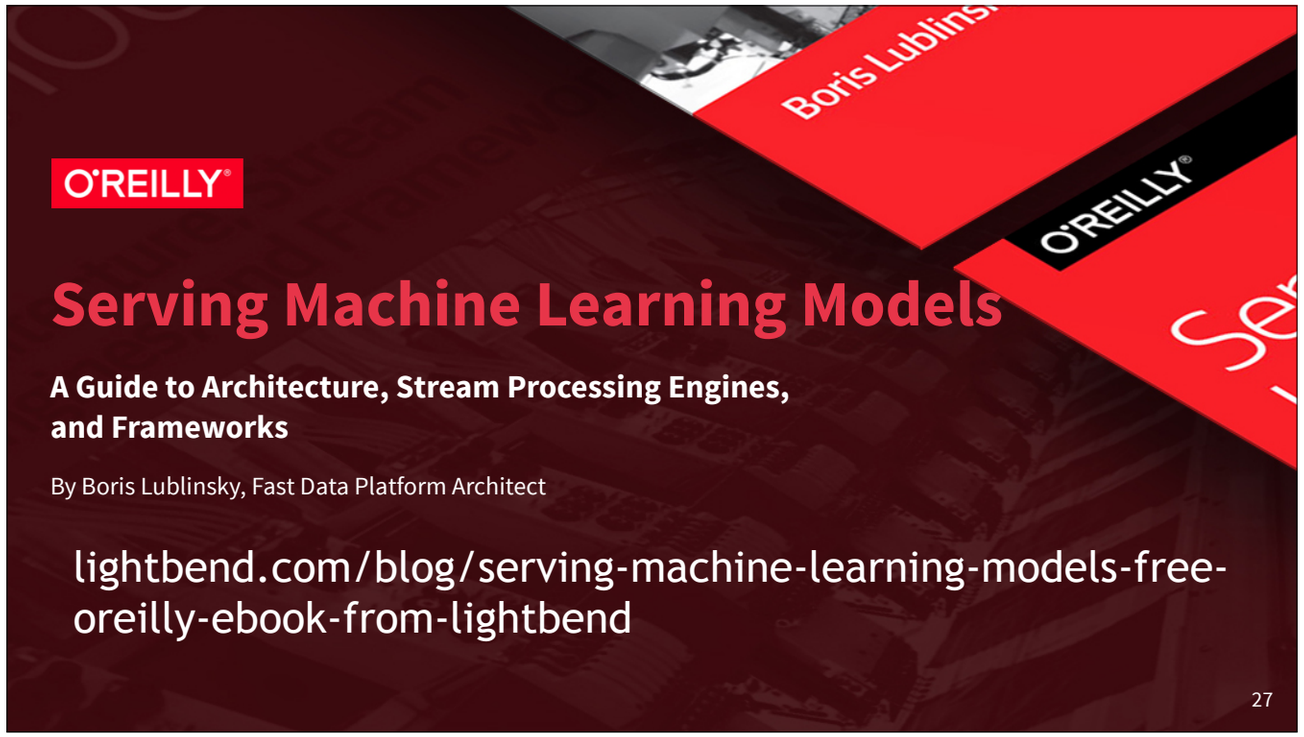


You have to write jobs, using their APIs, that conform to their programming model. But if you do, Spark and Flink do a great deal of work under the hood for you!



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



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

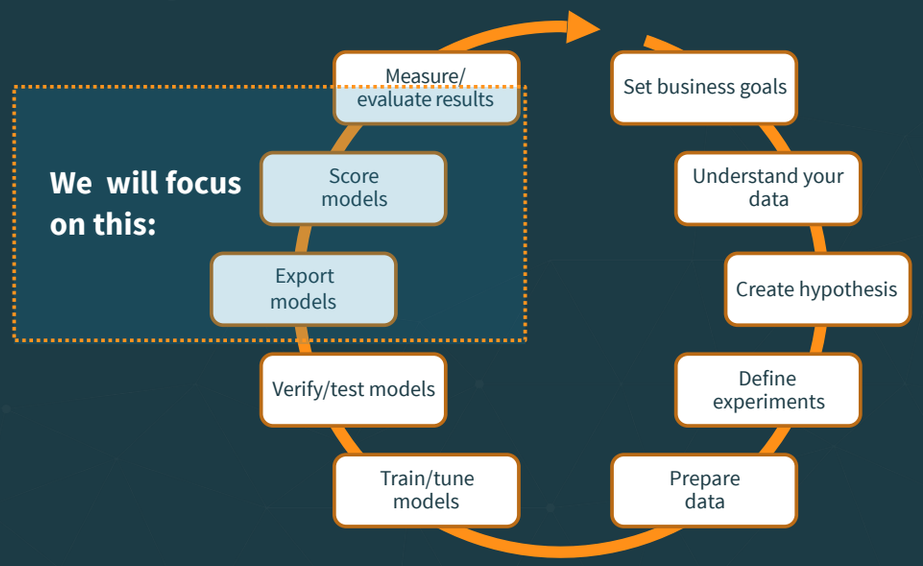
ML Is Simple

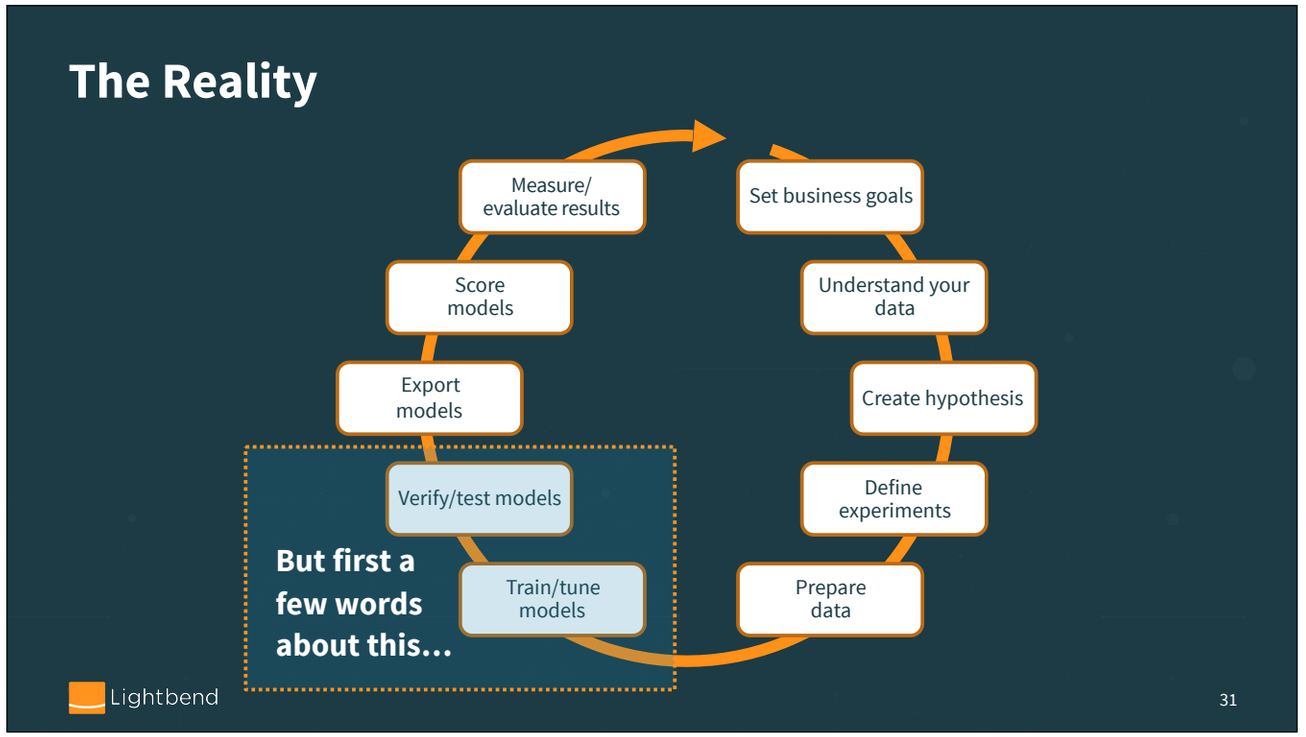
Get a lot of data
Sprinkle some magic
And be happy with results

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

The Reality

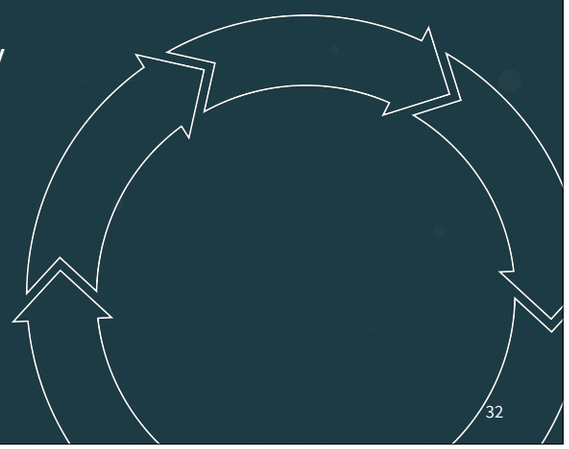

We will focus on this:
Measure/ evaluate results
Score models
Export models
Verify/test models
Train/tune models
Set business goals
Understand your data
Create hypothesis
Define experiments
Prepare data



- A brief diversion about this part of the pipeline.

Another Consideration – Model Lifecycles

- Models tend to *drift*
  - More precisely, they grow stale as data changes
- Update frequencies vary – from hourly to yearly



Trends in Model Training…

- Original approach - Batch retrain at ad-hoc for fixed intervals.
  - Using Hadoop, off-line data science tool chains, etc.
- Challenges:
  - How do you deliver updated models to production?
  - What if you have *thousands* of models?
  - When should you retrain?

Trends in Model Training…

- Moving to automated retraining
  - Spark, X as a Service (where X = TensorFlow, …)
- Challenges:
  - How do you deliver updated models to production? CI/CD pipeline and techniques we'll discuss
  - What if you have *thousands* of models? *Must measure and automate everything*
  - When should you retrain? *Metrics for model drift… (next slide)*

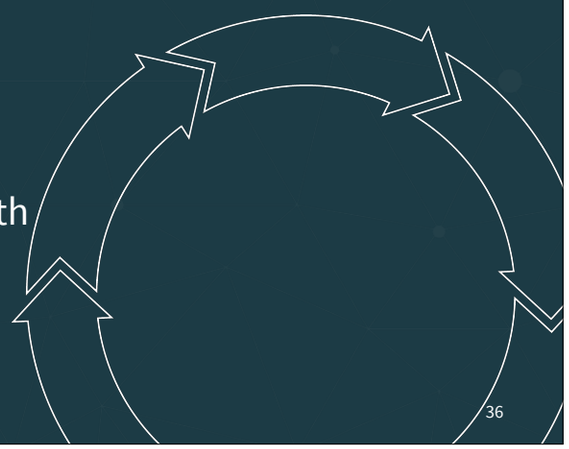
Trends in Model Training…

- One example of recent work
  - *Continuum: a platform for cost-aware low-latency continual learning*
    - https://blog.acolyer.org/2018/11/21/continuum-a-platform-for-cost-aware-low-latency-continual-learning/
    - Attempts to balance cost concerns, preserve low latency, yet remain sensitive to degradation from drift

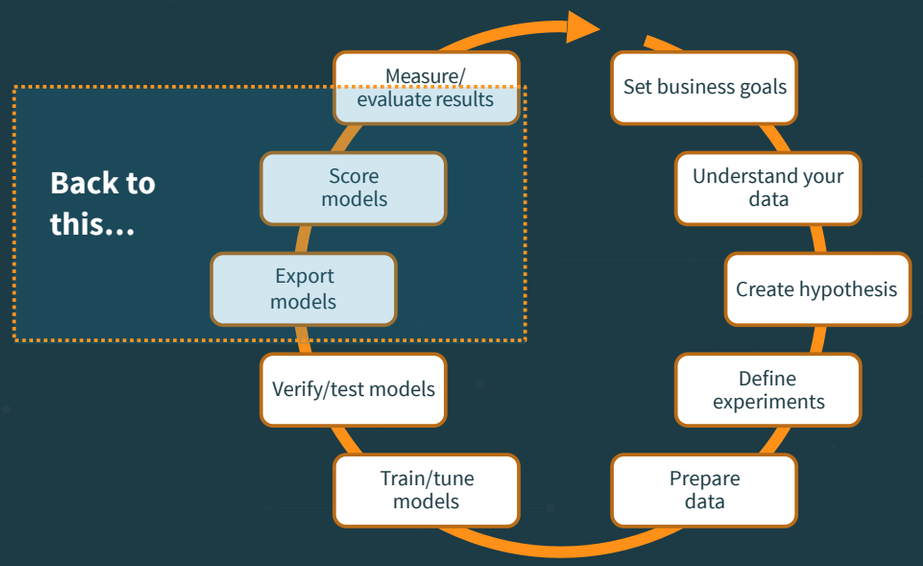
This blog post discusses “Continuum” and gives you a a good, overall sense of research directions and concerns people are attempting to address.

Another Consideration – Model Auditing

- Your organization may need to track model versions for auditing:
  - What model instance was used to score this (controversial?) record?
  - Why did it score it a particular way?
  - What were the model parameters?
  - Which other records were scored with this model?



The Reality


Back to 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)

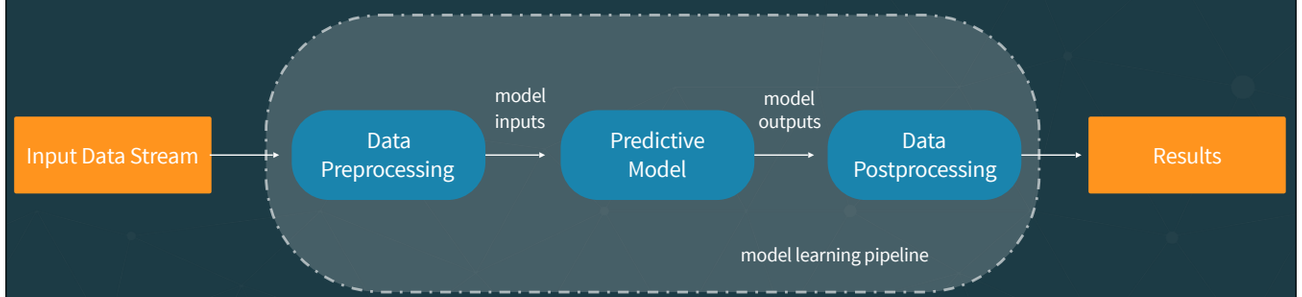
Linear regression: $y = a_c + a_1 * x1 + \ldots + a_n * x_n$

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

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.

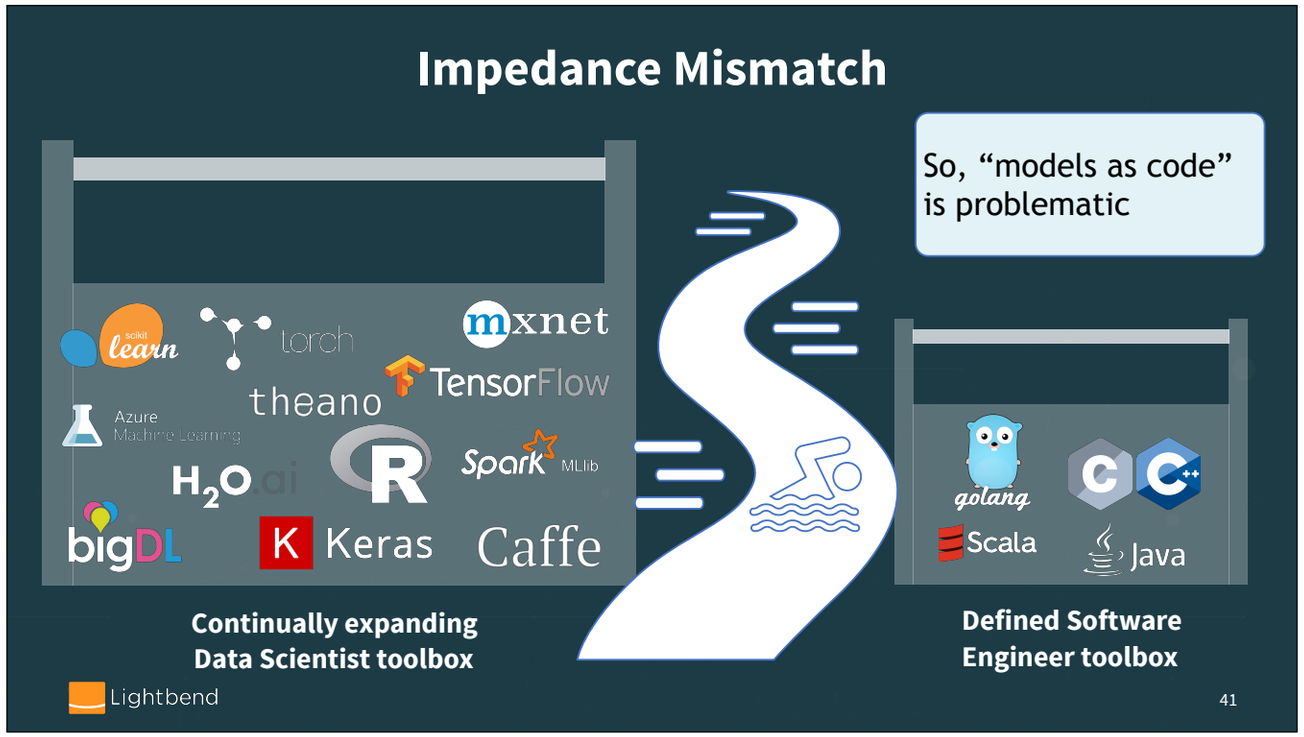


UC Berkeley AMPLab introduced machine learning pipelines as a graph defining the complete chain of data transformation
The advantage of such approach
It captures the whole processing pipeline including data preparation transformations, machine learning itself and any required post processing of the ML 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.
This notion of machine learning pipelines has been adopted by many applications including SparkML, Tensorflow, PMML, etc.

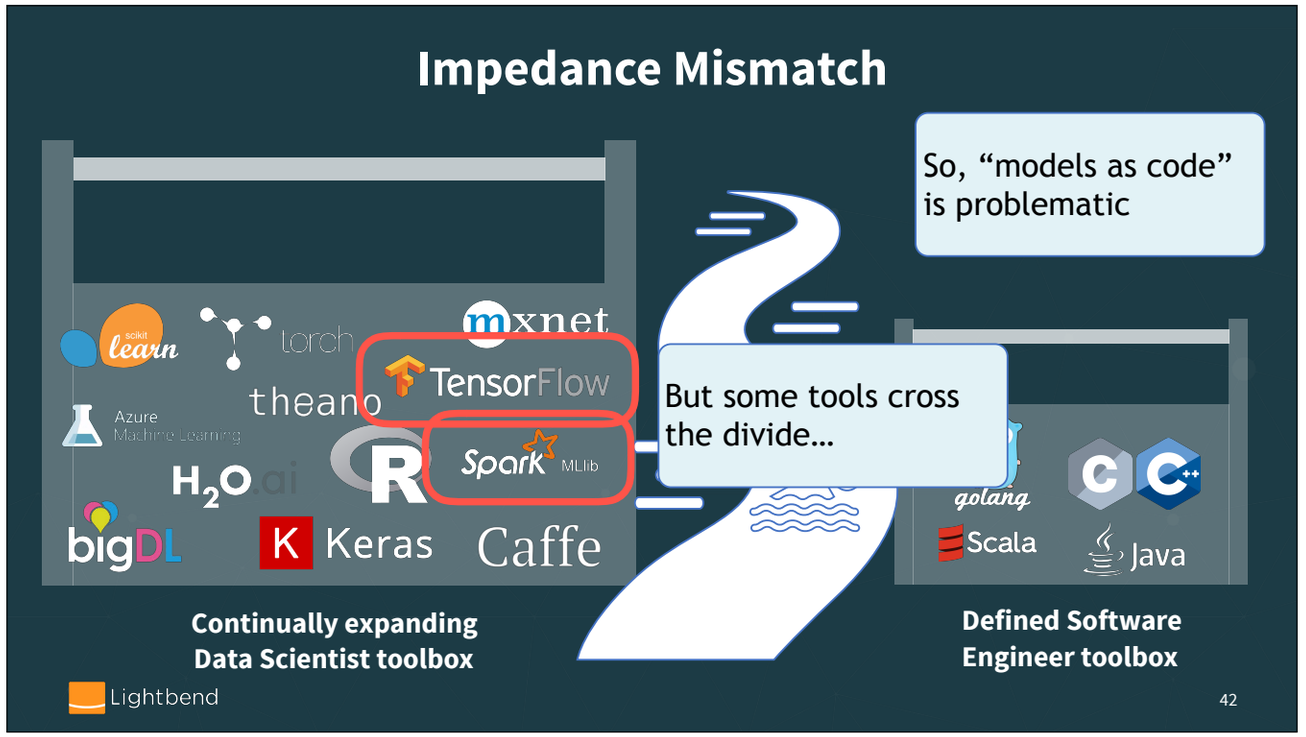
Traditional Approach to Model Serving

- *Model as code*: source code in some language implements the model
- This code is linked into the model serving applications

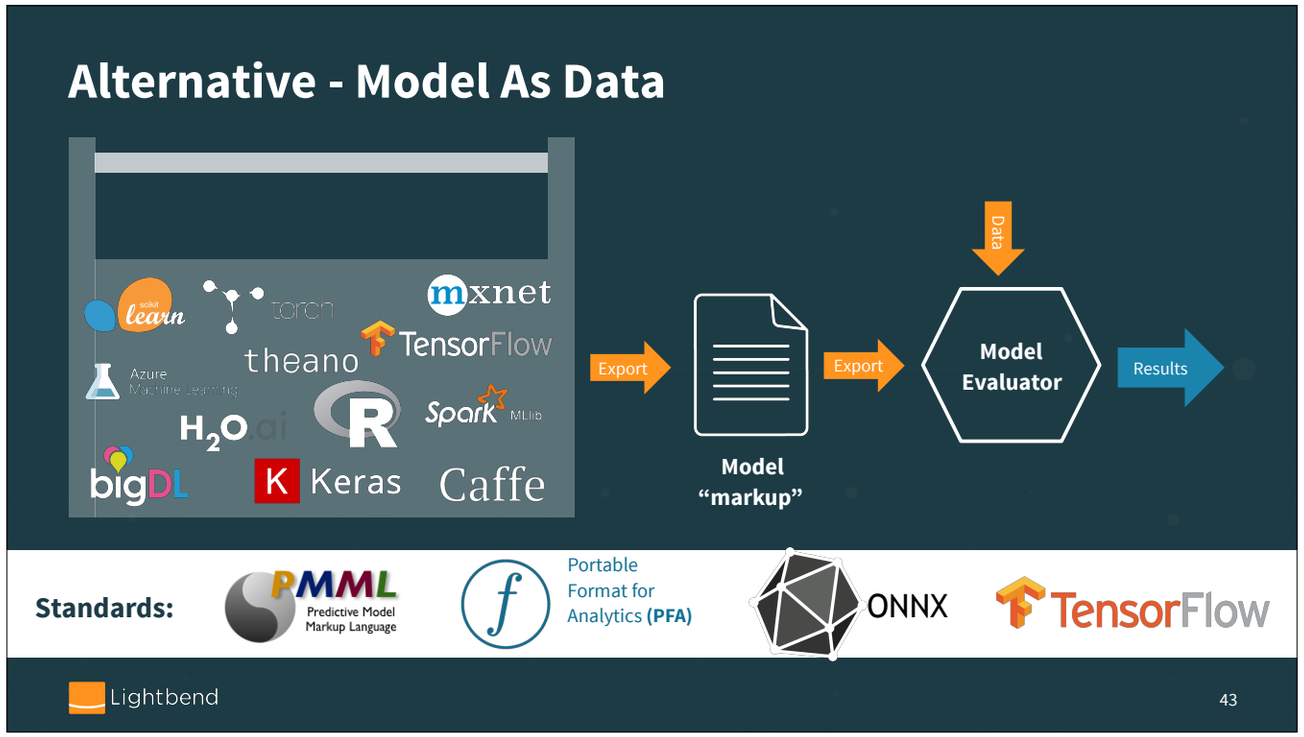
Why is this problematic?



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.



We’ll return to this point below.



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.
ONNX is a new standard for deep learning models, but it is not supported by Tensorlow.
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

Considerations for Interchange Tools

- Do you *training* tools support an exchange format (PMML, PFA, …)?
- Do you *serving* tools support the format?
- Is there support on both ends for the model types you want to use, e.g., random forests, neural networks, …?
- Does the *serving* implementation faithfully reproduce the results of your *training* environment?

Implementations for these tools have been spotty, so carefully consider these questions when evaluating this approach.

Exporting Models 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

See also this list of products: http://dmg.org/pmml/products.html

Exporting NN Models With ONNX

- Created by Microsoft and Facebook
  - https://thenewstack.io/facebook-microsoft-bring-interoperable-models-machine-learning-toolkits/
- Supported tools: https://onnx.ai/supported-tools
- Git Repo: https://github.com/onnx

- Designed for when you use one NN framework for R&D, another for production, but…
  - It is new and not mature
  - Tensorflow is supported, but not by Google

For our purposes here, you might use ONNX if you are only concerned with serving neural networks, not other kinds of ML. You'll still need to decide what tool to run in your production environment and decide the best way to integrate with your microservices.

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

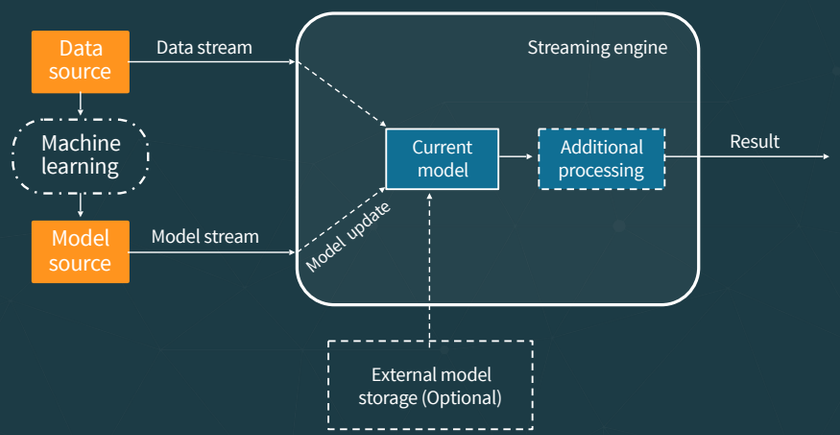
Evaluating Tensorflow Model

- Tensorflow is implemented in C++ with a Python interface.
- In order to simplify Tensorflow usage from Java, in 2017 Google introduced the Tensorflow Java API.
  - Supports importing an exported model and using it for scoring.
  - Not yet recommended for training TF models.

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

The Solution We'll Discuss Today

A streaming system that allows updating models without interruption of execution (dynamically controlled stream).



Lightbend

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 Code Abstraction (Scala and Java)

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

trait ModelFactory {
  def create(d : ModelDescriptor) : Option[Model]
  def restore(bytes : Array[Byte]) : Model
}
```

```java
public interface Model extends Serializable {
  public Object score(Object input);
  Unit cleanup();
  byte[] toBytes();
  long getType();
}

public interface ModelFactory {
  Optional<Model> create(ModelDescriptor d);
  Model restore(byte[] bytes);
}
```


Corresponding Scala code that can be generated from the description.

Side Note: Monitoring

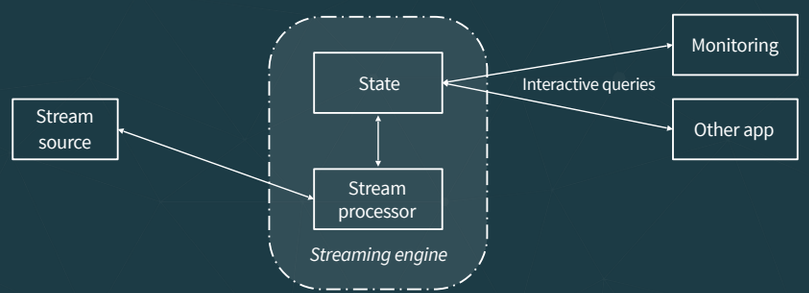
Model monitoring should provide information about usage, behavior, performance and lifecycle of the deployed models

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

Queryable State

Ad hoc query of the stream state. Different than the normal data flow.

- Treats the stream as a lightweight *embedded database.*
- *Directly query the current state* of the stream.
  - No need to materialize that state to a datastore first.

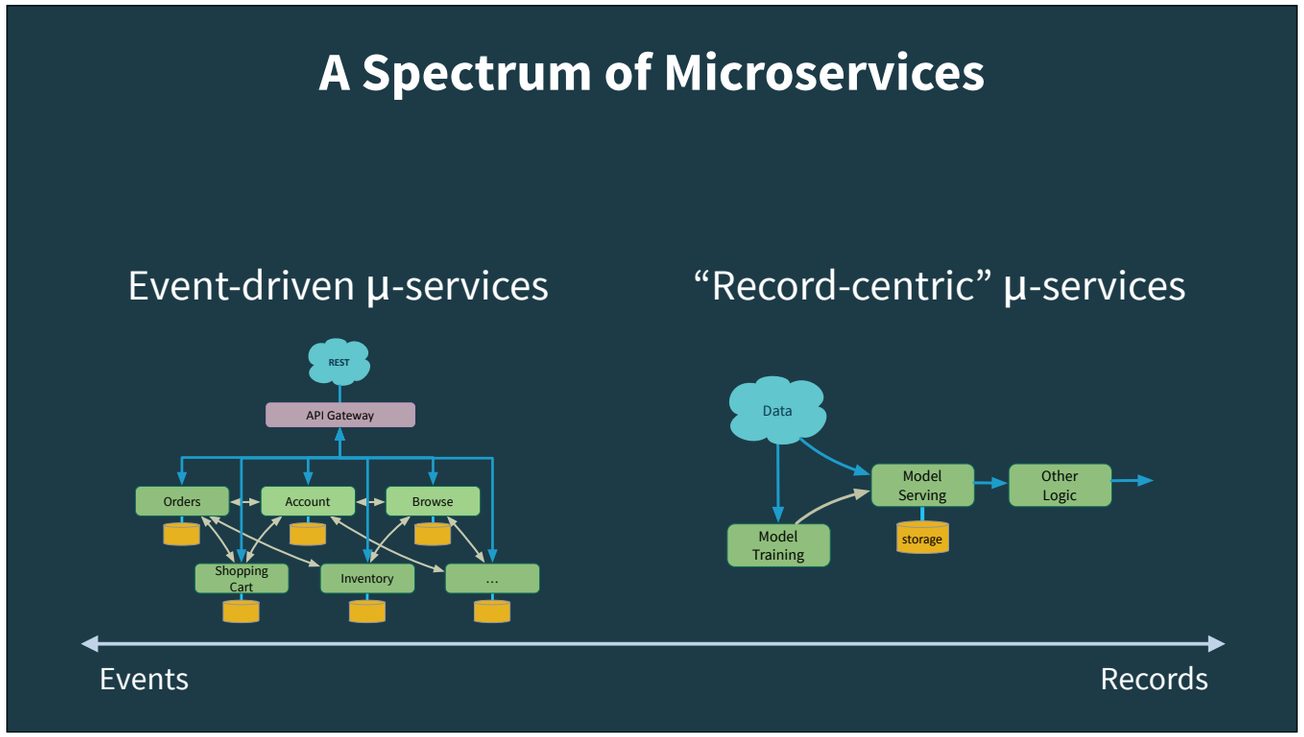


Lightbend

Kafka Streams and Flink have built-in support for this and it’s 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.

Microservices for Streaming Data

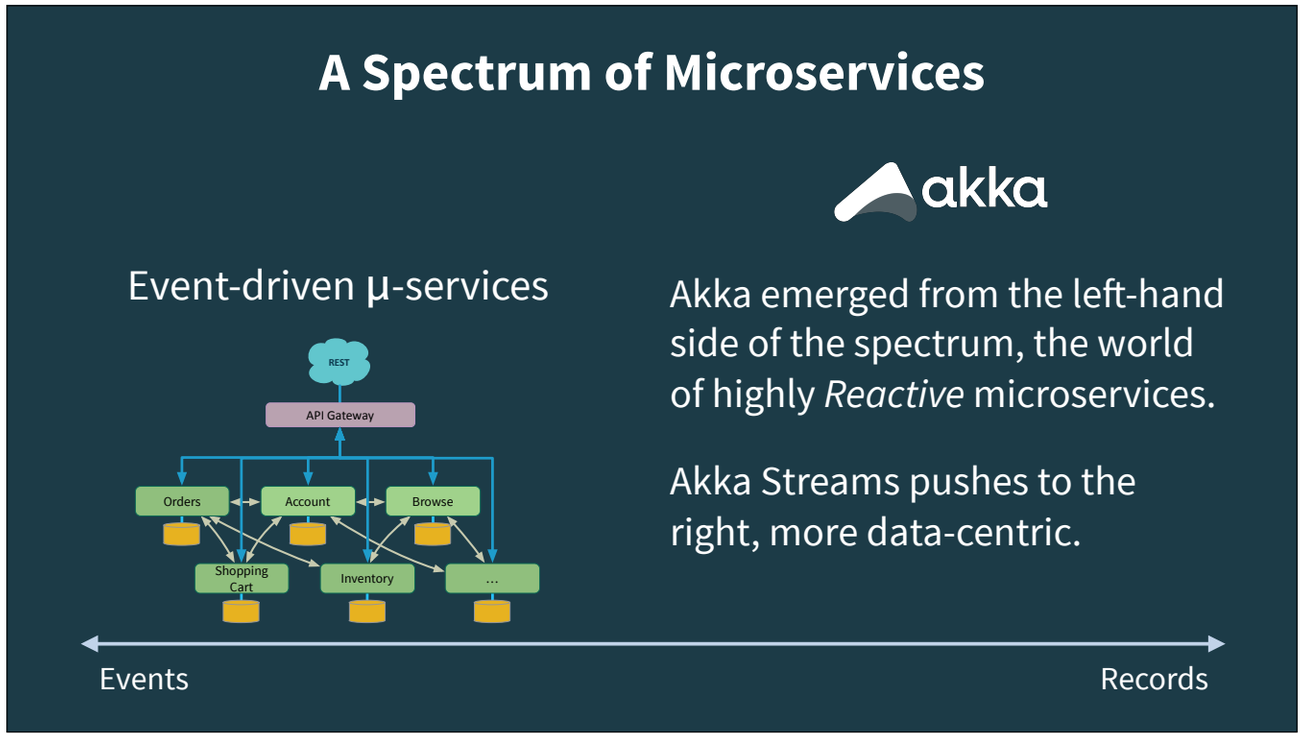
Akka Streams vs. Kafka Streams



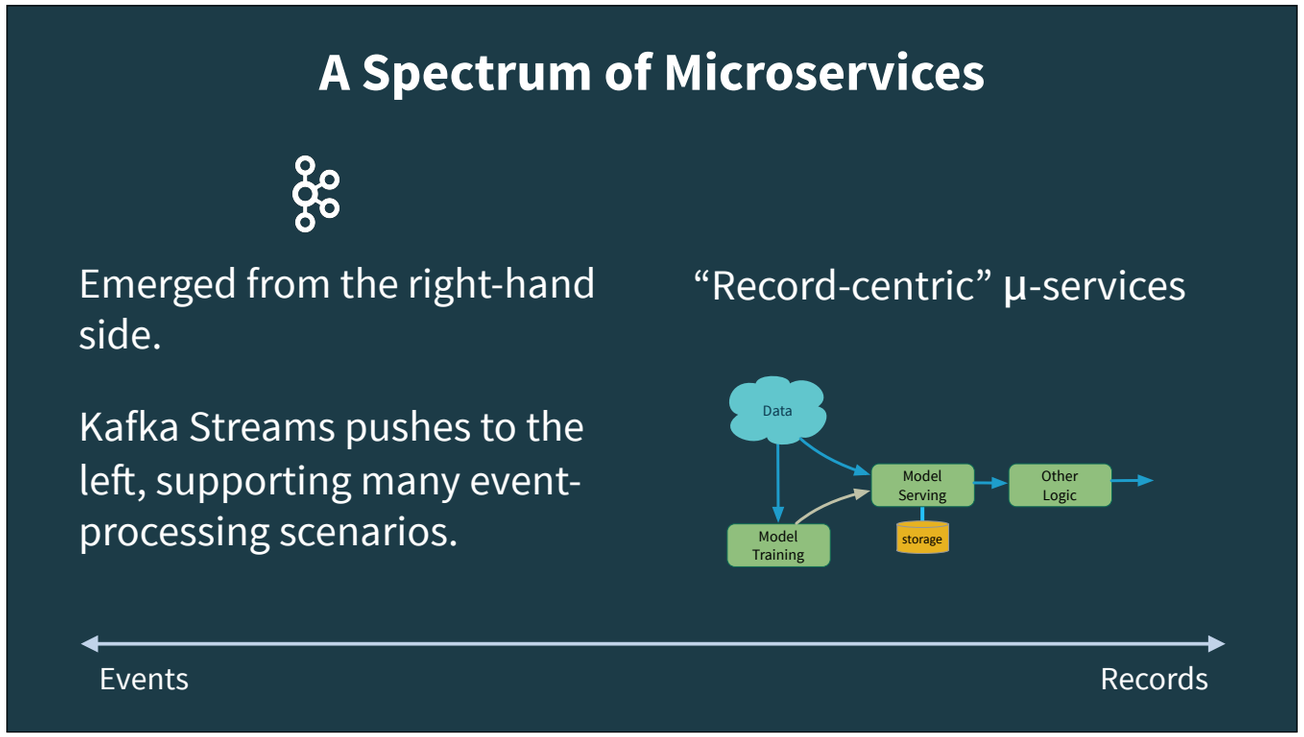
By event-driven microservices, I mean that each individual datum is treated as a specific event that triggers some activity, like steps in a shopping session. Each event requires individual handling, routing, responses, etc. REST, CQRS, and Event Sourcing are ideal for this.

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.

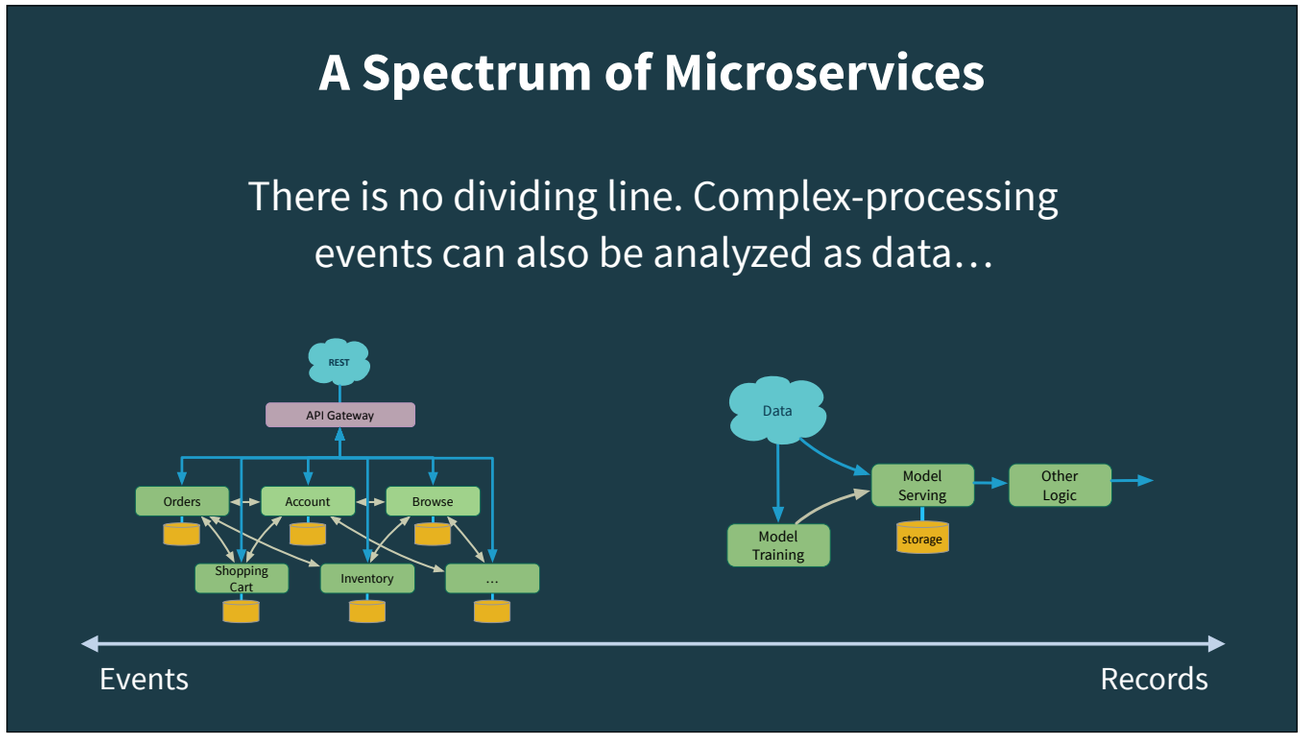
It’s a spectrum because we might take those events and also route them through a data pipeline, like computing statistics or scoring against a machine learning model (as here), perhaps for fraud detection, recommendations, etc.



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.



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.



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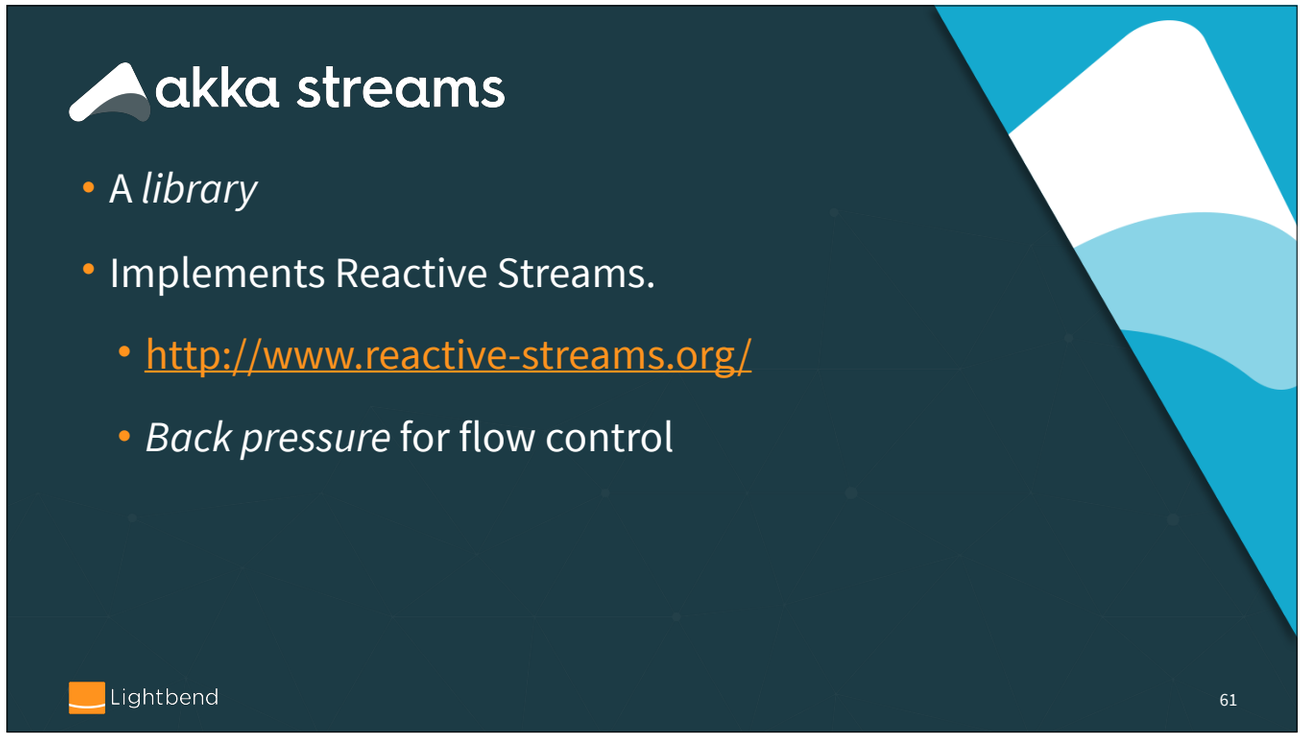
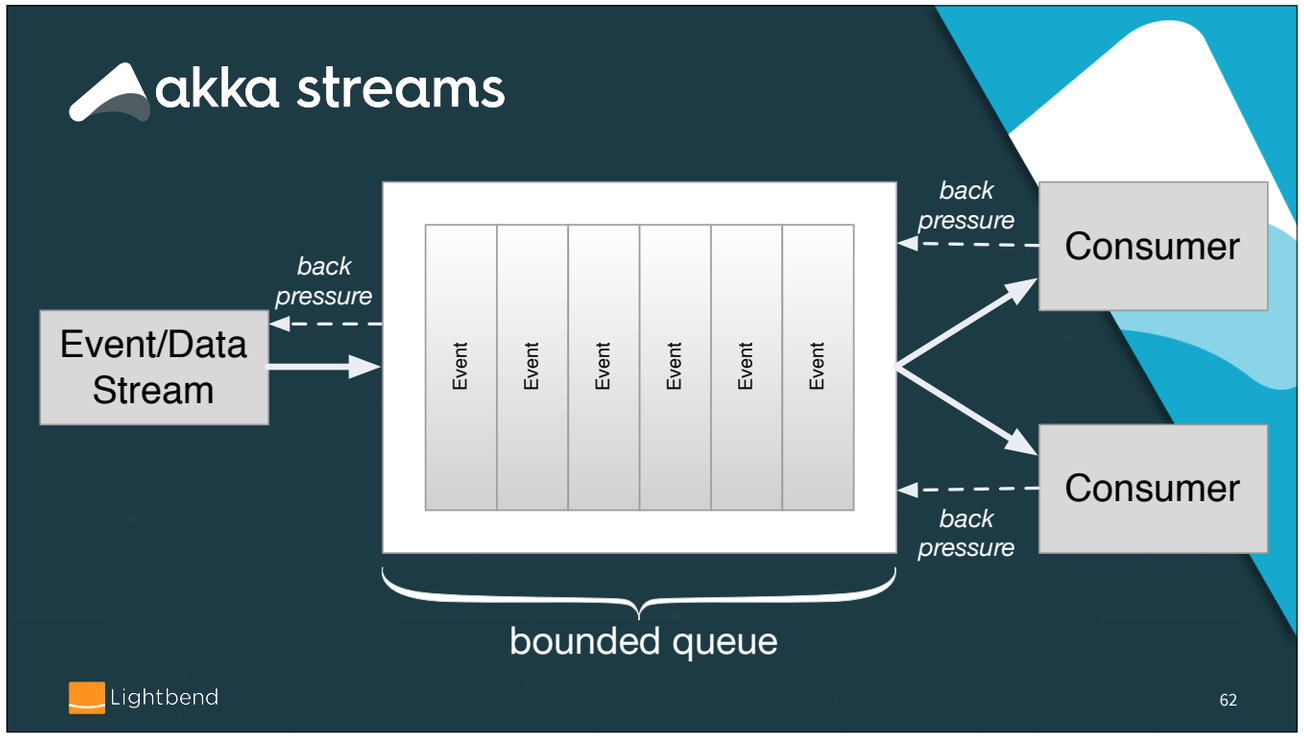
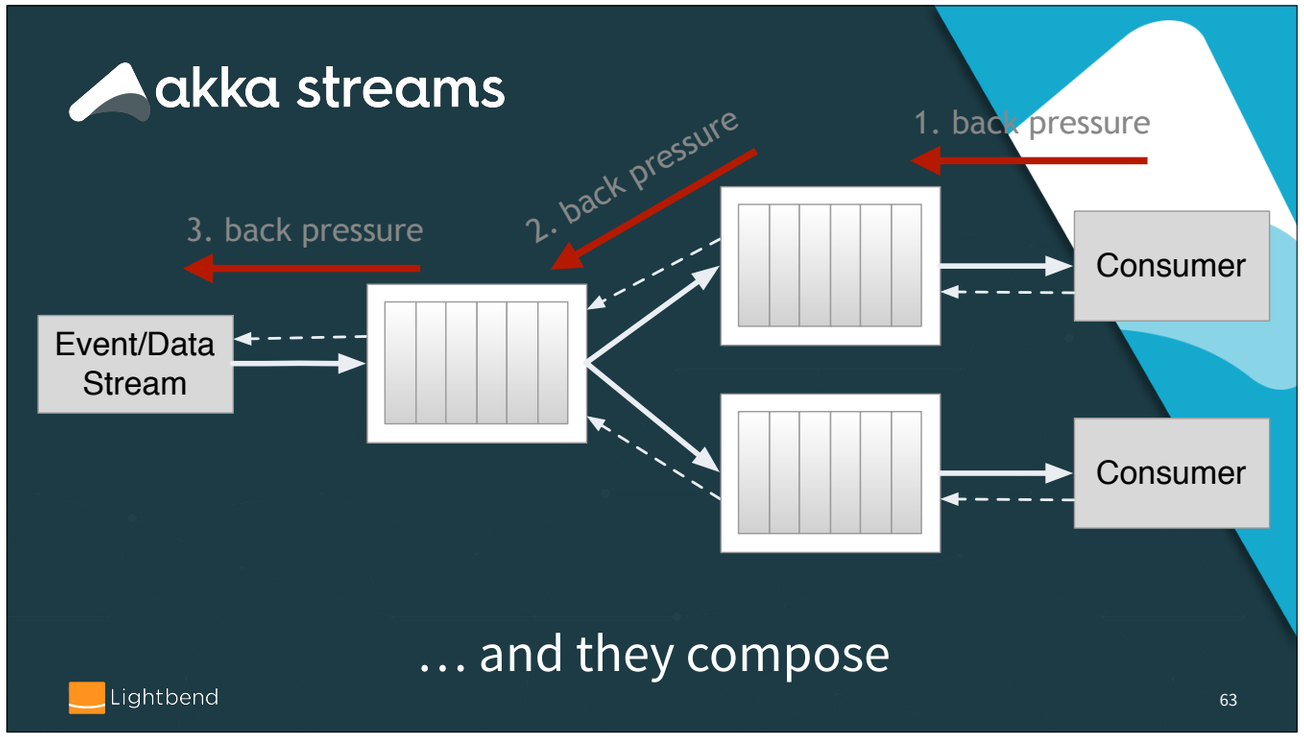
Akka Streams



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.



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

akka streams

- 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.

akka streams

- A very simple example to get the “gist”:
  - Calculate the factorials for n = 1 to 10

```
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))
```

```
1
2
6
24
120
720
5040
40320
362880
3628800
```


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

```scala
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")
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val source: Source[Int, NotUsed] = Source(1 to 10)
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factorials.runWith(Sink.foreach(println))
```

Imports!

```
1
2
6
24
120
720
5040
40320
362880
3628800
```

```scala
import akka.stream._
import akka.stream.scaladsl._
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factorials.runWith(Sink.foreach(println))
```

```
1
2
6
5040
40320
362880
3628800
```

Initialize and specify now the stream is “materialized”

```scala
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")
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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))
```

```
1
2
6
40320
362880
3628800
```

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

```scala
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")
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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))
```

```
1
2
6
24
120
362880
3628800
```

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

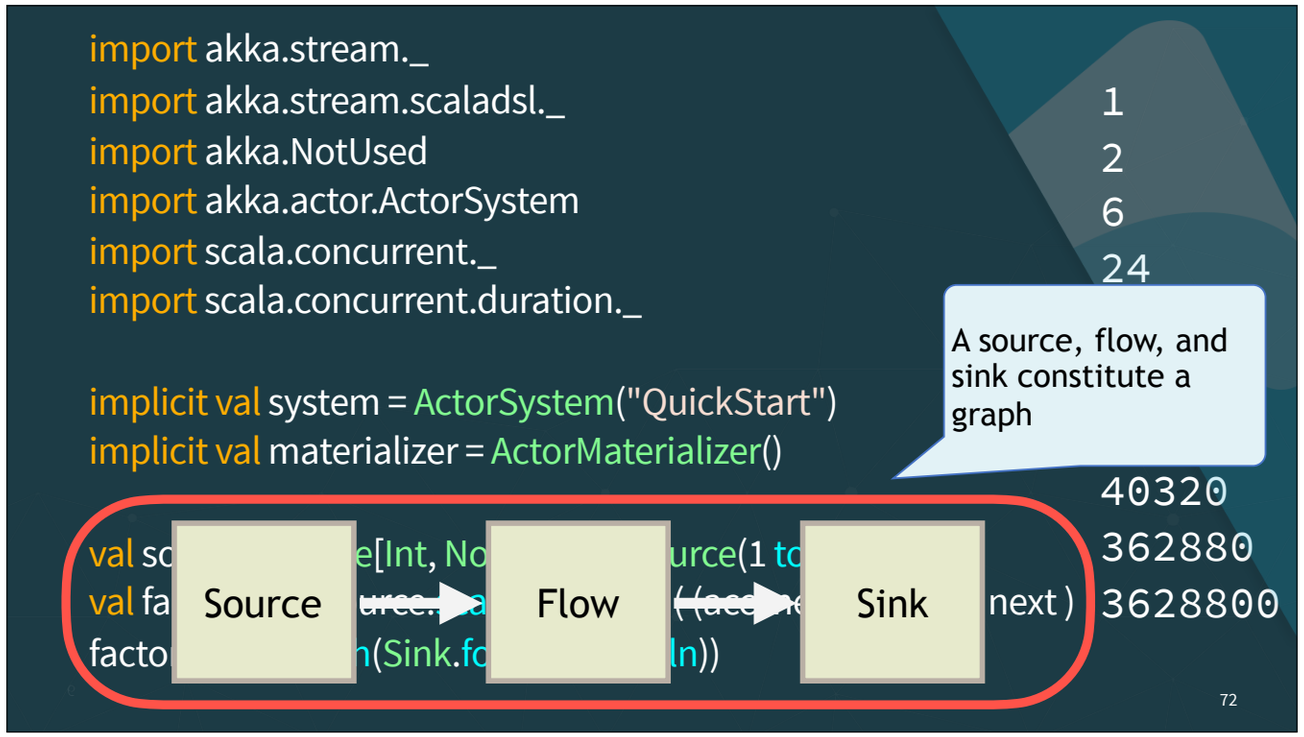
```
import akka.stream._
import akka.stream.scaladsl._
import akka.NotUsed
import akka.actor.ActorSystem
import scala.concurrent._
import scala.concurrent.duration._

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.runWithSink.foreach(println))
```

```
1
2
6
24
120
720
3628800
```

Output to a Sink, and run it



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

akka streams

- 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!)

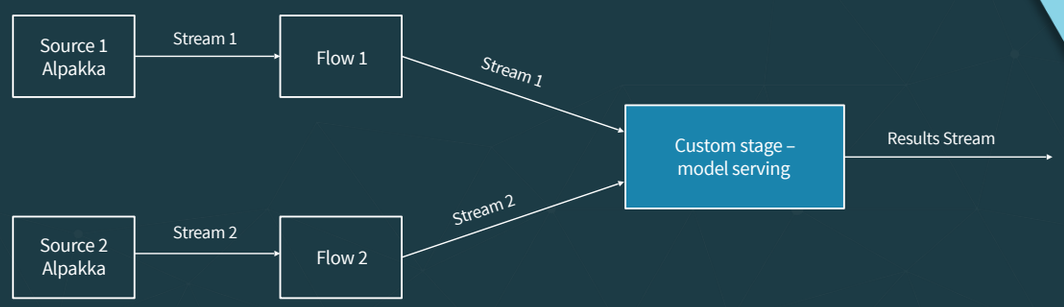
Implementations

- 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…
- Third approach: Make REST calls to a separate service, e.g., Tensor Flow Serving and Clipper

We provide two implementations. You could generalize the second approach (async calls) to invoke an external service. We won't provide examples of this option, but return later with some additional considerations about it.

Using a Custom Stage

Create a custom stage, a fully type-safe way to encapsulate new functionality. Like adding a new “operator” to Akka Streams.

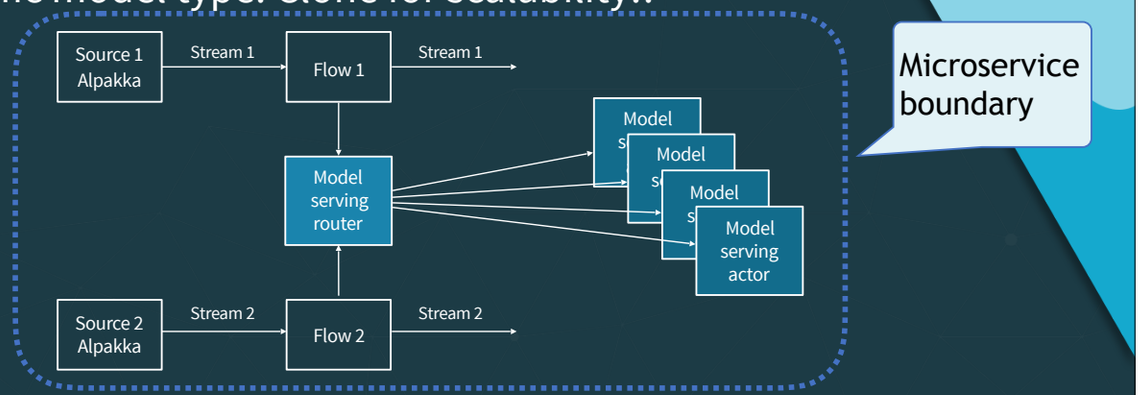


Lightbend

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 Invocations of 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!!

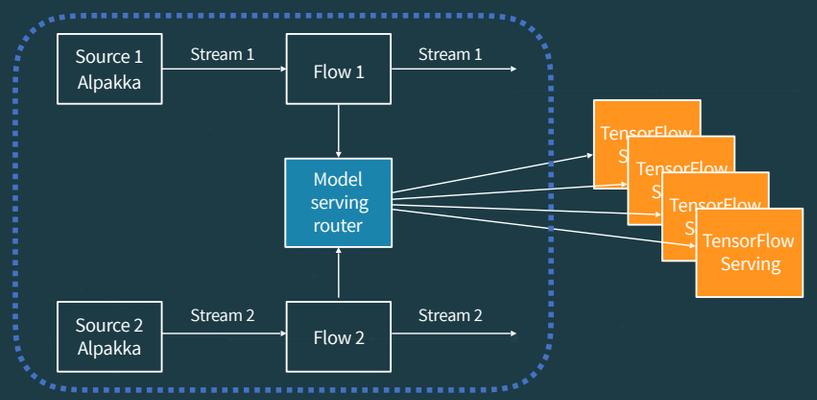


Microservice boundary

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

Using Invocations of Other Services

Use the same router actor idiom to forward requests to external services.

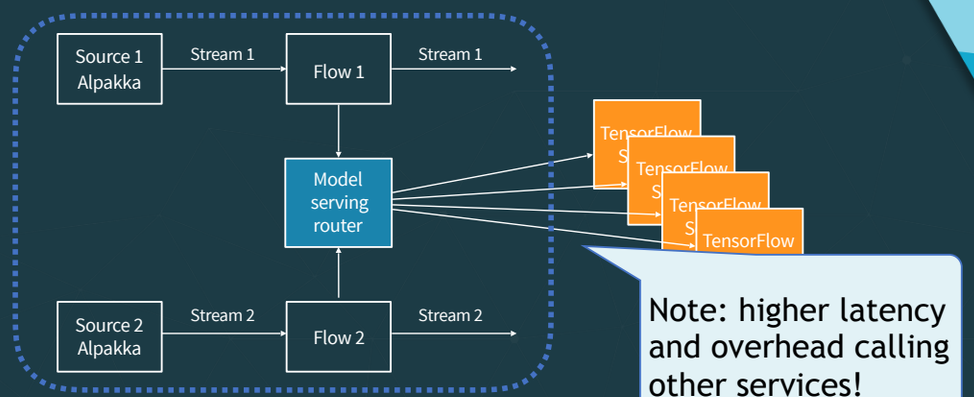


Lightbend

Use the same routing layer idiom: an actor that will implement model serving for a specific model (based on some key) and route messages appropriately to the external service. This way our system will serve models in parallel.

Using Invocations of Other Services

Use the same router actor idiom to forward requests to external services.



You should profile the performance impact going over a remote connection to a separate service. In contrast, actors in the previous example can be in the same process, where messaging is only a little less efficient than a function call.

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

Akka Streams Example

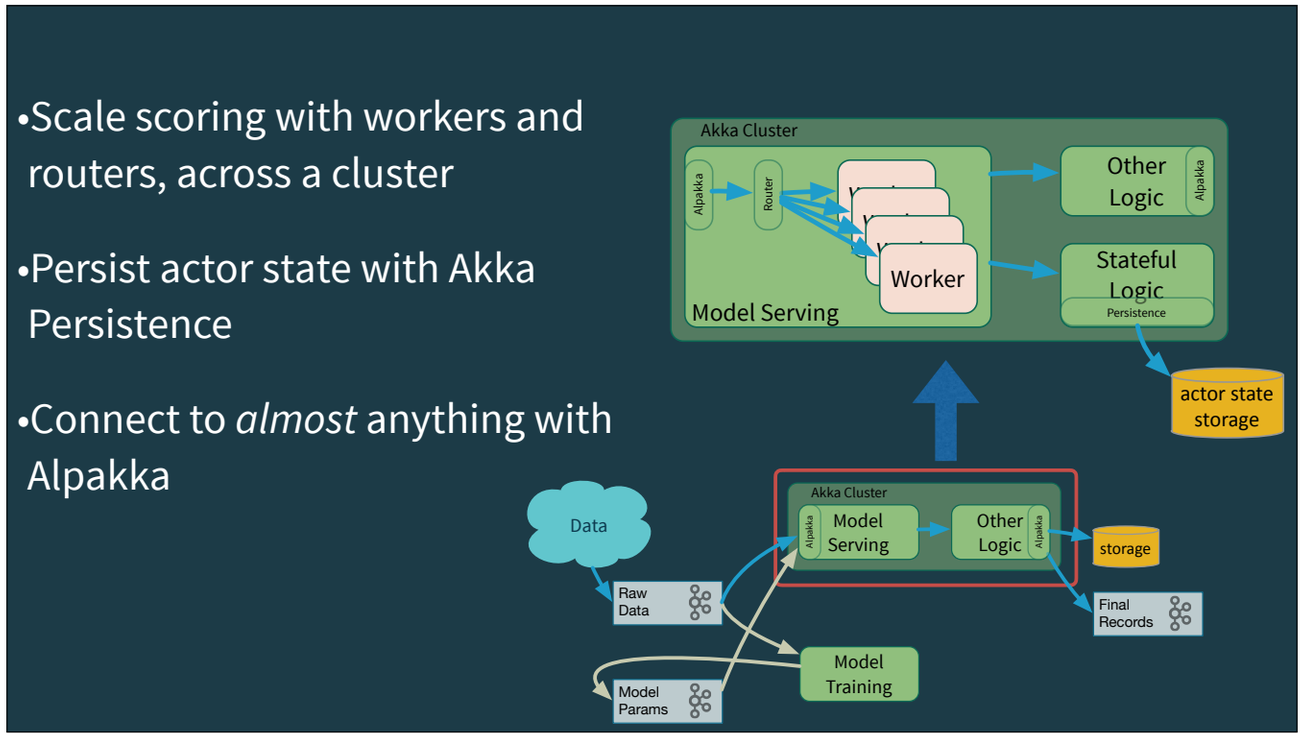
Check Queryable state

- For custom stage go to
  http://localhost:5500/state
- For actor-based implementation go to:
  http://localhost:5500/models
  http://localhost:5500/state/wine

Exercises!

- To find them, search for `// Exercise` comments in the code base.
- We'll suggest some you might try first.

Other Production Concerns

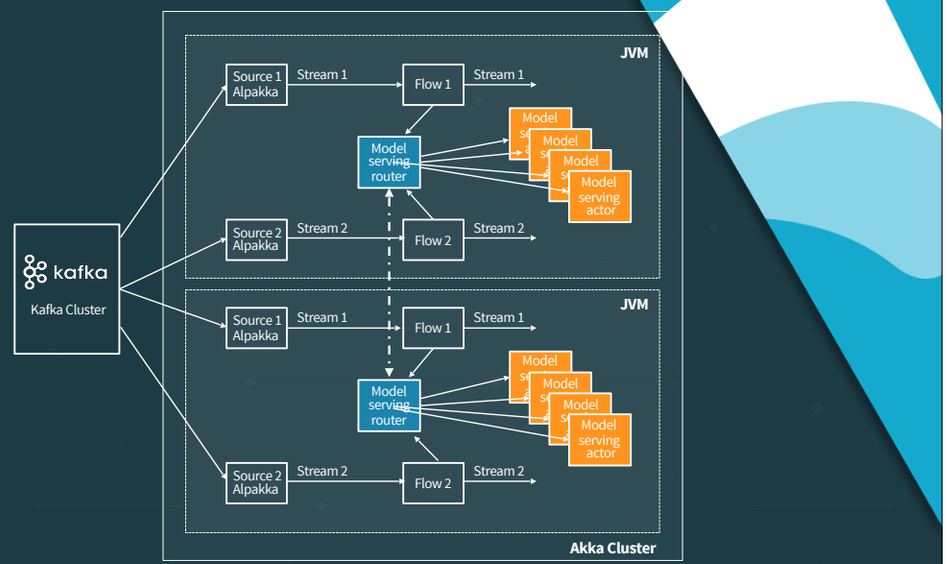


Here's our streaming microservice example adapted for Akka Streams. We'll still use Kafka topics in some places and assume we're using the same implementation for the "Model Training" microservice. Alpakka provides the interface to Kafka, DBs, file systems, etc. We're showing two microservices as before, 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

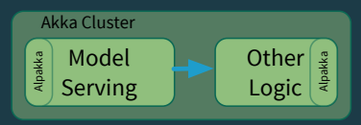
Two approaches for scalability:

- Kafka partitioned topic; add partitions and corresponding listeners.
- Akka cluster sharing: split model serving actor instances across the cluster.

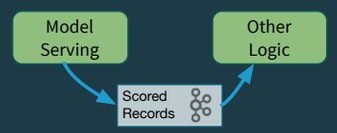


A great article http://michalplachta.com/2016/01/23/scalability-using-sharding-from-akka-cluster/ goes into a lot of details on both implementation and testing

Go Direct or Through Kafka?



vs.



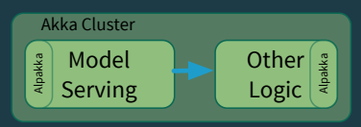
?

Extremely low latency

Higher latency (e.g., queue depth)

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?



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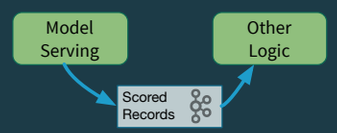


?

Extremely low latency

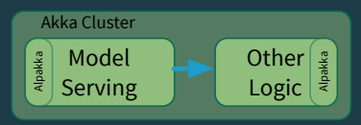
Higher latency (e.g., queue depth)

Minimal I/O and memory overhead; avoid marshaling

Higher I/O and processing (marshaling) overhead

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?



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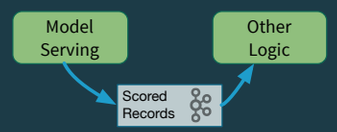


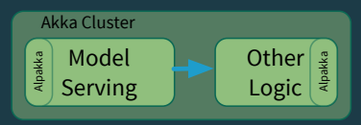
?

Reactive Streams back pressure

Very deep buffer (partition limited by disk size)

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?



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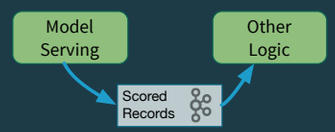


?

Reactive Streams back pressure

Direct coupling between sender and receiver, but indirectly through an ActorRef

Very deep buffer (partition limited by disk size)

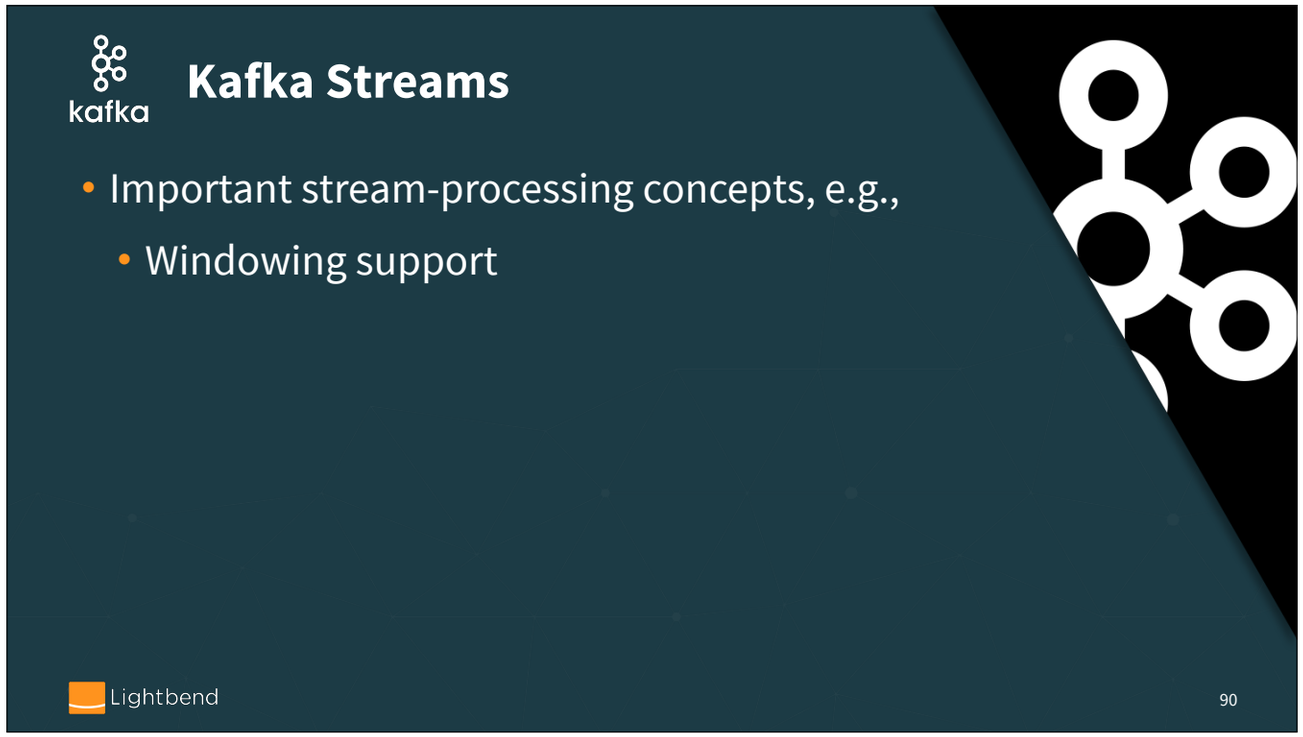
Strong decoupling - M producers, N consumers, completely disconnected

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

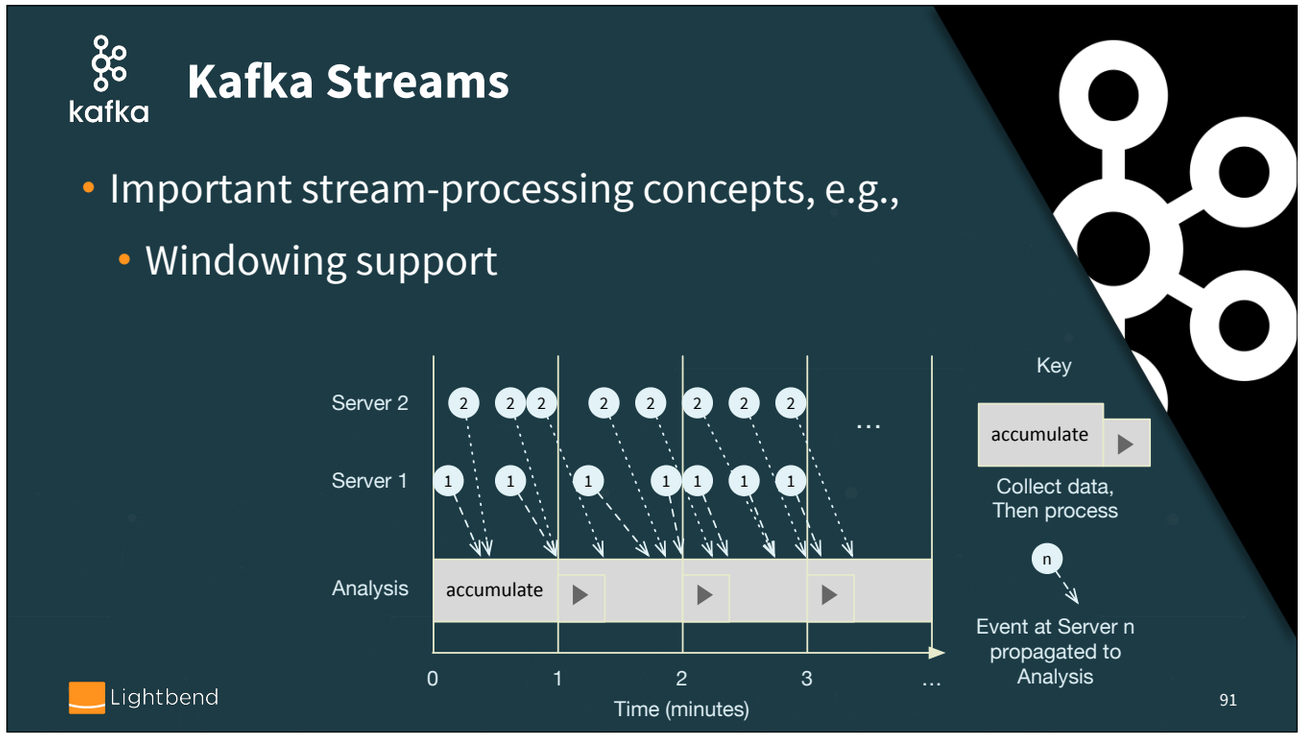
Kafka Streams

Lightbend

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.



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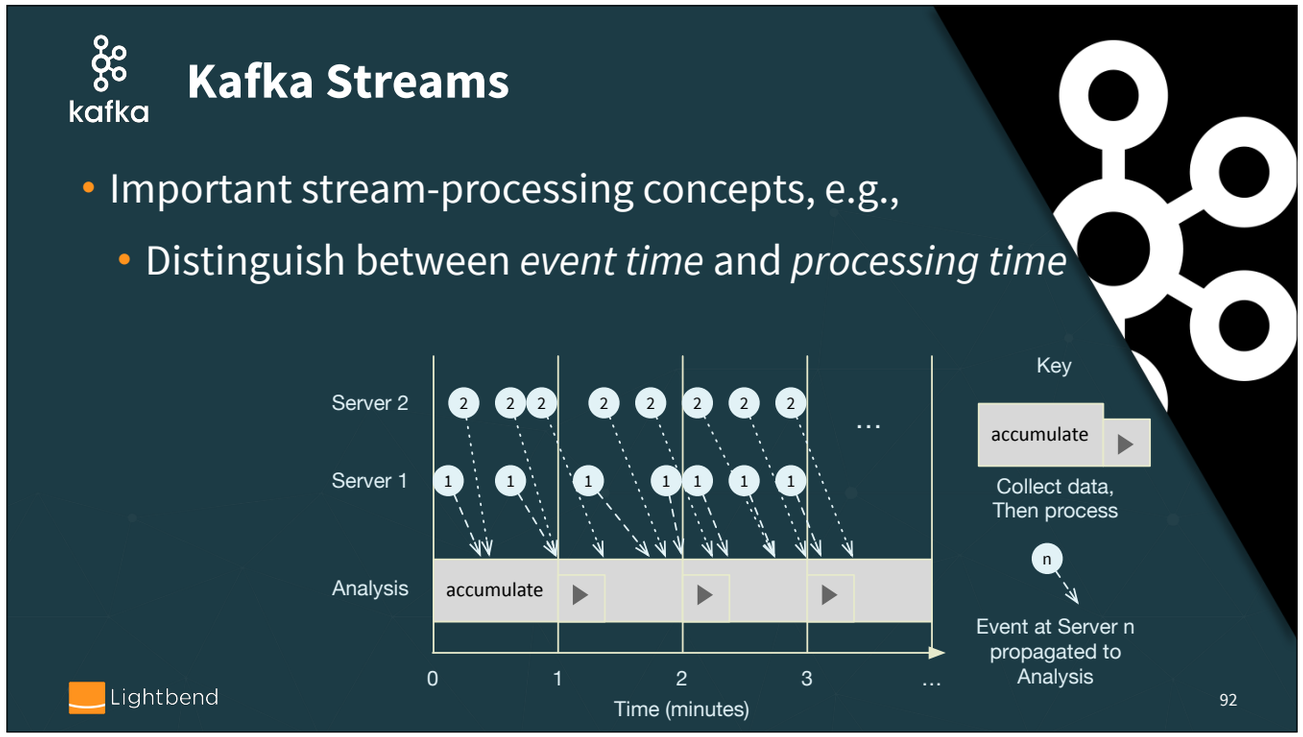

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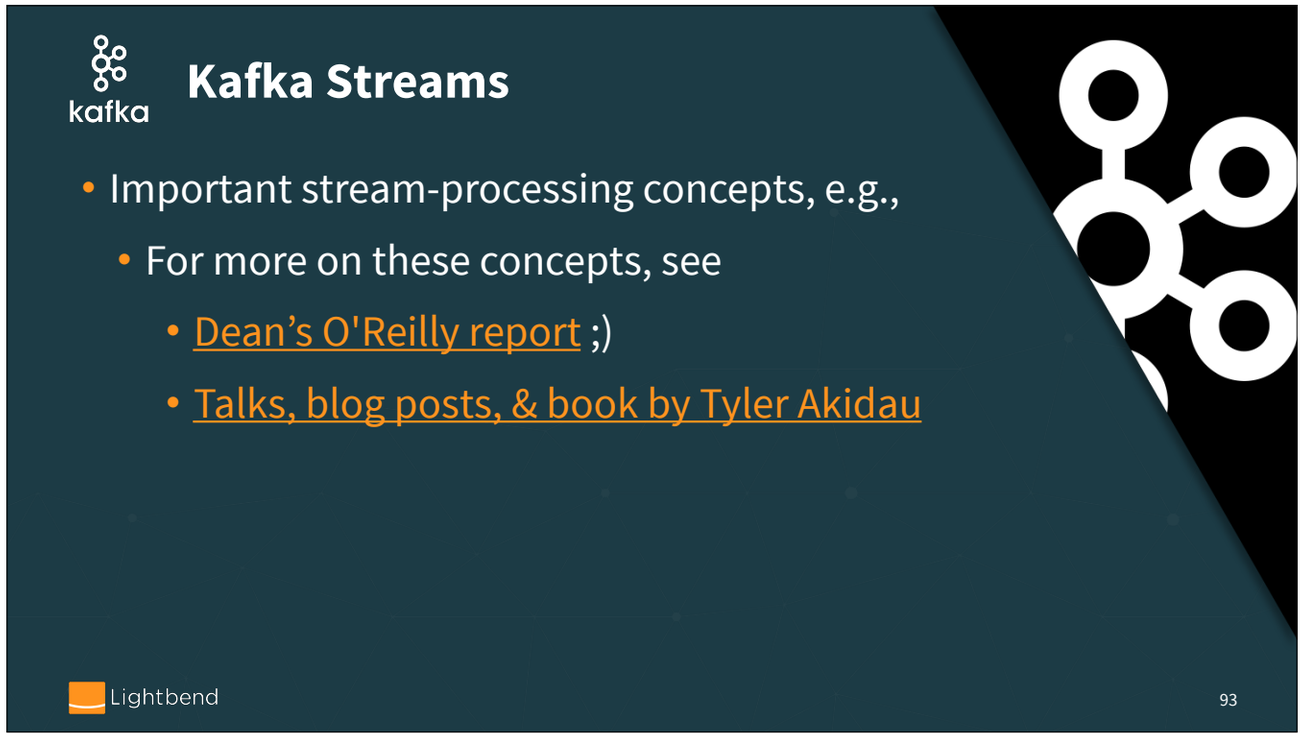

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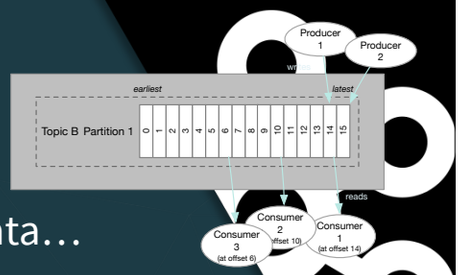
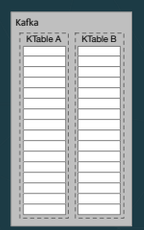
Kafka Streams

- KStream - per-record transformations
  - The typical way you want to process data…
- KTable - key/value store of supplemental data
  - Useful for management of application state





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
  - Use Alpakka or 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:
  - Processor Topology API
    - Lowest-level API
    - Compare to Apache Storm
  - DSL based on collection transformations
    - Compare to Spark, Flink, Scala collections APIs.

Kafka Streams

- Started with a Java API
- Lightbend donated a Scala API to 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, implemented as separate application (i.e., not a library like in Spark and 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

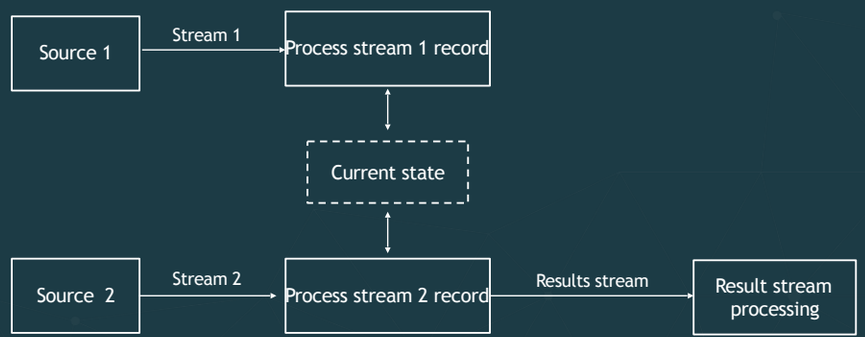
- Ideally suited for:
  - ETL -> KStreams
  - State -> KTable
  - Joins, including Stream and Table joins
  - “Effectively once” semantics
- Commercial support from Confluent, Lightbend, Hadoop vendors, and others

kafka

Kafka Streams: “Effectively Once”

- A distributed transaction model.
- It is *exactly once*, **if** catastrophic failures don’t happen…

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

Model Serving With Kafka Streams

Check Queryable state

- For in Memory implementation

  http://localhost:8888/state/value
- For build in Standard Store

  http://localhost:8888/state/instances

  http://localhost:8888/state/value
- For Custom store

  http://localhost:8888/state/instances

  http://localhost:8888/state/value

Model Serving:
Other Production Concerns

Additional Concerns for Model Serving

- Model tracking
- Speculative model execution

Model tracking - Motivation

- You update your model periodically
- You score a particular record **R** with model version **N**
- Later, you audit the data and wonder why **R** was scored the way it was

- You can’t answer the question unless you know which model version was actually used for **R**

”Explainability” is an important problem in Deep Learning; knowing why the model produced the results it produced.

Model tracking

- Need a model repository
- Possible info stored for each model instance:
  - Name
  - Version (or other unique ID)
  - Creation date
  - Quality metric
  - Parameters
  - …

Model tracking

- You also need to augment the records with the model ID, as well as the score.
  - Input Record

  - Output Record with Score, model version ID

Speculative execution

According to Wikipedia speculative execution is:

- an **optimization** technique
- The system performs work that may not be needed,
  - before it's known if it will be needed
- If and when it **is** needed, we don't have to wait
  - or results are discarded if not needed

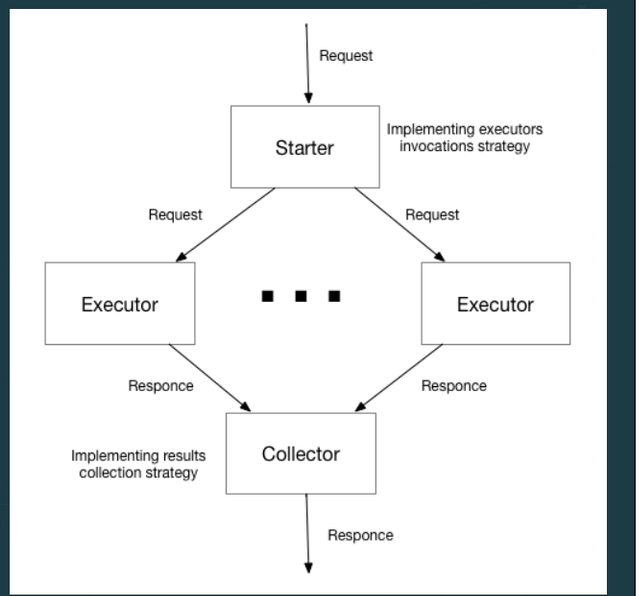
Speculative execution

- Provides more **concurrency** if extra **resources** are available.
- Used for:
  - **branch prediction** in **pipelined processors**,
  - value prediction for exploiting value locality,
  - prefetching **memory** and **files**,
  - etc.

Why not use it with machine learning??

General Architecture for speculative execution

- Starter (proxy) controlling parallelism and invocation strategy.
- Parallel execution by identical executors
- Collector responsible for bringing results from multiple executors together

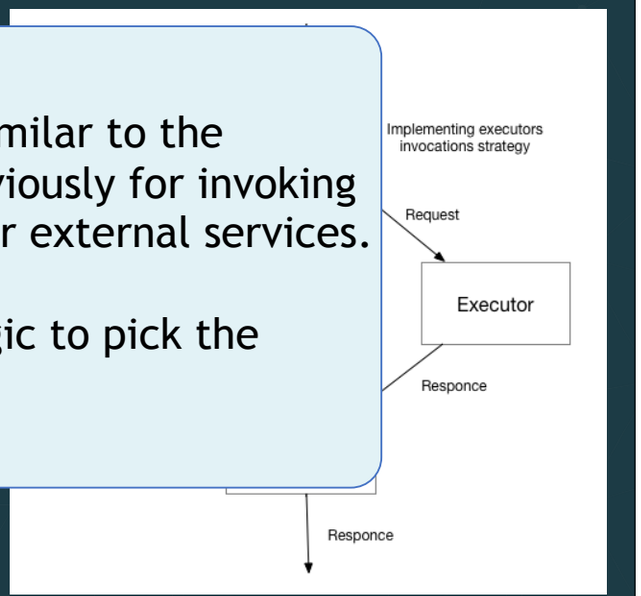


General Architecture for speculative execution

- Starter (
  parallelis
  strategy.
- Parallel e
  executor
- Collecto
  bringing
  executors

Look familiar? It's similar to the pattern we saw previously for invoking a "farm" of actors or external services.

But we must add logic to pick the result to return.



Applicability for model serving (1/3)

- Guarantee execution time, i.e., meet our latency SLA!
  - Several models:
    - A smart model, but takes time *T1* for a given record
    - A “less smart”, but fast model with a fixed upper-limit on execution time, *T2* << *T1*
  - If timeout T occurs, where *T1* > *T* > *T2*, return the less smart result
    - Do you understand why *T1* > *T* > *T2* is required?

Because the timeout T has to be long enough that the fast model has time to finish, so T must be longer than T2, and this is only useful if T1 is often longer than T, our latency window.
This technique is “speculative”, because we try both models, taking a compromise result if the good result takes too long to return.

Applicability for model serving (2/3)

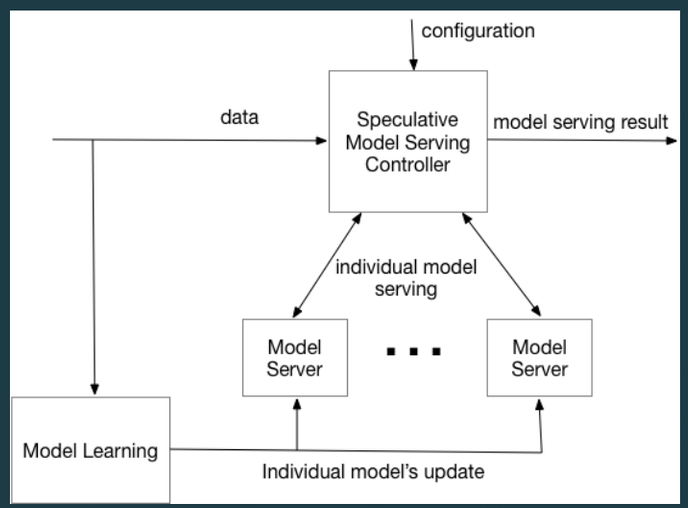
- Consensus based model serving
  - If we have 3 or more models, score with all of them and return the majority result

Applicability for model serving (3/3)

- Quality based model serving.
  - If we have a quality metric, pick the result with the best result.

Of course, you can combine these techniques.

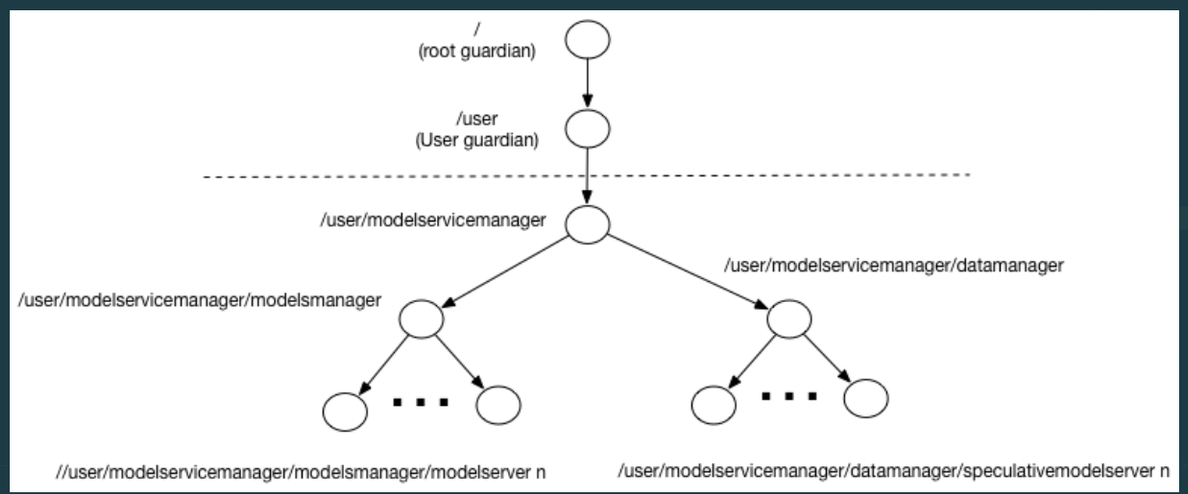
Architecture



https://developer.lightbend.com/blog/2018-05-24-speculative-model-serving/index.html

This blog post provides more information on this technique.

One Design Using Actors



Exercises

For a full-day tutorial

Exercises

- Exercises are embedded in the source code
  - Search for `// Exercise` in the code
  - Additional exercises are described in the README.
- In most cases, an exercise is repeated in each variant of the Akka Streams and Kafka Streams implementations. Pick the one you find most interesting…

Exercises

- See the end of the README for a list of resources that will be useful as you modify the code, e.g,
  - Scala Library (Scaladocs)
  - Akka Streams:
    - Scala: Reference, Scaladocs
    - Java: Reference, Javadocs
  - Kafka Streams:
    - Scaladocs, Javadocs

Suggestions (1/4)

- ModelServerProcessor.java/scala, around line 55 in both
- StandardStoreStreamBuilder.java/scala: createStreams()
- CustomStoreStreamBuilder.java/scala: createStreams()
- MemoryStoreStreamBuilder.java/scala: createStreams()
  - Rather than just print results, write them to a new Kafka topic

Suggestions (2/4)

- ModelServingManager.java/scala: getModelServer()
- DataProcessor.java/scala (all of the variants!)
  - Implement either speculative execution or a worker “farm” for parallelism, rather than a single model instance.
  - We’ve only given you one model at a time to work with. Use a hack with multiple copies of the model, but add noise to the result to simulate different model results

This exercise is described in several classes for both Akka Streams and Kafka Streams.

Suggestions (3/4)

- AkkaModelServer.java/scala: main()
- CustomStoreStreamBuilder.java/scala, DataProcessor.java/scala, ModelProcessor.java/scala (all of the variants!)
  - They provide implementations of error handling, when input wine records fail to parse. Improve the implementations to write to a special Kafka topic instead.
  - Extend the idioms to handle model errors.

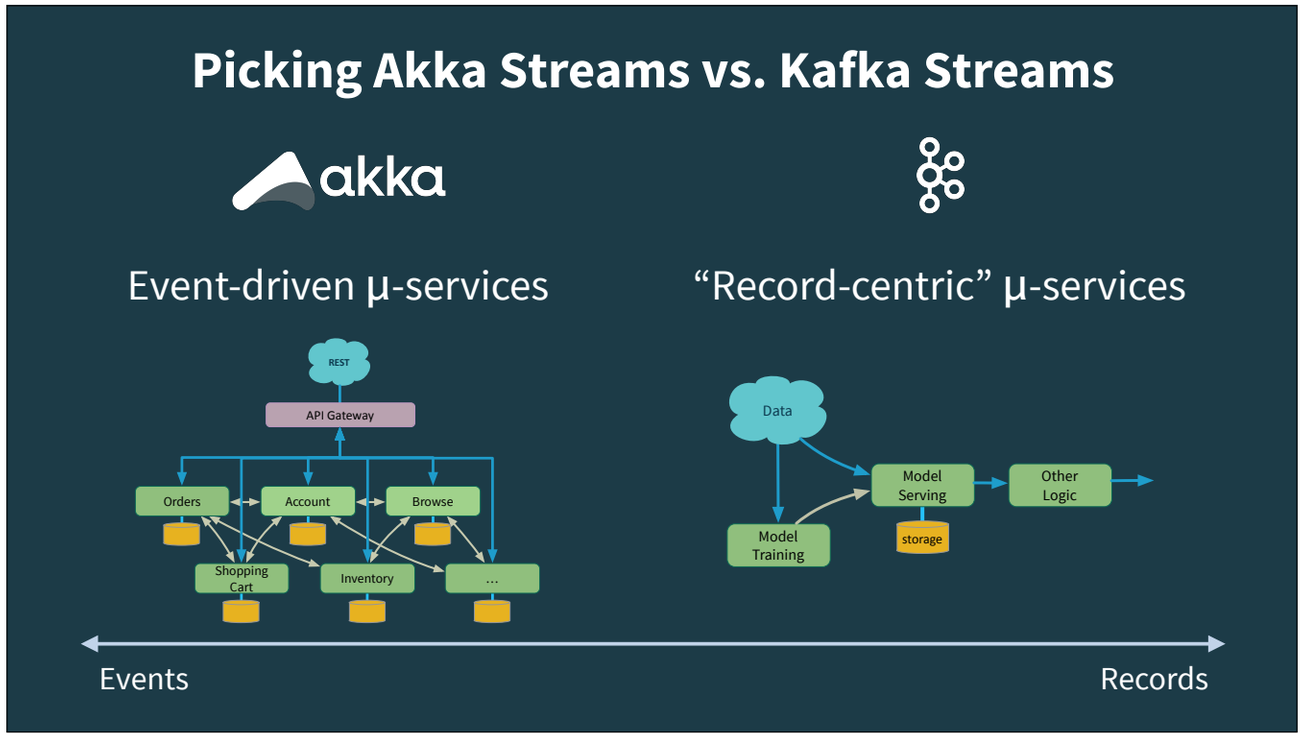
This exercise is described in several classes for both Akka Streams and Kafka Streams.

Suggestions (4/4)

- model project
  - It hard-codes information about the example wine records. Can you make it more generic? See the suggestions in PMMLModel.java/scala or TensorFlowModel.java/scala
- Can you make other areas where WineRecord is assumed more generic?

This exercise is described in several classes for both Akka Streams and Kafka Streams.

Wrapping 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”.

Next Steps (1/2)

- Study the different model serving techniques
- Study the “model” subproject
- Look at how the following are implemented
    1. queryable state
    2. embedded web servers
    3. use of Akka Persistence
    4. model serialization

Next Steps (2/2)

- Do more exercises
  - Search for `// Exercise` in the code
  - See the README
- Ask us for help on anything…
- Provide us with feedback on how we can improve
- Visit lightbend.com/fast-data-platform
- Profit!!

Thank you! Check out our Fast Data Platform for commercial options for building and running microservices with Kafka, Akka Streams, and Kafka Streams.