Building Kafka-based Microservices with Akka Streams and Kafka Streams

Strata London 2018

Boris Lublinsky and Dean Wampler, Lightbend

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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?

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Fast Data Architectures for Streaming Applications

Getting Answers Now from Data Sets that Never End

By Dean Wampler, Ph. D., VP of Fast Data Engineering

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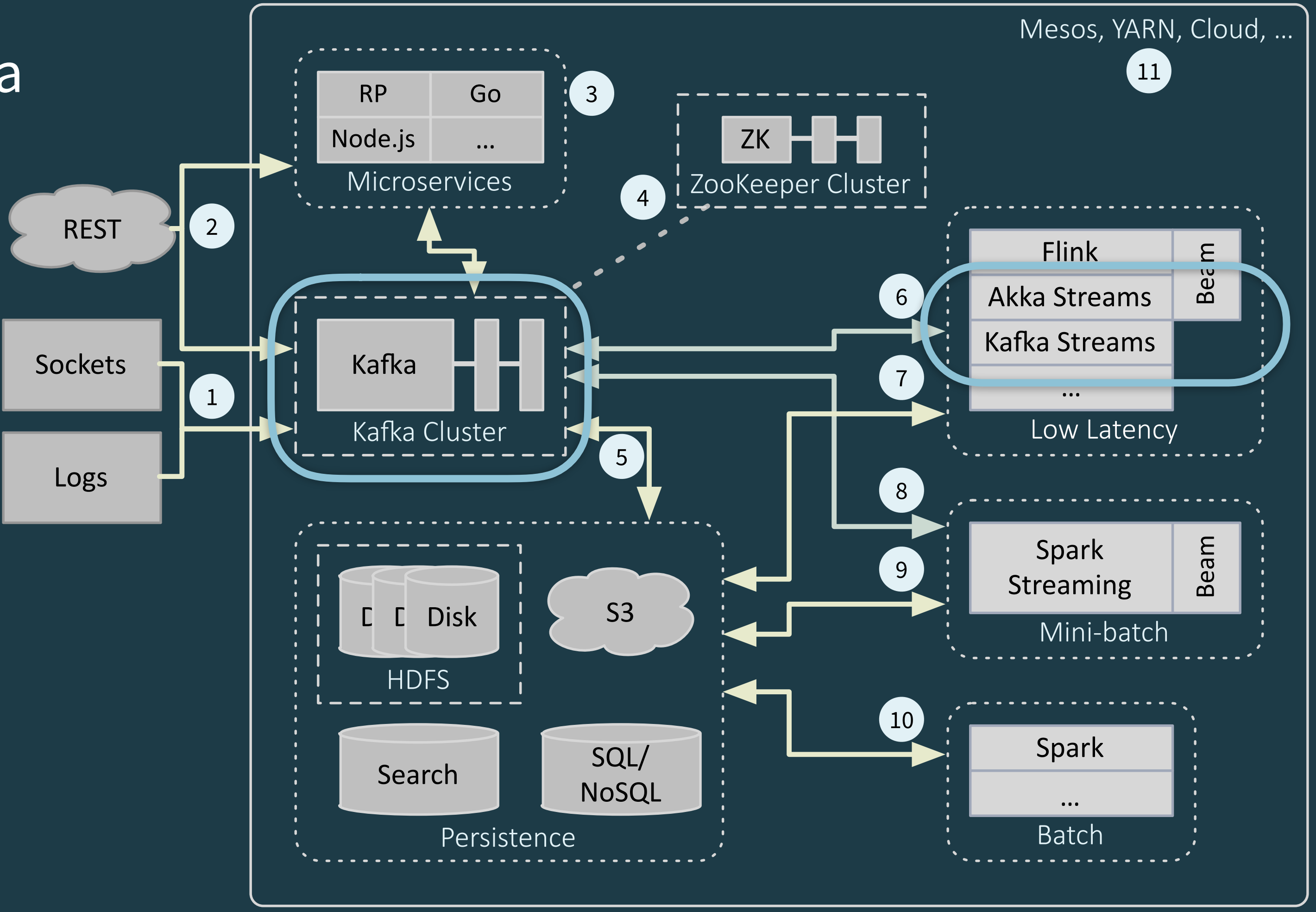
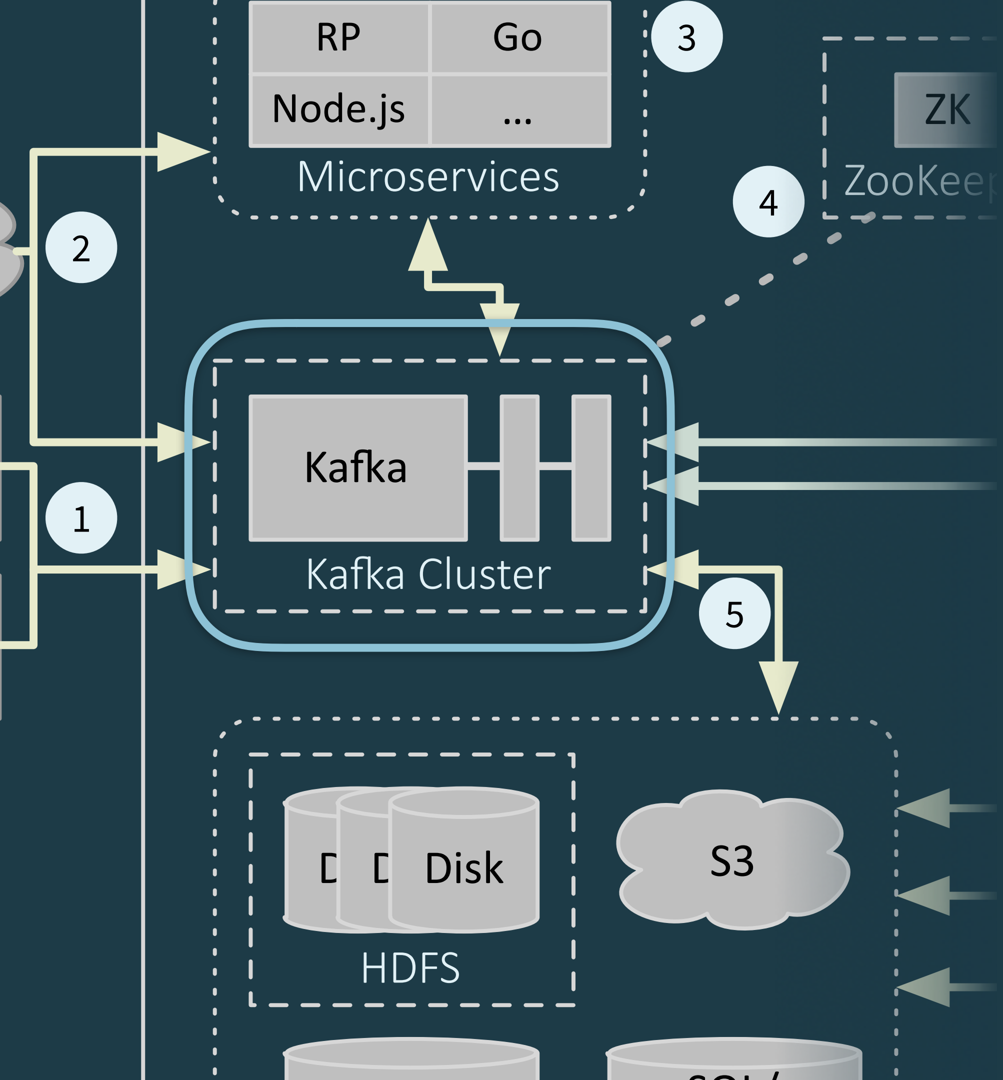
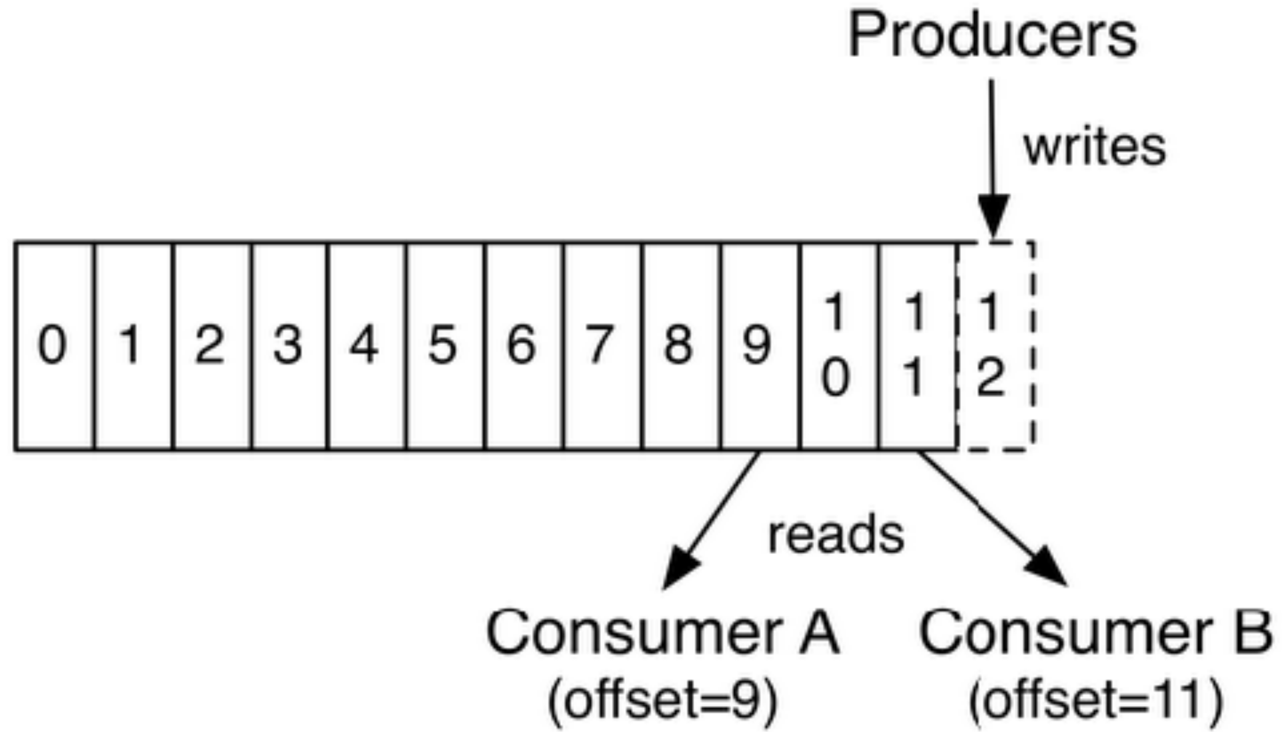
Today's focus:

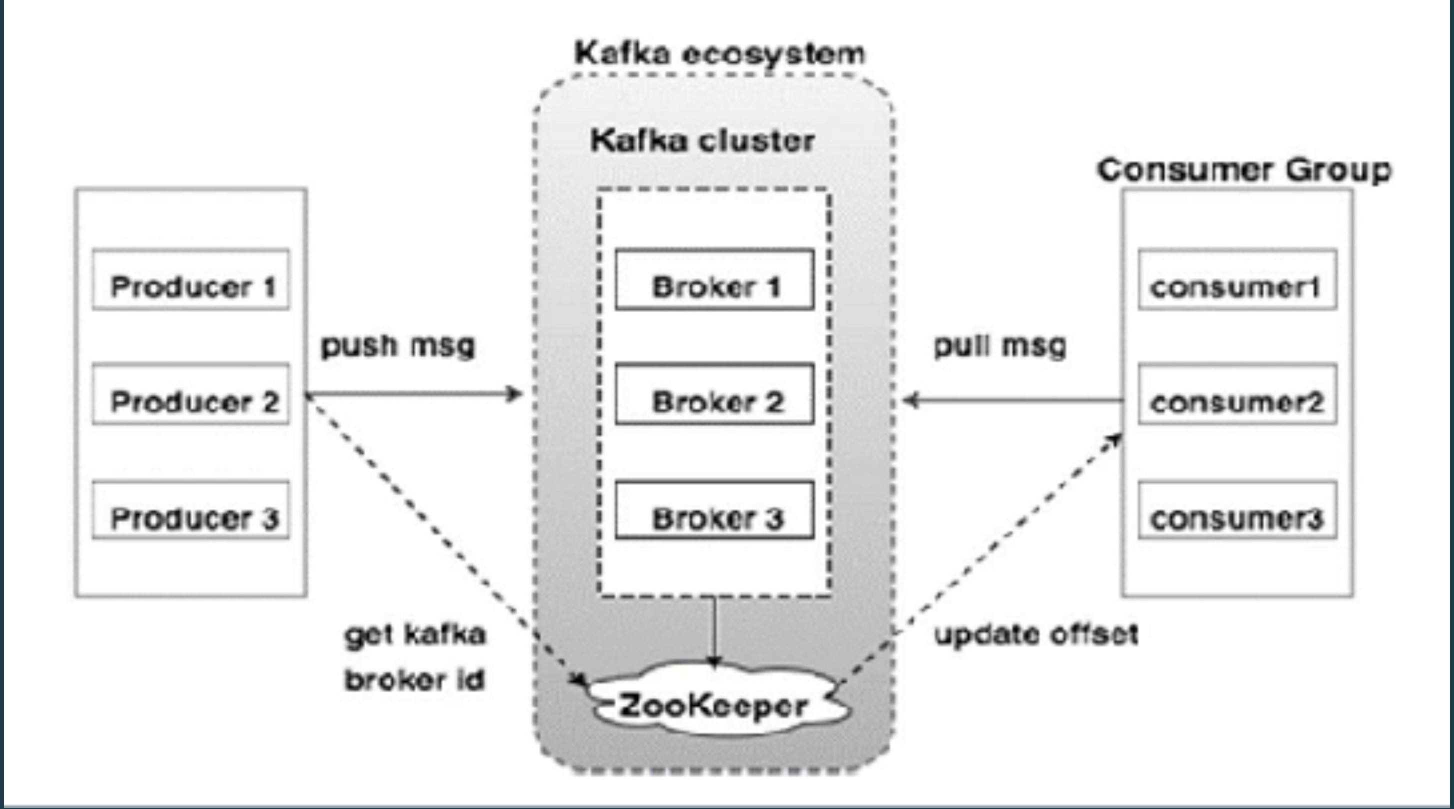
- Kafka - the data backplane
- Akka Streams and Kafka Streams - streaming microservices




RP
Go
Node.js
...
Microservices
3
ZK
4
2
Kafka
Kafka Cluster
1
5
Disk
S3
HDFS

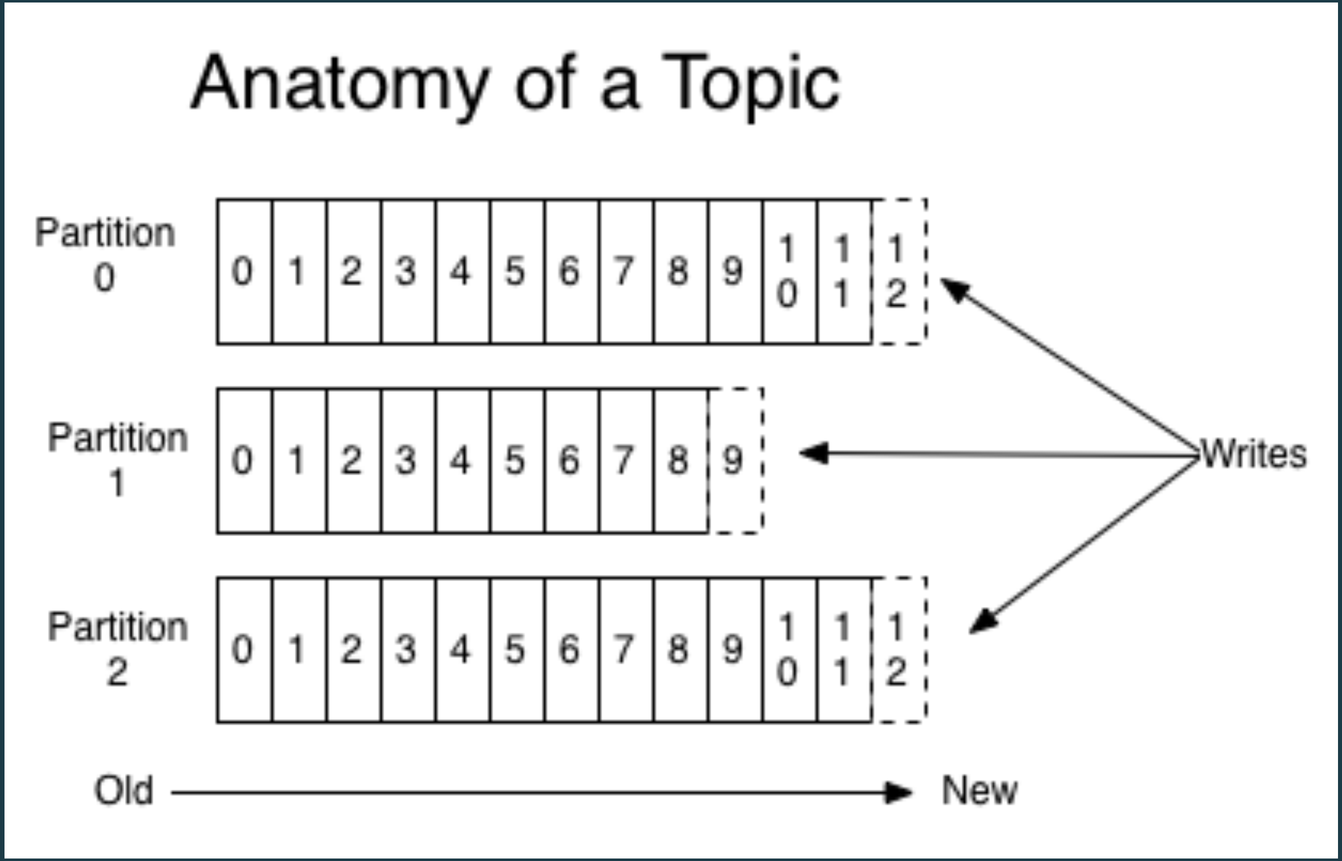
Why Kafka?


Producers
writes
0
1
2
3
4
5
6
7
8
9
10
11
12
reads
Consumer A
(offset=9)
Consumer B
(offset=11)

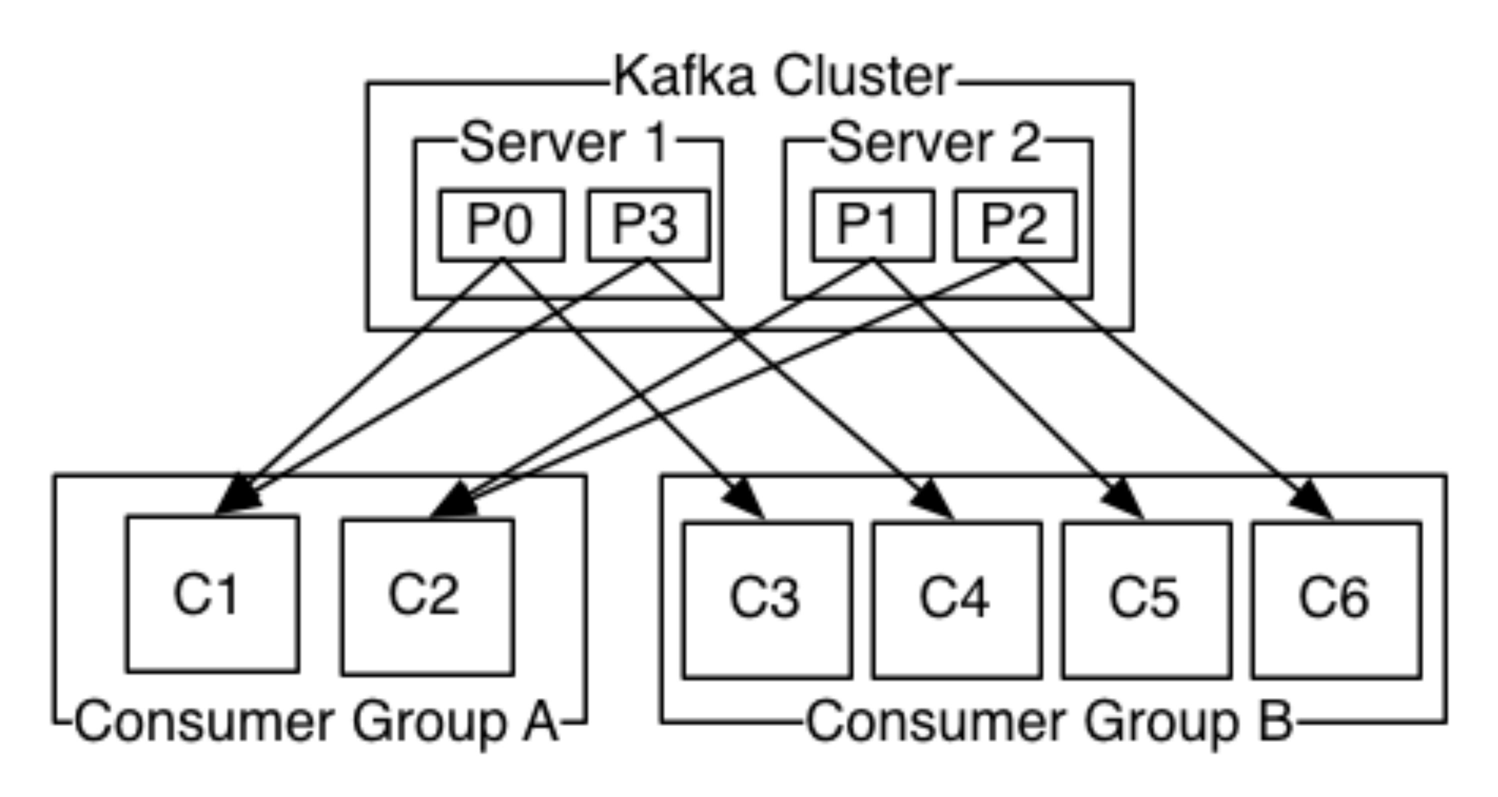


Kafka ecosystem
Kafka cluster
Consumer Group
Producer 1
Producer 2
Producer 3
push msg
Broker 1
Broker 2
Broker 3
pull msg
consumer1
consumer2
consumer3
get kafka
broker id
ZooKeeper
update offset

A Topic and Its Partitions



Consumer Groups



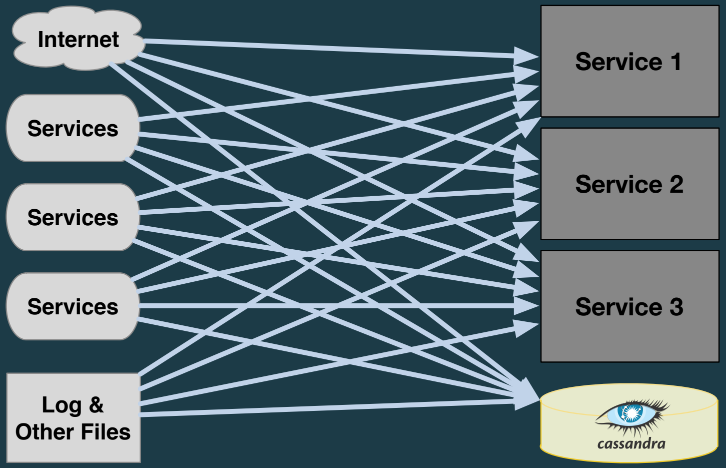
Kafka Producers and Consumers

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

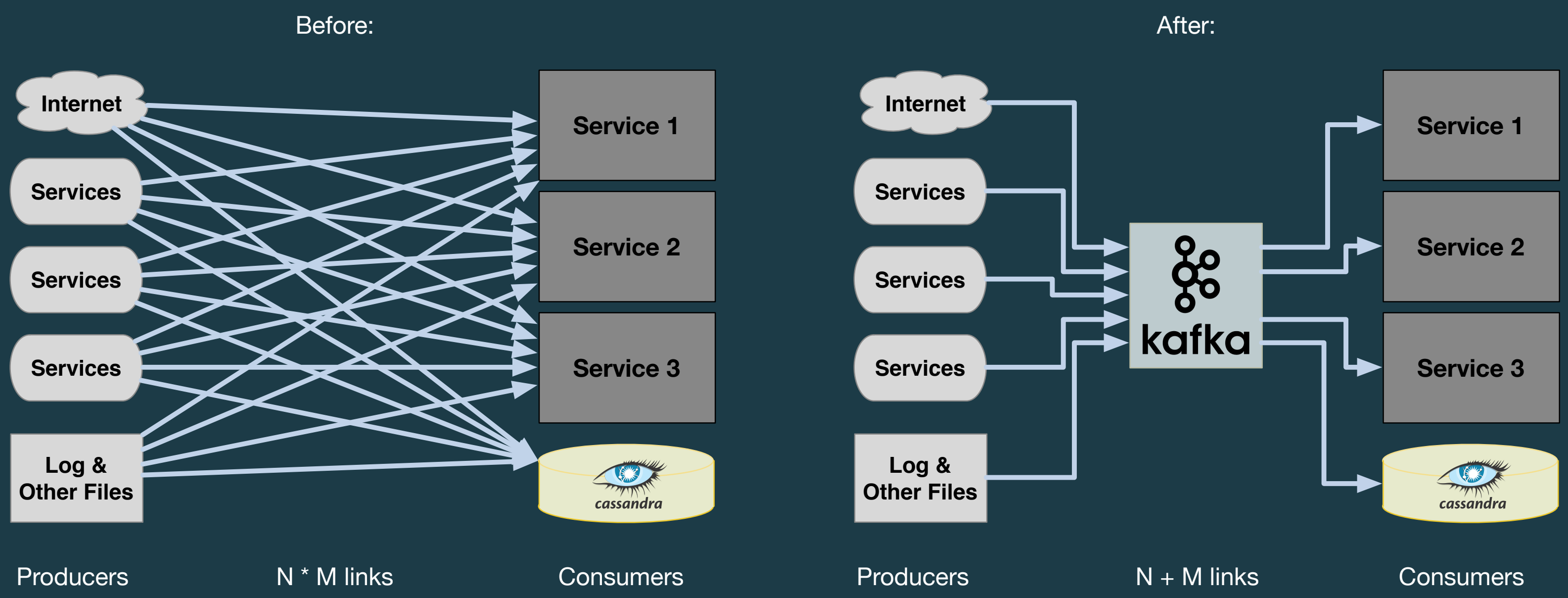
Architecture Benefits of Kafka

Before:



Producers N * M links Consumers

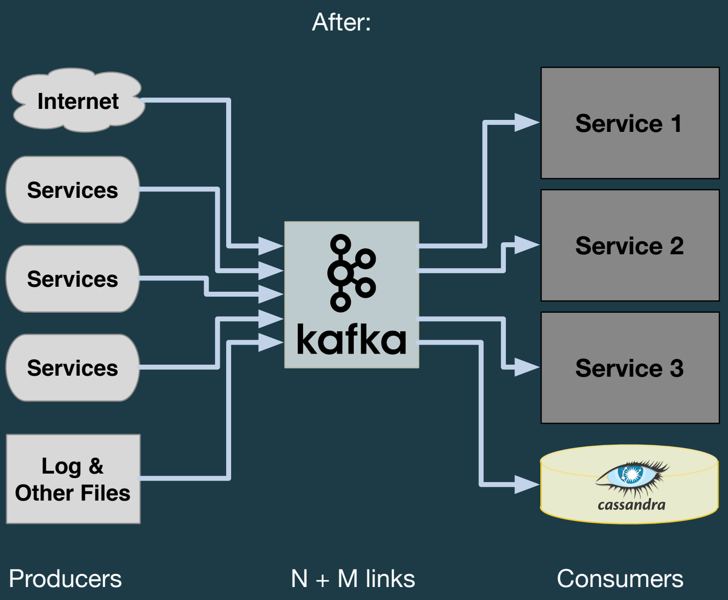
Architecture Benefits of Kafka



Architecture Benefits of Kafka

Kafka:

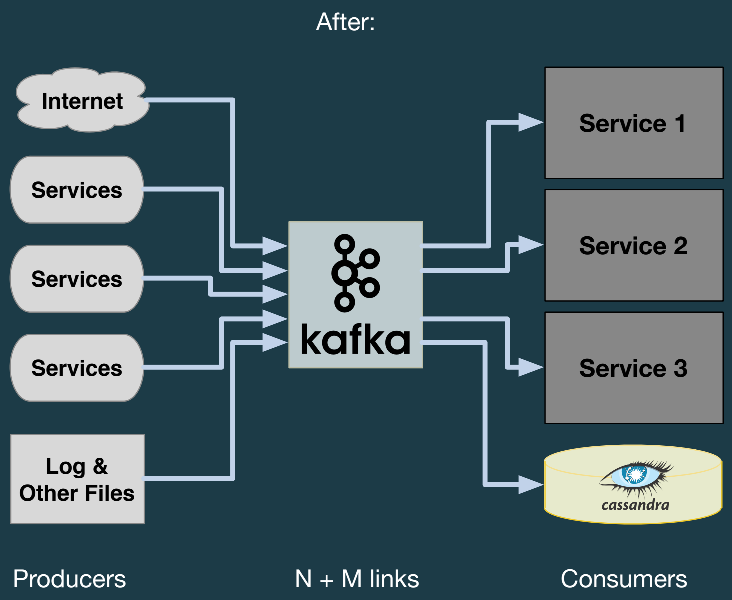
- Simplify dependencies between services
    - Improved data consistency
- Minimize data transmissions
- Reduce data loss when a service crashes



Architecture Benefits of Kafka

Kafka:

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



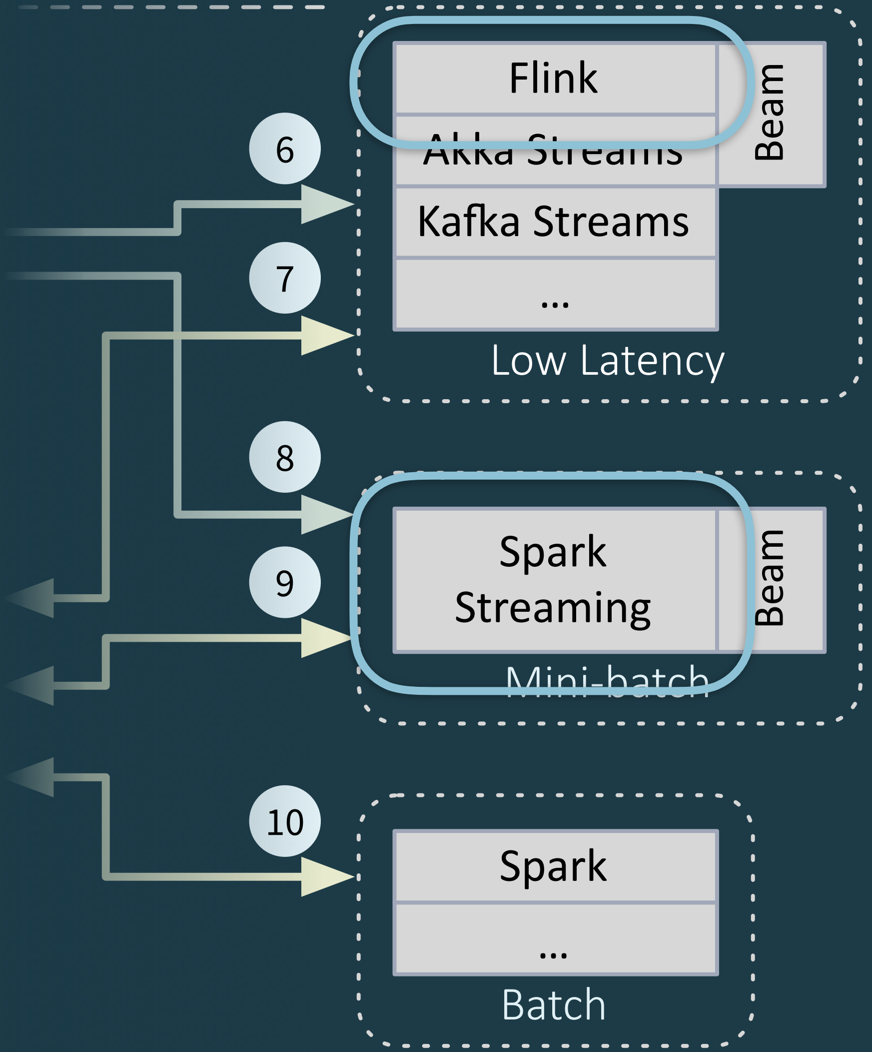
Streaming Architectures

Two options:

- Stream processing engines
- Streaming libraries

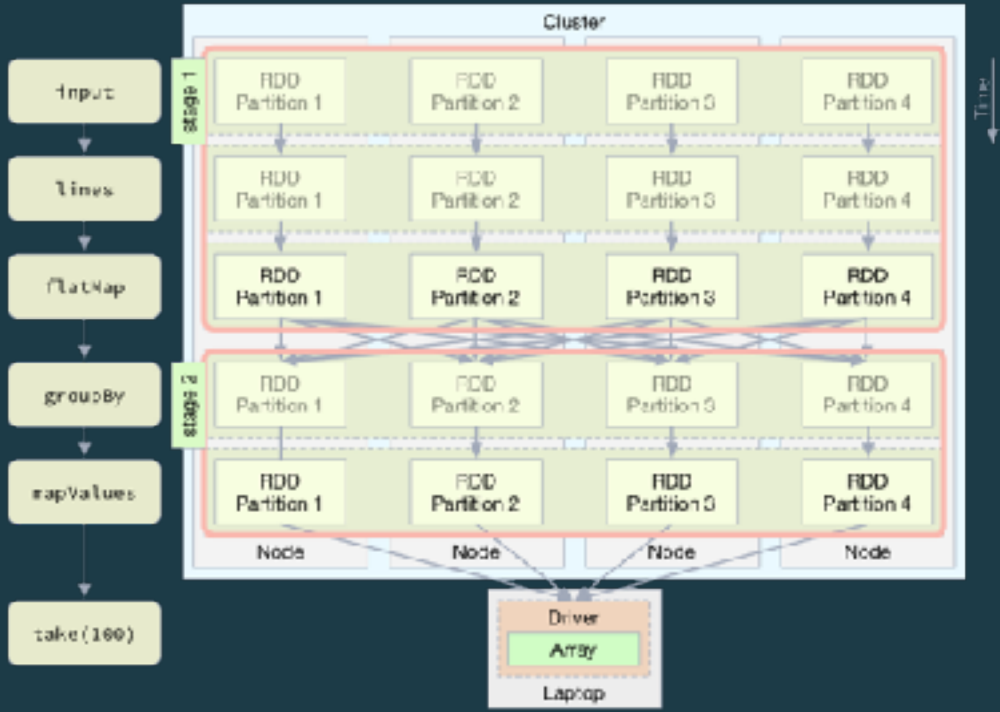
Streaming Engines:

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



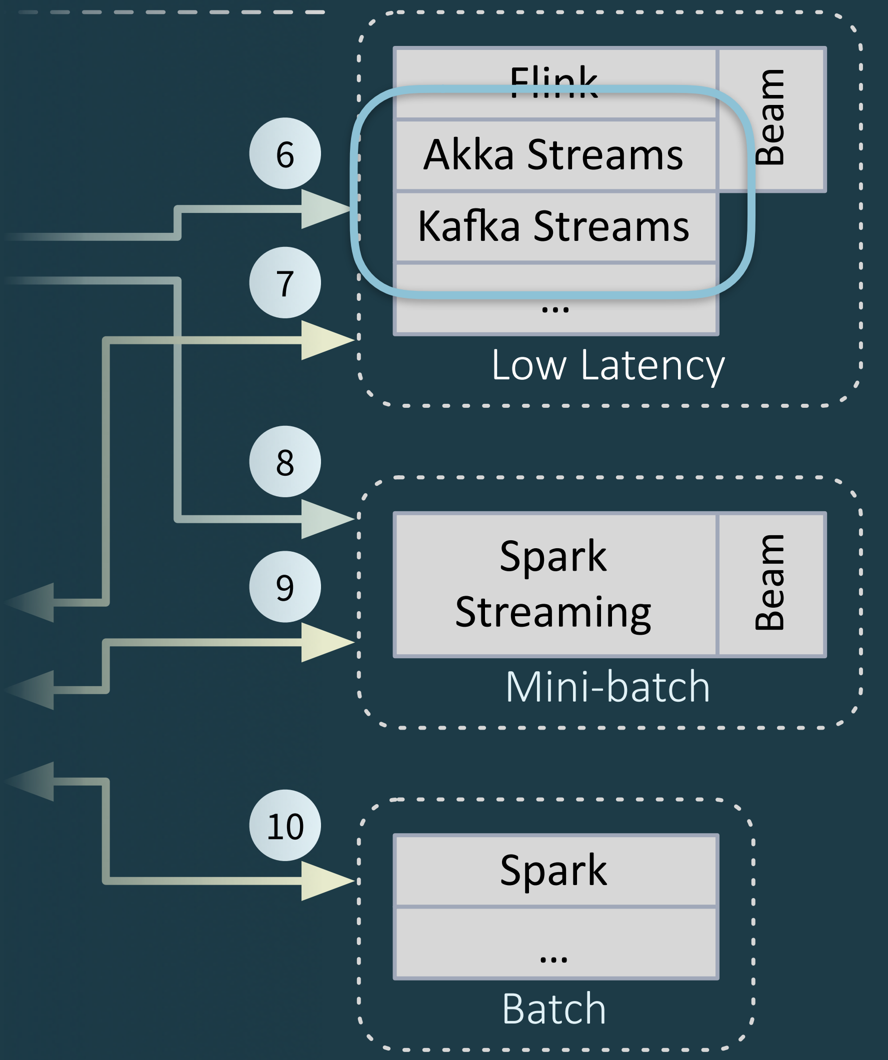
Streaming Engines:

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



Streaming Libraries:

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



Machine Learning and Model Serving: A Quick Introduction

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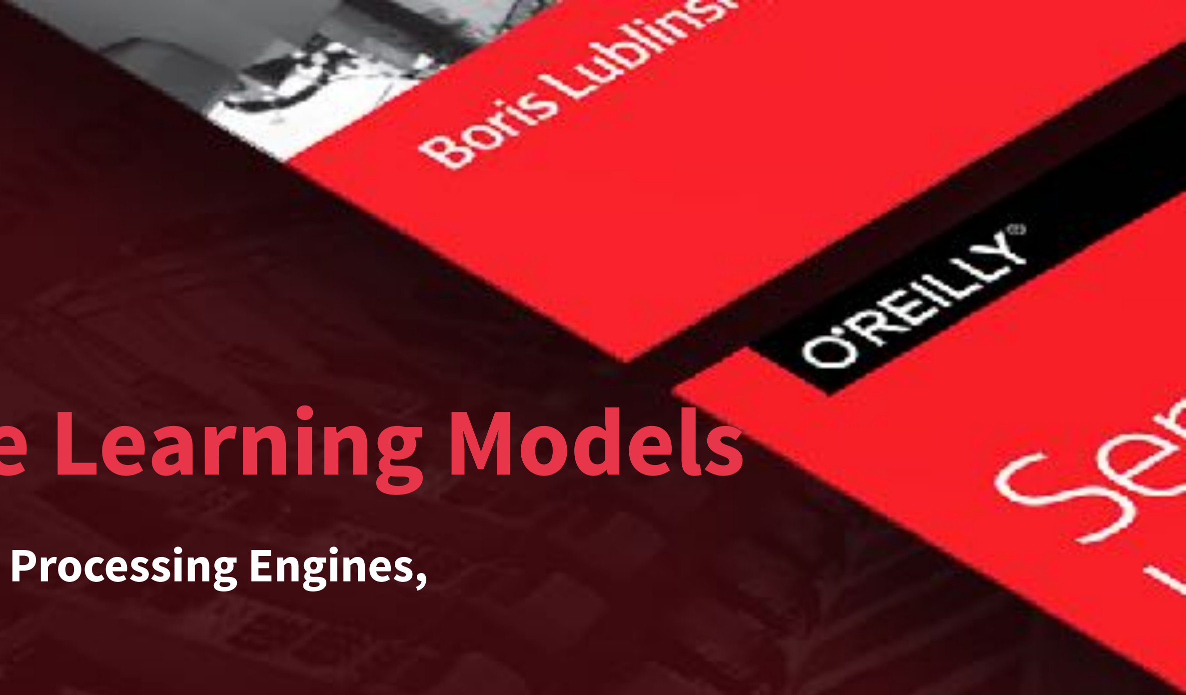

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Serving Machine Learning Models

A Guide to Architecture, Stream Processing Engines, and Frameworks

By Boris Lublinsky, Fast Data Platform Architect

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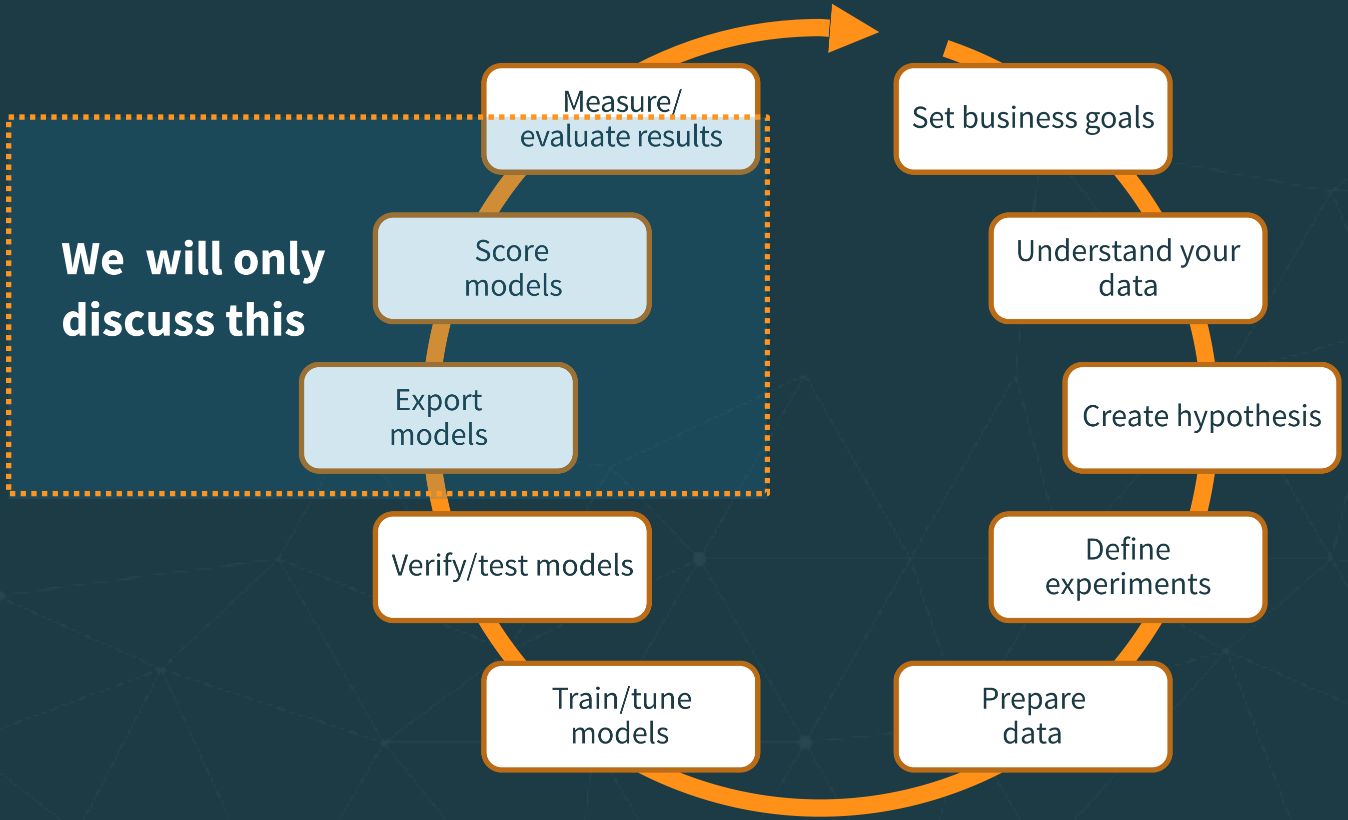
ML Is Simple

Maybe Not

Even If There Are Instructions

The Reality


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

What Is The Model?

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

for example:

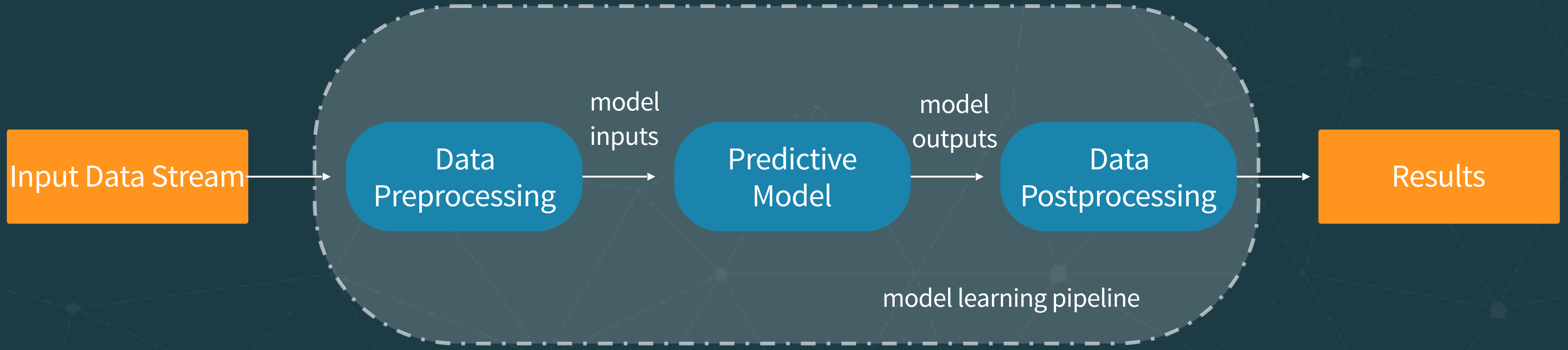
Linear regression: $y = a_c + a_1 * x1 + \ldots + a_n * x_n$

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.



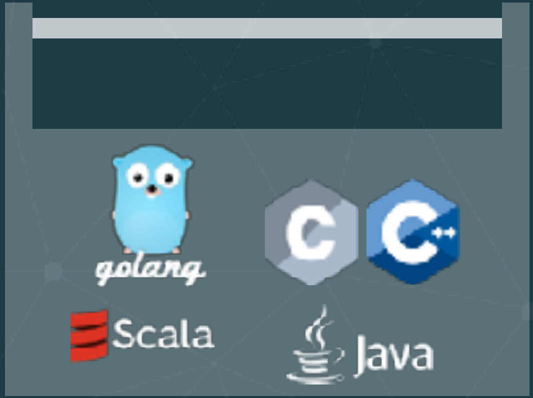
Traditional Approach to Model Serving

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

Why is this problematic?

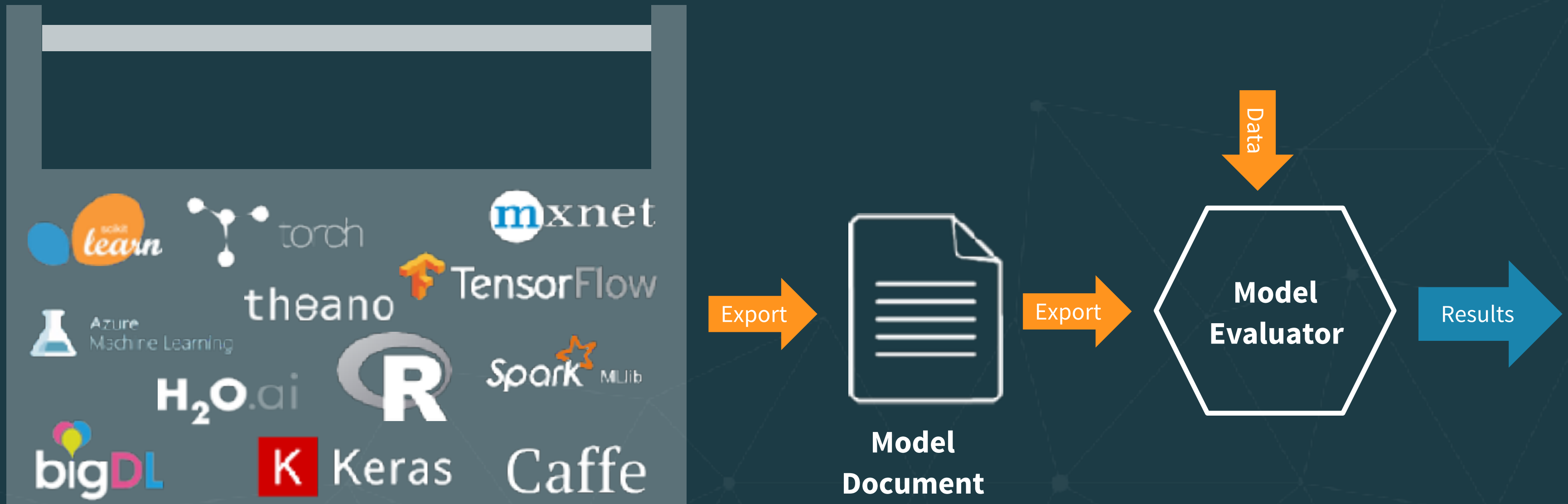
Impedance Mismatch

Continually expanding Data Scientist toolbox



Defined Software Engineer toolbox

Alternative - Model As Data



Standards

PMML Predictive Model Markup Language

Portable Format for Analytics **(PFA)**

TensorFlow

Exporting Model As Data With PMML

There are already a lot of export options

- https://github.com/jpmml/jpmml-sparkml
- https://github.com/jpmml/jpmml-sklearn
- https://github.com/jpmml/jpmml-r
- https://github.com/jpmml/jpmml-tensorflow

Evaluating PMML Model

There are also a few PMML evaluators

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

python 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.

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

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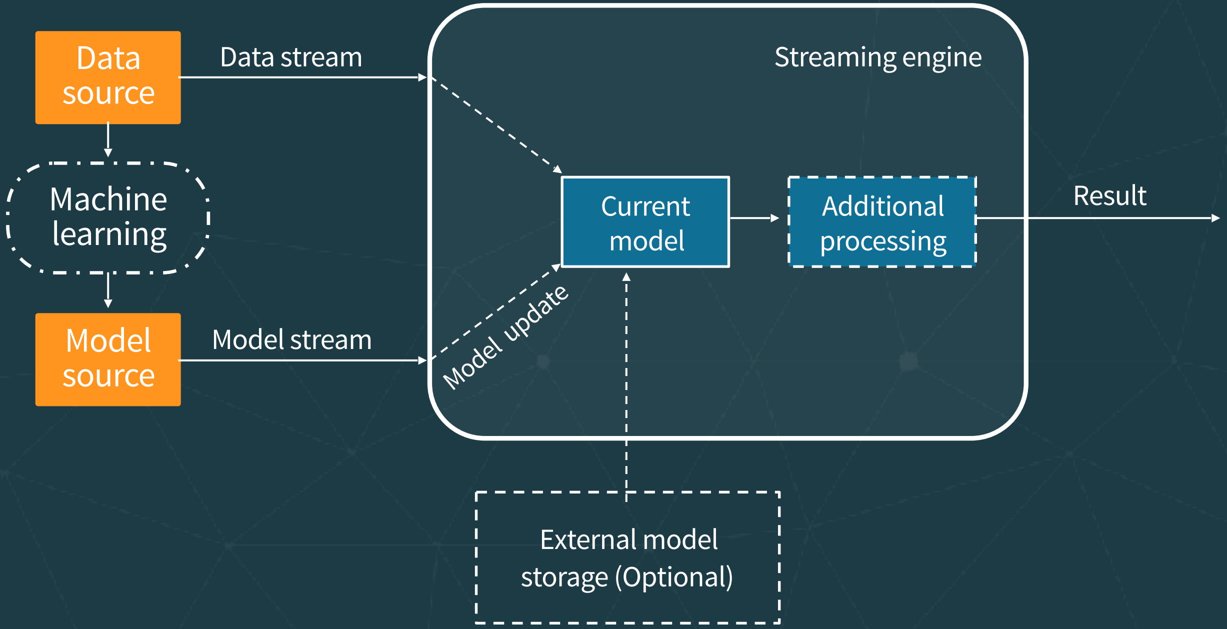
The Solution

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



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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;
  }
}
```

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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
}
```

Side Note: Monitoring

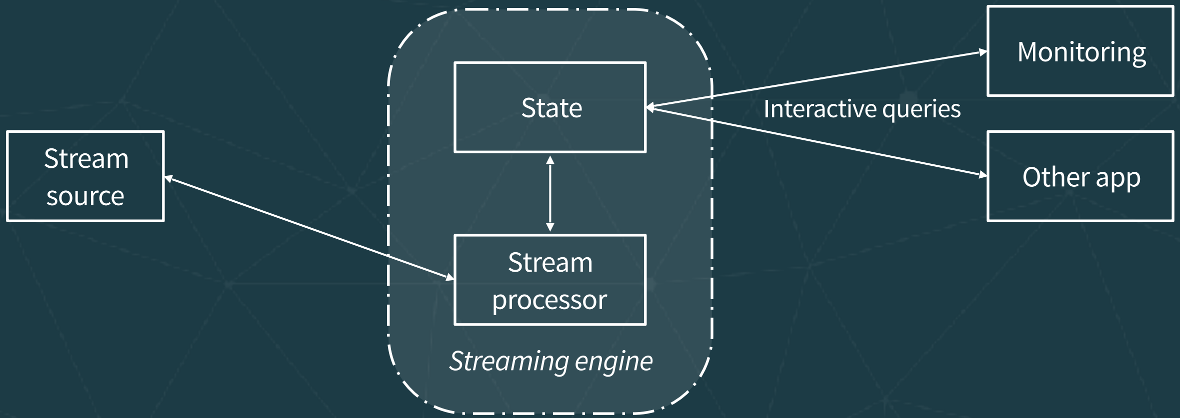
Model monitoring should provide information about usage, behavior, performance and lifecycle of the deployed models

```
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.



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Microservice All the Things!

Scott Hanselman @shanselman

Follow

Microservices, for when your in-process methods have too little latency.

> **Dave Cheney** @davecheney
> Microservices, for when function calls are too reliable.

4:11 AM - 25 Feb 2018

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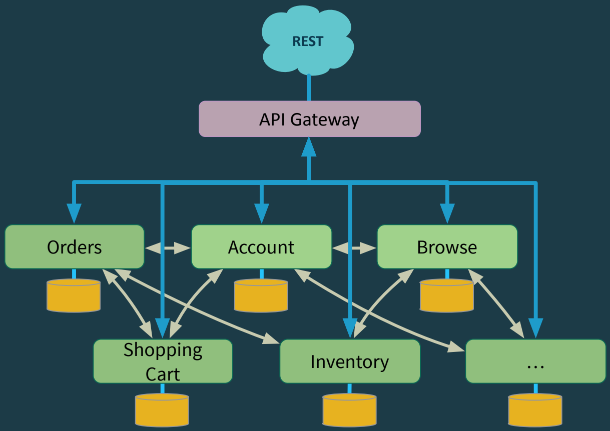
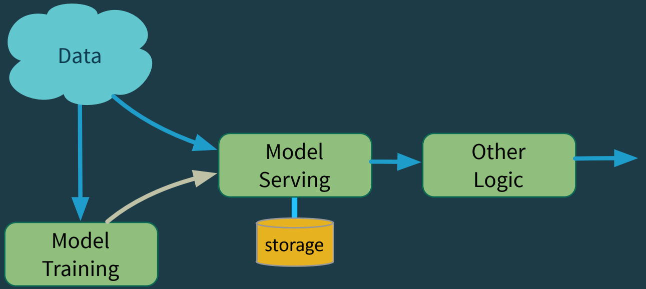
A Spectrum of Microservices

Event-driven µ-services



"Record-centric" µ-services

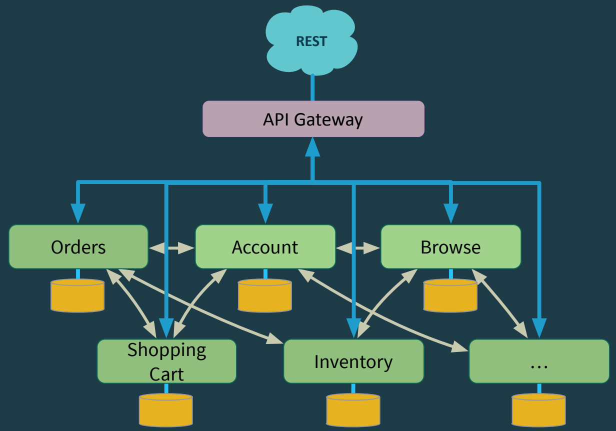


Events

Records

A Spectrum of Microservices

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

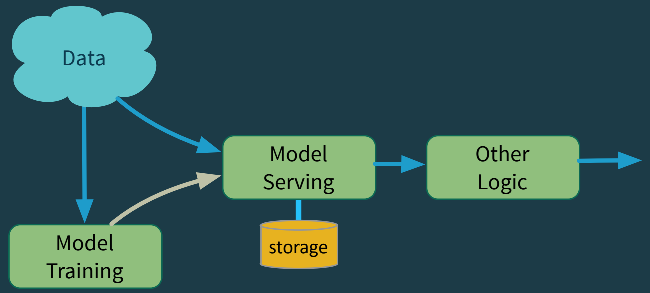
Records

A Spectrum of Microservices

Emerged from the right-hand side.

Kafka Streams pushes to the left, supporting many event-processing scenarios.

“Record-centric” μ-services



Events

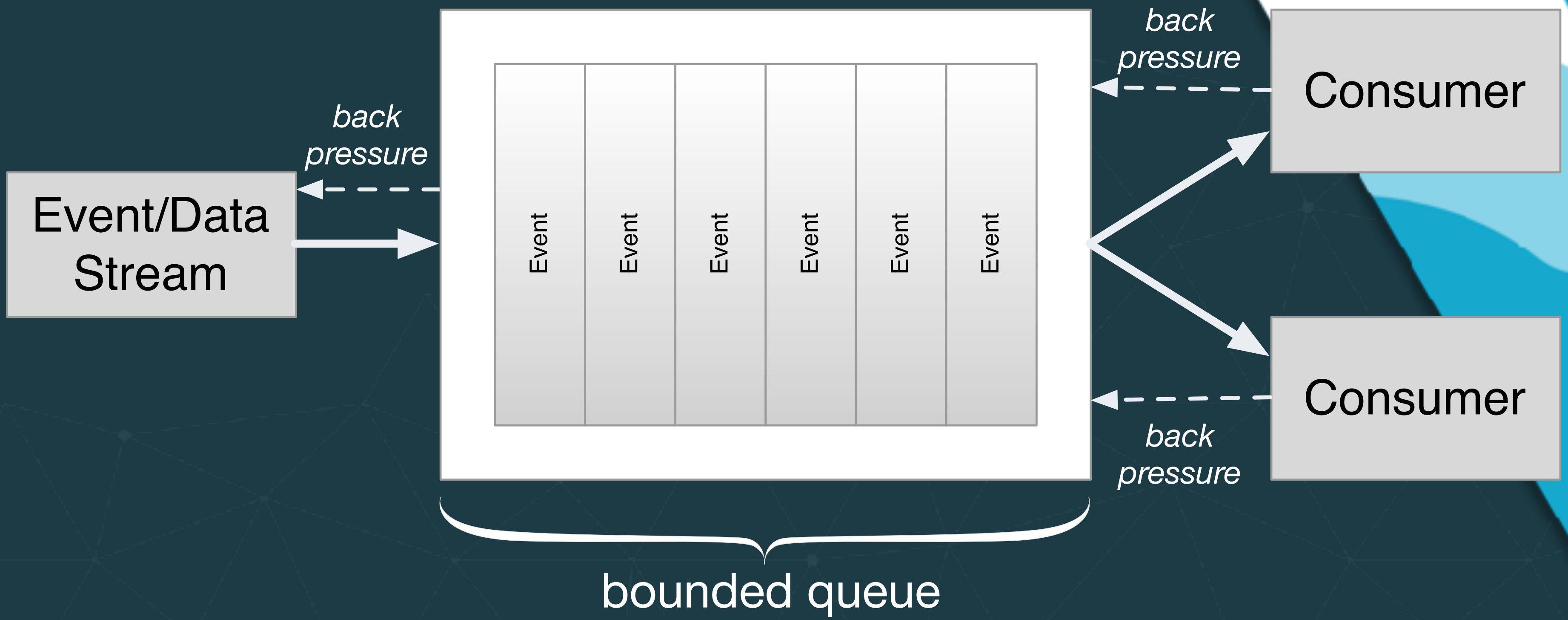
Records

Akka Streams

akka streams

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

akka streams



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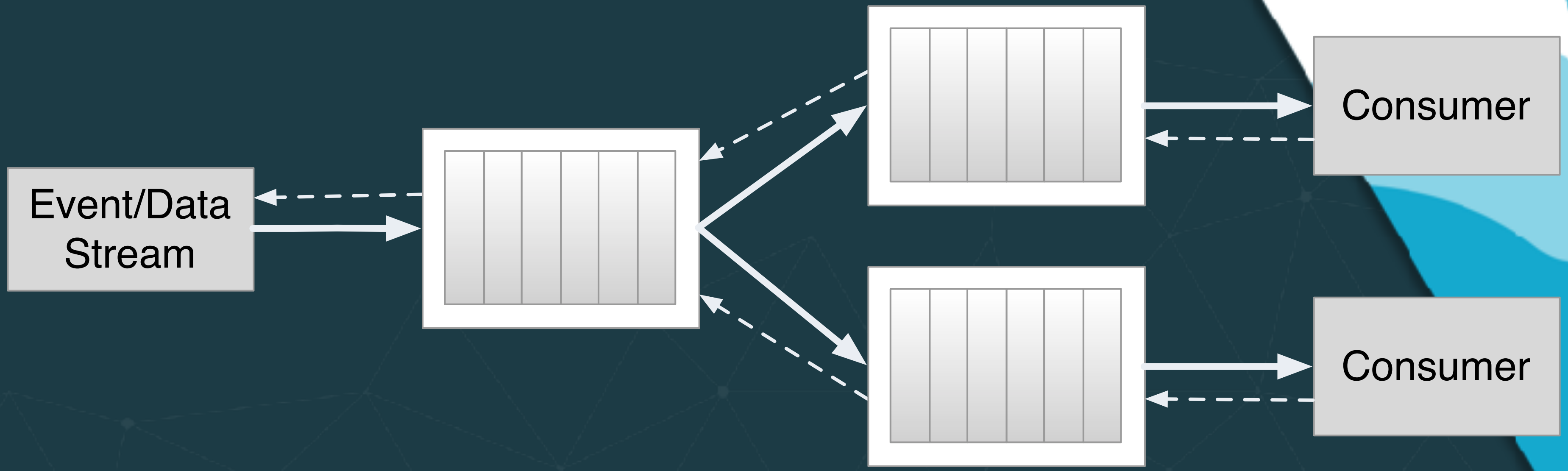
akka streams



… and they compose

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

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

```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")
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))
```

```scala
import akka.stream._
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```

Imports!

```scala
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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"

```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))
```

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))
```

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

```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")
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))
```

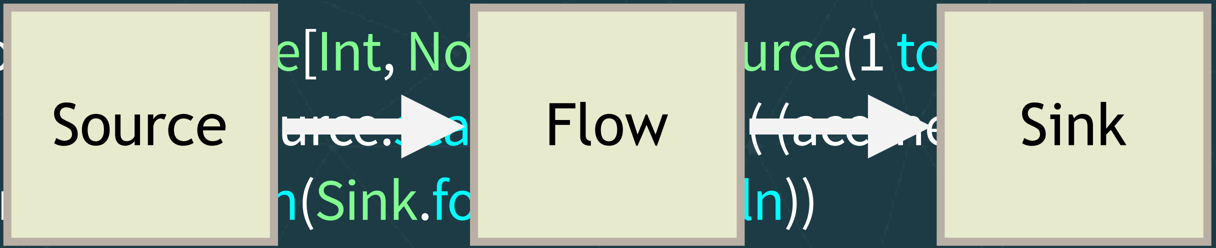
Output to a Sink,
and run it

```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")
implicit val materializer = ActorMaterializer()
```

A source, flow, and sink constitute a graph

```scala
val so  e[Int, No  urce(1 to
val fa  urce.sca  ((acc, ne  next )
facto  n(Sink.fo  ln))
```



akka streams

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

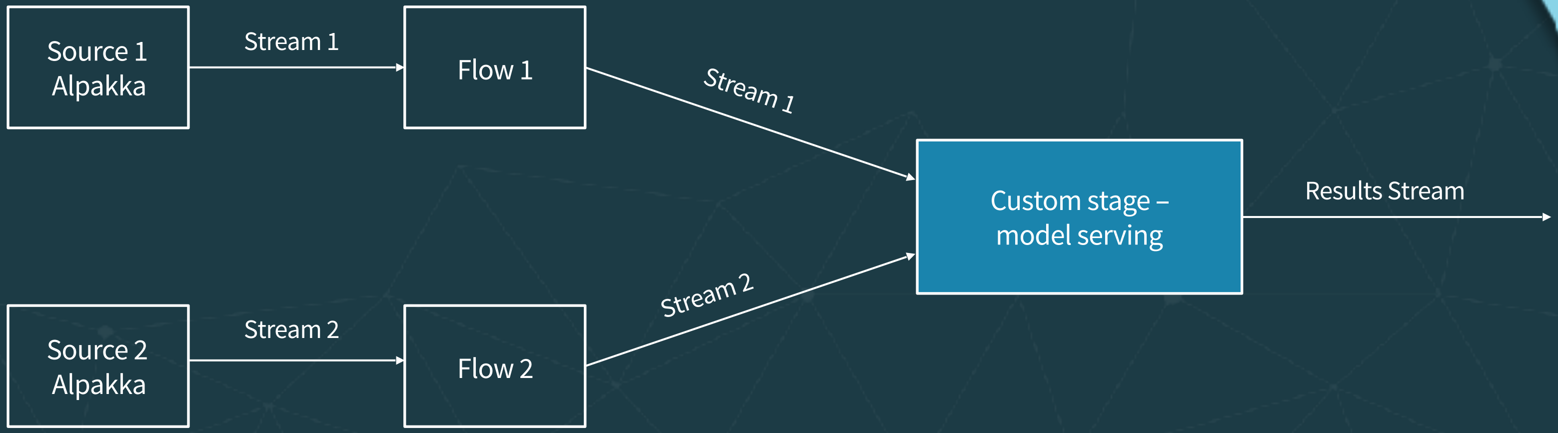
```
$ sbt
sbt:akkaKafkaTutorial> project akkaStreamsModelServer
sbt:akkaStreamsModelServer> console
scala> :load akkaStreamsModelServer/simple-akka-streams-example.sc
```

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…

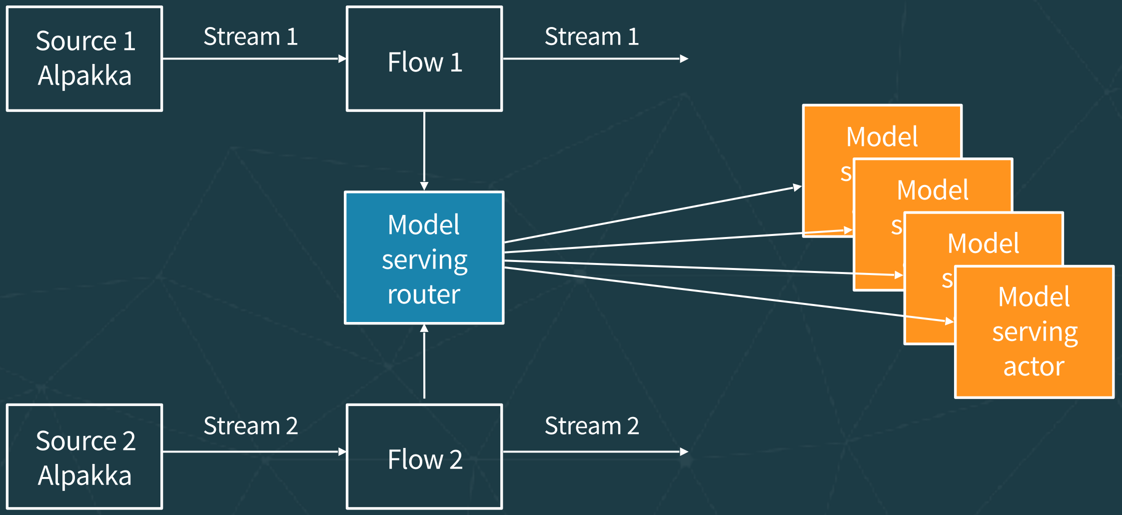
Using Custom Stage

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



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!!



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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

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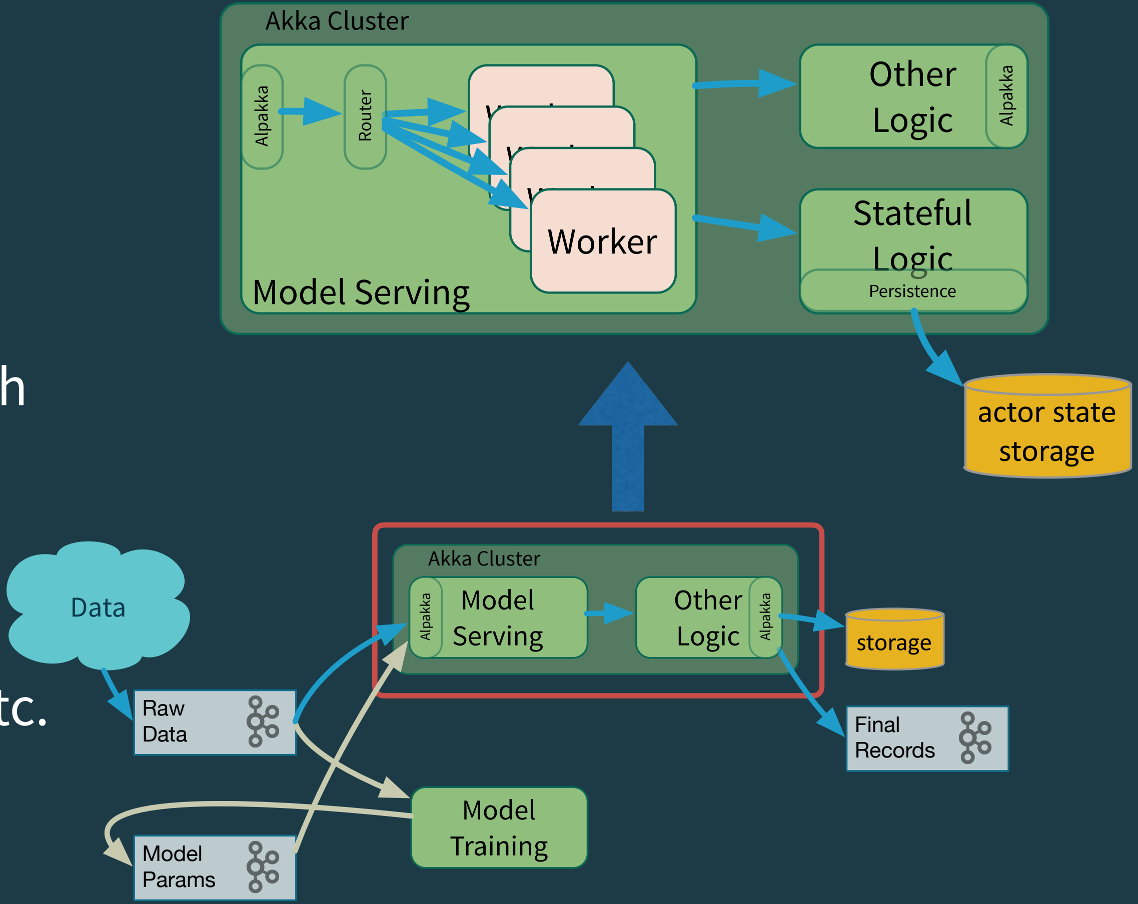
Exercises!

- We've prepared some exercises. We'll return to them after discussing Kafka Streams.
- To find them, search for "// Exercise".

Other Production Concerns

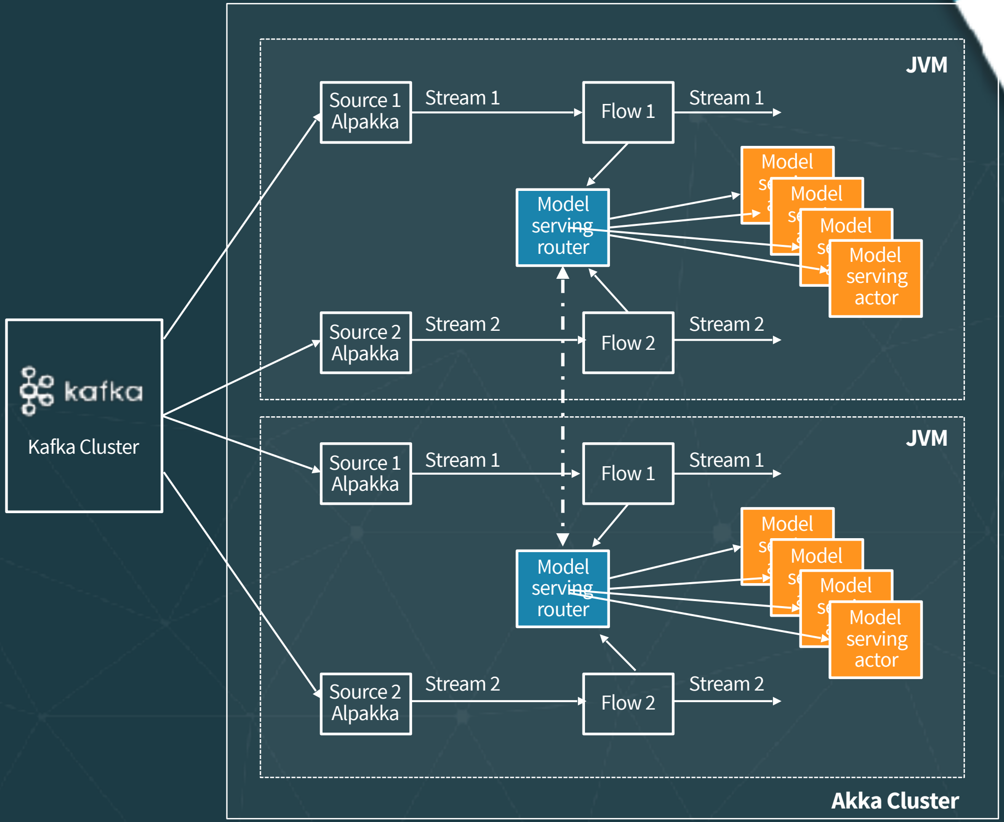
- Scale scoring with workers and routers, across a cluster
- Persist actor state with Akka Persistence
- Connect to *almost* anything with Alpakka
- *Lightbend Enterprise Suite*
  - for production monitoring, etc.



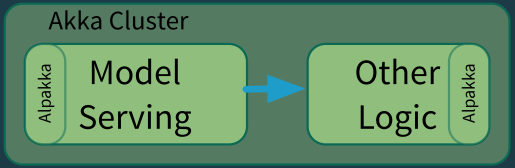
Using Akka Cluster

Two levels of scalability:

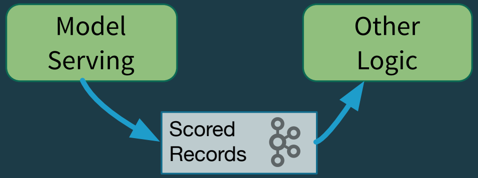
- Kafka partitioned topic allow to scale listeners according to the amount of partitions.
- Akka cluster sharing allows to split model serving actors across clusters.



Go Direct or Through Kafka?



vs.

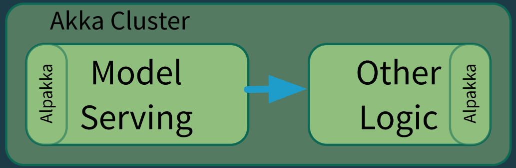


?

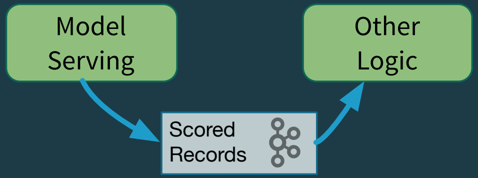
- Extremely low latency
- Minimal I/O and memory overhead
- No marshaling overhead (maybe…)

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

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

Kafka Streams

Kafka Streams

- Important stream-processing concepts, e.g.,
  - Distinguish between *event time* and *processing time*
  - Windowing support.
  - For more on these concepts, see
    - Dean's book ;)
    - Talks, blog posts, writing by Tyler Akidau

Kafka Streams

- KStream - per-record transformations
- KTable - key/value store of supplemental data
  - Efficient management of application state

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.

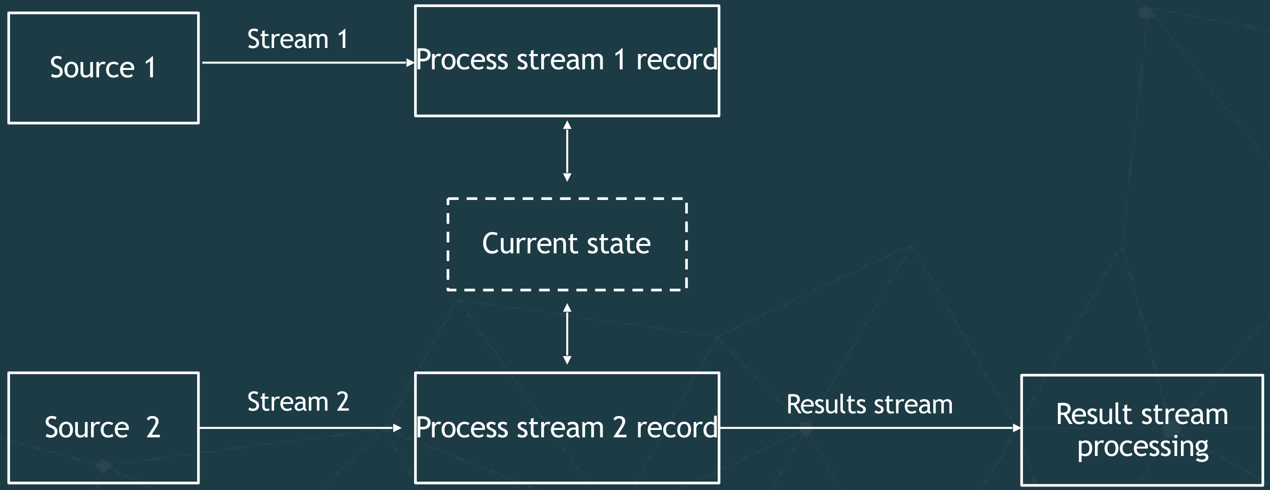
Kafka Streams

- 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)

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

Model Serving With Kafka Streams

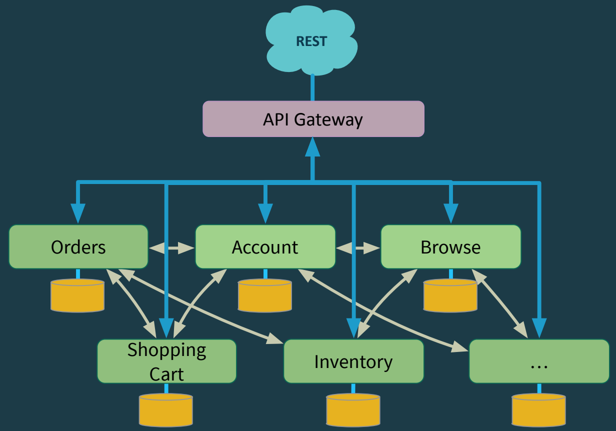
Code time

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

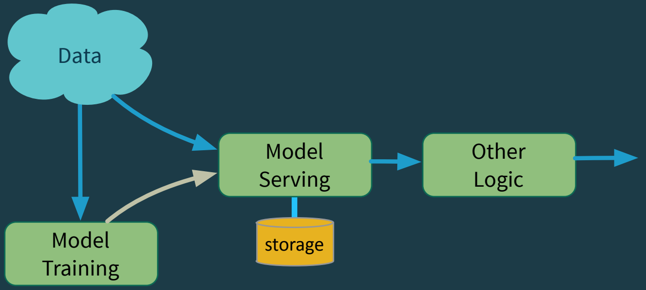
Wrapping Up

To Wrap Up

Event-driven μ-services



"Record-centric" μ-services



Events

Records

In Our Remaining Time Today… (1/2)

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 Today… (1/2)

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 clusters (Sean Glover)
  - 16:35–17:15 Wednesday, 23 May 2018, Capital Suite 8/9
- Processing fast data with Apache Spark: A tale of two APIs (Gerard Maas)
  - 11:15–11:55 Wednesday, 23 May 2018, Capital Suite 8/9
- Machine-learned model quality monitoring in fast data and streaming applications (Emre Velipasaoglu)
  - 14:55–15:35 Wednesday, 23 May 2018, Expo Hall

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