Hands-on Machine Learning with Kafka-based Streaming Pipelines

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Lightbend

If you have not done so already, download the tutorial from GitHub

https://github.com/lightbend/model-serving-tutorial

See the README for setup instructions.

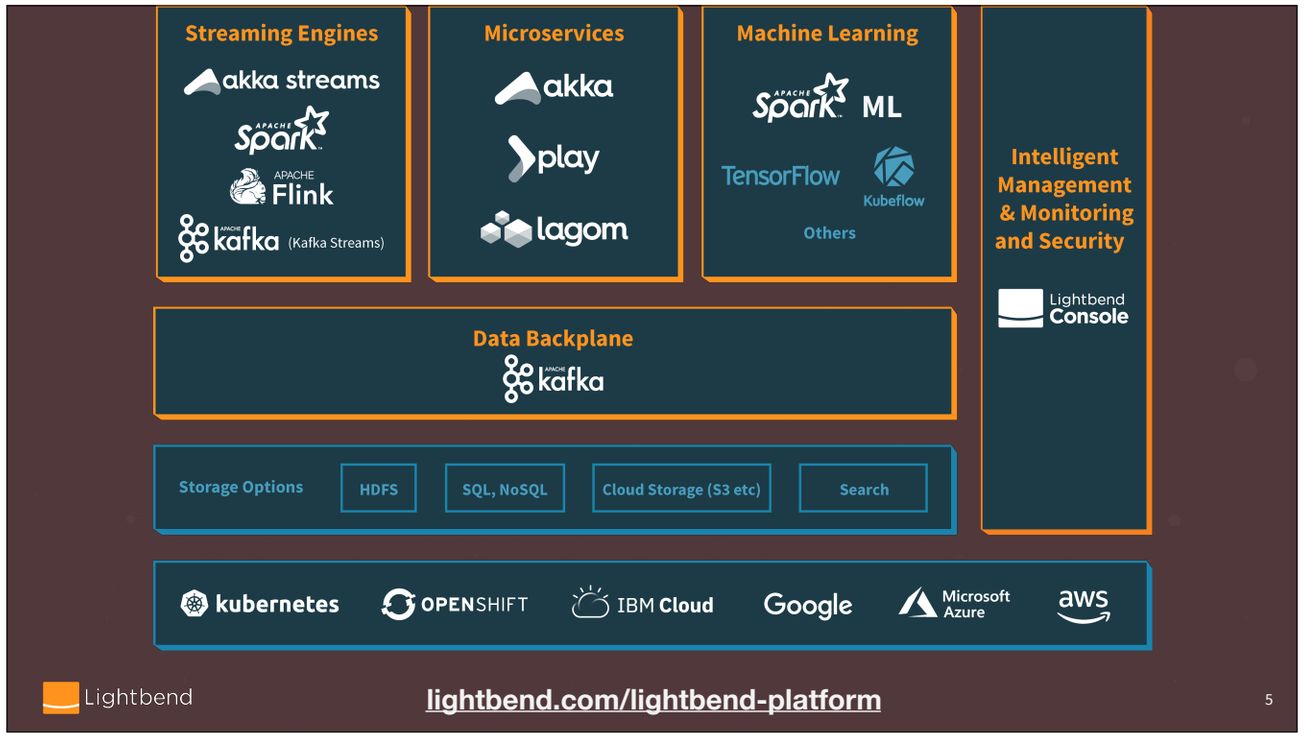
These slides are in the presentation folder.

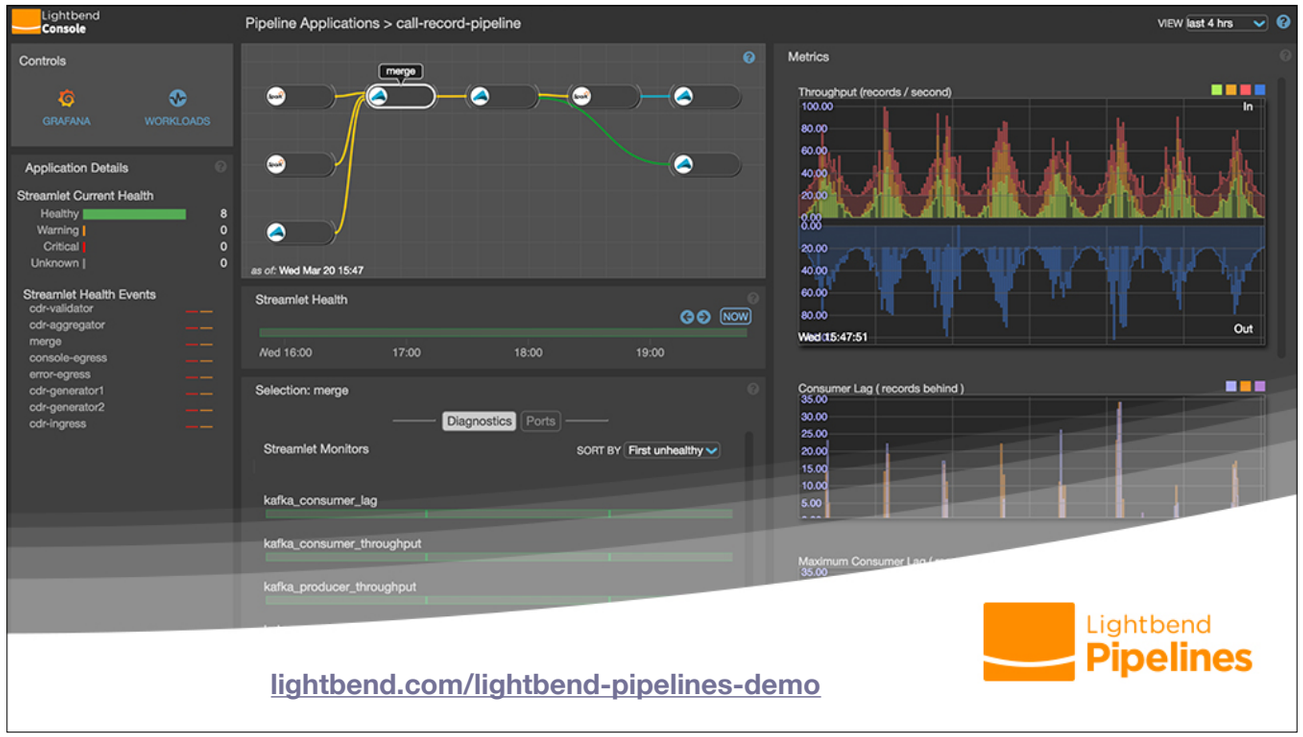
Outline

- Hidden technical debt in machine learning systems
- Model serving patterns
  - Embedding - models as code
  - Models as data
  - External services
  - Dynamically controlled streams
- Additional production concerns for model serving
- Wrap up

As we'll see dynamically controlled streams will revisit models as data

But first, introductions…


Streaming Engines
akka streams
Spark
Flink
kafka (Kafka Streams)
Microservices
akka
play
lagom
Machine Learning
Spark ML
TensorFlow
Kubeflow
Others
Intelligent Management & Monitoring and Security
Lightbend Console
Data Backplane
kafka
Storage Options
HDFS
SQL, NoSQL
Cloud Storage (S3 etc)
Search
kubernetes
OPENSHIFT
IBM Cloud
Google
Microsoft Azure
aws
Lightbend
lightbend.com/lightbend-platform
5



lightbend.com/lightbend-pipelines-demo

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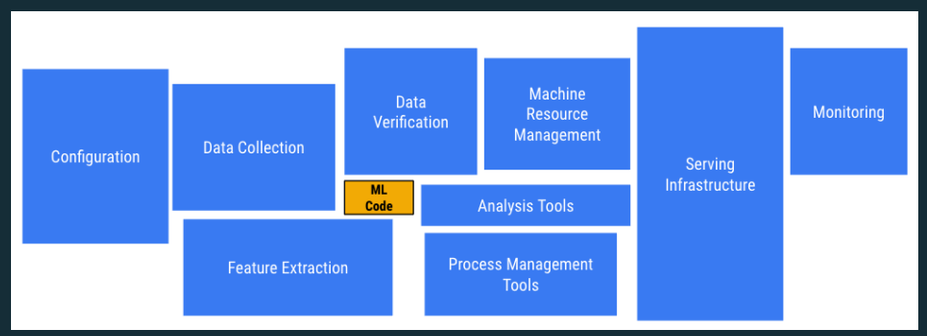
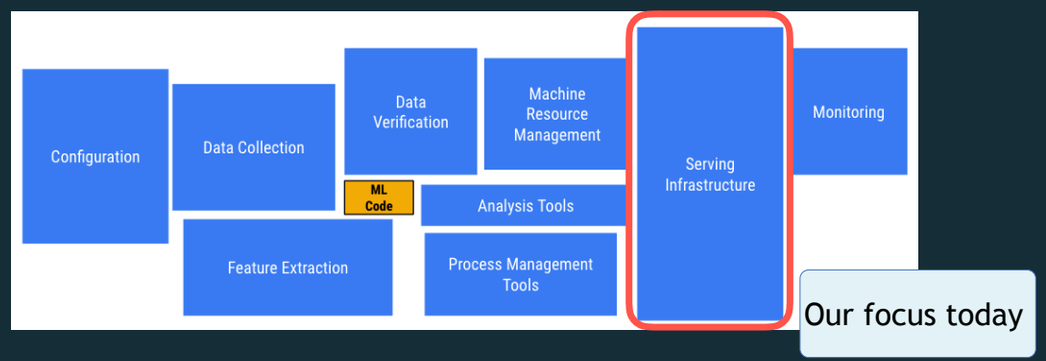
ML vs. Infrastructure Code



papers.nips.cc/paper/5656-hidden-technical-debt-in-machine-learning-systems.pdf

This paper discusses the challenges of real-world use of ML. The actual ML code is just a small part of the overall infrastructure and capabilities required.

ML vs. Infrastructure Code



papers.nips.cc/paper/5656-hidden-technical-debt-in-machine-learning-systems.pdf

This tutorial discusses a few aspects of that picture, focusing on architectures for *serving* models in productions. The architectures use minimal coupling to tool chains for *training* (e.g., through a Kafka topic), which enables a wide range of *training* options, making it easier to use your favorite data science tool chain for training.

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Model Serving Architectures

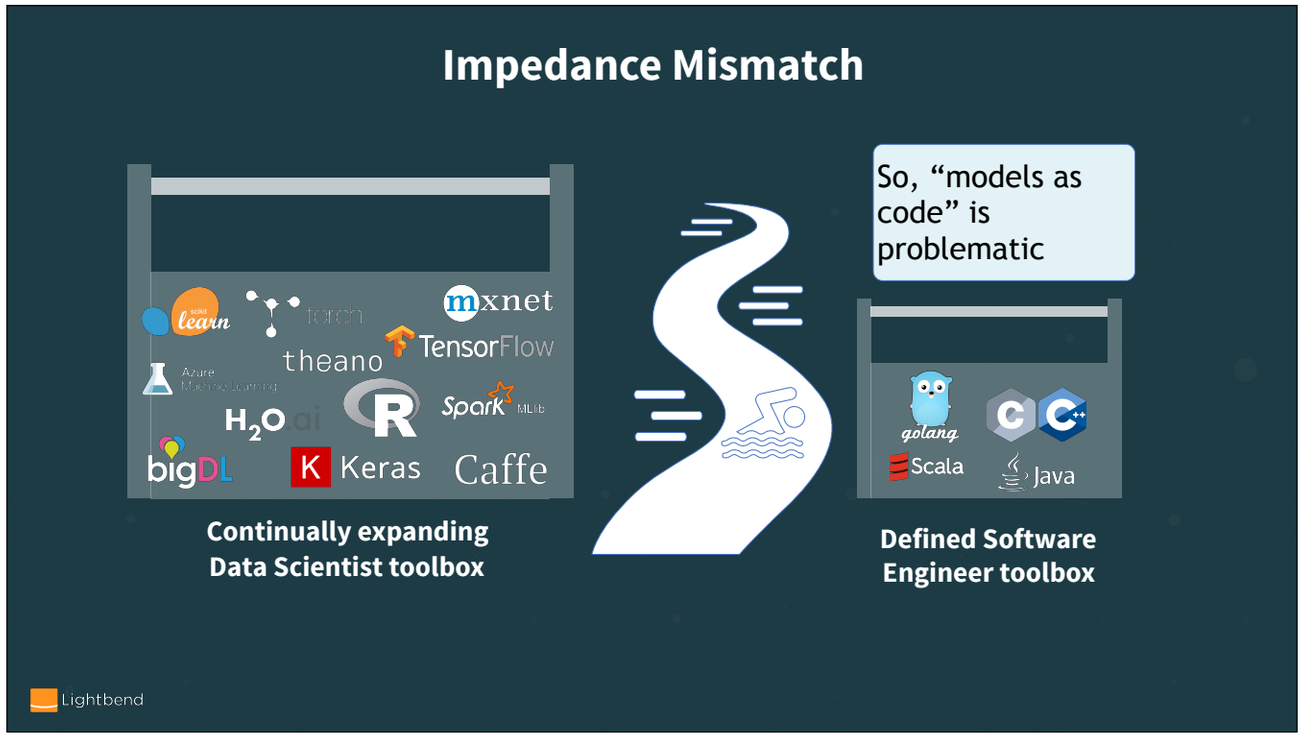
- Embedding - model as *code*, deployed into a stream engine
- Model as *data* - easier dynamic updates
- *Model Serving as a service* - use a separate service, access from the streaming engine
- *Dynamically controlled streams* - one way to implement model as data in a streaming engine

You can embed code for models, but we'll see this has many disadvantages. It's better to treat models as data, which allows you to update it as the "world" changes. We'll focus on two approaches for models as data.

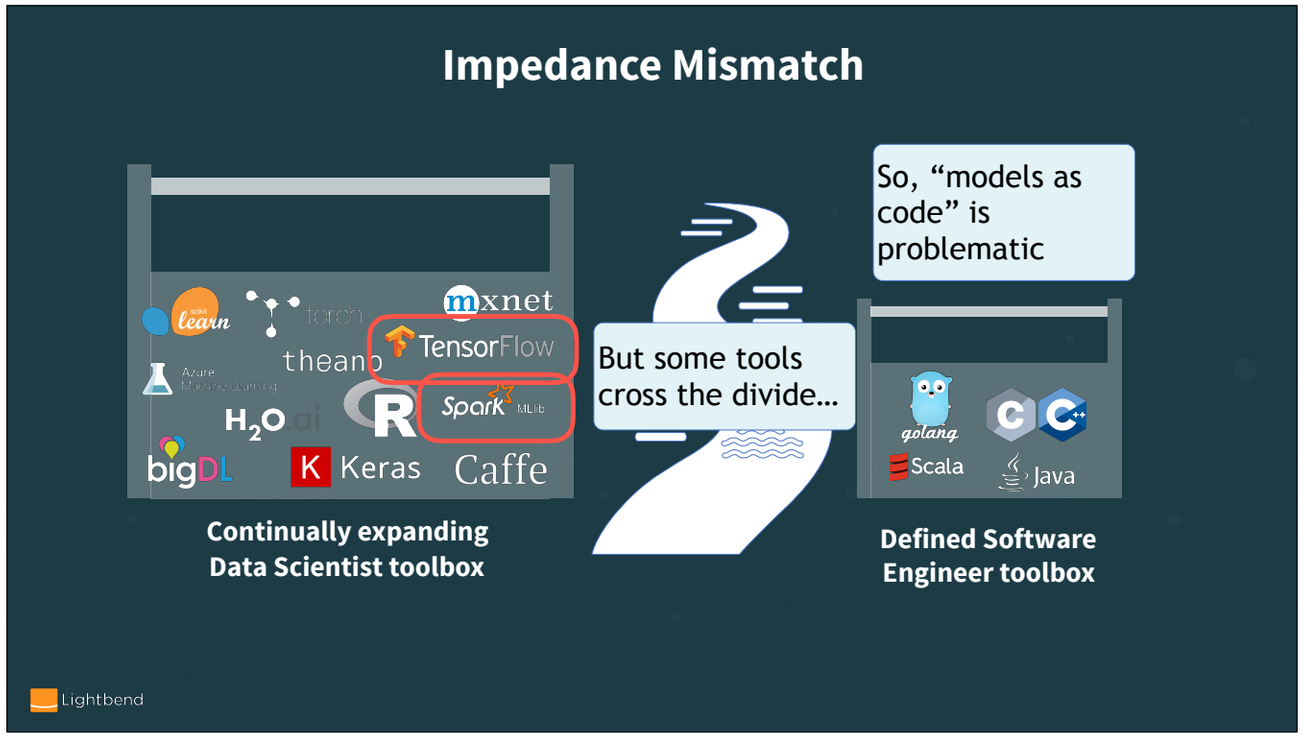
Embedding: Model as Code

- Implement the model as source code
- The model code is linked into the streaming application at build time

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 loose portability if we use tools crossing divide

Embedding: Model as Code

- It also *mostly* eliminates the possibility of updating the model at runtime, as the world changes*.

*Although some coding environments support dynamic loading of new code, do you really want to go there??

Most dynamically-typed languages, like Python, allow runtime loading of new code. Even the JVM supports this. However, it’s much easier to introduce bugs, security holes (SQL injection attacks anyone??), etc. We’ll also discuss other production concerns later, like auditing and data governance, which are harder to support using models as code.

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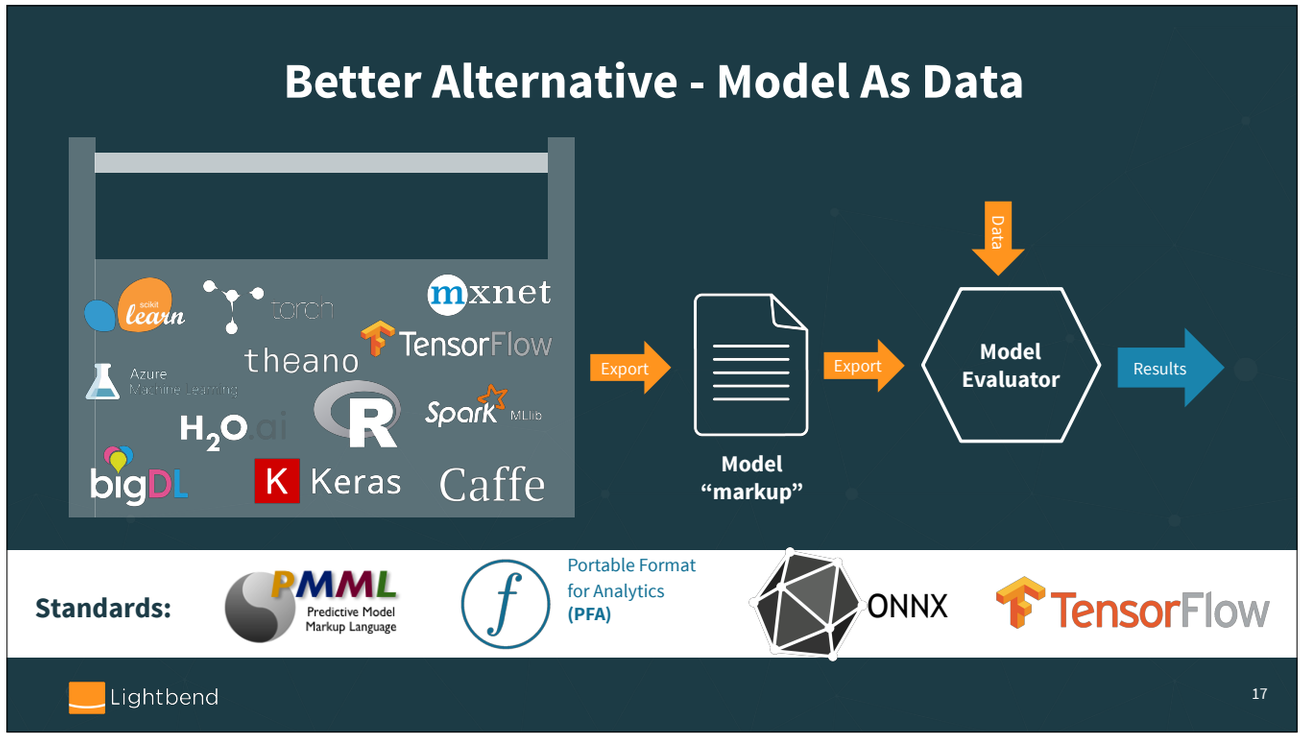
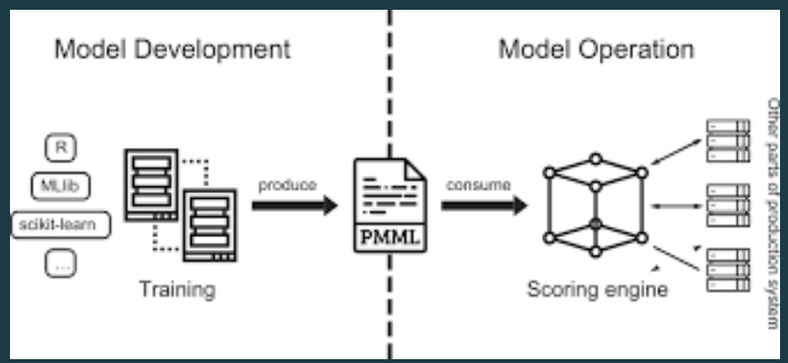


In order to overcome these differences, the Data Mining Group has introduced two standards - Predictive Model Markup Language (PMML) and Portable Format for Analytics (PFA), both suited for description of the models that need to be served. Introduction of these models led to creation of several software 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 TensorFlow.
TensorFlow itself is a de facto standard for ML, because it is so widely used for both training and serving, even though it uses proprietary formats.
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

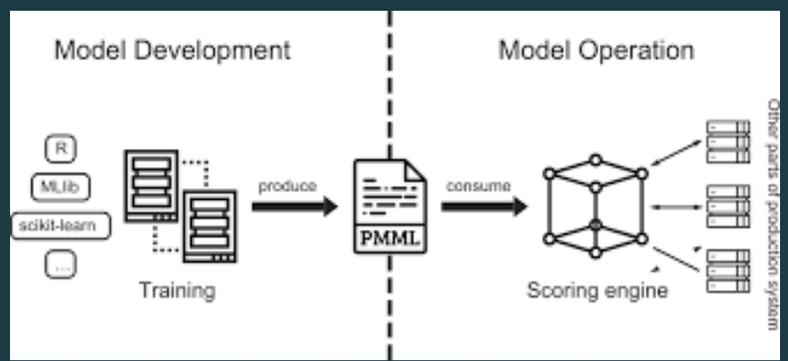
PMML



Predictive Model Markup Language (PMML) is an XML-based language that enables the definition and sharing of predictive models between applications.

https://www.wismutlabs.com/blog/agile-data-science-2/

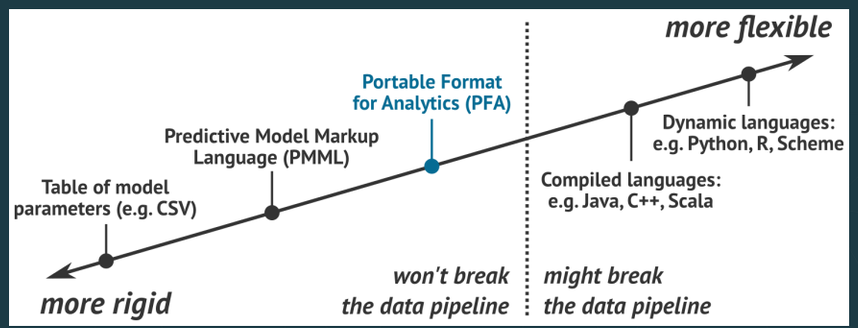
PMML



Implementations for:

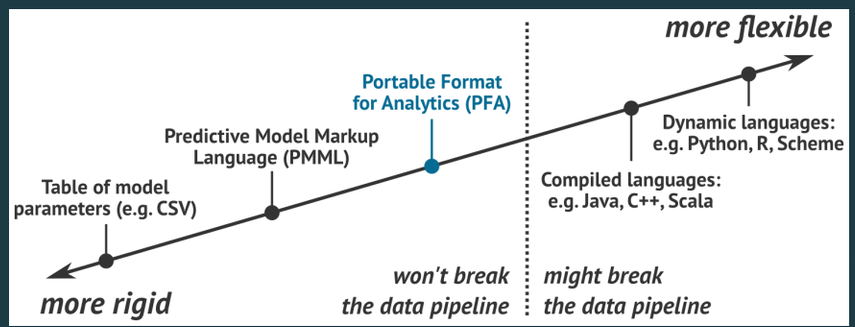
- Java (JPMML), R, Python Scikit-Learn, Spark here and here, …

PFA



Portable Format for Analytics (PFA) is an emerging standard for statistical models and data transformation engines. PFA combines the ease of portability across systems with algorithmic flexibility: models, pre-processing, and post-processing are all functions that can be arbitrarily composed, chained, or built into complex workflows.

PFA



Implementations for:

- Java (Hadrian), R (Aurelius), Python (Titus), Spark (Aardpfark), …

ONNX

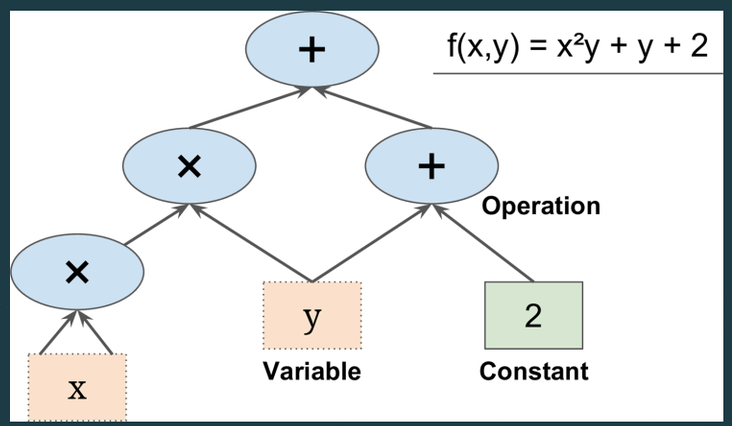
Open Neural Networks Exchange (ONNX) is an open standard format of machine learning models to offer interoperability between various AI frameworks. Led by Facebook, Microsoft, and AWS.

https://azure.microsoft.com/en-us/blog/onnx-runtime-for-inferencing-machine-learning-models-now-in-preview/

ONNX

- Supported Tools page.
- Converters for Keras, CoreML, LightGBM, Scikit-Learn, ….
- PyTorch,
- third-party support for TensorFlow

TensorFlow

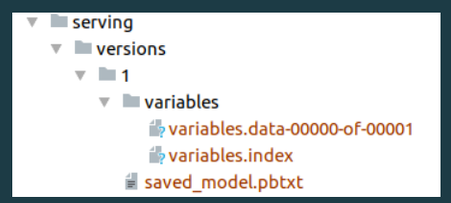


- TensorFlow model is represented as a computational graph of Tensors.
- Tensors are defined as multilinear functions which consist of various vector variables. (i.e., matrices of more than two dimensions)
- TensorFlow supports exporting graphs in the form of binary protocol buffers

https://learning.oreilly.com/library/view/hands-on-machine-learning/9781491962282/ch09.html

The mathematical concept of a Tensor is more sophisticated than just arrays of more than two dimensions.

TensorFlow Export Formats



SavedModel - Features:

- Multiple graphs sharing a single set of variables.
- Support for *SignatureDefs*
- Support for Assets

Normal (optimized) export of a TensorFlow Graph.

- Exports the Graph into a single file, that can be sent over Kafka, for example

Be careful about sending the whole graph into a Kafka topic. Kafka messages are normally not supposed to be large. The upper limit is about 1MB and even that's larger than you should normally use. One alternative, if the model is really big, is to write to a filesystem and send the path in the Kafka message ("pass by reference").

Considerations for Interchange Tools

- Do your *training* tools support exporting with a standard exchange format, e.g., PMML, PFA, etc.?
- Do your *serving* tools support the same format for import?
- Is there support on both ends for the model types you want to use, e.g., random forests, neural networks, etc.?
- Does the *serving* implementation faithfully reproduce the results of your *training* environment?

Implementations are spotty, both in terms of import, export coverage, model types, and faithfully reproducing the same results on both ends. I.e., if you use Scikit-Learn to train a random forest, do you get the same results if you run it in SparkML, after exchanging with PMML?

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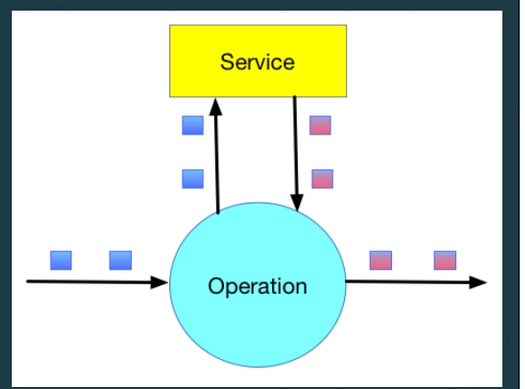
Model Serving as a Service

- *Advantages*
  - Simple integration with existing technologies and organizational processes
  - Easier to understand if you come from a non-streaming world
- *Disadvantages*
  - Worse latency: remote invocations instead of local function calls
  - Coupling the availability, scalability, and latency/throughput of your streaming application with the SLAs of the other service



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Model Serving as a Service: Challenges

- Launch ML runtime graphs, scale up/down, perform rolling updates
- Infrastructure optimization for ML
- Latency and throughput optimization
- Connect to business apps via various APIs, e.g. REST, gRPC
- Allow Auditing and clear versioning
- Integrate into Continuous Integration (CI)
- Allow Continuous Deployment (CD)
- Provide Monitoring

adapted from https://github.com/SeldonIO/seldon-core/blob/master/docs/challenges.md

The SeldonIO project has a nice list of the challenges you face when doing ML Serving as a Service

Model Serving as a Service: Challenges (1/7)

- Launch ML runtime graphs, scale up/down, perform rolling updates
  - The classic issues for deploying any modern *microservice*.
  - What procedures does my organization use to control what's deployed to production and when?
  - How do monitor performance?
  - When it's necessary to scale up or down, how…?
  - How should updates be handled?

Let's go through these in a bit more detail.

Model Serving as a Service: Challenges (2/7)

- Launch ML runtime graphs, scale up/down, perform rolling updates
- …
- How should updates be handled?
  - A/B testing - run two versions, measure which is best
  - Blue-Green testing - two parallel production systems, one for testing new deployments; flip to it once ready.

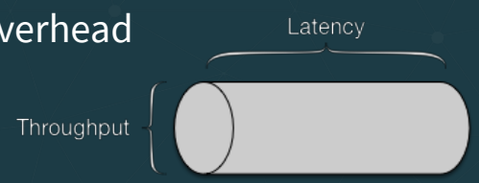
For updates, we'll ignore for now the case where I might run multiple models in production. We'll return to this later.

Model Serving as a Service: Challenges (3/7)

- Infrastructure optimization for ML
  - Closer collaboration with Data Science to:
    - feed live data for training,
    - serve up-to-date models.
  - Model training can be very compute-intensitive
  - Model serving algorithms can be expensive
  - Scoring is less deterministic than other services:
    - How do you know when it’s wrong?

Model Serving as a Service: Challenges (4/7)

- Latency and throughput optimization, and
- Connect to business apps via various APIs, e.g. REST, gRPC
  - Does your latency budget (SLA) tolerate remote RPC (e.g., HTTP(s) and gRPC)?
    - If not, see next sections!
  - Maximize throughput by:
    - bunching requests - less per/score overhead
    - call asynchronously from clients



Discuss two of the bullet points here…

Model Serving as a Service: Challenges (5/7)

- Allow Auditing and clear versioning
  - When was a particular model used to score a particular record?
    - E.g., “why was my loan application rejected?”
    - Which model was used? When was it deployed?
  - Regulatory compliance

The SeldonIO project has a nice list of the challenges you face when doing ML Serving as a Service

Model Serving as a Service: Challenges (6/7)

- Integrate into Continuous Integration (CI)
- Allow Continuous Deployment (CD)
  - Standard and modern techniques for build, test, and deployment
  - Probably new to the Data Science teams,
    - but hopefully familiar to the Data Engineers!
  - This also helps with auditing and versioning requirements

Consider two bullet points together, because they are closely related.

Model Serving as a Service: Challenges (7/7)

- Provide Monitoring
  - Standard production tool for *observability*
    - What's the throughput and latency for scoring?
      - Is throughput keeping up with the data volume?
      - Is latency meeting our SLAs?
    - When will I know that a problem has arisen?
      - Alerting essential!
      - Practice fault isolation and recovery scenarios

Model Serving as a Service: Challenges

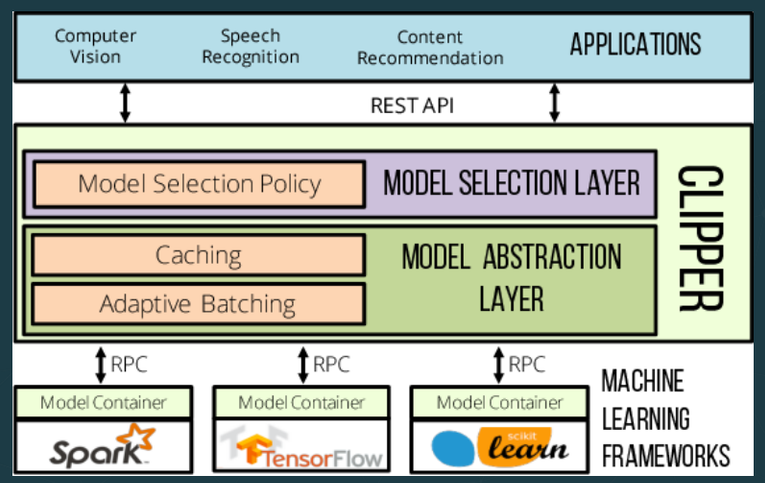
- Launch ML runtime graphs, scale up/down, perform rolling updates
- Infrastructure optimization for ML
- Latency and throughput optimization
- Connect to business and various APIs (e.g. REST, gRPC
- Allow Auditing and clear versioning
- Integrate into Continuous Integration (CI)
- Allow Continuous Deployment (CD)
- Provide monitoring

We'll return to some of these points later.

adapted from https://github.com/SeldonIO/seldon-core/blob/master/docs/challenges.md

Example Systems

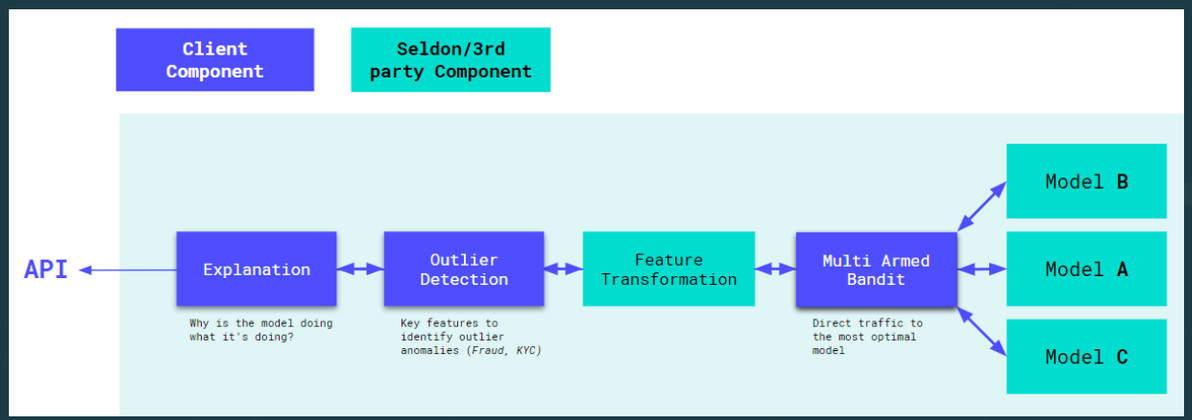
Example: Clipper



https://www.semanticscholar.org/paper/Clipper%3A-A-Low-Latency-Online-Prediction-Serving-Crankshaw-Wang/4ef862c9157ede9ff8cfbc80a612b6362dcb6e7c

Clipper introduces a modular architecture to simplify model deployment across frameworks and applications. Furthermore, by introducing caching, batching, and adaptive model selection techniques, Clipper reduces prediction latency and improves prediction throughput, accuracy, and robustness without modifying the underlying machine learning frameworks.

Example: Seldon Core

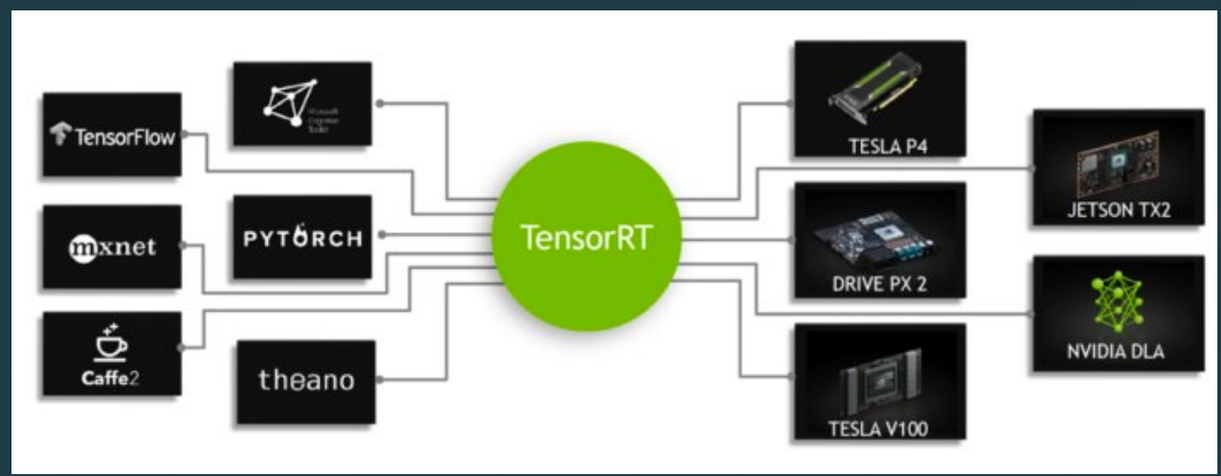


https://www.seldon.io/open-source/

Main characteristics:

- Allow data scientists to create models using any machine learning toolkit or programming language.
- Expose machine learning models via REST and gRPC for easy integration into business apps.
- Allow complex runtime inference graphs to be deployed as microservices. Composed of: models, routers, combiners and transformers.
- Handle full lifecycle management of the deployed model. Updating – Scaling – Monitoring – Security.

Example: TensorRT

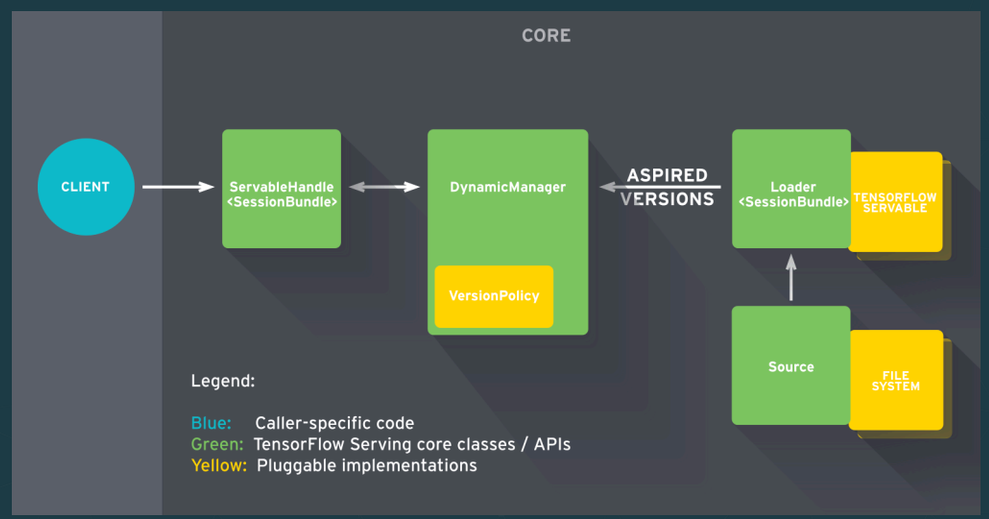


https://www.eetasia.com/news/article/Nvidia_CEO_in_China

NVIDIA TensorRT™ is a platform for high-performance deep learning inference. It includes a deep learning inference optimizer and runtime that delivers low latency and high-throughput for deep learning inference applications. TensorRT-based applications perform up to 40x faster than CPU-only platforms during inference. With TensorRT, you can optimize neural network models trained in all major frameworks, calibrate for lower precision with high accuracy, and finally deploy to hyperscale data centers, embedded, or automotive product platforms.

TensorRT provides INT8 and FP16 optimizations for production deployments of deep learning inference applications such as video streaming, speech recognition, recommendation and natural language processing. Reduced precision inference significantly reduces application latency, which is a requirement for many real-time services, auto and embedded applications.

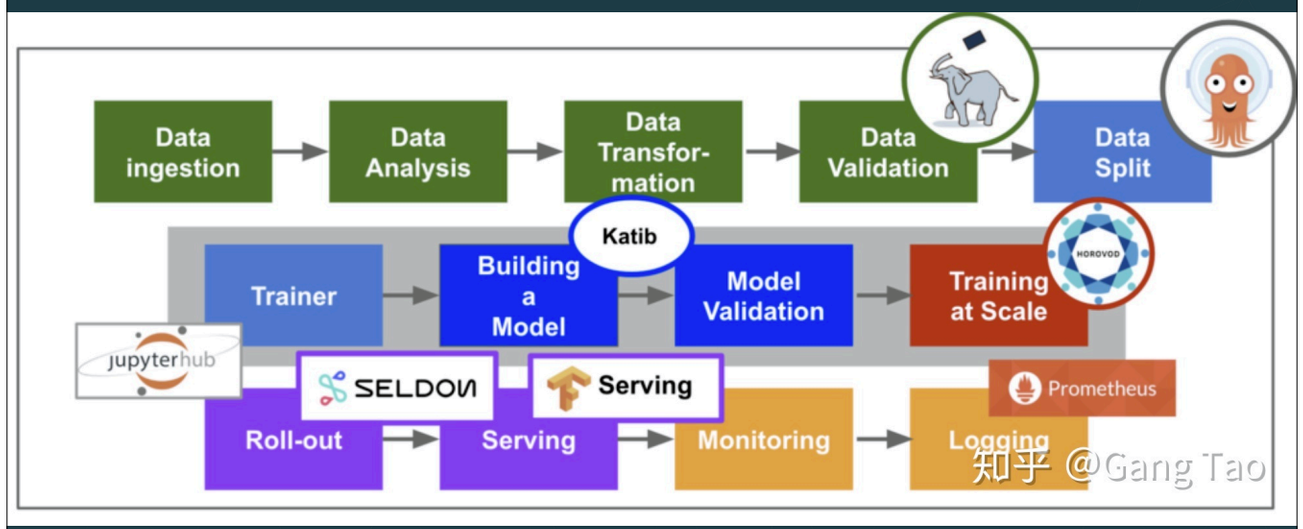
Example: TensorFlow serving



https://medium.com/sap-machine-learning-research/tensorflow-serving-in-enterprise-applications-our-experience-and-workarounds-part-1-33f65bfbf3d7

TensorFlow Serving is a flexible, high-performance serving system for machine learning models, designed for production environments. TensorFlow Serving makes it easy to deploy new algorithms and experiments, while keeping the same server architecture and APIs. TensorFlow Serving provides out-of-the-box integration with TensorFlow models, but can be easily extended to serve other types of models and data.

Example: Kubeflow



Lightbend

https://zhuanlan.zhihu.com/p/44692757

The Kubeflow project is dedicated to making deployments of machine learning (ML) workflows on Kubernetes simple, portable and scalable. Our goal is not to recreate other services, but to provide a straightforward way to deploy best-of-breed open-source systems for ML to diverse infrastructures. Anywhere you are running Kubernetes, you should be able to run Kubeflow.

Rendezvous Architecture Pattern

Handle ML logistics in a flexible, responsive, convenient, and realistic way.

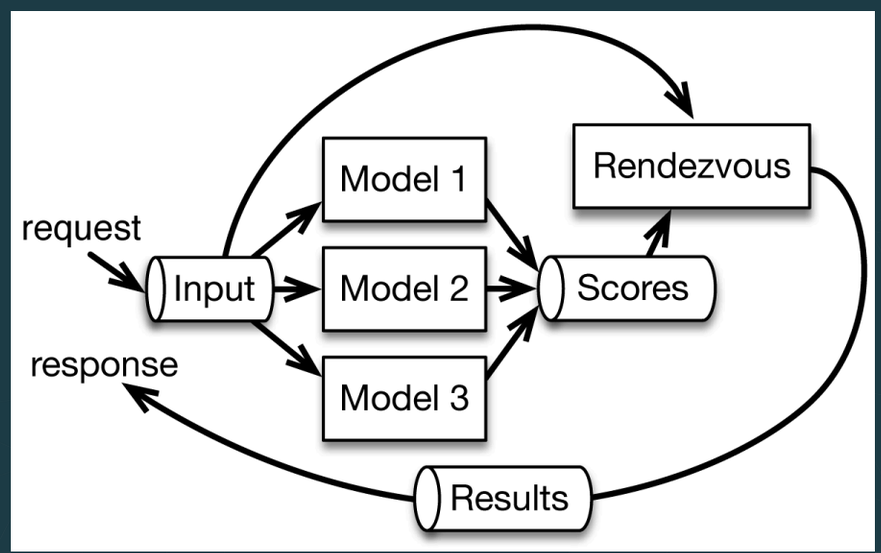
- For Data:
  - Collect data at scale from many sources.
    - Preserve raw data so that potentially valuable features are not lost.
  - Make data available to many applications (consumers), both on premise and distributed.

Rendezvous Architecture Pattern

Handle ML logistics in a flexible, responsive, convenient, and realistic way.

- Models:
  - Manage multiple models during development and production.
  - Improve evaluation methods for comparing models during development and production, including use of reference models for baseline successful performance.
  - Have new models poised for rapid deployment.

Rendezvous Architecture

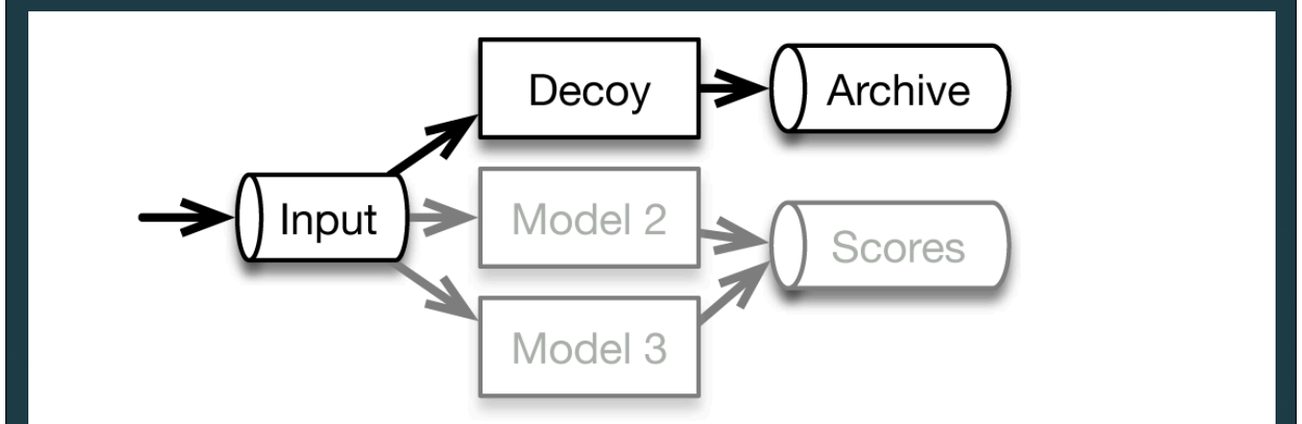


Lightbend

https://mapr.com/ebooks/machine-learning-logistics/ch03.html

All communications here are Kafka or similar log-oriented or message queue alternatives. An input is fanned out to multiple models that serve it simultaneously. The result goes to the scoring function, that combine all of the scoring results (based on certain criteria) and creates combined result.

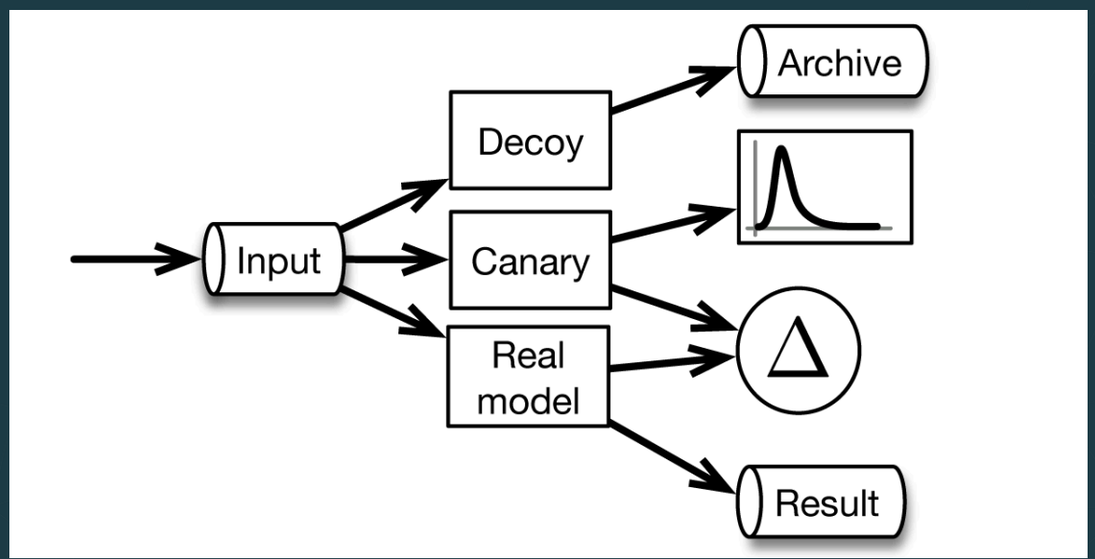
Rendezvous Architecture - Decoy



https://mapr.com/ebooks/machine-learning-logistics/ch03.html

If we want to collect data for the future training, we can deploy decoy, which is a pass through writing data to the archive. This allows to add data collection without disrupting actual model serving

Rendezvous Architecture - Canary



Lightbend

https://mapr.com/ebooks/machine-learning-logistics/ch03.html

All communications here are Kafka (or its variants). Here we want to validate a new model (canary deployment). This is done deploying a new model to listen to the same topic that the main model and comparing results between new and existing model. If the comparison is good, the new model can be safely deployed.

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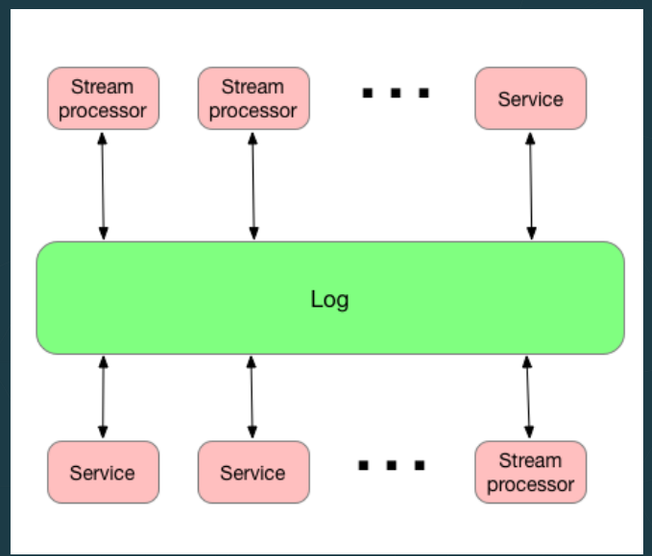
Log-Driven Enterprise

- Complete decoupling of services.
- All communications go through the log rather then services talking to each other directly.
- Specifically, stream processors don't talk explicitly to other services, but send async. messages through the log.

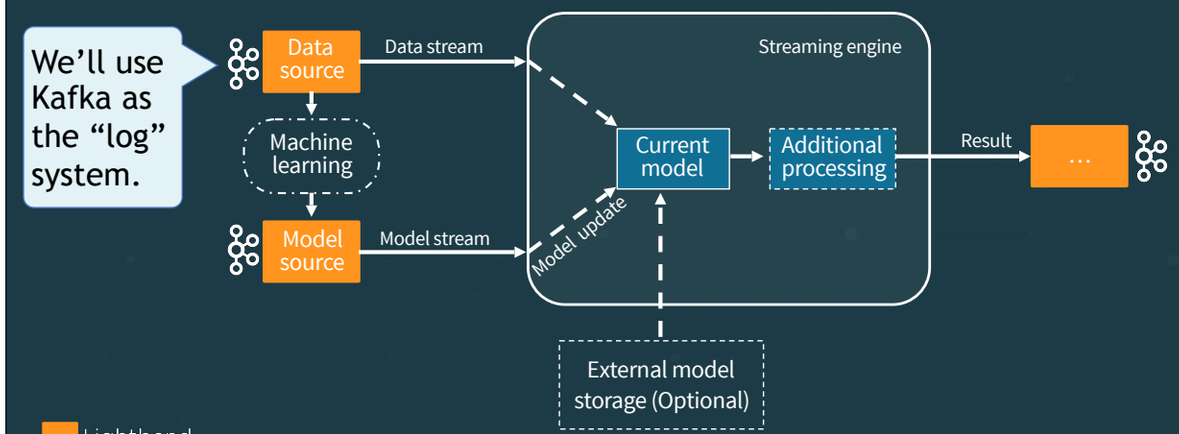
Example: Kafka



The majority of machine learning implementations are based on running model serving as a Rest service, which might not be appropriate for the high volume data processing or usage of the streaming system, which requires re coding/starting systems for model update, for example, Flink TensorFlow or Flink JPPML.

Model Serving in a Log-Driven Enterprise

Dynamically Controlled Stream: a streaming system supporting model updates without interruption of execution (Flink example, Spark streaming example)



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The majority of machine learning implementations are based on running model serving as a Rest service, which might not be appropriate for the high volume data processing or usage of the streaming system, which requires re coding/starting systems for model update, for example, Flink TensorFlow or Flink JPPML. The name of this pattern was coined by *data Artisans* (that's the correct spelling…)

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;                 // Could add PFA, ONNX, …
  };

  ModelType modeltype = 4;
  oneof MessageContent {
    // Byte array containing the model
    bytes data = 5;
    string location = 6;
  }
}
```

See the “protobufs” project in the example code.

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)

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

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

[RECORD,RESULT] are type parameters; compare to Java: <RECORD,RESULT>

See the “model” project in the example code.

Corresponding Scala code that could be generated from the description, although we hand code this logic in the examples and exercises.

Production Concern: 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
)
```

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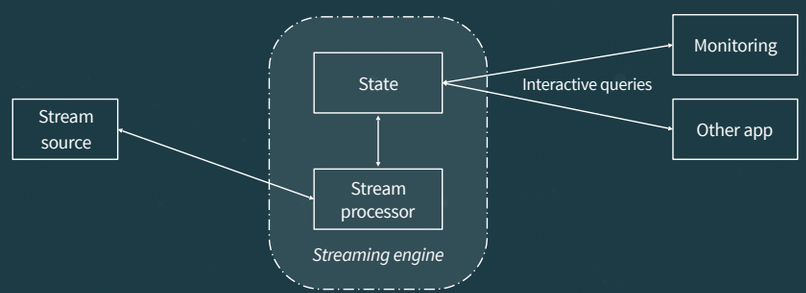
We'll return to production concerns...

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.



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Note the “ad hoc” part. It’s for times when a “normal” stream of output data isn’t the best fit, e.g., only periodic updates are needed, you really want to support a range of “impromptu” (ad hoc) queries, etc.
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.

Example used in this tutorial

Throughout the rest of tutorial we use models based on *Wine quality* data for training and scoring.

- The data is publicly available at https://www.kaggle.com/vishalyo990/prediction-of-quality-of-wine/data .
- A great notebook describing this data and providing several machine learning algorithms for this problem: https://www.kaggle.com/vishalyo990/prediction-of-quality-of-wine/notebook

TensorFlow Serving

TensorFlow Serving

Code time

- Let’s look at TF Serving first. We’ll use it with microservices shortly.
  - Open the example code project
  - We’ll walk through the project at a high level
  - Familiarize yourself with the *tensorflowserver* code
  - Load and start the TensorFlow model serving Docker image
    - See Using TensorFlow Serving in the README
  - Try the implementation and see if you have any questions

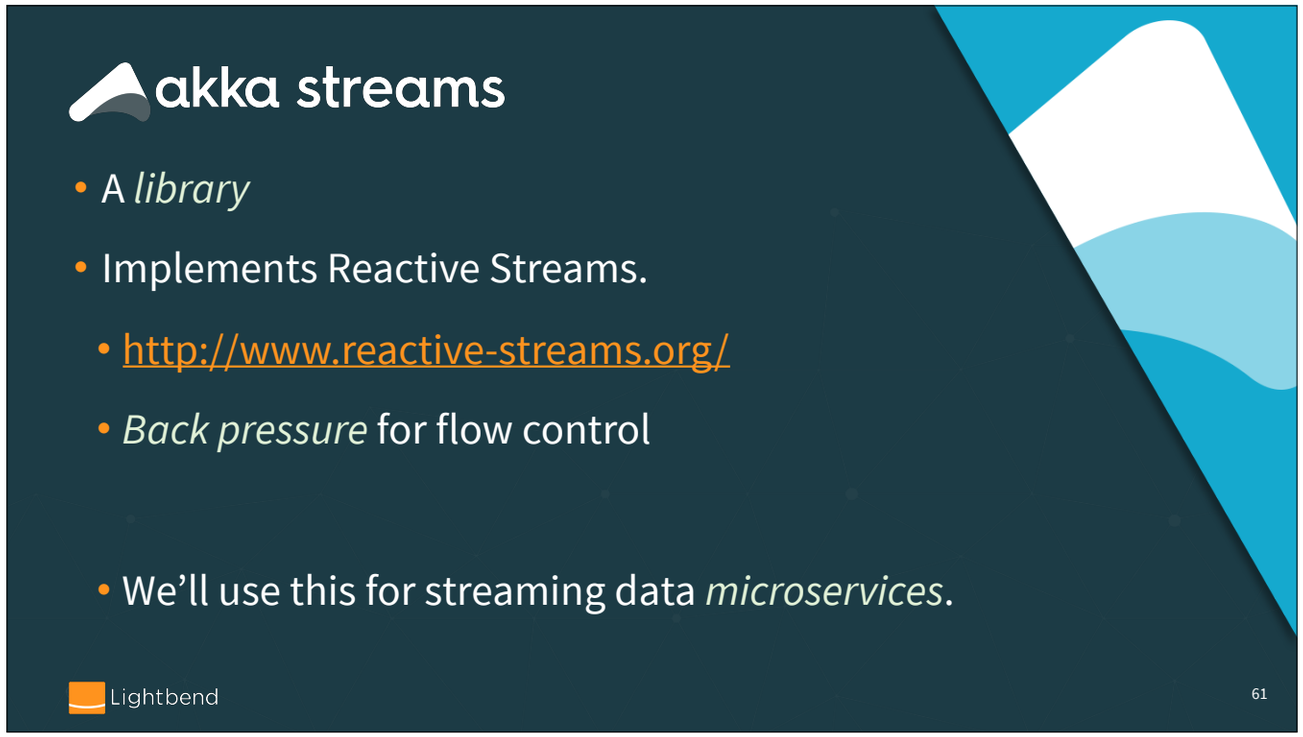
Akka Streams

TF Serving is Great! How Do I Use It?

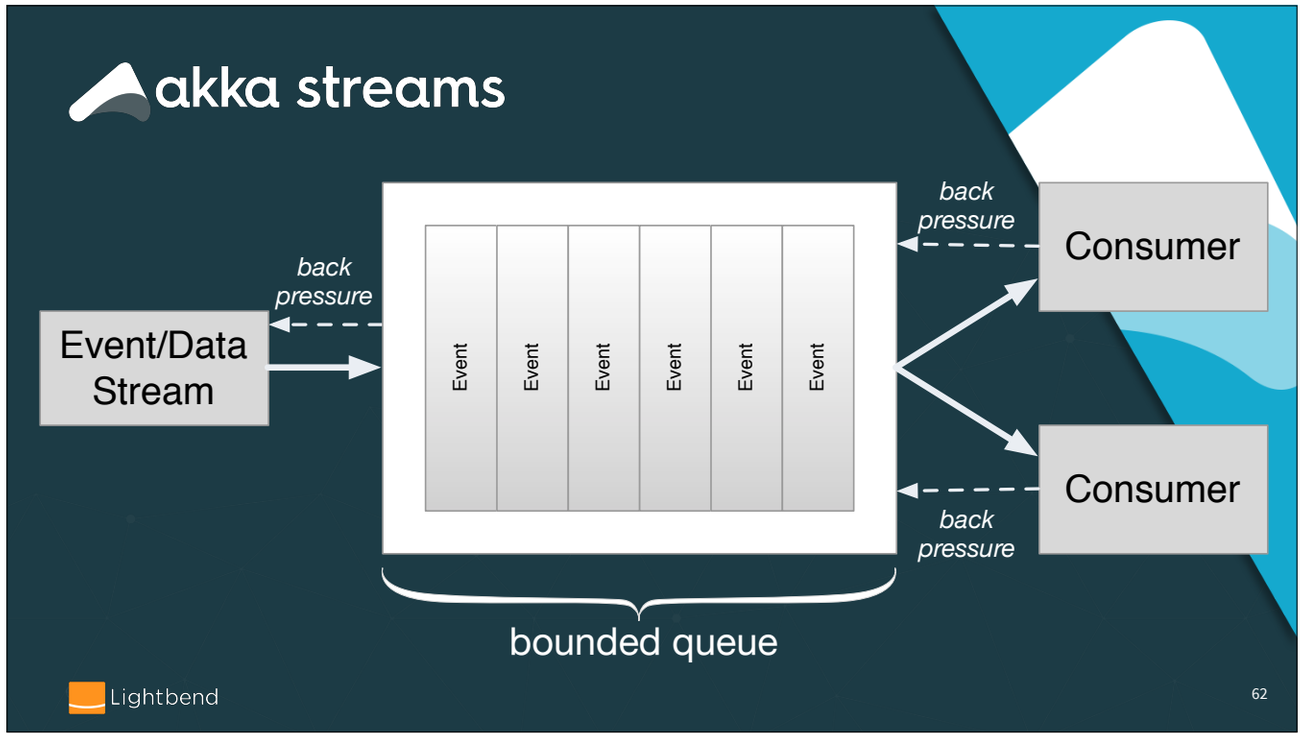
- How do we integrate model serving (or any other new stateful capability) into our microservices that need to do scoring?
- Let's see, using *Akka*.

Lightbend

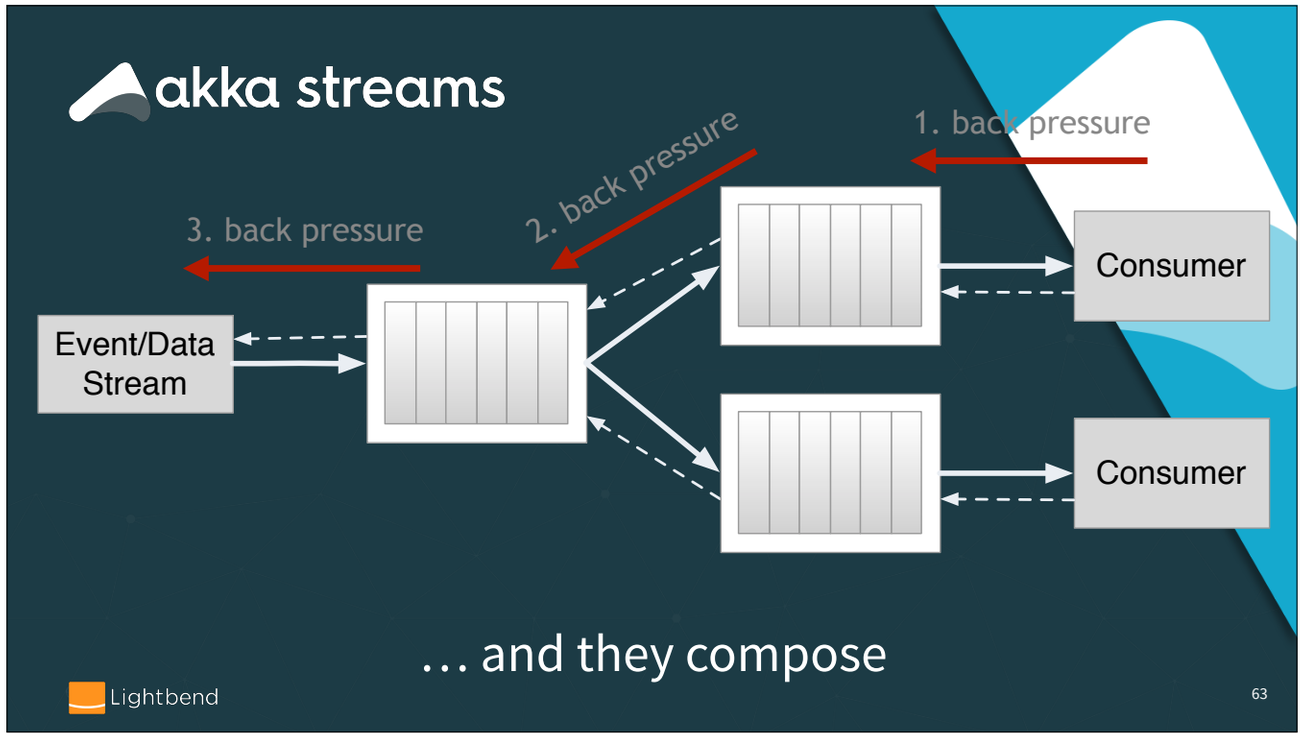
We provide two implementations. You could generalize the second approach (async calls) to invoke an external service. We won't provide examples of this option, but return later with some additional considerations about it.



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
    - similar to 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

```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))
```

```
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")
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))
```

Imports!

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

```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))
```

Initialize and specify now the stream is “materialized”

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

```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))
```

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

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

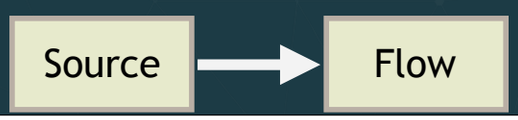
```
import akka.stream._
import akka.stream.scaladsl._
import akka.NotUsed
import akka.actor.ActorSystem
import scala.concurrent._
import scala.concurrent.duration._

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))
```

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

Scan the source and compute factorials, with a seed of 1, of type BigInt (a **flow**)



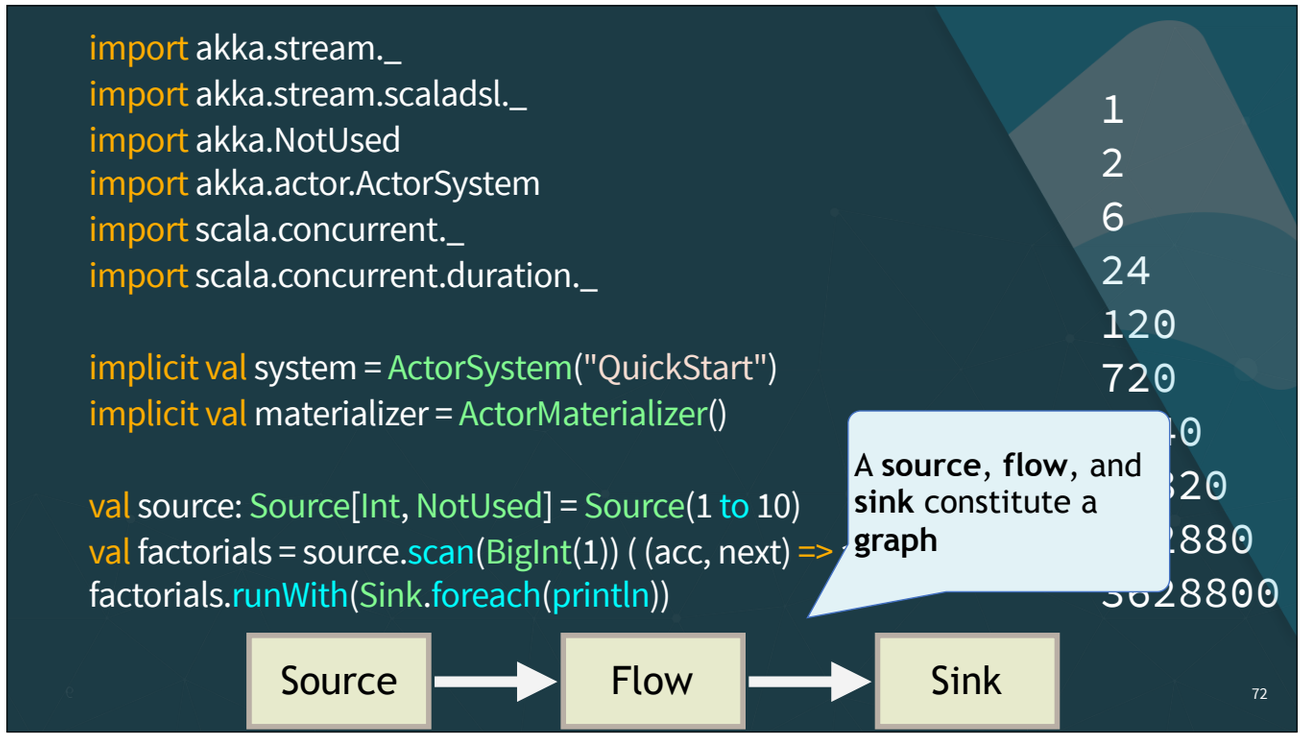
```
import akka.stream._
import akka.stream.scaladsl._
import akka.NotUsed
import akka.actor.ActorSystem
import scala.concurrent._
import scala.concurrent.duration._

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

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

Output to a **sink**, and run it

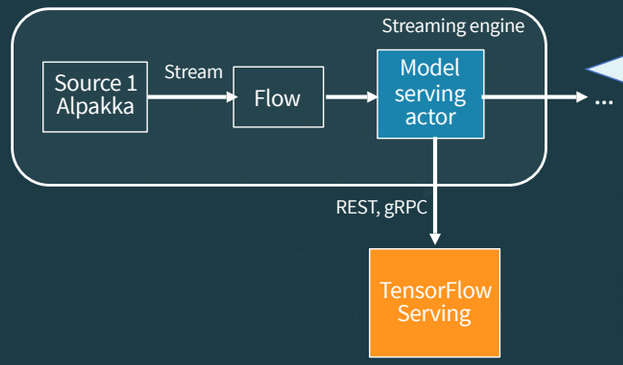
```
1
2
6
24
120
720
5040
40320
362880
3628800
```



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

Using TensorFlow Serving in Akka Streams

Use an *Akka Actor* to invoke TensorFlow Serving *asynchronously* (i.e., model serving as a service)



Actor holds the current state in memory - model parameters, scoring stats, ...

Could use this idiom for any *X as a Service* from a streaming data microservice

To summarize, we are using Akka Streams to write our streaming data pipeline and calling a custom Akka Actor to handle invoking of the scoring service.

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 can serve models in parallel.

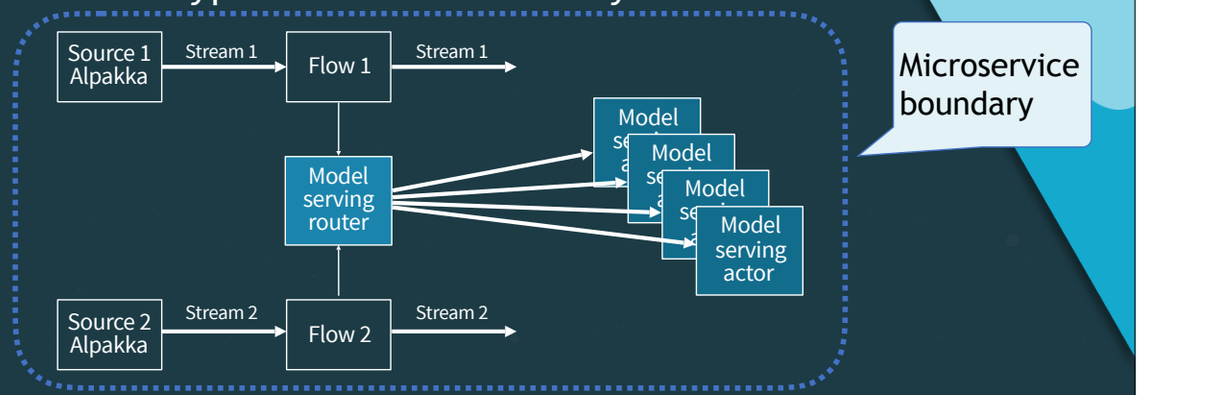
Embedded Model Serving

- Use *Akka Actors* to implement model serving within the microservice boundary, using a *library*.
  - Alternative to Serving as a Service

We provide both kinds of 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 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!!



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.

Akka Streams Example

Code time

1. Run the *client* project (if not already running)
2. Explore and run the *akkaServer* project

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

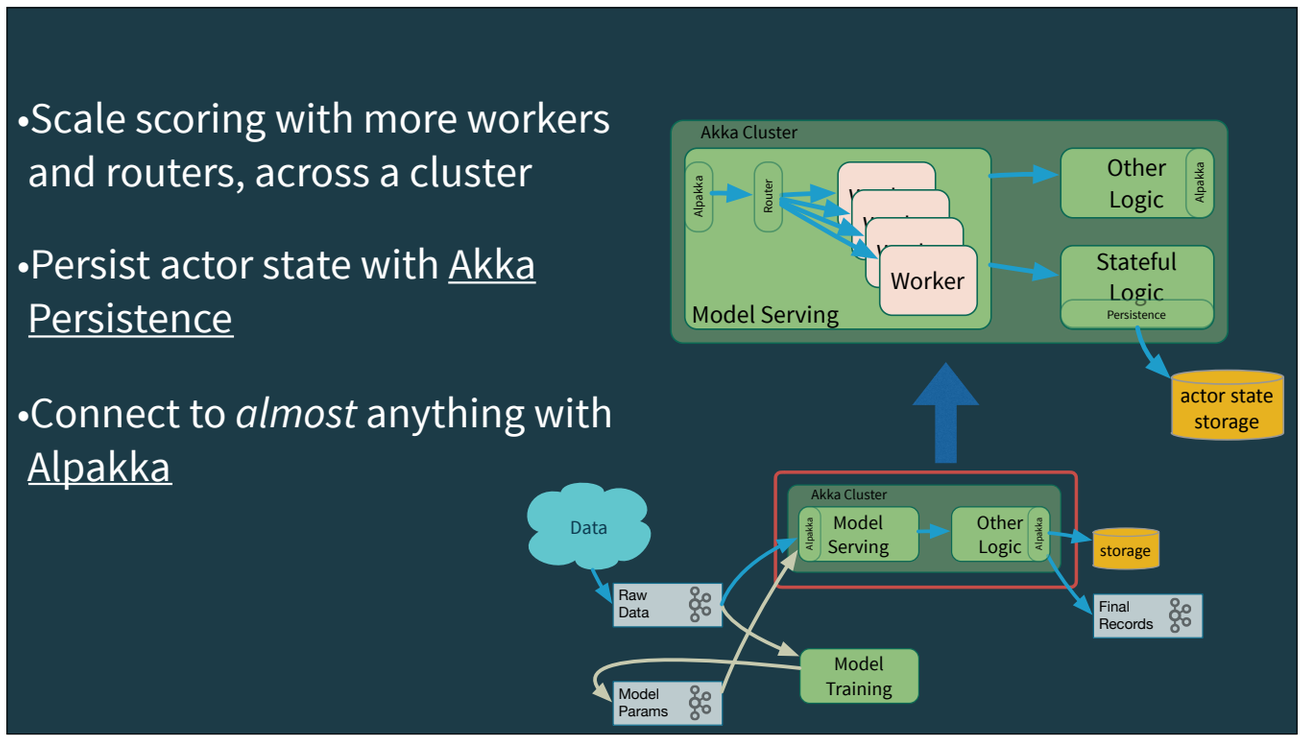
Akka Streams Example

- Implements *queryable state*
- Curl or open in a browser:

http://localhost:5500/models
http://localhost:5500/state/wine

Handling Other Production Concerns with Akka and Akka Streams

- Scale scoring with more workers and routers, across a cluster
- Persist actor state with Akka Persistence
- Connect to *almost* anything with Alpakka

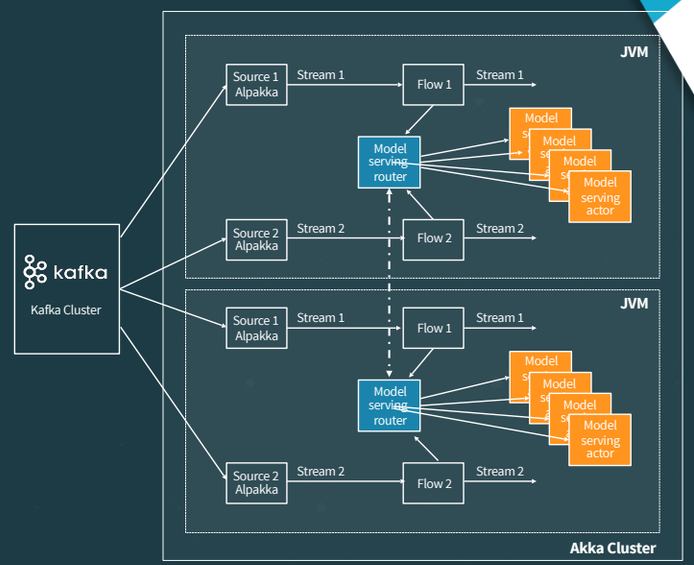


Here's our streaming microservice example adapted for Akka Streams. We'll still use Kafka topics in some places and assume we're using the same implementation for the "Model Training" microservice. Alpakka provides the interface to Kafka, DBs, file systems, etc. We're showing two microservices as before,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



Lightbend http://michalplachta.com/2016/01/23/scalability-using-sharding-from-akka-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

Apache Flink

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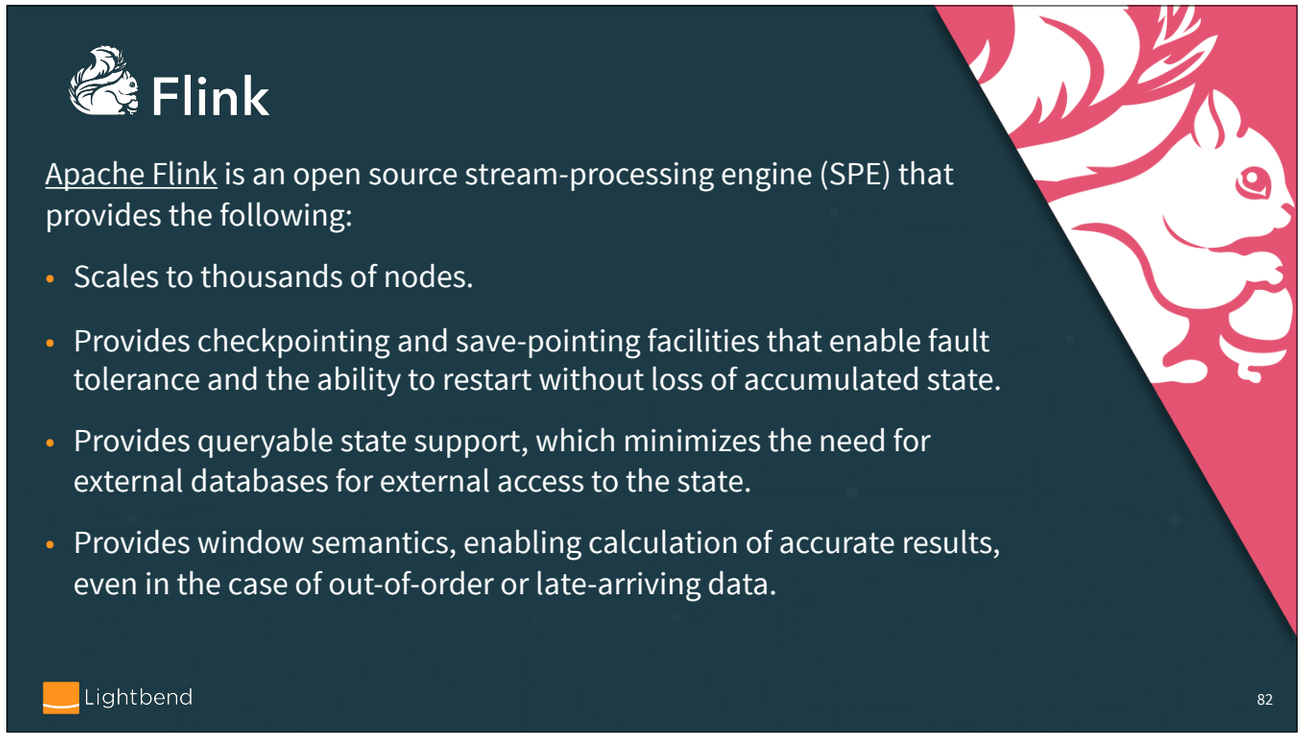
Same sample use case, now with Kafka Streams


Flink
Apache Flink is an open source stream-processing engine (SPE) that provides the following:
• Scales to thousands of nodes.
• Provides checkpointing and save-pointing facilities that enable fault tolerance and the ability to restart without loss of accumulated state.
• Provides queryable state support, which minimizes the need for external databases for external access to the state.
• Provides window semantics, enabling calculation of accurate results, even in the case of out-of-order or late-arriving data.
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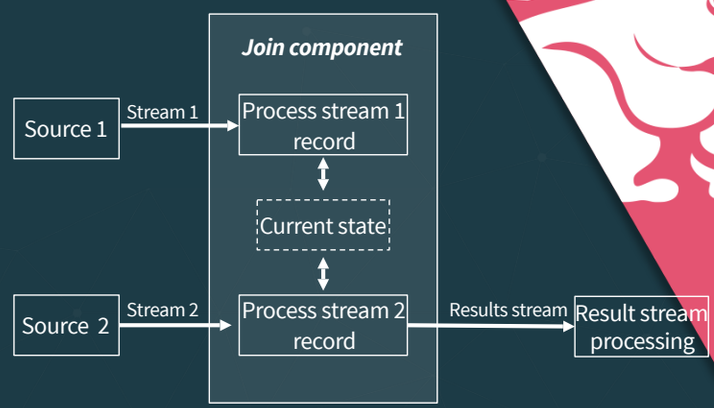
82

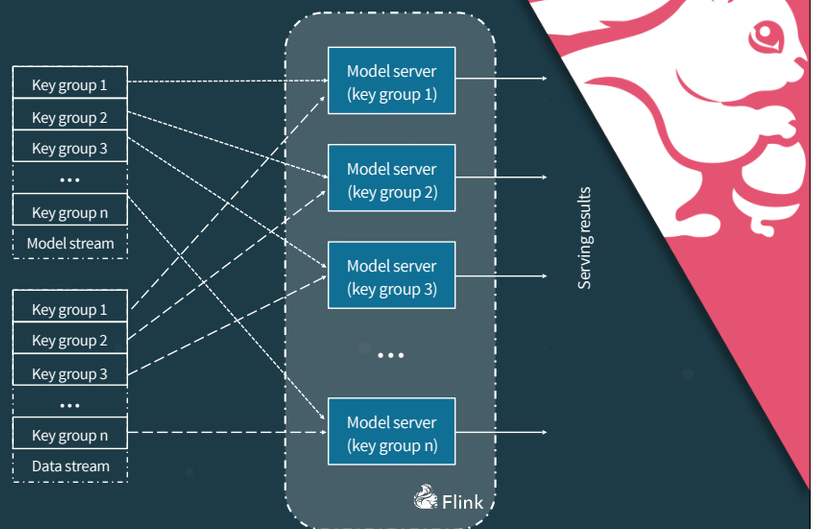
Flink Low Level Join

- Create a state object for one input (or both)
- Update the state upon receiving elements from its input
- Upon receiving elements from the other input, probe the state and produce the joined result
- Flink provides two implementation of low-level joins: key based join and partition based join



Key based join

Flink's *CoProcessFunction* allows key-based merge of 2 streams. When using this API, data is key-partitioned across multiple Flink executors. Records from both streams are routed (based on key) to the appropriate executor that is responsible for the actual processing.



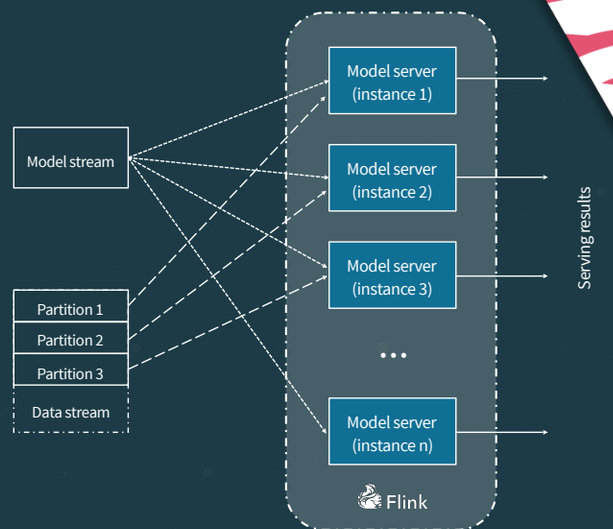
The main characteristics of this approach:

- Distribution of execution is based on key
- Individual models' scoring is implemented by a separate executor (a single executor can score multiple models), which means that scaling Flink leads to a better distribution of individual models and consequently better parallelization of scorings.
- A given model is always scored by a given executor, which means that depending on the data type distribution of input records, this approach can lead to "hot" executors

Based on this, key-based joins are an appropriate approach for the situations when it is necessary to score multiple data types with relatively even distribution.

Partition based join

Flink's *RichCoFlatMapFunction* allows merging of 2 streams in parallel (based on parallelization parameter). When using this API, on the partitioned stream, data from different partitions is processed by dedicated Flink executor.



Here are the main characteristics of this approach:

• The same model can be scored in one of several executors based on the partitioning of the data streams, which means that scaling of Flink (and input data partitioning) leads to better scoring throughput.

• Because the model stream is broadcast to all model server instances, which operate independently, some race conditions in the model update can exist, meaning that at the point of the model switch, some model jitter (models can be updated at different times in different instances, so for some short period of time different input records can be served by different models) can occur.

Based on these considerations, using global joins is an appropriate approach for the situations when it is necessary to score with one or a few models under heavy data load.

Flink Example

Code time

1. Run the *client* project (if not already running)
2. Explore and run *flinkServer* project
   a. ModelServingKeyedJob implements keyed join
   b. ModelServingFlatJob implements partitioned join

Apache Spark Structured Streaming

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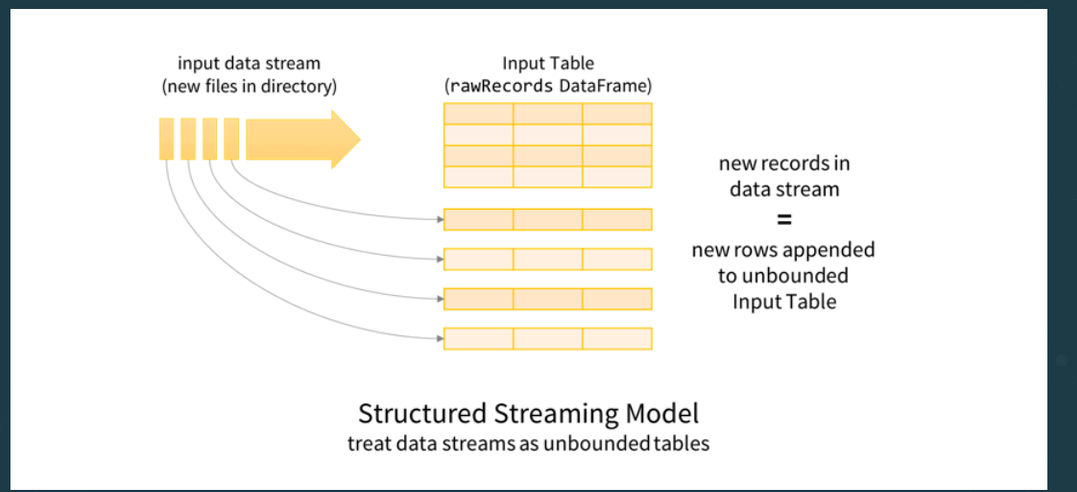
Same sample use case, now with Kafka Streams

Spark Structured Streaming

Apache Spark Structured Streaming is a scalable and fault-tolerant stream processing engine built on the Spark SQL engine.

- Scales to thousands of nodes.
- Express your streaming computation the same way you would express a batch SQL computation on static data:
  - The Spark SQL engine will take care of running it incrementally and continuously. It updates results as streaming data continues to arrive.
-

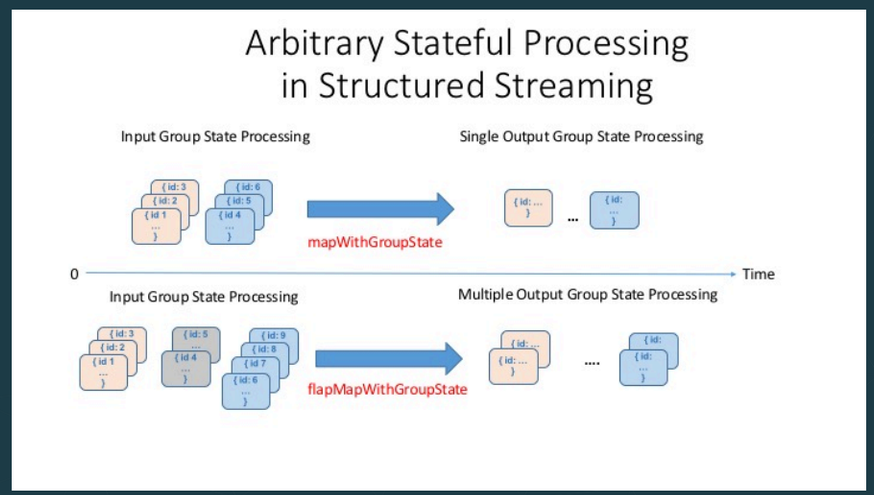
Spark Structured Streaming



Lightbend

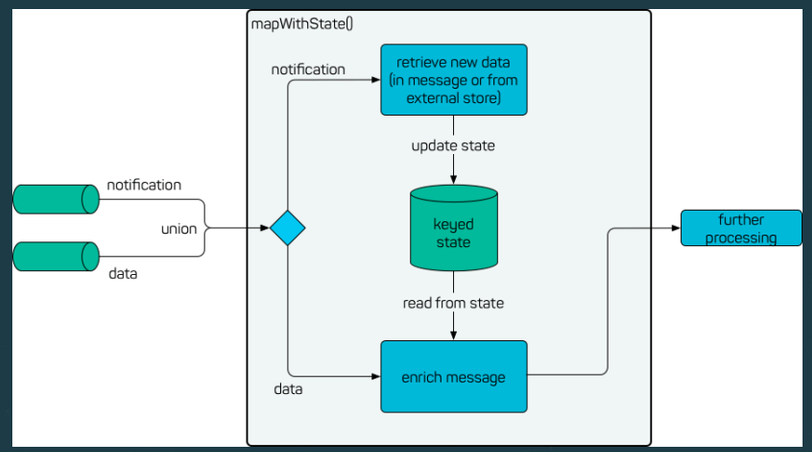
spark.apache.org/docs/latest/structured-streaming-programming-guide.html

Spark Structured Streaming - State



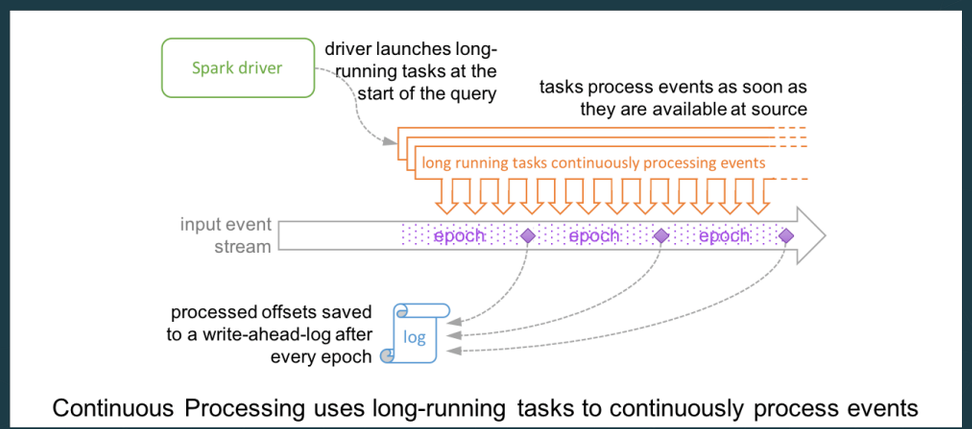
https://databricks.com/blog/2017/10/17/arbitrary-stateful-processing-in-apache-sparks-structured-streaming.html

Spark Structured Streaming - mapWithState



https://blog.codecentric.de/en/2017/07/lookup-additional-data-in-spark-streaming/

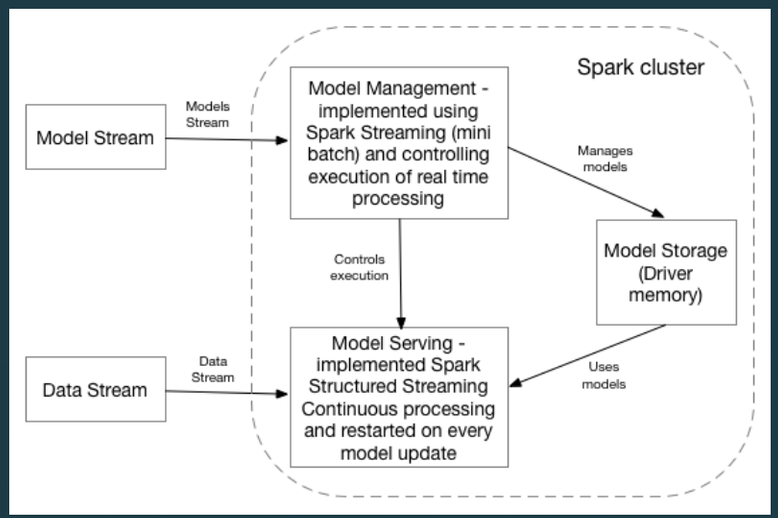
Spark Structured Streaming - continuous processing



Continuous Processing uses long-running tasks to continuously process events

https://databricks.com/blog/2018/03/20/low-latency-continuous-processing-mode-in-structured-streaming-in-apache-spark-2-3-0.html

Multi-loop continuous processing



Spark Example

Code time

1. Run the *client* project (if not already running)
2. Explore and run the *sparkServer* project
   a. SparkStructuredModelServer uses mapWithState.
   b. SparkStructuredStateModelServer implements multi-loop approach

Comparing Implementations

1. *Akka Streams* with Akka is a *library* providing great flexibility for implementations and deployments, but requires custom implementations for scaling and failover.
   - More flexibility, but more responsibility (i.e., do it yourself)
2. *Flink* and *Spark Streaming* are stream-processing *engines* (SPE) that automatically leverage cluster resources for scaling and failover. Computations are a set of operators and they handle execution parallelism for you, using different threads or different machines.
   - Less flexibility, but less responsibility

We know Akka Streams best, but other streaming libraries, like Kafka Streams, could be used, too. Be sure they have the flexibility you need for the model serving patterns we discussed! If not, they are JUST libraries, so you can use other libraries to provide missing functionality. We've even used Akka with Kafka Streams…

The sub-bullets summarize the tradeoffs.

Spark vs Flink

1. *Flink*: iterations are executed as cyclic data flows; a program (with all its operators) is scheduled just once and the data is fed back from the tail of an iteration to its head. This allows Flink to keep all additional data locally.
2. *Spark*: each iteration is a new set of tasks/operators scheduled and executed. Each iteration operates on the result of the previous iteration which is held in memory. For each new execution cycle, the results have to be moved to the new execution processes.

https://hal.inria.fr/hal-01347638v2/document

Spark vs Flink

1. In *Flink*, all additional data is kept locally, so arbitrarily complex structures can be used for its storage (although serializers are required for checkpointing). The serializers are only invoked out of band.
2. In *Spark*, all additional data is stored external to each mini-batch, so it has to be marshaled/unmarshaled for every mini-batch (for *every message* in continuous execution) to make this data available.
3. *Spark Structured Streaming* is based on SQL data types, which makes data storage even more complex (JVM vs. SQL datatyping).

Outline

- Hidden technical debt in machine learning systems
- Model serving patterns
  - Embedding - models as code
  - Models as data
  - External services
  - Dynamically controlled streams
- Additional production concerns for model serving
- Wrap up

Additional Production Concerns for Model Serving

- Production implications for *models as data*
- Software process concerns, e.g., CI/CD
- Another pattern: speculative execution of models

Models as Data - Implications

- If models are data, they are subject to all the same *Data Governance* concerns as the data itself!
  - Security and privacy considerations
  - Traceability, e.g., for auditing
  - …

We'll just discuss these two aspects of the larger topic of data governance

Security and Privacy Considerations

- Models are intellectual property
  - So controlled access is required
- How do we preserve privacy in model-training, scoring, and other data usage?
  - See these papers and articles on privacy preservation

The “papers” link is to a Google Scholar search with several papers on privacy preserving techniques, like *differential privacy.*

Model Traceability - 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**

We mentioned this example before. ”Explainability” is an important problem in Deep Learning; knowing why the model produced the results it produced.

Model Traceability Requirements

- A model repository
- Information stored for each model instance, e.g.:
  - Version ID
  - Name, description, etc.
  - Creation, deployment, and retirement dates
  - Model parameters
  - Quality metrics
  - …

Model Traceability in Use

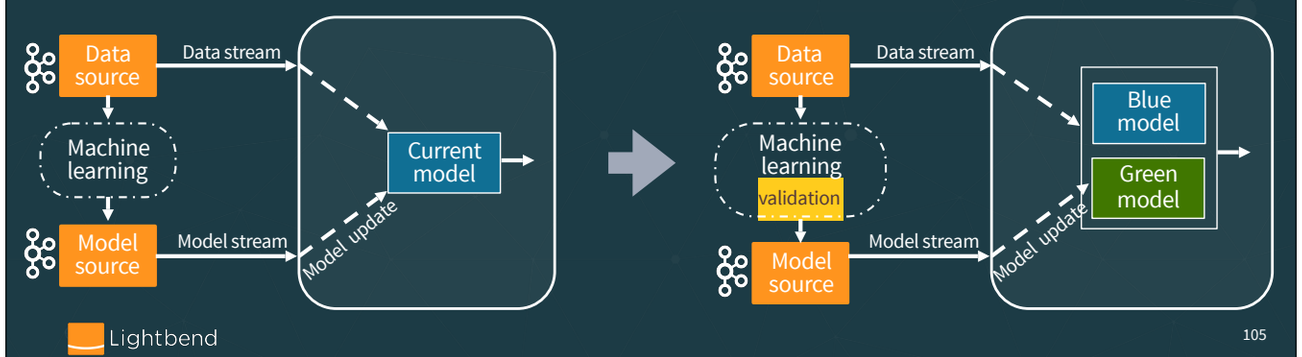
- You also need to augment the records with the model version ID, as well as the score.
  - Input Record

  - Output Record with Score, model version ID

You might be tempted to avoid this extra data; don’t you know the “deployment” date? This usually isn’t accurate enough to know which records were on the boundary of switchover, due to timestamp granularity, clock skew, etc.

Software Process

- How and when should new models be deployed? (CI/CD)
- Are there a quality control steps first?
- Should you do blue-green deployments, perhaps using a canary release as a validation step?



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Just the tip of the iceberg…

The blue-green deployments leads to our final topic…

Speculative Execution

According to Wikipedia, speculative execution is an **optimization** technique, where:

- 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.
- The results are discarded if they aren't needed.

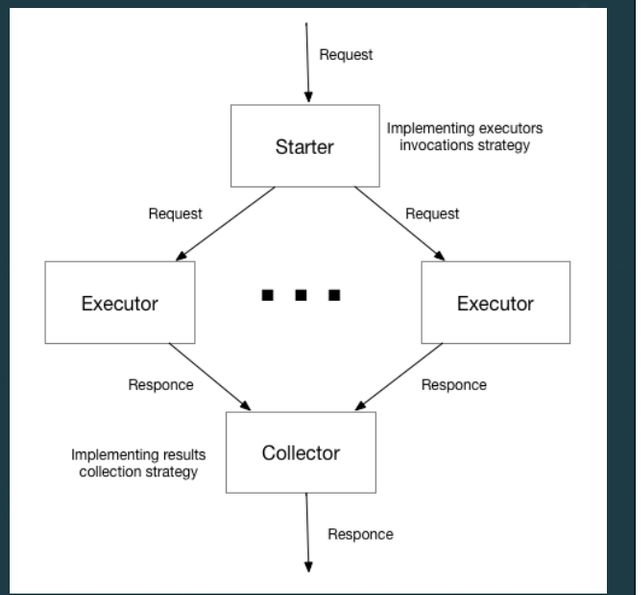
Speculative Execution

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

Why not use it with machine learning??

General Architecture for Speculative Execution

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

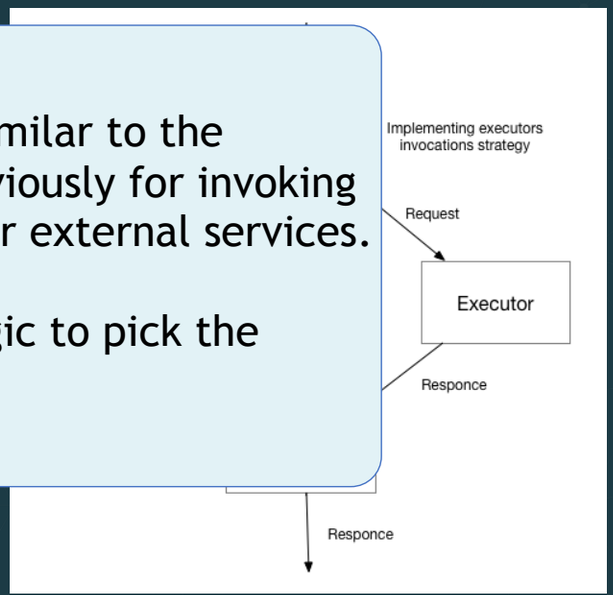


General Architecture for Speculative Execution

- Starter (p
  paralleli
  strategy
- Parallel e
- Collector
  bringing r
  together

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.



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Use Case - Guaranteed Execution Time

- I.e., meet a tight latency SLA
- Run several models:
  - A smart model, but takes time *T1* for a given record
  - A “less smart”, but faster model with a fixed upper-limit on execution time, with *T2* << *T1*
- If timeout (latency budget) *T* occurs, where *T2* < *T* < *T1*, return the less smart result
- But if *T1* < *T*, return that smarter result
  - (Is it clear why *T2* < *T* < *T1* is required?)

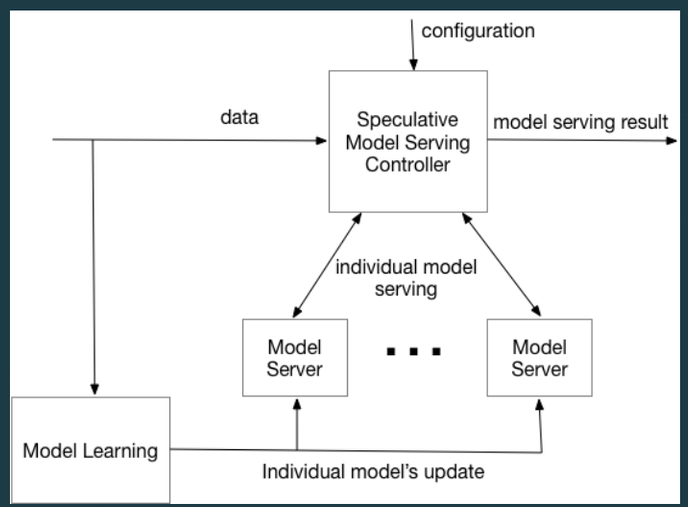
Because the timeout T has to be long enough that the fast model has time to finish, so T must be longer than T2, and this is only useful if T1 is often longer than T, our latency window.
This technique is “speculative”, because we try both models, taking a compromise result if the good result takes too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

Use Case - Ensembles of Models

- Consensus-based model serving
  - *N* models (*N* is *odd*)
  - Score with all of them and return the *majority* result
- Quality-based model serving
  - N models using the same *quality metric*
  - Pick the result for a given record with the best quality score
- Similarly for more sophisticated boosting and bagging systems

Consensus here is a majority vote system, a fairly crude *ensemble method*, while boosting and bagging are more sophisticated ensemble systems. Quality is roughly speaking an ensemble system, but here the models are treated independently, all with a quality metric, and the best score, based on that metric, is chosen.

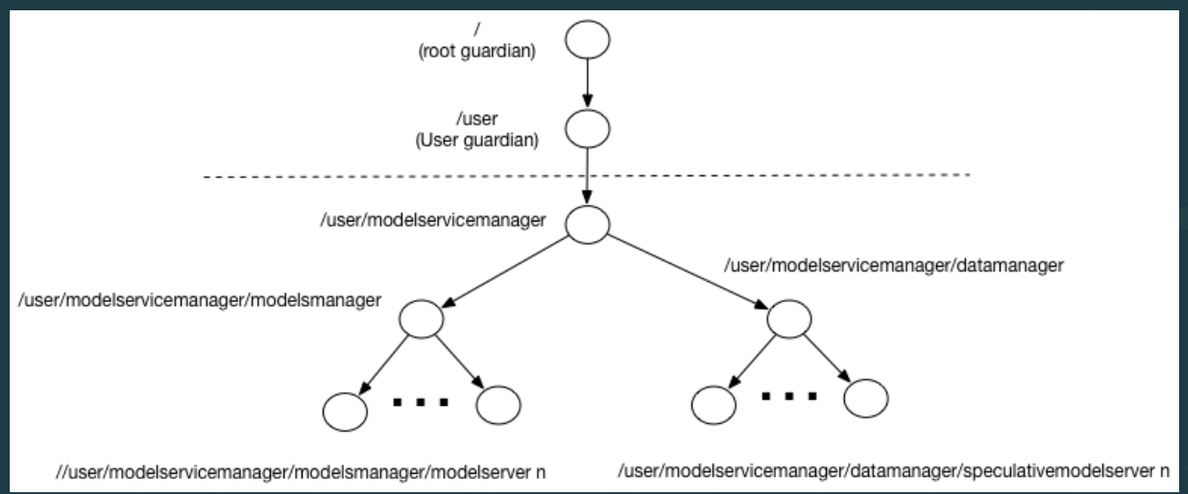
Architecture



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



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

The path-like strings are the Akka way of defining a hierarchy of actors and provide an abstract way to reference an actor that doesn't require you to know the actual process and machine where it's running.

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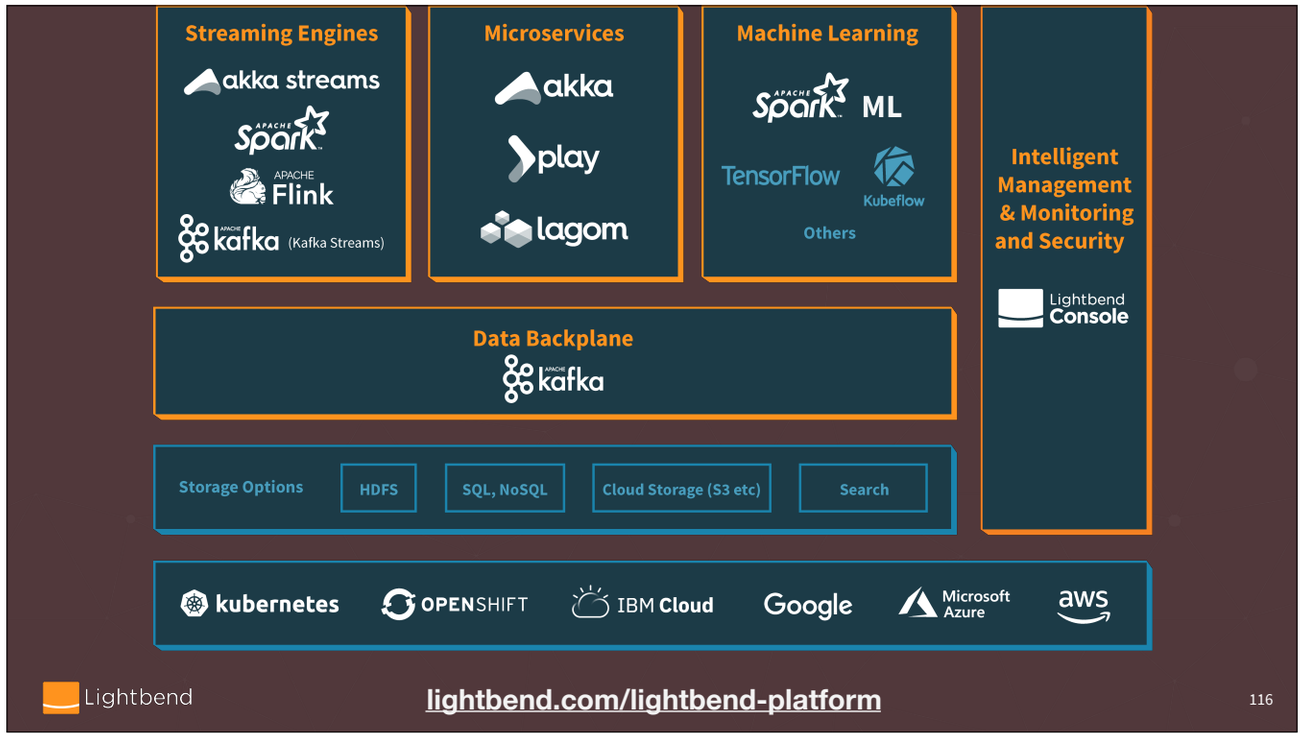
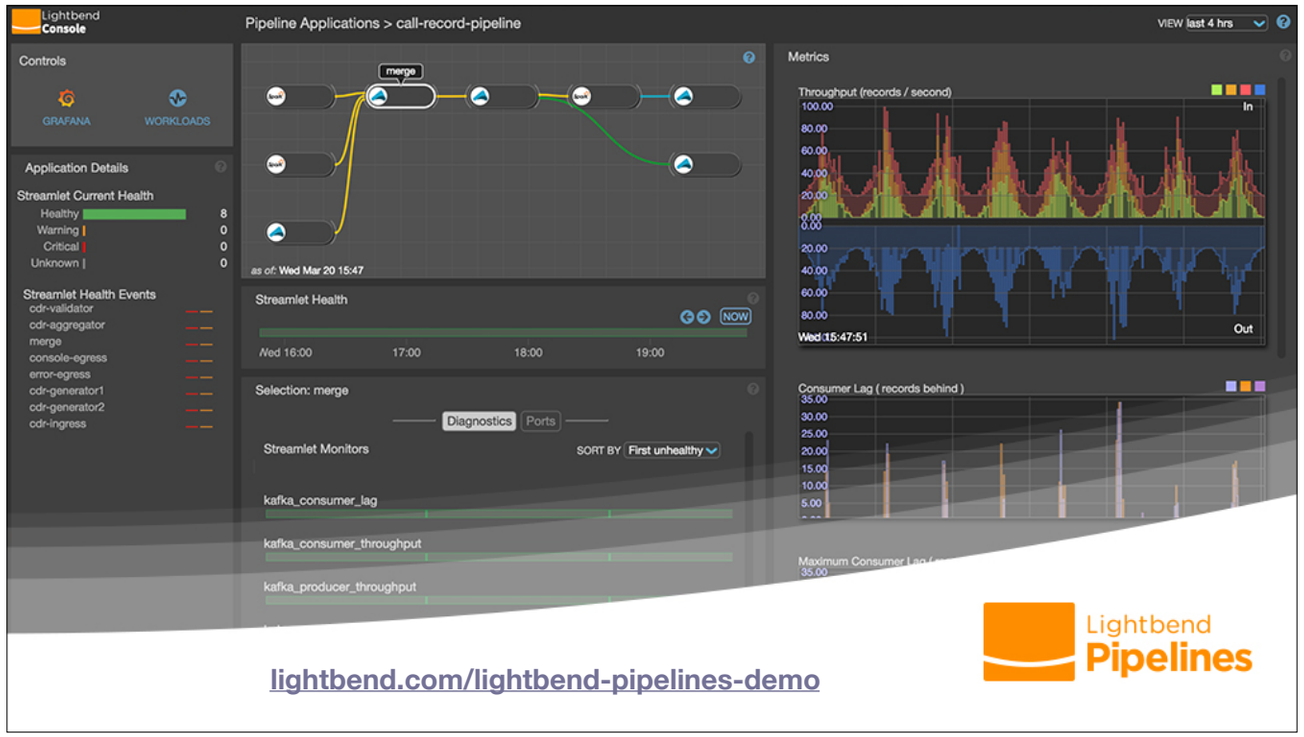
Recap

- Model serving is one small(-ish) part of the whole ML pipeline
- Use *logs* (e.g., Kafka) to connect most services
- *Models as data* provides the most flexibility
- Model serving can be implemented in “general” microservices, like *Akka Streams*, or data systems, like *Flink* and *Spark*
- Model serving can be *in-process* (embedded library) or an *external service* (e.g., TensorFlow Serving)
- Production concerns include integration with your CI/CD pipeline and data governance

Some of the main points we discussed.


Streaming Engines
akka streams
Spark
Flink
kafka (Kafka Streams)
Microservices
akka
play
lagom
Machine Learning
Spark ML
TensorFlow
Kubeflow
Others
Intelligent Management & Monitoring and Security
Lightbend Console
Data Backplane
kafka
Storage Options
HDFS
SQL, NoSQL
Cloud Storage (S3 etc)
Search
kubernetes
OPENSHIFT
IBM Cloud
Google
Microsoft Azure
aws
Lightbend
lightbend.com/lightbend-platform


Lightbend Console
Pipeline Applications > call-record-pipeline
VIEW last 4 hrs
Controls
GRAFANA
WORKLOADS
Application Details
Streamlet Current Health
Healthy 8
Warning 0
Critical 0
Unknown 0
Streamlet Health Events
cdr-validator
cdr-aggregator
merge
console-egress
error-egress
cdr-generator1
cdr-generator2
cdr-ingress
merge
as of: Wed Mar 20 15:47
Streamlet Health
NOW
Wed 16:00
17:00
18:00
19:00
Selection: merge
Diagnostics
Ports
Streamlet Monitors
SORT BY First unhealthy
kafka_consumer_lag
kafka_consumer_throughput
kafka_producer_throughput
Metrics
Throughput (records / second)
In
Out
Wed 15:47:51
Consumer Lag (records behind)
Maximum Consumer Lag
lightbend.com/lightbend-pipelines-demo
Lightbend Pipelines

Thanks for Coming! Questions?

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Don’t miss:

- Holden Karau, *et al., Cross-Cloud Model Training and Serving with Kubeflow,* this afternoon! room 2007
- Sean Glover, *Put Kafka in Jail with Strimzi* 4:20pm–5:00pm Wednesday. room 2006
- Dean Wampler, *Executive Briefing: What it takes to use machine learning in fast data pipelines* 3:50pm–4:30pm Thursday. room 2020

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Thank you! Please check out the other sessions with Dean and our colleague Sean Glover. Also, Holden, et al. have a tutorial this afternoon on Kubeflow. Check out our Fast Data Platform for commercial options for building and running microservices (with or without ML) using Kafka, Spark, Flink, Akka Streams, and Kafka Streams.