Executive Briefing: What it takes to use machine learning in fast data pipelines

Dean Wampler, Ph.D.
dean@lightbend.com
polyglotprogramming.com/talks

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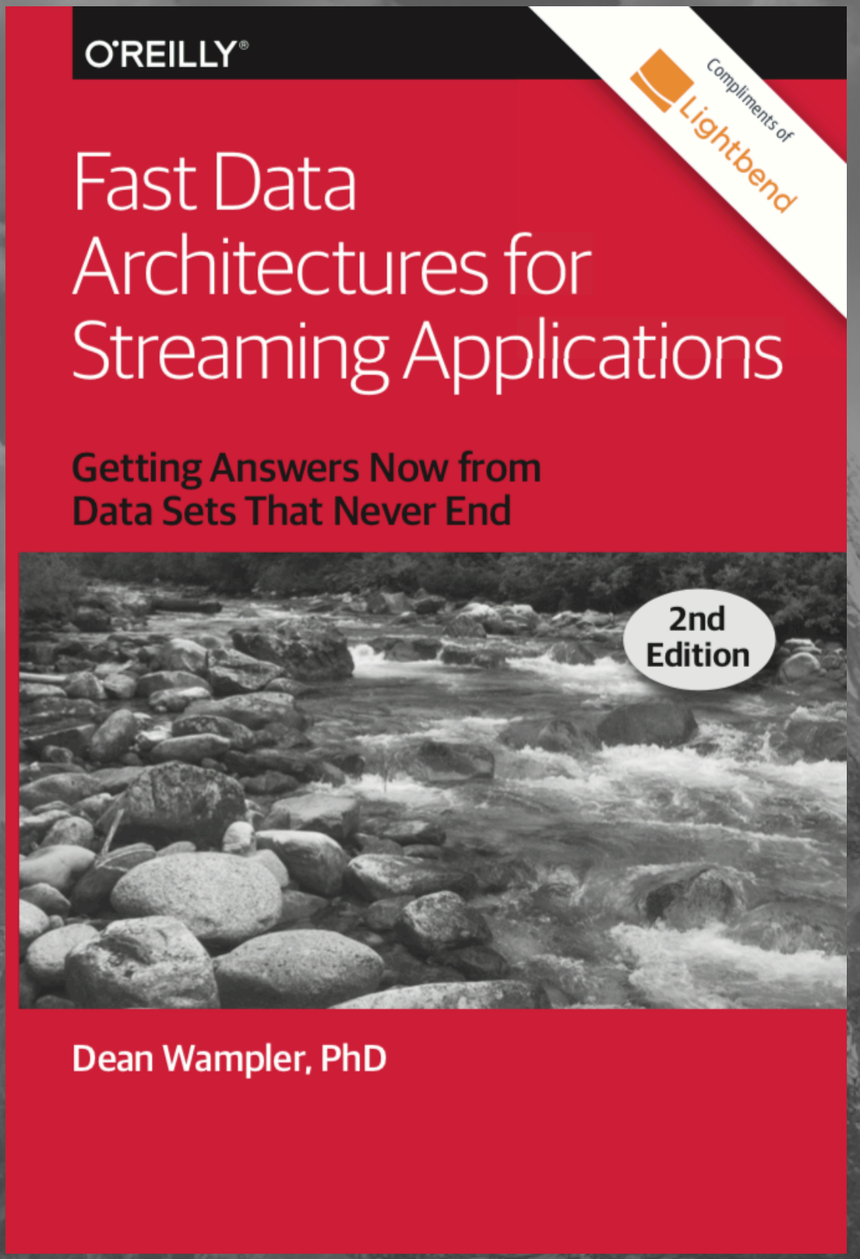
Data Streaming, in General

lbnd.io/fast-data-ebook



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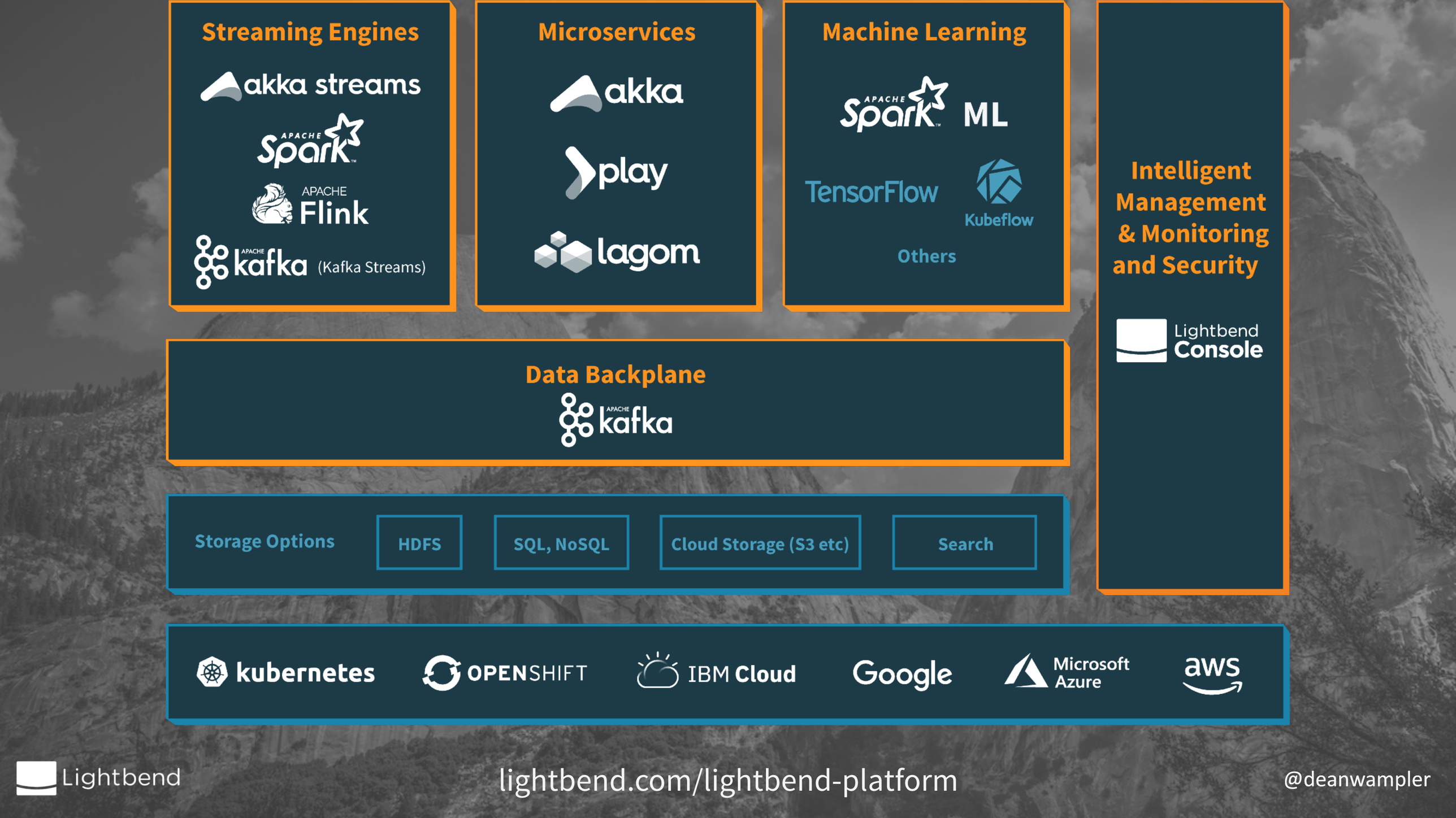
Streaming Engines
akka streams
Spark
Flink
kafka (Kafka Streams)
Microservices
akka
play
lagom
Machine Learning
Spark ML
TensorFlow
Kubeflow
Others
Intelligent Management & Monitoring and Security
Lightbend Console
Data Backplane
kafka
Storage Options
HDFS
SQL, NoSQL
Cloud Storage (S3 etc)
Search
kubernetes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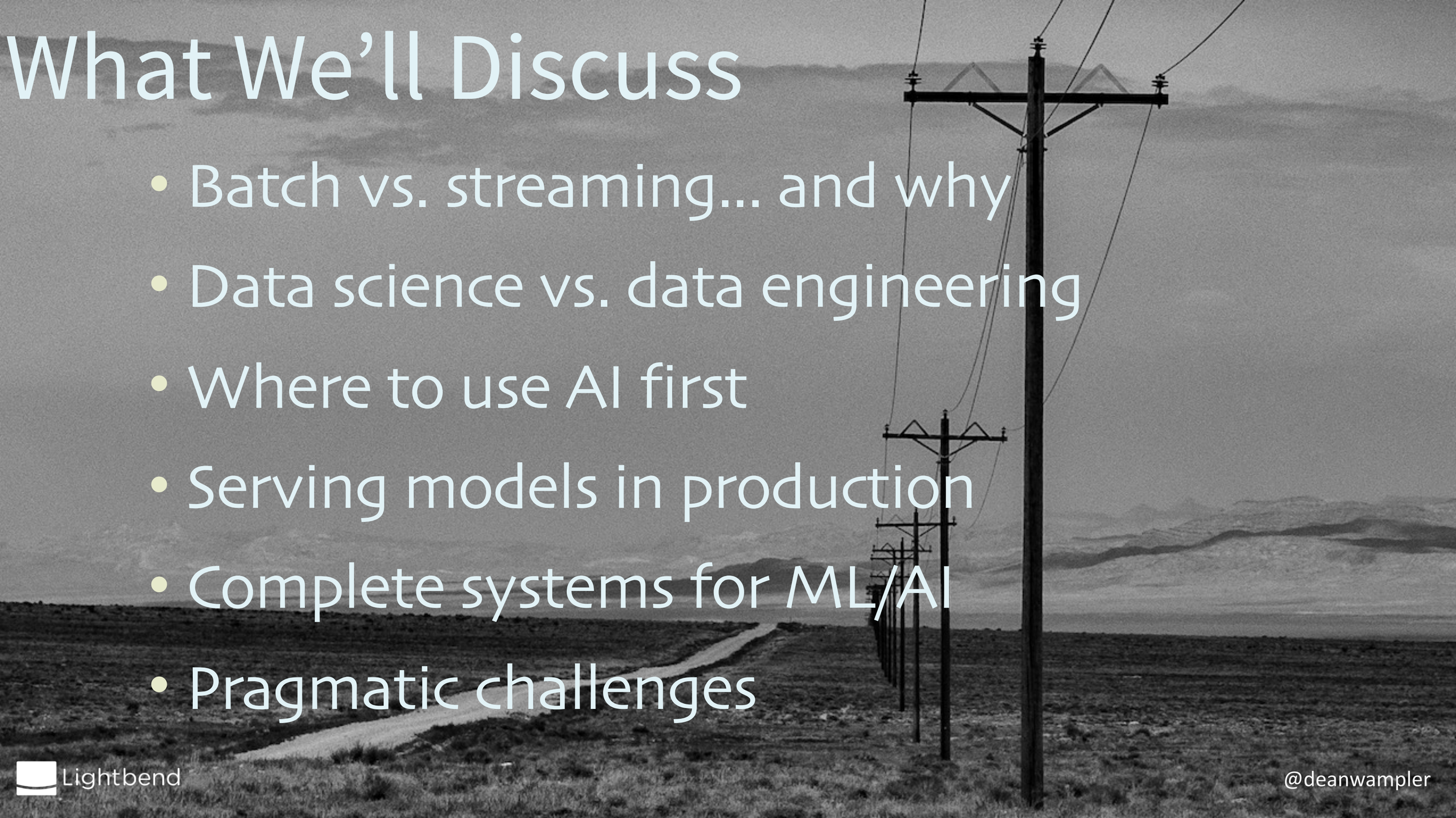
What we're up to at Lightbend…
lightbend.com/lightbend-pipelines-demo

Lightbend Pipelines

What We'll Discuss

- Batch vs. streaming... and why
- Data science vs. data engineering
- Where to use AI first
- Serving models in production
- Complete systems for ML/AI
- Pragmatic challenges



Batch vs. streaming… and why

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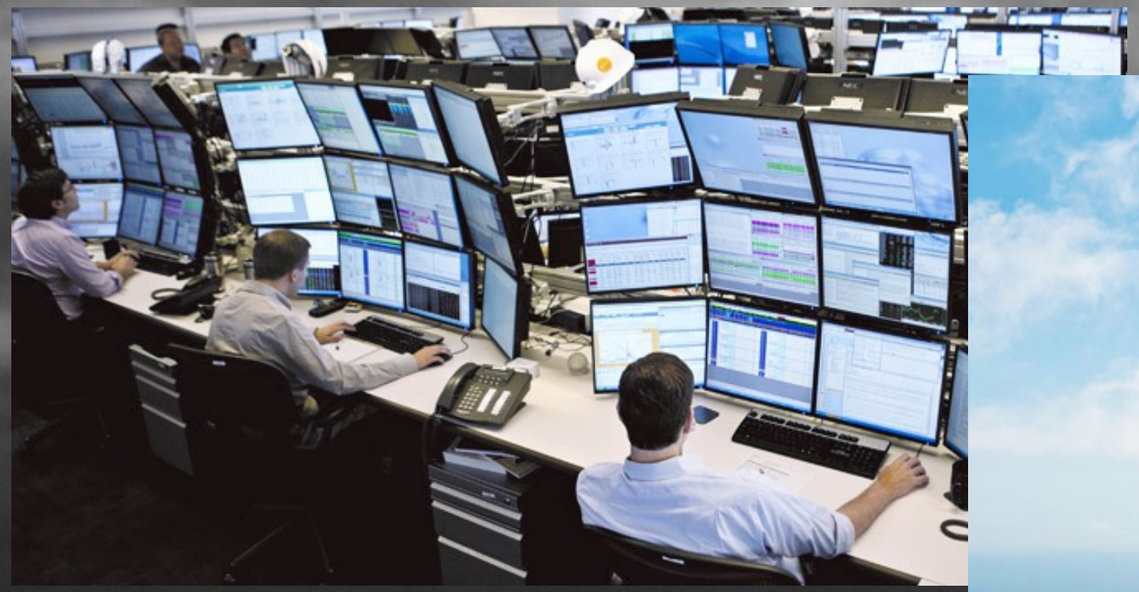

Finance

Telecom

Medical

Energy

... and IoT

State of the art phone!

Mobile

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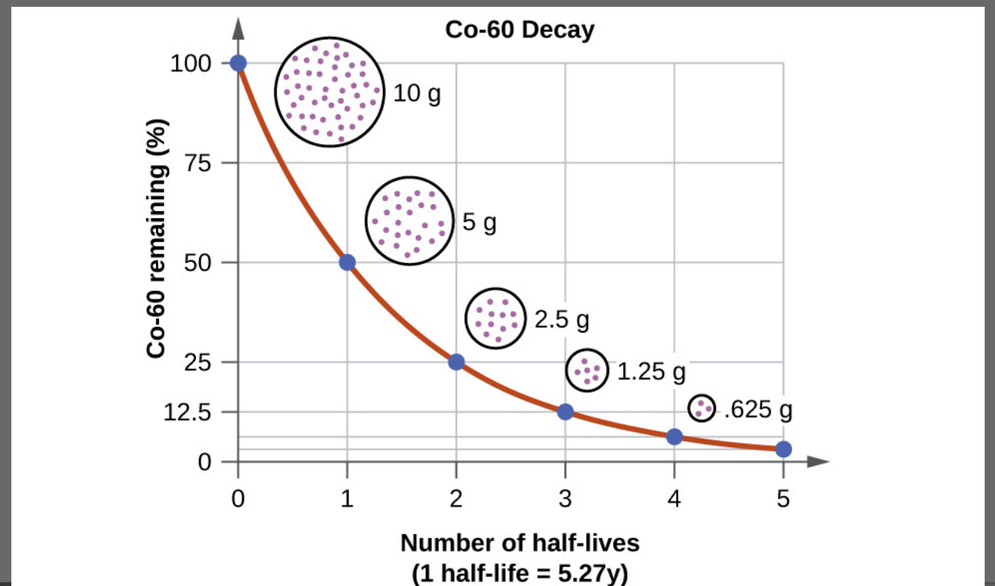
Information value has a half life; it decays with time




Data Science vs.
Data Engineering
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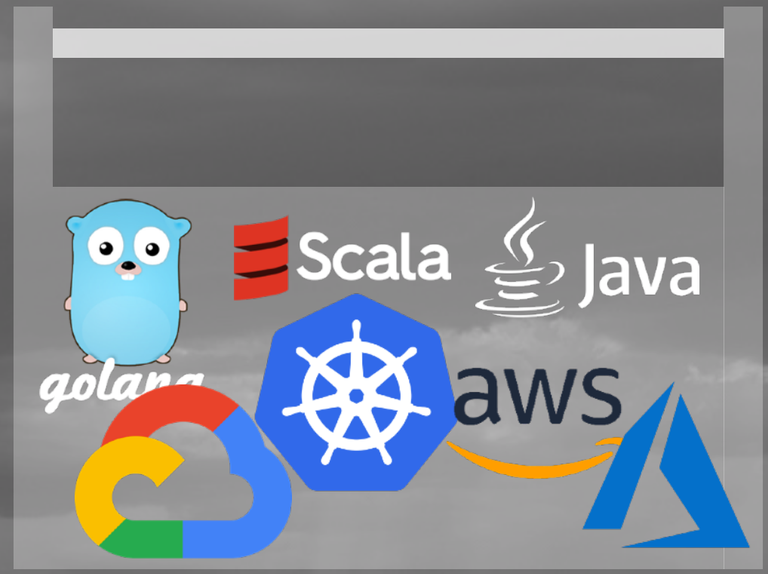
Data Science toolbox



Software Engineering toolbox

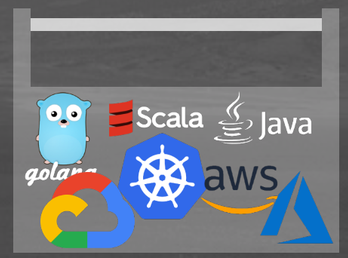
Data Scientists

- Comfortable with uncertainty
- Less process oriented
  - Iterative, experimental

Data Engineers

- Uncomfortable with uncertainty
- Process oriented
  - Agile Manifesto
  - … which does not mention data!

https://derwen.ai/s/6fqt




Furthermore, Streaming
Imposes New Requirements
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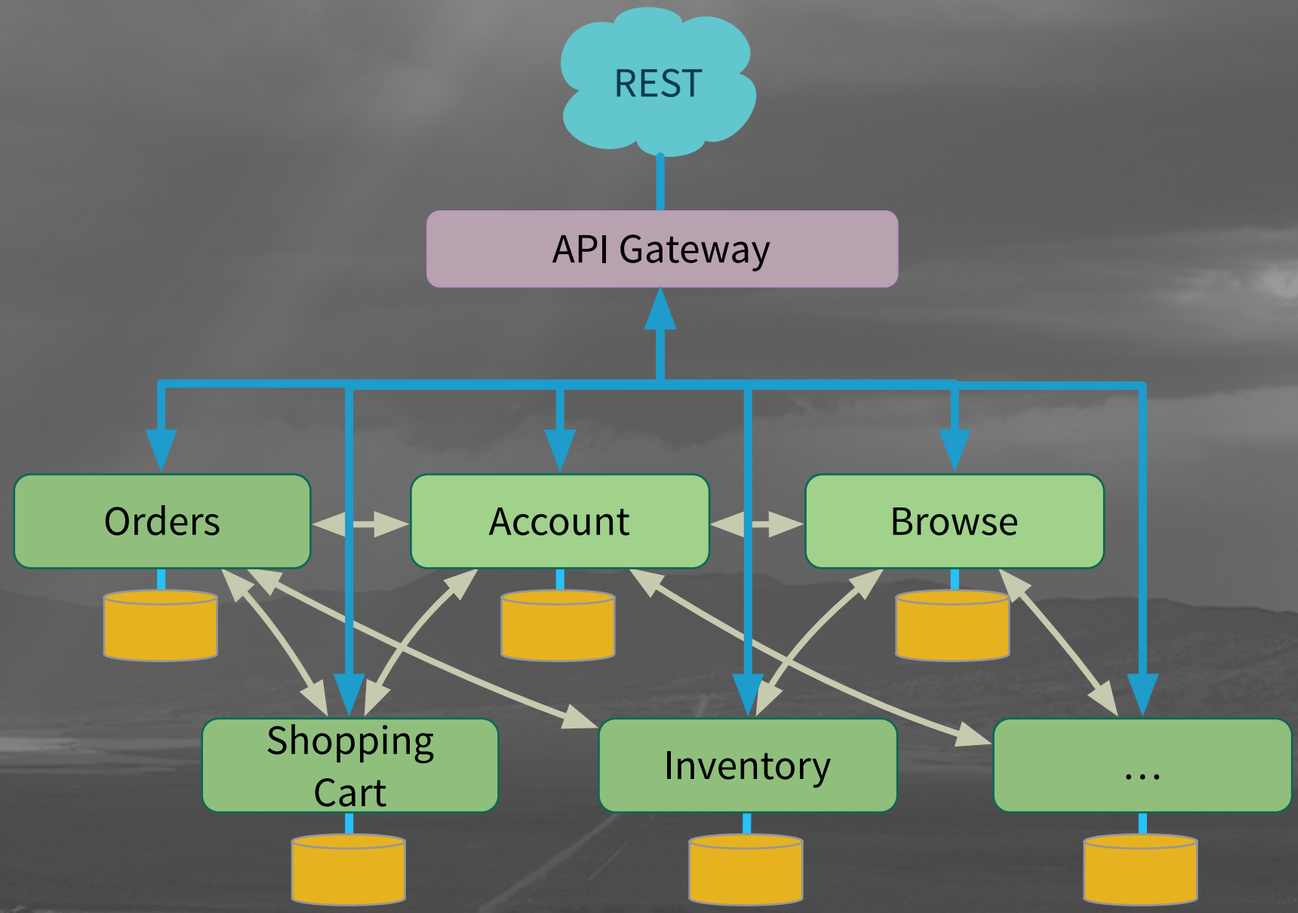
- Reliability - fault and "surprise" tolerant
- Availability - "always on"
- Low latency - for some definition of "low"
- Scalability - up and down
- Adaptability - ideally without restarts

Reminds Me of Microservices



Where to Apply AI First

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- "AI in the enterprise will build upon existing analytic applications."
  - Hybrid systems: enhance existing analytics with ML/AI models.

https://www.oreilly.com/ideas/9-ai-trends-on-our-radar

- Should we integrate legacy "expert systems" and how?

Serving Models in Production

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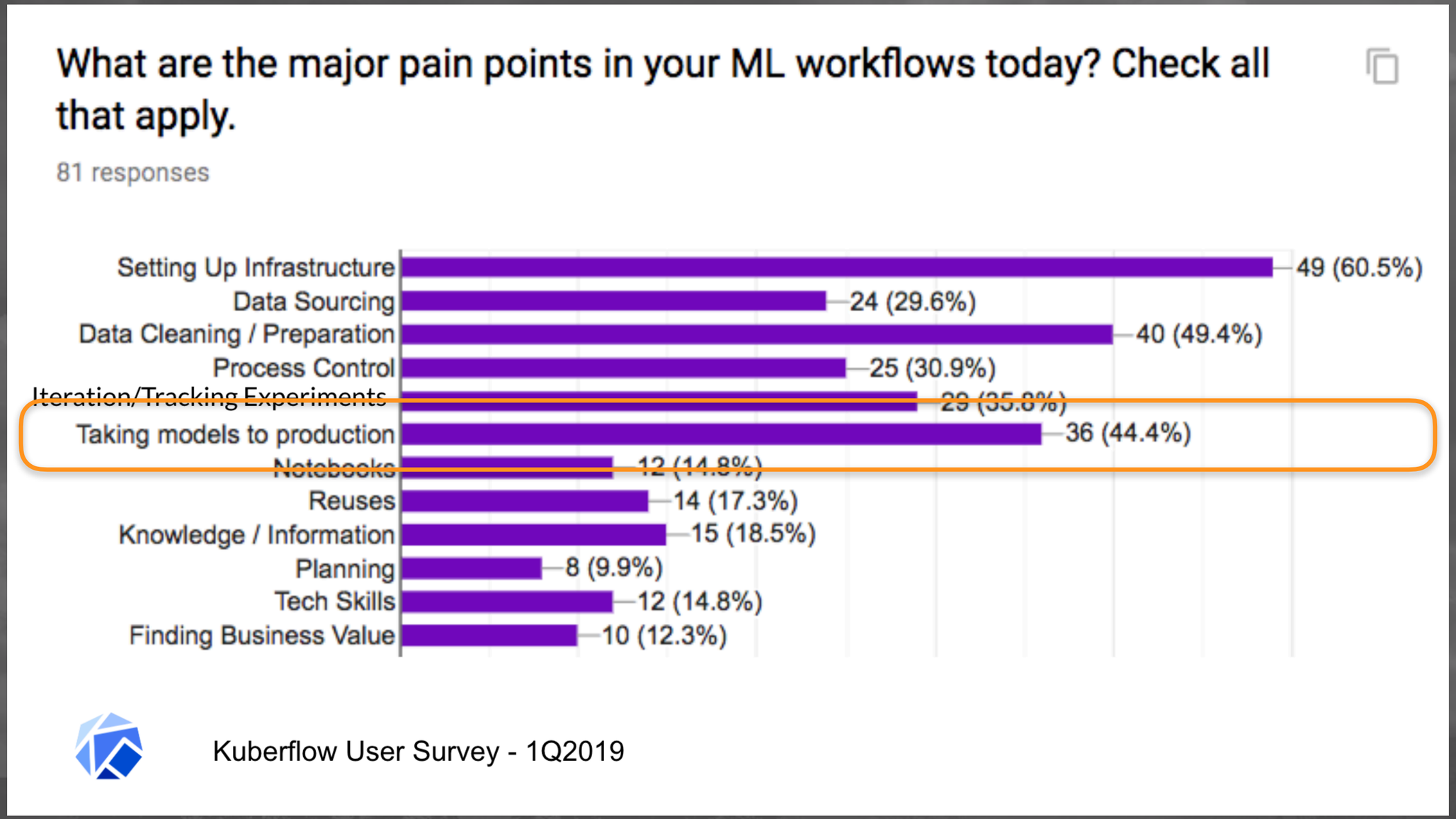
A Recent Kubeflow User Survey



From this Kubeflow Overview

Lack of Tool/Process Integration

- ~60% worry about missed opportunities
- ~50% worry about loss of data team productivity
- ~45% worry about slow time-to-market
- ~40% worry about customer dissatisfaction

From a forthcoming Lightbend survey

CI/CD Processes Required (1/3)

- Version control - for models and code
- Automated builds, tests and other quality checks, artifact delivery
- Launch Configurations: "dark" launches, A/B and other testing scenarios

CI/CD Processes Required (2/3)

- Monitoring
  - Performance overhead
  - Quality metrics match expectations from training?

CI/CD Processes Required (3/3)

- Auditing
  - Which model used to score this record?
  - Which records used to train this model?
  - Who accessed this model and when?

CI/CD Processes Required (3/3)

- Au
  - M
  - M
  - M

Models

Are

Data

But What's Different? (1/2)

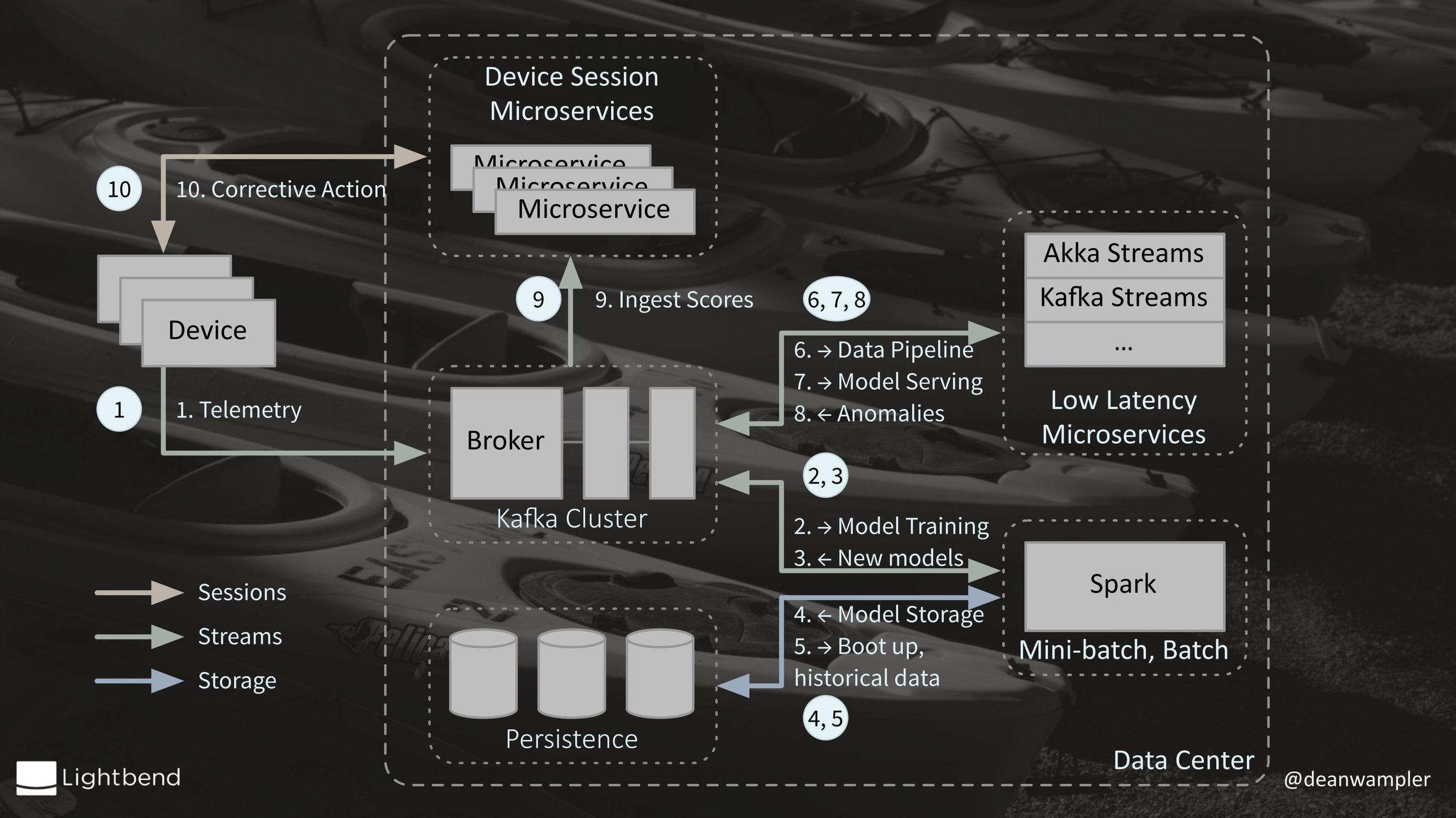
- Automation of model search, experimentation
  - E.g., hyperparameter tuning
- Data safety, fairness, and lineage
- Automation needs to measure reliability, SLAs,
- Reproducibility

https://www.oreilly.com/ideas/9-ai-trends-on-our-radar

But What's Different? (2/2)

How to integrate the extra indeterminacy in a DevOps world that prefers determinacy?

Example Architectures


Device Session Microservices
Microservice
Microservice
Microservice
10
10. Corrective Action
Device
1
1. Telemetry
9
9. Ingest Scores
Broker
Kafka Cluster
6, 7, 8
6. → Data Pipeline
7. → Model Serving
8. ← Anomalies
Akka Streams
Kafka Streams
...
Low Latency Microservices
2, 3
2. → Model Training
3. ← New models
Spark
Mini-batch, Batch
4. ← Model Storage
5. → Boot up, historical data
4, 5
Persistence
Sessions
Streams
Storage
Data Center
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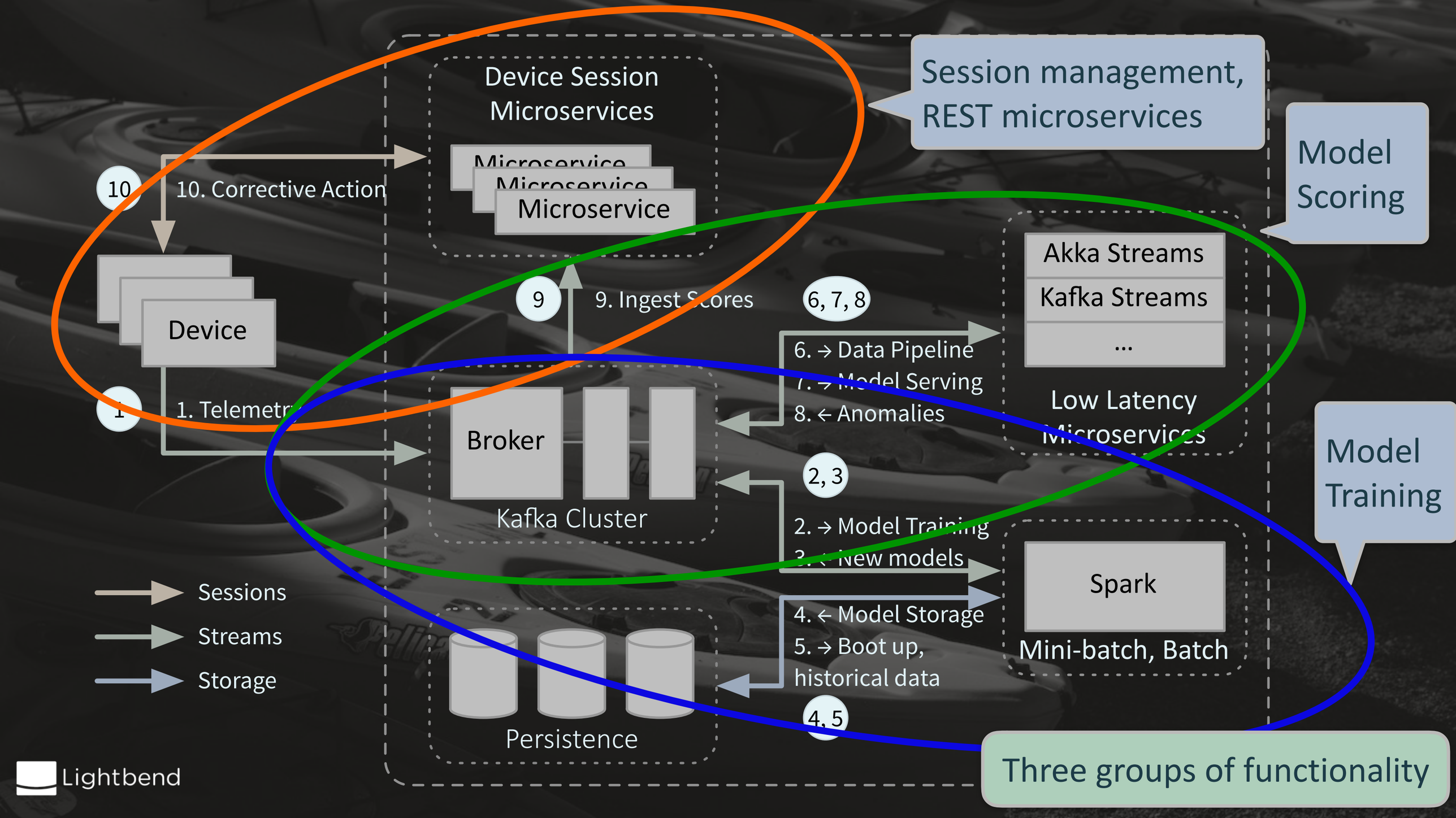
Session management, REST microservices
Model Scoring
Model Training
Device Session Microservices
Microservice
Microservice
Microservice
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10. Corrective Action
Device
1
1. Telemetry
9
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4. ← Model Storage
5. → Boot up, historical data
4, 5
Persistence
Sessions
Streams
Storage
Three groups of functionality
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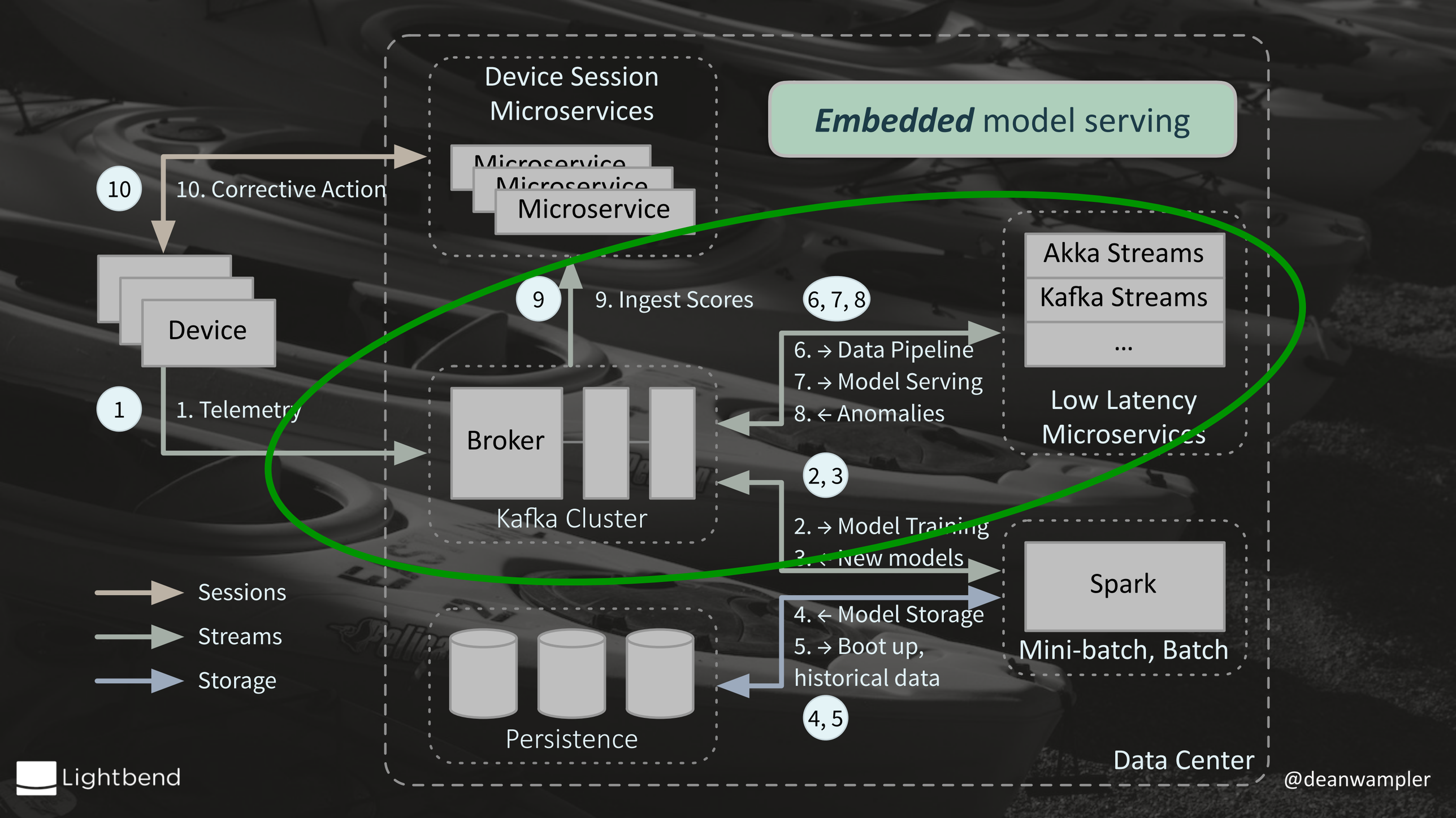
Device Session Microservices
Microservice
Microservice
Microservice
Embedded model serving
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9. Ingest Scores
6, 7, 8
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Persistence
Sessions
Streams
Storage
Data Center
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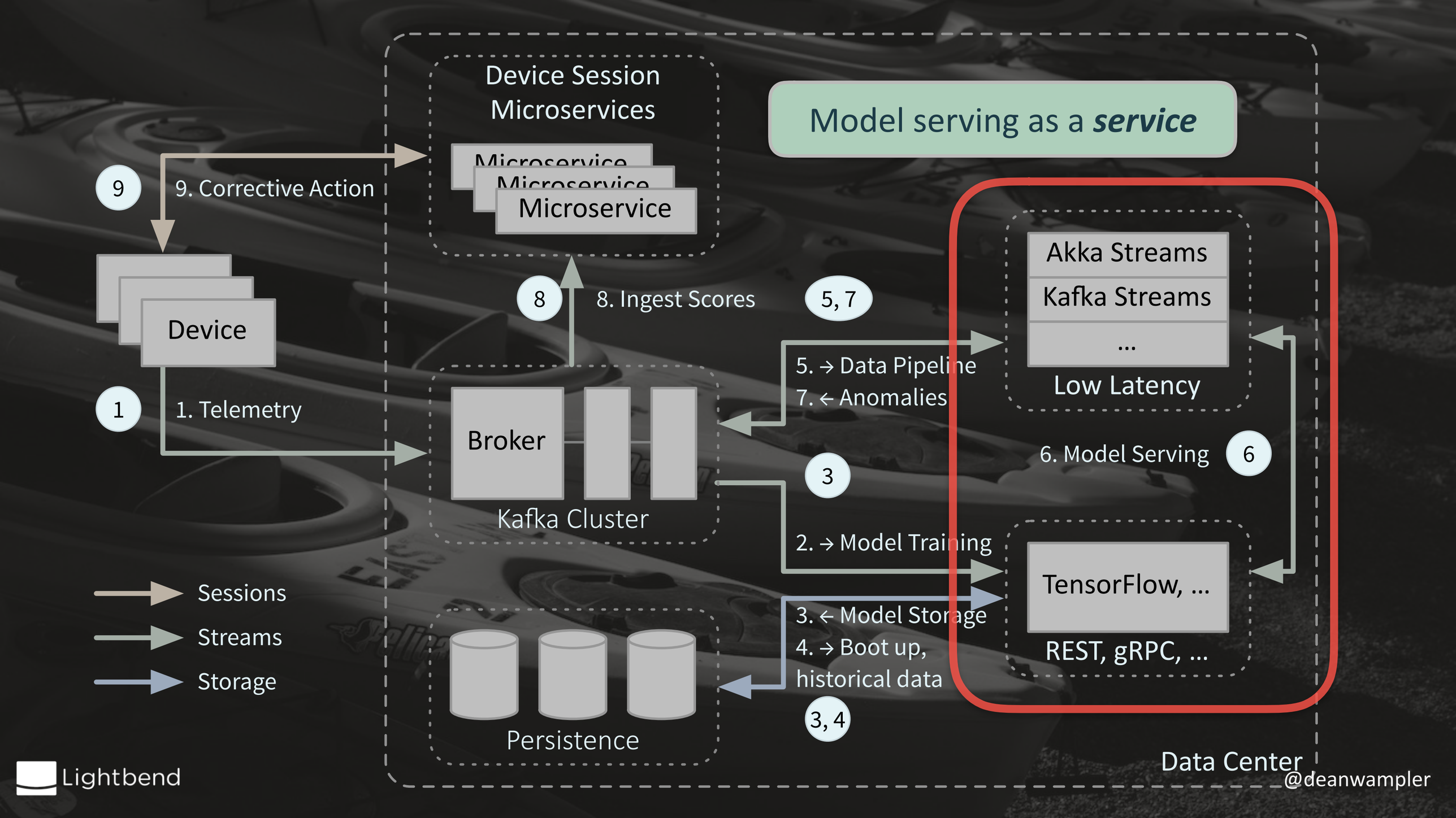
Model serving as a *service*
Device Session Microservices
Microservice
Microservice
Microservice
9
9. Corrective Action
Device
1
1. Telemetry
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8. Ingest Scores
Broker
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3
2. → Model Training
3. ← Model Storage
4. → Boot up, historical data
3, 4
Persistence
Akka Streams
Kafka Streams
...
Low Latency
6. Model Serving
6
TensorFlow, ...
REST, gRPC, ...
Sessions
Streams
Storage
Data Center
Lightbend
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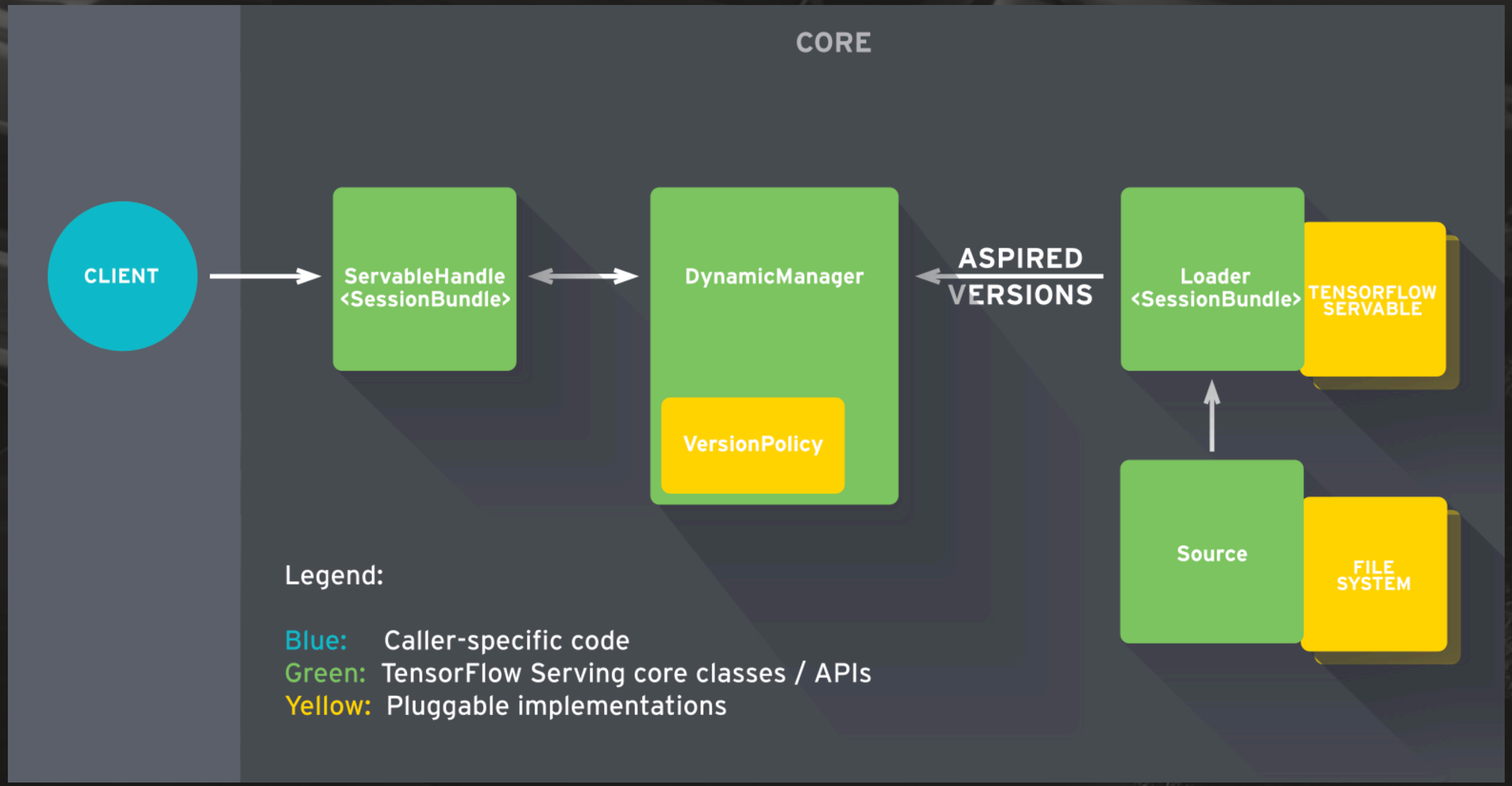
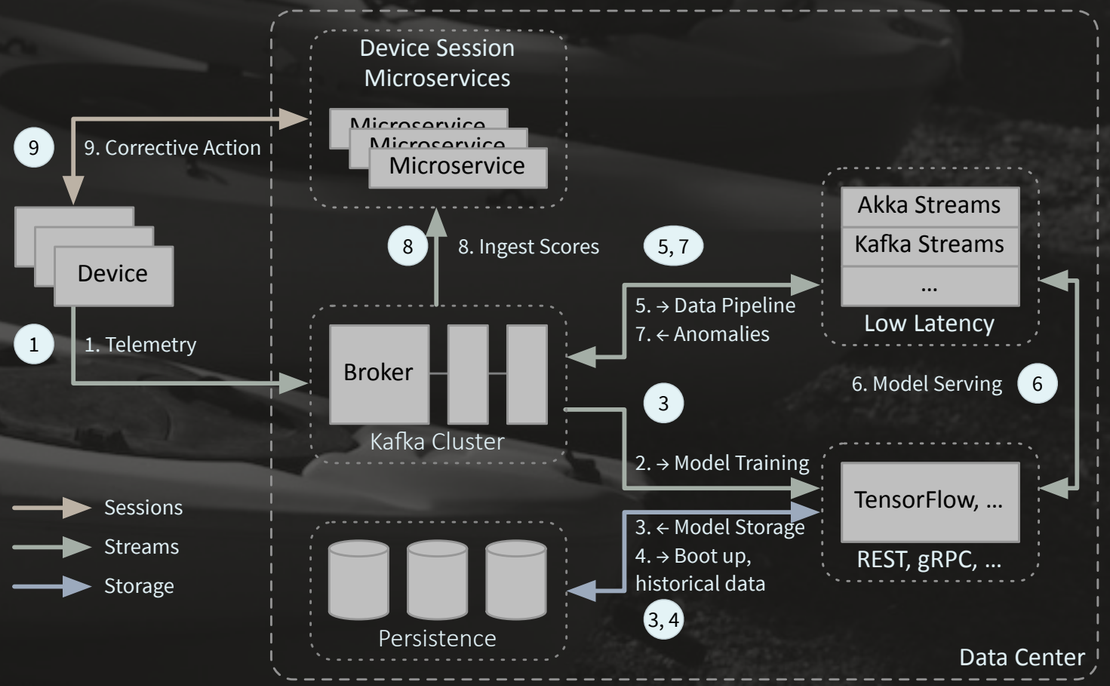
TensorFlow Serving



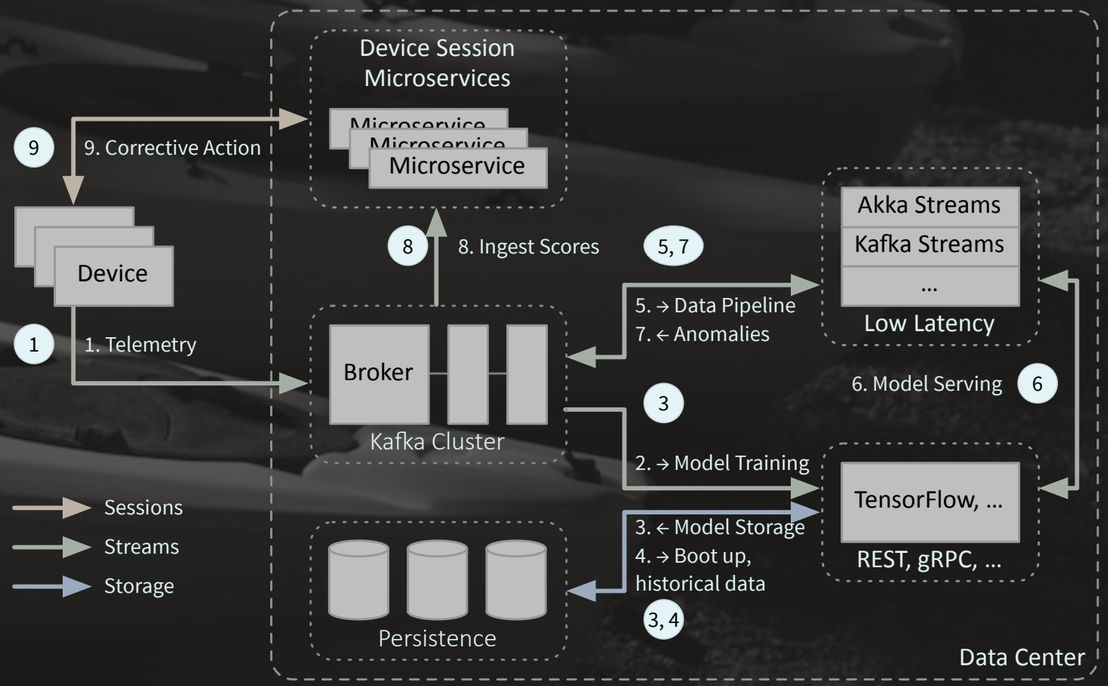
Model Serving as a Service

- Pros:
  - A familiar integration pattern
  - Decouples "concerns": AI tools, scalability, upgradability, …



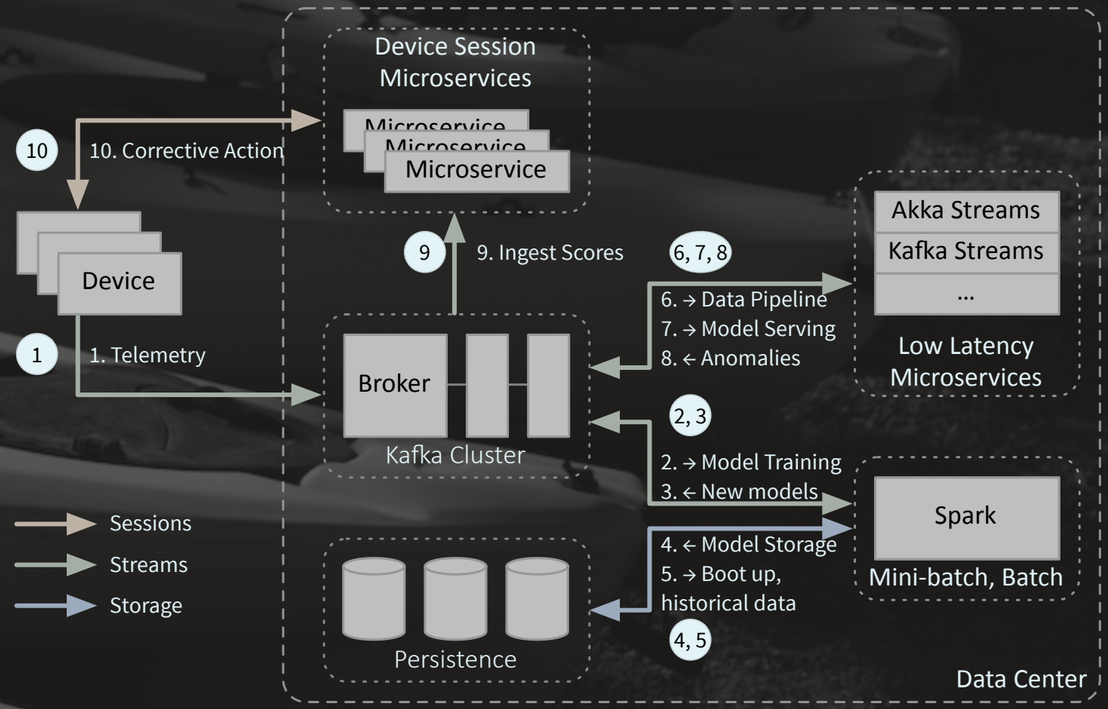
Model Serving as a Service

- Cons:
  - Overhead of invocation, e.g., REST
  - ML Pipeline becomes a unique production work flow



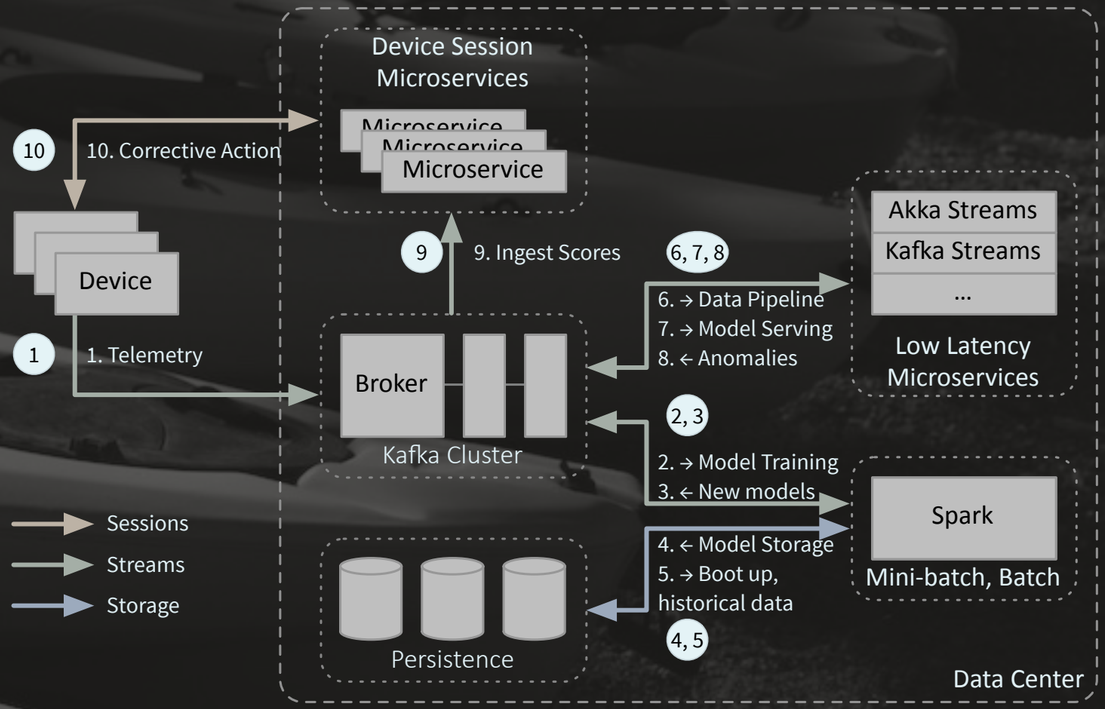
Embedded Model Serving

- Pros:
  - Lowest scoring overhead - interprocess communication only used for model updates
  - Performance tuning focuses on one system, the data pipeline

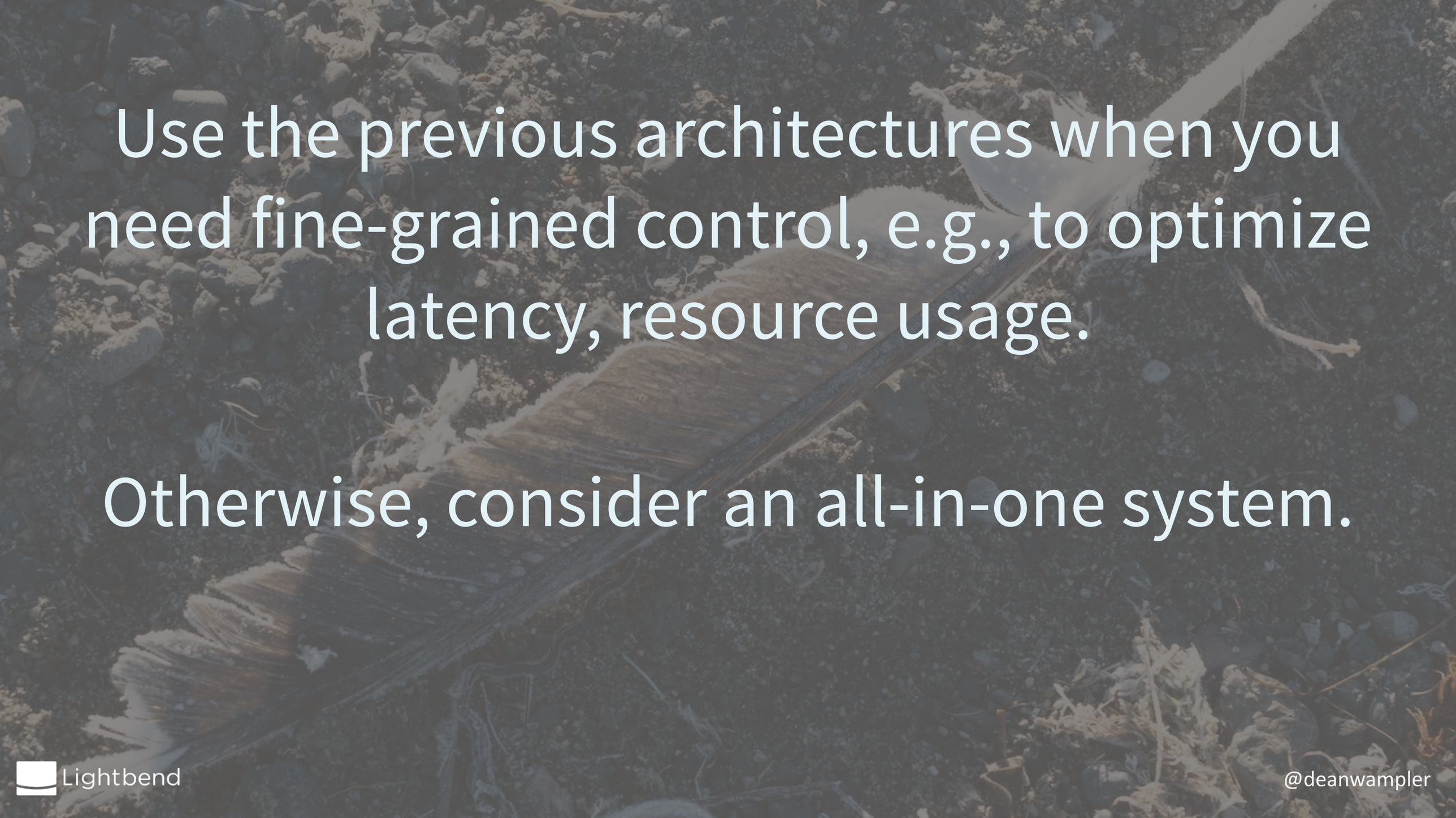


Embedded Model Serving

- Cons:
  - Model parameters must be serialized
  - Model serving library must be "compatible" with training system:
    - Algorithms, quality

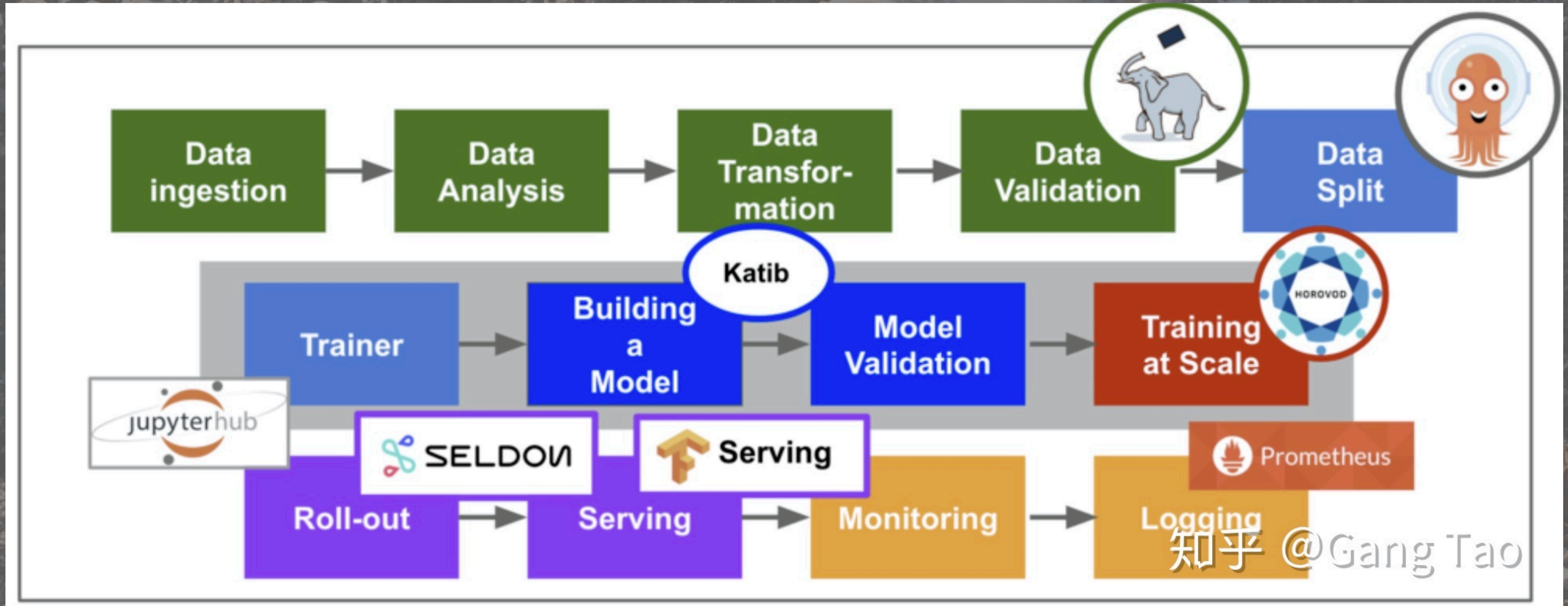



ML/AI Systems


Use the previous architectures when you need fine-grained control, e.g., to optimize latency, resource usage.
Otherwise, consider an all-in-one system.


• Kubeflow - for Kubernetes
• SageMaker - for AWS users
• MLFlow - from the Spark community
• …

Systems - Kubeflow



Pragmatic Challenges

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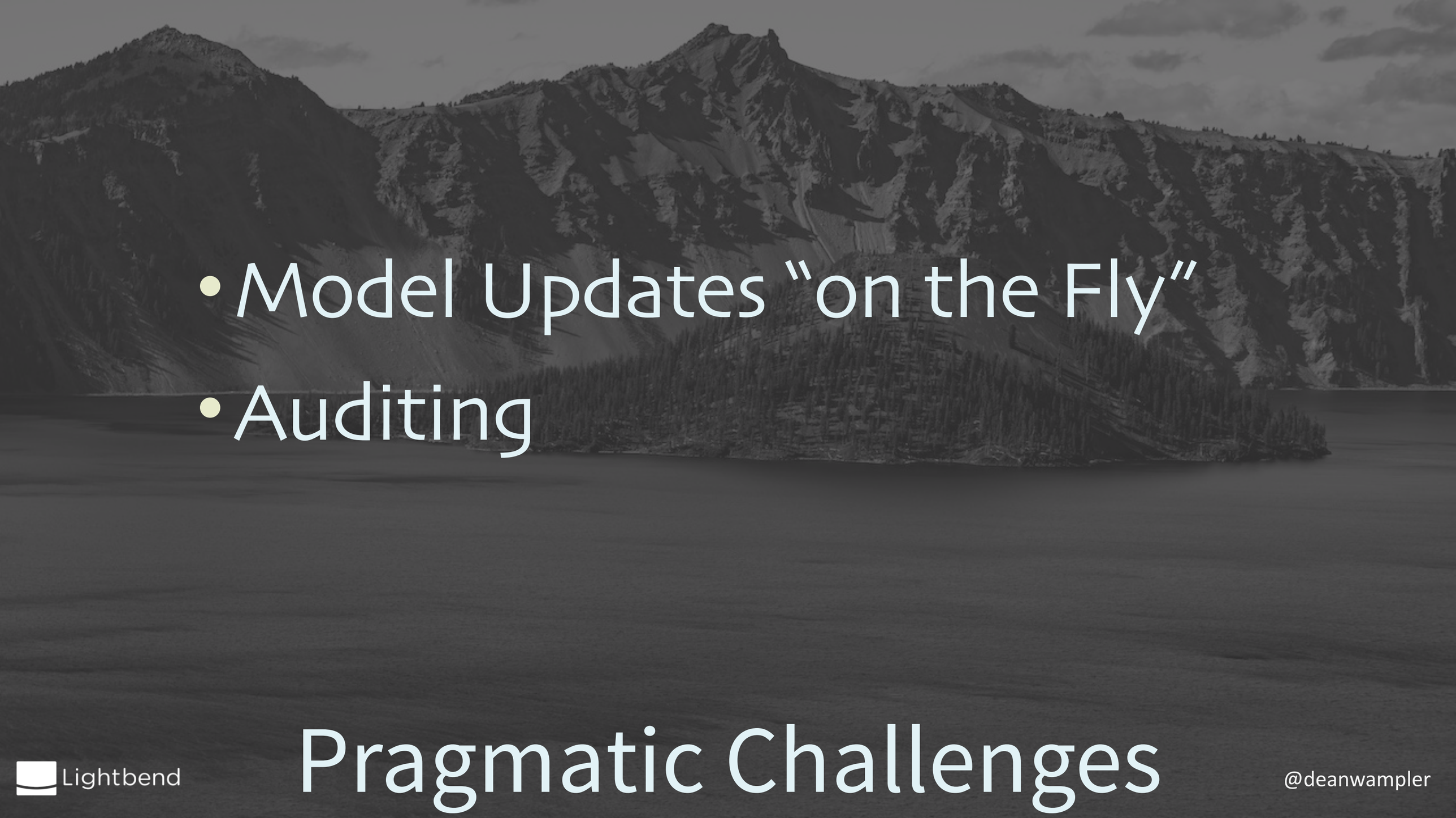


- Model Updates "on the Fly"
- Auditing

Pragmatic Challenges

Model Updates “on the Fly”

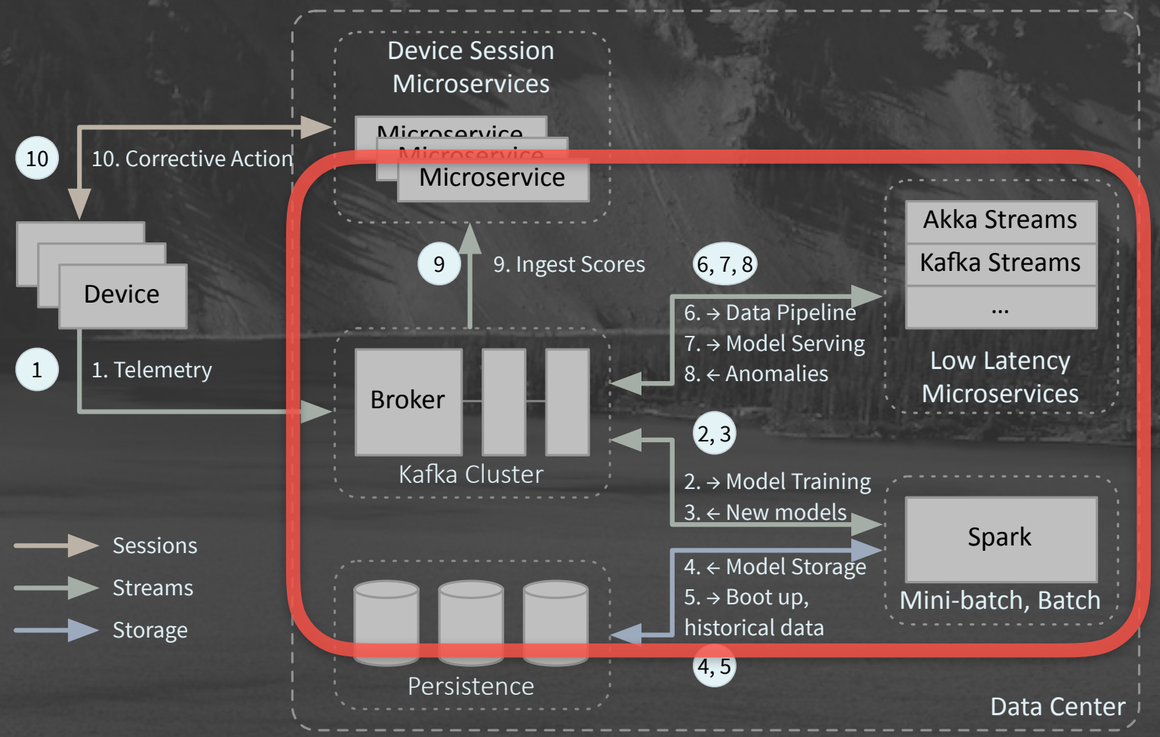
- “Concept Drift” - models grow stale
  - They have a “half life”, too
- Periodically retrain then serve the new model without downtime
  - (Continuous training is a research topic)

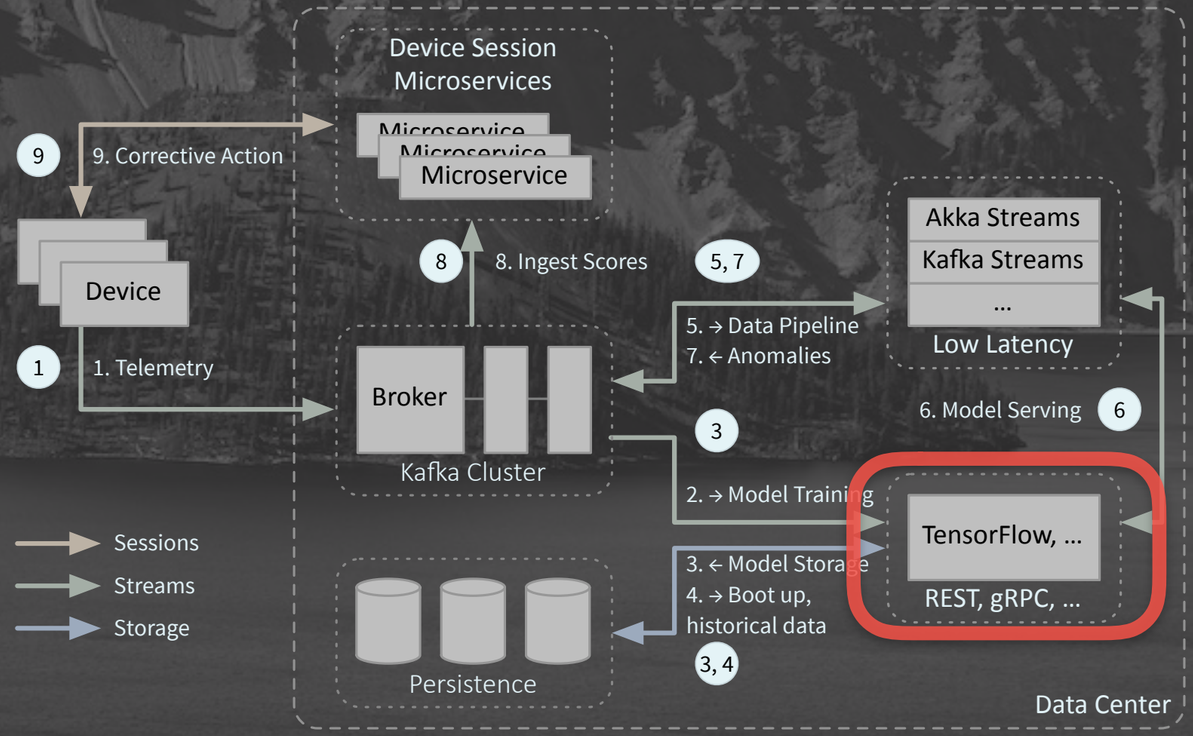
Retraining Considerations

- Trade off model performance vs. retraining cost
- How far back in the data set do you go?

Retraining Considerations

- Approaches:
  - Run "periodic" batch jobs - most mature
    - How far back in the data set do you go?
  - Online and incremental algorithms
  - Auto-adaptive ML (i.e., continual learning) - future capability





Complex to update embedded models!

Model updates can be straightforward

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Auditing

- Kind of Model
- Parameters and hyperparameters
- When trained
- Data used for training
- When deployed, undeployed, etc.
- …

Auditing

- Quality metrics
- Serving metrics (how many records, scoring times…)
- Provenance of decision to retrain
  - The metrics gathered above that were used to decide when to retrain


Dusty Milky Way
Mars last Summer

References

- Ideas:
  - Ben Lorica on 9 AI Trends
  - Paco Nathan's Data Governance Talk

References

- Ideas:
  - O'Reilly Radar: Data, AI, others
  - distill.pub
  - The Algorithm
  - The Gradient

References

- A few research papers, etc.
  - Incremental training
    - an example
  - Continual learning

References

- Kubeflow
- MLFlow
- DVC
- AWS SageMaker
- Fiddler (explainable AI)

References

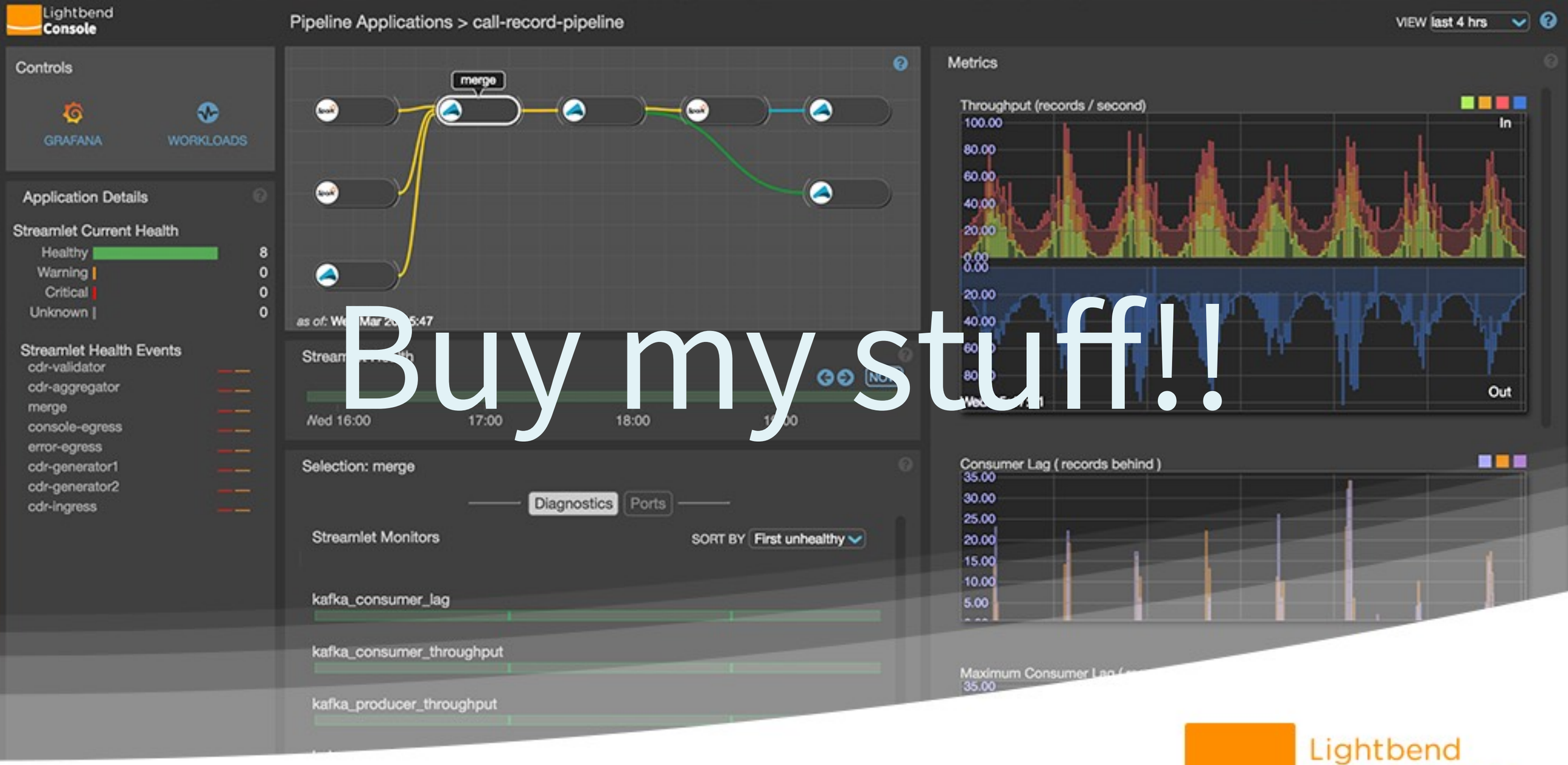
- General Information about Stream Processing
  - My O'Reilly Report on Architectures
  - Streaming Systems Book
  - Stream Processing with Apache Spark
  - Designing Data-Intensive Apps book

References

- Other Talks
  - Strata Talk on ML in a Streaming Context
  - Stream All the Things! (video)
  - Streaming Microservices with Akka Streams and Kafka Streams (video)

References

- Tutorials
  - Model serving in streams
  - Stream processing with Kafka and microservices



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Questions?

Dean Wampler, Ph.D.
dean@lightbend.com
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