goto; chicago Night

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

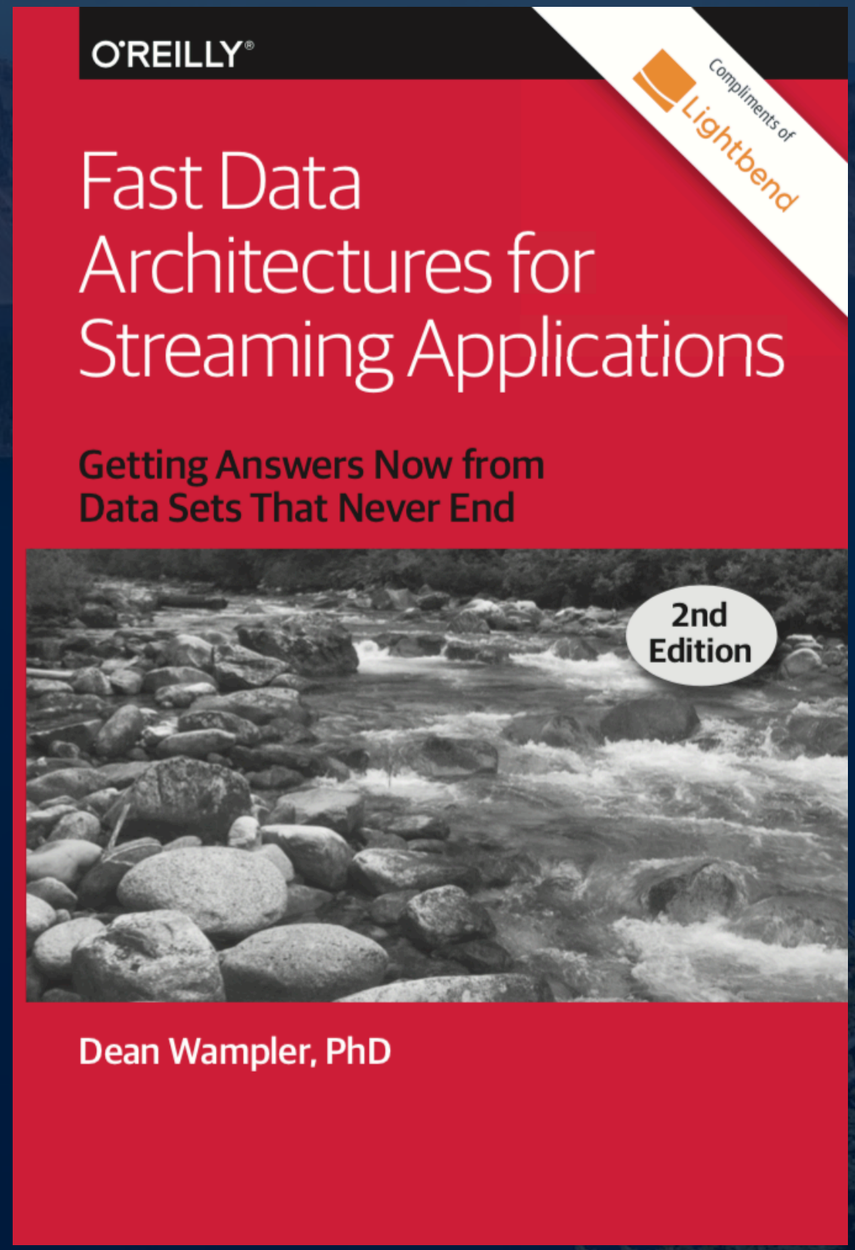
Trends Affecting System Architectures: Mobile Engagement, Streaming Data, and Machine Learning

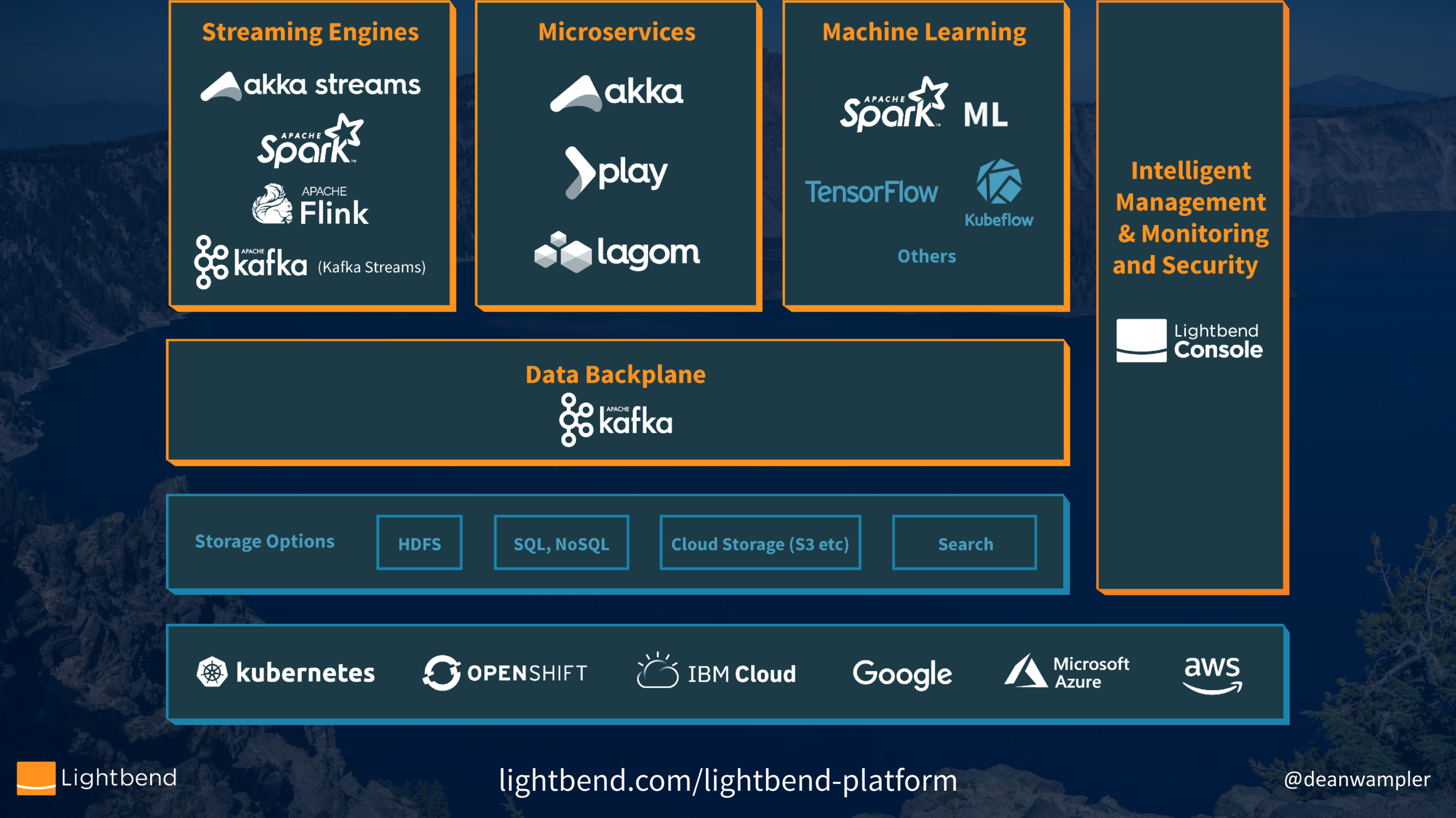
Lightbend

@deanwampler

Data Streaming Architectures

lbnd.io/fast-data-ebook




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
@deanwampler

What we're up to at Lightbend…
lightbend.com/lightbend-pipelines-demo

Lightbend Pipelines

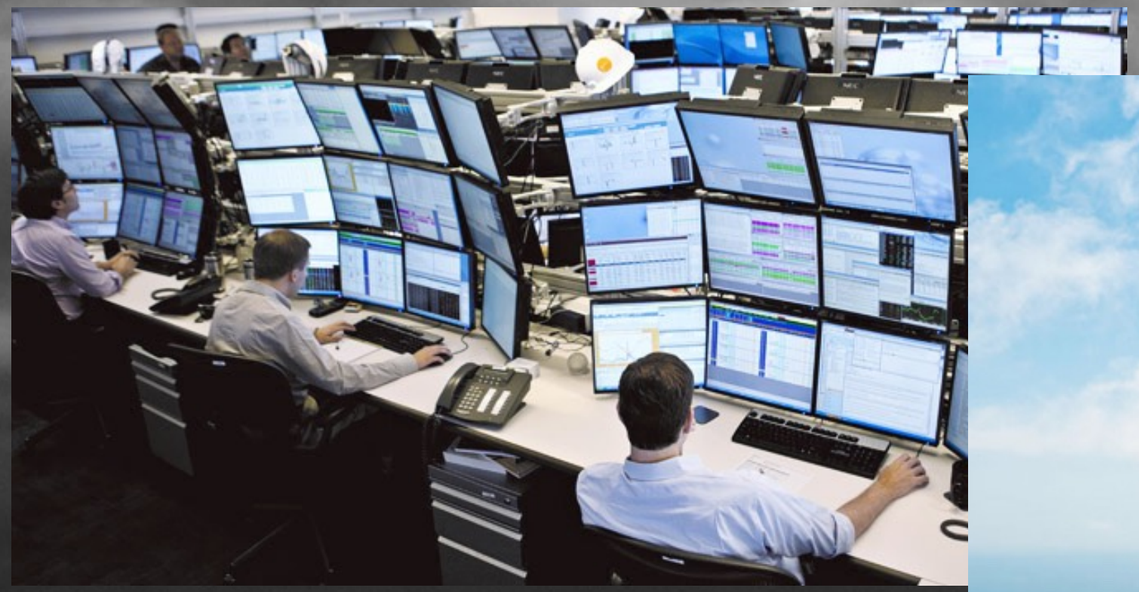
What We'll Discuss

Lightbend

What We'll Discuss

- Forces driving us towards stream processing
- Streaming architectures
  - Requirements
  - An example
- Mixing data science and data engineering
- Other production concerns

Forces driving us towards stream processing



Finance

Telecom

Medical

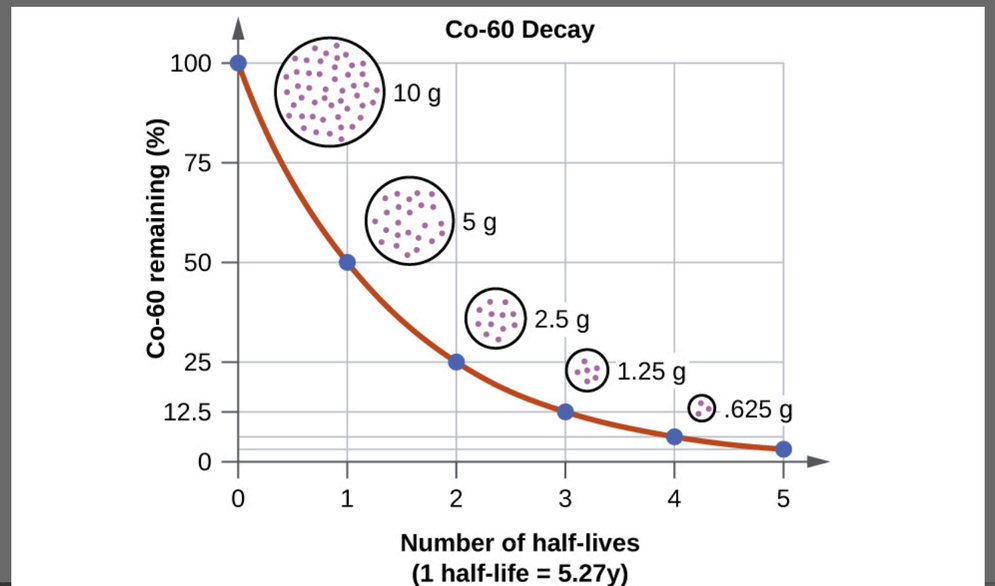
Energy

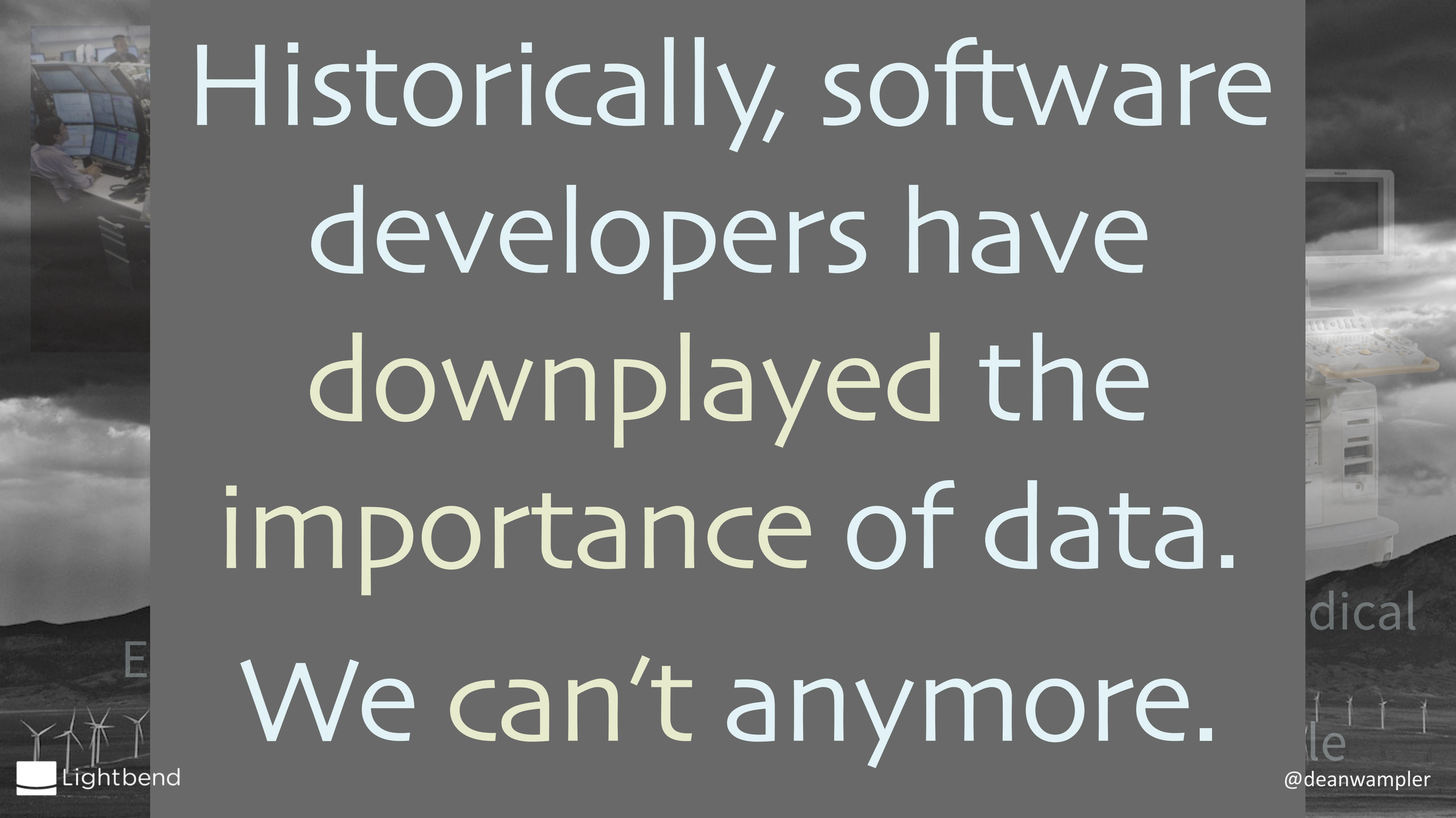
... and IoT

State of the art phone!

Mobile

Information value has a half life; it decays with time

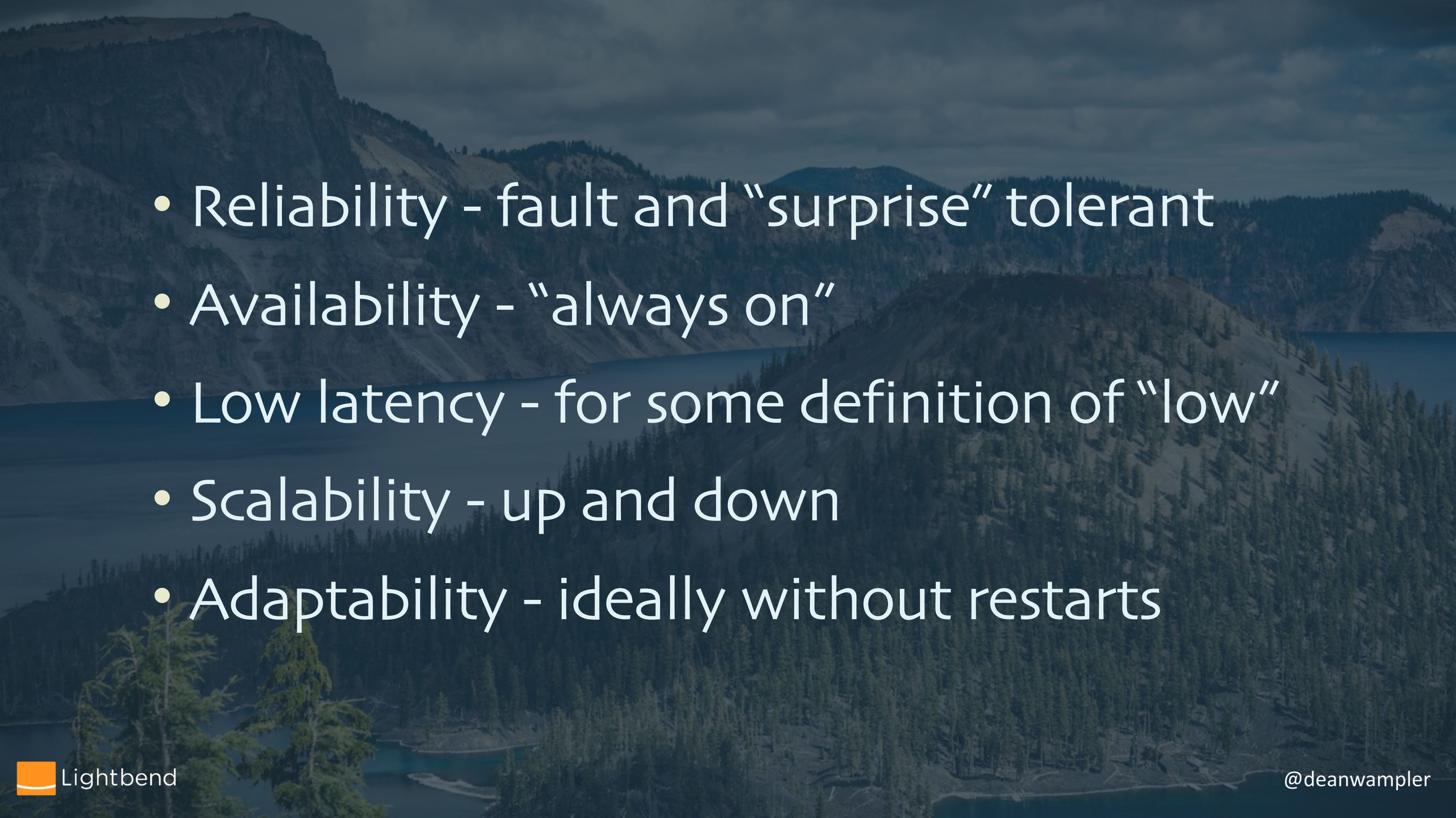




Historically, software developers have downplayed the importance of data.

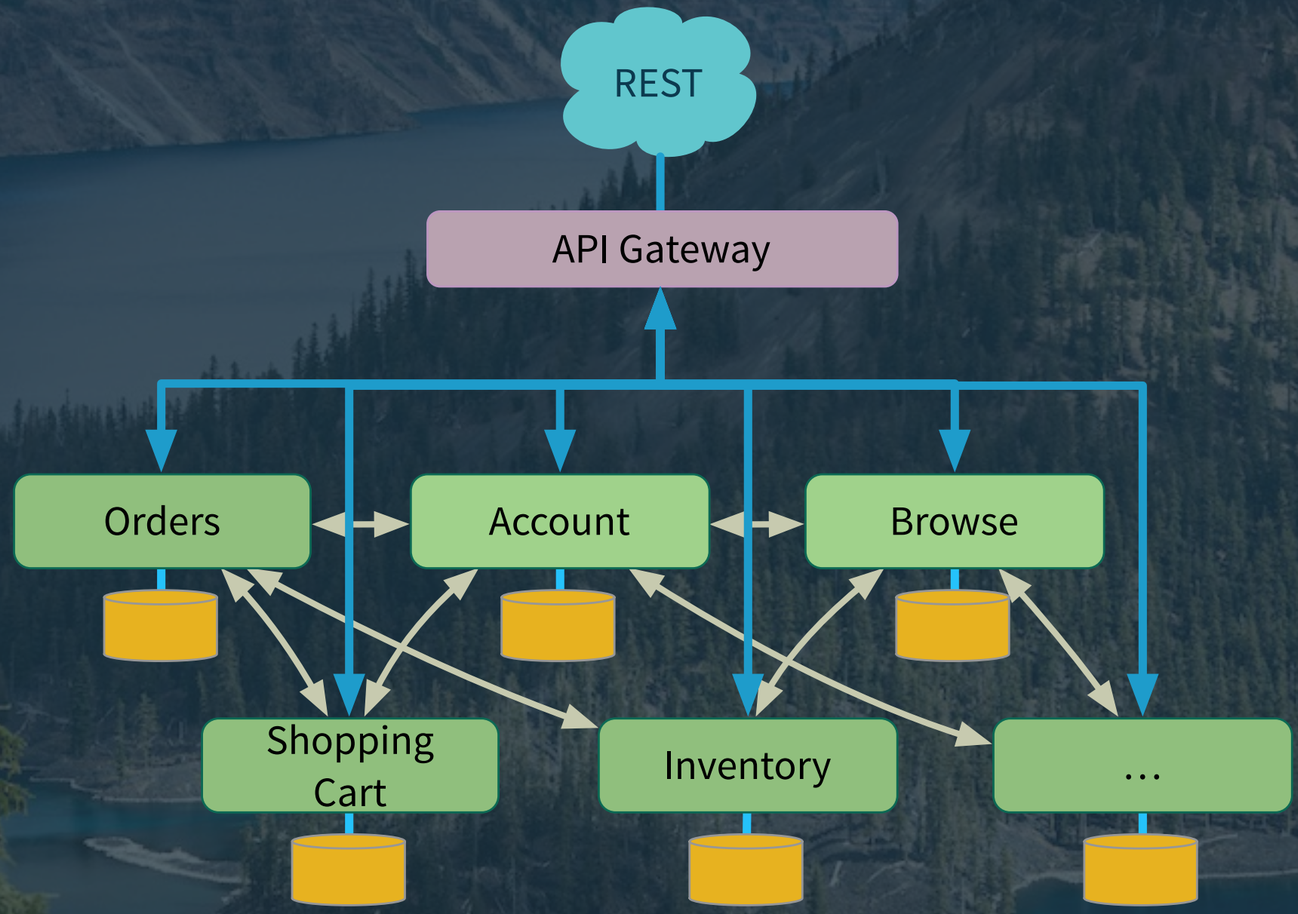
We can't anymore.

Streaming Architectures: Requirements



- 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



Streaming Architectures: An Example

Lightbend

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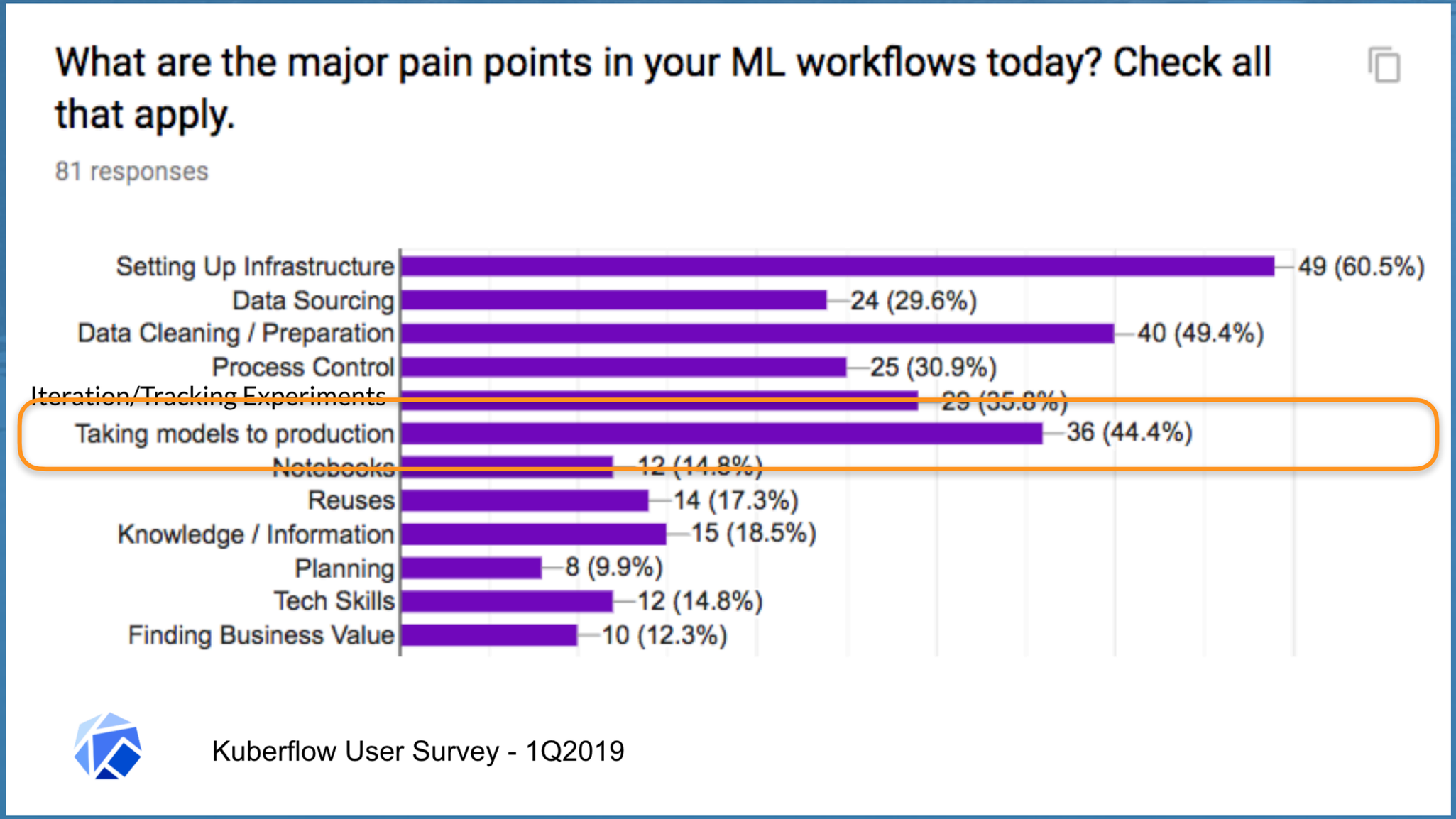
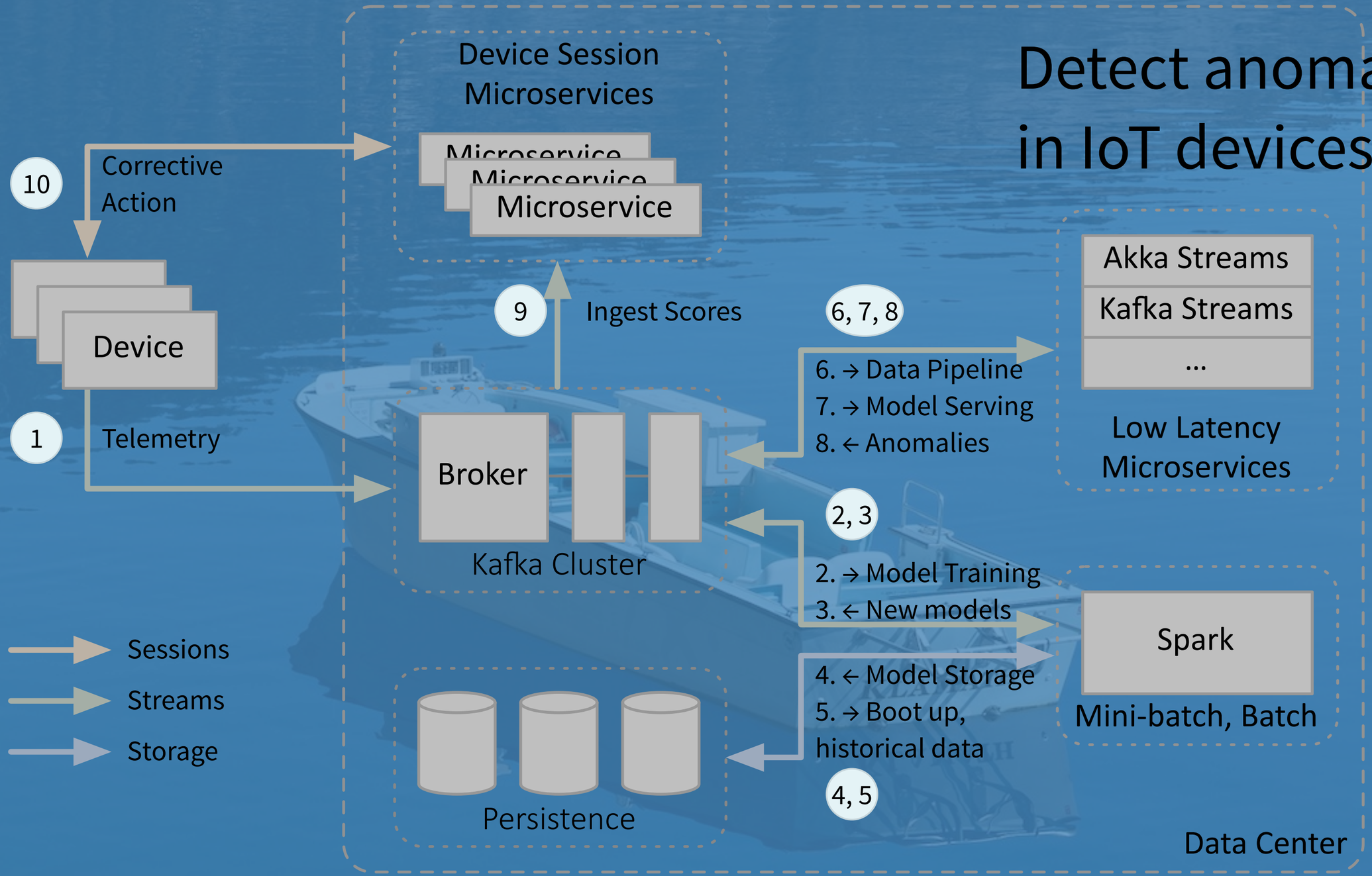
Problems We'll Highlight

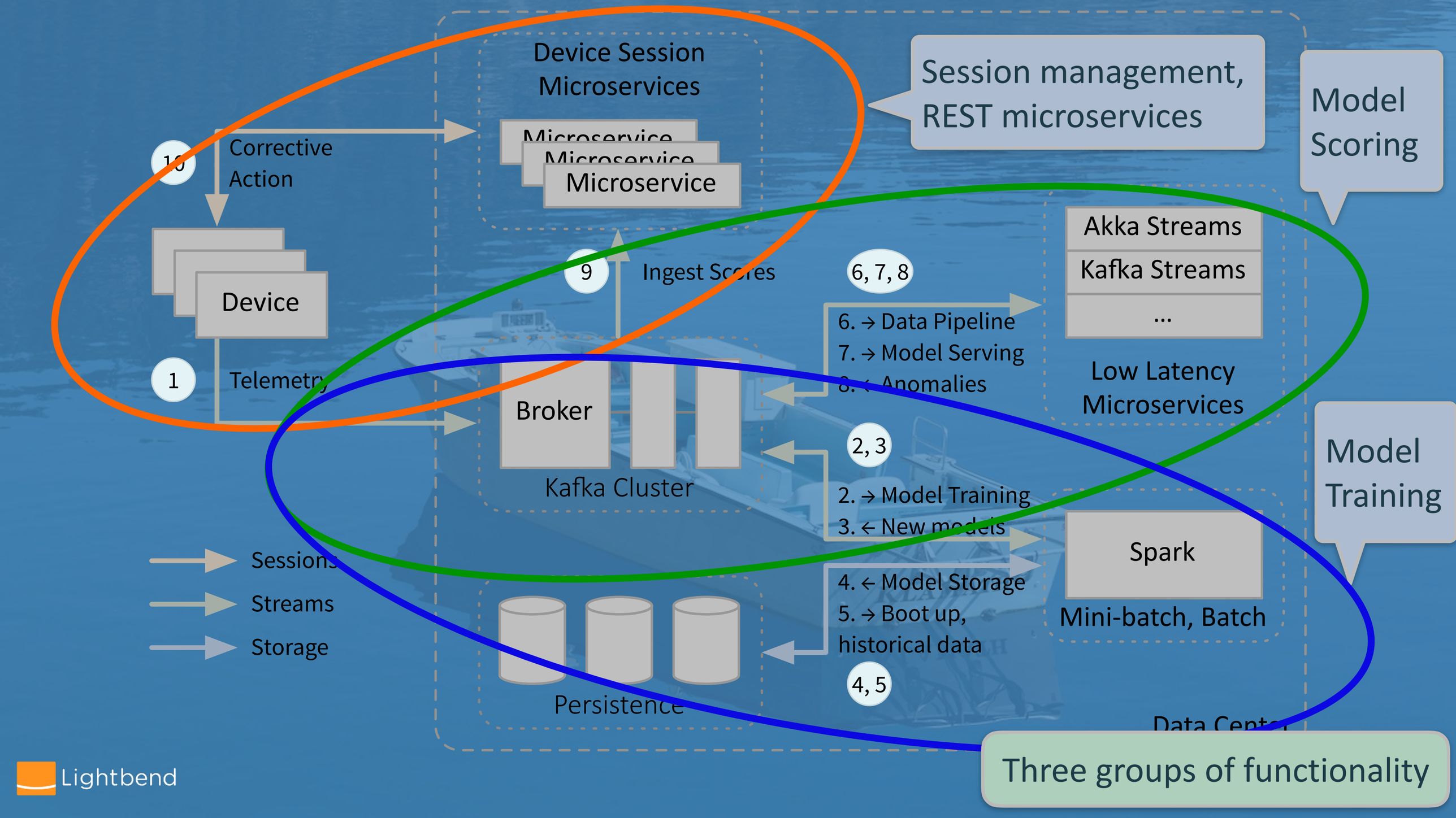


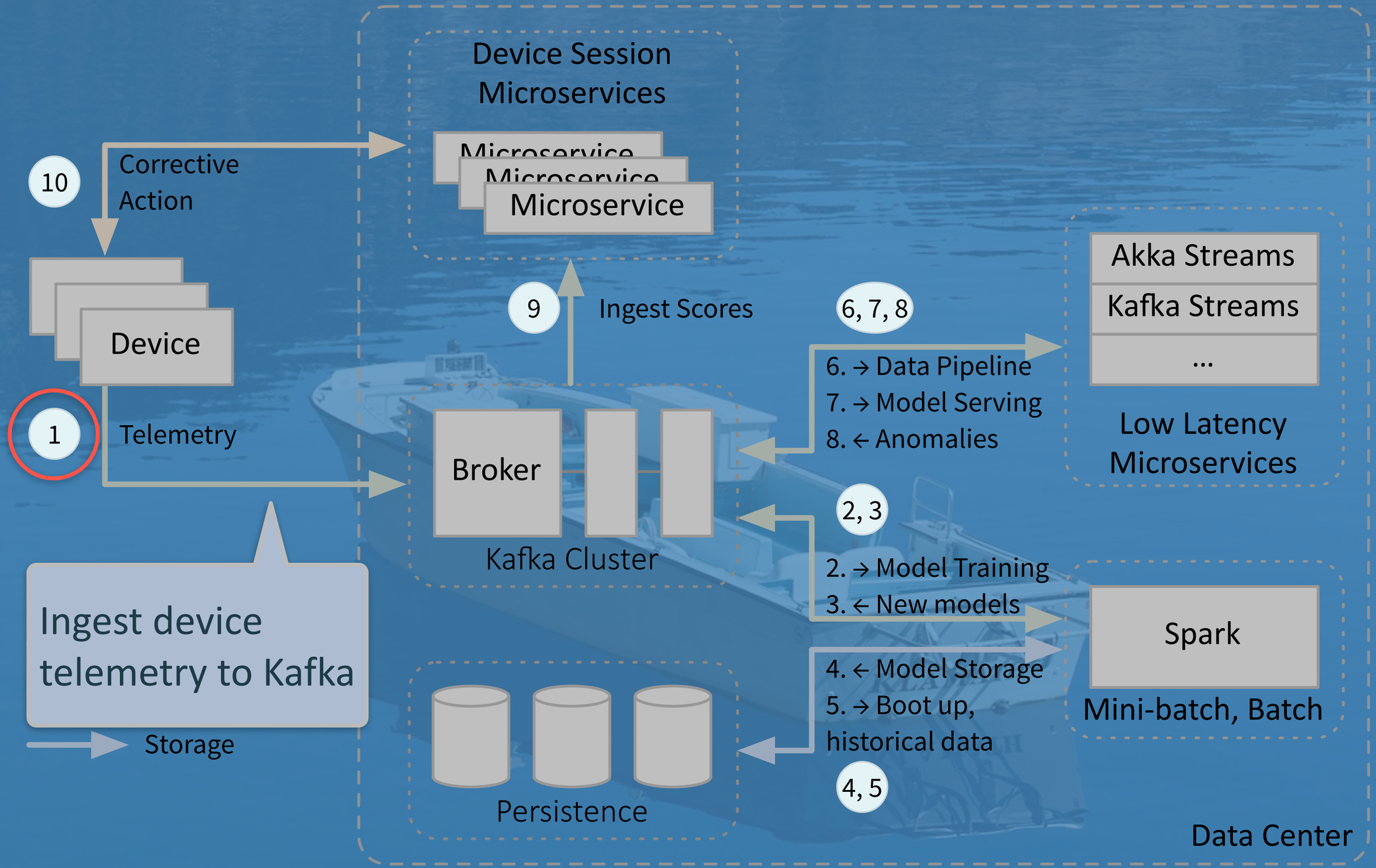
Kuberflow User Survey - 1Q2019

From this Kubeflow Overview

Detect anomalies in IoT devices




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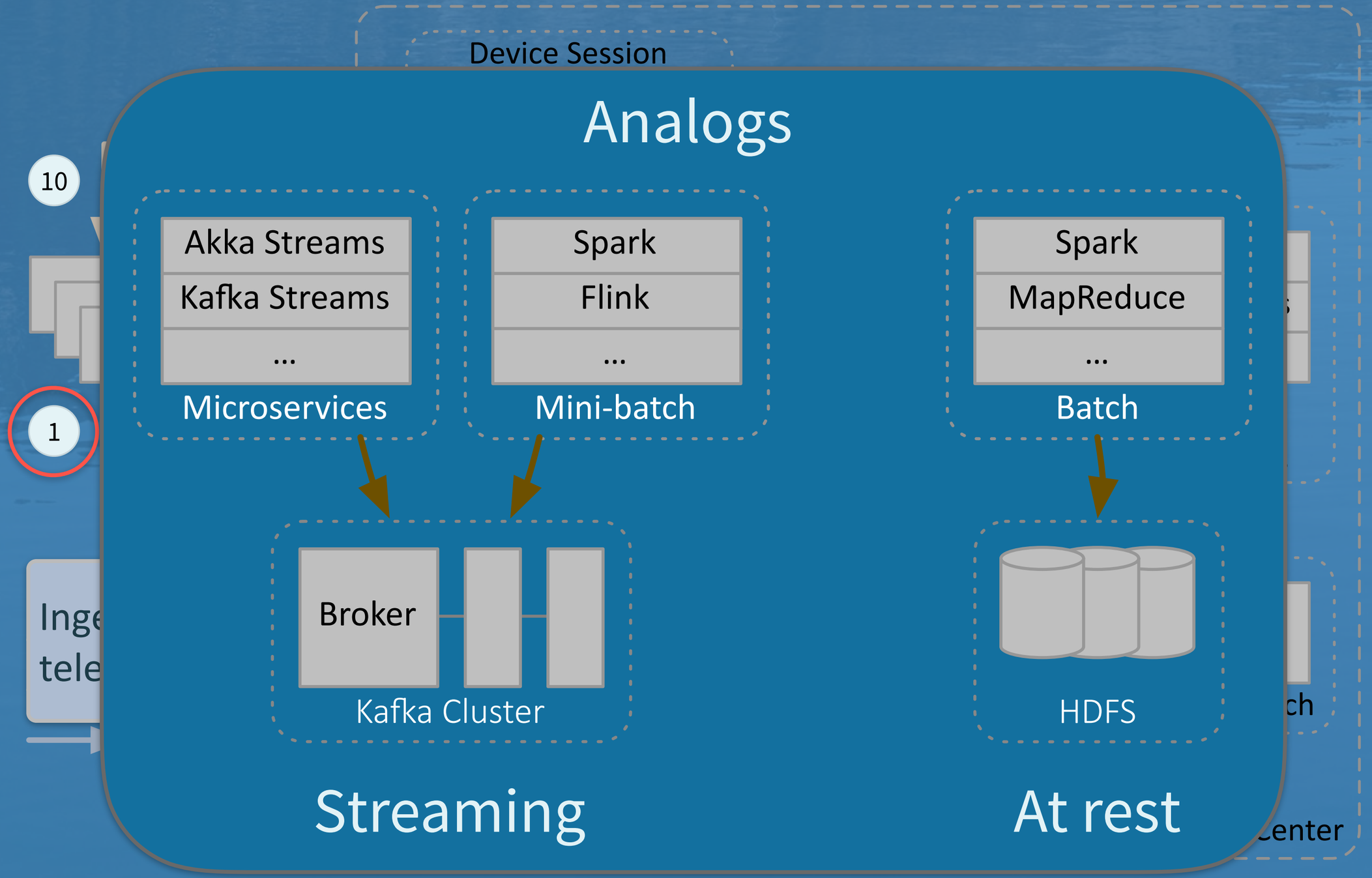
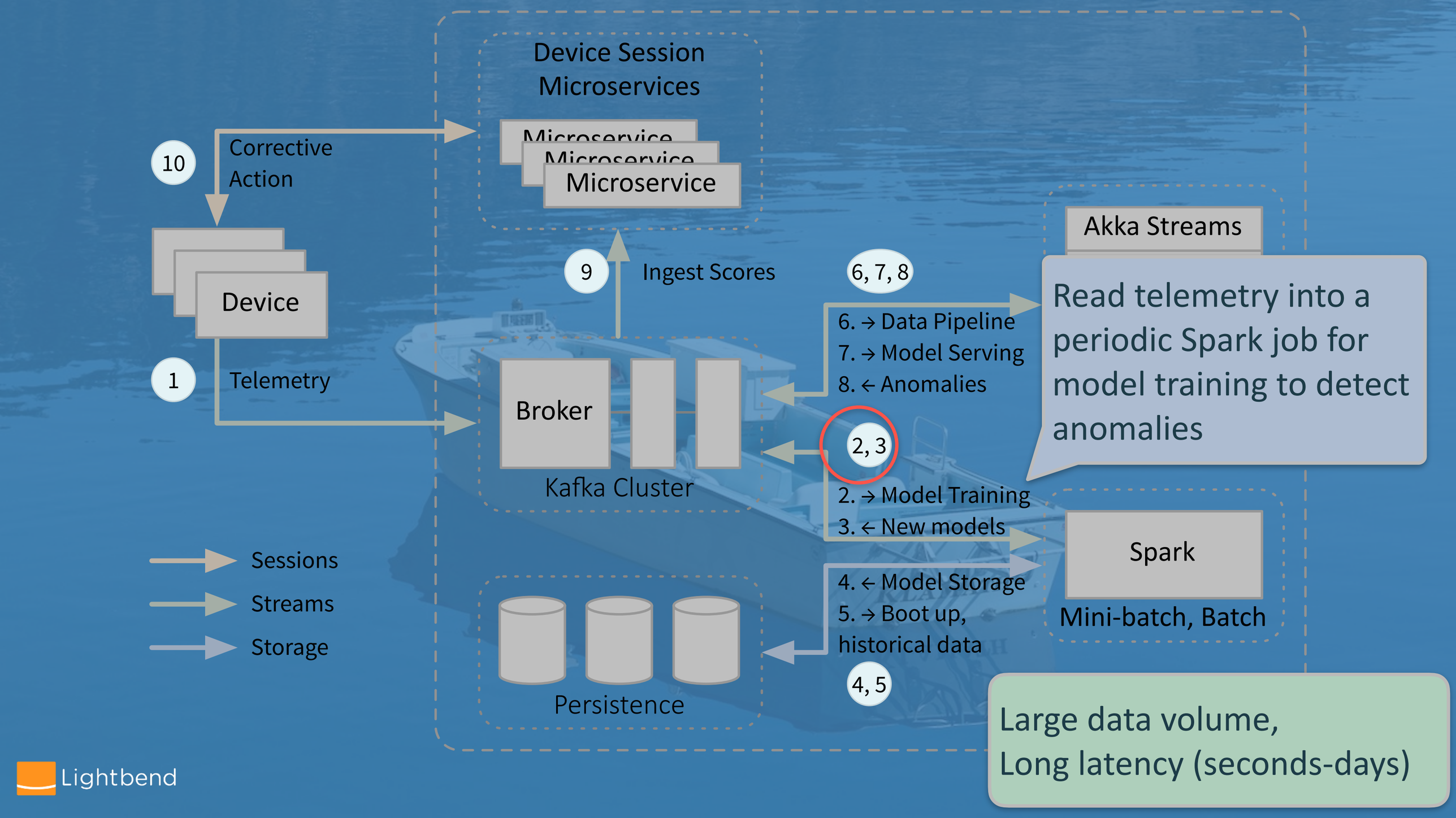
Persistence
Ingest device telemetry to Kafka
Storage
Data Center


Device Session
Analogs
10
1
Akka Streams
Kafka Streams
...
Microservices
Spark
Flink
...
Mini-batch
Spark
MapReduce
...
Batch
Broker
Kafka Cluster
HDFS
Streaming
At rest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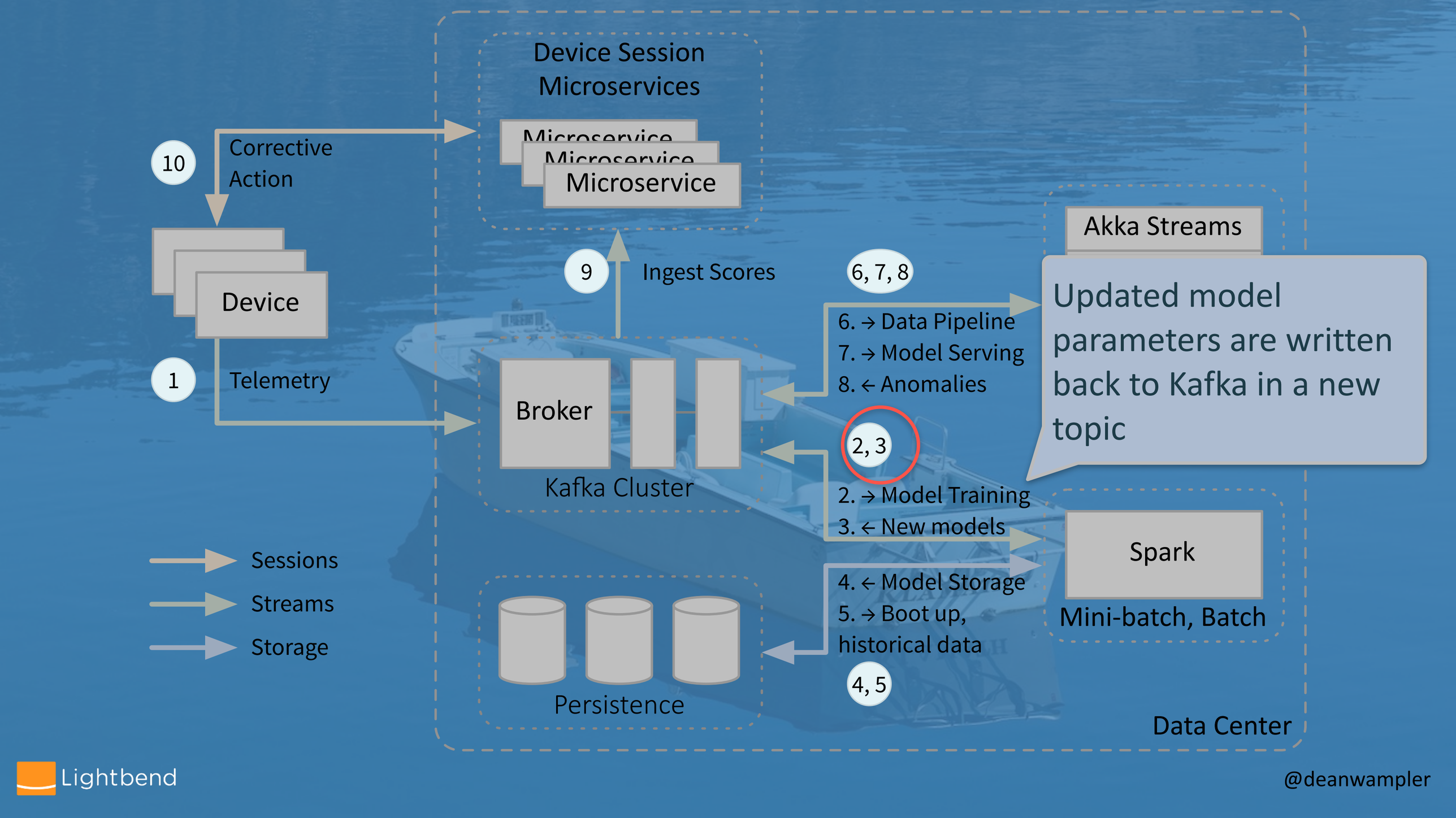
4. ← Model Storage
5. → Boot up, historical data
4, 5
Persistence
Akka Streams
Read telemetry into a periodic Spark job for model training to detect anomalies
Spark
Mini-batch, Batch
Sessions
Streams
Storage
Large data volume,
Long latency (seconds-days)
Lightbend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Ingest Scores
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Kafka Cluster
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8. ← Anomalies
Akka Streams
Updated model parameters are written back to Kafka in a new topic
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2. → Model Training
3. ← New models
Spark
Mini-batch, Batch
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5. → Boot up, historical data
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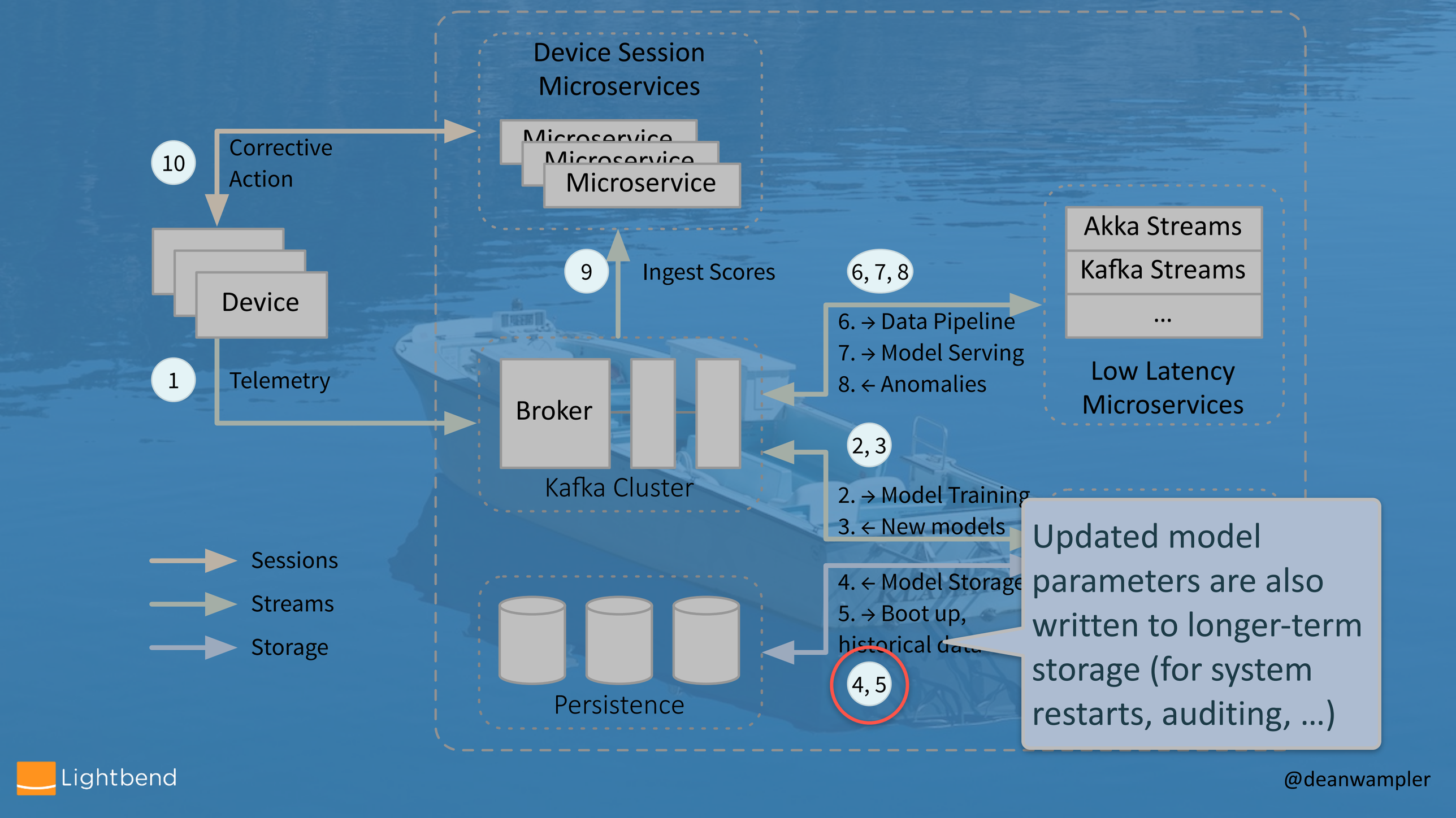
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2, 3
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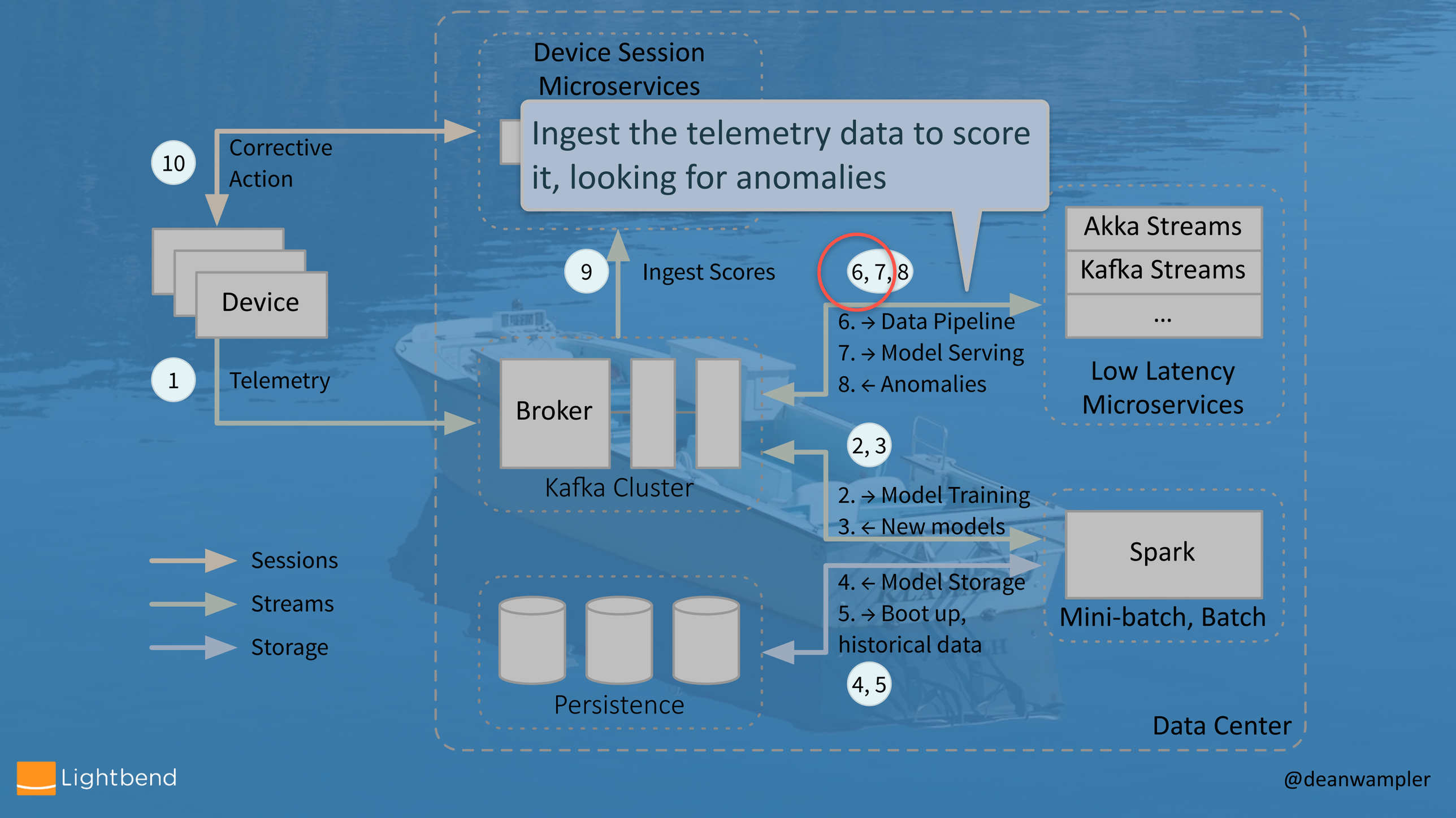
4, 5
Persistence
Sessions
Streams
Storage
Updated model parameters are also written to longer-term storage (for system restarts, auditing, ...)
Lightbend
@deanwampler


Device Session Microservices
Ingest the telemetry data to score it, looking for anomalies
10
Corrective Action
Device
1
Telemetry
9
Ingest Scores
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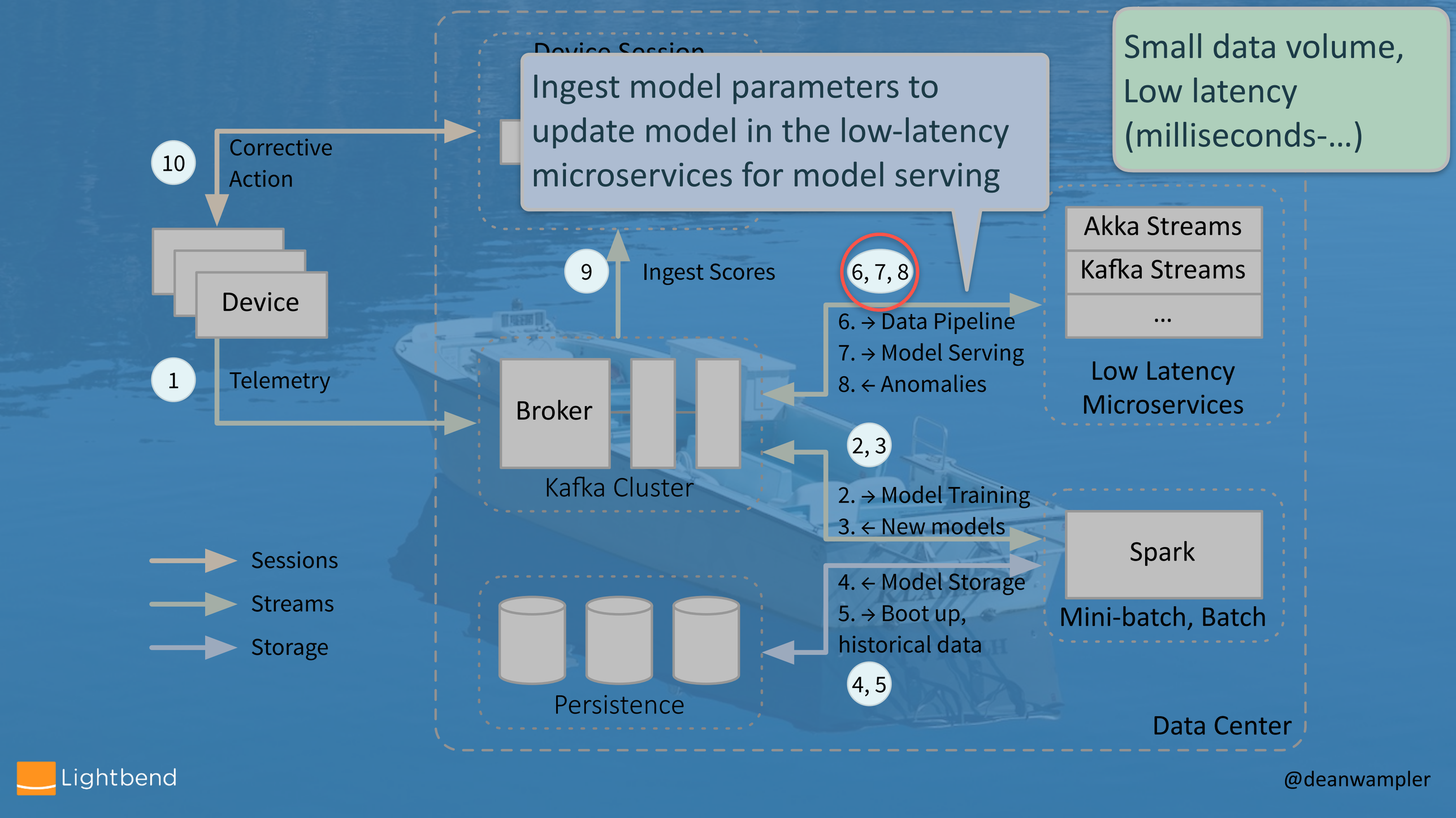
Small data volume, Low latency (milliseconds-...)
Ingest model parameters to update model in the low-latency microservices for model serving
10
Corrective Action
Device
1
Telemetry
9
Ingest Scores
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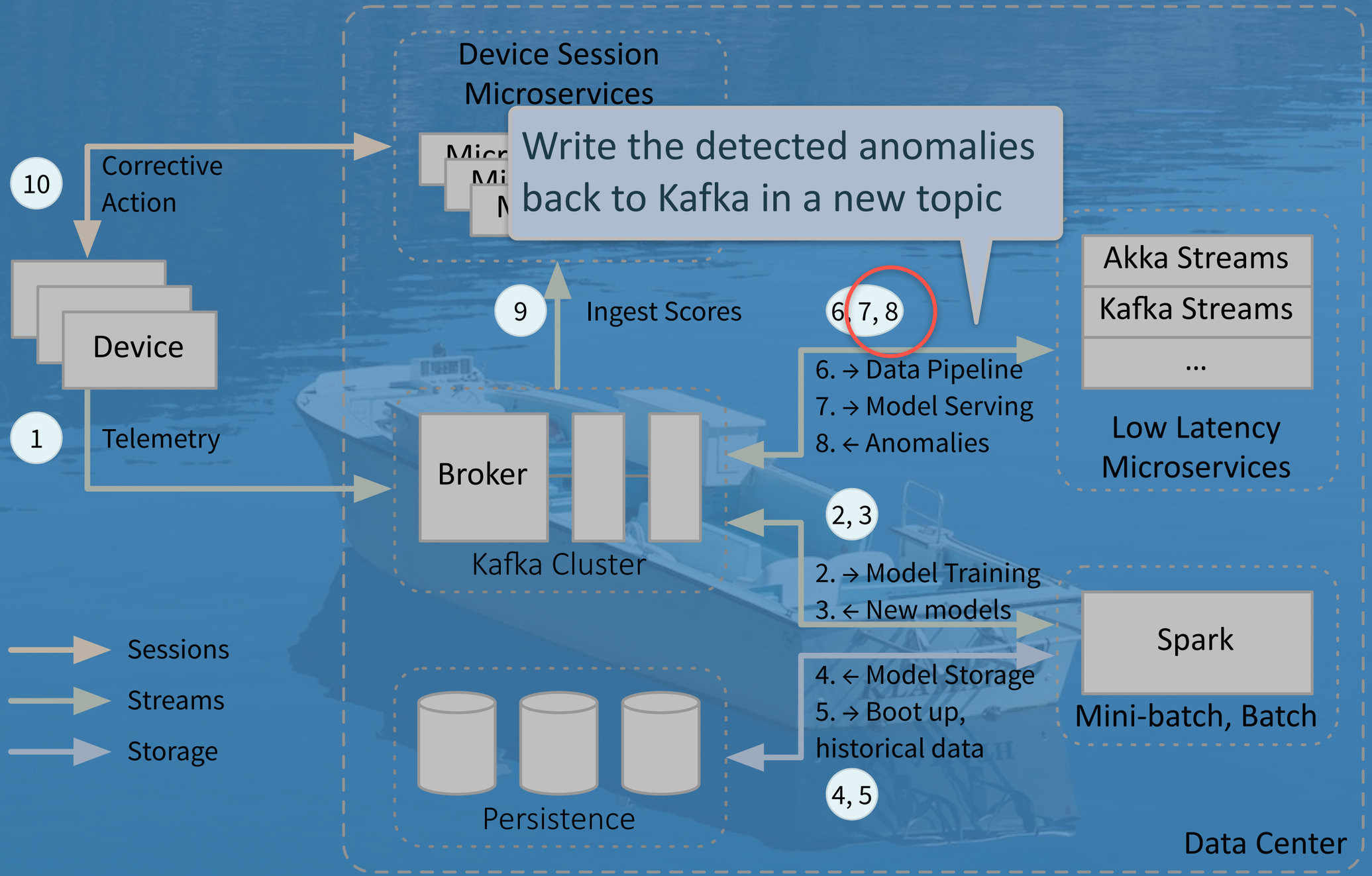
@deanwampler


Device Session Microservices
Write the detected anomalies back to Kafka in a new topic
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Corrective Action
Device
1
Telemetry
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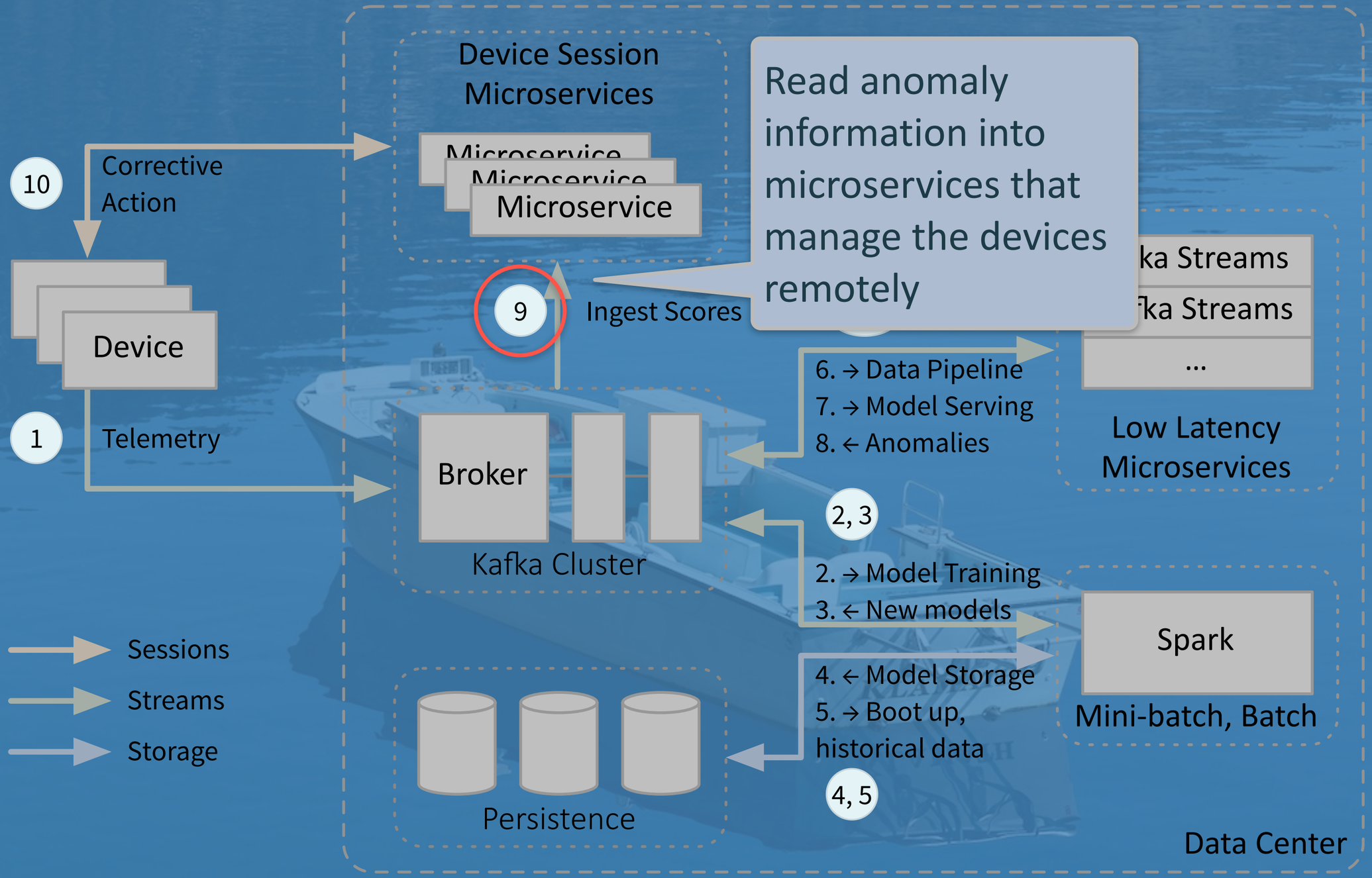
Device Session Microservices
Microservice
Microservice
Microservice
Read anomaly information into microservices that manage the devices remotely
10
Corrective Action
Device
1
Telemetry
9
Ingest Scores
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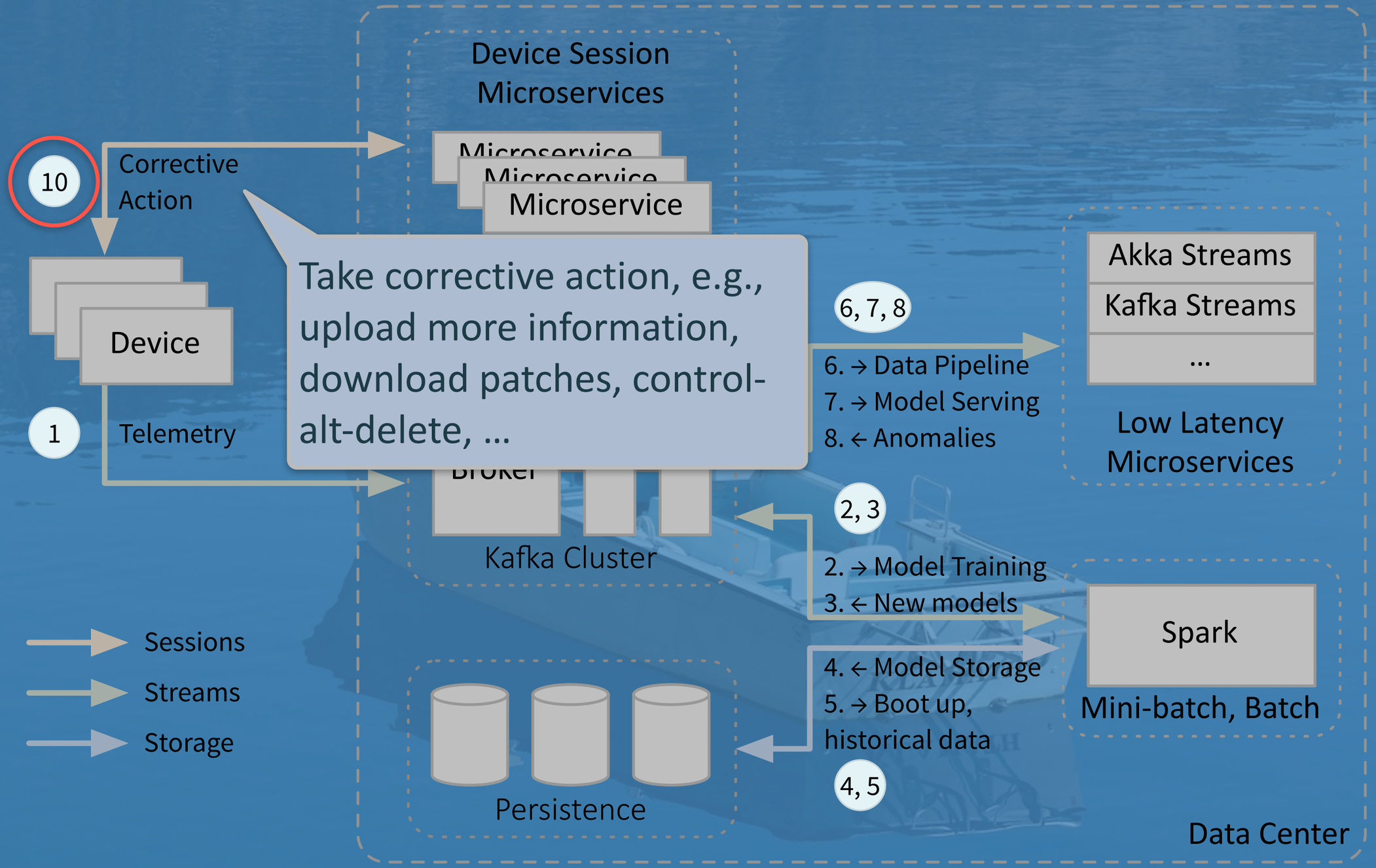
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Microservice
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Corrective Action
Device
1
Telemetry
Take corrective action, e.g., upload more information, download patches, control-alt-delete, …
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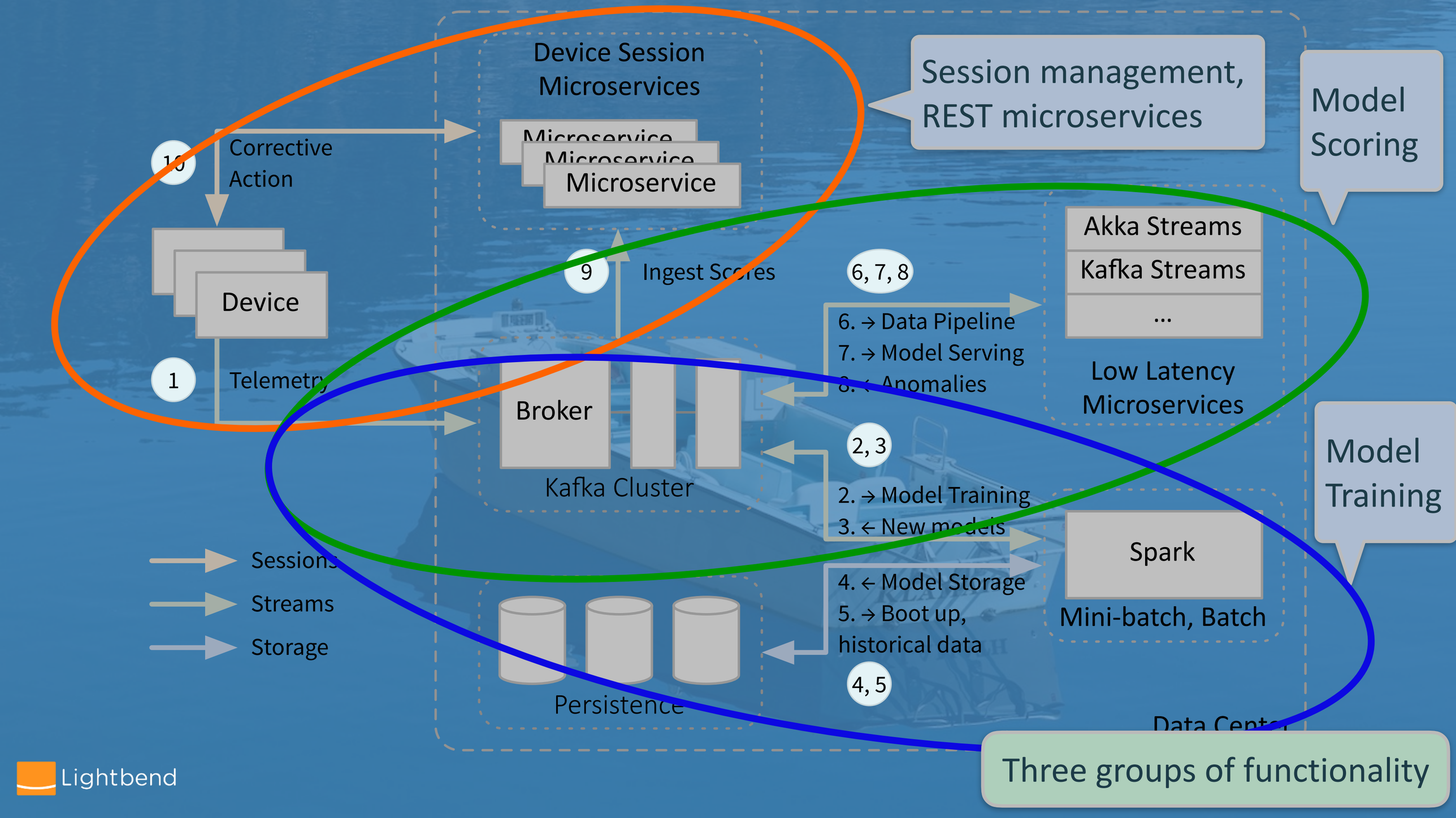
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Three groups of functionality
Lightbend

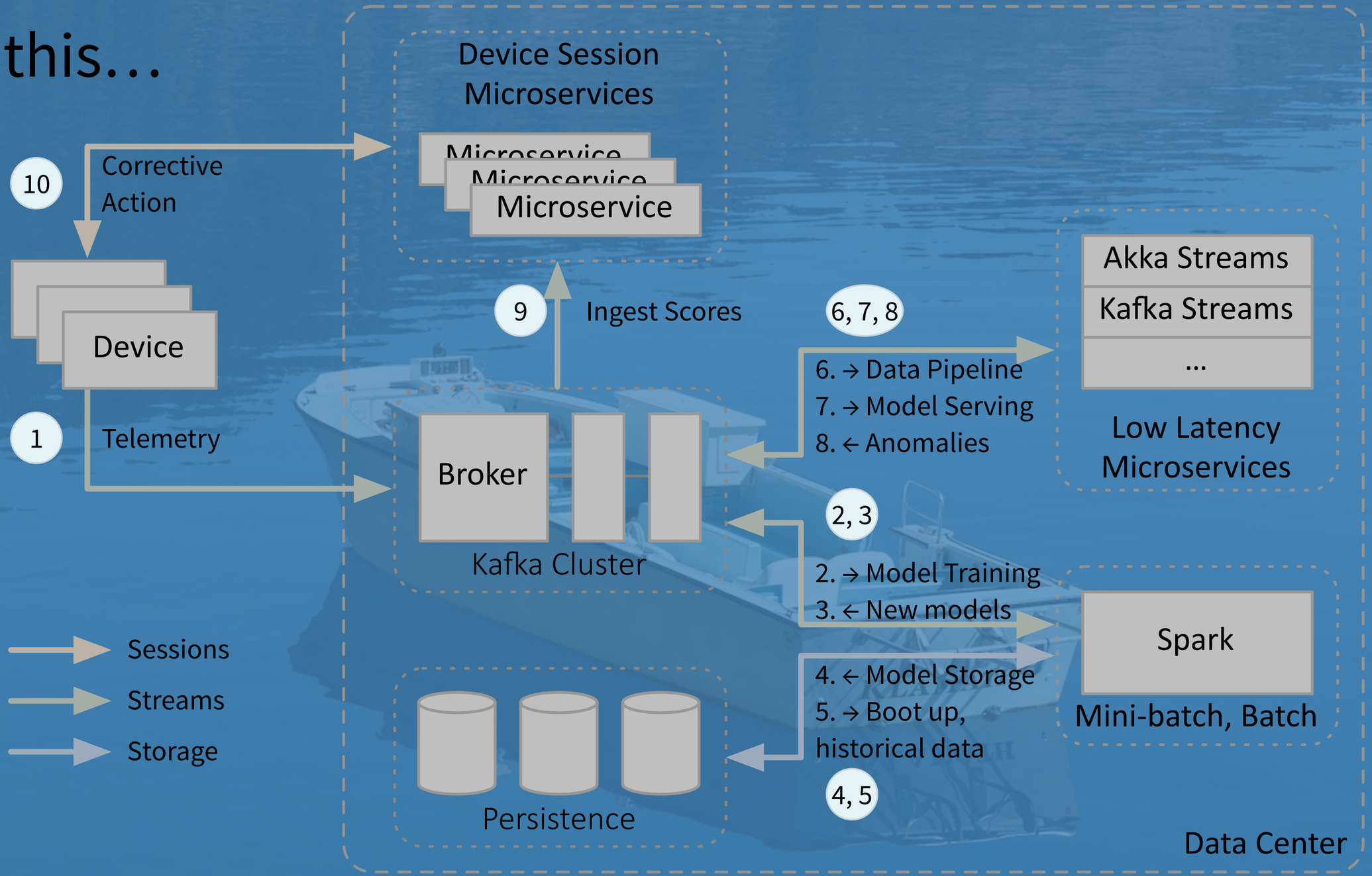
Streaming Architectures: An Example

Variation: Model Serving as a Service

Lightbend

@deanwampler

From this…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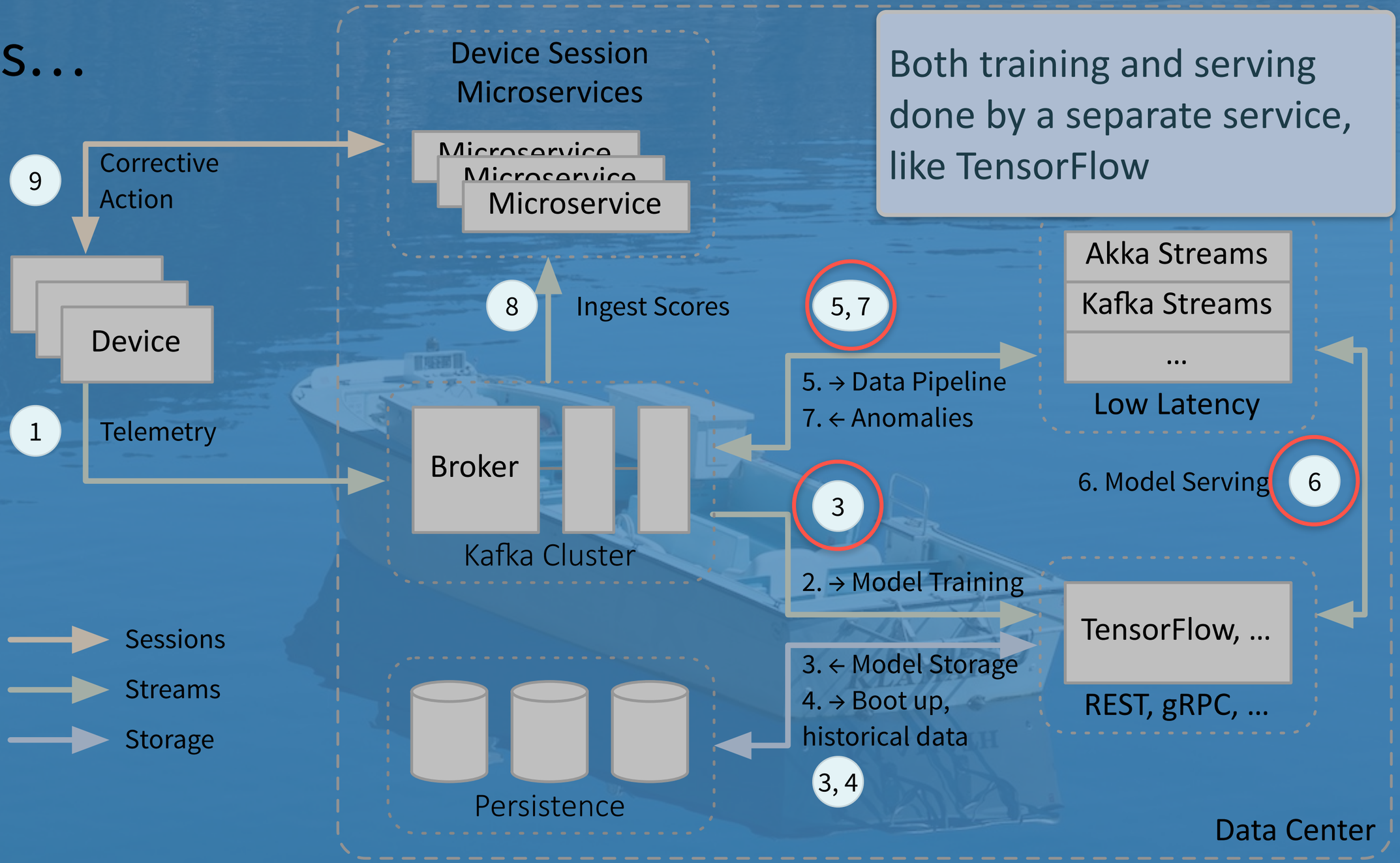


Both training and serving done by a separate service, like TensorFlow

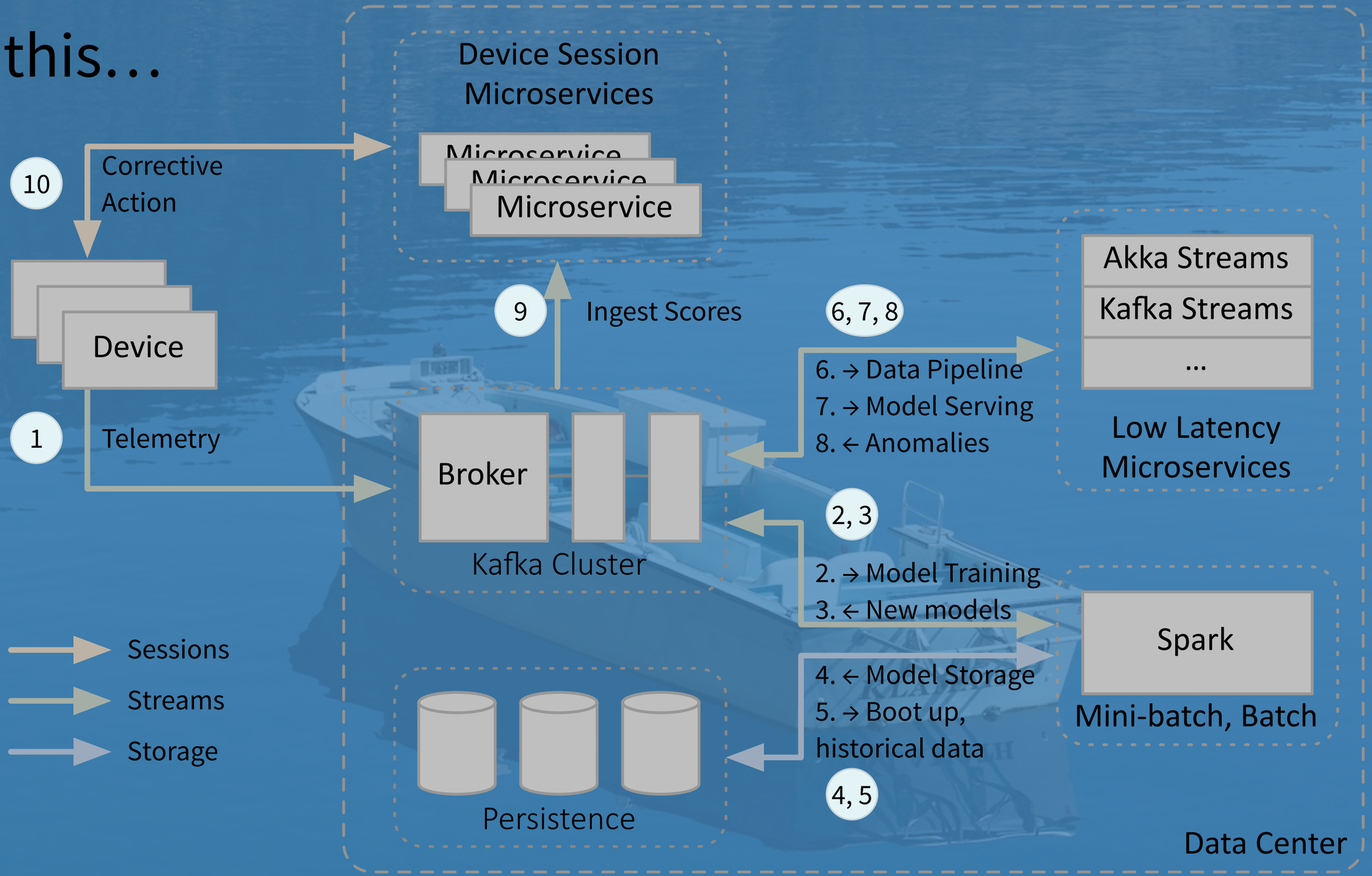
Streaming Architectures: An Example

Variation: Model Serving on the Edge

Lightbend

@deanwampler

From this…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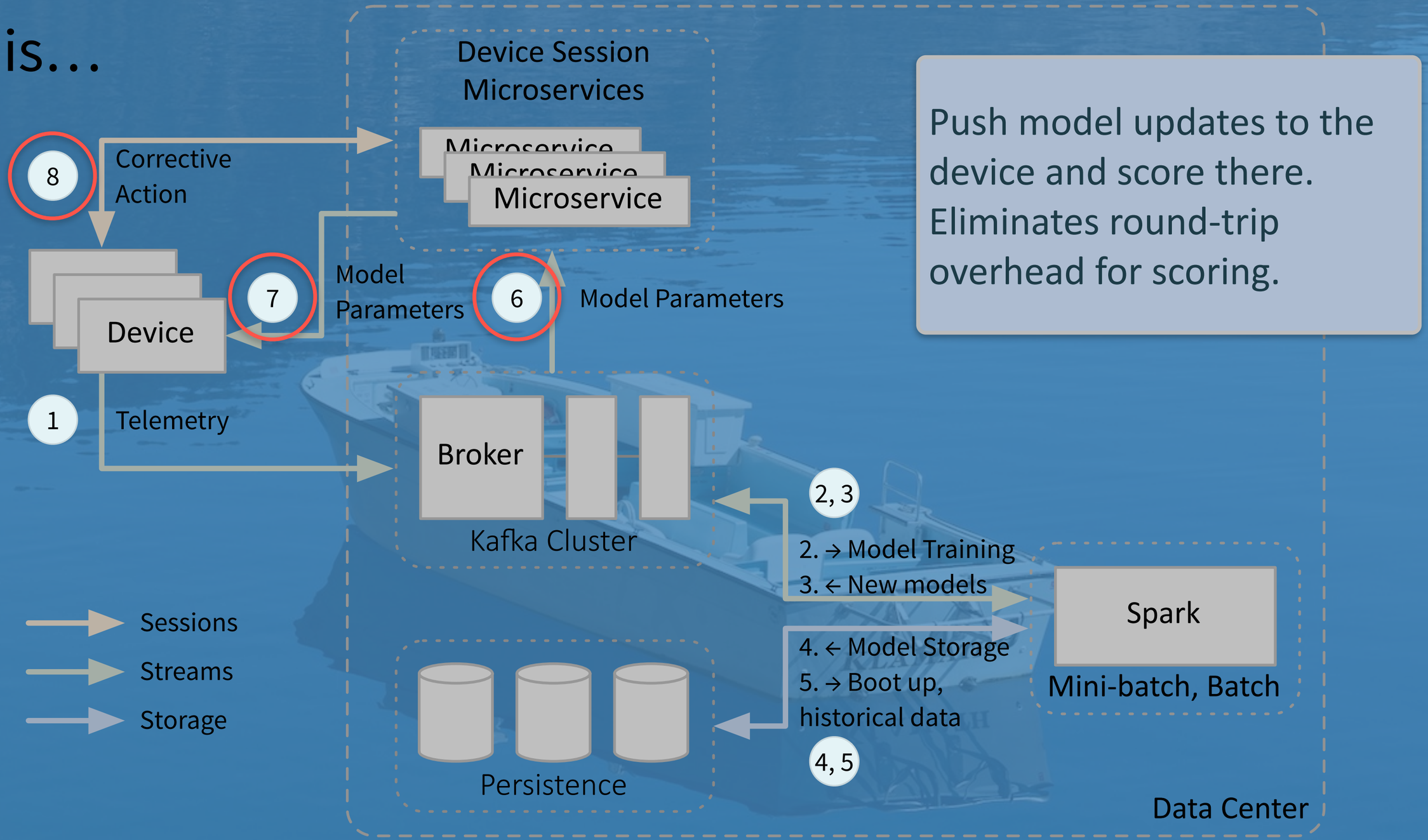

Push model updates to the device and score there. Eliminates round-trip overhead for scoring.

Mixing data science and data engineering

Lightbend

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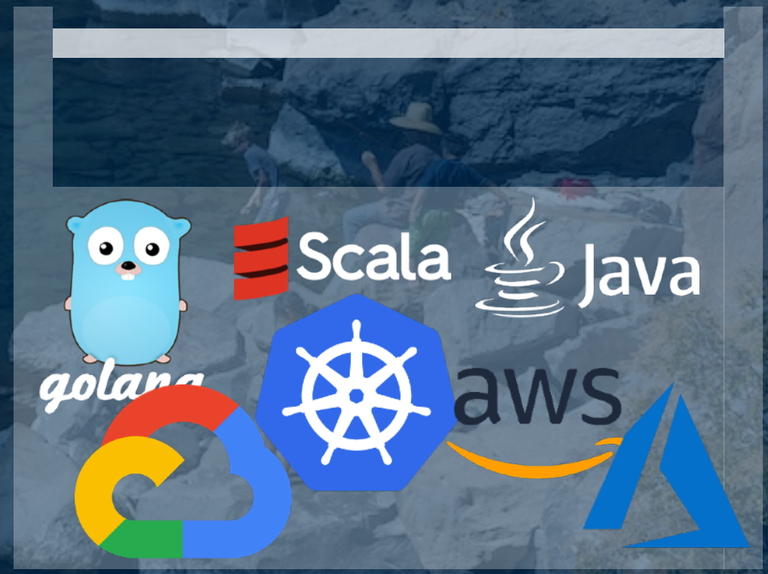
Tools

Data Science toolbox



Software
Engineering toolbox

Process

Data Science:

- Less process oriented
  - Iterative, experimental
  - … but still within the Scientific Method

Data Engineering:

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

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

Philosophy

Data Science:

- Comfortable with uncertainty
  - Probabilities and Statistics

Data Engineering:

- Uncomfortable with uncertainty
  - Prefer determinism
  - … while admitting that distributed systems aren't deterministic


Other Production Concerns
Lightbend
@deanwampler


Models
Are
Data

Auditing

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

Auditing

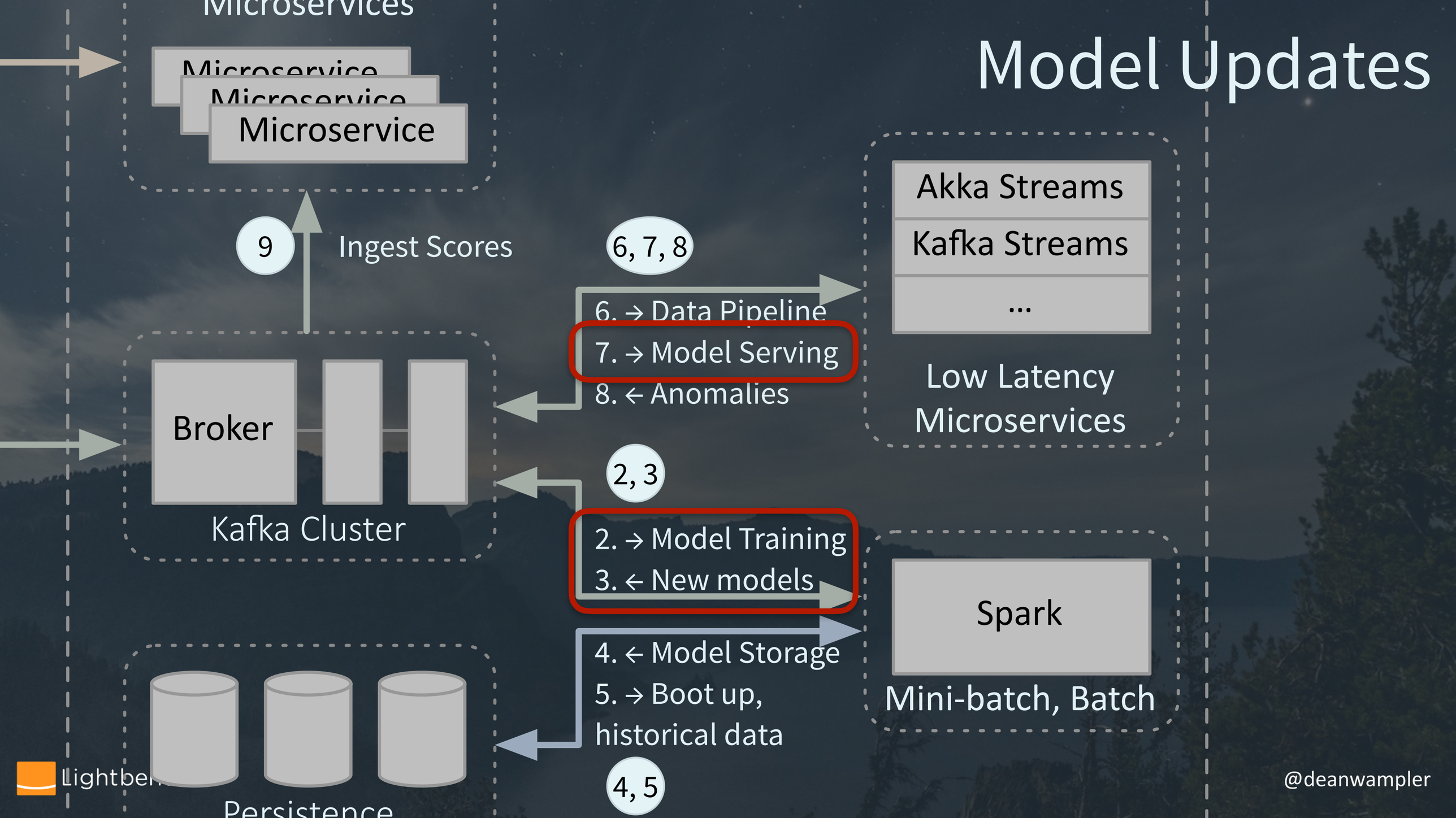
- Quality metrics
- Serving metrics (how many records, scoring times…)
- Provenance of decision to retrain
  - The metrics gathered above that were used to decide when to retrain

Auditing

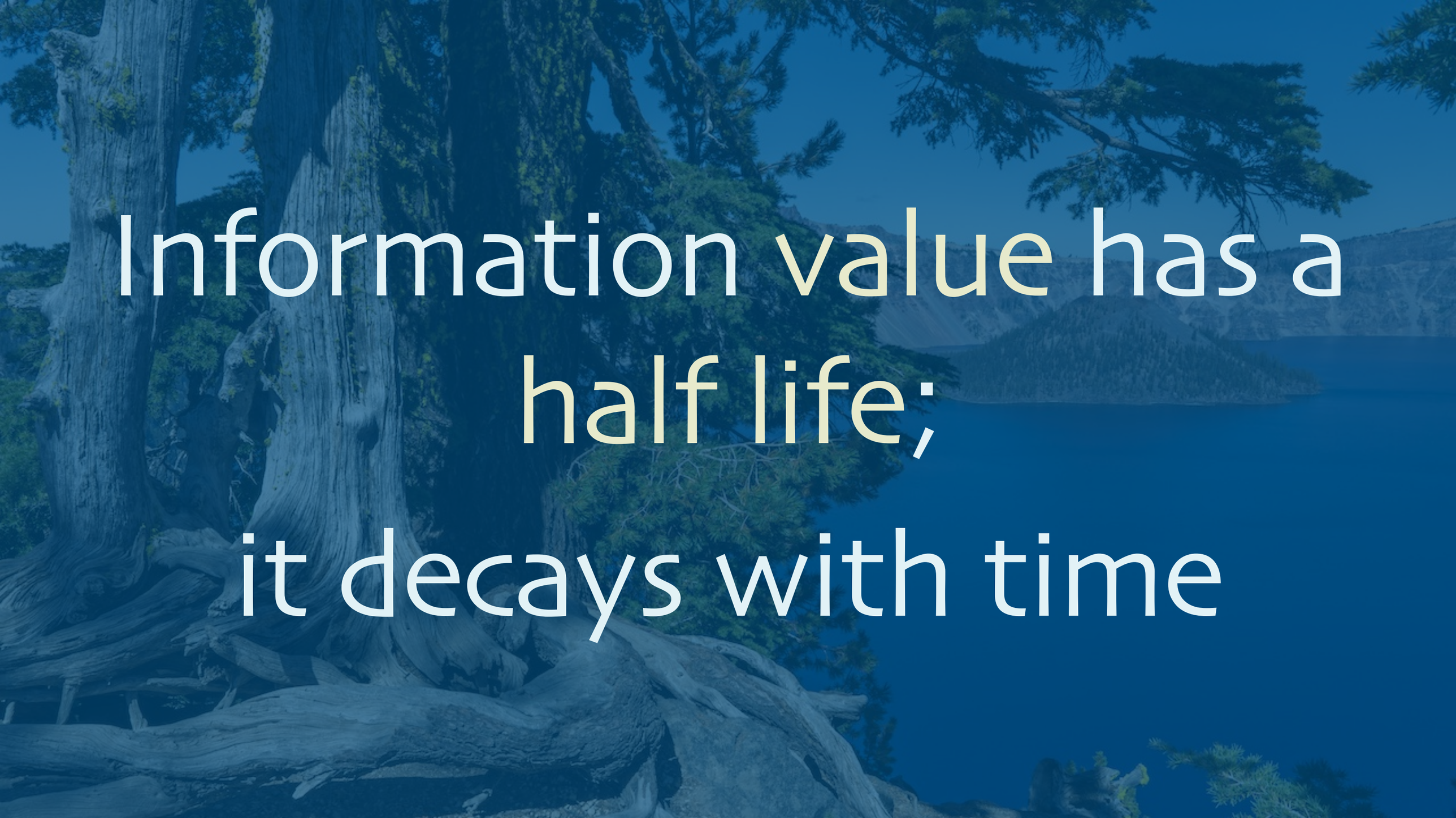
- … and maybe most important:
  - What model was used to score a particular record??

Models have a half life, too

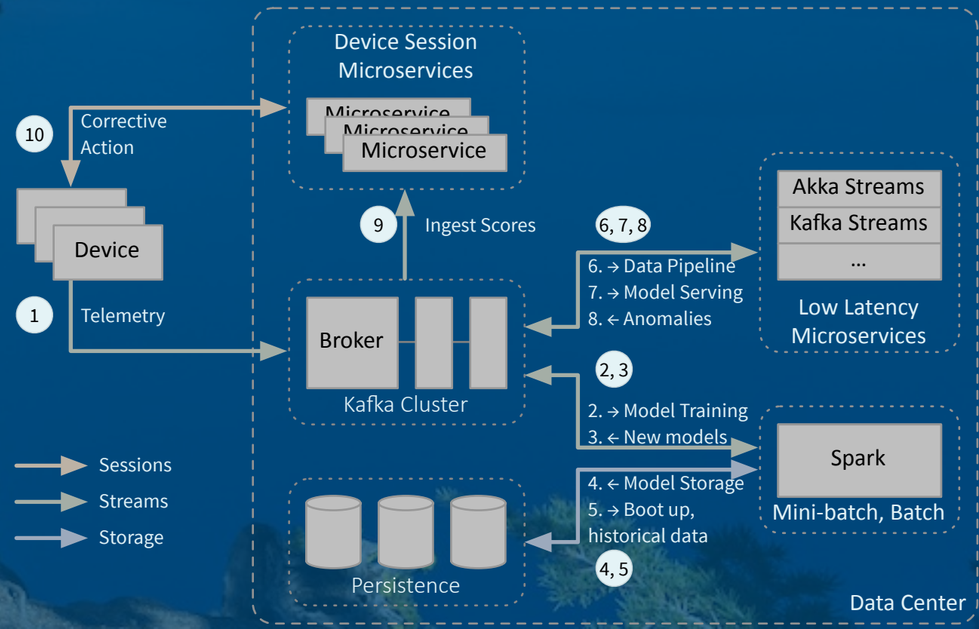
Model Updates



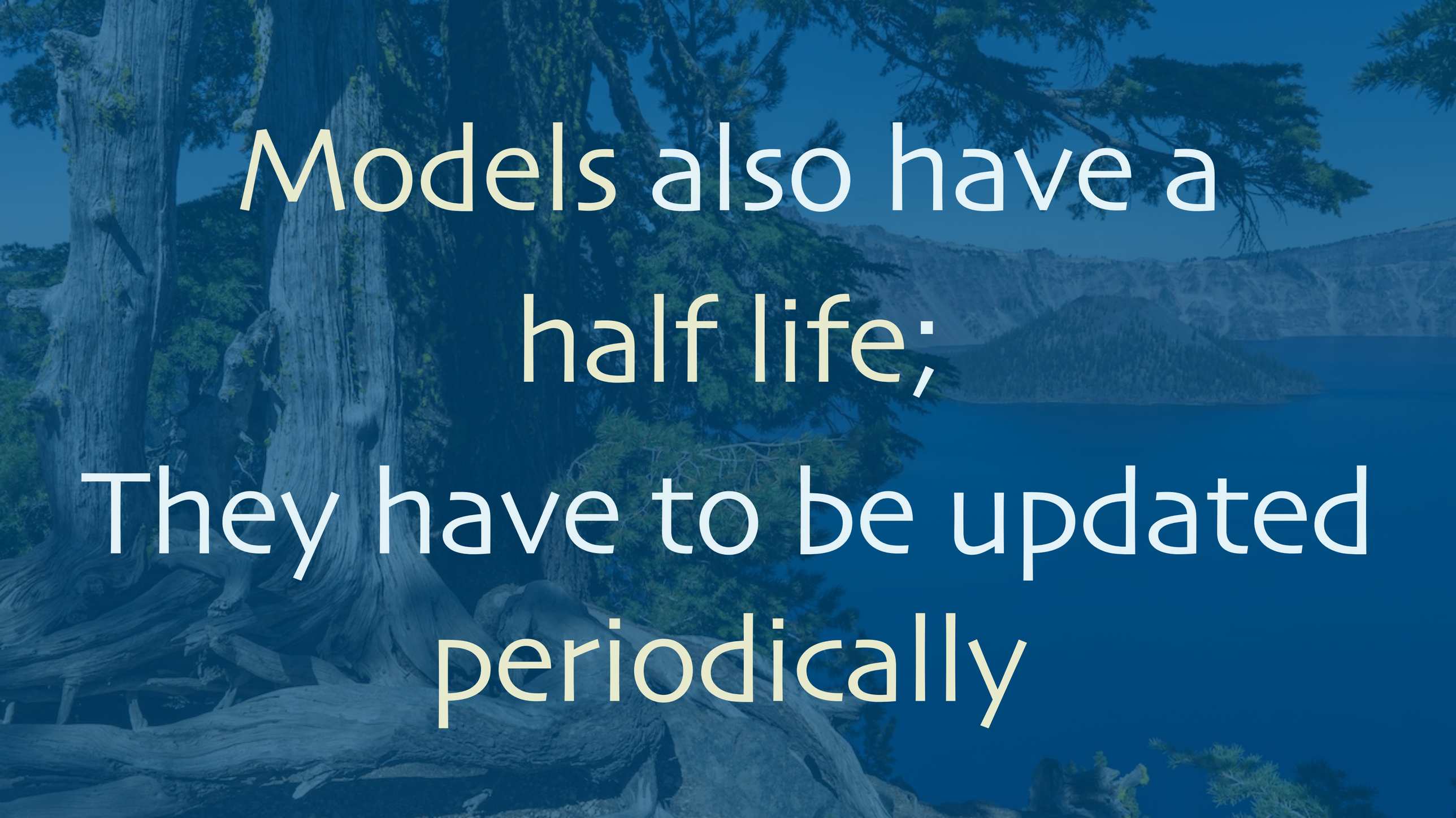
Recap


Information value has a
half life;
it decays with time

Streaming systems have similar requirements as microservices




Integrating
data science and
data engineering
is hard


Models also have a
half life;
They have to be updated
periodically


Dusty Milky Way
Mars last Summer

References

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

References

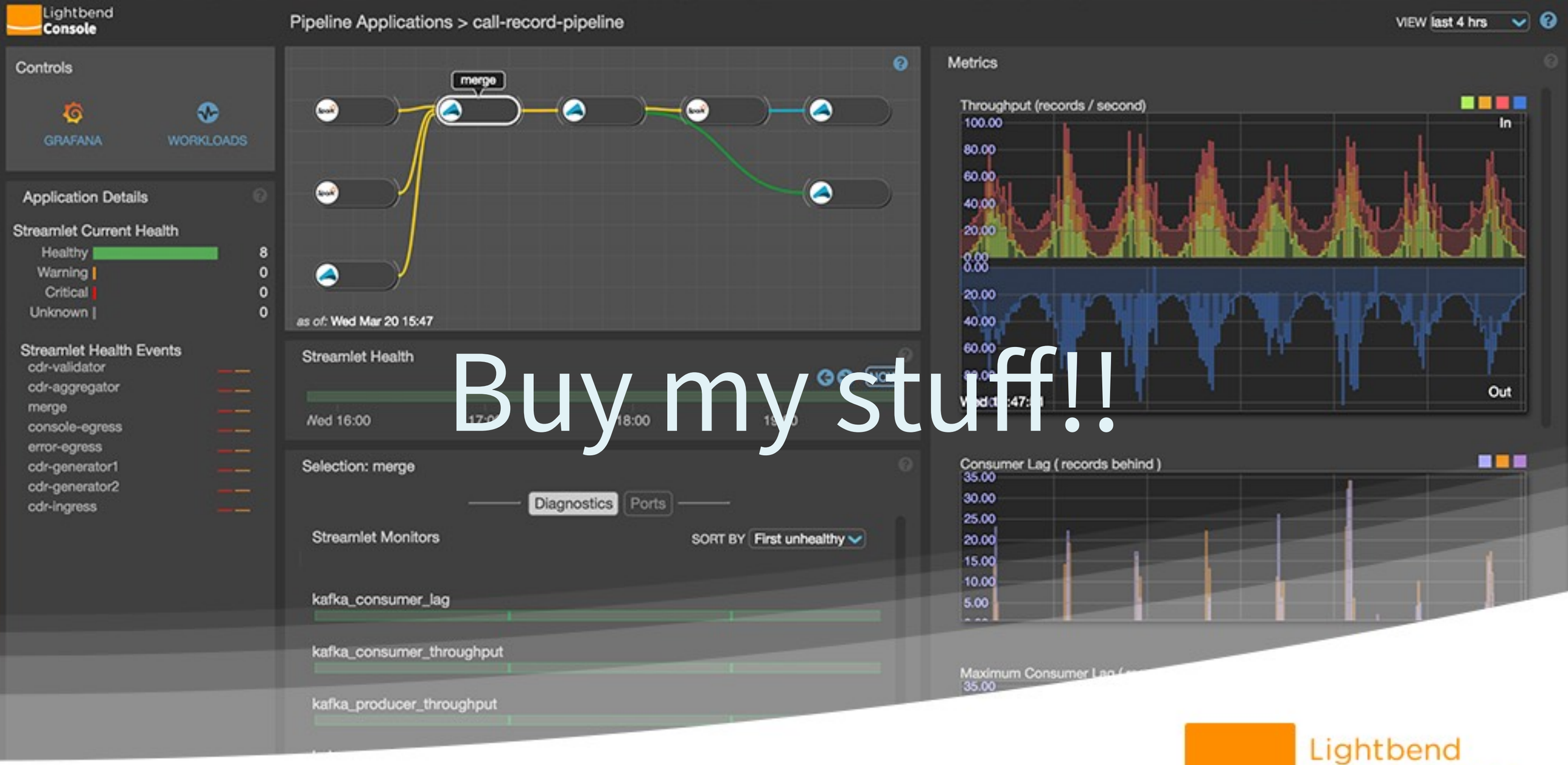
- General Information about Stream Processing
  - My O'Reilly Report on Architectures
  - Streaming Systems Book
  - Stream Processing with Apache Spark
  - Designing Data-Intensive Apps book

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



Buy my stuff!!

What we're up to at Lightbend…
lightbend.com/lightbend-pipelines-demo

Lightbend Pipelines


Questions?
Dean Wampler, Ph.D.
dean@lightbend.com
@deanwampler
lightbend.com/lightbend-platform
polyglotprogramming.com/talks
Lightbend
@deanwampler