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

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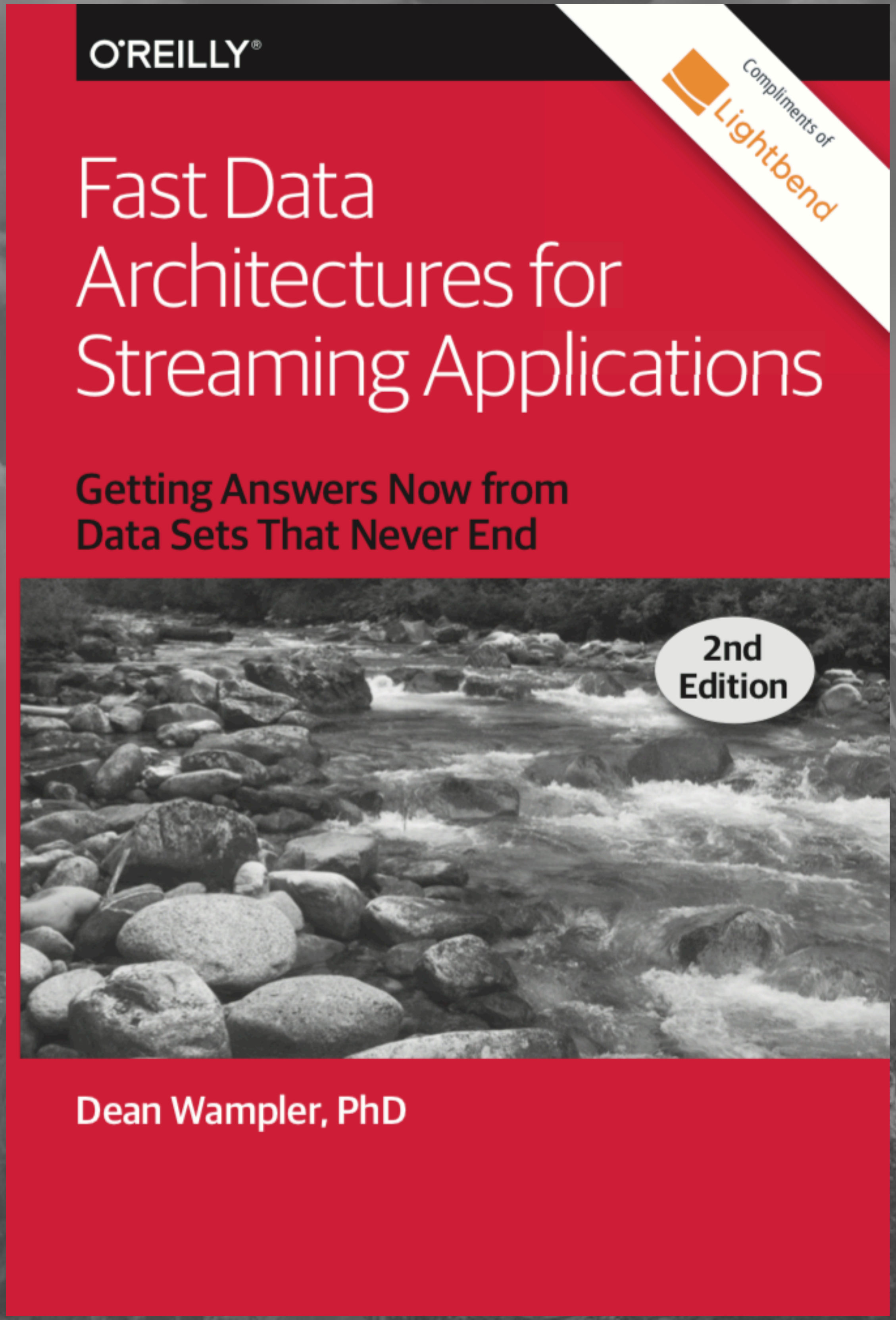
polyglotprogramming.com/talks

Data Streaming, in General

lbnd.io/fast-data-ebook



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What We'll Discuss

- Batch vs. streaming… and why
- Data science vs. data engineering
- Serving models in production
    - CI/CD Systems for ML
    - Example architecture
    - Updating Models in Production

Batch vs. streaming… and why

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Telecom
Finance
Medical
Energy
… and IoT
State of the art phone!
NOKIA
Mobile
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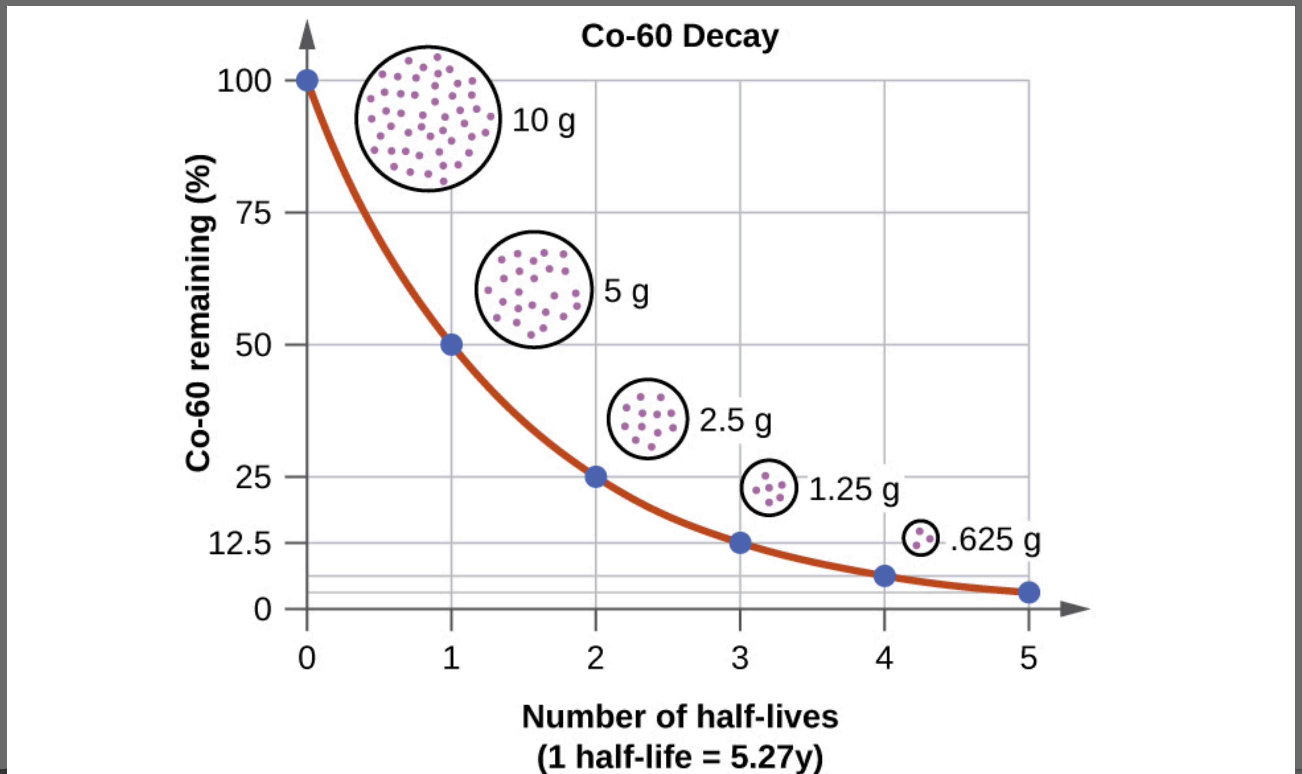
Information value has a half life; it decays with time




Data Science vs.
Data Engineering
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Data Science toolbox

Software Engineering toolbox

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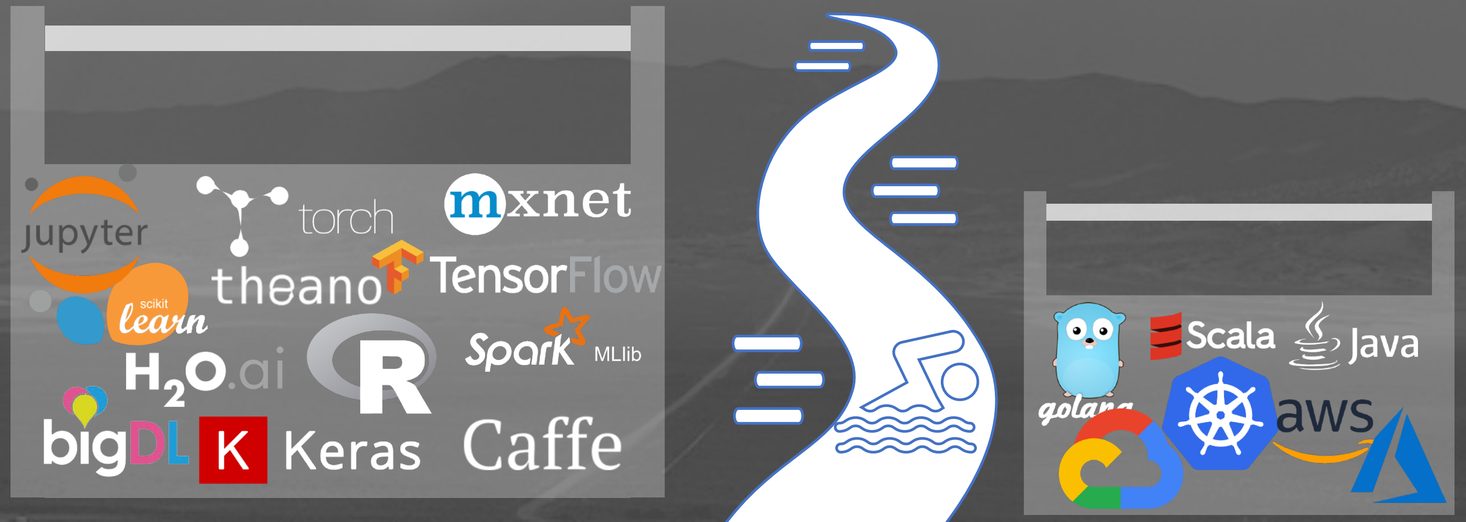
Data Scientists

- 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



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Streaming Imposes New Requirements

If you run something long enough, all rare problems eventually happen!

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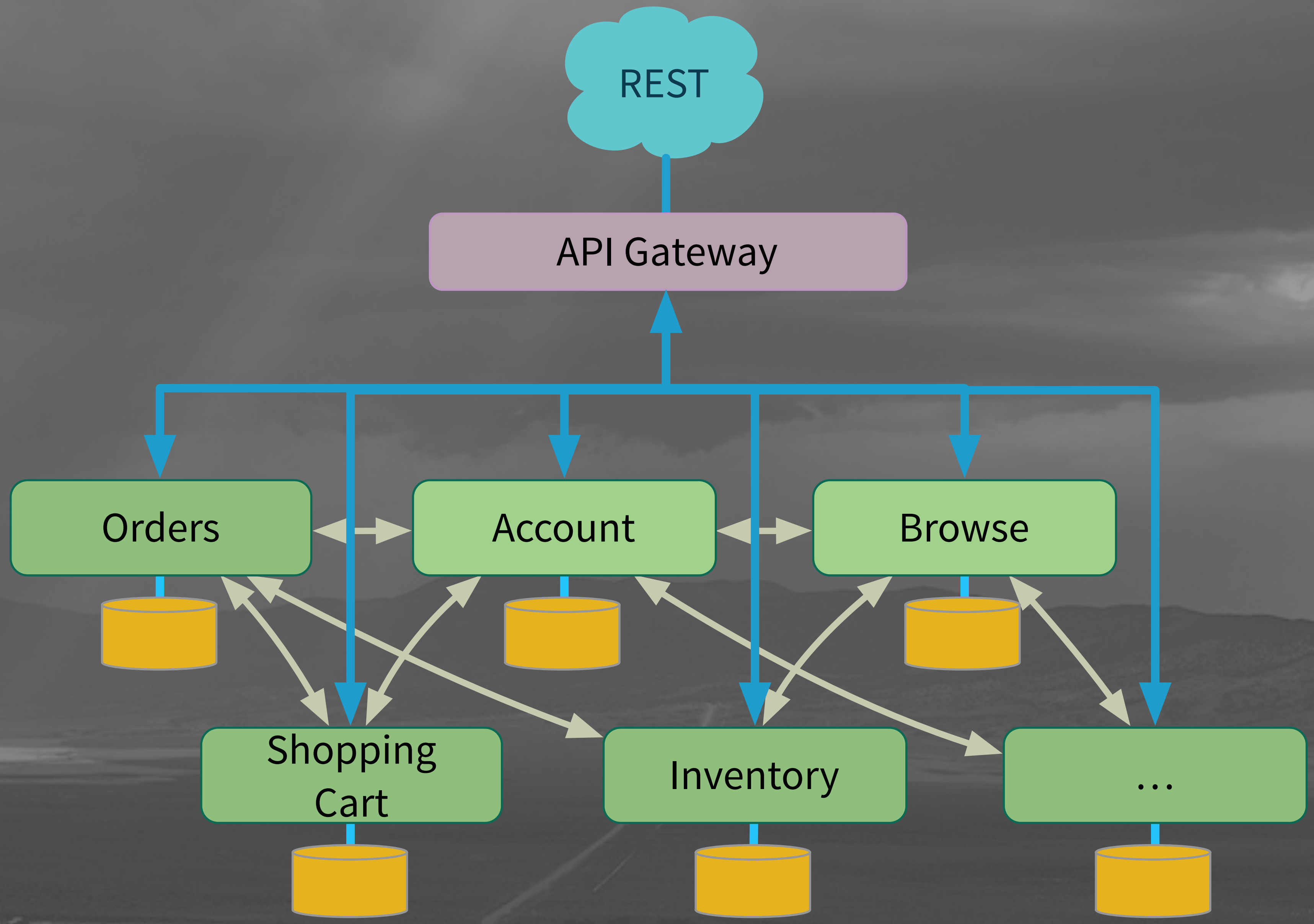
- Reliability - fault and “surprise” tolerant
- Availability - “always on”
- Low latency - for some definition of “low”
- Scalability - up and down
- Adaptability - ideally without restarts

In other words: Microservices



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Serving Models in Production
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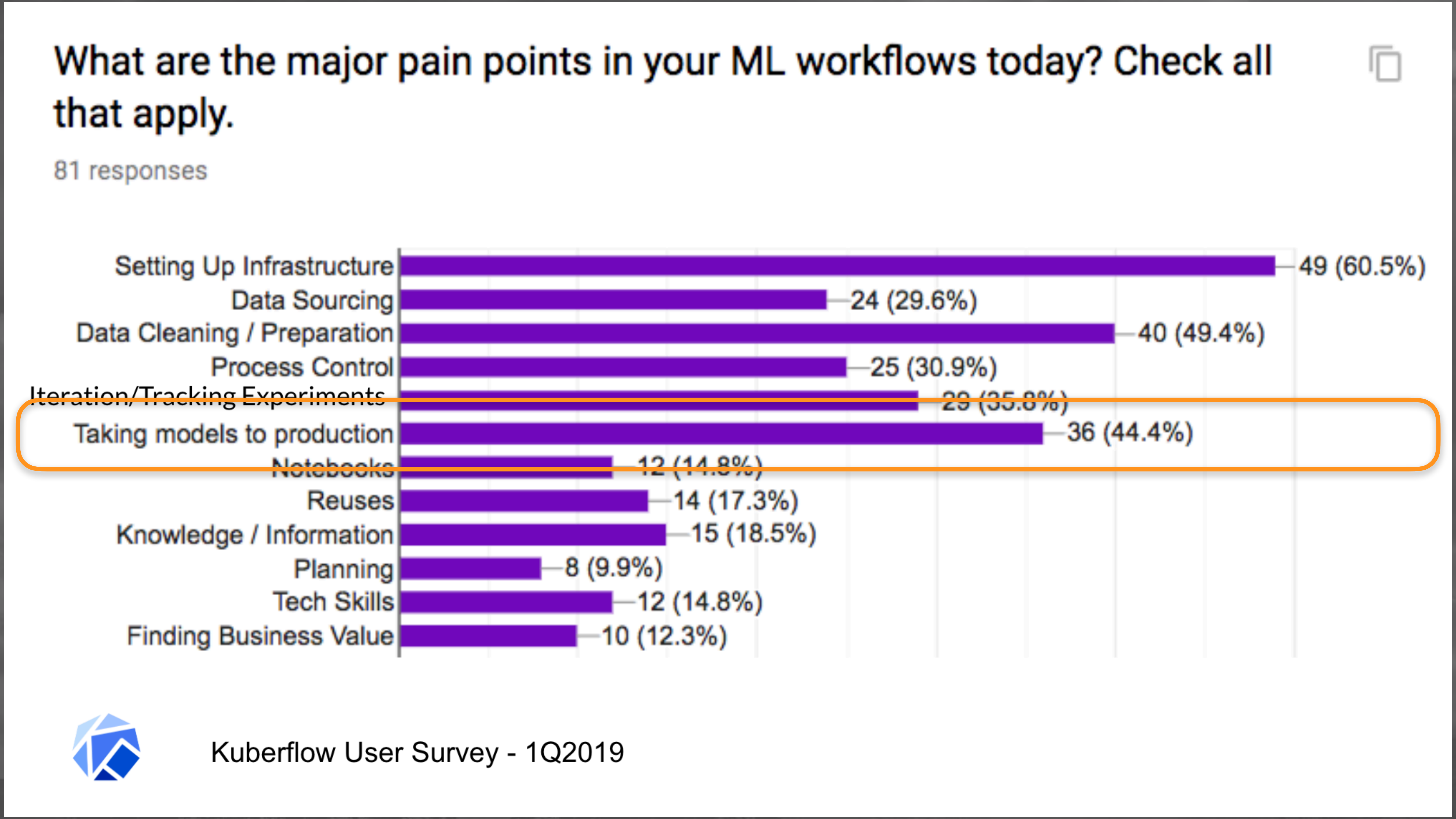
A Recent Kubeflow User Survey



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 recent Lightbend survey

Can You Answer this Question?

- Why did the model reject that loan application?

(After you've been sued for discrimination…)

Which model was it?

- Which version of the model was used?
- How was it trained?
- When was this model deployed?
- … and other questions you'll need to answer to understand what happened…


CI/CD for ML?
a.k.a “MLops”

CI/CD Process Required (1/4)

- Version control - for models and code
- Automation - builds, tests, quality checks, artifact management & delivery
  - Necessary for reproducibility

CI/CD Process Required (2/4)

- Supports different launch configurations:
  - "dark" launches
  - A/B, Canary, and other testing scenarios

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CI/CD Processes Required (3/4)

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

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Models Are Data

CI/CD Processes Required (3/4)

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

GDPR - What if a customer asks you to delete their data? Do you also delete the models trained with that data?

CI/CD Processes Required (4/4)

- Monitoring
  - Resource utilization changes?
  - Quality metrics:
    - Match performance during training?
    - Concept drift?

What’s Different from Microservice CI/CD?

- AutoML
- Data safety and lineage
- Model fairness and reproducibility
- Model and feature artifact management

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

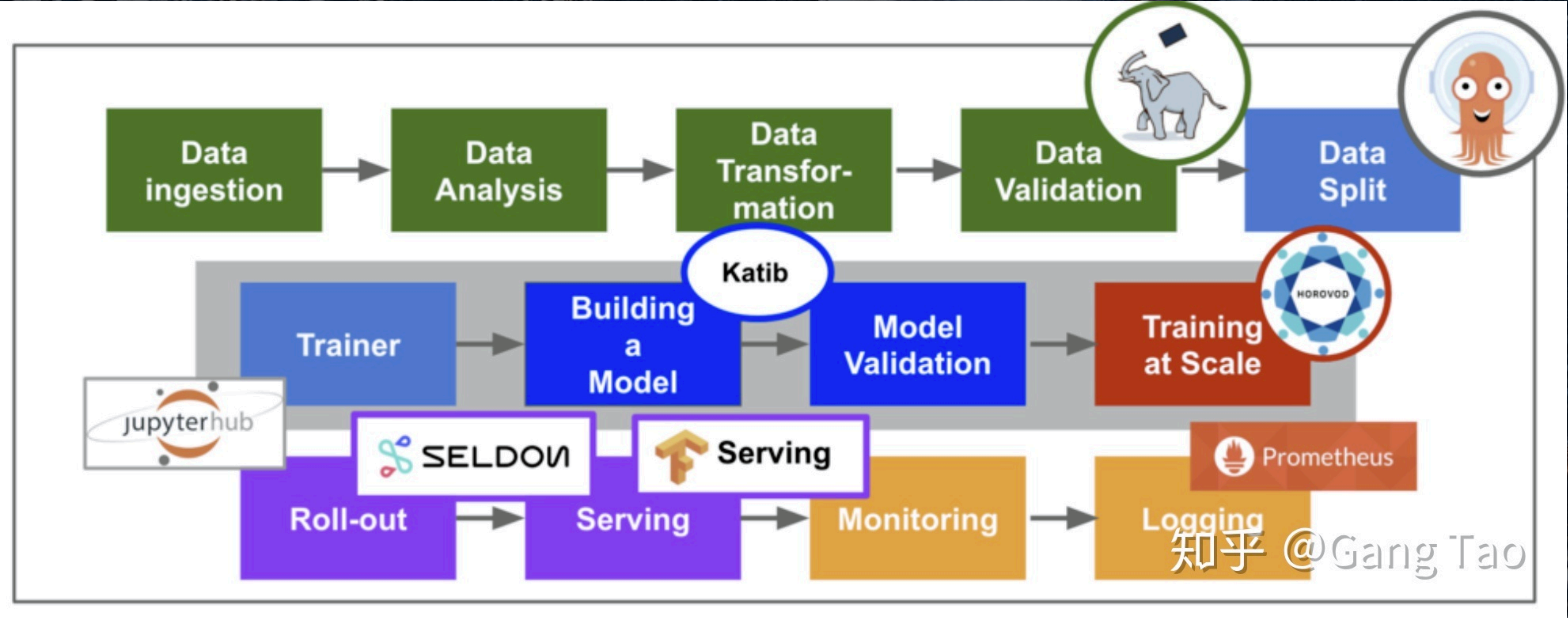
What’s Different from Microservice CI/CD?

- CI/CD prefers deterministic measures of quality. How should you support the extra statistical indeterminacy data science introduces?

CI/CD Suites for ML

- Kubeflow - for Kubernetes
- SageMaker - for AWS users
- MLFlow - from the Spark community
- … plus emerging vendors

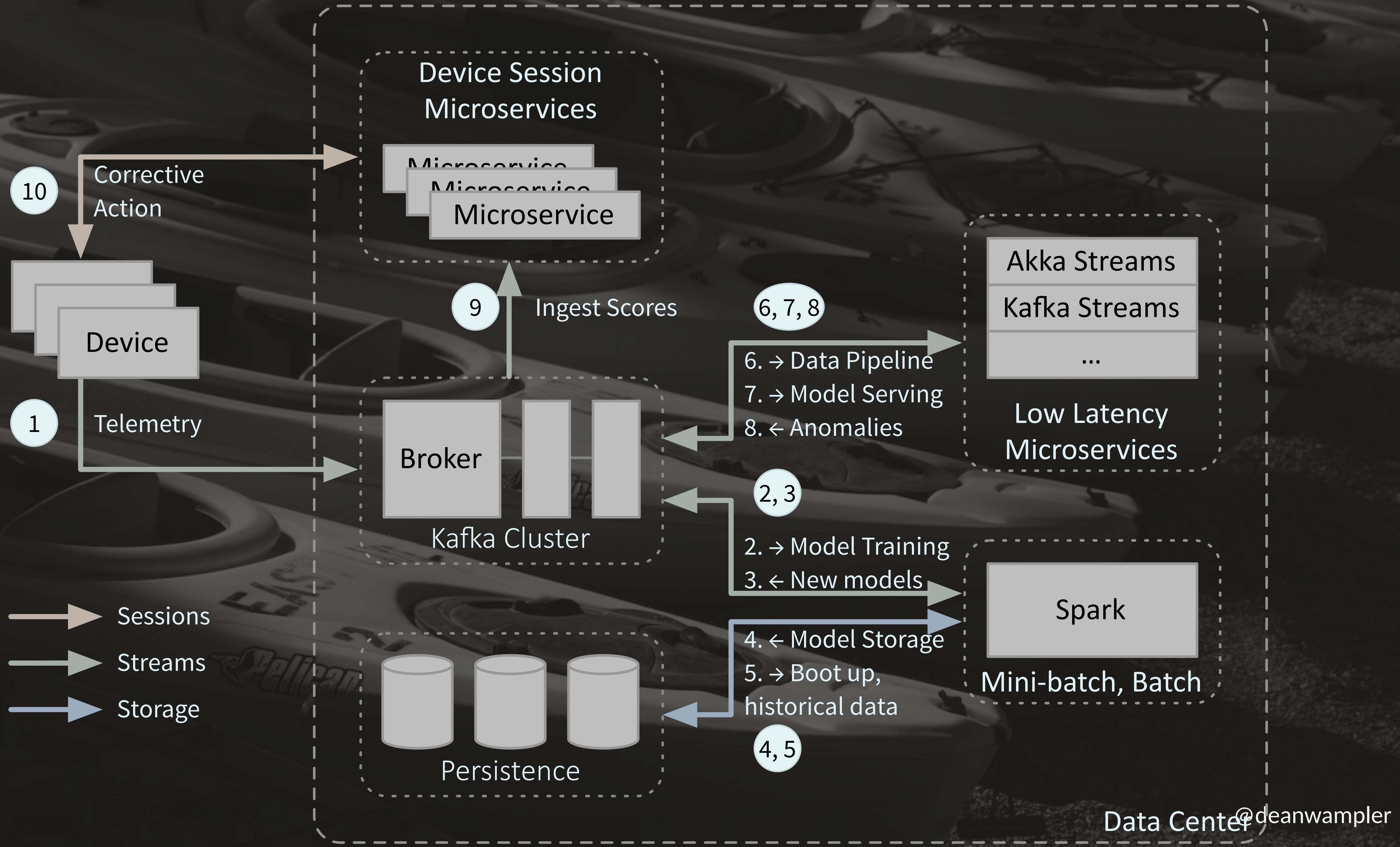
Systems - Kubeflow



Example Architectures

Example Architectures

Timely Information Integrated with Your Apps


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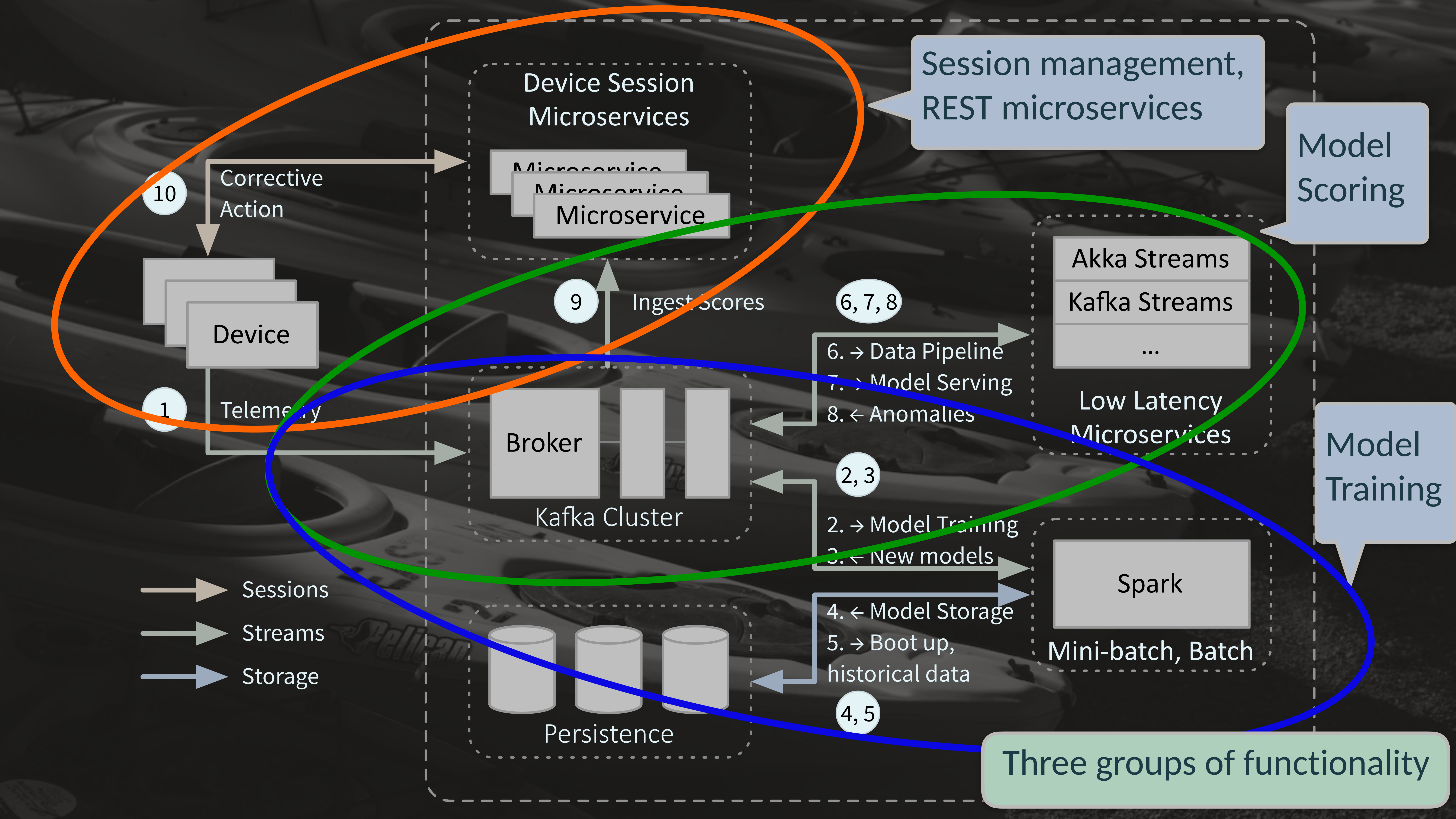

Device Session Microservices
Microservice
Session management, REST microservices
Model Scoring
10
Corrective Action
Device
9
Ingest Scores
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Sessions
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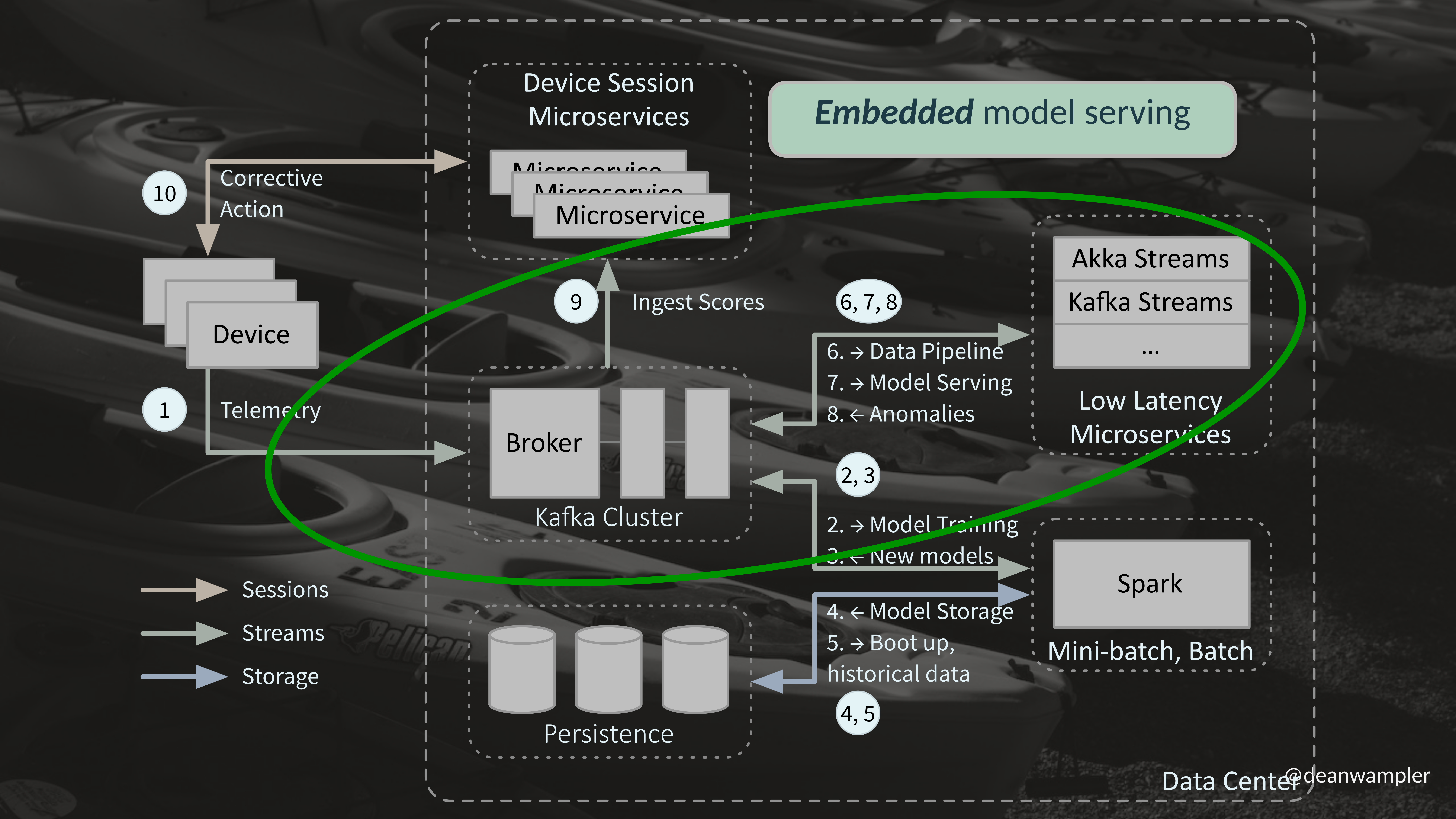
Persistence
Three groups of functionality


Embedded model serving
Device Session Microservices
Microservice
Corrective Action
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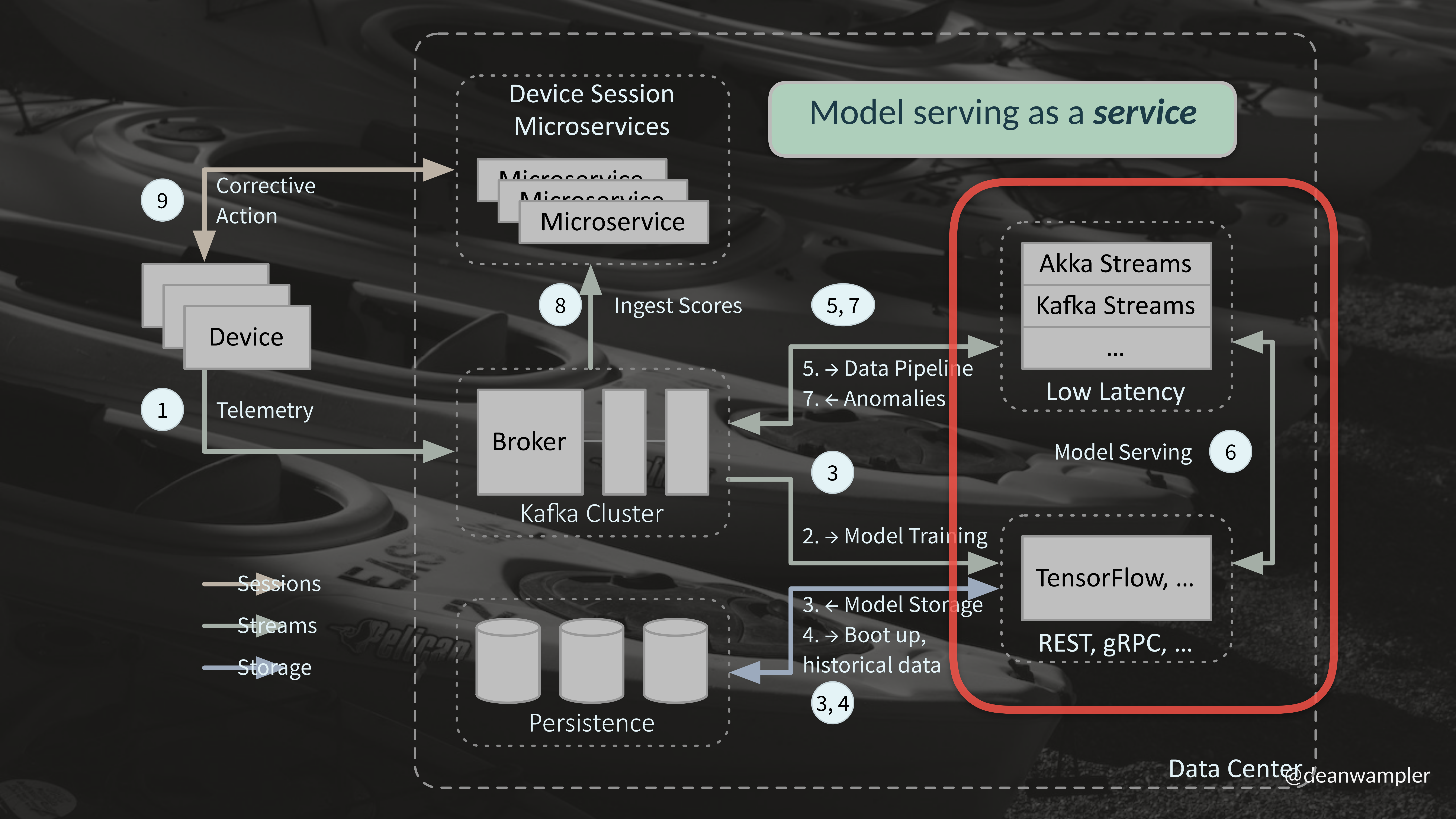
Model serving as a *service*
Device Session
Microservices
Microservice
9
Corrective
Action
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...
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Model Serving
6
3
2. → Model Training
TensorFlow, ...
REST, gRPC, ...
3. ← Model Storage
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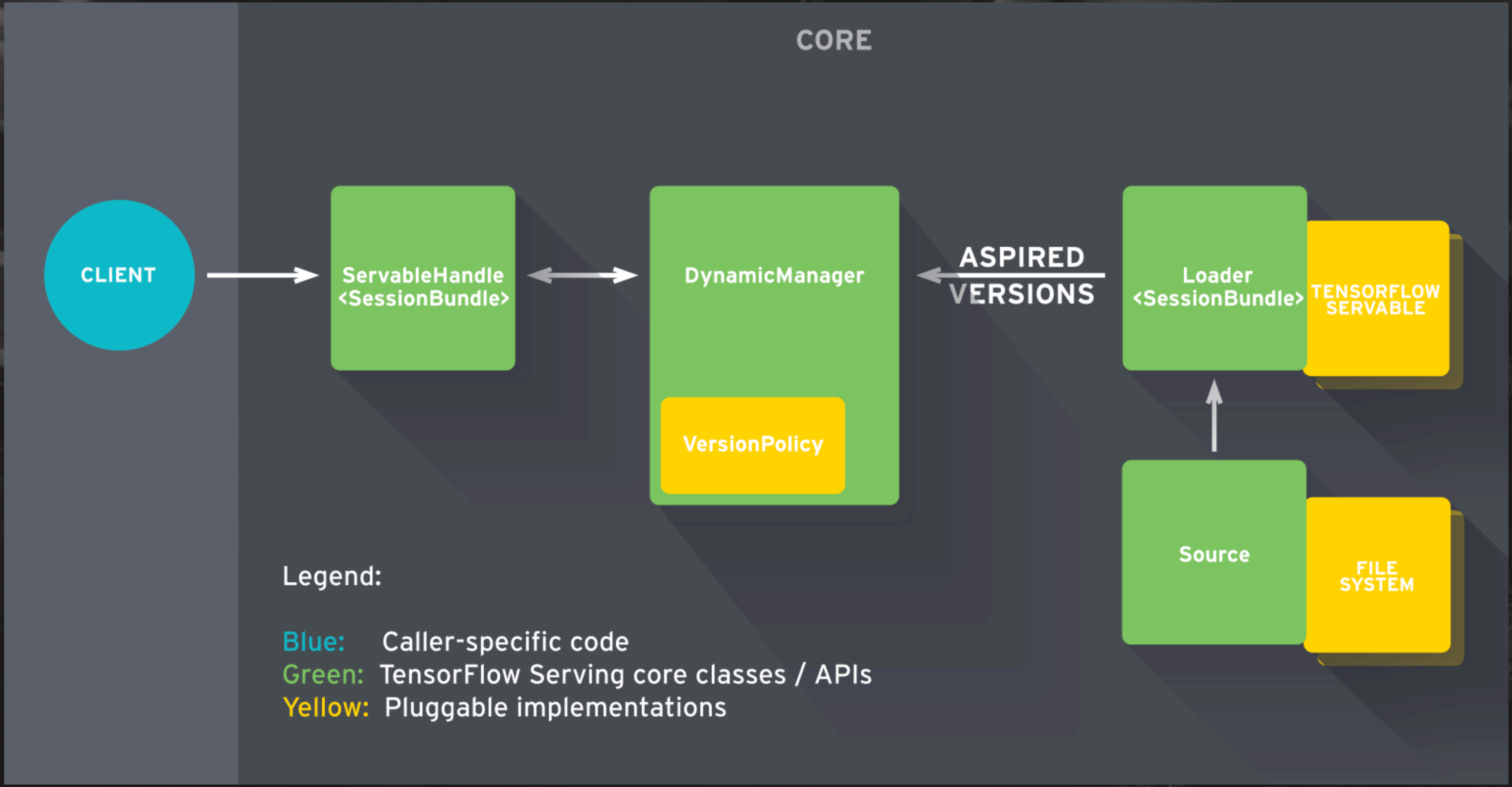
TensorFlow Serving



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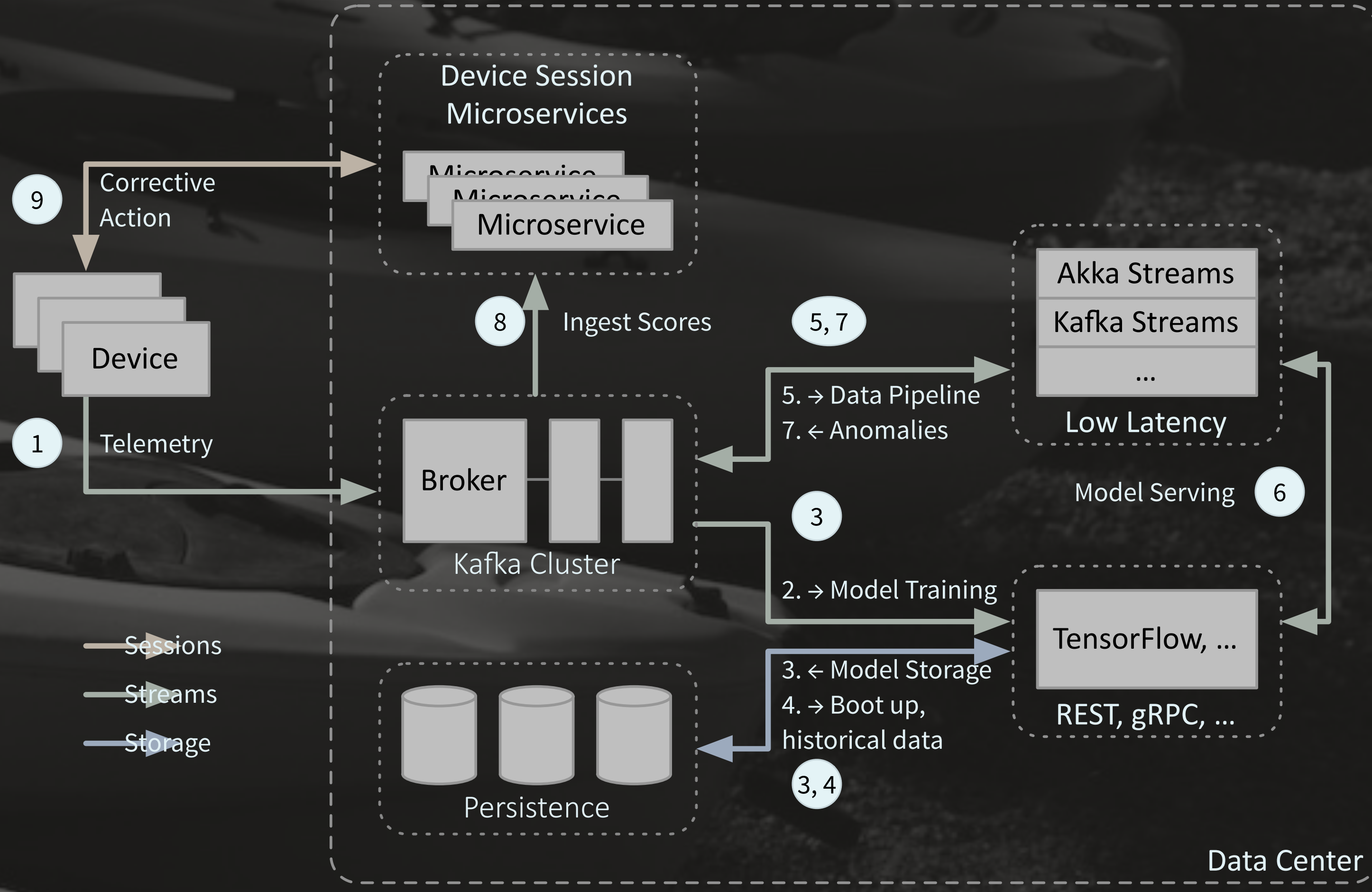
Model Serving as a Service

- Pros:
  - A familiar integration pattern
  - Decouples “concerns”: AI tools, scaling, upgrading, ...
  - One system for training and scoring



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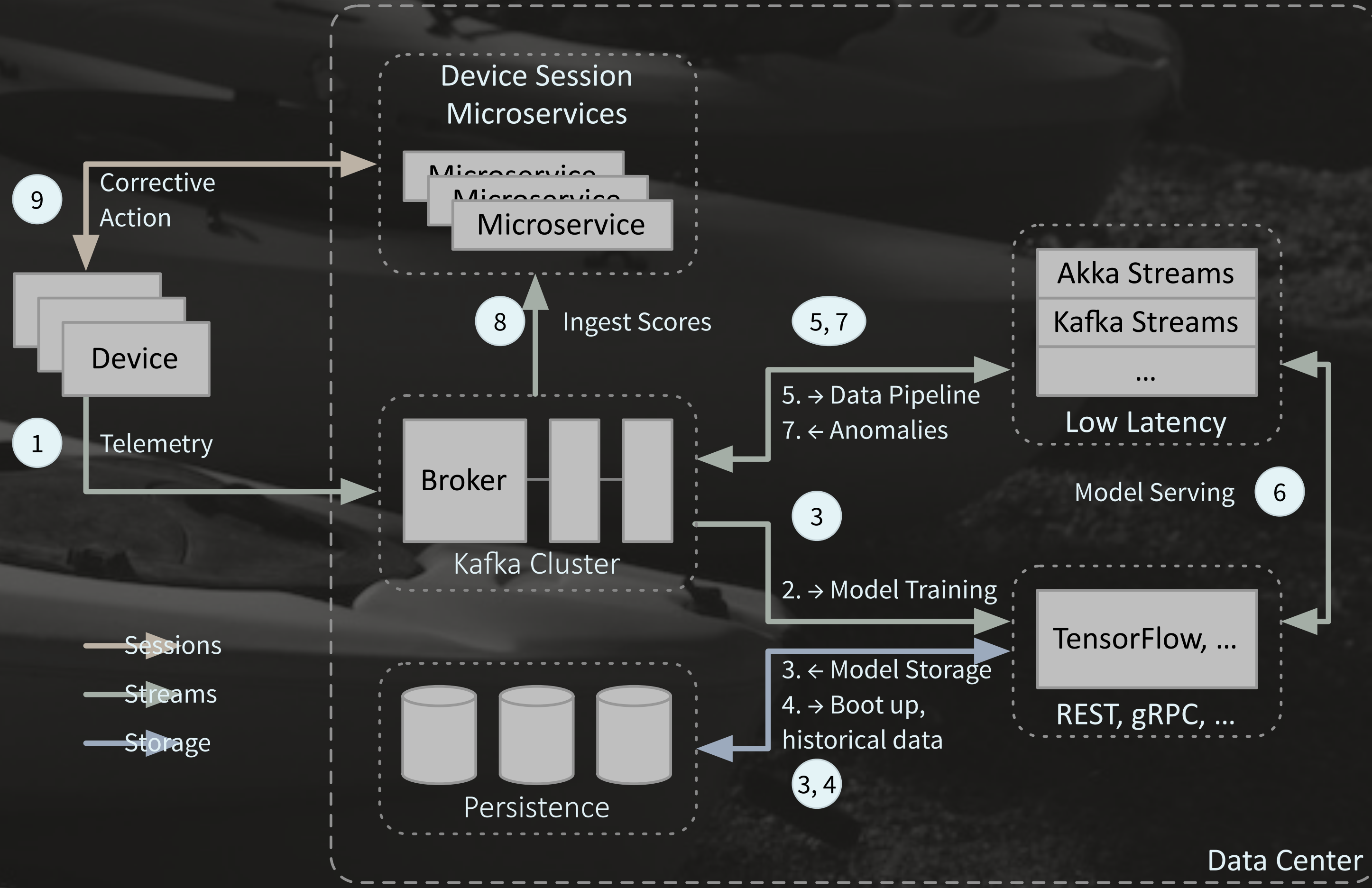
Model Serving as a Service

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



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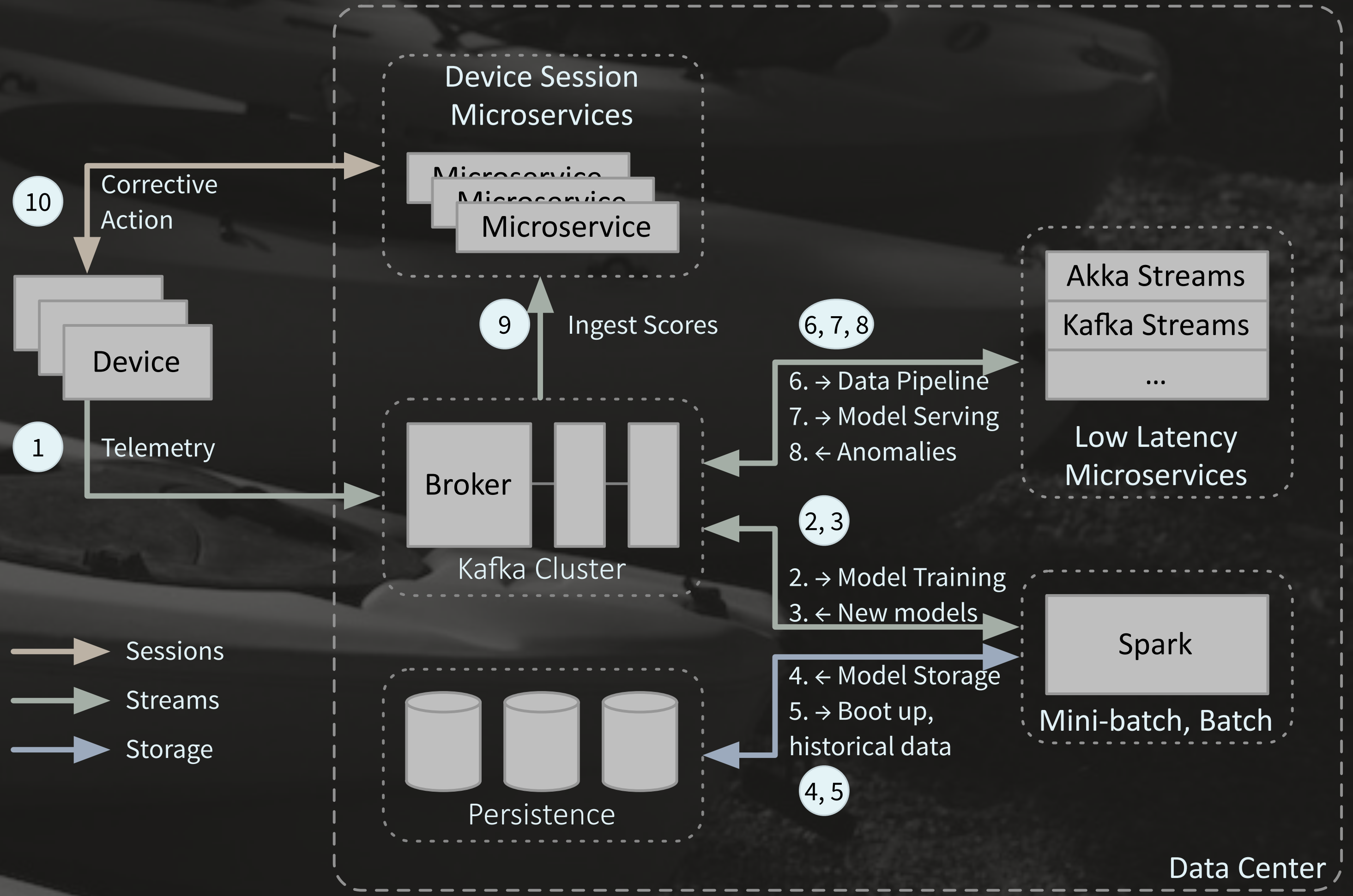
Embedded Model Serving

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



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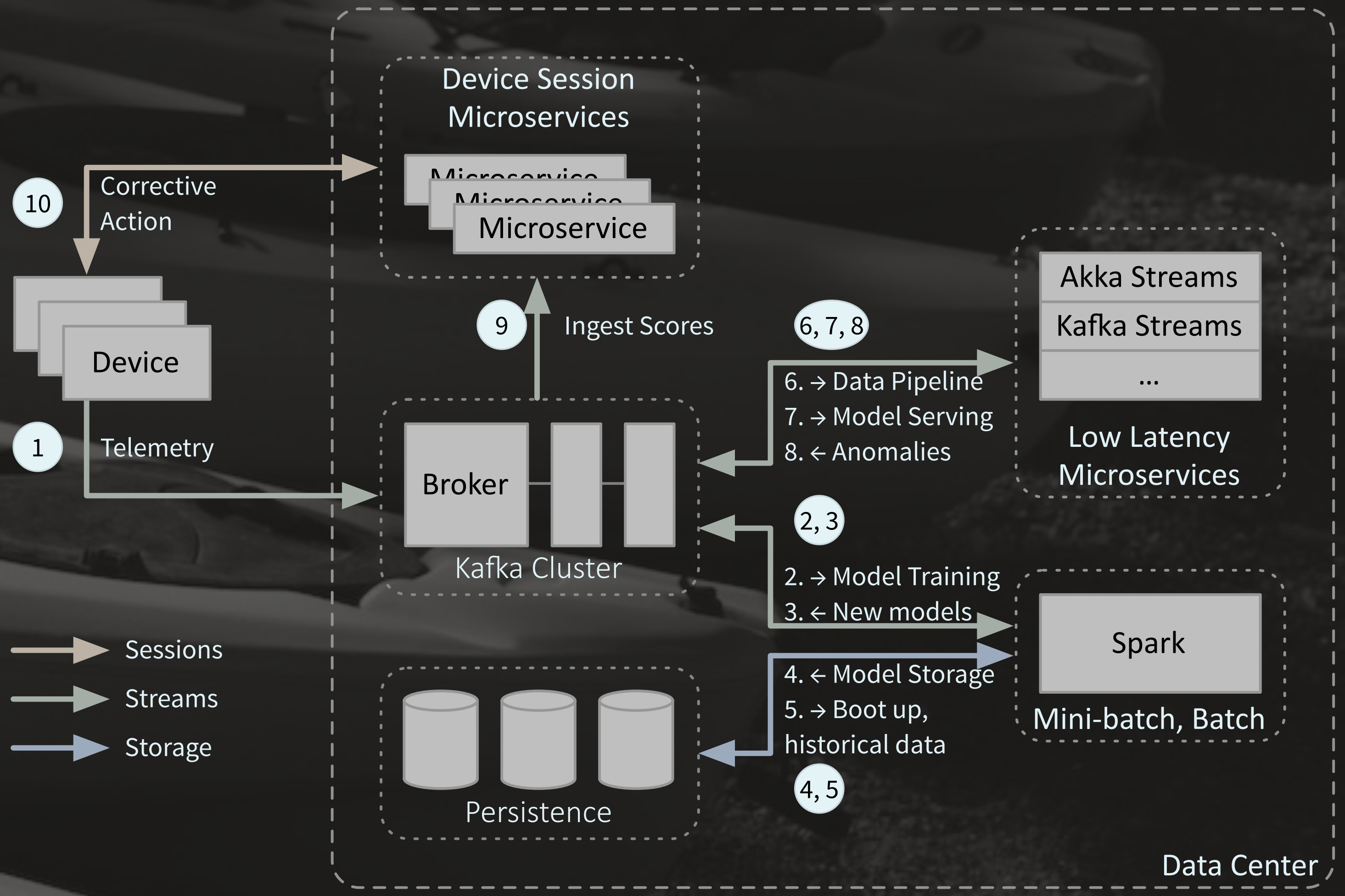
Embedded Model Serving

- Cons:
  - Model parameters must be serialized
  - More complexity
  - Model serving library must be “compatible” with training system



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Updating Models in Production

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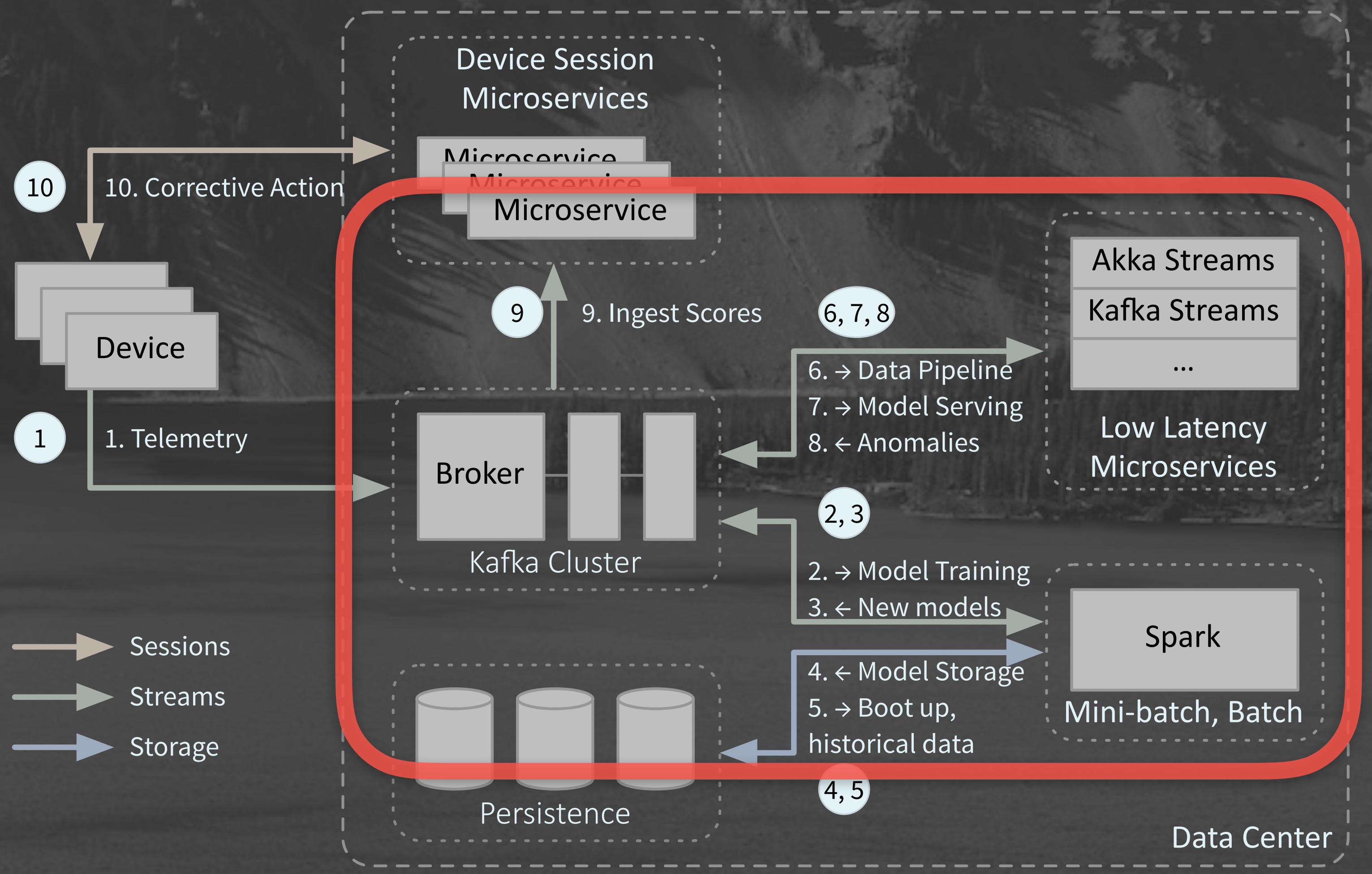
Model Updates

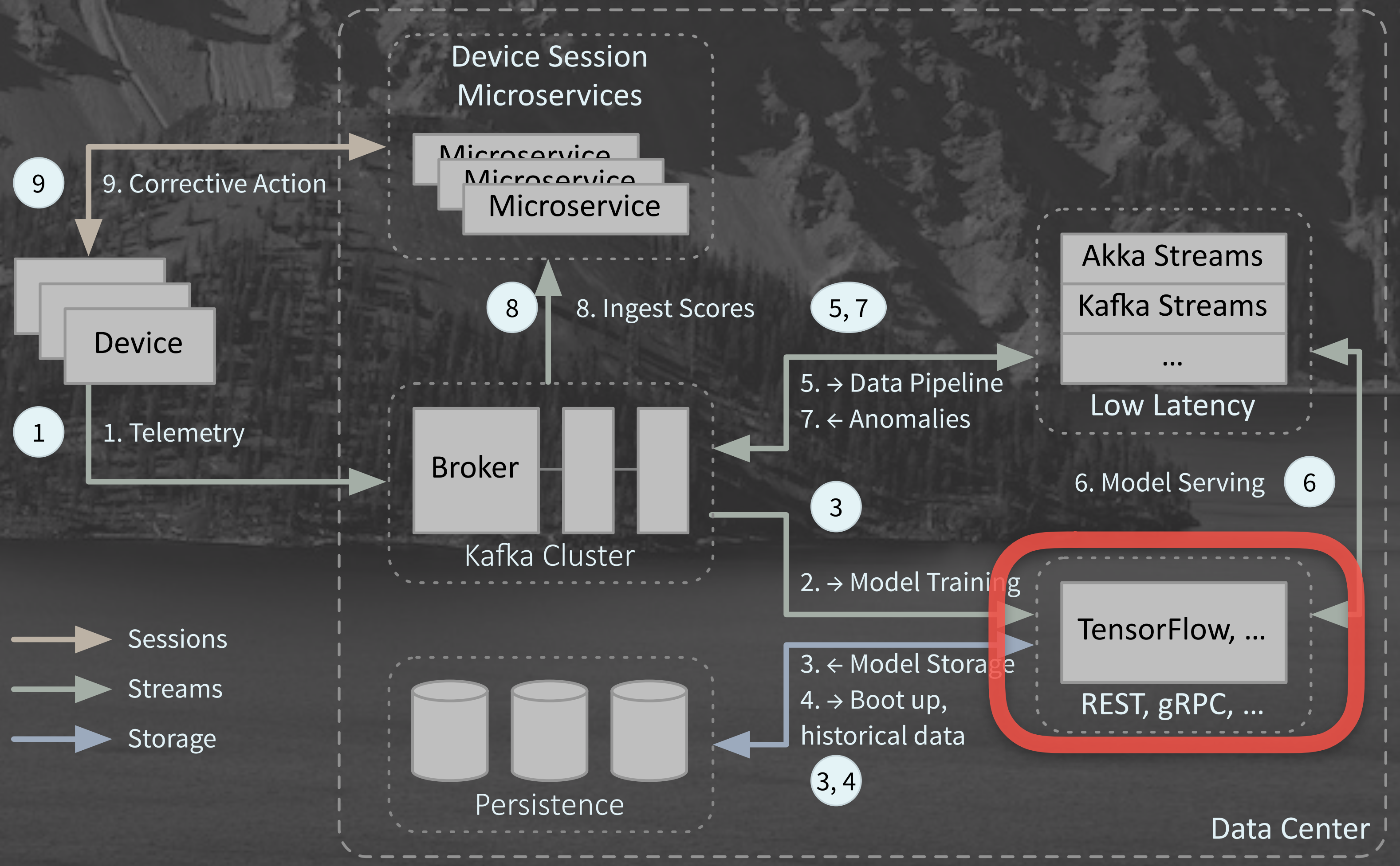
- Concept Drift - models grow stale
  - They have a half life, too
  - So, periodically retrain, then serve the new model, ideally without downtime

Retraining Considerations

- How do you measure model quality?
- What's the trade-off between model performance vs. retraining cost?
- How far back in the data set do you go when training?



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
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References

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

You can get these slides with the links here:
polyglotprogramming.com/talks

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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
  - Explainability

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

Questions?

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