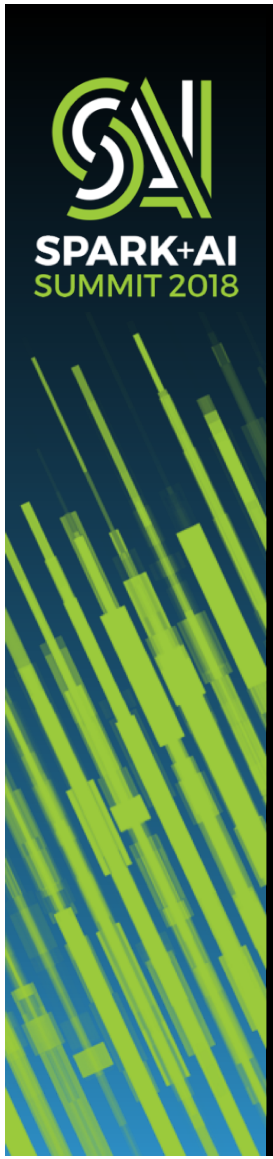

Scaling Machine Learning at Booking.com

Brammert Ottens, Booking.com
Luca Falsina, Booking.com

#ML8SAIS

Booking.com

Who are we?

Brammert Ottens

Senior Data Scientist

Luca Falsina

Senior Developer

Booking.com

- One of the **largest** travel e-commerce companies in the world
- **15.000** employees in 198 offices in 70 countries worldwide
- **133,577** destinations in 228 countries and territories worldwide
- Each day, more than **1,550,000** room nights are reserved on our platform

Outline

- Datascience @Booking.com
- The Machine Learning (ML) pipeline
- Offline ML
- Online model serving
- Model & features monitor and discoverability
- Future directions

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Datascience @ Booking.com

- We have a community of over 200 data scientists (DS)
- Each with different needs, expertise and preferred toolkits and methodologies

The mission of our track is to help scaling ML across our organization. How?

- Identify **common problems** (i.e. historical feature reconstruction)
- **Implement infra and tooling** to solve them
- **Train, educate and consult** internal users on these solutions

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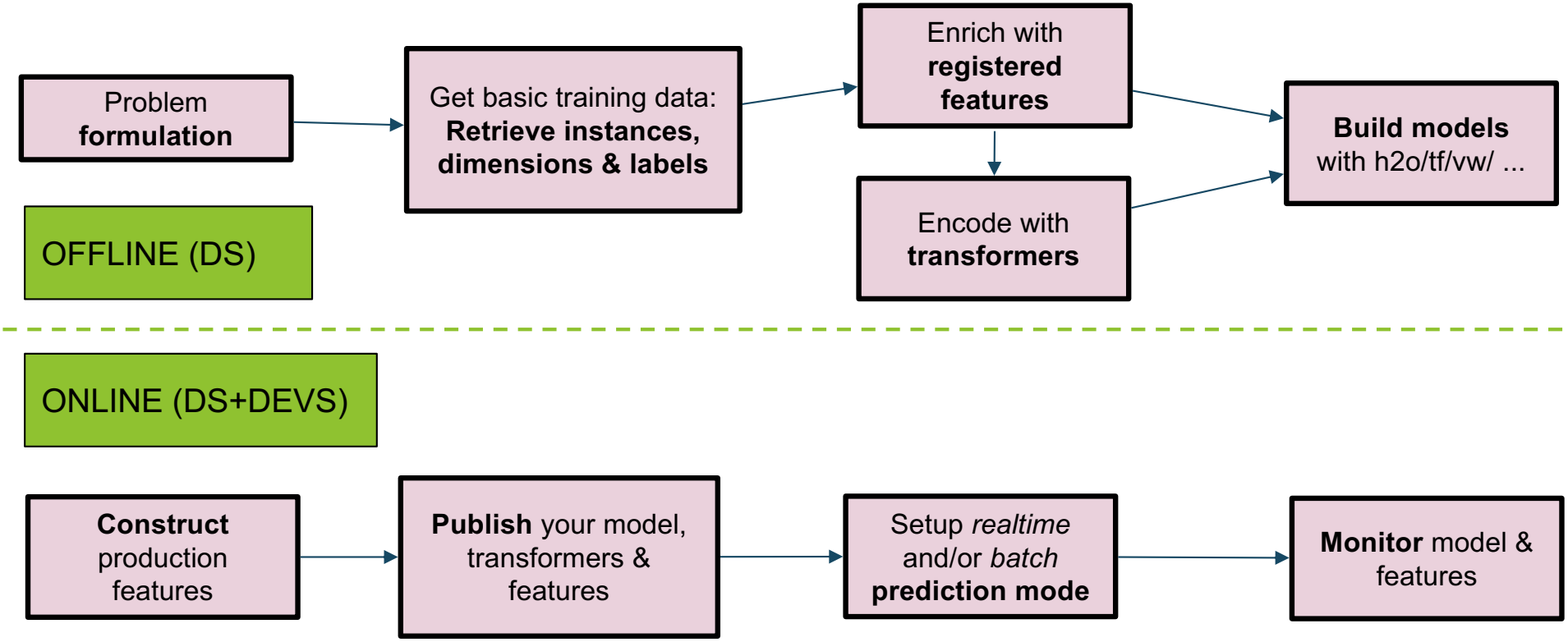
The “general” ML pipeline



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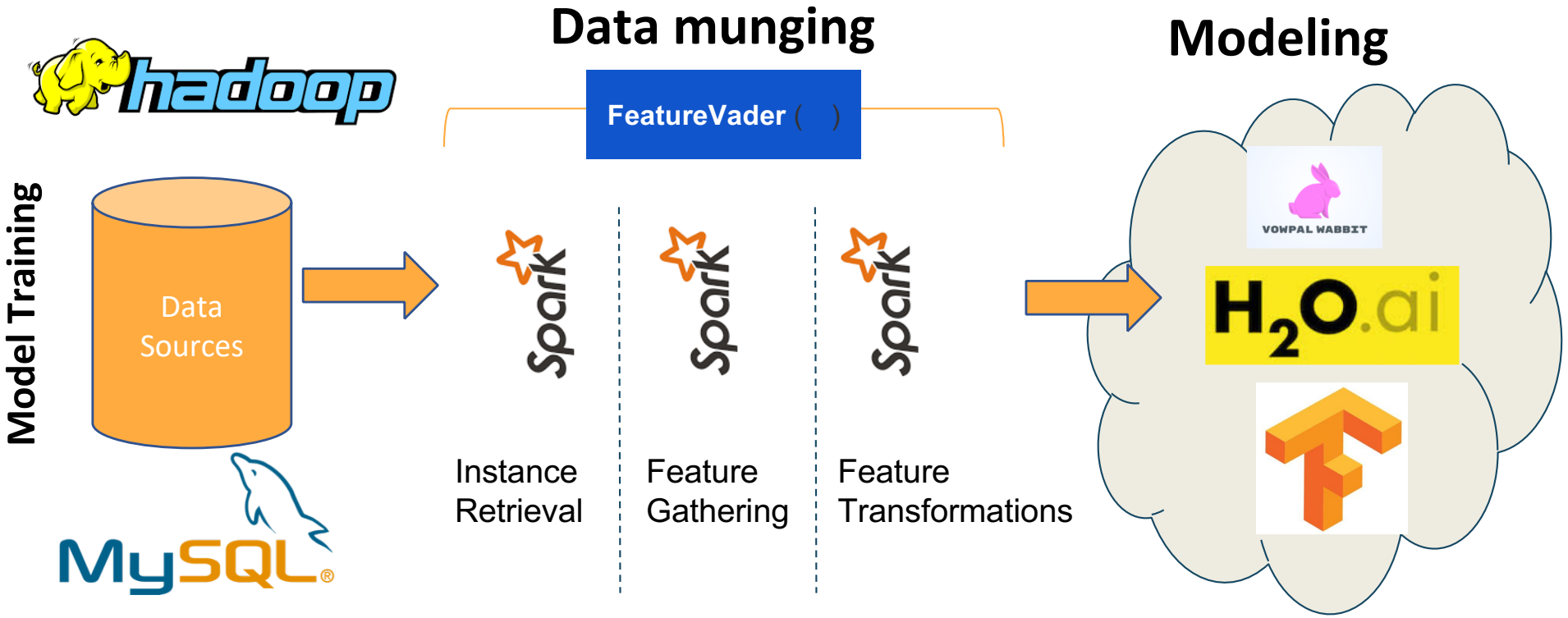
The “offline” world



OFFLINE DATA MUNGING

1. Extract relevant data from events
2. Feature engineering
3. Time coordinate matching
4. Scalability

Offline feature engineering

- **FeatureVader** (containing a feature registry):
  - Custom Spark ML Transformer:

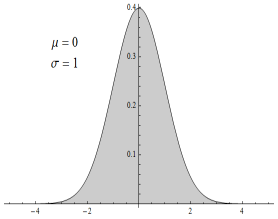
```
labeledInstances = spark.sql("""
            select
                userId
                , time
                , IF(x > 4, 1,0) label
            FROM data""")
fv = FeatureVader()
fv.setTimeStamp("time").setDesiredFeatures(["feature1", "feature2"])
withFeatures = fv.transform(labeledInstances)
```

userId	time	label
1001	25	1
1002	36	0

userId	time	label	feature1	feature2
1001	25	1	213.5	2 kids
1002	36	0	123.7	0 kids

Feature transformations

- Raw features are not enough.
- Transformations greatly increase model performance:



Feature transformations (WIP)

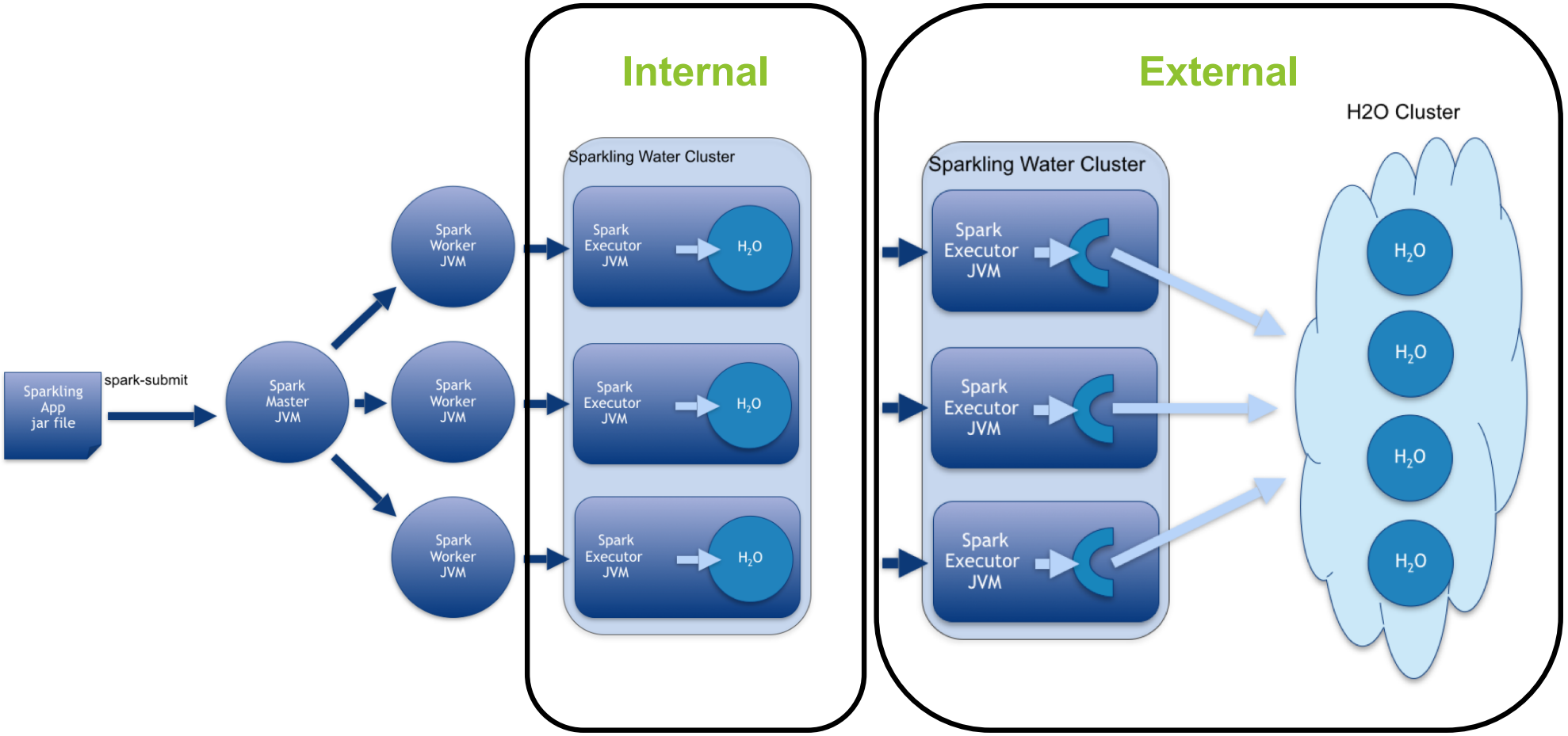
```
testimator = TargetEstimator()
                .setFeature("feature1")
                .setEncodedFeature("feature1_TE")
                .setResponse("label")

pipeline = new PipeLine(stages=[testimator])

pipeline_model = pipeline.fit(train)

pipelineWriter = PipelineWriter(pipelinemodel)

pipelineWriter.writeTo("pipeline_model.bojo")
```

Modeling

Several libraries in use at Booking.com

Modeling (H2O)

- Sparkling water
  - H2O integration with Spark
    - Best of both worlds: data munging in Spark + model training in H2O
  - Scalable to very large datasets (Billions of rows)
  - Distributed training
  - Internal vs external backend mode


Internal
External
Sparkling Water Cluster
Sparkling Water Cluster
H2O Cluster
Sparkling App jar file
spark-submit
Spark Master JVM
Spark Worker JVM
Spark Worker JVM
Spark Worker JVM
Spark Executor JVM
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Spark Executor JVM
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H2O
H2O
H2O
H2O
H2O

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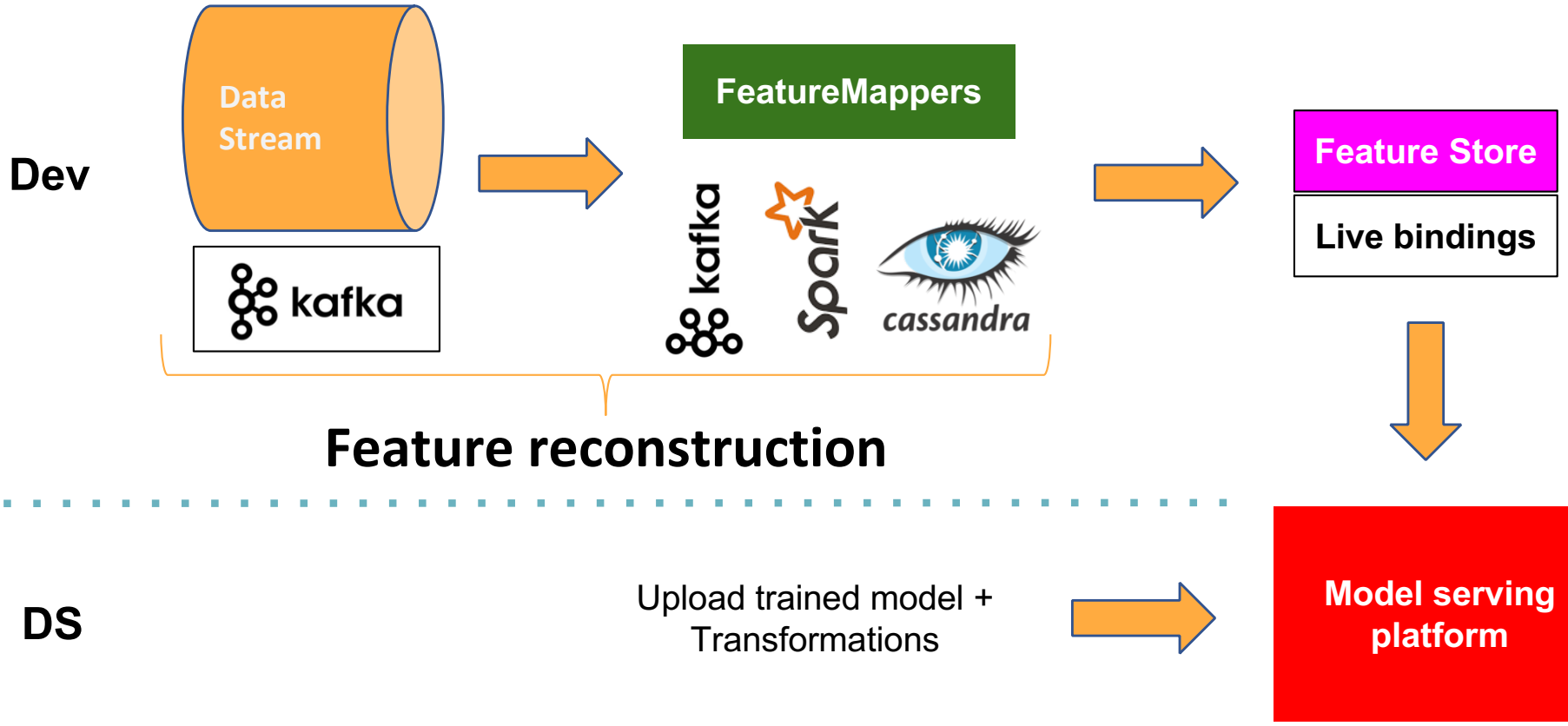
The “online” world



ONLINE DATA MUNGING

1. Nearly real-time processing

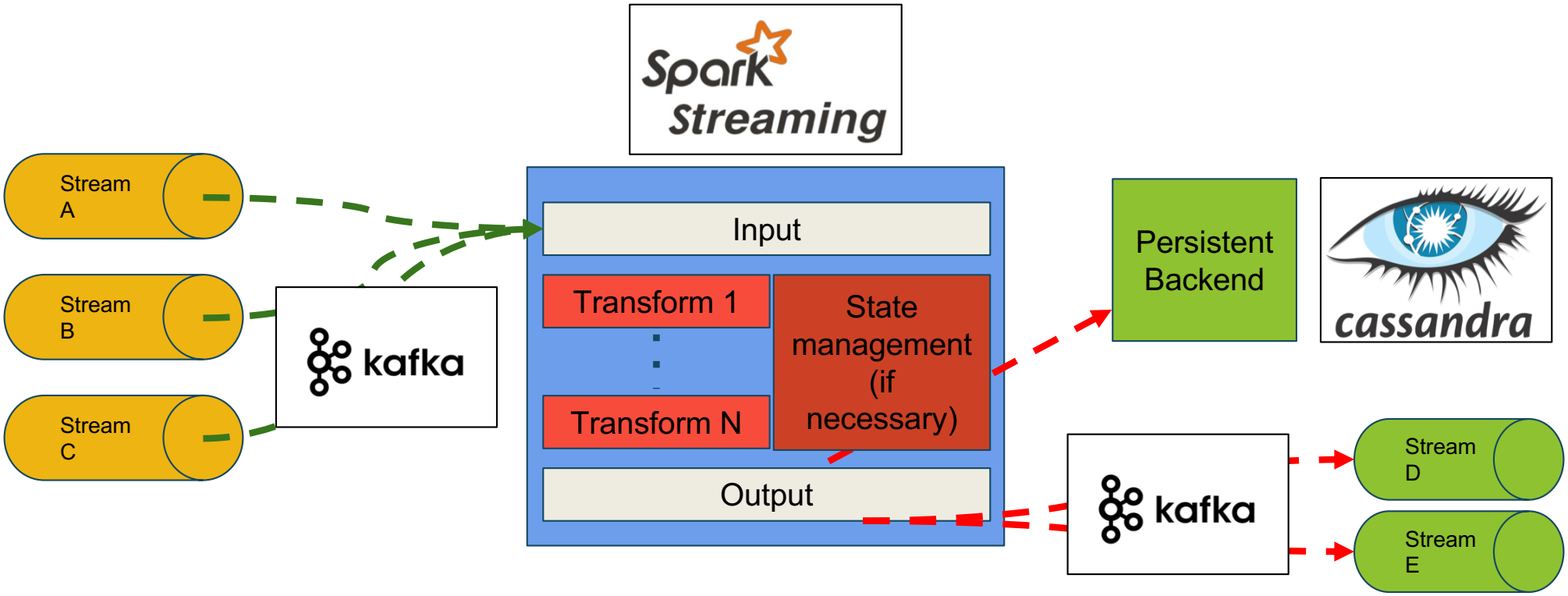
2. State(less/full) transformations

3. Containerized infrastructure

4. Nearly real-time serving

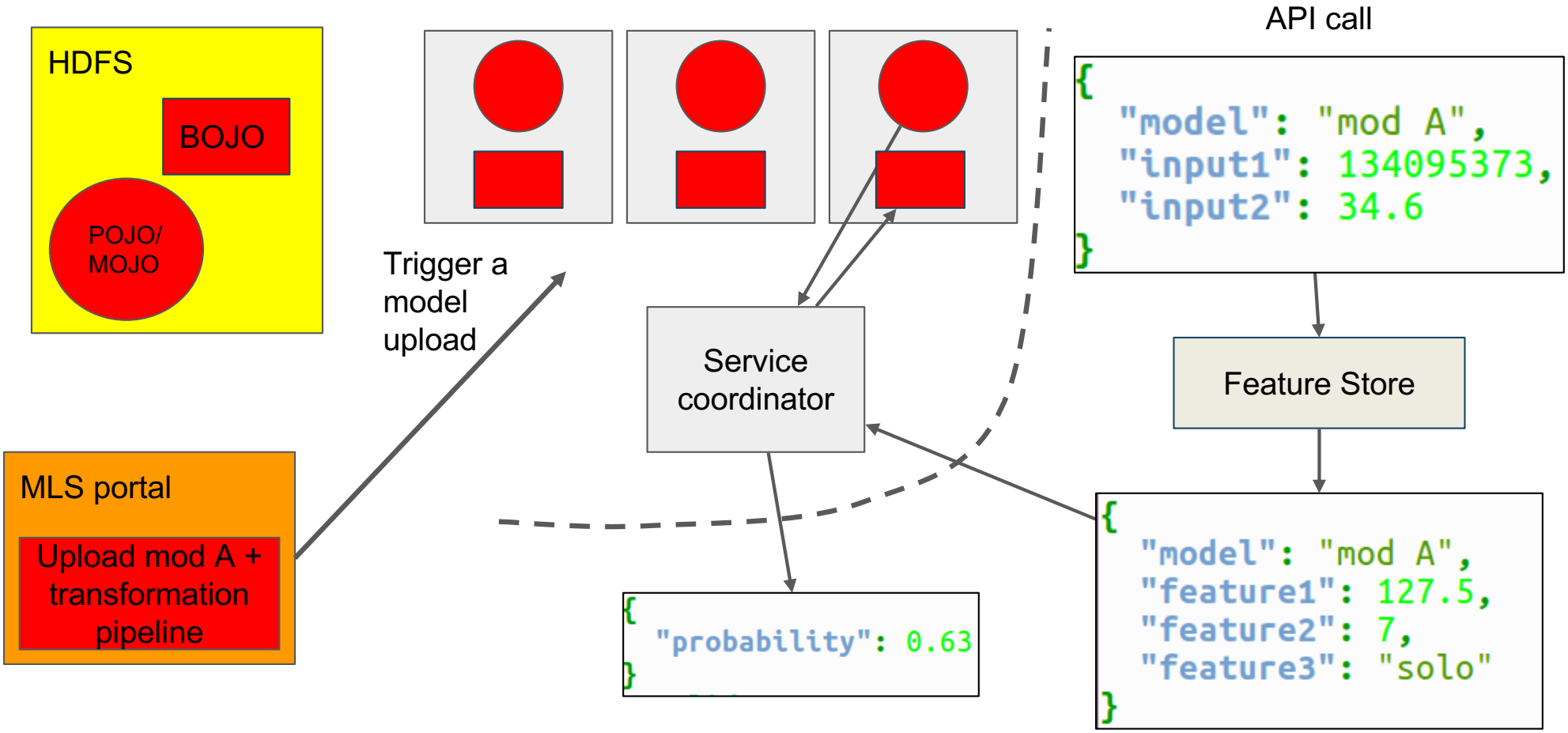
FeatureMappers

Online feature construction



Model serving platform

- Supports several model types (H2O, VW, TF, csv...)
- Allows both **single** and **batch** predictions
- Integration with *live feature bindings*



Example: Model upload & inference from frontend hosts

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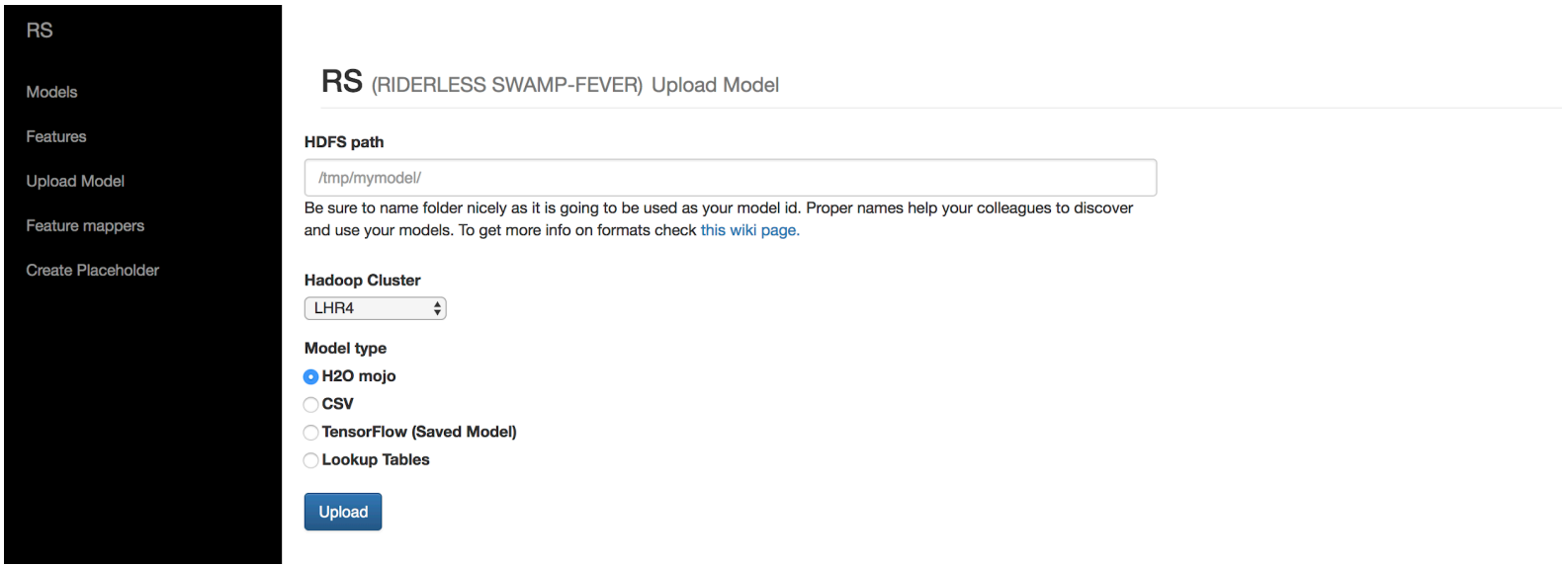
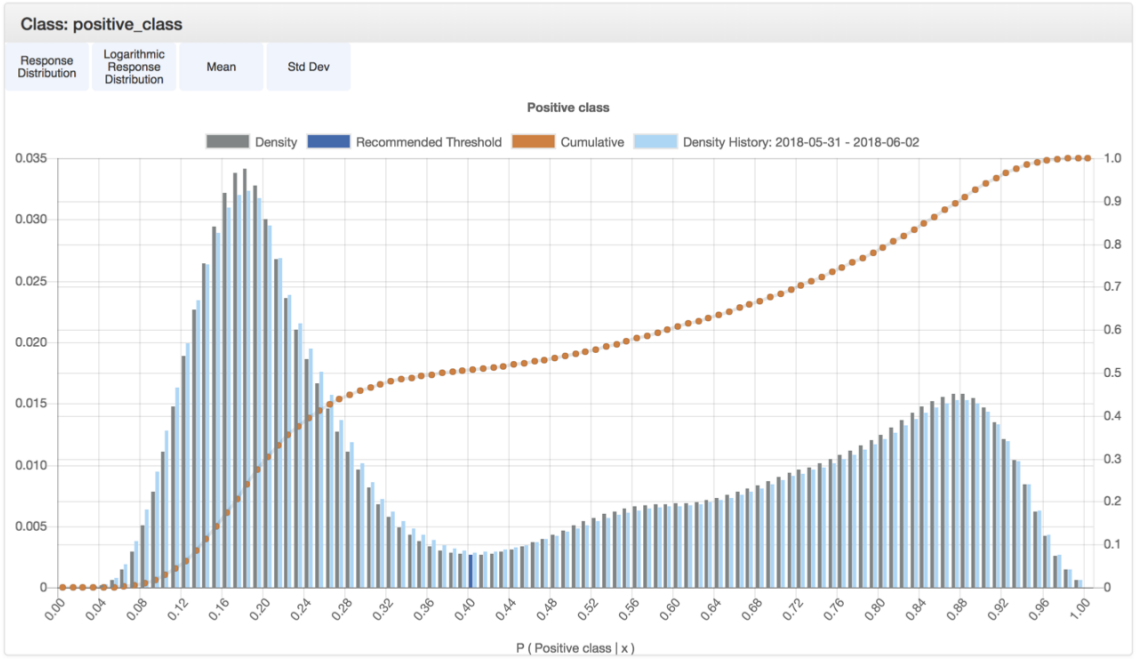
Model portal



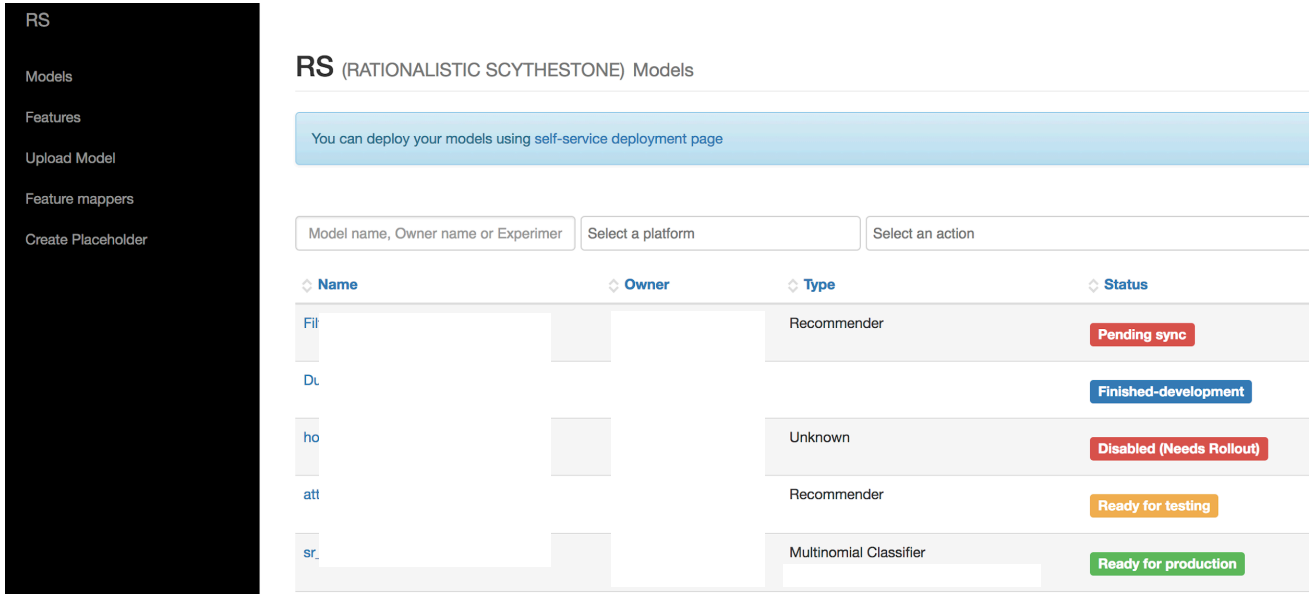
- Allow to define models and upload new versions

Model portal



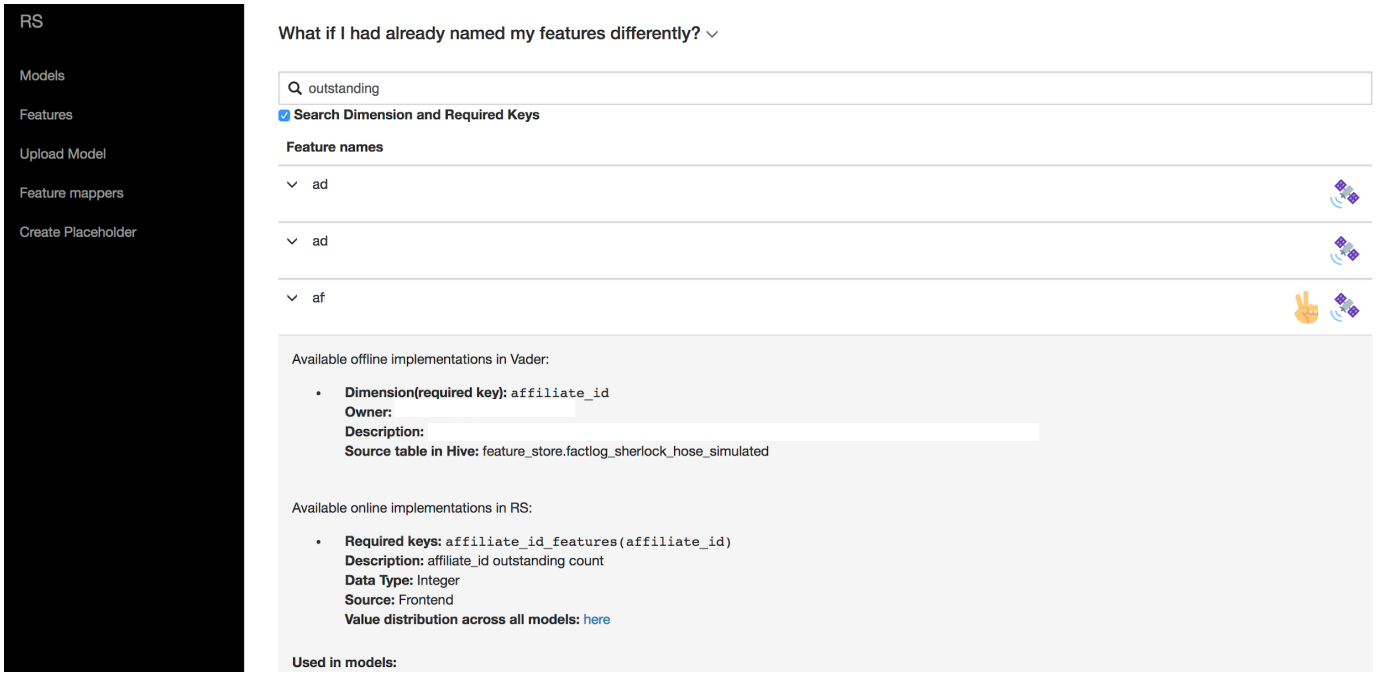
- Provide monitoring

Model portal



- Allow to discover and reuse existing models

Feature store portal

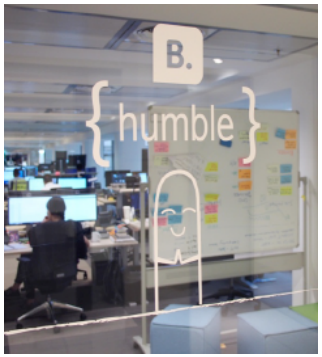


- Allow to discover and reuse features

Future directions

- Make the full pipeline smoother for faster iterations
- Limit involvement of devs (scarce resource) for ML work
  - Automatic reconstruction of features online from offline





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Brammert Ottens **brammert.ottens@**

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