

Bring Your Own Models (BYOM)- Machine Learning as a Service

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INTEL

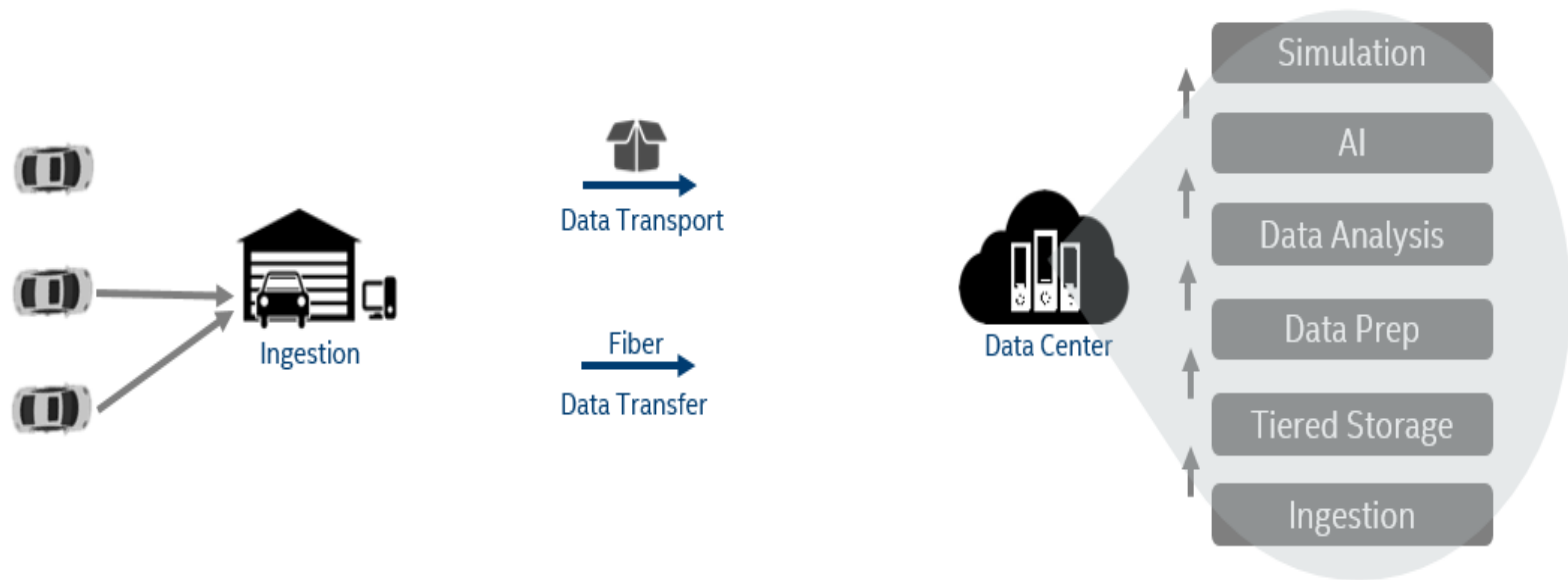
#ML9SAIS

Machine Learning Everywhere!

- Autonomous Vehicles
- Genomics
- Finance
- Supply Chain



Autonomous Vehicles R&D Data Center



Big Data

1 – 20 TB/car/hour

- Weather Conditions
- Time of Day
- Road Conditions
- Location
- Edge Cases

Object Detection Models
Environment Models
Driver Models
Privacy Preservation
Models

Under the bonnet

How a self-driving car works

Signals from **GPS (global positioning system)** satellites are combined with readings from tachometers, altimeters and gyroscopes to provide more accurate positioning than is possible with GPS alone

Lidar (light detection and ranging) sensors bounce pulses of light off the surroundings. These are analysed to identify lane markings and the edges of roads

Video cameras detect traffic lights, read road signs, keep track of the position of other vehicles and look out for pedestrians and obstacles on the road

Radar sensor

Ultrasonic sensors may be used to measure the position of objects very close to the vehicle, such as curbs and other vehicles when parking

The information from all of the sensors is analysed by a **central computer** that manipulates the steering, accelerator and brakes. Its software must understand the rules of the road, both formal and informal

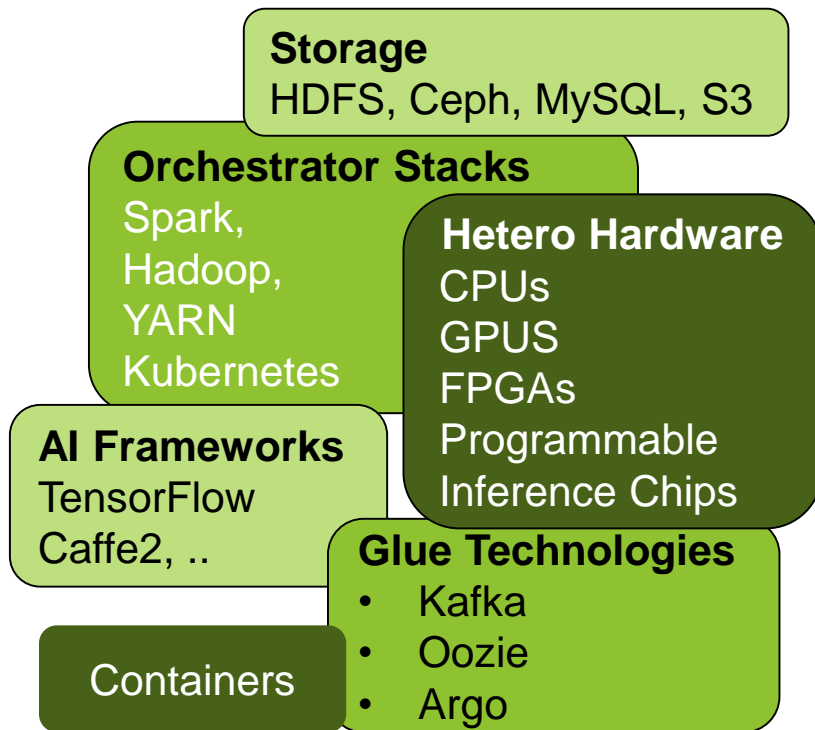
Radar sensors monitor the position of other vehicles nearby. Such sensors are already used in adaptive cruise-control systems

Source: The Economist

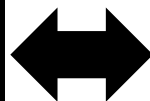
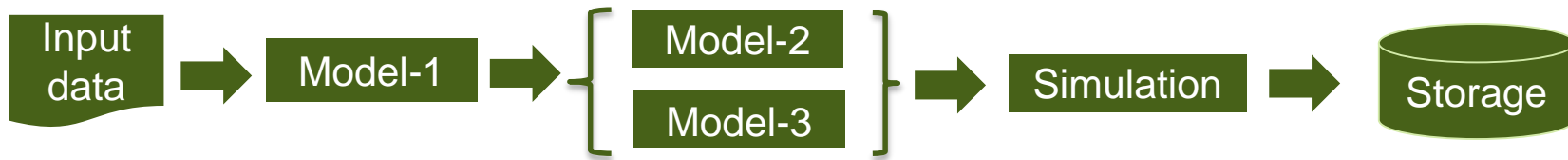
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Data Center Platform

- Fungible, Dynamic, Fast,
- Resilient
- Easy to Use



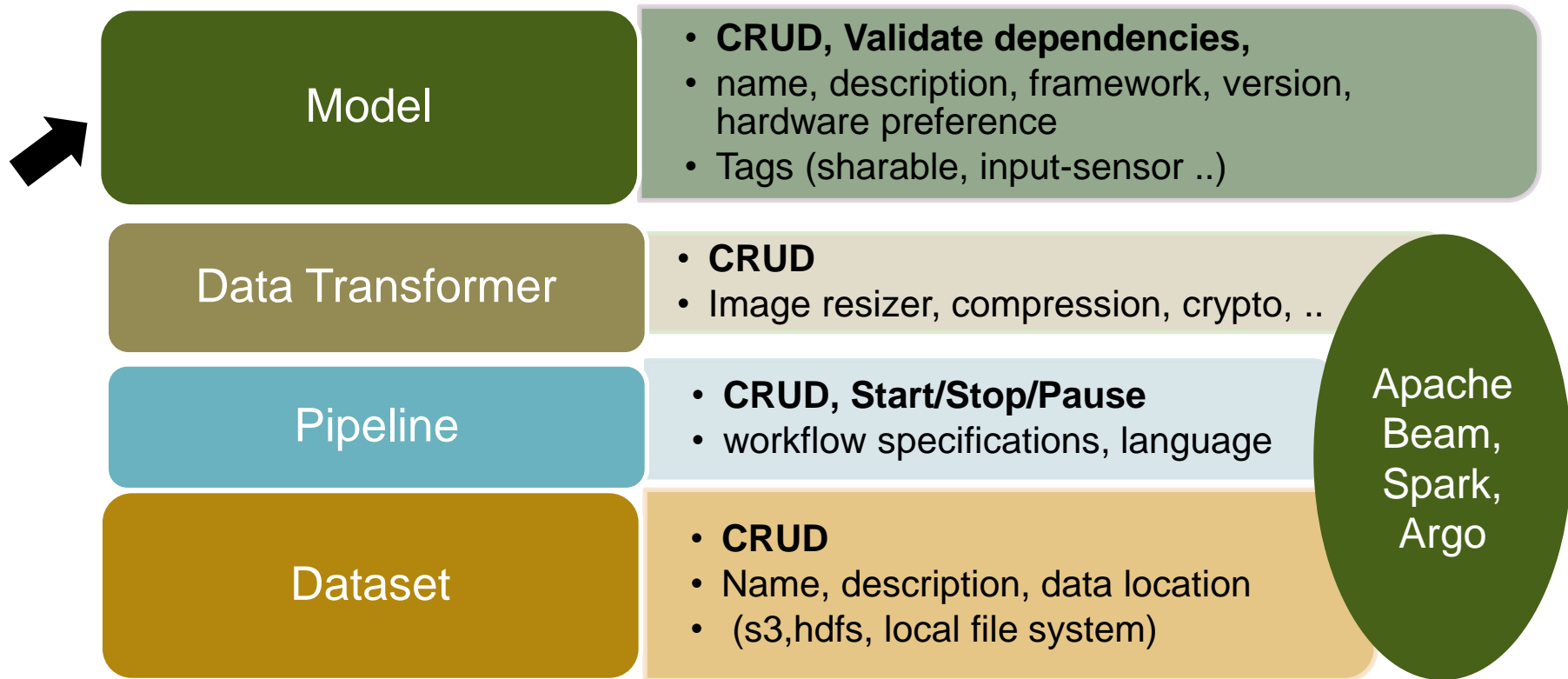
Models Galore, Usages Rich



MODEL

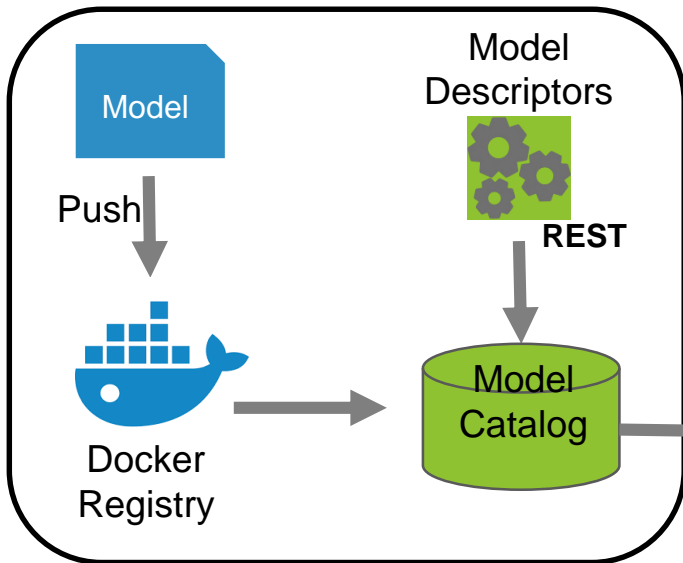
Name, Description,
type (mega | lean)
Framework & Version
Input, Output
ImageID: Container Registry ID
Training_Sets: { S1, S2 , S3}
Training_Label_Freq {L1:f1, L2:f2 ..}
Validation_Sets: {V1, V2}
Accuracy, Recall, Precision,
Speed, Size
Infrastructure:CPU/GPU/FPGA ..

Resources & API

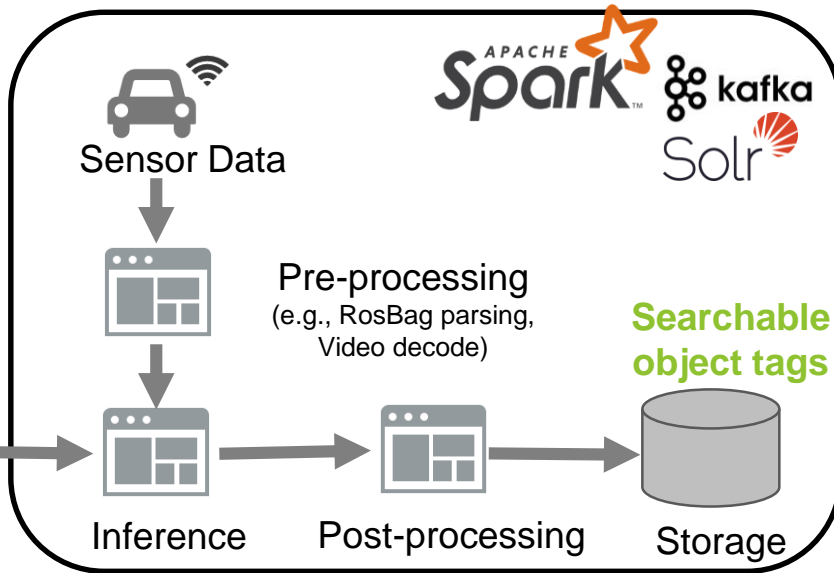


Model Deployment Pipeline

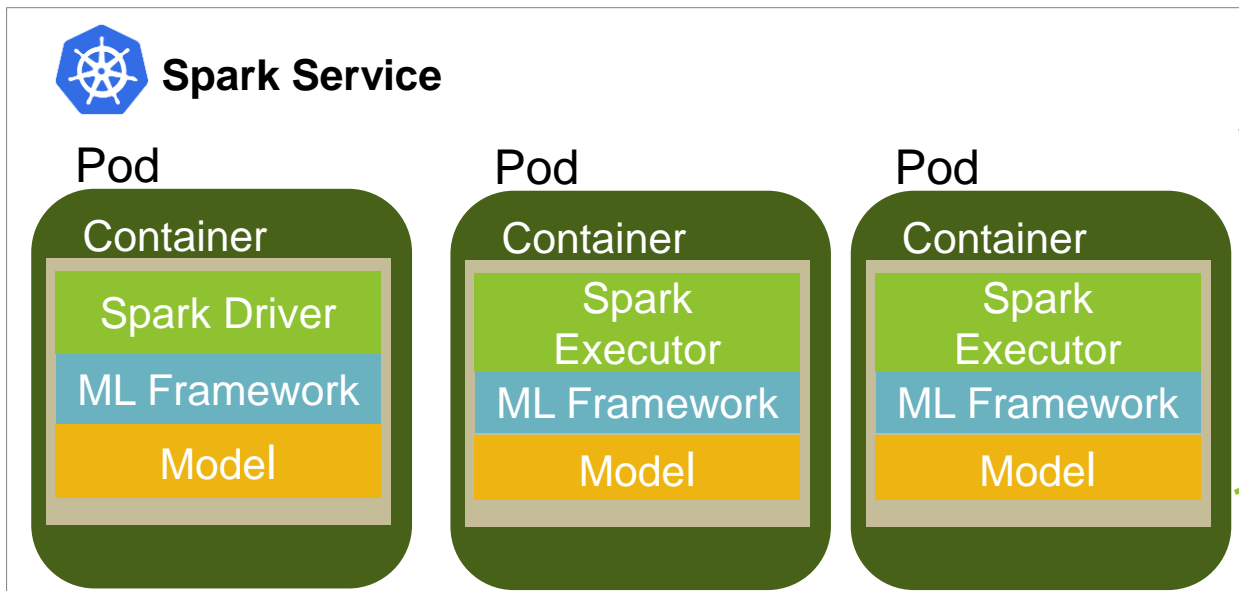
Model Creation and Registration



Batch/Real-time Inference



BYOM Options: Monolithic



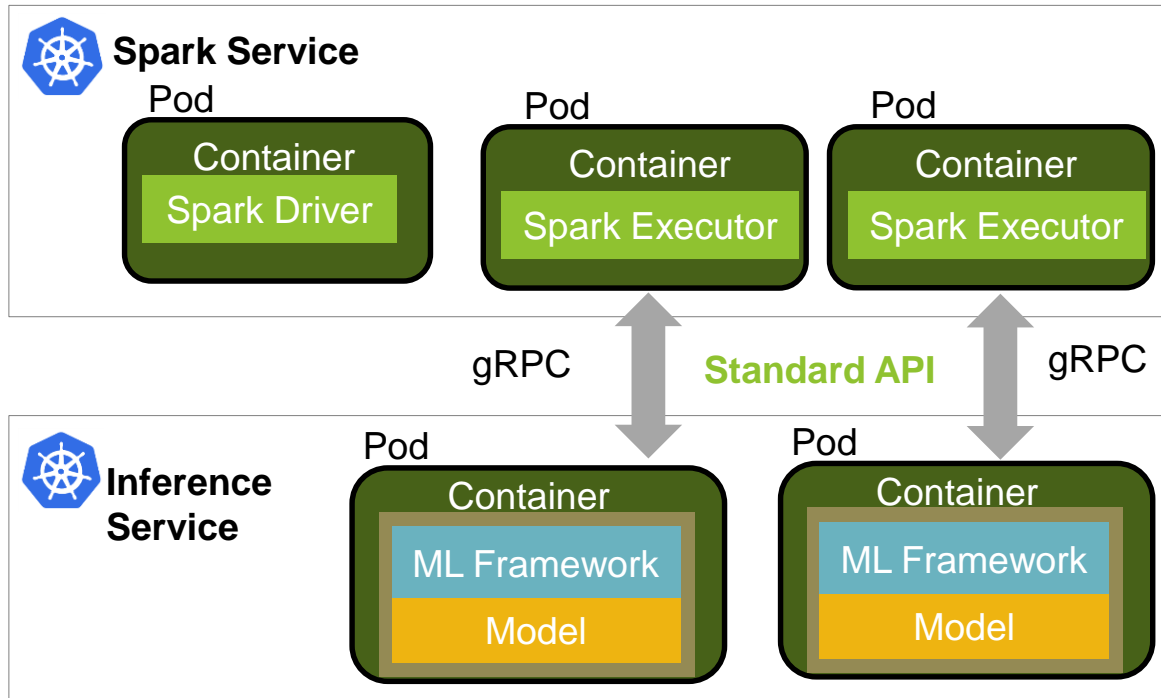
Pros

- Simple deployment
- Container life-cycle in full sync with workload
- No version tracking or mismatch concerns
- Data locality

Cons

- Larger container footprint
- Tight coupling between model and Spark engine

BYOM Options: Just-In-Time Compose



Pros

- Small container footprint
- Multi-framework friendly
- Auto scales
- Standard API

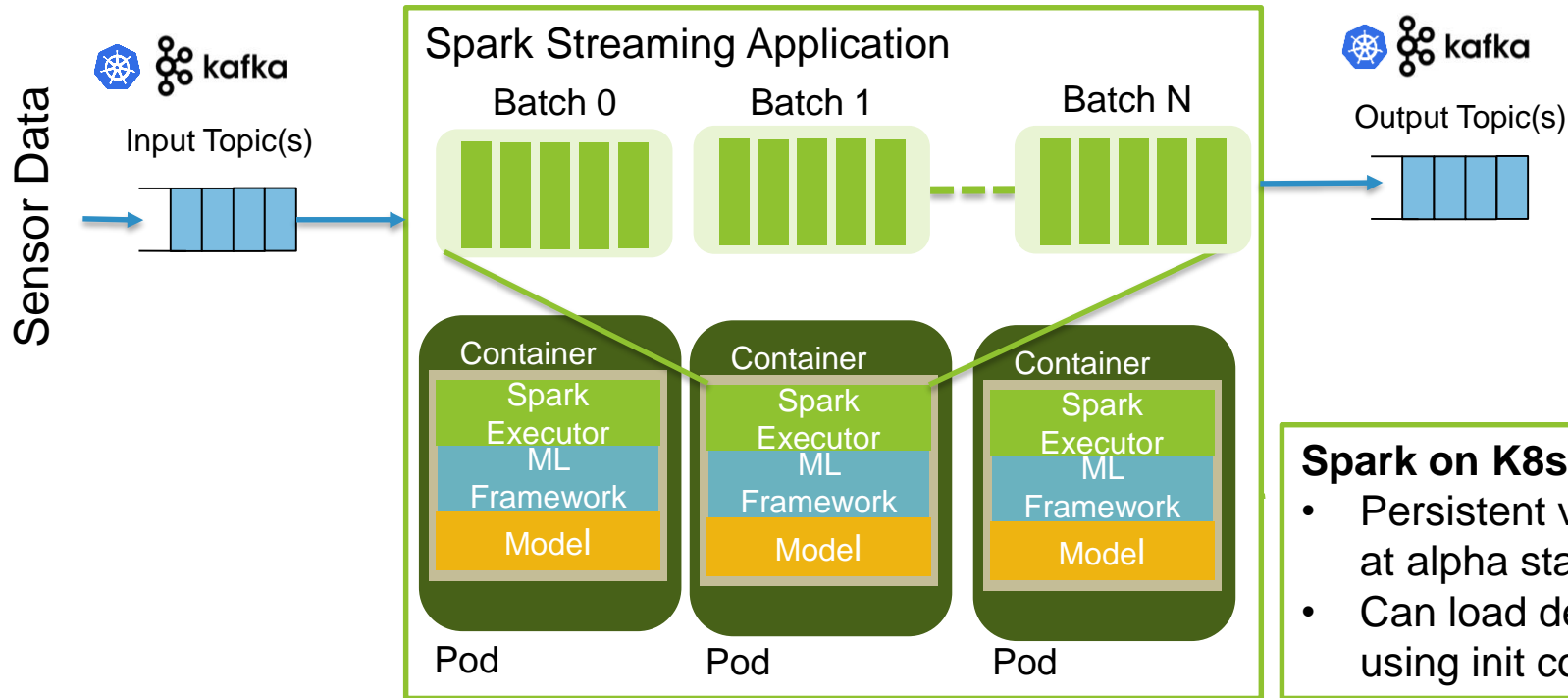


Cons

- More complex orchestration workflow
- Additional mechanisms needed for data locality, e.g., pod affinity

Deployment on K8s

Spark on K8s Operator



Spark on K8s operator

- Persistent volumes are at alpha stage
- Can load dependencies using init container

Demo

https://videoportal.intel.com/media/0_70vbt74e

Future

- Support for Just-in-time-Composition
 - Tackling dependencies
- Resource scheduling, HW accelerator aware
- Hardware specific models (CPU/GPU/FPGA ..)
- Pipeline options with speed, accuracy, and resource availability projections

Conclusion

- Across domains Bring-your-own-model genuine need for both R&D and Production Systems
- System and Orchestration developers typically not Machine Learning specialists –
 - reduce the barrier to adoption

Thank You!

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Please join us in the BYOM effort!

References

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Upstreamed: Dynamic Resource Allocation

Weiting Chen

Resources are allocated at start but applications can request change at runtime.

Dynamic resource allocation uses shuffle service container for data shuffle (instead of Docker storage)

