Access Services

Exposing the Results

Target == Dashboard == Bad Pipeline

- Data Scientist would focus on the dashboard/report instead of content
- Breaks reusability of data
- Time wasted on learning viz instead of increasing accuracy (or velocity)
- Monolithic instead of service oriented

Include intermediate Service

The data science pipeline has now to include the way the results can be consumed by the third parties (consumers, customers, …)

The question is what are the results of a data science pipeline?

Actually, not only the model (machine learning) needs to be exposed but also all the intermediate results that are worth considering persistent (f.i. features creation, cleaning, …)

Having services for those, say, views allows us to abstract the way they are created to the way they are used.

External scalability

The other clear advantage of services as part of the pipeline allows the team to separate the resources needed to serve the data to those necessary to compute them!

Example:

Let's say the dashboard is built directly using the streaming technology and the same cluster used to compute.

Then the computing resources will have to **also** follow the consuming patterns.

So, the more users the more computing power while the data may not have changed…

Horizontal Scalability

In the context of Big or Fast Data, it must be clear for everyone that views needs to be created on the data for each use case

(or a small subgroup of use cases)

This gives us another incentive to introduce micro services into the architecture, each of them will have the responsibilities to expose one of these views.

So we will be able to scale independently each feature of the data science product that we were in charge to produce, as a team.

Access Services

Exposing the Results

HTTP server

HTTP client/server implementation
using Akka as the core engine

```
val route =
  get {
    path(Segment / Segment) { (pathSegment1, pathSegment2) =>
      parameters("param1".as[Long], "param2".as[String]) {
        (param1, paramm2) = complete()
      }
    } ~
    path("path1") {
      complete(...)
    }
  }

Http().bindAndHandle(route, "localhost", 1111)
```

Providing DSLs for creating
routing, utils for un/marshalling
and more

HTTP server

```
val http = Http(context.system)

val HttpResponse(StatusCodes.OK, headers, entity, _) =
  http.singleRequest(HttpRequest(uri = url))

val responseAsString = entity.dataBytes.runFold(ByteString(""))(_ ++ _)
```

Http client uses Akka system (dispatcher) to create a non blocking/reactive client.

The client can issue a single request that will return an entity which streams the response as the server sends the bytes

This stream can be consumed reactively using the `runFold` method

Serve

Expose and Predict

Writing the service

Use notebook: ***04_Access Service.snb***

We'll expose the data from Cassandra in JSON as a time-series (***all*** and range)

We'll deploy the trained model to predict in real time

Resource Manager

Optimize Hardware Usage

Cluster

The distributed data science pipeline wouldn't be complete without considering the hardware on which each piece will have to run on

This shouldn't be neglected of course and it's necessary to use it efficiently. Each tools can be scaled independently which is the strength of our pipeline, on the other side, we need to provision the infrastructure to do so.

We need to find a way to avoid having a dedicated infrastructure for each tool! However, we have to mutualise the available resources

Resource Manager

A classical way to do resource management was to use virtual machines that will run components

However, the management of such virtual machines can become quickly a hassle

That's, rather than managing machines we shall focus on manage resources independently… here we talk about CPUs, Memory, bandwidth and so on.

Orchestration

The orchestration of the tasks running on the system is necessary to ensure:

- that the cluster is used efficiently
- the connected tools are provisioned enough to work

This kind of orchestration needs to either keep track of the overall state or react on state changes.

Example: how to deploy, scale and maintain a bag micro service instances?

Mesos

Two Levels Scheduler

Mesos

Cluster Resource negotiator

Scalable to 10,000s of nodes

Fault-tolerant, battle-tested

An SDK for distributed apps

Native Docker support

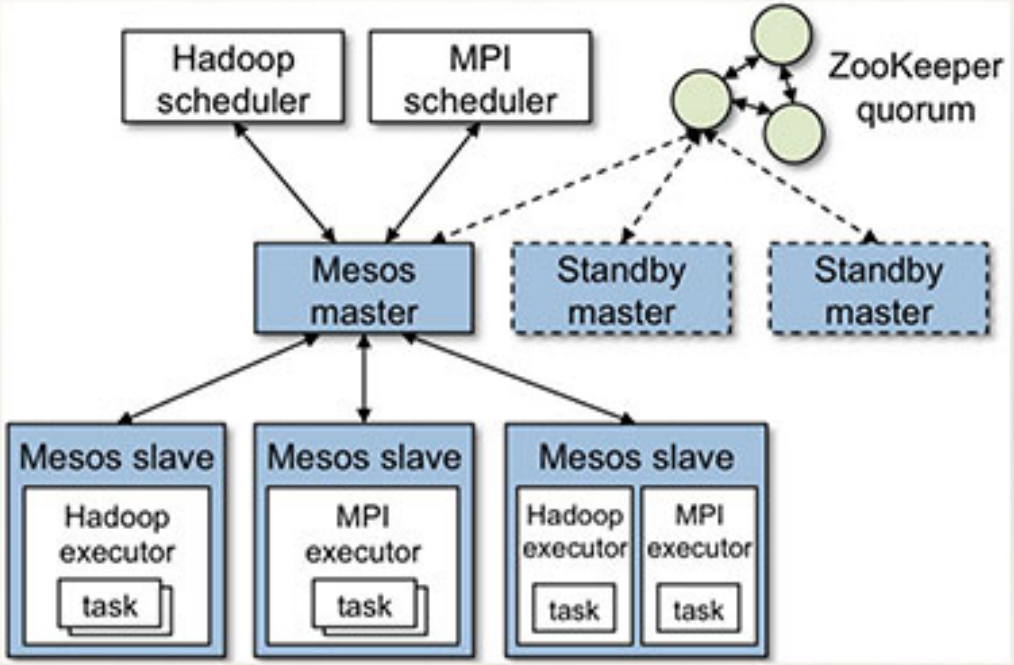
80% usage instead of 15%!

Architecture

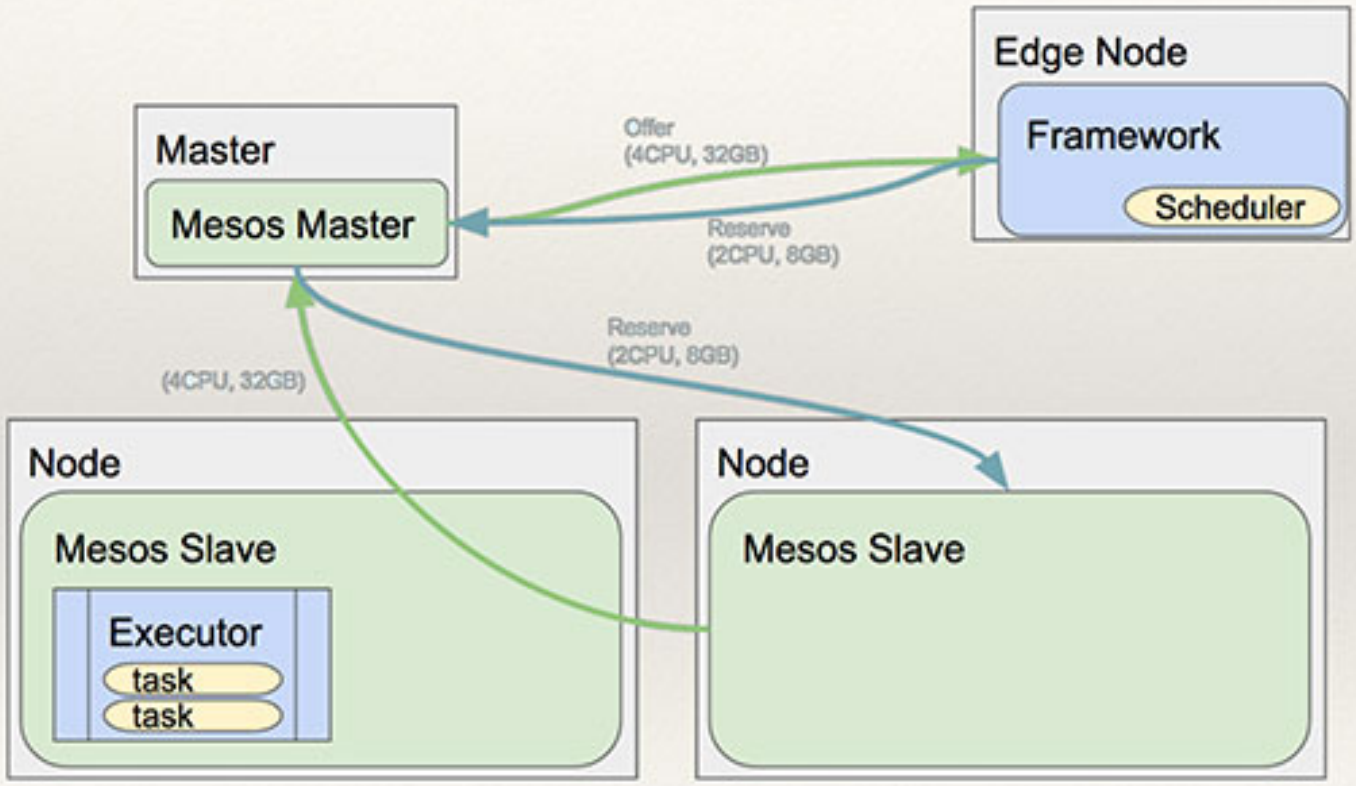
HA

2 levels schedulers!

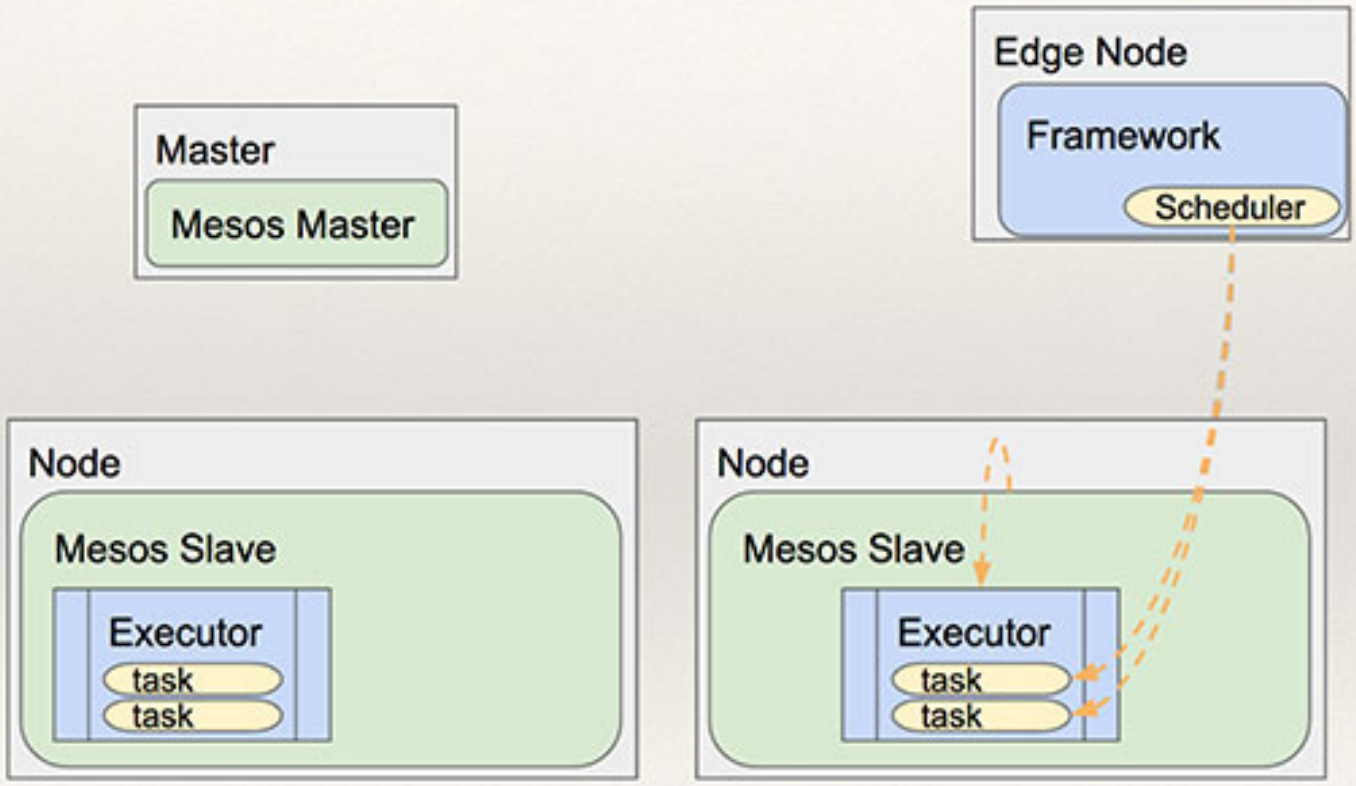
- masters
- frameworks



Message Oriented



Message Oriented



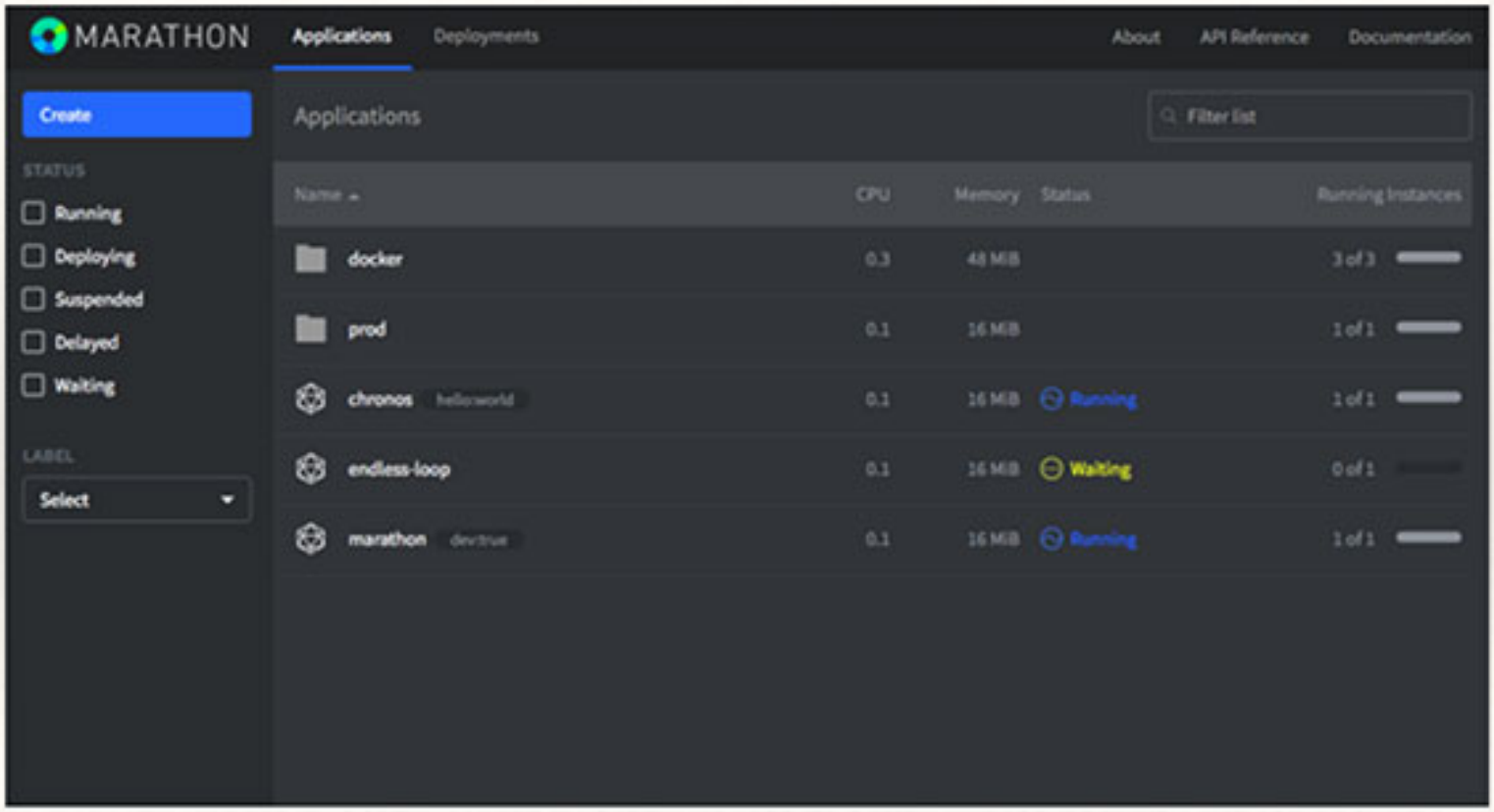
Useful Frameworks

For Mesos

Marathon

- HA run any number of Marathon schedulers, but only one gets elected as leader
- Constraints - e.g., only one instance of an application per rack, node, etc.
- Service Discovery & Load Balancing via HAProxy or the events API.
- Health Checks: check your application's health via HTTP or TCP checks.
- JSON/REST API for easy integration and scriptability
- Native Docker support

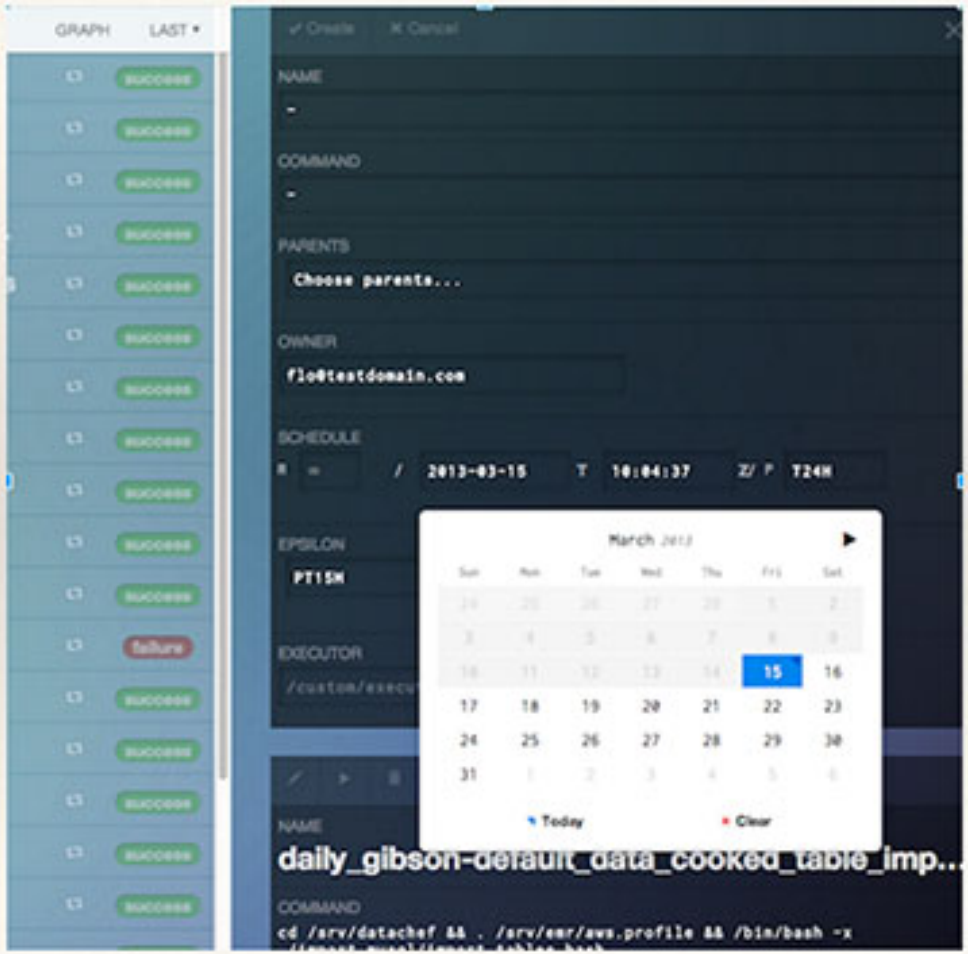
Marathon


MARATHON
Applications
Deployments
About
API Reference
Documentation
Create
Applications
Filter list
STATUS
Running
Deploying
Suspended
Delayed
Waiting
LABEL
Select
Name
CPU
Memory
Status
Running Instances
docker
0.3
48 MiB
3 of 3
prod
0.1
16 MiB
1 of 1
chronos
hello-world
0.1
16 MiB
Running
1 of 1
endless-loop
0.1
16 MiB
Waiting
0 of 1
marathon
dev:true
0.1
16 MiB
Running
1 of 1

Chronos

- 8601 Repeating Interval Notation
- Handles dependencies
- Job Stats (e.g. 50th, 75th, 95th and 99th percentile timing, failure/success)
- Job History (e.g. job duration, start time, end time, failure/success)
- Fault Tolerance (Hot Master)

Marathon


GRAPH
LAST
success
failure
Create
Cancel
NAME
COMMAND
PARENTS
Choose parents...
OWNER
flo@testdomain.com
SCHEDULE
2013-03-15
10:04:37
T24H
EPSILON
PT15M
EXECUTOR
March
Today
Clear
daily_gibson-default_data_cooked_table_imp...
cd /srv/datachef && . /srv/env/aws.profile && /bin/bash -x

Assessment #3

Extend Service Access

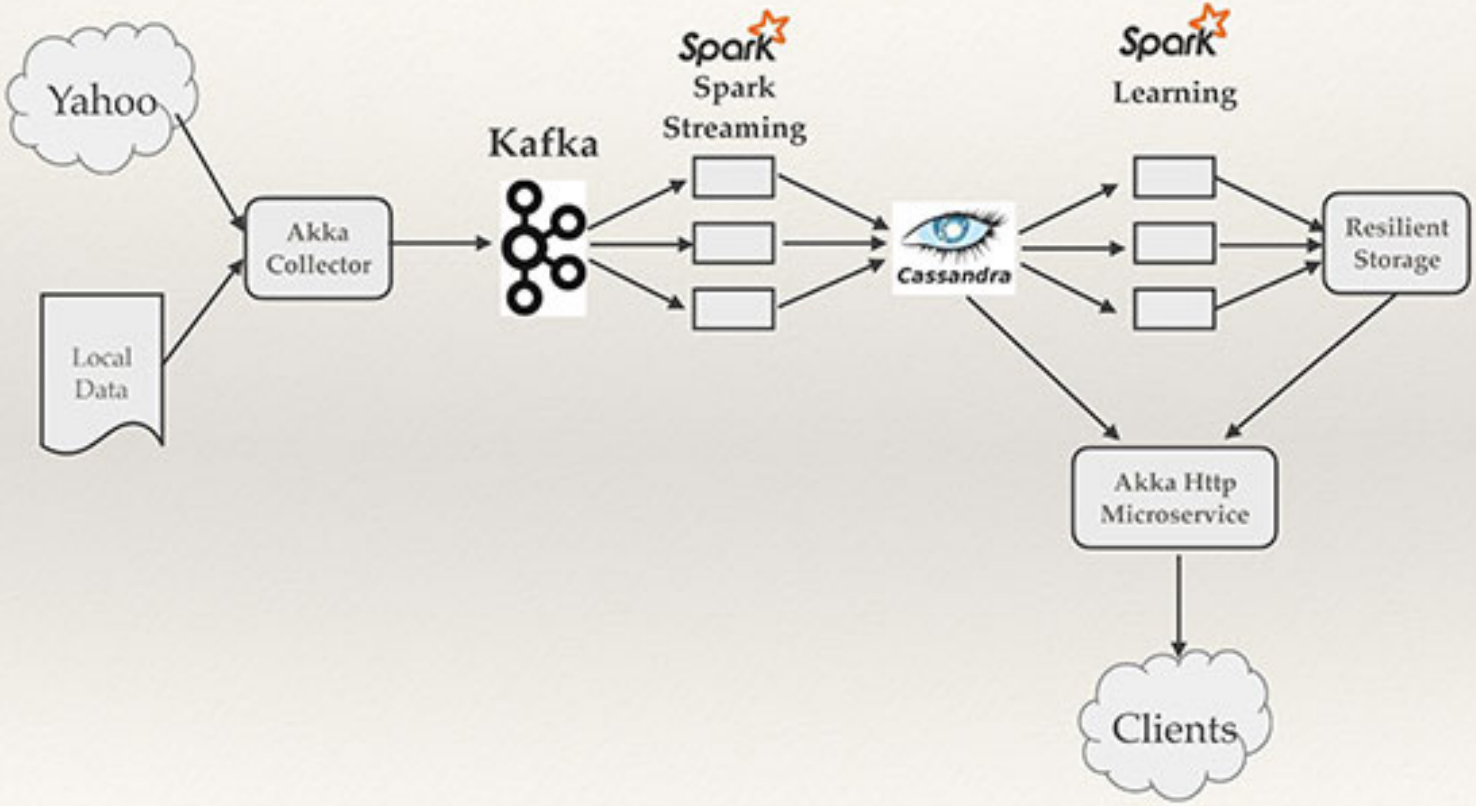
Extending Access Layer

- Use the notebook provided in the slack room: ***Assessment 3.snb***
- The task is to extend the access layer with a new micro service that will have the responsibility to return the last quote for JPM.
- This service used in combination with the original prediction one allows to compare and plot the error. Check the ***Client Example.snb***

Wrap Up

From Big Data to Micro Service

Distributed Data Science Pipeline



Follow Up

- Use Mesos
- Productize notebooks using SBT, Docker or similar
- Face the challenge to build an enterprise ready, sustainable and maintainable solution…
- By first introducing schemas at each step!
- Don't get stuck with existing implementations, new models are created and developed to leverage the power of distributed systems and the amount of available data!

Follow Up

- Use Mesos
- Productise notebooks using SBT, Docker or similar
- Face the challenge to build an enterprise ready, sustainable and maintainable solution…
- **Track dependencies between data, users, processing, code, machines, containers, models, … to help sharing and maintain the data science work with its context**
  (, semantic)