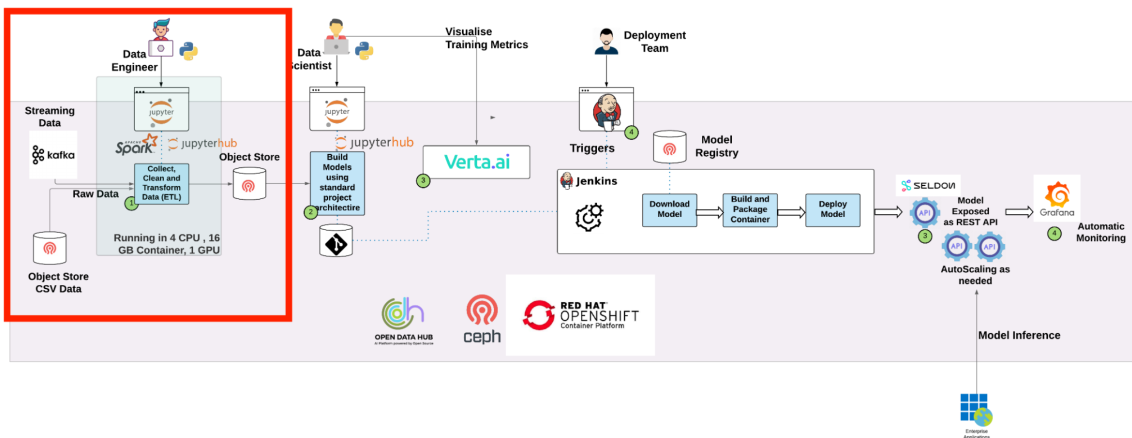
Lab 2 - Data Engineering

Introduction

In the previous lab, you explored the Open Data Hub component Superset - which provides easy to create charts and dashboards using the in-memory data engine Trino. Trino and Superset allow data residing anywhere to be accessed using a low latency in memory engine using SQL.

The Open Data Hub exposes a second data focused tool - for Extract Transform Load (ETL) of data originating in multiple data sources, i.e. Apache Spark. Spark allows finer grained ETL control than SQL/Trino does, e.g. using Regex to match data patterns. Spark provides a further toolset to allow data professionals to prepare quality data for consumption by data scientists and AI models.

This diagram illustrates the workflow we're implementing - the beginning part of the overall AI/ML workflow:

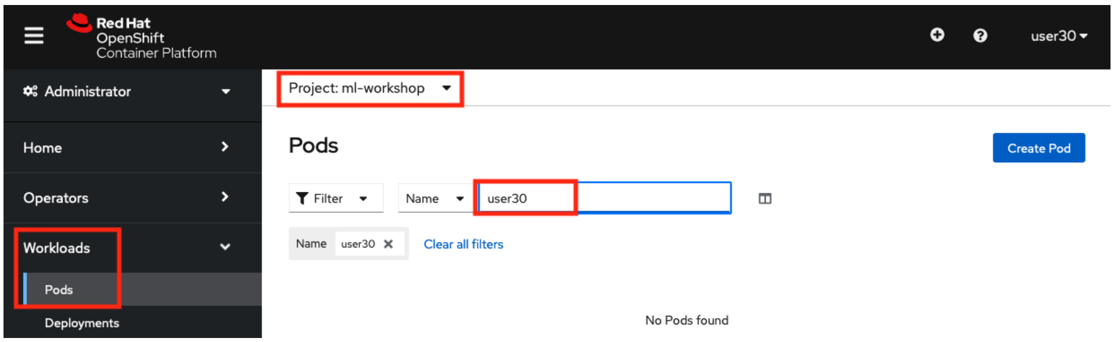


You can see, we source raw data from Kafka and S3 object storage. We use Jupyter notebooks to do some simple data engineering - combining these datasets on customerId using Spark. We then push that prepared data (a CSV file) to another bucket in our S3 object store, called Minio.

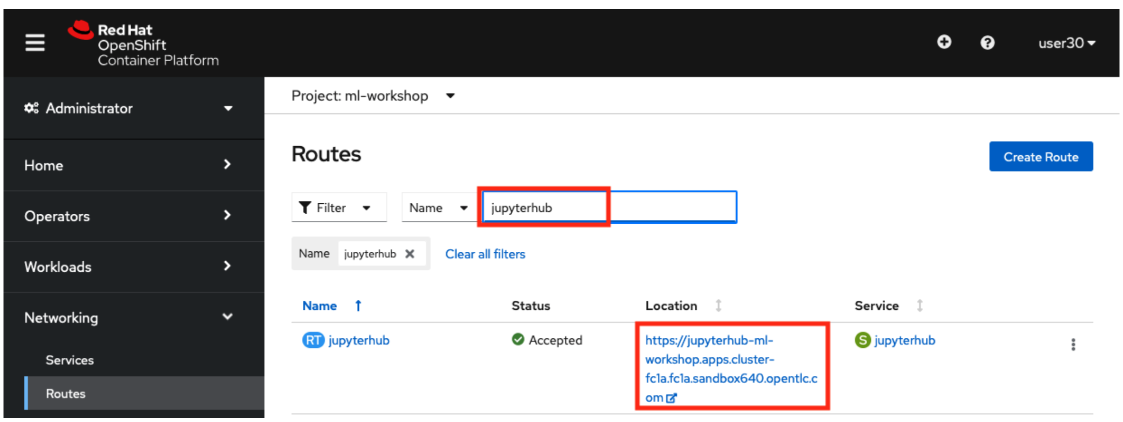
Instructions for the Spark workshop

Login to OpenShift using the credentials your administrator gave you. Open a second tab on your browser, also logged into OpenShift. Ensure your workshop project ml-workshop is selected.

1. In tab 1, Choose the Administration dropdown , navigate to Workloads -> Pods
   Filter on your username, e.g. in my case user30. There won't be any pods shown - yet.

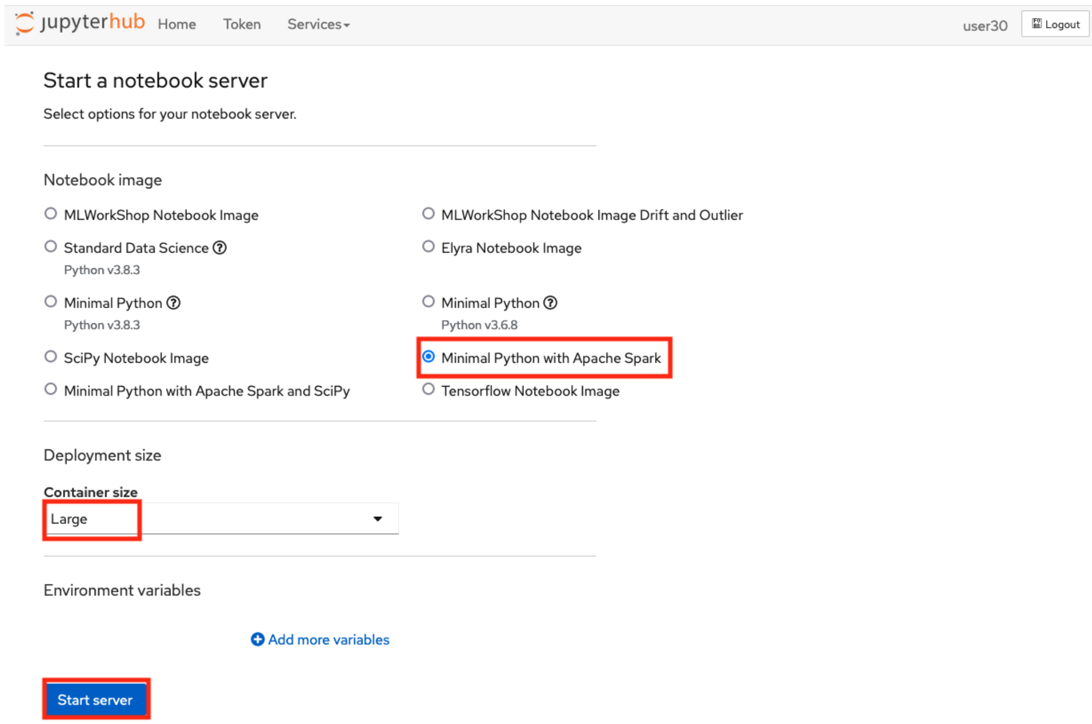


2. In tab 2, Choose the Administration dropdown , navigate to Network -> Routes. Filter on *Jupyterhub* - and open the route.



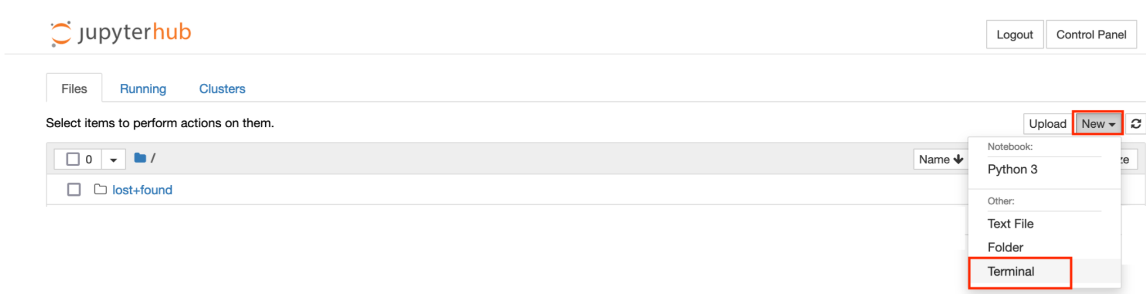
Continue with tab 2. In a moment you'll see the following screen. Select

- *Minimal Python with Apache Spark* as shown.
- A *Large* container - allocating the maximum amount of CPU and memory available.



Start Server. A few moments later the *files* view appears. The first thing we want to do is pull down our notebooks from our repository *https://github.com/masoodfaisal/ml-workshop.*

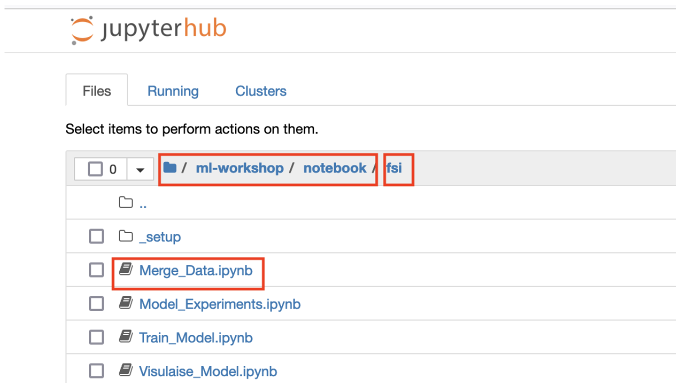
Choose New Terminal



Then paste this command into new Terminal and click enter:

git clone https://github.com/masoodfaisal/ml-workshop

Once done you can close that tab. Now refresh the *files* page - you'll see the *ml-workshop* folder. Now drill into ml-workshop -> notebook. Depending on your track ***telco*** or ***fsi***, choose the appropriate subfolder (in this example ***fsi***).



Now open up Merge_Data.ipynb, the file the data engineer uses to prepare their data.

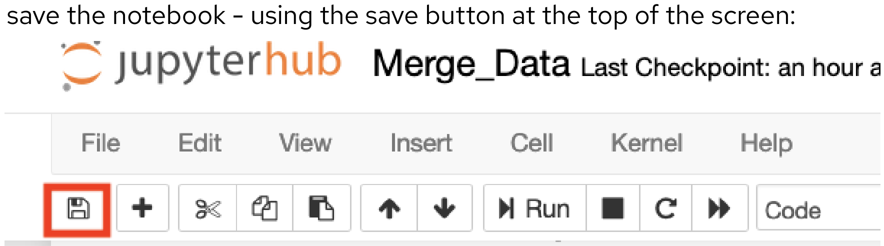
Before we get going, you need to make a small change to the code.

Scroll down to the last cell and change the user to match the one provided by your instructor.

`user_id = "<your username>"`

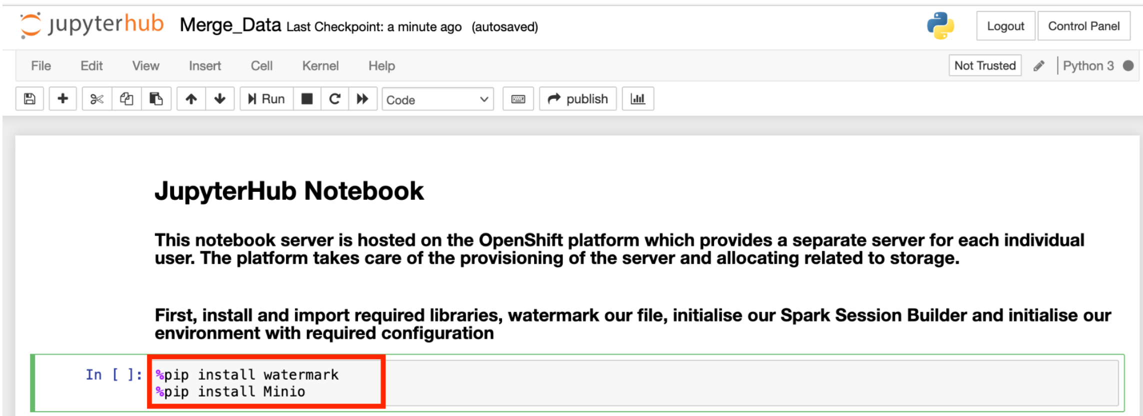
Change the user_id to be your user_id and save the notebook - using the save button at the top of the screen.

save the notebook - using the save button at the top of the screen:



You are now good to go!

Place the cursor inside the first cell with the *pip install* commands as shown.



To execute a cell, type the **SHIFT + RETURN** keys together. Walk through the entire file this way, executing as you go. (if there are any blank cells, skip through them using SHIFT + RETURN).

Here's a high level description of what's happening in the various cells:

1 In [ ]:
```
%pip install watermark
%pip install Minio
```

2 In [ ]:
```
import os
import json
from pyspark import SparkConf
from pyspark.sql import SparkSession, SQLContext
from pyspark.sql.functions import from_json, col, to_json, struct
import watermark
from minio import Minio

%matplotlib inline
%load_ext watermark
```

3 In [ ]:
```
%watermark -n -v -m -g -iv
```

In [ ]:
```

```

4 In [ ]:
```
sparkSessionBuilder = SparkSession\
    .builder\
    .appName("Customer Churn ingest Pipeline")
```

5 In [ ]:
```
os.environ['PYSPARK_SUBMIT_ARGS'] = \
'--packages \
org.postgresql:postgresql:42.2.10,\
org.apache.spark:spark-sql-kafka-0-10_2.11:2.4.5,\
org.apache.kafka:kafka-clients:2.4.0,\
org.apache.spark:spark-streaming_2.11:2.4.5,\
org.apache.hadoop:hadoop-aws:2.7.3 \
--conf spark.jars.ivy=/tmp \
--conf spark.hadoop.fs.s3a.endpoint=http://minio-ml-workshop:9000 \
--conf spark.hadoop.fs.s3a.access.key=minio \
--conf spark.hadoop.fs.s3a.secret.key=minio123 \
--conf spark.hadoop.fs.s3a.path.style.access=true \
--conf spark.hadoop.fs.s3a.impl=org.apache.hadoop.fs.s3a.S3AFileSystem \
--master spark://' + os.environ['SPARK_CLUSTER'] + ':7077 pyspark-shell '
```

Connect to Spark Cluster provided by OpenShift Platform

6 In [ ]:
```
spark = sparkSessionBuilder.getOrCreate()
spark.sparkContext.setLogLevel("INFO")
print('Spark context started.')
```

1. *pip install xxxx*, installs various libraries that aren't contained in our case container image
2. import the python libraries we need
3. *watermark* outputs the versions of various components, libraries, operating system attributes etc.
4. Here we create a Spark session, a precursor to firing up our own Spark server.
5. Here we set up various environment variables, including connection access to our S3 object store, in our case implemented using the open-source component Minio.
6. Here we actually start our Spark server. This cell can take several minutes to start.

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7 In [ ]:
```
dataFrame_Customer = spark.read\
                .options(delimeter=',', inferSchema='True', header='True') \
                .csv("s3a://rawdata/Customer-Churn_P1.csv")
dataFrame_Customer.printSchema()
```

8 In [ ]:
```
# dataFrame_Products = spark.read\
#                 .options(delimeter=',', inferSchema='True', header='True') \
#                 .csv("s3a://rawdata/Customer-Churn_P2.csv")
# dataFrame_Products.printSchema()
```

9 In [ ]:
```
from pyspark.sql.types import *
from  pyspark.sql.functions import *

srcKafkaBrokers = "odh-message-bus-kafka-bootstrap:9092"
srcKakaTopic = "data"

...
```

10 In [ ]:
```
dataFrom_All = dataFrame_Customer.join(dfObj, "customerID", how="full")
```

Push prepared data to object storage and stop Spark cluster to save resources

Note - be sure to change this user_id on the next line to your username (something in the range user1 ... user30)

11 In [ ]:
```
user_id = "user29"
file_location = "s3a://data/full_data_csv" + user_id
dataFrom_All.repartition(1).write.mode("overwrite")\
    .option("header", "true")\
    .format("csv").save(file_location)
```

12 In [ ]:
```
spark.stop()
```

7. Here we pull in our data from S3 - our CSV based demographic data for each of our approximately 7000 customers.
8. Commented out - ignore
9. Here we pull in our data from Kafka - our product consumption data for each of our approximately 7000 customers.
10. We join these 2 datasets, on the common column to each: *customerID*.
11. We push our data to our object store - filename contains our username.
12. We are all done now - we stop our Spark server.

This is our data engineering workshop finished. It's a simple exercise, though the same toolset could be used for much more complex data engineering tasks.

Before we move on, as evidence of this self provisioned cluster, dedicated entirely to you as a user, move back to the Pods view, you saw above, keeping your username as a filter. Notice OpenShift has created a 3-node Spark cluster for us:

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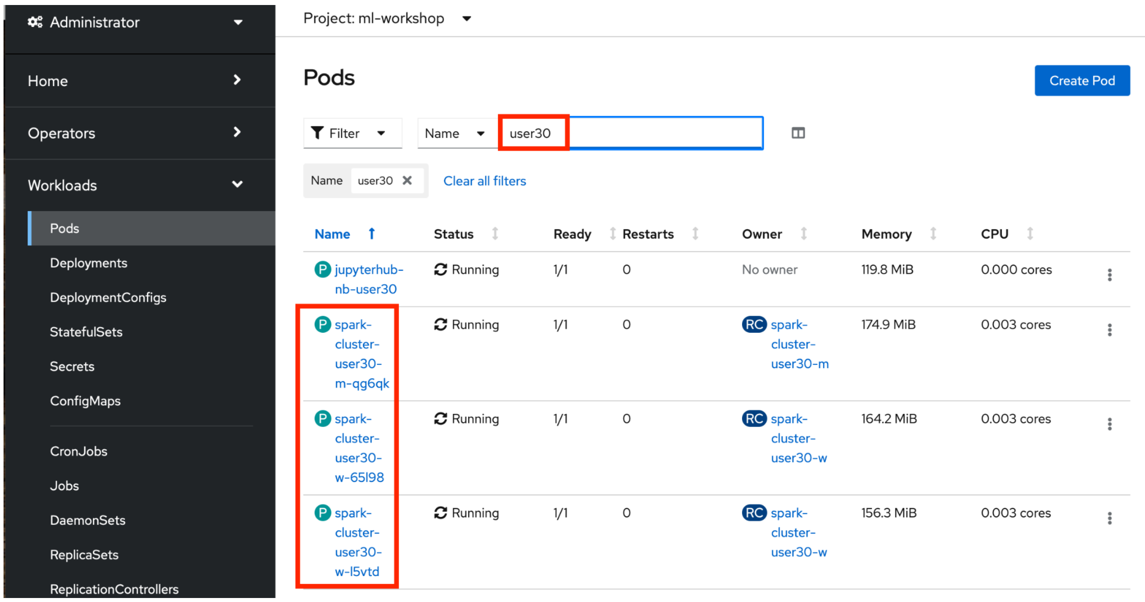
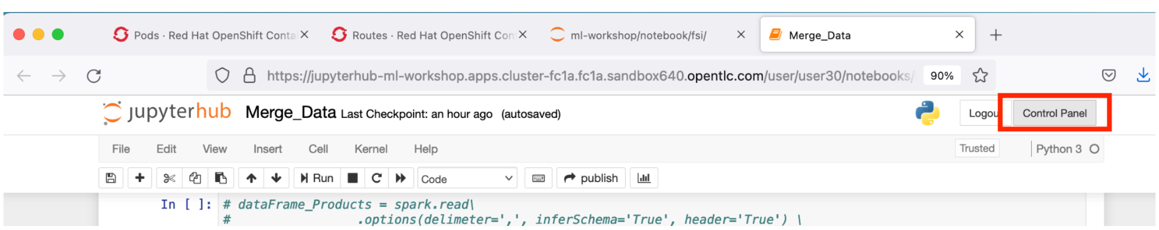


Now we need to close down our Jupyter server. Choose *Control Panel* and shown - then on the next screen, choose Stop My Server.



Immediately move back to your *Pods* screen - and observe your Spark pods being destroyed.

Name	Status	Ready	Restarts	Owner	Memory	CPU
P spark-cluster-user30-m-qg6qk	Terminating	1/1	0	RC spark-cluster-user30-m	174.9 MiB	0.004 cores
P spark-cluster-user30-w-65l98	Terminating	1/1	0	RC spark-cluster-user30-w	164.6 MiB	0.004 cores
P spark-cluster-user30-w-l5vtd	Terminating	1/1	0	RC spark-cluster-user30-w	158.3 MiB	0.004 cores

This is a powerful demonstration of OpenShift's self service capabilities. No waiting for IT to provision you a server, no waiting around for access to a scarce Spark server. All self service, on demand, and those resources returned back to the central pool when finished.