Lab 3 - ML OPs

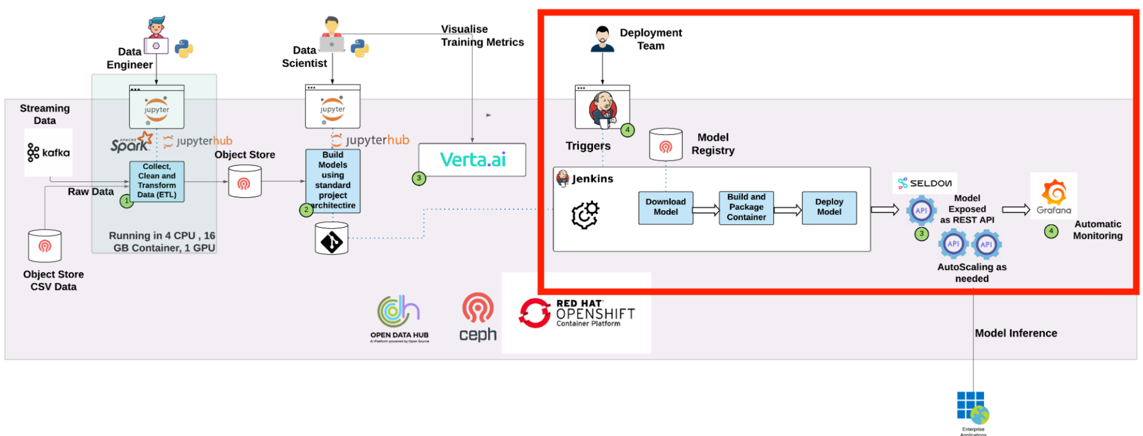
Introduction

Now as a data scientist, we've selected our chosen experiment, trained the model (a DecisionTreeClassifier) and finally we've pushed it to S3 Object storage.

Using the experiment id, as the identifier to retrieve from S3, we run our ML OPs pipeline and move the model and associated encoders to a *production* or *simulated production* environment. In this way, you add speed and potentially quality and security to this deployment process.

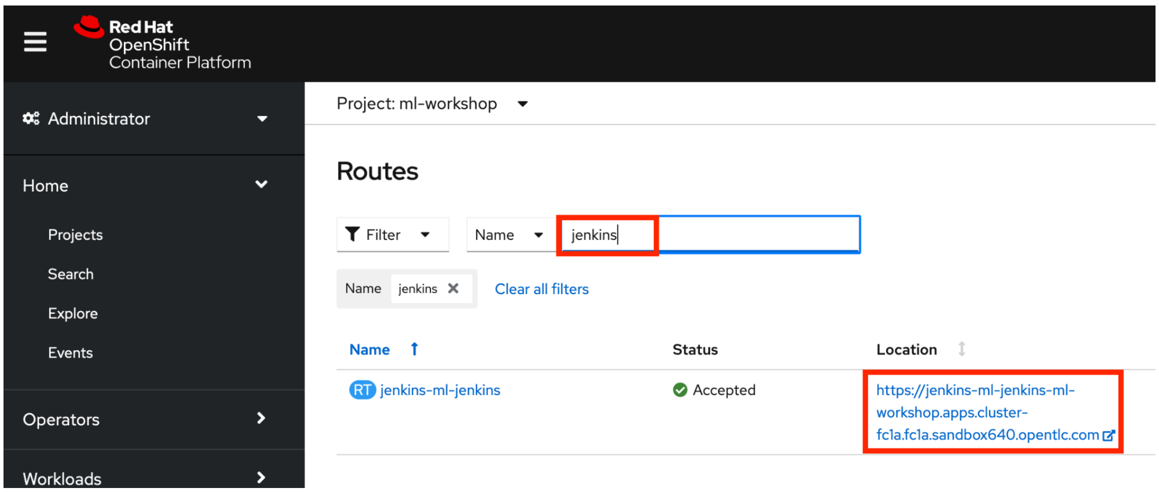
We also utilise the model serving component Seldon, which wraps the model behind a RESTful API, making the model easily available in this way for inference. As the flow is fully automated, we also ease and in fact eliminate the integration effort between application development and data scientists teams.

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

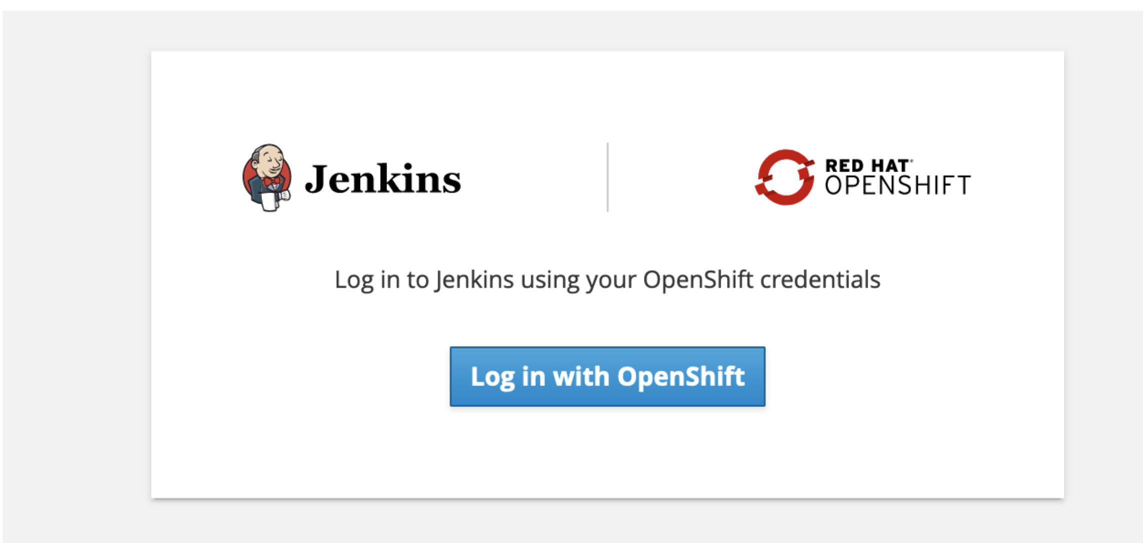


Instructions to run the ML OPs workshop

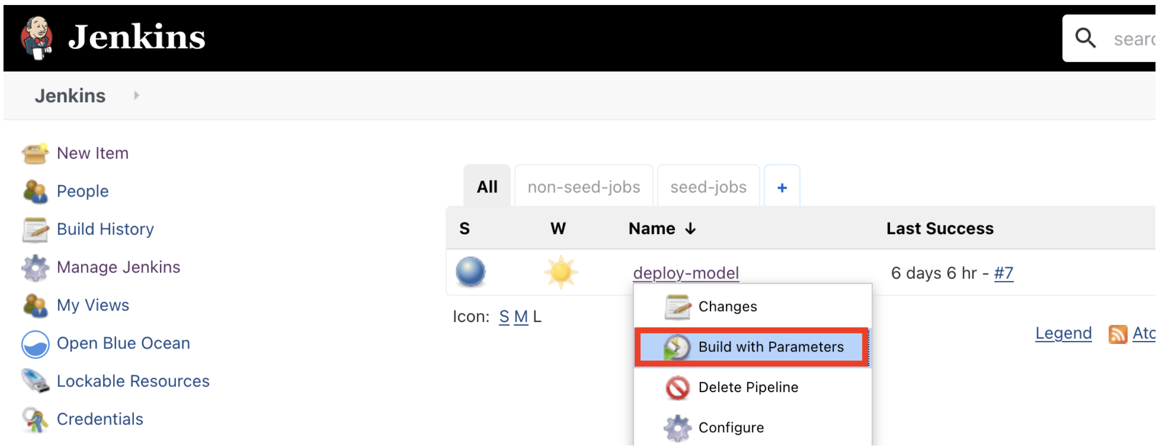
Login to OpenShift using the credentials your administrator gave you. Ensure your workshop project ml-workshop is selected.
Choose the Administration dropdown , navigate to Network -> Routes. Filter on *jenkins* - and open the *Jenkins* route as shown.



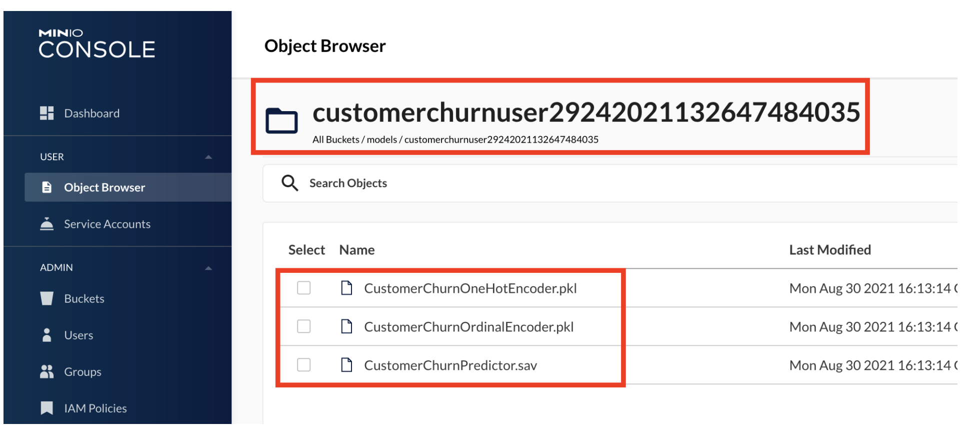
When prompted enter your OpenShift credentials *userXX* and *openshift*, substituting *userXX* for your username.



Once in, you'll see a pipeline called deploy-model. Hover over it and an arrow will appear beside it. Choose Build with Parameters from the drop down menu.

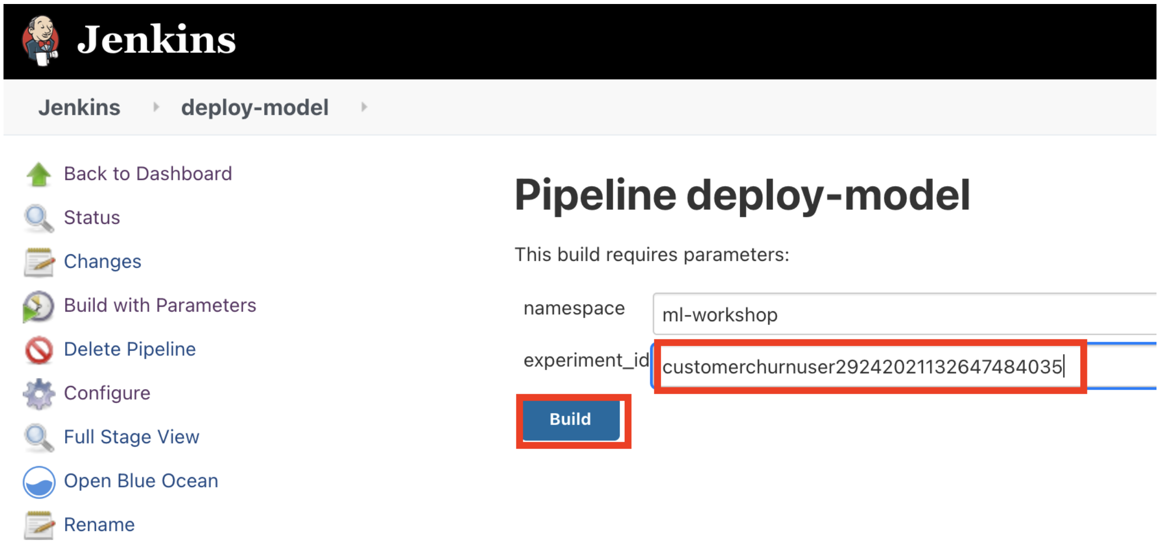


Remember the last exercise where you found your experiment outputs in the storage?



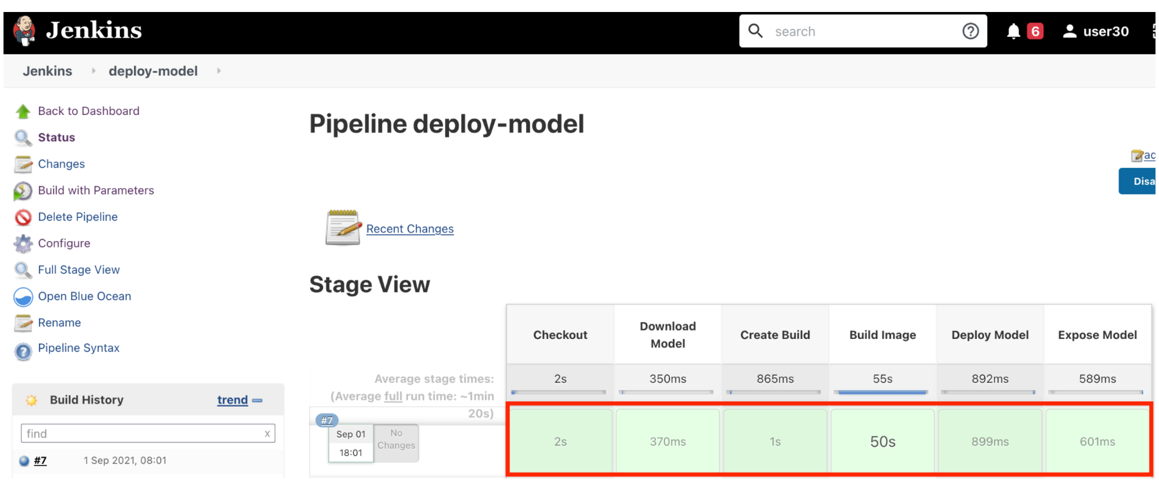
You need to use that experiment ID in this next step.

1. Enter the experiment id you retrieved at the end of the last workshop, in my case *customerchurnuser29242021132647484035.*
2. **Click Build**



Click **Build**

After a few seconds, you should see your pipeline begin and progress through the steps to completion you see highlighted here:

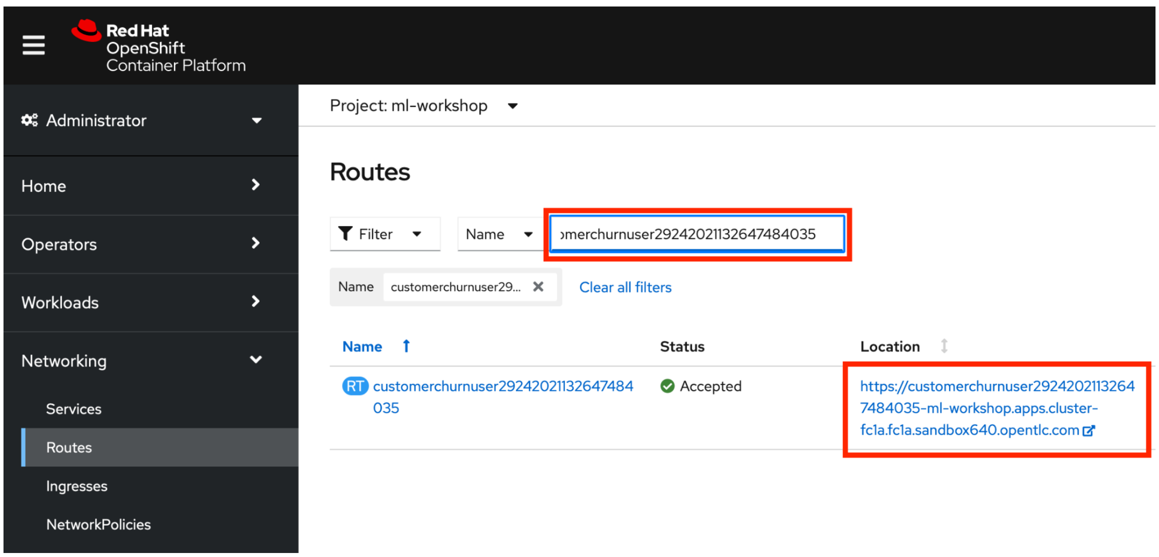


The pipeline then starts to package your model into an image and deploy it on to OpenShift. Proceed to the next section when the pipeline has completed.

Testing the Model via an API

You are now ready to test the API to your model.

1. Open the OpenShift tab on your browser.
2. Select the **Administrator** perspective in the left panel.
3. Click **Networking > Routes**
4. Filter on your experiment ID as shown below.

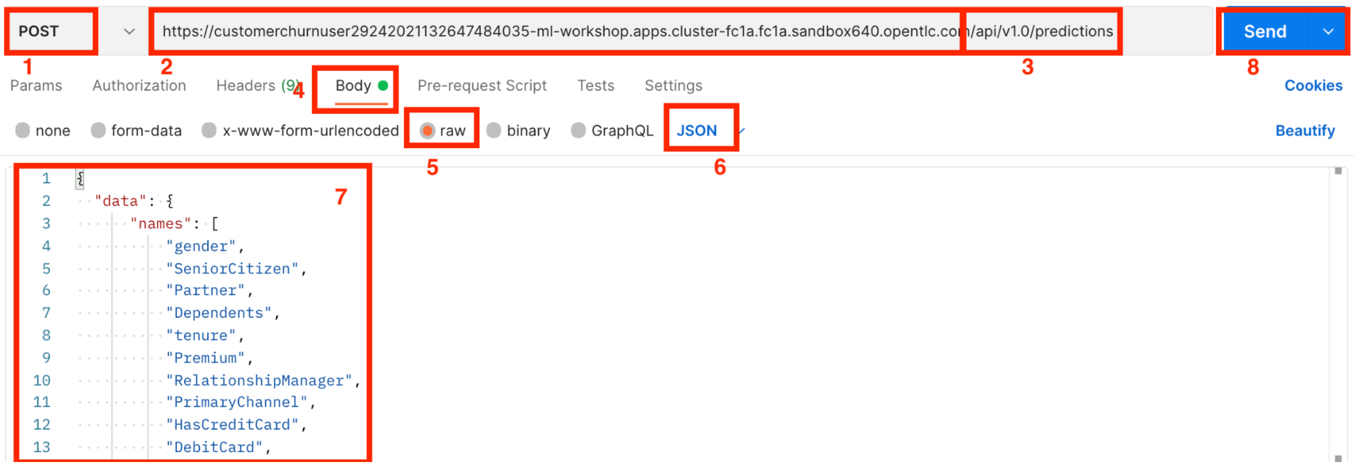


The URL under the Locations column is the URL our pipeline has created for us - which we will use to make inference calls to our model. Make note of your URL, in my case

https://customerchurnuser29242021132647484035-ml-workshop.apps.cluster-fc1a.fc1a.sandbox640.opentlc.com

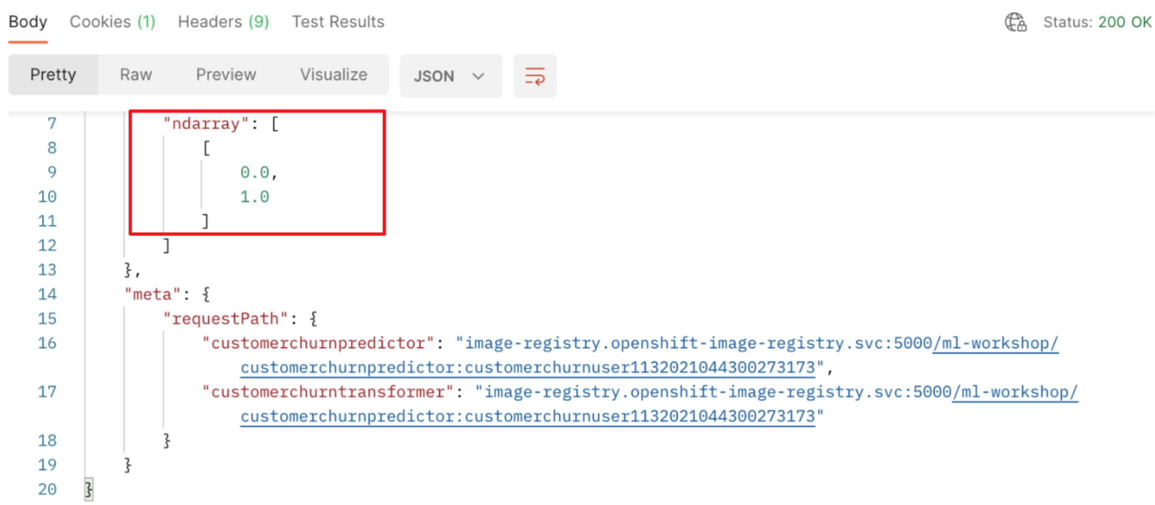
In order to make an inference call, you can use tools such as Postman, or the command line using curl, or there are various online options. I'll use *Postman* to illustrate. If you do not have Postman you can access a free web version here: https://web.postman.co/home

Open Postman, and create a new Workspace and add a new Request to it. Populate is as follows:



1. Choose the POST method
2. Take your inference URL from the previous step
3. append the path ***/api/v1.0/predictions*** to that
   to form the full URL, in my case
   https://customerchurnuser29242021132647484035-ml-workshop.apps.cluster-fc1a.fc1a.sandbox640.opentlc.com/api/v1.0/predictions
4. Select Body
5. Choose raw
6. and JSON as shown as the content type.
7. Paste the JSON located below in [Appendix 1 - Sample Inference Request Body](#) into the Body box.
   Notice this represents a customer, we're asking the model to predict how likely it is they will churn. Notice also, we're passing in string values such as Brokerage etc.
   Conversion using the *Ordinal* and *One-Hot* encoders to numeric values will be done by the running container exposing the API.
   This simplifies these API calls greatly for Application developers making these inference calls.
8. Click Send to make your inference call

Here you see a sample response.



Observe the True/False response. In this model we made a design choice to produce binary prediction: “Will likely Churn,” and “Will not likely Churn” - which are represented as true (1.0) or false (0.0). An alternative approach could be to produce a likelihood as a percentage.

Appendix 1 - Sample Inference Request Body


```
{
 "data": {
   "names": [
     "gender",
     "SeniorCitizen",
     "Partner",
     "Dependents",
     "tenure",
     "Premium",
     "RelationshipManager",
     "PrimaryChannel",
     "HasCreditCard",
     "DebitCard",
     "IncomeProtection",
     "WealthManagement",
     "HomeEquityLoans",
     "MoneyMarketAccount",
     "CreditRating",
     "PaperlessBilling",
     "AccountType",
     "MonthlyCharges",
     "TotalCharges"
   ],
   "ndarray": [
     [
       "Female",
       1,
       "Yes",
       "No",
       0,
       "Yes",
       "Yes",
       "Mobile",
       "Yes",
       "Yes",
       "No",
       "No",
       "Yes",
       "Yes",
       "Low",
       "No",
       "Brokerage",
       100,
       300
     ]
   ]
 }
}
```