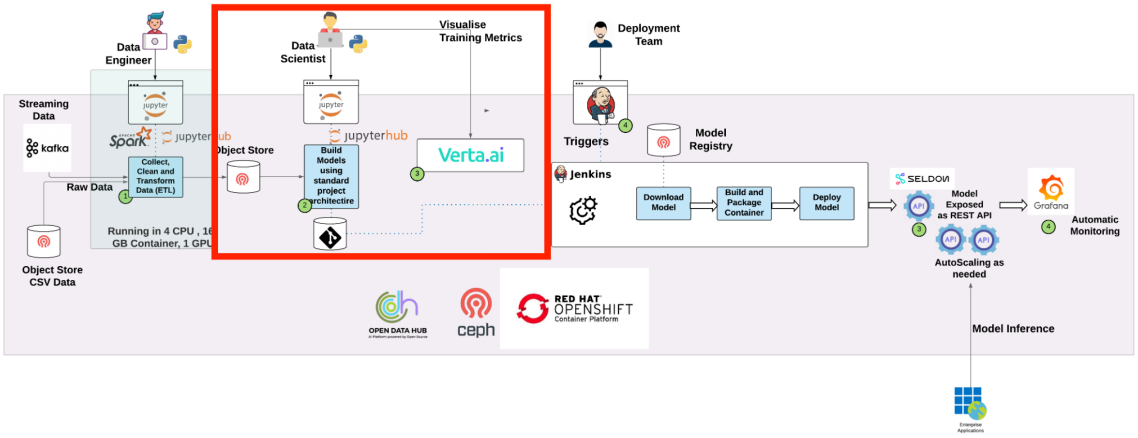
Lab 2 - Data Science

Introduction

Next we feature three Jupyter notebooks the data scientist uses, pulling the prepared CSV data that the data engineer pushed to S3 object storage in the previous lab:

1. They first visualise the data - to understand patterns in the data and whether there are any errors they need to fix before experimenting and training their models.
2. They then experiment with different algorithms, parameters and hyperparameters. They push each experiment to the model repository, Verta. This repository contains all of the data and the actual model binaries should they wish to
    a. Compare different experiments
    b. Return to and retrieve any experiment they ran
    c. Share their experiments with others. In this way, we're allowing silos between different actors in the workflow
3. They then choose one of their experiments, which they wish to proceed with and push to production - in the next part of the workflow, the ML OPs phase

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

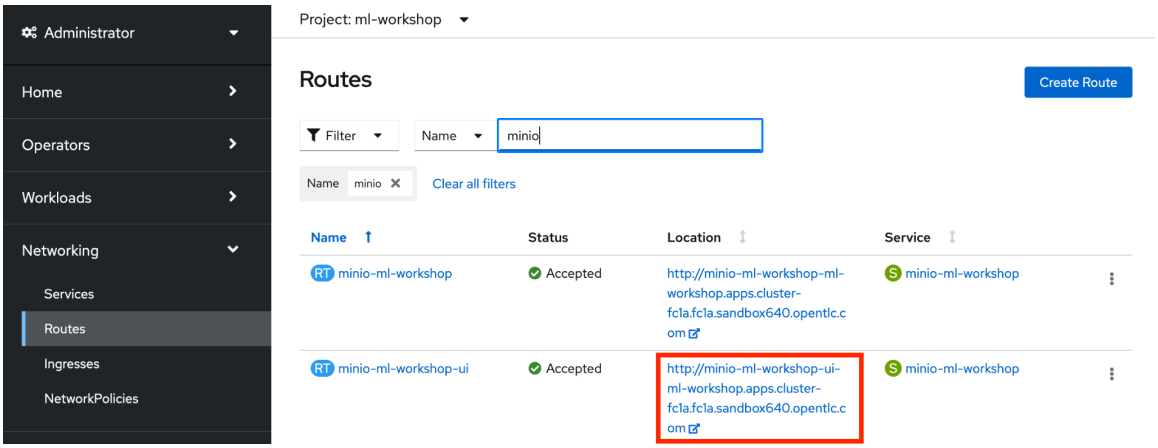


Instructions to access your prepared data file from the previous lab

You need to access the prepared CSV data file you created and pushed to S3 object storage, in the previous lab under the Data Engineer persona.

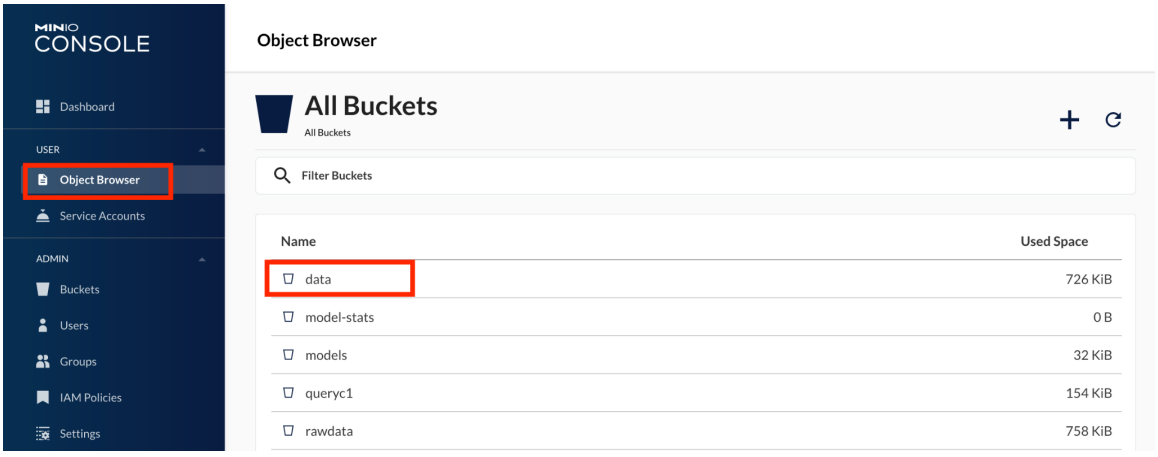
Login to OpenShift using the credentials your administrator gave you. Ensure your workshop project ml-workshop is selected.

The first thing you need to do is retrieve the path and file pertaining to your username - which you as a data engineer created previously.
Choose the Administration dropdown , navigate to Network -> Routes. Filter on *minio* - and open the *minio-ml-workshop-ui* route as shown.

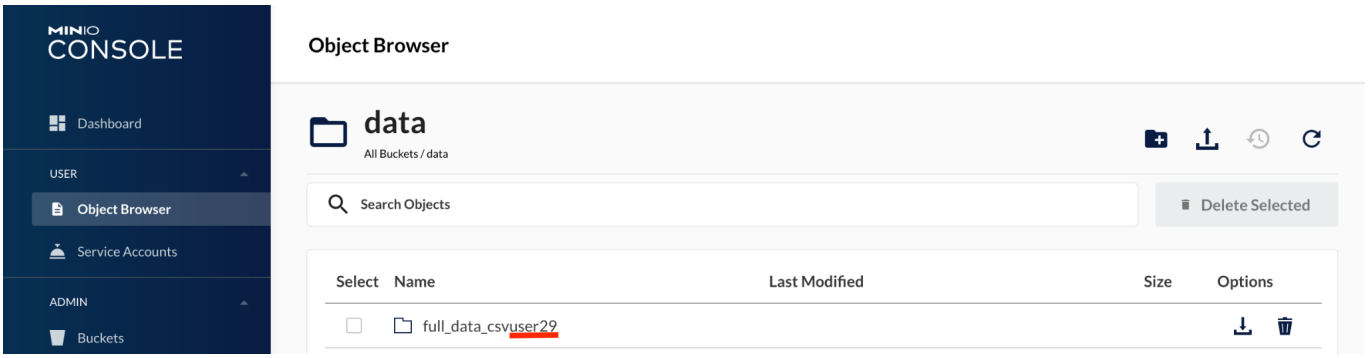


Enter the username and password minio / minio123

Choose Object Browser on the left and click into the data bucket as shown:

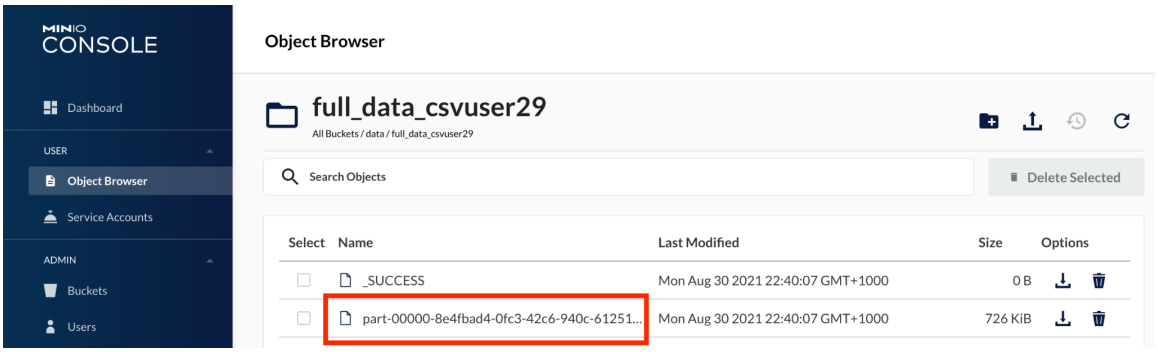


Click into the folder ***full_data_csvuserXX*** that contains **your username**, e.g. this is the folder for user29:



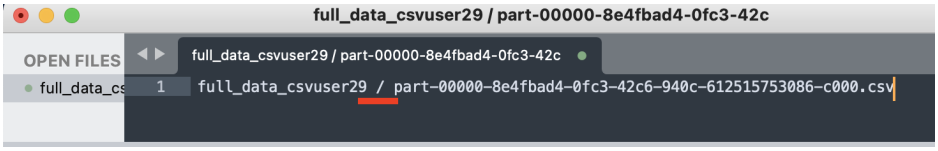
Note - there will be many folders there - be sure to select the one containing **your username.**

Click on the long filename:



Here you can retrieve your CSV file - which we'll refer to throughout this section as **YOUR_CSV_FILE.** To do this select your folder and filename as shown:

Paste this into a text editor of your choice - I use Sublime Text. Delete the two embedded spaces on either side of the forward slash:



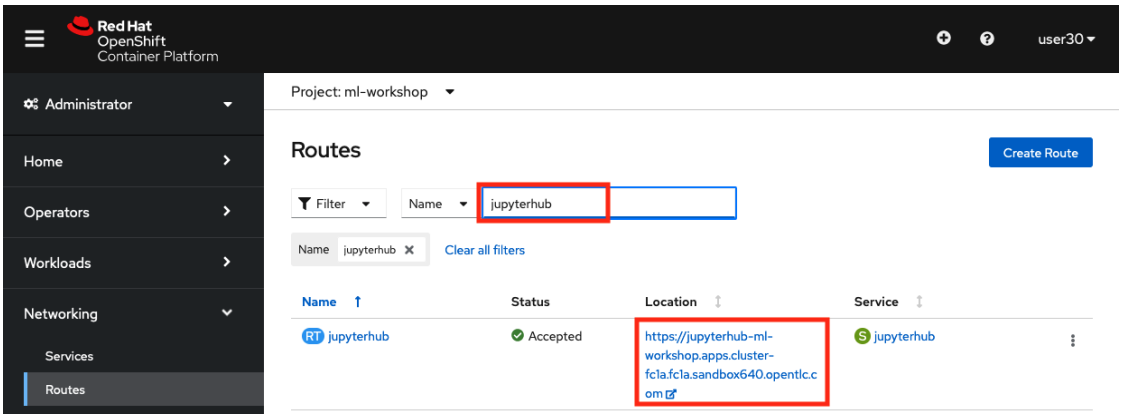
You file should now look like this:

Keep this file open for the 3 data science focused notebook exercises. As mentioned we'll refer to this long filename string as **YOUR_CSV_FILE** - which you'll paste into your notebooks below**.**

Instructions for the first Data Science workshop - Visualisation

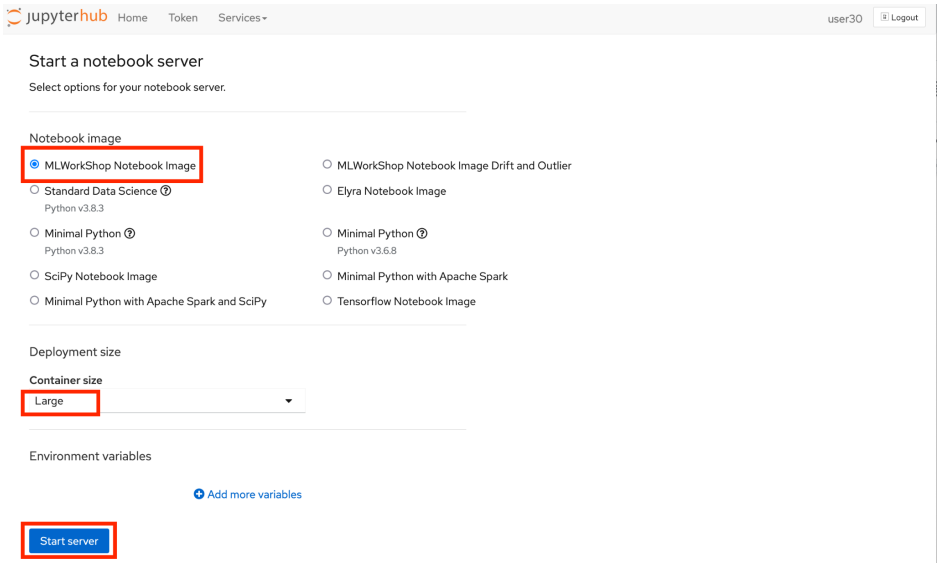
Now to our Data Science focused Jupyter notebooks.

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



Because you shutdown your Jupyter server at the end of the last workshop, you'll again be presented with the Jupyter screen where you choose the base image to work with. As we're now assuming the role of a data scientist, you'll choose:

- a different base image, the *MLWorkShop Notebook Image*
- A *Large* container - allocating the maximum amount of CPU and memory available.



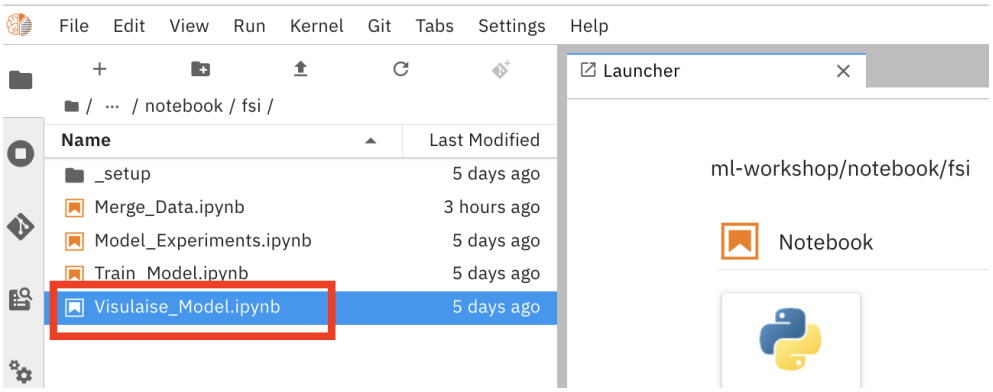
This is a custom image our OpenShift administrator has created - containing the exact tools we as a team or organisation require - optionally with the desired versions of each of the tools it contains. This is another powerful feature, allowing a consistent toolset to be used - eliminating any version mismatches we often see when practitioners use different tool versions.

Click *Start Server*. A few moments later the *files* view appears. You'll notice

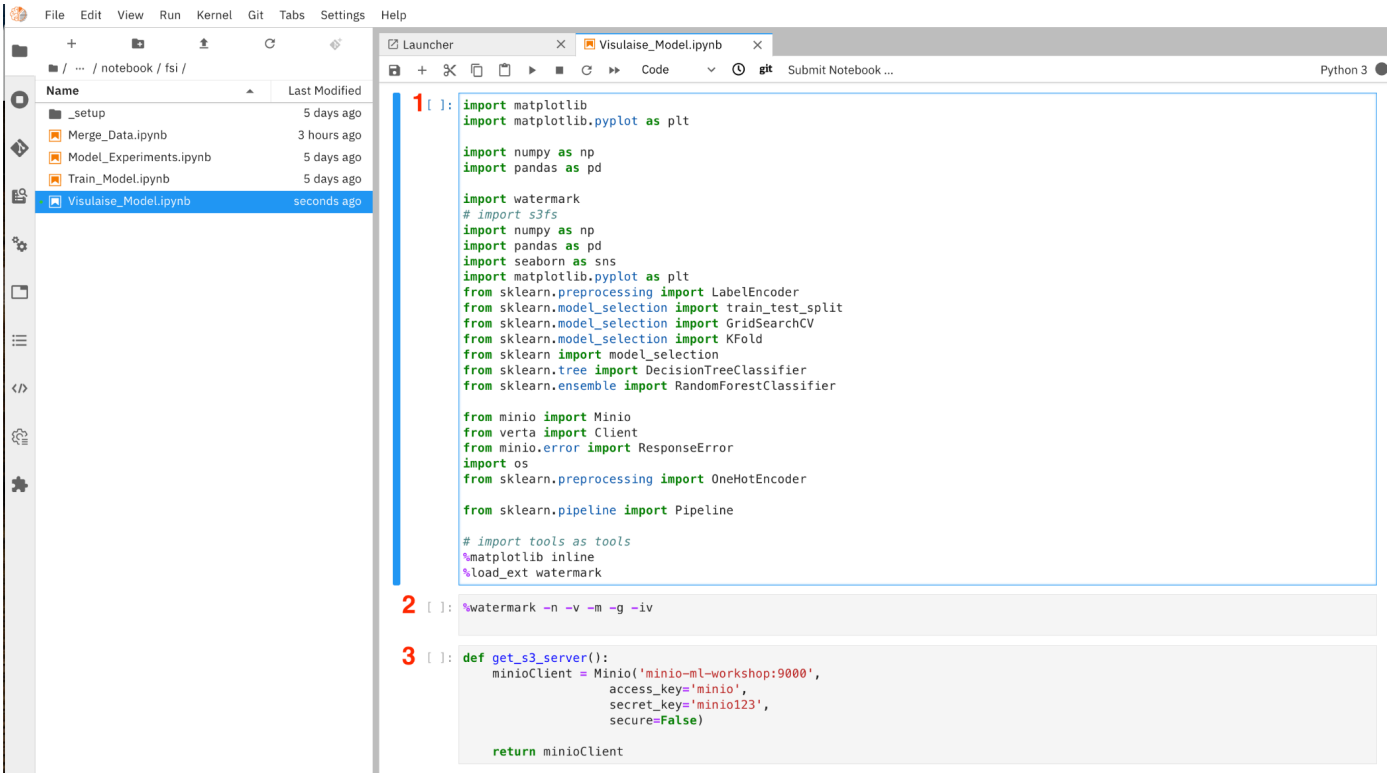
- a different GUI look and feel - a more up to date version known as *Elyra*.
- the same *ml-workshop* folder we previously pulled down from our GitHub repository https://github.com/masoodfaisal/ml-workshop

Again drill into ml-workshop -> notebook. Depending on your track ***telco*** or ***fsi***, choose the appropriate subfolder (in this example ***fsi***).

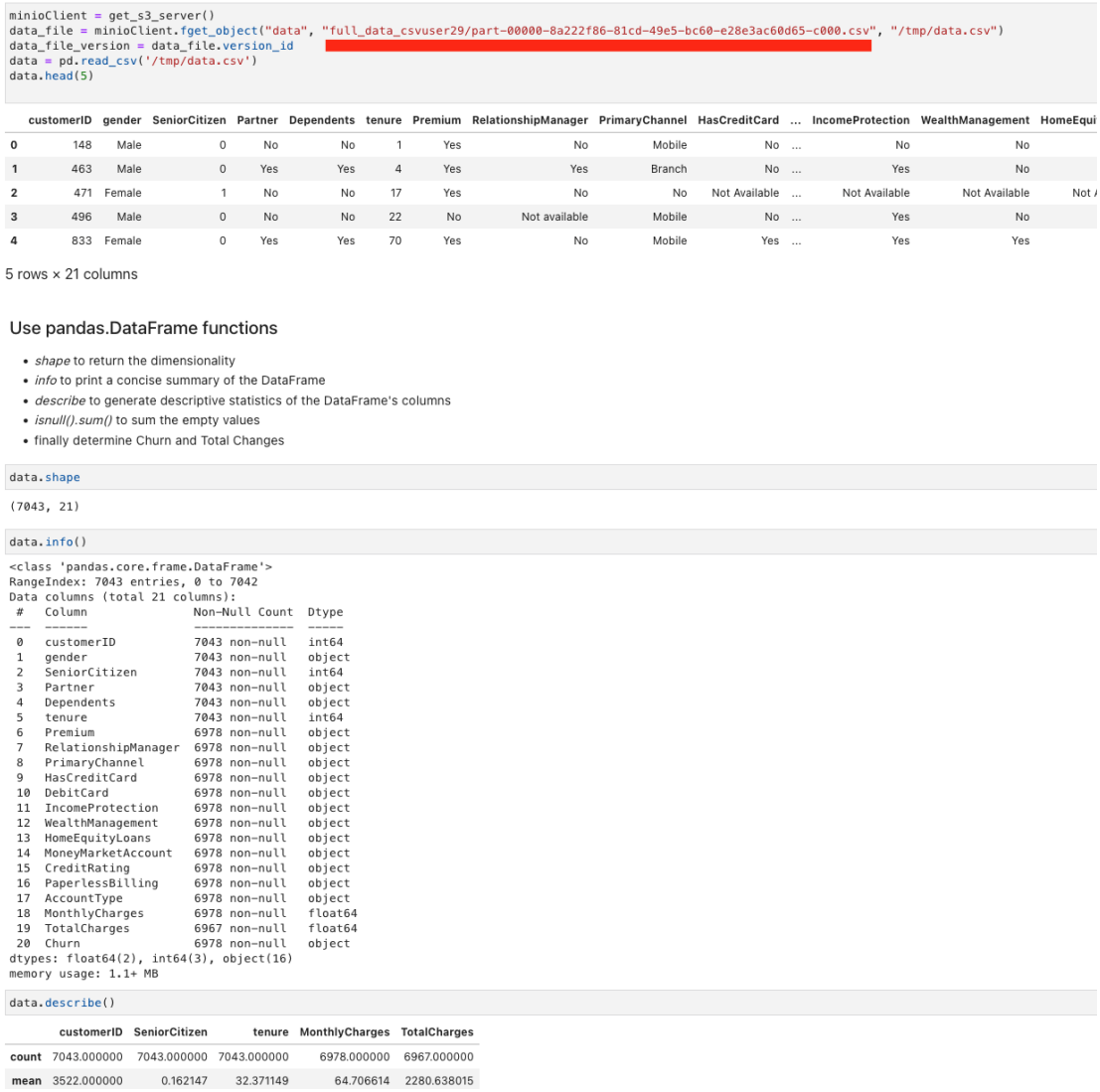
Double click the file Visulaise_Model.ipynb as shown (the name is a little misleading - it's really there to visualise the data not the model):



Now, as previously, select the first cell and walk through each cell executing you go by clicking SHIFT + RETURN. Make sure you **pause** and make the changes **as indicated in red**, before executing certain cells.



1. Import our desired Python libraries. (notice we don't need to do any ***pip install***s - our administrator has bundled all of our required libraries into this base container image - which we selected earlier the *MLWorkShop Notebook Image*)
2. *watermark* outputs the versions of various components, libraries, operating system attributes etc.
3. Here we connect to our S3 object store, Minio, using the URL and credentials shown



```
4
minioClient = get_s3_server()
data_file = minioClient.fget_object("data", "full_data_csvuser29/part-00000-8a222f86-81cd-49e5-bc60-e28e3ac60d65-c000.csv", "/tmp/data.csv")
data_file_version = data_file.version_id
data = pd.read_csv('/tmp/data.csv')
data.head(5)
```

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	Premium	RelationshipManager	PrimaryChannel	HasCreditCard	...	IncomeProtection	WealthManagement	HomeEqui
0	148	Male	0	No	No	1	Yes	No	Mobile	No	...	No	No	
1	463	Male	0	Yes	Yes	4	Yes	Yes	Branch	No	...	Yes	No	
2	471	Female	1	No	No	17	Yes	No	No	Not Available	...	Not Available	Not Available	Not A
3	496	Male	0	No	No	22	No	Not available	Mobile	No	...	Yes	No	
4	833	Female	0	Yes	Yes	70	Yes	No	Mobile	Yes	...	Yes	Yes	

5 rows × 21 columns

Use pandas.DataFrame functions

- *shape* to return the dimensionality
- *info* to print a concise summary of the DataFrame
- *describe* to generate descriptive statistics of the DataFrame's columns
- *isnull().sum()* to sum the empty values
- finally determine Churn and Total Changes

```
5
data.shape
```

```
(7043, 21)
```

```
6
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 21 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   customerID           7043 non-null   int64
 1   gender               7043 non-null   object
 2   SeniorCitizen        7043 non-null   int64
 3   Partner              7043 non-null   object
 4   Dependents           7043 non-null   object
 5   tenure               7043 non-null   int64
 6   Premium              6978 non-null   object
 7   RelationshipManager  6978 non-null   object
 8   PrimaryChannel       6978 non-null   object
 9   HasCreditCard        6978 non-null   object
 10  DebitCard            6978 non-null   object
 11  IncomeProtection     6978 non-null   object
 12  WealthManagement     6978 non-null   object
 13  HomeEquityLoans      6978 non-null   object
 14  MoneyMarketAccount   6978 non-null   object
 15  CreditRating         6978 non-null   object
 16  PaperlessBilling     6978 non-null   object
 17  AccountType          6978 non-null   object
 18  MonthlyCharges       6978 non-null   float64
 19  TotalCharges         6967 non-null   float64
 20  Churn                6978 non-null   object
dtypes: float64(2), int64(3), object(16)
memory usage: 1.1+ MB
```

```
7
data.describe()
```

	customerID	SeniorCitizen	tenure	MonthlyCharges	TotalCharges
count	7043.000000	7043.000000	7043.000000	6978.000000	6967.000000
mean	3522.000000	0.162147	32.371149	64.706614	2280.638015

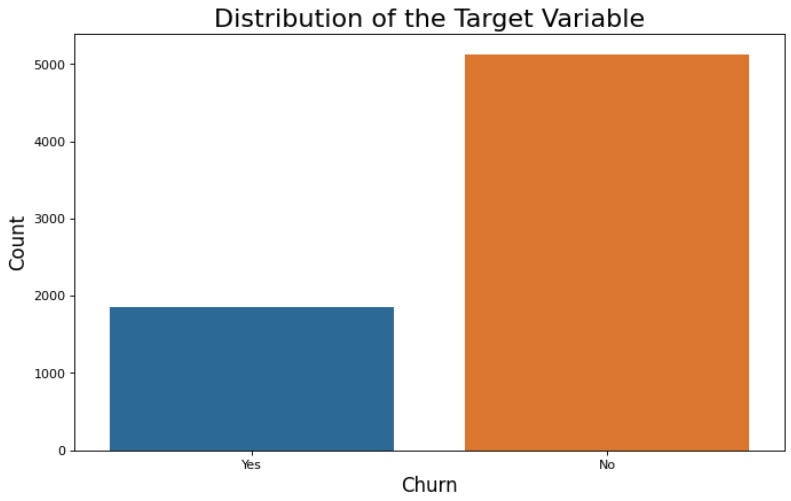
4. **You need to modify this cell before you execute it.**
   Here we retrieve the CSV we prepared in the Data Engineer lab earlier. To do that replace the string that's underlined in the screenshot with the string representing your file, **YOUR_CSV_FILE** from earlier in this lab. Save the file and continue executing.
   In this cell we also output the first 5 lines of the file - so the data scientist can get a quick view of the data.
5. We output the dimensions of the data in rows and columns (features)
6. Here we output various data around the columns (features) including their types, names etc
7. Using *describe(),* we output various statistical data associated with the entire dataset, max, mean etc. values for numeric columns.

8
```
[8]: data.isnull().sum()
```

```
[8]: customerID              0
     gender                  0
     SeniorCitizen           0
     Partner                 0
     Dependents              0
     tenure                  0
     Premium                65
     RelationshipManager    65
     PrimaryChannel         65
     HasCreditCard          65
     DebitCard              65
     IncomeProtection       65
     WealthManagement       65
     HomeEquityLoans        65
     MoneyMarketAccount     65
     CreditRating           65
     PaperlessBilling       65
     AccountType            65
     MonthlyCharges         65
     TotalCharges           76
     Churn                  65
     dtype: int64
```

9
```
[9]: fig = plt.figure(figsize=(10,6), dpi=80)
ax = sns.countplot(x="Churn", data=data)
ax.set_title('Distribution of the Target Variable', fontsize=20)
ax.set_xlabel('Churn', fontsize = 15)
ax.set_ylabel('Count', fontsize = 15)
```

```
[9]: Text(0, 0.5, 'Count')
```



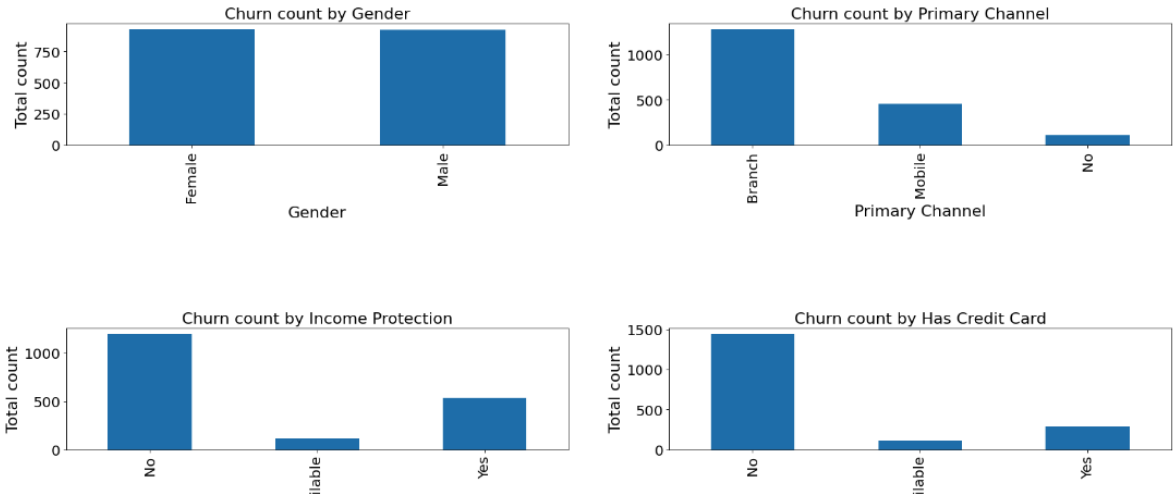
10
```
[10]: # Convert binary variable into numeric so plotting is easier. We need to later take mean
data['Churn'] = data['Churn'].map({'Yes': 1, 'No': 0})
```

8. We output the sum of rows with null values with nulls - to assess data for errors, e.g null for *charges* indicates an error.
9. Here we output the total count of the ***labeled*** column, Churn. We need a decent spread, and we have it - with just over 2 to 1.
10. Here we make a simple conversion from Yes and No to 1 and 0, to facilitate plotting.

11

```
[11]: fig, ((ax1,ax2),(ax3,ax4), (ax5,ax6)) = plt.subplots(ncols=2, nrows=3, figsize=(25,17), dpi = 80)
plt.subplots_adjust(left=None, bottom=None, right=None, top=None ,wspace=None, hspace=1.5)
plt.rc('xtick', labelsize = 12)    # fontsize of the tick labels
plt.rc('ytick', labelsize = 12)

data.groupby('gender').Churn.sum().plot(kind='bar', ax = ax1)
ax1.set_ylabel('Total count',fontsize = 20)
ax1.set_xlabel('Gender',fontsize = 20)
ax1.tick_params(labelsize = 18)
ax1.set_title('Churn count by Gender',fontsize = 20)

data.groupby('PrimaryChannel').Churn.sum().plot(kind='bar', ax=ax2)
ax2.set_ylabel('Total count',fontsize = 20)
ax2.set_xlabel('Primary Channel',fontsize = 20)
ax2.tick_params(labelsize = 18)
ax2.set_title('Churn count by Primary Channel',fontsize = 20)

data.groupby('IncomeProtection').Churn.sum().plot(kind='bar', ax=ax3)
ax3.set_ylabel('Total count',fontsize = 20)
ax3.set_xlabel('Income Protection',fontsize = 20)
ax3.tick_params(labelsize = 18)
ax3.set_title('Churn count by Income Protection',fontsize = 20)

data.groupby('HasCreditCard').Churn.sum().plot(kind='bar', ax=ax4)
ax4.set_ylabel('Total count',fontsize = 20)
ax4.set_xlabel('Has Credit Card',fontsize = 20)
ax4.tick_params(labelsize = 18)
ax4.set_title('Churn count by Has Credit Card',fontsize = 20)

data.groupby('WealthManagement').Churn.sum().plot(kind='bar',ax=ax5)
ax5.set_ylabel('Total count',fontsize = 20)
ax5.set_xlabel('Wealth Management',fontsize = 20)
ax5.tick_params(labelsize = 18)
ax5.set_title('Churn count by Wealth Management',fontsize = 20)

data.groupby('CreditRating').Churn.sum().plot(kind='bar',ax=ax6)
ax6.set_ylabel('Total count',fontsize = 20)
ax6.set_xlabel('Credit Rating Type',fontsize = 20)
ax6.tick_params(labelsize = 18)
ax6.set_title('Churn count by Credit Rating',fontsize = 20)
```

```
[11]: Text(0.5, 1.0, 'Churn count by Credit Rating')
```



11. This cell visually outputs churn count by various features in the data set

12
```
data.replace(" ", np.nan, inplace=True)
```

13
```
data.isna().sum()
```

```
customerID              0
gender                  0
SeniorCitizen           0
Partner                 0
Dependents              0
tenure                  0
Premium                65
RelationshipManager    65
PrimaryChannel         65
HasCreditCard          65
DebitCard              65
IncomeProtection       65
WealthManagement       65
HomeEquityLoans        65
MoneyMarketAccount     65
CreditRating           65
PaperlessBilling       65
AccountType            65
MonthlyCharges         65
TotalCharges           76
Churn                  65
dtype: int64
```

14
```
data['TotalCharges'] = pd.to_numeric(data['TotalCharges'])
```

15
```
mean = data['TotalCharges'].mean()
data.fillna(mean, inplace=True)
# Now we know that total charges has nan values
data.isna().sum()
```

```
customerID             0
gender                 0
SeniorCitizen          0
Partner                0
Dependents             0
tenure                 0
Premium                0
RelationshipManager    0
PrimaryChannel         0
HasCreditCard          0
DebitCard              0
IncomeProtection       0
WealthManagement       0
HomeEquityLoans        0
MoneyMarketAccount     0
CreditRating           0
PaperlessBilling       0
AccountType            0
MonthlyCharges         0
TotalCharges           0
Churn                  0
dtype: int64
```

16
```
plt.figure(figsize=(10,8), dpi=80)
# Sns.set(rc={'figure.figsize':(25,15)})
ax = sns.catplot(x="CreditRating", y="TotalCharges", hue="Churn", kind="box", data=data, height = 6,aspect = 1.5,palette = 'RdBu')
plt.title('Comparison of Total Charges for each CreditRating',fontsize = 20)
plt.xlabel('CreditRating',fontsize = 15)
plt.ylabel('Total Charges',fontsize = 15)
```

```
Text(17.690962577160498, 0.5, 'Total Charges')
<Figure size 800x640 with 0 Axes>
```

12. Replace spaces with numpy NAN values
13. Output sum of NAN and None values
14. Convert to numeric
15. Fill NANs with the mean
16. Here we output a box plot - a useful visualization of 2 dimensions by the labeled column *Churn*

Instructions for second Data Science workshop - Experiment with Models

At this point, as a data scientist, we have a good understanding of the data. Now it's time to start experimenting with different models, parameters and hyper parameters.

As we experiment, we want our notebook to create an experiment id for every experiment (which is guaranteed to be unique within our team, as it uses user id and timestamp as a basis).

This experiment id is then used as an identifier when we push our experiment metadata and binaries to our model repository, Verta. In this way, we retrieve and repeat any experiment we have done, as well as share this experiment with other team members, breaking down silos between teams and individuals in AI//ML workflows.

Open up Model_Experiments.ipynb and begin executing as before using SHIFT+RETURN to proceed through the notebook. Follow the descriptions of each cell.
Note there are 3 changes you'll need to make to your cells - which we'll highlight below:

[1]:
```
import os
# os.environ["MODIN_ENGINE"] = "ray"
```

[2]:
```
import matplotlib
import matplotlib.pyplot as plt

import numpy as np
# import pandas as pd
# import modin.pandas as pd

import watermark
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import KFold
from sklearn import model_selection
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from datetime import datetime
import verta.integrations.sklearn
from minio import Minio
from verta import Client
from minio.error import ResponseError
import os
from sklearn.preprocessing import OneHotEncoder

from sklearn.pipeline import Pipeline


# import tools as tools
%matplotlib inline
%load_ext watermark
```

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

1. Do imports - more applicable when we want to use *Ray*.
2. More imports of libraries we need
3. See *watermark* description of this cell above in - ***first Data Science workshop - Visualisation***

4

```
dateTimeObj = datetime.now()
timestampStr = dateTimeObj.strftime("%d%Y%H%M%S%f")
experiment_name = "customerchurnuser29"
experiment_id = experiment_name + timestampStr

def get_s3_server():
    minioClient = Minio('minio-ml-workshop:9000',
                        access_key='minio',
                        secret_key='minio123',
                        secure=False)

    return minioClient

def get_verta():
    client = Client("http://172.30.46.176:3000")
    return client

def get_meta_store():
    client = get_verta()
    proj = client.set_project("ml-workshop")
    client.set_experiment(experiment_name)
    run = client.set_experiment_run(experiment_id)
    return run
```

In this next section, on the second line, insert the value you retrieved from Minio object st
name of your csv file in Minio. This is the file pushed by the data engineer in the format: fu

In my case this value is: full_data_csvuser29/part-00000-59149e08-583c-46a5-bfa0-0b3abecbf1a3-c

We refer to this fully qualified name in the Github instructions as CSV-FILE

5

```
minioClient = get_s3_server()
data_file = minioClient.fget_object("data", "full_data_csvuser29/part-00000-8a222f86-81cd-49e5-bc60-e
data_file_version = data_file.version_id
data = pd.read_csv('/tmp/data.csv')
data.head(5)
```

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	Premium	RelationshipManager	PrimaryChannel	HasC
0	148	Male	0	No	No	1	Yes	No	Mobile	
1	463	Male	0	Yes	Yes	4	Yes	Yes	Branch	
2	471	Female	1	No	No	17	Yes	No	No	No
3	496	Male	0	No	No	22	No	Not available	Mobile	
4	833	Female	0	Yes	Yes	70	Yes	No	Mobile	

5 rows × 21 columns

Use pandas.DataFrame functions

- *shape* to return the dimensionality
- *info* to print a concise summary of the DataFrame
- *describe* to generate descriptive statistics of the DataFrame's columns
- *isnull().sum()* to sum the empty values
- finally determine Churn and Total Changes

6

```
data.shape
```

```
(7043, 21)
```

7

```
data.info()
```

4. **You need to modify this cell before you execute it.**
   Replace the third line replacing user29 with your userid. Save the file
   Next we connect to Minio to pull our raw data from.
   Also connect to Verta to push our experiment data to. Set project within Verta to be ml-workshop.
5. **You need to modify this cell before you execute it.**
   Here we retrieve the CSV we prepared in the Data Engineer lab earlier. To do that replace the string that's underlined in the screenshot with the string representing your file, **YOUR_CSV_FILE** from earlier in this lab. Save the file and continue executing.
   In this cell we also output the first 5 lines of the file - so the data scientist can get a quick view of the data.
6. see *data.shape* cell description above in - ***first Data Science workshop - Visualisation***
7. see *data.info* cell description above in - ***first Data Science workshop - Visualisation***

Run all the way down to cell 15, *Feature Engineering Pipeline*, as all cells until then are discussed above in - ***first Data Science workshop - Visualisation***

15

```
import category_encoders as ce
import joblib

names = ['gender', 'Partner', 'Dependents', 'Premium', 'HomeEquityLoans', 'MoneyMarketAccount', 'PaperlessBilling', 'Churn']
# for column in names:
#     labelencoder(column)

enc = ce.ordinal.OrdinalEncoder(cols=names)
enc.fit(data)
joblib.dump(enc, 'enc.pkl')
labelled_set = enc.transform(data)
labelled_set.tail(5)
```

```
/opt/app-root/lib/python3.6/site-packages/category_encoders/utils.py:21: FutureWarning: is_categorical is deprecated and will be removed in
on.  Use is_categorical_dtype instead
  elif pd.api.types.is_categorical(cols):
```

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	Premium	RelationshipManager	PrimaryChannel	HasCreditCard	...	IncomeProtection	WealthMan
7038	6490	1	0	1	1	1	1	No	No	Not Available	...	Not Available	Not
7039	6634	2	0	1	1	1	1	Yes	Branch	No	...	No	
7040	6638	1	0	2	1	69	1	No	Mobile	Yes	...	No	
7041	6721	1	0	2	2	70	1	Yes	Mobile	No	...	Yes	
7042	6819	2	0	1	1	3	1	No	Mobile	Yes	...	No	

5 rows × 21 columns

16

```
names = ['RelationshipManager', 'PrimaryChannel', 'CreditRating', 'AccountType', 'HasCreditCard', 'DebitCard',
         'IncomeProtection', 'WealthManagement']

ohe = ce.OneHotEncoder(cols=names)
ohe.fit(labelled_set)
joblib.dump(ohe, 'ohe.pkl')
final_set = ohe.transform(labelled_set)
final_set.tail(5)
```

```
/opt/app-root/lib/python3.6/site-packages/category_encoders/utils.py:21: FutureWarning: is_categorical is deprecated and will be removed in
on.  Use is_categorical_dtype instead
  elif pd.api.types.is_categorical(cols):
```

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	Premium	RelationshipManager_1	RelationshipManager_2	RelationshipManager_3	...	CreditRating
7038	6490	1	0	1	1	1	1	1	0	0	...	
7039	6634	2	0	1	1	1	1	0	1	0	...	
7040	6638	1	0	2	1	69	1	1	0	0	...	
7041	6721	1	0	2	2	70	1	0	1	0	...	
7042	6819	2	0	1	1	3	1	1	0	0	...	

5 rows × 46 columns

17

Now we use scikit-learn's 'train_test_split' function to randomly split our data into training and testing sets. Then remove th
and *customerID* fields from our training and testing datasets and output the shaope of our data.

```
labels = final_set['Churn']
X_train, X_test, y_train, y_test = train_test_split(final_set, labels, test_size=0.2)
X_train.pop('Churn')
X_train.pop('customerID')
X_test.pop('Churn')
X_test.pop('customerID')
print ('Training Data Shape',X_train.shape, y_train.shape)
print ('Testing Data Shape',X_test.shape, y_test.shape)
```

```
Training Data Shape (5634, 44) (5634,)
Testing Data Shape (1409, 44) (1409,)
```

18

```
# Data For cross validation and GridSearch
Y = final_set['Churn']
X = final_set.drop(['Churn', 'customerID'], axis=1)
print ('Training Data Shape', X.shape)
print ('Testing Data Shape', Y.shape)
```

15. Here we use an Ordinal Encoder to convert simple binary values to a numeric representation. Output the data after applying the Ordinal Encoder.
16. Here we use a One Hot Encoder to convert multi valued features to a numeric representation. Output the data after applying the One Hot Encoder.
17. Here we split our data set into a training and a testing set, and discard unwanted columns customer id and our labeled column Churn.
18. Further data set refinement.

Create DecisionTreeClassifier object, extract hyper parameters, and then GridSearch will best_mod

19
```
# Create decision tree object
DT = DecisionTreeClassifier()
# List of parameters
# entropy
criterion = ['gini']
max_depth = [5,10,15]
min_samples_split = [2,4,6]
min_samples_leaf = [4,5,6,8]
# Save all the lists in the variable
hyperparameters = dict(max_depth=max_depth, criterion=criterion,min_samples_leaf = min_samples_leaf ,min_samples
```

20
```
model = GridSearchCV(DT, hyperparameters, cv=5, verbose=0)
best_model = model.fit(X,Y)
```

21
```
# Mean cross validated score
print('Mean Cross-Validated Score: ',best_model.best_score_)
print('Best Parameters',best_model.best_params_)
# You can also print the best penalty and C value individually from best_model.best_estimator_.get_params()
print('Best criteria:', best_model.best_estimator_.get_params()['criterion'])
print('Best depth:', best_model.best_estimator_.get_params()['max_depth'])
```

```
Mean Cross-Validated Score:  0.7936973756371378
Best Parameters {'criterion': 'gini', 'max_depth': 5, 'min_samples_leaf': 6, 'min_samples_split': 2}
Best criteria: gini
Best depth: 5
```

Use K-Folds cross-validator to split data in train/test sets. Create a dictionary of hyperparameter ca
DecisionTreeClassifier, assess results, print and store hyper parameters and accuracy and tag using

22
```
kfold = KFold(n_splits = 3)
hyperparameters = dict(max_depth=5, criterion='gini',min_samples_leaf = 3 ,min_samples_split = 10)
model = DecisionTreeClassifier(max_depth=5, criterion='gini',min_samples_leaf = 3 ,min_samples_split = 10)
model = model.fit(X_train, y_train)
joblib.dump(model, 'dct.pkl')
results = model_selection.cross_val_score(model,X,Y,cv = kfold)
print(results)
print('Accuracy',results.mean()*100)
store = get_meta_store()
store.log_hyperparameters(hyperparameters)
store.log_model(model)
store.log_metric('Accuracy',results.mean()*100)
store.log_tag("DecisionTreeClassifier")
# get_meta_store().log_dataset_version("raw_data", dataset_version)
```

```
[0.78321976 0.80579216 0.79037069]
Accuracy 79.31275370082314
connection successfully established
created new Project: ml-workshop in personal workspace
created new Experiment: customerchurnuser29
created new ExperimentRun: customerchurnuser29072021012111535042
upload complete (custom_modules)
upload complete (model.pkl)
upload complete (model_api.json)
```

Like before, in this next section, on the third line, change experiment_name by appending your use
your username is user1:

```
experiment_name = "customerchurnuser1"
```

19. Create a DecisionTreeClassifier with these hyper parameters
20. User GridSearch to output the best model / hyper parameters from the combinations supplied to its *fit* method.
21. Print out those best model parameters
22. Use K-Folds cross-validator to split data into train/test sets. Create a dictionary of hyperparameter candidates, train model using a DecisionTreeClassifier. Print and store hyper parameters and accuracy in Verta and tag using 'DecisionTreeClassifier''. The ***store*** method lushes this metadata to Verta, which you'll see below.

Create RandomForestClassifier object, extract hyper parameters, and then the best_model

23
```
dateTimeObj = datetime.now()
timestampStr = dateTimeObj.strftime("%d%Y%H%M%S%f")
experiment_name = "customerchurnuser29"
experiment_id = experiment_name + timestampStr


# Create random forest object
RF = RandomForestClassifier()
n_estimators = [18,22]
criterion = ['gini', 'entropy']
# Create a list of all of the parameters
max_depth = [30,40,50]
min_samples_split = [6,8]
min_samples_leaf = [8,10,12]
# Merge the list into the variable
hyperparameters = dict(n_estimators = n_estimators,max_depth=max_depth, criterion=criterion,min_samples_leaf = min_samples_l
# Fit your model using gridsearch
model = GridSearchCV(RF, hyperparameters, cv=5, verbose=0)
best_model = model.fit(X, Y)
```

Extract best scores, params, criteria and depth from our model.

24
```
# Mean cross validated score
print('Mean Cross-Validated Score: ',best_model.best_score_)
print('Best Parameters',best_model.best_params_)
# You can also print the best penalty and C value individually from best_model.best_estimator_.get_params()
print('Best criteria:', best_model.best_estimator_.get_params()['criterion'])
print('Best depth:', best_model.best_estimator_.get_params()['max_depth'])
print('Best estimator:', best_model.best_estimator_.get_params()['n_estimators'])
```

```
Mean Cross-Validated Score:  0.803778570391638
Best Parameters {'criterion': 'gini', 'max_depth': 50, 'min_samples_leaf': 12, 'min_samples_split': 6, 'n_estimators': 18}
Best criteria: gini
Best depth: 50
Best estimator: 18
```

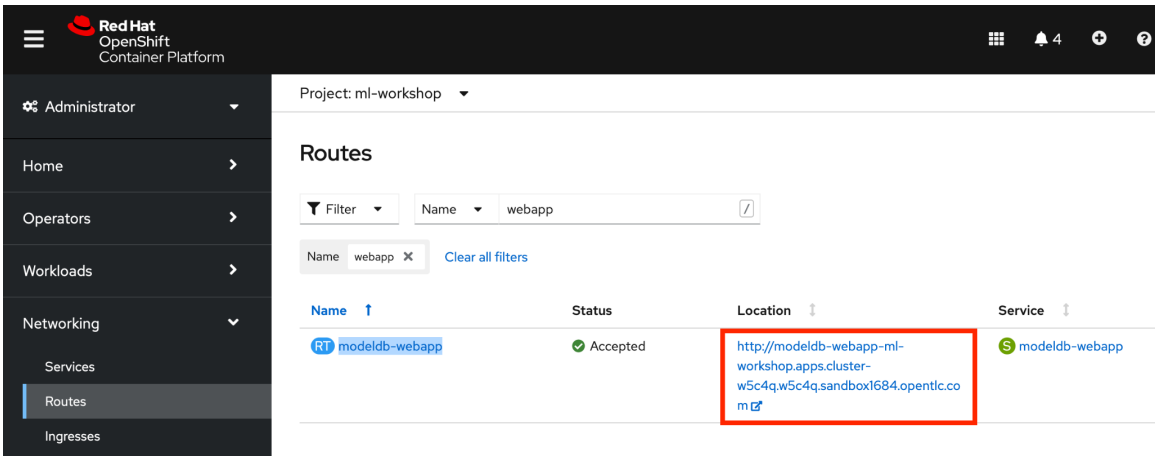
As above, use K-Folds cross-validator to split data in train/test sets. Create a dictionary of hyperparameter cai and store hyper parameters and accuracy and tag using 'RandomForestClassifier'

25
```
kfold = KFold(n_splits = 3)
hyperparameters = dict(max_depth=40, criterion='gini',min_samples_leaf = 12 ,min_samples_split = 8, n_estimators = 22)
model = RandomForestClassifier(max_depth=40, criterion='gini',min_samples_leaf = 12 ,min_samples_split = 8, n_estimators = 2
model = model.fit(X_train, y_train)
joblib.dump(model, 'rft.pkl')
results = model_selection.cross_val_score(model,X,Y,cv = kfold)
print(results)
print('Accuracy',results.mean()*100)
store = get_meta_store()
store.log_hyperparameters(hyperparameters)
store.log_model(model)
store.log_metric('Accuracy',results.mean()*100)
store.log_tag("RandomForestClassifier")
store.log_attribute("data_file_location", "data/full_data_csv/a.csv")
store.log_attribute("data_file_version", data_file_version)
```

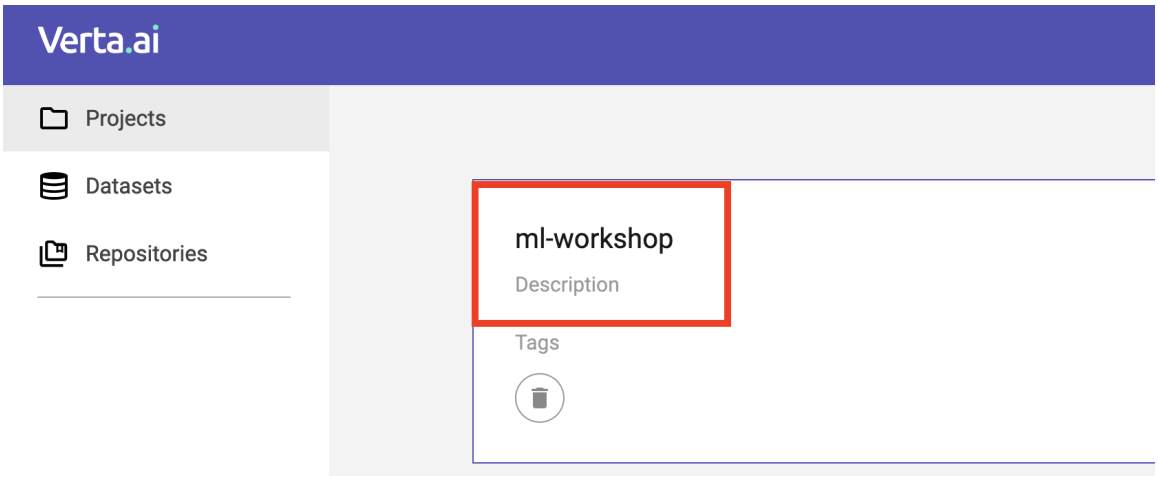
23. **You need to modify this cell before you execute it.**
    Modify the 3rd line substituting your username in place of user29.
    Then we create a Random Forest Classifier with these hyper parameters.
24. This cell and cell 25 are equivalents of the previous Decision Tree classifier cells.

Instructions to access your model visualisation and repository Verta.

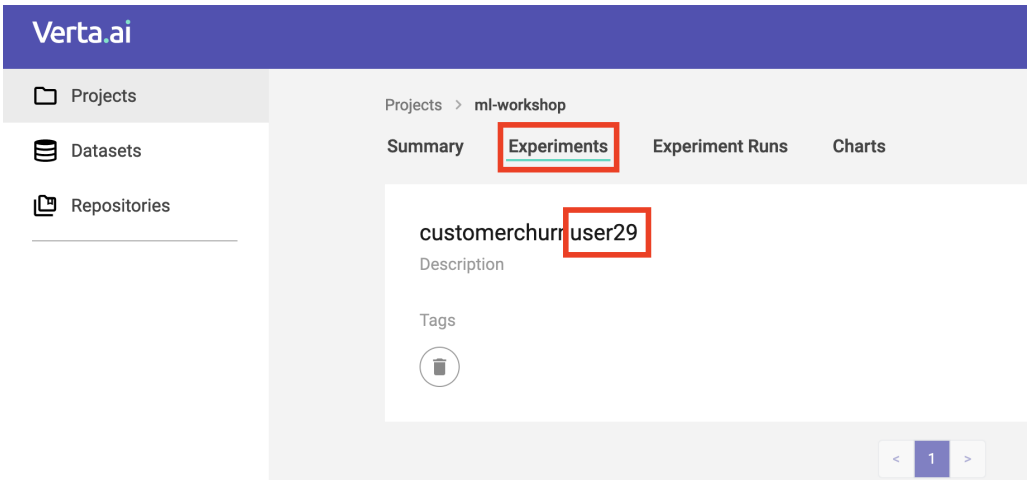
In OpenShift choose the Administration dropdown , navigate to Network -> Routes. Filter on *webapp* - and open the *modeldb-webapp* route, which is our Verta tool, as shown. You won't need to supply and credentials.



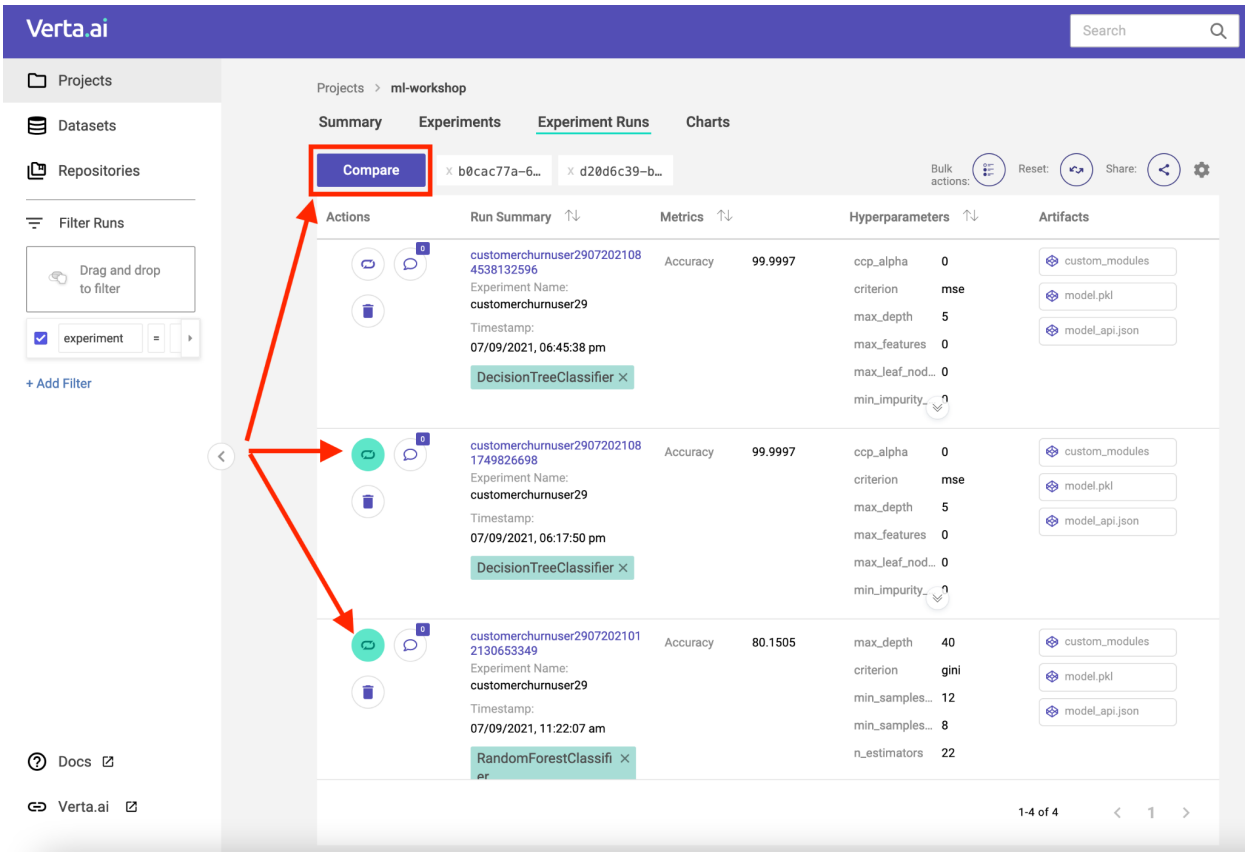
Drill into *ml-workshop*, this is the high level project name we used to push all of our experiments in the *Model_Experiments.ipynb* notebook.



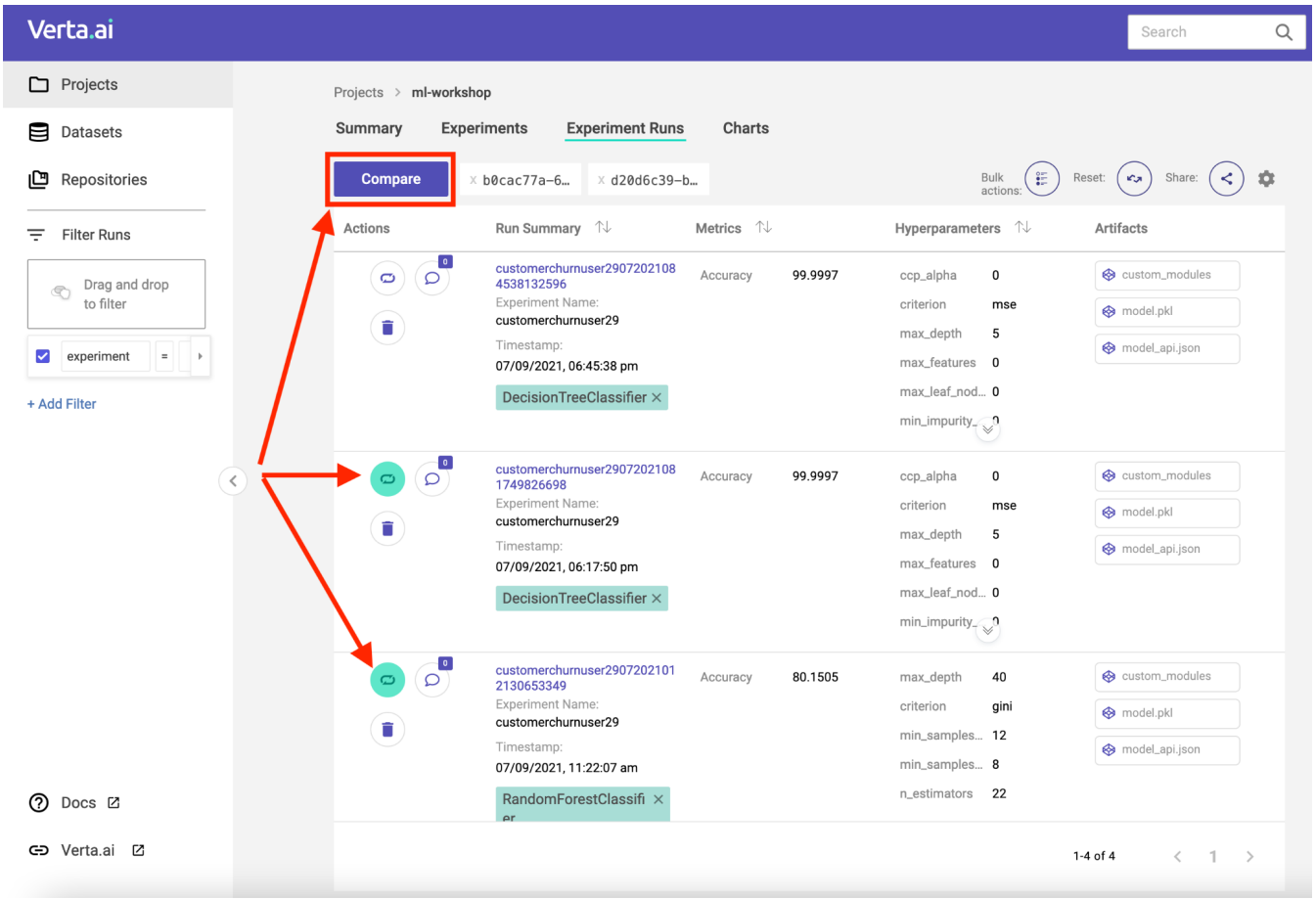
Choose *Experiments* and notice all experiments all experiments are grouped by your username, in my case customerchurn**user29**. This is the result of your text substitution in the previous section, where set your experiment names to be customerchurn**userXX.**



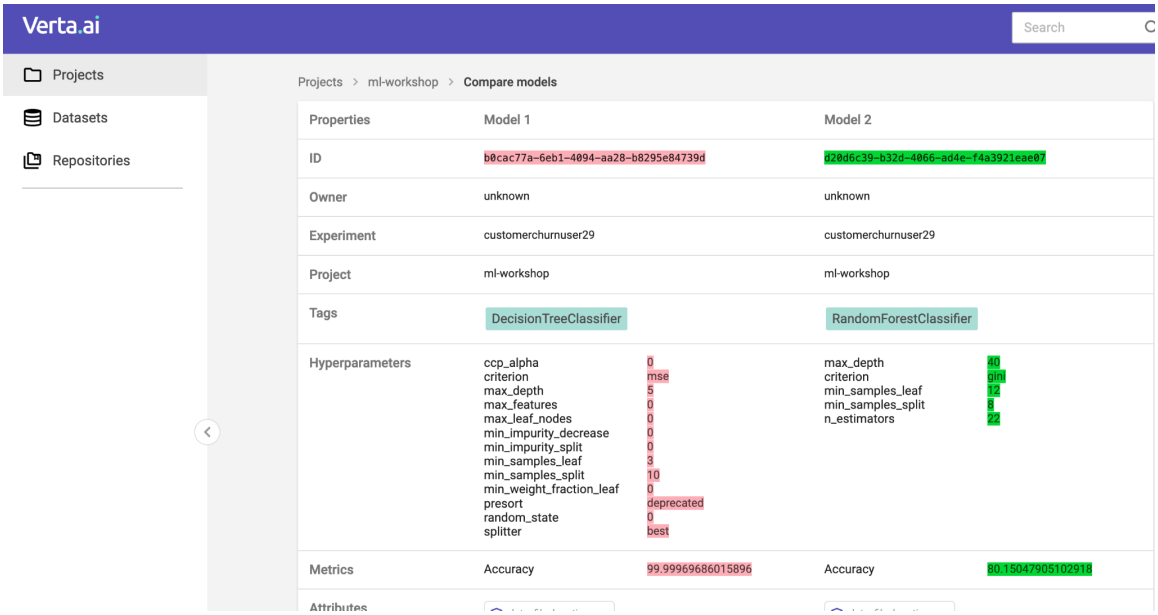
Find your folder containing your username. Drill into that folder:



Notice all of the data we sent to Verta using the ***store*** method earlier are here in Verta. Parameters, Hyper parameters, Accuracies, Binaries etc. Notice if we click the green looped arrows against any 2 experiments, the compare method becomes available. Do that and click it.

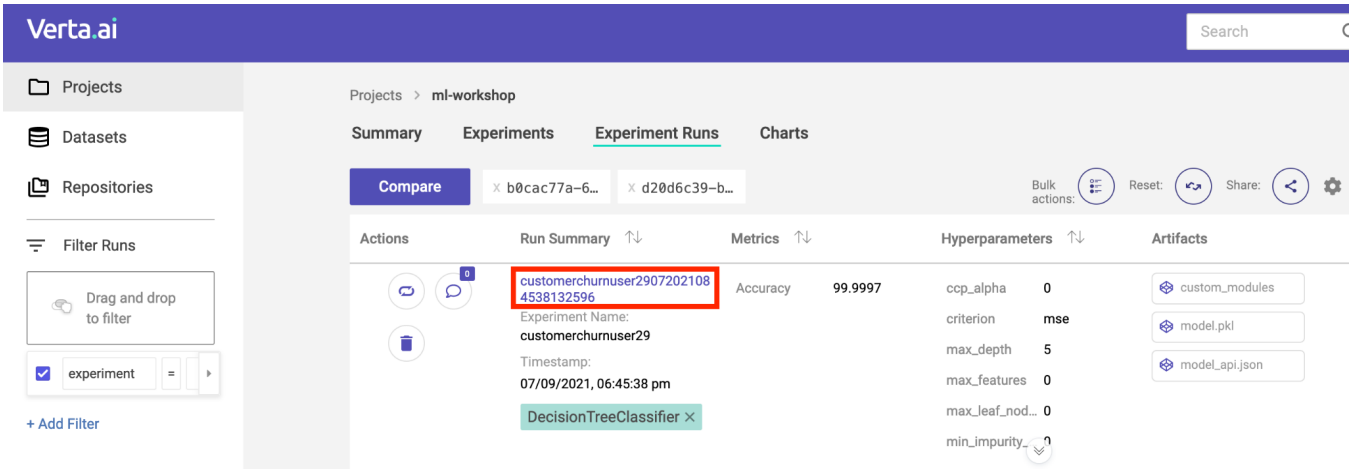


Notice we can compare values side by side.



Return to the previous screen by clicking your browser's Back button.

Finally notice every experiment gets allocated an Experiment Id, containing a timestamp and the user's username. This ensures that the ID is unique across our team. We will also use this id when we push our chosen model to production using the ML OPs pipeline later.

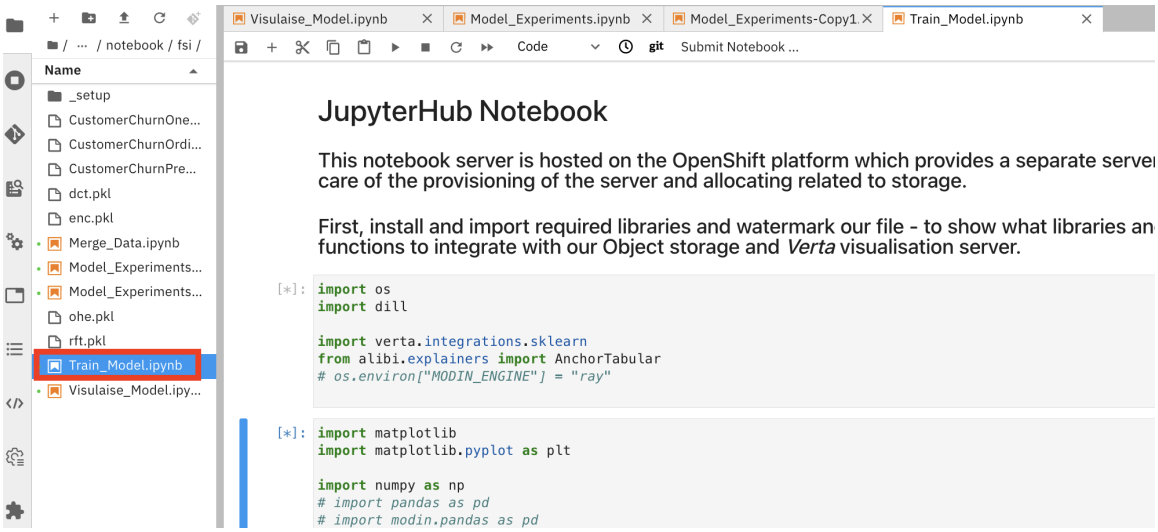


Feel free to browse around Verta, more than is shown than I described.

Instructions for the third Data Science step - Train Model

Now following examination of our experiments In Varta, let's assume for performance reasons, as a data scientist, you've decided to proceed with the Decision Tree Classifier experiment and push that model to production.

We do that in the Train_Model notebook. Go ahead and open that.



You've already encountered most of the cells here in the 2 previous notebooks. Therefore, I'll only deal with the cells you need to change and the new cells.

You'll need to change each of these 2 cells, cell 4 and cell 5:

- Cell 4:
  As previously, replace the third line replacing user29 with your userid. Save the file
  Next we connect to Minio to pull our raw data from.
  Also connect to Verta to push our experiment data to. Set project within Verta to be ml-workshop.
- Cell 5:
  Here again, we retrieve the CSV we prepared in the Data Engineer lab earlier. To do that replace the string that's underlined in the screenshot with the string representing your file, **YOUR_CSV_FILE** from earlier in this lab. Save the file and continue executing.
  In this cell we also output the first 5 lines of the file - so the data scientist can get a quick view of the data.

[4]:
```
dateTimeObj = datetime.now()
timestampStr = dateTimeObj.strftime("%d%Y%H%M%S%f")
experiment_name = "customerchurnuser29"
experiment_id = experiment_name + timestampStr


def get_s3_server():
    minioClient = Minio('minio-ml-workshop:9000',
                        access_key='minio',
                        secret_key='minio123',
                        secure=False)

    return minioClient

def get_verta():
    client = Client("http://172.30.46.176:3000")
    return client

def get_meta_store():
    client = get_verta()
    proj = client.set_project("ml-workshop")
    client.set_experiment(experiment_name)
    run = client.set_experiment_run(experiment_id)
    return run
```

In this next section, on the second line, insert the value you retrieved from Minio object storage earlier - represer
name of your csv file in Minio. This is the file pushed by the data engineer in the format: full_data_csv{USERNAM

In my case this value is: full_data_csvuser29/part-00000-59149e08-583c-46a5-bfa0-0b3abecbf1a3-c000.csv (yours will be diffe

We refer to this fully qualified name in the Github instructions as CSV-FILE

[5]:
```
minioClient = get_s3_server()
data_file = minioClient.fget_object("data", "full_data_csvuser29/part-00000-8a222f86-81cd-49e5-bc60-e28e3ac60d65-c000.csv", "/t
data_file_version = data_file.version_id
data = pd.read_csv('/tmp/data.csv')
data.head(5)
```

Save the file and work your way through the file, executing as you go by clicking SHIFT+RETURN

As we've chosen to proceed with Decision Tree Classifier experiment, notice we use the same hyper parameters etc here as we did previously:

```
[14]: from sklearn.tree import DecisionTreeRegressor

def train_and_save_model():
    kfold = KFold(n_splits = 3)
    model = DecisionTreeRegressor(max_depth=5, criterion='mse',min_samples_leaf = 3 ,min_samples_split = 10)
    store = get_meta_store()
    model = model.fit(X_train, y_train, run=store)
    joblib.dump(model, 'CustomerChurnPredictor.sav')
    results = model_selection.cross_val_score(model,X,Y,cv = kfold)
    print(results)
    print('Accuracy',results.mean()*100)

    store.log_model(model, overwrite=True)
    store.log_metric('Accuracy',results.mean()*100)
    store.log_tag("DecisionTreeClassifier")
    store.log_attribute("data_file_location", "data/full_data_csv/a.csv")
    store.log_attribute("data_file_version", data_file_version)

    return model
```

Notice here, we create an *Explainer* object, which we could use to deploy later.

```
[15]: from alibi.utils.data import gen_category_map

def explain_model(model, X_train, X_test_record):
    fnames = X_train.columns.tolist()
    predict_fn = lambda x: model.predict_proba(x)
    explainer = AnchorTabular(predict_fn, fnames)
    explainer = explainer.fit(X_train.values, disc_perc=[25, 50, 75])
    explanation = explainer.explain(X_test_record.values[0])
    print('Anchor: %s' % explanation['anchor'])
    print('Precision: %.2f' % explanation['precision'])
    print('Coverage: %.2f' % explanation['coverage'])
    return explainer
```

(Due to time constraints, we don't do that in today's hands-on-workshop)

Finally of note, in this notebook we create binaries for

- The model,
- the 2 encoders, Ordinal and One Hot encoders
- The explainer

In this cell we use our minioClient, to push these binaries to the models S3 bucket, in a folder named with your experimentId (according to your username, the substitution you just made in cell 4).

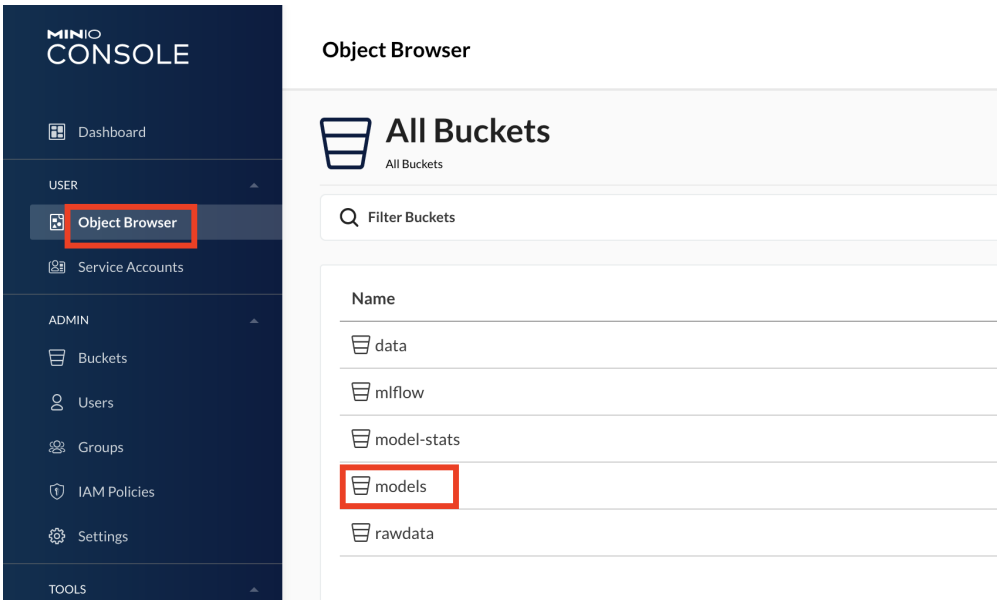
```
minioClient = get_s3_server()
minioClient.fput_object(bucket_name='models', object_name=experiment_id  +'/CustomerChurnPredictor.sav' , file_path='./CustomerChurnPredictor.sav')
minioClient.fput_object(bucket_name='models', object_name=experiment_id  +'/CustomerChurnPredictorAlibi.dill' , file_path='./CustomerChurnPredictorAlibi.dill')
minioClient.fput_object(bucket_name='models', object_name=experiment_id  +'/CustomerChurnOrdinalEncoder.pkl' , file_path='./CustomerChurnOrdinalEncoder.pkl')
minioClient.fput_object(bucket_name='models', object_name=experiment_id  +'/CustomerChurnOneHotEncoder.pkl' , file_path='./CustomerChurnOneHotEncoder.pkl')
```

Instructions to view your model binaries in S3 object storage.

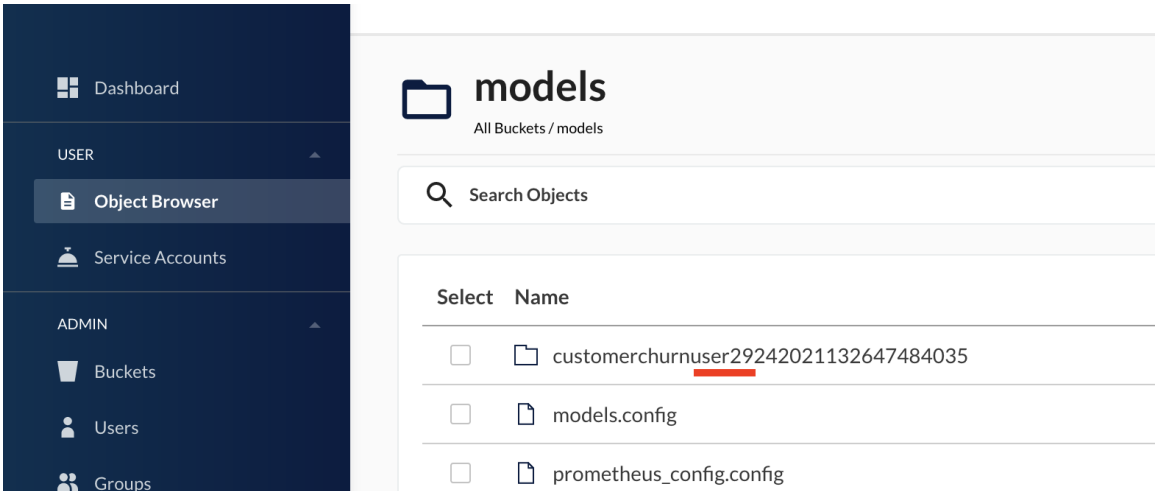
As just mentioned, we push our models to S3 object storage, implemented using the Minio tool. Though the same means could be used to push them to an enterprise storage solution, such as Ceph.

Open Minio, as described above in the section ***Instructions to access your prepared data file from the previous lab.***

Choose *Object Browser*, and open the *models* bucket:



Find the folder containing your username - this is mine for user29. Click into yours.



Note the binary artifacts that will be used to deploy your model to production in the next workshop ML OPs.

Also copy your experiment id, in my case *customerchurnuser29242021132647484035*. You need it in the ML OPs workshop.