DeepSphere.AI
Enterprise AI and IIoT for Analytics

A Machine Learning Laboratory Manual

Customer Churn

Use Case Implementation - GCP

A Machine Learning Laboratory Manual

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A Machine Learning Laboratory Manual

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1.1. Disclaimer

- We share this information for learning purposes only. We developed this material based on our prior experience, skills, knowledge, and expertise. Our perspective on the tools, technologies, systems, applications, processes, methodologies, and others used in these materials may differ from others. We advise the users to use these materials at their own risk.

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1.2. DeepSphere.AI and Google Cloud

- DeepSphere.AI (DS.AI) is a global leader in providing an advanced and higher educational platform for schools. DS.AI provides an intelligent learning management system (iLMS) to learn applied artificial intelligence, data science, and data engineering at a personalized level. DS.AI iLMS platform hosted on Amazon web services (AWS) and the learning resources developed on Google Cloud Platform(GCP) and SAP Litmos.

- To create social readiness and awareness about applied AI, DS.AI continues to develop learning resources to educate and empower schools, colleges, universities, organizations, and public entities. This article is part of a series of learning resources. There will be several articles in the future which will be published to master applied AI on Google Cloud. We use several GCP services to develop these learning resources, including storage services, compute services, network services; and other products and services.

- Our goal is to go beyond concepts, ideas, visions, and strategies to provide practical problem-solving applied AI skills, knowledge, and expertise that will result in on-the-job learning experience. To achieve our goals and objectives, we use GCP products and services, including BigQuery, AutoML, AutoML Tables, Dataproc, Dataflow, Data Studio, etc.

1.3. Executive Summary

- The purpose of this document is to provide adequate information to users to implement Customer Churn in Google Cloud Platform. In order to achieve this, we are using supervised machine learning models like Logistic Regression or XGBoost.

1.4. Problem Statement

- Companies or Organizations often face huge customer attrition or churn. When customers leave the company, they not only lose the revenue but also lose the resources spent to acquire these customers in the first place. This is a serious concern for the companies.

- In this Implementation we are trying to predict customers who are mostly likely to churn using machine learning modelling. This implementation helps the companies to know in advance the customers who are more likely to leave the business at some point in time. With this prediction, the companies can come up with retention strategies and policies.

1.5. Business Challenges

Companies need to build and deploy effective customer churn prediction models to succeed in today’s complex business scenarios. Acquiring new customers always costs heavily. Following are the challenges companies face when there is no customer prediction modelling in place

- No Sustainable and robust strategy for customer retention.
- No formula plan to reacquire the customers who have moved to other competitors.
- Issues in converting low revenue earning customers into highly profitable ones.
- Reducing customer defections and improving profits.
- Tracking customer satisfaction by product, segment and cost to serve.

All these business challenges are solved by the predictive churn models that aim at retaining customers and maximizing profits.

1.6. Model Selection

Model selection is the process of choosing between different machine learning approaches, e:g Decision Tree, Logistic Regression, etc, or choosing between different hyperparameters or sets of features for the same machine learning approach, e:g deciding between the polynomial degrees/complexities for linear regression.

The choice of the actual machine learning algorithm (e.g. SVM or logistic regression) is less important than one would think. There could be a "best" algorithm for any given problem, but often its performance is hardly better than other well-performing approaches for the same problem.

There may be certain qualities you might look for in a model:

- Interpretable - can we see or understand why the model is making the decisions it makes?
- Simple - easy to explain and understand
- Accurate
- Fast (to train and test)
- Scalable (it can be applied to a large dataset)

Our Problem here is a Supervised Classification Problem. The Problem is to predict customers who are more likely to churn. This type of problem can only be solved by the following models.

1. Logistic Regression.

2. XGBoost.

1.7. Feature Engineering

Feature engineering is the process of using domain knowledge of the data to create features that make machine learning algorithms work. If feature engineering is done correctly, it increases the predictive power of machine learning algorithms by creating features from raw data that help facilitate the machine learning process. Feature Engineering is an art.

Feature engineering is the most important art in machine learning which creates a huge difference between a good model and a bad model.

1.7.1. Advantages of Feature Engineering

- Good features provide you with the flexibility of choosing an algorithm; even if you choose a less complex model, you get good accuracy.
- If you choose good features, then even simple ML algorithms do well.
- Better features will lead you to better accuracy. You should spend more time on features engineering to generate the appropriate features for your dataset. If you derive the best and appropriate features, you have won most of the battle.

1.8. Data Management

- There are three types of data sets: Training, Test and Dev that are used at various stages of implementation. Training dataset is the largest of the three, while test data functions as a seal of approval and you don't need to use it till the end of the development.

1.8.1. What is a Training Data Set

- The training data set is the actual dataset used to train the model for performing various Machine Learning Operations (Regression, Classification, Clustering etc.). This is the actual data with which the models learn with various API and algorithms to train the machine to work automatically.

CustomerID	SUM(CustomerBuyingPattern.Average yearly purchase)	SUM(CustomerBuyingPattern.Last year purchase)	SUM(CustomerBuyingPattern.Quantity(in lots))	SUM(CustomerBuyingPattern.average Monthly wise purchase)
18928	317	32	71	30
18811	481	2	32	25
19651	437	34	55	39
18649	499	22	92	36
18056	329	3	90	32
...	...	...	...	...
19034	0	0	0	0
19732	0	0	0	0
18764	386	18	38	28
18836	1489	94	151	132
19654	0	0	0	0

Figure 1 - Training Data

The following section describes the data training data sets and its field level characteristics

- Customer
- Average Yearly Purchase
- Last Year Purchase
- Quantity
- Customer Lifetime in Years
- Price Amount
- Last Year Unit Price
- Product Average Unit Price
- Amount Spent in Lifetime
- Service Call
- Service Failure Rate

1.8.2. What is a Test Data Set

- Test data set helps you to validate that the training has happened efficiently in terms of either accuracy, or precision and so on. Such data is used in testing the models to analyze whether the model is responding and working appropriately.

CustomerID	SUM(CustomerBuyingPattern.Average yearly purchase)	SUM(CustomerBuyingPattern.Last year purchase)	SUM(CustomerBuyingPattern.Quantity(in lots))	SUM(CustomerBuyingPattern.average Monthly wise purchase)
19092	0	0	0	0
19787	1215	51	149	91
19440	1022	45	233	94
18746	1151	84	236	110
18821	318	7	65	32
...	...	...	...	...
19171	373	0	62	36
18939	462	11	64	39
18949	972	55	96	70
19653	863	33	114	79
19342	467	2	38	35

Figure 2 - Test Data

The following section describes the features that's used in the model.

- Customer
- Average Yearly Purchase
- Last Year Purchase
- Quantity
- Customer Lifetime in Years
- Price Amount
- Last Year Unit Price
- Product Average Unit Price
- Amount Spent in Lifetime
- Service Call
- Service Failure Rate

1.9. Learning Algorithm

- A Self Learning (not a human developed code) code, performs data analysis and extracts patterns (business characteristics) in data for business application development - A Modern approach to application/software development.

- Automatically understands and extracts data patterns when data changes (change in business circumstance) and performs data analysis based on the new/changed data set. No code change required to implement changes that took place in the data (change in business)

1.9.1. Machine Learning Libraries Used

- **Sklearn (Scikit Learn)**
- **Pandas**

1.9.2. Classification Models Used

- **Logistic Regression**
- **XGBoost**

1.10. Model Building Blocks

- There are several technical and functional components involved in implementing this model. Here are the key building blocks to implement this model.

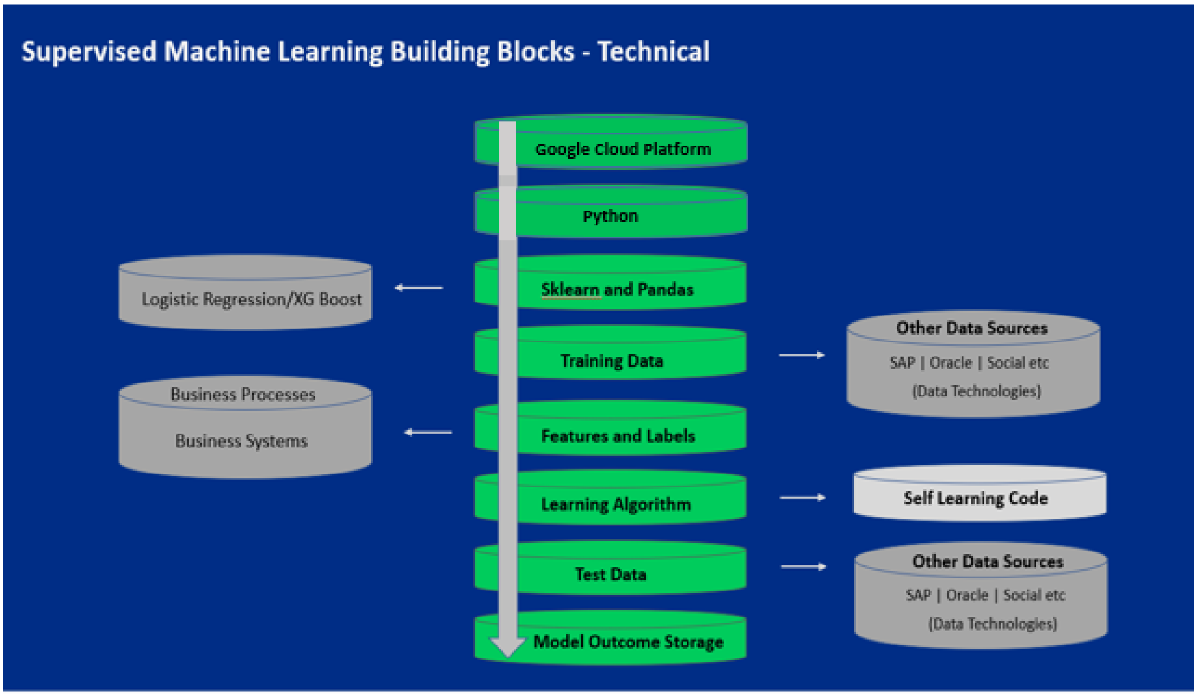


Figure 3 – Supervised Learning Building Blocks

1.11. Model Implementation High-level Steps

- A model implementation, to address a given problem involves several steps. Here are the key steps that are involved to implement a model. You can customize these steps as needed. We have developed these steps for learning purposes only.

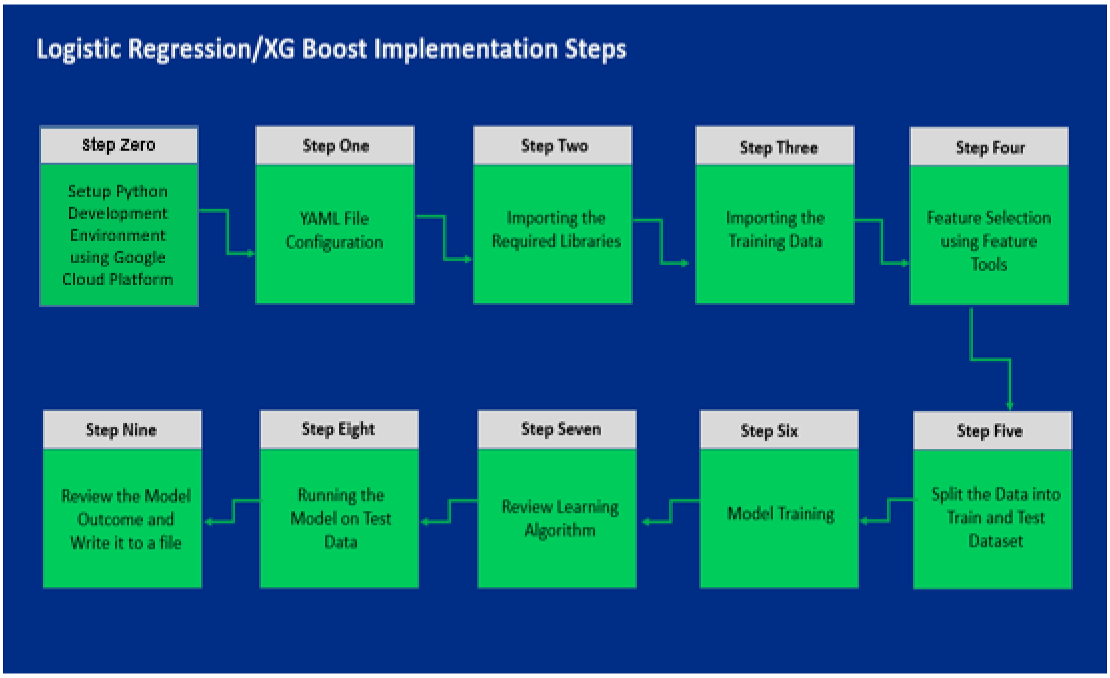


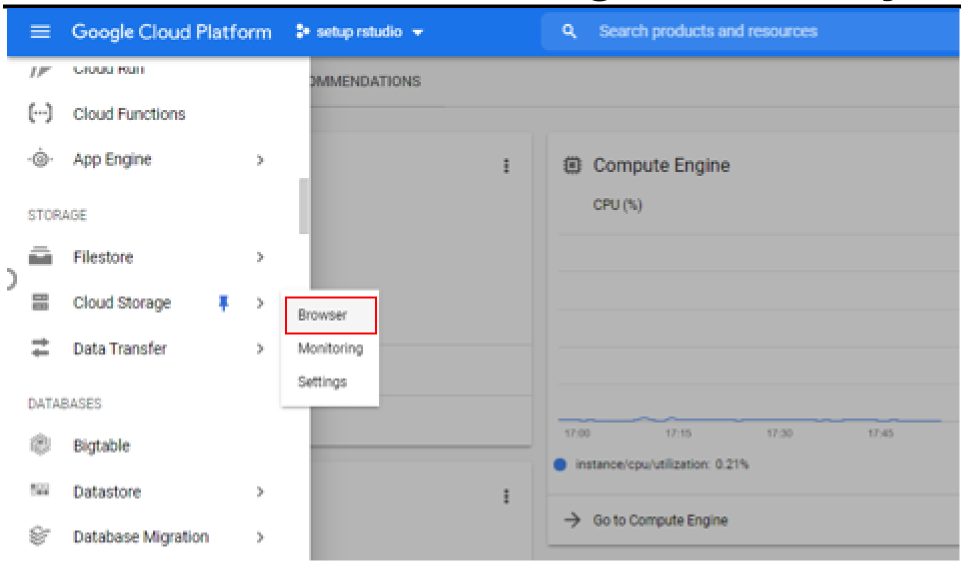
Figure 4 – Model Building Implementation Steps

1.12. Model Building Steps

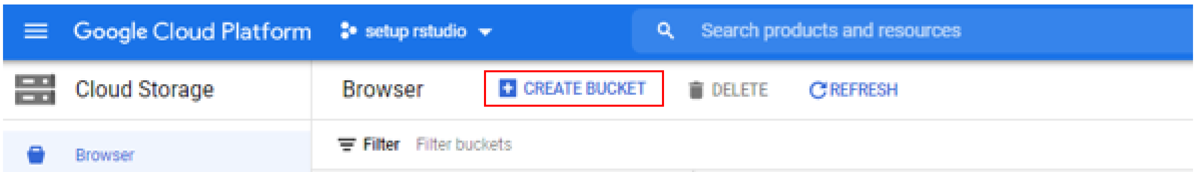
- As we are implementing this use case using Google Cloud Platform, let's see how to upload data and access it through Python.

1.12.1. Create a Google Storage Bucket

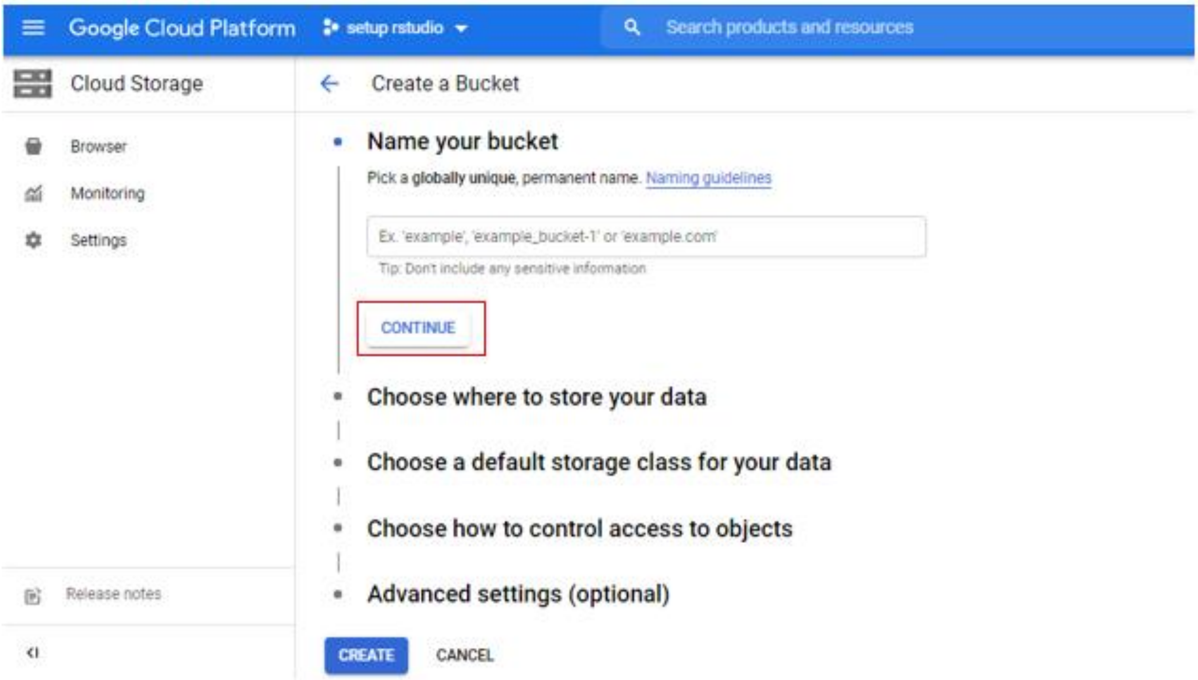
- First, we'll create a storage bucket using the below steps.
- Navigation Menu > Storage > Cloud Storage > Browser



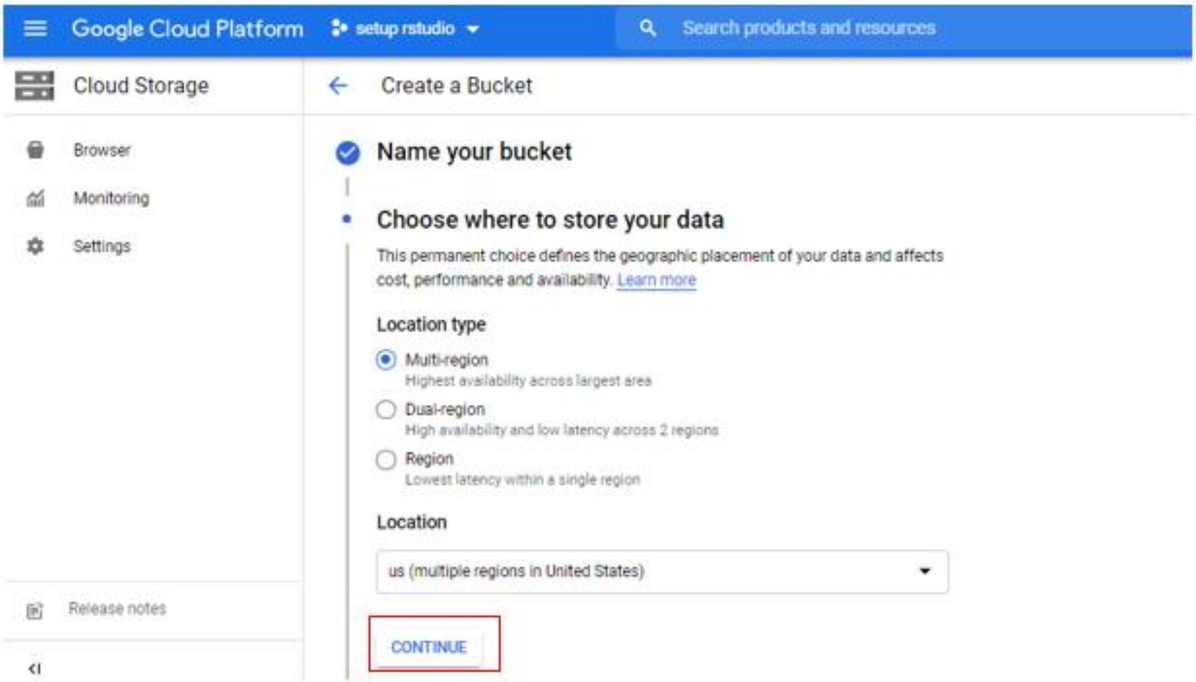
- Click on 'Create New Bucket' to open the bucket creation form.



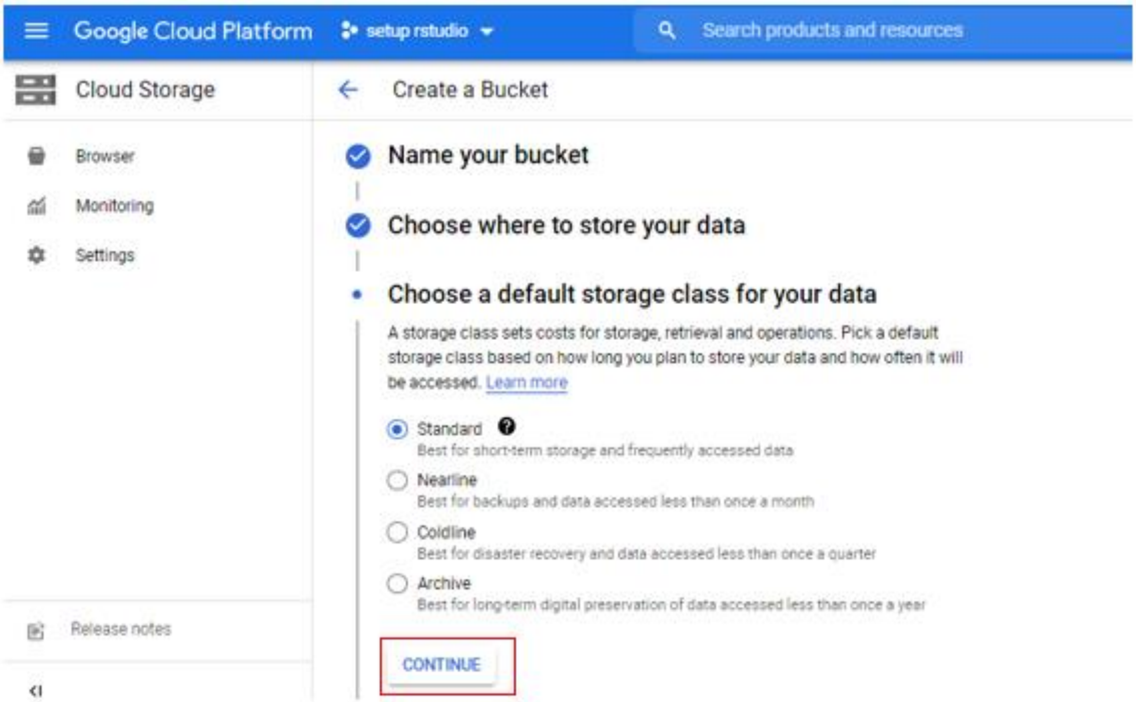
- Enter a unique Name for your bucket and click on Continue.



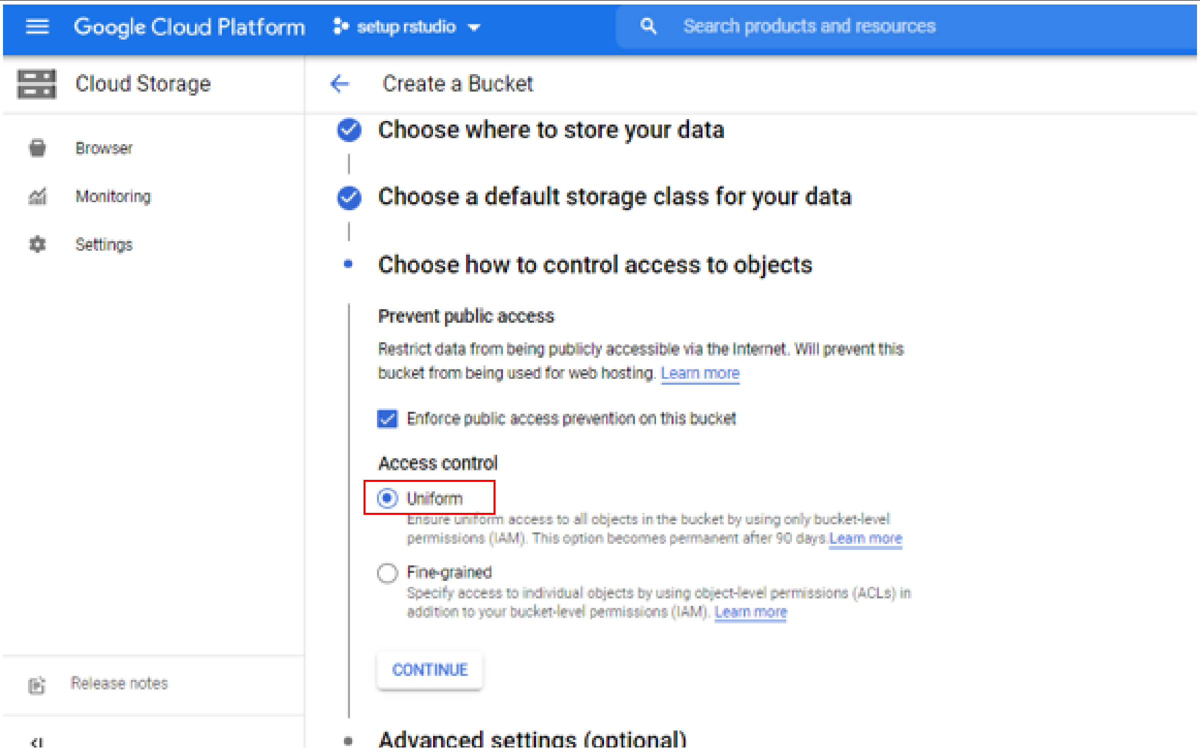
- Choose Region and location type, click on continue



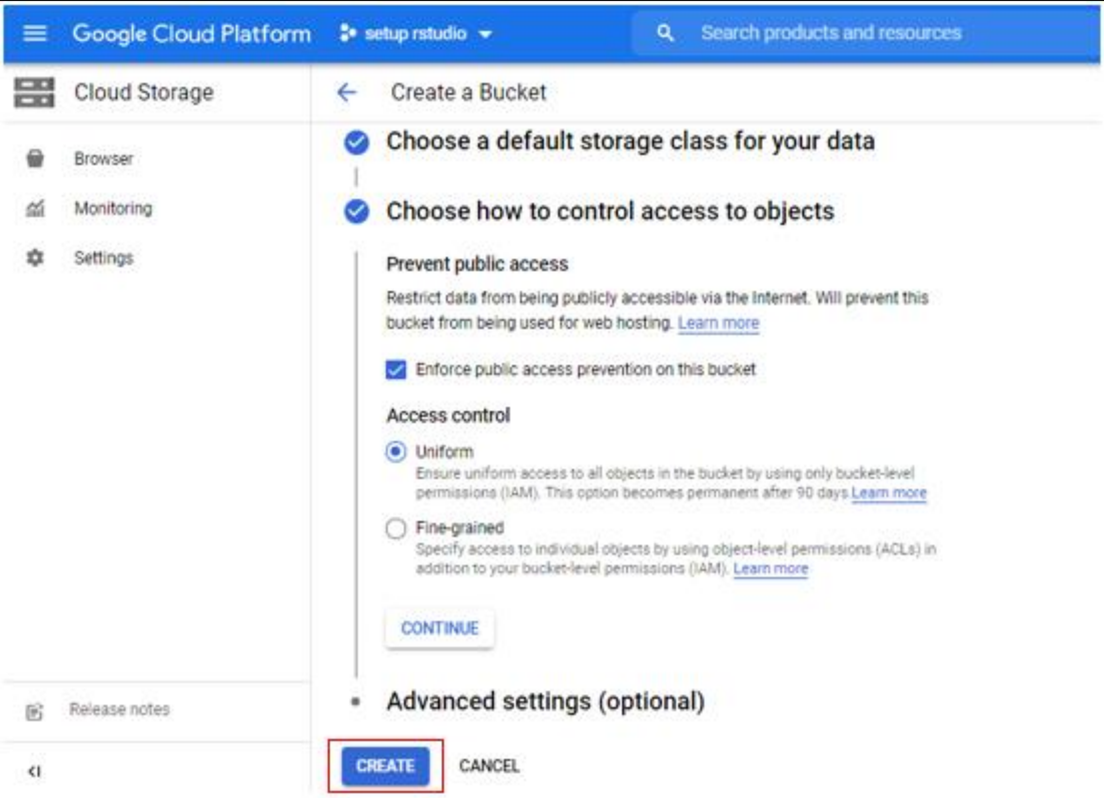
- Choose Standard for default storage class. and click on continue



- Choose Uniform for Access control, click on continue.

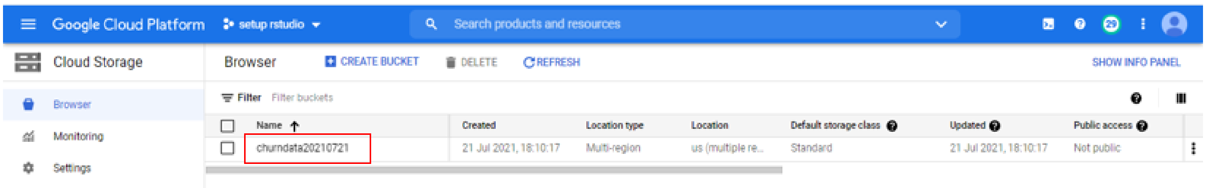


- Click on Create and your storage bucket will be created.

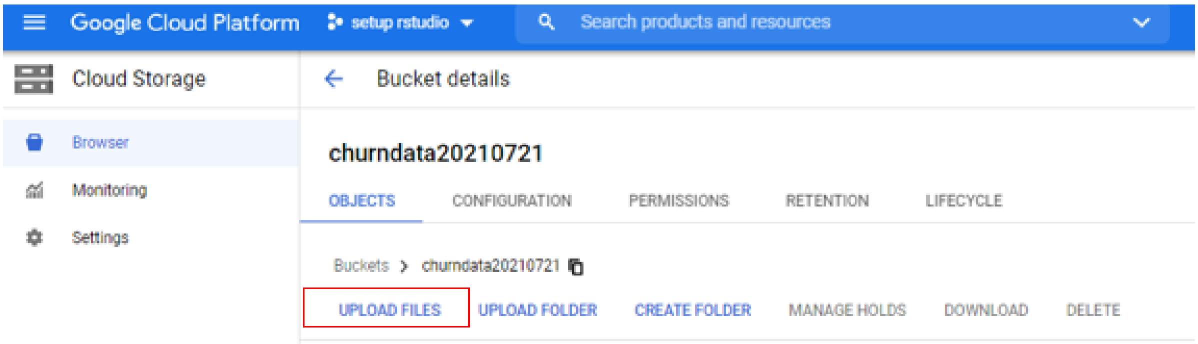


1.12.2. Moving Files into Google Storage Bucket

- Now, the storage bucket has been created. Click on the bucket name as shown below:

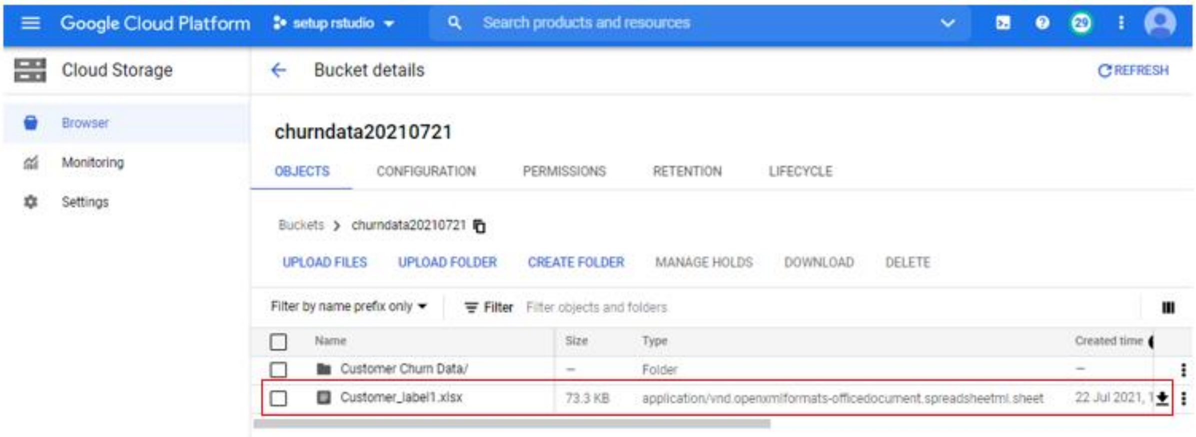


- To upload data/files into your bucket, click on 'Upload Files'



- **NOTE**: We can also upload a folder by clicking on 'Upload Folder'. In my case, I've uploaded a folder which contains all the required data to implement this use case.

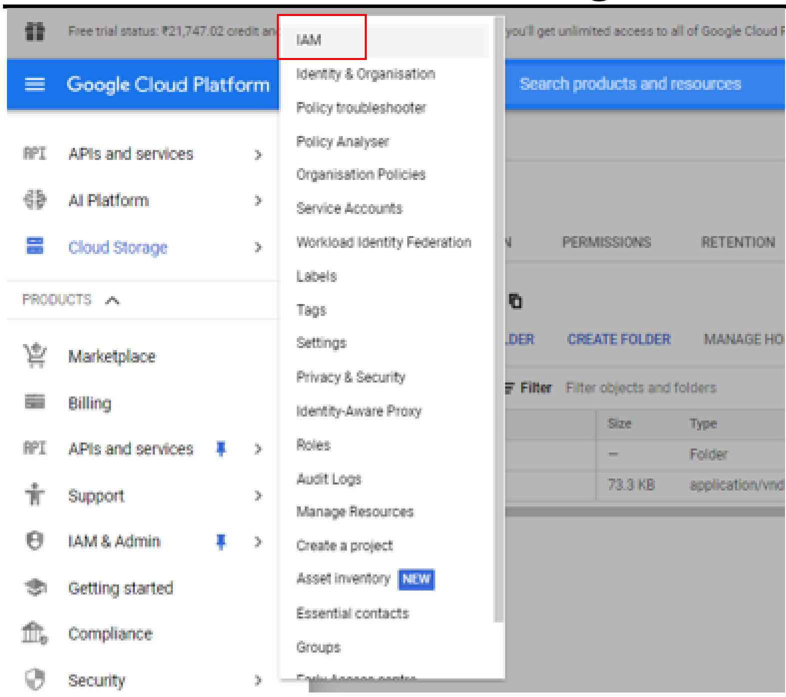
- In the file dialog, go to the files that you want to upload and select them. After the upload completes, you should see the file name and information about the file, such as its size and type.



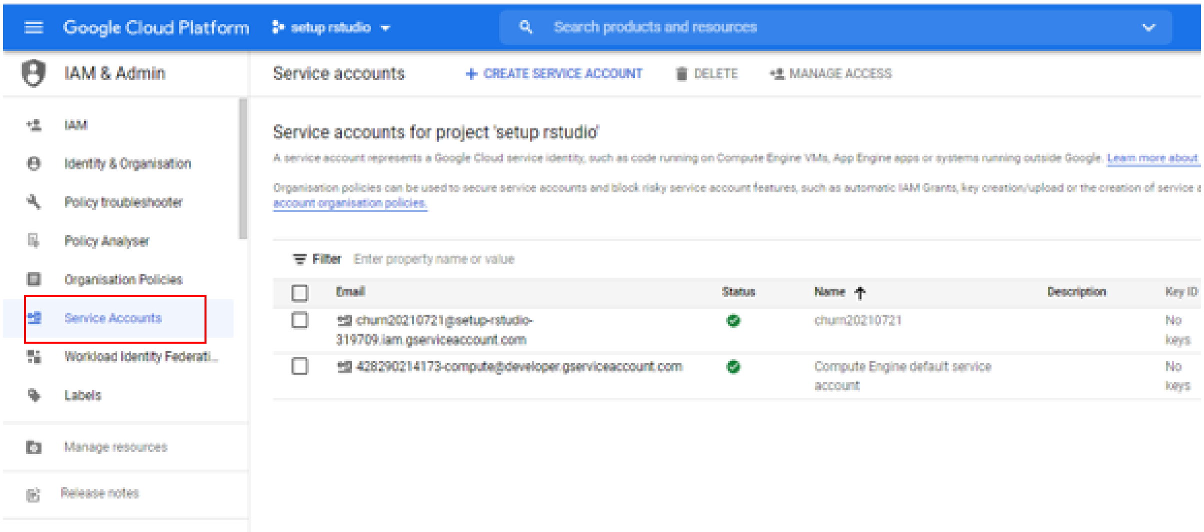
1.12.3. Create Service account and Private Key

- We'll first set up authentication by creating a service account and setting an environment variable.

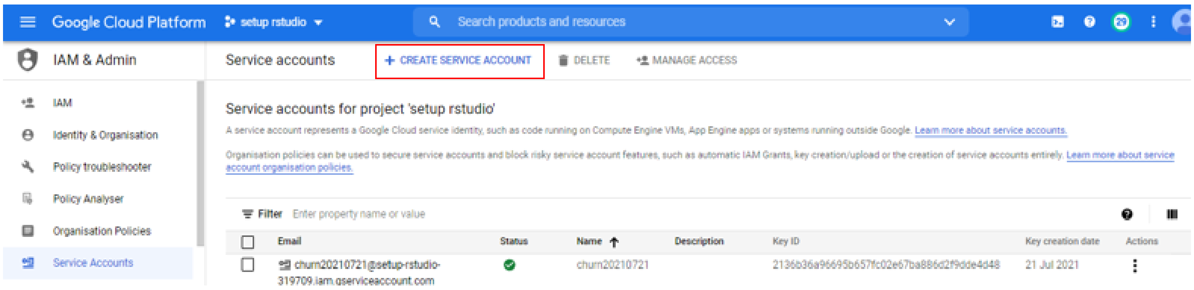
- Navigation menu > Products > IAM & Admin > IAM



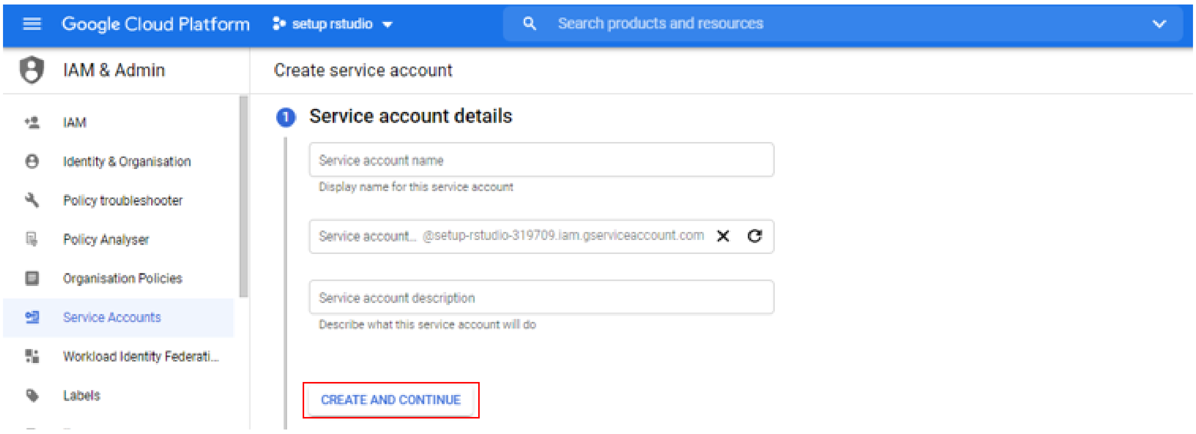
- Click on Service accounts



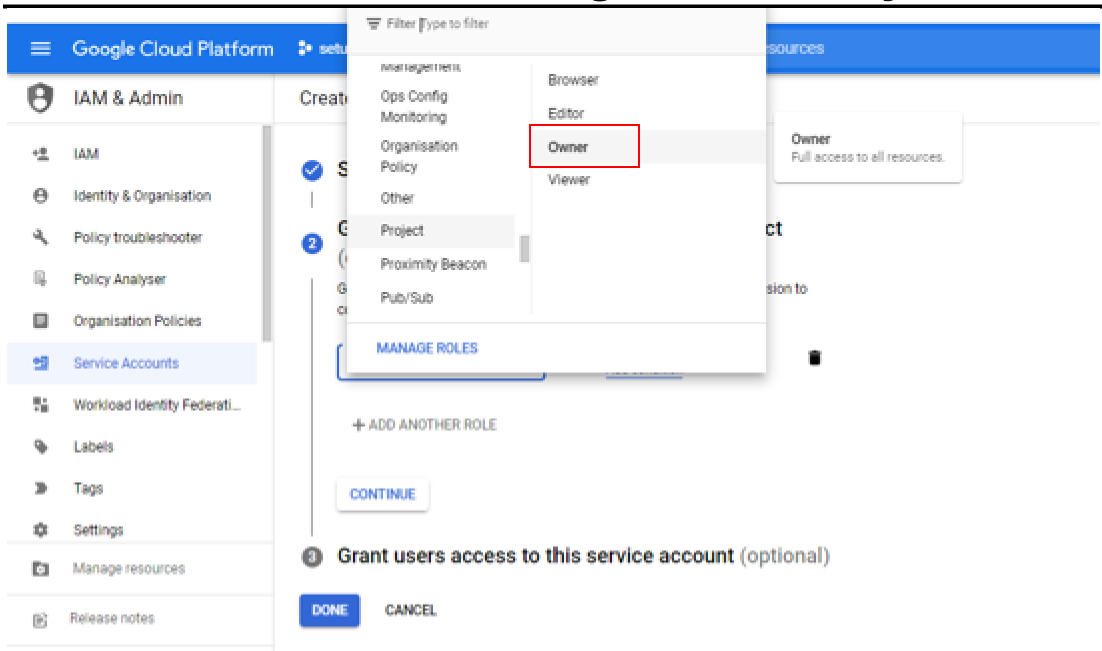
- Click on Create Service account



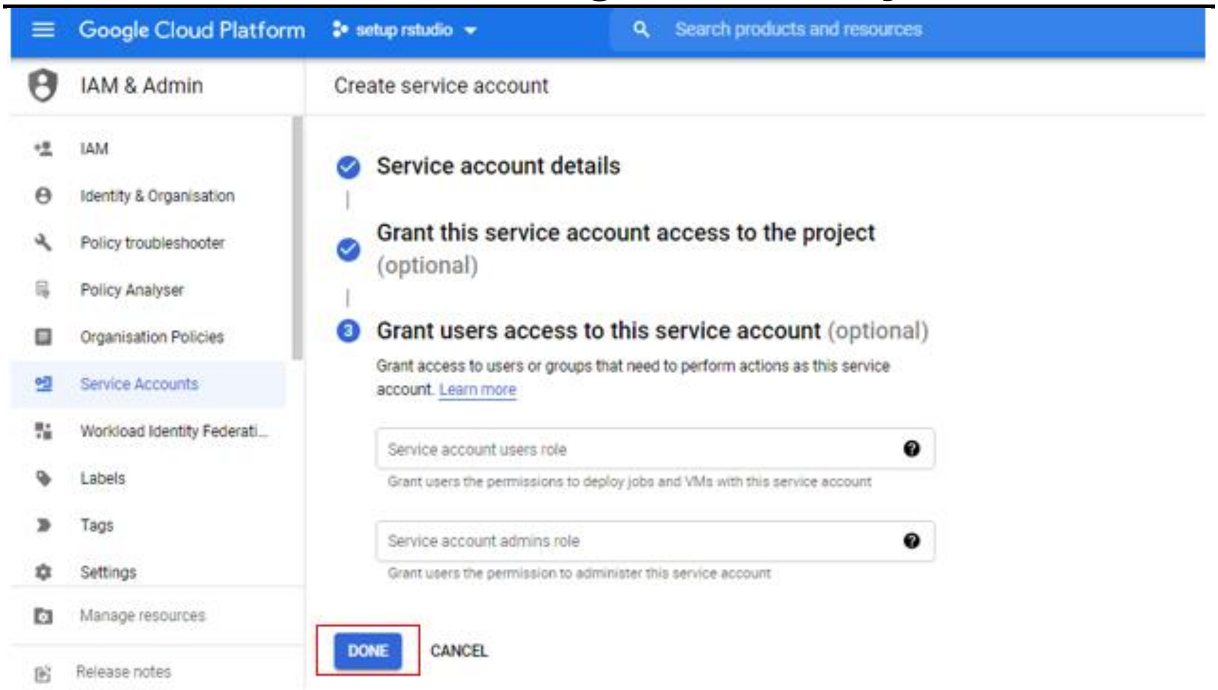
- Enter a name for the service account, click on Create and Continue



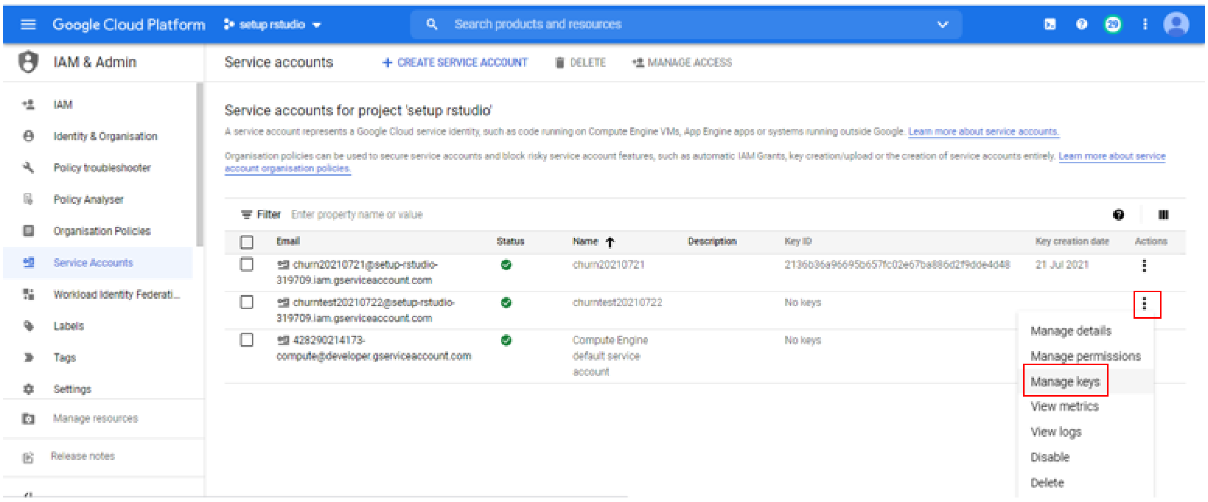
- Grant this service account access to your project so that it has permission to complete specific actions on the resources in your project.
- Under Project, select 'Owner' as your role. Click on continue.



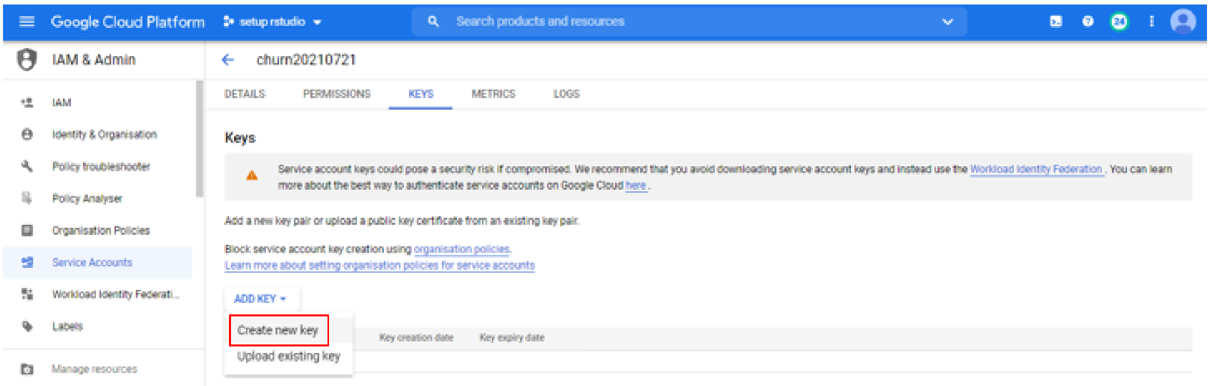
- Click on Done



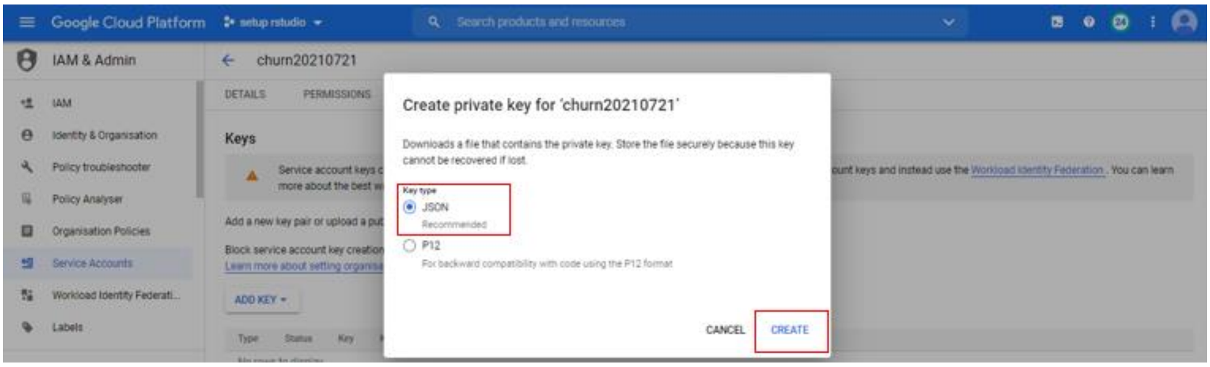
- Now, the service account has been created. Click on More Options (3 dots) and then Manage Keys as shown below:



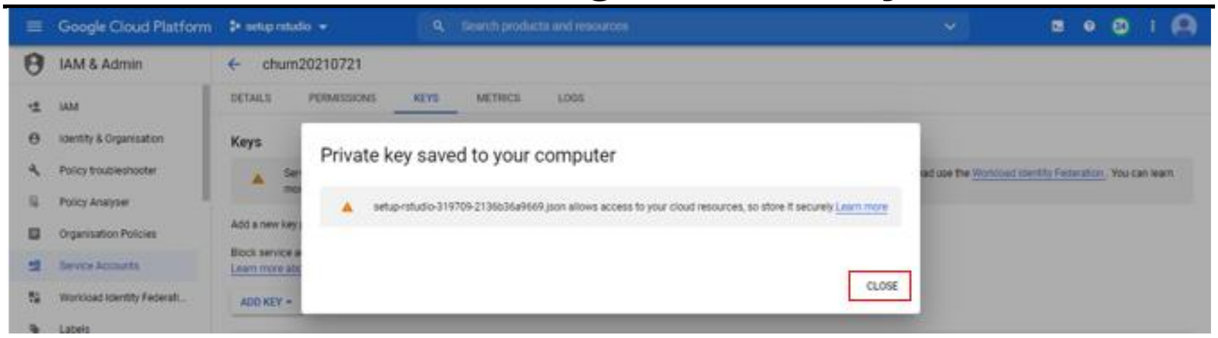
- Under Keys tab, click on Create New Key from the Add Key dropdown.



- Select the key type as JSON and click on Create



- Now, the key will be created and downloaded to your local system. You'll also get a pop up to indicate the key is saved to your computer as shown below.
- Click on Close

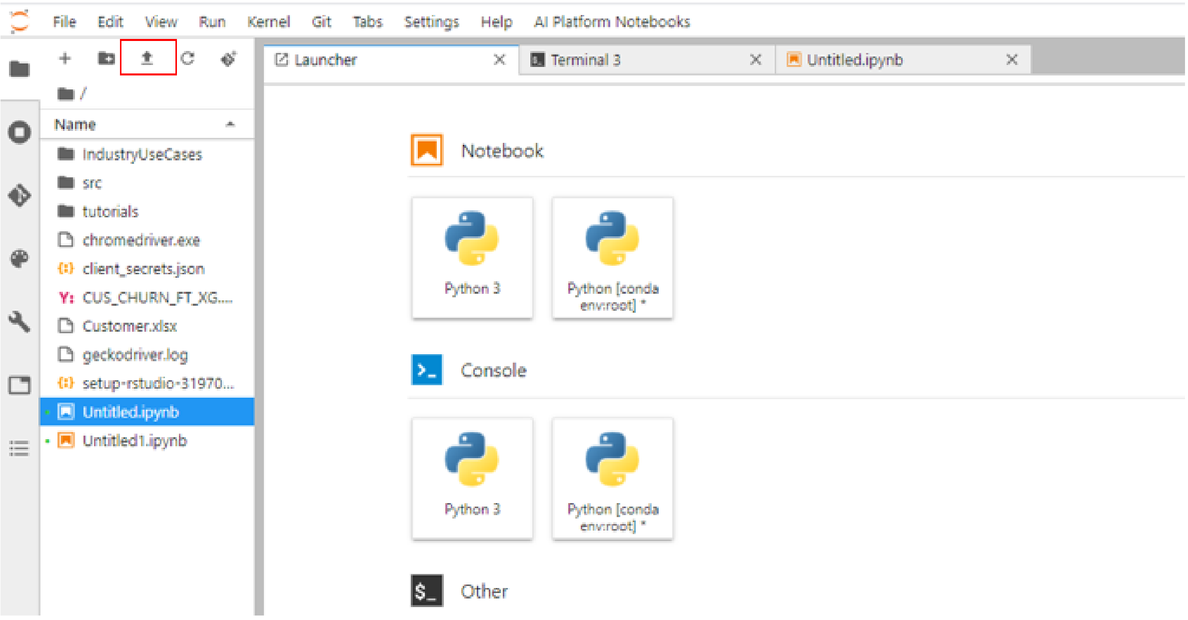


1.12.4. Access data from Google Storage Bucket using Python

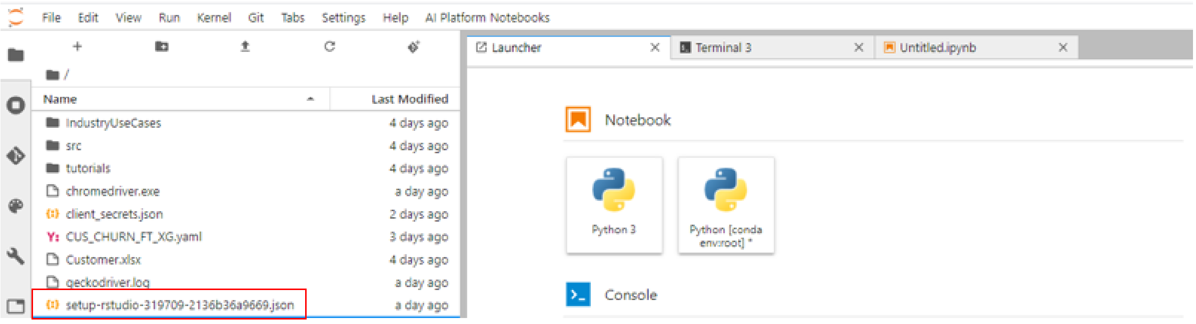
- Please follow the steps instructed [here]() to open the Jupyter Notebook using Notebook API.

- After you opened the notebook, you need to upload the downloaded key to the working environment by following the below steps:

- Click on the Upload icon:



- In the file dialog, go to the JSON file (key) you've downloaded and select it and it will be uploaded in the environment.



- You need to copy and paste the below data in the YAML file as shown below and import it in the working environment.

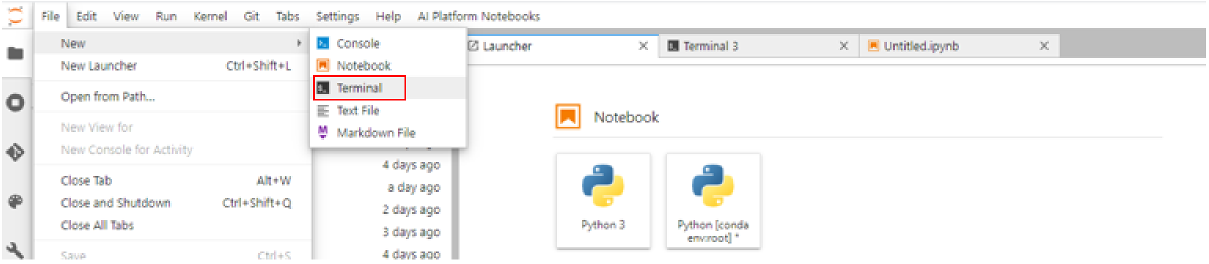
CUS_CHURN_FT_XG.yaml - Notepad

File Edit Format View Help

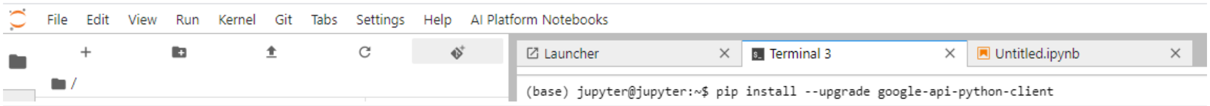
```
#  Date          : 04/05/2021
#  Version       : v1
#  (C)           : Deep Sphere, Inc.
#
##############################


##############################
[Data Source]
##############################
DATA_SOURCE1= FILE
DATA_SOURCE2= HDFS
DATA_SOURCE3= SAP
DATA_SOURCE4= ORACLE
DATA_SOURCE5= MS

##############################
[Data Source Connection String]
##############################

SAP_CONNECTION_STRING=""
HDFS_CONNECTION_STRING=""
ORACLE_CONNECTION_STRING=""
MS_CONNECTION_STRING=""

##############################
[FILE PATH]
##############################
```

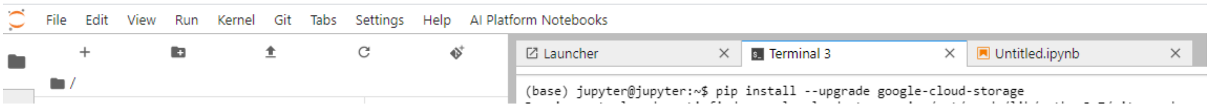
```
##############################
[FILE PATH]
##############################

TRAINING_DATA = /Customer Churn Data/Customer_label.xlsx

TRAINING_DATA_EXCEL_WORKSHEET = Customer_label

TRAINING_DATA(CUS) = /Customer Churn Data/Customer.xlsx'

TRAINING_DATA_EXCEL_WORKSHEET(CUS) = CUSTOMER

TRAINING_DATA(CBP) = /Customer Churn Data/customer_buying_pattern.xlsx'

TRAINING_DATA_EXCEL_WORKSHEET(CBP) = customer_buying_pattern

TRAINING_DATA(CPP) = /Customer Churn Data/Customer_Product_Price.xlsx'

TRAINING_DATA_EXCEL_WORKSHEET(CPP) = Customer_Product_Price

TRAINING_DATA(CSP) = /Customer Churn Data/Customer_Spending_Power.xlsx'

TRAINING_DATA_EXCEL_WORKSHEET(CSP) = Customer_Spending_Power

TRAINING_DATA(CSQ) = /Customer Churn Data/Customer_Service_Quality.xlsx'

TRAINING_DATA_EXCEL_WORKSHEET(CSQ) = Customer_Service_Quality

TRAINING_DATA(CS) = /Customer Churn Data/Customer_Satisfaction.xlsx'

TRAINING_DATA_EXCEL_WORKSHEET(CS) = Customer_Satisfaction

######################################################################
```

- Now, we'll see how to install the required libraries. Open the Terminal by following the below steps:
- Click on File > New > Terminal



- Run these codes in the terminal to install the libraries





- Import the required libraries

```
try:
    from google.cloud import storage
    import google.cloud.storage
    import json
    import os
    import sys
    import pandas as pd
    import io
    from io import BytesIO
except Exception as e:
    print("Error : {} ".format(e))
```

- Provide authentication credentials to your application code by setting the environment variable GOOGLE_APPLICATION_CREDENTIALS.

```
PATH = os.path.join(os.getcwd() , 'setup-rstudio-319709-2136b36a9669.json')
os.environ['GOOGLE_APPLICATION_CREDENTIALS'] = PATH
```

- Create a client object

```
storage_client = storage.Client(PATH)
storage_client
```

```
<google.cloud.storage.client.Client at 0x7f4aff19e810>
```

- Getting all files from the Google Storage Bucket which we created

```
bucket = storage_client.get_bucket('churndata20210721')
```

```
filename = [filename.name for filename in list(bucket.list_blobs(prefix='')) ]
filename
```

```
['Customer Churn Data/CUS_CHURN_FT_XG.yaml',
 'Customer Churn Data/Customer.xlsx',
 'Customer Churn Data/Customer_Product_Price.xlsx',
 'Customer Churn Data/Customer_Satisfaction.xlsx',
 'Customer Churn Data/Customer_Service_Quality.xlsx',
 'Customer Churn Data/Customer_Spending_Power.xlsx',
 'Customer Churn Data/Customer_label.xlsx',
 'Customer Churn Data/customer_buying_pattern.xlsx',
 'Customer_label1.xlsx']
```

- YAML file configuration

```
import configparser

import os

vAR_Config = configparser.ConfigParser(allow_no_value=True)

vAR_YAML_FILE_PATH = 'CUS_CHURN_FT_XG.yaml'

vAR_YAML_FILE_PATH

vAR_Config.read(vAR_YAML_FILE_PATH)

vAR_Data = vAR_Config.sections()

vAR_Config.sections()

vAR_Train_Data = vAR_Config['FILE PATH']['TRAINING_DATA']

vAR_Training_Data_Excel_Worsheet = vAR_Config['FILE PATH']['TRAINING_DATA_EXCEL_WORKSHEET']
print(vAR_Training_Data_Excel_Worsheet)

vAR_Train_Data_CUS = vAR_Config['FILE PATH']['TRAINING_DATA(CUS)']

vAR_Training_Data_Excel_Worsheet_CUS  = vAR_Config['FILE PATH']['TRAINING_DATA_EXCEL_WORKSHEET(CUS)']

print(vAR_Training_Data_Excel_Worsheet_CUS)

vAR_Training_Data_CBP = vAR_Config['FILE PATH']['TRAINING_DATA(CBP)']

vAR_Training_Data_Excel_Worsheet_CBP = vAR_Config['FILE PATH']['TRAINING_DATA_EXCEL_WORKSHEET(CBP)']
print(vAR_Training_Data_Excel_Worsheet_CBP)

vAR_Training_Data_CPP = vAR_Config['FILE PATH']['TRAINING_DATA(CPP)']

vAR_Training_Data_Excel_Worsheet_CPP = vAR_Config['FILE PATH']['TRAINING_DATA_EXCEL_WORKSHEET(CPP)']

print(vAR_Training_Data_Excel_Worsheet_CPP)

vAR_Training_Data_CSP = vAR_Config['FILE PATH']['TRAINING_DATA(CSP)']

vAR_Training_Data_Excel_Worsheet_CSP = vAR_Config['FILE PATH']['TRAINING_DATA_EXCEL_WORKSHEET(CSP)']

print(vAR_Training_Data_Excel_Worsheet_CSP)

vAR_Training_Data_CSQ = vAR_Config['FILE PATH']['TRAINING_DATA(CSQ)']

vAR_Training_Data_Excel_Worsheet_CSQ = vAR_Config['FILE PATH']['TRAINING_DATA_EXCEL_WORKSHEET(CSQ)']

print(vAR_Training_Data_Excel_Worsheet_CSQ)

vAR_Training_Data_CS = vAR_Config['FILE PATH']['TRAINING_DATA(CS)']

vAR_Training_Data_Excel_Worsheet_CS = vAR_Config['FILE PATH']['TRAINING_DATA_EXCEL_WORKSHEET(CS)']

print(vAR_Training_Data_Excel_Worsheet_CS)
```

- Import the Training data

```
import pandas as vAR_pd

import xgboost as vAR_xgb

from sklearn.model_selection import train_test_split

from sklearn.linear_model import LogisticRegression

from xgboost import XGBClassifier
import featuretools as ft
import warnings

warnings.filterwarnings('ignore')

Customer_Label = vAR_pd.read_excel(vAR_Train_Data)

Customer = vAR_pd.read_excel(vAR_Train_Data_CUS)

Customer_Buying_Pattern = vAR_pd.read_excel(vAR_Training_Data_CBP)

Customer_Product_Price = vAR_pd.read_excel(vAR_Training_Data_CPP)

Customer_Spending_Power = vAR_pd.read_excel(vAR_Training_Data_CSP)

Customer_Service_Quality = vAR_pd.read_excel(vAR_Training_Data_CSQ)

Customer_Satisfaction = vAR_pd.read_excel(vAR_Training_Data_CS)
```

- Checking for Missing values

```
print(Customer_Label.isnull().sum())

print(Customer.isnull().sum())

print(Customer_Buying_Pattern.isnull().sum())

print(Customer_Product_Price.isnull().sum())

print(Customer_Spending_Power.isnull().sum())

print(Customer_Service_Quality.isnull().sum())

print(Customer_Satisfaction.isnull().sum())
```

```
CustomerID          0
Customer Code       0
CustomerRegion      0
CustomerLocation    0
CustomerChurn       1
dtype: int64
CustomerID          0
Customer Code       0
CustomerRegion      0
CustomerLocation    0
dtype: int64
CustomerID                      0
```

- Handling Missing values

```
#Removing null values
Customer_Label.dropna(inplace=True)

#Re-Checking for null values
print(Customer_Label.isnull().sum())
```

```
CustomerID          0
Customer Code       0
CustomerRegion      0
CustomerLocation    0
CustomerChurn       0
dtype: int64
```

- Feature Selection using Feature tools

```
#DEFINING THE ENTITIES

es = ft.EntitySet(id="CUSTOMER_CHURN")

es1 = es.entity_from_dataframe(entity_id = 'Customer', dataframe = Customer, index='CustomerID')

es2 = es.entity_from_dataframe(entity_id = 'CustomerBuyingPattern', dataframe = Customer_Buying_Pattern, index='CBPID')

es3 = es.entity_from_dataframe(entity_id = 'CustomerProductPurchase', dataframe = Customer_Product_Price, index='CPPID')

es4 = es.entity_from_dataframe(entity_id = 'CustomerSpendingPower', dataframe = Customer_Spending_Power, index = 'CSPID')

es5 = es.entity_from_dataframe(entity_id = 'CustomerServiceQuality', dataframe = Customer_Service_Quality, index = 'CSQID')

es6 = es.entity_from_dataframe(entity_id = 'CustomerSatisfaction', dataframe = Customer_Satisfaction, index = 'CSID')

print(es)

#DEFINING THE RELATIONSHIPS

es.add_relationship(ft.Relationship(es['Customer']['CustomerID'],es['CustomerBuyingPattern']['CustomerID']))

es.add_relationship(ft.Relationship(es['Customer']['CustomerID'],es['CustomerProductPurchase']['CustomerID']))

es.add_relationship(ft.Relationship(es['Customer']['CustomerID'],es['CustomerSpendingPower']['CustomerID']))

es.add_relationship(ft.Relationship(es['Customer']['CustomerID'],es['CustomerServiceQuality']['CustomerID']))

es.add_relationship(ft.Relationship(es['Customer']['CustomerID'],es['CustomerSatisfaction']['CustomerID']))

#APPLYING DEEP SYNTHESIS
```

```
#APPLYING DEEP SYNTHESIS

feature_matrix_Customer, feature_defs = ft.dfs(entityset=es, target_entity="Customer", agg_primitives=["SUM"], max_depth=2)

feature_matrix_Customer


print(feature_matrix_Customer.shape)

#Removing Unwanted columns
vAR_Featuresft = feature_matrix_Customer.iloc[:,4:]
print(vAR_Featuresft.shape)
```

```
Entityset: CUSTOMER_CHURN
  Entities:
    Customer [Rows: 2103, Columns: 4]
    CustomerBuyingPattern [Rows: 2103, Columns: 8]
    CustomerProductPurchase [Rows: 2103, Columns: 6]
    CustomerSpendingPower [Rows: 2103, Columns: 6]
    CustomerServiceQuality [Rows: 2103, Columns: 6]
    CustomerSatisfaction [Rows: 2103, Columns: 6]
  Relationships:
    No relationships
(2103, 19)
(2103, 15)
```

- Defining the label

```
vAR_label = Customer_Label.iloc[:,4:]
vAR_label
```

	CustomerChurn
0	1.0
1	1.0
2	0.0
3	0.0
4	1.0

- Split the Data into train and Test

```
vAR_X_TRAIN, vAR_X_TEST, vAR_Y_TRAIN, vAR_Y_TEST = train_test_split(vAR_Featuresft, vAR_label, test_size=0.20, random_state=0)

vAR_X_TRAIN
```

	SUM(CustomerBuyingPattern.Last year purchase)	SUM(CustomerBuyingPattern.Quantity(in lots))	SUM(CustomerBuyingPattern.average Monthly wise purchase)	SUM(CustomerBuyingPattern.c lifetime
CustomerID				
18929.0	57.0	120.0	74.0	
18811.0	2.0	32.0	25.0	
19652.0	0.0	0.0	0.0	
18649.0	22.0	92.0	36.0	
18056.0	3.0	90.0	32.0	
...	...	...	...	
19035.0	29.0	100.0	24.0	
19733.0	0.0	0.0	0.0	

- Training the model

```
#Training the logistic regression model
vAR_Model1 = LogisticRegression()
vAR_Model1.fit(vAR_X_TRAIN,vAR_Y_TRAIN)

#Training the XGBoost model
vAR_Model2 = XGBClassifier(eta=0.01,gamma=10)
vAR_Model2.fit(vAR_X_TRAIN,vAR_Y_TRAIN)
```

```
[15:14:53] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'bina
ry:logistic' was changed from 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, eta=0.01, gamma=10,
              gpu_id=-1, importance_type='gain', interaction_constraints='',
              learning_rate=0.00999999978, max_delta_step=0, max_depth=6,
              min_child_weight=1, missing=nan, monotone_constraints='()',
              n_estimators=100, n_jobs=1, num_parallel_tree=1, random_state=0,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=1, subsample=1,
              tree_method='exact', validate_parameters=1, verbosity=None)
```

- Review the Learning Algorithm

```
vAR_Model2.predict(vAR_X_TRAIN)
```

```
array([0., 0., 0., ..., 0., 0., 0.])
```

- Running the model on test data

```
#Prediction using Logistic regression
vAR_Labels_predLG = vAR_Model1.predict(vAR_X_TEST)

#Prediction using XGBoost
vAR_Labels_predXG = vAR_Model2.predict(vAR_X_TEST)
```

- Checking Accuracy of the Model Output

```
# Checking accuracy for Logistic Regression
from sklearn.metrics import accuracy_score
print(accuracy_score(vAR_Y_TEST, vAR_Labels_predLG))

# Checking accuracy for XGBoost
from sklearn.metrics import accuracy_score
accuracy_score(vAR_Y_TEST, vAR_Labels_predXG)
```

```
0.5534441805225653
0.5653206650831354
```

1.12.5. Model Building Code Block

- We need to implement these code blocks after completing the below steps (which are explained from 1.12.1 section)
  1. Creating Google Storage Bucket using Console ,
  2. Uploading Datasets to Google Storage Bucket using Console,
  3. Create and Importing the JSON key file into the working environment,
  4. Importing the YAML configuration file into the working environment.

```
# Install the required libraries by running these commands in the terminal

pip install --upgrade google-api-python-client

pip install --upgrade google-cloud-storage


# Import the required libraries

try:
```

```
    from google.cloud import storage
    import google.cloud.storage
    import json
    import os
    import sys
    import pandas as pd
    import io
    from io import BytesIO
except Exception as e:
    print("Error : {} ".format(e))
```

Provide authentication credentials to your application code by setting the environment variable GOOGLE_APPLICATION_CREDENTIALS.

```
PATH = os.path.join(os.getcwd() , 'setup-rstudio-319709-2136b36a9669.json')
os.environ['GOOGLE_APPLICATION_CREDENTIALS'] = PATH
```

Create a client object

```
storage_client = storage.Client(PATH)
storage_client
```

Getting all files from the Google Storage Bucket which we created

```
bucket = storage_client.get_bucket('churndata20210721')

filename = [filename.name for filename in list(bucket.list_blobs(prefix='')) ]
filename
```

YAML file configuration

```
import configparser

import os

vAR_Config = configparser.ConfigParser(allow_no_value=True)

vAR_YAML_FILE_PATH = 'CUS_CHURN_FT_XG.yaml'
```

```
vAR_YAML_FILE_PATH

vAR_Config.read(vAR_YAML_FILE_PATH)

vAR_Data = vAR_Config.sections()

vAR_Config.sections()

vAR_Train_Data = vAR_Config['FILE PATH']['TRAINING_DATA']

vAR_Training_Data_Excel_Worsheet = vAR_Config['FILE PATH']['TRAINING_DATA_EXCEL_WORKSHEET']
print(vAR_Training_Data_Excel_Worsheet)

vAR_Train_Data_CUS = vAR_Config['FILE PATH']['TRAINING_DATA(CUS)']

vAR_Training_Data_Excel_Worsheet_CUS  = vAR_Config['FILE PATH']['TRAINING_DATA_EXCEL_WORKSHEET(CUS)']

print(vAR_Training_Data_Excel_Worsheet_CUS)

vAR_Training_Data_CBP = vAR_Config['FILE PATH']['TRAINING_DATA(CBP)']

vAR_Training_Data_Excel_Worsheet_CBP = vAR_Config['FILE PATH']['TRAINING_DATA_EXCEL_WORKSHEET(CBP)']

print(vAR_Training_Data_Excel_Worsheet_CBP)

vAR_Training_Data_CPP = vAR_Config['FILE PATH']['TRAINING_DATA(CPP)']

vAR_Training_Data_Excel_Worsheet_CPP = vAR_Config['FILE PATH']['TRAINING_DATA_EXCEL_WORKSHEET(CPP)']

print(vAR_Training_Data_Excel_Worsheet_CPP)

vAR_Training_Data_CSP = vAR_Config['FILE PATH']['TRAINING_DATA(CSP)']

vAR_Training_Data_Excel_Worsheet_CSP = vAR_Config['FILE PATH']['TRAINING_DATA_EXCEL_WORKSHEET(CSP)']
```

```
print(vAR_Training_Data_Excel_Worsheet_CSP)

vAR_Training_Data_CSQ = vAR_Config['FILE PATH']['TRAINING_DATA(CSQ)']

vAR_Training_Data_Excel_Worsheet_CSQ = vAR_Config['FILE
PATH']['TRAINING_DATA_EXCEL_WORKSHEET(CSQ)']

print(vAR_Training_Data_Excel_Worsheet_CSQ)

vAR_Training_Data_CS = vAR_Config['FILE PATH']['TRAINING_DATA(CS)']

vAR_Training_Data_Excel_Worsheet_CS = vAR_Config['FILE
PATH']['TRAINING_DATA_EXCEL_WORKSHEET(CS)']

print(vAR_Training_Data_Excel_Worsheet_CS)
```

Data to be updated in the YAML File (Copy and Paste it in your YAML file)

```
#  Date       : 23/07/2021
#  Version    : v1
#  (C)        : Deep Sphere, Inc.
#
###############################

###############################
[Data Source]
###############################
DATA_SOURCE1= FILE
DATA_SOURCE2= HDFS
DATA_SOURCE3= SAP
DATA_SOURCE4= ORACLE
DATA_SOURCE5= MS

###############################
[Data Source Connection String]
###############################

SAP_CONNECTION_STRING=""
HDFS_CONNECTION_STRING=""
ORACLE_CONNECTION_STRING=""
```

```
MS_CONNECTION_STRING=""

##############################
[FILE PATH]
##############################

TRAINING_DATA = /Customer Churn Data/Customer_label.xlsx

TRAINING_DATA_EXCEL_WORKSHEET = Customer_label

TRAINING_DATA(CUS) = /Customer Churn Data/Customer.xlsx'

TRAINING_DATA_EXCEL_WORKSHEET(CUS) = CUSTOMER

TRAINING_DATA(CBP) = /Customer Churn Data/customer_buying_pattern.xlsx'

TRAINING_DATA_EXCEL_WORKSHEET(CBP) = customer_buying_pattern

TRAINING_DATA(CPP) = /Customer Churn Data/Customer_Product_Price.xlsx'

TRAINING_DATA_EXCEL_WORKSHEET(CPP) = Customer_Product_Price

TRAINING_DATA(CSP) = /Customer Churn Data/Customer_Spending_Power.xlsx'

TRAINING_DATA_EXCEL_WORKSHEET(CSP) = Customer_Spending_Power

TRAINING_DATA(CSQ) = /Customer Churn Data/Customer_Service_Quality.xlsx'

TRAINING_DATA_EXCEL_WORKSHEET(CSQ) = Customer_Service_Quality

TRAINING_DATA(CS) = /Customer Churn Data/Customer_Satisfaction.xlsx'

TRAINING_DATA_EXCEL_WORKSHEET(CS) = Customer_Satisfaction

######################################################################
```

```
# Import the Training data

import pandas as vAR_pd
```

```
import xgboost as vAR_xgb

from sklearn.model_selection import train_test_split

from sklearn.linear_model import LogisticRegression

from xgboost import XGBClassifier
import featuretools as ft
import warnings

warnings.filterwarnings('ignore')

Customer_Label = vAR_pd.read_excel(vAR_Train_Data)

Customer = vAR_pd.read_excel(vAR_Train_Data_CUS)

Customer_Buying_Pattern = vAR_pd.read_excel(vAR_Training_Data_CBP)

Customer_Product_Price = vAR_pd.read_excel(vAR_Training_Data_CPP)

Customer_Spending_Power = vAR_pd.read_excel(vAR_Training_Data_CSP)

Customer_Service_Quality = vAR_pd.read_excel(vAR_Training_Data_CSQ)

Customer_Satisfaction = vAR_pd.read_excel(vAR_Training_Data_CS)


# Checking for Missing values

print(Customer_Label.isnull().sum())

print(Customer.isnull().sum())

print(Customer_Buying_Pattern.isnull().sum())

print(Customer_Product_Price.isnull().sum())

print(Customer_Spending_Power.isnull().sum())

print(Customer_Service_Quality.isnull().sum())
```

```
print(Customer_Satisfaction.isnull().sum())
```

Handling Missing values

```
#Removing null values
Customer_Label.dropna(inplace=True)

#Re-Checking for null values
print(Customer_Label.isnull().sum())
```

Feature Selection using Feature tools

```
#DEFINING THE ENTITIES

es = ft.EntitySet(id="CUSTOMER_CHURN")

es1 = es.entity_from_dataframe(entity_id = 'Customer', dataframe = Customer,
index='CustomerID')

es2 = es.entity_from_dataframe(entity_id = 'CustomerBuyingPattern', dataframe =
Customer_Buying_Pattern, index='CBPID')

es3 = es.entity_from_dataframe(entity_id = 'CustomerProductPurchase', dataframe =
Customer_Product_Price, index='CPPID')

es4 = es.entity_from_dataframe(entity_id = 'CustomerSpendingPower', dataframe =
Customer_Spending_Power, index = 'CSPID')

es5 = es.entity_from_dataframe(entity_id = 'CustomerServiceQuality', dataframe =
Customer_Service_Quality, index = 'CSQID')

es6 = es.entity_from_dataframe(entity_id = 'CustomerSatisfaction', dataframe =
Customer_Satisfaction, index = 'CSID')

print(es)

#DEFINING THE RELATIONSHIPS
```

es.add_relationship(ft.Relationship(es['Customer']['CustomerID'],es['CustomerBuyingPattern']['CustomerID']))

es.add_relationship(ft.Relationship(es['Customer']['CustomerID'],es['CustomerProductPurchase']['CustomerID']))

es.add_relationship(ft.Relationship(es['Customer']['CustomerID'],es['CustomerSpendingPower']['CustomerID']))

es.add_relationship(ft.Relationship(es['Customer']['CustomerID'],es['CustomerServiceQuality']['CustomerID']))

es.add_relationship(ft.Relationship(es['Customer']['CustomerID'],es['CustomerSatisfaction']['CustomerID']))

#APPLYING DEEP SYNTHESIS

feature_matrix_Customer, feature_defs = ft.dfs(entityset=es, target_entity="Customer", agg_primitives=["SUM"], max_depth=2)

feature_matrix_Customer

print(feature_matrix_Customer.shape)

#Removing Unwanted columns
vAR_Featuresft = feature_matrix_Customer.iloc[:,4:]
print(vAR_Featuresft.shape)

Defining the label

vAR_label = Customer_Label.iloc[:,4:]
vAR_label

Split the Data into train and Test

```
vAR_X_TRAIN, vAR_X_TEST, vAR_Y_TRAIN, vAR_Y_TEST = train_test_split(vAR_Featuresft, vAR_label, test_size=0.20, random_state=0)

vAR_X_TRAIN
```

Training the model

```
#Training the logistic regression model
vAR_Model1 = LogisticRegression()
print(vAR_Model1.fit(vAR_X_TRAIN,vAR_Y_TRAIN))

#Training the XGBoost model
vAR_Model2 = XGBClassifier(eta=0.01,gamma=10)
vAR_Model2.fit(vAR_X_TRAIN,vAR_Y_TRAIN)
```

Review the Learning Algorithm

```
vAR_Model2.predict(vAR_X_TRAIN)
```

Running the model on test data

```
#Prediction using Logistic regression
vAR_Labels_predLG = vAR_Model1.predict(vAR_X_TEST)

#Prediction using XGBoost
vAR_Labels_predXG = vAR_Model2.predict(vAR_X_TEST)
```

Checking Accuracy of the Model Output

```
# Checking accuracy for Logistic Regression
from sklearn.metrics import accuracy_score
print(accuracy_score(vAR_Y_TEST, vAR_Labels_predLG))

# Checking accuracy for XGBoost
from sklearn.metrics import accuracy_score
accuracy_score(vAR_Y_TEST, vAR_Labels_predXG)
```