PROJECT REPORT

TELECOM CUSTOMER CHURN PREDICTION POWERED BY AWS SAGEMAKER

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PROJECT: Telecom Customer Churn Prediction Powered By Aws Sagemaker

PROJECT DOMAIN: Machine Learning

CONTENTS:

1.INTRODUCTION

1.1 ABSTRACT:

At recent years, estimating the churners before they leave has gained importance in environment of increased competition in company strategy. churners are tried to detect by using Machine Learning techniques. Attribute reductions are tried for decreasing the runtime and increasing achievement of models and performance was measured by using different classification method. In addition, outlier analysis is applied to dataset and then effects on classification results are examined. This classification methods are tested in two datasets which are taken from Telecommunication Companies. Recall and Precision Rates are used as performance criteria.

1.2 OVERVIEW

The telecommunications sector has become one of the main industries in developed countries. The technical progress and the increasing number of operators raised the level of competition. Companies are working hard to survive in this competitive market depending on multiple strategies.Customers' churn is a considerable concern in service sectors with high competitive services. On the other hand, predicting the customers who are likely to leave the company will represent potentially large additional revenue source if it is done in the early phase .Many research confirmed that machine learning technology is highly efficient to predict this situation. This technique is applied through learning from previous data

2.LITERATURE SURVEY:

2.1EXISTING PROBLEM:

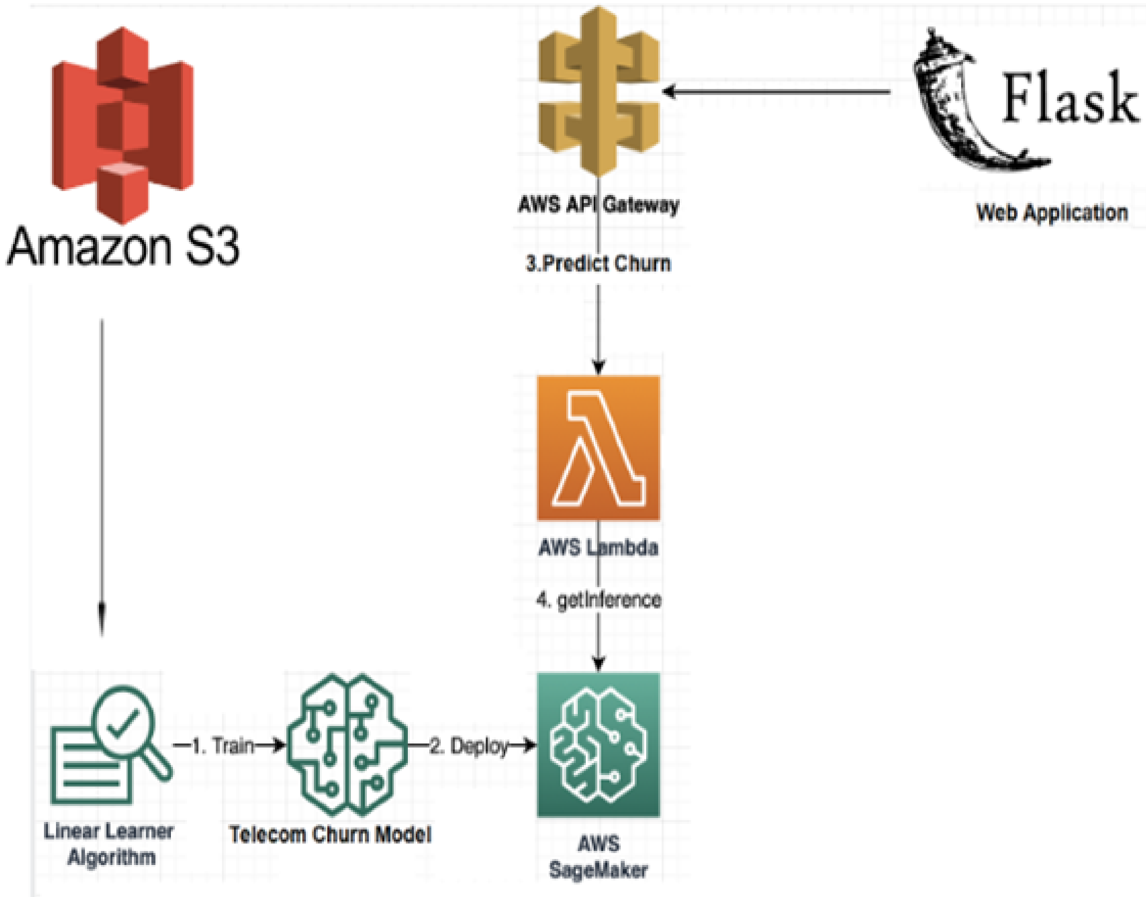
Customer churn is a major problem and one of the most important concerns for large companies. Telecommunication industry always suffers from very high churn rates when one industry offers a better plan than the previous there is a high possibility of the customer churning from the present due to a better plan in such a scenario it is very difficult to avoid losses but through prediction, we can keep it to a minimal level.Due to the direct effect on the revenues of the companies, companies are seeking to develop means to predict potential customers to churn. Therefore, finding factors that increase customer churn is important to take necessary actions to reduce it.

2.2PROPOSED SOLUTION:

Churn prediction helps in identifying those customers who are likely to leave a company. The main contribution of our work is to develop a churn prediction model which assists telecom operators to predict customers who are most likely subject to churn. Build & Deploy a Machine Learning model to predict the customer churn using Amazon SageMaker and predictions can be obtained by using its Endpoint.Create a python - flask application that interacts with the model deployed on AWS Sagemaker with the help of AWS API Gateway and AWS Lambda Services.

3.THEORITICAL ANALYSIS:

3.1. BLOCK DIAGRAM:



3.2. SOFTWARE DESIGNING:

1. Amazon S3
2. AWS API Gateway
3. AWS Lambda
4. Amazon SageMaker
5. Python3
6. Flask integration

4.EXPERIMENTAL INVESTIGATIONS:

Aws Cloud:

Aws Cloud Provides Many Services Such as Sagemaker,lambda and Api Gateway,etc..

Sagemaker:

Amazon SageMaker is a fully managed service that provides every developer and data scientistwith the ability to build, train, and deploy machine learning (ML) models quickly. SageMakerremoves the heavy lifting from each step of the machine learning process to make it easier todevelop high quality models.

Lambda:

With Lambda, you can run code for virtually any type of application or backend service - all

with zero administration. Just upload your code and Lambda takes care of everything required

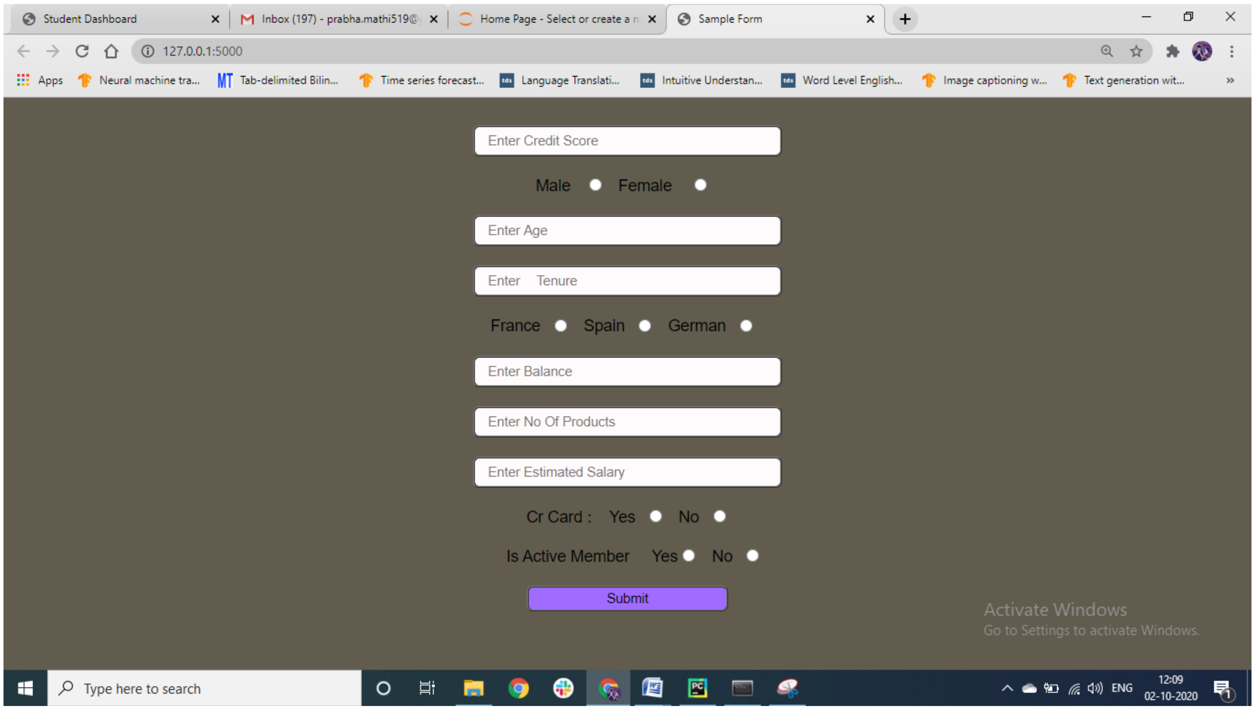
to run and scale your code with high availability. You can set up your code to automatically

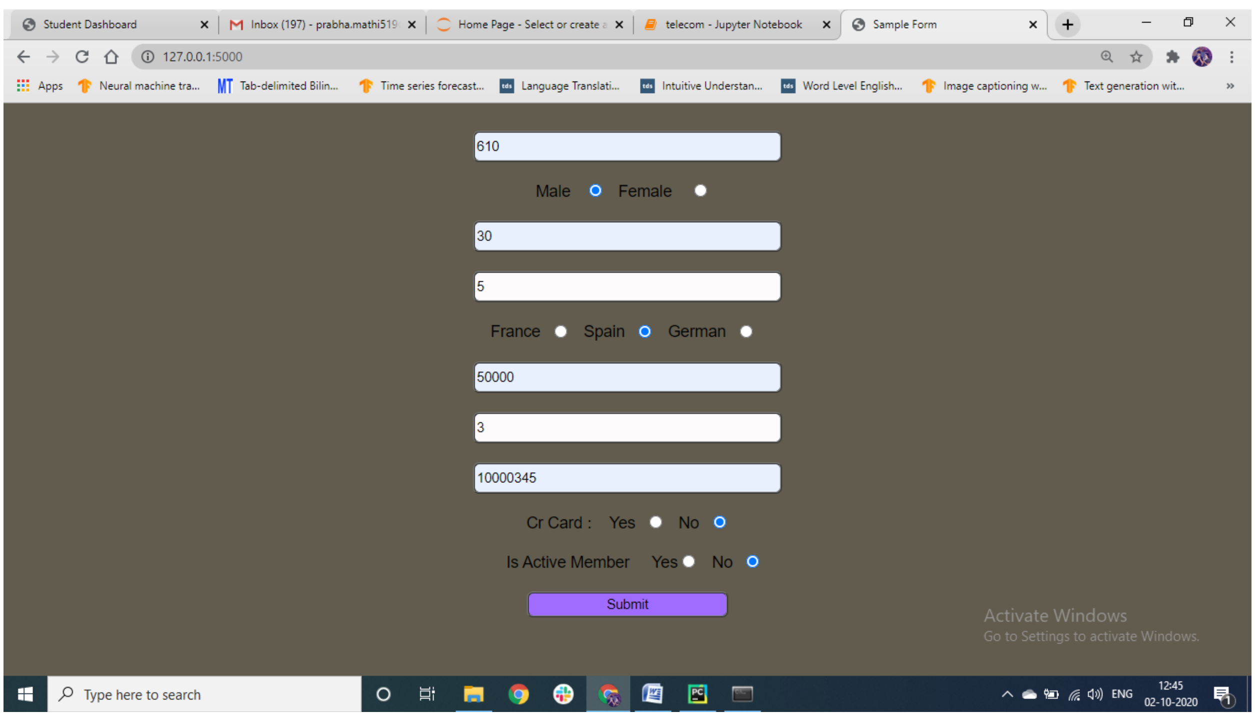
trigger from other AWS services

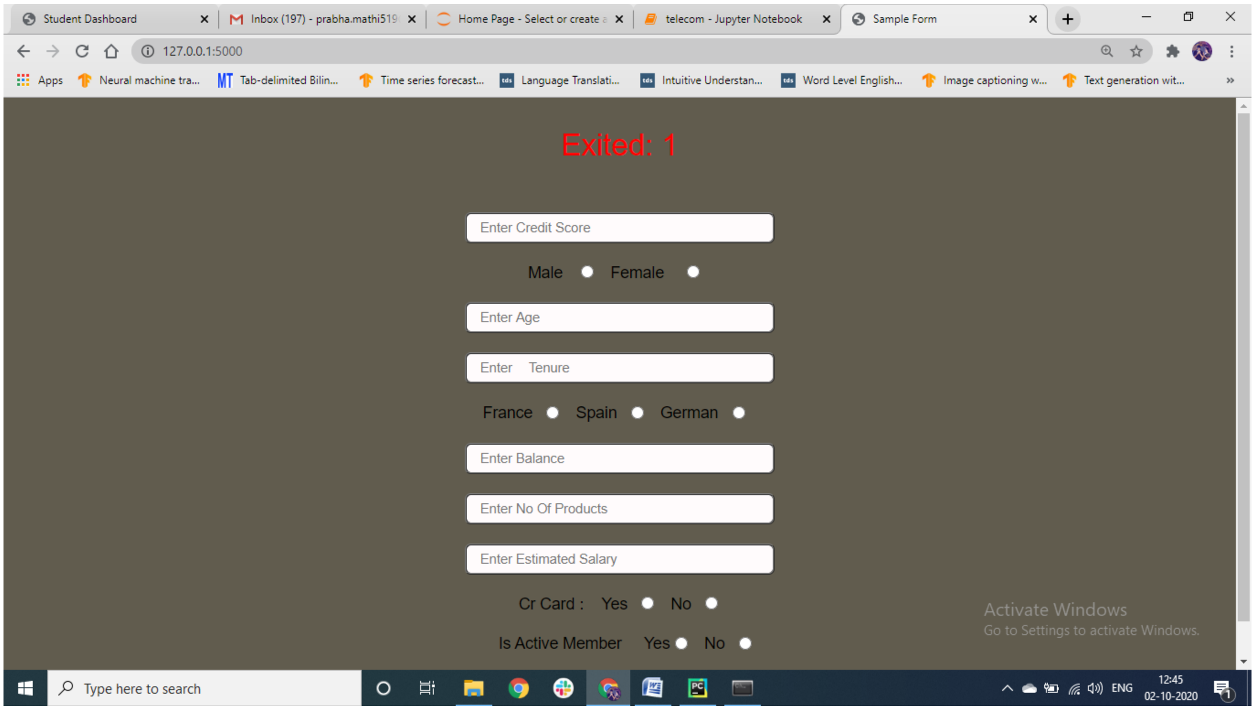
Api Gateway:

Amazon API Gateway is an AWS service for creating, publishing, maintaining, monitoring, andsecuring REST,HTTP, and WebSocket APIs at any scale. API developers can create APIs that access AWS or other web services, as well as data stored in the AWS Cloud APIGateway creates RESTful APIs that Are HTTP-based.

5.RESULT:


Enter Credit Score
Male
Female
Enter Age
Enter Tenure
France
Spain
German
Enter Balance
Enter No Of Products
Enter Estimated Salary
Cr Card : Yes No
Is Active Member Yes No
Submit


610
Male
Female
30
5
France
Spain
German
50000
3
10000345
Cr Card : Yes No
Is Active Member Yes No
Submit



6.ADVANTAGES:

1. Easy to understand and efficient training algorithm(xgclassifier algorithm).
2. Always find a “good solution”

7.APPLICATIONS:

1. It is used in costumer churn prediction in telecom industries
2. It is used in costumer churn prediction in banking industries
3. It is used in CRM(Customer Relationship Management)

8.FUTURE SCOPE:

There are straightforward decision rules based models and complex classification models for churn forecast undertaking has been proposed in the writing. While these strategies are productive in playing out the churn forecast undertaking, they require manual component designing procedure which tedious and blunder inclined. At the point when the outcome are not acquired at the right time we can't take the fundamental activities to abstain from churning so we need even more a logical answer for abstain from churning.

9.CONCLUSION:

The importance of this type of research in the telecom market is to help companies make more profit. It has become known that predicting churn is one of the most important sources of income to telecom companies. We have applied feature engineering, effective feature transformation and selection approach to make the features ready for machine learning algorithms. The use of the Social Network Analysis features enhance the results of predicting the churn in telecom.

10.BIBILOGRAPHY:

Qureshii SA, Rehman AS, Qamar AM, Kamal A, Rehman A. Telecommunication subscribers' churn prediction model using machine learning. In: Eighth international conference on digital information management.

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
```

```
dataset=pd.read_csv('telecom.csv')
dataset.head()
```

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalar
0	1	15634602	Hargrave	619	France	Female	42	2	0.00	1	1	1	101348.8
1	2	15647311	Hill	608	Spain	Female	41	1	83807.86	1	0	1	112542.5
2	3	15619304	Onio	502	France	Female	42	8	159660.80	3	1	0	113931.5
3	4	15701354	Boni	699	France	Female	39	1	0.00	2	0	0	93826.6
4	5	15737888	Mitchell	850	Spain	Female	43	2	125510.82	1	1	1	79084.1

```
dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 14 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   RowNumber        10000 non-null  int64  
 1   CustomerId       10000 non-null  int64  
 2   Surname          10000 non-null  object 
 3   CreditScore      10000 non-null  int64  
 4   Geography        10000 non-null  object 
 5   Gender           10000 non-null  object 
 6   Age              10000 non-null  int64  
 7   Tenure           10000 non-null  int64  
 8   Balance          10000 non-null  float64
 9   NumOfProducts    10000 non-null  int64  
 10  HasCrCard        10000 non-null  int64  
 11  IsActiveMember   10000 non-null  int64  
 12  EstimatedSalary  10000 non-null  float64
 13  Exited           10000 non-null  int64  
dtypes: float64(2), int64(9), object(3)
memory usage: 1.1+ MB
```

```
dataset.describe()
```

	RowNumber	CustomerId	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary
count	10000.00000	1.000000e+04	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.00000	10000.000000	10000.000000
mean	5000.50000	1.569094e+07	650.528800	38.921800	5.012800	76485.889288	1.530200	0.70550	0.515100	100090.239881
std	2886.89568	7.193619e+04	96.653299	10.487806	2.892174	62397.405202	0.581654	0.45584	0.499797	57510.492818
min	1.00000	1.556570e+07	350.000000	18.000000	0.000000	0.000000	1.000000	0.00000	0.000000	11.580000
25%	2500.75000	1.562853e+07	584.000000	32.000000	3.000000	0.000000	1.000000	0.00000	0.000000	51002.110000
50%	5000.50000	1.569074e+07	652.000000	37.000000	5.000000	97198.540000	1.000000	1.00000	1.000000	100193.915000
75%	7500.25000	1.575323e+07	718.000000	44.000000	7.000000	127644.240000	2.000000	1.00000	1.000000	149388.247500
max	10000.00000	1.581569e+07	850.000000	92.000000	10.000000	250898.090000	4.000000	1.00000	1.000000	199992.480000

```
dataset.shape
```

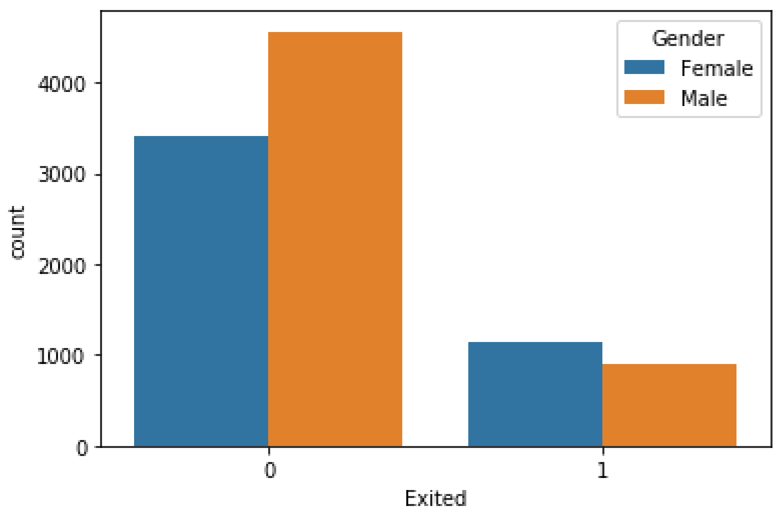
```
(10000, 14)
```

```
dataset.isnull().sum()
```

```
RowNumber          0
CustomerId         0
Surname            0
CreditScore        0
Geography          0
Gender             0
Age                0
Tenure             0
Balance            0
NumOfProducts      0
HasCrCard          0
IsActiveMember     0
EstimatedSalary    0
Exited             0
dtype: int64
```

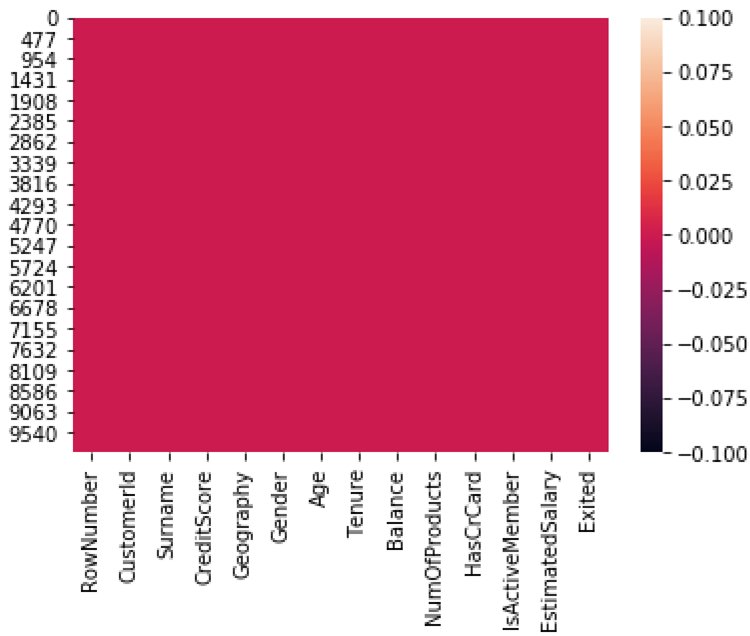
```
1  sns.countplot(x='Exited',hue='Gender',data=dataset)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f09f27584e0>
```




```
1  sns.heatmap(dataset.isnull())
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f09f1ebe5c0>
```




```python
dataset=dataset.drop(['RowNumber', 'CustomerId', 'Surname'],axis=1)
dataset.head()
```

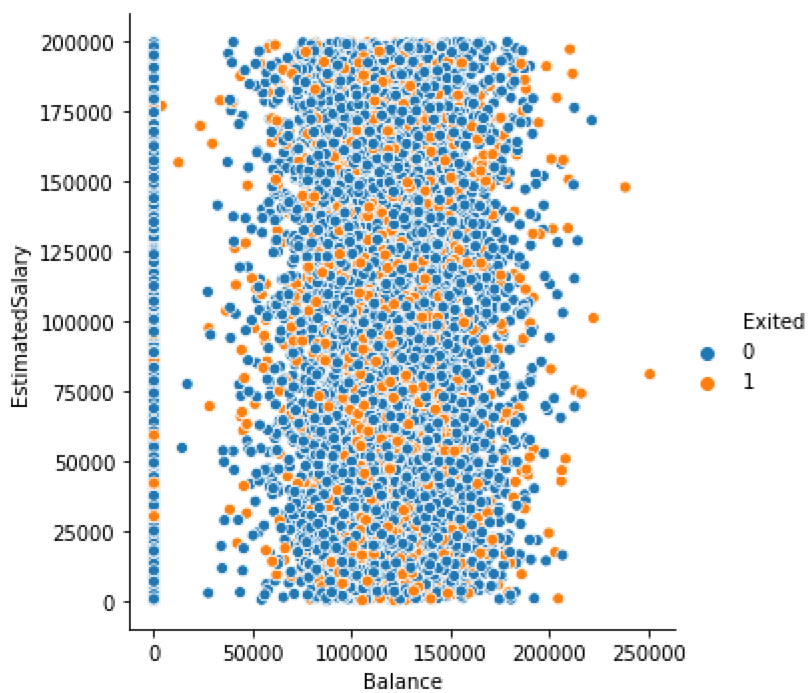
	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
0	619	France	Female	42	2	0.00	1	1	1	101348.88	1
1	608	Spain	Female	41	1	83807.86	1	0	1	112542.58	0
2	502	France	Female	42	8	159660.80	3	1	0	113931.57	1
3	699	France	Female	39	1	0.00	2	0	0	93826.63	0
4	850	Spain	Female	43	2	125510.82	1	1	1	79084.10	0

```python
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
lb1=LabelEncoder()
lb2=LabelEncoder()
dataset['Gender']=lb1.fit_transform(dataset['Gender'])
dataset['Geography']=lb2.fit_transform(dataset['Geography']
)
dataset.head()
```

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
0	619	0	0	42	2	0.00	1	1	1	101348.88	1
1	608	2	0	41	1	83807.86	1	0	1	112542.58	0
2	502	0	0	42	8	159660.80	3	1	0	113931.57	1
3	699	0	0	39	1	0.00	2	0	0	93826.63	0
4	850	2	0	43	2	125510.82	1	1	1	79084.10	0

```
sns.relplot(x='Balance',y='EstimatedSalary',hue='Exited',data=dataset)
```

```
<seaborn.axisgrid.FacetGrid at 0x7f09f0bc90f0>
```




```
data_in=dataset.iloc[:,:-1]
data_out=dataset.iloc[:,-1]
sc=MinMaxScaler(feature_range=(0,1))
data_in=sc.fit_transform(data_in)
keys=dataset.keys()[:-1]
dici={}
for i in range(len(keys)):
    dici.update({keys[i]:data_in[:,i]})
final_data=pd.DataFrame(dici)
final_data.head()
```

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary
0	0.538	0.0	0.0	0.324324	0.2	0.000000	0.000000	1.0	1.0	0.506735
1	0.516	1.0	0.0	0.310811	0.1	0.334031	0.000000	0.0	1.0	0.562709
2	0.304	0.0	0.0	0.324324	0.8	0.636357	0.666667	1.0	0.0	0.569654
3	0.698	0.0	0.0	0.283784	0.1	0.000000	0.333333	0.0	0.0	0.469120
4	1.000	1.0	0.0	0.337838	0.2	0.500246	0.000000	1.0	1.0	0.395400

```
final_data=pd.concat([dataset.iloc[:,-1],final_data],axis=1)
final_data.head()
```

	Exited	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary
0	1	0.538	0.0	0.0	0.324324	0.2	0.000000	0.000000	1.0	1.0	0.506735
1	0	0.516	1.0	0.0	0.310811	0.1	0.334031	0.000000	0.0	1.0	0.562709
2	1	0.304	0.0	0.0	0.324324	0.8	0.636357	0.666667	1.0	0.0	0.569654
3	0	0.698	0.0	0.0	0.283784	0.1	0.000000	0.333333	0.0	0.0	0.469120
4	0	1.000	1.0	0.0	0.337838	0.2	0.500246	0.000000	1.0	1.0	0.395400

```
import boto3,re,os,json,sagemaker
from sagemaker import get_execution_role
train,test=train_test_split(final_data,test_size=0.2)
role=get_execution_role()
my_region=boto3.session.Session().region_name
containers = {'us-west-2': '433757028032.dkr.ecr.us-west-2.amazonaws.com/xgboost:latest',
              'us-east-1': '811284229777.dkr.ecr.us-east-1.amazonaws.com/xgboost:latest',
              'us-east-2': '825641698319.dkr.ecr.us-east-2.amazonaws.com/xgboost:latest',
              'eu-west-1': '685385470294.dkr.ecr.eu-west-1.amazonaws.com/xgboost:latest'}
prefix='sagemaker/Telecom'
bucket_name='buildathonproject1'
final_data.to_csv('train.csv',index=False,header=False)
boto3.Session().resource('s3').Bucket(bucket_name).Object(o
```

```
s.path.join(prefix,'train/train.csv')).upload_file('train.csv')
s3_input_train=sagemaker.s3_input(s3_data='s3://{}/{}/train'.format(bucket_name, prefix),content_type='csv')
sess=sagemaker.Session()
telecom_model=sagemaker.estimator.Estimator(containers[my_region],role,train_instance_count=1,train_instance_type='ml.m5.large',output_path='s3://{}/{}/output'.format(bucket_name,prefix),sagemaker_session=sess)
telecom_model.set_hyperparameters(max_depth=5,eta=0.2,gamma=4,min_child_weight=6,subsample=0.8,silent=0,objective='binary:logistic',num_round=100)
telecom_model.fit({'train':s3_input_train})
```

```
2020-09-30 07:50:56 Starting - Starting the training job...
2020-09-30 07:50:59 Starting - Launching requested ML instances......
2020-09-30 07:52:21 Starting - Preparing the instances for training......
2020-09-30 07:53:12 Downloading - Downloading input data...
2020-09-30 07:53:48 Training - Downloading the training image..Arguments: train
[2020-09-30:07:54:03:INFO] Running standalone xgboost training.
[2020-09-30:07:54:03:INFO] Path /opt/ml/input/data/validation does not exist!
[2020-09-30:07:54:03:INFO] File size need to be processed in the node: 0.99mb. Available memory size in the node: 172.35mb
[2020-09-30:07:54:03:INFO] Determined delimiter of CSV input is ','
[07:54:03] S3DistributionType set as FullyReplicated
[07:54:03] 10000x10 matrix with 100000 entries loaded from /opt/ml/input/data/train?format=csv&label_column=0&delimiter=,
[07:54:03] src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 38 extra nodes, 6 pruned nodes, max_depth=5
[0]#011train-error:0.1448
[07:54:03] src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 32 extra nodes, 12 pruned nodes, max_depth=5
[1]#011train-error:0.144
[07:54:03] src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 38 extra nodes, 4 pruned nodes, max_depth=5
[2]#011train-error:0.144
[07:54:03] src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 38 extra nodes, 6 pruned nodes, max_depth=5
[3]#011train-error:0.144
```

```
detector=telecom_model.deploy(initial_instance_count=1,instance_type='ml.m5.large')
```

```
Parameter image will be renamed to image_uri in SageMaker Python SDK v2.
```

```
-------------!
```

```
detector.endpoint
```

```
'xgboost-2020-09-30-07-50-56-779'
```

```
from sagemaker.predictor import csv_serializer
test_data_array=test.drop('Exited',axis=1).values #load the
```

```
data into an array
detector.content_type = 'text/csv' # set the data type for an inference
detector.serializer = csv_serializer # set the serializer type
predictions=detector.predict(test_data_array).decode('utf-8') # predict!
predictions_array = np.fromstring(predictions[1:], sep=',')
print(predictions)
```


0.357669651508,0.141457110643,0.329746335745,0.026482027024,0.0712991580367,0.0263096913695,0.0375938378274,0.0215682908893,
0.0678913518786,0.115104779601,0.414443165064,0.015394564718,0.0659468099475,0.983116984367,0.564640462399,0.767752766609,0.2
11881354451,0.0556389167905,0.266310662031,0.0520670227706,0.0255261678249,0.0819280520082,0.121003270149,0.0237068850547,0.0
298531763256,0.400649666786,0.0279733166099,0.645623505116,0.144340574741,0.773866117001,0.0724500715733,0.0210663992912,0.66
0542488098,0.312410950661,0.805181801319,0.835865318775,0.0263171419501,0.255656123161,0.150213211775,0.17395016551,0.3088148
23627,0.0194727368653,0.290218800306,0.0748643428087,0.0298329666257,0.0253355037421,0.0449019707739,0.259558230639,0.0533759
184182,0.781935751438,0.0273960605264,0.157540291548,0.0343550741673,0.335181176662,0.0296571981162,0.091909609735,0.01418924
51793,0.157416403294,0.0391214042902,0.450152218342,0.292664647102,0.0937503576279,0.0576719790697,0.0443506836891,0.03734270
48326,0.155199185014,0.0502981394529,0.0710270255804,0.446701139212,0.572361409664,0.180645704269,0.7317096591,0.083087496459
5,0.0461247563362,0.0191855877638,0.0121706062928,0.0155159085989,0.364274173975,0.382801711559,0.412225365639,0.006050311494
62,0.11486851424,0.1565214097 5,0.0366217754781,0.130395650864,0.0441899485886,0.635700643063,0.0170651581138,0.036082673817 9,
0.0455167926848,0.01267759688 2,0.0177081599832,0.0138631332666,0.66416233778,0.176358506083,0.531168580055,0.0239507853985,0.
0872323140502,0.837302923203,0.0105954483151,0.0460762195289,0.0309317186475,0.163216099143,0.601965308189,0.0419460423291,0.
0393777601421,0.0375836156309,0.017990315333,0.346629232168,0.064279101789,0.101827032864,0.265378087759,0.975147724152,0.070
0022429228,0.049429371953,0.0824607014656,0.144094198942,0.0924224555492,0.303251862526,0.215495213866,0.235083475709,0.02136
01496071,0.0220698155463,0.0728238001466,0.00614333618432,0.488911926746,0.10665551573,0.0739371702075,0.0133571783081,0.0279
69064191,0.697656035423,0.265094041824,0.0515954867005,0.082623578608,0.00672792643309,0.0578222945333,0.362552344799,0.03714
24034238,0.15151129663,0.172684624791,0.0699690058827,0.509014189243,0.287413448095,0.0959527418017,0.026997230947,0.52917981
1478,0.0673849955201,0.021628184244,0.0224863402545,0.546940028667,0.0326875001192,0.0189216658473,0.094791404902 9,0.04943434

LambdaFunction:

```
import io
import boto3
import json
import csv
def lambda_handler(event, context):
    ENDPOINT_NAME = os.environ['envirornment_variable']
    runtime= boto3.client('runtime.sagemaker')
    print(ENDPOINT_NAME)
    print("Received event: " , json.dumps(event, indent=2))
    data = json.loads(json.dumps(event))
    print("Data:",data)
    payload = data['data']
    print("Payload:",payload)
    response =
```

```
    runtime.invoke_endpoint(EndpointName=ENDPOINT_NAME,
                                       ContentType='text/csv',
                                       Body=payload)
    print(response)
    result = json.loads(response['Body'].read().decode())
    print(result)

    if result>0.5:
        return "P"
    else:
        return "N"
```

```
Response:
"P"

Request ID:
"566ea769-7ad5-4604-8ed9-1bbb57eae67b"

Function logs:
START RequestId: 566ea769-7ad5-4604-8ed9-1bbb57eae67b Version: $LATEST
xgboost-2020-09-30-07-50-56-779
Received event:  {
  "data": "61,0,0,42.2,0.00,1,1,1,1348.88"
}
Data: {'data': '61,0,0,42.2,0.00,1,1,1,1348.88'}
Payload: 61,0,0,42.2,0.00,1,1,1,1348.88
{'ResponseMetadata': {'RequestId': 'a6c2f8a7-66e3-43f8-9b17-82f71d81e0c7', 'HTTPStatusCode': 200, 'HTTPHeaders': {'x-amzn-requestid': 'a6c2f8
0.760711729527
```