Experiment Number

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Branch ::	CSE - IoT	Sec/Grp ::	1/A
Semester ::	6th	Date ::	14th Mar, 2022
Subject ::	ML Lab	CODE ::	CSD-386

1. Aim :

To implement the logistic regression on the given data set and tune the model with the appropriate selection of of solver.

- DATA-SET LINK: https://www.kaggle.com/dinaouahbi/churndatacsv

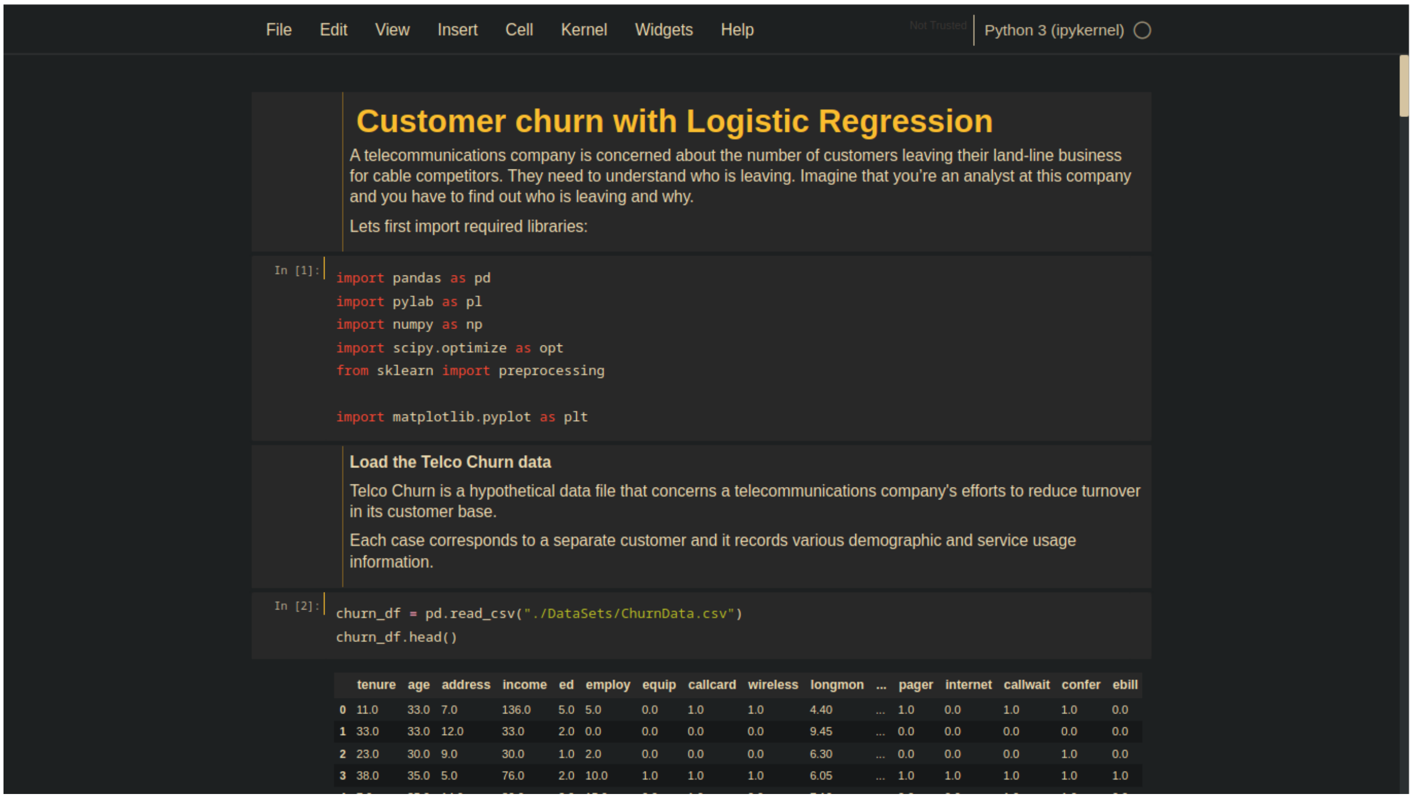
2. Task :

1. Customer churn with Logistic Regression: A telecommunications company is concerned about the number of customers leaving their land-line business for cable competitors. They need to understand who is leaving. Imagine that you're an analyst at this company and you have to find out who is leaving and why.

3. Algorithm :

- Import required Libraries
- Load the Telco Churn Data
- Data pre-processing and selection
- Training and Testing
- Confussion Matrix

4. Code :



Customer churn with Logistic Regression

A telecommunications company is concerned about the number of customers leaving their land-line business for cable competitors. They need to understand who is leaving. Imagine that you're an analyst at this company and you have to find out who is leaving and why.

Lets first import required libraries:

In [1]:
```
import pandas as pd
import pylab as pl
import numpy as np
import scipy.optimize as opt
from sklearn import preprocessing

import matplotlib.pyplot as plt
```

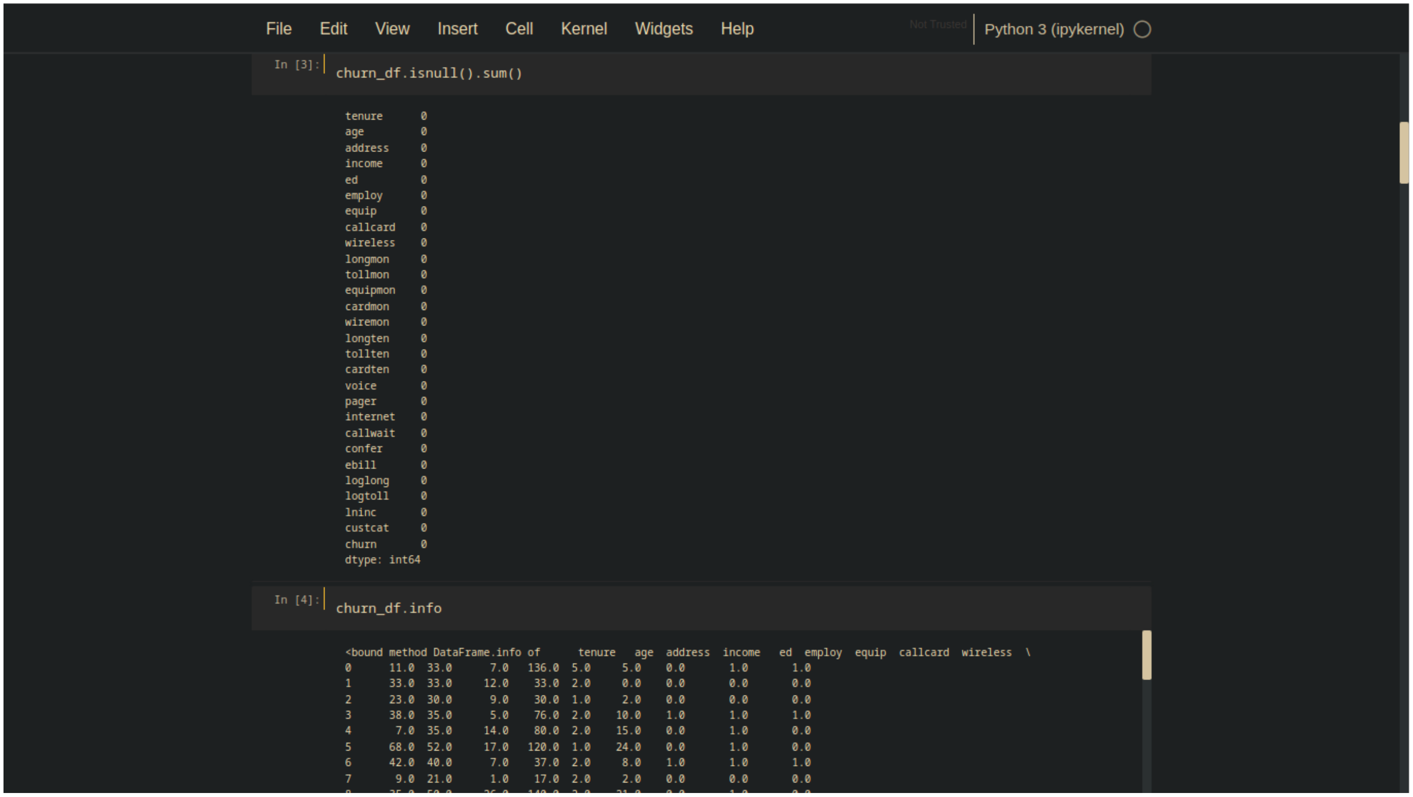
Load the Telco Churn data

Telco Churn is a hypothetical data file that concerns a telecommunications company's efforts to reduce turnover in its customer base.

Each case corresponds to a separate customer and it records various demographic and service usage information.

In [2]:
```
churn_df = pd.read_csv("./DataSets/ChurnData.csv")
churn_df.head()
```

	tenure	age	address	income	ed	employ	equip	callcard	wireless	longmon	...	pager	internet	callwait	confer	ebill
0	11.0	33.0	7.0	136.0	5.0	5.0	0.0	1.0	1.0	4.40	...	1.0	0.0	1.0	1.0	0.0
1	33.0	33.0	12.0	33.0	2.0	0.0	0.0	0.0	0.0	9.45	...	0.0	0.0	0.0	0.0	0.0
2	23.0	30.0	9.0	30.0	1.0	2.0	0.0	0.0	0.0	6.30	...	0.0	0.0	0.0	1.0	0.0
3	38.0	35.0	5.0	76.0	2.0	10.0	1.0	1.0	1.0	6.05	...	1.0	1.0	1.0	1.0	1.0

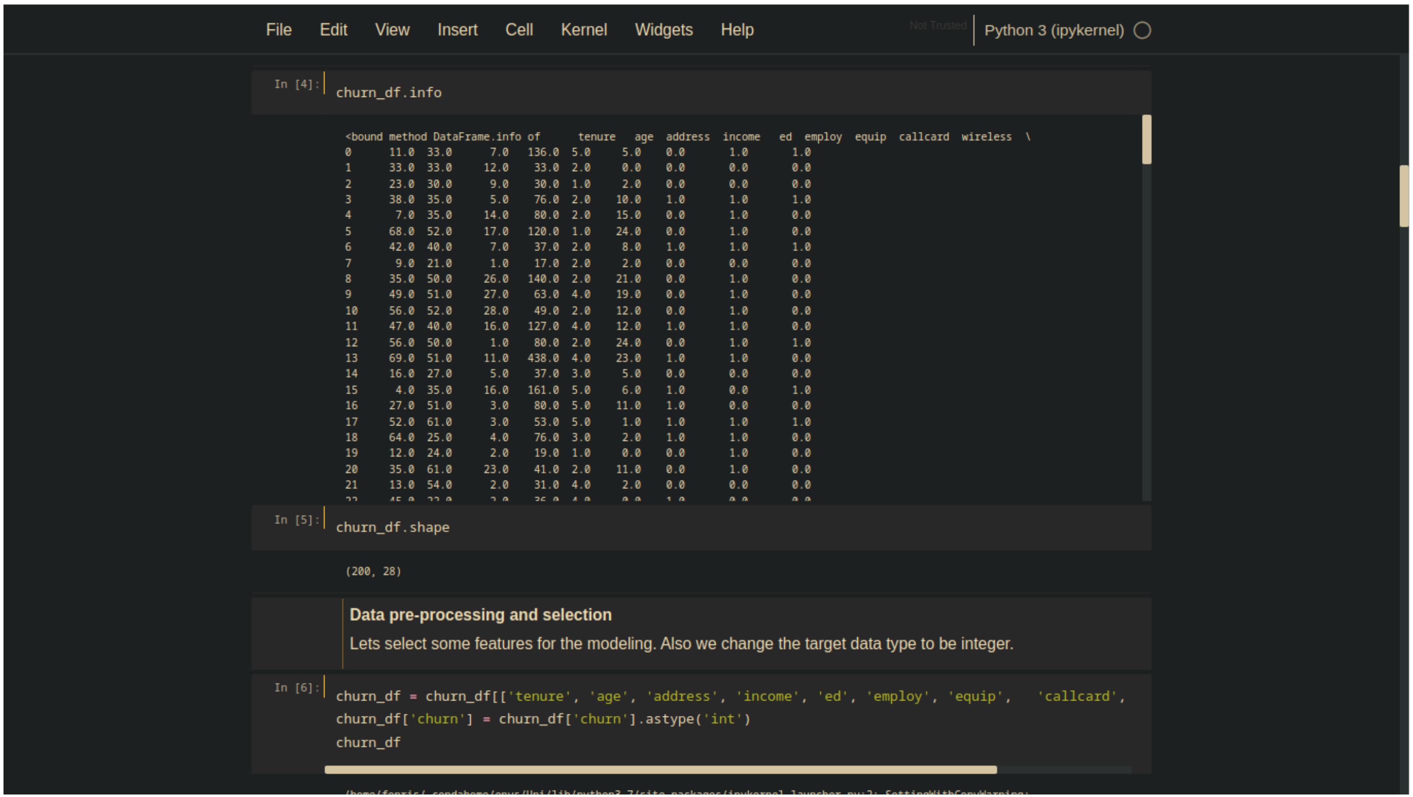


In [3]:
```
churn_df.isnull().sum()
```

```
tenure      0
age         0
address     0
income      0
ed          0
employ      0
equip       0
callcard    0
wireless    0
longmon     0
tollmon     0
equipmon    0
cardmon     0
wiremon     0
longten     0
tollten     0
cardten     0
voice       0
pager       0
internet    0
callwait    0
confer      0
ebill       0
loglong     0
logtoll     0
lninc       0
custcat     0
churn       0
dtype: int64
```

In [4]:
```
churn_df.info
```

```
<bound method DataFrame.info of      tenure   age  address  income   ed  employ  equip  callcard  wireless  \
0      11.0  33.0      7.0   136.0  5.0     5.0    0.0       1.0       1.0
1      33.0  33.0     12.0    33.0  2.0     0.0    0.0       0.0       0.0
2      23.0  30.0      9.0    30.0  1.0     2.0    0.0       0.0       0.0
3      38.0  35.0      5.0    76.0  2.0    10.0    1.0       1.0       1.0
4       7.0  35.0     14.0    80.0  2.0    15.0    0.0       1.0       0.0
5      68.0  52.0     17.0   120.0  1.0    24.0    0.0       1.0       0.0
6      42.0  40.0      7.0    37.0  2.0     8.0    1.0       1.0       1.0
7       9.0  21.0      1.0    17.0  2.0     2.0    0.0       0.0       0.0
```



In [4]:
```
churn_df.info
```

```
<bound method DataFrame.info of      tenure   age  address  income   ed  employ  equip  callcard  wireless  \
0      11.0  33.0      7.0   136.0  5.0     5.0    0.0       1.0       1.0
1      33.0  33.0     12.0    33.0  2.0     0.0    0.0       0.0       0.0
2      23.0  30.0      9.0    30.0  1.0     2.0    0.0       0.0       0.0
3      38.0  35.0      5.0    76.0  2.0    10.0    1.0       1.0       1.0
4       7.0  35.0     14.0    80.0  2.0    15.0    0.0       1.0       0.0
5      68.0  52.0     17.0   120.0  1.0    24.0    0.0       1.0       0.0
6      42.0  40.0      7.0    37.0  2.0     8.0    1.0       1.0       1.0
7       9.0  21.0      1.0    17.0  2.0     2.0    0.0       0.0       0.0
8      35.0  50.0     26.0   140.0  2.0    21.0    0.0       1.0       0.0
9      49.0  51.0     27.0    63.0  4.0    19.0    0.0       1.0       0.0
10     56.0  52.0     28.0    49.0  2.0    12.0    0.0       1.0       0.0
11     47.0  40.0     16.0   127.0  4.0    12.0    1.0       1.0       0.0
12     56.0  50.0      1.0    80.0  2.0    24.0    0.0       1.0       1.0
13     69.0  51.0     11.0   438.0  4.0    23.0    1.0       1.0       0.0
14     16.0  27.0      5.0    37.0  3.0     5.0    0.0       0.0       0.0
15      4.0  35.0     16.0   161.0  5.0     6.0    1.0       0.0       1.0
16     27.0  51.0      3.0    80.0  5.0    11.0    1.0       0.0       0.0
17     52.0  61.0      3.0    53.0  5.0     1.0    1.0       1.0       1.0
18     64.0  25.0      4.0    76.0  3.0     2.0    1.0       1.0       0.0
19     12.0  24.0      2.0    19.0  1.0     0.0    0.0       1.0       0.0
20     35.0  61.0     23.0    41.0  2.0    11.0    0.0       1.0       0.0
21     13.0  54.0      2.0    31.0  4.0     2.0    0.0       0.0       0.0
```

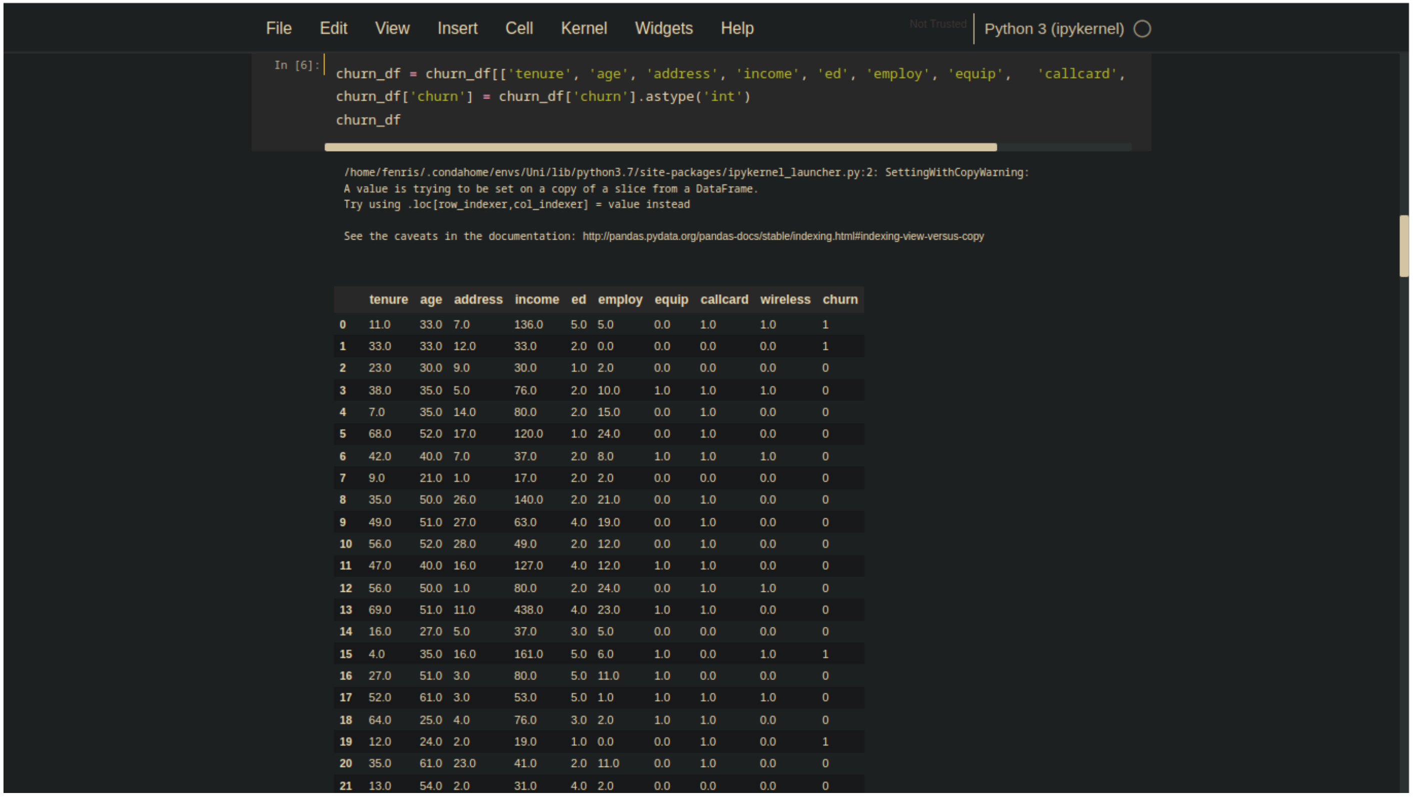
In [5]:
```
churn_df.shape
```

```
(200, 28)
```

Data pre-processing and selection

Lets select some features for the modeling. Also we change the target data type to be integer.

In [6]:
```
churn_df = churn_df[['tenure', 'age', 'address', 'income', 'ed', 'employ', 'equip',   'callcard',
churn_df['churn'] = churn_df['churn'].astype('int')
churn_df
```

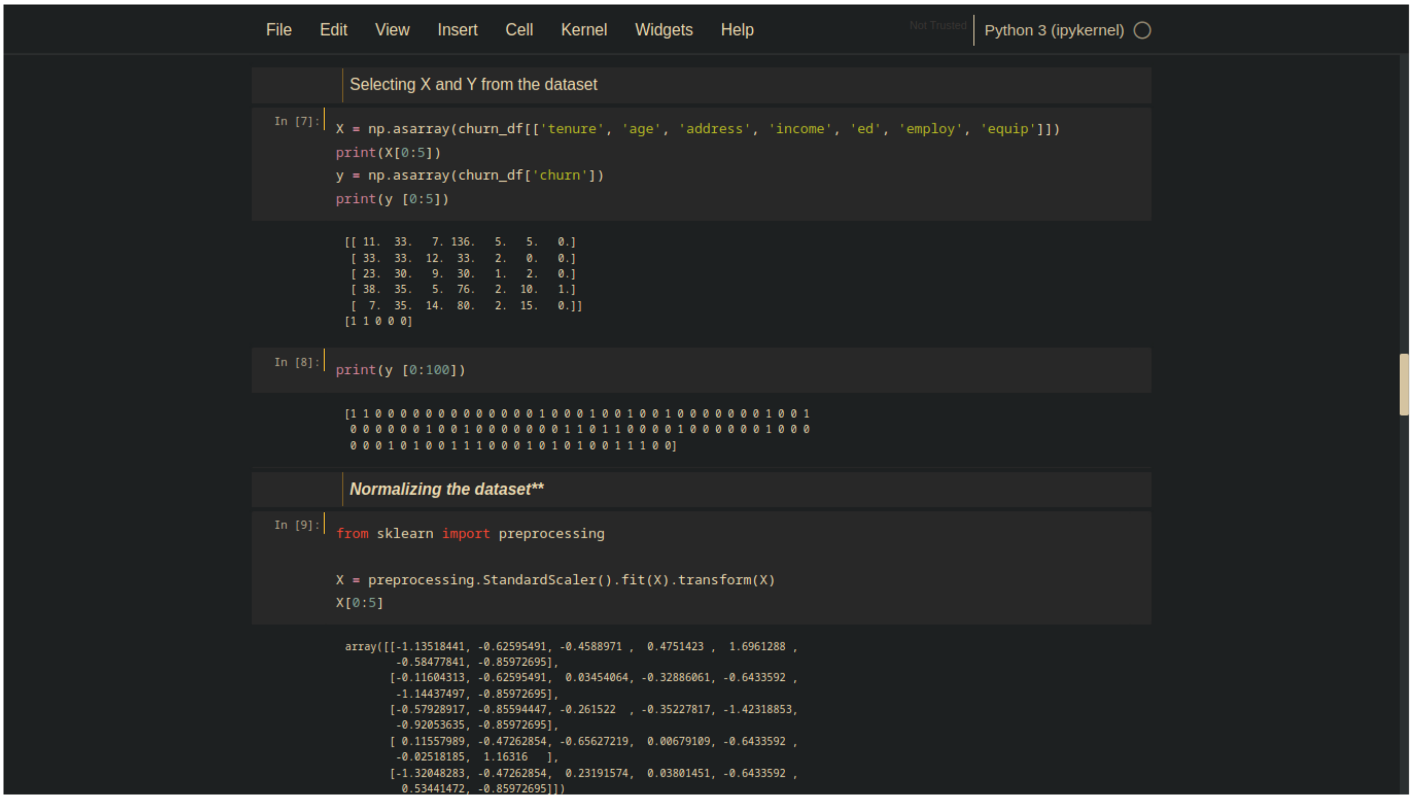


In [6]:
```
churn_df = churn_df[['tenure', 'age', 'address', 'income', 'ed', 'employ', 'equip',   'callcard',
churn_df['churn'] = churn_df['churn'].astype('int')
churn_df
```

```
/home/fenris/.condahome/envs/Uni/lib/python3.7/site-packages/ipykernel_launcher.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#indexing-view-versus-copy
```

	tenure	age	address	income	ed	employ	equip	callcard	wireless	churn
0	11.0	33.0	7.0	136.0	5.0	5.0	0.0	1.0	1.0	1
1	33.0	33.0	12.0	33.0	2.0	0.0	0.0	0.0	0.0	1
2	23.0	30.0	9.0	30.0	1.0	2.0	0.0	0.0	0.0	0
3	38.0	35.0	5.0	76.0	2.0	10.0	1.0	1.0	1.0	0
4	7.0	35.0	14.0	80.0	2.0	15.0	0.0	1.0	0.0	0
5	68.0	52.0	17.0	120.0	1.0	24.0	0.0	1.0	0.0	0
6	42.0	40.0	7.0	37.0	2.0	8.0	1.0	1.0	1.0	0
7	9.0	21.0	1.0	17.0	2.0	2.0	0.0	0.0	0.0	0
8	35.0	50.0	26.0	140.0	2.0	21.0	0.0	1.0	0.0	0
9	49.0	51.0	27.0	63.0	4.0	19.0	0.0	1.0	0.0	0
10	56.0	52.0	28.0	49.0	2.0	12.0	0.0	1.0	0.0	0
11	47.0	40.0	16.0	127.0	4.0	12.0	1.0	1.0	0.0	0
12	56.0	50.0	1.0	80.0	2.0	24.0	0.0	1.0	1.0	0
13	69.0	51.0	11.0	438.0	4.0	23.0	1.0	1.0	0.0	0
14	16.0	27.0	5.0	37.0	3.0	5.0	0.0	0.0	0.0	0
15	4.0	35.0	16.0	161.0	5.0	6.0	1.0	0.0	1.0	1
16	27.0	51.0	3.0	80.0	5.0	11.0	1.0	0.0	0.0	0
17	52.0	61.0	3.0	53.0	5.0	1.0	1.0	1.0	1.0	0
18	64.0	25.0	4.0	76.0	3.0	2.0	1.0	1.0	0.0	0
19	12.0	24.0	2.0	19.0	1.0	0.0	0.0	1.0	0.0	1
20	35.0	61.0	23.0	41.0	2.0	11.0	0.0	1.0	0.0	0
21	13.0	54.0	2.0	31.0	4.0	2.0	0.0	0.0	0.0	0



Selecting X and Y from the dataset

```
In [7]: X = np.asarray(churn_df[['tenure', 'age', 'address', 'income', 'ed', 'employ', 'equip']])
        print(X[0:5])
        y = np.asarray(churn_df['churn'])
        print(y [0:5])
```

```
[[ 11.  33.   7. 136.   5.   5.   0.]
 [ 33.  33.  12.  33.   2.   0.   0.]
 [ 23.  30.   9.  30.   1.   2.   0.]
 [ 38.  35.   5.  76.   2.  10.   1.]
 [  7.  35.  14.  80.   2.  15.   0.]]
[1 1 0 0 0]
```

```
In [8]: print(y [0:100])
```

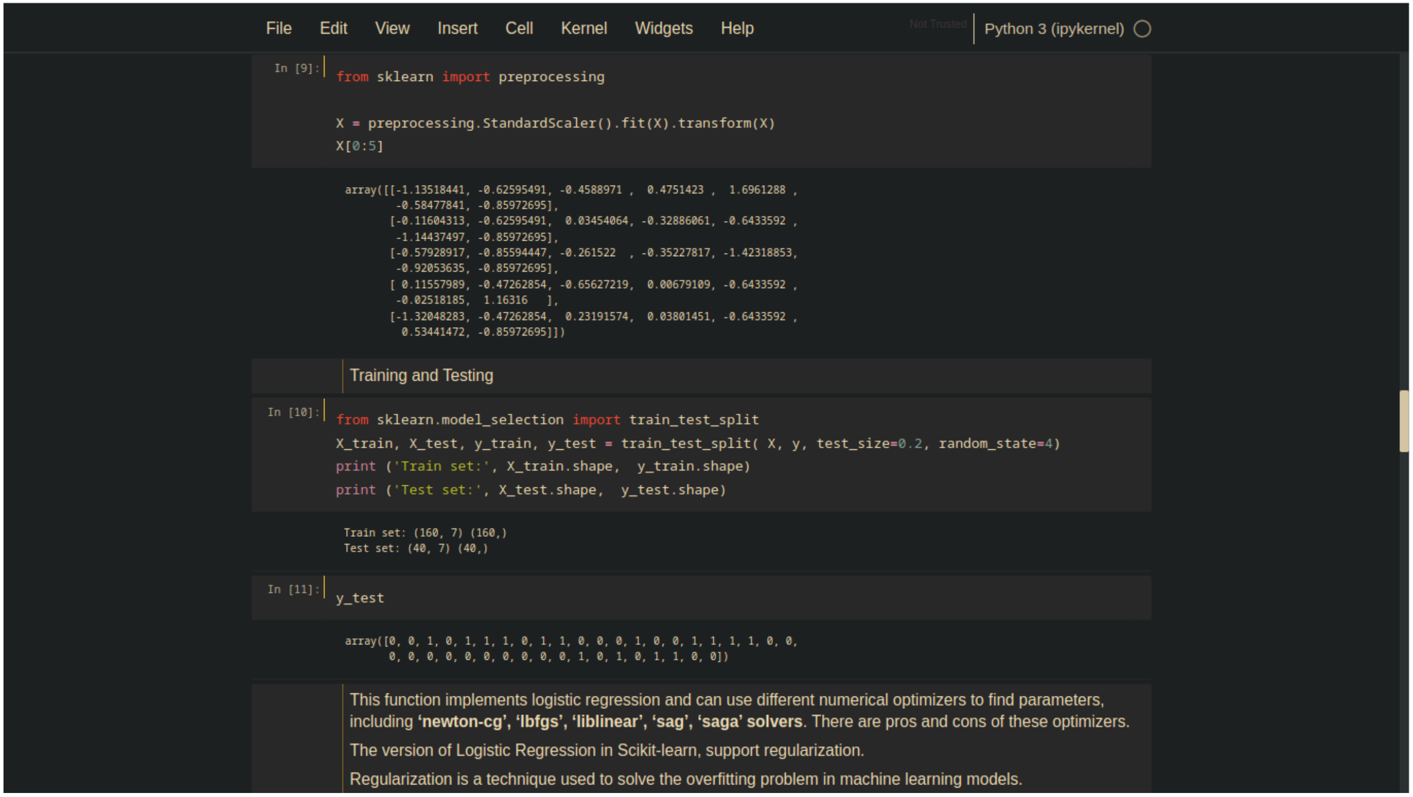
```
[1 1 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 1 0 0 1 0 0 1 0 0 0 0 0 0 0 1 0 0 1
 0 0 0 0 0 0 1 0 0 1 0 0 0 0 0 0 0 1 1 0 1 1 0 0 0 0 1 0 0 0 0 0 0 1 0 0 0
 0 0 0 1 0 1 0 0 1 1 1 0 0 0 1 0 1 0 1 0 0 1 1 1 0 0]
```

Normalizing the dataset*

```
In [9]: from sklearn import preprocessing

        X = preprocessing.StandardScaler().fit(X).transform(X)
        X[0:5]
```

```
array([[-1.13518441, -0.62595491, -0.4588971 ,  0.4751423 ,  1.6961288 ,
        -0.58477841, -0.85972695],
       [-0.11604313, -0.62595491,  0.03454064, -0.32886061, -0.6433592 ,
        -1.14437497, -0.85972695],
       [-0.57928917, -0.85594447, -0.261522  , -0.35227817, -1.42318853,
        -0.92053635, -0.85972695],
       [ 0.11557989, -0.47262854, -0.65627219,  0.00679109, -0.6433592 ,
        -0.02518185,  1.16316   ],
       [-1.32048283, -0.47262854,  0.23191574,  0.03801451, -0.6433592 ,
         0.53441472, -0.85972695]])
```



```
In [9]: from sklearn import preprocessing

        X = preprocessing.StandardScaler().fit(X).transform(X)
        X[0:5]
```

```
array([[-1.13518441, -0.62595491, -0.4588971 ,  0.4751423 ,  1.6961288 ,
        -0.58477841, -0.85972695],
       [-0.11604313, -0.62595491,  0.03454064, -0.32886061, -0.6433592 ,
        -1.14437497, -0.85972695],
       [-0.57928917, -0.85594447, -0.261522  , -0.35227817, -1.42318853,
        -0.92053635, -0.85972695],
       [ 0.11557989, -0.47262854, -0.65627219,  0.00679109, -0.6433592 ,
        -0.02518185,  1.16316   ],
       [-1.32048283, -0.47262854,  0.23191574,  0.03801451, -0.6433592 ,
         0.53441472, -0.85972695]])
```

Training and Testing

```
In [10]: from sklearn.model_selection import train_test_split
         X_train, X_test, y_train, y_test = train_test_split( X, y, test_size=0.2, random_state=4)
         print ('Train set:', X_train.shape,  y_train.shape)
         print ('Test set:', X_test.shape,  y_test.shape)
```

```
Train set: (160, 7) (160,)
Test set: (40, 7) (40,)
```

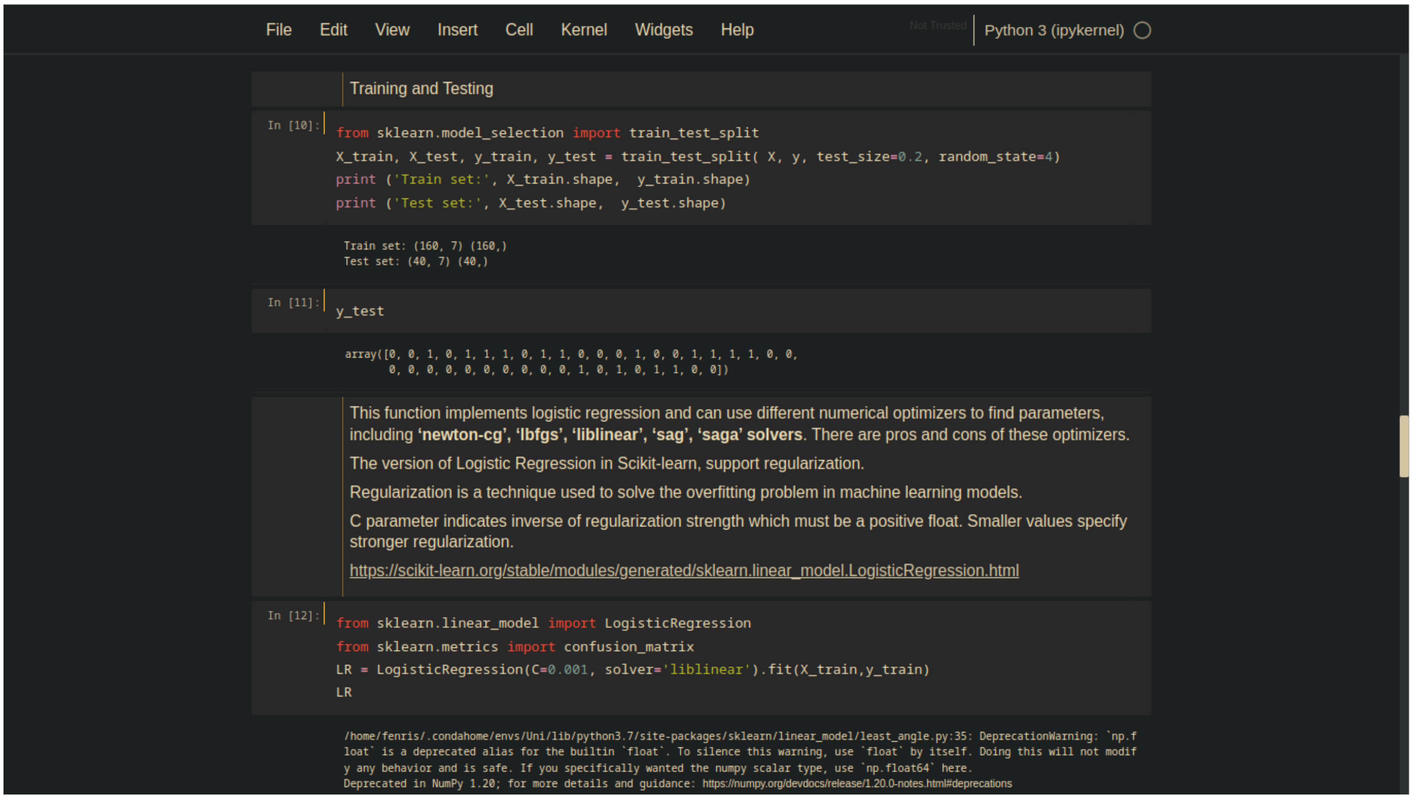
```
In [11]: y_test
```

```
array([0, 0, 1, 0, 1, 1, 1, 0, 1, 1, 0, 0, 0, 1, 0, 0, 1, 1, 1, 1, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 1, 1, 0, 0])
```

This function implements logistic regression and can use different numerical optimizers to find parameters, including **‘newton-cg’, ‘lbfgs’, ‘liblinear’, ‘sag’, ‘saga’ solvers**. There are pros and cons of these optimizers.

The version of Logistic Regression in Scikit-learn, support regularization.

Regularization is a technique used to solve the overfitting problem in machine learning models.



Training and Testing

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split( X, y, test_size=0.2, random_state=4)
print ('Train set:', X_train.shape,  y_train.shape)
print ('Test set:', X_test.shape,  y_test.shape)
```

```
Train set: (160, 7) (160,)
Test set: (40, 7) (40,)
```

```
y_test
```

```
array([0, 0, 1, 0, 1, 1, 1, 0, 1, 1, 0, 0, 0, 1, 0, 0, 1, 1, 1, 1, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 1, 1, 0, 0])
```

This function implements logistic regression and can use different numerical optimizers to find parameters, including **‘newton-cg’, ‘lbfgs’, ‘liblinear’, ‘sag’, ‘saga’ solvers**. There are pros and cons of these optimizers.

The version of Logistic Regression in Scikit-learn, support regularization.

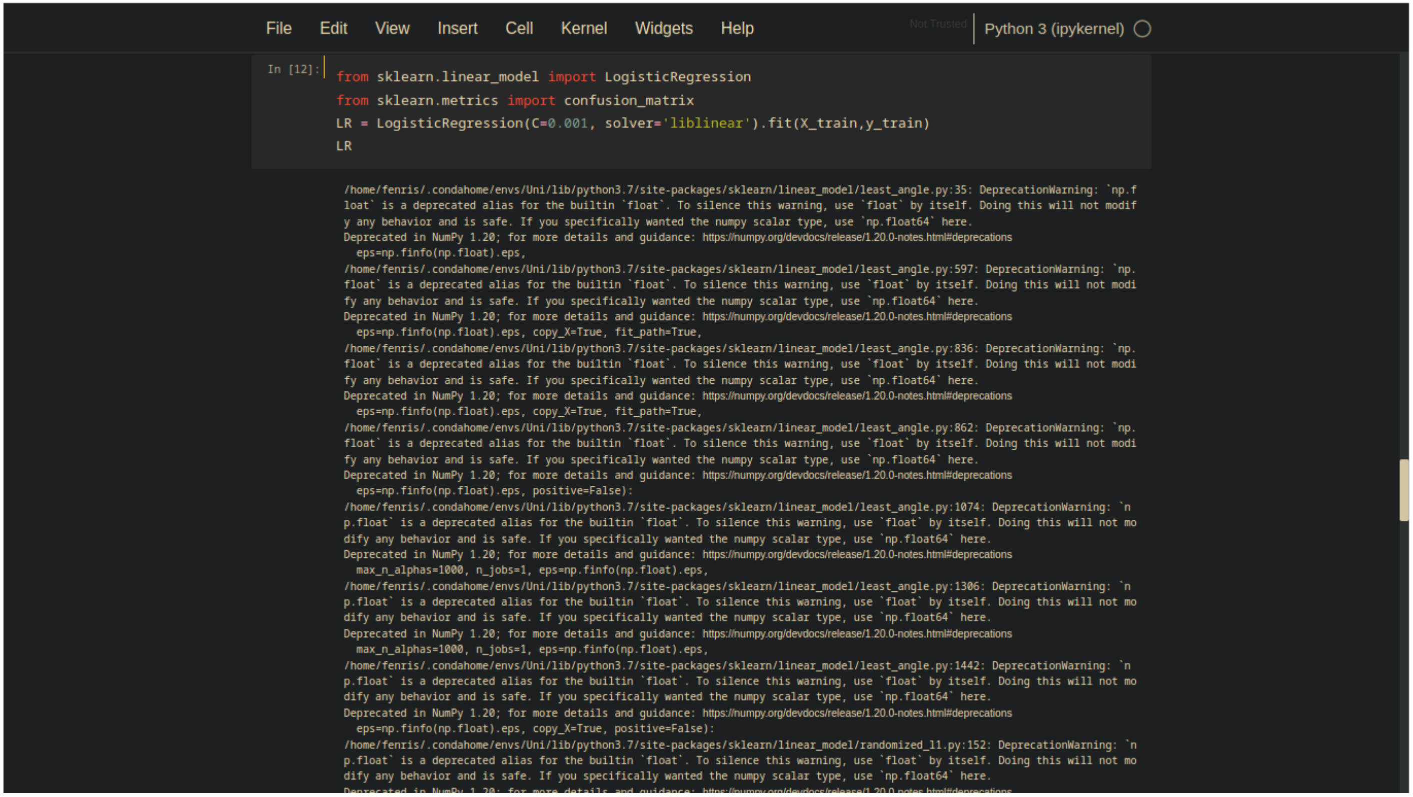
Regularization is a technique used to solve the overfitting problem in machine learning models.

C parameter indicates inverse of regularization strength which must be a positive float. Smaller values specify stronger regularization.

https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LogisticRegression.html

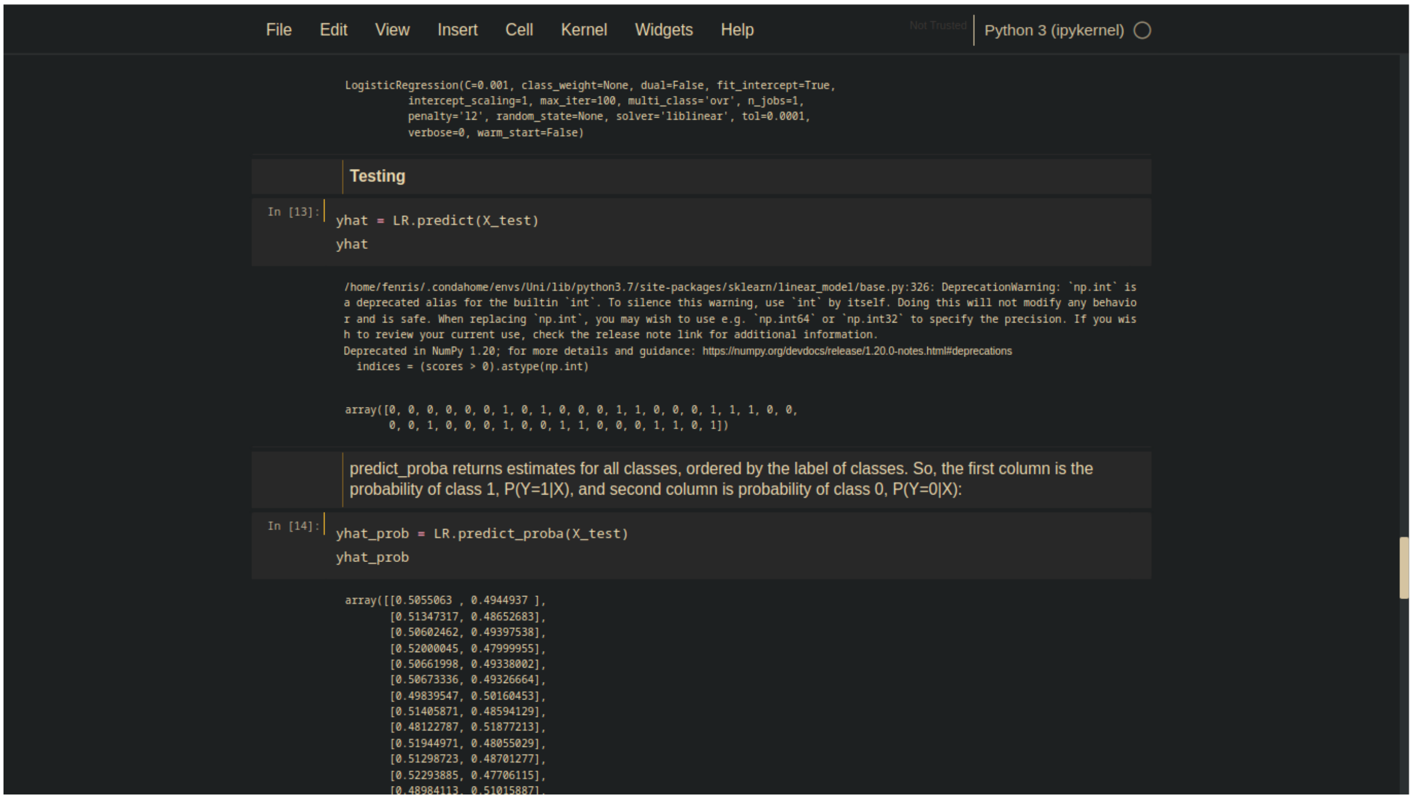
```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix
LR = LogisticRegression(C=0.001, solver='liblinear').fit(X_train,y_train)
LR
```

```
/home/fenris/.condahome/envs/Uni/lib/python3.7/site-packages/sklearn/linear_model/least_angle.py:35: DeprecationWarning: `np.f
loat` is a deprecated alias for the builtin `float`. To silence this warning, use `float` by itself. Doing this will not modif
y any behavior and is safe. If you specifically wanted the numpy scalar type, use `np.float64` here.
Deprecated in NumPy 1.20; for more details and guidance: https://numpy.org/devdocs/release/1.20.0-notes.html#deprecations
```



```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix
LR = LogisticRegression(C=0.001, solver='liblinear').fit(X_train,y_train)
LR
```

```
/home/fenris/.condahome/envs/Uni/lib/python3.7/site-packages/sklearn/linear_model/least_angle.py:35: DeprecationWarning: `np.f
loat` is a deprecated alias for the builtin `float`. To silence this warning, use `float` by itself. Doing this will not modif
y any behavior and is safe. If you specifically wanted the numpy scalar type, use `np.float64` here.
Deprecated in NumPy 1.20; for more details and guidance: https://numpy.org/devdocs/release/1.20.0-notes.html#deprecations
  eps=np.finfo(np.float).eps,
/home/fenris/.condahome/envs/Uni/lib/python3.7/site-packages/sklearn/linear_model/least_angle.py:597: DeprecationWarning: `np.
float` is a deprecated alias for the builtin `float`. To silence this warning, use `float` by itself. Doing this will not modi
fy any behavior and is safe. If you specifically wanted the numpy scalar type, use `np.float64` here.
Deprecated in NumPy 1.20; for more details and guidance: https://numpy.org/devdocs/release/1.20.0-notes.html#deprecations
  eps=np.finfo(np.float).eps, copy_X=True, fit_path=True,
/home/fenris/.condahome/envs/Uni/lib/python3.7/site-packages/sklearn/linear_model/least_angle.py:836: DeprecationWarning: `np.
float` is a deprecated alias for the builtin `float`. To silence this warning, use `float` by itself. Doing this will not modi
fy any behavior and is safe. If you specifically wanted the numpy scalar type, use `np.float64` here.
Deprecated in NumPy 1.20; for more details and guidance: https://numpy.org/devdocs/release/1.20.0-notes.html#deprecations
  eps=np.finfo(np.float).eps, copy_X=True, fit_path=True,
/home/fenris/.condahome/envs/Uni/lib/python3.7/site-packages/sklearn/linear_model/least_angle.py:862: DeprecationWarning: `np.
float` is a deprecated alias for the builtin `float`. To silence this warning, use `float` by itself. Doing this will not modi
fy any behavior and is safe. If you specifically wanted the numpy scalar type, use `np.float64` here.
Deprecated in NumPy 1.20; for more details and guidance: https://numpy.org/devdocs/release/1.20.0-notes.html#deprecations
  eps=np.finfo(np.float).eps, positive=False):
/home/fenris/.condahome/envs/Uni/lib/python3.7/site-packages/sklearn/linear_model/least_angle.py:1074: DeprecationWarning: `n
p.float` is a deprecated alias for the builtin `float`. To silence this warning, use `float` by itself. Doing this will not mo
dify any behavior and is safe. If you specifically wanted the numpy scalar type, use `np.float64` here.
Deprecated in NumPy 1.20; for more details and guidance: https://numpy.org/devdocs/release/1.20.0-notes.html#deprecations
  max_n_alphas=1000, n_jobs=1, eps=np.finfo(np.float).eps,
/home/fenris/.condahome/envs/Uni/lib/python3.7/site-packages/sklearn/linear_model/least_angle.py:1306: DeprecationWarning: `n
p.float` is a deprecated alias for the builtin `float`. To silence this warning, use `float` by itself. Doing this will not mo
dify any behavior and is safe. If you specifically wanted the numpy scalar type, use `np.float64` here.
Deprecated in NumPy 1.20; for more details and guidance: https://numpy.org/devdocs/release/1.20.0-notes.html#deprecations
  max_n_alphas=1000, n_jobs=1, eps=np.finfo(np.float).eps,
/home/fenris/.condahome/envs/Uni/lib/python3.7/site-packages/sklearn/linear_model/least_angle.py:1442: DeprecationWarning: `n
p.float` is a deprecated alias for the builtin `float`. To silence this warning, use `float` by itself. Doing this will not mo
dify any behavior and is safe. If you specifically wanted the numpy scalar type, use `np.float64` here.
Deprecated in NumPy 1.20; for more details and guidance: https://numpy.org/devdocs/release/1.20.0-notes.html#deprecations
  eps=np.finfo(np.float).eps, copy_X=True, positive=False):
/home/fenris/.condahome/envs/Uni/lib/python3.7/site-packages/sklearn/linear_model/randomized_l1.py:152: DeprecationWarning: `n
p.float` is a deprecated alias for the builtin `float`. To silence this warning, use `float` by itself. Doing this will not mo
dify any behavior and is safe. If you specifically wanted the numpy scalar type, use `np.float64` here.
Deprecated in NumPy 1.20; for more details and guidance: https://numpy.org/devdocs/release/1.20.0-notes.html#deprecations
```



```
LogisticRegression(C=0.001, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
          penalty='l2', random_state=None, solver='liblinear', tol=0.0001,
          verbose=0, warm_start=False)
```

Testing

```
In [13]: yhat = LR.predict(X_test)
         yhat
```

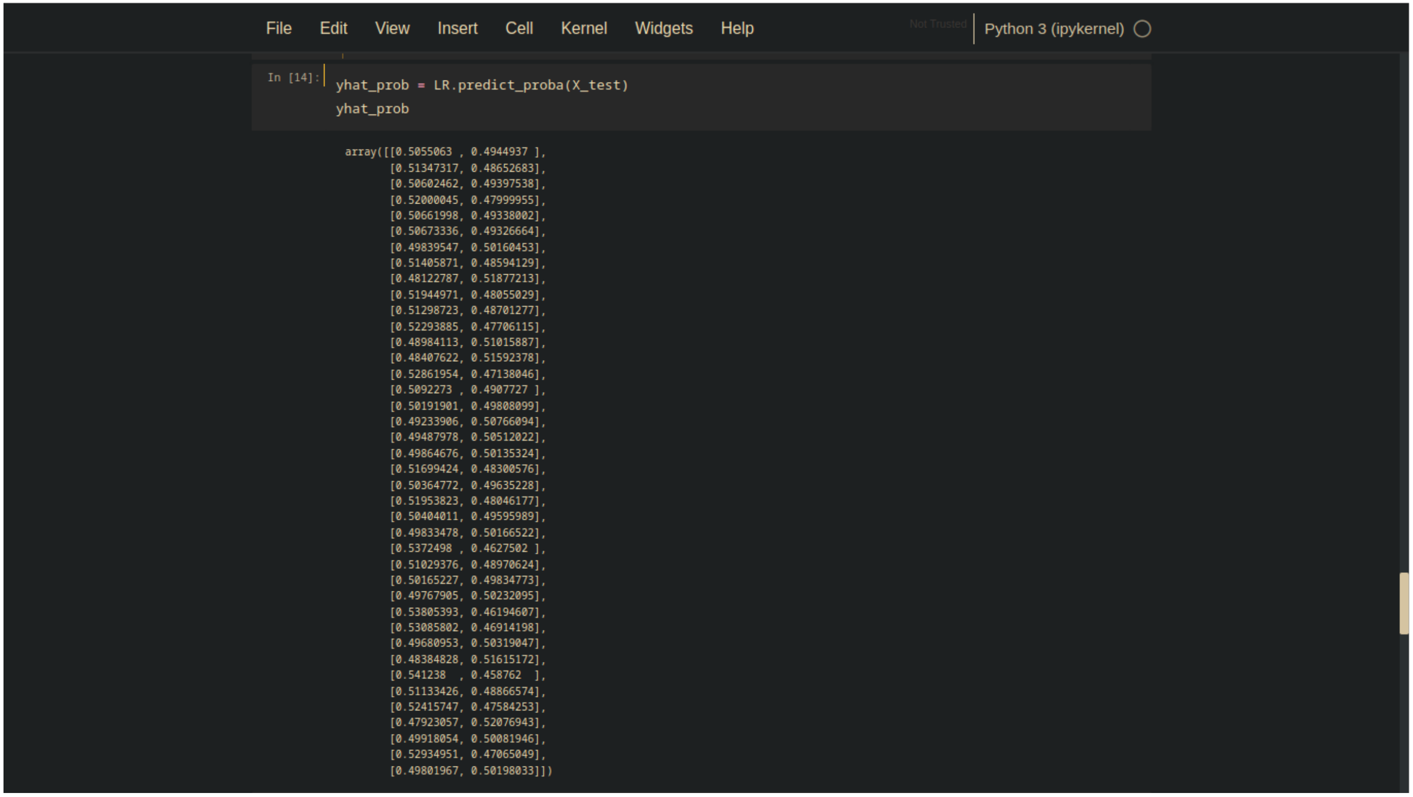
```
/home/fenris/.condahome/envs/Uni/lib/python3.7/site-packages/sklearn/linear_model/base.py:326: DeprecationWarning: `np.int` is
a deprecated alias for the builtin `int`. To silence this warning, use `int` by itself. Doing this will not modify any behavio
r and is safe. When replacing `np.int`, you may wish to use e.g. `np.int64` or `np.int32` to specify the precision. If you wis
h to review your current use, check the release note link for additional information.
Deprecated in NumPy 1.20; for more details and guidance: https://numpy.org/devdocs/release/1.20.0-notes.html#deprecations
  indices = (scores > 0).astype(np.int)
```

```
array([0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 1, 1, 0, 0, 0, 1, 1, 1, 0, 0,
       0, 0, 1, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 1, 1, 0, 1])
```

predict_proba returns estimates for all classes, ordered by the label of classes. So, the first column is the probability of class 1, P(Y=1|X), and second column is probability of class 0, P(Y=0|X):

```
In [14]: yhat_prob = LR.predict_proba(X_test)
         yhat_prob
```

```
array([[0.5055063 , 0.4944937 ],
       [0.51347317, 0.48652683],
       [0.50602462, 0.49397538],
       [0.52000045, 0.47999955],
       [0.50661998, 0.49338002],
       [0.50673336, 0.49326664],
       [0.49839547, 0.50160453],
       [0.51405871, 0.48594129],
       [0.48122787, 0.51877213],
       [0.51944971, 0.48055029],
       [0.51298723, 0.48701277],
       [0.52293885, 0.47706115],
       [0.48984113, 0.51015887],
```



```
In [14]: yhat_prob = LR.predict_proba(X_test)
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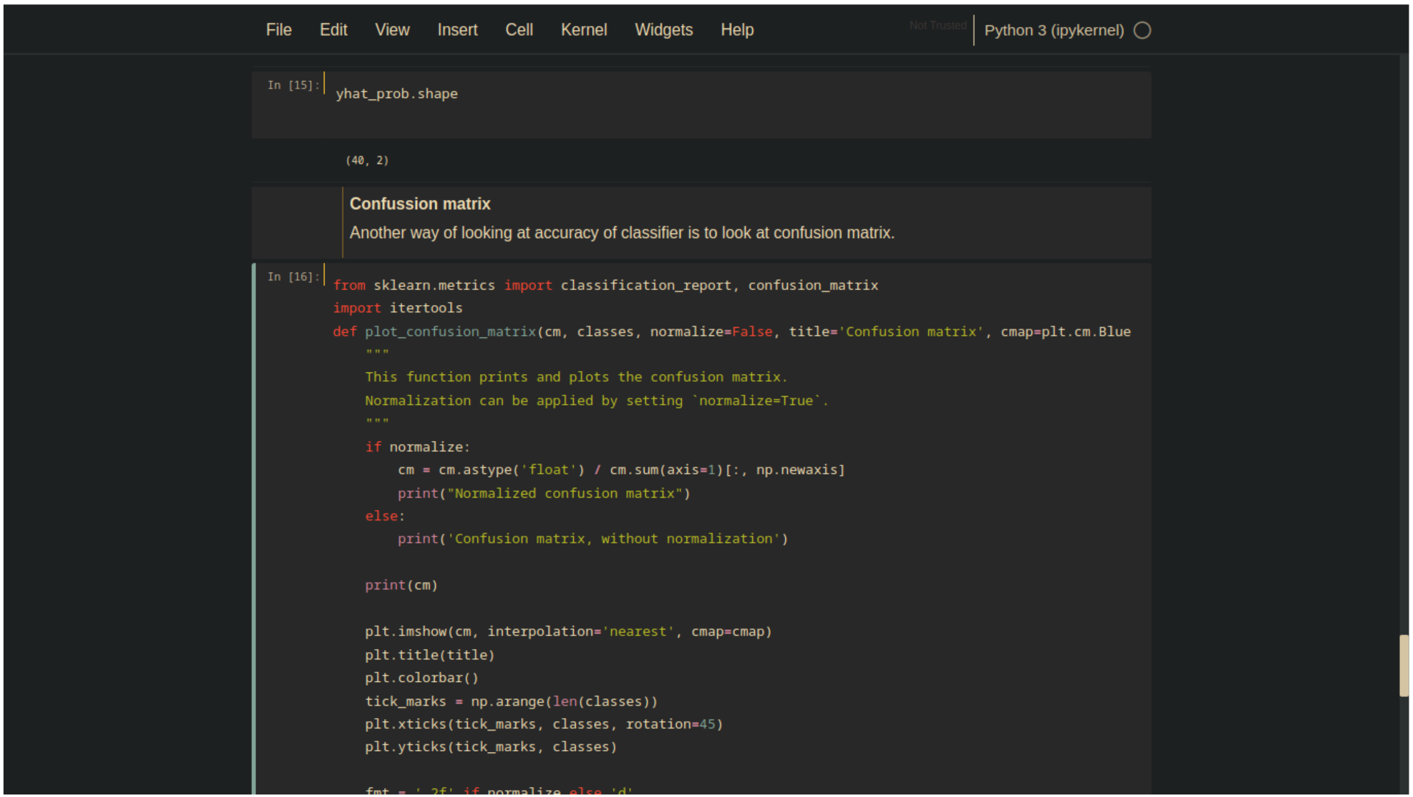
```
array([[0.5055063 , 0.4944937 ],
       [0.51347317, 0.48652683],
       [0.50602462, 0.49397538],
       [0.52000045, 0.47999955],
       [0.50661998, 0.49338002],
       [0.50673336, 0.49326664],
       [0.49839547, 0.50160453],
       [0.51405871, 0.48594129],
       [0.48122787, 0.51877213],
       [0.51944971, 0.48055029],
       [0.51298723, 0.48701277],
       [0.52293885, 0.47706115],
       [0.48984113, 0.51015887],
       [0.48407622, 0.51592378],
       [0.52861954, 0.47138046],
       [0.5092273 , 0.4907727 ],
       [0.50191901, 0.49808099],
       [0.49233906, 0.50766094],
       [0.49487978, 0.50512022],
       [0.49864676, 0.50135324],
       [0.51699424, 0.48300576],
       [0.50364772, 0.49635228],
       [0.51953823, 0.48046177],
       [0.50404011, 0.49595989],
       [0.49833478, 0.50166522],
       [0.5372498 , 0.4627502 ],
       [0.51029376, 0.48970624],
       [0.50165227, 0.49834773],
       [0.49767905, 0.50232095],
       [0.53805393, 0.46194607],
       [0.53085802, 0.46914198],
       [0.49680953, 0.50319047],
       [0.48384828, 0.51615172],
       [0.541238  , 0.458762  ],
       [0.51133426, 0.48866574],
       [0.52415747, 0.47584253],
       [0.47923057, 0.52076943],
       [0.49918054, 0.50081946],
       [0.52934951, 0.47065049],
       [0.49801967, 0.50198033]])
```



```
yhat_prob.shape
```

```
(40, 2)
```

Confussion matrix

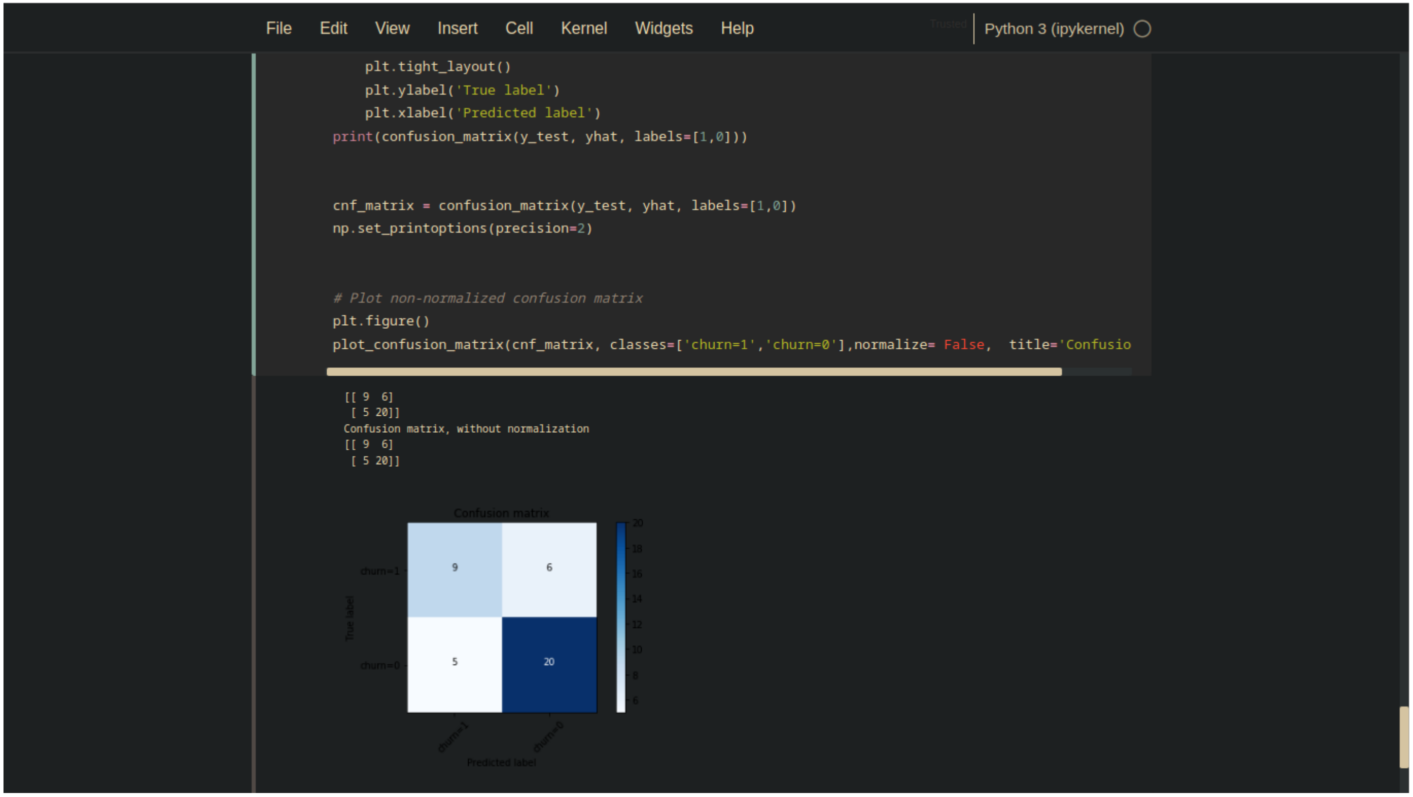
Another way of looking at accuracy of classifier is to look at confusion matrix.

```
from sklearn.metrics import classification_report, confusion_matrix
import itertools
def plot_confusion_matrix(cm, classes, normalize=False, title='Confusion matrix', cmap=plt.cm.Blue
    """
    This function prints and plots the confusion matrix.
    Normalization can be applied by setting `normalize=True`.
    """
    if normalize:
        cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
        print("Normalized confusion matrix")
    else:
        print('Confusion matrix, without normalization')

    print(cm)

    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation=45)
    plt.yticks(tick_marks, classes)

    fmt = '.2f' if normalize else 'd'
```

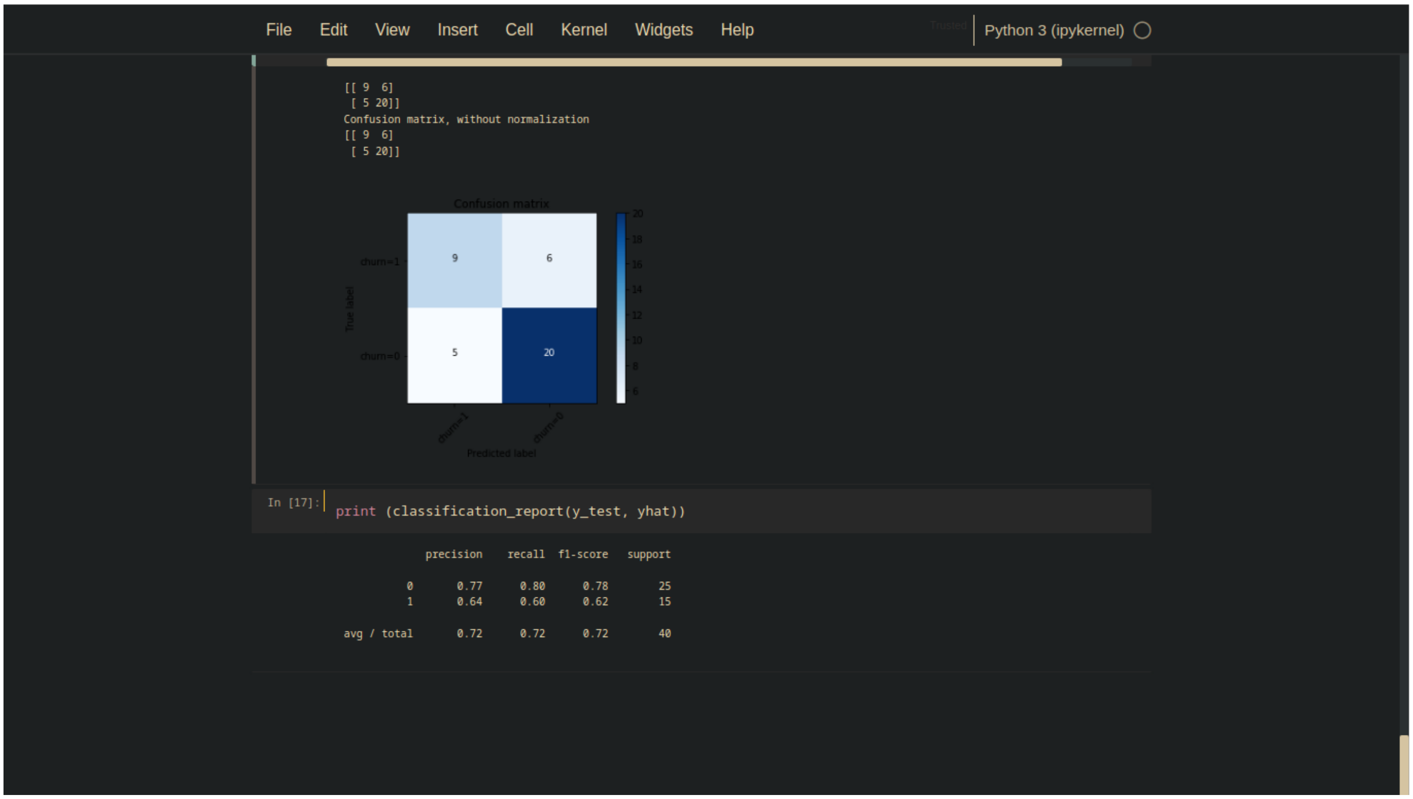


```
    plt.tight_layout()
    plt.ylabel('True label')
    plt.xlabel('Predicted label')
print(confusion_matrix(y_test, yhat, labels=[1,0]))


cnf_matrix = confusion_matrix(y_test, yhat, labels=[1,0])
np.set_printoptions(precision=2)


# Plot non-normalized confusion matrix
plt.figure()
plot_confusion_matrix(cnf_matrix, classes=['churn=1','churn=0'],normalize= False,  title='Confusio
```

```
[[ 9  6]
 [ 5 20]]
Confusion matrix, without normalization
[[ 9  6]
 [ 5 20]]
```



```
[[ 9  6]
 [ 5 20]]
Confusion matrix, without normalization
[[ 9  6]
 [ 5 20]]
```

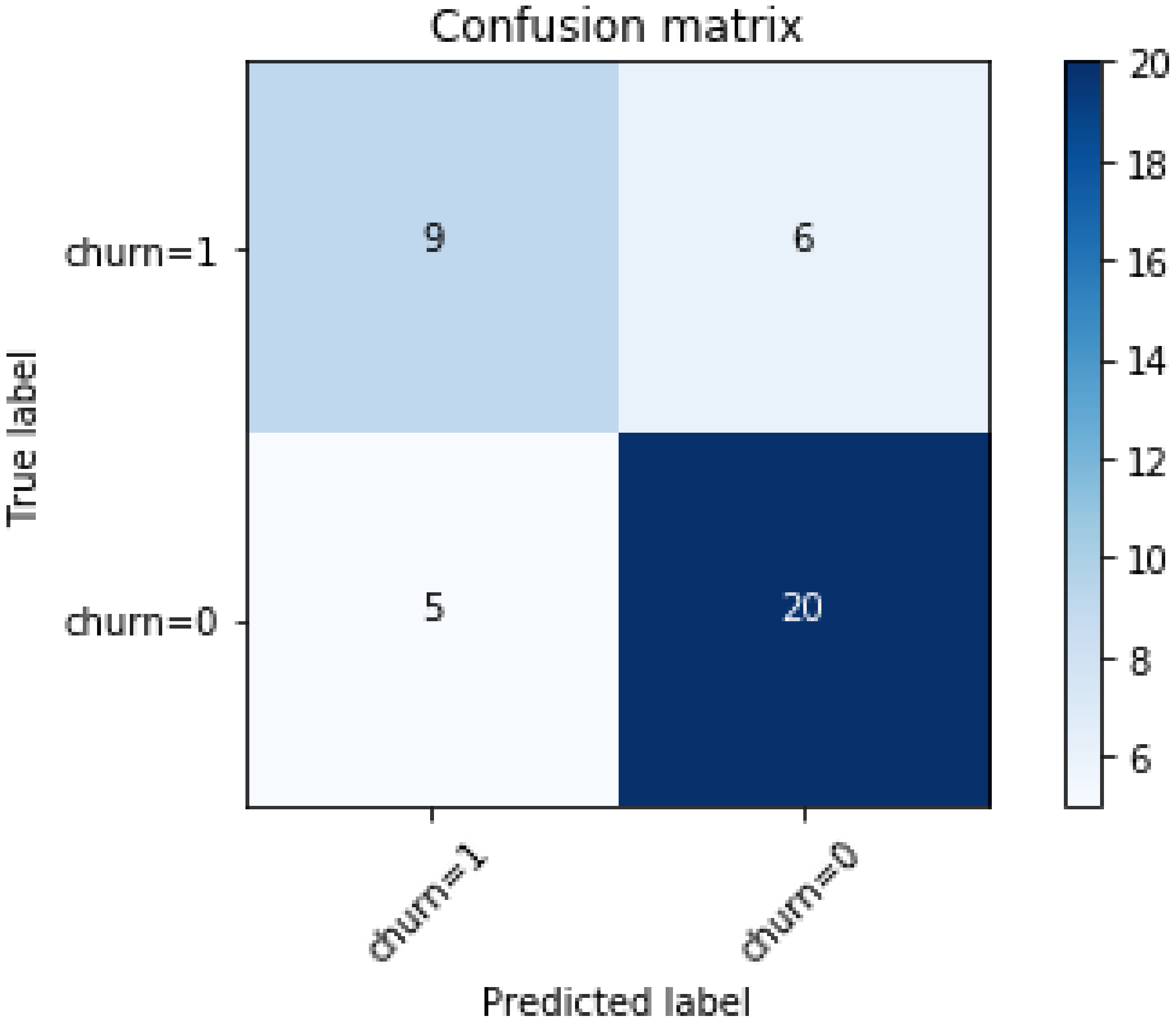
```
In [17]: print (classification_report(y_test, yhat))
```

```
             precision    recall  f1-score   support

          0       0.77      0.80      0.78        25
          1       0.64      0.60      0.62        15

avg / total       0.72      0.72      0.72        40
```

5. Observations :



Learning Outcomes :

- Logistic Regression.
- Tuning the model with the appropriate selection of of solver.
- I have learnt about EDA
- I have learnt about Data pre-processing and selection
- I have learnt about Training and Testing
- I have learnt about missing value analysis
- I have learnt Confussion Matrix.

S. No.	Parameters	Marks Obtained	Maximum Marks
1.			
2.			
3.			