Business Case for PRCL -0019

Project Summary :

Requirement

FicZon Inc is an IT solution provider with products ranging from on-premises products to SAS based solutions. FicZon major leads generation channel is digital and through their website.FicZon business is majorly dependent on the sales force effectiveness. As the market is maturing and more new competitors entering the market, FicZon is experiencing the dip in sales. Effective sales is dependent on lead quality and as of now, this is based on manual categorization and highly depended on sales staff. Though there is a quality process, which continuously updates the lead categorization, it's value is in for post analysis, rather than conversation.FicZon wants to explore Machine Learning to pre-categorize the lead quality and as result, expecting significant increase in sales effectiveness.

PROJECT GOAL:

1. Data exploration insights – Sales effectiveness.
2. ML model to predict the Lead Category.

Analysis

- The data is supervised and categorical. The predictor variables are nominal. The target variable 'Status' is nominal as well.
- Most of the columns had a lot of different labels, so we compressed and merged the labels such that only the main ones were included and then used Label Encoding. The predictor variable was categorized into two types 'Good Lead' and 'Bad Lead'.
- SMOTE is used ajdusting the sampling data. For training the data and predicting the target, algorithms used are Logistic Regression, Support Vector Machine, Decision Tree, Random Forest, Naive Bayes, K-Nearest Neighbor, XGBoost Classifier and Artificial Neural Network.

Summary

The project is done with the purpose of finding out the Lead Quality, whether the lead should be followed or not. The company motive is to invest in the right prospects. So therefore we divided the Lead as 'Good' or 'Bad'. This resulted in increase of accuracy drastically. The following steps were carried out:

1. Import the data, find out the predictor and target and drop columns which has no use in analysis.
2. Compress and merge the labels such that only the main ones are included and use Label Encoding.
3. Split it into test and train and use SMOTE.
4. Train the data using algorithms like Logistic Regression, Support Vector Machine, Decision Tree, Random Forest, Naive Bayes, K-Nearest Neighbor, XGBoost Classifier and Artificial Neural Network and check the accuracy to find out which algorithm is the best.

5. Export the model with highest accuracy.

Results

- XGBoost Classifier gave an accuracy of 70%.

```
# Importing the necessary libraries
from sqlalchemy import create_engine
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split, GridSearchCV, RandomizedSearchCV
from imblearn.over_sampling import SMOTE
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
```

```
import warnings
warnings.filterwarnings('ignore')
%matplotlib inline
```

Data

Importing Raw Data`

```
db_host = '18.136.56.185'
username = 'dm_team2'
user_pass = '-------'
db_name = 'project_sales'

conn = create_engine('mysql+pymysql://'+username+':'+user_pass+'@'+db_host+'/'+db_name)
conn.table_names()
```

```
['data']
```

```
query = 'select * from data'
```

```
# Importing raw data through SQL Server
data = pd.read_sql(query,conn)
```

Source Code

Exploratory Data Analysis

```
data.shape
```

```
(7422, 9)
```

```
data.head()
```

	Created	Product_ID	Source	Mobile	EMAIL	Sales_Agent	Location	Delivery_Mode	Status
0	14-11-2018 10:05		Website	984XXXXXXX	aXXXXXXX@gmail.com	Sales-Agent-11		Mode-5	Open
1	14-11-2018 09:22		Website	XXXXXXX	#VALUE!	Sales-Agent-10		Mode-5	Open
2	14-11-2018 09:21		Website	XXXXXXX	dXXXXXXX@yahoo.com	Sales-Agent-10		Mode-5	Open
3	14-11-2018 08:46		Website	XXXXXXX	wXXXXXXX@gmail.com	Sales-Agent-10		Mode-5	Open
4	14-11-2018 07:34		Website	XXXXXXX	cXXXXXXX@gmail.com	Sales-Agent-10		Mode-5	Open

```
# Dropping the columns which are of no use in analysis
data.drop(['Mobile'],axis=1,inplace=True)
data.drop(['EMAIL'],axis=1,inplace=True)
data.drop(['Created'],axis=1,inplace=True)
```

```
# Dropping rows with missing data because they are few
data.replace('',np.nan,inplace=True)
data.dropna(inplace=True)
data.reset_index(inplace=True,drop=True)
data.shape
```

```
(7328, 6)
```

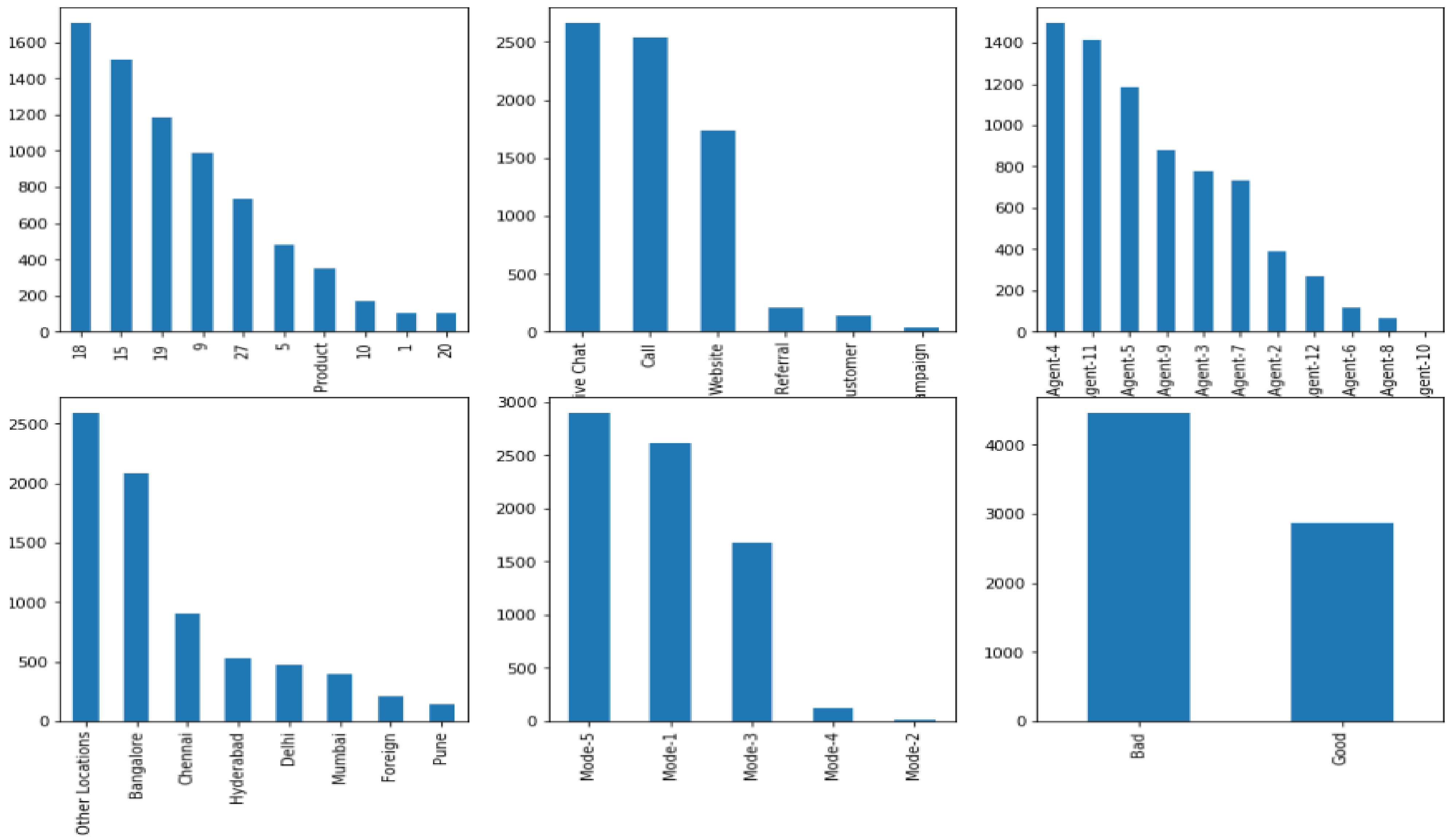
```
# Compressing and Merging the labes in column
data.Source.replace(['Live Chat-Direct','Live Chat-Google Organic','Live Chat -PPC','Live Chat-Blog','Live Chat-Quora',
                    'Live Chat-CPC','Live Chat-Google Ads','Live Chat-Adwords Remarketing','Live Chat-Youtube',
                    'Live Chat-Justdial'],'Live Chat',inplace=True)
data.Source.replace(['Existing Client','CRM form','Personal Contact'],'Existing Customer',inplace=True)
data.Source.replace('By Recommendation','Customer Referral',inplace=True)
data.Source.replace(['US Website','Just Dial'],'Website',inplace=True)
data.Source.replace(['E-mail Campaign','SMS Campaign','E-Mail Message','Other'],'Campaign',inplace=True)
```

```python
data.head()
```

	Product_ID	Source	Sales_Agent	Location	Delivery_Mode	Status
0	9	Live Chat	Sales-Agent-3	Bangalore	Mode-1	Good
1	19	Call	Sales-Agent-4	Other Locations	Mode-5	Good
2	18	Website	Sales-Agent-11	Other Locations	Mode-1	Good
3	15	Website	Sales-Agent-7	Hyderabad	Mode-1	Bad
4	18	Call	Sales-Agent-7	Bangalore	Mode-1	Good

```python
# Plotting the labels in each column
plt.figure(figsize=(15,10))
plt.subplot(2,3,1)
data.Product_ID.value_counts().plot(kind='bar')
plt.subplot(2,3,2)
data.Source.value_counts().plot(kind='bar')
plt.subplot(2,3,3)
data.Sales_Agent.value_counts().plot(kind='bar')
plt.subplot(2,3,4)
data.Location.value_counts().plot(kind='bar')
plt.subplot(2,3,5)
data.Delivery_Mode.value_counts().plot(kind='bar')
plt.subplot(2,3,6)
data.Status.value_counts().plot(kind='bar')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x1777f1b10f0>
```



Data Processing/ Data Munging

```
# Label encoding all the columns
enc = LabelEncoder()
for i in (0,1,2,3,4,5):
    data.iloc[:,i] = enc.fit_transform(data.iloc[:,i])
data.head()
```

	Product_ID	Source	Sales_Agent	Location	Delivery_Mode	Status
0	8	4	4	0	0	1
1	4	0	5	6	4	1
2	3	5	1	6	0	1
3	2	5	8	4	0	0
4	3	0	8	0	0	1

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7328 entries, 0 to 7327
Data columns (total 6 columns):
Product_ID       7328 non-null int32
Source           7328 non-null int32
Sales_Agent      7328 non-null int32
Location         7328 non-null int32
Delivery_Mode    7328 non-null int32
Status           7328 non-null int32
dtypes: int32(6)
memory usage: 171.8 KB
```

```
# Checking the correlation coeffecient
data.corr()
```

	Product_ID	Source	Sales_Agent	Location	Delivery_Mode	Status
Product_ID	1.000000	0.074868	0.056065	-0.226961	-0.181464	0.138943
Source	0.074868	1.000000	-0.023186	-0.003034	-0.216516	-0.015411
Sales_Agent	0.056065	-0.023186	1.000000	-0.140876	-0.224688	0.137074
Location	-0.226961	-0.003034	-0.140876	1.000000	0.414193	-0.347418
Delivery_Mode	-0.181464	-0.216516	-0.224688	0.414193	1.000000	-0.220445
Status	0.138943	-0.015411	0.137074	-0.347418	-0.220445	1.000000

```
y = data.Status
X = data.iloc[:,[0,1,2,3,4]]
```

```
# Splitting into training and testing data for accuracy
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.3,random_state=10)
```

```
X_train.shape
```

```
(5129, 5)
```

```
X_test.shape
```

```
(2199, 5)
```

```
# SMOTE for sampling technique
smote = SMOTE()
X_train, y_train = smote.fit_sample(X_train,y_train)
```

```
X_train.shape
```

```
(6294, 5)
```

```
X_test.shape
```

```
(2199, 5)
```

Models

1. Logistic Regression

```
# Training the model
from sklearn.linear_model import LogisticRegression
model_logr = LogisticRegression()
model_logr.fit(X_train,y_train)
```

```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='warn',
          n_jobs=None, penalty='l2', random_state=None, solver='warn',
          tol=0.0001, verbose=0, warm_start=False)
```

```
# Predicting the model
y_predict_log = model_logr.predict(X_test)
```

```
# Finding accuracy, precision, recall and confusion matrix
print(accuracy_score(y_test,y_predict_log))
print(classification_report(y_test,y_predict_log))
```

```
0.6575716234652115
              precision    recall  f1-score   support

           0       0.74      0.66      0.70      1319
           1       0.56      0.65      0.60       880

   micro avg       0.66      0.66      0.66      2199
   macro avg       0.65      0.66      0.65      2199
weighted avg       0.67      0.66      0.66      2199
```

```
print(confusion_matrix(y_test,y_predict_log))
```

```
[[872 447]
 [306 574]]
```

2. Support Vector Machine

```
# Training the model
from sklearn.svm import SVC
parameters = {'kernel': ['rbf'], 'gamma': [0.1,1,5], 'C': [0.1,1,10,100]}
rbf_svc = RandomizedSearchCV(SVC(),parameters).fit(X_train,y_train)
```

```
rbf_svc.best_params_
```

```
{'kernel': 'rbf', 'gamma': 1, 'C': 1}
```

```
# Predicting the model
y_predict_svm = rbf_svc.predict(X_test)
```

```
# Finding accuracy, precision, recall and confusion matrix
print(accuracy_score(y_test,y_predict_svm))
print(classification_report(y_test,y_predict_svm))
```

```
0.6816734879490678
              precision    recall  f1-score   support

           0       0.75      0.71      0.73      1319
           1       0.59      0.65      0.62       880

   micro avg       0.68      0.68      0.68      2199
   macro avg       0.67      0.68      0.67      2199
weighted avg       0.69      0.68      0.68      2199
```

```
print(confusion_matrix(y_test,y_predict_svm))
```

```
[[930 389]
 [311 569]]
```

3. Decision Tree with GridSearchCV

```
# Training the model
from sklearn.tree import DecisionTreeClassifier

classifier_dtg=DecisionTreeClassifier(random_state=42,splitter='best')
parameters=[{'min_samples_split':[2,3,4,5],'criterion':['gini']},{'min_samples_split':[2,3,4,5],'criterion':['entropy']}]

model_griddtree=GridSearchCV(estimator=classifier_dtg, param_grid=parameters, scoring='accuracy',cv=10)
model_griddtree.fit(X_train,y_train)
```

```
GridSearchCV(cv=10, error_score='raise-deprecating',
       estimator=DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=None,
            max_features=None, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, presort=False, random_state=42,
            splitter='best'),
       fit_params=None, iid='warn', n_jobs=None,
       param_grid=[{'min_samples_split': [2, 3, 4, 5], 'criterion': ['gini']}, {'min_samples_split': [2, 3, 4, 5], 'crite
rion': ['entropy']}],
       pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
       scoring='accuracy', verbose=0)
```

```
model_griddtree.best_params_
```

```
{'criterion': 'gini', 'min_samples_split': 2}
```

```
# Predicting the model
y_predict_dtree = model_griddtree.predict(X_test)
```

```
# Finding accuracy, precision, recall and confusion matrix
print(accuracy_score(y_test,y_predict_dtree))
print(classification_report(y_test,y_predict_dtree))
```

```
0.6807639836289222
              precision    recall  f1-score   support

           0       0.74      0.73      0.73      1319
           1       0.60      0.61      0.60       880

   micro avg       0.68      0.68      0.68      2199
   macro avg       0.67      0.67      0.67      2199
weighted avg       0.68      0.68      0.68      2199
```

```
print(confusion_matrix(y_test,y_predict_dtree))
```

```
[[961 358]
 [344 536]]
```

4. Random Forest with GridSearchCV

```
# Training the model
from sklearn.ensemble import RandomForestClassifier

classifier_rfg=RandomForestClassifier(random_state=33,n_estimators=23)
parameters=[{'min_samples_split':[2,3,4,5],'criterion':['gini','entropy'],'min_samples_leaf':[1,2,3]}]

model_gridrf=GridSearchCV(estimator=classifier_rfg, param_grid=parameters, scoring='accuracy',cv=10)
model_gridrf.fit(X_train,y_train)
```

```
GridSearchCV(cv=10, error_score='raise-deprecating',
       estimator=RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
            max_depth=None, max_features='auto', max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, n_estimators=23, n_jobs=None,
            oob_score=False, random_state=33, verbose=0, warm_start=False),
       fit_params=None, iid='warn', n_jobs=None,
       param_grid=[{'min_samples_split': [2, 3, 4, 5], 'criterion': ['gini', 'entropy'], 'min_samples_leaf': [1, 2, 3]}],
       pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
       scoring='accuracy', verbose=0)
```

```
model_gridrf.best_params_
```

```
{'criterion': 'entropy', 'min_samples_leaf': 1, 'min_samples_split': 5}
```

```
# Predicting the model
y_predict_rf = model_gridrf.predict(X_test)
```

```
# Finding accuracy, precision, recall and confusion matrix
print(accuracy_score(y_test,y_predict_rf))
print(classification_report(y_test,y_predict_rf))
```

```
0.6889495225102319
              precision    recall  f1-score   support

           0       0.75      0.71      0.73      1319
           1       0.60      0.65      0.63       880

   micro avg       0.69      0.69      0.69      2199
   macro avg       0.68      0.68      0.68      2199
weighted avg       0.69      0.69      0.69      2199
```

```
print(confusion_matrix(y_test,y_predict_rf))
```

```
[[942 377]
 [307 573]]
```

5. Naive Bayes Bernoulli

```
# Training the model
from sklearn.naive_bayes import BernoulliNB
model_nb = BernoulliNB()
model_nb.fit(X_train,y_train)
```

```
BernoulliNB(alpha=1.0, binarize=0.0, class_prior=None, fit_prior=True)
```

```
# Predicting the model
y_predict_nb = model_nb.predict(X_test)
```

```
# Finding accuracy, precision, recall and confusion matrix
print(accuracy_score(y_test,y_predict_nb))
print(classification_report(y_test,y_predict_nb))
```

```
0.6380172805820827
              precision    recall  f1-score   support

           0       0.70      0.70      0.70      1319
           1       0.55      0.55      0.55       880

   micro avg       0.64      0.64      0.64      2199
   macro avg       0.62      0.62      0.62      2199
weighted avg       0.64      0.64      0.64      2199
```

```
print(confusion_matrix(y_test,y_predict_nb))
```

```
[[918 401]
 [395 485]]
```

6. K-Nearest Nieghbor

```
# Training the model
from sklearn.neighbors import KNeighborsClassifier
model_knn = KNeighborsClassifier(n_neighbors=6,metric='euclidean') # Maximum accuracy for n=10
model_knn.fit(X_train,y_train)
```

```
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='euclidean',
           metric_params=None, n_jobs=None, n_neighbors=6, p=2,
           weights='uniform')
```

```
# Predicting the model
y_predict_knn = model_knn.predict(X_test)
```

```
# Finding accuracy, precision, recall and confusion matrix
print(accuracy_score(y_test,y_predict_knn))
print(classification_report(y_test,y_predict_knn))
```

```
0.6684856753069577
              precision    recall  f1-score   support

           0       0.71      0.76      0.73      1319
           1       0.59      0.54      0.56       880

   micro avg       0.67      0.67      0.67      2199
   macro avg       0.65      0.65      0.65      2199
weighted avg       0.66      0.67      0.67      2199
```

```
print(confusion_matrix(y_test,y_predict_knn))
```

```
[[997 322]
 [407 473]]
```

7. XGBoost Classifier

```
# Training the model
from xgboost import XGBClassifier
model_xgb = XGBClassifier(n_estimators=450,max_depth=17,gamma=5,learning_rate=0.01,random_state=10)
model_xgb.fit(X_train,y_train)
```

```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
       colsample_bytree=1, gamma=5, learning_rate=0.01, max_delta_step=0,
       max_depth=17, min_child_weight=1, missing=None, n_estimators=450,
       n_jobs=1, nthread=None, objective='binary:logistic',
       random_state=10, reg_alpha=0, reg_lambda=1, scale_pos_weight=1,
       seed=None, silent=True, subsample=1)
```

```
# Predicting the model
y_predict_xgb = model_xgb.predict(X_test.values)
```

```
# Finding accuracy, precision, recall and confusion matrix
print(accuracy_score(y_test,y_predict_xgb))
print(classification_report(y_test,y_predict_xgb))
```

```
0.6912232833105957
              precision    recall  f1-score   support

           0       0.77      0.70      0.73      1319
           1       0.60      0.68      0.64       880

   micro avg       0.69      0.69      0.69      2199
   macro avg       0.68      0.69      0.68      2199
weighted avg       0.70      0.69      0.69      2199
```

```
print(confusion_matrix(y_test,y_predict_xgb))
```

```
[[918 401]
 [278 602]]
```

8. Artificial Neural Network

```
# Training the model
from sklearn.neural_network import MLPClassifier
model_mlp = MLPClassifier(hidden_layer_sizes=(100,100,100),batch_size=10,learning_rate_init=0.01,max_iter=2000,random_st
model_mlp.fit(X_train,y_train)
```

```
MLPClassifier(activation='relu', alpha=0.0001, batch_size=10, beta_1=0.9,
       beta_2=0.999, early_stopping=False, epsilon=1e-08,
       hidden_layer_sizes=(100, 100, 100), learning_rate='constant',
       learning_rate_init=0.01, max_iter=2000, momentum=0.9,
       n_iter_no_change=10, nesterovs_momentum=True, power_t=0.5,
       random_state=10, shuffle=True, solver='adam', tol=0.0001,
       validation_fraction=0.1, verbose=False, warm_start=False)
```

```
# Predicting the model
y_predict_mlp = model_mlp.predict(X_test)
```

```
# Finding accuracy, precision, recall and confusion matrix
print(accuracy_score(y_test,y_predict_mlp))
print(classification_report(y_test,y_predict_mlp))
```

```
0.6703046839472487
              precision    recall  f1-score   support

           0       0.79      0.62      0.69      1319
           1       0.57      0.75      0.64       880

   micro avg       0.67      0.67      0.67      2199
   macro avg       0.68      0.68      0.67      2199
weighted avg       0.70      0.67      0.67      2199
```

```
print(confusion_matrix(y_test,y_predict_mlp))
```

```
[[818 501]
 [224 656]]
```

```
# Exporting the trained model
from sklearn.externals import joblib
joblib.dump(model_xgb,'FicZon_Sales_Lead.ml')
```

```
['FicZon_Sales_Lead.ml']
```