Introduction to Machine Learning

Assignment

The Data School

Student Name : Joseph Hencil Peter

NRIC: S7967093F

Description: ML Model to predict a customer will become a serious delinquent in terms of loan repayment.

Objectives

After completing this assignment, you should be able to independently:

1. Perform Basic Data Preparation and Analysis on a Dataset
2. Train a Machine Learning Model Based on Problem Type
3. Fine Tune a Machine Learning Model
4. Evaluate a Machine Learning Model
5. Save a Trained Machine Learning Model for Future Use

Problem Statement

Banks play a crucial role in market economies. They decide whether customers are eligible for loans and the terms of the loans. For markets and society to function, individuals and companies need access to credit.

Credit scoring algorithms, which make a guess at the probability of default, are adopted by banks to determine whether or not a loan should be granted.

This assignment requires you to delve into the art of credit scoring, and predict whether a customer will become a serious delinquent in terms of loan repayment.

Dataset

You will need the following files for this assignment:

1. loan_default.csv
2. Data Dictionary for loan_default

Instructions

1. Based on what you have learnt in the course, perform necessary data preparation to get a clean dataset.

2. Select a suitable Machine Learning model to solve the problem (i.e. classification / regression?).
3. Train, fine tune and evaluate your Machine Learning model(s).
4. Recommend the best model and save the model as a "pickle" file for future deployment.

The template below has been provided to guide you in the training of your Machine Learning model. Feel free to include more steps where necessary to achieve the goal of the assignment.

Step 1: Import Data and Perform Data Preparation

In [1]:
```
#import libraries
#for dataframe and array
import pandas as pd
import numpy as np

#modelling libraries
import statsmodels.api as sm
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn import metrics
from sklearn import model_selection
from sklearn.model_selection import KFold
from sklearn.model_selection import GridSearchCV, StratifiedKFold
import random

#visualization libraries
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns


#saving trainined models
import joblib
```

1.1 Import Data from CSV file

In [2]:
```
df = pd.read_csv("loan_default.csv")
```

In [3]:
```
df.head()
```

Out[3]:

	RevolvingUtilizationOfUnsecuredLines	Age	NumberOfTime30-59DaysPastDueNotWorse	DebtRatio	MonthlyIncome	Number(
0	0.766127	45	2	0.802982	9120.0	
1	0.957151	40	0	0.121876	2600.0	
2	0.658180	38	1	0.085113	3042.0	
3	0.233810	30	0	0.036050	3300.0	
4	0.907239	49	1	0.024926	63588.0	

2. Examine the state of the data

In [4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150000 entries, 0 to 149999
Data columns (total 11 columns):
 #   Column                                Non-Null Count   Dtype  
---  ------                                --------------   -----  
 0   RevolvingUtilizationOfUnsecuredLines  150000 non-null  float64
 1   Age                                   150000 non-null  int64  
 2   NumberOfTime30-59DaysPastDueNotWorse  150000 non-null  int64  
 3   DebtRatio                             150000 non-null  float64
 4   MonthlyIncome                         120269 non-null  float64
 5   NumberOfOpenCreditLinesAndLoans       150000 non-null  int64  
 6   NumberOfTimes90DaysLate               150000 non-null  int64  
 7   NumberRealEstateLoansOrLines          150000 non-null  int64  
 8   NumberOfTime60-89DaysPastDueNotWorse  150000 non-null  int64  
 9   NumberOfDependents                    146076 non-null  float64
 10  SeriousDelinquency                    150000 non-null  int64  
dtypes: float64(4), int64(7)
memory usage: 12.6 MB
```

3. Basic Statistical Analysis

In [5]:
```
df.describe()
```

Out[5]:

	RevolvingUtilizationOfUnsecuredLines	Age	NumberOfTime30-59DaysPastDueNotWorse	DebtRatio	Month
count	150000.000000	150000.000000	150000.000000	150000.000000	1.20
mean	6.048438	52.295207	0.421033	353.005076	6.67
std	249.755371	14.771866	4.192781	2037.818523	1.43
min	0.000000	0.000000	0.000000	0.000000	0.00
25%	0.029867	41.000000	0.000000	0.175074	3.40
50%	0.154181	52.000000	0.000000	0.366508	5.40
75%	0.559046	63.000000	0.000000	0.868254	8.24
max	50708.000000	109.000000	98.000000	329664.000000	3.00

In [6]:
```
np.unique(df.SeriousDelinquency   )
```

Out[6]: array([0, 1], dtype=int64)

In [7]:
```
np.sum(df.SeriousDelinquency == 0)
```

Out[7]: 139974

In [8]:
```
np.sum(df.SeriousDelinquency == 1)
```

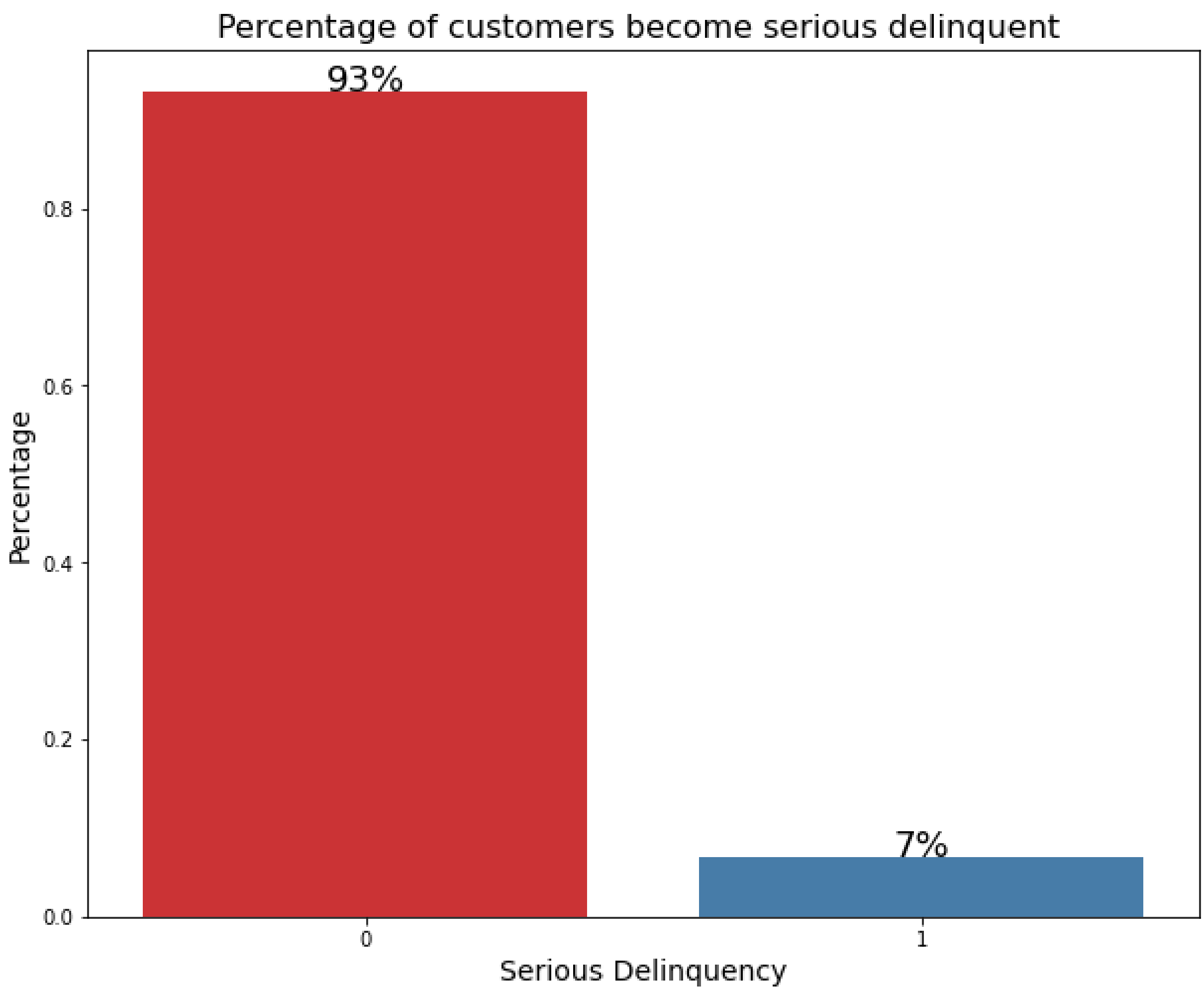
Out[8]: 10026

In [9]:

```
#Plot the target variable using bar chart
plt.figure(figsize=(10,8))
g = sns.barplot(df['SeriousDelinquency'], df['SeriousDelinquency'], palette='Set1', est:

#Anotating the graph
for p in g.patches:
        width, height = p.get_width(), p.get_height()
        x, y = p.get_xy()
        g.text(x+width/2,
               y+height,
               '{:.0%}'.format(height),
               horizontalalignment='center',fontsize=18)

#Setting the labels
plt.xlabel('Serious Delinquency', fontsize=14)
plt.ylabel('Percentage', fontsize=14)
plt.title('Percentage of customers become serious delinquent ', fontsize=16)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: P
ass the following variables as keyword args: x, y. From version 0.12, the only valid p
ositional argument will be `data`, and passing other arguments without an explicit key
word will result in an error or misinterpretation.
  warnings.warn(
```

Out[9]: Text(0.5, 1.0, 'Percentage of customers become serious delinquent ')



Above chart clearly shows that the given data is imbalanced.

In [ ]:

Step 2: Train a Suitable Machine Learning Model

Observation

This is a classification problem

Logistic algorithm will be used to train and test the model

2.1 Extract model Inputs(X) and output(y)

In [10]:
```
df.head(10)
```
Out[10]:

	RevolvingUtilizationOfUnsecuredLines	Age	NumberOfTime30-59DaysPastDueNotWorse	DebtRatio	MonthlyIncome	Numb
0	0.766127	45	2	0.802982	9120.0	
1	0.957151	40	0	0.121876	2600.0	
2	0.658180	38	1	0.085113	3042.0	
3	0.233810	30	0	0.036050	3300.0	
4	0.907239	49	1	0.024926	63588.0	
5	0.213179	74	0	0.375607	3500.0	
6	0.305682	57	0	5710.000000	NaN	
7	0.754464	39	0	0.209940	3500.0	
8	0.116951	27	0	46.000000	NaN	
9	0.189169	57	0	0.606291	23684.0	

In [11]:
```
pd.isna(df).sum()
```
Out[11]:
```
RevolvingUtilizationOfUnsecuredLines        0
Age                                         0
NumberOfTime30-59DaysPastDueNotWorse        0
DebtRatio                                   0
MonthlyIncome                           29731
NumberOfOpenCreditLinesAndLoans             0
NumberOfTimes90DaysLate                     0
NumberRealEstateLoansOrLines                0
NumberOfTime60-89DaysPastDueNotWorse        0
NumberOfDependents                       3924
SeriousDelinquency                          0
dtype: int64
```

NumberOfDependents and MonthlyIncome variables have NaN values.

assign 0 to NumberOfDependents if the value is NaN

assign the average (MonthlyIncome) value to MonthlyIncome if the value is NaN

In [12]:
```
df['MonthlyIncome'] = df['MonthlyIncome'].replace(np.nan,  np.average(df[np.isnan(df['Mo
```

In [13]:
```
df['NumberOfDependents'] = df['NumberOfDependents'].replace(np.nan,  0)
```

In [ ]:
```

```

In [14]:
```
df_clean = df
```

In [15]:
```
dfy = df_clean.SeriousDelinquency # model output variable
dfX = df_clean.drop(['SeriousDelinquency'], axis=1) # model input variables
```

In [16]:
```
dfy.head()
```

Out[16]:
```
0    1
1    0
2    0
3    0
4    0
Name: SeriousDelinquency, dtype: int64
```

In [17]:
```
dfX.head()
```

Out[17]:

	RevolvingUtilizationOfUnsecuredLines	Age	NumberOfTime30-59DaysPastDueNotWorse	DebtRatio	MonthlyIncome	Number(
0	0.766127	45	2	0.802982	9120.0	
1	0.957151	40	0	0.121876	2600.0	
2	0.658180	38	1	0.085113	3042.0	
3	0.233810	30	0	0.036050	3300.0	
4	0.907239	49	1	0.024926	63588.0	

In [18]:
```
#convert dfX and dfY from Pandas Dataframes type to Numpy arrays
X = dfX.values
y = dfy.values
```

In [19]:
```
#split the input and output into training (80%)  and test dataset (20%)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42
```

2.2 Train the base model

In [20]:
```
#train the base logistic regression model
lgBase = LogisticRegression(random_state=42, solver='lbfgs', max_iter=200)
lgBase.fit(X_train, y_train)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\linear_model\_logistic.py:763: Conv
ergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html (https://scikit-learn.o
rg/stable/modules/preprocessing.html)
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression (htt
ps://scikit-learn.org/stable/modules/linear_model.html#logistic-regression)
  n_iter_i = _check_optimize_result(
```

Out[20]:
```
LogisticRegression(max_iter=200, random_state=42)
```

2.3 Evaluate the base model using holdout validation

In [21]:
```
# Enter your code here:
#calculate the training accuracy
train_accuracy = lgBase.score(X_train, y_train)
print("Training Accuracy: %.2f%%" %(train_accuracy * 100))
```

```
Training Accuracy: 93.31%
```

In [22]:
```
#calculate the testing accuracy
test_accuracy = lgBase.score(X_test, y_test)
print("Test Accuracy: %.2f%%" %(test_accuracy * 100))
```

```
Test Accuracy: 93.49%
```

Step 3: Fine Tune the Base Model

statsmodel package has been used to calculate the p-value for each features. So non-significant features can be removed.

3.1 Use statsmodel

In [23]:
```
#add a constant to the X_train dataset and rename it as X_train_sm
X_train_sm = sm.add_constant(X_train)
```

In [24]:
```
#prepare second model using statistical model's logit function
lgSM = sm.Logit(y_train, X_train_sm).fit()
```

```
Optimization terminated successfully.
         Current function value: 0.225543
         Iterations 8
```

In [25]:
```
lgSM.summary()
```

Out[25]:

Logit Regression Results

Dep. Variable:	y	**No. Observations:**	120000
Model:	Logit	**Df Residuals:**	119989
Method:	MLE	**Df Model:**	10
Date:	Sun, 26 Sep 2021	**Pseudo R-squ.:**	0.08490
Time:	00:10:09	**Log-Likelihood:**	-27065.
converged:	True	**LL-Null:**	-29576.
Covariance Type:	nonrobust	**LLR p-value:**	0.000

	coef	std err	z	P>|z|	[0.025	0.975]
const	-1.3486	0.047	-28.972	0.000	-1.440	-1.257
x1	-3.431e-05	7.07e-05	-0.485	0.628	-0.000	0.000
x2	-0.0292	0.001	-31.629	0.000	-0.031	-0.027
x3	0.5065	0.012	40.858	0.000	0.482	0.531
x4	-5.902e-05	1.32e-05	-4.457	0.000	-8.5e-05	-3.31e-05
x5	-2.965e-05	3.29e-06	-9.017	0.000	-3.61e-05	-2.32e-05
x6	-0.0048	0.003	-1.709	0.087	-0.010	0.001
x7	0.4966	0.017	29.178	0.000	0.463	0.530
x8	0.0604	0.012	5.091	0.000	0.037	0.084
x9	-0.9710	0.020	-48.960	0.000	-1.010	-0.932
x10	0.0932	0.010	9.093	0.000	0.073	0.113

In [26]:
```
dfX.columns
```

Out[26]:
```
Index(['RevolvingUtilizationOfUnsecuredLines', 'Age',
       'NumberOfTime30-59DaysPastDueNotWorse', 'DebtRatio', 'MonthlyIncome',
       'NumberOfOpenCreditLinesAndLoans', 'NumberOfTimes90DaysLate',
       'NumberRealEstateLoansOrLines', 'NumberOfTime60-89DaysPastDueNotWorse',
       'NumberOfDependents'],
      dtype='object')
```

select the features with p value smaller than 0.05

selected features: 'Age','NumberOfTime30-59DaysPastDueNotWorse', 'DebtRatio',

'MonthlyIncome','NumberOfTimes90DaysLate','NumberRealEstateLoansOrLines',

'NumberOfTime60-89DaysPastDueNotWorse','NumberOfDependents'

3.2 Train and Evaluate the new model using using selected features

In [27]:
```
dfX_new = dfX[['Age','NumberOfTime30-59DaysPastDueNotWorse', 'DebtRatio', 'MonthlyIncome
```

In [28]:
```
dfX_new.head(5)
```

Out[28]:

	Age	NumberOfTime30-59DaysPastDueNotWorse	DebtRatio	MonthlyIncome	NumberOfTimes90DaysLate	NumberRealEstateL
0	45	2	0.802982	9120.0	0	
1	40	0	0.121876	2600.0	0	
2	38	1	0.085113	3042.0	1	
3	30	0	0.036050	3300.0	0	
4	49	1	0.024926	63588.0	0	

In [29]:
```
#initialize features for training
X_new = dfX_new.values
X_train_new, X_test_new, y_train_new, y_test_new = train_test_split(X_new, y, test_size=
lg_new = LogisticRegression(random_state=42, solver='lbfgs', max_iter=200)
lg_new.fit(X_train_new, y_train_new)
```

Out[29]:
```
LogisticRegression(max_iter=200, random_state=42)
```

In [30]:
```
train_accuracy_new = lg_new.score(X_train_new, y_train_new)
print("Training Accuracy : %.2f%%" % (train_accuracy_new * 100))
```

```
Training Accuracy : 93.38%
```

In [31]:
```
test_accuracy_new = lg_new.score(X_test_new, y_test_new)
print("Test Accuracy : %.2f%%" % (test_accuracy_new * 100))
```

```
Test Accuracy : 93.45%
```

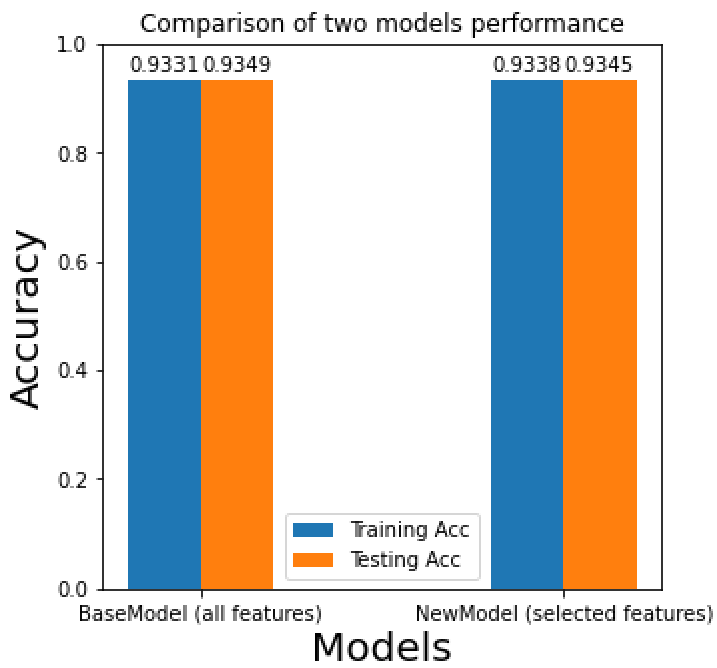
Step 4: Evaluate the Models

4.1 Create bar chart to compare the performance of both models

In [32]:
```
# define x-axis and y-axis data values
x_labels = ['BaseModel (all features)', 'NewModel (selected features)']
x_axis_train = [train_accuracy, train_accuracy_new]
x_axis_test = [test_accuracy, test_accuracy_new]
```

In [33]:

```python
# set the label locations and with of the bars
x= np.arange(len(x_labels))
width = 0.2

plt.figure(figsize=(5,5))

# plot side by side bars
bar1 = plt.bar(x - width/2, x_axis_train, width, label='Training Acc')
bar2 = plt.bar(x + width/2, x_axis_test, width, label='Testing Acc')

#customize the plot

plt.title('Comparison of two models performance')
plt.ylabel('Accuracy', fontsize=20)
plt.xlabel('Models', fontsize=20)
plt.xticks(x, x_labels)
plt.ylim(bottom=0, top=1.0)
plt.legend()


def labelBar(bars):
    for bar in bars:
        acc = bar.get_height()
        plt.annotate('{:.4f}'.format(acc),
                     xy=(bar.get_x() + bar.get_width()/2, acc),
                     xytext=(0,2),
                     textcoords="offset points",
                     ha="center", va="bottom")
labelBar(bar1)
labelBar(bar2)
```



4.2 Evaluate the best model using confusion matrix

4.2.1 Use Base Model (Model 1) and perform prediction for evaluation

In [34]:
```
y_pred = lgBase.predict(X_test)

#confusion matrix
conf_matrix = metrics.confusion_matrix(y_test, y_pred)
conf_matrix
```

Out[34]:
```
array([[27976,    68],
       [ 1885,    71]], dtype=int64)
```

In [35]:
```
# print scores

print("Accuracy : %.2f" % metrics.accuracy_score(y_test, y_pred))
print("Precisison : %.2f" % metrics.precision_score(y_test, y_pred))
print("Recall : %.2f" % metrics.recall_score(y_test, y_pred))
print("F1 score : %.2f" % metrics.f1_score(y_test, y_pred))
```

```
Accuracy : 0.93
Precisison : 0.51
Recall : 0.04
F1 score : 0.07
```

4.2.2 Use New Model (Model 2) and perform prediction for evaluation

In [36]:
```
#use second model and perform prediction
y_pred_new = lg_new.predict(X_test_new)

#confusion matrix
conf_matrix_new = metrics.confusion_matrix(y_test_new, y_pred_new)
conf_matrix_new
```

Out[36]:
```
array([[27952,    92],
       [ 1873,    83]], dtype=int64)
```

In [37]:
```
# print scores

print("Accuracy : %.2f" % metrics.accuracy_score(y_test_new, y_pred_new))
print("Precisison : %.2f" % metrics.precision_score(y_test_new, y_pred_new))
print("Recall : %.2f" % metrics.recall_score(y_test_new, y_pred_new))
print("F1 score : %.2f" % metrics.f1_score(y_test_new, y_pred_new))
```

```
Accuracy : 0.93
Precisison : 0.47
Recall : 0.04
F1 score : 0.08
```

4.2.3 Observation from the evaluation

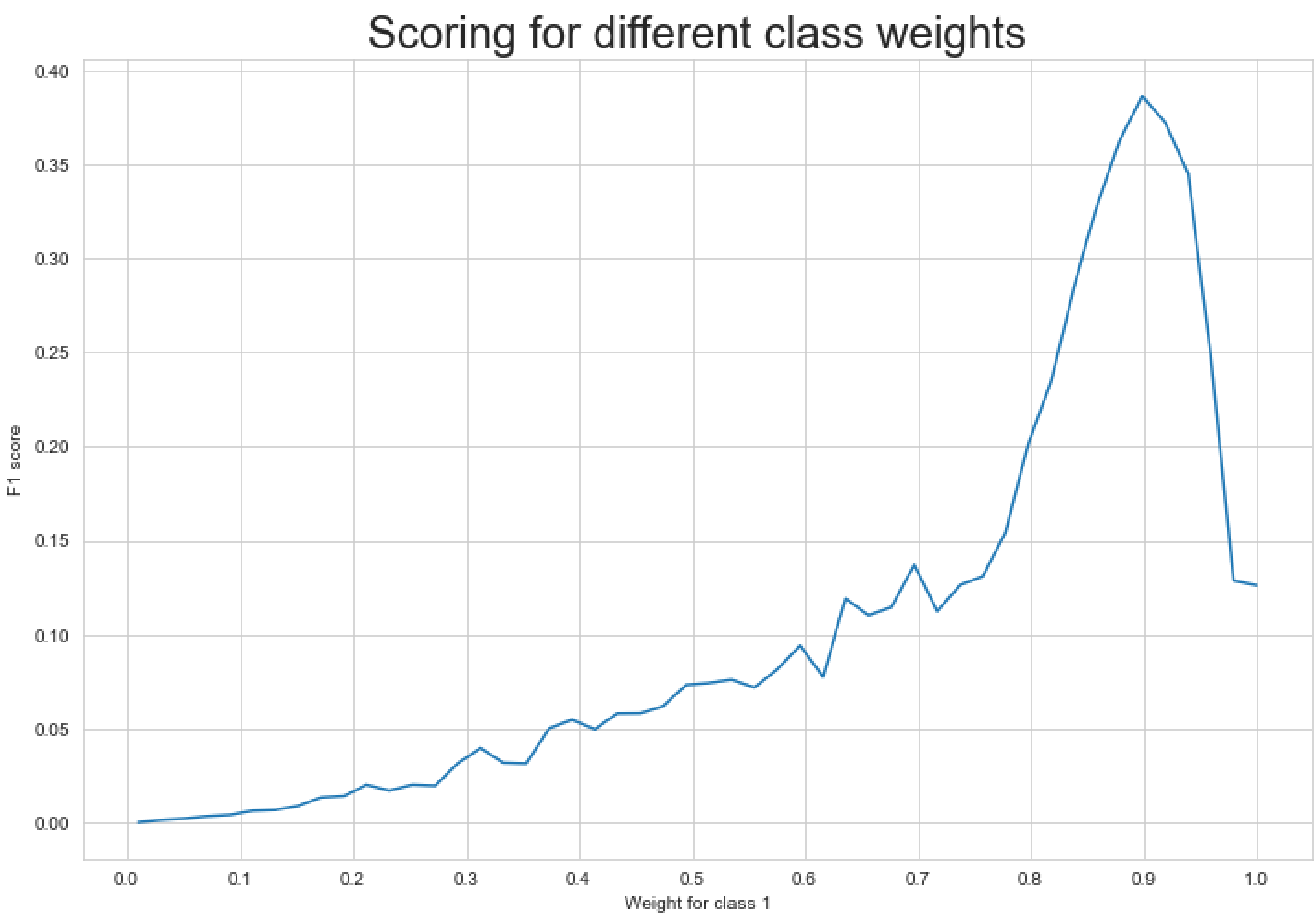
F1 score is too low as the given data is imbalanced. So weighted average to be applied to improve the F1 score.

Caluclate the Class weights

In [38]:
```
LogisticReg = LogisticRegression(solver='lbfgs')

#Setting the range for class weights
weights = np.linspace(0.0,0.99,50)

#Creating a  dictionary grid for grid search
param_grid = {'class_weight': [{0:x, 1:1.0-x} for x in weights]}

#Fitting the grid search value to the train data with 5 folds
gridsearch = GridSearchCV(estimator= LogisticReg,
                          param_grid= param_grid,
                          cv=StratifiedKFold(),
                          n_jobs=-1,
                          scoring='f1',
                          verbose=2).fit(X_train_new, y_train_new)

#Ploting the result score for different values of weight
sns.set_style('whitegrid')
plt.figure(figsize=(12,8))
weigh_data = pd.DataFrame({ 'score': gridsearch.cv_results_['mean_test_score'], 'weight
sns.lineplot(weigh_data['weight'], weigh_data['score'])
plt.xlabel('Weight for class 1')
plt.ylabel('F1 score')
plt.xticks([round(i/10,1) for i in range(0,11,1)])
plt.title('Scoring for different class weights', fontsize=24)
```

```
Fitting 5 folds for each of 50 candidates, totalling 250 fits

C:\ProgramData\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: P
ass the following variables as keyword args: x, y. From version 0.12, the only valid p
ositional argument will be `data`, and passing other arguments without an explicit key
word will result in an error or misinterpretation.
  warnings.warn(
```

Out[38]:
```
Text(0.5, 1.0, 'Scoring for different class weights')
```



Based on the above graph, Class 1 can be given weight : .89 and Class 0 can be given weight : 11

In [39]:
```
#re-train using new class weight and evaluate
```

(i) Retrain the model using class weight - Base Model (Model 1)

In [40]:
```
lg_wa_base = LogisticRegression(random_state=42, solver='lbfgs', max_iter=200,
                                         class_weight={0: 0.11, 1: 0.89})
lg_wa_base.fit(X_train, y_train)
```

Out[40]:
```
LogisticRegression(class_weight={0: 0.11, 1: 0.89}, max_iter=200,
                   random_state=42)
```

In [41]:
```
#test data accuracy
y_pred_test_wa_base = lg_wa_base.predict(X_test)
#confusion matrix
conf_matrix_test_wa_base = metrics.confusion_matrix(y_test, y_pred_test_wa_base)
print("confusion matrix \n",conf_matrix_test_wa_base)
print("Accuracy : %.2f" % metrics.accuracy_score(y_test, y_pred_test_wa_base))
print("Precisison : %.2f" % metrics.precision_score(y_test, y_pred_test_wa_base))
print("Recall : %.2f" % metrics.recall_score(y_test, y_pred_test_wa_base))
print("F1 score : %.2f" % metrics.f1_score(y_test, y_pred_test_wa_base))
```

```
confusion matrix
 [[26627  1417]
 [ 1235   721]]
Accuracy : 0.91
Precisison : 0.34
Recall : 0.37
F1 score : 0.35
```

(i) Retrain the model using class weight - New Model (Model 2)

In [42]:
```
lg_wa_new = LogisticRegression(random_state=42, solver='lbfgs', max_iter=200,
                                         class_weight={0: 0.11, 1: 0.89})
lg_wa_new.fit(X_train_new, y_train_new)
```

Out[42]:
```
LogisticRegression(class_weight={0: 0.11, 1: 0.89}, max_iter=200,
                   random_state=42)
```

In [43]:
```
#test data accuracy
y_pred_test_wa_new = lg_wa_new.predict(X_test_new)
#confusion matrix
conf_matrix_test_wa_new = metrics.confusion_matrix(y_test_new, y_pred_test_wa_new)
print("confusion matrix \n",conf_matrix_test_wa_new)
print("Accuracy : %.2f" % metrics.accuracy_score(y_test_new, y_pred_test_wa_new))
print("Precisison : %.2f" % metrics.precision_score(y_test_new, y_pred_test_wa_new))
print("Recall : %.2f" % metrics.recall_score(y_test_new, y_pred_test_wa_new))
print("F1 score : %.2f" % metrics.f1_score(y_test_new, y_pred_test_wa_new))
```

```
confusion matrix
 [[27043  1001]
 [ 1244   712]]
Accuracy : 0.93
Precisison : 0.42
Recall : 0.36
F1 score : 0.39
```

Step 5: Recommend the Best Model and Explain the

Reasons

Enter your answer here:

New Model (or Model 2) with the selected features is recommended due to the following reasons:

1. New Model (or Model 2) gives better accuracy than the base model. Especially, F1 score of Model 2 is much better than Model 1
2. New Model (or Model 2) use only cherry-picked features but model 1 use all the features.

Hence, New Model (or Model 2) is recommended.

Step 6: Save the Best Model for Future Use

In [44]:
```
# Enter your code here:
modelFile = "logistic_regression_model.pkl"
joblib.dump(lg_wa_new, modelFile )
```

Out[44]:
```
['logistic_regression_model.pkl']
```

End of Assignment