Fraud Analytics Assignment

Title: Example-dependent cost-sensitive regression

Group members:

Name : Dindorkar Mayuresh Rajesh

Roll No : CS23MTECH14007

Name : Sanyam Kaul

Roll No : CS23MTECH14011

Name : Shrenik Ganguli

Roll No : CS23MTECH14014

Name : Morey Piyush Prabhakar

Roll No : AI23MTECH14003

In [1]:

```
# Library used for genetic algorithm
!pip install pygad
```

```
Requirement already satisfied: pygad in c:\users\sanya\anaconda3\lib\site-packages
(3.3.1)
Requirement already satisfied: cloudpickle in c:\users\sanya\anaconda3\lib\site-pa
ckages (from pygad) (2.2.1)
Requirement already satisfied: matplotlib in c:\users\sanya\anaconda3\lib\site-pac
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Requirement already satisfied: numpy in c:\users\sanya\anaconda3\lib\site-packages
(from pygad) (1.24.3)
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te-packages (from matplotlib->pygad) (1.0.5)
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ackages (from matplotlib->pygad) (0.11.0)
Requirement already satisfied: fonttools>=4.22.0 in c:\users\sanya\anaconda3\lib\s
ite-packages (from matplotlib->pygad) (4.25.0)
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ite-packages (from matplotlib->pygad) (1.4.4)
Requirement already satisfied: packaging>=20.0 in c:\users\sanya\anaconda3\lib\sit
e-packages (from matplotlib->pygad) (23.1)
Requirement already satisfied: pillow>=6.2.0 in c:\users\sanya\anaconda3\lib\site-
packages (from matplotlib->pygad) (9.4.0)
Requirement already satisfied: pyparsing<3.1,>=2.3.1 in c:\users\sanya\anaconda3\l
ib\site-packages (from matplotlib->pygad) (3.0.9)
Requirement already satisfied: python-dateutil>=2.7 in c:\users\sanya\anaconda3\li
b\site-packages (from matplotlib->pygad) (2.8.2)
Requirement already satisfied: six>=1.5 in c:\users\sanya\anaconda3\lib\site-packa
ges (from python-dateutil>=2.7->matplotlib->pygad) (1.16.0)
```

Importing libraries:

In [2]:

```
import numpy as np
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
import pandas as pd
from sklearn.preprocessing import StandardScaler
import warnings
```

```
from sklearn.linear_model import LogisticRegression
import seaborn as sns
warnings.filterwarnings("ignore")
import pygad
from scipy.optimize import minimize
```

Utility Functions:

In [3]:
```
def count_labels(data, column_name):
    return data[column_name].value_counts()
```

In [4]:
```
def plot_bar_chart(label_counts):
    labels = label_counts.index.tolist()
    counts = label_counts.values
    plt.bar(np.arange(len(labels)), counts, color=['blue', 'orange'])
    plt.ylabel('Count')
    plt.xlabel('Status')
    plt.title(f'Count of labels in the Status column')
    plt.xticks(np.arange(len(labels)), labels)
    plt.show()
```

In [5]:
```
def perform_scaling(X_train, X_test):
    std_scaler = StandardScaler()
    X_train = std_scaler.fit_transform(X_train)
    X_test = std_scaler.transform(X_test)
    return std_scaler, X_train, X_test
```

In [6]:
```
# Returns FP, TP, TN, FNC
def get_cost_matrix_values(Y_train):
    num_of_samples = X_train.shape[0]
    return np.full(num_of_samples, 6), np.full(num_of_samples, 6), np.zeros(num_of_
```

In [7]:
```
def compute_sigmoid(a):
    return 1 / (1 + np.exp(-a))
```

In [8]:
```
def calculate_saving(simple_lr_cost, cost_of_cslr):
    return (simple_lr_cost - cost_of_cslr) / simple_lr_cost
```

Reading the dataset:

In [9]:
```
df = pd.read_csv('costsensitiveregression.csv')
df.head()
```

Out[9]:

	NotCount	YesCount	ATPM	PFD	PFG	SFD	SFG	WP	WS	AH	AN	Status	FNC
0	2	21	0.0	0.000	0.0	0.0	0.0	0.000000	0.0	0.0	0.0	0	0.0
1	23	0	0.0	0.044	0.0	0.0	0.0	0.306179	0.0	0.0	0.0	1	0.0
2	1	22	0.0	0.000	0.0	0.0	0.0	0.000000	0.0	0.0	0.0	0	0.0
3	5	18	0.0	0.000	0.0	0.0	0.0	0.000000	0.0	0.0	0.0	1	0.0
4	1	22	0.0	0.000	0.0	0.0	0.0	0.000000	0.0	0.0	0.0	0	0.0

In [10]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 147636 entries, 0 to 147635
Data columns (total 13 columns):
 #   Column    Non-Null Count   Dtype
---  ------    --------------   -----
 0   NotCount  147636 non-null  int64
 1   YesCount  147636 non-null  int64
 2   ATPM      147636 non-null  float64
 3   PFD       147636 non-null  float64
 4   PFG       147636 non-null  float64
 5   SFD       147636 non-null  float64
 6   SFG       147636 non-null  float64
 7   WP        147636 non-null  float64
 8   WS        147636 non-null  float64
 9   AH        147636 non-null  float64
 10  AN        147636 non-null  float64
 11  Status    147636 non-null  int64
 12  FNC       147636 non-null  float64
dtypes: float64(10), int64(3)
memory usage: 14.6 MB
```

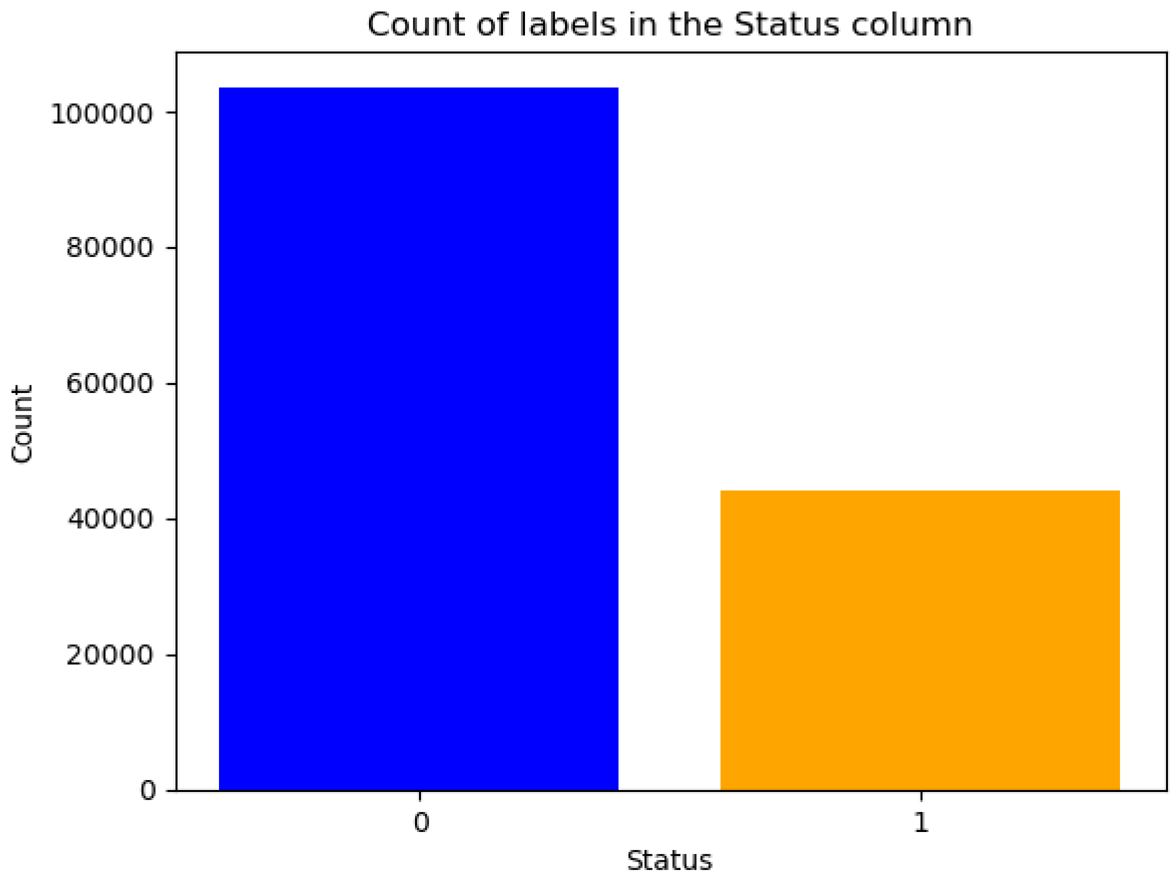
Checking null values in the dataset:

In [11]:
```
df.isnull().sum()
```

Out[11]:
```
NotCount    0
YesCount    0
ATPM        0
PFD         0
PFG         0
SFD         0
SFG         0
WP          0
WS          0
AH          0
AN          0
Status      0
FNC         0
dtype: int64
```

Count plot for feature 'Status':

In [12]:
```
label_counts = count_labels(df, 'Status')
plot_bar_chart(label_counts)
```



Data Pre-processing:

Segregating the dataset into dependant and Independant features:

In [13]:
```
X, Y = df.iloc[:, :-2], df.iloc[:, -2:]
```

Segregating dataset into train and test sets:

In [14]:
```
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2, random_sta
```

Scaling the data

In [15]:
```
std_scaler, X_train, X_test = perform_scaling(X_train, X_test)
```

Bahnsen's Approach:

Creating cost matrix:

In [16]:
```
FP, TP, TN, FNC = get_cost_matrix_values(Y_train)
```

Cost Sensitive Logistic regression Implementation:

$$J^c(\theta) = \frac{1}{N}\sum_{i=1}^{N}\Big(y_i(h_\theta(\mathbf{x}_i)C_{TP_i} + (1 - h_\theta(\mathbf{x}_i))C_{FN_i})$$
$$+(1 - y_i)(h_\theta(\mathbf{x}_i)C_{FP_i} + (1 - h_\theta(\mathbf{x}_i))C_{TN_i})\Big).$$

In [17]:
```
TO_AVOID_DIVIDE_BY_ZERO_ERROR = 1e-08
def cost_sensitive_logistic_regression_cost_function(Y, Y_hat, TP, TN, FP, FN):
        cost = (1 - Y) * (Y_hat * FP + (1 - Y_hat) * TN)
        return np.mean(cost + (Y * (Y_hat * TP + (1 - Y_hat) * FN)))

def calculate_fitness(generation_instance, weights, weight_index):
        Y_hat = compute_sigmoid(X_train @ weights)
        return np.reciprocal(cost_sensitive_logistic_regression_cost_function(Y = Y
                                                                                 FN =
class ExampleDependantCostSensitiveRegression():
    def __init__(self, generation_iterations = 20, count_parents_mating = 6, traini
                 type_of_parent_selection = 'sss', per_pop_solutions = 35, number_of
                  per_gene_mutation_percent = 10, type_of_mutation = 'random',
                  printing_function = lambda ga_instance: print('Generation: {} have
        super(ExampleDependantCostSensitiveRegression, self).__init__()
        self.type_of_crossover = type_of_crossover
        self.count_parents_mating = count_parents_mating
        self.printing_function = printing_function
        self.training_function = training_function
        self.per_pop_solutions = per_pop_solutions
        self.number_of_genes = number_of_genes
        self.generation_iterations = generation_iterations
        self.type_of_parent_selection = type_of_parent_selection
        self.per_gene_mutation_percent = per_gene_mutation_percent
        self.keep_parents = keep_parents
        self.type_of_mutation = type_of_mutation


    def get_genetic_instance(self):
        return pygad.GA(fitness_func = self.training_function, mutation_type = self
                        parent_selection_type = self.type_of_parent_selection, sol_
                        on_generation = self.printing_function, num_genes = self.nu
                        mutation_percent_genes = self.per_gene_mutation_percent)

    def train(self, genetic_instance):
        genetic_instance.run()

    def get_trained_weights(self, genetic_instance):
        return genetic_instance.best_solution()

    def predict(self, X_test, weights):
        print(X_test.shape)
        return compute_sigmoid(X_test @ weights)
```

Runnung the genetic algorithm to obtain best weights of cost sensitive logistic regression:

In [18]:
```
obj = ExampleDependantCostSensitiveRegression()
genetic_instance = obj.get_genetic_instance()
obj.train(genetic_instance)
```

```
Generation: 1 have Fitness value: 0.1785177923840861
Generation: 2 have Fitness value: 0.23552389919258399
Generation: 3 have Fitness value: 0.23797253904953258
Generation: 4 have Fitness value: 0.24101333065378686
Generation: 5 have Fitness value: 0.24367988868208634
Generation: 6 have Fitness value: 0.24725999218699146
Generation: 7 have Fitness value: 0.247991582409019
Generation: 8 have Fitness value: 0.25082783431455935
Generation: 9 have Fitness value: 0.2521244468433215
Generation: 10 have Fitness value: 0.2527666828003852
Generation: 11 have Fitness value: 0.25375708711372835
Generation: 12 have Fitness value: 0.254543170875537 7
Generation: 13 have Fitness value: 0.2564385236785665
Generation: 14 have Fitness value: 0.25750940827977065
Generation: 15 have Fitness value: 0.2577795767401475
Generation: 16 have Fitness value: 0.25864999669636574
Generation: 17 have Fitness value: 0.2591323707833581
Generation: 18 have Fitness value: 0.260169090703135
Generation: 19 have Fitness value: 0.26024322265451755
Generation: 20 have Fitness value: 0.2605248751790192
```

In [19]:
```
trained_weights, _, _ = obj.get_trained_weights(genetic_instance)
print('Trained weights:', trained_weights)
predictions = obj.predict(X_test, trained_weights)
predictions = np.array([1 if x >= 0.5 else 0 for x in predictions])
cost_of_cslr = cost_sensitive_logistic_regression_cost_function(Y = Y_test.iloc[:,0
print("Cost for Cost Sensitive Logistic Regression:", cost_of_cslr)
```

```
Trained weights: [ 5.79669059 -7.0959525   5.99533002  3.19614711 -0.97488652  2.3
7395127
  0.29067918  3.14980413  2.49213836  0.32127434  0.0661056 ]
(29528, 11)
Cost for Cost Sensitive Logistic Regression: 3.8526688022216202
```

Comparing the results with inbuilt Logistic Regressor of ScikitLearn:

In [20]:
```
simple_lr = LogisticRegression()
simple_lr.fit(X_train, Y_train.iloc[:,0])
simple_lr_pred = simple_lr.predict(X_test)

simple_lr_pred = np.array([1 if x >= 0.5 else 0 for x in simple_lr_pred])
simple_lr_cost = cost_sensitive_logistic_regression_cost_function(Y = Y_test.iloc[:
print("Cost for Simple (Sklearn's) Logistic Regression:", simple_lr_cost)
```

```
Cost for Simple (Sklearn's) Logistic Regression: 27.71167158971146
```

Calculating the cost saving score:

In [21]:
```
print("Simple LR score Vs Cost sensitive LR saving score:", calculate_saving(cost_c
```

```
Simple LR score Vs Cost sensitive LR saving score: 0.8609730636512016
```

Guhnmann's Approach (Variant A):

$$\int_0^1 a_i \cdot (y_i \cdot (-\log f(g(x_i, \beta)))) \, \mathrm{d}f \stackrel{!}{=} c_i$$

In [22]:
```
def weighted_logistic_loss(weights, X, y, cost_matrix):
    # Extract model parameters
    w = weights[:-1]
    b = weights[-1]

    # Compute predicted probabilities
    z = np.dot(X, w) + b
    probs = 1 / (1 + np.exp(-z))

    # Compute logistic loss with misclassification costs
    loss = -np.mean(cost_matrix[:, 0] * y[:,0] * np.log(probs + 1e-15 ) +
                    cost_matrix[:, 1] * y[:,0] * np.log(1 - probs + 1e-15 ) +
                    cost_matrix[:, 2] * (1 - y[:,0]) * np.log(probs + 1e-15 ) +
                    cost_matrix[:, 3] * (1 - y[:,0]) * np.log(1 - probs + 1e-15 ))

    return loss
```

In [23]:
```
def cost_sensitive_logistic_regression(X_train, y_train, X_test, y_test, cost_matri
    # Initialize weights (including bias term)
    num_features = X_train.shape[1]
    initial_weights = np.zeros(num_features + 1)

    # Define callback function to print iteration information
    def callback(weights):
        print(f"Loss: {weighted_logistic_loss(weights, X_train, y_train, cost_matri

    # Minimize the weighted logistic loss with iteration callback
    res = minimize(weighted_logistic_loss, initial_weights, args=(X_train, y_train,
    weights = res.x

    # Extract optimal weights and bias
    w = weights[:-1]
    b = weights[-1]

    # Predict on test data
    z = np.dot(X_test, w) + b
    y_pred = np.round(1 / (1 + np.exp(-z)))

    print('Finished')
    return weights
```

In [24]:
```
# Split features and target variable
X = df.iloc[:, :-2].values  # Features (columns 0 to 10)
y = df.iloc[:, -2:].values   # Target variable (column 11)

# Standardize features
scaler = StandardScaler()
X = scaler.fit_transform(X)

# Split the dataset into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta

# Define the cost matrix based on your problem
False_positive = np.full(len(y_train), 4)
True_positive = np.full(len(y_train), 4)
True_negative = np.zeros(len(y_train))
cost_matrix = np.column_stack((False_positive, y_train[:,1], True_positive, True_ne
```

```
# Train cost-sensitive logistic regression model
weights = cost_sensitive_logistic_regression(X_train, y_train, X_test, y_test, cost
```

```
Loss: 18.285193352358363
Loss: 12.109292869353467
Loss: 11.605889248016902
Loss: 10.854695121334833
Loss: 10.005322628099108
Loss: 9.938750775096162
Loss: 9.82102061061701
Loss: 9.654153797429135
Loss: 9.413174322729056
Loss: 9.159201120332899
Loss: 8.853975828469498
Loss: 8.630809870690786
Loss: 8.535067006824622
Loss: 8.494091806095675
Loss: 8.477056068355825
Loss: 8.469877809773024
Loss: 8.466031656435044
Loss: 8.462488766571093
Loss: 8.459722469851604
Loss: 8.457842755576396
Finished
```

In [25]:
```
cost_of_cslr = weighted_logistic_loss(weights,X_train, y_train, cost_matrix)
```

In [26]:
```
print("Cost for Cost Sensitive Logistic Regression (Guhnmann's approach):", cost_of
```

```
Cost for Cost Sensitive Logistic Regression (Guhnmann's approach): 8.4578427555763
96
```

In [27]:
```
print("Simple LR score Vs Cost sensitive LR saving (Guhnmann's approach) score:", c
```

```
Simple LR score Vs Cost sensitive LR saving (Guhnmann's approach) score: 0.6947913
182286504
```

Results:

- Ran all the logistic regreession algorithms for 20 epochs

Approach	Average Cost	Savings Score wtr Simple Logistic Regression
Simple Logistic Regression	27.71	NA
Cost Sensitive Logistic Regression (Bahnsen's Approach)	3.93	0.85
Cost Sensitive Logistic Regression (Guhnman's Approach)	8.45	0.69

In [ ]: