Logistic-SGD

December 28, 2025

1 Mini Project: Predicting Malaria Diagnosis using SGD

This project involves building a machine learning model to predict whether a person is diagnosed with malaria. Logistic Regression, optimized with Stochastic Gradient Descent (SGD), will be implemented to solve this binary classification problem. We will apply Stochastic Gradient Descent (SGD) to predict the likelihood of a person being diagnosed with malaria based on a set of features in a given dataset. We will implement Logistic Regression and optimize the parameters using SGD. The dataset may include features like symptoms, environmental factors, or measurements that correlate with malaria infection. The task is a binary classification problem (Malaria = 1, No Malaria = 0).

[2]:
```python
#import necessary libraries
import pandas as pd
from sklearn.preprocessing import StandardScaler

# load the dataset
# https://www.kaggle.com/datasets/programmer3/malaria-diagnosis-dataset
df = pd.read_csv('Malaria_Dataset.csv')
# display the first few rows of the dataset
print(df.head())
```

```
  IP_Number  Age     Sex Residence_Area               DOA    Discharge_Date  \
0  14xxxx31   52  Female      Mangalore  31-10-2015 20:42  05-11-2015 05:16
1  28xxxx34   75  Female        Shimoga  03-02-2015 23:28  13-02-2015 19:27
2  96xxxx43   30  Female      Mangalore  15-11-2019 12:31  19-11-2019 14:31
3  49xxxx87   89  Female      Mangalore  17-05-2017 17:50  23-05-2017 13:22
4  48xxxx10   62    Male        Shimoga  26-06-2015 15:29  27-06-2015 23:35

   Fever  Headache  Abdominal_Pain  General_Body_Malaise  …  Vomiting  \
0      0         0               0                     1  …         0
1      1         0               1                     1  …         0
2      1         1               1                     1  …         0
3      0         0               0                     0  …         1
4      0         1               0                     1  …         1

   Confusion  Backache  Chest_Pain  Coughing  Joint_Pain  Primary_Code  \
0          0         1           0         0           0         B50.9
1          1         0           1         1           1         B50.9
```

```
2          1         1            1         0            1         B50.9
3          1         1            1         0            1           B54
4          1         0            0         0            0         B51.0

                                        Diagnosis_Type Target  Risk_Score
0                             Mixed Malaria Infection       0           3
1                             Mixed Malaria Infection       1          11
2                             Mixed Malaria Infection       1          13
3       Plasmodium vivax Malaria without complication       0           5
4   Plasmodium falciparum Malaria without complica…      1           8

[5 rows x 21 columns]
```

[3]:
```
#summary of variables
print(df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1622 entries, 0 to 1621
Data columns (total 21 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   IP_Number            1622 non-null   object
 1   Age                  1622 non-null   int64
 2   Sex                  1622 non-null   object
 3   Residence_Area       1622 non-null   object
 4   DOA                  1622 non-null   object
 5   Discharge_Date       1622 non-null   object
 6   Fever                1622 non-null   int64
 7   Headache             1622 non-null   int64
 8   Abdominal_Pain       1622 non-null   int64
 9   General_Body_Malaise 1622 non-null   int64
 10  Dizziness            1622 non-null   int64
 11  Vomiting             1622 non-null   int64
 12  Confusion            1622 non-null   int64
 13  Backache             1622 non-null   int64
 14  Chest_Pain           1622 non-null   int64
 15  Coughing             1622 non-null   int64
 16  Joint_Pain           1622 non-null   int64
 17  Primary_Code         1622 non-null   object
 18  Diagnosis_Type       1622 non-null   object
 19  Target               1622 non-null   int64
 20  Risk_Score           1622 non-null   int64
dtypes: int64(14), object(7)
memory usage: 266.2+ KB
None
```

[4]:
```
# check for missing values and duplicates and display on same table
missing_values = df.isnull().sum()
```

```
duplicate_values = df.duplicated().sum()

summary_df = pd.DataFrame({'Missing Values': missing_values, 'Duplicate Values':
    [duplicate_values]*len(missing_values)})
print(summary_df)
```

```
                     Missing Values  Duplicate Values
IP_Number                         0                 0
Age                               0                 0
Sex                               0                 0
Residence_Area                    0                 0
DOA                               0                 0
Discharge_Date                    0                 0
Fever                             0                 0
Headache                          0                 0
Abdominal_Pain                    0                 0
General_Body_Malaise              0                 0
Dizziness                         0                 0
Vomiting                          0                 0
Confusion                         0                 0
Backache                          0                 0
Chest_Pain                        0                 0
Coughing                          0                 0
Joint_Pain                        0                 0
Primary_Code                      0                 0
Diagnosis_Type                    0                 0
Target                            0                 0
Risk_Score                        0                 0
```

[5]:
```
# summary statistics of the dataset
print(df.describe())
```

```
               Age        Fever     Headache  Abdominal_Pain  \
count  1622.000000  1622.000000  1622.000000     1622.000000
mean     44.705302     0.474723     0.507398        0.496917
std      26.025626     0.499515     0.500099        0.500145
min       1.000000     0.000000     0.000000        0.000000
25%      22.000000     0.000000     0.000000        0.000000
50%      44.000000     0.000000     1.000000        0.000000
75%      68.000000     1.000000     1.000000        1.000000
max      89.000000     1.000000     1.000000        1.000000

       General_Body_Malaise    Dizziness     Vomiting    Confusion  \
count           1622.000000  1622.000000  1622.000000  1622.000000
mean               0.479038     0.504316     0.500000     0.479655
std                0.499714     0.500136     0.500154     0.499740
min                0.000000     0.000000     0.000000     0.000000
25%                0.000000     0.000000     0.000000     0.000000
```

```
50%                   0.000000      1.000000      0.500000      0.000000
75%                   1.000000      1.000000      1.000000      1.000000
max                   1.000000      1.000000      1.000000      1.000000

          Backache   Chest_Pain     Coughing   Joint_Pain       Target  \
count  1622.000000  1622.000000  1622.000000  1622.000000  1622.000000
mean      0.509864     0.500617     0.483970     0.511714     0.719482
std       0.500057     0.500154     0.499897     0.500017     0.449391
min       0.000000     0.000000     0.000000     0.000000     0.000000
25%       0.000000     0.000000     0.000000     0.000000     0.000000
50%       1.000000     1.000000     0.000000     1.000000     1.000000
75%       1.000000     1.000000     1.000000     1.000000     1.000000
max       1.000000     1.000000     1.000000     1.000000     1.000000

        Risk_Score
count  1622.000000
mean      8.405055
std       3.088743
min       0.000000
25%       6.000000
50%       9.000000
75%      11.000000
max      17.000000
```

[6]:
```
# convert sex to numeric
# create a mapping dictionary
gender_mapping = {'Female': 0, 'Male': 1}
# apply the mapping to the 'Sex' column
df['Sex'] = df['Sex'].map(gender_mapping)

# show df
print(df.head())
```

```
  IP_Number  Age  Sex Residence_Area               DOA    Discharge_Date  \
0  14xxxx31   52    0      Mangalore  31-10-2015 20:42  05-11-2015 05:16
1  28xxxx34   75    0        Shimoga  03-02-2015 23:28  13-02-2015 19:27
2  96xxxx43   30    0      Mangalore  15-11-2019 12:31  19-11-2019 14:31
3  49xxxx87   89    0      Mangalore  17-05-2017 17:50  23-05-2017 13:22
4  48xxxx10   62    1        Shimoga  26-06-2015 15:29  27-06-2015 23:35

   Fever  Headache  Abdominal_Pain  General_Body_Malaise  …  Vomiting  \
0      0         0               0                     1  …         0
1      1         0               1                     1  …         0
2      1         1               1                     1  …         0
3      0         0               0                     0  …         1
4      0         1               0                     1  …         1

   Confusion  Backache  Chest_Pain  Coughing  Joint_Pain  Primary_Code  \
```

```
0           0         1           0         0           0           B50.9
1           1         0           1         1           1           B50.9
2           1         1           1         0           1           B50.9
3           1         1           1         0           1             B54
4           1         0           0         0           0           B51.0

                                     Diagnosis_Type Target  Risk_Score
0                            Mixed Malaria Infection      0           3
1                            Mixed Malaria Infection      1          11
2                            Mixed Malaria Infection      1          13
3      Plasmodium vivax Malaria without complication      0           5
4  Plasmodium falciparum Malaria without complica…      1           8

[5 rows x 21 columns]
```

[7]:
```
# drop unnecessary columns [IP_Number, Residence_Area, DOA, Discharge_Date,␣
↪Primary_Code, Diagnosis_Type]
df = df.drop(['IP_Number', 'Residence_Area', 'DOA', 'Discharge_Date',␣
↪'Primary_Code', 'Diagnosis_Type'], axis=1)
print(df.head())
```

```
   Age  Sex  Fever  Headache  Abdominal_Pain  General_Body_Malaise  Dizziness  \
0   52    0      0         0               0                     1          0
1   75    0      1         0               1                     1          1
2   30    0      1         1               1                     1          0
3   89    0      0         0               0                     0          1
4   62    1      0         1               0                     1          0

   Vomiting  Confusion  Backache  Chest_Pain  Coughing  Joint_Pain  Target  \
0         0          0         1           0         0           0       0
1         0          1         0           1         1           1       1
2         0          1         1           1         0           1       1
3         1          1         1           1         0           1       0
4         1          1         0           0         0           0       1

   Risk_Score
0           3
1          11
2          13
3           5
4           8
```

[8]:
```
# Prepare features and target variable
X = df.drop('Target', axis=1) # Features
y = df['Target'] # Target variable
```

[9]:
```
# Standardizing the dataset since SGD is sensitive to feature scaling
from sklearn.preprocessing import StandardScaler
```

```
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

[10]:
```
# split the dataset into training and testing sets
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2,␣
↪random_state=42)
```

[11]:
```
# implement logistic regression
import numpy as np

def sigmoid(z):
    return 1 / (1 + np.exp(-z))

class SgdLogisticRegression:
    def __init__(self, lr=0.01, epochs=100, batch_size=32, verbose=False):
        self.lr = lr
        self.epochs = epochs
        self.batch_size = batch_size
        self.verbose = verbose
        self.loss_history = []

    def fit(self, X, y):
        X = np.asarray(X, dtype=float)
        y = np.asarray(y, dtype=float)
        n_samples, n_features = X.shape
        rng = np.random.default_rng(42)
        self.coef_ = np.zeros(n_features)
        self.intercept_ = 0.0
        self.loss_history = []

        for epoch in range(1, self.epochs + 1):
            idx = rng.permutation(n_samples)
            X_shuffled = X[idx]
            y_shuffled = y[idx]

            for start in range(0, n_samples, self.batch_size):
                end = start + self.batch_size
                X_batch = X_shuffled[start:end]
                y_batch = y_shuffled[start:end]

                preds = sigmoid(X_batch.dot(self.coef_) + self.intercept_)
                error = preds - y_batch
                grad_w = X_batch.T.dot(error) / len(y_batch)
                grad_b = error.mean()

                self.coef_ -= self.lr * grad_w
```

```
                self.intercept_ -= self.lr * grad_b

            # compute log-loss for monitoring
            preds_full = sigmoid(X.dot(self.coef_) + self.intercept_)
            eps = 1e-15
            loss = -np.mean(y * np.log(preds_full + eps) + (1 - y) * np.log(1 -␣
↪preds_full + eps))
            self.loss_history.append(loss)
            if self.verbose and epoch % 10 == 0:
                print(f"Epoch {epoch}/{self.epochs} - Log-loss: {loss:.6f}")

    def predict_proba(self, X):
        X = np.asarray(X, dtype=float)
        z = X.dot(self.coef_) + self.intercept_
        probs = sigmoid(z)
        return np.vstack([1 - probs, probs]).T

    def predict(self, X, threshold=0.5):
        probs = self.predict_proba(X)[:, 1]
        return (probs >= threshold).astype(int)

# training configuration
epochs = 100
learning_rate = 0.01
batch_size = 32

# instantiate and train the model
sgd_model = SgdLogisticRegression(lr=learning_rate, epochs=epochs,␣
↪batch_size=batch_size, verbose=True)
sgd_model.fit(X_train, y_train)
loss_history = sgd_model.loss_history
```

```
Epoch 10/100 - Log-loss: 0.326674
Epoch 20/100 - Log-loss: 0.251487
Epoch 30/100 - Log-loss: 0.215209
Epoch 40/100 - Log-loss: 0.192835
Epoch 50/100 - Log-loss: 0.177276
Epoch 60/100 - Log-loss: 0.165648
Epoch 70/100 - Log-loss: 0.156489
Epoch 80/100 - Log-loss: 0.149040
Epoch 90/100 - Log-loss: 0.142803
Epoch 100/100 - Log-loss: 0.137468
```

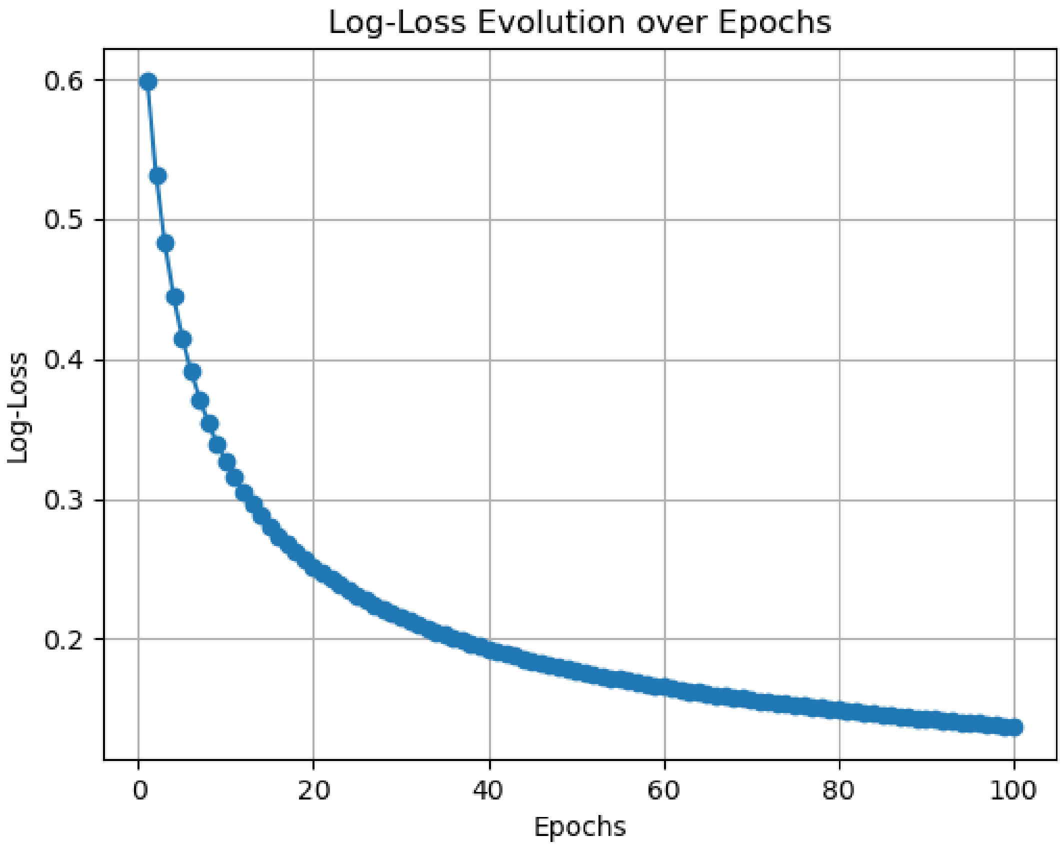
[12]:

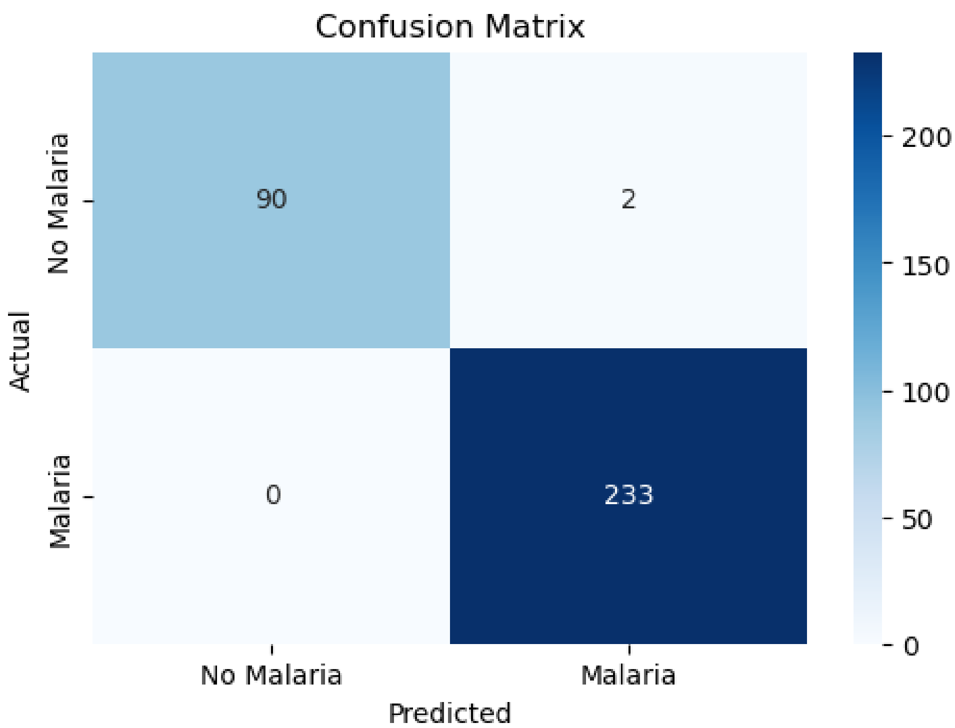
```
# log loss evolution
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import confusion_matrix
```

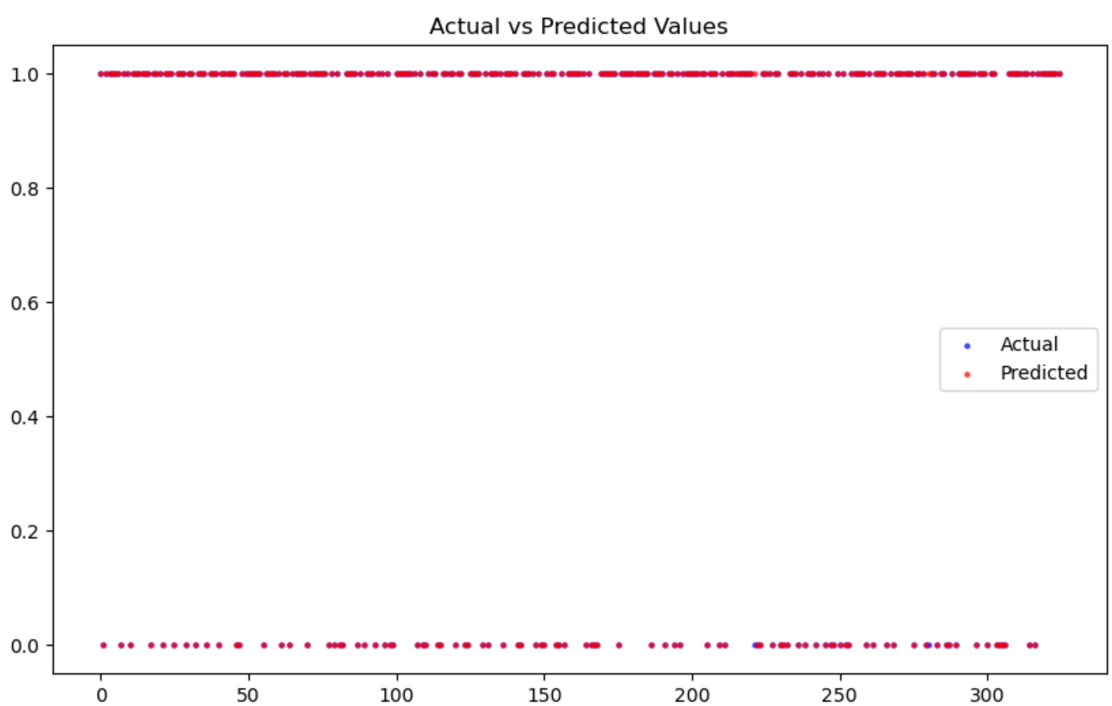
```
plt.plot(range(1, epochs + 1), loss_history, marker='o')
plt.title('Log-Loss Evolution over Epochs')
plt.xlabel('Epochs')
plt.ylabel('Log-Loss')
plt.grid()
plt.show()

# confusion matrix and classification report
# make predictions
y_pred = sgd_model.predict(X_test)
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(6, 4))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=['No Malaria',␣
↪'Malaria'], yticklabels=['No Malaria', 'Malaria'])
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.title('Confusion Matrix')
plt.show()

# actual vs predicted
plt.figure(figsize=(10, 6))
plt.scatter(range(len(y_test)), y_test, color='blue', label='Actual', alpha=0.
↪6, s=5)
plt.scatter(range(len(y_pred)), y_pred, color='red', label='Predicted', alpha=0.
↪6, s=5)
plt.title('Actual vs Predicted Values')
plt.legend()
plt.show()
```


Log-Loss Evolution over Epochs
Log-Loss
0.6
0.5
0.4
0.3
0.2
0
20
40
60
80
100
Epochs


Confusion Matrix
No Malaria
Malaria
Actual
90
2
0
233
No Malaria
Malaria
Predicted
200
150
100
50
0


Actual vs Predicted Values
1.0
0.8
0.6
0.4
0.2
0.0
0
50
100
150
200
250
300
Actual
Predicted

[13]:
```
# make predictions
y_pred = sgd_model.predict(X_test)

# evaluate the model
from sklearn.metrics import accuracy_score, classification_report,␣
↪confusion_matrix
accuracy = accuracy_score(y_test, y_pred)
print(f'Accuracy: {accuracy:.4f}')
print('Classification Report:')
print(classification_report(y_test, y_pred))
```

```
Accuracy: 0.9938
Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.98      0.99        92
           1       0.99      1.00      1.00       233

    accuracy                           0.99       325
   macro avg       1.00      0.99      0.99       325
weighted avg       0.99      0.99      0.99       325
```

1.1 Report

This report summarizes the development and evaluation of a logistic regression model designed to predict malaria diagnosis using data from the Malaria_Dataset.csv file. The dataset was preprocessed by removing non-predictive administrative columns (IP_Number, Residence_Area, DOA, Discharge_Date, Primary_Code, and Diagnosis_Type), encoding the categorical Sex feature as 0 for Female and 1 for Male, and standardizing all numerical features with StandardScaler. An 80/20 train-test split was applied with a fixed random state of 42 for reproducibility, resulting in a test set of 325 samples.

A logistic regression model was implemented from scratch, utilizing the sigmoid activation function and optimized via mini-batch stochastic gradient descent on the binary cross-entropy loss function. Training was conducted over 100 epochs with a learning rate of 0.01 and a batch size of 32, during which the log-loss steadily declined from approximately 0.60 to 0.14, demonstrating effective convergence.

The model achieved outstanding performance with an accuracy of 0.9938. The confusion matrix revealed 90 true negatives, 233 true positives, 2 false positives, and 0 false negatives, indicating near-perfect detection of malaria cases (recall of 1.00 for the positive class) and very high precision overall. The classification report further confirmed precision, recall, and F1-scores near 1.00 for both classes, with macro and weighted averages around 0.99.

Overall, the SGD-trained logistic regression model demonstrated exceptional predictive capability on this dataset split, making it highly reliable for identifying malaria cases with minimal errors.