logistic_regression

August 4, 2025

1 Logistic Regression Predictor – Heart Disease

1.0.1 Project Description:

This project explores the application of logistic regression for predicting the 10-year risk of coronary heart disease (CHD) using the publicly available Framingham Heart Study dataset. Through implementation of both custom gradient descent and scikit-learn's logistic regression models, this project aims to compare performance across regularized and non-regularized models. The analysis includes model training, testing, evaluation, and exploration of performance challenges.

1.0.2 Objectives:

- Implement logistic regression from scratch using gradient descent, including both standard and L2-regularized versions.
- Evaluate and compare model performance using log loss, confusion matrix, and classification metrics (precision, recall, f1-score).
- Use scikit-learn's LogisticRegression to benchmark results and observe convergence behaviors.
- Analyze the effect of class imbalance on model performance, particularly on recall for the minority class.

1.0.3 Public dataset source:

Kaggle Heart Disease Prediction Data Set The dataset is publically available on the Kaggle website, and it is from an ongoing cardiovascular study on residents of the town of Framingham, Massachusetts. The classification goal is to predict whether the patient has 10-year risk of future coronary heart disease (CHD). The dataset provides the patients' information. It includes over 4,000 records and 15 attributes.

[137]:
```
# Import libraries
import pandas as pd
# import numpy as np
import autograd.numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import autograd
from autograd import grad
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import log_loss, confusion_matrix, classification_report
```

[11]:
```
# Establish file path and import data
path = 'heart_disease_prediction_data.csv'
df = pd.read_csv(path)
df.head()
```

[11]:
```
   male  age  education  currentSmoker  cigsPerDay  BPMeds  prevalentStroke  \
0     1   39        4.0              0         0.0     0.0                0
1     0   46        2.0              0         0.0     0.0                0
2     1   48        1.0              1        20.0     0.0                0
3     0   61        3.0              1        30.0     0.0                0
4     0   46        3.0              1        23.0     0.0                0

   prevalentHyp  diabetes  totChol  sysBP  diaBP    BMI  heartRate  glucose  \
0             0         0    195.0  106.0   70.0  26.97       80.0     77.0
1             0         0    250.0  121.0   81.0  28.73       95.0     76.0
2             0         0    245.0  127.5   80.0  25.34       75.0     70.0
3             1         0    225.0  150.0   95.0  28.58       65.0    103.0
4             0         0    285.0  130.0   84.0  23.10       85.0     85.0

   TenYearCHD
0           0
1           0
2           0
3           1
4           0
```

[12]:
```
df.describe()
```

[12]:
```
              male          age    education  currentSmoker   cigsPerDay  \
count  4238.000000  4238.000000  4133.000000    4238.000000  4209.000000
mean      0.429212    49.584946     1.978950       0.494101     9.003089
std       0.495022     8.572160     1.019791       0.500024    11.920094
min       0.000000    32.000000     1.000000       0.000000     0.000000
25%       0.000000    42.000000     1.000000       0.000000     0.000000
50%       0.000000    49.000000     2.000000       0.000000     0.000000
75%       1.000000    56.000000     3.000000       1.000000    20.000000
max       1.000000    70.000000     4.000000       1.000000    70.000000

            BPMeds  prevalentStroke  prevalentHyp     diabetes      totChol  \
count  4185.000000      4238.000000   4238.000000  4238.000000  4188.000000
mean      0.029630         0.005899      0.310524     0.025720   236.721585
std       0.169584         0.076587      0.462763     0.158316    44.590334
min       0.000000         0.000000      0.000000     0.000000   107.000000
25%       0.000000         0.000000      0.000000     0.000000   206.000000
50%       0.000000         0.000000      0.000000     0.000000   234.000000
75%       0.000000         0.000000      1.000000     0.000000   263.000000
max       1.000000         1.000000      1.000000     1.000000   696.000000
```

```
             sysBP        diaBP          BMI    heartRate      glucose  \
count  4238.000000  4238.000000  4219.000000  4237.000000  3850.000000
mean    132.352407    82.893464    25.802008    75.878924    81.966753
std      22.038097    11.910850     4.080111    12.026596    23.959998
min      83.500000    48.000000    15.540000    44.000000    40.000000
25%     117.000000    75.000000    23.070000    68.000000    71.000000
50%     128.000000    82.000000    25.400000    75.000000    78.000000
75%     144.000000    89.875000    28.040000    83.000000    87.000000
max     295.000000   142.500000    56.800000   143.000000   394.000000

        TenYearCHD
count  4238.000000
mean      0.151958
std       0.359023
min       0.000000
25%       0.000000
50%       0.000000
75%       0.000000
max       1.000000
```

[94]:

```
def logistic_model(X,y_true,alpha,max_its):
    # Initialize weights
    n_samples, n_features = X.shape
    w = np.zeros(n_features)
    b = 0.0
    cost_history = []

    for k in range(max_its):
        # Computer linear combination
        # Equivalent to X^T dot W
        z = X @ w + b
        #Clip z to prevent overflow in exp
        # z = np.clip(z, -500, 500)
        # Apply the sigmoid function to get prediction
        y_pred = 1 / (1 + np.exp(-z))

        # Clip for numerical stability
        epsilon = 1e-10
        y_pred = np.clip(y_pred, epsilon, 1 - epsilon)

        # Compute loss
        log_loss = -np.mean(y_true * np.log(y_pred) + (1 - y_true) * np.log(1 -␣
 ↪y_pred))

        # Gradient descent
        grad_w = (X.T @ (y_pred - y_true)) / n_samples
```

```python
        grad_b = np.sum(y_pred - y_true) / n_samples

        # Update parameters
        w -= alpha * grad_w
        b -= alpha * grad_b

        # Recompute loss
        cost_history.append(log_loss)

        # Print every 100 iterations
        if k % 100 == 0:
            print(f"Iteration {k}: log loss = {log_loss:.4f}")
    return cost_history, w, b
```

[ ]:

```python
# Assign features and target
cols =␣
↪['age','education','currentSmoker','cigsPerDay','BPMeds','prevalentStroke','prevalentHyp','
X = df[cols].values
X = np.nan_to_num(X, nan=0.0, posinf=1e6, neginf=-1e6) # There are Nan values␣
↪in X
y = df['TenYearCHD'].values # 10 year risk of coronary heart disease CHD

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
↪random_state=42)
```

[102]:

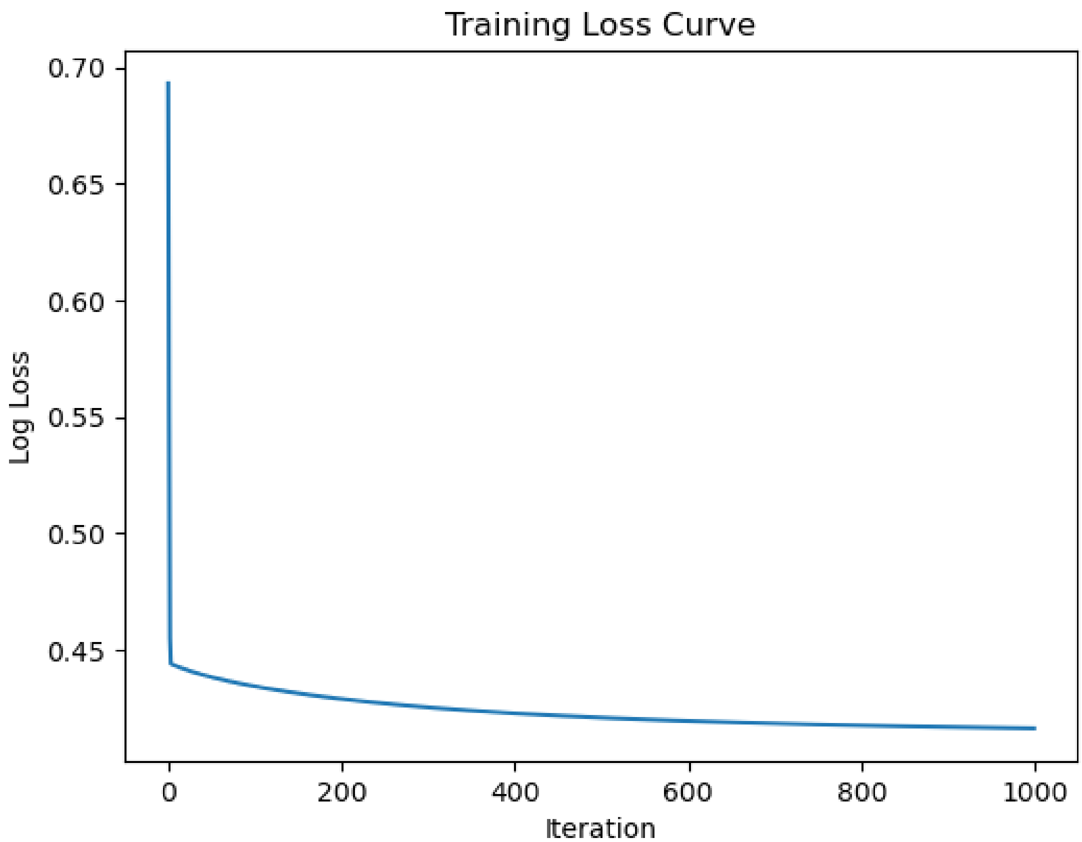
```python
# Run the model
cost_history, w, b = logistic_model(X_train, y_train, alpha=0.0001,␣
↪max_its=1000)

print("Learned weights:", w)
print("Intercept (b):", b)
```

```
Iteration 0: log loss = 0.6931
Iteration 100: log loss = 0.4344
Iteration 200: log loss = 0.4291
Iteration 300: log loss = 0.4254
Iteration 400: log loss = 0.4229
Iteration 500: log loss = 0.4210
Iteration 600: log loss = 0.4196
Iteration 700: log loss = 0.4185
Iteration 800: log loss = 0.4177
Iteration 900: log loss = 0.4170
Learned weights: [ 0.01299961 -0.00288027 -0.00032512  0.01063011  0.00043393
0.00014152
  0.00235764  0.00033767 -0.0039659   0.01624741 -0.01501058 -0.01797544
 -0.03121035  0.00527281]
```

```
Intercept (b): -0.0009814646746594351
```

[105]:
```python
plt.plot(cost_history)
plt.xlabel("Iteration")
plt.ylabel("Log Loss")
plt.title("Training Loss Curve")
plt.show()
```



[100]:
```python
def logit_predict(X,y_true,w,b):
    z = X @ w + b
    y_pred = 1 / (1 + np.exp(-z))
    log_loss = -np.mean(y_true * np.log(y_pred) + (1 - y_true) * np.log(1 -␣
 ↪y_pred))
    return log_loss
```

[103]:
```python
test_loss = logit_predict(X_test, y_test, w , b)

print("Test loss:", test_loss)
```

```
Test loss: 0.4158411852148352
```

The training loss over time smoothly decreases with no erratic jumps and approaches a typical value for a decent classifier. The test loss is better than random and close to the training loss, which, for a simple logistic regression model without regularization, is a good baseline.

Training a model on an imbalanced dataset (classe) might cause it to favor the majority and be wrong in the minority, leading to a higher loss.

[ ]:
```
np.unique(y_train, return_counts=True)
```

[ ]:
```
(array([0, 1]), array([2510,  456]))
```

1.1 L2 Regularization

L2 regularization (aka Ridge penalty) helps to prevent overfitting by penalizing large weights.

[113]:
```
def L2_logistic_model(X, y_true, alpha=0.01, max_its=1000, reg_lambda=0.1):
    n_samples, n_features = X.shape
    # w = np.zeros(n_features)
    w = np.random.normal(0, 0.01, size=n_features)
    b = 0.0
    cost_history = []

    for k in range(max_its):
        z = X @ w + b
        y_pred = 1 / (1 + np.exp(-z))
        y_pred = np.clip(y_pred, 1e-10, 1 - 1e-10)

        # L2-regularized loss
        log_loss = -np.mean(y_true * np.log(y_pred) + (1 - y_true) * np.log(1 -
 ↪y_pred))
        l2_penalty = (reg_lambda / (2 * n_samples)) * np.sum(w ** 2)
        total_loss = log_loss + l2_penalty

        # Gradient with L2
        grad_w = (X.T @ (y_pred - y_true)) / n_samples + (reg_lambda /
 ↪n_samples) * w
        grad_b = np.sum(y_pred - y_true) / n_samples

        w -= alpha * grad_w
        b -= alpha * grad_b

        cost_history.append(total_loss)

        if k % 100 == 0:
            print(f"Iteration {k}: total loss = {total_loss:.4f}")
    return cost_history, w, b
```

[115]:
```python
cost_history, w, b = L2_logistic_model(X_train, y_train, alpha=0.0001,␣
↪max_its=1000)

print("Learned weights:", w)
print("Intercept (b):", b)
```

```
Iteration 0: total loss = 0.6813
Iteration 100: total loss = 0.4416
Iteration 200: total loss = 0.4350
Iteration 300: total loss = 0.4306
Iteration 400: total loss = 0.4272
Iteration 500: total loss = 0.4247
Iteration 600: total loss = 0.4227
Iteration 700: total loss = 0.4211
Iteration 800: total loss = 0.4198
Iteration 900: total loss = 0.4188
Learned weights: [ 0.00573789 -0.00780144 -0.00715728  0.00818497 -0.00283553
-0.0033222
  0.00508599  0.00311879 -0.00370077  0.01675258 -0.01352605 -0.01552556
 -0.03011105  0.00530281]
Intercept (b): -0.0009019435868228638
```

[120]:
```python
def L2_logit_predict(X,y_true,w,b, reg_lambda = 0.1):
    z = X @ w + b
    y_pred = 1 / (1 + np.exp(-z))
    log_loss = -np.mean(y_true * np.log(y_pred) + (1 - y_true) * np.log(1 -␣
↪y_pred))
    l2_penalty = (reg_lambda / (2 * n_samples)) * np.sum(w ** 2)
    total_loss = log_loss + l2_penalty
    return total_loss
```

[122]:
```python
total_loss = L2_logit_predict(X_test, y_test, w , b)

print("Test loss:", total_loss)
```

```
Test loss: 0.4164469804049391
```

L2 training loss is slightly higher because I added a penalty term to discourage large weights, but the difference between the two is very small. Test loss is almost identical, which may suggest that the model is not overfitting in the first place. Also, the data are relatively clean and low dimensional.

1.2 Scikit-Learn

[130]:
```python
# Fit sklearn logistic regression
reg_lambda = 0.1
# model = LogisticRegression(penalty='l2', C=1/reg_lambda, solver='lbfgs',␣
↪max_iter=1000)
```

```
model = LogisticRegression(penalty='l2', C=1/reg_lambda, solver='lbfgs',␣
 ↪max_iter=5000)
model.fit(X_train, y_train)

# Predictions
y_pred_prob = model.predict_proba(X_test)[:, 1] # Raw probabilities
y_pred = model.predict(X_test) # Predicted classes

# Evaluate
test_log_loss = log_loss(y_test, y_pred_prob)

print("Scikit-learn Test Log Loss:", test_log_loss)
```

```
Scikit-learn Test Log Loss: 0.38161662995104506
```

[134]:
```
# Mean accuracy
model.score(X_test,y_test)
```

[134]: 0.8584905660377359

[135]:
```
print(confusion_matrix(y_test,y_pred))
```

```
[[1076    8]
 [ 172   16]]
```

[138]:
```
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.86      0.99      0.92      1084
           1       0.67      0.09      0.15       188

    accuracy                           0.86      1272
   macro avg       0.76      0.54      0.54      1272
weighted avg       0.83      0.86      0.81      1272
```

The recall may be very low once again because of the class imbalance. Could potentially use class weighting to improve this performance by penalizing when the model misclassifies the minority class more heavily.