exp13

November 9, 2025

1 Logistic Regression (from scratch)

1.1 1) Setup & Imports

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.impute import SimpleImputer
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.metrics import accuracy_score, confusion_matrix,␣
 ↪classification_report
```

1.2 2) Parameters

Change these and re-run the relevant cells below.

[2]:
```
# ---- Parameters ----
DATA_PATH = 'loan_data.csv'    # Path to your CSV
TEST_SIZE = 0.2
RANDOM_STATE = 42

# Optimizer-specific defaults (you can override later or via widgets)
BGD_LEARNING_RATE = 0.1
BGD_EPOCHS = 1000

ADAM_LEARNING_RATE = 0.01
ADAM_EPOCHS = 1000
ADAM_BETA1 = 0.9
ADAM_BETA2 = 0.999
ADAM_EPSILON = 1e-8
```

1.3 3) From-Scratch Logistic Regression Class

[3]:
```
# --- 1. The Logistic Regression Model Class ---

class LogisticRegression:
    """
    A from-scratch implementation of Logistic Regression with two optimizers:
    1. Batch Gradient Descent (BGD)
    2. Adam Optimizer
    """

    def __init__(self, learning_rate=0.01, n_epochs=1000,
                 beta1=0.9, beta2=0.999, epsilon=1e-8):
        self.learning_rate = learning_rate
        self.n_epochs = n_epochs
        self.beta1 = beta1
        self.beta2 = beta2
        self.epsilon = epsilon
        self.weights = None
        self.bias = None
        self.cost_history = []

    def _sigmoid(self, z):
        z_clipped = np.clip(z, -500, 500)
        return 1 / (1 + np.exp(-z_clipped))

    def _initialize_params(self, n_features):
        self.weights = np.zeros(n_features)
        self.bias = 0

    def _compute_cost(self, y_true, y_pred):
        m = y_true.shape[0]
        epsilon = 1e-9
        y_pred_clipped = np.clip(y_pred, epsilon, 1 - epsilon)
        cost = -(1/m) * np.sum(
            y_true * np.log(y_pred_clipped) + (1 - y_true) * np.log(1 -␣
↪y_pred_clipped)
        )
        return cost

    def fit_bgd(self, X, y):
        print("Starting training with Batch Gradient Descent...")
        m_samples, n_features = X.shape
        self._initialize_params(n_features)
        self.cost_history = []

        for i in range(self.n_epochs):
```

```
            linear_model = X @ self.weights + self.bias
            y_pred = self._sigmoid(linear_model)
            cost = self._compute_cost(y, y_pred)
            self.cost_history.append(cost)
            dw = (1 / m_samples) * (X.T @ (y_pred - y))
            db = (1 / m_samples) * np.sum(y_pred - y)
            self.weights -= self.learning_rate * dw
            self.bias -= self.learning_rate * db
            if (i+1) % 100 == 0:
                print(f"BGD Epoch {i+1}/{self.n_epochs}, Cost: {cost:.4f}")

    def fit_adam(self, X, y):
        print("Starting training with Adam Optimizer...")
        m_samples, n_features = X.shape
        self._initialize_params(n_features)
        self.cost_history = []
        m_w, v_w, m_b, v_b = 0, 0, 0, 0

        for i in range(self.n_epochs):
            t = i + 1
            linear_model = X @ self.weights + self.bias
            y_pred = self._sigmoid(linear_model)
            cost = self._compute_cost(y, y_pred)
            self.cost_history.append(cost)
            dw = (1 / m_samples) * (X.T @ (y_pred - y))
            db = (1 / m_samples) * np.sum(y_pred - y)
            m_w = self.beta1 * m_w + (1 - self.beta1) * dw
            m_b = self.beta1 * m_b + (1 - self.beta1) * db
            v_w = self.beta2 * v_w + (1 - self.beta2) * (dw**2)
            v_b = self.beta2 * v_b + (1 - self.beta2) * (db**2)
            m_w_corr = m_w / (1 - self.beta1**t)
            m_b_corr = m_b / (1 - self.beta1**t)
            v_w_corr = v_w / (1 - self.beta2**t)
            v_b_corr = v_b / (1 - self.beta2**t)
            self.weights -= self.learning_rate * m_w_corr / (np.sqrt(v_w_corr) + self.epsilon)
            self.bias -= self.learning_rate * m_b_corr / (np.sqrt(v_b_corr) + self.epsilon)
            if (i+1) % 100 == 0:
                print(f"Adam Epoch {i+1}/{self.n_epochs}, Cost: {cost:.4f}")

    def predict_proba(self, X):
        linear_model = X @ self.weights + self.bias
        return self._sigmoid(linear_model)

    def predict(self, X, threshold=0.5):
        probas = self.predict_proba(X)
```

```
        return (probas >= threshold).astype(int)
```

1.4 4) Helper Functions

[4]:
```
def plot_confusion_matrix(y_true, y_pred, title):
    cm = confusion_matrix(y_true, y_pred)
    plt.figure(figsize=(6, 4))
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
                xticklabels=['Rejected (0)', 'Approved (1)'],
                yticklabels=['Rejected (0)', 'Approved (1)'])
    plt.xlabel('Predicted')
    plt.ylabel('Actual')
    plt.title(title)
    plt.show()

def evaluate_and_report(model_name, y_true, y_pred):
    acc = accuracy_score(y_true, y_pred)
    print(f"\n{model_name} Accuracy: {acc:.4f}")
    print(f"{model_name} Classification Report:")
    print(classification_report(y_true, y_pred, target_names=['Rejected (0)',␣
 ↪'Approved (1)']))
    return acc
```

1.5 5) Load Data

[6]:
```
# Make sure DATA_PATH points to your CSV.
try:
    data = pd.read_csv(r"C:\\Sarvesh\\Mtech\\Foundation of Data␣
 ↪Engineering\\Assignments\\EX 13\\loan_data.csv")
except FileNotFoundError:
    raise FileNotFoundError("Error: '{r'C:\\Sarvesh\\Mtech\\Foundation of Data␣
 ↪Engineering\\Assignments\\EX 13\\loan_data.csv'}' not found. Place it next␣
 ↪to this notebook or update DATA_PATH.")

print('Data loaded successfully. Shape:', data.shape)
# Drop rows with missing target
data.dropna(subset=['loan_status'], inplace=True)
X = data.drop('loan_status', axis=1)
y = data['loan_status'].values

print('Preview features:')
display(X.head(3))
print('Preview target:')
display(pd.Series(y).head(3))
```

```
Data loaded successfully. Shape: (45000, 14)
Preview features:
```

```
   person_age person_gender person_education  person_income  person_emp_exp  \
0        22.0        female           Master        71948.0               0
1        21.0        female      High School        12282.0               0
2        25.0        female      High School        12438.0               3

  person_home_ownership  loan_amnt loan_intent  loan_int_rate  \
0                  RENT    35000.0    PERSONAL          16.02
1                   OWN     1000.0   EDUCATION          11.14
2              MORTGAGE     5500.0     MEDICAL          12.87

   loan_percent_income  cb_person_cred_hist_length  credit_score  \
0                 0.49                         3.0           561
1                 0.08                         2.0           504
2                 0.44                         3.0           635

  previous_loan_defaults_on_file
0                             No
1                            Yes
2                             No
```

```
Preview target:
```

```
0    1
1    0
2    1
dtype: int64
```

1.6 6) Build Preprocessing Pipelines

[7]:

```
numeric_features = X.select_dtypes(include=np.number).columns
categorical_features = X.select_dtypes(include='object').columns
print(f"Numerical features: {list(numeric_features)}")
print(f"Categorical features: {list(categorical_features)}")

numeric_transformer = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='median')),
    ('scaler', StandardScaler())
])
categorical_transformer = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='most_frequent')),
    ('onehot', OneHotEncoder(handle_unknown='ignore'))
])

preprocessor = ColumnTransformer(
    transformers=[
        ('num', numeric_transformer, numeric_features),
        ('cat', categorical_transformer, categorical_features)
    ],
```

```
    remainder='passthrough'
)
```

```
Numerical features: ['person_age', 'person_income', 'person_emp_exp',
'loan_amnt', 'loan_int_rate', 'loan_percent_income',
'cb_person_cred_hist_length', 'credit_score']
Categorical features: ['person_gender', 'person_education',
'person_home_ownership', 'loan_intent', 'previous_loan_defaults_on_file']
```

1.7 7) Train/Test Split & Transform

[8]:
```
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=TEST_SIZE, random_state=RANDOM_STATE, stratify=y
)
print(f"Training set size: {X_train.shape[0]}")
print(f"Test set size: {X_test.shape[0]}")

print('Fitting preprocessor and transforming training data...')
X_train_processed = preprocessor.fit_transform(X_train)

print('Transforming test data...')
X_test_processed = preprocessor.transform(X_test)

if not isinstance(X_train_processed, np.ndarray):
    X_train_processed = X_train_processed.toarray()
    X_test_processed = X_test_processed.toarray()

print('Preprocessing complete. Shapes:', X_train_processed.shape,␣
 ↪X_test_processed.shape)
```

```
Training set size: 36000
Test set size: 9000
Fitting preprocessor and transforming training data…
Transforming test data…
Preprocessing complete. Shapes: (36000, 27) (9000, 27)
```

1.8 8) Train — Batch Gradient Descent (BGD)

[9]:
```
model_bgd = LogisticRegression(learning_rate=BGD_LEARNING_RATE,␣
 ↪n_epochs=BGD_EPOCHS)
model_bgd.fit_bgd(X_train_processed, y_train)
```

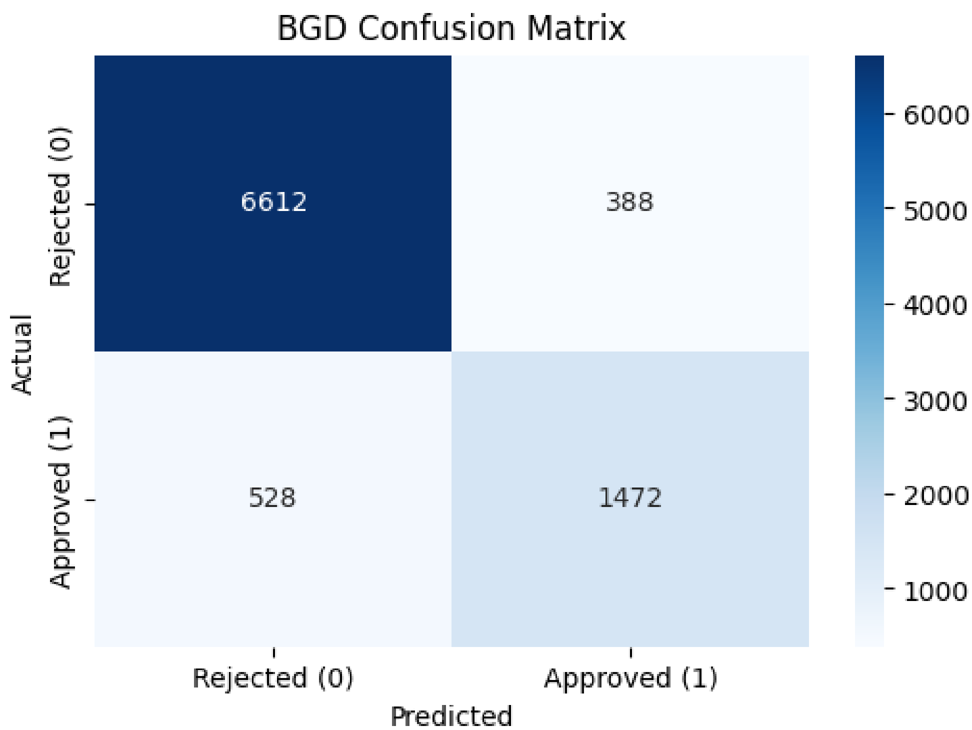
```
Starting training with Batch Gradient Descent…
BGD Epoch 100/1000, Cost: 0.3134
BGD Epoch 200/1000, Cost: 0.2761
BGD Epoch 300/1000, Cost: 0.2605
BGD Epoch 400/1000, Cost: 0.2518
BGD Epoch 500/1000, Cost: 0.2462
```

```
BGD Epoch 600/1000, Cost: 0.2423
BGD Epoch 700/1000, Cost: 0.2394
BGD Epoch 800/1000, Cost: 0.2372
BGD Epoch 900/1000, Cost: 0.2354
BGD Epoch 1000/1000, Cost: 0.2340
```

1.9 9) Evaluate — BGD

[10]:
```
y_pred_bgd = model_bgd.predict(X_test_processed)
acc_bgd = evaluate_and_report('BGD Model', y_test, y_pred_bgd)
plot_confusion_matrix(y_test, y_pred_bgd, 'BGD Confusion Matrix')
```

```
BGD Model Accuracy: 0.8982
BGD Model Classification Report:
              precision    recall  f1-score   support

Rejected (0)       0.93      0.94      0.94      7000
Approved (1)       0.79      0.74      0.76      2000

    accuracy                           0.90      9000
   macro avg       0.86      0.84      0.85      9000
weighted avg       0.90      0.90      0.90      9000
```



1.10 10) Train — Adam Optimizer

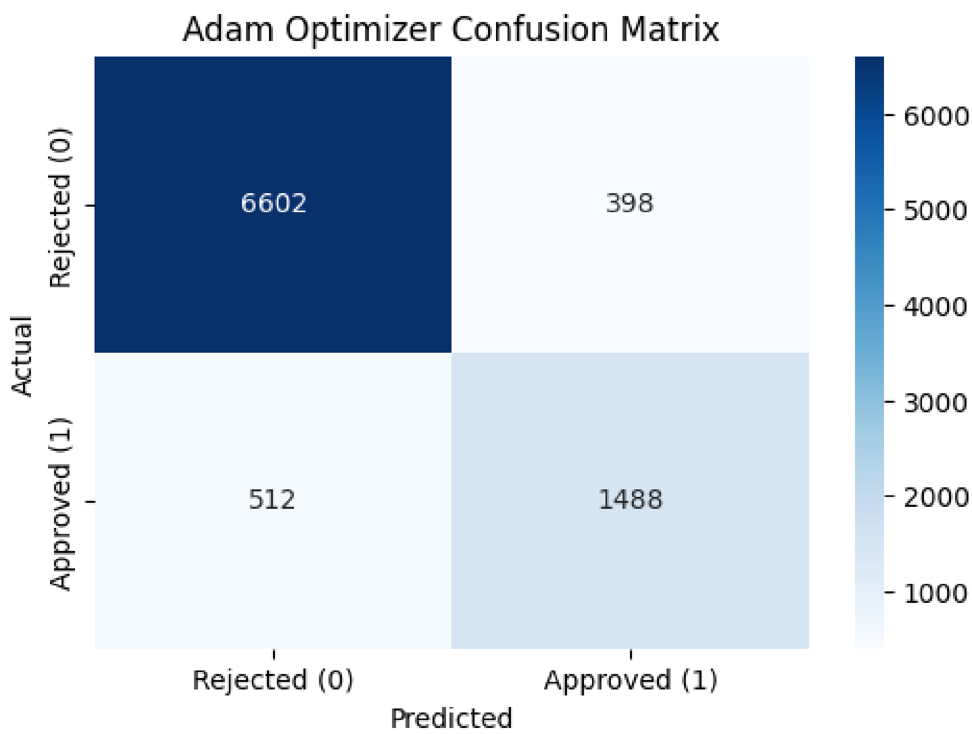
[11]:
```
model_adam = LogisticRegression(
    learning_rate=ADAM_LEARNING_RATE,
    n_epochs=ADAM_EPOCHS,
    beta1=ADAM_BETA1, beta2=ADAM_BETA2, epsilon=ADAM_EPSILON
)
model_adam.fit_adam(X_train_processed, y_train)
```

```
Starting training with Adam Optimizer…
Adam Epoch 100/1000, Cost: 0.2927
Adam Epoch 200/1000, Cost: 0.2544
Adam Epoch 300/1000, Cost: 0.2402
Adam Epoch 400/1000, Cost: 0.2332
Adam Epoch 500/1000, Cost: 0.2295
Adam Epoch 600/1000, Cost: 0.2274
Adam Epoch 700/1000, Cost: 0.2261
Adam Epoch 800/1000, Cost: 0.2252
Adam Epoch 900/1000, Cost: 0.2246
Adam Epoch 1000/1000, Cost: 0.2241
```

1.11 11) Evaluate — Adam

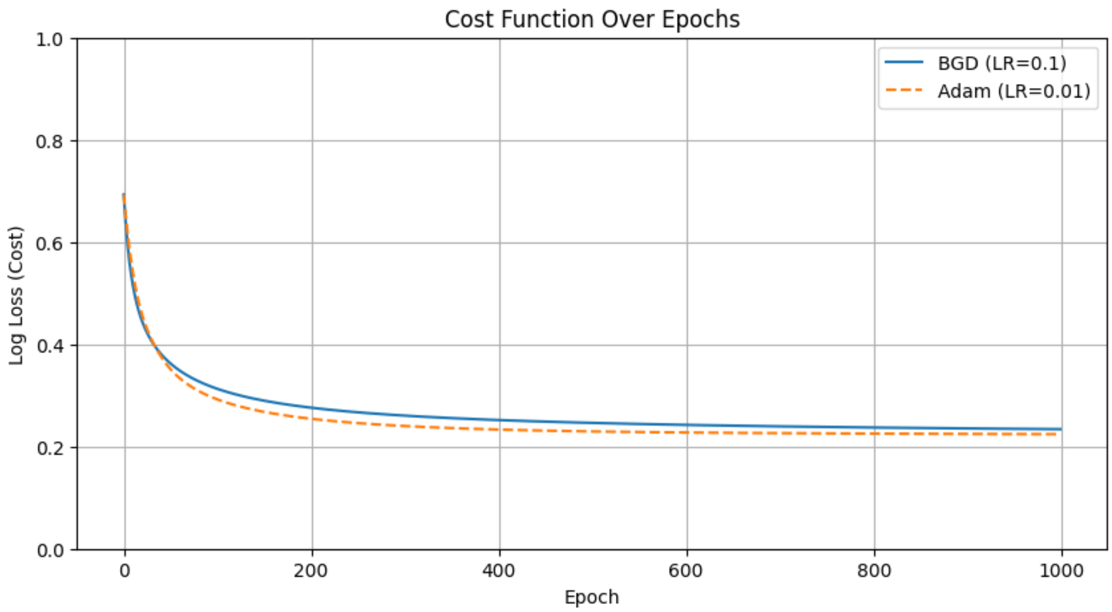
[12]:
```
y_pred_adam = model_adam.predict(X_test_processed)
acc_adam = evaluate_and_report('Adam Model', y_test, y_pred_adam)
plot_confusion_matrix(y_test, y_pred_adam, 'Adam Optimizer Confusion Matrix')
```

```
Adam Model Accuracy: 0.8989
Adam Model Classification Report:
              precision    recall  f1-score   support

Rejected (0)       0.93      0.94      0.94      7000
Approved (1)       0.79      0.74      0.77      2000

    accuracy                           0.90      9000
   macro avg       0.86      0.84      0.85      9000
weighted avg       0.90      0.90      0.90      9000
```



1.12 12) Compare Cost Histories

[13]:
```
plt.figure(figsize=(10,5))
plt.plot(model_bgd.cost_history, label=f'BGD (LR={BGD_LEARNING_RATE})')
plt.plot(model_adam.cost_history, label=f'Adam (LR={ADAM_LEARNING_RATE})',␣
↪linestyle='--')
plt.title('Cost Function Over Epochs')
plt.xlabel('Epoch')
plt.ylabel('Log Loss (Cost)')
plt.legend()
plt.ylim(0, 1)
plt.grid(True)
plt.show()
```



Cost Function Over Epochs
BGD (LR=0.1)
Adam (LR=0.01)
Log Loss (Cost)
Epoch
1.0
0.8
0.6
0.4
0.2
0.0
0
200
400
600
800
1000