Logistic_Regression_UsingPytorch

October 7, 2024

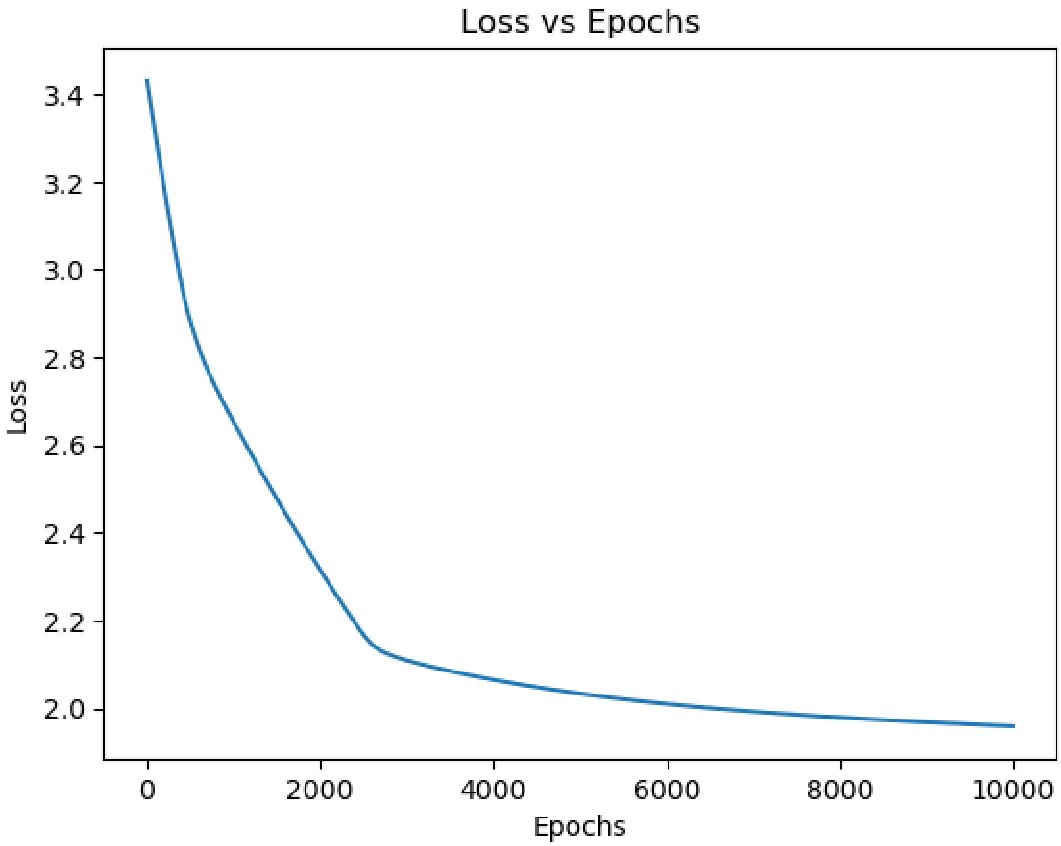
[1]:
```
import numpy as np

# Step 1: Load the labels (first column) and features
Y_labels = np.genfromtxt('/home/darksst/Desktop/Fall24/
↪StatisticalDecisionTheory/Data/Image/segmentation.data',
                         delimiter=',', dtype=str, encoding=None, usecols=0,␣
↪skip_header=5)

# Load the feature columns (usecols 5, 6, 7, 8, 9 for vedge-mean, vedge-sd,␣
↪hedge-mean, hedge-sd, intensity-mean)
X = np.genfromtxt('/home/darksst/Desktop/Fall24/StatisticalDecisionTheory/Data/
↪Image/segmentation.data',
                  delimiter=',', dtype=float, encoding=None, usecols=(5, 6, 7,␣
↪8, 9), skip_header=5)

# Step 2: One-hot encode the class labels
unique_classes = np.unique(Y_labels)  # Get the unique class names
num_classes = len(unique_classes)

# Create a one-hot encoded matrix for the labels
Y = np.zeros((Y_labels.shape[0], num_classes))
for i, label in enumerate(Y_labels):
    Y[i, np.where(unique_classes == label)[0][0]] = 1

# Initialize the parameter matrix B with zeros
B = np.zeros((X.shape[1], Y.shape[1]))

# Print shapes to verify everything is correct
print(f"Feature matrix (X) shape: {X.shape}")
print(f"One-hot encoded labels (Y) shape: {Y.shape}")
print(f"Parameter matrix (B) shape: {B.shape}")
```

```
Feature matrix (X) shape: (210, 5)
One-hot encoded labels (Y) shape: (210, 7)
Parameter matrix (B) shape: (5, 7)
```

[2]:
```python
import torch
import torch.nn as nn
import torch.optim as optim
import matplotlib.pyplot as plt

# Convert the NumPy arrays to PyTorch tensors
X_tensor = torch.tensor(X, dtype=torch.float32)  # Feature matrix
Y_tensor = torch.tensor(Y, dtype=torch.float32)  # One-hot encoded labels

# Define the Logistic Regression model using PyTorch
class LogisticRegression(nn.Module):
    def __init__(self, dimension_input, dimension_output):
        super(LogisticRegression, self).__init__()
        self.linear = nn.Linear(dimension_input, dimension_output)

    def forward(self, x):
        # Forward pass (logits)
        return self.linear(x)

# Set the input and output dimensions
dimension_input = X_tensor.shape[1]   # Number of features
dimension_output = Y_tensor.shape[1]  # Number of classes (one-hot encoding)

# Initialize the model
model = LogisticRegression(dimension_input, dimension_output)

# Define the loss function (CrossEntropyLoss handles softmax + loss internally)
criterion = nn.CrossEntropyLoss()

# Define the optimizer
optimizer = optim.SGD(model.parameters(), lr=0.0001)

# Number of epochs
epochs = 10000

# Initialize a list to store the loss values for plotting
loss_values = []

# Training loop
for epoch in range(epochs):
    # Forward pass: compute logits
    logits = model(X_tensor)

    # Compute the loss (CrossEntropyLoss expects raw logits, no need for␣
↪softmax)
    loss = criterion(logits, torch.max(Y_tensor, 1)[1])  # Convert Y_tensor␣
↪from one-hot to class labels
```

```python
    # Zero the gradients from the previous step
    optimizer.zero_grad()

    # Backward pass: compute gradients
    loss.backward()

    # Update the model parameters
    optimizer.step()

    # Store the loss value for plotting
    loss_values.append(loss.item())

# Print the final model parameters
print("Final parameters after training:", model.linear.weight, model.linear.
 ↪bias)
print("Final Loss:", loss_values[-1])

# Plot the loss over epochs using Matplotlib
plt.plot(range(epochs), loss_values)
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.title('Loss vs Epochs')
plt.show()
```

```
Final parameters after training: Parameter containing:
tensor([[-0.2686,  0.0679, -0.0367,  0.3721, -0.1195],
        [ 0.3704,  0.3619, -0.2582,  0.1548,  0.1294],
        [-0.1458,  0.1476,  0.0107,  0.0808,  0.1370],
        [-0.2795,  0.1655, -0.0229,  0.1832,  0.0687],
        [ 0.3183, -0.0171, -0.1804,  0.2289,  0.1424],
        [ 0.3996, -0.1315,  0.2426, -0.2876, -0.1482],
        [-0.3680,  0.1303, -0.0515, -0.0277,  0.1631]], requires_grad=True)
Parameter containing:
tensor([-0.1911, -0.0436,  0.3000, -0.0807,  0.2985, -0.1704, -0.2639],
       requires_grad=True)
Final Loss: 1.958688735961914
```


Loss vs Epochs
Loss
Epochs
3.4
3.2
3.0
2.8
2.6
2.4
2.2
2.0
0
2000
4000
6000
8000
10000