mlp_torch

November 18, 2025

[16]:
```python
"""
Demo: Multi-Layer Perceptron (MLP) on scikit-learn Digits dataset using PyTorch

Steps:
1) Load the 8x8 handwritten digits dataset (1797 samples)
2) Split into train/test
3) Scale features (very important for MLP)
4) Build an MLP in PyTorch
5) Train with mini-batches using Adam optimizer
6) Evaluate accuracy and F1
7) Plot training loss and confusion matrix
"""

import numpy as np
import matplotlib.pyplot as plt

from sklearn.datasets import load_digits
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import (
    accuracy_score, f1_score, confusion_matrix,
    ConfusionMatrixDisplay, classification_report
)

# PyTorch: A tensor-based deep learning framework
# PyTorch's Python package name: torch
# A tensor is just a container for numbers that can have any number of␣
↪dimensions
# Everything in PyTorch - neural networks, layers, losses, optimizers,␣
↪gradients -
# is built to work with torch.Tensor, not NumPy arrays.

# NumPy = calculator
# PyTorch = calculator + GPU + automatic differentiation + neural network tools

import torch
import torch.nn as nn # Neural network layers
```

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import torch.optim as optim # Optimization algorithms (Adam, SGD, etc.)
from torch.utils.data import TensorDataset #a dataset wrapper around tensors
from torch.utils.data import DataLoader #a tool that automatically creates␣
↪batches and shuffles data

# ---------------------------
# 1. Define MLP model in PyTorch
# ---------------------------
class MLP(nn.Module):
    def __init__(self, input_dim=64, hidden1=64, hidden2=32, num_classes=10):
        super().__init__()
        # Define the Layers
        self.net = nn.Sequential(
            nn.Linear(input_dim, hidden1),
            nn.ReLU(),
            nn.Linear(hidden1, hidden2),
            nn.ReLU(),
            nn.Linear(hidden2, num_classes)
        )

    def forward(self, x):
        # x: (batch_size, input_dim)
        return self.net(x) # self.net(x) automatically runs it through all␣
↪layers in order


def main():
    # Choose device (GPU if available, otherwise CPU)
    device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
    print(f"Using device: {device}")

    # ---------------------------
    # 2. Load data
    # ---------------------------
    digits = load_digits()
    X = digits.data          # shape: (n_samples, 64) flattened 8x8 images
    y = digits.target        # labels: 0..9

    # Train/test split
    X_train, X_test, y_train, y_test = train_test_split(
        X, y, test_size=0.2, random_state=42, stratify=y
    )

    # ---------------------------
    # 3. Scale features (standardization)
    # ---------------------------
    scaler = StandardScaler()
```

```
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled  = scaler.transform(X_test)

# ----------------------------
# 4. Convert to PyTorch tensors and DataLoaders
# ----------------------------
# Converts X_train_scaled (NumPy array) -> X_train_tensor (PyTorch tensor)␣
↪so PyTorch can use them for training on CPU or GPU.
# Feature matrices X Must use float32 because neural network weights are␣
↪floats
# Labels y Must be dtype=torch.long because nn.CrossEntropyLoss() requires␣
↪integer class labels

X_train_tensor = torch.tensor(X_train_scaled, dtype=torch.float32)
y_train_tensor = torch.tensor(y_train, dtype=torch.long)

X_test_tensor = torch.tensor(X_test_scaled, dtype=torch.float32)
y_test_tensor = torch.tensor(y_test, dtype=torch.long)

# Create datasets that pair (X, y) together
# Makes batching easy
# Makes shuffling easy

train_ds = TensorDataset(X_train_tensor, y_train_tensor)
test_ds  = TensorDataset(X_test_tensor, y_test_tensor)

# Build DataLoaders for mini-batch training
train_loader = DataLoader(train_ds, batch_size=64, shuffle=True)
# Testing does not backpropagate = no gradients
# Larger batches makes evaluation faster, No need to shuffle
test_loader  = DataLoader(test_ds, batch_size=256, shuffle=False)


# ----------------------------
# 5. Create model, loss function, optimizer
# ----------------------------
# Build the model
model = MLP(input_dim=64, hidden1=64, hidden2=32, num_classes=10).to(device)
criterion = nn.CrossEntropyLoss() # Define the loss function
optimizer = optim.Adam(model.parameters(), lr=1e-3) #Choose the optimizer
# model.parameters() gives Adam access to all weights and biases in the␣
↪network.
# So the optimizer can update them during training.

# ----------------------------
# 6. Training loop
# ----------------------------
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num_epochs = 50
epoch_losses = []

model.train() # tells PyTorch turn on the training behavior for all layers
for epoch in range(num_epochs):
    running_loss = 0.0

    for X_batch, y_batch in train_loader:
        X_batch = X_batch.to(device)
        y_batch = y_batch.to(device)

        # 1) Zero gradients
        optimizer.zero_grad()

        # 2) Forward pass
        outputs = model(X_batch)        # shape: (batch_size, 10)

        # 3) Compute loss
        loss = criterion(outputs, y_batch)

        # 4) Backward pass
        loss.backward() # computes gradients with respect to all model␣
↪parameters (weights & biases)

        # 5) Update weights
        optimizer.step() # gradient descent

        running_loss += loss.item() * X_batch.size(0)
        # loss.item() is average loss per sample in the batch
        # loss = (loss_1 + loss_2 + ... + loss_64) / 64
        # loss.item() * X_batch.size(0) is the total loss in the batch

    # Average loss over the epoch
    epoch_loss = running_loss / len(train_loader.dataset)
    epoch_losses.append(epoch_loss)
    print(f"Epoch {epoch+1}/{num_epochs} - Loss: {epoch_loss:.4f}")

# ---------------------------
# 7. Evaluation on test set
# ---------------------------
model.eval() # Switch model to evaluation mode
all_preds = []
all_true  = []

with torch.no_grad(): # Disable gradient computation
    for X_batch, y_batch in test_loader:
        X_batch = X_batch.to(device)
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        y_batch = y_batch.to(device)

        outputs = model(X_batch)             # (batch_size, 10)
        preds = torch.argmax(outputs, dim=1) # Convert scores to predicted digit

        all_preds.append(preds.cpu().numpy()) # Convert tensors back to NumPy arrays
        all_true.append(y_batch.cpu().numpy())

y_pred = np.concatenate(all_preds) # Combine all test batches
y_true = np.concatenate(all_true)

acc = accuracy_score(y_true, y_pred)
f1w = f1_score(y_true, y_pred, average='weighted') # F1-weighted = F1 score weighted by class frequency
f1m = f1_score(y_true, y_pred, average='macro') # F1-macro = average F1 across all classes

print(f"\nAccuracy: {acc:.4f} | F1 (weighted): {f1w:.4f} | F1 (macro): {f1m:.4f}")
print("\nClassification Report:\n")
print(classification_report(y_true, y_pred, digits=4))

# ---------------------------
# 8. Plot training loss curve
# ---------------------------
plt.figure(figsize=(7,4))
plt.plot(epoch_losses, marker='o')
plt.xlabel("Epoch")
plt.ylabel("Training Loss")
plt.title("PyTorch MLP Training Loss Curve (Digits)")
plt.tight_layout()
plt.show()

# ---------------------------
# 9. Confusion Matrix
# ---------------------------
cm = confusion_matrix(y_true, y_pred)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=digits.target_names)
plt.figure(figsize=(7,6))
disp.plot(values_format='d')
plt.title("Confusion Matrix - PyTorch MLP on Digits")
plt.tight_layout()
plt.show()
```

```python
if __name__ == "__main__":
    main()
```

```
Using device: cpu
Epoch 1/50 - Loss: 2.2042
Epoch 2/50 - Loss: 1.8379
Epoch 3/50 - Loss: 1.2728
Epoch 4/50 - Loss: 0.7501
Epoch 5/50 - Loss: 0.4433
Epoch 6/50 - Loss: 0.2878
Epoch 7/50 - Loss: 0.2043
Epoch 8/50 - Loss: 0.1566
Epoch 9/50 - Loss: 0.1244
Epoch 10/50 - Loss: 0.1013
Epoch 11/50 - Loss: 0.0851
Epoch 12/50 - Loss: 0.0719
Epoch 13/50 - Loss: 0.0622
Epoch 14/50 - Loss: 0.0537
Epoch 15/50 - Loss: 0.0464
Epoch 16/50 - Loss: 0.0407
Epoch 17/50 - Loss: 0.0361
Epoch 18/50 - Loss: 0.0318
Epoch 19/50 - Loss: 0.0284
Epoch 20/50 - Loss: 0.0254
Epoch 21/50 - Loss: 0.0227
Epoch 22/50 - Loss: 0.0205
Epoch 23/50 - Loss: 0.0186
Epoch 24/50 - Loss: 0.0168
Epoch 25/50 - Loss: 0.0152
Epoch 26/50 - Loss: 0.0138
Epoch 27/50 - Loss: 0.0128
Epoch 28/50 - Loss: 0.0115
Epoch 29/50 - Loss: 0.0108
Epoch 30/50 - Loss: 0.0098
Epoch 31/50 - Loss: 0.0090
Epoch 32/50 - Loss: 0.0084
Epoch 33/50 - Loss: 0.0078
Epoch 34/50 - Loss: 0.0072
Epoch 35/50 - Loss: 0.0066
Epoch 36/50 - Loss: 0.0063
Epoch 37/50 - Loss: 0.0058
Epoch 38/50 - Loss: 0.0054
Epoch 39/50 - Loss: 0.0051
Epoch 40/50 - Loss: 0.0048
Epoch 41/50 - Loss: 0.0045
Epoch 42/50 - Loss: 0.0042
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Epoch 43/50 - Loss: 0.0039
Epoch 44/50 - Loss: 0.0037
Epoch 45/50 - Loss: 0.0035
Epoch 46/50 - Loss: 0.0034
Epoch 47/50 - Loss: 0.0031
Epoch 48/50 - Loss: 0.0030
Epoch 49/50 - Loss: 0.0029
Epoch 50/50 - Loss: 0.0027

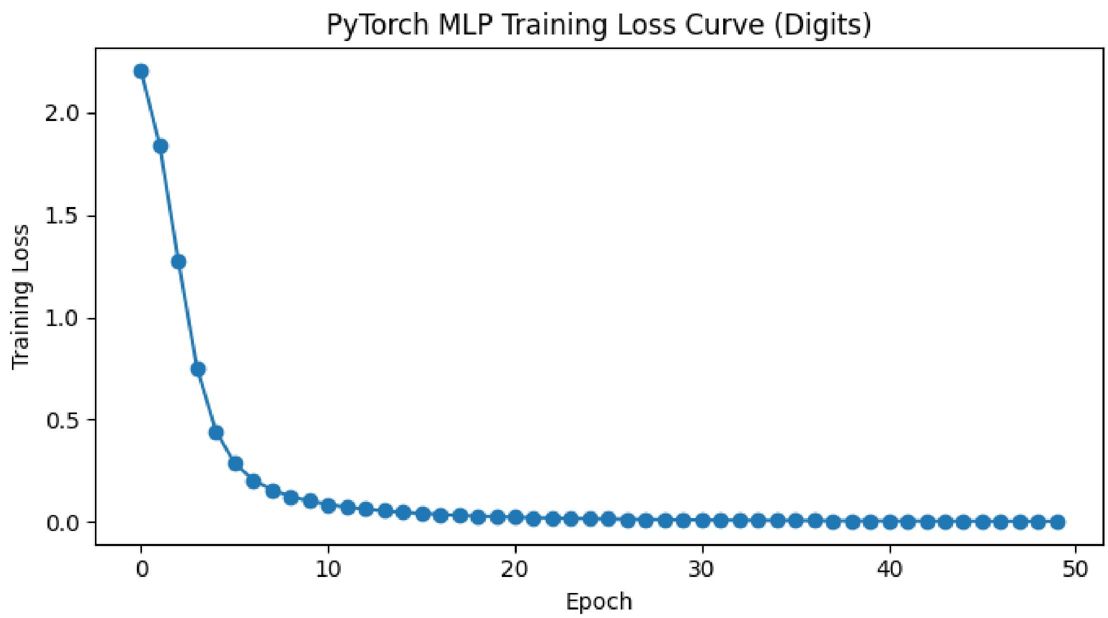
Accuracy: 0.9750 | F1 (weighted): 0.9749 | F1 (macro): 0.9747

Classification Report:

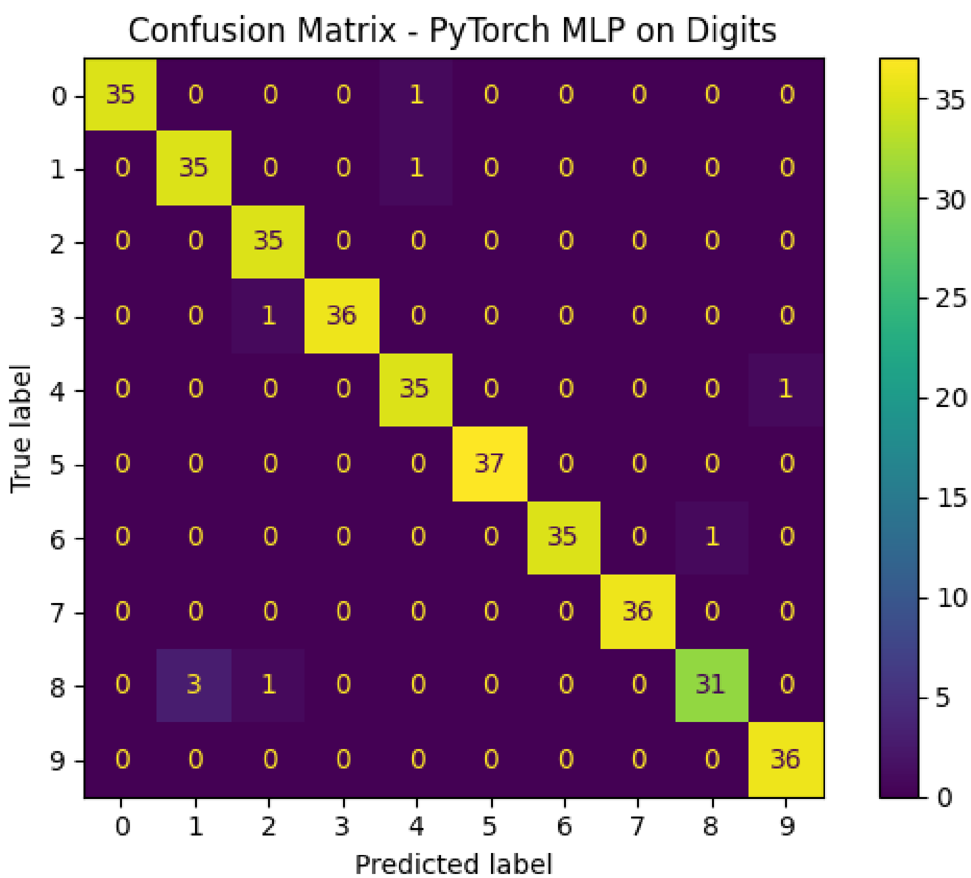
              precision    recall  f1-score   support

           0     1.0000    0.9722    0.9859        36
           1     0.9211    0.9722    0.9459        36
           2     0.9459    1.0000    0.9722        35
           3     1.0000    0.9730    0.9863        37
           4     0.9459    0.9722    0.9589        36
           5     1.0000    1.0000    1.0000        37
           6     1.0000    0.9722    0.9859        36
           7     1.0000    1.0000    1.0000        36
           8     0.9688    0.8857    0.9254        35
           9     0.9730    1.0000    0.9863        36

    accuracy                         0.9750       360
   macro avg     0.9755    0.9748    0.9747       360
weighted avg     0.9757    0.9750    0.9749       360
```



<Figure size 700x600 with 0 Axes>



[11]:
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# Precision=TP/(TP+FP)
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[12]:
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# Recall(Sensitivity)=TP/(TP+FN)
```

[13]:
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# F1 Score = 2 × (Precision×Recall)/(Precision+Recall)
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