Đề kiểm tra lập trình nhập môn phân tích dữ liệu và học sâu

Sinh viên không được phép sử dụng internet

Sinh viên sau khi làm bài xong xuất ra file PDF đồng thời nộp lên Fit-lab và push lên git-hub

Sinh viên làm bắt đầu làm bài từ 15h40 - 18h00

```
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```
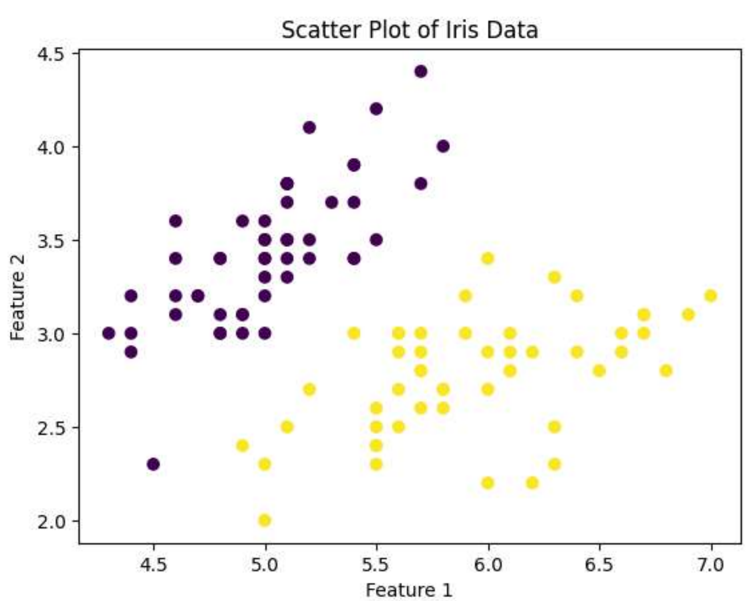

```
import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import Dataset, DataLoader, random_split
import numpy as np
from sklearn.datasets import load_iris
import matplotlib.pyplot as plt
```

```
#Bước 1: Load data
def load_dataset():
    X, y = load_iris(return_X_y=True)
    X = X[y!=2]
    y = y[y!=2]
    return X,y
#Điền ở đây
    X,y = load_dataset()
    print(x.shape, y.shape)
```

Kết quả: (100, 4) (100,)

```
#Trực quan hóa dữ liệu data
#Điền code ở đây
plt.scatter(X[:, 0], X[:, 1], c=y, cmap='viridis')
plt.xlabel('Feature 1')
plt.ylabel('Feature 2')
plt.title('Scatter Plot of Iris Data')
plt.show()
```



Kết quả

![image.png]

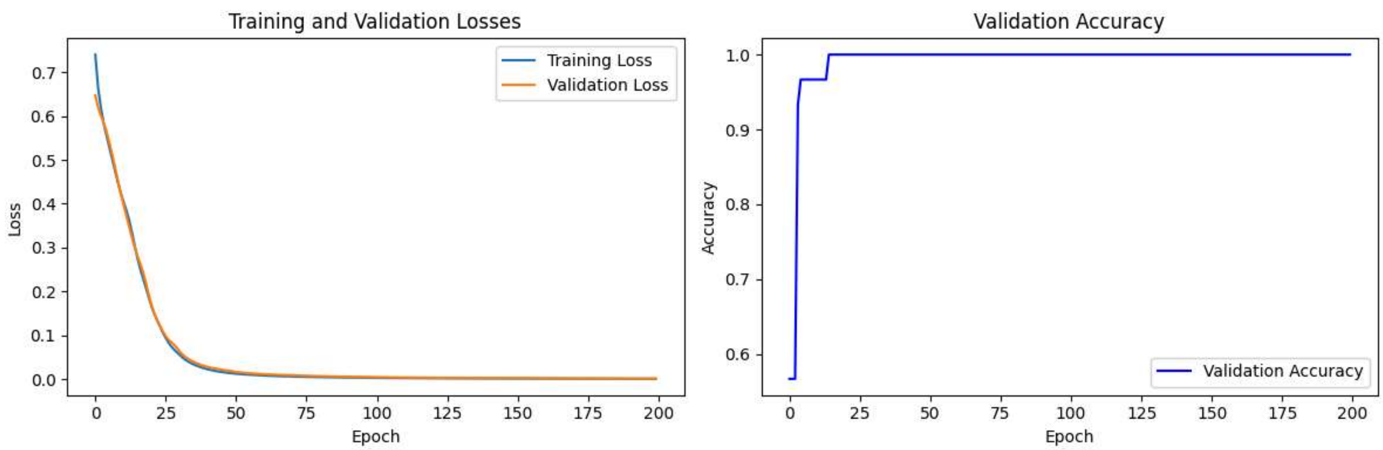
```
# Bước 2: Định nghĩa mô hình hồi quy logistic bằng PyTorch
class LogisticRegressTorch(nn.Module):
    def __init__(self, n_features):
        super(LogisticRegressTorch, self).__init__()
        self.linear = nn.Linear(n_features, 1)                 # tạo một lớp tuyến tính (nn.Linear) với n_features đầu vào và 1 đầu ra

    def forward(self, x):
        return torch.sigmoid(self.linear(x))



# Bước 3: Định nghĩa lớp dữ liệu
class IrisTorch(Dataset):
    def __init__(self, X, y):
        self.X = torch.tensor(X, dtype=torch.float32)
        self.y = torch.tensor(y, dtype=torch.float32).unsqueeze(1)

    def __len__(self):
        return  len(self.X)#Điền ở đây theo comment            #trả về số lượng mẫu trong tập dữ liệu (số lượng hàng trong self.X)

    def __getitem__(self, idx):
        return  self.X[idx], self.y[idx]#Điền ở đây theo comment            #trả về một cặp đặc trưng và nhãn tương ứng với chỉ số idx


# Tạo dữ liệu
dataset = IrisTorch(X, y)


# Bước 4: Chia tập dữ liệu thành tập huấn luyện và tập kiểm tra bằng cách chia ngẫu nhiên 70,30.
train_size =int(0.7 * len(dataset))                                               #70%
test_size =len(dataset) - train_size                                                #30%
train_dataset, test_dataset = random_split(dataset, [train_size, test_size])


# Tạo DataLoader
batch_size = 64
train_loader = DataLoader(train_dataset, batch_size=batch_size, shuffle=True)
test_loader = DataLoader(test_dataset, batch_size=batch_size, shuffle=False)


# Bước 5: Định nghĩa criterion và optimizer
n_features = X.shape[1]

model = nn.Sequential(
    nn.Linear(n_features, 128),
    nn.ReLU(),
    nn.Linear(128, 64),
    nn.ReLU(),
    nn.Linear(64, 1)
)

criterion = nn.BCEWithLogitsLoss()
optimizer = torch.optim.Adam(model.parameters(), lr=0.001)
```

```
n_epochs = 200
train_losses = []
test_losses = []
test_accuracies = []

for epoch in range(n_epochs):
    model.train()
    train_loss = 0.0
    for inputs, targets in train_loader:
        optimizer.zero_grad()
        outputs = model(inputs)
        loss = criterion(outputs, targets)
        loss.backward()
        optimizer.step()
        train_loss += loss.item() * inputs.size(0)

    train_loss /= len(train_loader.dataset)
    train_losses.append(train_loss)

    # Evaluation on test set
    model.eval()
    test_loss = 0.0
    correct = 0
    total = 0
    with torch.no_grad():
        for inputs, targets in test_loader:
            outputs = model(inputs)
            loss = criterion(outputs, targets)
            test_loss += loss.item() * inputs.size(0)

            predicted = (outputs >= 0.5).float()  # Binary classification thresholding
            total += targets.size(0)
            correct += (predicted == targets).sum().item()

    test_loss /= len(test_loader.dataset)
    test_losses.append(test_loss)

    accuracy = correct / total
    test_accuracies.append(accuracy)

    print(f'Epoch {epoch+1}/{n_epochs}, Train Loss: {train_loss:.4f}, Test Loss: {test_loss:.4f}, Test Accuracy: {accuracy:.4f}')
```

```
Epoch 1/200, Train Loss: 0.7400, Test Loss: 0.6470, Test Accuracy: 0.5667
Epoch 2/200, Train Loss: 0.6638, Test Loss: 0.6196, Test Accuracy: 0.5667
Epoch 3/200, Train Loss: 0.6184, Test Loss: 0.6002, Test Accuracy: 0.5667
Epoch 4/200, Train Loss: 0.5827, Test Loss: 0.5836, Test Accuracy: 0.9333
Epoch 5/200, Train Loss: 0.5551, Test Loss: 0.5644, Test Accuracy: 0.9667
Epoch 6/200, Train Loss: 0.5284, Test Loss: 0.5392, Test Accuracy: 0.9667
Epoch 7/200, Train Loss: 0.5020, Test Loss: 0.5125, Test Accuracy: 0.9667
Epoch 8/200, Train Loss: 0.4753, Test Loss: 0.4832, Test Accuracy: 0.9667
Epoch 9/200, Train Loss: 0.4486, Test Loss: 0.4524, Test Accuracy: 0.9667
Epoch 10/200, Train Loss: 0.4251, Test Loss: 0.4243, Test Accuracy: 0.9667
Epoch 11/200, Train Loss: 0.4046, Test Loss: 0.3988, Test Accuracy: 0.9667
Epoch 12/200, Train Loss: 0.3858, Test Loss: 0.3739, Test Accuracy: 0.9667
Epoch 13/200, Train Loss: 0.3634, Test Loss: 0.3481, Test Accuracy: 0.9667
Epoch 14/200, Train Loss: 0.3349, Test Loss: 0.3228, Test Accuracy: 0.9667
Epoch 15/200, Train Loss: 0.3043, Test Loss: 0.3002, Test Accuracy: 1.0000
Epoch 16/200, Train Loss: 0.2753, Test Loss: 0.2808, Test Accuracy: 1.0000
Epoch 17/200, Train Loss: 0.2504, Test Loss: 0.2628, Test Accuracy: 1.0000
Epoch 18/200, Train Loss: 0.2289, Test Loss: 0.2428, Test Accuracy: 1.0000
Epoch 19/200, Train Loss: 0.2079, Test Loss: 0.2192, Test Accuracy: 1.0000
Epoch 20/200, Train Loss: 0.1860, Test Loss: 0.1924, Test Accuracy: 1.0000
Epoch 21/200, Train Loss: 0.1652, Test Loss: 0.1681, Test Accuracy: 1.0000
Epoch 22/200, Train Loss: 0.1478, Test Loss: 0.1493, Test Accuracy: 1.0000
Epoch 23/200, Train Loss: 0.1343, Test Loss: 0.1338, Test Accuracy: 1.0000
Epoch 24/200, Train Loss: 0.1201, Test Loss: 0.1205, Test Accuracy: 1.0000
Epoch 25/200, Train Loss: 0.1061, Test Loss: 0.1086, Test Accuracy: 1.0000
Epoch 26/200, Train Loss: 0.0941, Test Loss: 0.0983, Test Accuracy: 1.0000
Epoch 27/200, Train Loss: 0.0835, Test Loss: 0.0903, Test Accuracy: 1.0000
Epoch 28/200, Train Loss: 0.0745, Test Loss: 0.0842, Test Accuracy: 1.0000
Epoch 29/200, Train Loss: 0.0673, Test Loss: 0.0786, Test Accuracy: 1.0000
Epoch 30/200, Train Loss: 0.0612, Test Loss: 0.0713, Test Accuracy: 1.0000
Epoch 31/200, Train Loss: 0.0550, Test Loss: 0.0633, Test Accuracy: 1.0000
Epoch 32/200, Train Loss: 0.0491, Test Loss: 0.0563, Test Accuracy: 1.0000
Epoch 33/200, Train Loss: 0.0443, Test Loss: 0.0507, Test Accuracy: 1.0000
Epoch 34/200, Train Loss: 0.0402, Test Loss: 0.0464, Test Accuracy: 1.0000
Epoch 35/200, Train Loss: 0.0367, Test Loss: 0.0427, Test Accuracy: 1.0000
Epoch 36/200, Train Loss: 0.0336, Test Loss: 0.0395, Test Accuracy: 1.0000
Epoch 37/200, Train Loss: 0.0308, Test Loss: 0.0365, Test Accuracy: 1.0000
Epoch 38/200, Train Loss: 0.0284, Test Loss: 0.0339, Test Accuracy: 1.0000
```

```
Epoch 39/200, Train Loss: 0.0262, Test Loss: 0.0316, Test Accuracy: 1.0000
```

```
# Vẽ biểu đồ loss và accuracy
plt.figure(figsize=(12, 4))
plt.subplot(1, 2, 1)
plt.plot(train_losses, label='Training Loss')
plt.plot(test_losses, label='Validation Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.title('Training and Validation Losses')
plt.legend()

# Plotting accuracy
plt.subplot(1, 2, 2)
plt.plot(test_accuracies, label='Validation Accuracy', color='blue')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.title('Validation Accuracy')
plt.legend()

plt.tight_layout()
plt.show()
```



Kết quả:

image.png