assignment2_q2

March 9, 2024

Assignment 2

This assignment requires you to implement image recognition methods. Please understand and use relevant libraries. You are expected to solve both questions.

Data preparation and rules

Please use the images of the MNIST hand-written digits recognition dataset. You may use torchvision.datasets library to obtain the images and splits. You should have 60,000 training images and 10,000 test images. Use test images only to evaluate your model performance.

[ ]:
```
import cv2
import numpy as np
import os
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
from sklearn.svm import SVC
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import make_pipeline
from sklearn.model_selection import train_test_split
```

Q2: CNNs and Transformers [6 points] 1. [2.5 points] Set up a modular codebase for training a CNN (LeNet) on the task of handwritten digit recognition. You should have clear functional separation between the data (dataset and dataloader), model (nn.Module), and trainer (train/test epoch loops). Implement logging: using Weights & Biases is highly recommended, alternatively, create your own plots using other plotting libraries. Log the training and evaluation losses and accuracies at every epoch, show the plots for at least one training and evaluation run. Note 1: Seed random numbers for reproducibility (running the notebook again should give you the same results!).

[ ]:
```
import torch
from torchvision import datasets, transforms
from torch.utils.data import DataLoader

def load_data(batch_size=64):
    transform = transforms.Compose([transforms.Resize((32, 32)),
                                    transforms.ToTensor(),
                                    transforms.Normalize((0.5,), (0.5,))])

    # Download and load the training data
```

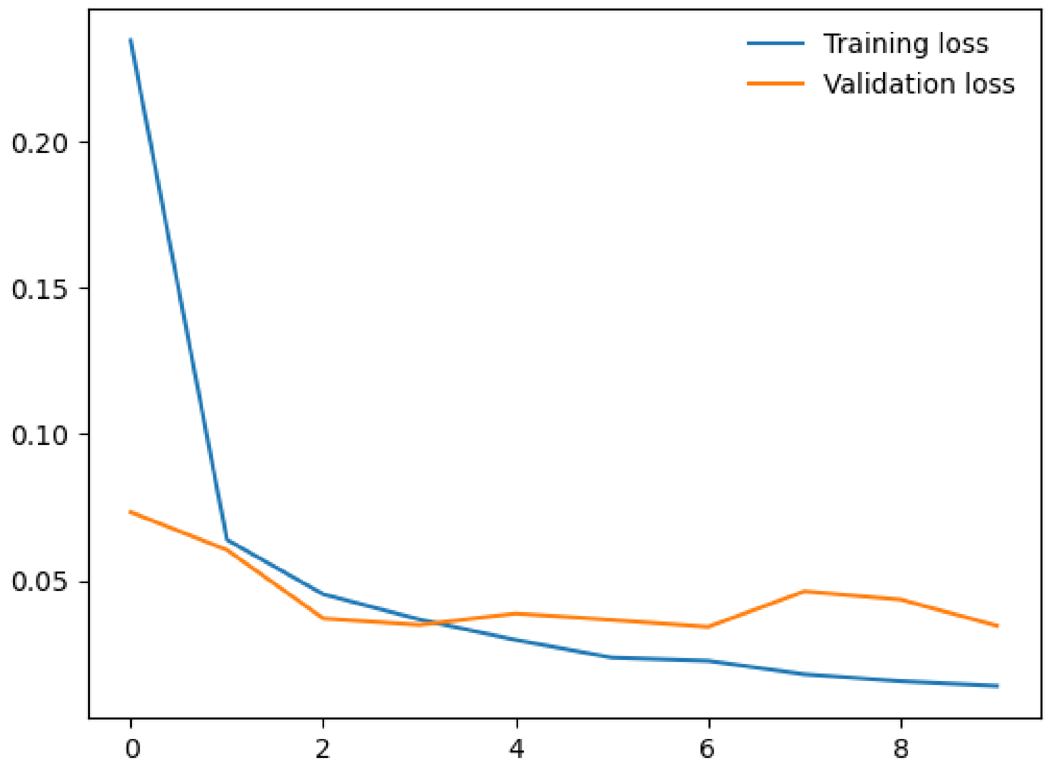
```
    trainset = datasets.MNIST('~/.pytorch/MNIST_data/', download=True,␣
↪train=True, transform=transform)
    trainloader = DataLoader(trainset, batch_size=batch_size, shuffle=True)

    # Download and load the test data
    testset = datasets.MNIST('~/.pytorch/MNIST_data/', download=True,␣
↪train=False, transform=transform)
    testloader = DataLoader(testset, batch_size=batch_size, shuffle=True)

    return trainloader, testloader
```

[ ]:
```
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
import matplotlib.pyplot as plt

class LeNet(nn.Module):
    def __init__(self):
        super(LeNet, self).__init__()
        self.conv1 = nn.Conv2d(1, 6, 5) # Input channel, Output channels,␣
↪Kernel size
        self.conv2 = nn.Conv2d(6, 16, 5)
        self.fc1 = nn.Linear(16*5*5, 120)
        self.fc2 = nn.Linear(120, 84)
        self.fc3 = nn.Linear(84, 10)

    def forward(self, x):
        x = F.max_pool2d(F.relu(self.conv1(x)), (2, 2))
        x = F.max_pool2d(F.relu(self.conv2(x)), 2)
        x = x.view(-1, 16*5*5)
        x = F.relu(self.fc1(x))
        x = F.relu(self.fc2(x))
        x = self.fc3(x)
        return x


def train_and_evaluate(model, trainloader, testloader, epochs=10):
    criterion = nn.CrossEntropyLoss()
    optimizer = optim.Adam(model.parameters(), lr=0.001)

    train_losses, test_losses = [], []
    for e in range(epochs):
        running_loss = 0
        for images, labels in trainloader:
            optimizer.zero_grad()
            output = model(images)
            loss = criterion(output, labels)
```

```python
            loss.backward()
            optimizer.step()
            running_loss += loss.item()

        else:
            test_loss = 0
            accuracy = 0

            with torch.no_grad():
                model.eval()
                for images, labels in testloader:
                    log_ps = model(images)
                    test_loss += criterion(log_ps, labels)

                    ps = torch.exp(log_ps)
                    top_p, top_class = ps.topk(1, dim=1)
                    equals = top_class == labels.view(*top_class.shape)
                    accuracy += torch.mean(equals.type(torch.FloatTensor))

            model.train()
            train_losses.append(running_loss/len(trainloader))
            test_losses.append(test_loss/len(testloader))

            print(f"Epoch {e+1}/{epochs}.. "
                  f"Train loss: {running_loss/len(trainloader):.3f}.. "
                  f"Test loss: {test_loss/len(testloader):.3f}.. "
                  f"Test accuracy: {accuracy/len(testloader):.3f}")

    plt.plot(train_losses, label='Training loss')
    plt.plot(test_losses, label='Validation loss')
    plt.legend(frameon=False)
    plt.show()


if __name__ == "__main__":
    torch.manual_seed(42)  # For reproducibility
    trainloader, testloader = load_data()
    model = LeNet()
    train_and_evaluate(model, trainloader, testloader)
    torch.save(model.state_dict(), 'lenet_mnist.pth')
```

```
Epoch 1/10.. Train loss: 0.234.. Test loss: 0.073.. Test accuracy: 0.976
Epoch 2/10.. Train loss: 0.064.. Test loss: 0.060.. Test accuracy: 0.981
Epoch 3/10.. Train loss: 0.045.. Test loss: 0.037.. Test accuracy: 0.988
Epoch 4/10.. Train loss: 0.037.. Test loss: 0.035.. Test accuracy: 0.988
Epoch 5/10.. Train loss: 0.030.. Test loss: 0.039.. Test accuracy: 0.987
Epoch 6/10.. Train loss: 0.024.. Test loss: 0.037.. Test accuracy: 0.989
Epoch 7/10.. Train loss: 0.023.. Test loss: 0.034.. Test accuracy: 0.989
```

```
Epoch 8/10.. Train loss: 0.018.. Test loss: 0.046.. Test accuracy: 0.987
Epoch 9/10.. Train loss: 0.016.. Test loss: 0.044.. Test accuracy: 0.986
Epoch 10/10.. Train loss: 0.014.. Test loss: 0.035.. Test accuracy: 0.990
```



2. [1 point] Show the results for 6 different settings of hyperparameters. You may want to change the batch size, learning rate, and optimizer. Explain the trends in classification accuracy that you observe. Which hyperpa- rameters are most important?

[ ]:
```
from tqdm import tqdm
import torch
import torchvision
import torchvision.transforms as transforms
from torch.utils.data import DataLoader
import torch.nn as nn
import torch.optim as optim
import matplotlib.pyplot as plt

def train_and_evaluate(batch_size, learning_rate, optimizer_choice, epochs=5,␣
 ↪momentum=0.9, weight_decay=0.0):

    transform = transforms.Compose([transforms.ToTensor(), transforms.
 ↪Normalize((0.5,), (0.5,))])
```

```python
    trainset = torchvision.datasets.MNIST(root='./data', train=True,␣
↪download=True, transform=transform)
    trainloader = DataLoader(trainset, batch_size=batch_size, shuffle=True)
    testset = torchvision.datasets.MNIST(root='./data', train=False,␣
↪download=True, transform=transform)
    testloader = DataLoader(testset, batch_size=batch_size, shuffle=False)


    model = LeNet()
    criterion = nn.CrossEntropyLoss()

    optimizer = None
    if optimizer_choice == 'Adam':
        optimizer = optim.Adam(model.parameters(), lr=learning_rate,␣
↪weight_decay=weight_decay)
    elif optimizer_choice == 'SGD':
        optimizer = optim.SGD(model.parameters(), lr=learning_rate,␣
↪momentum=momentum, weight_decay=weight_decay)
    elif optimizer_choice == 'RMSprop':
        optimizer = optim.RMSprop(model.parameters(), lr=learning_rate,␣
↪weight_decay=weight_decay)

    for epoch in range(epochs):
        model.train()
        running_loss = 0.0
        for images, labels in tqdm(trainloader, desc=f"Epoch {epoch+1}/
↪{epochs}", leave=False):
            optimizer.zero_grad()
            outputs = model(images)
            loss = criterion(outputs, labels)
            loss.backward()
            optimizer.step()
            running_loss += loss.item()
        print(f"Epoch {epoch+1}, Training Loss: {running_loss/len(trainloader):.
↪4f}")


    model.eval()
    correct = 0
    total = 0
    with torch.no_grad():
        for images, labels in testloader:
            outputs = model(images)
            _, predicted = torch.max(outputs.data, 1)
            total += labels.size(0)
            correct += (predicted == labels).sum().item()
```

```
    accuracy = 100 * correct / total
    print(f"Accuracy on the test set: {accuracy:.2f}%")
    return accuracy
```

[ ]:
```
# Hyperparameters sets to experiment with
hyperparameters_sets = [
    {'batch_size': 32, 'learning_rate': 0.001, 'optimizer_choice': 'Adam'},
    {'batch_size': 64, 'learning_rate': 0.0001, 'optimizer_choice': 'Adam'},
    {'batch_size': 64, 'learning_rate': 0.002, 'optimizer_choice': 'Adam'},
    {'batch_size': 128, 'learning_rate': 0.001, 'optimizer_choice': 'SGD',␣
 ↪'momentum': 0.9},
    {'batch_size': 128, 'learning_rate': 0.005, 'optimizer_choice': 'SGD',␣
 ↪'momentum': 0.5},
    {'batch_size': 256, 'learning_rate': 0.001, 'optimizer_choice': 'RMSprop'},
    {'batch_size': 256, 'learning_rate': 0.0005, 'optimizer_choice': 'RMSprop'},
    {'batch_size': 512, 'learning_rate': 0.001, 'optimizer_choice': 'Adam'},
    {'batch_size': 64, 'learning_rate': 0.001, 'optimizer_choice': 'Adam',␣
 ↪'weight_decay': 0.0001},
    {'batch_size': 128, 'learning_rate': 0.0001, 'optimizer_choice': 'Adam',␣
 ↪'weight_decay': 0.001},
    {'batch_size': 128, 'learning_rate': 0.001, 'optimizer_choice': 'SGD',␣
 ↪'momentum': 0.9, 'weight_decay': 0.0001},
]
```

[ ]:
```
from tqdm import tqdm
import torch
import torchvision
import torchvision.transforms as transforms
from torch.utils.data import DataLoader
import torch.nn as nn
import torch.optim as optim
import matplotlib.pyplot as plt

def train_and_evaluate(batch_size, learning_rate, optimizer_choice, epochs=5,␣
 ↪momentum=0.9, weight_decay=0.0):
    # Load and preprocess the MNIST dataset
    transform = transforms.Compose([transforms.ToTensor(), transforms.
 ↪Normalize((0.5,), (0.5,))])
    trainset = torchvision.datasets.MNIST(root='./data', train=True,␣
 ↪download=True, transform=transform)
    trainloader = DataLoader(trainset, batch_size=batch_size, shuffle=True)
    testset = torchvision.datasets.MNIST(root='./data', train=False,␣
 ↪download=True, transform=transform)
    testloader = DataLoader(testset, batch_size=batch_size, shuffle=False)
```

```
    # Model instantiation
    model = LeNet()
    criterion = nn.CrossEntropyLoss()

    # Optimizer selection
    optimizer = None
    if optimizer_choice == 'Adam':
        optimizer = optim.Adam(model.parameters(), lr=learning_rate,␣
↪weight_decay=weight_decay)
    elif optimizer_choice == 'SGD':
        optimizer = optim.SGD(model.parameters(), lr=learning_rate,␣
↪momentum=momentum, weight_decay=weight_decay)
    elif optimizer_choice == 'RMSprop':
        optimizer = optim.RMSprop(model.parameters(), lr=learning_rate,␣
↪weight_decay=weight_decay)

    # Training loop
    for epoch in range(epochs):
        model.train()
        running_loss = 0.0
        for images, labels in tqdm(trainloader, desc=f"Epoch {epoch+1}/
↪{epochs}", leave=False):
            optimizer.zero_grad()
            outputs = model(images)
            loss = criterion(outputs, labels)
            loss.backward()
            optimizer.step()
            running_loss += loss.item()
        print(f"Epoch {epoch+1}, Training Loss: {running_loss/len(trainloader):.
↪4f}")

    # Evaluation loop
    model.eval()
    correct = 0
    total = 0
    with torch.no_grad():
        for images, labels in testloader:
            outputs = model(images)
            _, predicted = torch.max(outputs.data, 1)
            total += labels.size(0)
            correct += (predicted == labels).sum().item()

    accuracy = 100 * correct / total
    print(f"Accuracy on the test set: {accuracy:.2f}%")
    return accuracy
```

[ ]:
```
def perform_grid_search(hyperparameters_sets):
    best_accuracy = 0
    best_hyperparameters = None
    results = []

    for i, hparams in enumerate(hyperparameters_sets, 1):
        print(f"Experiment {i} with params {hparams}")
        accuracy = train_and_evaluate(**hparams)
        results.append({'params': hparams, 'accuracy': accuracy})

        if accuracy > best_accuracy:
            best_accuracy = accuracy
            best_hyperparameters = hparams

    print(f"Best performing hyperparameters: {best_hyperparameters}")
    print(f"Best accuracy: {best_accuracy:.2f}%")
    return best_hyperparameters, best_accuracy, results
```

[ ]:
```
best_hyperparameters, best_accuracy, results =␣
↪perform_grid_search(hyperparameters_sets)

accuracies = [result['accuracy'] for result in results]
labels = [f"Exp {i+1}" for i, _ in enumerate(results)]

plt.figure(figsize=(12, 8))
bars = plt.bar(labels, accuracies, color='skyblue')
plt.xlabel('Experiment')
plt.ylabel('Accuracy (%)')
plt.title('Grid Search Results')
plt.xticks(rotation=45)

# Annotating each bar with its height value
for bar in bars:
    height = bar.get_height()
    plt.text(bar.get_x() + bar.get_width() / 2.0, height, f'{height:.2f}%',␣
↪ha='center', va='bottom')

plt.show()
```

```
Experiment 1 with params {'batch_size': 32, 'learning_rate': 0.001,
'optimizer_choice': 'Adam'}


Epoch 1, Training Loss: 0.1945


Epoch 2, Training Loss: 0.0643
```

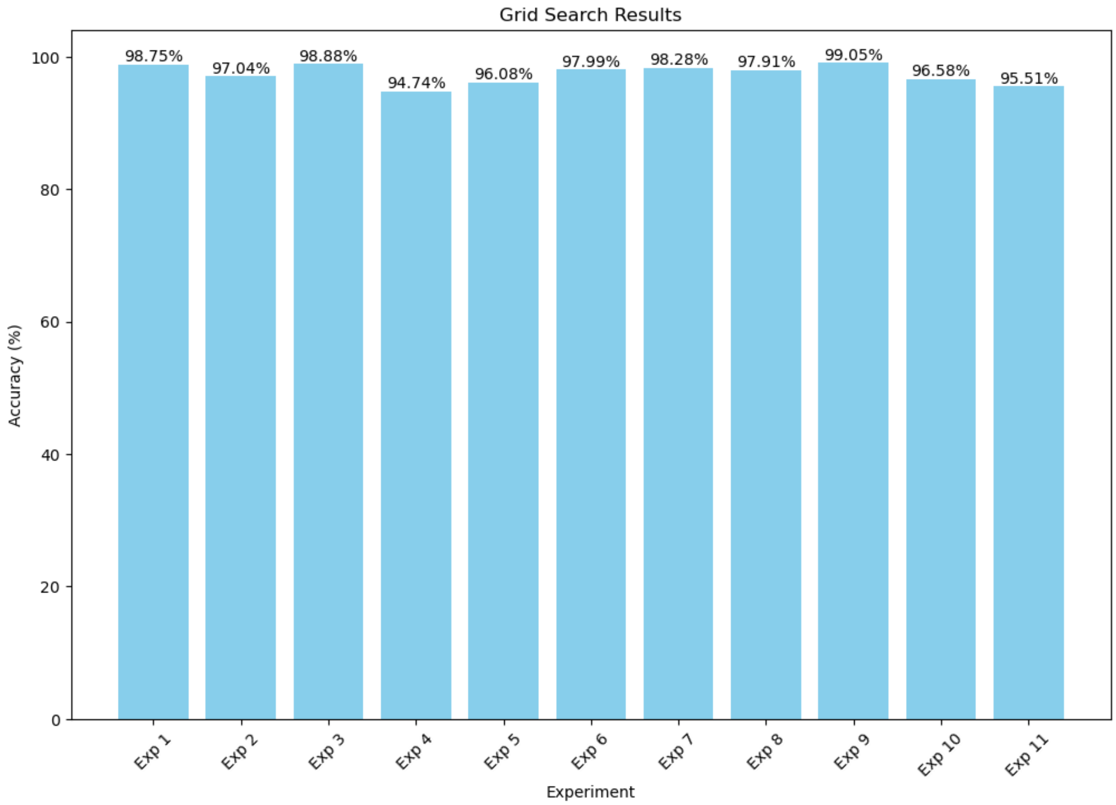
```
Epoch 3, Training Loss: 0.0473

Epoch 4, Training Loss: 0.0380

Epoch 5, Training Loss: 0.0311
Accuracy on the test set: 98.75%
Experiment 2 with params {'batch_size': 64, 'learning_rate': 0.0001,
'optimizer_choice': 'Adam'}

Epoch 1, Training Loss: 0.7952

Epoch 2, Training Loss: 0.2208

Epoch 3, Training Loss: 0.1647

Epoch 4, Training Loss: 0.1338

Epoch 5, Training Loss: 0.1139
Accuracy on the test set: 97.04%
Experiment 3 with params {'batch_size': 64, 'learning_rate': 0.002,
'optimizer_choice': 'Adam'}

Epoch 1, Training Loss: 0.1944

Epoch 2, Training Loss: 0.0567

Epoch 3, Training Loss: 0.0428

Epoch 4, Training Loss: 0.0347

Epoch 5, Training Loss: 0.0308
Accuracy on the test set: 98.88%
Experiment 4 with params {'batch_size': 128, 'learning_rate': 0.001,
'optimizer_choice': 'SGD', 'momentum': 0.9}
```

```
Epoch 1, Training Loss: 2.2775

Epoch 2, Training Loss: 1.2730

Epoch 3, Training Loss: 0.3692

Epoch 4, Training Loss: 0.2545

Epoch 5, Training Loss: 0.1967
Accuracy on the test set: 94.74%
Experiment 5 with params {'batch_size': 128, 'learning_rate': 0.005,
'optimizer_choice': 'SGD', 'momentum': 0.5}

Epoch 1, Training Loss: 2.2865

Epoch 2, Training Loss: 1.5796

Epoch 3, Training Loss: 0.3295

Epoch 4, Training Loss: 0.2069

Epoch 5, Training Loss: 0.1613
Accuracy on the test set: 96.08%
Experiment 6 with params {'batch_size': 256, 'learning_rate': 0.001,
'optimizer_choice': 'RMSprop'}

Epoch 1, Training Loss: 0.3245

Epoch 2, Training Loss: 0.0921

Epoch 3, Training Loss: 0.0663

Epoch 4, Training Loss: 0.0522
```

```
Epoch 5, Training Loss: 0.0436
Accuracy on the test set: 97.99%
Experiment 7 with params {'batch_size': 256, 'learning_rate': 0.0005,
'optimizer_choice': 'RMSprop'}


Epoch 1, Training Loss: 0.4506


Epoch 2, Training Loss: 0.1307


Epoch 3, Training Loss: 0.0960


Epoch 4, Training Loss: 0.0775


Epoch 5, Training Loss: 0.0657
Accuracy on the test set: 98.28%
Experiment 8 with params {'batch_size': 512, 'learning_rate': 0.001,
'optimizer_choice': 'Adam'}


Epoch 1, Training Loss: 0.8013


Epoch 2, Training Loss: 0.1961


Epoch 3, Training Loss: 0.1253


Epoch 4, Training Loss: 0.0938


Epoch 5, Training Loss: 0.0775
Accuracy on the test set: 97.91%
Experiment 9 with params {'batch_size': 64, 'learning_rate': 0.001,
'optimizer_choice': 'Adam', 'weight_decay': 0.0001}


Epoch 1, Training Loss: 0.2587


Epoch 2, Training Loss: 0.0690
```

```
Epoch 3, Training Loss: 0.0511


Epoch 4, Training Loss: 0.0404


Epoch 5, Training Loss: 0.0338
Accuracy on the test set: 99.05%
Experiment 10 with params {'batch_size': 128, 'learning_rate': 0.0001,
'optimizer_choice': 'Adam', 'weight_decay': 0.001}


Epoch 1, Training Loss: 1.1639


Epoch 2, Training Loss: 0.2788


Epoch 3, Training Loss: 0.2010


Epoch 4, Training Loss: 0.1633


Epoch 5, Training Loss: 0.1397
Accuracy on the test set: 96.58%
Experiment 11 with params {'batch_size': 128, 'learning_rate': 0.001,
'optimizer_choice': 'SGD', 'momentum': 0.9, 'weight_decay': 0.0001}


Epoch 1, Training Loss: 2.2264


Epoch 2, Training Loss: 0.7824


Epoch 3, Training Loss: 0.3306


Epoch 4, Training Loss: 0.2312


Epoch 5, Training Loss: 0.1831
Accuracy on the test set: 95.51%
Best performing hyperparameters: {'batch_size': 64, 'learning_rate': 0.001,
```

```
'optimizer_choice': 'Adam', 'weight_decay': 0.0001}
Best accuracy: 99.05%
```



3. [0.5 points] Compare the best performing CNN (from above) against the SIFT-BoVW-SVM approach. Explain the differences.

CNN's best performance comes to arouny d 99 percent whereas the maximum SIFT-BOVW-SVM reaches is around 80 percent. The later approach has lower accuracy in general as it manually extracts and quantizes the features each time. It also has a higher run time compared to CNNs.

Feature	CNN	SIFT-BoVW-SVM
Feature Extraction	Automatically learns from data, capturing hierarchical patterns.	Manually extracts and quantizes local features.
Classification Strategy	Includes an integrated classification layer.	Uses SVM classifier based on quantized feature vectors.

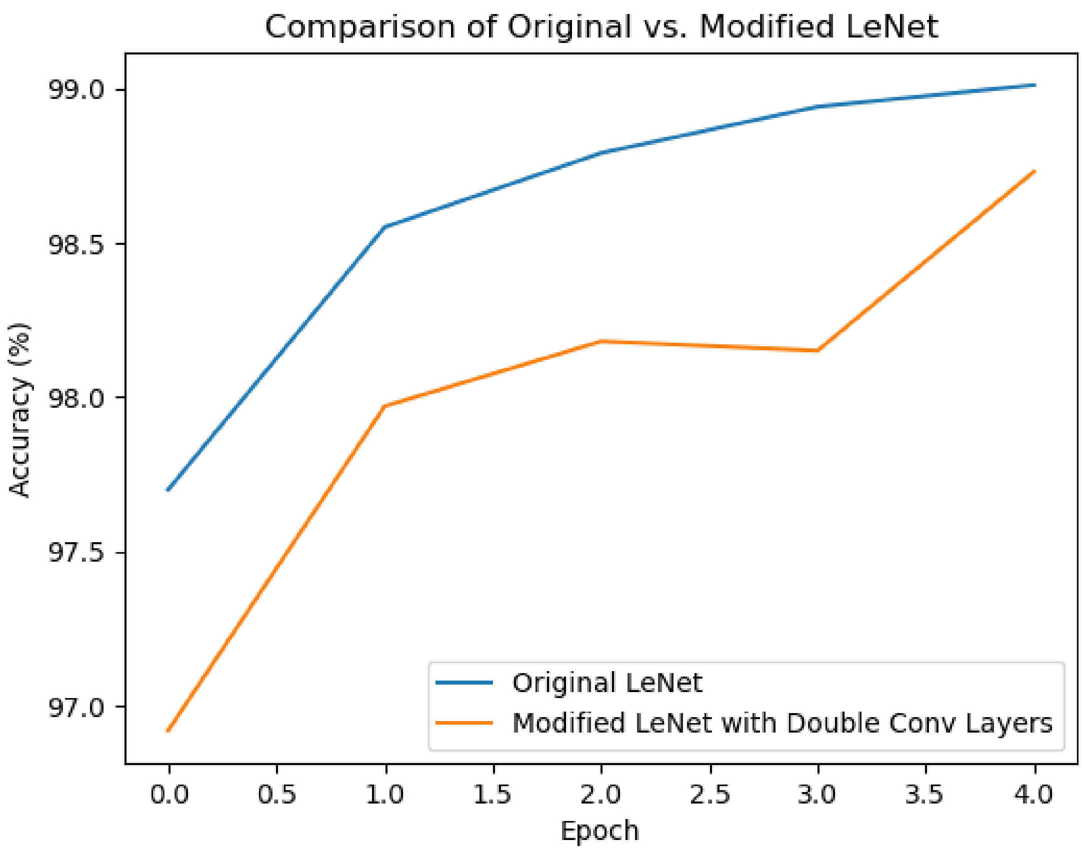
Feature	CNN	SIFT-BoVW-SVM
Performance	Tends to outperform on complex image classification tasks due to end-to-end learning.	Can be effective in scenarios with limited data or where local features are crucial, but generally lags behind CNNs.
Use Cases	Preferred for a wide range of image classification tasks, requires large datasets.	Suitable for tasks benefiting from robustness to scale and rotation, or where computational resources are limited.

4. [0.5 points] How does the performance change if you double the number of convolutional layers?

[ ]:
```
import torch.nn.functional as F


class ModifiedLeNet(nn.Module):
    def __init__(self):
        super(ModifiedLeNet, self).__init__()
        self.conv1 = nn.Conv2d(1, 6, 5)
        self.conv1_1 = nn.Conv2d(6, 6, 5, padding=2) # Additional layer
        self.pool = nn.MaxPool2d(2, 2)
        self.conv2 = nn.Conv2d(6, 16, 5)
        self.conv2_1 = nn.Conv2d(16, 16, 5, padding=2) # Additional layer
        self.fc1 = nn.Linear(16 * 4 * 4, 120)
        self.fc2 = nn.Linear(120, 84)
        self.fc3 = nn.Linear(84, 10)

    def forward(self, x):
        x = self.pool(F.relu(self.conv1(x)))
        x = F.relu(self.conv1_1(x))
        x = self.pool(F.relu(self.conv2(x)))
        x = F.relu(self.conv2_1(x))
        x = x.view(-1, 16 * 4 * 4)
        x = F.relu(self.fc1(x))
        x = F.relu(self.fc2(x))
        x = self.fc3(x)
        return x

def train_and_evaluate(model_class, batch_size, learning_rate,␣
 ↪optimizer_choice, epochs=5):
```

```
    transform = transforms.Compose([transforms.ToTensor(), transforms.
↪Normalize((0.5,), (0.5,))])
    trainset = torchvision.datasets.MNIST(root='./data', train=True,␣
↪download=True, transform=transform)
    trainloader = DataLoader(trainset, batch_size=batch_size, shuffle=True)
    testset = torchvision.datasets.MNIST(root='./data', train=False,␣
↪download=True, transform=transform)
    testloader = DataLoader(testset, batch_size=batch_size, shuffle=False)


    model = model_class()
    criterion = nn.CrossEntropyLoss()

    if optimizer_choice == 'Adam':
        optimizer = optim.Adam(model.parameters(), lr=learning_rate)
    elif optimizer_choice == 'SGD':
        optimizer = optim.SGD(model.parameters(), lr=learning_rate, momentum=0.
↪9)

    accuracies = []

    # Training loop
    for epoch in range(epochs):
        model.train()
        running_loss = 0.0
        for images, labels in tqdm(trainloader, desc=f"Epoch {epoch+1}/
↪{epochs}", leave=False):
            optimizer.zero_grad()
            outputs = model(images)
            loss = criterion(outputs, labels)
            loss.backward()
            optimizer.step()
            running_loss += loss.item()

        # Evaluation loop
        model.eval()
        correct = 0
        total = 0
        with torch.no_grad():
            for images, labels in testloader:
                outputs = model(images)
                _, predicted = torch.max(outputs.data, 1)
                total += labels.size(0)
                correct += (predicted == labels).sum().item()

        accuracy = 100 * correct / total
        accuracies.append(accuracy)
```

```python
    return accuracies

# Common hyperparameters
batch_size = 64
learning_rate = 0.001
optimizer_choice = 'Adam'


original_accuracies = train_and_evaluate(model_class=LeNet,␣
 ↪batch_size=batch_size, learning_rate=learning_rate,␣
 ↪optimizer_choice=optimizer_choice, epochs=5)

modified_accuracies = train_and_evaluate(model_class=ModifiedLeNet,␣
 ↪batch_size=batch_size, learning_rate=learning_rate,␣
 ↪optimizer_choice=optimizer_choice, epochs=5)

# Plotting
plt.plot(original_accuracies, label='Original LeNet')
plt.plot(modified_accuracies, label='Modified LeNet with Double Conv Layers')
plt.xlabel('Epoch')
plt.ylabel('Accuracy (%)')
plt.title('Comparison of Original vs. Modified LeNet')
plt.legend()
plt.show()
```



5. [0.5 points] How does the performance change as you increase the number of training samples: [0.6K, 1.8K, 6K, 18K, 60K]? Explain the trends in classification accuracy that you observe. Note 1: Make sure that all classes are represented equally within different subsets of the training sets.

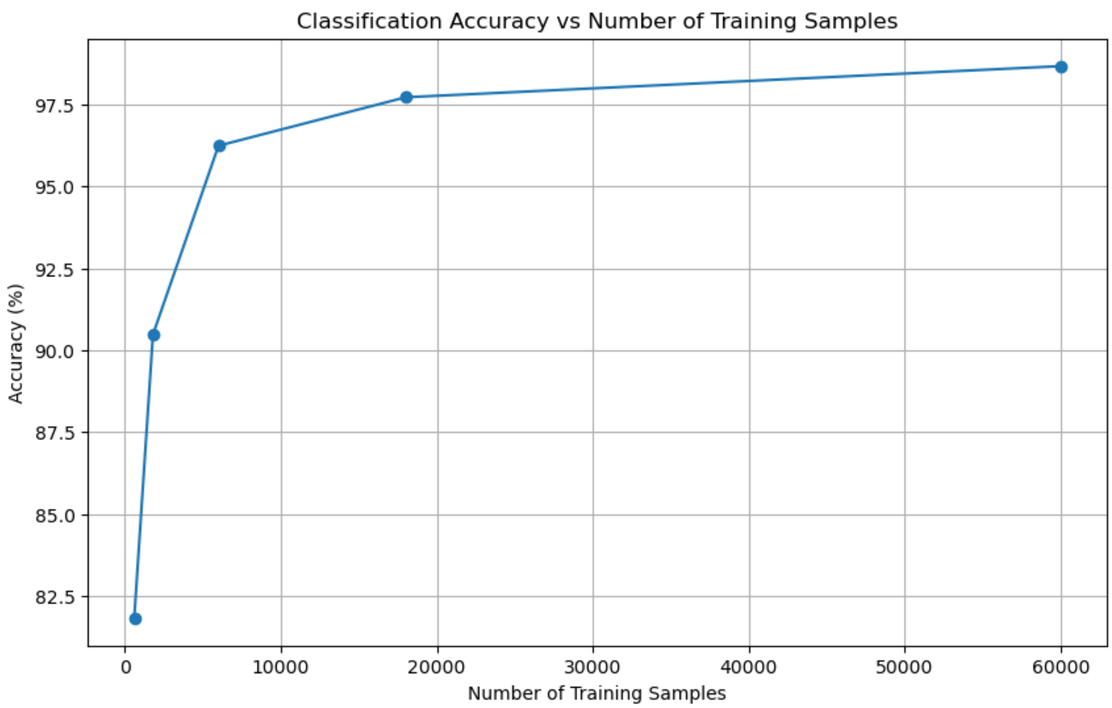
[ ]:
```python
import torch.nn.functional as F
from tqdm import tqdm
import matplotlib.pyplot as plt
import torch.optim as optim
import torch.nn as nn

from torchvision.datasets import MNIST
from torch.utils.data import DataLoader, Subset
import numpy as np
import torchvision.transforms as transforms

def create_balanced_subset(dataset, subset_size_per_class=100):
    targets = np.array(dataset.targets)
    indices = []
```

```
    for class_idx in range(10):  # MNIST has 10 classes
        class_indices = np.where(targets == class_idx)[0]
        np.random.shuffle(class_indices)
        indices.extend(class_indices[:subset_size_per_class])

    np.random.shuffle(indices)
    return Subset(dataset, indices)


transform = transforms.Compose([transforms.ToTensor(), transforms.Normalize((0.
↪5,), (0.5,))])
full_train_dataset = MNIST(root='./data', train=True, download=True,␣
↪transform=transform)
test_dataset = MNIST(root='./data', train=False, download=True,␣
↪transform=transform)

test_loader = DataLoader(test_dataset, batch_size=64, shuffle=False)

def train_and_evaluate(model_class, train_loader, test_loader,␣
↪optimizer_choice, epochs=5, learning_rate=0.001):
    model = model_class()
    criterion = nn.CrossEntropyLoss()

    if optimizer_choice == 'Adam':
        optimizer = optim.Adam(model.parameters(), lr=learning_rate)
    elif optimizer_choice == 'SGD':
        optimizer = optim.SGD(model.parameters(), lr=learning_rate, momentum=0.
↪9)

    accuracies = []

    for epoch in range(epochs):
        model.train()
        for images, labels in tqdm(train_loader, desc=f"Epoch {epoch+1}/
↪{epochs}", leave=False):
            optimizer.zero_grad()
            outputs = model(images)
            loss = criterion(outputs, labels)
            loss.backward()
            optimizer.step()

        model.eval()
        correct = 0
        total = 0
        with torch.no_grad():
            for images, labels in test_loader:
```

```
                outputs = model(images)
                _, predicted = torch.max(outputs.data, 1)
                total += labels.size(0)
                correct += (predicted == labels).sum().item()

        accuracy = 100 * correct / total
        accuracies.append(accuracy)

    return accuracies[-1]  # Return accuracy of the last epoch for simplicity

subset_sizes = [600, 1800, 6000, 18000, 60000]  # Adjusted for balanced subsets␣
↪across 10 classes
results = []

for size in subset_sizes:
    subset_size_per_class = size // 10
    balanced_train_dataset = create_balanced_subset(full_train_dataset,␣
↪subset_size_per_class)
    train_loader = DataLoader(balanced_train_dataset, batch_size=64,␣
↪shuffle=True)

    print(f"Training with subset size: {size}")
    accuracy = train_and_evaluate(LeNet, train_loader, test_loader, 'Adam',␣
↪epochs=5)
    results.append(accuracy)
    print(f"Accuracy: {accuracy}%\n")

# Plotting the results
plt.figure(figsize=(10, 6))
plt.plot(subset_sizes, results, marker='o')
plt.xlabel('Number of Training Samples')
plt.ylabel('Accuracy (%)')
plt.title('Classification Accuracy vs Number of Training Samples')
plt.grid(True)
plt.show()
```

```
Training with subset size: 600


Accuracy: 81.83%

Training with subset size: 1800


Accuracy: 90.48%

Training with subset size: 6000
```

```
Accuracy: 96.24%

Training with subset size: 18000

Accuracy: 97.72%

Training with subset size: 60000

Accuracy: 98.67%
```



6. [1 point] Replace the CNN model with a 2 layer TransformerEncoder. Using a ViT style prediction scheme, evaluate classification accuracy when training with 6K and 60K images. How do the results compare against CNNs? Explain the trends.

[ ]:
```python
from torchvision.datasets import MNIST
from torchvision import transforms
from torch.utils.data import DataLoader, Subset
import numpy as np
```

```
transform = transforms.Compose([
    transforms.ToTensor(),
    transforms.Normalize((0.5,), (0.5,))
])


full_train_dataset = MNIST(root='./data', train=True, download=True,␣
 ↪transform=transform)

small_train_dataset = Subset(full_train_dataset, np.random.
 ↪choice(len(full_train_dataset), 6000, replace=False))

test_dataset = MNIST(root='./data', train=False, download=True,␣
 ↪transform=transform)

batch_size = 64
full_train_loader = DataLoader(full_train_dataset, batch_size=batch_size,␣
 ↪shuffle=True)
small_train_loader = DataLoader(small_train_dataset, batch_size=batch_size,␣
 ↪shuffle=True)
test_loader = DataLoader(test_dataset, batch_size=batch_size, shuffle=False)
```

[ ]:
```
import torch
from torch import nn

class ViT(nn.Module):
    def __init__(self, image_size=28, patch_size=7, num_classes=10, dim=128,␣
 ↪depth=6, heads=8, mlp_dim=256):
        super().__init__()
        num_patches = (image_size // patch_size) ** 2
        patch_dim = patch_size * patch_size * 1  # '1' for the number of␣
 ↪channels in MNIST images
        self.patch_size = patch_size

        self.pos_embedding = nn.Parameter(torch.randn(1, num_patches + 1, dim))
        self.patch_to_embedding = nn.Linear(patch_dim, dim)
        self.cls_token = nn.Parameter(torch.randn(1, 1, dim))

        # Create a transformer encoder layer
        encoder_layer = nn.TransformerEncoderLayer(d_model=dim, nhead=heads,␣
 ↪dim_feedforward=mlp_dim, batch_first=True)
        # Stack multiple layers into a transformer encoder
        self.transformer = nn.TransformerEncoder(encoder_layer,␣
 ↪num_layers=depth)

        self.to_cls_token = nn.Identity()
```

```
        self.mlp_head = nn.Sequential(
            nn.Linear(dim, mlp_dim),
            nn.ReLU(),
            nn.Linear(mlp_dim, num_classes)
        )

    def forward(self, img):
        # Reshape img to patches without einops
        batch_size, channels, height, width = img.shape
        p = self.patch_size
        img = img.unfold(2, p, p).unfold(3, p, p)  # Create patches
        img = img.contiguous().view(batch_size, -1, p * p * channels)  #␣
↪Reshape to [batch_size, num_patches, patch_dim]

        x = self.patch_to_embedding(img)

        cls_tokens = self.cls_token.expand(batch_size, -1, -1)
        x = torch.cat((cls_tokens, x), dim=1)
        x += self.pos_embedding[:, :(x.size(1))]
        x = self.transformer(x)

        x = self.to_cls_token(x[:, 0])
        return self.mlp_head(x)
```

[ ]:
```
import torch
from torch import nn
import torch.optim as optim

def train_and_evaluate(model, train_loader, test_loader, epochs=10):
    device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
    model = model.to(device)
    criterion = nn.CrossEntropyLoss()
    optimizer = optim.Adam(model.parameters(), lr=0.001)

    # List to store accuracy per epoch
    accuracy_per_epoch = []

    # Training loop
    for epoch in range(epochs):
        model.train()
        running_loss = 0.0
        for images, labels in train_loader:
            images, labels = images.to(device), labels.to(device)

            optimizer.zero_grad()
            outputs = model(images)
```

```
            loss = criterion(outputs, labels)
            loss.backward()
            optimizer.step()

            running_loss += loss.item()

        avg_loss = running_loss / len(train_loader)
        print(f'Epoch {epoch+1}, Loss: {avg_loss}')

        # Evaluation
        model.eval()
        correct = 0
        total = 0
        with torch.no_grad():
            for images, labels in test_loader:
                images, labels = images.to(device), labels.to(device)
                outputs = model(images)
                _, predicted = torch.max(outputs.data, 1)
                total += labels.size(0)
                correct += (predicted == labels).sum().item()

        accuracy = 100 * correct / total
        accuracy_per_epoch.append(accuracy)
        print(f'Epoch {epoch+1}, Accuracy on the test set: {accuracy:.2f}%')

    return accuracy_per_epoch
```

[ ]:
```
vit_model_small = ViT()
vit_model_full = ViT()

accuracies_small_dataset = []
accuracies_full_dataset = []

print("Training ViT on small dataset")
accuracies_small_dataset = train_and_evaluate(vit_model_small,␣
 ↪small_train_loader, test_loader, epochs=10)

print("\nTraining ViT on full dataset")
accuracies_full_dataset = train_and_evaluate(vit_model_full, full_train_loader,␣
 ↪test_loader, epochs=10)
```

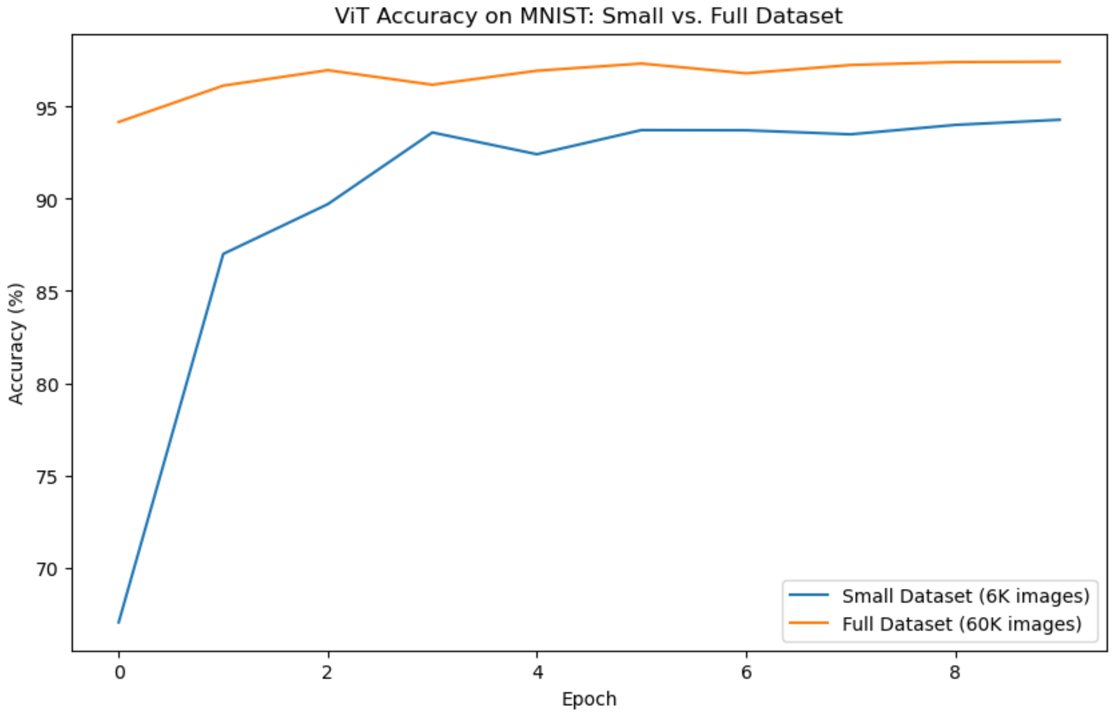
```
Training ViT on small dataset
Epoch 1, Loss: 1.6951778353528772
Epoch 1, Accuracy on the test set: 67.02%
Epoch 2, Loss: 0.6363104724503578
Epoch 2, Accuracy on the test set: 87.01%
Epoch 3, Loss: 0.39881180591405707
Epoch 3, Accuracy on the test set: 89.71%
```

```
Epoch 4, Loss: 0.2967303366737163
Epoch 4, Accuracy on the test set: 93.60%
Epoch 5, Loss: 0.23990465423211138
Epoch 5, Accuracy on the test set: 92.42%
Epoch 6, Loss: 0.20916587090555658
Epoch 6, Accuracy on the test set: 93.73%
Epoch 7, Loss: 0.187813295051455
Epoch 7, Accuracy on the test set: 93.72%
Epoch 8, Loss: 0.15276464376043766
Epoch 8, Accuracy on the test set: 93.50%
Epoch 9, Loss: 0.14063390112541457
Epoch 9, Accuracy on the test set: 94.01%
Epoch 10, Loss: 0.11832679025432531
Epoch 10, Accuracy on the test set: 94.29%

Training ViT on full dataset
Epoch 1, Loss: 0.48091244304191266
Epoch 1, Accuracy on the test set: 94.17%
Epoch 2, Loss: 0.17842635018989317
Epoch 2, Accuracy on the test set: 96.14%
Epoch 3, Loss: 0.15665175678478535
Epoch 3, Accuracy on the test set: 96.98%
Epoch 4, Loss: 0.14350737393426616
Epoch 4, Accuracy on the test set: 96.19%
Epoch 5, Loss: 0.13697317075520468
Epoch 5, Accuracy on the test set: 96.95%
Epoch 6, Loss: 0.1290458645070913
Epoch 6, Accuracy on the test set: 97.34%
Epoch 7, Loss: 0.12646704010252377
Epoch 7, Accuracy on the test set: 96.81%
Epoch 8, Loss: 0.1206178736881907
Epoch 8, Accuracy on the test set: 97.26%
Epoch 9, Loss: 0.12430670312238432
Epoch 9, Accuracy on the test set: 97.42%
Epoch 10, Loss: 0.11417914432650214
Epoch 10, Accuracy on the test set: 97.44%
```

[ ]:

```python
import matplotlib.pyplot as plt

# Plot settings
plt.figure(figsize=(10, 6))
plt.plot(accuracies_small_dataset, label='Small Dataset (6K images)')
plt.plot(accuracies_full_dataset, label='Full Dataset (60K images)')
plt.xlabel('Epoch')
plt.ylabel('Accuracy (%)')
plt.title('ViT Accuracy on MNIST: Small vs. Full Dataset')
plt.legend()
```

```
plt.show()
```



The analysis of Vision Transformers (ViTs) and Convolutional Neural Networks (CNNs) across various dataset sizes yields key insights into their performance:

- **ViT Highlights:**
  - Exhibits significant improvement and adaptability on a small dataset (6K images), with accuracy jumping from 67.02% to 94.29%.
  - Scales well with a larger dataset (60K images), achieving a notable accuracy increase from 94.17% to 97.44%.
- **CNN Highlights:**
  - Shows consistent performance growth with increasing dataset sizes, starting at 81.83% accuracy (600 images) and peaking at 98.67% (60K images).
- **Comparative Analysis:**
  - ViTs demonstrate strong scalability and adaptability, challenging the notion they solely excel with massive datasets.
  - CNNs slightly outperform ViTs in peak accuracy on the full dataset but ViTs show promising efficiency across dataset sizes.

In summary, while both architectures improve with more data, ViTs' performance on smaller datasets is notably impressive. Despite CNNs achieving marginally higher maximum accuracy, the gap narrows, affirming ViTs as a competitive alternative for image classification tasks.

Challenges: 1. navigating the nitty gritties of pytorch 2. integration with wandb- issues with API 3. Long run time so, tuning and debugging was a lengthy process learning: 1. Understanding to deploy CNN and Transformer models from pytorch 2. Logging and experimenting