HW2

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1 Homework 2

Name: Stanly Gomes

Student ID: 801118166

GitHub Repository: https://github.com/NaraPvP/RealTimeML

[2]:
```
# import libraries
from tqdm import tqdm
import torch
from torch import nn
from torch.nn import functional as F
from torch.utils.data import DataLoader, random_split, Subset

import numpy as np
import pandas as pd
import cv2
from matplotlib import pyplot as plt
from ptflops import get_model_complexity_info

import torchvision
from torchvision import transforms, datasets
from torchmetrics.classification import MulticlassAccuracy, BinaryAccuracy
from torchmetrics import ConfusionMatrix
```

[3]:
```
device = "cuda" if torch.cuda.is_available() else "cpu"
device
```

[3]: 'cuda'

[4]:
```
# Import datasets
training_data = datasets.FashionMNIST(
    root="data",
    train=True,
    download=True,
    transform=transforms.Compose([
        transforms.ToTensor(),
        transforms.Normalize((0.2860), (0.3530))
```

```
    ])
)
validation_data = datasets.FashionMNIST(
    root="data",
    train=False,
    download=True,
    transform=transforms.Compose([
        transforms.ToTensor(),
        transforms.Normalize((0.2860), (0.3530))
    ])
)
image, label = training_data[0]
image.shape
```

[4]:
```
torch.Size([1, 28, 28])
```

1.1 Testing before HW

[5]:
```
LeNet_trainLoader = DataLoader(training_data,
                               batch_size=32,
                               shuffle=True)
LeNet_valLoader = DataLoader(validation_data,
                             batch_size=32,
                             shuffle=False)
```

[6]:
```
# Test training with baseline model
class basic_model(nn.Module):
    def __init__(self, input_shape: int, output_shape: int):
        super().__init__()
        self.net = nn.Sequential(
            nn.Flatten(),
            nn.Linear(input_shape, 10),
            nn.ReLU(),
            nn.Linear(10, output_shape),
            nn.ReLU()
        )
    def forward(self, x):
        return self.net(x)
```

[9]:
```
baseline_model = basic_model(torch.numel(image),
                             len(validation_data.classes))
baseline_model.to(device)
next(baseline_model.parameters()).device
```

[9]:
```
device(type='cuda', index=0)
```

[11]:
```
loss_fn = nn.CrossEntropyLoss()
optimizer = torch.optim.SGD(params=baseline_model.parameters(),
                            lr=0.1)
```

[12]:
```
from timeit import default_timer as timer
def print_train_time(start, end, device: torch.device=None):
    total_time = end - start
    print(f"{device} Training Time: {total_time:.3f} seconds")
    return total_time
```

[25]:
```
# Define train_step function
def train_step(model: nn.Module,
               data_loader: DataLoader,
               loss_fn: nn.Module,
               optim: torch.optim.Optimizer,
               accuracy_fn,
               device: torch.device):
    """Performs training step on a dataloader batch"""
    train_loss, train_acc = 0, 0
    model.train()
    for batch, (x, y) in enumerate(data_loader):
        # Move data to device
        x, y = x.to(device), y.to(device)

        # Forward pass (outputs log likelihood for each class)
        y_pred = model(x)
        # Calculate Loss/Acc of batch
        loss = loss_fn(y_pred, y)
        train_loss += loss
        # argmax is used to convert from log likelihood to prediction labels
        train_acc += accuracy_fn(y_pred.argmax(dim=1), y)

        # Zero the gradience for optimizer
        optim.zero_grad()

        # Backpropagate loss
        loss.backward()

        # Step optimizer based on loss
        optim.step()

    train_loss /= len(data_loader)
    train_acc /= len(data_loader)
    print(f"Train loss: {train_loss:.5f} | Train accuracy: {train_acc:.2f}%")
```

[26]:
```
# Define val_step function
def val_step(model: nn.Module,
```

```
             data_loader: DataLoader,
             loss_fn: nn.Module,
             accuracy_fn,
             device: torch.device):
    """Performs validation step on val dataloader"""
    val_loss, val_acc = 0, 0
    model.eval()

    # Turn on inference mode context manager (increases speed)
    with torch.inference_mode():
        for x, y in data_loader:
            x, y = x.to(device), y.to(device)
            # Forward pass
            val_pred = model(x)

            # Calculate loss
            val_loss += loss_fn(val_pred, y)
            val_acc += accuracy_fn(val_pred.argmax(dim=1), y)

        val_loss /= len(data_loader)
        val_acc /= len(data_loader)
        print(f"Val loss: {val_loss:.5f} | Val accuracy: {val_acc:.2f}%\n")
```

[28]:

```
# Start baseline training
train_time_start = timer()
epochs = 5
accuracy_fn = MulticlassAccuracy(num_classes=10).to(device)
baseline_model.to(device)
for epoch in tqdm(range(epochs)):
    print(f"Epoch: {epoch}\n--------")
    train_step(model=baseline_model,
               data_loader=LeNet_trainLoader,
               loss_fn=loss_fn,
               optim=optimizer,
               accuracy_fn=accuracy_fn,
               device=device
              )
    val_step(model=baseline_model,
             data_loader=LeNet_valLoader,
             loss_fn=loss_fn,
             accuracy_fn=accuracy_fn,
             device=device
            )
train_time_end = timer()
baseline_train_time = print_train_time(start=train_time_start,
                                       end=train_time_end,
                                       device=device)
```

```
  0%|
| 0/5 [00:00<?, ?it/s]

Epoch: 0
--------
Train loss: 0.63527 | Train accuracy: 0.73%

 20%|
| 1/5 [00:18<01:13, 18.26s/it]

Val loss: 0.70415 | Val accuracy: 0.71%

Epoch: 1
--------
Train loss: 0.62827 | Train accuracy: 0.73%

 40%|
| 2/5 [00:36<00:54, 18.23s/it]

Val loss: 0.67965 | Val accuracy: 0.72%

Epoch: 2
--------
Train loss: 0.62226 | Train accuracy: 0.74%

 60%|
| 3/5 [00:54<00:35, 17.92s/it]

Val loss: 0.66804 | Val accuracy: 0.72%

Epoch: 3
--------
Train loss: 0.61543 | Train accuracy: 0.74%

 80%|
| 4/5 [01:10<00:17, 17.39s/it]

Val loss: 0.75736 | Val accuracy: 0.71%

Epoch: 4
--------
Train loss: 0.61206 | Train accuracy: 0.74%

100%|
     | 5/5 [01:27<00:00, 17.42s/it]

Val loss: 0.66061 | Val accuracy: 0.73%

cuda Training Time: 87.114 seconds
```

[61]:
```python
# Setup
class Setup:
    def __init__(self, epochs, lr, batch_size, directory, train_percent,␣
 ↪num_classes):
        self.epochs = epochs
        self.lr = lr
        self.batch_size = batch_size
        self.directory = directory
        self.train_percent = train_percent
        self.num_classes = num_classes

        if torch.cuda.is_available():
            self.device = torch.device("cuda")
        else:
            self.device = torch.device("cpu")
```

[62]:
```python
setup = Setup(epochs=10,
              lr=0.001,
              batch_size=32,
              directory="data",
              train_percent=0.8,
              num_classes=len(training_data.classes))
```

[63]:
```python
# Base LeNet Model
class LeNet(nn.Module):
    def __init__(self, input_features: int, num_classes):
        super().__init__()
        self.conv = nn.Sequential(
            nn.Conv2d(input_features, 6, kernel_size=5, padding=2), # 28 +␣
 ↪(2*2(padding)) - (5(kernelSize)-1) = 28
            nn.Sigmoid(),
            nn.AvgPool2d(kernel_size=2, stride=2), # 28 / 2 = 14
            nn.Conv2d(6, 16, kernel_size=5), # 14 - (5-1) = 10
            nn.Sigmoid(),
            nn.AvgPool2d(kernel_size=2, stride=2) # 10 / 2 = 5
        )
        self.classifier = nn.Sequential(
            nn.Flatten(),
            nn.Linear(16*5*5, 120), nn.Sigmoid(),
            nn.Linear(120, 84), nn.Sigmoid(),
            nn.Linear(84, num_classes)
        )
    def forward(self, x):
        x = self.conv(x)
        x = self.classifier(x)
        return x
```

[64]:
```
model = LeNet(input_features=1, num_classes=10).to(device)
print(model)
next(model.parameters()).device
```

```
LeNet(
  (conv): Sequential(
    (0): Conv2d(1, 6, kernel_size=(5, 5), stride=(1, 1), padding=(2, 2))
    (1): Sigmoid()
    (2): AvgPool2d(kernel_size=2, stride=2, padding=0)
    (3): Conv2d(6, 16, kernel_size=(5, 5), stride=(1, 1))
    (4): Sigmoid()
    (5): AvgPool2d(kernel_size=2, stride=2, padding=0)
  )
  (classifier): Sequential(
    (0): Flatten(start_dim=1, end_dim=-1)
    (1): Linear(in_features=400, out_features=120, bias=True)
    (2): Sigmoid()
    (3): Linear(in_features=120, out_features=84, bias=True)
    (4): Sigmoid()
    (5): Linear(in_features=84, out_features=10, bias=True)
  )
)
```

[64]:
```
device(type='cuda', index=0)
```

[65]:
```
LeNet_trainLoader = DataLoader(training_data, batch_size=setup.batch_size,␣
 ↪shuffle=True)
LeNet_valLoader = DataLoader(validation_data, batch_size=setup.batch_size,␣
 ↪shuffle=False)
```

[66]:
```
# Find mean and std for normalization
# loader = DataLoader(training_data, batch_size=len(training_data),␣
 ↪num_workers=1)
# data = next(iter(loader))
# data[0].mean(), data[0].std()
```

[67]:
```
# Define train_step function
def train_step(model: nn.Module,
               data_loader: DataLoader,
               loss_fn: nn.Module,
               optim: torch.optim.Optimizer,
               accuracy_fn,
               device: torch.device):
    """Performs training step on a dataloader batch"""
    train_loss, train_acc = 0, 0
    model.train()
    for batch, (x, y) in enumerate(data_loader):
        # Move data to device
```

```python
        x, y = x.to(device), y.to(device)

        # Forward pass (outputs log likelihood for each class)
        y_pred = model(x)
        # Calculate Loss/Acc of batch
        loss = loss_fn(y_pred, y)
        train_loss += loss
        # argmax is used to convert from log likelihood to prediction labels
        train_acc += accuracy_fn(y_pred.argmax(dim=1), y)

        # Zero the gradience for optimizer
        optim.zero_grad()

        # Backpropagate loss
        loss.backward()

        # Step optimizer based on loss
        optim.step()

    train_loss /= len(data_loader)
    train_acc /= len(data_loader)
    print(f"Train loss: {train_loss:.5f} | Train accuracy: {train_acc:.2f}%")
```

[68]:
```python
# Define val_step function
def val_step(model: nn.Module,
             data_loader: DataLoader,
             loss_fn: nn.Module,
             accuracy_fn,
             device: torch.device):
    """Performs validation step on val dataloader"""
    val_loss, val_acc = 0, 0
    model.eval()

    # Turn on inference mode context manager (increases speed)
    with torch.inference_mode():
        for x, y in data_loader:
            x, y = x.to(device), y.to(device)
            # Forward pass
            val_pred = model(x)

            # Calculate loss
            val_loss += loss_fn(val_pred, y)
            val_acc += accuracy_fn(val_pred.argmax(dim=1), y)

        val_loss /= len(data_loader)
        val_acc /= len(data_loader)
        print(f"Val loss: {val_loss:.5f} | Val accuracy: {val_acc:.2f}%\n")
```

[69]:
```python
from timeit import default_timer as timer
```

[70]:
```python
loss_fn = nn.CrossEntropyLoss()
optimizer = torch.optim.SGD(params=model.parameters(),
                            lr=0.1)
model.cuda()
accuracy_fn = MulticlassAccuracy(num_classes=10).to(device)
epochs = 5

train_time_start_base = timer()
for epoch in tqdm(range(epochs)):
    print(f"Epoch: {epoch}\n---------")
    train_step(model=model,
               data_loader=LeNet_trainLoader,
               loss_fn=loss_fn,
               optim=optimizer,
               accuracy_fn = accuracy_fn,
               device=device)
    val_step(model=model,
             data_loader=LeNet_valLoader,
             loss_fn=loss_fn,
             accuracy_fn=accuracy_fn,
             device=device)
train_time_end_base = timer()
```

```
  0%|
| 0/5 [00:00<?, ?it/s]

Epoch: 0
---------
Train loss: 2.31322 | Train accuracy: 0.10%

 20%|
| 1/5 [00:17<01:11, 17.88s/it]

Val loss: 2.30364 | Val accuracy: 0.10%

Epoch: 1
---------
Train loss: 1.63804 | Train accuracy: 0.37%

 40%|
| 2/5 [00:36<00:54, 18.14s/it]

Val loss: 1.03820 | Val accuracy: 0.55%

Epoch: 2
---------
Train loss: 0.87912 | Train accuracy: 0.64%
```

```
 60%|
| 3/5 [00:53<00:35, 17.79s/it]

Val loss: 0.79643 | Val accuracy: 0.68%

Epoch: 3
---------
Train loss: 0.68088 | Train accuracy: 0.71%

 80%|
| 4/5 [01:11<00:17, 17.75s/it]

Val loss: 0.63893 | Val accuracy: 0.73%

Epoch: 4
---------
Train loss: 0.60204 | Train accuracy: 0.74%

100%|
     | 5/5 [01:28<00:00, 17.71s/it]

Val loss: 0.60390 | Val accuracy: 0.74%
```

[79]:

```python
# Save model results
def model_results(model: nn.Module,
                  data_loader: DataLoader,
                  loss_fn: nn.Module,
                  accuracy_fn,
                  device: torch.device):
    loss, acc = 0, 0
    model.eval() # Evaluation mode
    with torch.inference_mode():
        for x, y in data_loader:
            x, y = x.to(device), y.to(device)
            y_pred = model(x)

            loss += loss_fn(y_pred, y)
            acc += accuracy_fn(y_pred.argmax(dim=1), y)
        loss /= len(data_loader)
        acc /= len(data_loader)
    return {"Model": model.__class__.__name__,
            "Loss": loss.item(),
            "Accuracy": float(acc)}
```

[80]:

```python
baseline_LeNet_results = model_results(model=model,
                                       data_loader=LeNet_valLoader,
                                       loss_fn=loss_fn,
```

```
                                             accuracy_fn=accuracy_fn,
                                             device=device
                                            )
baseline_LeNet_results
```

[80]: {'Model': 'LeNet', 'Loss': 0.603901207447052, 'Accuracy': 0.7416631579399109}

1.2 Problem 1:

Let's modernize LeNet as we did in the lectures. Implement and test the following changes over FashionMNIST

1. Replace the average pooling with max-pooling.
2. Replace the softmax layer with ReLU.

Start training from scratch based on FashinMNIST. Compare the training loss, training accuracy, and validation accuracy against the baseline we did in the lectures.

[101]:
```
class LeNet_modern(nn.Module):
    def __init__(self, input_features: int, num_classes):
        super().__init__()
        self.conv = nn.Sequential(
            nn.Conv2d(input_features, 6, kernel_size=5, padding=2), # 28 +␣
 ↪(2*2(padding)) - (5(kernelSize)-1) = 28
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=2, stride=2), # 28 / 2 = 14
            nn.Conv2d(6, 16, kernel_size=5), # 14 - (5-1) = 10
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=2, stride=2) # 10 / 2 = 5
        )
        self.classifier = nn.Sequential(
            nn.Flatten(),
            nn.Linear(16*5*5, 120), nn.Sigmoid(),
            nn.Linear(120, 84), nn.Sigmoid(),
            nn.Linear(84, num_classes)
        )
    def forward(self, x):
        x = self.conv(x)
        x = self.classifier(x)
        return x
```

[102]:
```
LeNet_P1 = LeNet_modern(input_features=1,
                        num_classes=10).to(device)
LeNet_P1
```

[102]:
```
LeNet_modern(
  (conv): Sequential(
    (0): Conv2d(1, 6, kernel_size=(5, 5), stride=(1, 1), padding=(2, 2))
    (1): ReLU()
```

```
    (2): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
    (3): Conv2d(6, 16, kernel_size=(5, 5), stride=(1, 1))
    (4): ReLU()
    (5): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
  )
  (classifier): Sequential(
    (0): Flatten(start_dim=1, end_dim=-1)
    (1): Linear(in_features=400, out_features=120, bias=True)
    (2): Sigmoid()
    (3): Linear(in_features=120, out_features=84, bias=True)
    (4): Sigmoid()
    (5): Linear(in_features=84, out_features=10, bias=True)
  )
)
```

[103]:
```
LeNet_trainLoader = DataLoader(training_data, batch_size=setup.batch_size,␣
 ↪shuffle=True)
LeNet_valLoader = DataLoader(validation_data, batch_size=setup.batch_size,␣
 ↪shuffle=False)
```

[104]:
```
# Define train_step function
def train_step(model: nn.Module,
               data_loader: DataLoader,
               loss_fn: nn.Module,
               optim: torch.optim.Optimizer,
               accuracy_fn,
               device: torch.device):
    """Performs training step on a dataloader batch"""
    train_loss, train_acc = 0, 0
    model.train()
    for batch, (x, y) in enumerate(data_loader):
        # Move data to device
        x, y = x.to(device), y.to(device)

        # Forward pass (outputs log likelihood for each class)
        y_pred = model(x)
        # Calculate Loss/Acc of batch
        loss = loss_fn(y_pred, y)
        train_loss += loss.item()
        # argmax is used to convert from log likelihood to prediction labels

        # Zero the gradience for optimizer
        optim.zero_grad()

        # Backpropagate loss
```

```
        loss.backward()

        # Step optimizer based on loss
        optim.step()

        acc = accuracy_fn(y_pred.argmax(dim=1), y)
        train_acc += acc.item()

    train_loss /= len(data_loader)
    train_acc /= len(data_loader)
    return train_loss, train_acc
```

[105]:

```
# Define val_step function
def val_step(model: nn.Module,
             data_loader: DataLoader,
             loss_fn: nn.Module,
             accuracy_fn,
             device: torch.device):
    """Performs validation step on val dataloader"""
    val_loss, val_acc = 0, 0
    model.eval()

    # Turn on inference mode context manager (increases speed)
    with torch.inference_mode():
        for x, y in data_loader:
            x, y = x.to(device), y.to(device)
            # Forward pass
            val_pred = model(x)

            # Calculate loss
            loss = loss_fn(val_pred, y)
            val_loss += loss.item()

            acc = accuracy_fn(val_pred.argmax(dim=1), y)
            val_acc += acc.item()

        val_loss /= len(data_loader)
        val_acc /= len(data_loader)
        return val_loss, val_acc
```

[106]:

```
# Create train function
def train(model: nn.Module,
          train_dataloader: DataLoader,
          val_dataloader: DataLoader,
          optim: torch.optim.Optimizer,
          loss_fn: nn.Module,
          accuracy_fn,
```

```
          epochs: int,
          device: torch.device):
    results = {"Train Loss": [],
               "Train Accuracy": [],
               "Val Loss": [],
               "Val Accuracy": []}
    for epoch in tqdm(range(epochs)):
        train_loss, train_acc = train_step(model=model,
                                           data_loader=train_dataloader,
                                           loss_fn=loss_fn,
                                           optim=optim,
                                           accuracy_fn=accuracy_fn,
                                           device=device)
        val_loss, val_acc = val_step(model=model,
                                     data_loader=val_dataloader,
                                     loss_fn=loss_fn,
                                     accuracy_fn=accuracy_fn,
                                     device=device)

        print(f"Epoch: {epoch+1}\n--------------- "
              f"Train Loss: {train_loss:.4f}, "
              f"Train Accuracy: {train_acc:.4f}, "
              f"Val Loss: {val_loss:.4f}, "
              f"Val Accuracy: {val_acc:.4f}"
             )
        results["Train Loss"].append(train_loss)
        results["Train Accuracy"].append(train_acc)
        results["Val Loss"].append(val_loss)
        results["Val Accuracy"].append(val_acc)
    return results
```

[107]:
```
from timeit import default_timer as timer
```

[108]:
```
loss_fn = nn.CrossEntropyLoss()
optimizer = torch.optim.SGD(params=LeNet_P1.parameters(),
                            lr=0.1)
accuracy_fn = MulticlassAccuracy(num_classes=10).to(device)
epochs = 5

train_time_start_base = timer()

P1_model_history = train(model=LeNet_P1,
                         train_dataloader=LeNet_trainLoader,
                         val_dataloader=LeNet_valLoader,
                         optim=optimizer,
                         loss_fn=loss_fn,
                         accuracy_fn=accuracy_fn,
```

```
                             epochs=epochs,
                             device="cuda")

train_time_end_base = timer()
P1_total_time = print_train_time(start=train_time_start,
                                 end=train_time_end,
                                 device=device)
```

```
 20%|
| 1/5 [01:21<05:25, 81.42s/it]

Epoch: 1
--------------- Train Loss: 1.0552, Train Accuracy: 0.5820, Val Loss: 0.6339,
Val Accuracy: 0.7254

 40%|
| 2/5 [02:41<04:02, 80.81s/it]

Epoch: 2
--------------- Train Loss: 0.4766, Train Accuracy: 0.7972, Val Loss: 0.4436,
Val Accuracy: 0.8149

 60%|
| 3/5 [04:04<02:43, 81.56s/it]

Epoch: 3
--------------- Train Loss: 0.3761, Train Accuracy: 0.8342, Val Loss: 0.3660,
Val Accuracy: 0.8392

 80%|
| 4/5 [05:24<01:20, 80.88s/it]

Epoch: 4
--------------- Train Loss: 0.3258, Train Accuracy: 0.8494, Val Loss: 0.3419,
Val Accuracy: 0.8470

100%|
     | 5/5 [06:08<00:00, 73.73s/it]

Epoch: 5
--------------- Train Loss: 0.2984, Train Accuracy: 0.8596, Val Loss: 0.3310,
Val Accuracy: 0.8512
cuda Training Time: 87.114 seconds
```

[115]:
```
# Testing training time with cpu (QUICKER THAN GPU FOR THIS MODEL)
LeNet_P1_cpu = LeNet_modern(input_features=1,
                            num_classes=10)
optimizer_cpu=torch.optim.SGD(params=LeNet_P1_cpu.parameters(),
                            lr=0.1)
accuracy_fn_cpu = MulticlassAccuracy(num_classes=10)
```

```
P1_model_history_cpu = train(model=LeNet_P1_cpu,
                             train_dataloader=LeNet_trainLoader,
                             val_dataloader=LeNet_valLoader,
                             optim=optimizer_cpu,
                             loss_fn=loss_fn,
                             accuracy_fn=accuracy_fn_cpu,
                             epochs=epochs,
                             device="cpu")
```

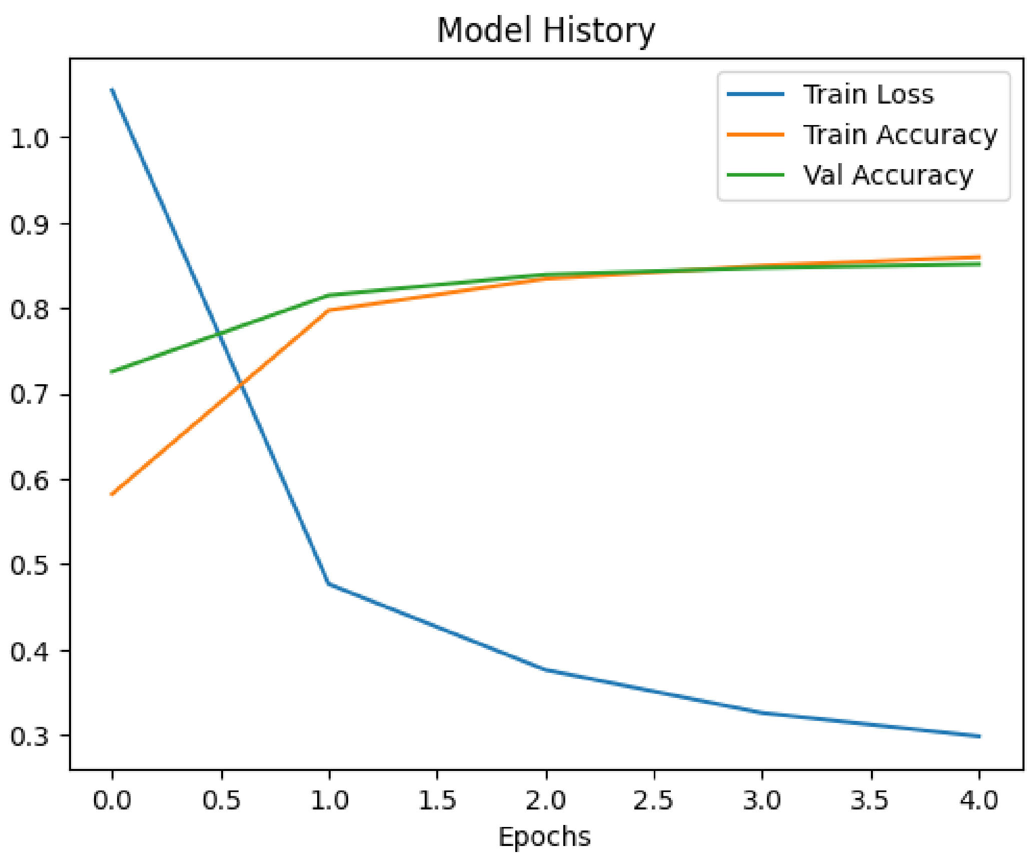
```
 20%|
| 1/5 [00:15<01:03, 15.76s/it]

Epoch: 1
--------------- Train Loss: 1.1362, Train Accuracy: 0.5494, Val Loss: 0.5712,
Val Accuracy: 0.7403

 40%|
| 2/5 [00:31<00:46, 15.62s/it]

Epoch: 2
--------------- Train Loss: 0.4892, Train Accuracy: 0.7842, Val Loss: 0.4340,
Val Accuracy: 0.8154

 60%|
| 3/5 [00:51<00:35, 17.69s/it]

Epoch: 3
--------------- Train Loss: 0.3862, Train Accuracy: 0.8320, Val Loss: 0.3779,
Val Accuracy: 0.8342

 80%|
| 4/5 [01:13<00:19, 19.54s/it]

Epoch: 4
--------------- Train Loss: 0.3365, Train Accuracy: 0.8468, Val Loss: 0.3658,
Val Accuracy: 0.8328

100%|
     | 5/5 [01:35<00:00, 19.14s/it]

Epoch: 5
--------------- Train Loss: 0.3077, Train Accuracy: 0.8546, Val Loss: 0.3305,
Val Accuracy: 0.8466
```

[155]:
```
# Plot history
from typing import Tuple, Dict, List
def plot_history(results: Dict[str, List[float]]):
    loss = results["Train Loss"]
    val_loss = results["Val Loss"]
    acc = results["Train Accuracy"]
```

```
    val_acc = results["Val Accuracy"]

    epochs = range(len(results["Train Loss"]))

    plt.figure()
    # Plot loss and accuracy
    plt.plot(epochs, loss, label="Train Loss")
    plt.plot(epochs, acc, label="Train Accuracy")
    plt.plot(epochs, val_acc, label="Val Accuracy")
    plt.title("Model History")
    plt.xlabel("Epochs")
    plt.legend()
```

[156]:

```
# P1 Plot
plot_history(P1_model_history)
```



[132]:

```
# Ptflops Summary
from ptflops import get_model_complexity_info
```

```
with torch.cuda.device(0):
  macs, params = get_model_complexity_info(LeNet_P1, (1, 28, 28),␣
 ↪as_strings=True,
                                           print_per_layer_stat=True,␣
 ↪verbose=True)
  print('{:<30}  {:<8}'.format('Computational complexity: ', macs))
  print('{:<30}  {:<8}'.format('Number of parameters: ', params))
```

```
Warning: module Flatten is treated as a zero-op.
Warning: module Sigmoid is treated as a zero-op.
Warning: module LeNet_modern is treated as a zero-op.
LeNet_modern(
  61.71 k, 100.000% Params, 435.65 KMac, 100.000% MACs,
  (conv): Sequential(
    2.57 k, 4.168% Params, 376.51 KMac, 86.426% MACs,
    (0): Conv2d(156, 0.253% Params, 122.3 KMac, 28.074% MACs, 1, 6,
kernel_size=(5, 5), stride=(1, 1), padding=(2, 2))
    (1): ReLU(0, 0.000% Params, 4.7 KMac, 1.080% MACs, )
    (2): MaxPool2d(0, 0.000% Params, 4.7 KMac, 1.080% MACs, kernel_size=2,
stride=2, padding=0, dilation=1, ceil_mode=False)
    (3): Conv2d(2.42 k, 3.915% Params, 241.6 KMac, 55.458% MACs, 6, 16,
kernel_size=(5, 5), stride=(1, 1))
    (4): ReLU(0, 0.000% Params, 1.6 KMac, 0.367% MACs, )
    (5): MaxPool2d(0, 0.000% Params, 1.6 KMac, 0.367% MACs, kernel_size=2,
stride=2, padding=0, dilation=1, ceil_mode=False)
  )
  (classifier): Sequential(
    59.13 k, 95.832% Params, 59.13 KMac, 13.574% MACs,
    (0): Flatten(0, 0.000% Params, 0.0 Mac, 0.000% MACs, start_dim=1,
end_dim=-1)
    (1): Linear(48.12 k, 77.983% Params, 48.12 KMac, 11.046% MACs,
in_features=400, out_features=120, bias=True)
    (2): Sigmoid(0, 0.000% Params, 0.0 Mac, 0.000% MACs, )
    (3): Linear(10.16 k, 16.472% Params, 10.16 KMac, 2.333% MACs,
in_features=120, out_features=84, bias=True)
    (4): Sigmoid(0, 0.000% Params, 0.0 Mac, 0.000% MACs, )
    (5): Linear(850, 1.377% Params, 850.0 Mac, 0.195% MACs, in_features=84,
out_features=10, bias=True)
  )
)
Computational complexity:       435.65 KMac
Number of parameters:           61.71 k
```

1.3 Problem 2

Try to change the size of the LeNet style network to improve its accuracy in addition to max-pooling and ReLU.

1. Adjust the convolution window size.
2. Adjust the number of output channels (width of each layer).
3. Adjust the number of convolution layers.
4. Adjust the number of fully connected layers.
5. Explore the learning rates.

For all training adjustments, restart training from scratch based on FashinMNIST. Compare the training loss, training accuracy, and validation accuracy against each other and the baseline in problem 1. Argue which adjustment presents the better benefit and generalization. Measure and compare theoretical computation complexity (number of operations and parameters size) using ptflops https://pypi.org/project/ptflops/

1.3.1 1. Adjust convolution window size

[119]:
```
# Changed kernel_size from 5 to 3, padding from 2 to 1
class LeNet_P2_1(nn.Module):
    def __init__(self, input_features: int, num_classes):
        super().__init__()
        self.conv = nn.Sequential(
            nn.Conv2d(input_features, 6, kernel_size=3, padding=1), # 28 +␣
↪(2*1(padding)) - (3(kernelSize)-1) = 28
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=2, stride=2), # 28 / 2 = 14
            nn.Conv2d(6, 16, kernel_size=3), # 14 - (3-1) = 12
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=2, stride=2) # 12 / 2 = 6
        )
        self.classifier = nn.Sequential(
            nn.Flatten(),
            nn.Linear(16*6*6, 120), nn.Sigmoid(),
            nn.Linear(120, 84), nn.Sigmoid(),
            nn.Linear(84, num_classes)
        )
    def forward(self, x):
        x = self.conv(x)
        x = self.classifier(x)
        return x
```

[120]:
```
P2_1_model = LeNet_P2_1(input_features=1,
                        num_classes=10)
```

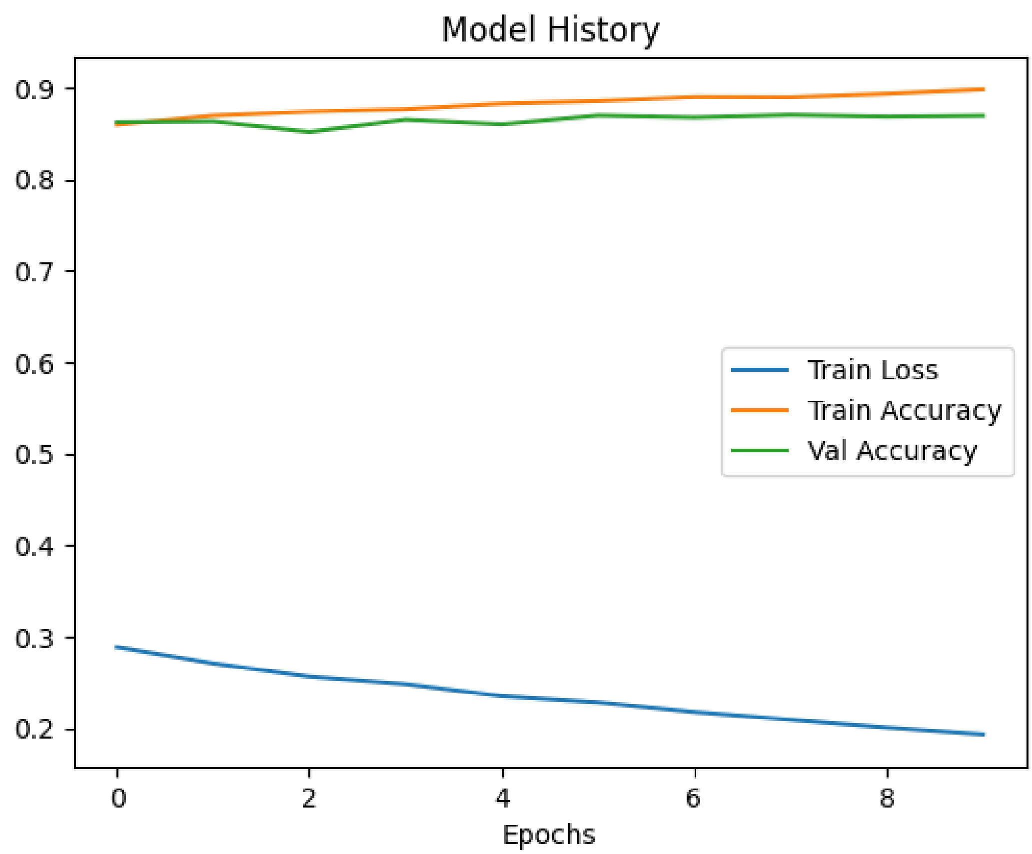
[153]:
```
optimizer_cpu=torch.optim.SGD(params=P2_1_model.parameters(),
                              lr=0.1)
accuracy_fn_cpu = MulticlassAccuracy(num_classes=10)
P2_1_model_history = train(model=P2_1_model,
                           train_dataloader=LeNet_trainLoader,
                           val_dataloader=LeNet_valLoader,
                           optim=optimizer_cpu,
```

```
                               loss_fn=loss_fn,
                               accuracy_fn=accuracy_fn_cpu,
                               epochs=10,
                               device="cpu")
```

```
 10%|
| 1/10 [00:14<02:13, 14.82s/it]

Epoch: 1
--------------- Train Loss: 0.2882, Train Accuracy: 0.8596, Val Loss: 0.3052,
Val Accuracy: 0.8623

 20%|
| 2/10 [00:29<01:58, 14.81s/it]

Epoch: 2
--------------- Train Loss: 0.2705, Train Accuracy: 0.8695, Val Loss: 0.3003,
Val Accuracy: 0.8632

 30%|
| 3/10 [00:45<01:45, 15.09s/it]

Epoch: 3
--------------- Train Loss: 0.2561, Train Accuracy: 0.8740, Val Loss: 0.3281,
Val Accuracy: 0.8518

 40%|
| 4/10 [01:00<01:30, 15.09s/it]

Epoch: 4
--------------- Train Loss: 0.2478, Train Accuracy: 0.8766, Val Loss: 0.2900,
Val Accuracy: 0.8651

 50%|
| 5/10 [01:15<01:15, 15.03s/it]

Epoch: 5
--------------- Train Loss: 0.2348, Train Accuracy: 0.8827, Val Loss: 0.3045,
Val Accuracy: 0.8600

 60%|
| 6/10 [01:30<01:00, 15.05s/it]

Epoch: 6
--------------- Train Loss: 0.2279, Train Accuracy: 0.8855, Val Loss: 0.2771,
Val Accuracy: 0.8696

 70%|
| 7/10 [01:45<00:45, 15.01s/it]

Epoch: 7
--------------- Train Loss: 0.2174, Train Accuracy: 0.8899, Val Loss: 0.2869,
Val Accuracy: 0.8675
```

```
 80%|
| 8/10 [01:59<00:29, 14.97s/it]

Epoch: 8
--------------- Train Loss: 0.2090, Train Accuracy: 0.8896, Val Loss: 0.2791,
Val Accuracy: 0.8702

 90%|
| 9/10 [02:14<00:14, 14.95s/it]

Epoch: 9
--------------- Train Loss: 0.2003, Train Accuracy: 0.8934, Val Loss: 0.2897,
Val Accuracy: 0.8683

100%|
    | 10/10 [02:29<00:00, 14.97s/it]

Epoch: 10
--------------- Train Loss: 0.1929, Train Accuracy: 0.8981, Val Loss: 0.2815,
Val Accuracy: 0.8694
```

[157]:
```
# P2_1 Plot, very similar to P1
plot_history(P2_1_model_history)
```



[158]:
```
with torch.cuda.device(0):
  macs, params = get_model_complexity_info(P2_1_model, (1, 28, 28),␣
↪as_strings=True,
                                            print_per_layer_stat=True,␣
↪verbose=True)
  print('{:<30}  {:<8}'.format('Computational complexity: ', macs))
  print('{:<30}  {:<8}'.format('Number of parameters: ', params))
```

```
Warning: module Flatten is treated as a zero-op.
Warning: module Sigmoid is treated as a zero-op.
Warning: module LeNet_P2_1 is treated as a zero-op.
LeNet_P2_1(
  81.19 k, 100.000% Params, 268.03 KMac, 100.000% MACs,
  (conv): Sequential(
    940, 1.158% Params, 187.78 KMac, 70.058% MACs,
    (0): Conv2d(60, 0.074% Params, 47.04 KMac, 17.550% MACs, 1, 6,
kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): ReLU(0, 0.000% Params, 4.7 KMac, 1.755% MACs, )
    (2): MaxPool2d(0, 0.000% Params, 4.7 KMac, 1.755% MACs, kernel_size=2,
stride=2, padding=0, dilation=1, ceil_mode=False)
    (3): Conv2d(880, 1.084% Params, 126.72 KMac, 47.278% MACs, 6, 16,
kernel_size=(3, 3), stride=(1, 1))
    (4): ReLU(0, 0.000% Params, 2.3 KMac, 0.860% MACs, )
    (5): MaxPool2d(0, 0.000% Params, 2.3 KMac, 0.860% MACs, kernel_size=2,
stride=2, padding=0, dilation=1, ceil_mode=False)
  )
  (classifier): Sequential(
    80.25 k, 98.842% Params, 80.25 KMac, 29.942% MACs,
    (0): Flatten(0, 0.000% Params, 0.0 Mac, 0.000% MACs, start_dim=1,
end_dim=-1)
    (1): Linear(69.24 k, 85.277% Params, 69.24 KMac, 25.833% MACs,
in_features=576, out_features=120, bias=True)
    (2): Sigmoid(0, 0.000% Params, 0.0 Mac, 0.000% MACs, )
    (3): Linear(10.16 k, 12.518% Params, 10.16 KMac, 3.792% MACs,
in_features=120, out_features=84, bias=True)
    (4): Sigmoid(0, 0.000% Params, 0.0 Mac, 0.000% MACs, )
    (5): Linear(850, 1.047% Params, 850.0 Mac, 0.317% MACs, in_features=84,
out_features=10, bias=True)
  )
)
Computational complexity:       268.03 KMac
Number of parameters:           81.19 k
```

1.3.2 2. Adjust the number of output channels (width of each layer).

[123]:
```
# Increased output channels of each Conv2d by multiplier of 2
class LeNet_P2_2(nn.Module):
    def __init__(self, input_features: int, num_classes):
        super().__init__()
        self.conv = nn.Sequential(
            nn.Conv2d(input_features, 16, kernel_size=5, padding=2), # 28 +␣
↪(2*2(padding)) - (5(kernelSize)-1) = 28
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=2, stride=2), # 28 / 2 = 14
            nn.Conv2d(16, 32, kernel_size=5), # 14 - (5-1) = 10
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=2, stride=2) # 10 / 2 = 5
        )
        self.classifier = nn.Sequential(
            nn.Flatten(),
            nn.Linear(32*5*5, 120), nn.Sigmoid(),
            nn.Linear(120, 84), nn.Sigmoid(),
            nn.Linear(84, num_classes)
        )
    def forward(self, x):
        x = self.conv(x)
        x = self.classifier(x)
        return x
```

[152]:
```
P2_2_model = LeNet_P2_2(input_features=1,
                        num_classes=10)
optimizer_cpu=torch.optim.SGD(params=P2_2_model.parameters(),
                            lr=0.1)
accuracy_fn_cpu = MulticlassAccuracy(num_classes=10)
P2_2_model_history = train(model=P2_2_model,
                         train_dataloader=LeNet_trainLoader,
                         val_dataloader=LeNet_valLoader,
                         optim=optimizer_cpu,
                         loss_fn=loss_fn,
                         accuracy_fn=accuracy_fn_cpu,
                         epochs=10,
                         device="cpu")
```

```
 10%|
| 1/10 [00:20<03:02, 20.30s/it]

Epoch: 1
--------------- Train Loss: 1.0413, Train Accuracy: 0.5907, Val Loss: 0.5221,
Val Accuracy: 0.7709

 20%|
| 2/10 [00:40<02:43, 20.48s/it]
```

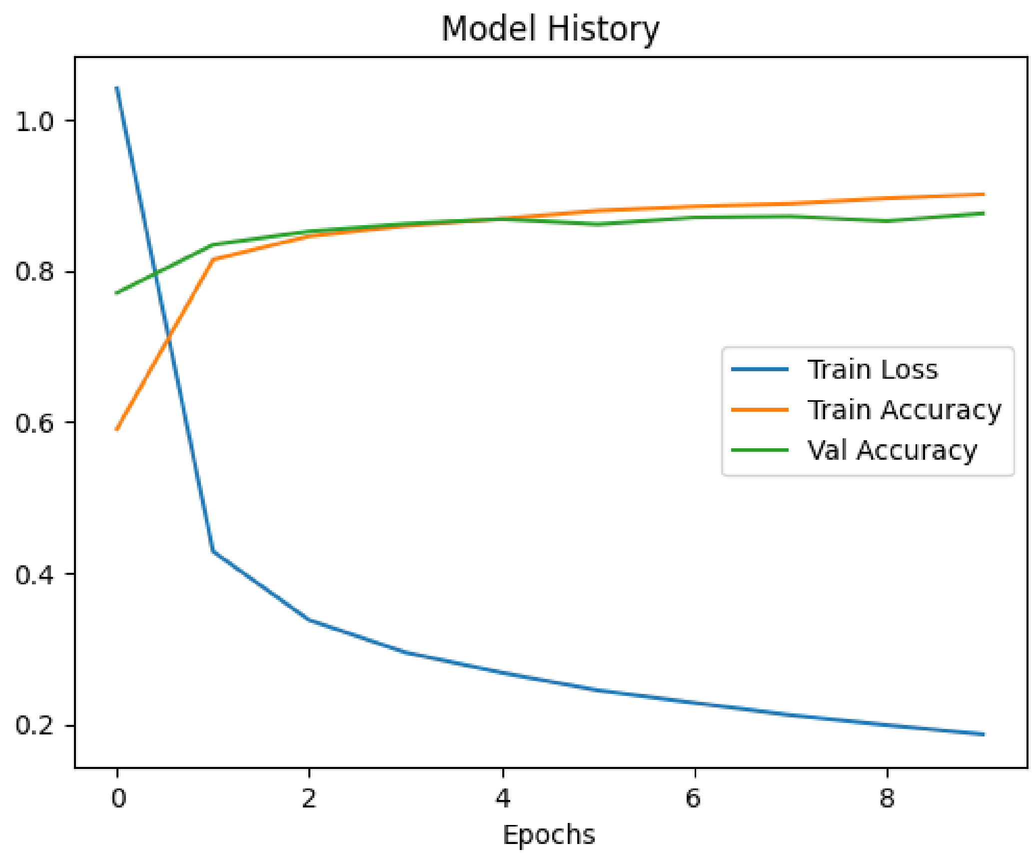
```
Epoch: 2
--------------- Train Loss: 0.4285, Train Accuracy: 0.8149, Val Loss: 0.3807,
Val Accuracy: 0.8345

 30%|
| 3/10 [01:01<02:22, 20.39s/it]

Epoch: 3
--------------- Train Loss: 0.3377, Train Accuracy: 0.8460, Val Loss: 0.3349,
Val Accuracy: 0.8523

 40%|
| 4/10 [01:22<02:03, 20.60s/it]

Epoch: 4
--------------- Train Loss: 0.2949, Train Accuracy: 0.8595, Val Loss: 0.3072,
Val Accuracy: 0.8620

 50%|
| 5/10 [01:42<01:41, 20.35s/it]

Epoch: 5
--------------- Train Loss: 0.2681, Train Accuracy: 0.8691, Val Loss: 0.2924,
Val Accuracy: 0.8684

 60%|
| 6/10 [02:01<01:20, 20.14s/it]

Epoch: 6
--------------- Train Loss: 0.2448, Train Accuracy: 0.8795, Val Loss: 0.2911,
Val Accuracy: 0.8615

 70%|
| 7/10 [02:22<01:01, 20.33s/it]

Epoch: 7
--------------- Train Loss: 0.2282, Train Accuracy: 0.8852, Val Loss: 0.2969,
Val Accuracy: 0.8705

 80%|
| 8/10 [02:42<00:40, 20.18s/it]

Epoch: 8
--------------- Train Loss: 0.2121, Train Accuracy: 0.8889, Val Loss: 0.2668,
Val Accuracy: 0.8720

 90%|
| 9/10 [03:01<00:19, 19.82s/it]

Epoch: 9
--------------- Train Loss: 0.1989, Train Accuracy: 0.8959, Val Loss: 0.2782,
Val Accuracy: 0.8657

100%|
    | 10/10 [03:20<00:00, 20.04s/it]
```

```
Epoch: 10
--------------- Train Loss: 0.1866, Train Accuracy: 0.9013, Val Loss: 0.2569,
Val Accuracy: 0.8761
```

[159]:
```
# P2_2 Plot, performed slightly worse with overfitting at the end
plot_history(P2_2_model_history)

with torch.cuda.device(0):
  macs, params = get_model_complexity_info(P2_2_model, (1, 28, 28),␣
↪as_strings=True,
                                           print_per_layer_stat=True,␣
↪verbose=True)
  print('{:<30}  {:<8}'.format('Computational complexity: ', macs))
  print('{:<30}  {:<8}'.format('Number of parameters: ', params))
```

```
Warning: module Flatten is treated as a zero-op.
Warning: module Sigmoid is treated as a zero-op.
Warning: module LeNet_P2_2 is treated as a zero-op.
LeNet_P2_2(
  120.38 k, 100.000% Params, 1.75 MMac, 100.000% MACs,
  (conv): Sequential(
    13.25 k, 11.005% Params, 1.64 MMac, 93.871% MACs,
    (0): Conv2d(416, 0.346% Params, 326.14 KMac, 18.658% MACs, 1, 16,
kernel_size=(5, 5), stride=(1, 1), padding=(2, 2))
    (1): ReLU(0, 0.000% Params, 12.54 KMac, 0.718% MACs, )
    (2): MaxPool2d(0, 0.000% Params, 12.54 KMac, 0.718% MACs, kernel_size=2,
stride=2, padding=0, dilation=1, ceil_mode=False)
    (3): Conv2d(12.83 k, 10.659% Params, 1.28 MMac, 73.411% MACs, 16, 32,
kernel_size=(5, 5), stride=(1, 1))
    (4): ReLU(0, 0.000% Params, 3.2 KMac, 0.183% MACs, )
    (5): MaxPool2d(0, 0.000% Params, 3.2 KMac, 0.183% MACs, kernel_size=2,
stride=2, padding=0, dilation=1, ceil_mode=False)
  )
  (classifier): Sequential(
    107.13 k, 88.995% Params, 107.13 KMac, 6.129% MACs,
    (0): Flatten(0, 0.000% Params, 0.0 Mac, 0.000% MACs, start_dim=1,
end_dim=-1)
    (1): Linear(96.12 k, 79.846% Params, 96.12 KMac, 5.499% MACs,
in_features=800, out_features=120, bias=True)
    (2): Sigmoid(0, 0.000% Params, 0.0 Mac, 0.000% MACs, )
    (3): Linear(10.16 k, 8.443% Params, 10.16 KMac, 0.581% MACs,
in_features=120, out_features=84, bias=True)
    (4): Sigmoid(0, 0.000% Params, 0.0 Mac, 0.000% MACs, )
    (5): Linear(850, 0.706% Params, 850.0 Mac, 0.049% MACs, in_features=84,
out_features=10, bias=True)
  )
```

```
)
Computational complexity:       1.75 MMac
Number of parameters:           120.38 k
```



1.3.3 3. Adjust the number of convolution layers.

[130]:
```
# Added another "block" of conv2d, relu, and Maxpool.
# Also adjusted original conv2d layers to have padding=2
class LeNet_P2_3(nn.Module):
    def __init__(self, input_features: int, num_classes):
        super().__init__()
        self.conv = nn.Sequential(
            nn.Conv2d(input_features, 6, kernel_size=5, padding=2), # 28 +
↪(2*2(padding)) - (5(kernelSize)-1) = 28
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=2, stride=2), # 28 / 2 = 14
            nn.Conv2d(6, 16, kernel_size=5, padding=2), # 14
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=2, stride=2), # 14 / 2 = 7
            nn.Conv2d(16, 32, kernel_size=2), # 7 - (2-1) = 6
```

```
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=2, stride=2) # 6 / 2 = 3
        )
        self.classifier = nn.Sequential(
            nn.Flatten(),
            nn.Linear(32*3*3, 120), nn.Sigmoid(),
            nn.Linear(120, 84), nn.Sigmoid(),
            nn.Linear(84, num_classes)
        )
    def forward(self, x):
        x = self.conv(x)
        x = self.classifier(x)
        return x
```

[151]:
```
P2_3_model = LeNet_P2_3(input_features=1,
                        num_classes=10)
optimizer_cpu=torch.optim.SGD(params=P2_3_model.parameters(),
                            lr=0.1)
accuracy_fn_cpu = MulticlassAccuracy(num_classes=10)
P2_3_model_history = train(model=P2_3_model,
                         train_dataloader=LeNet_trainLoader,
                         val_dataloader=LeNet_valLoader,
                         optim=optimizer_cpu,
                         loss_fn=loss_fn,
                         accuracy_fn=accuracy_fn_cpu,
                         epochs=10,
                         device="cpu")
```

```
 10%|
| 1/10 [00:17<02:33, 17.05s/it]

Epoch: 1
--------------- Train Loss: 1.3923, Train Accuracy: 0.4526, Val Loss: 0.6881,
Val Accuracy: 0.6990

 20%|
| 2/10 [00:34<02:19, 17.41s/it]

Epoch: 2
--------------- Train Loss: 0.5629, Train Accuracy: 0.7549, Val Loss: 0.4766,
Val Accuracy: 0.7955

 30%|
| 3/10 [00:51<02:01, 17.29s/it]

Epoch: 3
--------------- Train Loss: 0.4236, Train Accuracy: 0.8159, Val Loss: 0.3938,
Val Accuracy: 0.8279

 40%|
| 4/10 [01:09<01:43, 17.30s/it]
```

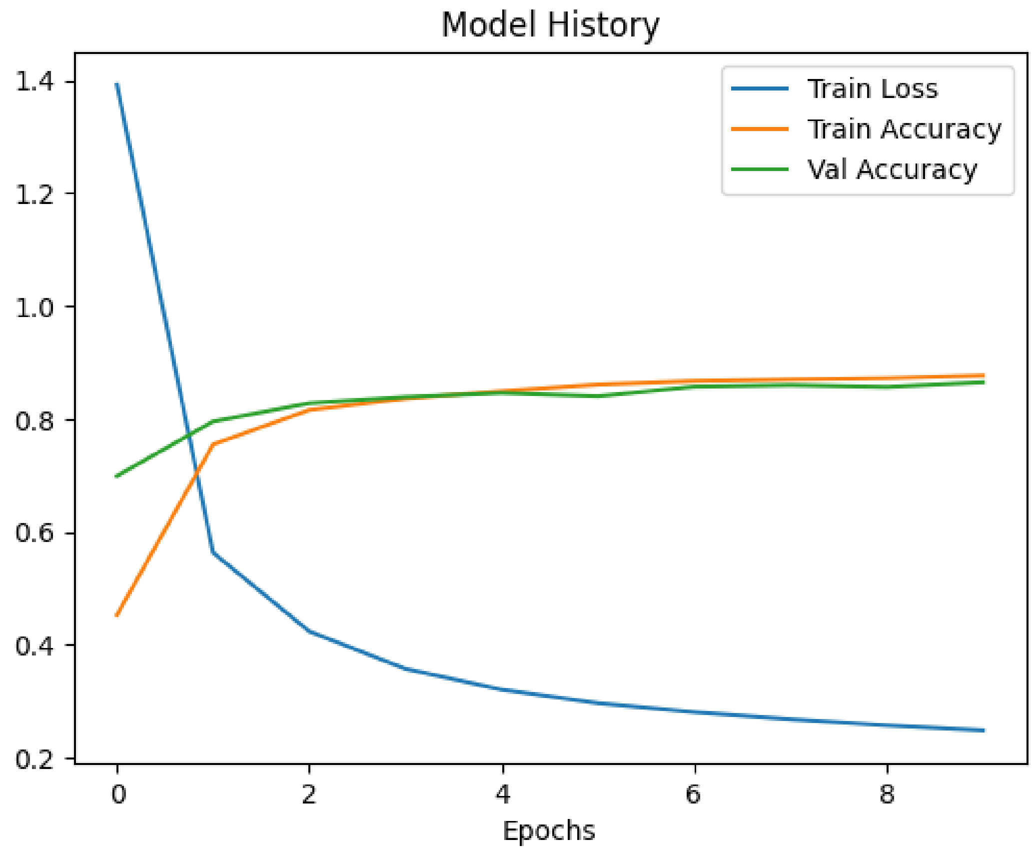
```
Epoch: 4
--------------- Train Loss: 0.3573, Train Accuracy: 0.8360, Val Loss: 0.3591,
Val Accuracy: 0.8388

 50%|
| 5/10 [01:26<01:26, 17.23s/it]

Epoch: 5
--------------- Train Loss: 0.3206, Train Accuracy: 0.8493, Val Loss: 0.3449,
Val Accuracy: 0.8460

 60%|
| 6/10 [01:43<01:09, 17.30s/it]

Epoch: 6
--------------- Train Loss: 0.2965, Train Accuracy: 0.8608, Val Loss: 0.3603,
Val Accuracy: 0.8401

 70%|
| 7/10 [02:01<00:52, 17.48s/it]

Epoch: 7
--------------- Train Loss: 0.2807, Train Accuracy: 0.8670, Val Loss: 0.3171,
Val Accuracy: 0.8572

 80%|
| 8/10 [02:19<00:35, 17.57s/it]

Epoch: 8
--------------- Train Loss: 0.2681, Train Accuracy: 0.8700, Val Loss: 0.2961,
Val Accuracy: 0.8599

 90%|
| 9/10 [02:36<00:17, 17.44s/it]

Epoch: 9
--------------- Train Loss: 0.2573, Train Accuracy: 0.8721, Val Loss: 0.3059,
Val Accuracy: 0.8567

100%|
    | 10/10 [02:54<00:00, 17.41s/it]

Epoch: 10
--------------- Train Loss: 0.2485, Train Accuracy: 0.8769, Val Loss: 0.2969,
Val Accuracy: 0.8648
```

[160]:

```
# P2_3 performed about the same as base
with torch.cuda.device(0):
  macs, params = get_model_complexity_info(P2_3_model, (1, 28, 28),␣
 ↪as_strings=True,
                                            print_per_layer_stat=True,␣
 ↪verbose=True)
```

```
  print('{:<30}  {:<8}'.format('Computational complexity: ', macs))
  print('{:<30}  {:<8}'.format('Number of parameters: ', params))
plot_history(P2_3_model_history)
```

```
Warning: module Flatten is treated as a zero-op.
Warning: module Sigmoid is treated as a zero-op.
Warning: module LeNet_P2_3 is treated as a zero-op.
LeNet_P2_3(
  50.35 k, 100.000% Params, 734.4 KMac, 100.000% MACs,
  (conv): Sequential(
    4.65 k, 9.240% Params, 688.7 KMac, 93.778% MACs,
    (0): Conv2d(156, 0.310% Params, 122.3 KMac, 16.654% MACs, 1, 6,
kernel_size=(5, 5), stride=(1, 1), padding=(2, 2))
    (1): ReLU(0, 0.000% Params, 4.7 KMac, 0.641% MACs, )
    (2): MaxPool2d(0, 0.000% Params, 4.7 KMac, 0.641% MACs, kernel_size=2,
stride=2, padding=0, dilation=1, ceil_mode=False)
    (3): Conv2d(2.42 k, 4.799% Params, 473.54 KMac, 64.479% MACs, 6, 16,
kernel_size=(5, 5), stride=(1, 1), padding=(2, 2))
    (4): ReLU(0, 0.000% Params, 3.14 KMac, 0.427% MACs, )
    (5): MaxPool2d(0, 0.000% Params, 3.14 KMac, 0.427% MACs, kernel_size=2,
stride=2, padding=0, dilation=1, ceil_mode=False)
    (6): Conv2d(2.08 k, 4.131% Params, 74.88 KMac, 10.196% MACs, 16, 32,
kernel_size=(2, 2), stride=(1, 1))
    (7): ReLU(0, 0.000% Params, 1.15 KMac, 0.157% MACs, )
    (8): MaxPool2d(0, 0.000% Params, 1.15 KMac, 0.157% MACs, kernel_size=2,
stride=2, padding=0, dilation=1, ceil_mode=False)
  )
  (classifier): Sequential(
    45.69 k, 90.760% Params, 45.69 KMac, 6.222% MACs,
    (0): Flatten(0, 0.000% Params, 0.0 Mac, 0.000% MACs, start_dim=1,
end_dim=-1)
    (1): Linear(34.68 k, 68.883% Params, 34.68 KMac, 4.722% MACs,
in_features=288, out_features=120, bias=True)
    (2): Sigmoid(0, 0.000% Params, 0.0 Mac, 0.000% MACs, )
    (3): Linear(10.16 k, 20.188% Params, 10.16 KMac, 1.384% MACs,
in_features=120, out_features=84, bias=True)
    (4): Sigmoid(0, 0.000% Params, 0.0 Mac, 0.000% MACs, )
    (5): Linear(850, 1.688% Params, 850.0 Mac, 0.116% MACs, in_features=84,
out_features=10, bias=True)
  )
)
Computational complexity:       734.4 KMac
Number of parameters:           50.35 k
```



1.3.4 4. Adjust the number of fully connected layers.

[142]:
```
# Add another Linear layer to gradually get to num_classes
# Changed linear layers to have ReLU activation function
class LeNet_P2_4(nn.Module):
    def __init__(self, input_features: int, num_classes):
        super().__init__()
        self.conv = nn.Sequential(
            nn.Conv2d(input_features, 6, kernel_size=5, padding=2), # 28 +␣
↪(2*2(padding)) - (5(kernelSize)-1) = 28
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=2, stride=2), # 28 / 2 = 14
            nn.Conv2d(6, 16, kernel_size=5), # 14 - (5-1) = 10
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=2, stride=2) # 10 / 2 = 5
        )
        self.classifier = nn.Sequential(
            nn.Flatten(),
            nn.Linear(16*5*5, 120), nn.ReLU(),
```

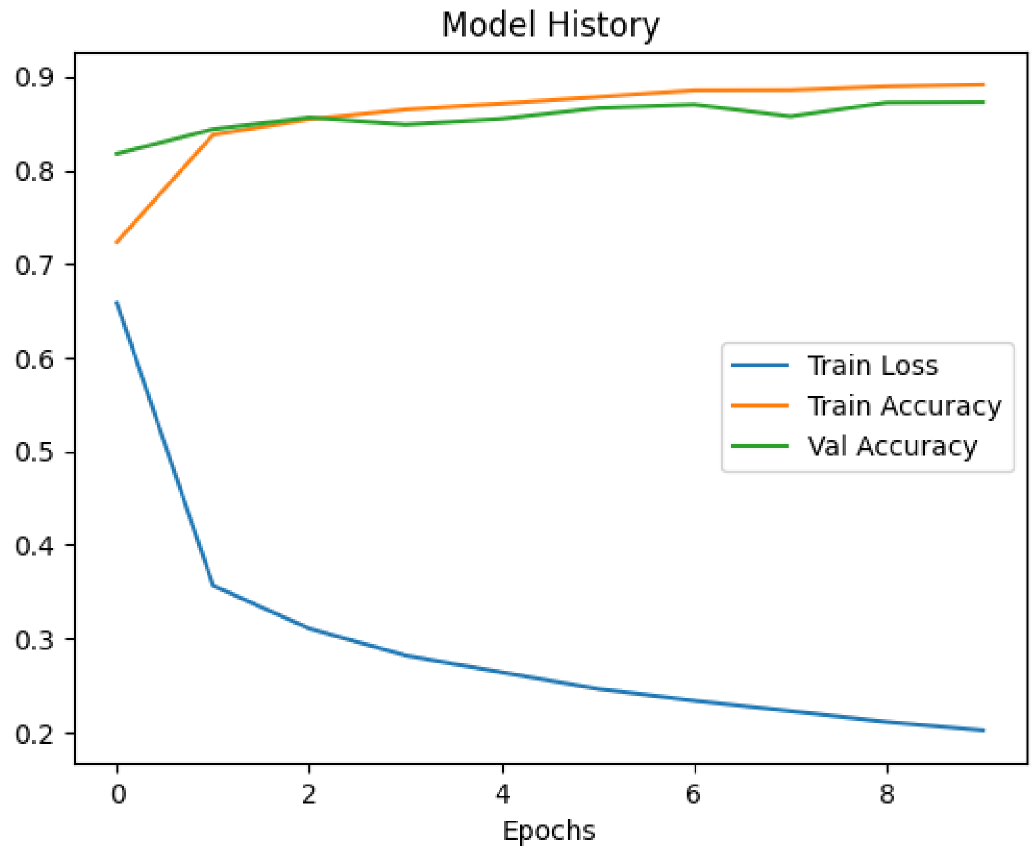
```python
            nn.Linear(120, 84), nn.ReLU(),
            nn.Linear(84, int(84/2)), nn.ReLU(),
            nn.Linear(int(84/2), num_classes)
        )
    def forward(self, x):
        x = self.conv(x)
        x = self.classifier(x)
        return x
```

[150]:
```python
P2_4_model = LeNet_P2_4(input_features=1,
                        num_classes=10).to("cuda")
optimizer_gpu=torch.optim.SGD(params=P2_4_model.parameters(),
                            lr=0.1)
accuracy_fn_gpu = MulticlassAccuracy(num_classes=10).to("cuda")
P2_4_model_history = train(model=P2_4_model,
                         train_dataloader=LeNet_trainLoader,
                         val_dataloader=LeNet_valLoader,
                         optim=optimizer_gpu,
                         loss_fn=loss_fn,
                         accuracy_fn=accuracy_fn_gpu,
                         epochs=10,
                         device="cuda")
```

```
 10%|
| 1/10 [00:19<02:51, 19.05s/it]

Epoch: 1
--------------- Train Loss: 0.6583, Train Accuracy: 0.7233, Val Loss: 0.4145,
Val Accuracy: 0.8177

 20%|
| 2/10 [00:38<02:34, 19.28s/it]

Epoch: 2
--------------- Train Loss: 0.3564, Train Accuracy: 0.8379, Val Loss: 0.3462,
Val Accuracy: 0.8438

 30%|
| 3/10 [00:58<02:15, 19.40s/it]

Epoch: 3
--------------- Train Loss: 0.3106, Train Accuracy: 0.8544, Val Loss: 0.3257,
Val Accuracy: 0.8564

 40%|
| 4/10 [01:18<01:59, 19.96s/it]

Epoch: 4
--------------- Train Loss: 0.2819, Train Accuracy: 0.8648, Val Loss: 0.3303,
Val Accuracy: 0.8487
```

```
 50%|
| 5/10 [01:40<01:42, 20.46s/it]

Epoch: 5
--------------- Train Loss: 0.2638, Train Accuracy: 0.8711, Val Loss: 0.3089,
Val Accuracy: 0.8549

 60%|
| 6/10 [02:01<01:22, 20.71s/it]

Epoch: 6
--------------- Train Loss: 0.2462, Train Accuracy: 0.8782, Val Loss: 0.2962,
Val Accuracy: 0.8664

 70%|
| 7/10 [02:22<01:02, 20.96s/it]

Epoch: 7
--------------- Train Loss: 0.2335, Train Accuracy: 0.8853, Val Loss: 0.2817,
Val Accuracy: 0.8701

 80%|
| 8/10 [02:43<00:41, 20.95s/it]

Epoch: 8
--------------- Train Loss: 0.2225, Train Accuracy: 0.8855, Val Loss: 0.3188,
Val Accuracy: 0.8575

 90%|
| 9/10 [03:03<00:20, 20.41s/it]

Epoch: 9
--------------- Train Loss: 0.2109, Train Accuracy: 0.8895, Val Loss: 0.2773,
Val Accuracy: 0.8722

100%|
    | 10/10 [03:22<00:00, 20.29s/it]

Epoch: 10
--------------- Train Loss: 0.2019, Train Accuracy: 0.8915, Val Loss: 0.2892,
Val Accuracy: 0.8727
```

[161]:
```
# P2_4 showed better training but began to overfit
plot_history(P2_4_model_history)
```



[162]:
```
with torch.cuda.device(0):
  macs, params = get_model_complexity_info(P2_4_model, (1, 28, 28),␣
↪as_strings=True,
                                            print_per_layer_stat=True,␣
↪verbose=True)
  print('{:<30}  {:<8}'.format('Computational complexity: ', macs))
  print('{:<30}  {:<8}'.format('Number of parameters: ', params))
```

```
Warning: module Flatten is treated as a zero-op.
Warning: module LeNet_P2_4 is treated as a zero-op.
LeNet_P2_4(
  64.86 k, 100.000% Params, 439.04 KMac, 100.000% MACs,
  (conv): Sequential(
    2.57 k, 3.966% Params, 376.51 KMac, 85.758% MACs,
    (0): Conv2d(156, 0.241% Params, 122.3 KMac, 27.857% MACs, 1, 6,
kernel_size=(5, 5), stride=(1, 1), padding=(2, 2))
    (1): ReLU(0, 0.000% Params, 4.7 KMac, 1.071% MACs, )
    (2): MaxPool2d(0, 0.000% Params, 4.7 KMac, 1.071% MACs, kernel_size=2,
stride=2, padding=0, dilation=1, ceil_mode=False)
    (3): Conv2d(2.42 k, 3.725% Params, 241.6 KMac, 55.029% MACs, 6, 16,
```

```
kernel_size=(5, 5), stride=(1, 1))
    (4): ReLU(0, 0.000% Params, 1.6 KMac, 0.364% MACs, )
    (5): MaxPool2d(0, 0.000% Params, 1.6 KMac, 0.364% MACs, kernel_size=2,
stride=2, padding=0, dilation=1, ceil_mode=False)
  )
  (classifier): Sequential(
    62.28 k, 96.034% Params, 62.53 KMac, 14.242% MACs,
    (0): Flatten(0, 0.000% Params, 0.0 Mac, 0.000% MACs, start_dim=1,
end_dim=-1)
    (1): Linear(48.12 k, 74.195% Params, 48.12 KMac, 10.960% MACs,
in_features=400, out_features=120, bias=True)
    (2): ReLU(0, 0.000% Params, 120.0 Mac, 0.027% MACs, )
    (3): Linear(10.16 k, 15.672% Params, 10.16 KMac, 2.315% MACs,
in_features=120, out_features=84, bias=True)
    (4): ReLU(0, 0.000% Params, 84.0 Mac, 0.019% MACs, )
    (5): Linear(3.57 k, 5.505% Params, 3.57 KMac, 0.813% MACs, in_features=84,
out_features=42, bias=True)
    (6): ReLU(0, 0.000% Params, 42.0 Mac, 0.010% MACs, )
    (7): Linear(430, 0.663% Params, 430.0 Mac, 0.098% MACs, in_features=42,
out_features=10, bias=True)
  )
)
Computational complexity:       439.04 KMac
Number of parameters:           64.86 k
```

1.3.5 5. Explore the learning rates

[149]:
```
# LR = 0.01
# Assuming to use LeNet_modern for this part
P2_5_model = LeNet_modern(input_features=1,
                          num_classes=10).to("cuda")
# Decreased learning rate from 0.1 to 0.01
optimizer_gpu=torch.optim.SGD(params=P2_5_model.parameters(),
                            lr=0.01)
# Increasing epochs due to smaller LR
accuracy_fn_gpu = MulticlassAccuracy(num_classes=10).to("cuda")
P2_5_model_history = train(model=P2_5_model,
                         train_dataloader=LeNet_trainLoader,
                         val_dataloader=LeNet_valLoader,
                         optim=optimizer_gpu,
                         loss_fn=loss_fn,
                         accuracy_fn=accuracy_fn_gpu,
                         epochs=20,
                         device="cuda")
```

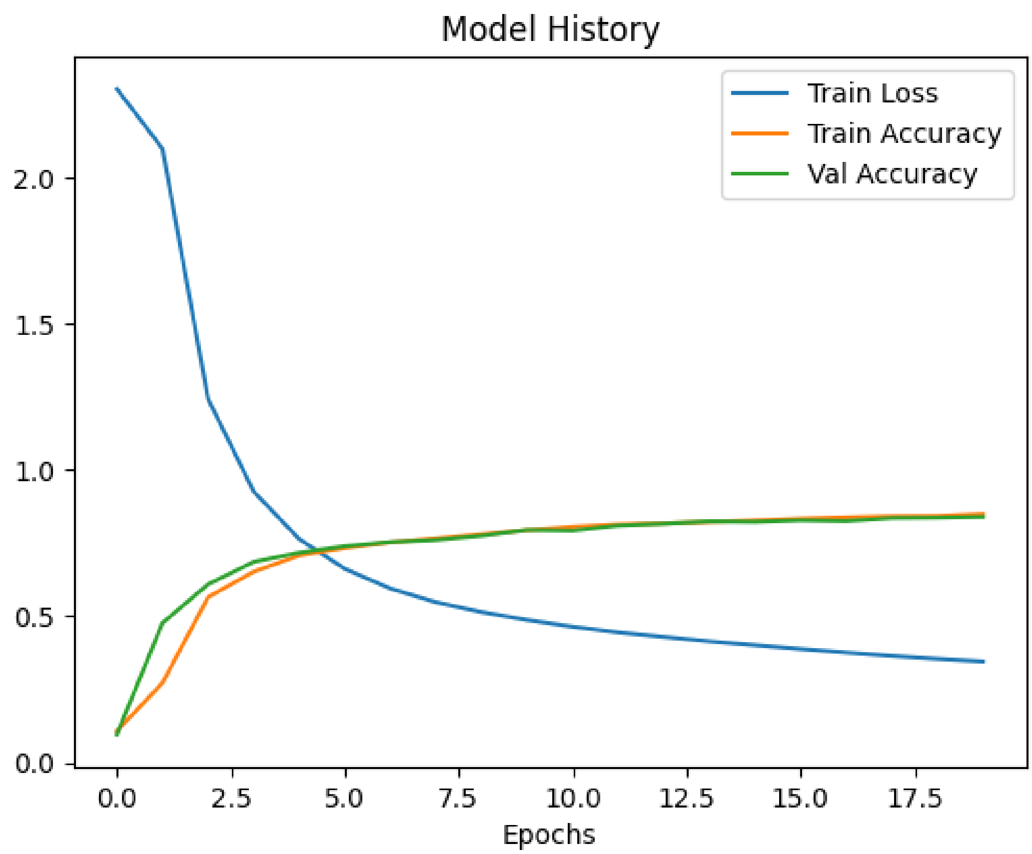
```
  5%|
| 1/20 [00:21<06:50, 21.59s/it]
```

```
Epoch: 1
--------------- Train Loss: 2.3014, Train Accuracy: 0.1077, Val Loss: 2.2941,
Val Accuracy: 0.0962

 10%|
| 2/20 [00:43<06:31, 21.76s/it]

Epoch: 2
--------------- Train Loss: 2.0975, Train Accuracy: 0.2720, Val Loss: 1.5970,
Val Accuracy: 0.4767

 15%|
| 3/20 [01:05<06:13, 21.98s/it]

Epoch: 3
--------------- Train Loss: 1.2425, Train Accuracy: 0.5649, Val Loss: 1.0419,
Val Accuracy: 0.6089

 20%|
| 4/20 [01:26<05:46, 21.67s/it]

Epoch: 4
--------------- Train Loss: 0.9259, Train Accuracy: 0.6518, Val Loss: 0.8459,
Val Accuracy: 0.6853

 25%|
| 5/20 [01:49<05:27, 21.87s/it]

Epoch: 5
--------------- Train Loss: 0.7636, Train Accuracy: 0.7074, Val Loss: 0.7193,
Val Accuracy: 0.7171

 30%|
| 6/20 [02:10<05:02, 21.57s/it]

Epoch: 6
--------------- Train Loss: 0.6618, Train Accuracy: 0.7333, Val Loss: 0.6478,
Val Accuracy: 0.7392

 35%|
| 7/20 [02:31<04:40, 21.54s/it]

Epoch: 7
--------------- Train Loss: 0.5944, Train Accuracy: 0.7523, Val Loss: 0.5914,
Val Accuracy: 0.7531

 40%|
| 8/20 [02:53<04:21, 21.81s/it]

Epoch: 8
--------------- Train Loss: 0.5476, Train Accuracy: 0.7656, Val Loss: 0.5523,
Val Accuracy: 0.7606

 45%|
| 9/20 [03:15<03:58, 21.72s/it]
```

```
Epoch: 9
--------------- Train Loss: 0.5140, Train Accuracy: 0.7795, Val Loss: 0.5209,
Val Accuracy: 0.7748

 50%|
| 10/20 [03:36<03:34, 21.50s/it]

Epoch: 10
--------------- Train Loss: 0.4871, Train Accuracy: 0.7938, Val Loss: 0.5007,
Val Accuracy: 0.7945

 55%|
| 11/20 [03:58<03:13, 21.54s/it]

Epoch: 11
--------------- Train Loss: 0.4639, Train Accuracy: 0.8052, Val Loss: 0.4884,
Val Accuracy: 0.7924

 60%|
| 12/20 [04:19<02:50, 21.33s/it]

Epoch: 12
--------------- Train Loss: 0.4445, Train Accuracy: 0.8134, Val Loss: 0.4639,
Val Accuracy: 0.8095

 65%|
| 13/20 [04:40<02:28, 21.26s/it]

Epoch: 13
--------------- Train Loss: 0.4291, Train Accuracy: 0.8170, Val Loss: 0.4464,
Val Accuracy: 0.8158

 70%|
| 14/20 [05:01<02:08, 21.37s/it]

Epoch: 14
--------------- Train Loss: 0.4138, Train Accuracy: 0.8218, Val Loss: 0.4296,
Val Accuracy: 0.8236

 75%|
| 15/20 [05:22<01:45, 21.18s/it]

Epoch: 15
--------------- Train Loss: 0.4007, Train Accuracy: 0.8276, Val Loss: 0.4159,
Val Accuracy: 0.8222

 80%|
| 16/20 [05:44<01:25, 21.34s/it]

Epoch: 16
--------------- Train Loss: 0.3877, Train Accuracy: 0.8334, Val Loss: 0.4013,
Val Accuracy: 0.8275

 85%|
| 17/20 [06:05<01:04, 21.36s/it]
```

```
Epoch: 17
--------------- Train Loss: 0.3756, Train Accuracy: 0.8378, Val Loss: 0.4089,
Val Accuracy: 0.8250

 90%|
| 18/20 [06:26<00:42, 21.36s/it]

Epoch: 18
--------------- Train Loss: 0.3641, Train Accuracy: 0.8414, Val Loss: 0.3890,
Val Accuracy: 0.8352

 95%|
     | 19/20 [06:47<00:21, 21.23s/it]

Epoch: 19
--------------- Train Loss: 0.3541, Train Accuracy: 0.8422, Val Loss: 0.3738,
Val Accuracy: 0.8363

100%|
    | 20/20 [07:06<00:00, 21.35s/it]

Epoch: 20
--------------- Train Loss: 0.3452, Train Accuracy: 0.8489, Val Loss: 0.3716,
Val Accuracy: 0.8392
```

[164]:
```
plot_history(P2_5_model_history)
```



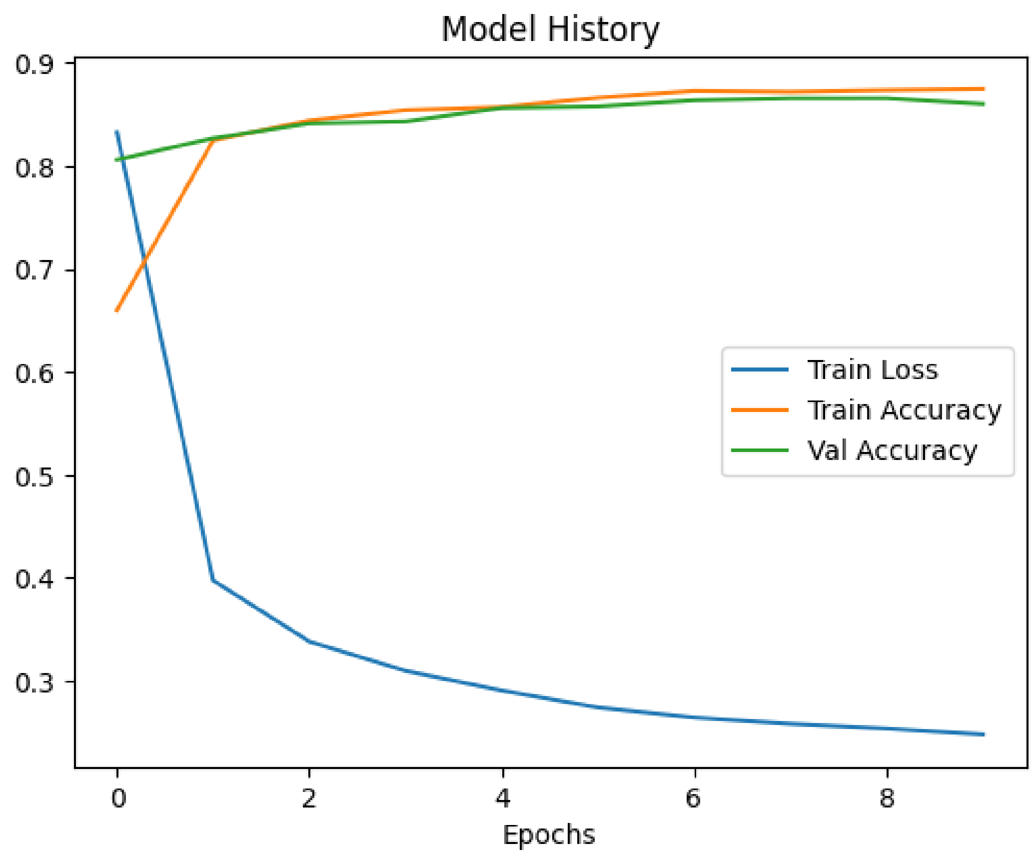
[165]:
```
# LR = 0.2
P2_5b_model = LeNet_modern(input_features=1,
                           num_classes=10).to("cuda")
# Increased learning rate from 0.1 to 0.2
optimizer_gpu=torch.optim.SGD(params=P2_5b_model.parameters(),
                             lr=0.2)
accuracy_fn_gpu = MulticlassAccuracy(num_classes=10).to("cuda")
P2_5b_model_history = train(model=P2_5b_model,
                           train_dataloader=LeNet_trainLoader,
                           val_dataloader=LeNet_valLoader,
                           optim=optimizer_gpu,
                           loss_fn=loss_fn,
                           accuracy_fn=accuracy_fn_gpu,
                           epochs=10,
                           device="cuda")
```

```
 10%|
| 1/10 [00:21<03:16, 21.82s/it]

Epoch: 1
--------------- Train Loss: 0.8327, Train Accuracy: 0.6600, Val Loss: 0.4520,
```

```
Val Accuracy: 0.8061

 20%|
| 2/10 [00:41<02:45, 20.69s/it]

Epoch: 2
--------------- Train Loss: 0.3974, Train Accuracy: 0.8249, Val Loss: 0.3847,
Val Accuracy: 0.8269

 30%|
| 3/10 [01:01<02:20, 20.07s/it]

Epoch: 3
--------------- Train Loss: 0.3380, Train Accuracy: 0.8442, Val Loss: 0.3484,
Val Accuracy: 0.8414

 40%|
| 4/10 [01:20<01:59, 19.98s/it]

Epoch: 4
--------------- Train Loss: 0.3096, Train Accuracy: 0.8543, Val Loss: 0.3467,
Val Accuracy: 0.8433

 50%|
| 5/10 [01:41<01:40, 20.10s/it]

Epoch: 5
--------------- Train Loss: 0.2905, Train Accuracy: 0.8573, Val Loss: 0.3153,
Val Accuracy: 0.8565

 60%|
| 6/10 [02:01<01:21, 20.31s/it]

Epoch: 6
--------------- Train Loss: 0.2739, Train Accuracy: 0.8663, Val Loss: 0.3046,
Val Accuracy: 0.8579

 70%|
| 7/10 [02:22<01:00, 20.27s/it]

Epoch: 7
--------------- Train Loss: 0.2643, Train Accuracy: 0.8730, Val Loss: 0.2931,
Val Accuracy: 0.8638

 80%|
| 8/10 [02:43<00:41, 20.58s/it]

Epoch: 8
--------------- Train Loss: 0.2581, Train Accuracy: 0.8721, Val Loss: 0.2934,
Val Accuracy: 0.8658

 90%|
| 9/10 [03:02<00:20, 20.17s/it]
```

```
Epoch: 9
--------------- Train Loss: 0.2535, Train Accuracy: 0.8737, Val Loss: 0.2942,
Val Accuracy: 0.8659

100%|
    | 10/10 [03:23<00:00, 20.36s/it]

Epoch: 10
--------------- Train Loss: 0.2478, Train Accuracy: 0.8749, Val Loss: 0.3070,
Val Accuracy: 0.8603
```

[166]:
```
plot_history(P2_5b_model_history)
```



[167]:
```
with torch.cuda.device(0):
  macs, params = get_model_complexity_info(P2_5b_model, (1, 28, 28),␣
 ↪as_strings=True,
                                           print_per_layer_stat=True,␣
 ↪verbose=True)
  print('{:<30}  {:<8}'.format('Computational complexity: ', macs))
```

```
print('{:<30}  {:<8}'.format('Number of parameters: ', params))
```

```
Warning: module Flatten is treated as a zero-op.
Warning: module Sigmoid is treated as a zero-op.
Warning: module LeNet_modern is treated as a zero-op.
LeNet_modern(
  61.71 k, 100.000% Params, 435.65 KMac, 100.000% MACs,
  (conv): Sequential(
    2.57 k, 4.168% Params, 376.51 KMac, 86.426% MACs,
    (0): Conv2d(156, 0.253% Params, 122.3 KMac, 28.074% MACs, 1, 6,
kernel_size=(5, 5), stride=(1, 1), padding=(2, 2))
    (1): ReLU(0, 0.000% Params, 4.7 KMac, 1.080% MACs, )
    (2): MaxPool2d(0, 0.000% Params, 4.7 KMac, 1.080% MACs, kernel_size=2,
stride=2, padding=0, dilation=1, ceil_mode=False)
    (3): Conv2d(2.42 k, 3.915% Params, 241.6 KMac, 55.458% MACs, 6, 16,
kernel_size=(5, 5), stride=(1, 1))
    (4): ReLU(0, 0.000% Params, 1.6 KMac, 0.367% MACs, )
    (5): MaxPool2d(0, 0.000% Params, 1.6 KMac, 0.367% MACs, kernel_size=2,
stride=2, padding=0, dilation=1, ceil_mode=False)
  )
  (classifier): Sequential(
    59.13 k, 95.832% Params, 59.13 KMac, 13.574% MACs,
    (0): Flatten(0, 0.000% Params, 0.0 Mac, 0.000% MACs, start_dim=1,
end_dim=-1)
    (1): Linear(48.12 k, 77.983% Params, 48.12 KMac, 11.046% MACs,
in_features=400, out_features=120, bias=True)
    (2): Sigmoid(0, 0.000% Params, 0.0 Mac, 0.000% MACs, )
    (3): Linear(10.16 k, 16.472% Params, 10.16 KMac, 2.333% MACs,
in_features=120, out_features=84, bias=True)
    (4): Sigmoid(0, 0.000% Params, 0.0 Mac, 0.000% MACs, )
    (5): Linear(850, 1.377% Params, 850.0 Mac, 0.195% MACs, in_features=84,
out_features=10, bias=True)
  )
)
Computational complexity:       435.65 KMac
Number of parameters:           61.71 k
```

1.4 Problem 3: Apply dropout on best performing model

[171]:
```
# P2_4 model performed the best, so dropout will be added
class LeNet_P3(nn.Module):
    def __init__(self, input_features: int, num_classes):
        super().__init__()
        self.conv = nn.Sequential(
            nn.Conv2d(input_features, 6, kernel_size=5, padding=2), # 28 +␣
 ↪(2*2(padding)) - (5(kernelSize)-1) = 28
            nn.ReLU(),
```

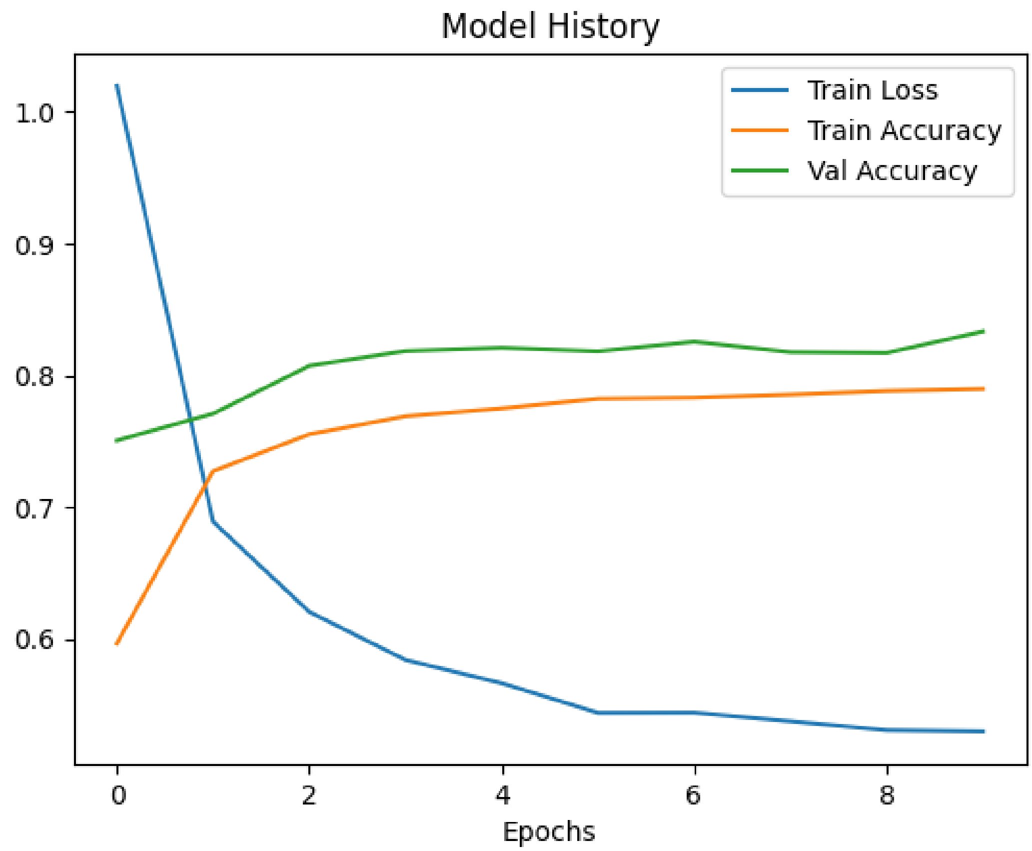
```
            nn.MaxPool2d(kernel_size=2, stride=2), # 28 / 2 = 14
            nn.Dropout2d(0.4),
            nn.Conv2d(6, 16, kernel_size=5), # 14 - (5-1) = 10
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=2, stride=2), # 10 / 2 = 5
            nn.Dropout2d(0.4)
        )
        self.classifier = nn.Sequential(
            nn.Flatten(),
            nn.Linear(16*5*5, 120), nn.Dropout(0.3), nn.ReLU(),
            nn.Linear(120, 84), nn.Dropout(0.3), nn.ReLU(),
            nn.Linear(84, int(84/2)), nn.Dropout(0.3), nn.ReLU(),
            nn.Linear(int(84/2), num_classes)
        )
    def forward(self, x):
        x = self.conv(x)
        x = self.classifier(x)
        return x
```

[173]:
```
P3_model = LeNet_P3(input_features=1,
                    num_classes=10).to("cuda")
optimizer_gpu=torch.optim.SGD(params=P3_model.parameters(),
                            lr=0.1)
accuracy_fn_gpu = MulticlassAccuracy(num_classes=10).to("cuda")
P3_model_history = train(model=P3_model,
                         train_dataloader=LeNet_trainLoader,
                         val_dataloader=LeNet_valLoader,
                         optim=optimizer_gpu,
                         loss_fn=loss_fn,
                         accuracy_fn=accuracy_fn_gpu,
                         epochs=10,
                         device="cuda")
```

```
 10%|
| 1/10 [00:21<03:13, 21.54s/it]

Epoch: 1
--------------- Train Loss: 1.0198, Train Accuracy: 0.5966, Val Loss: 0.5656,
Val Accuracy: 0.7506

 20%|
| 2/10 [00:43<02:52, 21.52s/it]

Epoch: 2
--------------- Train Loss: 0.6889, Train Accuracy: 0.7273, Val Loss: 0.5044,
Val Accuracy: 0.7710

 30%|
| 3/10 [01:05<02:32, 21.78s/it]
```

```
Epoch: 3
--------------- Train Loss: 0.6204, Train Accuracy: 0.7553, Val Loss: 0.4459,
Val Accuracy: 0.8073

 40%|
| 4/10 [01:26<02:09, 21.59s/it]

Epoch: 4
--------------- Train Loss: 0.5839, Train Accuracy: 0.7690, Val Loss: 0.4235,
Val Accuracy: 0.8186

 50%|
| 5/10 [01:49<01:49, 21.97s/it]

Epoch: 5
--------------- Train Loss: 0.5663, Train Accuracy: 0.7750, Val Loss: 0.4090,
Val Accuracy: 0.8210

 60%|
| 6/10 [02:11<01:27, 21.96s/it]

Epoch: 6
--------------- Train Loss: 0.5438, Train Accuracy: 0.7823, Val Loss: 0.4074,
Val Accuracy: 0.8183

 70%|
| 7/10 [02:33<01:05, 21.99s/it]

Epoch: 7
--------------- Train Loss: 0.5440, Train Accuracy: 0.7831, Val Loss: 0.3969,
Val Accuracy: 0.8256

 80%|
| 8/10 [02:54<00:43, 21.97s/it]

Epoch: 8
--------------- Train Loss: 0.5374, Train Accuracy: 0.7855, Val Loss: 0.3965,
Val Accuracy: 0.8177

 90%|
| 9/10 [03:16<00:21, 21.91s/it]

Epoch: 9
--------------- Train Loss: 0.5306, Train Accuracy: 0.7882, Val Loss: 0.3896,
Val Accuracy: 0.8171

100%|
    | 10/10 [03:39<00:00, 21.93s/it]

Epoch: 10
--------------- Train Loss: 0.5297, Train Accuracy: 0.7897, Val Loss: 0.3771,
Val Accuracy: 0.8333
```

[174]:
```
plot_history(P3_model_history)
```



The dropout version does not perform as well as the best performing model of Problem 2. The generalization gap is steadily decreasing in the dropout version, but the val accuracy is behind by 4% and wouldn't increase with more epochs.

1.5 Problem 4: AlexNet Adaptation for FashionMNIST

[185]:
```
class AlexNet_small(nn.Module):
    def __init__(self, input_features: int, num_classes):
        super().__init__()
        self.conv = nn.Sequential(
            nn.Conv2d(input_features, 96, kernel_size=9, padding=2), # 28 +
 ↪(2*2(padding)) - (9(kernelSize)-1) = 24
            nn.ReLU(), nn.MaxPool2d(kernel_size=2, stride=2), # 24 / 2 = 6
            nn.Conv2d(96, 256, kernel_size=5, padding=2), # 14 + (2*3) - (5-1)
 ↪= 16
            nn.ReLU(), nn.MaxPool2d(kernel_size=2, stride=2), # 14 / 2 = 8
            nn.Conv2d(256, 384, kernel_size=2, padding=1), nn.ReLU(),
            nn.Conv2d(384, 384, kernel_size=2, padding=1), nn.ReLU(),
```

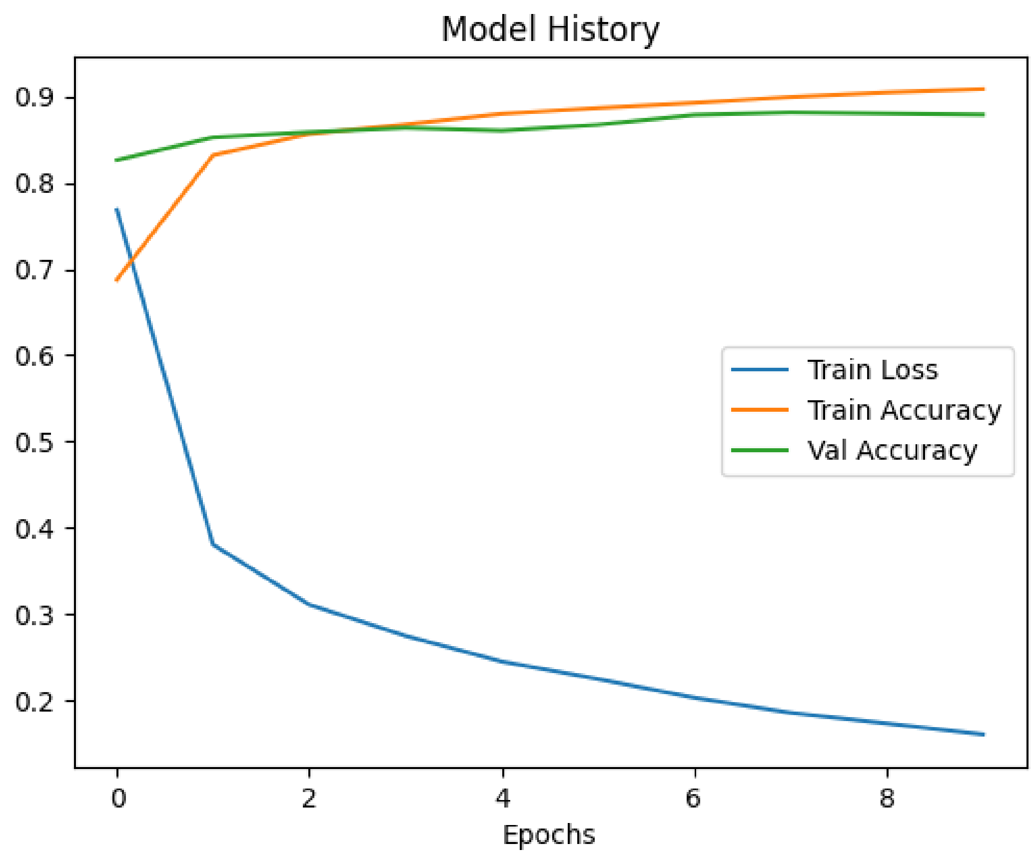
```
            nn.Conv2d(384, 256, kernel_size=2, padding=1), nn.ReLU(),
            nn.MaxPool2d(kernel_size=2, stride=2) # 8 / 2 = 4
        )
        self.classifier = nn.Sequential(
            nn.Flatten(),
            nn.Linear(256*4*4, 920), nn.ReLU(), nn.Dropout(p=0.5),
            nn.Linear(920, int(920/2)), nn.ReLU(), nn.Dropout(p=0.5),
            nn.Linear(int(920/2), num_classes)
        )
    def forward(self, x):
        x = self.conv(x)
        x = self.classifier(x)
        return x
```

[186]:
```
P4_model = AlexNet_small(input_features=1,
                    num_classes=10).to("cuda")
optimizer_gpu=torch.optim.SGD(params=P4_model.parameters(),
                            lr=0.1)
accuracy_fn_gpu = MulticlassAccuracy(num_classes=10).to("cuda")
P4_model_history = train(model=P4_model,
                         train_dataloader=LeNet_trainLoader,
                         val_dataloader=LeNet_valLoader,
                         optim=optimizer_gpu,
                         loss_fn=loss_fn,
                         accuracy_fn=accuracy_fn_gpu,
                         epochs=10,
                         device="cuda")
```

```
 10%|
| 1/10 [00:24<03:37, 24.17s/it]

Epoch: 1
--------------- Train Loss: 0.7683, Train Accuracy: 0.6874, Val Loss: 0.3917,
Val Accuracy: 0.8261

 20%|
| 2/10 [00:48<03:12, 24.05s/it]

Epoch: 2
--------------- Train Loss: 0.3797, Train Accuracy: 0.8317, Val Loss: 0.3291,
Val Accuracy: 0.8524

 30%|
| 3/10 [01:11<02:46, 23.80s/it]

Epoch: 3
--------------- Train Loss: 0.3101, Train Accuracy: 0.8564, Val Loss: 0.3088,
Val Accuracy: 0.8585

 40%|
| 4/10 [01:35<02:23, 23.92s/it]
```

```
Epoch: 4
--------------- Train Loss: 0.2740, Train Accuracy: 0.8675, Val Loss: 0.2911,
Val Accuracy: 0.8634

 50%|
| 5/10 [01:59<01:59, 23.96s/it]

Epoch: 5
--------------- Train Loss: 0.2442, Train Accuracy: 0.8797, Val Loss: 0.3048,
Val Accuracy: 0.8603

 60%|
| 6/10 [02:23<01:35, 23.98s/it]

Epoch: 6
--------------- Train Loss: 0.2239, Train Accuracy: 0.8865, Val Loss: 0.2905,
Val Accuracy: 0.8670

 70%|
| 7/10 [02:47<01:11, 23.97s/it]

Epoch: 7
--------------- Train Loss: 0.2023, Train Accuracy: 0.8924, Val Loss: 0.2622,
Val Accuracy: 0.8784

 80%|
| 8/10 [03:11<00:48, 24.02s/it]

Epoch: 8
--------------- Train Loss: 0.1847, Train Accuracy: 0.8993, Val Loss: 0.2540,
Val Accuracy: 0.8814

 90%|
| 9/10 [03:36<00:24, 24.11s/it]

Epoch: 9
--------------- Train Loss: 0.1723, Train Accuracy: 0.9045, Val Loss: 0.2621,
Val Accuracy: 0.8800

100%|
    | 10/10 [04:00<00:00, 24.01s/it]

Epoch: 10
--------------- Train Loss: 0.1597, Train Accuracy: 0.9086, Val Loss: 0.2688,
Val Accuracy: 0.8787
```

[187]:
```
plot_history(P4_model_history)
```



AlexNet_small performed slightly better than the previous models tested, but at a cost of computational complexity and parameter size. Due to the increased size of the model, it would be better to design a less complex model

[188]:
```
with torch.cuda.device(0):
  macs, params = get_model_complexity_info(P4_model, (1, 28, 28),␣
 ↪as_strings=True,
                                           print_per_layer_stat=True,␣
 ↪verbose=True)
  print('{:<30}  {:<8}'.format('Computational complexity: ', macs))
  print('{:<30}  {:<8}'.format('Number of parameters: ', params))
```

```
Warning: module Flatten is treated as a zero-op.
Warning: module Dropout is treated as a zero-op.
Warning: module AlexNet_small is treated as a zero-op.
AlexNet_small(
  6.2 M, 100.000% Params, 186.44 MMac, 100.000% MACs,
  (conv): Sequential(
    2.0 M, 32.269% Params, 182.24 MMac, 97.748% MACs,
    (0): Conv2d(7.87 k, 0.127% Params, 4.53 MMac, 2.432% MACs, 1, 96,
kernel_size=(9, 9), stride=(1, 1), padding=(2, 2))
```

```
    (1): ReLU(0, 0.000% Params, 55.3 KMac, 0.030% MACs, )
    (2): MaxPool2d(0, 0.000% Params, 55.3 KMac, 0.030% MACs, kernel_size=2,
stride=2, padding=0, dilation=1, ceil_mode=False)
    (3): Conv2d(614.66 k, 9.918% Params, 88.51 MMac, 47.473% MACs, 96, 256,
kernel_size=(5, 5), stride=(1, 1), padding=(2, 2))
    (4): ReLU(0, 0.000% Params, 36.86 KMac, 0.020% MACs, )
    (5): MaxPool2d(0, 0.000% Params, 36.86 KMac, 0.020% MACs, kernel_size=2,
stride=2, padding=0, dilation=1, ceil_mode=False)
    (6): Conv2d(393.6 k, 6.351% Params, 19.29 MMac, 10.344% MACs, 256, 384,
kernel_size=(2, 2), stride=(1, 1), padding=(1, 1))
    (7): ReLU(0, 0.000% Params, 18.82 KMac, 0.010% MACs, )
    (8): Conv2d(590.21 k, 9.524% Params, 37.77 MMac, 20.260% MACs, 384, 384,
kernel_size=(2, 2), stride=(1, 1), padding=(1, 1))
    (9): ReLU(0, 0.000% Params, 24.58 KMac, 0.013% MACs, )
    (10): Conv2d(393.47 k, 6.349% Params, 31.87 MMac, 17.094% MACs, 384, 256,
kernel_size=(2, 2), stride=(1, 1), padding=(1, 1))
    (11): ReLU(0, 0.000% Params, 20.74 KMac, 0.011% MACs, )
    (12): MaxPool2d(0, 0.000% Params, 20.74 KMac, 0.011% MACs, kernel_size=2,
stride=2, padding=0, dilation=1, ceil_mode=False)
  )
  (classifier): Sequential(
    4.2 M, 67.731% Params, 4.2 MMac, 2.252% MACs,
    (0): Flatten(0, 0.000% Params, 0.0 Mac, 0.000% MACs, start_dim=1,
end_dim=-1)
    (1): Linear(3.77 M, 60.821% Params, 3.77 MMac, 2.022% MACs,
in_features=4096, out_features=920, bias=True)
    (2): ReLU(0, 0.000% Params, 920.0 Mac, 0.000% MACs, )
    (3): Dropout(0, 0.000% Params, 0.0 Mac, 0.000% MACs, p=0.5, inplace=False)
    (4): Linear(423.66 k, 6.836% Params, 423.66 KMac, 0.227% MACs,
in_features=920, out_features=460, bias=True)
    (5): ReLU(0, 0.000% Params, 460.0 Mac, 0.000% MACs, )
    (6): Dropout(0, 0.000% Params, 0.0 Mac, 0.000% MACs, p=0.5, inplace=False)
    (7): Linear(4.61 k, 0.074% Params, 4.61 KMac, 0.002% MACs, in_features=460,
out_features=10, bias=True)
  )
)
Computational complexity:       186.44 MMac
Number of parameters:           6.2 M
```

1.6 Problem 5: Design better model for 28x28 image training, beating revised AlexNet accuracy while keeping lower theoretical complexity

[220]:

```
# Smaller version of VGG
class VGG_s(nn.Module):
    def __init__(self, input_features: int,
                 hidden_outputs: int,
                 num_classes: int):
```

```
        super().__init__()
        self.conv_block1 = nn.Sequential(
            nn.Conv2d(input_features, hidden_outputs, # 28
                      kernel_size=3,
                      padding=1),
            nn.ReLU(),
            nn.Conv2d(hidden_outputs, hidden_outputs, kernel_size=3,␣
↪padding=1), # 28
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=2, stride=2) # 28/2 = 14
        )
        self.conv_block2 = nn.Sequential(
            nn.Conv2d(hidden_outputs, hidden_outputs*2, kernel_size=3,␣
↪padding=1), # 14
            nn.ReLU(),
            nn.Conv2d(hidden_outputs*2, hidden_outputs*2, kernel_size=3,␣
↪padding=1), # 14
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=2) # 14/2 = 7
        )
        self.classifier = nn.Sequential(
            nn.Flatten(),
            nn.Linear((hidden_outputs*2)*7*7, int((hidden_outputs*2*7*7)/2)),␣
↪nn.ReLU(),
            nn.Linear(int((hidden_outputs*2*7*7)/2),␣
↪int(((hidden_outputs*2*7*7)/2)/2)), nn.ReLU(),
            nn.Linear(int(((hidden_outputs*2*7*7)/2)/2), num_classes),
            nn.Softmax(dim=1)
        )
    def forward(self, x):
        x = self.conv_block1(x)
        x = self.conv_block2(x)
        x = self.classifier(x)
        return x
```

[223]:
```
P5_model = VGG_s(input_features=1,
                 hidden_outputs=14,
                 num_classes=10).to("cuda")
with torch.cuda.device(0):
  macs, params = get_model_complexity_info(P5_model, (1, 28, 28),␣
↪as_strings=True,
                                           print_per_layer_stat=True,␣
↪verbose=True)
  print('{:<30}  {:<8}'.format('Computational complexity: ', macs))
  print('{:<30}  {:<8}'.format('Number of parameters: ', params))
```

```
Warning: module Flatten is treated as a zero-op.
```

```
Warning: module Softmax is treated as a zero-op.
Warning: module VGG_s is treated as a zero-op.
VGG_s(
  1.19 M, 100.000% Params, 4.82 MMac, 100.000% MACs,
  (conv_block1): Sequential(
    1.92 k, 0.161% Params, 1.54 MMac, 31.877% MACs,
    (0): Conv2d(140, 0.012% Params, 109.76 KMac, 2.277% MACs, 1, 14,
kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): ReLU(0, 0.000% Params, 10.98 KMac, 0.228% MACs, )
    (2): Conv2d(1.78 k, 0.149% Params, 1.39 MMac, 28.917% MACs, 14, 14,
kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (3): ReLU(0, 0.000% Params, 10.98 KMac, 0.228% MACs, )
    (4): MaxPool2d(0, 0.000% Params, 10.98 KMac, 0.228% MACs, kernel_size=2,
stride=2, padding=0, dilation=1, ceil_mode=False)
  )
  (conv_block2): Sequential(
    10.64 k, 0.891% Params, 2.1 MMac, 43.603% MACs,
    (0): Conv2d(3.56 k, 0.298% Params, 696.98 KMac, 14.458% MACs, 14, 28,
kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): ReLU(0, 0.000% Params, 5.49 KMac, 0.114% MACs, )
    (2): Conv2d(7.08 k, 0.594% Params, 1.39 MMac, 28.803% MACs, 28, 28,
kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (3): ReLU(0, 0.000% Params, 5.49 KMac, 0.114% MACs, )
    (4): MaxPool2d(0, 0.000% Params, 5.49 KMac, 0.114% MACs, kernel_size=2,
stride=2, padding=0, dilation=1, ceil_mode=False)
  )
  (classifier): Sequential(
    1.18 M, 98.948% Params, 1.18 MMac, 24.520% MACs,
    (0): Flatten(0, 0.000% Params, 0.0 Mac, 0.000% MACs, start_dim=1,
end_dim=-1)
    (1): Linear(941.88 k, 78.916% Params, 941.88 KMac, 19.539% MACs,
in_features=1372, out_features=686, bias=True)
    (2): ReLU(0, 0.000% Params, 686.0 Mac, 0.014% MACs, )
    (3): Linear(235.64 k, 19.743% Params, 235.64 KMac, 4.888% MACs,
in_features=686, out_features=343, bias=True)
    (4): ReLU(0, 0.000% Params, 343.0 Mac, 0.007% MACs, )
    (5): Linear(3.44 k, 0.288% Params, 3.44 KMac, 0.071% MACs, in_features=343,
out_features=10, bias=True)
    (6): Softmax(0, 0.000% Params, 0.0 Mac, 0.000% MACs, dim=1)
  )
)
Computational complexity:       4.82 MMac
Number of parameters:           1.19 M
```

[224]:

```
optimizer_gpu=torch.optim.SGD(params=P5_model.parameters(),
                            lr=0.1)
accuracy_fn_gpu = MulticlassAccuracy(num_classes=10).to("cuda")
```

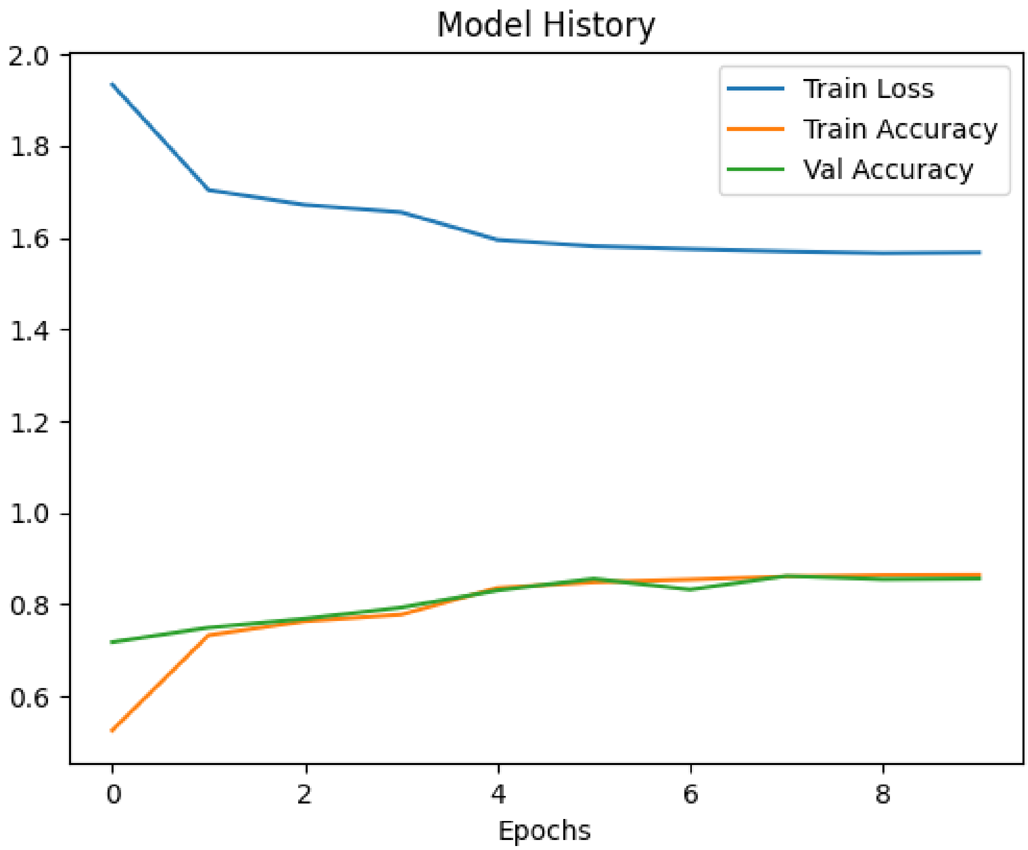
```python
P5_model_history = train(model=P5_model,
                         train_dataloader=LeNet_trainLoader,
                         val_dataloader=LeNet_valLoader,
                         optim=optimizer_gpu,
                         loss_fn=loss_fn,
                         accuracy_fn=accuracy_fn_gpu,
                         epochs=10,
                         device="cuda")
```

```
 10%|
| 1/10 [00:19<02:57, 19.75s/it]

Epoch: 1
--------------- Train Loss: 1.9334, Train Accuracy: 0.5257, Val Loss: 1.7225,
Val Accuracy: 0.7179

 20%|
| 2/10 [00:40<02:42, 20.35s/it]

Epoch: 2
--------------- Train Loss: 1.7034, Train Accuracy: 0.7330, Val Loss: 1.6856,
Val Accuracy: 0.7496

 30%|
| 3/10 [01:00<02:21, 20.24s/it]

Epoch: 3
--------------- Train Loss: 1.6712, Train Accuracy: 0.7636, Val Loss: 1.6664,
Val Accuracy: 0.7688

 40%|
| 4/10 [01:21<02:02, 20.34s/it]

Epoch: 4
--------------- Train Loss: 1.6550, Train Accuracy: 0.7778, Val Loss: 1.6403,
Val Accuracy: 0.7934

 50%|
| 5/10 [01:41<01:41, 20.33s/it]

Epoch: 5
--------------- Train Loss: 1.5950, Train Accuracy: 0.8362, Val Loss: 1.6018,
Val Accuracy: 0.8306

 60%|
| 6/10 [02:01<01:20, 20.25s/it]

Epoch: 6
--------------- Train Loss: 1.5808, Train Accuracy: 0.8484, Val Loss: 1.5773,
Val Accuracy: 0.8559

 70%|
| 7/10 [02:21<01:00, 20.31s/it]
```

```
Epoch: 7
--------------- Train Loss: 1.5748, Train Accuracy: 0.8543, Val Loss: 1.6005,
Val Accuracy: 0.8324

 80%|
| 8/10 [02:42<00:40, 20.26s/it]

Epoch: 8
--------------- Train Loss: 1.5696, Train Accuracy: 0.8613, Val Loss: 1.5689,
Val Accuracy: 0.8622

 90%|
| 9/10 [03:02<00:20, 20.45s/it]

Epoch: 9
--------------- Train Loss: 1.5657, Train Accuracy: 0.8643, Val Loss: 1.5779,
Val Accuracy: 0.8548

100%|
    | 10/10 [03:23<00:00, 20.39s/it]

Epoch: 10
--------------- Train Loss: 1.5672, Train Accuracy: 0.8650, Val Loss: 1.5758,
Val Accuracy: 0.8562
```

[226]:

```
plot_history(P5_model_history)
```


Model History
Train Loss
Train Accuracy
Val Accuracy
2.0
1.8
1.6
1.4
1.2
1.0
0.8
0.6
0
2
4
6
8
Epochs