CMU 10-715: Homework 6 Report

Implementation of Convolutional Neural Networks

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1 Results

a I trained the classifiers for **3000** steps on Google Colab's GPU.

b Refer table 1 for the final results of the training.

Model	Pooling	Training Time	Train Acc	Test Acc	Steps
$\boldsymbol{M_{max}}$	max	518.707s	79.900	64.080	3000
$\boldsymbol{M_{avg}}$	avg	515.660s	75.672	62.380	3000
$\boldsymbol{M_{no}}$	no	528.855s	99.936	60.360	3000

Table 1: Table showing the final training and testing accuracies, total training time (including evaluation), and training steps for the three models with different pooling configurations

We can observe from the table that models $\boldsymbol{M_{avg}}$ and $\boldsymbol{M_{max}}$ have similar training times which is markedly less than that of $\boldsymbol{M_{no}}$. This is because of removal of the subsampling pooling layers. In the CNN architecture under consideration, the `Conv2d` layers have a stride of 1 and do not result in much shrinkage to the feature maps's size. It is the pooling layers (**max** or **avg** configurations) with a stride of 2 that result in shrinkage of the feature maps' dimensions across the layers as the number of feature maps grow. Consequently, the first fully connected layer that comes up after the `nn.Flatten()` have smaller input dimensions in the case of $\boldsymbol{M_{avg}}$ and $\boldsymbol{M_{max}}$ (numerically, = 400) compared to $\boldsymbol{M_{no}}$ (input dim for first FC = 9216). Hence, there are far more parameters and bigger computation graph (for back-propagation) in the no pooling case (the pooling layers have no trainable parameters). This overparameterization is also evident in the way $\boldsymbol{M_{no}}$ overfits to the training data, as can be seen in table 1. Though there are additional computations in the pooling layers in $\boldsymbol{M_{avg}}$ and $\boldsymbol{M_{max}}$ models, it is seemingly outweighed by the computational time of $\boldsymbol{M_{no}}$ from its additional parameters, computational graph nodes, and back-propagation updates.

c Refer figure 1.

d Refer figure 2.

e Refer figure 3.

Let's first compare the output of conv1 to the input image. We see that the six output feature maps of conv1 layer all capture/highlight varied

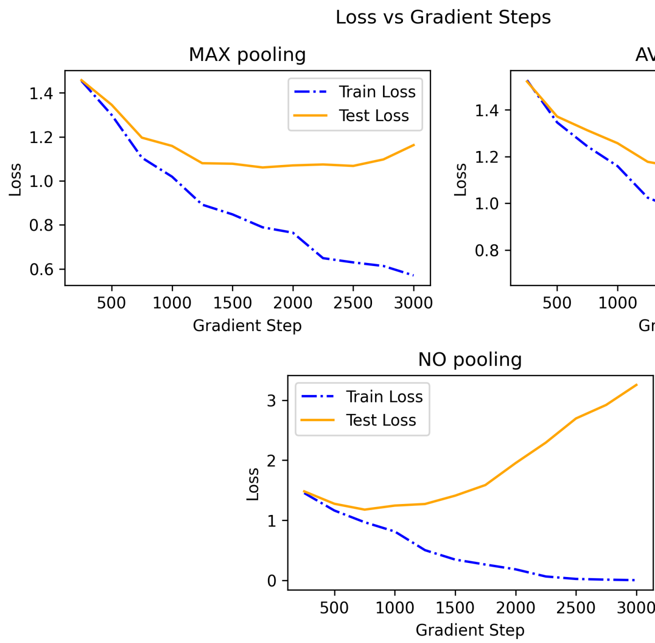


Figure 1: Loss vs Gradient Step plots for models $\boldsymbol{M_{max}}$, $\boldsymbol{M_{avg}}$, and $\boldsymbol{M_{no}}$ till 3000 training steps

features in the same input image, but they are truncated on the sides (we can notice missing pixels on the edges due to the convolution with no padding). In each of the feature maps, we can observe some characteristic edge or feature of the frog being highlighted and others being blurred out.

Now, let's compare the output of poo11 to the output of conv1. Clearly, the six images are now more pixelated due to the subsampling pooling layer that reduced the width and height dimensions by half. We can still observe that the features/edges that were highlighted in the six features maps after conv1 respectively seem to be preserved in the six feature maps after pool1 layer, but they are smoothened out and not sharp now. This might be due to the usage of average pooling - the boundaries of the features identified by conv1 are no longer uniform/sharp but contain mixed pixel values due to being affected by neighboring pixel values.

To sum it up, the convolution layers seem to be identifying features in the input image that it considers predictive of the output labels and the pooling layers seem to perform the job of reducing their dimensions for reducing overparameterization and computation cost, preserving as much

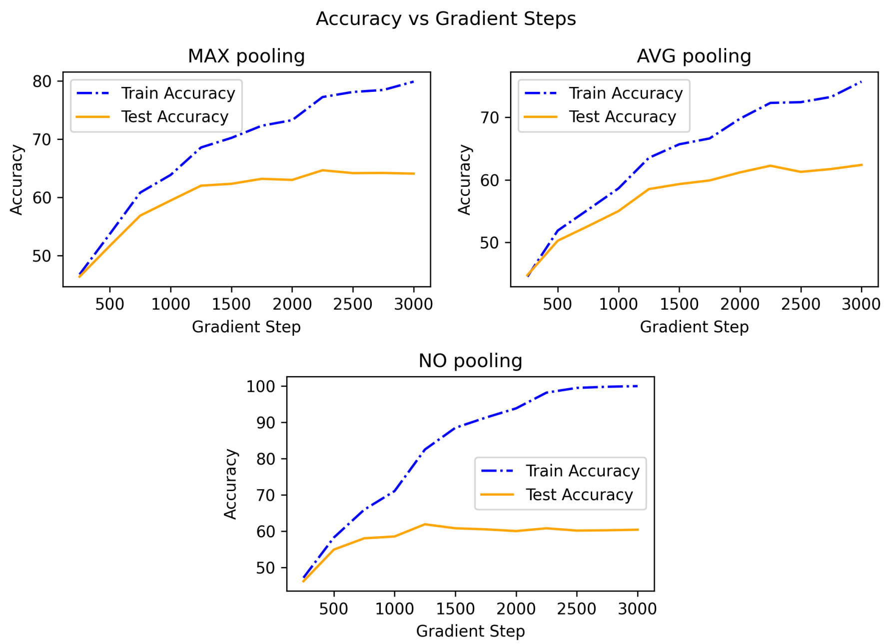


Figure 2: Accuracy vs Gradient Step plots for models $\boldsymbol{M_{max}}$, $\boldsymbol{M_{avg}}$, and $\boldsymbol{M_{no}}$ till 3000 training steps

information extracted by the convolutional layers as possible. Max pooling might be doing better than average pooling (as seen in table 1) because it will preserve the values of the important pixels without distorting them, thereby preserving information in a better manner than average pooling.

f The architecture of the convolutional neural network that I designed ($\boldsymbol{M_{custom}}$) is as follows:

Input image → 2D convolution with output channels = 8, kernel size 5, stride 1 and padding = 'same' → ReLU → Max Pooling with kernel size 2, stride 2 and no padding → 2D convolution with output channels = 16, kernel size 5, stride 1 and padding = 'same' → ReLU → Max Pooling with kernel size 2, stride 2 and no padding → 2D convolution with output channels = 64, kernel size 3, stride 1 and padding = 'same' → ReLU → Max Pooling with kernel size 2, stride 2 and no padding → 2D convolution with output channels = 128, kernel size 4, stride 1 and no padding → ReLU → Fully connected linear layer with input dim = 128, output dim = 80 → ReLU → Fully connected linear layer with input dim = 80, output dim = 10 → Output

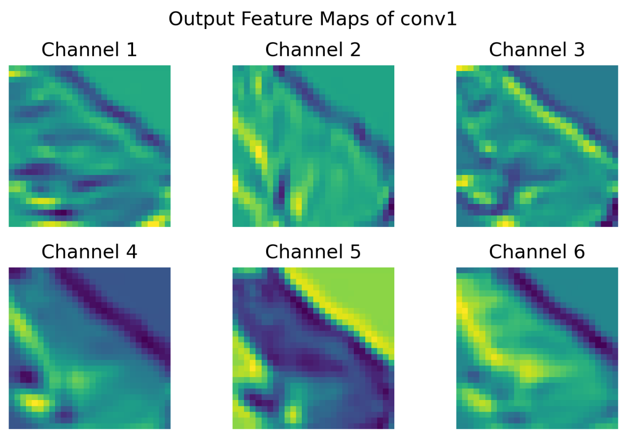
The intuitions behind the modifications to LeNet architecture were drawn from the various observations during this assignment: used padding = 'same' for the convolutional layers for it to see the feature maps completely and not lose information at the sides of the feature maps (since images did extend till the sides); tried to create a slightly deeper network hence added an additional convolutional layer; to fight over-parameterization replaced the first FC layer by a convolutional layer and used subsampling layer after every convolutional layer; used max pooling since it performed better than average pooling by extracting extreme features well; finally, gradually increased number of output channels of convolutional layers as the feature map dimensions halved after the pooling layers.

I trained $\boldsymbol{M_{custom}}$ for the same number of training steps as LeNet for a fair comparison and obtained the final results as summarized in 2. The custom model does contain an additional layer and hence more parameters, that leads to the increased training set accuracy. But, the testing set accuracy ($\implies$ generalization performance) also increases by a non-trivial amount and validates the intuitions behind the architecture. The overall training time taken by $\boldsymbol{M_{custom}}$ is higher than $\boldsymbol{M_{max}}$ as expected due to deeper network, and just lesser than $\boldsymbol{M_{no}}$, but the improved performance compensates for this marginal increase in training time.
$\boldsymbol{M_{custom}}$ actually achieves highest its best performance at ≈ 2250 steps, with a test accuracy of 70.940 and train accuracy of 91.222, which can be obtained by early stopping the training.

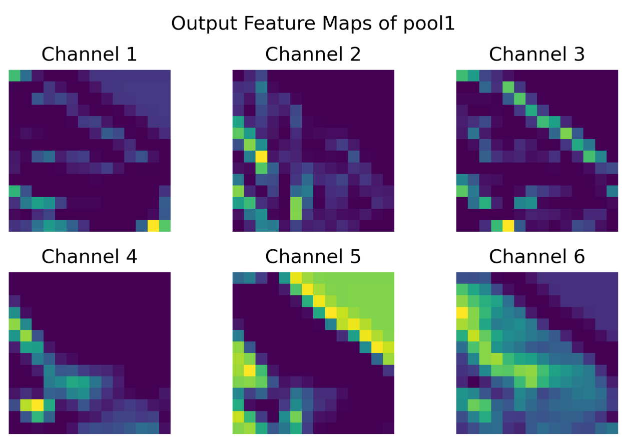
Model	**Pooling**	**Training Time**	**Train Acc**	**Test Acc**	**Steps**
$\boldsymbol{M_{max}}$	max	518.707s	79.900	64.080	3000
$\boldsymbol{M_{custom}}$	max	527.135s	94.538	69.340	3000

Table 2: Table showing the final training and testing accuracies, total training time (including evaluation), and training steps for the best LeNet model ($\boldsymbol{M_{max}}$) and custom architectured CNN model

(a) The original image - one 32×32 image



(b) Output of the first layer (after the first convolutional layer but before the ReLU) - six 28×28 images



(c) Output of the second layer (after the first pooling layer and before the second convolutional layer) - six 14×14 images

Figure 3: Visualization of input image and initial layer outputs for the input image

2 Code

Colab_Cell_1

```
from google.colab import drive
drive.mount('/content/drive')

%cd /content/drive/MyDrive/10-715/HW6
!mkdir -p ./results ./plots ./models
```

Colab_Cell_2

```
%matplotlib inline

import time
import numpy as np
import matplotlib.pyplot as plt
import torch as t
from torch import nn
from torch import optim
from torch.nn import functional as F
import torchvision
import torchvision.transforms as transforms
import pickle
import itertools


def divide_no_nan(a, b):
    """
    a/b where the resulted NaN or Inf are replaced by 0.
    """
    result = a / b
    result[result != result] = .0
    result[result == np.inf] = .0
    return result


class WeightNormConstrainer(object):
    def __init__(self, norm):
      self.norm = norm

    def __call__(self, module):
      if hasattr(module, 'weight'):
          w = module.weight.data
```

```
          wn = t.norm(w, p=2, dim=1).detach()
          ind = t.gt(wn, self.norm)
          div = (divide_no_nan(wn, self.norm) * ind) + (1 * t.logical_not(ind))
          div = div.unsqueeze_(1)
          w.div_(div)

class _LeNet(nn.Module):
    def __init__(self, layers):
      super(_LeNet, self).__init__()
      self.input_layer = nn.Sequential(*layers['input_layer'])
      self.hidden_layers = nn.Sequential(*layers['hidden_layers'])
      self.output_layer = nn.Sequential(*layers['output_layer'])
      self.activation = {}

    def layer_features(self, x):
      input_layer = self.input_layer(x)
      hidden = self.hidden_layers(input_layer)
      logits = self.output_layer(hidden)
      layer_features = {'input_layer': input_layer.data.cpu().numpy(),
                        'hidden': hidden.data.cpu().numpy(),
                        'logits': logits.data.cpu().numpy()}
      return layer_features

    def get_activation(self, name):
        def hook(model, input, output):
            self.activation[name] = output.detach().cpu().numpy()
        return hook

    def get_intermediate(self, x):
        #TODO: complete this function to return the outputs of first conv and first pooling layer - Done
        # Returns the output as a numpy aray for ease of plotting it later
        self.input_layer[1].register_forward_hook(self.get_activation('conv1'))
        pool1_out = self.input_layer(x)
        return self.activation['conv1'], pool1_out.detach().cpu().numpy()
    def forward(self, x):
      input_layer = self.input_layer(x)
      hidden = self.hidden_layers(input_layer)
      logits = self.output_layer(hidden)
      return logits
```

```python
# We recommend you make this modules as the first component of your input layers
class Reshape(t.nn.Module):
    def forward(self, x):
      return x.view(-1,3,32,32)

class LeNet(object):
    def __init__(self, params, use_custom=False):
        super().__init__()
        self.params = params
        self.device = t.device('cuda' if t.cuda.is_available() else 'cpu')
        self.activations = {'logistic': nn.Sigmoid(), 'relu': nn.ReLU()}
        self.pooling = {'avg':nn.AvgPool2d(kernel_size=2, stride=2),'max':nn.MaxPool2d(kernel_size=2, stride=2)}
        # Instantiate model
        t.manual_seed(self.params['random_seed'])
        np.random.seed(self.params['random_seed'])
        layers = self._initialize_network() if not use_custom else self._initialize_network_custom()
        self.model = _LeNet(layers).to(self.device)

    def _initialize_network(self):
        # TODO: complete this function - Done
        # You may have to use Reshape() and nn.Flatten()
        # The architecture may be slightly different with no pooling
        if self.params['pooling'] != 'no':
            input_layers = [
                Reshape(),
                nn.Conv2d(3, 6, kernel_size=5, stride=1, padding=0),
                self.activations[self.params['activation']],
                self.pooling[self.params['pooling']]
            ]
            hidden_layers = [
                nn.Conv2d(6, 16, kernel_size=5, stride=1, padding=0),
                self.activations[self.params['activation']],
                self.pooling[self.params['pooling']],
                # nn.Conv2d(16, 120, kernel_size=5, stride=1, padding=0),
                # self.activations[self.params['activation']],
                nn.Flatten(),
                nn.Linear(400, 120),
                self.activations[self.params['activation']],
                nn.Linear(120, 84),
                self.activations[self.params['activation']]
            ]
```

```
            output_layer = [
                nn.Linear(84, 10)
            ]
        else:
            input_layers = [
                Reshape(),
                nn.Conv2d(3, 6, kernel_size=5, stride=1, padding=0),
                self.activations[self.params['activation']]
            ]
            hidden_layers = [
                nn.Conv2d(6, 16, kernel_size=5, stride=1, padding=0),
                self.activations[self.params['activation']],
                # nn.Conv2d(16, 120, kernel_size=5, stride=1, padding=0),
                # self.activations[self.params['activation']],
                nn.Flatten(),
                nn.Linear(9216, 120),
                self.activations[self.params['activation']],
                nn.Linear(120, 84),
                self.activations[self.params['activation']]
            ]
            output_layer = [
                nn.Linear(84, 10)
            ]
        layers = {'input_layer': input_layers,
          'hidden_layers': hidden_layers,
          'output_layer': output_layer}
        return layers

    def _initialize_network_custom(self):
        # Custom CNN network
        assert self.params['pooling'] != 'no'

        input_layers = [
            Reshape(),
            nn.Conv2d(3, 8, kernel_size=5, stride=1, padding='same'),
            self.activations[self.params['activation']],
            self.pooling[self.params['pooling']]
        ]
        hidden_layers = [
            nn.Conv2d(8, 16, kernel_size=5, stride=1, padding='same'),
            self.activations[self.params['activation']],
            self.pooling[self.params['pooling']],
            nn.Conv2d(16, 64, kernel_size=3, stride=1, padding='same'),
            self.activations[self.params['activation']],
```

```
            self.pooling[self.params['pooling']],
            nn.Conv2d(64, 128, kernel_size=4, stride=1, padding=0),
            self.activations[self.params['activation']],
            nn.Flatten(),
            nn.Linear(128, 80),
            self.activations[self.params['activation']]
        ]
        output_layer = [
            nn.Linear(80, 10)
        ]

        layers = {'input_layer': input_layers,
          'hidden_layers': hidden_layers,
          'output_layer': output_layer}
        return layers


    def evaluate_accuracy(self, dataloader):
        self.model.eval()
        with t.no_grad():
            n_correct = 0
            n_samples = 0
            for batch in iter(dataloader):
                batch_x = t.flatten(batch[0].to(self.device), start_dim=1)
                batch_y = batch[1].to(self.device)
                logits = self.model(batch_x)
                y_hat = t.argmax(logits, dim=1)
                correct = t.sum(y_hat==batch_y)
                n_correct += correct.data.cpu().numpy()
                n_samples += len(batch_x)
        accuracy = (n_correct/n_samples) * 100
        self.model.train()
        return accuracy

    def evaluate_cross_entropy(self, dataloader):
        self.model.eval()
        loss_func = nn.CrossEntropyLoss()
        with t.no_grad():
            n_samples = 0
            total_loss = 0
            for batch in iter(dataloader):
                pass
                # TODO: Write the code to measure the cross_entropy
                # (Hint, look at the evaluate_accuracy method)
```

```
                # Be careful with the eval and train modes of the model
                # This should be same as HW5 - Done
                batch_x = t.flatten(batch[0].to(self.device), start_dim=1)
                batch_y = batch[1].to(self.device)

                logits = self.model(batch_x)
                loss = loss_func(logits, batch_y)

                total_loss += loss.item() * len(batch_x)
                n_samples += len(batch_x)

        cross_entropy = total_loss/n_samples

        self.model.train()

        return cross_entropy

    def adjust_lr(self, optimizer, lr_decay):
        for param_group in optimizer.param_groups:
            param_group['lr'] = param_group['lr'] * lr_decay

    def adjust_momentum(self, optimizer, step, momentum_change_steps,
                        initial_momentum, final_momentum):
        mcs = momentum_change_steps
        s = min(step, mcs)
        momentum = (initial_momentum) * ((mcs-s)/mcs) + \
                   (final_momentum) * (s/mcs)
        for param_group in optimizer.param_groups:
            param_group['momentum'] = momentum

    def save_weights(self, path):
        t.save(self.model.state_dict(), path)

    def load_weights(self, path):
        self.model.load_state_dict(t.load(path,
                                   map_location=t.device(self.device)))
        self.model.eval()

    def fit(self, insample_dataloader, outsample_dataloader):
        # Instantiate optimization tools
        loss = nn.CrossEntropyLoss()
        optimizer = optim.SGD([{'params':
    ↪   self.model.input_layer.parameters()},
```

```python
                                    {'params': self.model.hidden_layers.parameters()},
                                    {'params': self.model.output_layer.parameters(),
                                     'weight_decay': self.params['output_l2_decay']}],
                                    lr=self.params['initial_lr'],
                                    momentum=self.params['initial_momentum'])

        constrainer = WeightNormConstrainer(norm=self.params['weight_norm'])
        # Initialize counters and trajectories
        step = 0
        epoch = 0
        metric_trajectories = {'step':  [],
                               'epoch':  [],
                               'insample_accuracy': [],
                               'outsample_accuracy': [],
                               'insample_cross_entropy': [],
                               'outsample_cross_entropy': []
                               }

        print('\n'+'='*36+f' Fitting LeNet ({self.params["pooling"]} pooling) '+'='*36)
        while step <= self.params['iterations']:

            # Train
            epoch += 1
            start_time = time.time()
            self.model.train()
            for batch in iter(insample_dataloader):
                step+=1
                if step > self.params['iterations']:
                    continue

                batch_x = t.flatten(batch[0].to(self.device), start_dim=1)
                batch_y = batch[1].to(self.device)

                optimizer.zero_grad()

                # TODO: make predictions, compute the cross entropy loss and perform backward propagation
                # This should be same as HW5 - Done
                logits = self.model(batch_x)
                cross_entropy = loss(logits, batch_y)
```

```
                cross_entropy.backward()

                t.nn.utils.clip_grad_norm_(self.model.parameters(), 20)
                optimizer.step()

                # Evaluate metrics
                if (step % self.params['display_step'] == 0):
                    in_cross_entropy   = self.evaluate_cross_entropy(insample_dataloader)
                    out_cross_entropy  = self.evaluate_cross_entropy(outsample_dataloader)
                    in_accuracy        = self.evaluate_accuracy(insample_dataloader)
                    out_accuracy       = self.evaluate_accuracy(outsample_dataloader)

                    print('Epoch:', '%d,' % epoch,
                          'Step:', '%d,' % step,
                          'In Loss: {:.7f},'.format(in_cross_entropy),
                          'Out Loss: {:.7f},'.format(out_cross_entropy),
                          'In Acc: {:03.3f},'.format(in_accuracy),
                          'Out Acc: {:03.3f}'.format(out_accuracy))

                    metric_trajectories['insample_cross_entropy'].append(in_cross_entropy)
                    metric_trajectories['outsample_cross_entropy'].append(out_cross_entropy)
                    metric_trajectories['insample_accuracy'].append(in_accuracy)
                    metric_trajectories['outsample_accuracy'].append(out_accuracy)
                    metric_trajectories['step'].append(step)
                    metric_trajectories['epoch'].append(epoch)

                # Update optimizer learning rate
                if step % self.params['adjust_lr_step'] == 0:
                    self.adjust_lr(optimizer=optimizer, lr_decay=self.params['lr_decay'])

                # Update optimizer momentum
                if step % self.params['adjust_momentum_step'] == 0 and \
                    step < self.params['momentum_change_steps']:
                    self.adjust_momentum(optimizer=optimizer, step=step,
```

```
                                         momentum_change_steps=self.params['momentum_change_steps'],
                                         initial_momentum=self.params['initial_momentum'],
                                         final_momentum=self.params['final_momentum'])

                # Constraint max_norm of weights
                if self.params['apply_weight_norm'] and \
                  (step % self.params['adjust_norm_step'] == 0):
                    self.model.apply(constrainer)

            print(f"Time elapsed for epoch {epoch}: {time.time()-start_time} seconds")

        # Store trajectories
        print('\n'+'='*35+' Finished Train '+'='*35)
        self.trajectories = metric_trajectories


def main(POOLING, custom=False):
    params = {'model': 'lenet',
          'display_step': 250,
          'batch_size': 256,
          'iterations': 3000, # 3000 or 500
          'initial_lr': 0.05,
          'lr_decay': 0.5,
          'adjust_lr_step': 1000,
          'initial_momentum': 0.9,
          'final_momentum': 0.95,
          'momentum_change_steps': 5_000,
          'adjust_momentum_step': 2_000,
          'apply_weight_norm': True,
          'weight_norm': 3.5,
          'adjust_norm_step': 1_000,
          'output_l2_decay': 0.001,
          'pooling': POOLING, # TODO try three options: 'max', 'avg','no'
          'activation':'relu',
          'random_seed': 0}

    transform = transforms.Compose([transforms.ToTensor(), transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))])
    trainset = torchvision.datasets.CIFAR10(root='./data', train=True, download=True, transform=transform)
```

```
    insample_dataloader = t.utils.data.DataLoader(trainset, batch_size=params['batch_size'], shuffle=True)
    testset = torchvision.datasets.CIFAR10(root='./data', train=False, download=True, transform=transform)
    outsample_dataloader = t.utils.data.DataLoader(testset, batch_size=params['batch_size'], shuffle=False)

    clf = LeNet(params, custom)

    t0 = time.time()
    clf.fit(insample_dataloader, outsample_dataloader)
    print(f"Total time elapsed for training: {time.time()-t0} seconds")

    # TODO: save trajectories and/or plot trajectories, final accuracy, and time elapsed - Done
    # TODO: plot the intermediate outputs using get_intermediate in _LeNet
    # To avoid unnecesary pain, saving classifier weights
    if not custom:
        clf.save_weights(f'./models/model_{POOLING}.pth')
        clf.load_weights(f'./models/model_{POOLING}.pth')

        with open(f'./results/results_{POOLING}.pkl', 'wb') as file:
            pickle.dump(clf.trajectories, file)

        # Pick one sample from the training set (so that its easier to explain what the model is learning)
        index = 1
        batch_x, batch_y = next(itertools.islice(iter(insample_dataloader), index, None))
        sample_x, sample_y = t.flatten(batch_x[:1].to(clf.device), start_dim=1), batch_y[0].item()
        conv1_out, pool1_out = clf.model.get_intermediate(sample_x)
        sample_x = sample_x.detach().cpu().numpy()
        intermediates = {
            'input': sample_x,
            'label': sample_y,
            'conv1': conv1_out,
            'pool1': pool1_out
        }

        with open(f'./results/visualize_{POOLING}.pkl', 'wb') as file:
            pickle.dump(intermediates, file)

    del clf
```

```python

if __name__ == '__main__':
    for POOLING in ['max']:
        main(POOLING, True) # The second argument is True to train custom architecture; False for training LeNet arhcitecture
```

Colab_Cell_3

```python
import gc
import torch

# Code to clear any memory trace left by previous models to get proper training times
gc.collect()
with torch.no_grad():
    torch.cuda.empty_cache()
```

Colab_Cell_4

```python
%matplotlib inline
import matplotlib.gridspec as gridspec
import matplotlib.pyplot as plt
from google.colab import files

plt.rcParams['figure.dpi'] = 300
plt.rcParams['savefig.dpi'] = 300

# Function to plot the accuracy and loss graphs for the three configurations of LeNet
def plot():
    trajectories = []
    config = ['max', 'avg', 'no']
    for POOLING in config:
        with open(f'./results/results_{POOLING}.pkl', 'rb') as file:
            trajectories.append(pickle.load(file))

    idx = 0
    def plot_trajectory(trajectory_name):
        nonlocal idx, trajectories, config
        plot_name = 'Loss' if trajectory_name == 'cross_entropy' else 'Accuracy'
        gs = gridspec.GridSpec(4, 4)
        m = 0
```

```python

        plt.figure(idx, figsize = (8,6))
        for i in range(0, 4, 2):
            for j in range(0, 4, 2):
                if m == 3:
                    break
                if m < 2:
                    ax = plt.subplot(gs[i:i+2, j:j+2])
                else:
                    ax = plt.subplot(gs[i:i+2, 1:3])

                ax.plot(trajectories[m]['step'], trajectories[m][f'insample_{trajectory_name}'], linestyle='-.', color='b', label=f'Train {plot_name}')
                ax.plot(trajectories[m]['step'], trajectories[m][f'outsample_{trajectory_name}'], linestyle='-', color='orange', label=f'Test {plot_name}')
                ax.set_ylabel(plot_name)
                ax.set_xlabel('Gradient Step')
                ax.set_title(f'{config[m].upper()} pooling')
                ax.legend(loc='best')

                m+=1

        plt.tight_layout(rect=[0, 0.03, 1, 0.95])
        plt.suptitle(f'{plot_name} vs Gradient Steps')
        plt.savefig(f'./plots/{plot_name}.png')
        plt.show()
        files.download(f'./plots/{plot_name}.png')
        idx += 1

    plot_trajectory('cross_entropy')
    plot_trajectory('accuracy')

plot()
```

Colab_Cell_5

```python
%matplotlib inline
import matplotlib.pyplot as plt
from google.colab import files

plt.rcParams['figure.dpi'] = 300
```

```python
plt.rcParams['savefig.dpi'] = 300

# Function to plot the feature map visualizations for a given configuration of LeNet
def visualize(POOLING='avg'):
    with open(f'./results/visualize_{POOLING}.pkl', 'rb') as file:
        intermediates = pickle.load(file)

    idx = 0
    def visualize_images(out, out_name, nrows=2, ncols=3):
        nonlocal idx
        fig = plt.figure(idx, figsize=(ncols*2,nrows*2))
        for fig_idx in range(1, nrows*ncols+1):
            ax = fig.add_subplot(nrows, ncols, fig_idx)
            ax.imshow(out[fig_idx-1], interpolation='nearest')
            if out_name != 'input':
                ax.set_title(f'Channel {fig_idx}')
            ax.axis('off')
        plt.suptitle(f'Output Feature Maps of {out_name}' if out_name != 'input' else 'Input Image')
        plt.tight_layout(rect=[0, 0.03, 1, 0.95])
        plt.savefig(f'./plots/visualize_{out_name}.png')
        plt.show()
        files.download(f'./plots/visualize_{out_name}.png')
        idx += 1

    print(intermediates['label'])
    visualize_images(np.transpose(intermediates['input'].reshape((1, 3, 32, 32)), (0, 2, 3, 1)), 'input', 1, 1)
    visualize_images(intermediates['conv1'].reshape((-1, 28, 28)), 'conv1', 2, 3)
    visualize_images(intermediates['pool1'].reshape((-1, 14, 14)), 'pool1', 2, 3)

visualize('avg')
```