Submission instructions

Submission must be in pairs, unless otherwise authorized.

Submit by 28/2/2024

- This notebook contains all the questions. You should follow the instructions below.
- Solutions for both theoretical and practical parts should be written in this notebook

Moodle submission

You should submit three files:

- IPYNB notebook:
  - All the wet and dry parts, including code, graphs, discussion, etc.
- PDF file:
  - Export the notebook to PDF. Make sure that all the cells are visible.
- Pickle file:
  - As requested in Q2.a

All files should be in the following format: "HW1_ID1_ID2.file"
Good Luck!

Question 1

I. Softmax Derivative (10pt)

Derive the gradients of the softmax function and demonstrate how the expression can be reformulated solely by using the softmax function, i.e., in some expression where only $softmax(x)$, but not x, is present). Recall that the softmax function is defined as follows:

$$softmax(x)_i = \frac{e^{x_i}}{\sum_{j=1}^{N} e^{x_j}}$$

I. Softmax Derivative - Answer:

we will use the quotient rule: \ $\frac{d}{dx}\left(\frac{f(x)}{g(x)}\right) = \frac{g(x)f'(x) - f(x)g'(x)}{(g(x))^2}$

such that:

$f(x) = e^{x_i} \setminus g(x) = \sum_{j=1}^{N} e^{x_j} --> \frac{d}{dx_k} g(x) = e^{x_k}$

Split into 2 cases:

1. $i = k$: \ $\frac{d}{dx_i} f(x) = e^{x_i}$ \

$$\frac{\partial \text{softmax}(x)_i}{\partial x_k} = \frac{e^{x_i} \sum_{j=1}^{N} e^{x_j} - e^{x_k} e^{x_i}}{\left(\sum_{j=1}^{N} e^{x_j}\right)^2}$$

$$\frac{e^{x_i}}{\sum_{j=1}^{N} e^{x_j}} \cdot \left[\frac{\sum_{j=1}^{N} e^{x_j} - e^{x_k}}{\sum_{j=1}^{N} e^{x_j}}\right]$$

$$\frac{e^{x_i}}{\sum_{j=1}^{N} e^{x_j}} \cdot \left[1 - \frac{e^{x_k}}{\sum_{j=1}^{N} e^{x_j}}\right]$$

$$\text{by definition of softmax:}$$

$$= \text{softmax}(x)_i \cdot [1 - \text{softmax}(x)_k]$$

$$= \text{softmax}(x)_i \cdot [1 - \text{softmax}(x)_i]$$

1. $i \neq k$: \ $\frac{d}{dx_k} f(x) = 0$ --> const, independent of x_k

$$\frac{\partial \text{softmax}(x)_i}{\partial x_k} = \frac{0 \cdot \sum_{j=1}^{N} e^{x_j} - e^{x_k} e^{x_i}}{\left(\sum_{j=1}^{N} e^{x_j}\right)^2}$$

$$= \frac{-e^{x_k} e^{x_i}}{\left(\sum_{j=1}^{N} e^{x_j}\right)^2}$$

$$\frac{e^{x_i}}{\sum_{j=1}^{N} e^{x_j}} \cdot \left[\frac{-e^{x_k}}{\sum_{j=1}^{N} e^{x_j}}\right]$$

$$\text{by definition of softmax:}$$

$$= \text{- softmax}(x)_i \cdot \text{softmax}(x)_k$$

Hence:

$$\frac{\partial \text{softmax}(x)_i}{\partial x_k} = \begin{cases} \text{softmax}(x)_i \cdot (1 - \text{softmax}(x)_i) & \text{if } i = k \\ -\text{softmax}(x)_i \cdot \text{softmax}(x)_k & \text{if } i \neq k \end{cases}$$

II. Cross-Entropy Gradient (10pt)

Derive the gradient of cross-entropy loss with regard to the inputs of a softmax function. i.e., find the gradients with respect to the softmax input vector θ, when the prediction is denoted by $\hat{y} = softmax(\theta)$. Remember the cross entropy function is:

$$CE(y, \hat{y}) = -\sum_i y_i log(\hat{y}_i)$$

where y is the one-hot label vector, and $\hat{y}$ is the predicted probability vector for all classes.

II. Cross-Entropy Gradient - Answer

$$\frac{\partial \text{CE}(y, \hat{y})}{\partial \theta} = -\sum_i y_i \cdot \frac{\partial \log(\hat{y}_i)}{\partial \theta}$$

$$\text{chain rule:}$$

$$= -\sum_i y_i \cdot \frac{\partial \log(\hat{y}_i)}{\partial \hat{y}_i} \cdot \frac{\partial \hat{y}_i}{\partial \theta}$$

$$= -\sum_i y_i \cdot \frac{1}{\hat{y}_i} \cdot \frac{\partial \hat{y}_i}{\partial \theta}$$

$$= -\sum_i \frac{y_i}{\hat{y}_i} \cdot \frac{\partial \hat{y}_i}{\partial \theta}$$

$$\text{such that: } \frac{\partial \hat{y}_i}{\partial \theta} \text{ is the softmax derivative we previously found:}$$

$$\frac{\partial \hat{y}_i}{\partial \theta} = \begin{cases} \hat{y}_i \cdot (1 - \hat{y}_i) & \text{if } i = k \\ -\hat{y}_i \cdot \hat{y}_k & \text{if } i \neq k \end{cases}$$

$$\frac{\partial \text{CE}(y, \hat{y})}{\partial \theta} = -\sum_{i=k} \frac{y_i}{\hat{y}_i} \cdot \hat{y}_i \cdot (1 - \hat{y}_i) - \sum_{i \neq k} \frac{y_i}{\hat{y}_i} \cdot (-\hat{y}_i \cdot \hat{y}_k)$$

$$= -y_k \cdot (1 - \hat{y}_k) + \sum_{i \neq k} y_i \cdot \hat{y}_k$$

$$= -y_k + y_k \cdot \hat{y}_k + \sum_{i \neq k} y_i \cdot \hat{y}_k$$

$$= -y_k + \sum_i y_i \cdot \hat{y}_k$$

$$= -y_k + \hat{y}_k \cdot \sum_i y_i$$

$$\sum_i y_i = 1, \text{y is one-hot vector}$$

Hence:

$$\frac{\partial \text{CE}(y, \hat{y})}{\partial \theta} = \hat{y}_k - y_k$$

Question 2

I. Derivative Of Activation Functions (10pt)

> Indented block

The following cell contains an implementation of some activation functions. Implement the corresponding derivatives.

```python
import torch

def sigmoid(x):
    return 1 / (1 + torch.exp(-x))


def tanh(x):
    return torch.div(torch.exp(x) - torch.exp(-x), torch.exp(x) + torch.exp(-x))


def softmax(x):
    exp_x = torch.exp(x.T - torch.max(x, dim=-1).values).T  # Subtracting max(x) for 
    return exp_x / exp_x.sum(dim=-1, keepdim=True)
```

```python
def d_sigmoid(x):
    # x: sigmoid output
    return x * (1 - x)

def d_tanh(x):
    # x: tanh output
    return 1 - x * x

def d_softmax(x):
    # x: softmax output
    #return x * (1 - x)
    n = x.size(-1)
    softmax_matrix = x.unsqueeze(-1) * (torch.eye(n) - x.unsqueeze(-2))
    return softmax_matrix.sum(dim=-1)
```

II. Train a Fully Connected network on MNIST (30pt)

In the following exercise, you will create a classifier for the MNIST dataset. You should write your own training and evaluation code and meet the following constraints:

- You are only allowed to use torch tensor manipulations.
- You are NOT allowed to use:
  - Auto-differentiation - backward()
  - Built-in loss functions
  - Built-in activations
  - Built-in optimization
  - Built-in layers (torch.nn)

     </h4>

a) The required classifier class is defined.

- You should implement the backward pass of the model.
- Train the model and plot the model's accuracy and loss (both on train and test sets) as a function of the epochs.
- You should save the model's weights and biases. Change the student_ids to yours.

In this section, you **must** use the "set_seed" function with the given seed and **sigmoid** as an activation function.

```python
import torch
import torchvision
from torch.utils.data import DataLoader

import os
import matplotlib.pyplot as plt
import seaborn as sns; sns.set()

# Constants
SEED = 42
EPOCHS = 16
BATCH_SIZE = 32
NUM_OF_CLASSES = 10

# Setting seed
def set_seed(seed):
    torch.manual_seed(seed)
    torch.cuda.manual_seed(seed)
    torch.backends.cudnn.deterministic = True
    torch.backends.cudnn.benchmark = False
    os.environ["PYTHONHASHSEED"] = str(seed)


# Transformation for the data
transform = torchvision.transforms.Compose(
    [torchvision.transforms.ToTensor(),
     torch.flatten])


# Cross-Entropy loss implementation
def one_hot(y, num_of_classes=10):
    hot = torch.zeros((y.size()[0], num_of_classes))
    hot[torch.arange(y.size()[0]), y] = 1
    return hot

def cross_entropy(y, y_hat):
    return -torch.sum(one_hot(y) * torch.log(y_hat)) / y.size()[0]
```

```
C:\Users\USER\anaconda3\lib\site-packages\scipy\__init__.py:138: UserWarning: A NumPy version >=1.16.5 and <1.23.0 is required for this version of SciPy (detected version 1.24.3)
  warnings.warn(f"A NumPy version >={np_minversion} and <{np_maxversion} is required f
or this version of "
```

```python
# Create dataloaders
train_dataset = torchvision.datasets.MNIST(root='./data', train=True,
                                           download=True, transform=transform)
train_dataloader = torch.utils.data.DataLoader(train_dataset, batch_size=BATCH_SIZE)


test_dataset = torchvision.datasets.MNIST(root='./data', train=False,
                                          download=True, transform=transform)
test_dataloader = torch.utils.data.DataLoader(test_dataset, batch_size=BATCH_SIZE,)
```

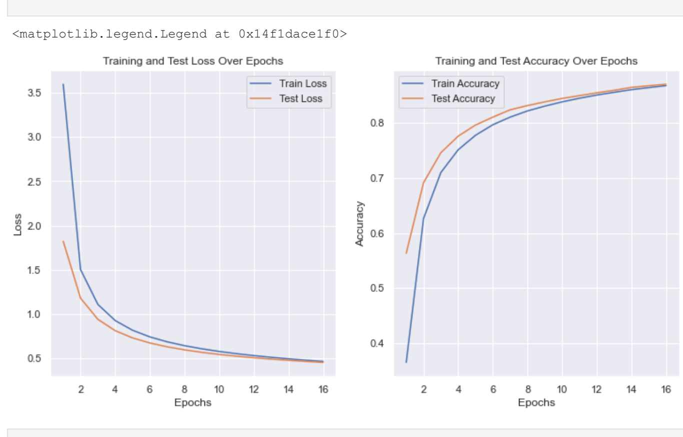
```python
class FullyConnectedNetwork:
    def __init__(self, input_size, output_size, hidden_size1, activiation_func, lr=0.0
        # parameters
        self.input_size = input_size
        self.output_size = output_size
        self.hidden_size1 = hidden_size1

        # activation function
        self.activation_func = activiation_func

        # weights
        self.W1 = torch.randn(self.input_size, self.hidden_size1)
        self.b1 = torch.zeros(self.hidden_size1)

        self.W2 = torch.randn(self.hidden_size1, self.output_size)
        self.b2 = torch.zeros(self.output_size)

        self.lr = lr

    def forward(self, x): # added self to z1,h1,z2 - to use in backward function
        self.z1 = torch.matmul(x, self.W1) + self.b1
        self.h1 = self.activation_func(self.z1)
        self.z2 = torch.matmul(self.h1, self.W2) + self.b2
        y_hat = softmax(self.z2)
        return y_hat

    def backward(self, x, y, y_hat):
        batch_size = y.size(0)
        #dloss_dyhat = (1/batch_size)* (y_hat-y)

        dloss_dz2 = (1/batch_size)* (y_hat-y)
        dloss_dw2 = torch.matmul(torch.t(self.h1), dloss_dz2)
        dloss_db2 = torch.matmul(torch.t(dloss_dz2), torch.ones(batch_size))

        dloss_dh1 = torch.matmul(dloss_dz2, torch.t(self.W2))
        dloss_dz1 = dloss_dh1 * d_sigmoid(self.h1)

        dloss_dw1 = torch.matmul(torch.t(x), dloss_dz1)
        dloss_db1 =torch.matmul(torch.t(dloss_dz1), torch.ones(batch_size))

        self.W2 = self.W2 - self.lr * dloss_dw2
        self.b2 = self.b2 - self.lr * dloss_db2
        self.W1 = self.W1 - self.lr * dloss_dw1
        self.b1 = self.b1 -  self.lr * dloss_db1
```

```python
set_seed(SEED)
model = FullyConnectedNetwork(784, 10, 128, sigmoid, lr=0.01)
```

```python
train_loss = []
train_accuracy = []
test_loss = []
test_accuracy = []

for epoch in range(EPOCHS):

    # Training
    epoch_train_loss = 0.0
    correct_train_predictions = 0
    total_train_samples = 0

    for (inputs, labels) in train_dataloader:
        y_hat = model.forward(inputs)
        model.backward(inputs, one_hot(labels), y_hat)

        epoch_train_loss += cross_entropy(labels, y_hat).item()

        _, predicted_labels = torch.max(y_hat, 1)
        correct_train_predictions += (predicted_labels == labels).sum().item()
        total_train_samples += labels.size(0)

    train_accuracy.append(correct_train_predictions / total_train_samples)
    train_loss.append(epoch_train_loss / len(train_dataloader))

    # Testing
    epoch_test_loss = 0.0
    correct_test_predictions = 0
    total_test_samples = 0

    with torch.no_grad():
        for (test_inputs, test_labels) in test_dataloader:
            test_y_hat = model.forward(test_inputs)
            epoch_test_loss += cross_entropy(test_labels, test_y_hat).item()

            _, predicted_labels = torch.max(test_y_hat, 1)
            correct_test_predictions += (predicted_labels == test_labels).sum().item(
            total_test_samples += test_labels.size(0)

    test_accuracy.append(correct_test_predictions / total_test_samples)
    test_loss.append(epoch_test_loss / len(test_dataloader))

    # Print or log the results if needed
    #print(f"Epoch {epoch + 1}/{EPOCHS} - Train Loss: {train_loss[-1]}, Train Accurac
```

```python
# Plot the accuracy and loss as a function of the epochs
plt.figure(figsize=(12, 6))
plt.subplot(1, 2, 1)
plt.plot(range(1, EPOCHS + 1), train_loss, label='Train Loss')
plt.plot(range(1, EPOCHS + 1), test_loss, label='Test Loss')
plt.title('Training and Test Loss Over Epochs')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()

plt.subplot(1, 2, 2)
plt.plot(range(1, EPOCHS + 1), train_accuracy, label='Train Accuracy')
plt.plot(range(1, EPOCHS + 1), test_accuracy, label='Test Accuracy')
plt.title('Training and Test Accuracy Over Epochs')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
```

```
<matplotlib.legend.Legend at 0x14f1dace1f0>
```




```python
students_ids = "318862323_206418642"
torch.save({"W1": model.W1, "W2": model.W2, "b1": model.b1, "b2": model.b2}, f"HW1_{st
```

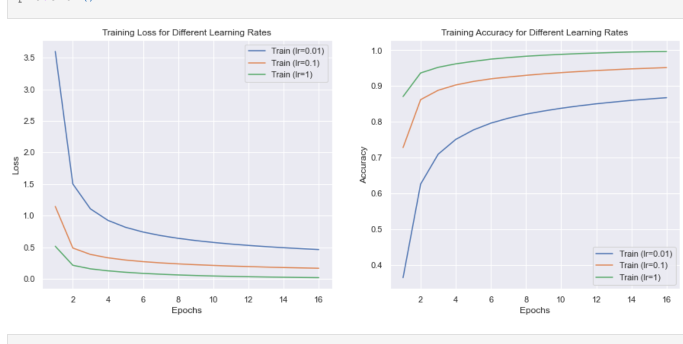
b) Train the model with various learning rates (at least 3).

- Plot the model's accuracy and loss (both on train and test sets) as a function of the epochs.
- Discuss the differences in training with different learning rates. Support your answer with plots.

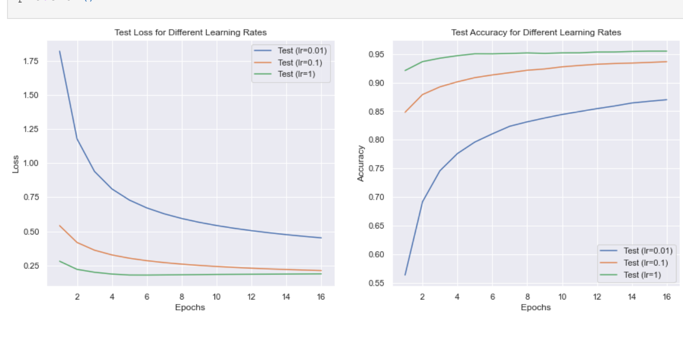
```python
# Use this:

learning_rates = [0.01, 0.1, 1]

train_losses = []
train_accuracies = []
test_losses = []
test_accuracies = []

for lr in learning_rates:
    train_loss = []
    train_accuracy = []
    test_loss = []
    test_accuracy = []



    set_seed(SEED)
    model = FullyConnectedNetwork(784, 10, 128, sigmoid, lr=lr)



    for epoch in range(EPOCHS):

        # Training
        epoch_train_loss = 0.0
        correct_train_predictions = 0
        total_train_samples = 0

        for (inputs, labels) in train_dataloader:
            y_hat = model.forward(inputs)
            model.backward(inputs, one_hot(labels), y_hat)

            epoch_train_loss += cross_entropy(labels, y_hat).item()

            _, predicted_labels = torch.max(y_hat, 1)
            correct_train_predictions += (predicted_labels == labels).sum().item()
            total_train_samples += labels.size(0)

        train_accuracy.append(correct_train_predictions / total_train_samples)
        train_loss.append(epoch_train_loss / len(train_dataloader))

        # Testing
        epoch_test_loss = 0.0
        correct_test_predictions = 0
        total_test_samples = 0

        with torch.no_grad():
            for (test_inputs, test_labels) in test_dataloader:
                test_y_hat = model.forward(test_inputs)
                epoch_test_loss += cross_entropy(test_labels, test_y_hat).item()

                _, predicted_labels = torch.max(test_y_hat, 1)
                correct_test_predictions += (predicted_labels == test_labels).sum().it
                total_test_samples += test_labels.size(0)

        test_accuracy.append(correct_test_predictions / total_test_samples)
        test_loss.append(epoch_test_loss / len(test_dataloader))

        # Print or log the results if needed
        #print(f"Epoch {epoch + 1}/{EPOCHS} - Train Loss: {train_loss[-1]}, Train Acc


    train_losses.append(train_loss)
    train_accuracies.append(train_accuracy)
    test_losses.append(test_loss)
    test_accuracies.append(test_accuracy)
```

plot of the accuracies and the losses of the train and test sets as a function of epoch:

```python
plt.figure(figsize=(15, 6))

epochs_range = range(1, EPOCHS + 1)

# training loss
plt.subplot(1, 2, 1)
for i, lr in enumerate(learning_rates):
    plt.plot(epochs_range, train_losses[i], label=f'Train (lr={lr})')

plt.title('Training Loss for Different Learning Rates')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()


plt.subplot(1, 2, 2)
for i, lr in enumerate(learning_rates):
    plt.plot(epochs_range, train_accuracies[i], label=f'Train (lr={lr})')

plt.title('Training Accuracy for Different Learning Rates')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()



plt.show()
```




```python
plt.figure(figsize=(15, 6))

# training loss
plt.subplot(1, 2, 1)
for i, lr in enumerate(learning_rates):
    plt.plot(epochs_range, test_losses[i], label=f'Test (lr={lr})')

plt.title('Test Loss for Different Learning Rates')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()


plt.subplot(1, 2, 2)
for i, lr in enumerate(learning_rates):
    plt.plot(epochs_range, test_accuracies[i], label=f'Test (lr={lr})')

plt.title('Test Accuracy for Different Learning Rates')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()



plt.show()
```



discussion:

as we can see, as we can see in the plot above, when we use larger learning rate, we get better results - higher accuracy and lower loss. That is, because our train set is too small, so if we will use a small learning rate, the model parameters are updated very slowly, and we will have to run a lot of epoch in order to reach a good solution. A bigger learning rate will help us update the model better.

Question 3

I. Implement and Train a CNN (30pt)

You are a data scientist at a supermarket. Your manager asked you to write a new image classifiaction algorithem for the self checkout cashiers. The images are of products from your grocery store (dataset files are attched in the Moodle).
Your code and meet the following constraints:

- Your classifier must be CNN based
- You are not allowed to use any pre-trained model

  In order to satisfy your boss you have to reach 65% accuracy on the test set. You will get a bonus for your salary (and 10 points to your grade) if your model's number of paramters is less than 100K. You can reutilize code from the tutorials.

- Train the model and plot the model's accuracy and loss (both on train and validation sets) as a function of the epochs.
- Report the test set accurecy.
- Discus the progress you made and describe your final model.

```python
import torch
import torch.nn as nn
from torchvision import transforms
from torch.utils.data import TensorDataset, DataLoader
from PIL import Image
import pandas as pd
import matplotlib.pyplot as plt


# Hyper parameters
num_epochs = 30
batch_size = 150
learning_rate = 0.0005
target_size = (264, 264)
```

```python
# Define the CNN model
class CNN(nn.Module):
    def __init__(self):
        super(CNN, self).__init__()
        self.layer1 = nn.Sequential(
            nn.Conv2d(3, 21, kernel_size=3, padding=1),  # 3- channels (RGB), 21- the
            nn.BatchNorm2d(21),  # input channels are the output channels from prev la
            nn.ReLU(),
            nn.MaxPool2d(4))  # lower dimension times 4 (64, 64)
        self.layer2 = nn.Sequential(
            nn.Conv2d(21, 42, kernel_size=3, padding=1),
            nn.BatchNorm2d(42),
            nn.ReLU(),
            nn.MaxPool2d(4))  # lower dimension times 4 (16, 16)
        self.layer3 = nn.Sequential(
            nn.Conv2d(42, 84, kernel_size=3, padding=1),
            nn.BatchNorm2d(84),
            nn.ReLU(),
            nn.MaxPool2d(4))  # lower dimension times 4 (4, 4)
        self.fc = nn.Linear(4 * 4 * 84, 43)  # 43 labels
        self.dropout = nn.Dropout(p=0.5)
        self.logsoftmax = nn.LogSoftmax(dim=1)

    def forward(self, x):
        out = self.layer1(x)
        out = self.layer2(out)
        out = self.layer3(out)
        out = out.view(out.size(0), -1)
        out = self.dropout(out)
        out = self.fc(out)
        return self.logsoftmax(out)
```

```python
# build model, define loss and optimizer
cnn = CNN()

if torch.cuda.is_available():
    cnn = cnn.cuda()

# Loss and Optimizer
weight_decay = (5e-5)

criterion = nn.NLLLoss()
optimizer = torch.optim.Adam(cnn.parameters(), lr=learning_rate, weight_decay=1e-2)
print('number of parameters: ', sum(param.numel() for param in cnn.parameters()))

# Image Preprocessing
transform = transforms.Compose([
    transforms.Resize(target_size),
    transforms.ToTensor(),
    transforms.Normalize((0.4914, 0.4822, 0.4465),
                         (0.247, 0.2434, 0.2615)),
])


mean = [0.485, 0.456, 0.406]
std = [0.229, 0.224, 0.225]

# Image Preprocessing
transform = transforms.Compose([
    transforms.Resize(target_size),
    transforms.ToTensor(),
    transforms.Normalize(mean=mean, std=std),
])


# Load class labels from CSV
classes = pd.read_csv("GroceryStoreDataset\classes.csv")
```

```
number of parameters:  98533
```

```python
def int_to_str_label(classes, pred_int_lst):
    pred_str_lst = []
    for pred_int in pred_int_lst:
        pred_str = classes[classes['Coarse Class ID (int)'] == pred_int]['Coarse Class
        pred_str_lst.append(pred_str)
    return pred_str_lst
```

```python
# Data Preprocessing
def load_data(file_path):
    images = []
    labels = []
    full_file_path = os.path.join("GroceryStoreDataset", file_path)
    with open(full_file_path, "r") as file:
        for line in file:
            image_path, label_idx = line.strip().split(",")
            full_image_path = os.path.join("GroceryStoreDataset", image_path)
            image = Image.open(full_image_path)
            image = transform(image)
            images.append(image)
            labels.append(int(label_idx))
    return images, labels
```

```python
# Upload input data
train_images, train_labels = load_data("train.txt")
test_images, test_labels = load_data("test.txt")
val_images, val_labels = load_data("val.txt")
```

```python
def create_dataloader(images, labels):
    # Convert the lists to tensors
    images = torch.stack(images)
    labels = torch.tensor(labels)
    # Create a TensorDataset from the image tensors and labels
    dataset = TensorDataset(images, labels)
    # Create a DataLoader to iterate over the dataset in batches
    dataloader = DataLoader(dataset, batch_size=batch_size, shuffle=True)
    return dataset, dataloader
```

```python
# Create train & test data_loaders:
train_dataset, train_dataloader = create_dataloader(train_images, train_labels)
test_dataset, test_dataloader = create_dataloader(test_images, test_labels)
val_dataset, val_dataloader = create_dataloader(val_images, val_labels)
```

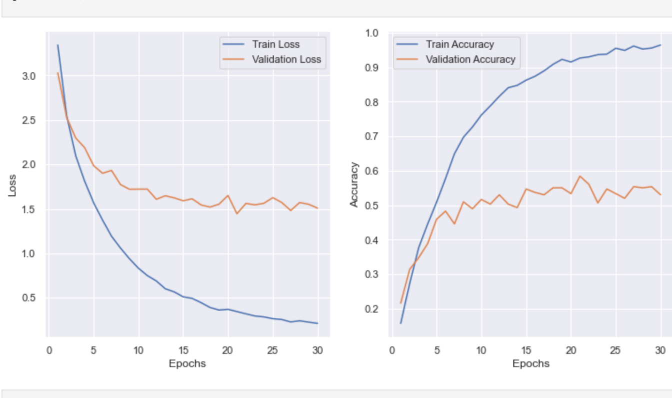
```python
# Create empty lists to store the accuracy and loss values for the train and validati
train_losses = []
train_accuracies = []
val_losses = []
val_accuracies = []

# Training loop for CNN model
max_accuracy_val = 0
for epoch in range(num_epochs):
    # Train the model
    cnn.train()  # Set the model to training mode
    total_loss_train = 0
    total_correct_train = 0
    total_train = 0
    train_predictions = []
    for images, labels in train_dataloader:
        # Forward pass
        outputs_train = cnn(images)
        loss_train = criterion(outputs_train, labels)
        total_loss_train += loss_train.item()

        # Backward pass
        optimizer.zero_grad()
        loss_train.backward()
        optimizer.step()

        # Calculate accuracy
        _, predicted = torch.max(outputs_train.data, 1)
        train_str_pred = int_to_str_label(classes, predicted.tolist())
        train_predictions.extend(train_str_pred)
        total_train += labels.size(0)
        total_correct_train += (predicted == labels).sum().item()

    # Calculate average loss and accuracy for the train set in this epoch
    train_loss_epoch = total_loss_train / len(train_dataloader)
    train_accuracy_epoch = total_correct_train / total_train
    train_losses.append(train_loss_epoch)
    train_accuracies.append(train_accuracy_epoch)

    # Validate the model
    cnn.eval()  # Set the model to evaluation mode
    total_loss_val = 0
```

```python
        total_correct_val = 0
        total_val = 0
        val_predictions = []
        with torch.no_grad():
            for images, labels in val_dataloader:
                if torch.cuda.is_available():
                    images = images.cuda()
                    labels = labels.cuda()

                # Forward pass
                outputs_val = cnn(images)
                loss_val = criterion(outputs_val, labels)
                total_loss_val += loss_val.item()

                # Calculate accuracy
                _, predicted = torch.max(outputs_val.data, 1)
                val_str_pred = int_to_str_label(classes, predicted.tolist())
                val_predictions.extend(val_str_pred)
                total_val += labels.size(0)
                total_correct_val += (predicted == labels).sum().item()

        # Calculate average loss and accuracy for the validation set
        val_loss_epoch = total_loss_val / len(val_dataloader)
        val_accuracy_epoch = total_correct_val / total_val
        val_losses.append(val_loss_epoch)
        val_accuracies.append(val_accuracy_epoch)

        if val_accuracy_epoch > max_accuracy_val:
            max_accuracy_val = val_accuracy_epoch
            torch.save(cnn.state_dict(), 'best_cnn.pth')

        # Print the results for the current epoch
        print(f'Epoch [{epoch+1}/{num_epochs}], Train Loss: {train_loss_epoch:.4f}, Train
              f'Validation Loss: {val_loss_epoch:.4f}, Validation Accuracy: {val_accuracy_
```

```
The history saving thread hit an unexpected error (OperationalError('disk I/O error')).History will not be written to the database.
Epoch [1/30], Train Loss: 3.3430, Train Accuracy: 15.76%, Validation Loss: 3.0308, Validation Accuracy: 21.62%
Epoch [2/30], Train Loss: 2.5463, Train Accuracy: 27.31%, Validation Loss: 2.5274, Validation Accuracy: 31.42%
Epoch [3/30], Train Loss: 2.0990, Train Accuracy: 37.65%, Validation Loss: 2.2982, Validation Accuracy: 34.80%
Epoch [4/30], Train Loss: 1.8122, Train Accuracy: 44.55%, Validation Loss: 2.1886, Validation Accuracy: 38.85%
Epoch [5/30], Train Loss: 1.5696, Train Accuracy: 50.87%, Validation Loss: 1.9863, Validation Accuracy: 45.95%
Epoch [6/30], Train Loss: 1.3741, Train Accuracy: 57.77%, Validation Loss: 1.9006, Validation Accuracy: 48.31%
Epoch [7/30], Train Loss: 1.1931, Train Accuracy: 64.96%, Validation Loss: 1.9328, Validation Accuracy: 44.59%
Epoch [8/30], Train Loss: 1.0600, Train Accuracy: 69.73%, Validation Loss: 1.7741, Validation Accuracy: 51.01%
Epoch [9/30], Train Loss: 0.9399, Train Accuracy: 72.69%, Validation Loss: 1.7208, Validation Accuracy: 48.99%
Epoch [10/30], Train Loss: 0.8334, Train Accuracy: 76.17%, Validation Loss: 1.7222, Validation Accuracy: 51.69%
Epoch [11/30], Train Loss: 0.7501, Train Accuracy: 78.83%, Validation Loss: 1.7226, Validation Accuracy: 50.34%
Epoch [12/30], Train Loss: 0.6901, Train Accuracy: 81.59%, Validation Loss: 1.6082, Validation Accuracy: 53.04%
Epoch [13/30], Train Loss: 0.6023, Train Accuracy: 84.09%, Validation Loss: 1.6480, Validation Accuracy: 50.34%
Epoch [14/30], Train Loss: 0.5667, Train Accuracy: 84.77%, Validation Loss: 1.6239, Validation Accuracy: 49.32%
Epoch [15/30], Train Loss: 0.5115, Train Accuracy: 86.29%, Validation Loss: 1.5915, Validation Accuracy: 54.73%
Epoch [16/30], Train Loss: 0.4941, Train Accuracy: 87.42%, Validation Loss: 1.6136, Validation Accuracy: 53.72%
Epoch [17/30], Train Loss: 0.4456, Train Accuracy: 88.98%, Validation Loss: 1.5447, Validation Accuracy: 53.04%
Epoch [18/30], Train Loss: 0.3912, Train Accuracy: 90.87%, Validation Loss: 1.5203, Validation Accuracy: 55.07%
Epoch [19/30], Train Loss: 0.3628, Train Accuracy: 92.31%, Validation Loss: 1.5533, Validation Accuracy: 55.07%
Epoch [20/30], Train Loss: 0.3708, Train Accuracy: 91.55%, Validation Loss: 1.6511, Validation Accuracy: 53.38%
Epoch [21/30], Train Loss: 0.3459, Train Accuracy: 92.69%, Validation Loss: 1.4454, Validation Accuracy: 58.45%
Epoch [22/30], Train Loss: 0.3201, Train Accuracy: 93.03%, Validation Loss: 1.5621, Validation Accuracy: 56.08%
Epoch [23/30], Train Loss: 0.2964, Train Accuracy: 93.67%, Validation Loss: 1.5456, Validation Accuracy: 50.68%
Epoch [24/30], Train Loss: 0.2855, Train Accuracy: 93.83%, Validation Loss: 1.5630, Validation Accuracy: 54.73%
Epoch [25/30], Train Loss: 0.2657, Train Accuracy: 95.53%, Validation Loss: 1.6267, Validation Accuracy: 53.38%
Epoch [26/30], Train Loss: 0.2564, Train Accuracy: 94.92%, Validation Loss: 1.5722, Validation Accuracy: 52.03%
Epoch [27/30], Train Loss: 0.2292, Train Accuracy: 96.17%, Validation Loss: 1.4819, Validation Accuracy: 55.41%
Epoch [28/30], Train Loss: 0.2424, Train Accuracy: 95.30%, Validation Loss: 1.5719, Validation Accuracy: 55.07%
Epoch [29/30], Train Loss: 0.2271, Train Accuracy: 95.61%, Validation Loss: 1.5523, Validation Accuracy: 55.41%
Epoch [30/30], Train Loss: 0.2129, Train Accuracy: 96.48%, Validation Loss: 1.5083, Validation Accuracy: 53.04%
```

In [22]:

```python
# Plot the accuracy and loss as a function of the epochs
plt.figure(figsize=(12, 6))
plt.subplot(1, 2, 1)
plt.plot(range(1, num_epochs + 1), train_losses, label='Train Loss')
plt.plot(range(1, num_epochs + 1), val_losses, label='Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()

plt.subplot(1, 2, 2)
plt.plot(range(1, num_epochs + 1), train_accuracies, label='Train Accuracy')
plt.plot(range(1, num_epochs + 1), val_accuracies, label='Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()

plt.show()
```



In [23]:

```python
# Test Set
cnn.load_state_dict(torch.load('best_cnn.pth'))
cnn.eval()
```

[illegible]

can't do as they lack the sufficient hardware). These pre-trained models can be used to fine-tune on other/small datasets or used as components in other tasks (like using a pre-trained classifier for object detection).

All pre-trained models expect input images normalized in the same way, i.e. mini-batches of 3-channel RGB images of shape (3 x H x W), where H and W are expected to be at least 224. The images have to be loaded in to a range of [0, 1] and then normalized using mean = [0.485, 0.456, 0.406] and std = [0.229, 0.224, 0.225].

You can use the following transform to normalize:

`normalize = transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225])` Read more here

1. Load a pre-trained VGG16 with PyTorch using torchvision.models.vgg16(pretrained=True, progress=True, **kwargs) (read more here). Don't forget to use the model in evaluation mode (`model.eval()`).
2. Load the images in the 'birds' folder and display them.
3. Pre-process the images to fit VGG16's architecture. What steps did you take?
4. Feed the images (forward pass) to the model. What are the outputs?
5. Choose an image of a dog in the 'dogs' folder, display it and feed it to network. What are the outputs?
6. For the first 3 filters in the first layer of VGG16, plot the filters, and then plot their response (their output) for the image from question 5. Explain your observations.

Q3.P2.(1+ 3) Load pre-traind VGG16 model & pre-process the images

In [25]:

```python
import random as rnd
import torch
import torchvision.models
from torchvision import transforms
from PIL import Image
import matplotlib.pyplot as plt
import os


# Pre-process the images to fit VGG16's architecture
transform = transforms.Compose([
    transforms.Resize((224, 224)),
    transforms.ToTensor(),
    transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225])
])

# Load the pre-trained VGG16 model
model = torchvision.models.vgg16(pretrained=True, progress=True)
```

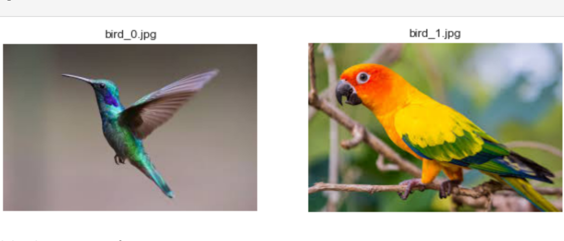
```
C:\Users\USER\anaconda3\lib\site-packages\torchvision\models\_utils.py:208: UserWarning: The parameter 'pretrained' is deprecated since 0.13 and may be removed in the future, please use 'weights' instead.
  warnings.warn(
C:\Users\USER\anaconda3\lib\site-packages\torchvision\models\_utils.py:223: UserWarning: Arguments other than a weight enum or `None` for 'weights' are deprecated since 0.13 and may be removed in the future. The current behavior is equivalent to passing `weights=VGG16_Weights.IMAGENET1K_V1`. You can also use `weights=VGG16_Weights.DEFAULT` to get the most up-to-date weights.
  warnings.warn(msg)
```

Pre-process of the images:

Q3.P2.2 Birds images load & Display

In [26]:

```python
images_names_birds = os.listdir('birds')

fig, axes = plt.subplots(nrows=1, ncols=len(images_names_birds), figsize=(10, 5))

birds_images = []
images = []
for i, image_name in enumerate(images_names_birds):
    image_path = f'birds/{image_name}'
    image = Image.open(image_path)  # upload
    images.append(image)

    # Display the image
    axes[i].imshow(image)
    axes[i].axis('off')
    axes[i].set_title(image_name)

    image = transform(image)  # convert to tensor
    birds_images.append(image)  # store

plt.show()
```



Q3.P2.4 Forward pass

In [27]:

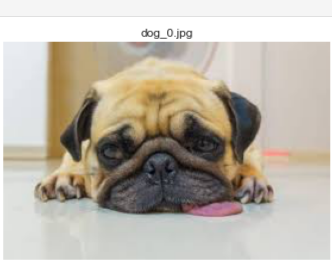
```python
# Concatenate all the images tensors to a single batch
batch_images_tensor = torch.stack(birds_images)

# Set the model to evaluation mode
model.eval()

outputs = model(batch_images_tensor)  # Forward pass
print(outputs.shape)


_, predicted = torch.max(outputs.data, 1)

for i, image_name in enumerate(images_names_birds):
    print(f'{image_name}: pred label {predicted[i].item()}')
```

```
torch.Size([2, 1000])
bird_0.jpg: pred label 94
bird_1.jpg: pred label 90
```

Q3.P2.5 Dog image

In [28]:

```python
# '5' - dogs
images_names_dogs = os.listdir('dogs')

random_dog_image_name = rnd.choice(images_names_dogs)

random_dog_image_path = f'dogs/{random_dog_image_name}'
random_dog_image = Image.open(random_dog_image_path)

plt.imshow(random_dog_image)
plt.axis('off')
plt.title(random_dog_image_name)
plt.show()
```



In [29]:

```python
dog_image_tensor = transform(random_dog_image)
dog_image_tensor = dog_image_tensor.unsqueeze(0) # Add batch dimension

model.eval()
output = model(dog_image_tensor)  # Forward pass

print(output.shape)  # tensor of size 1000 (the probabilities)
_, predicted = torch.max(output.data, 1)
print(f'{random_dog_image_name}: pred label: {predicted.item()}')
```

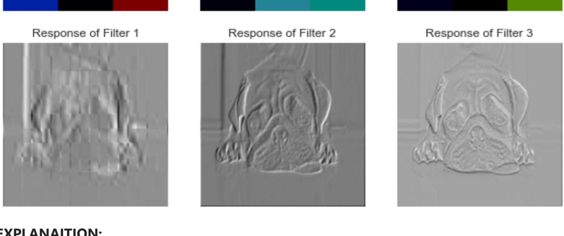
```
torch.Size([1, 1000])
dog_0.jpg: pred label: 254
```

Q3.P2.6 Plot of filters & Response

In [30]:

```python
first_layer = model.features[0]  # Get the first layer of the model
filters = first_layer.weight[:3]  # Get the 3 first filters

fig, axes = plt.subplots(nrows=1, ncols=3, figsize=(10, 10))
# Plot the filters
for i in range(3):
    filter_i = filters[i].detach().numpy()
    axes[i].imshow(filter_i.transpose(1, 2, 0))
    axes[i].axis('off')
    axes[i].set_title(f'Filter {i+1}')
plt.show()

fig, axes = plt.subplots(nrows=1, ncols=3, figsize=(10, 10))
# Plot the responses of the filters
with torch.no_grad():
    output = first_layer(dog_image_tensor)
    output = output.squeeze(0)  # Add batch dimension
    for i in range(3):
        axes[i].imshow(output[i].numpy(), cmap='gray')
        axes[i].axis('off')
        axes[i].set_title(f'Response of Filter {i+1}')
    plt.show()
```

```
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
```



EXPLAINAITION:

The plots of the responses show the areas in the image where the filters have high activations. Darker areas indicate higher activation values. Those activations represent the features that the filters are detecting in the image. It seems like those responses are more sensitive to low-level features such as edges and textures.

In [ ]: