EEE 443

Mini Project

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Table of Contents

Question 1

1.a)

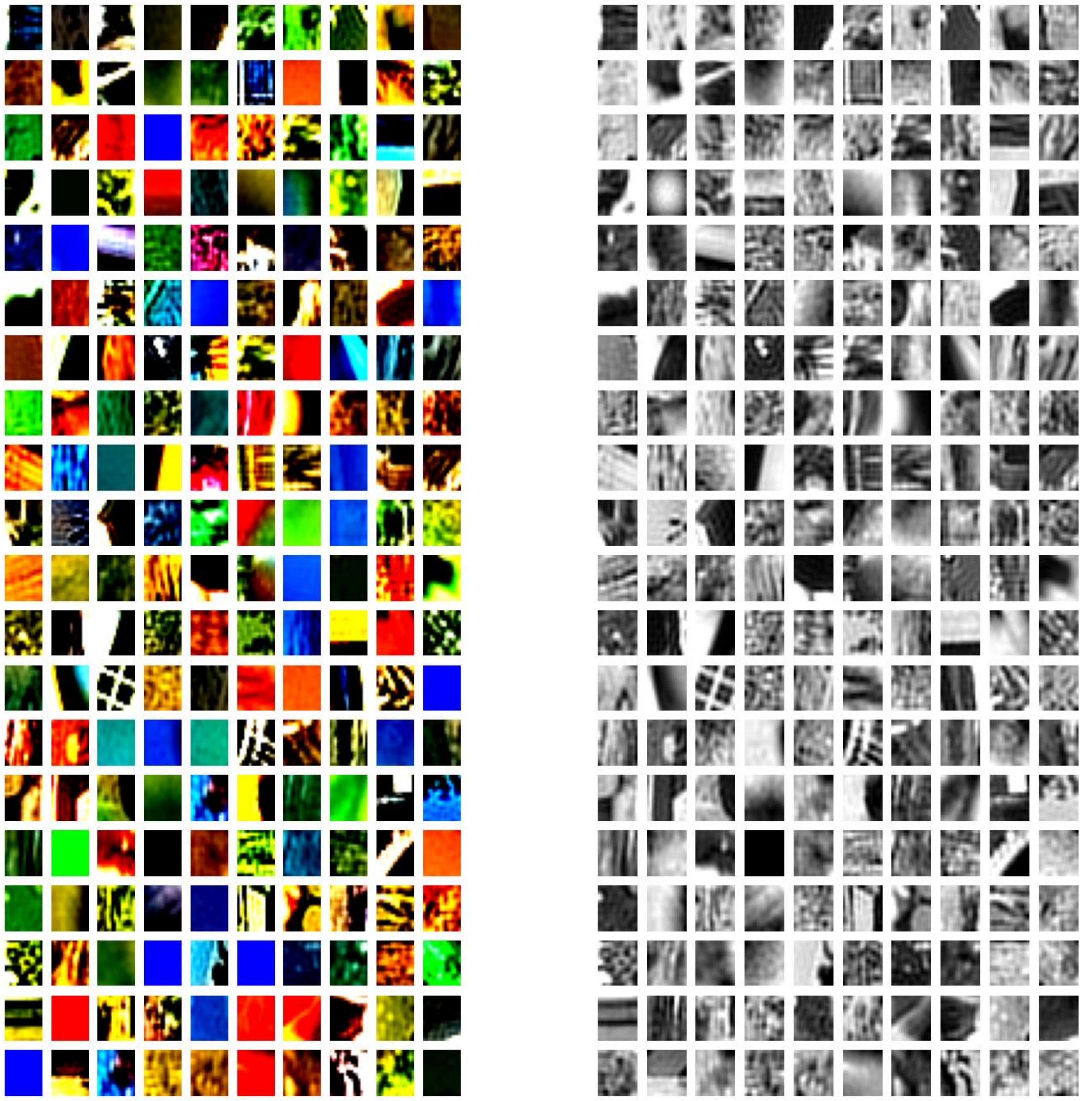


Figure 1: 200 randomly chosen RGB images and their greyscale versions

As can be observed, greyscale images are similar to RGB images. Moreover, some edges and lines are more evident in preprocessed greyscale versions, which is important for neural network when extracting features from these samples.

1.b)

In this part, it is important to incorporate the KL-divergence into the backward derivations. For this purpose, following equations and their code adaptations have been utilized:

$$\hat{\rho}_j = \frac{1}{m} \sum_{i=1}^{m} \left[a_j^{(2)} \left(x^{(i)} \right) \right]$$

Figure 2: Average activation of hidden unit j [1]

```
p_j = np.mean(A1,axis=1,keepdims=True)
```

$$\delta_i^{(2)} = \left(\left(\sum_{j=1}^{s_2} W_{ji}^{(2)} \delta_j^{(3)} \right) + \beta \left(-\frac{\rho}{\hat{\rho}_i} + \frac{1-\rho}{1-\hat{\rho}_i} \right) \right) f'\left(z_i^{(2)}\right).$$

Figure 3: Error gradient combined with KL-divergence [1]

```
dA1 = np.matmul(W2.T,dZ2) + beta * (-(rho/p_j) + (1-rho)/(1-p_j))
dZ1 = dA1 * d_activation_1
```

Following parameters have been found optimal for hidden layer size 64:

- $\rho = 0.03$
- $\beta = 0.01$
- $\lambda = 5 * 10{-}4$
- Learning Rate = 0.6
- Momentum Rate = 0.4
- Batch Size = 32
- Epochs = 200

1.c)

Figure 4: The first layer connection weights as separate images

Hidden layer features include some shapes and patterns with different variations. These features are not representative of natural images but they can be used for specific tasks such as object detection etc. As can be observed from the images, some patterns are more frequent which suggests resemblance of the greyscale images in the dataset.

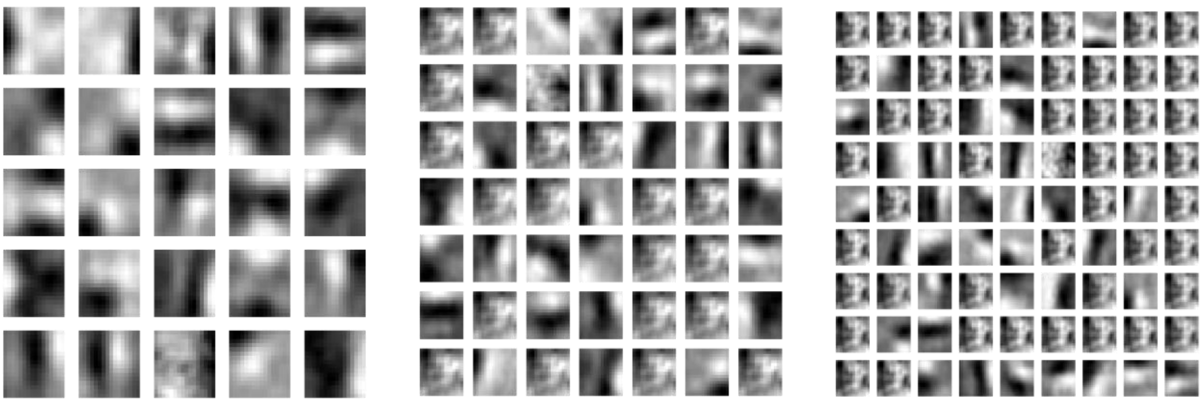
1.d)

a) $L_{hid} = 25$ b) $L_{hid} = 49$ c) $L_{hid} = 81$

Figure 5: $\lambda = 0$

a) $L_{hid} = 25$ b) $L_{hid} = 49$ c) $L_{hid} = 81$

Figure 6: $\lambda = 10^{-5}$



a) $L_{hid} = 25$ b) $L_{hid} = 49$ c) $L_{hid} = 81$

Figure 7: $\lambda = 10^{-3}$

As the hidden layer size increases, more features are extracted. This circumstance is promising but there might occur a large number of same patterns which is redundant for the network. This affects network's performance because increasing feature dimension needs more time for the operations. If there are mostly redundant features, this means performance decrease for the network. The regularization parameter λ affects the network from underfitting and overfitting perspectives. Lower values of the parameter may cause overfitting and higher values may cause underfitting. Compared λ values $\{0, 10^{-5}, 10^{-3}\}$, I have found more meaningful shapes for $\lambda=10^{-3}$. The reason is that other 2 values overfits the data. However, when I tried $\lambda=10^{-2}$ hoping to see improvements, the result was disappointing. The network was not able to decrease the loss, which is an underfitting case. For $\lambda=10^{-3}$, $L_{hid} = 49$ is the optimal one because $L_{hid} = 81$ has mostly redundant features and $L_{hid} = 49$ has more valuable features than $L_{hid} = 25$.

Question 2

After many iterations, optimal parameters have been found as:

- Learning Rate = 0.0006
- Batch Size = 200
- Momentum Rate = 0.85
- Epochs = 50

2.a)

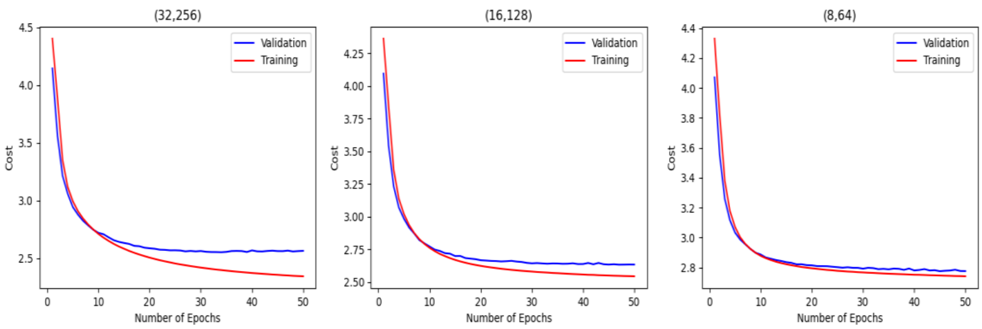


Figure 8: Cross entropy loss on training and validation sets for 3 different dimensions

(32,256) seems to give better results than others. However, as the dimension increases, we can observe tendency towards the overfitting case, comparing the difference between losses of training and validation sets.

2.b)

This function has been called for (32,256).

```
get_candidates(We,x_test,words)
```

```
b'but' b'it' b"'s" ----> [b'not', b'a', b'good', b'just', b'the', b'still', b'been', b'going', b'part', b'also']
b'are' b'the' b'only' ----> [b'one', b'way', b'team', b'people', b'three', b'two', b'place', b'right', b'house', b'.']
b'it' b'is' b'the' ----> [b'same', b'first', b'best', b'only', b'law', b'right', b'other', b'way', b'last', b'case']
b'and' b'they' b'do' ----> [b'nt', b'it', b'.', b'what', b',', b'not', b'well', b'know', b'all', b'that']
b'get' b'out' b'of' ----> [b'here', b'it', b'the', b'there', b'this', b'my', b'that', b'school', b'business', b'a']
```

Figure 9: Predictions are listed for 5 different triagrams

5 triagrams from the test set have been selected and first 10 sorted output have been listed, meaning that the first word in the list is the most probable fourth word for given triagram. Network predictions are mostly sensible.

Question 3

3.a)

This network has 2 MLP hidden layers with sizes 64 and 32.

After many iterations, optimal parameters have been found as:

- Learning Rate = 0.0001
- Batch Size = 32
- Momentum Rate = 0.85
- Epochs = 50

The learning process of RNN was not stable with default parameters because of vanishing/exploding gradients. Therefore, I tried several different parameters to make it stable. These parameters provided stable learning process for the network.

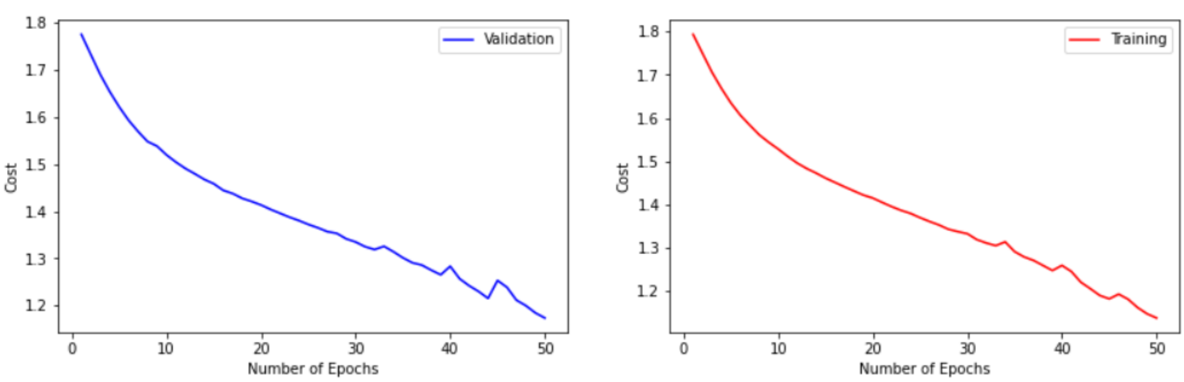


Figure 10: RNN cross entropy loss plots for both validation and training

```
Test accuracy:49.666666666666664
Train accuracy:58.370370370370374
```

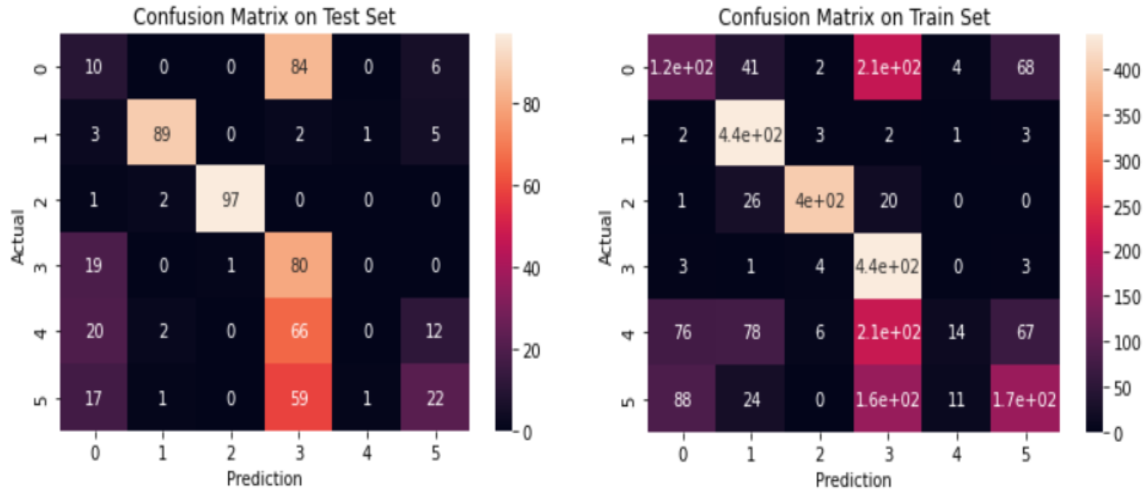


Figure 11: RNN confusion matrices for test and train set

The results are not good. In RNN, there is a trade-off between making the learning process more stable and the amount of learning. Although I was able to achieve stableness, my network did not learn much. More epoch numbers would overcome this circumstance but there is a limitation that 50 epochs are determined as maximum.

3.b)

This network has 2 MLP hidden layers with sizes 64 and 32.

After many iterations, optimal parameters have been found as:

- Learning Rate = 0.001
- Batch Size = 32
- Momentum Rate = 0.85
- Epochs = 50

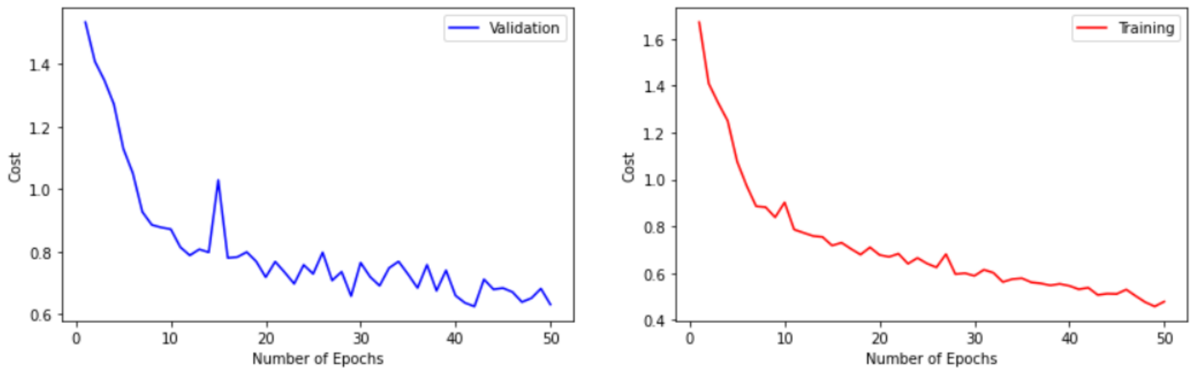


Figure 12: LSTM cross entropy loss plots for both validation and training

```
Test accuracy:67.0

Train accuracy:84.0
```

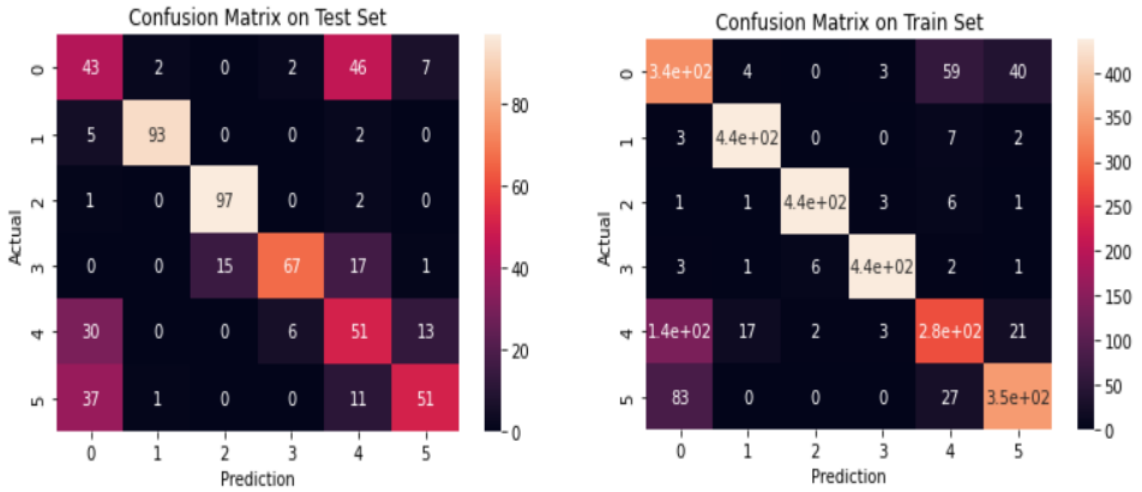


Figure 13: LSTM confusion matrices for test and train set

The results are better than RNN case. LSTM is able to deal with vanishing/exploding gradient problem due to its structure comprising of gates. The current network does not get affected much from gradient updates as RNN does. Therefore, LSTM is more stable than RNN.

3.c)

This network has 2 MLP hidden layers with sizes 64 and 32.

After many iterations, optimal parameters have been found as:

- Learning Rate = 0.0005
- Batch Size = 32
- Momentum Rate = 0.85
- Epochs = 50

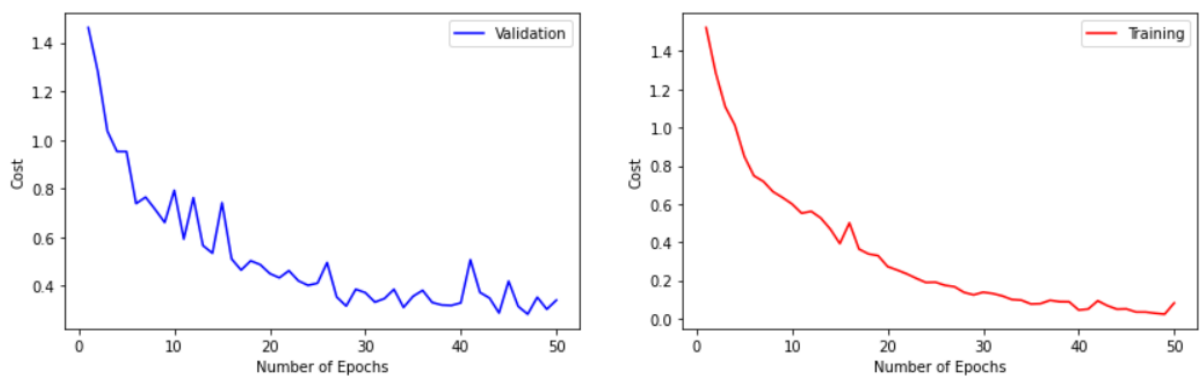


Figure 14: GRU cross entropy loss plots for both validation and training

```
Test accuracy:83.16666666666667
Train accuracy:97.77777777777777
```

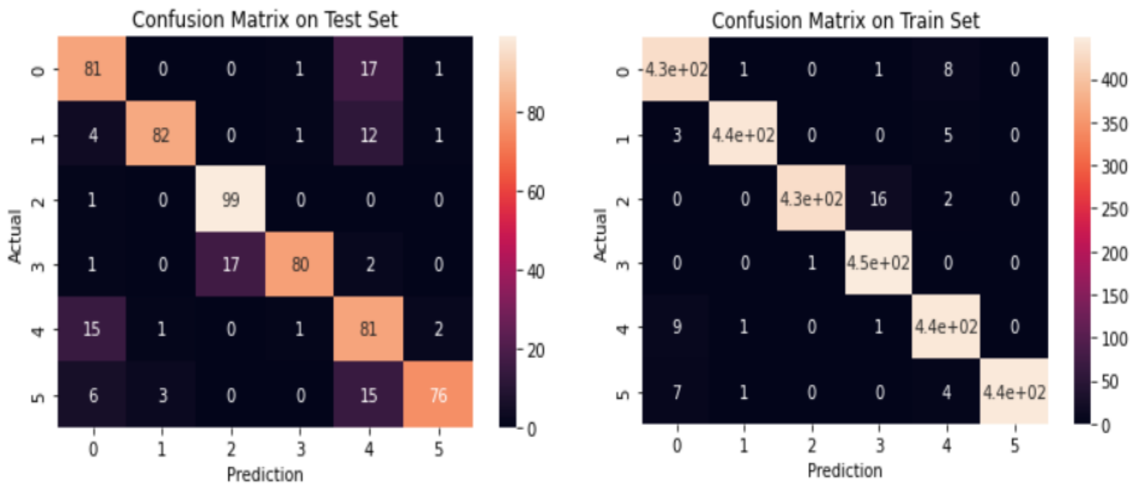


Figure 15: GRU confusion matrices for test and train set

GRU has the best performance over RNN and LSTM. Similar to LSTM, GRU is able to overcome vanishing/exploding gradient problem and it has stable learning process. GRU has less gates than LSTM which makes it more memory efficient. Moreover, training time of GRU is relatively smaller than the training time of LSTM for 50 epochs. Consequently, I prefer GRU over other 2 networks. The reason is that it has more test accuracy and is more efficient than RNN and LSTM.

References

[1] *Unsupervised feature learning and Deep Learning Tutorial*. [Online]. Available: http://ufldl.stanford.edu/tutorial/unsupervised/Autoencoders/. [Accessed: 17-Dec-2022].

Appendix

```
import sys
import pandas as pd
import numpy as np
import h5py
import matplotlib.pyplot as plt
import seaborn as sns

question = sys.argv[1]

def arda_baris_ortlek_21903472_hw1(question):
    if question == '1':
        q1()
    elif question == '2':
        q2()
    elif question == '3':
        q3()



def q1():
    def load_dataset(path):
        return np.array(h5py.File(path)["data"])



    rgb_images = load_dataset("data1.h5")
    print(rgb_images.shape)

    # Convert RGB images to greyscale
    # Y = 0.2126 ∗ R + 0.7152 ∗ G + 0.0722 ∗ B
```

```
gray_image = 0.2126 * rgb_images[:, 0, :, :] + 0.7152 * \
    rgb_images[:, 1, :, :] + 0.0722 * rgb_images[:, 2, :, :]
# Remove the mean pixel intensity of each image from itself
gray_image = gray_image.reshape(
    gray_image.shape[0], gray_image.shape[1]*gray_image.shape[2])
mean_arr = np.mean(gray_image, axis=1, keepdims=True)
grey_image = gray_image - mean_arr
#clip, normalize, map
std = np.std(gray_image)
gray_image = np.clip(gray_image, -3*std, 3*std)
gray_image = (gray_image - gray_image.min()) / \
    (gray_image.max() - gray_image.min())  # data ranges 0 to 1
gray_image = 0.1 + gray_image*0.9  # data ranges 0.1 to 0.9
gray_image = gray_image.reshape(-1, 16, 16)
# Reshape rgb to (10240,16,16,3)
rgb_images = np.transpose(rgb_images, (0, 2, 3, 1))

# Plot random 200 samples
fig_gray, ax_gray = plt.subplots(20, 10, figsize=(10, 20))
fig_rgb, ax_rgb = plt.subplots(20, 10, figsize=(10, 20))

for i in range(20):
    for j in range(10):
        image_index = np.random.randint(0, gray_image.shape[0])
        ax_gray[i, j].imshow(gray_image[image_index], cmap="gray")
        ax_gray[i, j].axis("off")
        ax_rgb[i, j].imshow(rgb_images[image_index])
        ax_rgb[i, j].axis("off")

fig_gray.savefig("gray.png")
```

```python
fig_rgb.savefig("rgb.png")
plt.close("all")

#WX.T +b
def init_parameters(l_pre, l_post):
    np.random.seed(33)
    w0 = np.sqrt(6/(l_pre + l_post))

    W1 = np.random.uniform(-w0, w0, size=(l_post, l_pre))
    b1 = np.random.uniform(-w0, w0, size=(l_post, 1))
    W2 = np.random.uniform(-w0, w0, size=(l_pre, l_post))
    b2 = np.random.uniform(-w0, w0, size=(l_pre, 1))

    We = {"W1": W1, "b1": b1, "W2": W2, "b2": b2}
    return We

# Returns the output and the derivative of activation function
def sigmoid(Z):
    A = 1 / (1 + np.exp(-Z))
    derivative = (1-A)*A
    return A, derivative



def forward_propagate(We, data):
    W1 = We["W1"]
    W2 = We["W2"]
    b1 = We["b1"]
    b2 = We["b2"]

    Z1 = np.matmul(W1, data.T) + b1
```

```
    A1, d_activation_1 = sigmoid(Z1)
    Z2 = np.matmul(W2, A1) + b2
    A2, d_activation_2 = sigmoid(Z2)

    return (Z1, A1, Z2, A2, d_activation_1, d_activation_2)

# Does forward and back propagation, calculates cost and related gradients
def aeCost(We, data, params):
    N = data.shape[0]

    W1 = We["W1"]
    W2 = We["W2"]
    b1 = We["b1"]
    b2 = We["b2"]

    l_in = params["Lin"]
    l_hid = params["Lhid"]
    lambda_ = params["lambda"]
    beta = params["beta"]
    rho = params["rho"]

    data = data.reshape(N, 256)
    # Forward propogate
    Z1, A1, Z2, A2, d_activation_1, d_activation_2 = forward_propagate(
        We, data)

    # Calculate cost
    avarage_squared_error = (1/(2*N)) * (np.sum(np.linalg.norm(data.T-A2)**2))
    tykhonov_regularization = lambda_ * 0.5 * \
        (np.sum(np.square(W1))+np.sum(np.square(W2)))
```

```
    p_j = np.mean(A1, axis=1, keepdims=True)
    kl_divergence = beta * \
      np.sum(rho*np.log(rho/p_j) + (1-rho)*np.log((1-rho)/(1-p_j)))
    J = avarage_squared_error + tykhonov_regularization + kl_divergence

    # Backward propagate and J_grad
    dA2 = (1/N)*(data.T - A2) * -1
    dZ2 = dA2 * d_activation_2
    dA1 = np.matmul(W2.T, dZ2) + beta * (-(rho/p_j) + (1-rho)/(1-p_j))
    dZ1 = dA1 * d_activation_1
    d_tykhonov_1 = lambda_ * W1
    d_tykhonov_2 = lambda_ * W2
    dW1 = (np.matmul(dZ1, data) + d_tykhonov_1)
    db1 = np.sum(dZ1, axis=1, keepdims=True)
    dW2 = (np.matmul(dZ2, A1.T) + d_tykhonov_2)
    db2 = np.sum(dZ2, axis=1, keepdims=True)

    J_grad = {"dW1": dW1, "dW2": dW2, "db1": db1, "db2": db2}
    #print(f"MSE={avarage_squared_error} KL={kl_divergence}
REG={tykhonov_regularization} TOTAL={J}")
    return J, J_grad



  def update_parameters(We, J_grad, learning_rate, change_dict, momentum_rate):
    W1 = We["W1"]
    W2 = We["W2"]
    b1 = We["b1"]
    b2 = We["b2"]

    dW1 = J_grad["dW1"]
    dW2 = J_grad["dW2"]
```

```
        db1 = J_grad["db1"]
        db2 = J_grad["db2"]

        c_W1 = change_dict["W1"]
        c_W2 = change_dict["W2"]
        c_b1 = change_dict["b1"]
        c_b2 = change_dict["b2"]

        delta_W1 = learning_rate*dW1 + c_W1*momentum_rate
        delta_W2 = learning_rate*dW2 + c_W2*momentum_rate
        delta_b1 = learning_rate*db1 + c_b1*momentum_rate
        delta_b2 = learning_rate*db2 + c_b2*momentum_rate

        W1 = W1 - delta_W1
        W2 = W2 - delta_W2
        b1 = b1 - delta_b1
        b2 = b2 - delta_b2

        We = {"W1": W1, "b1": b1, "W2": W2, "b2": b2}
        change_dict = {"W1": delta_W1, "b1": delta_b1,
                    "W2": delta_W2, "b2": delta_b2}
        return We, change_dict



    def gradient_descent(We, params, data, epoch, learning_rate, change_dict,
momentum_rate, batch_size):
        N = data.shape[0]
        iteration_per_epoch = int(N / batch_size)
        for i in range(epoch):
            mini_batch_start_index = 0
            mini_batch_end_index = batch_size
```

```
        sample_order = np.random.permutation(N)
        data = data[sample_order]
        J_mean = 0
        for j in range(iteration_per_epoch):
            mini_batch_data = data[mini_batch_start_index:mini_batch_end_index]
            J, J_grad = aeCost(We, mini_batch_data, params)
            We, change_dict = update_parameters(
                We, J_grad, learning_rate, change_dict, momentum_rate)
            mini_batch_start_index = mini_batch_end_index
            mini_batch_end_index = mini_batch_end_index + batch_size
            J_mean = J_mean + J

        J_mean = J_mean / iteration_per_epoch
        print(f"Epoch = {i+1} ---> Training error: {J_mean}")

    return We


We = init_parameters(256, 64)
params = {"Lin": 256, "Lhid": 64, "lambda": 5e-4, "beta": 0.01, "rho": 0.03}
change_dict = {"W1": 0, "b1": 0, "W2": 0, "b2": 0}
We = gradient_descent(We, params, gray_image, 200, 0.6, change_dict, 0.4, 32)

# plot weights
fig_w, ax_w = plt.subplots(8, 8, figsize=(16, 16))
neuron_number = 0
for i in range(8):
    for j in range(8):
        ax_w[i, j].imshow(We["W1"][neuron_number].reshape(16, 16), cmap="gray")
        ax_w[i, j].axis("off")
```

```
            neuron_number = neuron_number + 1

    plt.show()




def q2():

    def load_word_dataset(path):
        x_train = np.array(h5py.File(path)["trainx"]).T
        y_train = np.array(h5py.File(path)["traind"]).T
        x_val = np.array(h5py.File(path)["valx"]).T
        y_val = np.array(h5py.File(path)["vald"]).T
        x_test = np.array(h5py.File(path)["testx"]).T
        y_test = np.array(h5py.File(path)["testd"]).T
        words = np.array(h5py.File(path)["words"])

        return x_train, y_train, x_val, y_val, x_test, y_test, words



    x_train, y_train, x_val, y_val, x_test, y_test, words = load_word_dataset(
        "data2.h5")
    print(x_train.shape)
    print(y_train.shape)
    print(x_val.shape)
    print(y_val.shape)
    print(x_test.shape)
    print(y_test.shape)
    print(words.shape)
```

```
print(x_train.min())


print(words)


# Returns the output and the derivative of activation function
def sigmoid(Z):
    A = 1 / (1 + np.exp(-Z))
    derivative = (1-A)*A
    return A, derivative


#WX + b



def init(D, P):
    np.random.seed(33)
    word_embedding = np.random.normal(0, 0.01, (250, D))
    W1 = np.random.normal(0, 0.01, (P, 3*D))
    b1 = np.random.normal(0, 0.01, (P, 1))
    W2 = np.random.normal(0, 0.01, (250, P))
    b2 = np.random.normal(0, 0.01, (250, 1))
    We = {"W1": W1, "b1": b1, "W2": W2, "b2": b2}
    return word_embedding, We



def word_embedding_to_input_vector(word_embedding, x_train):
    N = x_train.shape[1]
    D = word_embedding.shape[1]
    input_vector = np.zeros((3*D, N))
    for i in range(N):
        first_word = word_embedding[x_train[0, i]-1, :]
```

```
        second_word = word_embedding[x_train[1, i]-1, :]
        third_word = word_embedding[x_train[2, i]-1, :]

        concat = np.concatenate((first_word, second_word, third_word))
        concat = concat.T
        input_vector[:, i] = concat

    return input_vector



def cross_entropy(y_pred, y):
    return -np.sum(y*np.log(y_pred)) / y_pred.shape[1]



def forward_propagate(We, data):
    W1 = We["W1"]
    W2 = We["W2"]
    b1 = We["b1"]
    b2 = We["b2"]

    Z1 = np.matmul(W1, data) + b1
    A1, d_activation_1 = sigmoid(Z1)
    Z2 = np.matmul(W2, A1) + b2
    # calculate softmax
    # overcome exponential related overflows
    exps = np.exp(Z2-np.amax(Z2, axis=0))
    A2 = exps/np.sum(exps, axis=0)
    return (Z1, A1, Z2, A2, d_activation_1)

# Make y arrays one hot encoded
```

```
def y_to_one_hot_encoded(y):
    return np.eye(250)[:, y.ravel()-1]



y_train_ = y_to_one_hot_encoded(y_train)
y_val_ = y_to_one_hot_encoded(y_val)
y_test_ = y_to_one_hot_encoded(y_test)
print(y_train_.shape)
print(y_val_.shape)
print(y_test_.shape)



def cost(We, word_embedding, x_train, y_train_):
    W1 = We["W1"]
    W2 = We["W2"]
    b1 = We["b1"]
    b2 = We["b2"]

    # Create input vectors for training and validation
    input_vector_train = word_embedding_to_input_vector(
        word_embedding, x_train)

    # Forward propagate for training
    (Z1, A1, Z2, A2, d_activation_1) = forward_propagate(We, input_vector_train)

    # Calculate training cost for this batch
    batch_training_cost = cross_entropy(A2, y_train_)

    # Backward propagate
    dZ2 = A2 - y_train_
```

```
        dA1 = np.matmul(W2.T, dZ2)
        dZ1 = dA1 * d_activation_1
        dW1 = np.matmul(dZ1, input_vector_train.T)
        db1 = np.sum(dZ1, axis=1, keepdims=True)
        dW2 = np.matmul(dZ2, A1.T)
        db2 = np.sum(dZ2, axis=1, keepdims=True)
        dA0 = np.matmul(W1.T, dZ1)  # gradient for the input vector

        grads = {"dW1": dW1, "dW2": dW2, "db1": db1, "db2": db2, "dA0": dA0}
        return batch_training_cost, grads



    def update_parameters(We, grads, learning_rate, word_embedding, x_train, start_index,
end_index, momentum_dict, momentum_rate):
        dW1 = grads["dW1"]
        dW2 = grads["dW2"]
        db1 = grads["db1"]
        db2 = grads["db2"]
        dA0 = grads["dA0"]

        W1 = We["W1"]
        W2 = We["W2"]
        b1 = We["b1"]
        b2 = We["b2"]

        cW1 = momentum_dict["cW1"]
        cW2 = momentum_dict["cW2"]
        cb1 = momentum_dict["cb1"]
        cb2 = momentum_dict["cb2"]
        cA0 = momentum_dict["cA0"]
```

```
# Update word_embedding grads
word_count = word_embedding.shape[0]
D = word_embedding.shape[1]
x_grad = np.zeros((word_count, D))

# Sum grads for same words
for i in range(end_index-start_index):
    triagram = dA0[:, i].T
    first_word_grad = triagram[0:D]
    second_word_grad = triagram[D:2*D]
    third_word_grad = triagram[2*D:]

    x_grad[(x_train[0][start_index+i])-1, :] += first_word_grad
    x_grad[(x_train[1][start_index+i])-1, :] += second_word_grad
    x_grad[(x_train[2][start_index+i])-1, :] += third_word_grad

#word_embedding = word_embedding - learning_rate * x_grad
delta_word_embedding = learning_rate * x_grad + momentum_rate * cA0
delta_W1 = learning_rate * dW1 + momentum_rate * cW1
delta_W2 = learning_rate * dW2 + momentum_rate * cW2
delta_b1 = learning_rate * db1 + momentum_rate * cb1
delta_b2 = learning_rate * db2 + momentum_rate * cb2
# Update
W1 = W1 - delta_W1
W2 = W2 - delta_W2
b1 = b1 - delta_b1
b2 = b2 - delta_b2
word_embedding = word_embedding - delta_word_embedding

We = {"W1": W1, "b1": b1, "W2": W2, "b2": b2}
```

```
    momentum_dict = {"cW1": delta_W1, "cW2": delta_W2,
                "cb1": delta_b1, "cb2": delta_b2, "cA0": delta_word_embedding}
    return We, word_embedding, momentum_dict


def gradient_descent(We, epoch, learning_rate, batch_size, x_train, y_train_, x_val, y_val_,
word_embedding, momentum_dict, momentum_rate):
    N = x_train.shape[1]
    iteration_per_epoch = int(N / batch_size)
    validation_cost = []
    training_cost = []
    for i in range(epoch):
        mini_batch_start_index = 0
        mini_batch_end_index = batch_size
        sample_order = np.random.permutation(N)
        x_train = x_train[:, sample_order]
        y_train_ = y_train_[:, sample_order]
        train_per_batch = []

        for j in range(iteration_per_epoch):
            mini_batch_data_x = x_train[:,
                                mini_batch_start_index:mini_batch_end_index]
            mini_batch_data_y = y_train_[
                :, mini_batch_start_index:mini_batch_end_index]
            J, grads = cost(We, word_embedding,
                        mini_batch_data_x, mini_batch_data_y)
            We, word_embedding, momentum_dict = update_parameters(
                We, grads, learning_rate, word_embedding, x_train, mini_batch_start_index,
mini_batch_end_index, momentum_dict, momentum_rate)
            mini_batch_start_index = mini_batch_end_index
            mini_batch_end_index = mini_batch_end_index + batch_size
```

```
            train_per_batch.append(J)

            if mini_batch_end_index > N:
                mini_batch_end_index = N

        # Training cost
        training_cost_per_epoch = np.mean(train_per_batch)
        training_cost.append(training_cost_per_epoch)
        # calculate validation cost
        val_input_vector = word_embedding_to_input_vector(
            word_embedding, x_val)
        (Z1, A1, Z2, A2_val, d_activation_1) = forward_propagate(We, val_input_vector)
        val_cost = cross_entropy(A2_val, y_val_)
        print(
            f"Epoch = {i+1} ---> Validation cost: {val_cost} Training
cost:{training_cost_per_epoch}")
        validation_cost.append(val_cost)
        if len(validation_cost) > 1:
            delta_err = np.abs(validation_cost[-1] - validation_cost[-2])
            if delta_err < 1e-5:
                print("Training will be stopped because of low validation delta")

    return We, word_embedding, momentum_dict, validation_cost, training_cost


word_embedding, We = init(32, 256)
momentum_dict = {"cW1": 0, "cW2": 0, "cb1": 0, "cb2": 0, "cA0": 0}
We, word_embedding, momentum_dict, validation_cost, training_cost = gradient_descent(
    We, 50, 0.0006, 200, x_train, y_train_, x_val, y_val_, word_embedding,
momentum_dict, 0.85)
```

```
word_embedding_2, We_2 = init(16, 128)
momentum_dict = {"cW1": 0, "cW2": 0, "cb1": 0, "cb2": 0, "cA0": 0}
We_2, word_embedding_2, momentum_dict, validation_cost_2, training_cost_2 = gradient_descent(
    We_2, 50, 0.0006, 200, x_train, y_train_, x_val, y_val_, word_embedding_2, momentum_dict, 0.85)

word_embedding_3, We_3 = init(8, 64)
momentum_dict = {"cW1": 0, "cW2": 0, "cb1": 0, "cb2": 0, "cA0": 0}
We_3, word_embedding_3, momentum_dict, validation_cost_3, training_cost_3 = gradient_descent(
    We_3, 50, 0.0006, 200, x_train, y_train_, x_val, y_val_, word_embedding_3, momentum_dict, 0.85)

fig, ax = plt.subplots(1, 3, figsize=(18, 4))
ax[0].plot([x for x in range(1, len(validation_cost)+1)],
        validation_cost, color="blue", label="Validation")
ax[0].plot([x for x in range(1, len(training_cost)+1)],
        training_cost, color="red", label="Training")
ax[0].set_xlabel("Number of Epochs")
ax[0].set_ylabel("Cost")
ax[0].set_title("(32,256)")
ax[0].legend(loc="best")
ax[1].plot([x for x in range(1, len(validation_cost_2)+1)],
        validation_cost_2, color="blue", label="Validation")
ax[1].plot([x for x in range(1, len(training_cost_2)+1)],
        training_cost_2, color="red", label="Training")
ax[1].set_xlabel("Number of Epochs")
ax[1].set_ylabel("Cost")
ax[1].set_title("(16,128)")
ax[1].legend(loc="best")
ax[2].plot([x for x in range(1, len(validation_cost_3)+1)],
```

```
            validation_cost_3, color="blue", label="Validation")
    ax[2].plot([x for x in range(1, len(training_cost_3)+1)],
            training_cost_3, color="red", label="Training")
    ax[2].set_xlabel("Number of Epochs")
    ax[2].set_ylabel("Cost")
    ax[2].set_title("(8,64)")
    ax[2].legend(loc="best")
    plt.show()

    #get candidates for (32,256)
    def get_candidates(We, x, words):
        np.random.seed(33)
        input_vector_train = word_embedding_to_input_vector(word_embedding, x)
        (Z1, A1, Z2, A2, d_activation_1) = forward_propagate(We, input_vector_train)
        sorted_A2_ind = np.argsort(A2, axis=0)[::-1]
        random_samples = np.random.randint(1, A2.shape[1], size=(5))
        sorted_A2_ind_random_samples = sorted_A2_ind[:, random_samples]
        x_random_samples = x[:, random_samples]
        for i in range(5):
            print(f"{words[x_random_samples[0,i]-1]} {words[x_random_samples[1,i]-1]}
{words[x_random_samples[2,i]-1]} ----> {[words[ind] for ind in
sorted_A2_ind_random_samples[:10,i].T]}")


    get_candidates(We, x_test, words)


def q3():

    def load_q3_dataset(path):
        x = np.array(h5py.File(path)["trX"]).transpose(2, 1, 0).astype(“float64)
```

```
    y = np.array(h5py.File(path)["trY"]).T.astype("float64)
    sample_size = x.shape[2]
    val_size = int(sample_size / 10)
    shuffled_indexes = np.random.permutation(sample_size)
    x = x[:, :, shuffled_indexes]
    y = y[:, shuffled_indexes]
    x_val = x[:, :, :val_size]
    y_val = y[:, :val_size]
    x_train = x[:, :, val_size:]
    y_train = y[:, val_size:]
    x_test = np.array(h5py.File(path)["tstX"]).transpose(2, 1, 0).astype("float64)
    y_test = np.array(h5py.File(path)["tstY"]).T.astype("float64)

    return x_train, y_train, x_val, y_val, x_test, y_test



x_train, y_train, x_val, y_val, x_test, y_test = load_q3_dataset("data3.h5")
print(x_train.shape)
print(y_train.shape)
print(x_val.shape)
print(y_val.shape)
print(x_test.shape)
print(y_test.shape)

#WX + b
# Parameters determine neuron numbers for related mlp hidden layers
def init_q3_params_1(mlp_first_h_layer_size, mlp_second_h_layer_size):
    # Recurrent layer, mlp hidden layer, mlp hidden layer, output layer
    # Whh Wxh W1 W2 W3 bhh bhx b1 b2 b3
    np.random.seed(33)
```

```
# Xavier Uniform Distribution
recurrent_layer_neuron_size = 128
output_layer_neuron_size = 6
input_layer_neuron_size = 3

# Wxh input layer to recurrent layer
w0 = np.sqrt(6/(input_layer_neuron_size + recurrent_layer_neuron_size))
Wxh = np.random.uniform(-w0, w0,
            size=(recurrent_layer_neuron_size, input_layer_neuron_size))

# Whh recurrent layer to recurrent layer
w0 = np.sqrt(6/(recurrent_layer_neuron_size + recurrent_layer_neuron_size))
Whh = np.random.uniform(-w0, w0, size=(recurrent_layer_neuron_size,
            recurrent_layer_neuron_size))
bh = np.random.uniform(-w0, w0, size=(recurrent_layer_neuron_size, 1))

# W1 recurrent layer to first mlp hidden layer
w0 = np.sqrt(6/(mlp_first_h_layer_size + recurrent_layer_neuron_size))
W1 = np.random.uniform(-w0, w0, size=(mlp_first_h_layer_size,
          recurrent_layer_neuron_size))
b1 = np.random.uniform(-w0, w0, size=(mlp_first_h_layer_size, 1))

# W2 first mlp hidden layer to second mlp hidden layer
w0 = np.sqrt(6/(mlp_first_h_layer_size + mlp_second_h_layer_size))
W2 = np.random.uniform(-w0, w0,
          size=(mlp_second_h_layer_size, mlp_first_h_layer_size))
b2 = np.random.uniform(-w0, w0, size=(mlp_second_h_layer_size, 1))

# W3 second mlp hidden layer to output layer
```

```
    w0 = np.sqrt(6/(output_layer_neuron_size + mlp_second_h_layer_size))
    W3 = np.random.uniform(-w0, w0,
                           size=(output_layer_neuron_size, mlp_second_h_layer_size))
    b3 = np.random.uniform(-w0, w0, size=(output_layer_neuron_size, 1))

    We = {"Whh": Whh, "bh": bh, "Wxh": Wxh, "W1": W1,
        "b1": b1, "W2": W2, "b2": b2, "W3": W3, "b3": b3}
    return We


def cross_entropy_q3(y_pred, y):
    return -np.sum(y*np.log(y_pred)) / y_pred.shape[1]


def activation(Z, activation):
    A = None
    d_activation = None

    if activation == "tanh":
        A = np.tanh(Z)
        d_activation = 1 - A ** 2

    elif activation == "sigmoid":
        Z = np.float64(Z)
        A = 1 / (1 + np.exp(-Z))
        d_activation = A * (1 - A)

    elif activation == "relu":
        A = Z * (Z > 0)
        d_activation = 1 * (Z > 0)
```

```
    elif activation == "softmax":
        # overcome exponential related overflows
        exps = np.exp(Z-np.amax(Z, axis=0))
        A = exps/np.sum(exps, axis=0)

    return A, d_activation



def forward_propagate_recurrent(We, data):
    Wxh = We["Wxh"]
    Whh = We["Whh"]
    bh = We["bh"]

    dim, time, samples = data.shape
    recurrent_layer_size = Wxh.shape[0]

    # initialize state variables
    h = np.zeros((recurrent_layer_size, time, samples))
    h_prev = np.zeros((recurrent_layer_size, samples))
    d_activations_recurrent = np.zeros((recurrent_layer_size, time, samples))

    for t in range(time):
        current_data = data[:, t, :]
        Z = np.matmul(Wxh, current_data) + np.matmul(Whh, h_prev) + bh
        h[:, t, :], d_activations_recurrent[:, t, :] = activation(Z, "tanh")
        h_prev = h[:, t, :]

    return h, d_activations_recurrent
```

```
def forward_propagation_q3_1(We, data):
    W1 = We["W1"]
    W2 = We["W2"]
    W3 = We["W3"]
    b1 = We["b1"]
    b2 = We["b2"]
    b3 = We["b3"]

    # recurrent layer
    h, d_activations_recurrent = forward_propagate_recurrent(We, data)
    A0 = h[:, -1, :]  # final state

    # relu layers
    Z1 = np.matmul(W1, A0) + b1
    A1, d_activation_1 = activation(Z1, "relu")
    Z2 = np.matmul(W2, A1) + b2
    A2, d_activation_2 = activation(Z2, "relu")

    # softmax layer
    Z3 = np.matmul(W3, A2) + b3
    A3, _ = activation(Z3, "softmax")

    return (h, Z1, A1, Z2, A2, Z3, A3, d_activation_1, d_activation_2,
d_activations_recurrent)



def cost_q3_1(We, x_train, y_train):
    W1 = We["W1"]
    W2 = We["W2"]
    W3 = We["W3"]
```

```
b1 = We["b1"]
b2 = We["b2"]
b3 = We["b3"]
Wxh = We["Wxh"]
Whh = We["Whh"]
bh = We["bh"]

# Forward propagate for training
(h, Z1, A1, Z2, A2, Z3, A3, d_activation_1, d_activation_2,
d_activations_recurrent) = forward_propagation_q3_1(We, x_train)

# Calculate training cost for this batch
batch_training_cost = cross_entropy_q3(A3, y_train)

# Backward propagate until recurrent layer
dZ3 = A3 - y_train
dW3 = np.matmul(dZ3, A2.T)
db3 = np.sum(dZ3, axis=1, keepdims=True)
dA2 = np.matmul(W3.T, dZ3)
dZ2 = dA2 * d_activation_2
dW2 = np.matmul(dZ2, A1.T)
db2 = np.sum(dZ2, axis=1, keepdims=True)
dA1 = np.matmul(W2.T, dZ2)
dZ1 = dA1 * d_activation_1
dW1 = np.matmul(dZ1, h[:, -1, :].T)  # W1 takes final state
db1 = np.sum(dZ1, axis=1, keepdims=True)

# gradient of the final state
d_state = np.matmul(W1.T, dZ1)  # dh(t)
```

```
# initialize gradients regarding recurrent layer
dWxh = 0
dWhh = 0
dbh = 0

dim, time, sample = h.shape

for t in reversed(range(time)):
    x_train_current = x_train[:, t, :]
    d_activation_recurrent_current = d_activations_recurrent[:, t, :]
    dZ_current = d_state * d_activation_recurrent_current  # dZ for given time

    if t > 0:
        h_prev = h[:, t-1, :]
    else:
        h_prev = np.zeros((Wxh.shape[0], sample))

    # Sum gradients from different times
    dWxh = dWxh + np.matmul(dZ_current, x_train_current.T)
    dWhh = dWhh + np.matmul(dZ_current, h_prev.T)
    dbh = dbh + np.sum(dZ_current, axis=1, keepdims=True)

    # Update dh(t) to dh(t-1) if t > 0
    if t > 0:
        d_state = np.matmul(Whh.T, dZ_current)

grads = {"dW1": dW1, "dW2": dW2, "dW3": dW3, "db1": db1,
        "db2": db2, "db3": db3, "dWxh": dWxh, "dWhh": dWhh, "dbh": dbh}
return batch_training_cost, grads
```

```
def update_parameters_q3_1(We, grads, learning_rate, momentum_dict, momentum_rate, batch_size):
    dW1 = grads["dW1"]
    dW2 = grads["dW2"]
    dW3 = grads["dW3"]
    dWxh = grads["dWxh"]
    dWhh = grads["dWhh"]
    db1 = grads["db1"]
    db2 = grads["db2"]
    db3 = grads["db3"]
    dbh = grads["dbh"]

    W1 = We["W1"]
    W2 = We["W2"]
    W3 = We["W3"]
    b1 = We["b1"]
    b2 = We["b2"]
    b3 = We["b3"]
    Wxh = We["Wxh"]
    Whh = We["Whh"]
    bh = We["bh"]

    cW1 = momentum_dict["cW1"]
    cW2 = momentum_dict["cW2"]
    cW3 = momentum_dict["cW3"]
    cWxh = momentum_dict["cWxh"]
    cWhh = momentum_dict["cWhh"]
    cb1 = momentum_dict["cb1"]
    cb2 = momentum_dict["cb2"]
    cb3 = momentum_dict["cb3"]
```

```
cbh = momentum_dict["cbh"]

delta_W1 = learning_rate * dW1 / batch_size + momentum_rate * cW1
delta_W2 = learning_rate * dW2 / batch_size + momentum_rate * cW2
delta_W3 = learning_rate * dW3 / batch_size + momentum_rate * cW3
delta_Wxh = learning_rate * dWxh / batch_size + momentum_rate * cWxh
delta_Whh = learning_rate * dWhh / batch_size + momentum_rate * cWhh
delta_b1 = learning_rate * db1 / batch_size + momentum_rate * cb1
delta_b2 = learning_rate * db2 / batch_size + momentum_rate * cb2
delta_b3 = learning_rate * db3 / batch_size + momentum_rate * cb3
delta_bh = learning_rate * dbh / batch_size + momentum_rate * cbh

# Update
W1 = W1 - delta_W1
W2 = W2 - delta_W2
W3 = W3 - delta_W3
Wxh = Wxh - delta_Wxh
Whh = Whh - delta_Whh
b1 = b1 - delta_b1
b2 = b2 - delta_b2
b3 = b3 - delta_b3
bh = bh - delta_bh

We = {"Whh": Whh, "bh": bh, "Wxh": Wxh, "W1": W1,
    "b1": b1, "W2": W2, "b2": b2, "W3": W3, "b3": b3}
momentum_dict = {"cW1": delta_W1, "cW2": delta_W2, "cW3": delta_W3, "cWxh": delta_Wxh,
                 "cWhh": delta_Whh, "cb1": delta_b1, "cb2": delta_b2, "cb3": delta_b3, "cbh": delta_bh}
return We, momentum_dict
```

```
def gradient_descent_q3_1(We, epoch, learning_rate, batch_size, x_train, y_train, x_val, y_val, momentum_dict, momentum_rate):
    N = x_train.shape[2]
    iteration_per_epoch = int(N / batch_size)
    validation_cost = []
    training_cost = []
    for i in range(epoch):
        mini_batch_start_index = 0
        mini_batch_end_index = batch_size
        sample_order = np.random.permutation(N)
        x_train_data = x_train[:, :, sample_order]
        y_train_data = y_train[:, sample_order]
        train_per_batch = []
        for j in range(iteration_per_epoch):
            mini_batch_data_x = x_train_data[:, :,
                                mini_batch_start_index:mini_batch_end_index]
            mini_batch_data_y = y_train_data[:,
                                mini_batch_start_index:mini_batch_end_index]
            J, grads = cost_q3_1(We, mini_batch_data_x, mini_batch_data_y)
            We, momentum_dict = update_parameters_q3_1(
                We, grads, learning_rate, momentum_dict, momentum_rate, batch_size)
            mini_batch_start_index = mini_batch_end_index
            mini_batch_end_index = mini_batch_end_index + batch_size
            train_per_batch.append(J)
            if mini_batch_end_index > N:
                mini_batch_end_index = N

        # Training cost
        training_cost_per_epoch = np.mean(train_per_batch)
        training_cost.append(training_cost_per_epoch)
```

```
        # calculate validation cost
        (h, Z1, A1, Z2, A2, Z3, A3, d_activation_1, d_activation_2,
        d_activations_recurrent) = forward_propagation_q3_1(We, x_val)
        val_cost = cross_entropy_q3(A3, y_val)
        print(
            f"Epoch = {i+1} ---> Validation cost: {val_cost} Training
cost:{training_cost_per_epoch}")
        validation_cost.append(val_cost)
        if len(validation_cost) > 1:
            delta_err = np.abs(validation_cost[-1] - validation_cost[-2])
            if delta_err < 1e-5:
                print("Training will be stopped because of low validation delta")
    return We, momentum_dict, validation_cost, training_cost



We = init_q3_params_1(64, 32)
momentum_dict = {"cW1": 0, "cW2": 0, "cW3": 0, "cWxh": 0,
                 "cWhh": 0, "cb1": 0, "cb2": 0, "cb3": 0, "cbh": 0}
We, momentum_dict, validation_cost, training_cost = gradient_descent_q3_1(
    We, 50, 0.0001, 32, x_train, y_train, x_val, y_val, momentum_dict, 0.85)

fig, ax = plt.subplots(1, 2, figsize=(14, 4))
ax[0].plot([x for x in range(1, len(validation_cost)+1)],
        validation_cost, color="blue", label="Validation")
ax[0].set_xlabel("Number of Epochs")
ax[0].set_ylabel("Cost")
ax[0].legend(loc="best")
ax[1].plot([x for x in range(1, len(training_cost)+1)],
        training_cost, color="red", label="Training")
ax[1].set_xlabel("Number of Epochs")
ax[1].set_ylabel("Cost")
```

```
ax[1].legend(loc="best")

plt.show()


def confusion_matrix(y, pred):
    class_count = len(np.unique(y))
    conf_matrix = np.zeros((class_count, class_count))
    for i in range(len(y)):
        conf_matrix[y[i]][pred[i]] += 1
    return conf_matrix


def calculate_accuracy(y, pred):
    count = 0
    for i in range(len(y)):
        if y[i] == pred[i]:
            count = count + 1
    return (100 * count / len(y))


(h, Z1, A1, Z2, A2, Z3, A3_test, d_activation_1, d_activation_2,
d_activations_recurrent) = forward_propagation_q3_1(We, x_test)
(h, Z1, A1, Z2, A2, Z3, A3_train, d_activation_1, d_activation_2,
d_activations_recurrent) = forward_propagation_q3_1(We, x_train)

pred_test = np.argmax(A3_test, axis=0)
pred_train = np.argmax(A3_train, axis=0)
y_test_ = np.argmax(y_test, axis=0)
y_train_ = np.argmax(y_train, axis=0)
```

```
test_accuracy = calculate_accuracy(y_test_, pred_test)
train_accuracy = calculate_accuracy(y_train_, pred_train)
test_cf = confusion_matrix(y_test_, pred_test)
train_cf = confusion_matrix(y_train_, pred_train)
print(f"Test accuracy:{test_accuracy}")
print(f"Train accuracy:{train_accuracy}")

sns.heatmap(test_cf, annot=True)
plt.title("Confusion Matrix on Test Set")
plt.ylabel("Actual")
plt.xlabel("Prediction")
plt.show()

sns.heatmap(train_cf, annot=True)
plt.title("Confusion Matrix on Train Set")
plt.ylabel("Actual")
plt.xlabel("Prediction")
plt.show()

# Question 3.2
#WX + b
# Parameters determine neuron numbers for related mlp hidden layers
def init_q3_params_2(mlp_first_h_layer_size, mlp_second_h_layer_size):
    # lstm layer, mlp hidden layer, mlp hidden layer, output layer
    np.random.seed(1)

    # Xavier Uniform Distribution
    recurrent_layer_neuron_size = 128
    output_layer_neuron_size = 6
    input_layer_neuron_size = 3
```

```
stacked_size = recurrent_layer_neuron_size + input_layer_neuron_size

# lstm related params
w0 = np.sqrt(6/(recurrent_layer_neuron_size + stacked_size))
Wf = np.random.uniform(-w0, w0,
                size=(recurrent_layer_neuron_size, stacked_size))
Wi = np.random.uniform(-w0, w0,
                size=(recurrent_layer_neuron_size, stacked_size))
Wc = np.random.uniform(-w0, w0,
                size=(recurrent_layer_neuron_size, stacked_size))
Wo = np.random.uniform(-w0, w0,
                size=(recurrent_layer_neuron_size, stacked_size))
bf = np.random.uniform(-w0, w0, size=(recurrent_layer_neuron_size, 1))
bi = np.random.uniform(-w0, w0, size=(recurrent_layer_neuron_size, 1))
bc = np.random.uniform(-w0, w0, size=(recurrent_layer_neuron_size, 1))
bo = np.random.uniform(-w0, w0, size=(recurrent_layer_neuron_size, 1))

# W1 recurrent layer to first mlp hidden layer
w0 = np.sqrt(6/(mlp_first_h_layer_size + recurrent_layer_neuron_size))
W1 = np.random.uniform(-w0, w0, size=(mlp_first_h_layer_size,
                recurrent_layer_neuron_size))
b1 = np.random.uniform(-w0, w0, size=(mlp_first_h_layer_size, 1))

# W2 first mlp hidden layer to second mlp hidden layer
w0 = np.sqrt(6/(mlp_first_h_layer_size + mlp_second_h_layer_size))
W2 = np.random.uniform(-w0, w0,
                size=(mlp_second_h_layer_size, mlp_first_h_layer_size))
b2 = np.random.uniform(-w0, w0, size=(mlp_second_h_layer_size, 1))

# W3 second mlp hidden layer to output layer
```

```
    w0 = np.sqrt(6/(output_layer_neuron_size + mlp_second_h_layer_size))
    W3 = np.random.uniform(-w0, w0,
                     size=(output_layer_neuron_size, mlp_second_h_layer_size))
    b3 = np.random.uniform(-w0, w0, size=(output_layer_neuron_size, 1))

    We = {"Wf": Wf, "Wi": Wi, "Wc": Wc, "Wo": Wo, "bf": bf, "bi": bi, "bc": bc,
        "bo": bo, "W1": W1, "b1": b1, "W2": W2, "b2": b2, "W3": W3, "b3": b3}
    return We



def forward_propagate_lstm(We, data):
    Wf = We["Wf"]
    Wc = We["Wc"]
    Wi = We["Wi"]
    Wo = We["Wo"]
    bf = We["bf"]
    bi = We["bi"]
    bc = We["bc"]
    bo = We["bo"]

    dim, time, samples = data.shape
    recurrent_layer_size = Wf.shape[0]

    # Initialize related variables
    stacked = np.zeros((dim+recurrent_layer_size, time, samples))
    h_prev = np.zeros((recurrent_layer_size, samples))
    c_prev = np.zeros((recurrent_layer_size, samples))
    c = np.zeros((recurrent_layer_size, time, samples))
    tanhc = np.zeros((recurrent_layer_size, time, samples))
    h_forget = np.zeros((recurrent_layer_size, time, samples))
```

```
h_input = np.zeros((recurrent_layer_size, time, samples))
h_candidate = np.zeros((recurrent_layer_size, time, samples))
h_output = np.zeros((recurrent_layer_size, time, samples))
d_activation_tanhc = np.zeros((recurrent_layer_size, time, samples))
d_activation_h_forget = np.zeros(((recurrent_layer_size, time, samples)))
d_activation_h_input = np.zeros(((recurrent_layer_size, time, samples)))
d_activation_h_candidate = np.zeros(
    ((recurrent_layer_size, time, samples)))
d_activation_h_output = np.zeros(((recurrent_layer_size, time, samples)))

for t in range(time):
    stacked[:, t, :] = np.row_stack((h_prev, data[:, t, :]))
    curr_stacked = stacked[:, t, :]

    h_forget[:, t, :], d_activation_h_forget[:, t, :] = activation(
        np.matmul(Wf, curr_stacked) + bf, "sigmoid")
    h_input[:, t, :], d_activation_h_input[:, t, :] = activation(
        np.matmul(Wi, curr_stacked) + bi, "sigmoid")
    h_candidate[:, t, :], d_activation_h_candidate[:, t, :] = activation(
        np.matmul(Wc, curr_stacked) + bc, "tanh")
    h_output[:, t, :], d_activation_h_output[:, t, :] = activation(
        np.matmul(Wo, curr_stacked) + bo, "sigmoid")

    c[:, t, :] = h_forget[:, t, :] * c_prev + \
        h_input[:, t, :] * h_candidate[:, t, :]
    tanhc[:, t, :], d_activation_tanhc[:, t,
                                  :] = activation(c[:, t, :], "tanh")
    h_prev = tanhc[:, t, :] * h_output[:, t, :]
    c_prev = c[:, t, :]
```

```
    cache = (stacked, h_prev, c, tanhc, h_forget, h_input, h_candidate, h_output,
d_activation_tanhc,
            d_activation_h_forget, d_activation_h_candidate, d_activation_h_input,
d_activation_h_output)
    return cache



def forward_propagation_q3_2(We, data):
    W1 = We["W1"]
    W2 = We["W2"]
    W3 = We["W3"]
    b1 = We["b1"]
    b2 = We["b2"]
    b3 = We["b3"]

    # recurrent layer
    cache = forward_propagate_lstm(We, data)
    A0 = cache[1]  # final state

    # relu layers
    Z1 = np.matmul(W1, A0) + b1
    A1, d_activation_1 = activation(Z1, "relu")
    Z2 = np.matmul(W2, A1) + b2
    A2, d_activation_2 = activation(Z2, "relu")

    # softmax layer
    Z3 = np.matmul(W3, A2) + b3
    A3, _ = activation(Z3, "softmax")

    return (Z1, A1, Z2, A2, Z3, A3, d_activation_1, d_activation_2, cache)
```

```
def cost_q3_2(We, x_train, y_train):
    W1 = We["W1"]
    W2 = We["W2"]
    W3 = We["W3"]
    b1 = We["b1"]
    b2 = We["b2"]
    b3 = We["b3"]
    Wf = We["Wf"]
    Wi = We["Wi"]
    Wc = We["Wc"]
    Wo = We["Wo"]
    bf = We["bf"]
    bi = We["bi"]
    bc = We["bc"]
    bo = We["bo"]

    # Forward propagate for training
    (Z1, A1, Z2, A2, Z3, A3, d_activation_1, d_activation_2,
    cache) = forward_propagation_q3_2(We, x_train)
    stacked, h_prev, c, tanhc, h_forget, h_input, h_candidate, h_output, d_activation_tanhc,
d_activation_h_forget, d_activation_h_candidate, d_activation_h_input,
d_activation_h_output = cache

    # Calculate training cost for this batch
    batch_training_cost = cross_entropy_q3(A3, y_train)

    # Backward propagate until recurrent layer
    dZ3 = A3 - y_train
    dW3 = np.matmul(dZ3, A2.T)
    db3 = np.sum(dZ3, axis=1, keepdims=True)
```

```
dA2 = np.matmul(W3.T, dZ3)
dZ2 = dA2 * d_activation_2
dW2 = np.matmul(dZ2, A1.T)
db2 = np.sum(dZ2, axis=1, keepdims=True)
dA1 = np.matmul(W2.T, dZ2)
dZ1 = dA1 * d_activation_1
dW1 = np.matmul(dZ1, h_prev.T)  # W1 takes final state
db1 = np.sum(dZ1, axis=1, keepdims=True)

# gradient of the final state
d_state = np.matmul(W1.T, dZ1)  # dh(t)
d_z = d_state

# Sizes to be used
dim, time, sample = h_forget.shape

# initialize gradients regarding lstm layer
dWf = 0
dWi = 0
dWc = 0
dWo = 0
dbf = 0
dbi = 0
dbc = 0
dbo = 0

for t in reversed(range(time)):
    stacked_curr = stacked[:, t, :]

    if t > 0:
```

```
            c_prev = c[:, t-1, :]
        else:
            c_prev = np.zeros((dim, sample))

        dc = d_z * h_output[:, t, :] * d_activation_tanhc[:, t, :]
        dhf = dc * c_prev * d_activation_h_forget[:, t, :]
        dhi = dc * h_candidate[:, t, :] * d_activation_h_input[:, t, :]
        dhc = dc * h_input[:, t, :] * d_activation_h_candidate[:, t, :]
        dho = d_z * tanhc[:, t, :] * d_activation_h_output[:, t, :]

        # Sum gradients
        dWf += np.matmul(dhf, stacked_curr.T)
        dWi += np.matmul(dhi, stacked_curr.T)
        dWc += np.matmul(dhc, stacked_curr.T)
        dWo += np.matmul(dho, stacked_curr.T)
        dbf += np.sum(dhf, axis=1, keepdims=True)
        dbi += np.sum(dhi, axis=1, keepdims=True)
        dbc += np.sum(dhc, axis=1, keepdims=True)
        dbo += np.sum(dho, axis=1, keepdims=True)

        # d_z should be updated
        # Since stack is used for weights only pick previous layers
        dxf = np.matmul(Wf.T[:dim, :], dhf)
        dxc = np.matmul(Wc.T[:dim, :], dhc)
        dxi = np.matmul(Wi.T[:dim, :], dhi)
        dxo = np.matmul(Wo.T[:dim, :], dho)

        d_z = dxf + dxc + dxi + dxo

    grads = {"dW1": dW1, "dW2": dW2, "dW3": dW3, "db1": db1, "db2": db2, "db3": db3,
"dWf": dWf,
```

```
            "dWi": dWi, "dWc": dWc, "dWo": dWo, "dbf": dbf, "dbi": dbi, "dbc": dbc, "dbo": dbo}
    return batch_training_cost, grads



def update_parameters_q3_2(We, grads, learning_rate, momentum_dict, momentum_rate, batch_size):
    W1 = We["W1"]
    W2 = We["W2"]
    W3 = We["W3"]
    b1 = We["b1"]
    b2 = We["b2"]
    b3 = We["b3"]
    Wf = We["Wf"]
    Wi = We["Wi"]
    Wc = We["Wc"]
    Wo = We["Wo"]
    bf = We["bf"]
    bi = We["bi"]
    bc = We["bc"]
    bo = We["bo"]

    delta_W1 = learning_rate * grads["dW1"] + \
        momentum_rate * momentum_dict["cW1"]
    delta_W2 = learning_rate * grads["dW2"] + \
        momentum_rate * momentum_dict["cW2"]
    delta_W3 = learning_rate * grads["dW3"] + \
        momentum_rate * momentum_dict["cW3"]
    delta_b1 = learning_rate * grads["db1"] + \
        momentum_rate * momentum_dict["cb1"]
    delta_b2 = learning_rate * grads["db2"] + \
```

```
    momentum_rate * momentum_dict["cb2"]
delta_b3 = learning_rate * grads["db3"] + \
    momentum_rate * momentum_dict["cb3"]
delta_Wf = learning_rate * grads["dWf"] + \
    momentum_rate * momentum_dict["cWf"]
delta_Wi = learning_rate * grads["dWi"] + \
    momentum_rate * momentum_dict["cWi"]
delta_Wc = learning_rate * grads["dWc"] + \
    momentum_rate * momentum_dict["cWc"]
delta_Wo = learning_rate * grads["dWo"] + \
    momentum_rate * momentum_dict["cWo"]
delta_bf = learning_rate * grads["dbf"] + \
    momentum_rate * momentum_dict["cbf"]
delta_bi = learning_rate * grads["dbi"] + \
    momentum_rate * momentum_dict["cbi"]
delta_bc = learning_rate * grads["dbc"] + \
    momentum_rate * momentum_dict["cbc"]
delta_bo = learning_rate * grads["dbo"] + \
    momentum_rate * momentum_dict["cbo"]

# Update
W1 = W1 - delta_W1
W2 = W2 - delta_W2
W3 = W3 - delta_W3
b1 = b1 - delta_b1
b2 = b2 - delta_b2
b3 = b3 - delta_b3
Wf = Wf - delta_Wf
Wi = Wi - delta_Wi
Wc = Wc - delta_Wc
```

```
        Wo = Wo - delta_Wo
        bf = bf - delta_bf
        bi = bi - delta_bi
        bc = bc - delta_bc
        bo = bo - delta_bo

        We = {"Wf": Wf, "Wi": Wi, "Wc": Wc, "Wo": Wo, "bf": bf, "bi": bi, "bc": bc,
            "bo": bo, "W1": W1, "b1": b1, "W2": W2, "b2": b2, "W3": W3, "b3": b3}
        momentum_dict = {"cW1": delta_W1, "cW2": delta_W2, "cW3": delta_W3, "cb1": delta_b1, "cb2": delta_b2, "cb3": delta_b3, "cWf": delta_Wf,
                        "cWi": delta_Wi, "cWc": delta_Wc, "cWo": delta_Wo, "cbf": delta_bf, "cbi": delta_bi, "cbc": delta_bc, "cbo": delta_bo}
        return We, momentum_dict


    def gradient_descent_q3_2(We, epoch, learning_rate, batch_size, x_train, y_train, x_val, y_val, momentum_dict, momentum_rate):
        N = x_train.shape[2]
        iteration_per_epoch = int(N / batch_size)
        validation_cost = []
        training_cost = []
        for i in range(epoch):
            mini_batch_start_index = 0
            mini_batch_end_index = batch_size
            sample_order = np.random.permutation(N)
            x_train_data = x_train[:, :, sample_order]
            y_train_data = y_train[:, sample_order]
            train_per_batch = []
            for j in range(iteration_per_epoch):
                mini_batch_data_x = x_train_data[:, :,
                                    mini_batch_start_index:mini_batch_end_index]
                mini_batch_data_y = y_train_data[:,
```

```
                        mini_batch_start_index:mini_batch_end_index]
            J, grads = cost_q3_2(We, mini_batch_data_x, mini_batch_data_y)
            We, momentum_dict = update_parameters_q3_2(
                We, grads, learning_rate, momentum_dict, momentum_rate, batch_size)
            mini_batch_start_index = mini_batch_end_index
            mini_batch_end_index = mini_batch_end_index + batch_size
            train_per_batch.append(J)
            if mini_batch_end_index > N:
                mini_batch_end_index = N

        # Training cost
        training_cost_per_epoch = np.mean(train_per_batch)
        training_cost.append(training_cost_per_epoch)

        # Forward propagate for validation
        (Z1, A1, Z2, A2, Z3, A3_val, d_activation_1, d_activation_2,
        cache) = forward_propagation_q3_2(We, x_val)
        # Calculate validation cost for this batch
        val_cost = cross_entropy_q3(A3_val, y_val)
        print(
            f"Epoch = {i+1} ---> Validation cost: {val_cost} Training
cost:{training_cost_per_epoch}")
        validation_cost.append(val_cost)
        if len(validation_cost) > 1:
            delta_err = np.abs(validation_cost[-1] - validation_cost[-2])
            if delta_err < 1e-5:
                print("Training will be stopped because of low validation delta")

    return We, momentum_dict, validation_cost, training_cost
```

```
We = init_q3_params_2(64, 32)
momentum_dict = {"cW1": 0, "cW2": 0, "cW3": 0, "cb1": 0, "cb2": 0, "cb3": 0,
                 "cWf": 0, "cWi": 0, "cWc": 0, "cWo": 0, "cbf": 0, "cbi": 0, "cbc": 0, "cbo": 0}
We, momentum_dict, validation_cost, training_cost = gradient_descent_q3_2(
    We, 50, 0.001, 32, x_train, y_train, x_val, y_val, momentum_dict, 0.85)

fig, ax = plt.subplots(1, 2, figsize=(14, 4))
ax[0].plot([x for x in range(1, len(validation_cost)+1)],
        validation_cost, color="blue", label="Validation")
ax[0].set_xlabel("Number of Epochs")
ax[0].set_ylabel("Cost")
ax[0].legend(loc="best")
ax[1].plot([x for x in range(1, len(training_cost)+1)],
        training_cost, color="red", label="Training")
ax[1].set_xlabel("Number of Epochs")
ax[1].set_ylabel("Cost")
ax[1].legend(loc="best")

plt.show()

(Z1, A1, Z2, A2, Z3, A3_test, d_activation_1, d_activation_2,
cache) = forward_propagation_q3_2(We, x_test)
(Z1, A1, Z2, A2, Z3, A3_train, d_activation_1, d_activation_2,
cache) = forward_propagation_q3_2(We, x_train)

pred_test = np.argmax(A3_test, axis=0)
pred_train = np.argmax(A3_train, axis=0)
y_test_ = np.argmax(y_test, axis=0)
y_train_ = np.argmax(y_train, axis=0)
test_accuracy = calculate_accuracy(y_test_, pred_test)
```

```
train_accuracy = calculate_accuracy(y_train_, pred_train)
test_cf = confusion_matrix(y_test_, pred_test)
train_cf = confusion_matrix(y_train_, pred_train)
print(f"Test accuracy:{test_accuracy}")
print(f"Train accuracy:{train_accuracy}")

sns.heatmap(test_cf, annot=True)
plt.title("Confusion Matrix on Test Set")
plt.ylabel("Actual")
plt.xlabel("Prediction")
plt.show()

sns.heatmap(train_cf, annot=True)
plt.title("Confusion Matrix on Train Set")
plt.ylabel("Actual")
plt.xlabel("Prediction")
plt.show()

# Question 3.3
#WX + b
# Parameters determine neuron numbers for related mlp hidden layers
def init_q3_params_3(mlp_first_h_layer_size, mlp_second_h_layer_size):
    # gru layer, mlp hidden layer, mlp hidden layer, output layer
    np.random.seed(33)

    # Xavier Uniform Distribution
    recurrent_layer_neuron_size = 128
    output_layer_neuron_size = 6
    input_layer_neuron_size = 3
```

```
# gru related params
w0 = np.sqrt(6/(recurrent_layer_neuron_size + input_layer_neuron_size))
w0_ = np.sqrt(6/(recurrent_layer_neuron_size +
        recurrent_layer_neuron_size))

Wz = np.random.uniform(-w0, w0,
            size=(recurrent_layer_neuron_size, input_layer_neuron_size))
Wr = np.random.uniform(-w0, w0,
            size=(recurrent_layer_neuron_size, input_layer_neuron_size))
Wh = np.random.uniform(-w0, w0,
            size=(recurrent_layer_neuron_size, input_layer_neuron_size))

bz = np.random.uniform(-w0, w0, size=(recurrent_layer_neuron_size, 1))
br = np.random.uniform(-w0, w0, size=(recurrent_layer_neuron_size, 1))
bh = np.random.uniform(-w0, w0, size=(recurrent_layer_neuron_size, 1))

Uz = np.random.uniform(-w0_, w0_, size=(recurrent_layer_neuron_size,
            recurrent_layer_neuron_size))
Ur = np.random.uniform(-w0_, w0_, size=(recurrent_layer_neuron_size,
            recurrent_layer_neuron_size))
Uh = np.random.uniform(-w0_, w0_, size=(recurrent_layer_neuron_size,
            recurrent_layer_neuron_size))

# W1 recurrent layer to first mlp hidden layer
w0 = np.sqrt(6/(mlp_first_h_layer_size + recurrent_layer_neuron_size))
W1 = np.random.uniform(-w0, w0, size=(mlp_first_h_layer_size,
            recurrent_layer_neuron_size))
b1 = np.random.uniform(-w0, w0, size=(mlp_first_h_layer_size, 1))

# W2 first mlp hidden layer to second mlp hidden layer
```

```
    w0 = np.sqrt(6/(mlp_first_h_layer_size + mlp_second_h_layer_size))
    W2 = np.random.uniform(-w0, w0,
                    size=(mlp_second_h_layer_size, mlp_first_h_layer_size))
    b2 = np.random.uniform(-w0, w0, size=(mlp_second_h_layer_size, 1))

    # W3 second mlp hidden layer to output layer
    w0 = np.sqrt(6/(output_layer_neuron_size + mlp_second_h_layer_size))
    W3 = np.random.uniform(-w0, w0,
                    size=(output_layer_neuron_size, mlp_second_h_layer_size))
    b3 = np.random.uniform(-w0, w0, size=(output_layer_neuron_size, 1))

    We = {"Wz": Wz, "Wr": Wr, "Wh": Wh, "Uz": Uz, "Ur": Ur, "Uh": Uh, "bz": bz,
        "br": br, "bh": bh, "W1": W1, "b1": b1, "W2": W2, "b2": b2, "W3": W3, "b3": b3}
    return We


def forward_propagate_gru(We, data):
    Wz = We["Wz"]
    Wr = We["Wr"]
    Wh = We["Wh"]
    bz = We["bz"]
    br = We["br"]
    bh = We["bh"]
    Uz = We["Uz"]
    Ur = We["Ur"]
    Uh = We["Uh"]

    dim, time, samples = data.shape
    recurrent_layer_size = Wz.shape[0]
```

```
    # Initialize related variables
    h = np.zeros((recurrent_layer_size, time, samples))
    h_prev = np.zeros((recurrent_layer_size, samples))
    z = np.zeros((recurrent_layer_size, time, samples))
    d_activation_z = np.zeros((recurrent_layer_size, time, samples))
    r = np.zeros((recurrent_layer_size, time, samples))
    d_activation_r = np.zeros((recurrent_layer_size, time, samples))
    h_ = np.zeros((recurrent_layer_size, time, samples))
    d_activation_h_ = np.zeros((recurrent_layer_size, time, samples))

    for t in range(time):
        x_cur = data[:, t, :]
        z[:, t, :], d_activation_z[:, t, :] = activation(
            np.matmul(Wz, x_cur) + np.matmul(Uz, h_prev) + bz, "sigmoid")
        r[:, t, :], d_activation_r[:, t, :] = activation(
            np.matmul(Wr, x_cur) + np.matmul(Ur, h_prev) + br, "sigmoid")
        h_[:, t, :], d_activation_h_[:, t, :] = activation(
            np.matmul(Wh, x_cur) + np.matmul(Uh, (r[:, t, :] * h_prev)) + bh, "tanh")
        h[:, t, :] = (1 - z[:, t, :]) * h_prev + z[:, t, :] * h_[:, t, :]
        h_prev = h[:, t, :]

    cache = (h, z, d_activation_z, r, d_activation_r, h_, d_activation_h_)
    return cache


def forward_propagation_q3_3(We, data):
    W1 = We["W1"]
    W2 = We["W2"]
    W3 = We["W3"]
    b1 = We["b1"]
```

```
    b2 = We["b2"]
    b3 = We["b3"]

    # recurrent layer
    cache = forward_propagate_gru(We, data)
    A0 = cache[0][:, -1, :]  # final state

    # relu layers
    Z1 = np.matmul(W1, A0) + b1
    A1, d_activation_1 = activation(Z1, "relu")
    Z2 = np.matmul(W2, A1) + b2
    A2, d_activation_2 = activation(Z2, "relu")

    # softmax layer
    Z3 = np.matmul(W3, A2) + b3
    A3, _ = activation(Z3, "softmax")

    return (Z1, A1, Z2, A2, Z3, A3, d_activation_1, d_activation_2, cache)


def cost_q3_3(We, x_train, y_train):
    W1 = We["W1"]
    W2 = We["W2"]
    W3 = We["W3"]
    b1 = We["b1"]
    b2 = We["b2"]
    b3 = We["b3"]
    Wz = We["Wz"]
    Wr = We["Wr"]
    Wh = We["Wh"]
```

```
Uz = We["Uz"]
Ur = We["Ur"]
Uh = We["Uh"]
bz = We["bz"]
br = We["br"]
bh = We["bh"]

# Forward propagate for training
(Z1, A1, Z2, A2, Z3, A3, d_activation_1, d_activation_2,
cache) = forward_propagation_q3_3(We, x_train)
(h, z, d_activation_z, r, d_activation_r, h_, d_activation_h_) = cache
h_prev = h[:, -1, :]

# Calculate training cost for this batch
batch_training_cost = cross_entropy_q3(A3, y_train)

# Backward propagate until recurrent layer
dZ3 = A3 - y_train
dW3 = np.matmul(dZ3, A2.T)
db3 = np.sum(dZ3, axis=1, keepdims=True)
dA2 = np.matmul(W3.T, dZ3)
dZ2 = dA2 * d_activation_2
dW2 = np.matmul(dZ2, A1.T)
db2 = np.sum(dZ2, axis=1, keepdims=True)
dA1 = np.matmul(W2.T, dZ2)
dZ1 = dA1 * d_activation_1
dW1 = np.matmul(dZ1, h_prev.T)  # W1 takes final state
db1 = np.sum(dZ1, axis=1, keepdims=True)

# gradient of the final state
```

```
d_state = np.matmul(W1.T, dZ1)  # dh(t)
d_z = d_state  # this d_z is not related with the parameter of z

# Sizes to be used
dim, time, sample = h.shape

# initialize gradients regarding lstm layer
dWz = 0
dWr = 0
dWh = 0
dbz = 0
dbr = 0
dbh = 0
dUz = 0
dUr = 0
dUh = 0

for t in reversed(range(time)):
    x_cur = x_train[:, t, :]

    if t > 0:
        h_prev = h[:, t-1, :]
    else:
        h_prev = np.zeros((dim, sample))

    dz = d_z * d_activation_z[:, t, :] * (h_[:, t, :] - h_prev)
    dh_ = d_z * d_activation_h_[:, t, :] * z[:, t, :]
    dr = np.matmul(Uh.T, dh_) * h_prev * d_activation_r[:, t, :]

    dWz += np.matmul(dz, x_cur.T)
```

```
            dUz += np.matmul(dz, h_prev.T)
            dbz += np.sum(dz, axis=1, keepdims=True)

            dWh += np.matmul(dh_, x_cur.T)
            dUh += np.matmul(dh_, h_prev.T)
            dbh += np.sum(dh_, axis=1, keepdims=True)

            dWr += np.matmul(dr, x_cur.T)
            dUr += np.matmul(dr, h_prev.T)
            dbr += np.sum(dr, axis=1, keepdims=True)

            # update d_z
            d1 = d_z * (1-z[:, t, :])
            d2 = np.matmul(Uz.T, dz)
            d3 = np.matmul(
                Uh.T, dh_) * (r[:, t, :] + h_prev * np.matmul(Ur.T, d_activation_r[:, t, :]))
            d_z = d1 + d2 + d3

        grads = {"dW1": dW1, "dW2": dW2, "dW3": dW3, "db1": db1, "db2": db2, "db3": db3, "dWz": dWz,
                 "dWr": dWr, "dWh": dWh, "dbz": dbz, "dbr": dbr, "dbh": dbh, "dUz": dUz, "dUr": dUr, "dUh": dUh}
        return batch_training_cost, grads



    def update_parameters_q3_3(We, grads, learning_rate, momentum_dict, momentum_rate, batch_size):
        W1 = We["W1"]
        W2 = We["W2"]
        W3 = We["W3"]
        b1 = We["b1"]
        b2 = We["b2"]
```

```
b3 = We["b3"]
Wz = We["Wz"]
Wr = We["Wr"]
Wh = We["Wh"]
bz = We["bz"]
br = We["br"]
bh = We["bh"]
Uz = We["Uz"]
Ur = We["Ur"]
Uh = We["Uh"]

delta_W1 = learning_rate * grads["dW1"] + \
    momentum_rate * momentum_dict["cW1"]
delta_W2 = learning_rate * grads["dW2"] + \
    momentum_rate * momentum_dict["cW2"]
delta_W3 = learning_rate * grads["dW3"] + \
    momentum_rate * momentum_dict["cW3"]
delta_b1 = learning_rate * grads["db1"] + \
    momentum_rate * momentum_dict["cb1"]
delta_b2 = learning_rate * grads["db2"] + \
    momentum_rate * momentum_dict["cb2"]
delta_b3 = learning_rate * grads["db3"] + \
    momentum_rate * momentum_dict["cb3"]
delta_Wz = learning_rate * grads["dWz"] + \
    momentum_rate * momentum_dict["cWz"]
delta_Wr = learning_rate * grads["dWr"] + \
    momentum_rate * momentum_dict["cWr"]
delta_Wh = learning_rate * grads["dWh"] + \
    momentum_rate * momentum_dict["cWh"]
delta_bz = learning_rate * grads["dbz"] + \
```

```
    momentum_rate * momentum_dict["cbz"]
delta_br = learning_rate * grads["dbr"] + \
    momentum_rate * momentum_dict["cbr"]
delta_bh = learning_rate * grads["dbh"] + \
    momentum_rate * momentum_dict["cbh"]
delta_Uz = learning_rate * grads["dUz"] + \
    momentum_rate * momentum_dict["cUz"]
delta_Ur = learning_rate * grads["dUr"] + \
    momentum_rate * momentum_dict["cUr"]
delta_Uh = learning_rate * grads["dUh"] + \
    momentum_rate * momentum_dict["cUh"]

# Update
W1 = W1 - delta_W1
W2 = W2 - delta_W2
W3 = W3 - delta_W3
b1 = b1 - delta_b1
b2 = b2 - delta_b2
b3 = b3 - delta_b3
Wz = Wz - delta_Wz
Wr = Wr - delta_Wr
Wh = Wh - delta_Wh
bz = bz - delta_bz
br = br - delta_br
bh = bh - delta_bh
Uz = Uz - delta_Uz
Ur = Ur - delta_Ur
Uh = Uh - delta_Uh

We = {"Wz": Wz, "Wr": Wr, "Wh": Wh, "Uz": Uz, "Ur": Ur, "Uh": Uh, "bz": bz,
```

```
            "br": br, "bh": bh, "W1": W1, "b1": b1, "W2": W2, "b2": b2, "W3": W3, "b3": b3}
    momentum_dict = {"cW1": delta_W1, "cW2": delta_W2, "cW3": delta_W3, "cb1": delta_b1, "cb2": delta_b2, "cb3": delta_b3, "cWz": delta_Wz,
                     "cWr": delta_Wr, "cWh": delta_Wh, "cbz": delta_bz, "cbr": delta_br, "cbh": delta_bh, "cUz": delta_Uz, "cUr": delta_Ur, "cUh": delta_Uh}
    return We, momentum_dict


def gradient_descent_q3_3(We, epoch, learning_rate, batch_size, x_train, y_train, x_val, y_val, momentum_dict, momentum_rate):
    N = x_train.shape[2]
    iteration_per_epoch = int(N / batch_size)
    validation_cost = []
    training_cost = []

    for i in range(epoch):
        mini_batch_start_index = 0
        mini_batch_end_index = batch_size
        sample_order = np.random.permutation(N)
        x_train_data = x_train[:, :, sample_order]
        y_train_data = y_train[:, sample_order]
        train_per_batch = []
        for j in range(iteration_per_epoch):
            mini_batch_data_x = x_train_data[:, :,
                                mini_batch_start_index:mini_batch_end_index]
            mini_batch_data_y = y_train_data[:,
                                mini_batch_start_index:mini_batch_end_index]
            J, grads = cost_q3_3(We, mini_batch_data_x, mini_batch_data_y)
            We, momentum_dict = update_parameters_q3_3(
                We, grads, learning_rate, momentum_dict, momentum_rate, batch_size)
            mini_batch_start_index = mini_batch_end_index
            mini_batch_end_index = mini_batch_end_index + batch_size
```

```
            train_per_batch.append(J)
            if mini_batch_end_index > N:
                mini_batch_end_index = N

        # Training cost
        training_cost_per_epoch = np.mean(train_per_batch)
        training_cost.append(training_cost_per_epoch)

        # Forward propagate for validation
        (Z1, A1, Z2, A2, Z3, A3_val, d_activation_1, d_activation_2,
        cache) = forward_propagation_q3_3(We, x_val)

        # Calculate validation cost for this batch
        val_cost = cross_entropy_q3(A3_val, y_val)
        print(
            f"Epoch = {i+1} ---> Validation cost: {val_cost} Training
cost:{training_cost_per_epoch}")
        validation_cost.append(val_cost)
        if len(validation_cost) > 1:
            delta_err = np.abs(validation_cost[-1] - validation_cost[-2])
            if delta_err < 1e-5:
                print("Training will be stopped because of low validation delta")

    return We, momentum_dict, validation_cost, training_cost



We = init_q3_params_3(64, 32)
momentum_dict = {"cW1": 0, "cW2": 0, "cW3": 0, "cb1": 0, "cb2": 0, "cb3": 0, "cWz": 0,
                "cWr": 0, "cWh": 0, "cbz": 0, "cbr": 0, "cbh": 0, "cUz": 0, "cUr": 0, "cUh": 0}
We, momentum_dict, validation_cost, training_cost = gradient_descent_q3_3(
    We, 50, 0.0005, 32, x_train, y_train, x_val, y_val, momentum_dict, 0.85)
```

```
fig, ax = plt.subplots(1, 2, figsize=(14, 4))
ax[0].plot([x for x in range(1, len(validation_cost)+1)],
        validation_cost, color="blue", label="Validation")
ax[0].set_xlabel("Number of Epochs")
ax[0].set_ylabel("Cost")
ax[0].legend(loc="best")
ax[1].plot([x for x in range(1, len(training_cost)+1)],
        training_cost, color="red", label="Training")
ax[1].set_xlabel("Number of Epochs")
ax[1].set_ylabel("Cost")
ax[1].legend(loc="best")

plt.show()

(Z1, A1, Z2, A2, Z3, A3_test, d_activation_1, d_activation_2,
cache) = forward_propagation_q3_3(We, x_test)
(Z1, A1, Z2, A2, Z3, A3_train, d_activation_1, d_activation_2,
cache) = forward_propagation_q3_3(We, x_train)

pred_test = np.argmax(A3_test, axis=0)
pred_train = np.argmax(A3_train, axis=0)
y_test_ = np.argmax(y_test, axis=0)
y_train_ = np.argmax(y_train, axis=0)
test_accuracy = calculate_accuracy(y_test_, pred_test)
train_accuracy = calculate_accuracy(y_train_, pred_train)
test_cf = confusion_matrix(y_test_, pred_test)
train_cf = confusion_matrix(y_train_, pred_train)
print(f"Test accuracy:{test_accuracy}")
print(f"Train accuracy:{train_accuracy}")
```

```
sns.heatmap(test_cf, annot=True)
plt.title("Confusion Matrix on Test Set")
plt.ylabel("Actual")
plt.xlabel("Prediction")
plt.show()

sns.heatmap(train_cf, annot=True)
plt.title("Confusion Matrix on Train Set")
plt.ylabel("Actual")
plt.xlabel("Prediction")
plt.show()
```

arda_baris_ortlek_21903472_hw1(question)