In []:

```
import os
import numpy as np
import time
import random
import tensorflow as tf
from tensorflow import keras

import matplotlib.pyplot as plt

np.random.seed(1234)
tf.random.set_seed(1234)
```

In []:

```
tf.config.list_physical_devices('GPU')
```

```
(X_train, y_train), (X_test, y_test) = keras.datasets.fashion_mnist.load_data() #
Load MNIST or FMNIST
assert X_train.shape == (60000, 28, 28)
assert X_test.shape == (10000, 28, 28)
assert y_train.shape == (60000,)
assert y_test.shape == (10000,)

# Display randomly selected data
indices = list(np.random.randint(X_train.shape[0],size=3))
for i in range(3):
    plt.subplot(1,3,i+1)
    plt.imshow(X_train[indices[i]].reshape(28,28), cmap='gray', interpolation='non
e')
    plt.title("Index {} Class {}".format(indices[i], y_train[indices[i]]))
    plt.tight_layout()
```

In []:

```
# Split train dataset into train and validation
        = X train[50000:60000]
X train = X train[0:50000]
        = y_{train}[50000:60000]
y_{train} = y_{train}[0:50000]
print("size of training set is", str(X_train.shape[0]), "samples")
print("every train example is", str(X_train.shape[1]), "by", str(X_train.shape[2
1))
print("size of validation set is", str(X val.shape[0]), "samples")
print("every validation example is", str(X val.shape[1]), "by", str(X val.shape[2
1))
X \text{ train} = X \text{ train.reshape}(50000, 28*28)
X \text{ val} = X \text{ val.reshape}(10000, 28*28)
X \text{ test} = X \text{ test.reshape}(10000, 28*28)
print("size of training set is", str(X_train.shape[0]), "samples")
print("every train example has", str(X train.shape[1]), "features")
print("size of validation set is", str(X_val.shape[0]), "samples")
print("every validation example has", str(X val.shape[1]), "features")
# Split dataset into batches
\#train\ ds = tf.data.Dataset.from\ tensor\ slices((X\ train,\ y\ train)).batch(16)
#test ds = tf.data.Dataset.from tensor slices((X test, y test)).batch(4)
```

```
#Normalize Data

X_train = X_train/255
X_val = X_val/255
X_test = X_test/255

print(f'max: ', np.max(X_train))
print(f'min: ', np.min(X_train))
```

```
size_input = X_train.shape[1]

size_hidden1 = 128
size_hidden2 = 128
size_hidden3 = 128

size_output = 10

number_of_train_examples = X_train.shape[0]
number_of_test_examples = X_test.shape[0]

y_train = tf.keras.utils.to_categorical(y_train, num_classes=10) # Other function
    is tf.one_hot(y_train,depth=10)
y_val = tf.keras.utils.to_categorical(y_val, num_classes=10)
y_test = tf.keras.utils.to_categorical(y_test, num_classes=10)
print(tf.shape(y_val))
```

```
# Define class to build mlp model
class MLP(object):
    def init (self, size input, size hidden1, size hidden2, size hidden3, size
output, device=None):
        size_input: int, size of input layer
        size hidden1: int, size of the 1st hidden layer
        size_hidden2: int, size of the 2nd hidden layer
        size output: int, size of output layer
        device: str or None, either 'cpu' or 'gpu' or None. If None, the device to
be used will be decided automatically during Eager Execution
        self.size input, self.size hidden1, self.size hidden2, self.size hidden3,
self.size_output, self.device =\
        size input, size hidden1, size hidden2, size hidden3, size output, device
        # Initialize weights between input mapping and a layer q(f(x)) = layer
        self.W1 = tf.Variable(tf.random.normal([self.size input, self.size hidden1
],stddev=0.1)) # Xavier(Fan-in fan-out) and Orthogonal
        # Initialize biases for hidden layer
        self.b1 = tf.Variable(tf.zeros([1, self.size hidden1])) # 0 or constant(0.
01)
        # Initialize weights between input layer and 1st hidden layer
        self.W2 = tf.Variable(tf.random.normal([self.size_hidden1, self.size_hidde
n2],stddev=0.1))
        # Initialize biases for hidden layer
        self.b2 = tf.Variable(tf.zeros([1, self.size hidden2]))
        # Initialize weights between 1st hidden layer and 2nd hidden layer
        self.W3 = tf.Variable(tf.random.normal([self.size hidden2, self.size hidde
n3], stddev=0.1))
        # Initialize biases for hidden layer
        self.b3 = tf.Variable(tf.zeros([1, self.size hidden3]))
        # Initialize weights between 2nd hidden layer and output layer
        self.W4 = tf.Variable(tf.random.normal([self.size hidden3, self.size outpu
tl,stddev=0.1)
        # Initialize biases for output layer
        self.b4 = tf.Variable(tf.zeros([1, self.size output]))
        # Initializing gamma and beta for all the layers for batch norm
        self.gamma = {"1": tf.Variable(tf.ones(self.W1.shape[-1])),
                      "2": tf.Variable(tf.ones(self.W2.shape[-1])),
                      "3": tf.Variable(tf.ones(self.W3.shape[-1]))
                      #"4": tf.Variable(tf.ones(self.W4.shape[-1]))
        self.beta = {"1": tf.Variable(tf.zeros(self.W1.shape[-1])),
                      "2": tf.Variable(tf.zeros(self.W2.shape[-1])),
                      "3": tf.Variable(tf.zeros(self.W3.shape[-1]))
                      #"4": tf.Variable(tf.zeros(self.W4.shape[-1]))
        # Define variables to be updated during backpropagation
```

```
self.variables = [self.W1, self.W2, self.W3, self.W4,
                          self.b1, self.b2, self.b3, self.b4,
                          self.gamma["1"], self.beta["1"],
                          self.gamma["2"], self.beta["2"],
                          self.gamma["3"], self.beta["3"]]
                          #self.gamma["4"], self.beta["4"]]
        self.mean = {"1": tf.Variable(tf.zeros(self.W1.shape[-1])),
                     "2": tf.Variable(tf.zeros(self.W2.shape[-1])),
                     "3": tf.Variable(tf.zeros(self.W3.shape[-1]))
                     #"4": tf.Variable(tf.zeros(self.W4.shape[-1])),
        }
        self.var = {"1": tf.Variable(tf.zeros(self.W1.shape[-1])),
                    "2": tf.Variable(tf.zeros(self.W2.shape[-1])),
                    "3": tf.Variable(tf.zeros(self.W3.shape[-1]))
                    #"4": tf.Variable(tf.zeros(self.W4.shape[-1])),
        }
    def forward(self, X, run):
        forward pass
        X: Tensor, inputs
        0.00
        if self.device is not None:
            with tf.device('gpu:0' if self.device=='gpu' else 'cpu'):
                if run == "train":
                    self.y = self.compute output train(X)
                else:
                    self.v = self.compute output test(X)
        else:
            if run == "train":
                self.y = self.compute output train(X)
            else:
                self.y = self.compute output test(X)
        return self.y
    def loss(self, y_pred, y_true):
        y_pred - Tensor of shape (batch_size, size_output)
        y_true - Tensor of shape (batch_size, size_output)
        #y_true_tf = tf.cast(tf.reshape(y_true, (-1, self.size_output)), dtype=tf.
float32)
        y_true_tf = tf.cast(y_true, dtype=tf.float32)
        y pred tf = tf.cast(y pred, dtype=tf.float32)
        cce = tf.keras.losses.CategoricalCrossentropy(from logits=True)
        loss_x = cce(y_true_tf, y_pred_tf)
        # Use keras or tf_softmax, both should work for any given model
        #loss x = tf.reduce mean(tf.nn.softmax cross entropy with logits(logits=y)
pred tf, labels=y true tf))
        return loss x
    def backward(self, X train, y train, opti):
```

```
backward pass
        optimizer = opti
        with tf.GradientTape() as tape:
            predicted = self.forward(X_train, "train")
            current loss = self.loss(predicted, y train)
        grads = tape.gradient(current loss, self.variables)
        optimizer.apply gradients(zip(grads, self.variables))
    def batch norm(self, inputs, layer):
        mean, var = tf.nn.moments(inputs, [0])
        self.mean[layer] = 0.9*self.mean[layer] + 0.1*mean
        self.var[layer] = 0.9*self.var[layer] + 0.1*var
        return tf.add(tf.divide(tf.multiply(self.gamma[layer], tf.subtract(inputs,
mean)), tf.sqrt(var+1e-8)), self.beta[layer])
    def compute output train(self, X):
        Custom method to obtain output tensor during forward pass
        # Cast X to float32
        X tf = tf.cast(X, dtype=tf.float32)
        \#X \ tf = X
        # Compute values in hidden layers
        z1 = tf.matmul(X tf, self.W1) + self.b1
        z1 = self.batch norm(z1, "1")
        h1 = tf.nn.relu(z1)
        z2 = tf.matmul(h1, self.W2) + self.b2
        z2 = self.batch norm(z2, "2")
        h2 = tf.nn.relu(z2)
        z3 = tf.matmul(h2, self.W3) + self.b3
        z3 = self.batch norm(z3, "3")
        h3 = tf.nn.relu(z3)
        # Compute output
        output = tf.matmul(h3, self.W4) + self.b4
        #output = self.batch_norm(output, "4")
        #Now consider two things , First look at inbuild loss functions if they wo
rk with softmax or not and then change this
        # Second add tf.Softmax(output) and then return this variable
        return (output)
    def compute_output_test(self, X):
        Custom method to obtain output tensor during forward pass
        # Cast X to float32
        X tf = tf.cast(X, dtype=tf.float32)
        \#X \ tf = X
```

```
# Compute values in hidden layers
        z1 = tf.matmul(X tf, self.W1) + self.b1
        z1 = tf.add(tf.divide(tf.multiply(self.gamma["1"], tf.subtract(z1, self.me
an["1"])), tf.sqrt(self.var["1"])), self.beta["1"])
        h1 = tf.nn.relu(z1)
        z2 = tf.matmul(h1, self.W2) + self.b2
        z2 = tf.add(tf.divide(tf.multiply(self.gamma["2"], tf.subtract(z2, self.me
an["2"])), tf.sqrt(self.var["2"])), self.beta["2"])
        h2 = tf.nn.relu(z2)
        z3 = tf.matmul(h2, self.W3) + self.b3
        z3 = tf.add(tf.divide(tf.multiply(self.gamma["3"], tf.subtract(z3, self.me
an["3"])), tf.sqrt(self.var["3"])), self.beta["3"])
        h3 = tf.nn.relu(z3)
        # Compute output
        output = tf.matmul(h3, self.W4) + self.b4
        #Now consider two things , First look at inbuild loss functions if they wo
rk with softmax or not and then change this
        # Second add tf.Softmax(output) and then return this variable
        return (output)
```

In [10]:

```
seeds = random.sample(range(1000, 9999), 3)
for trail in range(3):
   seed = seeds[trail]
   ion for seed {seed} ************\n')
   # Set number of epochs
   NUM EPOCHS = 10
   # Initialize model using CPU
   mlp on gpu = MLP(size input, size hidden1, size hidden2, size hidden3, size ou
tput, device='gpu')
   time start = time.time()
   opti = tf.keras.optimizers.SGD(learning rate = 0.1)
   for epoch in range(NUM EPOCHS):
       loss total = tf.zeros([1,1], dtype=tf.float32)
       lt = 0
       train ds = tf.data.Dataset.from tensor slices((X train, y train)).shuffle(
25, seed=epoch*(seed)).batch(128)
       kz = 0
       accuracy z = 0.0
       cur train acc = 0.0
       for inputs, outputs in train ds:
           qw, tr = tf.shape(inputs)
           kz = kz + 1
           preds = mlp on gpu.forward(inputs, "train")
           loss total = loss total + mlp on gpu.loss(preds, outputs)
           lt = lt + mlp_on_gpu.loss(preds, outputs)
           mlp on gpu.backward(inputs, outputs, opti)
       preds = mlp on gpu.forward(X train, "train")
       # Get probs, remember we only have logits from our forward function, we ne
ed to apply softmax on top of it to get probs
       preds = tf.nn.softmax(preds)
       correct prediction = tf.equal(tf.argmax(preds, 1), tf.argmax(y train, 1))
       accuracy z = accuracy z + tf.reduce mean(tf.cast(correct prediction, "floa
t"))
       cur_train_acc += accuracy_z.numpy()
       ds = cur train acc
       print('\nTrain Accuracy: {:.4f}'.format(ds))
       print('Number of Epoch = {} - Average Cross Entropy:= {} '.format(epoch +
1, np.sum(loss total) / X train.shape[0]))
       preds val = mlp on gpu.forward(X val, "train")
       preds val = tf.nn.softmax(preds val)
       correct prediction = tf.equal(tf.argmax(preds val, 1), tf.argmax(y val, 1
))
       # Calculate accuracy
       accuracy = tf.reduce mean(tf.cast(correct prediction, "float"))
```

```
cur val acc = accuracy.numpy()
        print('\nValidation Accuracy: {:.4f}'.format(cur val acc))
        plt.plot(epoch + 1, np.sum(loss_total) / X_train.shape[0], 'go')
    time taken = time.time() - time start
    plt.show()
    # Validate model
    print('\nTotal time taken (in seconds): {:.2f}'.format(time taken))
    #For per epoch time = Total Time / Number of epochs
    test loss total = tf.Variable(0, dtype=tf.float32)
    correct prediction = tf.Variable(0, dtype=tf.float32)
    test ds = tf.data.Dataset.from tensor slices((X test, y test)).batch(4)
    #test loss total = 0.0
    for inputs, outputs in test ds:
        preds = mlp on gpu.forward(inputs, "test")
        test loss total = test loss total + mlp on gpu.loss(preds, outputs)
    print('Test loss: {:.4f}'.format(np.sum(test loss total.numpy()) / X test.shap
e[0]))
    # Test model
    preds test = mlp on gpu.forward(X test, "test")
    preds test = tf.nn.softmax(preds test)
    correct prediction = tf.equal(tf.argmax(preds test, 1), tf.argmax(y test, 1))
    # Calculate accuracy
    accuracy = tf.reduce mean(tf.cast(correct prediction, "float"))
    cur test acc = accuracy.numpy()
    print('\nTest Accuracy: {:.2f}'.format(cur test acc))
```

******** Running MLP with pre-activation Batch Normalization for seed 2977 ***********

Train Accuracy: 0.8617

Number of Epoch = 1 - Average Cross Entropy:= 0.004356533813476562

Validation Accuracy: 0.8495

Train Accuracy: 0.8788

Number of Epoch = 2 - Average Cross Entropy:= 0.0029947314453125

Validation Accuracy: 0.8659

Train Accuracy: 0.8902

Number of Epoch = 3 - Average Cross Entropy:= 0.002642081604003906

Validation Accuracy: 0.8721

Train Accuracy: 0.9009

Number of Epoch = 4 - Average Cross Entropy:= 0.0024121412658691405

Validation Accuracy: 0.8759

Train Accuracy: 0.9096

Number of Epoch = 5 - Average Cross Entropy:= 0.002219288635253906

Validation Accuracy: 0.8788

Train Accuracy: 0.9147

Number of Epoch = 6 - Average Cross Entropy:= 0.002058863525390625

Validation Accuracy: 0.8795

Train Accuracy: 0.9211

Number of Epoch = 7 - Average Cross Entropy:= 0.001903658447265625

Validation Accuracy: 0.8822

Train Accuracy: 0.9256

Number of Epoch = 8 - Average Cross Entropy:= 0.0017605203247070312

Validation Accuracy: 0.8800

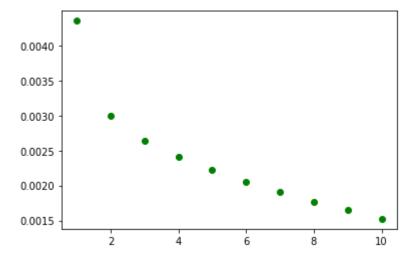
Train Accuracy: 0.9294

Number of Epoch = 9 - Average Cross Entropy:= 0.00164457275390625

Validation Accuracy: 0.8785

Train Accuracy: 0.9341

Number of Epoch = 10 - Average Cross Entropy:= 0.0015227243041992188



Total time taken (in seconds): 107.32

Test loss: 0.0958

Test Accuracy: 0.87

for seed 1427 ************

Train Accuracy: 0.8587

Number of Epoch = 1 - Average Cross Entropy:= 0.00438836181640625

Validation Accuracy: 0.8476

Train Accuracy: 0.8780

Number of Epoch = 2 - Average Cross Entropy:= 0.0030348040771484377

Validation Accuracy: 0.8601

Train Accuracy: 0.8888

Number of Epoch = 3 - Average Cross Entropy:= 0.0026650567626953126

Validation Accuracy: 0.8650

Train Accuracy: 0.9002

Number of Epoch = 4 - Average Cross Entropy:= 0.0024279241943359377

Validation Accuracy: 0.8714

Train Accuracy: 0.9047

Number of Epoch = 5 - Average Cross Entropy:= 0.0022358851623535156

Validation Accuracy: 0.8710

Train Accuracy: 0.9112

Number of Epoch = 6 - Average Cross Entropy:= 0.002071214599609375

Validation Accuracy: 0.8748

Train Accuracy: 0.9190

Number of Epoch = 7 - Average Cross Entropy:= 0.0019120587158203124

Validation Accuracy: 0.8759

Train Accuracy: 0.9236

Number of Epoch = 8 - Average Cross Entropy:= 0.0017844329833984374

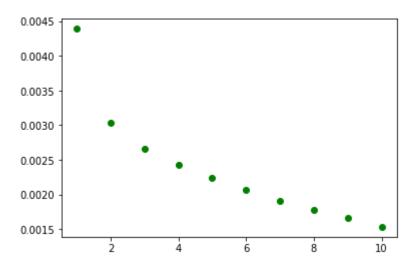
Validation Accuracy: 0.8789

Train Accuracy: 0.9290

Number of Epoch = 9 - Average Cross Entropy:= 0.0016624235534667968

Train Accuracy: 0.9308

Number of Epoch = 10 - Average Cross Entropy:= 0.0015360650634765624



Total time taken (in seconds): 115.79

Test loss: 0.1016

Test Accuracy: 0.87

******** Running MLP with pre-activation Batch Normalization for seed 9846 ************

Train Accuracy: 0.8614

Number of Epoch = 1 - Average Cross Entropy:= 0.004333209228515625

Validation Accuracy: 0.8449

Train Accuracy: 0.8805

Number of Epoch = 2 - Average Cross Entropy:= 0.0029972756958007813

Validation Accuracy: 0.8608

Train Accuracy: 0.8918

Number of Epoch = 3 - Average Cross Entropy:= 0.0026356414794921875

Validation Accuracy: 0.8692

Train Accuracy: 0.9004

Number of Epoch = 4 - Average Cross Entropy:= 0.0024016685485839843

Validation Accuracy: 0.8744

Train Accuracy: 0.9084

Number of Epoch = 5 - Average Cross Entropy:= 0.002214339141845703

Validation Accuracy: 0.8771

Train Accuracy: 0.9153

Number of Epoch = 6 - Average Cross Entropy:= 0.0020412139892578124

Validation Accuracy: 0.8782

Train Accuracy: 0.9199

Number of Epoch = 7 - Average Cross Entropy:= 0.0019056634521484375

Validation Accuracy: 0.8800

Train Accuracy: 0.9246

Number of Epoch = 8 - Average Cross Entropy:= 0.0017654421997070312

Validation Accuracy: 0.8798

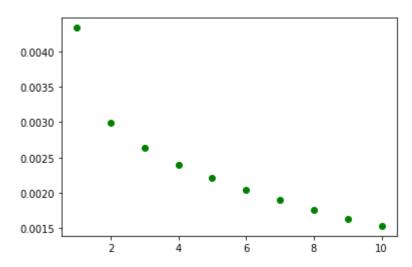
Train Accuracy: 0.9310

Number of Epoch = 9 - Average Cross Entropy:= 0.0016393472290039063

Train Accuracy: 0.9326

Number of Epoch = 10 - Average Cross Entropy:= 0.0015347804260253907

Validation Accuracy: 0.8825



Total time taken (in seconds): 111.65

Test loss: 0.0923

Test Accuracy: 0.88