In [7]:

```
import tensorflow as tf
import numpy as np
import matplotlib.pyplot as plt

np.random.seed(4321)
```

In [8]:

```
(x train, y train), (x test, y test) = tf.keras.datasets.fashion mnist.load data()
x \text{ val} = x \text{ train}[50000:60000]
x train = x train[0:50000]
y \text{ val} = y \text{ train}[50000:60000]
y train = y train[0:50000]
x train = x train.astype(np.float32).reshape(-1,28,28,1) / 255.0
x \text{ val} = x \text{ val.astype(np.float32).reshape(-1,28,28,1)} / 255.0
x_{test} = x_{test.astype(np.float32).reshape(-1,28,28,1) / 255.0
y train = tf.one hot(y train, depth=10)
y_val = tf.one_hot(y_val, depth=10)
y test = tf.one hot(y test, depth=10)
print(x train.shape)
print(x test.shape)
print(x val.shape)
train dataset = tf.data.Dataset.from tensor slices((x train, y train))
train_dataset = train_dataset.shuffle(buffer_size=1024).batch(128)
train dataset full = train dataset.shuffle(buffer size=1024).batch(len(train datas
et))
val dataset = tf.data.Dataset.from tensor slices((x val, y val))
val dataset = val_dataset.batch(128)
test dataset = tf.data.Dataset.from tensor slices((x test, y test))
test dataset = test dataset.batch(128)
print(len(train dataset))
print(len(test dataset))
(50000, 28, 28, 1)
```

```
(50000, 28, 28, 1)
(10000, 28, 28, 1)
(10000, 28, 28, 1)
391
79
```

In [9]:

```
class BatchNormalization(tf.keras.layers.Layer):
    def __init__(self, batch_size, training=False):
        super(BatchNormalization, self).__init__()
        self.convexCoeff = 0.9
        self.numCalls = 0
        self.batch size = batch_size
        self.training = training
        self.gamma = self.add weight(name='gamma', shape=[self.batch size,], initi
alizer=tf.initializers.ones, trainable=True)
        self.beta = self.add weight(name='beta', shape=[self.batch size,], initi
alizer=tf.initializers.zeros, trainable=True)
        self.mean = self.add weight(name='mean',
                                                     shape=[self.batch size,], initi
alizer=tf.initializers.zeros, trainable=False)
        self.var = self.add weight(name='var',
                                                     shape=[self.batch size,], initi
alizer=tf.initializers.zeros, trainable=False)
    def batch norm(self, inputs, training):
        self.numCalls += 1
        axes = list(range(len(inputs.shape) - 1))
        mean = tf.reduce mean(inputs, axes, keepdims=True)
        var = tf.reduce mean(tf.math.squared difference(inputs, tf.stop gradient(
mean)), axes, keepdims=True)
        if training:
            norm = tf.add(tf.multiply(self.gamma, tf.divide(tf.subtract(inputs, me
an), tf.sqrt(var+1e-7))), self.beta)
            mean = tf.squeeze(mean, axes)
            var = tf.squeeze(var, axes)
            moving_avg_mean = ((self.convexCoeff/self.numCalls)*mean) + (1-(self.c
onvexCoeff/self.numCalls)*self.mean)
            moving avg var = ((self.convexCoeff/self.numCalls)*var) + (1-(self.convexCoeff/self.numCalls)*var) + (1-(self.convexCoeff/self.numCalls)*var)
onvexCoeff/self.numCalls)*self.var)
            self.mean.assign(moving avg mean)
            self.var.assign(moving avg var)
        else:
            norm = tf.add(tf.multiply(self.gamma, tf.divide(tf.subtract(inputs, me
an), tf.sqrt(var+1e-7))), self.beta)
        return norm
```

In [10]:

```
class ImageRecognitionCNN(tf.keras.Model):
    def __init__(self, num_classes, device='cpu:0', checkpoint_directory=None):
           Define the parameterized layers used during forward-pass, the device
            where you would like to run the computation (GPU, TPU, CPU) on and the
checkpoint
            directory.
            Args:
                num_classes: the number of labels in the network.
                device: string, 'cpu:n' or 'gpu:n' (n can vary). Default, 'cpu:0'.
                checkpoint directory: the directory where you would like to save o
r
                                      restore a model.
        1.1.1
        super(ImageRecognitionCNN, self). init ()
        # Initialize layers
        self.conv1 = tf.keras.layers.Conv2D(64, 3, padding='same', activation=None
)
        self.conv2 = tf.keras.layers.Conv2D(64, 3,padding='same', activation=None)
        self.pool1 = tf.keras.layers.MaxPool2D()
        self.conv3 = tf.keras.layers.Conv2D(64, 3, padding='same', activation=None
)
        self.conv4 = tf.keras.layers.Conv2D(64, 3, padding='same', activation=None
)
        # self.pool2 = tf.keras.layers.MaxPool2D()
        # self.conv5 = tf.keras.layers.Conv2D(64, 3, padding='same', activation=No
ne)
        # self.pool2 = tf.keras.layers.MaxPool2D()
        # self.conv6 = tf.keras.layers.Conv2D(64, 3, 2, padding='same', activation
=None)
        # self.conv7 = tf.keras.layers.Conv2D(64, 1, padding='same', activation=No
ne)
        self.conv8 = tf.keras.layers.Conv2D(num classes, 1, padding='same', activa
tion=None)
        self.BN = BatchNormalization(64)
        # Define the device
        self.device = device
        # Define the checkpoint directory
        self.checkpoint directory = checkpoint directory
        self.acc = tf.keras.metrics.Accuracy()
    def predict(self, images, training):
        """ Predicts the probability of each class, based on the input sample.
            Args:
                images: 4D tensor. Either an image or a batch of images.
                training: Boolean. Either the network is predicting in
                          training mode or not.
```

```
x = self.conv1(images)
        x = self.BN.batch norm(x, training)
        x = tf.nn.relu(x)
        x = self.pool1(x)
        x = self.conv2(x)
        x = self.BN.batch_norm(x, training)
        x = tf.nn.relu(x)
        x = self.pool1(x)
        x = self.conv3(x)
        x = self.BN.batch norm(x, training)
        x = tf.nn.relu(x)
        x = self.pool1(x)
        x = self.conv4(x)
        x = self.BN.batch norm(x, training)
        x = tf.nn.relu(x)
        x = self.pool1(x)
        x = self.conv8(x)
        \#x = tf.nn.relu(x)
        #print(x.shape)
        x = tf.reshape(x, (-1, 1, 10))
        \#x = tf.keras.layers.Flatten(x)
        return x
    def loss fn(self, images, target, training):
        """ Defines the loss function used during
            training.
        0.00
        preds = self.predict(images, training)
        #print(preds.shape)
        #print(target.shape)
        loss = tf.nn.softmax cross entropy with logits(labels=target, logits=preds
)
        return loss
    def grads fn(self, images, target, training):
           Dynamically computes the gradients of the loss value
            with respect to the parameters of the model, in each
            forward pass.
        with tf.GradientTape() as tape:
            loss = self.loss_fn(images, target, training)
        return tape.gradient(loss, self.variables)
    def restore model(self):
        """ Function to restore trained model.
        with tf.device(self.device):
            # Run the model once to initialize variables
            dummy input = tf.constant(tf.zeros((1,48,48,1)))
            dummy pred = self.predict(dummy input, training=False)
            # Restore the variables of the model
            saver = tf.Saver(self.variables)
```

```
saver.restore(tf.train.latest checkpoint
                      (self.checkpoint directory))
def save_model(self, global_step=0):
    """ Function to save trained model.
    tf.Saver(self.variables).save(self.checkpoint_directory,
                                   global step=global step)
# def compute accuracy(self, input data):
      """ Compute the accuracy on the input data.
#
     with tf.device(self.device):
#
#
          #acc = tf.metrics.Accuracy()
#
          for step ,(images, targets) in enumerate(input_data):
              # Predict the probability of each class
#
              #print(targets.shape)
              logits = self.predict(images, training=False)
#
#
              # Select the class with the highest probability
#
              #print(logits.shape)
#
              logits = tf.nn.softmax(logits)
              logits = tf.reshape(logits, [-1, 10])
#
#
              targets = tf.reshape(targets, [-1,10])
              preds = tf.argmax(logits, axis=1)
#
#
              #ml.update state
#
              # Compute the accuracy
#
              #print(preds.shape)
#
              acc(tf.reshape(targets, preds))
      return acc
def compute accuracy 2(self, images, targets, training=False):
    """ Compute the accuracy on the input data.
    with tf.device(self.device):
        # Predict the probability of each class
        logits = self.predict(images, training)
        # Select the class with the highest probability
        logits = tf.nn.softmax(logits)
        logits = tf.reshape(logits, [-1, 10])
        targets = tf.reshape(targets, [-1,10])
        preds = tf.argmax(logits, axis=1)
        goal = tf.argmax(targets, axis=1)
        self.acc.update state(goal, preds)
        # Compute the accuracy
        result = self.acc.result().numpy()
    return result
def fit fc(self, training data, eval data, optimizer, num epochs=500,
        early_stopping_rounds=10, verbose=10, train_from_scratch=False):
    """ Function to train the model, using the selected optimizer and
        for the desired number of epochs. You can either train from scratch
        or load the latest model trained. Early stopping is used in order to
```

```
mitigate the risk of overfitting the network.
            Args:
                training data: the data you would like to train the model on.
                                Must be in the tf.data.Dataset format.
                eval data: the data you would like to evaluate the model on.
                            Must be in the tf.data.Dataset format.
                optimizer: the optimizer used during training.
                num epochs: the maximum number of iterations you would like to
                            train the model.
                early stopping rounds: stop training if the loss on the eval
                                       dataset does not decrease after n epochs.
                verbose: int. Specify how often to print the loss value of the net
work.
                train from scratch: boolean. Whether to initialize variables of th
e
                                    the last trained model or initialize them
                                    randomly.
        . . . .
        if train from scratch==False:
            self.restore model()
        # Initialize best loss. This variable will store the lowest loss on the
        # eval dataset.
        best loss = 999
        # Initialize classes to update the mean loss of train and eval
        train loss = tf.keras.metrics.Mean('train loss')
        eval loss = tf.keras.metrics.Mean('eval loss')
        acc_train = tf.keras.metrics.Mean('train_acc')
        acc_val = tf.keras.metrics.Mean('val acc')
        # Initialize dictionary to store the loss history
        self.history = {}
        self.history['train loss'] = []
        self.history['eval loss'] = []
        self.history['train acc'] = []
        self.history['val acc'] = []
        # Begin training
        with tf.device(self.device):
            for i in range(num epochs):
                # Training with gradient descent
                #training data x = training data.shuffle(buffer size=1024).batch(1)
28)
                for step, (images, target) in enumerate(training data):
                    grads = self.grads fn(images, target, True)
                    optimizer.apply_gradients(zip(grads, self.variables))
                # Compute the loss on the training data after one epoch
                for step, (images, target) in enumerate(training data):
                    loss = self.loss_fn(images, target, False)
                    accuracy = self.compute accuracy 2(images, target)
                    acc_train(accuracy)
                    train loss(loss)
```

```
self.history['train loss'].append(train loss.result().numpy())
                self.history['train acc'].append(acc train.result().numpy())
                # Reset metrics
                train loss.reset states()
                acc_train.reset_states()
                # Compute the loss on the eval data after one epoch
                for step, (images, target) in enumerate(eval data):
                    loss = self.loss fn(images, target, False)
                    accuracy = self.compute accuracy 2(images, target)
                    acc val(accuracy)
                    eval loss(loss)
                self.history['eval_loss'].append(eval_loss.result().numpy())
                self.history['val acc'].append(acc val.result().numpy())
                # Reset metrics
                eval loss.reset states()
                acc val.reset states()
                # Print train and eval losses
                if (i==0) | ((i+1)\%verbose==0):
                    print('Train loss at epoch %d: ' %(i+1), self.history['train l
oss'][-1])
                    print('Train Acc at epoch %d: ' %(i+1), self.history['train_ac
c'][-1])
                    print('Eval loss at epoch %d: ' %(i+1), self.history['eval los
s'][-1])
                    print('Eval Acc at epoch %d: ' %(i+1), self.history['val_acc']
[-1])
                # Check for early stopping
                if self.history['eval loss'][-1]<best loss:</pre>
                    best loss = self.history['eval loss'][-1]
                    count = early stopping rounds
                else:
                    count -= 1
                if count==0:
                    break
```

In [11]:

In [12]:

Train loss at epoch 1: 0.41589844 Train Acc at epoch 1: 0.85882115 Eval loss at epoch 1: 0.4369065 Eval Acc at epoch 1: 0.85934436 Train loss at epoch 2: 0.32678548 Train Acc at epoch 2: 0.8661574 Eval loss at epoch 2: 0.35857725 Eval Acc at epoch 2: 0.872446 Train loss at epoch 4: 0.25572088 Train Acc at epoch 4: 0.88545567 Eval loss at epoch 4: 0.30858925 Eval Acc at epoch 4: 0.8888894 Train loss at epoch 6: 0.21292028 Train Acc at epoch 6: 0.8964649 Eval loss at epoch 6: 0.28468505 Eval Acc at epoch 6: 0.8988403 Train loss at epoch 8: 0.18097195 Train Acc at epoch 8: 0.90486234 Eval loss at epoch 8: 0.27084717 Eval Acc at epoch 8: 0.90677863 Train loss at epoch 10: 0.15379688 Train Acc at epoch 10: 0.91195726 Eval loss at epoch 10: 0.2628677 Eval Acc at epoch 10: 0.91359943

In []: