```
import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import DataLoader
from torch.utils.data import sampler
#!pip install matplotlib
import matplotlib.pyplot as plt
import time
print(torch. version )
#!pip install torch===1.7.0 torchvision===0.8.1 torchaudio===0.7.0 -f https://download
import cv2
print(torch. version )
import torchvision.datasets as dset
import torchvision.transforms as T
from keras.datasets import cifar10
import numpy as np, numpy.linalg
USE GPU = True
dtype = torch.float64 # We will be using float throughout this tutorial.
if USE GPU and torch.cuda.is available():
   device = torch.device('cuda')
else:
    device = torch.device('cpu')
# Constant to control how frequently we print train loss.
print every = 100
print('using device:', device)
    1.8.1+cu101
    1.8.1+cu101
    using device: cpu
#class for forward pass and loss
class custom multiclass torch(torch.nn.Module):
    def init (self, N, P, C, K, f,a,b,c,beta, x patches train, x patches val, x pat
        super(custom multiclass torch, self). init ()
        #initialize several variables
        # parameters, N = number of images, K = number of patches, P = pooling size, (
        self.N = N
        self.P = P
        self.C = C
        self.K = K
        self.f = f
```

```
self.a = a
    self.b = b
    self.c = c
    self.beta = beta
    self.x patches train = x patches train
    self.x patches val = x patches val
    self.x patches test = x patches test
    #initialize tensor array variables as dictionaries
    self.Z 1 arr train = nn.ParameterDict({ })
    self.Z 1 arr prime train = nn.ParameterDict({})
    self.Z 2 arr train = nn.ParameterDict({})
    self.Z 2 arr prime train = nn.ParameterDict({})
    self.Z 4 arr train = nn.ParameterDict({})
    self.Z 4 arr prime train = nn.ParameterDict({})
    self.Z arr train = {}
    self.Z arr prime train = {}
    # fill in dictionaries with Z1 Z2 Z4 tensor parameters
    for i in range(1,self.K//self.P+1):
        for j in range(1, self.C+1):
            self.Z 1 arr train[str(i)+','+str(j)] = torch.nn.Parameter(data = to)
            self.Z 1 arr prime train[str(i)+','+str(j)] = torch.nn.Parameter(data
            self.Z_2_arr_train[str(i)+','+str(j)] = torch.nn.Parameter(data = to)
            self.Z 2 arr prime train[str(i)+','+str(j)] = torch.nn.Parameter(data
            self.Z 4 arr train[str(i)+','+str(j)] = torch.nn.Parameter(data = to)
            self.Z 4 arr prime train[str(i)+','+str(j)] = torch.nn.Parameter(data
            nn.init.xavier uniform (self.Z 1 arr train[str(i)+','+str(j)])
            nn.init.xavier uniform (self.Z 2 arr train[str(i)+','+str(j)])
            nn.init.xavier uniform (self.Z 4 arr train[str(i)+','+str(j)])
            nn.init.xavier uniform (self.Z 1 arr prime train[str(i)+','+str(j)])
            nn.init.xavier uniform (self.Z 2 arr prime train[str(i)+','+str(j)])
            nn.init.xavier uniform (self.Z 4 arr prime train[str(i)+','+str(j)])
            self.Z arr train[str(i)+','+str(j)] = torch.vstack((torch.hstack((self))))
            self.Z_arr_prime_train[str(i)+','+str(j)] = torch.vstack((torch.hstac))
def forward(self, i, setting = "train"):
    Z 1 new = \{\}
    Z 2 new = \{\}
```

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4_11ew - {}
Z 1 prime new = {}
Z 2 prime new = {}
Z = 4 \text{ prime new} = \{\}
Z \text{ new} = \{\}
Z new prime = {}
if setting == "train":
    xdata = self.x patches train
elif setting == "val":
    xdata = self.x patches_val
else:
    xdata = self.x patches test
#transform Z matrices into positve-semidefinite matrices
# #convertTo = "positive semidefinite"
convertTo = "other"
for key in self.Z arr train:
    if convertTo == "positive semidefinite":
        Z_new[key] = torch.matmul(self.Z_arr_train[key], self.Z_arr_train[key]
    elif convertTo == "symmetric:":
        Z_new[key] = 0.5 * (self.Z_arr_train[key]+self.Z_arr_train[key].T)
    else:
        Z_new[key] = self.Z_arr_train[key]
    Z = 1 \text{ new[key]} = Z \text{ new[key][:3*f**2,:3*f**2]}
    Z = 2 \text{ new[key]} = Z \text{ new[key]}[3*f**2,:3*f**2]
    Z = 4 \text{ new[key]} = Z \text{ new[key]}[3*f**2,3*f**2]
for key in self.Z arr prime train:
    if convertTo == "positive semidefinite":
        Z new prime[key] = torch.matmul(self.Z arr prime train[key], self.Z ar
    elif convertTo == "symmetric":
        Z new prime[key] = 0.5 * (self.Z arr prime train[key] + self.Z arr pri
    else:
        Z new prime[key] = self.Z arr prime train[key]
    Z 1 prime new[key] = Z new prime[key][:3*f**2,:3*f**2]
    Z 2 prime new[key] = Z new prime[key][3*f**2,:3*f**2]
    Z = A \text{ prime new[key]} = Z \text{ new prime[key]}[3*f**2,3*f**2]
#print(self.Z 1 arr train[1,2])
#print(self.Z 4 arr train[1,2])
ypred = torch.zeros((C))
# performing calculations for ypred scores
for t in range(1, self.C+1):
    constant part = 0
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for k in range(1,self.K//self.P+1):
            Z4diff = self.Z_4_arr_train[str(k)+","+str(t)] - self.Z_4_arr_prime_tr
            constant part += Z4diff
        constant part *= self.c
        #print(constant part)
        linear part = 0
        for k in range(1,self.K//self.P+1):
            for l in range(1,self.P+1):
                Z2diff = self.Z 2 arr train[str(k)+","+str(t)] - self.Z 2 arr prin
                x_{data} = x_{data}[i][(k-1)*P+l-1].view(-1, 1)
                linear part += torch.matmul(x data reshaped.T, Z2diff)
                #linear part += float(torch.matmul(x data reshaped.T, Z2diff)[0])
        linear part *= self.b/self.P
       quadratic part = 0
        for k in range(1,self.K//self.P+1):
            for l in range(1,self.P+1):
                Z1diff = self.Z 1 arr train[str(k)+","+str(t)] - self.Z 1 arr prin
                x_{data\_reshaped} = xdata[i][(k-1)*P+ l-1].view(-1, 1)
                newpart = torch.matmul(x data reshaped.T, Z1diff)
                newpart = torch.matmul(newpart, x_data_reshaped)
                quadratic part += newpart
                #quadratic part += float(newpart[0,0])
        quadratic part *= self.a/self.P
        #print(quadratic part, linear part, constant part)
       ypred[t-1] = quadratic part + linear part + constant part
       #randnum = np.random.randint(10)
       #ypred *= randnum
    return ypred
def customloss(self, Yhat, y):
    #convex L2 loss function
    objective1 = 0.5 * torch.norm(Yhat - y)**2
    # sum of Z4 scalars added to loss
    objective2 = 0
    for i in range(1,K//P+1):
        for j in range(1,C+1):
            objective2 += self.Z_4_arr_train[str(i)+","+str(j)] + self.Z_4_arr_pri
    objective = objective1+ self.beta * objective2
```

return objective

```
#load cifar data
(X_train, y_train), (X_test, y_test) = cifar10.load_data()
# shuffler = np.random.permutation(len(y train))
# X train = X train[shuffler]
# y_train = y_train[shuffler]
# shuffler2 = np.random.permutation(len(y test))
# X test = X test[shuffler2]
# y_test = y_test[shuffler2]
#subset data
X train = X train[:2000,:,:,:]
y_train = y_train[:2000]
X test = X test[:400,:,:,:]
y test = y test[:400]
#set up val/test split
X \text{ val} = X \text{ test}[:X \text{ test.shape}[0]//2,:,:,:]
X test = X test[X test.shape[0]//2:,:,:,:]
y val = y test[:y test.shape[0]//2]
y test = y test[:y test.shape[0]//2]
#parameters: f is filter size, P is pooling size, C is class count, a,b,c are the poly
f = 4
train images = X train.astype(np.float64)
train labels = y train.astype(np.float64)
test_images = X_test.astype(np.float64)
test labels = y test.astype(np.float64)
val images = X val.astype(np.float64)
val_labels = y_val.astype(np.float64)
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# #meaning out the images
# mean image = np.mean(train images, axis = 0)
# train images -= mean image
# test images -= mean image
# val images -= mean image
# # RGB 0 to 255
\# #-127.5 to +127.5
# #-1 to 1
# # scale to [-1, 1]
# train images /= 127.5
# test images /= 127.5
# val images /= 127.5
train images /= 255
train images *= 2
train images -= 1
test images /= 255
test images *= 2
test images -= 1
val images /= 255
val images *= 2
val images -= 1
train images v2 = np.swapaxes(train images.reshape(train images.shape[0], 3, 32, 32),
test images v2 = np.swapaxes(test images.reshape(test images.shape[0], 3, 32, 32), 2,
val images v2 = np.swapaxes(val images.reshape(val images.shape[0],3, 32, 32), 2, 3)
train images v3 = torch.tensor(train images v2, device = device, dtype = dtype)
test images v3 = torch.tensor(test images v2, device = device, dtype = dtype)
val images v3 = torch.tensor(val images v2, device = device, dtype = dtype)
#set s val = torch.nn.functional.unfold(val images v3, kernel size=(f,f), stride=f, page #set s val = torch.nn.functional.unfold(val images v3, kernel size=(f,f), stride=f, page #set s val = torch.nn.functional.unfold(val images v3, kernel size=(f,f), stride=f, page #set s val = torch.nn.functional.unfold(val images v3, kernel size=(f,f), stride=f, page #set s val = torch.nn.functional.unfold(val images v3, kernel size=(f,f), stride=f, page #set s val = torch.nn.functional.unfold(val images v3, kernel size=(f,f), stride=f, page #set s val = torch.nn.functional.unfold(val images v3, kernel size=(f,f), stride=f, page #set s val = torch.nn.functional.unfold(val images v3, kernel size=(f,f), stride=f, page #set s val = torch.nn.functional.unfold(val images v3, kernel size=(f,f), stride=f, page #set s val = torch.nn.functional.unfold(val images v3, kernel size=(f,f), stride=f, page #set s val = torch.nn.functional.unfold(val images v3, kernel size=(f,f), stride=f, page #set s val = torch.nn.functional.unfold(val images v3, kernel size=(f,f), stride=f, page #set s val = torch.nn.functional.unfold(val images v3, kernel size=(f,f), stride=f, page #set s val = torch.nn.functional.unfold(val images v3, kernel size=(f,f), stride=f, page #set s val = torch.nn.functional.unfold(val images v3, kernel size=(f,f), stride=f, page #set s val = torch.nn.functional.unfold(val images v3, kernel size=(f,f), stride=f, page #set s val = torch.nn.functional.unfold(val images v3, kernel size=(f,f), stride=f, page #set s val = torch.nn.functional.unfold(val images v3, kernel size=f, page #set s val = torch.nn.functional.unfold(val images v3, kernel size=f, page #set s val = torch.nn.functional.unfold(val images v3, kernel size=f, page #set s val = torch.nn.functional.unfold(val images v3, kernel size=f, page #set s val = torch.nn.functional.unfold(val images v3, kernel size=f, page #set s val = torch.nn.functional.unfold(val images v3, kernel size=f, page #set s val = torch.nn.functional.unfold(val images v3, kernel size=f, page #set s v
#setting up patches
patches train = torch.nn.functional.unfold(train images v3, kernel size=(f,f), stride=
patches test = torch.nn.functional.unfold(test images v3, kernel size=(f, f), stride=1
patches val = torch.nn.functional.unfold(val images v3, kernel size=(f,f), stride=f, r
patches train = patches train.permute(0,2,1)
patches test = patches test.permute(0,2,1)
patches val = patches val.permute(0,2,1)
N = X train.shape[0]
```

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K = patches train.shape[1]
Yhat train = None
Yhat test = None
P = K
C = 10
a = 0.09
b = 0.5
c = 0.47
beta = 1e-7
print("K: ", K)
print("N: ", N)
print("patches_train size: ", patches_train.size())
print("patches_val size: ", patches_val.size())
print("patches_test size: ", patches_test.size())
    Downloading data from https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz
    K: 64
    N: 2000
    patches train size: torch.Size([2000, 64, 48])
    patches val size: torch.Size([200, 64, 48])
    patches test size: torch.Size([200, 64, 48])
def train(model, loss fn, optimizer, epochs=1):
   model = model.to(device=device) # move the model parameters to CPU/GPU
   loss train = []
   accuracies train = []
   accuracies val = []
   start = time.time()
   times = []
   times.append(time.time)
   zzz = 0
   #accuracies train.append(check accuracy(X train, y train, model, segment = "train'
   for e in range(epochs):
       #idx = torch.randperm(train images.shape[0])
       #sample images = train images[idx].view(train images.size())
       #sample images = sample images[]
       for t, (x, y) in enumerate(zip(train images, train labels)):
          model.train() # put model to training mode
          scores = model(t, setting = "train")
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y hot = torch.zeros(scores.size(), dtype = dtype)

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y_hot[y] = 1
            #print("Scores before: ", scores)
            loss = loss fn(scores, y hot)
            loss_train.append(loss)
            # Zero out all of the gradients for the variables which the optimizer
            # will update.
            optimizer.zero grad()
            # backwards pass
            loss.backward()
            # update the parameters of the model using the gradients
            # computed by the backwards pass.
            optimizer.step()
            #print("Scores after: ", scores)
            #if t % 100 == 0:
            if t==0:
              times.append(time.time)
              print('Iteration %d, loss = %.4f' % (t, loss.item()))
              accuracies train.append(check accuracy(X train, y train, model, segment
              accuracies val.append(check accuracy(X val, y val, model, segment = "val
       # times.append(time.time)
        #print('Iteration %d, loss = %.4f' % (t, loss.item()))
        #accuracies train.append(check accuracy(X train, y train, model, segment = "t1
    for i in range(len(times)):
        times[i] -= start
    return loss train, accuracies train, accuracies val, times
def check accuracy(X, Y, model, segment = "train"):
    if segment=='train':
        print('Checking accuracy on train set')
    elif segment == "val":
        print('Checking accuracy on val set')
    else:
        print('Checking accuracy on test set')
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```
num correct = 0
    num samples = 0
    model.eval() # set model to evaluation mode
    with torch.no grad():
        for t, (x, y) in enumerate(zip(X, Y)):
            scores = model(t, setting = segment)
            max score idx = torch.argmax(scores)
            y = torch.tensor(y)
            #if t % 1000 == 0:
              #print(t, scores, y)
              #for name, param in model.named parameters():
                   if param.requires grad:
                       if name == "Z 2 arr train.1,1" or name == "Z 2 arr prime train.
                         print(name, param.data.T)
                      #break
            addvalue = 1 if (max_score_idx == y) else 0
            num correct += addvalue
            num samples += 1
        acc = float(num_correct) / num_samples
        print('Got %d / %d correct (%.2f)'% (num_correct, num_samples, 100 * acc))
        return acc
model = custom multiclass torch(N, P, C, K, f,a,b,c,beta, patches train, patches val,
count = 0
for param in model.parameters():
   #print(param.shape)
   count += 1
print(count)
    60
loss fn = model.customloss
optimizer = optim.Adam(model.parameters(), lr=1e-3, amsgrad=True)
#optimizer = optim.SGD(model.parameters(), lr=0.01, momentum=0.9)
loss train, accuracies train, accuracies val, times = train(model, loss fn, optimizer,
    Iteration 0, loss = 2.1351
    Checking accuracy on train set
    Got 220 / 2000 correct (11.00)
    Checking accuracy on val set
```

```
Got 22 / 200 correct (11.00)
    Iteration 0, loss = 0.5060
    Checking accuracy on train set
    Got 486 / 2000 correct (24.30)
    Checking accuracy on val set
    Got 44 / 200 correct (22.00)
plt.figure(figsize=(10,5))
plt.title('Training Accuracy')
#print(accuracies_train)
plt.plot(accuracies train)
plt.xlabel('Epochs')
plt.ylabel('Val Accuracy')
#plt.legend()
plt.show()
plt.figure(figsize=(10,5))
plt.title('Validation Accuracy')
#print(accuracies_val)
plt.plot(accuracies val)
plt.xlabel('Epochs')
plt.ylabel('Val Accuracy')
#plt.legend()
plt.show()
plt.figure(figsize=(10,5))
plt.title('Training Loss')
#print(loss train)
plt.plot(loss train)
plt.xlabel('Epochs')
plt.ylabel('Train Loss')
#plt.legend()
plt.show()
plt.figure(figsize=(10,5))
plt.title('Training Loss')
#print(loss train)
plt.plot(loss train)
plt.xlabel('Epochs')
plt.ylabel('Train Loss')
#plt.legend()
plt.show()
plt.figure(figsize=(10,5))
plt.title('Training Time')
#nrint/loss train)
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#princ(ross_crain)
plt.plot(times)
plt.xlabel('Epochs')
plt.ylabel('Time (seconds)')
#plt.legend()
plt.show()

check_accuracy(X_test, y_test, model, segment = "test")
```