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Coursework2: Convolutional Neural Networks

instructions

Please submit a version of this notebook containing your answers **together with your trained model** on CATe as CW2.zip. Write your answers in the cells below each question.

A PDF version of this notebook is also provided in case the figures do not render correctly.

The deadline for submission is 19:00, Thu 14th February, 2019

Setting up working environment

For this coursework you will need to train a large network, therefore we recommend you work with Google Colaboratory, which provides free GPU time. You will need a Google account to do so.

Please log in to your account and go to the following page: https://colab.research.google.com (https://colab.research.google.com). Then upload this notebook.

For GPU support, go to "Edit" -> "Notebook Settings", and select "Hardware accelerator" as "GPU".

You will need to install pytorch by running the following cell:

In [ ]:

```

```

In [1]:

```
!pip install torch torchvision
```

```
Requirement already satisfied: torch in /usr/local/lib/python3.6/dist-
packages (1.0.0)
Requirement already satisfied: torchvision in /usr/local/lib/python3.
6/dist-packages (0.2.1)
Requirement already satisfied: numpy in /usr/local/lib/python3.6/dist-
packages (from torchvision) (1.14.6)
Requirement already satisfied: six in /usr/local/lib/python3.6/dist-pa
ckages (from torchvision) (1.11.0)
Collecting pillow>=4.1.1 (from torchvision)
  Downloading https://files.pythonhosted.org/packages/85/5e/e91792f198
bbc5a0d7d3055ad552bc4062942d27eaf75c3e2783cf64eae5/Pillow-5.4.1-cp36-c
p36m-manylinux1_x86_64.whl (https://files.pythonhosted.org/packages/8
5/5e/e91792f198bbc5a0d7d3055ad552bc4062942d27eaf75c3e2783cf64eae5/Pill
ow-5.4.1-cp36-cp36m-manylinux1_x86_64.whl) (2.0MB)
    100% |████████████████████████████████| 2.0MB
14.1MB/s
Installing collected packages: pillow
  Found existing installation: Pillow 4.0.0
    Uninstalling Pillow-4.0.0:
      Successfully uninstalled Pillow-4.0.0
Successfully installed pillow-5.4.1
```

Introduction

For this coursework you will implement one of the most commonly used model for image recognition tasks, the Residual Network. The architecture is introduced in 2015 by Kaiming He, et al. in the paper "Deep residual learning for image recognition" (https://www.cv-foundation.org/openaccess/content_cvpr_2016/papers/He_Deep_Residual_Learning_CVPR_2016_paper.pdf).

In a residual network, each block contains some convolutional layers, plus "skip" connections, which allow the activations to by pass a layer, and then be summed up with the activations of the skipped layer. The image below illustrates a building block in residual networks.

resnet-block

Depending on the number of building blocks, resnets can have different architectures, for example ResNet-50, ResNet-101 and etc. Here you are required to build ResNet-18 to perform classification on the CIFAR-10 dataset, therefore your network will have the following architecture:

resnet

Part 1 (40 points)

In this part, you will use basic pytorch operations to define the 2D convolution and max pooling operation.

YOUR TASK

- implement the forward pass for Conv2D and MaxPool2D
- You can only fill in the parts which are specified as "YOUR CODE HERE"
- You are **NOT** allowed to use the torch.nn module and the conv2d/maxpooling functions in torch.nn.functional

In [1]:

```
import torch
import torch.nn as nn
import torch.nn.functional as F
```

In [2]:

```
class Conv2D(nn.Module):

    def __init__(self, inchannel, outchannel, kernel_size, stride, padding, bias = T

        super(Conv2D, self).__init__()

        self.inchannel = inchannel
        self.outchannel = outchannel
        self.kernel_size = kernel_size
        self.stride = stride
        self.padding = padding

        self.weights = nn.Parameter(torch.Tensor(outchannel, inchannel,
                                                  kernel_size, kernel_size))
        self.weights.data.normal_(-0.1, 0.1)

        if bias:
            self.bias = nn.Parameter(torch.Tensor(outchannel, ))
            self.bias.data.normal_(-0.1, 0.1)
        else:
            self.bias = None


    def forward(self, x):

        ###############################################################
        #                        YOUR CODE HERE                       #
        ###############################################################
        hout = ((x.shape[2] + 2 * self.padding - self.kernel_size)
                //self.stride)+1
        wout = ((x.shape[3] + 2 * self.padding - self.kernel_size)
                //self.stride)+1

        x_unf = F.unfold(x, kernel_size=self.kernel_size, padding=self.padding
                         , stride=self.stride)
        if self.bias:
            out_unf = (x_unf.transpose(1, 2).matmul(self.weights.view(
                        self.weights.size(0), -1).t()).transpose(1, 2))+self.bias.vie
        else:
            out_unf = (x_unf.transpose(1, 2).matmul(self.weights.view(
                        self.weights.size(0), -1).t()).transpose(1, 2))
        output = out_unf.view(x.shape[0], self.outchannel, hout, wout)

        ###############################################################
        #                        END OF YOUR CODE                     #
        ###############################################################



        return output
```

In [3]:

```
class MaxPool2D(nn.Module):

    def __init__(self, pooling_size):
        # assume pooling_size = kernel_size = stride

        super(MaxPool2D, self).__init__()

        self.pooling_size = pooling_size


    def forward(self, x):

        ##############################################################
        #                        YOUR CODE HERE                      #
        ##############################################################
        batch_size = x.shape[0]

        inchannel = x.shape[1]

        x = F.unfold(x,kernel_size=self.pooling_size, stride=self.pooling_size)

        x = x.reshape(batch_size,inchannel,self.pooling_size*self.pooling_size,-1)

        x = x.max(dim=2)[0]

        shape = torch.rand(1)

        shape[0] = x.shape[0]*x.shape[1]*x.shape[2]

        shape =torch.sqrt(shape/(batch_size*inchannel))

        output = x.reshape(batch_size,inchannel,int(shape),int(shape))


        ##############################################################
        #                        END OF YOUR CODE                    #
        ##############################################################


        return output
```

In [4]:

```
# define resnet building blocks

class ResidualBlock(nn.Module):
    def __init__(self, inchannel, outchannel, stride=1):

        super(ResidualBlock, self).__init__()

        self.left = nn.Sequential(Conv2D(inchannel, outchannel, kernel_size=3,
                                         stride=stride, padding=1, bias=False),
                                  nn.BatchNorm2d(outchannel),
                                  nn.ReLU(inplace=True),
                                  Conv2D(outchannel, outchannel, kernel_size=3,
                                         stride=1, padding=1, bias=False),
                                  nn.BatchNorm2d(outchannel))

        self.shortcut = nn.Sequential()

        if stride != 1 or inchannel != outchannel:

            self.shortcut = nn.Sequential(Conv2D(inchannel, outchannel,
                                                 kernel_size=1, stride=stride,
                                                 padding = 0, bias=False),
                                          nn.BatchNorm2d(outchannel) )

    def forward(self, x):

        out = self.left(x)

        out += self.shortcut(x)

        out = F.relu(out)

        return out
```

In [5]:

```
# define resnet

class ResNet(nn.Module):

    def __init__(self, ResidualBlock, num_classes = 10):

        super(ResNet, self).__init__()

        self.inchannel = 64
        self.conv1 = nn.Sequential(Conv2D(3, 64, kernel_size = 3, stride = 1,
                                          padding = 1, bias = False),
                                   nn.BatchNorm2d(64),
                                   nn.ReLU())

        self.layer1 = self.make_layer(ResidualBlock, 64, 2, stride = 1)
        self.layer2 = self.make_layer(ResidualBlock, 128, 2, stride = 2)
        self.layer3 = self.make_layer(ResidualBlock, 256, 2, stride = 2)
        self.layer4 = self.make_layer(ResidualBlock, 512, 2, stride = 2)
        self.maxpool = MaxPool2D(4)
        self.fc = nn.Linear(512, num_classes)


    def make_layer(self, block, channels, num_blocks, stride):

        strides = [stride] + [1] * (num_blocks - 1)

        layers = []

        for stride in strides:

            layers.append(block(self.inchannel, channels, stride))

            self.inchannel = channels

        return nn.Sequential(*layers)


    def forward(self, x):

        x = self.conv1(x)

        x = self.layer1(x)
        x = self.layer2(x)
        x = self.layer3(x)
        x = self.layer4(x)

        x = self.maxpool(x)

        x = x.view(x.size(0), -1)

        x = self.fc(x)


        return x


def ResNet18():
    return ResNet(ResidualBlock)
```

Part 2 (40 points)

In this part, you will train the ResNet-18 defined in the previous part on the CIFAR-10 dataset. Code for loading the dataset, training and evaluation are provided.

Your Task

1. Train your network to achieve the best possible test set accuracy after a maximum of 10 epochs of training.
2. You can use techniques such as optimal hyper-parameter searching, data pre-processing
3. If necessary, you can also use another optimiser
4. **Answer the following question:** Given such a network with a large number of trainable parameters, and a training set of a large number of data, what do you think is the best strategy for hyperparameter searching?

YOUR ANSWER FOR 2.4 HERE

A:In my opnion, Bayesian Optimisation is the best strategy for hyperparameter searching. Since the strategy will create a proxy model of the true model and train the hyperparameters on a more cheaper proxy model and return a really good result. And Training may be very cheaper compared with other strategies. Besides that, the training cycles is less.

In [6]:

```
import torch.optim as optim
from torch.utils.data import DataLoader
from torch.utils.data import sampler

import torchvision.datasets as dset

import numpy as np

import torchvision.transforms as T


transform = T.ToTensor()
################################################################
#                        YOUR CODE HERE                        #
################################################################
transform_train = T.Compose([
    T.RandomCrop(32, padding = 4),
    T.RandomHorizontalFlip(),
    T.ToTensor(),
    T.Normalize((0.4914,0.4822,0.4465),(0.2023,0.1994,0.2010))
])

transform_val = T.Compose([
    T.ToTensor(),
    T.Normalize((0.4914,0.4822,0.4465),(0.2023,0.1994,0.2010))
])

transform_test = T.Compose([

    T.ToTensor(),
    T.Normalize((0.4914,0.4822,0.4465),(0.2023,0.1994,0.2010))
])
# load data

NUM_TRAIN = 49000
print_every = 100


data_dir = './data'
cifar10_train = dset.CIFAR10(data_dir, train=True, download=True, transform=transfor
loader_train = DataLoader(cifar10_train, batch_size=64,
                          sampler=sampler.SubsetRandomSampler(range(NUM_TRAIN)))

cifar10_val = dset.CIFAR10(data_dir, train=True, download=True, transform=transform_
loader_val = DataLoader(cifar10_val, batch_size=64,
                        sampler=sampler.SubsetRandomSampler(range(NUM_TRAIN, 50000)
                        
cifar10_test = dset.CIFAR10(data_dir, train=False, download=True, transform=transfor
loader_test = DataLoader(cifar10_test, batch_size=64)
################################################################
#                        END OF YOUR CODE HERE                       #
################################################################

USE_GPU = True
dtype = torch.float32

if USE_GPU and torch.cuda.is_available():
    device = torch.device('cuda')
```

```python
else:
    device = torch.device('cpu')
```

```
Downloading https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz (h
ttps://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz) to ./data/cifa
r-10-python.tar.gz
Files already downloaded and verified
Files already downloaded and verified
```

In [7]:

```
def check_accuracy(loader, model):
    # function for test accuracy on validation and test set

    if loader.dataset.train:
        print('Checking accuracy on validation set')
    else:
        print('Checking accuracy on test set')
    num_correct = 0
    num_samples = 0
    model.eval()  # set model to evaluation mode
    with torch.no_grad():
        for x, y in loader:
            x = x.to(device=device, dtype=dtype)  # move to device
            y = y.to(device=device, dtype=torch.long)
            scores = model(x)
            _, preds = scores.max(1)
            num_correct += (preds == y).sum()
            num_samples += preds.size(0)
        acc = float(num_correct) / num_samples
        print('Got %d / %d correct (%.2f)' % (num_correct, num_samples, 100 * acc))
##############################################################
#                      YOUR CODE HERE                        #
##############################################################
    return acc
##############################################################
#                      END OF YOUR CODE                      #
##############################################################


def train_part(model, optimizer, epochs=1):
    """
    Train a model on CIFAR-10 using the PyTorch Module API.

    Inputs:
    - model: A PyTorch Module giving the model to train.
    - optimizer: An Optimizer object we will use to train the model
    - epochs: (Optional) A Python integer giving the number of epochs to train for

    Returns: Nothing, but prints model accuracies during training.
    """
    model = model.to(device=device)  # move the model parameters to CPU/GPU
    for e in range(epochs):
        print(len(loader_train))
        for t, (x, y) in enumerate(loader_train):
            model.train()  # put model to training mode
            x = x.to(device=device, dtype=dtype)  # move to device, e.g. GPU
            y = y.to(device=device, dtype=torch.long)

            scores = model(x)
            loss = F.cross_entropy(scores, y)

            # Zero out all of the gradients for the variables which the optimizer
            # will update.
            optimizer.zero_grad()

            loss.backward()

            # Update the parameters of the model using the gradients
```

```
            optimizer.step()

            if t % print_every == 0:
                print('Epoch: %d, Iteration %d, loss = %.4f' % (e, t, loss.item()))
                #check_accuracy(loader_val, model)
                print()
```

In [8]:

```
# code for optimising your network performance

##############################################################
#                        YOUR CODE HERE                      #
##############################################################

#setting up the range of all the hyperparameters. using Bayesian Optimisation
```

readme

I did data preprocessing using torchvision.transforms to do data standardization and data augmentation. Besides that, using bayesian optimisation of GPyOpt pakege to optimisate the learning_rate and weight_decay

In [9]:

```
!pip install GPy
!pip install GPyOpt
```

```
Collecting GPy
  Downloading https://files.pythonhosted.org/packages/98/7d/e55ffc3b16
b68e8b50ccecacec56715bcf49d5c2f204f5ba60374d419611/GPy-1.9.6.tar.gz (h
ttps://files.pythonhosted.org/packages/98/7d/e55ffc3b16b68e8b50ccecace
c56715bcf49d5c2f204f5ba60374d419611/GPy-1.9.6.tar.gz) (873kB)
    100% |████████████████████████████████| 880kB
17.3MB/s
Requirement already satisfied: numpy>=1.7 in /usr/local/lib/python3.6/
site-packages (from GPy) (1.15.4)
Requirement already satisfied: scipy>=0.16 in /usr/local/lib/python3.
6/site-packages (from GPy) (1.2.0)
Requirement already satisfied: six in /usr/local/lib/python3.6/site-pa
ckages (from GPy) (1.12.0)
Collecting paramz>=0.9.0 (from GPy)
  Downloading https://files.pythonhosted.org/packages/fd/78/b0f0164a32
518bfd3b98cb2e149b7a4d5504d13fb503b31a6c59b958ed18/paramz-0.9.4.tar.gz
(https://files.pythonhosted.org/packages/fd/78/b0f0164a32518bfd3b98cb2
e149b7a4d5504d13fb503b31a6c59b958ed18/paramz-0.9.4.tar.gz) (70kB)
    100% |████████████████████████████████| 71kB
 24.0MB/s
Requirement already satisfied: decorator>=4.0.10 in /usr/local/lib/pyt
hon3.6/site-packages (from paramz>=0.9.0->GPy) (4.3.0)
Building wheels for collected packages: GPy, paramz
  Running setup.py bdist_wheel for GPy ... done
  Stored in directory: /root/.cache/pip/wheels/97/82/1d/32a361e1ff2b4d
9129a60343831dd99cdc74440e2db1c55264
  Running setup.py bdist_wheel for paramz ... done
  Stored in directory: /root/.cache/pip/wheels/a9/fc/74/3bbd263c43ed98
d67343df24cebf0a0ee34afee40d769fda9c
Successfully built GPy paramz
menpo 0.8.1 has requirement matplotlib<2.0,>=1.4, but you'll have matp
lotlib 3.0.2 which is incompatible.
menpo 0.8.1 has requirement pillow<5.0,>=3.0, but you'll have pillow
 5.4.0 which is incompatible.
menpo 0.8.1 has requirement scipy<1.0,>=0.16, but you'll have scipy 1.
2.0 which is incompatible.
Installing collected packages: paramz, GPy
Successfully installed GPy-1.9.6 paramz-0.9.4
You are using pip version 10.0.1, however version 19.0.2 is available.
You should consider upgrading via the 'pip install --upgrade pip' comm
and.
Collecting GPyOpt
  Downloading https://files.pythonhosted.org/packages/9c/40/ca8f080d74
d9f4e29069faa944fcfb083e8693b6daaba0f1e4bc65c88650/GPyOpt-1.2.5.tar.gz
(https://files.pythonhosted.org/packages/9c/40/ca8f080d74d9f4e29069faa
944fcfb083e8693b6daaba0f1e4bc65c88650/GPyOpt-1.2.5.tar.gz) (55kB)
    100% |████████████████████████████████| 61kB
 4.9MB/s
Requirement already satisfied: numpy>=1.7 in /usr/local/lib/python3.6/
site-packages (from GPyOpt) (1.15.4)
Requirement already satisfied: scipy>=0.16 in /usr/local/lib/python3.
6/site-packages (from GPyOpt) (1.2.0)
Requirement already satisfied: GPy>=1.8 in /usr/local/lib/python3.6/si
te-packages (from GPyOpt) (1.9.6)
Requirement already satisfied: six in /usr/local/lib/python3.6/site-pa
```

```
ckages (from GPy>=1.8->GPyOpt) (1.12.0)
Requirement already satisfied: paramz>=0.9.0 in /usr/local/lib/python
3.6/site-packages (from GPy>=1.8->GPyOpt) (0.9.4)
Requirement already satisfied: decorator>=4.0.10 in /usr/local/lib/pyt
hon3.6/site-packages (from paramz>=0.9.0->GPy>=1.8->GPyOpt) (4.3.0)
Building wheels for collected packages: GPyOpt
  Running setup.py bdist_wheel for GPyOpt ... done
  Stored in directory: /root/.cache/pip/wheels/33/1d/87/dc02440831ba98
6b1547dd11a7dcd44e893b0527083066d869
Successfully built GPyOpt
menpo 0.8.1 has requirement matplotlib<2.0,>=1.4, but you'll have matp
lotlib 3.0.2 which is incompatible.
menpo 0.8.1 has requirement pillow<5.0,>=3.0, but you'll have pillow
 5.4.0 which is incompatible.
menpo 0.8.1 has requirement scipy<1.0,>=0.16, but you'll have scipy 1.
2.0 which is incompatible.
Installing collected packages: GPyOpt
Successfully installed GPyOpt-1.2.5
You are using pip version 10.0.1, however version 19.0.2 is available.
You should consider upgrading via the 'pip install --upgrade pip' comm
and.
```

In [10]:

```
import GPy
import GPyOpt
```

In [11]:

```
def objective(params):
  params = params.squeeze()
  model = ResNet18()
  optimizer = optim.Adam(model.parameters(),
                            lr = params[0],
                            weight_decay = params[1]
                          )
  print("lr, weight_decay: ",params[0],params[1])
  train_part(model, optimizer, epochs = 10)
  acc = check_accuracy(loader_val, model)
  return acc
bounds = [{'name':'lr','type':'continuous','domain':(1e-5,4e-2)},
          {'name':'weight_decay','type':'continuous','domain':(1e-5,4e-2)}
         ]
max_iter = 3
max_time = 100000000000
X = np.zeros((1,2))
X[0][0] = 0.001
X[0][1] = 0.0002
myProblem = GPyOpt.methods.BayesianOptimization(f = objective,X = X, domain = bounds
myProblem.run_optimization(max_iter=max_iter, max_time=max_time)
```

```
lr, weight_decay:  0.001 0.0002
766
Epoch: 0, Iteration 0, loss = 2.3881

Epoch: 0, Iteration 100, loss = 2.2943

Epoch: 0, Iteration 200, loss = 2.3912

Epoch: 0, Iteration 300, loss = 2.1228

Epoch: 0, Iteration 400, loss = 2.0888

Epoch: 0, Iteration 500, loss = 1.6861

Epoch: 0, Iteration 600, loss = 2.0077

Epoch: 0, Iteration 700, loss = 1.8688

766
Epoch: 1, Iteration 0, loss = 1.4942

Epoch: 1, Iteration 100, loss = 1.7033

Epoch: 1, Iteration 200, loss = 1.4706

Epoch: 1, Iteration 300, loss = 1.3405

Epoch: 1, Iteration 400, loss = 1.3695

Epoch: 1, Iteration 500, loss = 1.4843

Epoch: 1, Iteration 600, loss = 1.3124

Epoch: 1, Iteration 700, loss = 0.9776
```

```
766
Epoch: 2, Iteration 0, loss = 1.0886

Epoch: 2, Iteration 100, loss = 1.3372

Epoch: 2, Iteration 200, loss = 0.9965

Epoch: 2, Iteration 300, loss = 1.2475

Epoch: 2, Iteration 400, loss = 0.8870

Epoch: 2, Iteration 500, loss = 1.0062

Epoch: 2, Iteration 600, loss = 0.8223

Epoch: 2, Iteration 700, loss = 0.7185

766
Epoch: 3, Iteration 0, loss = 0.6992

Epoch: 3, Iteration 100, loss = 1.0069

Epoch: 3, Iteration 200, loss = 0.8881

Epoch: 3, Iteration 300, loss = 0.6308

Epoch: 3, Iteration 400, loss = 0.9445

Epoch: 3, Iteration 500, loss = 0.7540

Epoch: 3, Iteration 600, loss = 0.8057

Epoch: 3, Iteration 700, loss = 1.0313

766
Epoch: 4, Iteration 0, loss = 0.7787

Epoch: 4, Iteration 100, loss = 0.7333

Epoch: 4, Iteration 200, loss = 0.7128

Epoch: 4, Iteration 300, loss = 0.6606

Epoch: 4, Iteration 400, loss = 0.7723

Epoch: 4, Iteration 500, loss = 0.7408

Epoch: 4, Iteration 600, loss = 0.5901

Epoch: 4, Iteration 700, loss = 0.8007

766
Epoch: 5, Iteration 0, loss = 0.7952

Epoch: 5, Iteration 100, loss = 0.7019

Epoch: 5, Iteration 200, loss = 0.4165

Epoch: 5, Iteration 300, loss = 0.6903
```

```
Epoch: 5, Iteration 400, loss = 0.6339

Epoch: 5, Iteration 500, loss = 0.4677

Epoch: 5, Iteration 600, loss = 0.4711

Epoch: 5, Iteration 700, loss = 0.5835

766
Epoch: 6, Iteration 0, loss = 0.4765

Epoch: 6, Iteration 100, loss = 0.6818

Epoch: 6, Iteration 200, loss = 0.5150

Epoch: 6, Iteration 300, loss = 0.5365

Epoch: 6, Iteration 400, loss = 0.8594

Epoch: 6, Iteration 500, loss = 0.5770

Epoch: 6, Iteration 600, loss = 0.4752

Epoch: 6, Iteration 700, loss = 0.5795

766
Epoch: 7, Iteration 0, loss = 0.5759

Epoch: 7, Iteration 100, loss = 0.3704

Epoch: 7, Iteration 200, loss = 0.3392

Epoch: 7, Iteration 300, loss = 0.5618

Epoch: 7, Iteration 400, loss = 0.6053

Epoch: 7, Iteration 500, loss = 0.6023

Epoch: 7, Iteration 600, loss = 0.5952

Epoch: 7, Iteration 700, loss = 0.4318

766
Epoch: 8, Iteration 0, loss = 0.5294

Epoch: 8, Iteration 100, loss = 0.4897

Epoch: 8, Iteration 200, loss = 0.3798

Epoch: 8, Iteration 300, loss = 0.5580

Epoch: 8, Iteration 400, loss = 0.6300

Epoch: 8, Iteration 500, loss = 0.4359

Epoch: 8, Iteration 600, loss = 0.4987

Epoch: 8, Iteration 700, loss = 0.3898

766
```

```
Epoch: 9, Iteration 0, loss = 0.4385

Epoch: 9, Iteration 100, loss = 0.2538

Epoch: 9, Iteration 200, loss = 0.3927

Epoch: 9, Iteration 300, loss = 0.4345

Epoch: 9, Iteration 400, loss = 0.4950

Epoch: 9, Iteration 500, loss = 0.5151

Epoch: 9, Iteration 600, loss = 0.3612

Epoch: 9, Iteration 700, loss = 0.4331

Checking accuracy on validation set
Got 856 / 1000 correct (85.60)
lr, weight_decay:  0.017834577999293603 0.007457413913763551
766
Epoch: 0, Iteration 0, loss = 2.4392

Epoch: 0, Iteration 100, loss = 2.0446

Epoch: 0, Iteration 200, loss = 1.8761

Epoch: 0, Iteration 300, loss = 1.7988

Epoch: 0, Iteration 400, loss = 1.9468

Epoch: 0, Iteration 500, loss = 1.8385

Epoch: 0, Iteration 600, loss = 1.7574

Epoch: 0, Iteration 700, loss = 1.8708

766
Epoch: 1, Iteration 0, loss = 1.9474

Epoch: 1, Iteration 100, loss = 1.8296

Epoch: 1, Iteration 200, loss = 1.7774

Epoch: 1, Iteration 300, loss = 1.6867

Epoch: 1, Iteration 400, loss = 1.8905

Epoch: 1, Iteration 500, loss = 1.7628

Epoch: 1, Iteration 600, loss = 1.7996

Epoch: 1, Iteration 700, loss = 1.9430

766
Epoch: 2, Iteration 0, loss = 1.8016

Epoch: 2, Iteration 100, loss = 1.9070

Epoch: 2, Iteration 200, loss = 2.0114
```

```
Epoch: 2, Iteration 300, loss = 1.8763

Epoch: 2, Iteration 400, loss = 1.7305

Epoch: 2, Iteration 500, loss = 1.8701

Epoch: 2, Iteration 600, loss = 1.6229

Epoch: 2, Iteration 700, loss = 1.7842

766
Epoch: 3, Iteration 0, loss = 1.9137

Epoch: 3, Iteration 100, loss = 1.9083

Epoch: 3, Iteration 200, loss = 1.8817

Epoch: 3, Iteration 300, loss = 1.8099

Epoch: 3, Iteration 400, loss = 1.7005

Epoch: 3, Iteration 500, loss = 1.8736

Epoch: 3, Iteration 600, loss = 1.9258

Epoch: 3, Iteration 700, loss = 1.7219

766
Epoch: 4, Iteration 0, loss = 1.6560

Epoch: 4, Iteration 100, loss = 1.8191

Epoch: 4, Iteration 200, loss = 1.7708

Epoch: 4, Iteration 300, loss = 1.6862

Epoch: 4, Iteration 400, loss = 1.8247

Epoch: 4, Iteration 500, loss = 1.8352

Epoch: 4, Iteration 600, loss = 1.7491

Epoch: 4, Iteration 700, loss = 1.7931

766
Epoch: 5, Iteration 0, loss = 1.7749

Epoch: 5, Iteration 100, loss = 1.9159

Epoch: 5, Iteration 200, loss = 1.8238

Epoch: 5, Iteration 300, loss = 1.5560

Epoch: 5, Iteration 400, loss = 1.6737

Epoch: 5, Iteration 500, loss = 1.8314

Epoch: 5, Iteration 600, loss = 1.6986

Epoch: 5, Iteration 700, loss = 1.7902
```

```
766
Epoch: 6, Iteration 0, loss = 1.7199

Epoch: 6, Iteration 100, loss = 1.6432

Epoch: 6, Iteration 200, loss = 1.8996

Epoch: 6, Iteration 300, loss = 1.7594

Epoch: 6, Iteration 400, loss = 1.7917

Epoch: 6, Iteration 500, loss = 1.8570

Epoch: 6, Iteration 600, loss = 1.7053

Epoch: 6, Iteration 700, loss = 1.7111

766
Epoch: 7, Iteration 0, loss = 1.7725

Epoch: 7, Iteration 100, loss = 1.8454

Epoch: 7, Iteration 200, loss = 1.7216

Epoch: 7, Iteration 300, loss = 1.7683

Epoch: 7, Iteration 400, loss = 1.7379

Epoch: 7, Iteration 500, loss = 1.7229

Epoch: 7, Iteration 600, loss = 1.6953

Epoch: 7, Iteration 700, loss = 1.7770

766
Epoch: 8, Iteration 0, loss = 1.8519

Epoch: 8, Iteration 100, loss = 1.9043

Epoch: 8, Iteration 200, loss = 1.7501

Epoch: 8, Iteration 300, loss = 1.8312

Epoch: 8, Iteration 400, loss = 1.7051

Epoch: 8, Iteration 500, loss = 1.8243

Epoch: 8, Iteration 600, loss = 1.8129

Epoch: 8, Iteration 700, loss = 1.7334

766
Epoch: 9, Iteration 0, loss = 1.7949

Epoch: 9, Iteration 100, loss = 1.6672

Epoch: 9, Iteration 200, loss = 1.7302

Epoch: 9, Iteration 300, loss = 1.8249
```

```
Epoch: 9, Iteration 400, loss = 1.8436

Epoch: 9, Iteration 500, loss = 1.7359

Epoch: 9, Iteration 600, loss = 1.7087

Epoch: 9, Iteration 700, loss = 1.8101

Checking accuracy on validation set
Got 297 / 1000 correct (29.70)
lr, weight_decay:  0.02128023555651738 0.03310391349836247
766
Epoch: 0, Iteration 0, loss = 2.5384

Epoch: 0, Iteration 100, loss = 2.1381

Epoch: 0, Iteration 200, loss = 2.1142

Epoch: 0, Iteration 300, loss = 2.0413

Epoch: 0, Iteration 400, loss = 2.1018

Epoch: 0, Iteration 500, loss = 2.0743

Epoch: 0, Iteration 600, loss = 2.2199

Epoch: 0, Iteration 700, loss = 2.0292

766
Epoch: 1, Iteration 0, loss = 2.0157

Epoch: 1, Iteration 100, loss = 2.0032

Epoch: 1, Iteration 200, loss = 2.1634

Epoch: 1, Iteration 300, loss = 1.9626

Epoch: 1, Iteration 400, loss = 2.0697

Epoch: 1, Iteration 500, loss = 2.1806

Epoch: 1, Iteration 600, loss = 2.0892

Epoch: 1, Iteration 700, loss = 2.0477

766
Epoch: 2, Iteration 0, loss = 2.1612

Epoch: 2, Iteration 100, loss = 2.0031

Epoch: 2, Iteration 200, loss = 2.0227

Epoch: 2, Iteration 300, loss = 2.1827

Epoch: 2, Iteration 400, loss = 2.1480

Epoch: 2, Iteration 500, loss = 2.1399

Epoch: 2, Iteration 600, loss = 2.0429
```

```
Epoch: 2, Iteration 700, loss = 2.1571

766
Epoch: 3, Iteration 0, loss = 2.0057

Epoch: 3, Iteration 100, loss = 1.9757

Epoch: 3, Iteration 200, loss = 2.0267

Epoch: 3, Iteration 300, loss = 2.1541

Epoch: 3, Iteration 400, loss = 1.9918

Epoch: 3, Iteration 500, loss = 2.1662

Epoch: 3, Iteration 600, loss = 2.1523

Epoch: 3, Iteration 700, loss = 2.1169

766
Epoch: 4, Iteration 0, loss = 2.1898

Epoch: 4, Iteration 100, loss = 2.0425

Epoch: 4, Iteration 200, loss = 2.1490

Epoch: 4, Iteration 300, loss = 2.2228

Epoch: 4, Iteration 400, loss = 2.1010

Epoch: 4, Iteration 500, loss = 2.2432

Epoch: 4, Iteration 600, loss = 2.2138

Epoch: 4, Iteration 700, loss = 2.4889

766
Epoch: 5, Iteration 0, loss = 2.0269

Epoch: 5, Iteration 100, loss = 2.0775

Epoch: 5, Iteration 200, loss = 1.9776

Epoch: 5, Iteration 300, loss = 2.0660

Epoch: 5, Iteration 400, loss = 2.0357

Epoch: 5, Iteration 500, loss = 2.1158

Epoch: 5, Iteration 600, loss = 1.9955

Epoch: 5, Iteration 700, loss = 2.1882

766
Epoch: 6, Iteration 0, loss = 2.1112

Epoch: 6, Iteration 100, loss = 2.0269

Epoch: 6, Iteration 200, loss = 2.0795
```

```
Epoch: 6, Iteration 300, loss = 2.2339

Epoch: 6, Iteration 400, loss = 2.0908

Epoch: 6, Iteration 500, loss = 2.1337

Epoch: 6, Iteration 600, loss = 2.2328

Epoch: 6, Iteration 700, loss = 2.1409

766
Epoch: 7, Iteration 0, loss = 2.1239

Epoch: 7, Iteration 100, loss = 2.1757

Epoch: 7, Iteration 200, loss = 2.0848

Epoch: 7, Iteration 300, loss = 2.1403

Epoch: 7, Iteration 400, loss = 2.0619

Epoch: 7, Iteration 500, loss = 2.1638

Epoch: 7, Iteration 600, loss = 2.0667

Epoch: 7, Iteration 700, loss = 2.2284

766
Epoch: 8, Iteration 0, loss = 2.2607

Epoch: 8, Iteration 100, loss = 2.1481

Epoch: 8, Iteration 200, loss = 2.1813

Epoch: 8, Iteration 300, loss = 2.1537

Epoch: 8, Iteration 400, loss = 2.1603

Epoch: 8, Iteration 500, loss = 2.1250

Epoch: 8, Iteration 600, loss = 2.2422

Epoch: 8, Iteration 700, loss = 1.9941

766
Epoch: 9, Iteration 0, loss = 2.0961

Epoch: 9, Iteration 100, loss = 2.0972

Epoch: 9, Iteration 200, loss = 2.1126

Epoch: 9, Iteration 300, loss = 2.1233

Epoch: 9, Iteration 400, loss = 2.2548

Epoch: 9, Iteration 500, loss = 2.1046

Epoch: 9, Iteration 600, loss = 2.0936
```

```
Epoch: 9, Iteration 700, loss = 2.1273

Checking accuracy on validation set
Got 167 / 1000 correct (16.70)
lr, weight_decay:  0.005536587641274029 0.008573682236848965
766
Epoch: 0, Iteration 0, loss = 2.7690

Epoch: 0, Iteration 100, loss = 1.8514

Epoch: 0, Iteration 200, loss = 1.8859

Epoch: 0, Iteration 300, loss = 1.9022

Epoch: 0, Iteration 400, loss = 2.0576

Epoch: 0, Iteration 500, loss = 1.7686

Epoch: 0, Iteration 600, loss = 1.8214

Epoch: 0, Iteration 700, loss = 1.5686

766
Epoch: 1, Iteration 0, loss = 1.6034

Epoch: 1, Iteration 100, loss = 1.7004

Epoch: 1, Iteration 200, loss = 1.7954

Epoch: 1, Iteration 300, loss = 1.7542

Epoch: 1, Iteration 400, loss = 1.4746

Epoch: 1, Iteration 500, loss = 1.4312

Epoch: 1, Iteration 600, loss = 1.5744

Epoch: 1, Iteration 700, loss = 1.7567

766
Epoch: 2, Iteration 0, loss = 1.4713

Epoch: 2, Iteration 100, loss = 1.4428

Epoch: 2, Iteration 200, loss = 1.3777

Epoch: 2, Iteration 300, loss = 1.4059

Epoch: 2, Iteration 400, loss = 1.4227

Epoch: 2, Iteration 500, loss = 1.4099

Epoch: 2, Iteration 600, loss = 1.4932

Epoch: 2, Iteration 700, loss = 1.4789

766
Epoch: 3, Iteration 0, loss = 1.3623

Epoch: 3, Iteration 100, loss = 1.6571
```

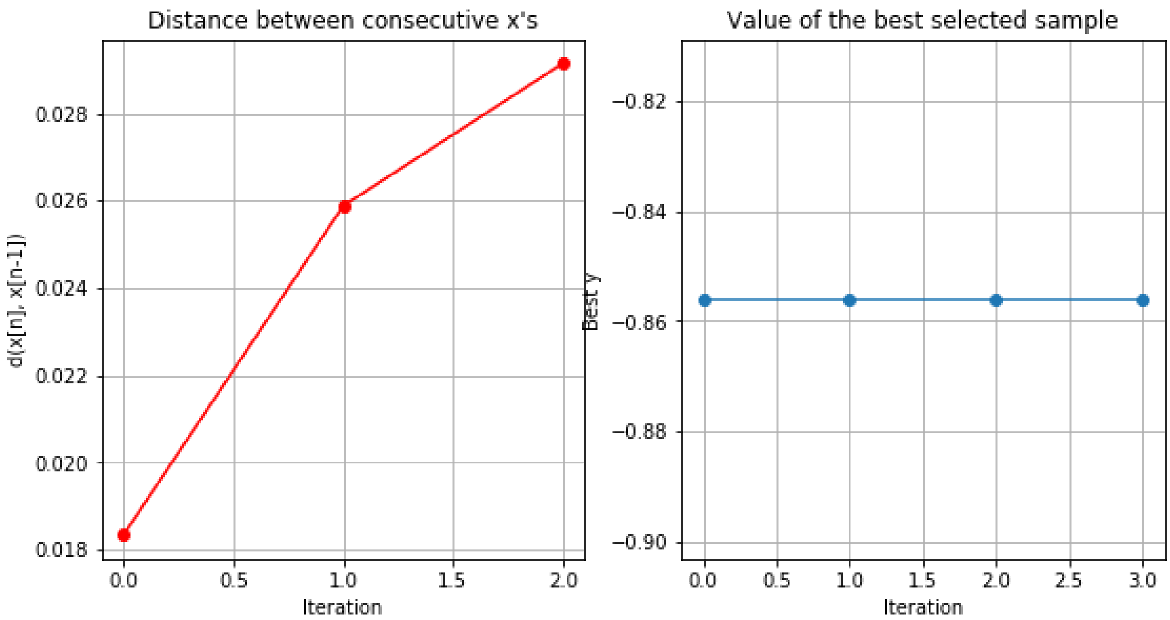
```
Epoch: 3, Iteration 200, loss = 1.4958

Epoch: 3, Iteration 300, loss = 1.3379

Epoch: 3, Iteration 400, loss = 1.3158

Epoch: 3, Iteration 500, loss = 1.5520

Epoch: 3, Iteration 600, loss = 1.3223

Epoch: 3, Iteration 700, loss = 1.4009

766
Epoch: 4, Iteration 0, loss = 1.3056

Epoch: 4, Iteration 100, loss = 1.4363

Epoch: 4, Iteration 200, loss = 1.3438

Epoch: 4, Iteration 300, loss = 1.7402

Epoch: 4, Iteration 400, loss = 1.3587

Epoch: 4, Iteration 500, loss = 1.3709

Epoch: 4, Iteration 600, loss = 1.4821

Epoch: 4, Iteration 700, loss = 1.2025

766
Epoch: 5, Iteration 0, loss = 1.2099

Epoch: 5, Iteration 100, loss = 1.6608

Epoch: 5, Iteration 200, loss = 1.3638

Epoch: 5, Iteration 300, loss = 1.2029

Epoch: 5, Iteration 400, loss = 1.3706

Epoch: 5, Iteration 500, loss = 1.5647

Epoch: 5, Iteration 600, loss = 1.1215

Epoch: 5, Iteration 700, loss = 1.3841

766
Epoch: 6, Iteration 0, loss = 1.2635

Epoch: 6, Iteration 100, loss = 1.6351

Epoch: 6, Iteration 200, loss = 1.3564

Epoch: 6, Iteration 300, loss = 1.2573

Epoch: 6, Iteration 400, loss = 1.2092

Epoch: 6, Iteration 500, loss = 1.2614
```

```
Epoch: 6, Iteration 600, loss = 1.2104

Epoch: 6, Iteration 700, loss = 1.3539

766
Epoch: 7, Iteration 0, loss = 1.3994

Epoch: 7, Iteration 100, loss = 1.2898

Epoch: 7, Iteration 200, loss = 1.1996

Epoch: 7, Iteration 300, loss = 1.3174

Epoch: 7, Iteration 400, loss = 1.2342

Epoch: 7, Iteration 500, loss = 1.4083

Epoch: 7, Iteration 600, loss = 1.3606

Epoch: 7, Iteration 700, loss = 1.2852

766
Epoch: 8, Iteration 0, loss = 1.3142

Epoch: 8, Iteration 100, loss = 1.3008

Epoch: 8, Iteration 200, loss = 1.2796

Epoch: 8, Iteration 300, loss = 1.4519

Epoch: 8, Iteration 400, loss = 1.2322

Epoch: 8, Iteration 500, loss = 1.4468

Epoch: 8, Iteration 600, loss = 1.1530

Epoch: 8, Iteration 700, loss = 1.1635

766
Epoch: 9, Iteration 0, loss = 0.9494

Epoch: 9, Iteration 100, loss = 1.2332

Epoch: 9, Iteration 200, loss = 1.2744

Epoch: 9, Iteration 300, loss = 1.3866

Epoch: 9, Iteration 400, loss = 1.5888

Epoch: 9, Iteration 500, loss = 1.1927

Epoch: 9, Iteration 600, loss = 1.3250

Epoch: 9, Iteration 700, loss = 1.1829

Checking accuracy on validation set
Got 369 / 1000 correct (36.90)
```

In [14]:

```
print("Best Hyperparameters: ", myProblem.x_opt)
print("Best Accuracy: ",myProblem.fx_opt)
myProblem.plot_convergence()
#############################################################
#                       END OF YOUR CODE HERE                       #
#############################################################


# define and train the network

model = ResNet18()
bestParams = myProblem.x_opt
optimizer = optim.Adam(model.parameters(), lr = bestParams[0], weight_decay = bestPa

train_part(model, optimizer, epochs = 10)


# report test set accuracy

check_accuracy(loader_test, model)

torch.save(model.state_dict(), 'model.pt')
```

```
Best Hyperparameters:  [0.001  0.0002]
Best Accuracy:  -0.856
```




```
766
Epoch: 0, Iteration 0, loss = 2.7106

Epoch: 0, Iteration 100, loss = 2.2778

Epoch: 0, Iteration 200, loss = 2.2613

Epoch: 0, Iteration 300, loss = 2.0905

Epoch: 0, Iteration 400, loss = 2.0409

Epoch: 0, Iteration 500, loss = 2.0135
```

```
Epoch: 0, Iteration 600, loss = 1.8899

Epoch: 0, Iteration 700, loss = 1.8358

766
Epoch: 1, Iteration 0, loss = 1.6023

Epoch: 1, Iteration 100, loss = 1.6534

Epoch: 1, Iteration 200, loss = 1.4879

Epoch: 1, Iteration 300, loss = 1.5091

Epoch: 1, Iteration 400, loss = 1.5850

Epoch: 1, Iteration 500, loss = 1.1482

Epoch: 1, Iteration 600, loss = 1.2440

Epoch: 1, Iteration 700, loss = 1.1733

766
Epoch: 2, Iteration 0, loss = 1.2480

Epoch: 2, Iteration 100, loss = 1.1660

Epoch: 2, Iteration 200, loss = 1.3320

Epoch: 2, Iteration 300, loss = 1.0468

Epoch: 2, Iteration 400, loss = 0.9363

Epoch: 2, Iteration 500, loss = 0.8560

Epoch: 2, Iteration 600, loss = 0.8993

Epoch: 2, Iteration 700, loss = 1.0031

766
Epoch: 3, Iteration 0, loss = 0.6398

Epoch: 3, Iteration 100, loss = 1.0184

Epoch: 3, Iteration 200, loss = 0.9299

Epoch: 3, Iteration 300, loss = 0.9323

Epoch: 3, Iteration 400, loss = 0.6531

Epoch: 3, Iteration 500, loss = 0.8739

Epoch: 3, Iteration 600, loss = 0.8476

Epoch: 3, Iteration 700, loss = 0.6931

766
Epoch: 4, Iteration 0, loss = 0.7510

Epoch: 4, Iteration 100, loss = 0.7403
```

```
Epoch: 4, Iteration 200, loss = 0.6704

Epoch: 4, Iteration 300, loss = 0.5437

Epoch: 4, Iteration 400, loss = 0.6358

Epoch: 4, Iteration 500, loss = 0.5224

Epoch: 4, Iteration 600, loss = 0.7831

Epoch: 4, Iteration 700, loss = 0.4541

766
Epoch: 5, Iteration 0, loss = 0.4747

Epoch: 5, Iteration 100, loss = 0.6313

Epoch: 5, Iteration 200, loss = 0.6025

Epoch: 5, Iteration 300, loss = 0.3635

Epoch: 5, Iteration 400, loss = 0.6116

Epoch: 5, Iteration 500, loss = 0.6325

Epoch: 5, Iteration 600, loss = 0.4841

Epoch: 5, Iteration 700, loss = 0.4604

766
Epoch: 6, Iteration 0, loss = 0.5317

Epoch: 6, Iteration 100, loss = 0.4976

Epoch: 6, Iteration 200, loss = 0.5879

Epoch: 6, Iteration 300, loss = 0.6389

Epoch: 6, Iteration 400, loss = 0.7046

Epoch: 6, Iteration 500, loss = 0.5182

Epoch: 6, Iteration 600, loss = 0.6148

Epoch: 6, Iteration 700, loss = 0.3974

766
Epoch: 7, Iteration 0, loss = 0.3819

Epoch: 7, Iteration 100, loss = 0.3500

Epoch: 7, Iteration 200, loss = 0.4960

Epoch: 7, Iteration 300, loss = 0.5296

Epoch: 7, Iteration 400, loss = 0.5977

Epoch: 7, Iteration 500, loss = 0.4467

Epoch: 7, Iteration 600, loss = 0.7439
```

```
Epoch: 7, Iteration 700, loss = 0.4757

766
Epoch: 8, Iteration 0, loss = 0.3840

Epoch: 8, Iteration 100, loss = 0.4964

Epoch: 8, Iteration 200, loss = 0.4863

Epoch: 8, Iteration 300, loss = 0.4777

Epoch: 8, Iteration 400, loss = 0.3383

Epoch: 8, Iteration 500, loss = 0.6338

Epoch: 8, Iteration 600, loss = 0.4809

Epoch: 8, Iteration 700, loss = 0.4399

766
Epoch: 9, Iteration 0, loss = 0.4134

Epoch: 9, Iteration 100, loss = 0.4172

Epoch: 9, Iteration 200, loss = 0.6042

Epoch: 9, Iteration 300, loss = 0.4991

Epoch: 9, Iteration 400, loss = 0.3542

Epoch: 9, Iteration 500, loss = 0.2245

Epoch: 9, Iteration 600, loss = 0.2673

Epoch: 9, Iteration 700, loss = 0.3980

Checking accuracy on test set
Got 8327 / 10000 correct (83.27)
```

In [ ]:

```
## Part 3 (20 points)
```

The code provided below will allow you to visualise the feature maps computed by different layers of your network. Run the code (install matplotlib if necessary) and **answer the following questions**:

1. Compare the feature maps from low-level layers to high-level layers, what do you observe?
2. Use the training log, reported test set accuracy and the feature maps, analyse the performance of your network. If you think the performance is sufficiently good, explain why; if not, what might be the problem and how can you improve the performance?
3. What are the other possible ways to analyse the performance of your network?

YOUR ANSWER FOR PART 3 HERE

1: the number of feature maps increases from low-level layers to high-level layers. And the low-level feature maps tends to be simpler like edge detection, etc, while the high level feature maps are more complex and begin to demonstrate the real features.

2: I think the performance of my convolutional neural network is not sufficiently good. First of all, the accuracy is not high enough. I think adding number of epochs or number of bayesian optimisation max iterations may help to improve the performance. Besides that, maybe a different approach of dataset preprocessing e.g. kai_ming would improve the performance

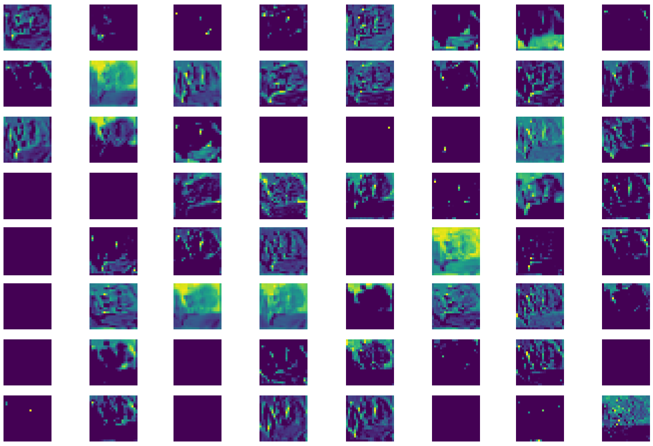
3: Confusion Matrix, Graphs of error rate

In [23]:

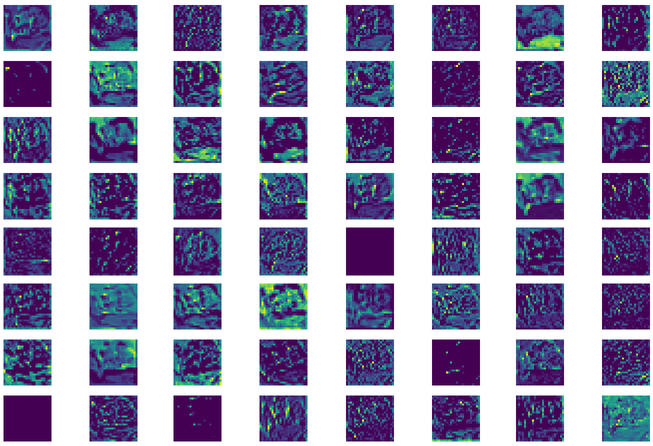
```
#!pip install matplotlib

import matplotlib.pyplot as plt

plt.tight_layout()


activation = {}
def get_activation(name):
    def hook(model, input, output):
        activation[name] = output.detach()
    return hook

vis_labels = ['conv1', 'layer1', 'layer2', 'layer3', 'layer4']

for l in vis_labels:

    getattr(model, l).register_forward_hook(get_activation(l))


data, _ = cifar10_test[0]
data = data.unsqueeze_(0).to(device = device, dtype = dtype)

output = model(data)



for idx, l in enumerate(vis_labels):

    act = activation[l].squeeze()

    if idx < 2:
        ncols = 8
    else:
        ncols = 32

    nrows = act.size(0) // ncols

    fig, axarr = plt.subplots(nrows, ncols)
    fig.suptitle(l)


    for i in range(nrows):
        for j in range(ncols):
            axarr[i, j].imshow(act[i * nrows + j].cpu())
            axarr[i, j].axis('off')
```

```
<Figure size 432x288 with 0 Axes>
```

conv1

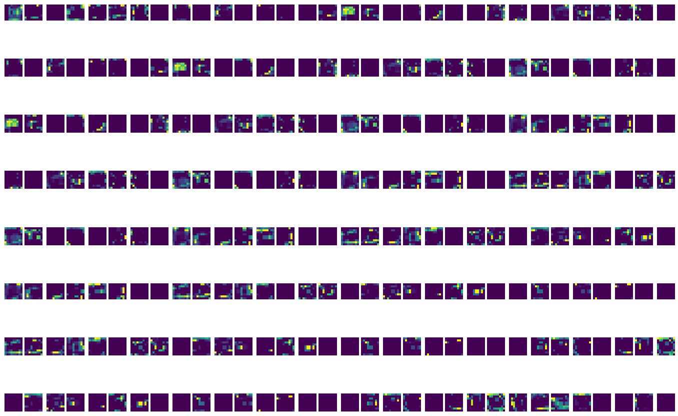


layer1

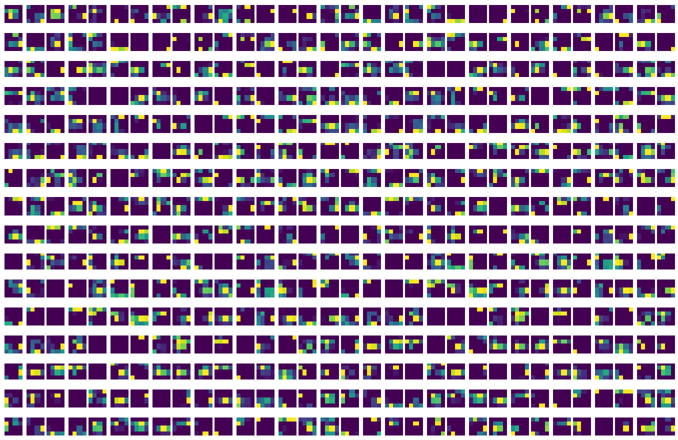


layer2

layer3



layer4



=============== END OF CW2 ===============