# HW5-Coding

January 3, 2024

# 1 Homework 5: Convolutional neural network (30 points)

In this part, you need to implement and train a convolutional neural network on the CIFAR-10 dataset with PyTorch. ### What is PyTorch?

PyTorch is a system for executing dynamic computational graphs over Tensor objects that behave similarly as numpy ndarray. It comes with a powerful automatic differentiation engine that removes the need for manual back-propagation.

## 1.0.1 Why?

- Our code will now run on GPUs! Much faster training. When using a framework like PyTorch or TensorFlow you can harness the power of the GPU for your own custom neural network architectures without having to write CUDA code directly (which is beyond the scope of this class).
- We want you to be ready to use one of these frameworks for your project so you can experiment more efficiently than if you were writing every feature you want to use by hand.
- We want you to stand on the shoulders of giants! TensorFlow and PyTorch are both excellent frameworks that will make your lives a lot easier, and now that you understand their guts, you are free to use them:)
- We want you to be exposed to the sort of deep learning code you might run into in academia or industry. ## How can I learn PyTorch?

Justin Johnson has made an excellent tutorial for PyTorch.

You can also find the detailed API doc here. If you have other questions that are not addressed by the API docs, the PyTorch forum is a much better place to ask than StackOverflow.

Install PyTorch and Skorch.

# []: !pip install -q torch skorch torchvision torchtext

```
[]: import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
import torchvision
import torchvision.transforms as transforms
import skorch
```

```
import sklearn
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
```

# 1.1 0. Tensor Operations (5 points)

Tensor operations are important in deep learning models. In this part, you are required to get famaliar to some common tensor operations in PyTorch.

## 1.1.1 1) Tensor squeezing, unsqueezing and viewing

Tensor squeezing, unsqueezing and viewing are important methods to change the dimension of a Tensor, and the corresponding functions are torch.squeeze, torch.unsqueeze and torch.Tensor.view. Please read the documents of the functions, and finish the following practice.

```
[]: # x is a tensor with size being (3, 2)
     x = torch.Tensor([[1, 2],
                        [3, 4],
                        [5, 6]])
     x.shape
     # Add two new dimensions to x by using the function torch.unsqueeze, so that
     \rightarrow the size of x becomes (3, 1, 2, 1).
     x = torch.unsqueeze(x, 1)
     x = torch.unsqueeze(x, 3)
     print(x.shape)
     # Remove the two dimensions justed added by using the function torch.squeeze,
     \rightarrow and change the size of x back to (3, 2).
     x = torch.squeeze(x, 3)
     x = torch.squeeze(x, 1)
     \# x = torch.squeeze(x, (0, 2)) \# in torch 2.0 this will work
     print(x.shape)
     \# x is now a two-dimensional tensor, or in other words a matrix. Now use the
     function torch. Tensor. view and change x to a one-dimensional vector with
     \rightarrow size being (6).
     x = x.view(6)
     print(x.shape)
```

```
torch.Size([3, 1, 2, 1])
torch.Size([3, 2])
torch.Size([6])
```

### 1.1.2 2) Tensor concatenation and stack

Tensor concatenation and stack are operations to combine small tensors into big tensors. The corresponding functions are torch.cat and torch.stack. Please read the documents of the functions, and finish the following practice.

```
[]: \# x is a tensor with size being (3, 2)
     x = torch.Tensor([[1, 2], [3, 4], [5, 6]])
     # y is a tensor with size being (3, 2)
     y = torch.Tensor([[-1, -2], [-3, -4], [-5, -6]])
     # Dur goal is to generate a tensor z with size as (2, 3, 2), and z[0, :, :] = x_{, \sqcup}
      \rightarrow z[1,:,:] = y.
     # Use torch.stack to generate such a z
     z = torch.stack((x, y))
     # print(z)
     print(z[0,:,:])
     # Use torch.cat and torch.unsqueeze to generate such a z
     # print('torch.unsqueeze(x, 0) = ', torch.unsqueeze(x, 0))
     z = torch.cat((torch.unsqueeze(x, 0), torch.unsqueeze(y, 0)))
     # print(z)
     print(z[1,:,:])
    tensor([[1., 2.],
             [3., 4.],
             [5., 6.]])
    tensor([[-1., -2.],
             [-3., -4.],
             [-5., -6.]]
```

#### 1.1.3 3) Tensor expansion

Tensor expansion is to expand a tensor into a larger tensor along singleton dimensions. The corresponding functions are torch. Tensor. expand and torch. Tensor. expand as. Please read the documents of the functions, and finish the following practice.

```
[]: # x is a tensor with size being (3)
x = torch.Tensor([1, 2, 3])

# Our goal is to generate a tensor z with size (2, 3), so that z[0,:,:] = x, □
→z[1,:,:] = x.

# [TO DO]
# Change the size of x into (1, 3) by using torch.unsqueeze.
```

```
x = torch.unsqueeze(x, 0)
print(x.shape)

# [TO DO]
# Then expand the new tensor to the target tensor by using torch.Tensor.expand.
z = x.expand(2, -1)
# print(z)
print(z.shape)
```

```
torch.Size([1, 3])
torch.Size([2, 3])
```

### 1.1.4 4) Tensor reduction in a given dimension

In deep learning, we often need to compute the mean/sum/max/min value in a given dimension of a tensor. Please read the document of torch.mean, torch.sum, torch.max, torch.min, torch.topk, and finish the following practice.

```
[]: # x is a random tensor with size being (10, 50)
     x = torch.randn(10, 50)
     # Compute the mean value for each row of x.
     # You need to generate a tensor x_mean of size (10), and x_mean[k, :] is the
     \rightarrowmean value of the k-th row of x.
     # dim = 1: eliminate the second(1)'s dimension
     x_mean = torch.mean(x, dim=1)
     # print(x_mean)
     print(x_mean[3, ])
     # Compute the sum value for each row of x.
     # You need to generate a tensor x_sum of size (10).
     x_sum = torch.sum(x, dim=1)
     print(x_sum.shape)
     # Compute the max value for each row of x.
     # You need to generate a tensor x_max of size (10).
     (x_max, indices) = torch.max(x, dim=1)
     # print(x_max, indices)
     print(x_max.shape)
     # Compute the min value for each row of x.
     # You need to generate a tensor x_min of size (10).
     (x_min, indices) = torch.min(x, dim=1)
     print(x_min.shape)
```

```
# Compute the top-5 values for each row of x.

# (wrong) You need to generate a tensor x_mean of size (10, 5), and x_top[k, :]

is the top-5 values of each row in x.

# (right) You need to generate a tensor, top-5 values of each row

(x_xtop, indices) = torch.topk(x, k=5, dim=1)

print((x_xtop.shape))
```

```
tensor(0.2702)
torch.Size([10])
torch.Size([10])
torch.Size([10])
torch.Size([10, 5])
```

#### 1.2 Convolutional Neural Networks

Implement a convolutional neural network for image classification on CIFAR-10 dataset.

CIFAR-10 is an image dataset of 10 categories. Each image has a size of 32x32 pixels. The following code will download the dataset, and split it into train and test. For this question, we use the default validation split generated by Skorch.

```
[]: train = torchvision.datasets.CIFAR10("./data", train=True, download=True)
test = torchvision.datasets.CIFAR10("./data", train=False, download=True)
```

Files already downloaded and verified Files already downloaded and verified

The following code visualizes some samples in the dataset. You may use it to debug your model if necessary.

```
[]: def plot(data, labels=None, num_sample=5):
    n = min(len(data), num_sample)
    for i in range(n):
        plt.subplot(1, n, i+1)
        plt.imshow(data[i], cmap="gray")
        plt.xticks([])
        plt.yticks([])
        if labels is not None:
            plt.title(labels[i])

train.labels = [train.classes[target] for target in train.targets]
    plot(train.data, train.labels)
```



# 1.2.1 1) Basic CNN implementation

Consider a basic CNN model

- It has 3 convolutional layers, followed by a linear layer.
- Each convolutional layer has a kernel size of 3, a padding of 1.
- ReLU activation is applied on every hidden layer.

Please implement this model in the following section. The hyperparameters is then be tuned and you need to fill the results in the table.

a) Implement convolutional layers (10 Points) Implement the initialization function and the forward function of the CNN.

```
[]: class CNN(nn.Module):
       def __init__(self, channels):
         super(CNN, self).__init__()
         # implement parameter definitions here
         # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
         # print('channels = ', channels)
         self.channels = channels
         self.backbone = nn.Sequential(
             nn.Conv2d(3, channels, kernel_size=3, padding=1),
             nn.ReLU(),
             nn.Conv2d(channels, channels, kernel_size=3, padding=1),
             nn.ReLU(),
             nn.Conv2d(channels, channels, kernel_size=3, padding=1),
             nn.ReLU(),
         )
         # regard the image has the same size 32 * 32
         self.f1 = nn.Linear(channels * 32 * 32, 10)
```

```
# *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

def forward(self, images):
    # implement the forward function here
    # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

images = self.backbone(images)

# flatten the image
images = images.view(images.shape[0], -1)
images = self.f1(images)

# ****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
return images
```

b) Tune hyperparameters Train the CNN model on CIFAR-10 dataset. We can tune the number of channels, optimizer, learning rate and the number of epochs for best validation accuracy.

```
[]: # implement hyperparameters, you can select and modify the hyperparameters by
     \rightarrow yourself here.
     optimizer = [torch.optim.SGD, torch.optim.Adam]
     learning_rate = [1e-3, 1e-2]
     channel = [128, 256, 512]
     train_data_normalized = torch.Tensor(train.data/255)
     train_data_normalized = train_data_normalized.permute(0,3,1,2)
     for l in learning_rate:
       for o in optimizer:
         for c in channel:
           print(f'The channel was \{c\}, the learning rate was \{1\} and the optimizer \cup
      →was {str(o)}')
           cnn = CNN(channels = c)
           model = skorch.NeuralNetClassifier(cnn, criterion=torch.nn.
      →CrossEntropyLoss,
                                         device="cuda",
                                         optimizer=o,
                                        # optimizer__momentum=0.90,
                                         lr=1,
                                         max_epochs=50,
                                         batch size=32,
                                         callbacks=[skorch.callbacks.
      →EarlyStopping(lower_is_better=True)])
```

# implement input normalization & type cast here
model.fit(train\_data\_normalized, np.asarray(train.targets))

The channel was 128, the learning rate was 0.001 and the optimizer was <class 'torch.optim.sgd.SGD'>

_	train_loss	valid_acc	valid_loss	dur
1	2.1158	0.3160	1.9293	
8.0129 2	1.8676	0.3645	1.8060	
7.0036				
3	1.7704	0.3984	1.7152	
7.0300	1 6017	0.4253	1 6460	
4 7.0520	1.6917	0.4253	1.6462	
5	1.6336	0.4405	1.5969	
7.0703				
6	1.5857	0.4537	1.5550	
7.0006				
7	1.5434	0.4653	1.5178	
7.0303	1 5060	0 4777	1 /055	
8 6.9867	1.5062	0.4777	1.4855	
9	1.4740	0.4851	1.4584	
7.0018				
10	1.4458	0.4927	1.4353	
7.0111				
11	1.4201	0.4999	1.4149	
7.0238	1 2061	0 5051	1 2060	
12 7.0131	1.3961	0.5051	1.3962	
13	1.3729	0.5109	1.3787	
7.0701				
14	1.3496	0.5166	1.3605	
7.0898				
15	1.3254	0.5228	1.3404	
7.0641 16	1 2002	0 5000	1 2100	
7.0448	1.3003	0.5288	1.3189	
17	1.2751	0.5329	1.2981	
7.0350				
18	1.2510	0.5411	1.2792	
7.0506				
19	1.2286	0.5472	1.2625	
7.0371 20	1.2082	0.5523	1.2481	
7.0452	1.2002	0.0023	1.2401	

21	1.1893	0.5558	1.2354
7.0610	1.1095	0.5550	1.2554
22	1.1714	0.5615	1.2241
7.0859			
23	1.1543	0.5647	1.2139
7.0981			
24	1.1376	0.5670	1.2042
7.1177			
25	1.1213	0.5722	1.1951
7.1225			
26	1.1052	0.5741	1.1863
7.1420	1 0000	0 5704	1 1701
27 7.1389	1.0892	0.5781	1.1781
7.1369 28	1.0733	0.5832	1.1701
7.1626	1.0700	0.0002	1.1101
29	1.0574	0.5866	1.1624
7.1693			
30	1.0415	0.5895	1.1553
7.1629			
31	1.0258	0.5915	1.1485
7.1485			
32	1.0102	0.5954	1.1422
7.1612	0.0040	0. 5004	4 4000
33	0.9948	0.5981	1.1362
7.1532 34	0.9796	0.6016	1.1305
7.1491	0.9790	0.0010	1.1505
35	0.9645	0.6052	1.1253
7.1466			
36	0.9495	0.6078	1.1203
7.1506			
37	0.9347	0.6089	1.1159
7.1595			
38	0.9200	0.6109	1.1117
7.1716	0.0054	0.6100	1 1070
39 7.1662	0.9054	0.6129	1.1079
40	0.8907	0.6141	1.1043
7.1629	0.0001	0.0111	1.1010
41	0.8761	0.6160	1.1011
7.1744			
42	0.8615	0.6161	1.0983
7.1671			
43	0.8469	0.6193	1.0959
7.1680	0.0005		
44	0.8323	0.6205	1.0939
7.1720			

45	0.8176	0.6211	1.0921	
7.1611				
46	0.8030	0.6235	1.0907	
7.1709				
47	0.7884	0.6242	1.0898	
7.1742				
48	0.7738	0.6250	1.0895	
7.1943				
49	0.7593	0.6255	1.0895	7.1965
50	0.7448	0.6266	1.0902	7.1881

The channel was 256, the learning rate was 0.001 and the optimizer was <class 'torch.optim.sgd.SGD'>

_	train_loss		valid_loss	dur
1	2.0442		1.8783	
16.4868				
2	1.8054	0.3976	1.7304	
16.5860				
3	1.7004	0.4273	1.6449	
16.6578				
4	1.6279	0.4455	1.5829	
16.6932				
5	1.5640	0.4653	1.5236	
16.7557				
6	1.5044	0.4785	1.4709	
16.7104				
7	1.4544	0.4940	1.4321	
16.7861	1 4149	0 5050	1 4020	
8 16.7697	1.4143	0.5052	1.4030	
9	1.3789	0.5118	1.3771	
16.7234	1.3703	0.3110	1.5771	
10.7201	1.3442	0.5204	1.3506	
16.7258	1.0112	0.0201	1.0000	
11	1.3091	0.5285	1.3241	
16.5999				
12	1.2755	0.5356	1.3007	
16.5341				
13	1.2457	0.5426	1.2806	
16.4736				
14	1.2194	0.5506	1.2631	
16.4122				
15	1.1957	0.5565	1.2472	
16.3709				
16	1.1736	0.5612	1.2330	
16.4181				
17	1.1525	0.5658	1.2197	
16.4600				

18	1.1320	0.5706	1.2072	
16.4435 19	1.1117	0.5745	1.1960	
16.4278	1.1111	0.3743	1.1900	
20	1.0917	0.5785	1.1856	
16.4144				
21	1.0720	0.5834	1.1760	
16.4010 22	1.0525	0.5882	1.1671	
16.3734	1.0020	0.0002	1.10/1	
23	1.0335	0.5924	1.1589	
16.3465				
24	1.0148	0.5960	1.1515	
16.3348 25	0.9964	0.5974	1.1447	
16.3804	0.0001	0.0071	1.111	
26	0.9784	0.5993	1.1385	
16.3272				
27 16 2609	0.9607	0.6022	1.1328	
16.3608 28	0.9431	0.6049	1.1276	
16.3947				
29	0.9255	0.6067	1.1225	
16.4668	0.0000	0.000	4 4470	
30 16.5375	0.9080	0.6086	1.1179	
31	0.8904	0.6086	1.1137	16.5316
32	0.8726	0.6107	1.1097	
16.6019				
33	0.8547	0.6129	1.1059	
16.6545 34	0.8366	0.6152	1.1026	
16.6232	0.0000	0.0102	1.1020	
35	0.8184	0.6159	1.0996	
16.6570				
36 16.5988	0.8000	0.6172	1.0973	
37	0.7814	0.6189	1.0957	
16.5260				
38	0.7628	0.6214	1.0950	
16.5240	0 57444	0 0007	1 0050	40 4540
39 40	0.7441 0.7254	0.6227 0.6224	1.0952 1.0965	16.4719 16.4138
40	0.7067	0.6222	1.0988	16.4675
42	0.6880	0.6223	1.1025	16.4783

The channel was 512, the learning rate was 0.001 and the optimizer was <class 'torch.optim.sgd.SGD'>

epoch	train_loss	valid_acc	valid_loss	dur
1 46.1175	1.9867	0.3623	1.8191	
46.1173 2 46.1142	1.7513	0.4171	1.6693	
3 45.7091	1.6400	0.4468	1.5838	
45.7091	1.5603	0.4680	1.5144	
5 45.4629	1.4935	0.4853	1.4582	
6 45.4543	1.4396	0.5000	1.4170	
7 45.3653	1.3952	0.5077	1.3844	
8 45.4058	1.3541	0.5188	1.3529	
9	1.3127	0.5287	1.3208	
10 46.3144	1.2729	0.5375	1.2915	
11 46.4242	1.2376	0.5454	1.2668	
12 46.3143	1.2072	0.5545	1.2464	
13 45.7325	1.1800	0.5601	1.2289	
14 45.9819	1.1545	0.5658	1.2133	
15 45.9304	1.1300	0.5724	1.1989	
16 45.4933	1.1059	0.5773	1.1857	
17 45.3715	1.0821	0.5817	1.1732	
18 45.4426	1.0587	0.5876	1.1618	
19 45.5602	1.0358	0.5915	1.1513	
20 46.1363	1.0134	0.5973	1.1418	
21 46.3644	0.9915	0.6005	1.1330	
22 45.7330	0.9700	0.6039	1.1250	
23 45.8170	0.9487	0.6072	1.1174	

24	0.9277	0.6107	1.1103	
45.4220				
25	0.9067	0.6116	1.1037	
45.4124				
26	0.8858	0.6138	1.0975	
45.3856				
27	0.8651	0.6175	1.0919	
45.7772	0.0444	0.0407	4 0070	
28	0.8444	0.6187	1.0870	
46.3898	0.8239	0.6195	1.0828	
29 46.3944	0.0239	0.0195	1.0020	
30	0.8035	0.6216	1.0797	
46.1950	0.0000	0.0210	1.0737	
31	0.7833	0.6235	1.0776	
45.4395				
32	0.7632	0.6250	1.0765	
45.5423				
33	0.7433	0.6255	1.0766	45.4350
34	0.7235	0.6264	1.0779	45.3818
35	0.7037	0.6283	1.0803	45.3848
36	0.6839	0.6295	1.0839	45.7210

The channel was 128, the learning rate was 0.001 and the optimizer was <class 'torch.optim.adam.Adam'>

dur	valid_loss	valid_acc	train_loss	epoch
	1.1889	0.5829	1.4839	1
				7.5850
	1.0072	0.6502	1.0473	2
				7.5615
7.5612	1.0422	0.6484	0.8172	3
7.5515	1.2363	0.6250	0.6176	4
7.5729	1.5414	0.5978	0.4350	5
7.5781	1.8818	0.6011	0.3217	6

Stopping since valid\_loss has not improved in the last 5 epochs.

The channel was 256, the learning rate was 0.001 and the optimizer was <class 'torch.optim.adam.Adam'>

epoch	train_loss	valid_acc	valid_loss	dur
1	1.7182	0.5077	1.3801	
16.8513 2	1.2644	0.5565	1.2567	
16.8689				
3 16.9014	1.0805	0.5825	1.1950	
4	0.8733	0.5819	1.2774	16.8458
5	0.6655	0.5767	1.5078	16.8153

6	0.5032	0.5598	1.8750	16.8164
7	0.3858	0 5273	2 4469	16 8811

The channel was 512, the learning rate was 0.001 and the optimizer was <class 'torch.optim.adam.Adam'>

dur	valid_loss	valid_acc	train_loss	epoch
	2.3026	0.1000	2.3566	1
				46.3657
46.2071	2.3026	0.1000	2.3028	2
45.8301	2.3026	0.1000	2.3028	3
46.2545	2.3026	0.1000	2.3028	4
46.7461	2.3026	0.1000	2.3028	5

Stopping since valid\_loss has not improved in the last 5 epochs.

The channel was 128, the learning rate was 0.01 and the optimizer was <class 'torch.optim.sgd.SGD'>

epoch	train_loss	valid_acc	valid_loss	dur
1	1.7802	0.4473	1.5509	
7.2227				
2	1.4604	0.4953	1.3926	
7.1891				
3	1.3259	0.5312	1.2938	
7.1699				
4	1.2092	0.5520	1.2376	
7.1683				
5	1.1174	0.5713	1.1887	
7.1695				
6	1.0313	0.5887	1.1468	
7.1558				
7	0.9441	0.6095	1.1049	
7.1596	0.0554	0.0040	4 0500	
8	0.8574	0.6212	1.0799	
7.1328	0 7744	0. 400.4	1 0010	7 4040
9	0.7744	0.6294	1.0816	
10	0.6936	0.6324	1.1068	
11	0.6121	0.6323	1.1574	
12	0.5278	0.6290	1.2431	7.1241

Stopping since valid\_loss has not improved in the last  $5\ \text{epochs.}$ 

The channel was 256, the learning rate was 0.01 and the optimizer was <class 'torch.optim.sgd.SGD'>

dur	valid_loss	valid_acc	train_loss	epoch
	1.4906	0.4675	1.7304	1
	1.3044	0.5328	1.3863	16.3829 2
				16.5476
	1.2175	0.5659	1.2254	3

16.5300				
4	1.1000	0.5942	1.1371	
16.5410				
5	0.9843	0.6187	1.0781	
16.5368				
6	0.8811	0.6341	1.0504	
16.4840				
7	0.7862	0.6431	1.0436	
16.4648				
8	0.6937	0.6450	1.0633	16.3988
9	0.5998	0.6420	1.1201	16.3038
10	0.5008	0.6338	1.2165	16.3112
11	0.3968	0.6297	1.3476	16.3209

The channel was 512, the learning rate was 0.01 and the optimizer was <class 'torch.optim.sgd.SGD'>

epoch	train_loss	valid_acc	valid_loss	dur
1	1.7122	0.4814	1.4455	
45.7170 2	1.3445	0.5414	1.2749	
45.8045				
3 46.0595	1.1590	0.5824	1.1645	
4	1.0109	0.6085	1.0983	
46.3534 5	0.8835	0.6283	1.0726	
46.3809	0.000	0.0200	1.0120	
6	0.7679	0.6391	1.0765	46.4801
7	0.6554	0.6344	1.1211	46.4627
8	0.5380	0.6302	1.2184	45.9412
9	0.4127	0.6206	1.3871	45.4630

Stopping since valid\_loss has not improved in the last 5 epochs.

The channel was 128, the learning rate was 0.01 and the optimizer was <class 'torch.optim.adam.Adam'>  $\,$ 

epoch	train_loss	valid_acc	valid_loss	dur
1	2.9942	0.1000	2.3039	
7.4479				
2	2.3042	0.1000	2.3039	7.4428
3	2.3042	0.1000	2.3039	7.4505
4	2.3042	0.1000	2.3039	7.4814
5	2.3042	0.1000	2.3039	7.4697

Stopping since valid\_loss has not improved in the last 5 epochs.

The channel was 256, the learning rate was 0.01 and the optimizer was <class 'torch.optim.adam.Adam'>

epoch	${\tt train\_loss}$	valid_acc	valid_loss	dur

1	8.8825	0.1000	2.3039	
16.5144				
2	2.3042	0.1000	2.3039	16.7190
3	2.3042	0.1000	2.3039	16.8494
4	2.3042	0.1000	2.3039	16.9722
5	2.3042	0.1000	2.3039	17.0036

The channel was 512, the learning rate was 0.01 and the optimizer was <class 'torch.optim.adam.Adam'>

dur	valid_loss	valid_acc	${\tt train\_loss}$	epoch
	2.3038	0.1000	55.4451	1
				46.9036
46.8506	2.3039	0.1000	2.3042	2
46.5957	2.3039	0.1000	2.3042	3
45.6649	2.3039	0.1000	2.3042	4
45.5824	2.3039	0.1000	2.3042	5

Stopping since valid loss has not improved in the last 5 epochs.

Write down validation accuracy of your model under different hyperparameter settings. Note the validation set is automatically split by Skorch during model.fit().

### 1.2.2 2) Full CNN implementation (10 points)

Based on the CNN in the previous question, implement a full CNN model with max pooling layer.

- Add a max pooling layer after each convolutional layer.
- Each max pooling layer has a kernel size of 2 and a stride of 2.

Please implement this model in the following section. The hyperparameters is then be tuned and fill the results in the table. You are also required to complete the questions.

a) Implement max pooling layers Similar to the CNN implementation in previous question, implement max pooling layers.

```
[]: class CNN_MaxPool(nn.Module):
    def __init__(self, channels):
        super(CNN_MaxPool, self).__init__()
    # implement parameter definitions here
        # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
    self.channels = channels
```

```
self.backbone = nn.Sequential(
      nn.Conv2d(3, channels, kernel_size=3, padding=1),
     nn.BatchNorm2d(channels),
     nn.ReLU(),
     nn.MaxPool2d(kernel_size=2, stride=2),
     nn.Dropout2d(p=0.2),
     nn.Conv2d(channels, channels, kernel_size=3, padding=1),
     nn.BatchNorm2d(channels),
     nn.ReLU(),
     nn.MaxPool2d(kernel_size=2, stride=2),
     nn.Dropout2d(p=0.2),
     nn.Conv2d(channels, channels, kernel_size=3, padding=1),
     nn.BatchNorm2d(channels),
     nn.ReLU(),
     nn.MaxPool2d(kernel_size=2, stride=2),
     nn.Dropout2d(p=0.2)
 )
  # regard the image has the same size 32 * 32
  # after 3 max pooling, the size is 32/2/2/2=4
 self.f1 = nn.Linear(channels * 4 * 4, 10)
  # *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
def forward(self, images):
  # implement the forward function here
 images = self.backbone(images)
  # flatten the image
 images = images.view(images.shape[0], -1)
 images = self.f1(images)
  # *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)****
 return images
```

**b)** Tune hyperparameters Based on the better optimizer found in the previous problem, we can tune the number of channels and learning rate for best validation accuracy.

```
[]: # implement hyperparameters, you can select and modify the hyperparameters by yourself here.

learning_rate = [1e-4, 1e-3, 1e-2]
channel = [128, 256, 512]
```

```
# Select the better optimizer by the result shown in the previous problem, you_
\hookrightarrow can select and modify it by yourself here.
better_optimizer = torch.optim.Adam
train_data_normalized = torch.Tensor(train.data/255)
train_data_normalized = train_data_normalized.permute(0,3,1,2)
for l in learning_rate:
   for c in channel:
     print(f'The channel was {c}, the learning rate was {l}')
      cnn = CNN_MaxPool(channels = c)
      model = skorch.NeuralNetClassifier(cnn, criterion=torch.nn.
→CrossEntropyLoss,
                                    device="cuda",
                                    optimizer=better_optimizer,
                                    lr=1,
                                    max_epochs=50,
                                    batch_size=32 * 8,
                                    callbacks=[skorch.callbacks.
→EarlyStopping(lower_is_better=True)])
      # implement input normalization & type cast here
      model.fit(train_data_normalized, np.asarray(train.targets))
```

The	channel	was	128,	the	learning	rate	was	0.0001
-----	---------	-----	------	-----	----------	------	-----	--------

epoch	train_loss	valid_acc	valid_loss	dur
1	1.8045	0.4908	1.4717	
3.2317 2	1.4935	0.5442	1.3015	
3.1580 3	1.3585	0.5886	1.1966	
3.1443 4	1.2596	0.6146	1.1193	
3.1602 5	1.1847	0.6342	1.0625	
3.1622 6	1.1234	0.6518	1.0135	
3.1547				
7 3.1650	1.0764	0.6625	0.9778	
8 3.1638	1.0358	0.6719	0.9484	
9 3.1614	0.9967	0.6813	0.9210	

10 3.1662	0.9698	0.6923	0.8992	
11	0.9418	0.6989	0.8795	
3.1710	0.9159	0.7008	0.8661	
3.1699 13	0.8987	0.7088	0.8503	
3.1751 14 3.1795	0.8736	0.7155	0.8327	
15 3.1766	0.8550	0.7192	0.8209	
16 3.1782	0.8351	0.7245	0.8086	
17 3.1833	0.8160	0.7282	0.7994	
18 3.1876	0.8006	0.7312	0.7842	
19 3.1829	0.7876	0.7328	0.7803	
20	0.7678	0.7339	0.7716	
21 3.1882	0.7583	0.7398	0.7576	
22 3.1923	0.7469	0.7415	0.7519	
23	0.7304		0.7504	3.1926
24 3.1946	0.7186	0.7418	0.7470	
25 3.1994	0.7094	0.7458	0.7346	
26	0.6931	0.7453	0.7383	3.1950
27 3.1931	0.6847	0.7467	0.7313	
28	0.6752	0.7515	0.7170	
29 3.1875	0.6627	0.7544	0.7119	
30	0.6524	0.7511	0.7180	3.1824
31	0.6418	0.7569	0.7052	
3.1839				
32 3.1801	0.6332	0.7589	0.6995	
33	0.6226	0.7579	0.6945	
34	0.6115	0.7575	0.6946	3.1858
35 3.1795	0.6090	0.7609	0.6869	
3.1793	0.5965	0.7622	0.6868	

3.1880				
37	0.5886	0.7613	0.6831	3.1852
38	0.5806	0.7669	0.6744	
3.1756				
39	0.5691	0.7656	0.6816	3.1742
40	0.5664	0.7697	0.6742	
3.1783				
41	0.5545	0.7657	0.6778	3.1825
42	0.5465	0.7708	0.6708	
3.1714				
43	0.5400	0.7692	0.6658	3.1728
44	0.5343	0.7663	0.6744	3.1602
45	0.5261	0.7737	0.6608	
3.1719				
46	0.5252	0.7717	0.6618	3.1673
47	0.5109	0.7700	0.6638	3.1695
48	0.5050	0.7716	0.6618	3.1599
49	0.4969	0.7755	0.6571	
3.1588				
50	0.4920	0.7733	0.6619	3.1607
The channe	1 was 256, the	learning rat	e was 0.0001	
epoch	train_loss	valid_acc	${\tt valid\_loss}$	dur
1	1.6336	0.5527	1.2881	
_	_,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,	0.0021	1.2001	
6.1969				
6.1969	1.2999	0.6045	1.1220	
6.1969 2 6.1984	1.2999	0.6045	1.1220	
6.1969 2 6.1984 3				
6.1969 2 6.1984 3 6.2124	1.2999	0.6045	1.1220	
6.1969 2 6.1984 3 6.2124 4	1.2999	0.6045	1.1220	
6.1969 2 6.1984 3 6.2124 4 6.2015	1.2999 1.1574 1.0544	0.6045 0.6433 0.6692	1.1220 1.0264 0.9555	
6.1969 2 6.1984 3 6.2124 4 6.2015	1.2999	0.6045	1.1220	
6.1969 2 6.1984 3 6.2124 4 6.2015 5 6.2078	1.2999 1.1574 1.0544 0.9872	0.6045 0.6433 0.6692 0.6815	1.1220 1.0264 0.9555 0.9150	
6.1969 2 6.1984 3 6.2124 4 6.2015 5 6.2078	1.2999 1.1574 1.0544	0.6045 0.6433 0.6692	1.1220 1.0264 0.9555	
6.1969 2 6.1984 3 6.2124 4 6.2015 5 6.2078 6 6.1982	1.2999 1.1574 1.0544 0.9872 0.9240	0.6045 0.6433 0.6692 0.6815 0.6962	1.1220 1.0264 0.9555 0.9150 0.8753	
6.1969 2 6.1984 3 6.2124 4 6.2015 5 6.2078 6 6.1982 7	1.2999 1.1574 1.0544 0.9872	0.6045 0.6433 0.6692 0.6815	1.1220 1.0264 0.9555 0.9150	
6.1969 2 6.1984 3 6.2124 4 6.2015 5 6.2078 6 6.1982 7 6.2226	1.2999 1.1574 1.0544 0.9872 0.9240 0.8772	0.6045 0.6433 0.6692 0.6815 0.6962 0.7051	1.1220 1.0264 0.9555 0.9150 0.8753 0.8505	
6.1969 2 6.1984 3 6.2124 4 6.2015 5 6.2078 6 6.1982 7 6.2226 8	1.2999 1.1574 1.0544 0.9872 0.9240	0.6045 0.6433 0.6692 0.6815 0.6962	1.1220 1.0264 0.9555 0.9150 0.8753	
6.1969 2 6.1984 3 6.2124 4 6.2015 5 6.2078 6 6.1982 7 6.2226 8 6.1924	1.2999 1.1574 1.0544 0.9872 0.9240 0.8772 0.8395	0.6045 0.6433 0.6692 0.6815 0.6962 0.7051 0.7134	1.1220 1.0264 0.9555 0.9150 0.8753 0.8505 0.8215	
6.1969 2 6.1984 3 6.2124 4 6.2015 5 6.2078 6 6.1982 7 6.2226 8 6.1924 9	1.2999 1.1574 1.0544 0.9872 0.9240 0.8772	0.6045 0.6433 0.6692 0.6815 0.6962 0.7051	1.1220 1.0264 0.9555 0.9150 0.8753 0.8505	
6.1969 2 6.1984 3 6.2124 4 6.2015 5 6.2078 6 6.1982 7 6.2226 8 6.1924 9 6.1769	1.2999 1.1574 1.0544 0.9872 0.9240 0.8772 0.8395 0.8040	0.6045 0.6433 0.6692 0.6815 0.6962 0.7051 0.7134 0.7197	1.1220 1.0264 0.9555 0.9150 0.8753 0.8505 0.8215	
6.1969 2 6.1984 3 6.2124 4 6.2015 5 6.2078 6 6.1982 7 6.2226 8 6.1924 9 6.1769 10	1.2999 1.1574 1.0544 0.9872 0.9240 0.8772 0.8395	0.6045 0.6433 0.6692 0.6815 0.6962 0.7051 0.7134	1.1220 1.0264 0.9555 0.9150 0.8753 0.8505 0.8215	
6.1969 2 6.1984 3 6.2124 4 6.2015 5 6.2078 6 6.1982 7 6.2226 8 6.1924 9 6.1769 10 6.1587	1.2999 1.1574 1.0544 0.9872 0.9240 0.8772 0.8395 0.8040 0.7724	0.6045 0.6433 0.6692 0.6815 0.6962 0.7051 0.7134 0.7197 0.7305	1.1220 1.0264 0.9555 0.9150 0.8753 0.8505 0.8215 0.7986	
6.1969 2 6.1984 3 6.2124 4 6.2015 5 6.2078 6 6.1982 7 6.2226 8 6.1924 9 6.1769 10 6.1587 11	1.2999 1.1574 1.0544 0.9872 0.9240 0.8772 0.8395 0.8040	0.6045 0.6433 0.6692 0.6815 0.6962 0.7051 0.7134 0.7197	1.1220 1.0264 0.9555 0.9150 0.8753 0.8505 0.8215	
6.1969 2 6.1984 3 6.2124 4 6.2015 5 6.2078 6 6.1982 7 6.2226 8 6.1924 9 6.1769 10 6.1587 11 6.1682	1.2999 1.1574 1.0544 0.9872 0.9240 0.8772 0.8395 0.8040 0.7724 0.7434	0.6045 0.6433 0.6692 0.6815 0.6962 0.7051 0.7134 0.7197 0.7305 0.7366	1.1220 1.0264 0.9555 0.9150 0.8753 0.8505 0.8215 0.7986 0.7737	
6.1969 2 6.1984 3 6.2124 4 6.2015 5 6.2078 6 6.1982 7 6.2226 8 6.1924 9 6.1769 10 6.1587 11 6.1682 12	1.2999 1.1574 1.0544 0.9872 0.9240 0.8772 0.8395 0.8040 0.7724	0.6045 0.6433 0.6692 0.6815 0.6962 0.7051 0.7134 0.7197 0.7305	1.1220 1.0264 0.9555 0.9150 0.8753 0.8505 0.8215 0.7986	
6.1969 2 6.1984 3 6.2124 4 6.2015 5 6.2078 6 6.1982 7 6.2226 8 6.1924 9 6.1769 10 6.1587 11 6.1682	1.2999 1.1574 1.0544 0.9872 0.9240 0.8772 0.8395 0.8040 0.7724 0.7434	0.6045 0.6433 0.6692 0.6815 0.6962 0.7051 0.7134 0.7197 0.7305 0.7366	1.1220 1.0264 0.9555 0.9150 0.8753 0.8505 0.8215 0.7986 0.7737	

6.1	383						
	14		0.6647	0.7519	0.7267		
6.1	318						
	15		0.6392	0.7543	0.7104		
6.1	295						
	16		0.6187	0.7574	0.7044		
6.1	260						
	17		0.5990	0.7591	0.6985		
6.1	007						
	18		0.5774	0.7591	0.6911	6.0768	
	19		0.5607	0.7651	0.6901		
6.0	741						
	20		0.5382	0.7668	0.6811		
6.1	156		0 5040	0.7600	0 0707		
C 1	21		0.5218	0.7682	0.6737		
0.1	021 22		0 5011	0.7710	0.6630		
6 1	216		0.5011	0.7710	0.0030		
0.1	23		0.4857	0.7717	0.6631	6 0020	
	23 24		0.4669	0.7751	0.6545	0.0929	
6 1	075		0.4003	0.7701	0.0040		
0.1	25		0.4572	0.7752	0.6540		
6.1	212		0.1012	0.1102	0.0010		
• • •	26		0.4396	0.7743	0.6600	6.1145	
	27		0.4239	0.7756	0.6529		
6.1	094						
	28		0.4048	0.7788	0.6474		
6.1	126						
	29		0.3948	0.7783	0.6507	6.1339	
	30		0.3807	0.7789	0.6526	6.1389	
	31		0.3655	0.7767	0.6542	6.1480	
	32		0.3515	0.7814	0.6444		
6.1	751						
	33		0.3393	0.7840	0.6455	6.1548	
	34		0.3247	0.7816	0.6497	6.1603	
	35		0.3153	0.7823	0.6487	6.1681	
	36		0.3007	0.7860	0.6388		
6.1	728						
	37		0.2920	0.7851	0.6449	6.1701	
	38		0.2808	0.7826	0.6554	6.1807	
	39		0.2743	0.7845	0.6524		
α±	40		0.2562	0.7842	0.6490	6.2041	_
ಎರಂ	bbrua	since	valid loss	has not impro	vea in the	⊥ast 5	e

The channel was 512, the learning rate was 0.0001 epoch train\_loss valid\_acc valid\_loss

dur	valid_loss	valid_acc	train_loss	epoch
	1.1599	0.5875	1.4867	1
				13.7566

2	1.1323	0.6544	0.9950	
13.8768				
3	0.9813	0.6778	0.9199	
13.9526				
4	0.8851	0.7036	0.8458	
14.0137				
5	0.8155	0.7077	0.8244	
14.0539				
6	0.7579	0.7197	0.7897	
14.0974				
7	0.7093	0.7321	0.7623	
14.0722				
8	0.6648	0.7351	0.7490	
14.0787				
9	0.6232	0.7519	0.7108	
14.0801				
10	0.5813	0.7579	0.6961	
13.9528				
11	0.5446	0.7622	0.6848	
13.9407	0.0110	011022	0.0020	
12	0.5114	0.7663	0.6737	
14.0248	0.0111	0.1000	0.0707	
13	0.4788	0.7650	0.6776	13.9431
14	0.4443	0.7624	0.6877	14.0306
15	0.4155	0.7715	0.6587	
14.0328				
16	0.3874	0.7740	0.6575	
13.8163	0.0011	0.111	0.0010	
17	0.3581	0.7736	0.6607	13.7884
				13.7004
18	0.3337	0.7801	0.6459	
13.7710				
19	0.3078	0.7799	0.6515	
20	0.2844	0.7740	0.6669	
21	0.2644	0.7758	0.6733	13.6630
22	0.2433	0.7715	0.6883	13.8098

The channel was 128, the learning rate was 0.001

epoch	train_loss	valid_acc	valid_loss	dur
1	1.5918	0.5432	1.2453	
3.1035				
2	1.1911	0.6467	1.0016	
3.1075				
3	1.0245	0.6690	0.9421	
3.1208				
4	0.9245	0.7108	0.8356	
3.1018				
5	0.8580	0.7191	0.8196	

3.1075				
6	0.8062	0.7294	0.7835	
3.1001				
7	0.7627	0.7342	0.7764	
3.0934				
8	0.7159	0.7441	0.7422	
3.0959				
9	0.6845	0.7535	0.7172	
3.1002				
10	0.6500	0.7504	0.7301	3.1135
11	0.6233	0.7222	0.8134	3.1064
12	0.5967	0.7500	0.7301	3.1062
13	0.5679	0.7382	0.7676	3.0977
14	0.5419	0.7573	0.7070	
3.1099				
15	0.5189	0.7275	0.8109	3.1219
16	0.5012	0.7383	0.7763	3.1253
17	0.4856	0.7759	0.6584	
3.1117				
18	0.4610	0.7671	0.6920	3.1101
19	0.4503	0.7484	0.7565	3.1313
20	0.4330	0.7603	0.7146	3.1280
21	0.4164	0.7584	0.7378	3.1179

The channel was 256, the learning rate was 0.001

epoch	train_loss	valid_acc	valid_loss	dur
1	1.6579	0.5450	1.2561	
6.1184				
2	1.1583	0.6407	1.0060	
6.1430				
3	0.9712	0.6851	0.9020	
6.1335				
4	0.8689	0.7178	0.8076	
6.1475				
5	0.7908	0.7155	0.8156	6.1657
6	0.7173	0.7254	0.7869	
6.1685				
7	0.6691	0.7162	0.8146	6.1811
8	0.6200	0.7231	0.8026	6.2037
9	0.5697	0.7593	0.6993	
6.1986				
10	0.5247	0.7511	0.7574	6.2029
11	0.4784	0.7777	0.6565	
6.2012				
12	0.4481	0.7608	0.7093	6.2085
13	0.4193	0.7678	0.7088	6.2271
14	0.3876	0.7664	0.7174	6.2404

15 0.3628 0.7653 0.7162 6.2230 Stopping since valid\_loss has not improved in the last 5 epochs. The channel was 512, the learning rate was 0.001

epoch	train_loss	valid_acc	${\tt valid\_loss}$	dur
1	1 9660	0 5020	1 2067	
13.8909	1.8660	0.5239	1.3267	
2	1.2144	0.6288	1.0492	
14.0318		0.0200		
3	0.9933	0.6585	1.0033	
14.0499				
4	0.8716	0.7019	0.8538	
14.0592				
5	0.7827	0.7338	0.7637	
13.9973				
6	0.7105	0.7051	0.8631	13.9783
7	0.6455	0.7081	0.8460	14.0149
8	0.5830	0.7151	0.8477	14.0355
9	0.5239	0.7465	0.7621	
14.0760				
10	0.4676	0.7337	0.8000	14.0717
11	0.4258	0.7354	0.8330	13.8616
12	0.4056	0.7492	0.8092	13.8587
13	0.3547	0.7633	0.7739	13.9999

The channel was 128, the learning rate was 0.01

epoch	train_loss	valid_acc	valid_loss	dur
1	2.4661	0.3902	1.6711	
3.1283				
2	1.4921	0.5048	1.3910	
3.1077				
3	1.2807	0.5838	1.1837	
3.1125				
4	1.1125	0.6630	0.9687	
3.0927				
5	0.9888	0.6790	0.9151	
3.0898				
6	0.9001	0.6382	1.0577	3.0995
7	0.8429	0.6774	0.9419	3.0966
8	0.7930	0.7120	0.8200	
3.0852				
9	0.7398	0.6705	0.9908	3.0919
10	0.7032	0.7199	0.8102	
3.0905				
11	0.6733	0.7302	0.7912	
3.0858				
12	0.6391	0.7149	0.8442	3.0781

13	0.6147	0.7170	0.8561	3.0809
14	0.5882	0.7029	0.8850	3.0770
15	0.5654	0.7282	0.8245	3.0779

The channel was 256, the learning rate was 0.01

epoch	train_loss	valid_acc	valid_loss	dur
1	3.5919	0.3983	1.6982	
6.0360				
2	1.4422	0.4942	1.4063	
6.0587				
3	1.2272	0.6151	1.1065	
6.0509				
4	1.0562	0.6300	1.0532	
6.0635				
5	0.9361	0.6477	1.0331	
6.0767				
6	0.8409	0.6235	1.1104	6.0766
7	0.7679	0.7008	0.8644	
6.0790				
8	0.6919	0.6667	0.9843	6.0795
9	0.6367	0.6870	0.9418	6.0814
10	0.5896	0.7083	0.8764	6.0957
11	0.5484	0.7123	0.8610	
6.1184				
12	0.4997	0.7515	0.7285	
6.1226				
13	0.4751	0.7501	0.7545	6.1230
14	0.4319	0.7270	0.8634	6.1406
15	0.4018	0.7519	0.7678	6.1402
16	0.3827	0.7382	0.8527	6.1434

Stopping since valid\_loss has not improved in the last 5 epochs.

The channel was 512, the learning rate was 0.01

epoch	train_loss	valid_acc	valid_loss	dur
1	6.0569	0.4086	1.6634	
13.7351				
2	1.5010	0.4979	1.4120	
13.8113				
3	1.2651	0.5863	1.1882	
13.7868				
4	1.0987	0.6096	1.1351	
13.8378				
5	0.9611	0.6584	0.9870	
13.8555				
6	0.8590	0.6933	0.8747	
13.9215				
7	0.7620	0.7215	0.8052	

```
13.9019
               0.6876
                            0.7403
                                          0.7532
13.9872
               0.6161
                            0.7516
                                          0.7395
13.9732
               0.5579
                            0.6949
                                          0.9249
                                                   13.9310
     10
     11
               0.4903
                            0.6445
                                           1.1340
                                                   13.9594
     12
               0.4353
                            0.7367
                                           0.7914 13.9665
               0.3780
                            0.7526
                                          0.7753 13.9434
```

Write down the validation accuracy of the model under different hyperparameter settings.

For the best model you have, test it on the test set.

```
[]: # implement the same input normalization & type cast here
     optimizer = torch.optim.Adam
     learning rate = 1e-4
     channel = 256
     cnn = CNN MaxPool(channels = channel)
     model = skorch.NeuralNetClassifier(cnn, criterion=torch.nn.CrossEntropyLoss,
                                        device="cuda",
                                        optimizer=optimizer,
                                        lr=learning_rate,
                                        max_epochs=50,
                                        batch_size=32 * 8,
                                        callbacks=[skorch.callbacks.
     →EarlyStopping(lower_is_better=True)])
     # implement input normalization & type cast here
     model.fit(train_data_normalized, np.asarray(train.targets))
     test_data_normalized = torch.Tensor(test.data/255)
     test_data_normalized = test_data_normalized.permute(0,3,1,2)
     test.predictions = model.predict(test_data_normalized)
     sklearn.metrics.accuracy_score(test.targets, test.predictions)
```

epoch train\_loss valid\_acc valid\_loss dur

1	1.6229	0.5552	1.2808	
5.7887 2	1.2905	0.6147	1.1130	
5.7904 3	1.1429	0.6455	1.0174	
5.7758 4	1.0483	0.6692	0.9528	
5.7884				
5 5.7653	0.9770	0.6930	0.8981	
6 5.7668	0.9212	0.7024	0.8618	
7 5.8012	0.8761	0.7114	0.8418	
8	0.8357	0.7177	0.8171	
5.7866 9	0.8008	0.7259	0.7928	
5.7409 10	0.7699	0.7294	0.7760	
5.7591				
11 5.7847	0.7416	0.7389		
12 5.7757	0.7144	0.7436	0.7479	
13 5.7796	0.6867	0.7459	0.7379	
14	0.6621	0.7522	0.7261	
5.7849 15	0.6387	0.7562	0.7117	
5.7848 16	0.6178	0.7578	0.7046	
5.7691 17	0.5950	0.7620	0.6940	
5.7612				
18 5.7960	0.5779	0.7624	0.6915	
19 5.7776	0.5589	0.7671	0.6826	
20	0.5397	0.7683	0.6823	
5.7812 21	0.5170	0.7703	0.6769	
5.7648 22	0.5039	0.7711	0.6676	
5.7785 23	0.4839	0.7740	0.6576	
5.7657				
24	0.4651	0.7744	0.6569	

5.7748				
25	0.4493	0.7770	0.6514	
5.7814				
26	0.4353	0.7772	0.6568	5.7899
27	0.4183	0.7785	0.6526	5.7753
28	0.4051	0.7792	0.6506	
5.7794				
29	0.3886	0.7831	0.6463	
5.7860				
30	0.3738	0.7800	0.6461	5.7802
31	0.3578	0.7841	0.6455	
5.7607				
32	0.3497	0.7830	0.6408	5.7976
33	0.3381	0.7836	0.6397	5.7657
34	0.3251	0.7826	0.6426	5.7709
35	0.3099	0.7844	0.6464	5.7790
36	0.2998	0.7850	0.6435	5.7733
37	0.2838	0.7862	0.6367	
5.7886				
38	0.2772	0.7858	0.6401	5.7790
39	0.2692	0.7871	0.6405	5.8318
40	0.2595	0.7866	0.6365	5.7907
41	0.2484	0.7872	0.6409	5.7713
42	0.2385	0.7827	0.6520	5.7901
43	0.2300	0.7860	0.6646	5.7787
44	0.2202	0.7845	0.6562	5.7917

#### []: 0.7804

How much **test accuracy** do you get? What can you conclude for the design of CNN structure and tuning of hyperparameters? (5 points)

#### Your Answer:

- 1. The test accuracy we got is 0.7804. The best model is the one with 256 channels for each layer and learning rate  $10^{-4}$ .
- 2. From the results above, we can conclude that the number of channels, learning rate and the optimizer are important hyperparameters, they could greatly influence the training speed and evaluation effects. Also the structure of CNN is also important, the max pooling layer could improve the performance of the model. And with dropout layer, the model could be more robust to against overfitting.

The number of channels which also influence the net structure, could effect performence as hyperparameter. It should not be too small or too large. The learning rate should not be too large, otherwise the model will not converge.