HW1_Q3

February 17, 2019

1 HW1 Q3 - Convolutional Neural Networks

In this question, we set up a CNN in order to perform the 'Cats vs Dogs' Kaggle challenge
First, we import some PyTorch libraries and direct them to use Google Colab's GPU:

```
In [0]: import torch
        import torch.nn as nn
        import torch.nn.functional as F
        import torch.utils.data
        import torchvision
        import torchvision.transforms as transforms
        from torch.utils.data import DataLoader, Sampler, Dataset
        from torchvision import datasets
        from torch.utils.data.sampler import SubsetRandomSampler, SequentialSampler
        from torch.autograd import Variable

        import os
        import numpy as np
        import PIL.Image
        import glob
        import matplotlib.pyplot as plt
```

```
In [0]: # Use the GPU
        device = torch.device('cuda')
```

In order to import the data for Kaggle from Google Drive, we need to jump through a few hoops, as seen below

```
In [0]: # Import the data

        from google.colab import drive

        drive.mount('/content/drive/')
```

```
Go to this URL in a browser: https://accounts.google.com/o/oauth2/auth?client_id=947318989803-

Enter your authorization code:
ůůůůůůůůůů
Mounted at /content/drive/
```

In [0]:
```
PATH = '/content/drive/My Drive/DL_A1/'


# apply several different transforms, as necessary
rotate = [-90, 90]
transform = transforms.Compose([
    transforms.ToPILImage(),
    transforms.RandomRotation(rotate),
    transforms.RandomHorizontalFlip(p=0.25),
    transforms.RandomResizedCrop(64, scale=(0.75, 1.0)),
    transforms.ToTensor()
])

# for the hyperparameter tunning, no transforms were applied

# transform = transforms.Compose([
#     transforms.ToPILImage(),
#     transforms.ToTensor()
# ])

# load the data, which was downloaded and saved
Data = np.load(PATH +'data.npz')
```

In [0]:
```
# we define the dataset class for the train, valid and test data
class dataset(Dataset):
  def __init__(self, X, Y, transform=None):
    self.X = X
    self.Y = Y
    self.transform = transform

  def __len__(self):
    return self.X.shape[0]

  def __getitem__(self, index):
    #temp = self.transform(self.X[index,:])
    #return temp, self.Y[index]\
    sequence, target = self.X[index], self.Y[index]
    if self.transform is not None:
      sequence = self.transform(sequence)
    if target is None:
      return sequence
    return sequence, target
```

In [0]:
```
# define the labels and datasets

test_labels = [None]*Data['Xte'].shape[0]
train_dataset = dataset(Data['Xtr'], Data['y'], transform)
test_dataset = dataset(Data['Xte'], test_labels, transform)
```

```
testIDS_list = np.hsplit(Data['testIds'], 1)
testIDS = testIDS_list[0]
```

In [0]:
```
# we will define this information now
batch_size = 64
learning_rate = 0.005
num_epochs = 150

num_classes = 2
num_of_workers = 4
```

To split the training data into a training and validation set, we need to establish a `sampler` for each that will pull out certain samples when called from the dataloader. In our case, we have a 20% validation split, with 16000 training examples and 4000 validation examples.

In [0]:
```
# Define a shuffled train and valid index list (non-overlapping)

a = np.arange(19998)
np.random.shuffle(a)

num_train_samples = 16000
num_valid_samples = 19998 - num_train_samples

train_index = a[:num_train_samples]
valid_index = a[num_train_samples:
                num_train_samples+num_valid_samples]
```

In [0]:
```
# Fix seed
np.random.seed(42)
torch.manual_seed(42)

# Define samplers for the data (to get validation split)

train_sampler = SubsetRandomSampler(train_index)

valid_sampler = SubsetRandomSampler(valid_index)
```

As a last step before training, we define training, validation, and test dataloaders that sample from the above `samplers` according to the defined batch size:

In [0]:
```
# Get dataloaders for train/valid/test
train_loader = torch.utils.data.DataLoader(train_dataset,
                                           batch_size=batch_size,
                                           sampler=train_sampler)

valid_loader = torch.utils.data.DataLoader(train_dataset,
                                           batch_size=batch_size,
                                           sampler=valid_sampler)
```

1.1 CNN architecture definition

Now we define the class for our CNN.

```
In [0]: # this is just a function to help with input/output size
        def output_size(input_size, kernel_size, stride, padding):
            '''
            Helper function to determine output size of a convolution/pooling.
            '''
            output = int((input_size - kernel_size + 2*(padding)) / stride) + 1
            return output
```

```
In [0]: # hyperparameter tunning
        # Define the CNN class

        class CNN(nn.Module):
          def __init__(self):
            super(CNN, self).__init__()
            self.conv1 = nn.Conv2d(3, 40, kernel_size=3, stride=1, padding=1)
            self.pool1 = nn.MaxPool2d(kernel_size=2, stride=2, padding=0)

            self.conv2 = nn.Conv2d(40, 40, kernel_size=3, stride=1, padding=1)
            self.pool2 = nn.MaxPool2d(kernel_size=2, stride=2, padding=0)

            self.fc1 = nn.Linear(10240, 175)
            self.fc2 = nn.Linear(175, 2)

          def forward(self, x):
            x = self.conv1(x)
            x = F.relu(x)
            x = self.pool1(x)
            x = F.relu(self.conv2(x))
            x = self.pool2(x)
            x = x.view(len(x), 10240)
            x = self.fc1(x)
            x = F.relu(x)
            x = self.fc2(x)
        #     x = F.softmax(x)

            return x
```

This CNN has two convolutional layers, each with a ReLU activation, a kernel size of 3, a stride of 1, and a padding level of 1. The first convolutional layer learns 18 feature maps and the second learns 64 feature maps. Both convolutional layers use max pooling after their operation, with a kernel size of 2 and stride of 2. During hyperparameter tuning, these values were modified

Finally, the data will pass through two fully connected layers and output to 2 units representing either a 'Cat' or a 'Dog'.

Below, we see an outline of this architecture. Note that the total number of trainable parameters is around 1.8 million per sample

```
In [0]: model = CNN().to(device)
        print(model)

        model_parameters = filter(lambda p: p.requires_grad, model.parameters())
        params = sum([np.prod(p.size()) for p in model_parameters])
        print('Number of parameters: {}'.format(params))
```

```
CNN(
  (conv1): Conv2d(3, 40, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (pool1): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  (conv2): Conv2d(40, 40, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (pool2): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  (fc1): Linear(in_features=10240, out_features=175, bias=True)
  (fc2): Linear(in_features=175, out_features=2, bias=True)
)
Number of parameters: 1808087
```

1.2 CNN training

Now we will define our loss function and stochastic gradient descent optimizer, and run over the training loop for our CNN.

```
In [0]: # Define loss and optimizer

        # depending on the method, either NLL or cross entropy loss was used (the latter inclu
        # the former allows for easy visualization of the data
        criterion = nn.CrossEntropyLoss()
        # criterion = nn.NLLLoss()
        optimizer = torch.optim.SGD(model.parameters(), lr=learning_rate)
```

2 Below is the training and validation loop - it is important to note that, due to random initialization, it can be difficult to reproduce results, and certain runs might converge faster or slower than others. As a reuslt, it might be necessary to run a model several times in order to obtain results seen in the report

```
In [0]: # Make a nice progress bar - tqdm on colab is a bit buggy though
        from tqdm import tqdm
        best_val_acc = 0
        # Train
        print('\nBeginning training.')
```

```
total_step = len(train_loader)
train_losses, train_accuracies = [], []
valid_losses, valid_accuracies = [], []

for epoch in range(num_epochs):
  print('Epoch {}/{}'.format(epoch+1, num_epochs))
  # Training set
  model.train()
  total_tr, correct_tr = 0, 0
  total_val, correct_val = 0, 0
  mean_train_loss = 0.0
  mean_valid_loss = 0.0
  mean_train_acc = 0.0
  mean_valid_acc = 0.0

  output_clear = []
  output_ambig = []
  misclass = []
  for i, (images, labels) in enumerate(tqdm(train_loader, position=0)):

    labels = torch.max(labels, 1)[1]
    images, labels = images.to(device), labels.long().to(device)
    optimizer.zero_grad()


    # Forward
    outputs = model(images)

    # Check if classifications are close (ambiguous) or far apart (clear)
    for j in range(outputs.shape[0]):
      outputs_cpu = outputs.cpu().detach().numpy()
      if abs(outputs_cpu[j,1]-outputs_cpu[j,0] > 0.4):
        output_clear.append(images[j].cpu().numpy())
      if abs(outputs_cpu[j,1]-outputs_cpu[j,0] < 0.1):
        output_ambig.append(images[j].cpu().numpy())


    loss = criterion(outputs, labels)




# try this implementation
    lambda1 = 0.5
    lambda2 = 2.75
    l1_regularization, l2_regularization = torch.tensor(0), torch.tensor(0)
#     for param in model.parameters():
#       l1_regularization += torch.norm(param, 1).long()
```

```
#       l2_regularization += torch.norm(param, 2).long()
#     loss = criterion(outputs, labels) + lambda2 * l2_regularization
    mean_train_loss += loss

    # Backward
    loss.backward()
    optimizer.step()

#     modify learning rate, if desired
#     if epoch%200 == 0:
#       learning_rate = learning_rate/5
#       optimizer = torch.optim.SGD(model.parameters(), lr=learning_rate)

    # Track loss and accuracy

    total_tr += labels.size(0)
    _, predicted_tr = torch.max(outputs.data, 1)
    correct_tr += (predicted_tr == labels).sum().item()
    incorrect_tr = (predicted_tr != labels).cpu().detach().numpy()

    # Keep track of wrongly classified items
    for k in range(outputs.shape[0]):
      if incorrect_tr[k] == 1: # If misclassified
        misclass.append(images[k].cpu().numpy())
    acc_tr = correct_tr/total_tr
    mean_train_acc += acc_tr


  mean_train_loss /= i+1
  mean_train_acc /= i+1
  pred_total = 0
  labels_total = 0

  # Validation set
  model.eval()
  for i, (images, labels) in enumerate(valid_loader):

    labels = torch.max(labels, 1)[1]
    images, labels = images.to(device), labels.long().to(device)
    valid_outputs = model(images)
    valid_loss = criterion(valid_outputs, labels)
    mean_valid_loss += valid_loss

    total_val += labels.size(0)
    _, predicted_val = torch.max(valid_outputs.data, 1)
    correct_val += (predicted_val == labels).sum().item()
    valid_acc = correct_val/total_val
    mean_valid_acc += valid_acc
```

```
        mean_valid_loss /= i+1
        mean_valid_acc /= i+1



        train_losses.append(mean_train_loss.item())
        train_accuracies.append(mean_train_acc)
        valid_losses.append(mean_valid_loss.item())
        valid_accuracies.append(mean_valid_acc)
        # Mod this when num epochs is too big
        print('\ntrain_loss: {}, train_acc: {}, valid_loss: {}, valid_acc: {}'.format(
            mean_train_loss.item(), mean_train_acc*100, mean_valid_loss.item(), mean_valid_ac
```

```
  0%|          | 0/250 [00:00<?, ?it/s]

Beginning training.
Epoch 1/150

100%|| 250/250 [00:17<00:00, 14.22it/s]


train_loss: 0.6929819583892822, train_acc: 49.72084538378913, valid_loss: 0.6921926140785217, v
Epoch 2/150

100%|| 250/250 [00:17<00:00, 14.55it/s]


train_loss: 0.6921353936195374, train_acc: 52.59876953187479, valid_loss: 0.691154420375824, va
Epoch 3/150

100%|| 250/250 [00:17<00:00, 14.38it/s]


train_loss: 0.6914548873901367, train_acc: 54.43658648789052, valid_loss: 0.6907534599304199, v
Epoch 4/150

100%|| 250/250 [00:17<00:00, 14.71it/s]
  0%|          | 0/250 [00:00<?, ?it/s]

train_loss: 0.6905708312988281, train_acc: 54.856947846587126, valid_loss: 0.6902555823326111,
Epoch 5/150
```

```
100%|| 250/250 [00:17<00:00, 14.19it/s]


train_loss: 0.6896244287490845, train_acc: 55.1715324341284, valid_loss: 0.6897340416908264, va
Epoch 6/150


100%|| 250/250 [00:17<00:00, 14.29it/s]
  0%|          | 0/250 [00:00<?, ?it/s]


train_loss: 0.6885411739349365, train_acc: 55.434398174448084, valid_loss: 0.6880851984024048,
Epoch 7/150


100%|| 250/250 [00:17<00:00, 14.30it/s]
  0%|          | 0/250 [00:00<?, ?it/s]


train_loss: 0.6873008608818054, train_acc: 57.00500528378507, valid_loss: 0.6856411099433899, v
Epoch 8/150


100%|| 250/250 [00:17<00:00, 14.21it/s]
  0%|          | 0/250 [00:00<?, ?it/s]


train_loss: 0.6859132647514343, train_acc: 57.47056194401951, valid_loss: 0.6847419738769531, v
Epoch 9/150


100%|| 250/250 [00:17<00:00, 14.38it/s]
  0%|          | 0/250 [00:00<?, ?it/s]


train_loss: 0.6837262511253357, train_acc: 56.88798342547131, valid_loss: 0.6832066178321838, v
Epoch 10/150


100%|| 250/250 [00:17<00:00, 14.60it/s]
  0%|          | 0/250 [00:00<?, ?it/s]


train_loss: 0.6820378303527832, train_acc: 57.45878078927399, valid_loss: 0.6787055730819702, v
Epoch 11/150


 20%|        | 50/250 [00:03<00:13, 14.73it/s]
```

```
---------------------------------------------------------------------------

KeyboardInterrupt                         Traceback (most recent call last)

<ipython-input-26-63bddf1c00bb> in <module>()
 68     total_tr += labels.size(0)
 69     _, predicted_tr = torch.max(outputs.data, 1)
---> 70     correct_tr += (predicted_tr == labels).sum().item()
 71     incorrect_tr = (predicted_tr != labels).cpu().detach().numpy()
 72


KeyboardInterrupt:
```

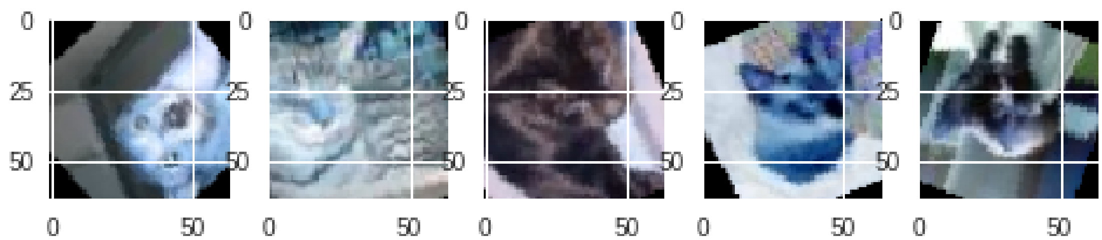
3 In order to plot the images, we will use the following code. Please note that the loops will take a while to run.

```
In [0]: output_ambig = np.array(output_ambig)
        output_clear = np.array(output_clear)
        misclass = np.array(misclass)

        # This is inefficient, but works!
        ambig_and_wrong, clear_and_wrong = [], []
        for item in misclass:
          if item in output_ambig:
            ambig_and_wrong.append(item)
          elif item in output_clear:
            clear_and_wrong.append(item)

        print('We have',len(ambig_and_wrong),' samples that were misclassified and were ambigu
        print('We have', len(clear_and_wrong),' samples that were clearly misclassified')
```

```
---------------------------------------------------------------------------

NameError                                 Traceback (most recent call last)

<ipython-input-2-87c9f051dfde> in <module>()
----> 1 output_ambig = np.array(output_ambig)
      2 output_clear = np.array(output_clear)
      3 misclass = np.array(misclass)


NameError: name 'output_ambig' is not defined
```

4 We can plot the images below. Please note that only some images were chosen for the report

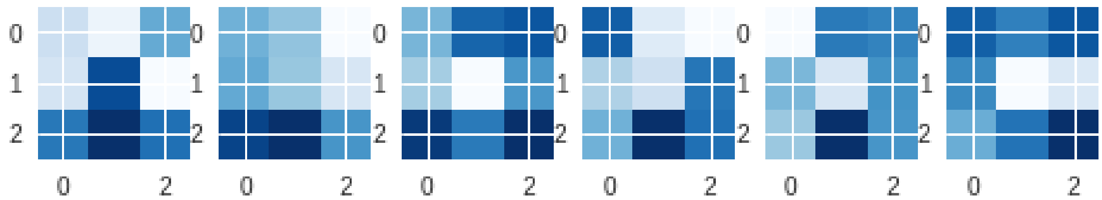
```
In [0]: w=20
        h=20
        fig=plt.figure(figsize=(8, 8))
        columns = 5
        rows = 1
        for i in range(5):
          img = np.transpose(ambig_and_wrong[i])
          fig.add_subplot(rows, columns, i + 1)
          plt.imshow(img)
        plt.show()
```

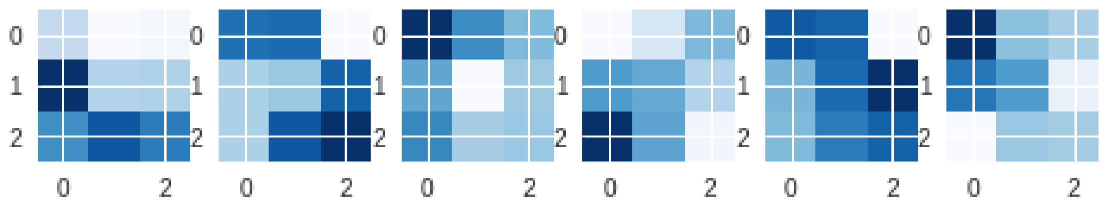


5 We can also plot the kernels too, although interpretation is more difficult

```
In [0]: # we can plot the kernels too

        def plot_kernels():
          w = 12
          h = 12
          fig=plt.figure(figsize=(8, 8))
          columns = 8
          rows = 6
          weight_cpu = model.conv2.weight.data.cpu()
          weight_np = weight_cpu.detach().numpy()
          for i in range(40):
            img = weight_np[i,0,:,:]
            fig.add_subplot(rows, columns, i + 1)
            plt.imshow(img, cmap = 'Blues')
          plt.show()

        plot_kernels()

        ---------------------------------------------------------------------------
```

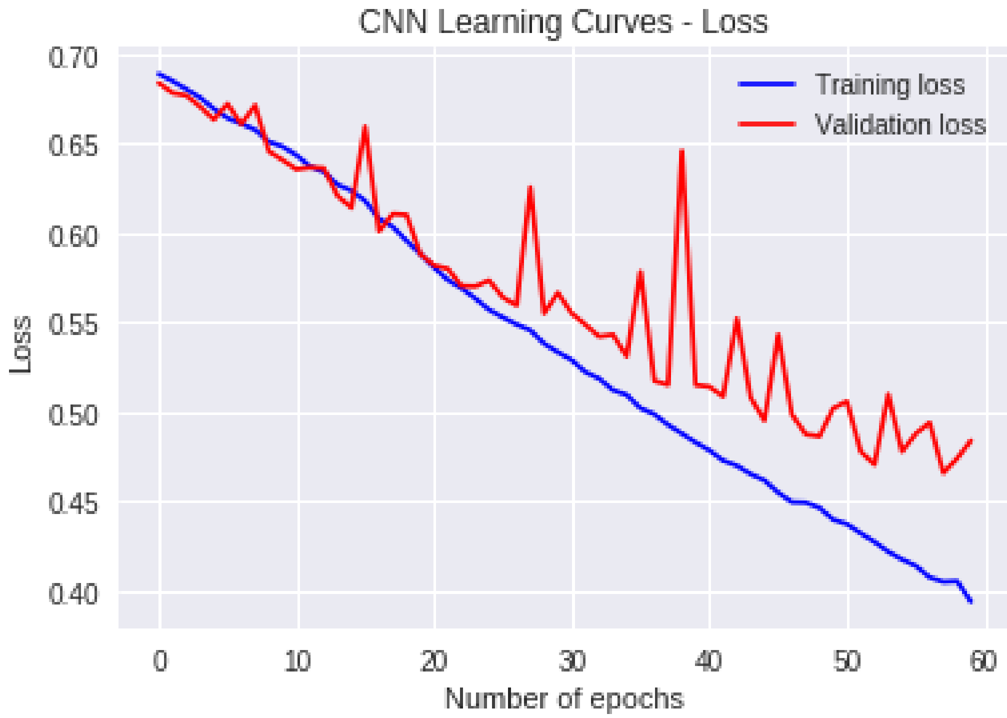
```
ValueError                                Traceback (most recent call last)

<ipython-input-87-e2570a5be5fb> in <module>()
     14   plt.show()
     15
---> 16 plot_kernels()


<ipython-input-87-e2570a5be5fb> in plot_kernels()
     10   for i in range(40):
     11     img = weight_np[i,0,:,:]
---> 12     fig.add_subplot(rows, columns, i + 1)
     13     plt.imshow(img, cmap = 'Blues')
     14   plt.show()


/usr/local/lib/python3.6/dist-packages/matplotlib/figure.py in add_subplot(self, *args
   1365                     self._axstack.remove(ax)
   1366
-> 1367             a = subplot_class_factory(projection_class)(self, *args, **kwargs)
   1368         self._axstack.add(key, a)
   1369         self.sca(a)


/usr/local/lib/python3.6/dist-packages/matplotlib/axes/_subplots.py in __init__(self, 
     58                     raise ValueError(
     59                         ("num must be 1 <= num <= {maxn}, not {num}"
---> 60                         ).format(maxn=rows*cols, num=num))
     61                 self._subplotspec = GridSpec(
     62                         rows, cols, figure=self.figure)[int(num) - 1]


ValueError: num must be 1 <= num <= 12, not 13
```

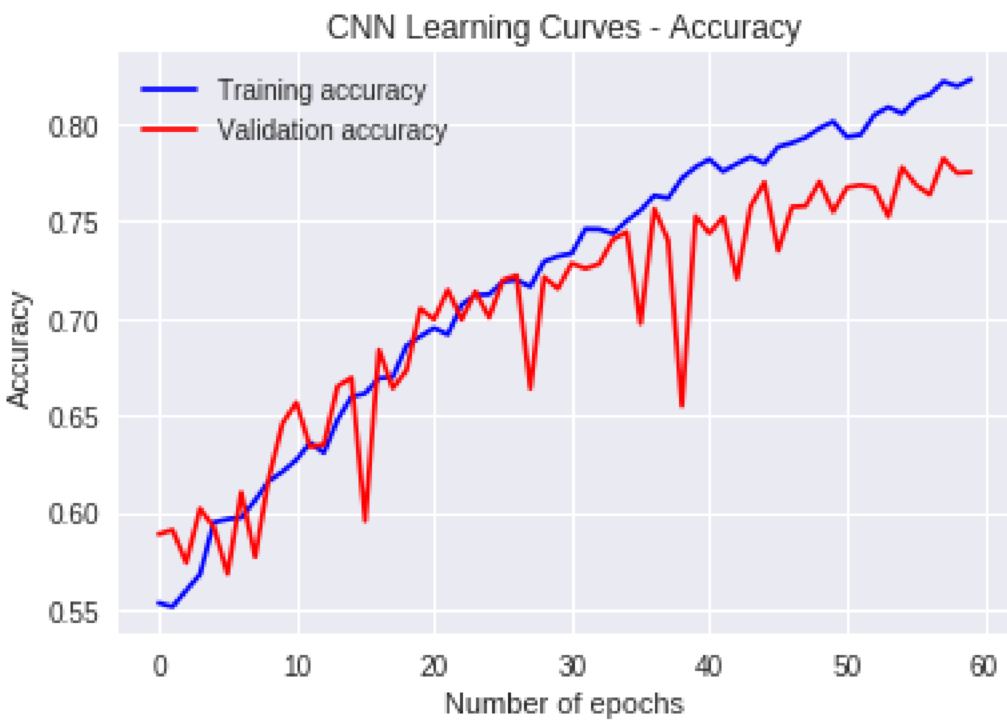




6 Finally, we can plot the learning curves for our training and validation run

```
In [0]: %matplotlib inline
        import matplotlib.pyplot as plt

        plt.title('CNN Learning Curves - Loss')
        plt.plot(range(num_epochs), train_losses, color='blue', label='Training loss')
        plt.plot(range(num_epochs), valid_losses, color='red', label='Validation loss')
        plt.xlabel('Number of epochs')
        plt.ylabel('Loss')
        plt.legend()
        plt.show()

        plt.title('CNN Learning Curves - Accuracy')
        plt.plot(range(num_epochs), train_accuracies, color='blue', label='Training accuracy')
        plt.plot(range(num_epochs), valid_accuracies, color='red', label='Validation accuracy'
        plt.xlabel('Number of epochs')
        plt.ylabel('Accuracy')
        plt.legend()
        plt.show()
```


CNN Learning Curves - Loss
Training loss
Validation loss
Loss
Number of epochs
0.70
0.65
0.60
0.55
0.50
0.45
0.40
0
10
20
30
40
50
60

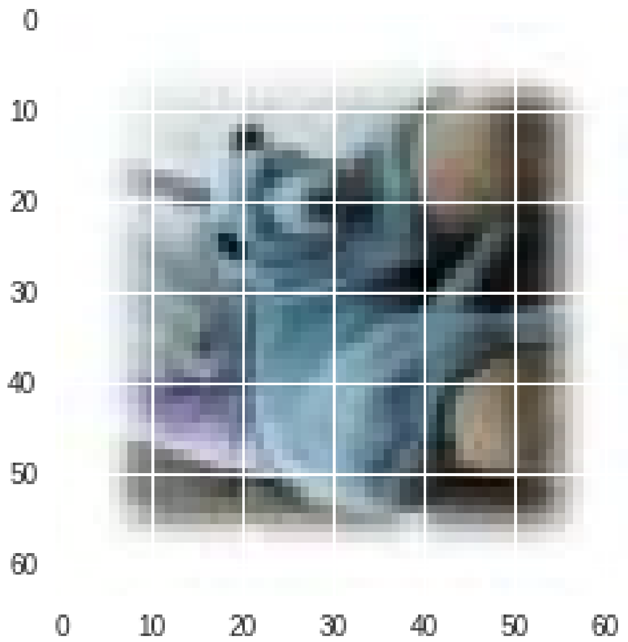

CNN Learning Curves - Accuracy
Training accuracy
Validation accuracy
Accuracy
Number of epochs
0.80
0.75
0.70
0.65
0.60
0.55
0
10
20
30
40
50
60

6.1 CNN Testing

Now we evaluate the test performance of our CNN.

```
In [0]: # define the transforms and dataloaders for the test set
        transform = transforms.Compose([
            transforms.ToPILImage(),
            transforms.ToTensor()
        ])

        test_sampler = SequentialSampler(np.arange(len(testIDS)))

        test_loader = torch.utils.data.DataLoader(test_dataset,
                                                  batch_size=batch_size,
                                                  sampler=test_sampler)

        # Test the model
        model.eval()
        with torch.no_grad():
          count = 1
          for images in test_loader:

            just_image = images[0,:,:,:]
            a = np.transpose(just_image)
            plt.imshow(a)


            images = images.to(device)
            outputs = model(images)

        #     convert and stack outputs
            outputs_cpu = outputs.cpu()
            temp = outputs_cpu.detach().numpy()
            if count == 1:
              test_out = temp
            else:
              test_out = np.vstack((test_out, temp))

            count += 1
        print('Beginning testing')
        print(len(test_out))
```

```
Beginning testing
4999
```




```
In [0]: # pickle and save results to submit for kaggle

        import pandas as pd
        import numpy as np
        import pickle
        import os
        import csv

        currPath = os.getcwd()
        prediction = []
        # convert softmax to cat/dog
        for i in range(len(test_out)):
          if test_out[i, 0] > test_out[i, 1]:
            prediction.append('Cat')
          else:
            prediction.append('Dog')




        # build csv and submit
        with open(PATH +'test_predicted.csv', 'w') as csvfile:
            # defined by the sample csv
            fieldnames = ['Id', 'label']
            writer = csv.DictWriter(csvfile, fieldnames=fieldnames)
            writer.writeheader()
```

```python
for i in range(len(prediction)):
  writer.writerow({'Id': testIDS[i], 'label':prediction[i]})
```

Include a comparison with the performance of the MLP from Q1, once we've done Q1.