dev1num3

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1 Assigment 1, part3

Link to github : https://github.com/HugoCote/Assignment-1-Part-3/

1.0.1 Members of the team :

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In [1]:
```
# deep learning library
import torch
import torchvision
import torch.optim as optim
import torch.nn as nn
import torch.nn.functional as F
import torch.nn.init as init # to initialize model
from torch.utils.data import Dataset, DataLoader
from torchvision import transforms, utils

# we use torch.cuda.Event(enable_timing=True) to measure time
# if you don't have cuda, you can use instead :
# from timeit import default_timer as timer
# import time

import collections # for ordered_dictionnary
import copy        # for copy.deepcopy( ... )
import math        # for ceiling function

# to display plot
import matplotlib.pyplot as plt
import numpy as np

# to import data
```

```
from __future__ import print_function, division
import os
from PIL import Image           #
import pandas as pd
from skimage import io, transform

import datetime                 # to format time in strings

import IPython.display # to display .png inside the notebook
```

Some cells could require a long time to evaluate, to warn the user that the evaluation of one such cell is completed, it outputs a sound.

```
In [2]: from IPython.display import Audio
        wave = np.sin(1.5*np.pi*400*np.arange(10000)/10000)
        # the following command line produces sound and is used after cells that
        # require more time to execute :
        Audio(wave, rate=10000, autoplay=True)

Out[2]: <IPython.lib.display.Audio object>
```

If you did not liked that sound, you should disable it By setting want_lound_warning to false.

```
In [3]: want_lound_warning = False
```

To perfrom the hyper-parameters search, we use the following library : It can be installed with the following command :
- pip install sobol_seq

```
In [4]: # !pip install sobol_seq
        import sobol_seq
```

1.0.2 Import the data used for training and validation

And instantiate two datasets, one with and one without data augmentation.
We tried different intensity of data augmentation. We named them :
- high
- medium
- medium-low
- low - normal (no data augmentation)

The differents transformations used for augmentation are : - Random horizontal flip - Random resize and crop - Randomly converting to grayscale - Random rotation

```
In [5]: random_seed= 2019 # for reproducibility
        batch_size = 8
        # fraction of samples that will belong to the validation dataset
        validation_split = .10
        shuffle_dataset = True
```

```
num_workers = 0        # dataloader issues with numworkers > 0

# used to scale tensor from [0 to 1] to [0 to 255]
# Without this, with the hyper-parameters tested, the models stay at
# 50% accuracy
def multby255 (pic) :
    return pic.mul(255)

# setting up data loader directory for training and validation
root = './data_catdogs/trainset/'

# different ways to augment the data
data_transforms = {
    'high': transforms.Compose([
        transforms.RandomGrayscale(p=0.15),
        transforms.RandomHorizontalFlip(p=0.5),
        transforms.RandomResizedCrop(90, scale=(0.80, 1.0), ratio=(0.75, 1.25), interpo
        transforms.CenterCrop(64),
        transforms.ToTensor(),
        transforms.Lambda(multby255)
    ]),
    'medium': transforms.Compose([
        transforms.RandomGrayscale(p=0.15),
        transforms.RandomHorizontalFlip(p=0.5),
        transforms.RandomResizedCrop(80, scale=(0.85, 1.0), ratio=(0.8, 1.2), interpola
        transforms.CenterCrop(64),
        transforms.ToTensor(),
        transforms.Lambda(multby255)
    ]),
    'medium-low': transforms.Compose([
        transforms.RandomGrayscale(p=0.4),
        transforms.RandomChoice([
            transforms.RandomHorizontalFlip(p=0.75),
            transforms.RandomRotation(15),
            transforms.RandomResizedCrop(64, scale=(0.95, 1.0), ratio=(0.95, 1.05))
        ]),
        transforms.ToTensor(),
        transforms.Lambda(multby255)
    ]),
    'low': transforms.Compose([
        transforms.RandomGrayscale(p=0.15),
        transforms.RandomHorizontalFlip(p=0.5),
        transforms.ToTensor(),
        transforms.Lambda(multby255)
    ]),
    'normal': transforms.Compose([
        transforms.ToTensor(),
        transforms.Lambda(multby255)
```

```
        ])
}

# to be able to train and valide on both the original and the augmented dataset
train_dataset_augm = torchvision.datasets.ImageFolder(root=root,transform=data_transfo
train_dataset_norm = torchvision.datasets.ImageFolder(root=root,transform=data_transfo

# Creating data indices for training and validation splits:
train_dataset_size = len(train_dataset_augm)
indices = list(range(train_dataset_size))
split = int(np.floor(validation_split * train_dataset_size))
if shuffle_dataset :
    np.random.seed(random_seed)
    np.random.shuffle(indices)
train_indices, val_indices = indices[split:], indices[:split]

# Creating data samplers:
train_sampler = torch.utils.data.SubsetRandomSampler(train_indices)
valid_sampler = torch.utils.data.SubsetRandomSampler(val_indices)

# The following code show how to instantiate dataloader for the training and validatio
batch_size = 32
train_norm_loader = DataLoader(train_dataset_norm, batch_size=batch_size, sampler=trai
train_augm_loader = DataLoader(train_dataset_augm, batch_size=batch_size, sampler=trai
valid_norm_loader = DataLoader(train_dataset_norm, batch_size=batch_size, sampler=vali
valid_augm_loader = DataLoader(train_dataset_augm, batch_size=batch_size, sampler=vali
```

Compute and display the size of each dataset We made a 10% split :
- 10% of labelled pictures belong to the validation dataset
- 90% of labelled pictures belong to the training dataset

In [6]:
```
dummy_train_loader = torch.utils.data.DataLoader(train_dataset_augm, batch_size=1, samp
dummy_valid_loader = torch.utils.data.DataLoader(train_dataset_augm, batch_size=1, samp
train_dataset_size  = dummy_train_loader.__len__()
valid_dataset_size   = dummy_valid_loader.__len__()
print("training   dataset size : " , train_dataset_size)
print("validation dataset size : " , valid_dataset_size)
del dummy_train_loader
del dummy_valid_loader
```

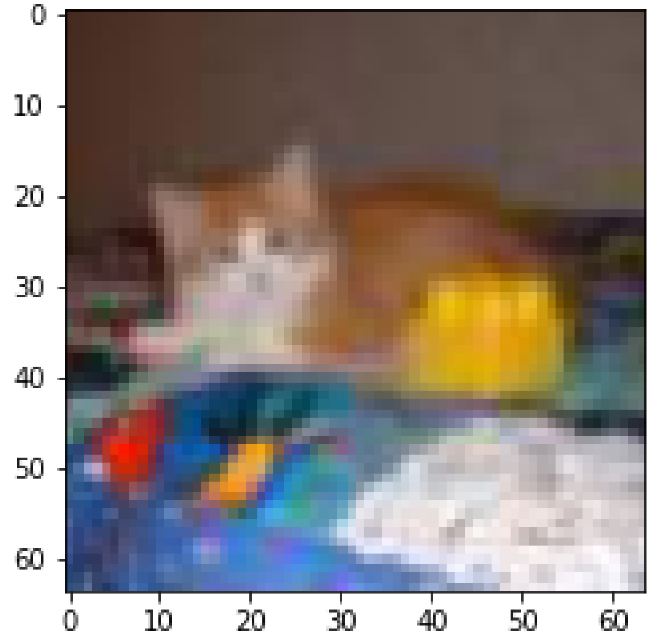
```
training   dataset size :  17999
validation dataset size :  1999
```

1.0.3 Display some samples

Using data augmentation. This is usefull to confirm that the augmented data preserve enough informations about the original data to be relevant for training i.e. pictures are not so modified that a human is not able to label them.

In [7]:
```python
batch_size = 8
pict_n_loader = torch.utils.data.DataLoader(train_dataset_norm, batch_size=batch_size,
pict_a_loader = torch.utils.data.DataLoader(train_dataset_augm, batch_size=batch_size,

# function to show an image
def imshow(img):
    npimg = img.numpy()  / 255
    plt.imshow(np.transpose(npimg, (1, 2, 0)))
    plt.show()

for i, (images, labels) in enumerate(pict_a_loader) :
    if i > 0 : break
    # show images
    imshow(torchvision.utils.make_grid(images ))
    # print labels
    print(' '.join('%5s' % labels[j].item() for j in range(min(batch_size,8))))
    sample_image = images[0]

imshow(torchvision.utils.make_grid( sample_image ))
```


```
    0     1     1     0     0     1     1     1
```



1.1 Set the device

```
In [8]: device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
        print(device)
```

```
cuda:0
```

1.2 The models

Here, we define the models that we will be using for the remaining of the notebook. They are all described.

Architecture of Classifier inspired by : https://github.com/MaximumEntropy/welcome_tutorials/tree/pyto

```
In [171]: class Classifier5(nn.Module):
              """
              Classifier5 :
              7 Convolutional layers using stride=1, no dilatation and padding to assure
              same convolution, all having :
                  - kernel of size 3 (first 3 layers) or 5 (last 4 layers)
                  - double the number of feature maps received from the previous layer
                  - followed by ReLU non-linearity
                  - and non-overlapping max pooling with kernel of size 2
                  - which means that each layer (made of those 3 steps) :
                      - receive as input n  feature maps of size 2m x 2m
                      - return  as outpu 2n feature maps of size  m x  m
```

```python
    With the exeption of :
        - the 4th layer does not have a max pooling
        - the last layer does not have ReLU non-linearity
    After the convolutional part of the model, the original 3x64x64 input
    picture is now a 512x1x1 vector.
    The 7 conv. layers are followed by one fully connected linear layer
    For the output of this model to be seen as a probabilie dist., it has to
    be fed to a F.softmax(...,dim=-1)
    """
    def __init__(self ):

        kernel_sz = np.array([5,5,5,3,3,3,3,3])
        pad = kernel_sz // 2

        super(Classifier5, self).__init__()
        self.conv = nn.Sequential(
            # Layer, input size = 64^2
            nn.Conv2d(in_channels=3, out_channels=16, kernel_size= (kernel_sz[0],kern
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=(2, 2), stride=2),

            # Layer 2, input size = 32^2
            nn.Conv2d(in_channels=16, out_channels=32, kernel_size= (kernel_sz[1],ker
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=(2, 2), stride=2),

            # Layer 3, input size = 16^2
            nn.Conv2d(in_channels=32, out_channels=64, kernel_size= (kernel_sz[2],ker
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=(2, 2), stride=2),

            # Layer 4, input size = 8^2
            nn.Conv2d(in_channels=64, out_channels=128, kernel_size= (kernel_sz[3],ke
            nn.ReLU(),

            # Layer 5, input size = 8^2
            nn.Conv2d(in_channels=128, out_channels=256, kernel_size= (kernel_sz[4],k
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=(2, 2), stride=2),

            # Layer 6, input size = 4^2
            nn.Conv2d(in_channels=256, out_channels=256, kernel_size= (kernel_sz[5],
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=(2, 2), stride=2),

            # Layer 7, input size = 2^2
            nn.Conv2d(in_channels=256, out_channels=512, kernel_size= (kernel_sz[6],
            # nn.ReLU(),
```

```python
            nn.MaxPool2d(kernel_size=(2, 2), stride=2)
        )
        #
        self.fct1b = nn.Linear(1*1*512, 2)

    def forward(self, x):
        x = self.conv(x)
        x = x.view(x.size()[0],-1)
        x = self.fct1b(x)
        return x

    def to_string(self):
        depth_to_string = "The depth of this model is fixed to 8"
        return depth_to_string + self.__doc__
```

In [172]:
```python
class Classifier5d(nn.Module):
    """
    Classifier5d, old version of Classifier5
    7 Convolutional layers using stride=1, no dilatation and padding to assure
    same convolution, all having :
        - kernel of size 3 (first 3 layers) or 5 (last 4 layers)
        - double the number of feature maps received from the previous layer
        - followed by ReLU non-linearity
        - and non-overlapping max pooling with kernel of size 2
        - which means that each layer (made of those 3 steps) :
            - receive as input n  feature maps of size 2m x 2m
            - return  as outpu 2n feature maps of size  m x  m
    With the exeption of :
        - the 4th layer does not have a max pooling
        - the last layer has tanh non-linearity
    After the convolutional part of the model, the original 3x64x64 input
    picture is now a 512x1x1 vector.
    The 7 conv. layers are followed by one fully connected layer ending
    with softmax non-linearity.
    """
    def __init__(self ):

        kernel_sz = np.array([5,5,3,3,3,3,3,3])
        pad = kernel_sz // 2
        pad[7] = 0

        super(Classifier5d, self).__init__()
        self.conv = nn.Sequential(
            # Layer, input size = 64^2
            nn.Conv2d(in_channels=3, out_channels=16, kernel_size= (kernel_sz[0],kern
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=(2, 2), stride=2),
```

```
            # Layer 2, input size = 32^2
            nn.Conv2d(in_channels=16, out_channels=32, kernel_size= (kernel_sz[1],ke
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=(2, 2), stride=2),

            # Layer 3, input size = 16^2
            nn.Conv2d(in_channels=32, out_channels=64, kernel_size= (kernel_sz[1],ke
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=(2, 2), stride=2),

            # Layer 4, input size = 8^2
            nn.Conv2d(in_channels=64, out_channels=128, kernel_size= (kernel_sz[3],k
            nn.ReLU(),

            # Layer 5, input size = 8^2
            nn.Conv2d(in_channels=128, out_channels=256, kernel_size= (kernel_sz[4],
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=(2, 2), stride=2),

            # Layer 6, input size = 4^2
            nn.Conv2d(in_channels=256, out_channels=256, kernel_size= (kernel_sz[5],
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=(2, 2), stride=2),

            # Layer 7, input size = 2^2
            nn.Conv2d(in_channels=256, out_channels=512, kernel_size= (kernel_sz[6],
            nn.Tanh(),
            nn.MaxPool2d(kernel_size=(2, 2), stride=2)
        )
        self.fct1b = nn.Linear(1*1*512, 2)

    def forward(self, x):
        x = self.conv(x)
        x = x.view(-1,1*1*512)
        x = F.relu(self.fct1b(x))
        x = F.softmax(x,dim=-1)
        return x

    def to_string(self):
        depth_to_string = "The depth of this model is fixed to 8"
        return depth_to_string + self.__doc__
```

```
In [173]: class Classifier7(nn.Module):
              """
              Classifier7 :
              6 Convolutional layers using stride=1, no dilatation and padding to assure
              same convolution, all having :
                  - kernel of size 3 (first 3 layers) or 5 (last 4 layers)
```

```
        - double the number of feature maps received from the previous layer
        - followed by ReLU non-linearity
        - and non-overlapping max pooling with kernel of size 2
        - which means that each layer (made of those 3 steps) :
            - receive as input n  feature maps of size 2m x 2m
            - return  as outpu 2n feature maps of size  m x  m
    With the exeption of :
        - the 4th and 6th layer does not have a max pooling
    After the convolutional part of the model, the original 3x64x64 input
    picture is now a 512x4x4 vector.
    The 7 conv. layers are followed by two fully connected layer :
        - the first as ReLU activation
        - the last is linear
    For the output of this model to be seen as a probabilie dist., it has
    to be fed to a F.softmax(...,dim=-1)
    """
    def __init__(self ):

        kernel_sz = np.array([5,5,5,3,3,3,3,3])
        pad = kernel_sz // 2

        super(Classifier7, self).__init__()
        self.conv = nn.Sequential(
            # Layer, input size = 64^2
            nn.Conv2d(in_channels=3, out_channels=16, kernel_size= (kernel_sz[0],kern
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=(2, 2), stride=2),

            # Layer 2, input size = 32^2
            nn.Conv2d(in_channels=16, out_channels=32, kernel_size= (kernel_sz[1],ker
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=(2, 2), stride=2),

            # Layer 3, input size = 16^2
            nn.Conv2d(in_channels=32, out_channels=64, kernel_size= (kernel_sz[2],ker
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=(2, 2), stride=2),

            # Layer 4, input size = 8^2
            nn.Conv2d(in_channels=64, out_channels=128, kernel_size= (kernel_sz[3],ke
            nn.ReLU(),

            # Layer 5, input size = 8^2
            nn.Conv2d(in_channels=128, out_channels=256, kernel_size= (kernel_sz[4],k
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=(2, 2), stride=2),

            # Layer 6, input size = 4^2
```

```
            nn.Conv2d(in_channels=256, out_channels=512, kernel_size= (kernel_sz[5],
            nn.ReLU()
        )
        #
        self.fct1 = nn.Linear(4*4*512, 512)
        self.fct2 = nn.Linear(512, 2)

    def forward(self, x):
        x = self.conv(x)
        x = x.view(x.size()[0],-1)
        x = F.relu(self.fct1(x))
        x = self.fct2(x)
        return x

    def to_string(self):
        depth_to_string = "The depth of this model is fixed to 8"
        return depth_to_string + self.__doc__
```

Model with vgg-like architecture, inspired by : https://pytorch.org/docs/0.4.0/_modules/torchvision/models/vgg.html

```
In [174]: class VGGClassifier(nn.Module):
    """
    VGGClassifier : a vgg-like model :
    The first part of the model is a made of 2 types of layers:
        A - a same convolution with kernel of size 3, padding of 1, no
            dilatation, stride = 1, with ReLU activations
        B - non-overlapping max pooling with kernel of size 2
    Each layer of type A :
        - can change the number of feature channels i.e. takes n1 feature
          channels and returns n2
        - will keep unchanged the size of the feature maps
    Each layer of type B :
        - will keep unchanged the number of feature channels and divide by
          2 the size of the feature maps
    The model takes as input a list channels_list that indicates which layers
    are of type A and B :
        - the number indicates a layer of type A and correspond to the number
          of feature channels of its output
        - \'M\' for max-pooling indicates a layer of type B
    After the convolutional part of the model, the original 3x64x64 input
    picture is now a vector.
    If there is 6 \'M\' on the channels_list (because of the size of the
    input, there cannot be more than 6), the size of this vector is the number
    of feature maps of the last layer of the convolutional part.
    The convolutional part is followed by 3 fully connected layer, the first
    two have ReLU activations. The parameter size can be used to increase the
    size of this part of the model. For the output of this model to be seen as
```

```
a probabilie dist., it has to be fed to a F.softmax(...,dim=-1)
"""
def __init__(self,
             channels_list = [50,'M',100,'M',150,200,'M',250,300,350,'M',400,450
             size = 500
            ):
    self.size   = size
    self.channels_list = channels_list
    self.depth  = 0

    for i in channels_list:
        if i == 'M' :
            continue
        self.depth += 1

    conv_out_channels = 0
    for i in reversed(channels_list) :
        if i == 'M' :
            continue
        conv_out_channels = i
        break

    super(VGGClassifier, self).__init__()
    self.features = self.make_layers(self.channels_list)
    self.classifier = nn.Sequential(
        nn.Linear(conv_out_channels, self.size),
        nn.ReLU(inplace=True),
        nn.Linear(self.size, self.size),
        nn.ReLU(inplace=True),
        nn.Linear(self.size, 2),
    )

def forward(self, x):
    x = self.features(x)
    x = x.view(x.size(0), -1)
    x = self.classifier(x)
    return x

def make_layers(self, channels_list):
    layers = []
    in_channels = 3
    for v in channels_list:
        if v == 'M':
            layers += [nn.MaxPool2d(kernel_size=2, stride=2)]
        else:
            layers += [nn.Conv2d(in_channels, v, kernel_size=3, padding=1)]
            layers += [nn.ReLU(inplace=True)]
            in_channels = v
```

```
        return nn.Sequential(*layers)

    def to_string(self):
        depth_to_string = "The depth of this instance is : {d}".format(d=self.depth)
        return depth_to_string + self.__doc__
```

2 Assignment Questions

In the following, we specifically addressed the questions asked regarding Problem 3.

2.1 Question 1

Describe the architecture (number of layers, filter sizes, pooling, etc.), and report the number of parameters. You can take inspiration from some modern deep neural network architectures such as the VGG networks to improve the performance.

2.2 Number of parameters in each model:

Using the following function, we may analyze the number of parameters in each models:

```
In [175]: def number_of_params( net , display_comp = False ) :
              nb_param   = 0
              depth      = 0 # count the number of different bias
              param_lst = " "
              for i, (key, value) in enumerate( net.state_dict().items() ) :
                  if key.endswith("bias") :
                      depth = depth + 1

                  if i == 0 :
                      param_lst = param_lst + "\n ({:<20}    ".format( key + ")" )
                  else :
                      param_lst = param_lst + "\n ({:<20}  + ".format( key + ")" )


                  nb_param_tmp = 1

                  for j , x in enumerate(value.size()) :
                      if j == 0 :
                          param_lst = param_lst + "{xx}".format( xx = x )
                      else :
                          param_lst = param_lst + "*{xx}".format( xx = x )

                      nb_param_tmp = nb_param_tmp * x

                  nb_param = nb_param + nb_param_tmp

              if display_comp:
                  print( "number of params = " , nb_param , " = ", param_lst  )
```

```
        return nb_param, depth
```

2.2.1 Display a description of the architecture of each models

Including the number of layers, kernel sizes, pooling, and a report of the number of parameters. The size of these models are around 2,6 and 13 millions parameters.

```
In [176]: list_of_models = [
              Classifier5(),
              Classifier7(),
              VGGClassifier()
          ]
          for net in list_of_models:
              print( "\n" + net.to_string() )
              _ , _ = number_of_params( net , display_comp = True )
```

```
The depth of this model is fixed to 8
    Classifier5 :
    7 Convolutional layers using stride=1, no dilatation and padding to assure
    same convolution, all having :
        - kernel of size 3 (first 3 layers) or 5 (last 4 layers)
        - double the number of feature maps received from the previous layer
        - followed by ReLU non-linearity
        - and non-overlapping max pooling with kernel of size 2
        - which means that each layer (made of those 3 steps) :
            - receive as input n  feature maps of size 2m x 2m
            - return  as outpu 2n feature maps of size  m x  m
    With the exeption of :
        - the 4th layer does not have a max pooling
        - the last layer does not have ReLU non-linearity
    After the convolutional part of the model, the original 3x64x64 input
    picture is now a 512x1x1 vector.
    The 7 conv. layers are followed by one fully connected linear layer
    For the output of this model to be seen as a probabilie dist., it has to
    be fed to a F.softmax(...,dim=-1)

number of params =  2205602  =
 (conv.0.weight)          16*3*5*5
 (conv.0.bias)          + 16
 (conv.3.weight)        + 32*16*5*5
 (conv.3.bias)          + 32
 (conv.6.weight)        + 64*32*5*5
 (conv.6.bias)          + 64
 (conv.9.weight)        + 128*64*3*3
 (conv.9.bias)          + 128
```

```
 (conv.11.weight)       + 256*128*3*3
 (conv.11.bias)         + 256
 (conv.14.weight)       + 256*256*3*3
 (conv.14.bias)         + 256
 (conv.17.weight)       + 512*256*3*3
 (conv.17.bias)         + 512
 (fct1b.weight)         + 2*512
 (fct1b.bias)           + 2

The depth of this model is fixed to 8
    Classifier7 :
    6 Convolutional layers using stride=1, no dilatation and padding to assure
    same convolution, all having :
        - kernel of size 3 (first 3 layers) or 5 (last 4 layers)
        - double the number of feature maps received from the previous layer
        - followed by ReLU non-linearity
        - and non-overlapping max pooling with kernel of size 2
        - which means that each layer (made of those 3 steps) :
            - receive as input n  feature maps of size 2m x 2m
            - return  as outpu 2n feature maps of size  m x  m
    With the exeption of :
        - the 4th and 6th layer does not have a max pooling
    After the convolutional part of the model, the original 3x64x64 input
    picture is now a 512x4x4 vector.
    The 7 conv. layers are followed by two fully connected layer :
        - the first as ReLU activation
        - the last is linear
    For the output of this model to be seen as a probabilie dist., it has
    to be fed to a F.softmax(...,dim=-1)

number of params =  5810338  =
 (conv.0.weight)          16*3*5*5
 (conv.0.bias)          + 16
 (conv.3.weight)        + 32*16*5*5
 (conv.3.bias)          + 32
 (conv.6.weight)        + 64*32*5*5
 (conv.6.bias)          + 64
 (conv.9.weight)        + 128*64*3*3
 (conv.9.bias)          + 128
 (conv.11.weight)       + 256*128*3*3
 (conv.11.bias)         + 256
 (conv.14.weight)       + 512*256*3*3
 (conv.14.bias)         + 512
 (fct1.weight)          + 512*8192
 (fct1.bias)            + 512
 (fct2.weight)          + 2*512
 (fct2.bias)            + 2
```

```
The depth of this instance is : 12
    VGGClassifier : a vgg-like model :
    The first part of the model is a made of 2 types of layers:
        A - a same convolution with kernel of size 3, padding of 1, no
            dilatation, stride = 1, with ReLU activations
        B - non-overlapping max pooling with kernel of size 2
    Each layer of type A :
        - can change the number of feature channels i.e. takes n1 feature
          channels and returns n2
        - will keep unchanged the size of the feature maps
    Each layer of type B :
        - will keep unchanged the number of feature channels and divide by
          2 the size of the feature maps
    The model takes as input a list channels_list that indicates which layers
    are of type A and B :
        - the number indicates a layer of type A and correspond to the number
          of feature channels of its output
        - 'M' for max-pooling indicates a layer of type B
    After the convolutional part of the model, the original 3x64x64 input
    picture is now a vector.
    If there is 6 'M' on the channels_list (because of the size of the
    input, there cannot be more than 6), the size of this vector is the number
    of feature maps of the last layer of the convolutional part.
    The convolutional part is followed by 3 fully connected layer, the first
    two have ReLU activations. The parameter size can be used to increase the
    size of this part of the model. For the output of this model to be seen as
    a probabilie dist., it has to be fed to a F.softmax(...,dim=-1)

number of params =  12918427  =
 (features.0.weight)      50*3*3*3
 (features.0.bias)      + 50
 (features.3.weight)    + 100*50*3*3
 (features.3.bias)      + 100
 (features.6.weight)    + 150*100*3*3
 (features.6.bias)      + 150
 (features.8.weight)    + 200*150*3*3
 (features.8.bias)      + 200
 (features.11.weight)   + 250*200*3*3
 (features.11.bias)     + 250
 (features.13.weight)   + 300*250*3*3
 (features.13.bias)     + 300
 (features.15.weight)   + 350*300*3*3
 (features.15.bias)     + 350
 (features.18.weight)   + 400*350*3*3
 (features.18.bias)     + 400
 (features.20.weight)   + 450*400*3*3
 (features.20.bias)     + 450
 (features.23.weight)   + 500*450*3*3
```

```
(features.23.bias)     + 500
(features.25.weight)   + 525*500*3*3
(features.25.bias)     + 525
(features.28.weight)   + 550*525*3*3
(features.28.bias)     + 550
(classifier.0.weight)  + 500*550
(classifier.0.bias)    + 500
(classifier.2.weight)  + 500*500
(classifier.2.bias)    + 500
(classifier.4.weight)  + 2*500
(classifier.4.bias)    + 2
```

Test a model To see if it works and if its output has the required shape

```
In [24]: mynet = VGGClassifier()
         # mynet = torchvision.models.vgg16( pretrained=False, num_classes=2, init_weights=Tru
         _ = mynet.to(device)
         batch_size = 16
         train_loader = torch.utils.data.DataLoader(train_dataset_norm, batch_size=batch_size,s
         criterion = nn.CrossEntropyLoss()
         want_to_test = True
         if want_to_test:
             with torch.no_grad() :
                 for i, data in enumerate(train_loader, 0):
                     # get the inputs
                     inputs, labels = data
                     inputs, labels = inputs.to(device), labels.to(device)
                     outputs = mynet(inputs)
                     loss = criterion(outputs, labels)
                     print( outputs.size() , labels.size() )
                     print( loss )
                     break
         del mynet
```

```
torch.Size([16, 2]) torch.Size([16])
tensor(0.7038, device='cuda:0')
```

3 Training

training algorithm below

```
In [25]: # make sound once done, should only be used to wrap a function that returns nothing
         def make_sound(func):
             def wrapper_make_sound(*args, **kwargs):
                 func(*args, **kwargs)
                 wave = np.sin(1.5*np.pi*400*np.arange(10000)/10000)
```

```
        audio = Audio(wave, rate=10000, autoplay=True)
        if want_lound_warning :
            return audio
    return wrapper_make_sound

# measure time with cuda events
def display_timer(func):
    def wrapper_display_timer(*args, **kwargs):
        torch.cuda.synchronize()
        start = torch.cuda.Event(enable_timing=True)
        end   = torch.cuda.Event(enable_timing=True)
        start.record()
        res = func(*args, **kwargs)
        end.record()
        torch.cuda.synchronize()
        print( "Time required = " , start.elapsed_time(end)*0.001 , " s ")
        return res
    return wrapper_display_timer

@make_sound
@display_timer
def training_phase( net, nb_epoch, optimizer, regul, patience, avg_loss, accuracy, tra
    # regul    : regularization parameter
    # patience : number of epoch without improvement before halting the training

    criterion_sum = nn.CrossEntropyLoss(reduction='sum') # to sum the loss of samples
    criterion     = nn.CrossEntropyLoss()
    max_valid_acc      = 50
    waiting_period     = 0
    abandon_train      = False
    for epoch in range( nb_epoch ):  # loop over the dataset multiple times

        running_loss  = torch.tensor([0], dtype=torch.float, device = device)
        correct       = torch.tensor([0], device = device)
        total         = torch.tensor([0], device = device)
        for i, data in enumerate(train_loader, 0):
            # get the inputs
            inputs, labels = data
            inputs, labels = inputs.to(device), labels.to(device)

            # zero the parameter gradients
            optimizer.zero_grad()

            # forward + backward + optimize
            outputs = net(inputs).squeeze()

            # we compute the L_2 norm of the weigths, skipping the biases
            norm_L2 = torch.tensor(0.0, dtype = torch.float, device=device)
```

```
            for param in net.parameters() :
                if len(param.shape) == 1 : # skip biases
                    continue
                norm_L2 += param.pow(2).sum()
            norm_L2 = torch.sqrt(norm_L2)

            loss = criterion(outputs, labels) + regul*norm_L2
            loss.backward()
            optimizer.step()

            # compute the correctness of the output labels
            with torch.no_grad() :
                _, predicted = torch.max(outputs.data, 1)
                total   += labels.size(0)
                correct += (predicted == labels).sum()
                loss_sum = criterion_sum(outputs, labels)

            # print statistics
            running_loss += loss_sum.item()
        else : # print every epoch
            avg_loss[epoch,0] = running_loss / total.float()
            accuracy[epoch,0] = 100 * correct.float() / total.float()

            valid_acc, valid_loss = measure_single_accuracy_and_loss(net, valid_loade
            avg_loss[epoch,1] = valid_loss
            accuracy[epoch,1] = valid_acc
            if valid_acc > max_valid_acc: # found new best accuracy
                max_valid_acc = valid_acc
                waiting_period= 0
            else :
                waiting_period+=1

            print( 'epoch = %3d, train loss = %.6f , train accuracy = %3f , valid los
                          % (epoch + 1, avg_loss[epoch,0], accuracy[epoch,0], avg_los
                 )
            # save the current model's state_dictionnary
            torch.cuda.synchronize()
            tmp_state_dict = {}
            for k, v in net.state_dict().items():
                tmp_state_dict[k] = v.cpu()
            state_dict_list.append( tmp_state_dict )
            torch.cuda.synchronize()

            if waiting_period > patience : # too much time since the last improvement
                abandon_train = True
        if abandon_train :
            print('Early stopping')
            break
```

```python
    else :
        print('Finished Training')

# measure accuracy of a single net, returns the accuracy
def measure_single_accuracy_and_loss( net, loader, criterion ):
    accuracy = torch.tensor([0.0], dtype=torch.float, device=device)
    avg_loss = torch.tensor([0.0], dtype=torch.float, device=device)
    with torch.no_grad():
        correct = torch.tensor([0], device=device)
        total   = torch.tensor([0], device=device)
        for data in loader:
            images, labels = data
            images, labels = images.to(device), labels.to(device)
            outputs = net(images).squeeze()
            loss = criterion(outputs, labels)
            _, predicted = torch.max(outputs.data, 1)
            total   += labels.size(0)
            correct += (predicted == labels).sum()
            avg_loss+= loss.item()
        accuracy = 100 * correct.float() / total.float()
        avg_loss = avg_loss/total.float()
    return accuracy, avg_loss
```

3.0.1 Plotting

Plotting function use to display accuracy and loss of a model across epochs during its training.

In [26]:
```python
# display 2 plots, accuracy and loss across epoch, their .shape must be n x 2,
# want_log indicates that user wants to save the plot to a file
# filename should not contains the extension of the file
def plot_1d_acc_and_loss(net, accuracy, loss, path_to_save, filename,
                          net_name="",want_log = False, figsize = (16,10), font_size =

    plt.rcParams.update({'font.size': font_size})
    plt.rcParams["figure.figsize"] = figsize
    plt.subplots_adjust(left=None, bottom=None, right=None, top=None, wspace=0.2, hspa

    nb_epoch =  accuracy.size()[0]

    x = np.linspace(1, nb_epoch, nb_epoch)

    y1a = copy.deepcopy(accuracy[:,1]).cpu().numpy()
    y1b = copy.deepcopy(accuracy[:,0]).cpu().numpy()
    line1a_label = "accuracy on the validation set"
    line1b_label = "accuracy on the training   set"

    y2a = copy.deepcopy(loss[:,1]).cpu().numpy()
    y2b = copy.deepcopy(loss[:,0]).cpu().numpy()
```

```python
line2a_label = "avg loss on the validation set"
line2b_label = "avg loss on the training   set"

plt.subplot(2,1,1)

plt.axhline(y=75,color="black")

line1a, = plt.plot(x, y1a, "o-", label=line1a_label)
line1a.set_dashes([2, 2])  # 2pt line, 2pt break

line1b, = plt.plot(x, y1b, "x-", label=line1b_label)
line1b.set_dashes([2, 2])  # 2pt line, 2pt break

str_title1 = "Accuracy during the training"
plt.title(str_title1)
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()

plt.subplot(2,1,2)

line2a, = plt.plot(x, y2a, "o-", label=line2a_label)
line2a.set_dashes([2, 2])  # 2pt line, 2pt break

line2b, = plt.plot(x, y2b, "x-", label=line2b_label)
line2b.set_dashes([2, 2])  # 2pt line, 2pt break

str_title1 = "Loss during the training"
plt.title(str_title1)
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()

# ytop = ...
# plt.ylim(0, ytop)     # set the ylim to bottom, top

if net_name != "" :
    plt.suptitle(net_name, fontsize=font_size)

# path_to_save = "./output/"
# filename     = datetime.datetime.now().strftime("%Y%B%d_%p%IH%MM")
if want_log :
    plt.savefig(path_to_save + filename + ".png")
plt.show()
```

3.0.2 Another ploting function

This function takes an Nx1-array of number "accuracy", a Nx2-array "hyper_param".
At position hyper_param[i,:] it shows a point which area is an increasing function of accuracy[i].
The scaling depends on the content of accuracy and on the scaling parameters.

```
In [27]: def plot_accuracy_2d(accuracy,hyper_param,path_to_save,filename,title="",axis_label=('
             figsize = (16,10)
             font_size = 16
             plt.rcParams.update({'font.size': font_size})
             plt.rcParams["figure.figsize"] = figsize
             plt.subplots_adjust(left=None, bottom=None, right=None, top=None, wspace=0.2, hspa

             x = hyper_param[:,0]
             y = hyper_param[:,1]

             N = hyper_param_sequence.__len__()
             val = accuracy
             val = val - val.min()
             val = val / val.max()

             # colors = np.ones(N)*(0.2)
             area = scaling[0]*(1+val)**scaling[1]

             str_title1 = "Accuracy of CNN, trained using different hyper-parameters \n"
             str_title2 = "Accuracy range from {min:.{prec}f}%(area of {rmin:.{prec}f}) to {ma
                   min  = _val.min(),
                   rmin = area.min(),
                   max  = _val.max(),
                   rmax = area.max(),
                   prec = 1
                 )

             str_title = title
             if str_title :
                 str_title = str_title + "\n"
             str_title = str_title + str_title1 + str_title2

             plt.title(str_title)
             plt.xlabel(axis_label[0])
             plt.ylabel(axis_label[1])

             xbot = x.min()
             xtop = x.max()
             xeps = (xtop-xbot)/100.0
             ybot = y.min()
             ytop = y.max()
             yeps = (ytop-ybot)/100.0
```

```
        plt.ylim(ybot-yeps, ytop+yeps)      # set the ylim to bottom, top
        plt.xlim(xbot-xeps, xtop+xeps)      # set the xlim to bottom, top

        plt.scatter(x, y, s=area)
        if want_log :
                plt.savefig(path_to_save + filename + ".png")
        plt.show()
```

3.0.3 Initialization method

We use glorot uniform initialization

```
In [19]: def glorot_init ( layer ) :
             """
             Weiths are generated from U[-d,d] where d = sqrt(6/(fan_in + fan_out)), biases ar
             """
             if type(layer) == nn.Linear or type(layer) == nn.Conv2d :
                 init.xavier_uniform_( layer.weight , gain=1 )
                 layer.bias.data.fill_(0.0)
```

3.1 Question 2

Plot the training error and validation error curves, along with the training and validation losses. Comment on them. What techniques (you did not implement) could be useful to improve the validation performance. How does your validation performance compare to the test set performance (that you can only get in Kaggle).

3.1.1 The training

Later in the notebook, we explain how we have searched for good choice for 3 hyper-parameters : learning rate, batch size and regularisation parameter. These suggestion are listed as comments. They take into account :
- if regularization is used
- which type of data augmentation is used - which model is used
Our best performing model achieves (with early stop and retrieving the state of the model that has among the best accuracy and minimal average loss on the validation dataset) :
- 86.59% accuracy on the test set accuracy on the validation dataset
- 86.51% accuracy on the kaggle test dataset

This model is a VGGClassifier with default arguments and this is the one that is used for the rest of the notebook.

```
In [68]: net1 = VGGClassifier()
         net1.apply( glorot_init )
         _ = net1.to(device)
```

```
In [56]: # define the loss function as the cross entropy and choose a learning rate that works
         # what we have found that works best using hyper-parameter space search
         # using Classifier5
         # using no regularization :
```

```
# using low     data augmentation : lr = 0.0003392602539062500, batch size = 21
# using medium  data augmentation : lr = 0.0005646362304687499, batch size = 18
# using high    data augmentation : lr = 0.0020221459960937504, batch size = 54
# using regularisation :
# using low     data augmentation : lr = 0.00236848          , batch size = 20, regu
# using med-low data augmentation : lr = 0.00129663          , batch size = 20, regu
# using Classifier7 and regularisation:
# using medium data augmentation : lr = 0.00110307          , batch size = 20, regu
# using VGGClassifier() and regularisation:
# using med-low data augmentation : lr = 0.008962506103515625 , batch size = 78, regu

lr = 0.008962506
optimizer      = optim.SGD(net1.parameters(), lr=lr, momentum=0.0, weight_decay=0)
patience       = 10
regularization = 0.00128163
nb_epoch  = 50

train_batch_size = 78
valid_batch_size = 4*64
train_loader = DataLoader(train_dataset_augm, batch_size=train_batch_size,sampler=tra
valid_loader = DataLoader(train_dataset_norm, batch_size=valid_batch_size,sampler=val
net1_state_dict_list = list()        # we save (all) the intermediate state of the mo

# accuracy and average loss across epoch, 0 (resp. 1) correspond to the training (rep
avg_loss1 = torch.empty(nb_epoch,2, dtype=torch.float, device = device)
accuracy1 = torch.empty(nb_epoch,2, dtype=torch.float, device = device)
```

In [57]:
```
training_phase( net1, nb_epoch, optimizer, regularization, patience, avg_loss1, accura
                train_loader, valid_loader, net1_state_dict_list )
```

```
epoch =   1, train loss = 0.685922 , train accuracy = 55.119728 , valid loss = 0.683861 , valid
epoch =   2, train loss = 0.672265 , train accuracy = 58.536587 , valid loss = 0.659204 , valid
epoch =   3, train loss = 0.655578 , train accuracy = 61.786766 , valid loss = 0.694026 , valid
epoch =   4, train loss = 0.640317 , train accuracy = 63.536861 , valid loss = 0.626098 , valid
epoch =   5, train loss = 0.622389 , train accuracy = 65.964775 , valid loss = 0.585430 , valid
epoch =   6, train loss = 0.600616 , train accuracy = 67.775986 , valid loss = 0.573021 , valid
epoch =   7, train loss = 0.588853 , train accuracy = 69.192734 , valid loss = 0.560543 , valid
epoch =   8, train loss = 0.568956 , train accuracy = 70.420578 , valid loss = 0.540174 , valid
epoch =   9, train loss = 0.548063 , train accuracy = 72.265129 , valid loss = 0.537523 , valid
epoch =  10, train loss = 0.531182 , train accuracy = 73.687424 , valid loss = 0.503379 , valid
epoch =  11, train loss = 0.504645 , train accuracy = 75.098618 , valid loss = 0.482370 , valid
epoch =  12, train loss = 0.491531 , train accuracy = 76.232010 , valid loss = 0.532841 , valid
epoch =  13, train loss = 0.478888 , train accuracy = 77.054283 , valid loss = 0.597730 , valid
epoch =  14, train loss = 0.462258 , train accuracy = 78.237679 , valid loss = 0.467779 , valid
epoch =  15, train loss = 0.451611 , train accuracy = 78.771042 , valid loss = 0.450362 , valid
epoch =  16, train loss = 0.439693 , train accuracy = 79.487747 , valid loss = 0.432755 , valid
epoch =  17, train loss = 0.419826 , train accuracy = 80.526695 , valid loss = 0.421892 , valid
epoch =  18, train loss = 0.407747 , train accuracy = 81.354523 , valid loss = 0.429784 , valid
```

```
epoch =  19, train loss = 0.396293 , train accuracy = 81.898994 , valid loss = 0.418983 , valic
epoch =  20, train loss = 0.382143 , train accuracy = 82.532364 , valid loss = 0.389223 , valic
epoch =  21, train loss = 0.375428 , train accuracy = 82.926826 , valid loss = 0.386734 , valic
epoch =  22, train loss = 0.358822 , train accuracy = 83.871323 , valid loss = 0.385910 , valic
epoch =  23, train loss = 0.352306 , train accuracy = 84.193565 , valid loss = 0.431182 , valic
epoch =  24, train loss = 0.336355 , train accuracy = 85.143616 , valid loss = 0.431225 , valic
epoch =  25, train loss = 0.323309 , train accuracy = 85.838104 , valid loss = 0.386133 , valic
epoch =  26, train loss = 0.314348 , train accuracy = 86.049225 , valid loss = 0.374538 , valic
epoch =  27, train loss = 0.298575 , train accuracy = 87.149284 , valid loss = 0.399724 , valic
epoch =  28, train loss = 0.288547 , train accuracy = 87.915993 , valid loss = 0.410586 , valic
epoch =  29, train loss = 0.283947 , train accuracy = 87.877106 , valid loss = 0.358216 , valic
epoch =  30, train loss = 0.266959 , train accuracy = 88.527138 , valid loss = 0.360780 , valic
epoch =  31, train loss = 0.259971 , train accuracy = 88.916054 , valid loss = 0.342412 , valic
epoch =  32, train loss = 0.246764 , train accuracy = 89.477196 , valid loss = 0.399721 , valic
epoch =  33, train loss = 0.241338 , train accuracy = 89.971664 , valid loss = 0.341208 , valic
epoch =  34, train loss = 0.228192 , train accuracy = 90.377243 , valid loss = 0.360942 , valic
epoch =  35, train loss = 0.220616 , train accuracy = 90.977280 , valid loss = 0.390295 , valic
epoch =  36, train loss = 0.211273 , train accuracy = 91.277290 , valid loss = 0.386609 , valic
epoch =  37, train loss = 0.202138 , train accuracy = 91.838432 , valid loss = 0.344394 , valic
epoch =  38, train loss = 0.199388 , train accuracy = 91.827324 , valid loss = 0.452072 , valic
epoch =  39, train loss = 0.181043 , train accuracy = 92.727371 , valid loss = 0.395017 , valic
epoch =  40, train loss = 0.174949 , train accuracy = 92.994057 , valid loss = 0.366413 , valic
epoch =  41, train loss = 0.175031 , train accuracy = 93.021835 , valid loss = 0.403222 , valic
epoch =  42, train loss = 0.164570 , train accuracy = 93.505196 , valid loss = 0.503415 , valic
epoch =  43, train loss = 0.158626 , train accuracy = 93.805214 , valid loss = 0.407118 , valic
epoch =  44, train loss = 0.148377 , train accuracy = 94.288574 , valid loss = 0.541897 , valic
epoch =  45, train loss = 0.142335 , train accuracy = 94.394135 , valid loss = 0.404406 , valic
epoch =  46, train loss = 0.130768 , train accuracy = 94.827492 , valid loss = 0.445834 , valic
epoch =  47, train loss = 0.127403 , train accuracy = 95.077507 , valid loss = 0.518060 , valic
epoch =  48, train loss = 0.125306 , train accuracy = 95.277519 , valid loss = 0.510292 , valic
Early stopping
Time required =  3443.366  s
```

```
Out[57]: <IPython.lib.display.Audio object>
```

3.1.2 If necessary,

you can use this code to retrieve a particular save state. This should be used to retrieve the state just before overfitting happens.

```
In [185]: want_to_retrieve = False
          indx_to_retrieve = 36    # warning : the epochs are shifted by one : index of epoch
          if want_to_retrieve :
              mynet = VGGClassifier()
              mynet.load_state_dict(net1_state_dict_list[indx_to_retrieve])
              _ = mynet.to(device)
```

When we runned the code The training had reached an early stop at epoch 48 after 57m23s. We retrieved the state of the model at index 36 (epoch 37), just before obvious overfitting. This state was achieving a minimum in the average loss and had close to maximum accuracy over the validation dataset. This is what we had :
epoch = 37, train loss = 0.202138 , train accuracy = 91.838432 , valid loss = 0.344394 , valid accuracy = 86.593300

Confidence intervals Now that we have a single value (y=86.59%) for the accuracy on the validation dataset (of size n=1999) we would want to build a 95% confidence interval for the probability of finding the good label. Here's how :
- Let x_i be 0 if the net finds the good label for picture i, 0 otherwise
- y_n = sum(x_i, for i from 1 to n) is a binomial random variable with parameters n= validation dataset size, p=Pr(x_i=1) - We use the Clopper–Pearson confidence interval method to build a 95% confidence interval for p knowing y_n = y

n = 1999; x = 0.8659*n; alpha1 = x; beta1 = n - x + 1; alpha2 = x + 1; beta2 = n - x; uinf = 0.025; usup = 1 - 0.025; vinf = N[InverseCDF[BetaDistribution[alpha1, beta1], uinf]] vsup = N[InverseCDF[BetaDistribution[alpha2, beta2], usup]]

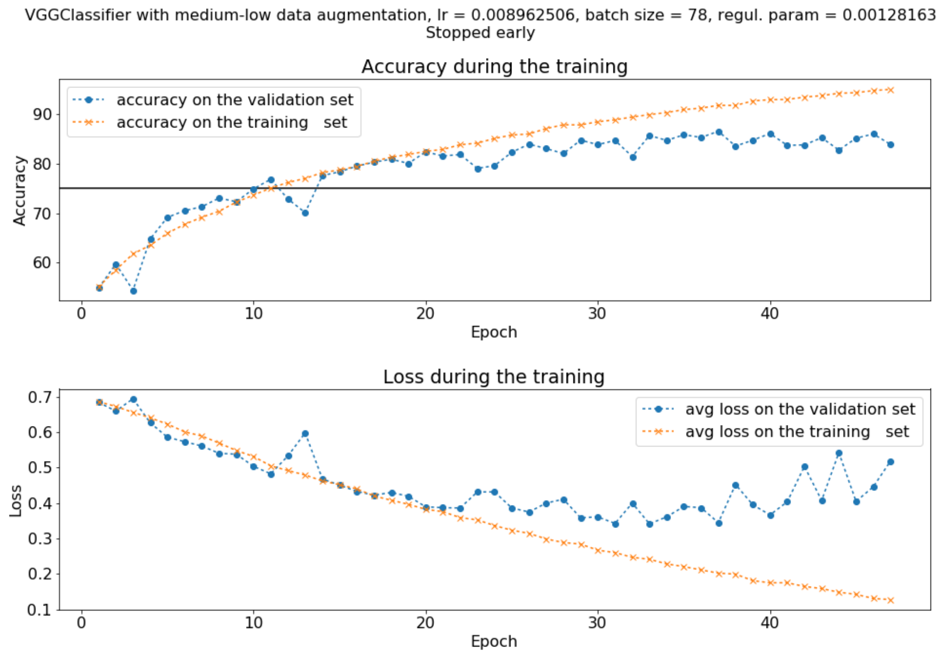
And it outputs the following 95% confidence interval for p (vinf = 0.850175, vsup = 0.880543).

That means that that we should be doing fine on the test dataset (the kaggle submission) assuming that the probability 'p' of finding the good label for one sample is the same for the validation and the test dataset. This assumption may not be true, but knowing that this interval does not contain 75% is a good thing.

3.1.3 Plot accuracy and loss on the training and validation dataset

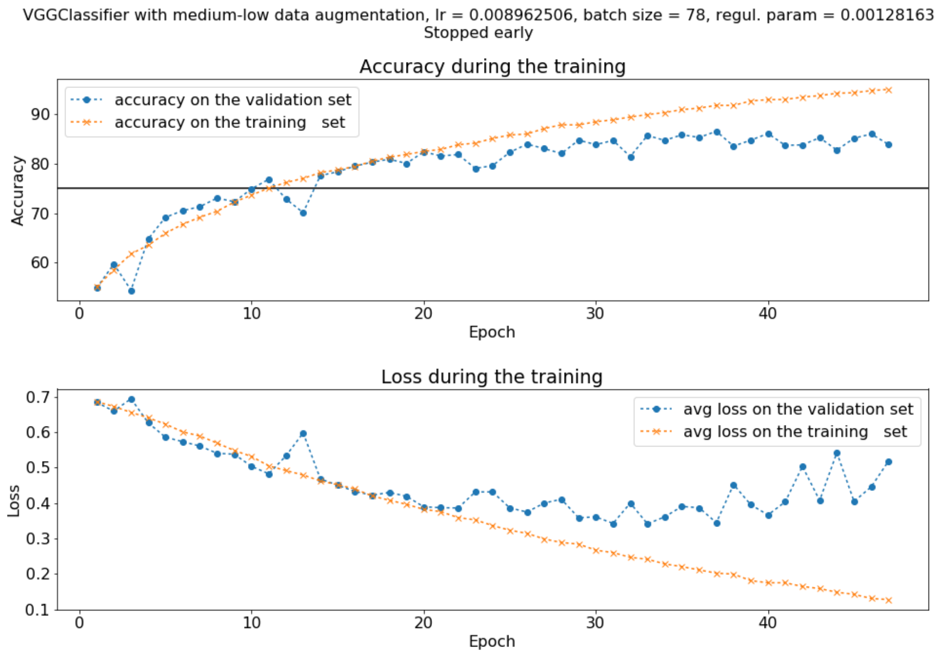
and save the result

```
In [61]: want_log       = False
         early_stop     = True
         early_stop_idx = 47
         title         = "VGGClassifier with medium-low data augmentation, lr = {lr}, batch size
                              lr=lr,
                              bs=train_batch_size,
                              rp=regularization
                          )
         if early_stop :
             title += "\nStopped early"
         path_to_save = "./output/"
         filename     = datetime.datetime.now().strftime("%Y%B%d_%p%IH%MM")

         plot_1d_acc_and_loss(net1, accuracy1[:early_stop_idx,:], avg_loss1[:early_stop_idx,:]
```



Plot the training error and validation error curves, along with the training and validation losses. Comment on them. Here we can see ... bla blabla.

```
In [62]: # Here's what we add when we runned the notebook :
         loading_path = "./output/2019February15_PM08H58M.png"
         IPython.display.display(IPython.display.Image(filename=loading_path))
```



4 Finding good hyper-parameters

Search for the right model We could considered the following two respects:

1. Architectrual decisions: those that change the structure of the model and its programming structs such as the number of layers, the size of hidden layers, non-linearities for activations, kernel parameters (e.g., its size and stride), initialization method, etc.
2. Tuning iteration hyper-parameters: which is usually done with grid search or random search > * mini-batch size > * learning rate

Between the two above, the architectrual decisions are more expensive to implement. Mindful of our recource limitation, we tried several architectures and comparing their validation errors brought, and we ended up choosing Classifier 5 over the rest.

As for the hyper-parameters search, we did not want to use grid search, because it amounts to search for too few point in each individual dimension. i.e. the cardinality of the projection of the points used in each dimension is significantly lower than the total number of points evaluated. In order to efficiently look for parameters, we opted for a low discrepency deterministic (so called quasi-random) sequence called sobol sequence that ensures a lower discrepancy than a true random (big holes in the resulting samples).

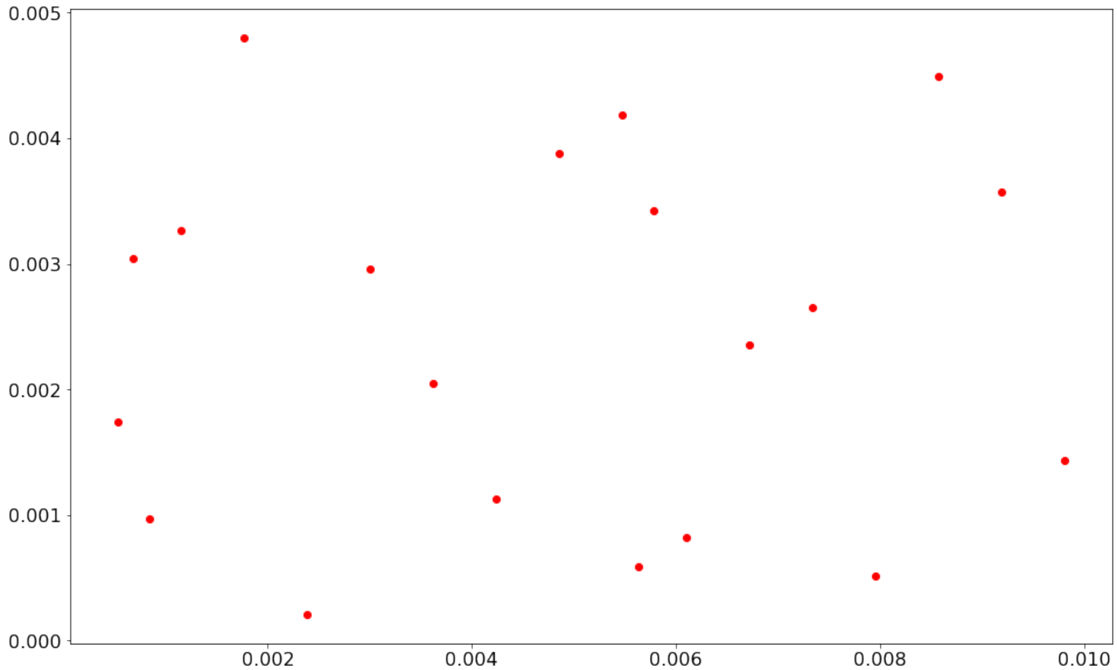
Here's what it looks like.
We define one class that wrap a sobol sequence.

```
In [123]: class HyperParameterSequence():
              """
```

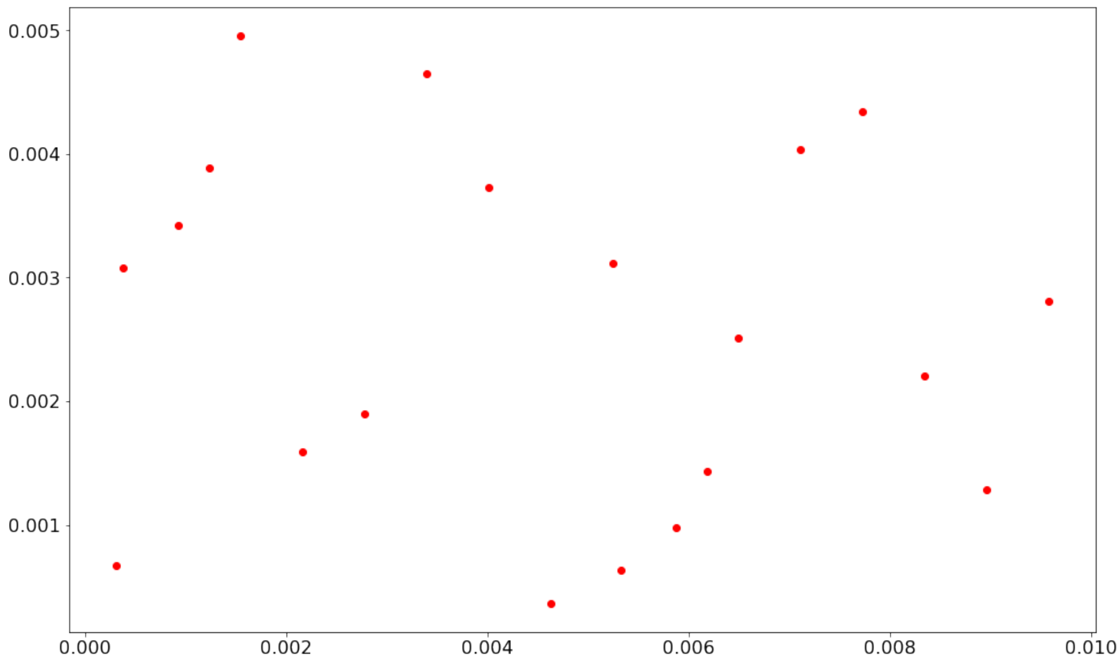
```
        n-dimensional Sobol sequence :
            - starting_point : the point in the (infinite) sobol sequence at which our s
                               for reproductibility, this number has to be remembered
            - nb_points      : number of consecutive points of the sequence we use for e
            - dim            : number of dimension of the search
            - c_interval     : list of lists each of the form [lower bound, upper bound]
        """
        def __init__(self,starting_point,nb_points,dim,c_interval):
            self.starting_point = starting_point
            self.nb_points      = nb_points
            self.dim            = dim
            self.c_min = np.empty(self.dim)
            self.c_max = np.empty(self.dim)
            for i in range(self.dim) :
                self.c_min[i] = c_interval[i][0]
                self.c_max[i] = c_interval[i][1]

            self.seq = np.empty((nb_points,3))
            start = starting_point
            end   = start + nb_points
            for i,j in enumerate(range(start,end,1)) :
                hyperparam_point ,_ = sobol_seq.i4_sobol(self.dim,j)
                # take the point in the unitary cube and map it to the desired box
                for k in range(self.dim) :
                    self.seq[i,k] = hyperparam_point[k]*(self.c_max[k]-self.c_min[k]) +se

        def __len__(self):
            return self.nb_points

        def get_dim(self):
            return self.dim

        def get_interval(self,k):
            return self.c_min[k], self.c_max[k]

        def __getitem__(self, idx):
            return self.seq[idx]

        def get_sequence(self):
            return self.seq
```

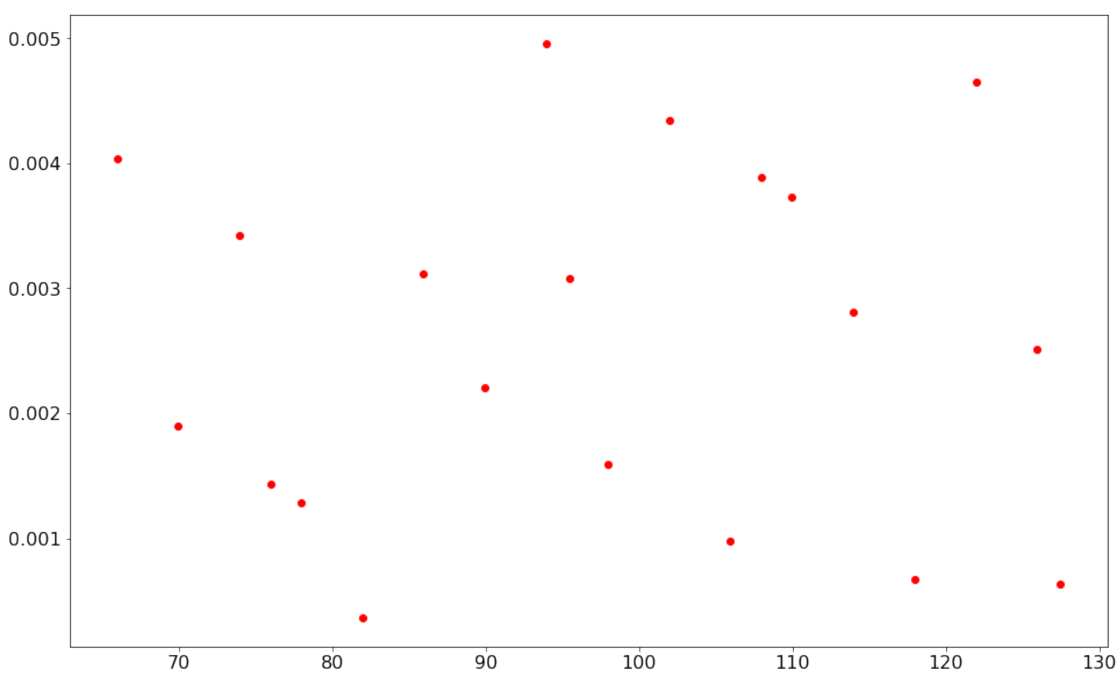
```
In [125]: # Vizualize a 2d sobol sequence in the desired search box
          starting_point = 8030
          nb_points      = 20
          lr_interval    = [0.0001, 0.01]
          re_interval    = [0.0001,0.005]
          intervals      = [lr_interval, re_interval]
```

```
hyper_param_sequence = HyperParameterSequence(starting_point,nb_points,2,intervals)
seq = hyper_param_sequence.get_sequence()
plt.plot(seq[:,0],seq[:,1], 'ro')
plt.show()
```




```
In [126]: # Vizualize 2 dimension hyper-planes of a 3d sobol sequence
          starting_point = 10030
          nb_points      = 20
          lr_interval    = [0.0001, 0.01]
          bs_interval    = [1*64,2*64]     # warning : if this is set too high, you can encount
          re_interval    = [0.0001,0.005]
          intervals      = [lr_interval, bs_interval, re_interval]
          hyper_param_sequence = HyperParameterSequence(starting_point,nb_points,3,intervals)
          seq = hyper_param_sequence.get_sequence()
          plt.plot(seq[:,0],seq[:,2], 'ro')
          plt.show()
          plt.plot(seq[:,1],seq[:,2], 'ro')
          plt.show()
```





What we plan to do : To find the most promising combination of learning rates, we use the following pseudocode:

Pseudocode

1. We generate a point in hyper-parameter space
2. We train an net for k epoch using these hyper-parameters
3. We pick the net that has the highest accuracy on the validation dataset
4. Continue training this net with the same fixed hyper-parameters

Searching hyper-parameters space in 3 dimensions :
- learning rate
- batch size
- regularisation parameter

```
In [30]: nb_epoch  = 3
         patience  = 2
         # current mlp with the best performance on the validation set, on its last epoch
         acc_max = 0
         idx_max = 0

         # we save (all) the intermediate state of the model during the learning phase, for ea
         state_dict_dict = dict()
         valid_batch_size = 4*64
         valid_loader = DataLoader(train_dataset_norm, batch_size=valid_batch_size,sampler=vali
         for i, hyperparam_point in enumerate(hyper_param_sequence):
             lr         = hyperparam_point[0]
             batch_size = math.ceil(hyperparam_point[1]) # cast to the correct type
             regul      = hyperparam_point[2]
             net_tmp = VGGClassifier()
             net_tmp.apply( glorot_init )
             _ = net_tmp.to(device)

             criterion = nn.CrossEntropyLoss(reduction='sum')
             optimizer = optim.SGD(net_tmp.parameters(), lr=lr, momentum=0.0, weight_decay=0)

             train_loader = DataLoader(train_dataset_augm, batch_size=batch_size,sampler=train_
             state_dict_list_tmp = list() # we save (all) the intermediate state of the model 

             # average loss across epoch
             avg_loss_tmp      = torch.empty(nb_epoch,2, dtype=torch.float, device = device)
             # accuracy[i, 0 (resp. 1)] is the training (reps. validation) accuracy of the net
             accuracy_tmp      = torch.empty(nb_epoch,2, dtype=torch.float, device = device)

             # print hyper-parameters
             print("point no. {i}, lr = {lr}, batch size = {batch_size}, regul={regul}".format
                         i=i,
                         lr=lr,
```

```
                        batch_size=batch_size,
                        regul=regul
                ))

            # we dump output to disable sound
            torch.cuda.synchronize()
            _ = training_phase( net_tmp, nb_epoch, optimizer, regul, patience, avg_loss_tmp,
                                     accuracy_tmp, train_loader, valid_loader, state_dict_list_
            state_dict_dict[i] = [[lr,batch_size,regul],state_dict_list_tmp,avg_loss_tmp,accu


            valid_accuracy = accuracy_tmp[-1,1] # last validation accuracy
            if valid_accuracy > acc_max :
                acc_max = valid_accuracy
                idx_max = i
            torch.cuda.synchronize()

        print("#####################")
        print("best net found : {i} , with validation accuracy = {va}".format(i=idx_max,va=ac
        if want_loud_warning :
            Audio(wave, rate=10000, autoplay=True)
```

```
point no. 0, lr = 0.006178131103515626, batch size = 76, regul=0.001434759521484375
epoch =   1, train loss = 0.685866 , train accuracy = 54.664146 , valid loss = 0.674845 , vali
epoch =   2, train loss = 0.672871 , train accuracy = 58.781044 , valid loss = 0.679346 , vali
epoch =   3, train loss = 0.659360 , train accuracy = 61.258961 , valid loss = 0.662868 , vali
Finished Training
Time required =  502.1490625  s
point no. 1, lr = 0.001228131103515625, batch size = 108, regul=0.0038847595214843746
epoch =   1, train loss = 0.690818 , train accuracy = 54.180786 , valid loss = 0.689068 , vali
epoch =   2, train loss = 0.686327 , train accuracy = 57.325405 , valid loss = 0.686039 , vali
epoch =   3, train loss = 0.681139 , train accuracy = 58.175453 , valid loss = 0.680879 , vali
Finished Training
Time required =  180.66470312500002  s
point no. 2, lr = 0.0009187561035156251, batch size = 74, regul=0.003425384521484375
epoch =   1, train loss = 0.691839 , train accuracy = 52.291794 , valid loss = 0.690343 , vali
epoch =   2, train loss = 0.686875 , train accuracy = 57.103172 , valid loss = 0.685423 , vali
epoch =   3, train loss = 0.681454 , train accuracy = 58.369911 , valid loss = 0.686156 , vali
Finished Training
Time required =  225.22684375  s
point no. 3, lr = 0.005868756103515626, batch size = 106, regul=0.000975384521484375
epoch =   1, train loss = 0.686939 , train accuracy = 54.975277 , valid loss = 0.677549 , vali
epoch =   2, train loss = 0.674015 , train accuracy = 58.347687 , valid loss = 0.657008 , vali
epoch =   3, train loss = 0.661800 , train accuracy = 60.714485 , valid loss = 0.639054 , vali
Finished Training
Time required =  216.96814062500002  s
point no. 4, lr = 0.008343756103515626, batch size = 90, regul=0.002200384521484375
epoch =   1, train loss = 0.686835 , train accuracy = 54.597477 , valid loss = 0.673481 , vali
```

```
epoch =   2, train loss = 0.672708 , train accuracy = 58.492138 , valid loss = 0.654444 , valid
epoch =   3, train loss = 0.663005 , train accuracy = 60.292240 , valid loss = 0.638610 , valid
Finished Training
Time required =  208.413671875  s
point no. 5, lr = 0.0033937561035156253, batch size = 122, regul=0.004650384521484375
epoch =   1, train loss = 0.689654 , train accuracy = 54.214123 , valid loss = 0.686127 , valid
epoch =   2, train loss = 0.680568 , train accuracy = 57.942108 , valid loss = 0.681511 , valid
epoch =   3, train loss = 0.672449 , train accuracy = 58.486584 , valid loss = 0.663968 , valid
Finished Training
Time required =  193.61839062500002  s
point no. 6, lr = 0.004631256103515626, batch size = 82, regul=0.000362884521484375
epoch =   1, train loss = 0.685447 , train accuracy = 55.203068 , valid loss = 0.706556 , valid
epoch =   2, train loss = 0.671755 , train accuracy = 58.731041 , valid loss = 0.663824 , valid
epoch =   3, train loss = 0.661130 , train accuracy = 61.131172 , valid loss = 0.652674 , valid
Finished Training
Time required =  290.4695625  s
point no. 7, lr = 0.009581256103515625, batch size = 114, regul=0.0028128845214843747
epoch =   1, train loss = 0.687758 , train accuracy = 54.547474 , valid loss = 0.682240 , valid
epoch =   2, train loss = 0.676364 , train accuracy = 58.164341 , valid loss = 0.673263 , valid
epoch =   3, train loss = 0.663117 , train accuracy = 60.364464 , valid loss = 0.671408 , valid
Finished Training
Time required =  184.215546875  s
point no. 8, lr = 0.007106256103515626, batch size = 66, regul=0.004037884521484375
epoch =   1, train loss = 0.683719 , train accuracy = 56.030891 , valid loss = 0.699001 , valid
epoch =   2, train loss = 0.667391 , train accuracy = 59.414413 , valid loss = 0.680178 , valid
epoch =   3, train loss = 0.649160 , train accuracy = 62.381245 , valid loss = 0.628365 , valid
Finished Training
Time required =  239.113875  s
point no. 9, lr = 0.002156256103515625, batch size = 98, regul=0.001587884521484375
epoch =   1, train loss = 0.688308 , train accuracy = 54.041893 , valid loss = 0.682598 , valid
epoch =   2, train loss = 0.676788 , train accuracy = 58.019890 , valid loss = 0.703180 , valid
epoch =   3, train loss = 0.670578 , train accuracy = 58.942162 , valid loss = 0.702606 , valid
Finished Training
Time required =  204.82440625  s
point no. 10, lr = 0.0015375061035156252, batch size = 94, regul=0.004956634521484375
epoch =   1, train loss = 0.690931 , train accuracy = 52.930717 , valid loss = 0.690067 , valid
epoch =   2, train loss = 0.687426 , train accuracy = 56.203121 , valid loss = 0.685838 , valid
epoch =   3, train loss = 0.682077 , train accuracy = 58.392132 , valid loss = 0.678740 , valid
Finished Training
Time required =  201.746234375  s
point no. 11, lr = 0.006487506103515625, batch size = 126, regul=0.0025066345214843746
epoch =   1, train loss = 0.687137 , train accuracy = 54.553032 , valid loss = 0.677833 , valid
epoch =   2, train loss = 0.679178 , train accuracy = 57.225403 , valid loss = 0.671482 , valid
epoch =   3, train loss = 0.668690 , train accuracy = 59.358852 , valid loss = 0.654090 , valid
Finished Training
Time required =  391.17971875  s
point no. 12, lr = 0.008962506103515625, batch size = 78, regul=0.001281634521484375
epoch =   1, train loss = 0.684106 , train accuracy = 55.325294 , valid loss = 0.676528 , valid
```

```
epoch =   2, train loss = 0.673142 , train accuracy = 58.819935 , valid loss = 0.669340 , valic
epoch =   3, train loss = 0.658953 , train accuracy = 60.964497 , valid loss = 0.638885 , valic
Finished Training
Time required =  436.73053125  s
point no. 13, lr = 0.004012506103515626, batch size = 110, regul=0.0037316345214843745
epoch =   1, train loss = 0.687297 , train accuracy = 54.875271 , valid loss = 0.692994 , valic
epoch =   2, train loss = 0.676870 , train accuracy = 57.925442 , valid loss = 0.689186 , valic
epoch =   3, train loss = 0.667833 , train accuracy = 59.769989 , valid loss = 0.663677 , valic
Finished Training
Time required =  446.13125  s
point no. 14, lr = 0.002775006103515625, batch size = 70, regul=0.001894134521484375
epoch =   1, train loss = 0.684204 , train accuracy = 55.814213 , valid loss = 0.736925 , valic
epoch =   2, train loss = 0.669186 , train accuracy = 59.564419 , valid loss = 0.670535 , valic
epoch =   3, train loss = 0.659597 , train accuracy = 60.447803 , valid loss = 0.634700 , valic
Finished Training
Time required =  251.426875  s
point no. 15, lr = 0.007725006103515626, batch size = 102, regul=0.004344134521484375
epoch =   1, train loss = 0.685369 , train accuracy = 55.236401 , valid loss = 0.679365 , valic
epoch =   2, train loss = 0.673450 , train accuracy = 59.003277 , valid loss = 0.657237 , valic
epoch =   3, train loss = 0.662159 , train accuracy = 60.636703 , valid loss = 0.699421 , valic
Finished Training
Time required =  574.60675  s
point no. 16, lr = 0.0052500061035156255, batch size = 86, regul=0.0031191345214843747
epoch =   1, train loss = 0.686815 , train accuracy = 54.708595 , valid loss = 0.695554 , valic
epoch =   2, train loss = 0.675823 , train accuracy = 57.792099 , valid loss = 0.661089 , valic
epoch =   3, train loss = 0.661904 , train accuracy = 60.208900 , valid loss = 0.654032 , valic
Finished Training
Time required =  417.813625  s
point no. 17, lr = 0.000300006103515625, batch size = 118, regul=0.000669134521484375
epoch =   1, train loss = 0.693041 , train accuracy = 51.486195 , valid loss = 0.692249 , valic
epoch =   2, train loss = 0.691775 , train accuracy = 55.030834 , valid loss = 0.691789 , valic
epoch =   3, train loss = 0.691060 , train accuracy = 53.930775 , valid loss = 0.691050 , valic
Finished Training
Time required =  299.41390625  s
point no. 18, lr = 0.000377349853515625, batch size = 96, regul=0.0030808532714843746
epoch =   1, train loss = 0.692339 , train accuracy = 52.419579 , valid loss = 0.691695 , valic
epoch =   2, train loss = 0.690665 , train accuracy = 54.308571 , valid loss = 0.690459 , valic
epoch =   3, train loss = 0.689216 , train accuracy = 56.569809 , valid loss = 0.689074 , valic
Finished Training
Time required =  601.55975  s
point no. 19, lr = 0.005327349853515626, batch size = 128, regul=0.000630853271484375
epoch =   1, train loss = 0.687477 , train accuracy = 54.297462 , valid loss = 0.678247 , valic
epoch =   2, train loss = 0.679432 , train accuracy = 56.742043 , valid loss = 0.668411 , valic
epoch =   3, train loss = 0.669451 , train accuracy = 59.253292 , valid loss = 0.651768 , valic
Finished Training
Time required =  219.72664062500002  s
#####################
best net found : 12 , with validation accuracy = 66.83341979980469
```

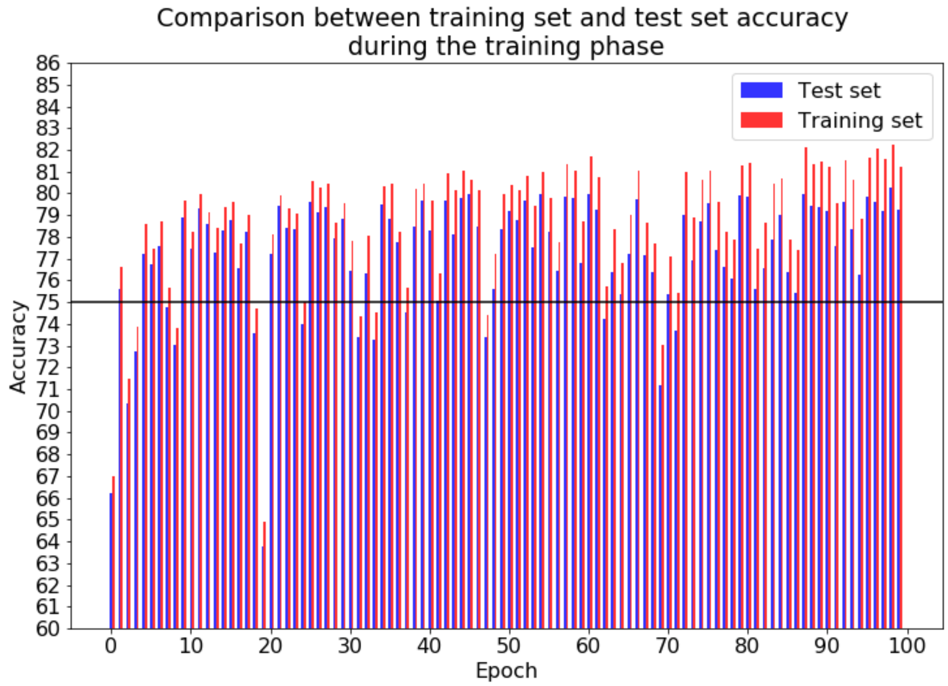
```
Out[30]: <IPython.lib.display.Audio object>
```

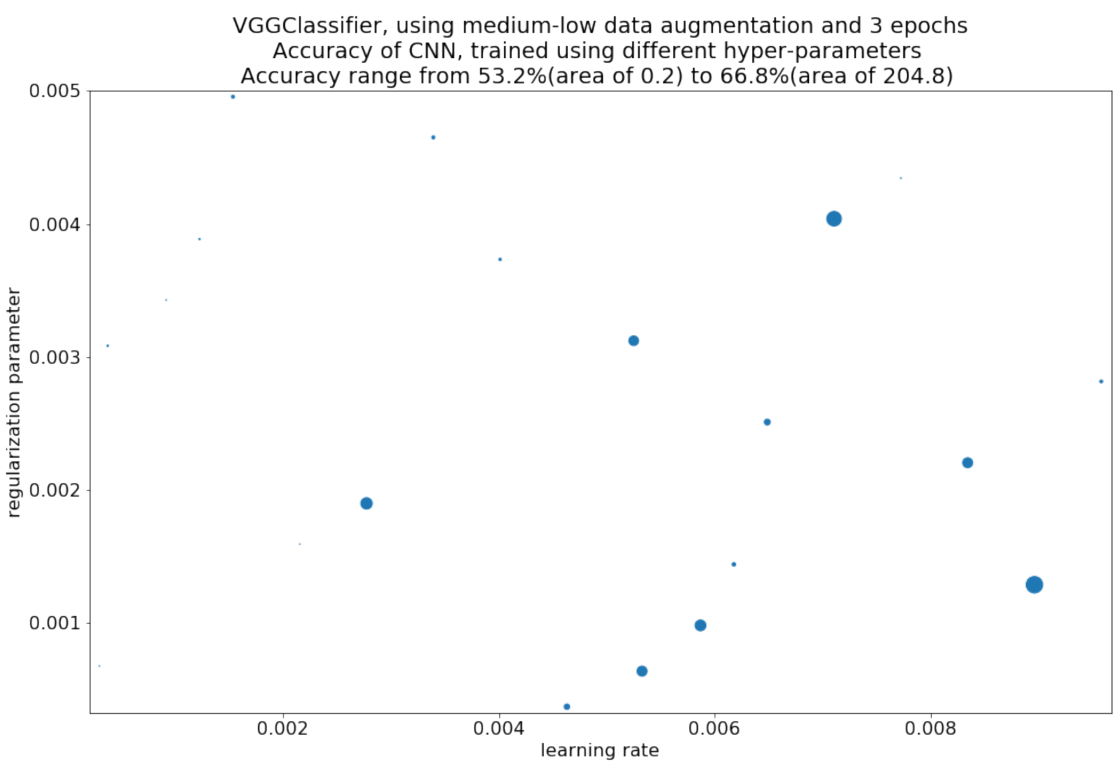
4.0.1 Display the result of the search

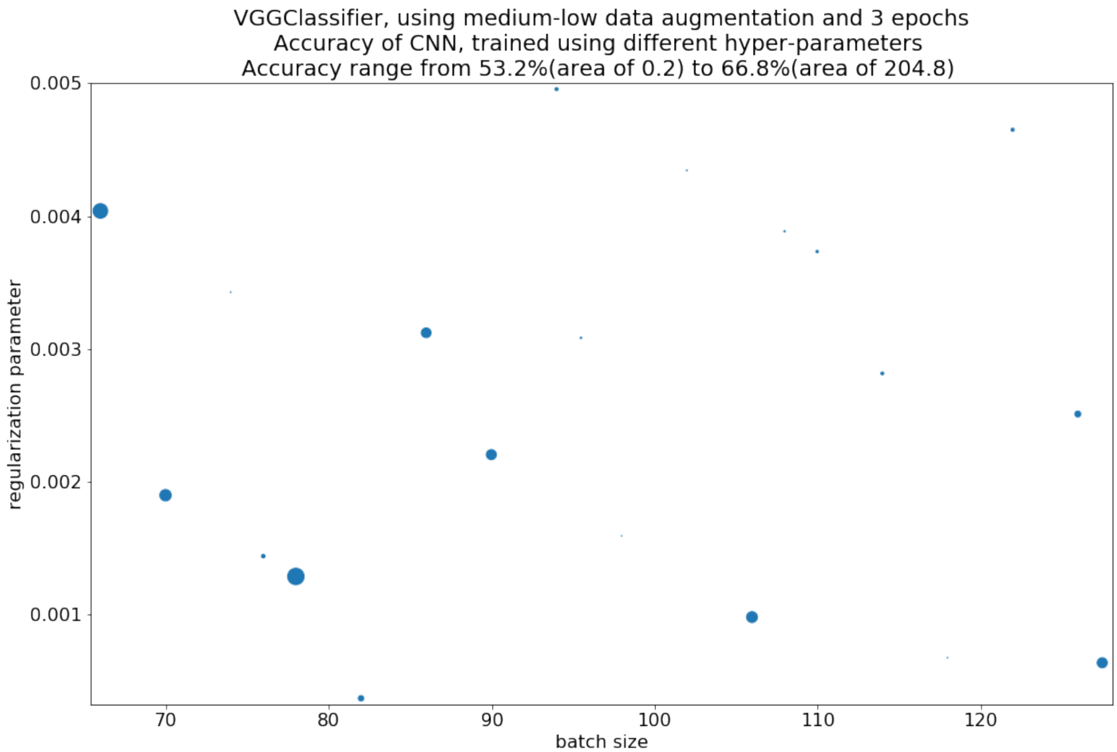
In the following plot, the bigger the area of the point, the higher is the accuracy of the model corresponding to its coordinated hyperparameters.

Big points are good, small points are bad.
We scale the area of the points to make the results easily understandable.

```
In [127]: want_log     = True
          path_to_save = "./output/"
          filename     = datetime.datetime.now().strftime("%Y%B%d_%p%IH%MM")
          title        = "VGGClassifier, using medium-low data augmentation and 3 epochs"

          # retrieve the sequence used for the search
          hyper_param  = hyper_param_sequence.get_sequence()
          N            = hyper_param_sequence.__len__()

          # define hyper-planes to display
          hyper_param_plane = np.empty((3,N,2))
          hyper_param_plane[0] = hyper_param[:,[0,1]]
          hyper_param_plane[1] = hyper_param[:,[0,2]]
          hyper_param_plane[2] = hyper_param[:,[1,2]]
          axis_label    = [
                  ("learning rate","batch size"),
                  ("learning rate","regularization parameter"),
                  ("batch size","regularization parameter")
              ]
          _val = np.empty(N)
          # retrieve previously measured accuracy
          for i in range(N):
              # [lr,batch_size],state_dict_list_tmp,avg_loss_tmp,accuracy_tmp
              _,_,_,acc = state_dict_dict[i]
              _val[i]   = acc[-1,1]

          for k in range(3):
              plot_accuracy_2d(_val,hyper_param_plane[k],path_to_save,filename + "{k}".format(
                                title,axis_label[k],want_log,scaling=(0.2,10))
```

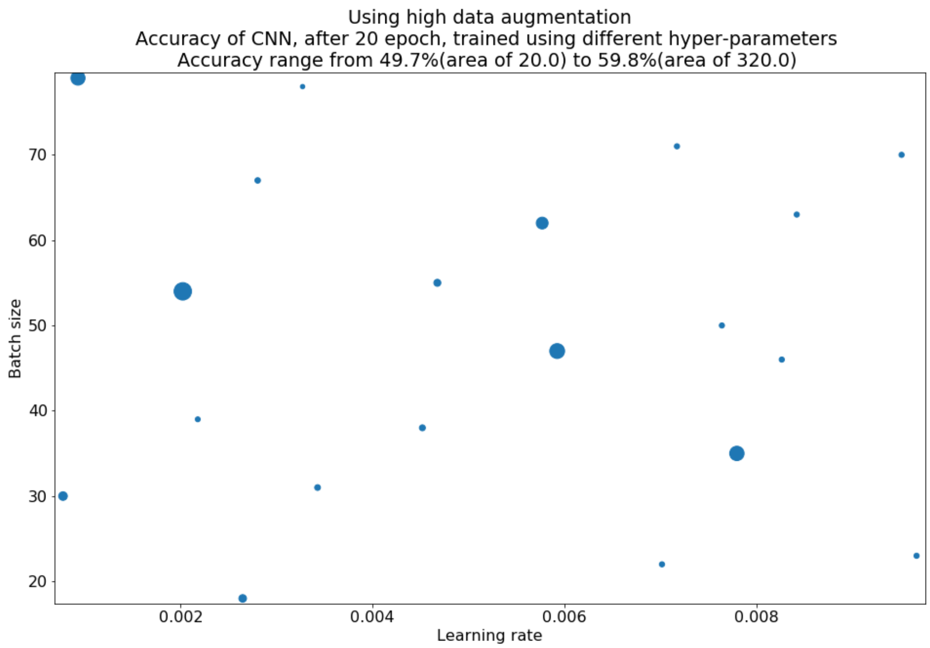

Comparison between training set and test set accuracy
during the training phase
Test set
Training set
Accuracy
Epoch


VGGClassifier, using medium-low data augmentation and 3 epochs
Accuracy of CNN, trained using different hyper-parameters
Accuracy range from 53.2%(area of 0.2) to 66.8%(area of 204.8)
regularization parameter
learning rate



5 Past stuff

In [165]:
```
# using Classifier5d
# using high data augmentation we found lr = 0.00075, batch size = 512
loading_path = "./output/2019February09_PM09H02M.png"
IPython.display.display(IPython.display.Image(filename=loading_path))
```

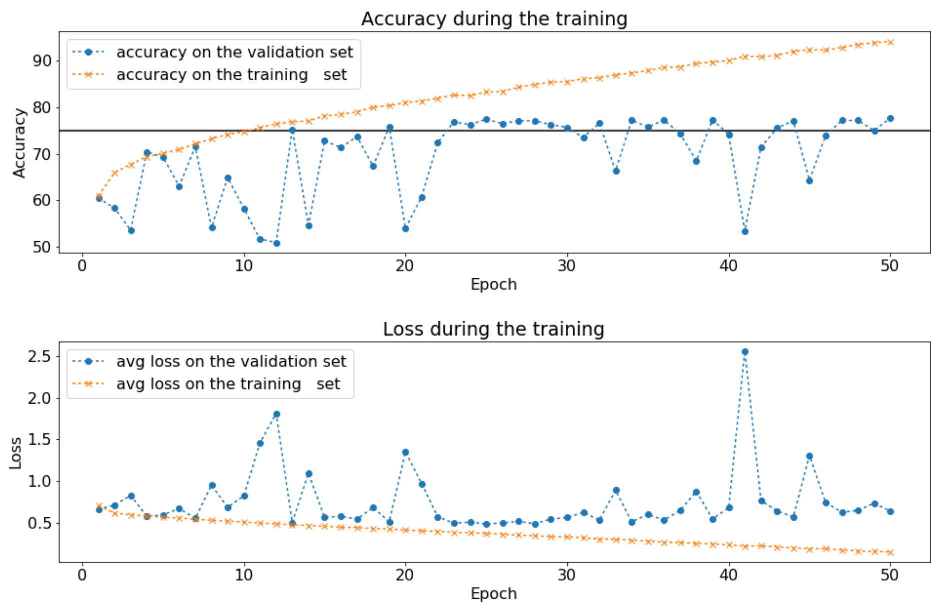


6 Our results

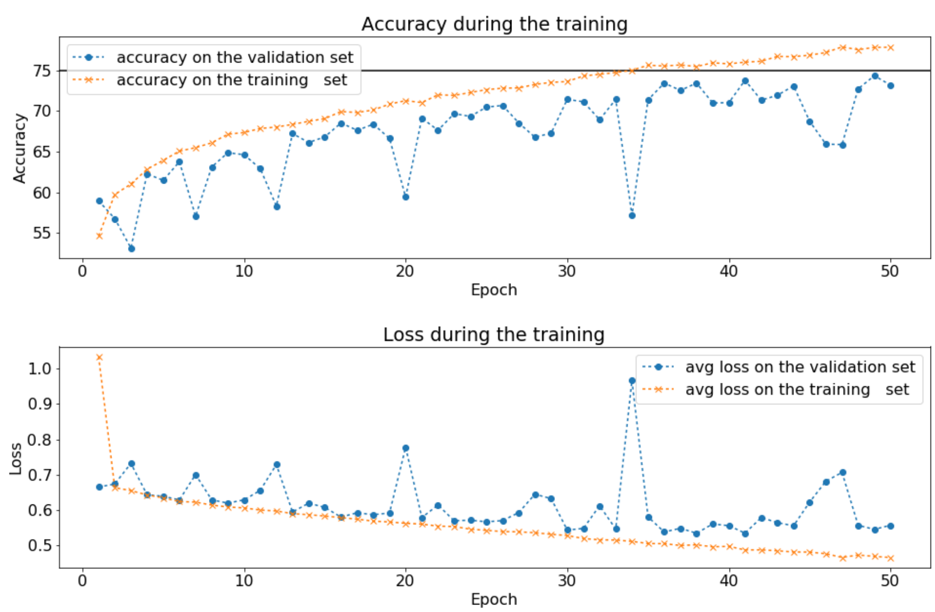
This next section is composed of a list of plots in group of two:
- The first shows the result of the search in the hyper-parameter space
- The second shows the result of taking those hyper-parameters and training a model with them
The discussion comes after the plots.

In [163]:
```
# Here's what we add when we runned the notebook with high data augmentation :
# and :
# starting_point = 4030
# nb_points      = 20
# lr_interval    = [0.01,0.00001]
# bs_interval    = [16,80]# Vizualize a 2d sobol sequence in the desired search box
# using high data augmentation we found lr = 0.0020221459960937504, batch size = 54
loading_path = "./output/2019February14_AM12H32M.png"
IPython.display.display(IPython.display.Image(filename=loading_path))
# Here's what we add when we runned the notebook :
loading_path = "./output/2019February14_AM01H03M.png"
IPython.display.display(IPython.display.Image(filename=loading_path))
```

Classifier5 with low data augmentation, lr = 0.0003393, batch size = 21

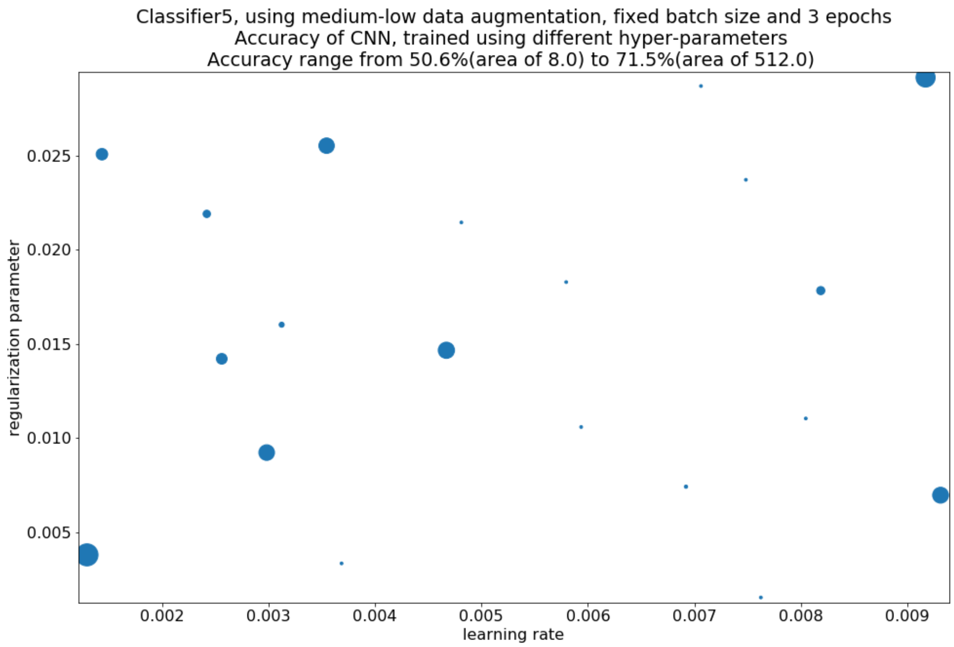


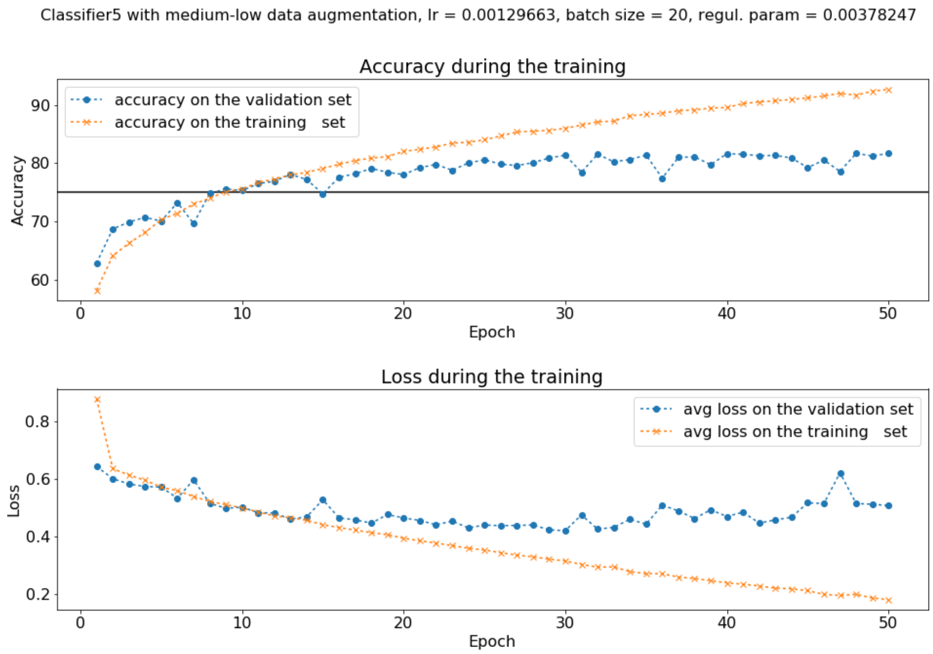
Classifier5 with high data augmentation, lr = 0.002022146, batch size = 54



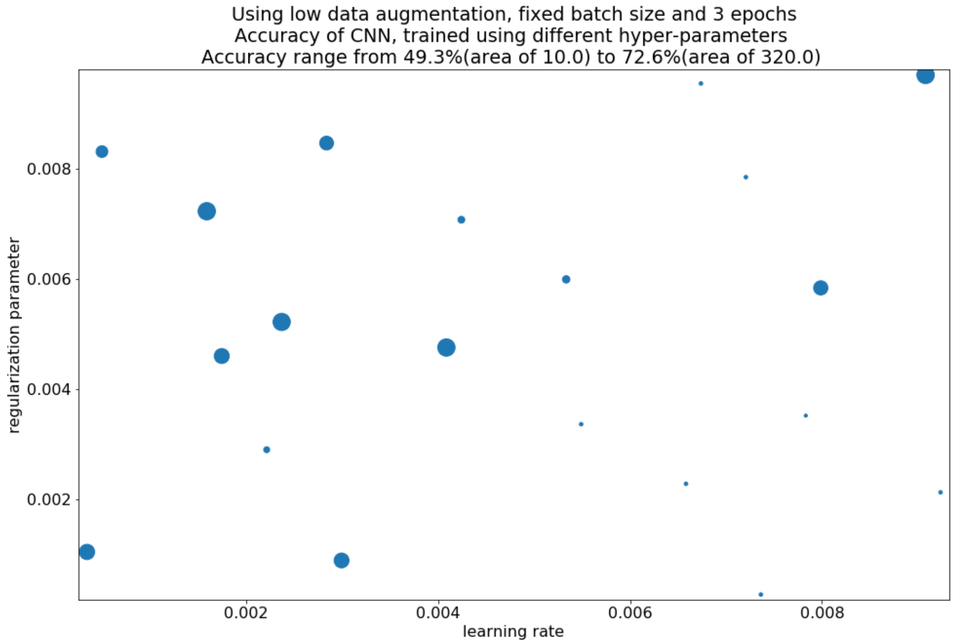
In [175]:
```
# Here's what we add when we runned the notebook with medium data augmentation :
# and :
```

```
# starting_point = 3030
# nb_points      = 20
# lr_interval    = [0.002,0.00005]
# bs_interval    = [16,2*64]
# using Classifier5, no regularization and medium  data augmentation :
# lr = 0.0005646362304687499, batch size = 18
loading_path = "./output/2019February13_PM10H33M.png"
IPython.display.display(IPython.display.Image(filename=loading_path))
loading_path = "./output/2019February13_PM11H49M.png"
IPython.display.display(IPython.display.Image(filename=loading_path))
```

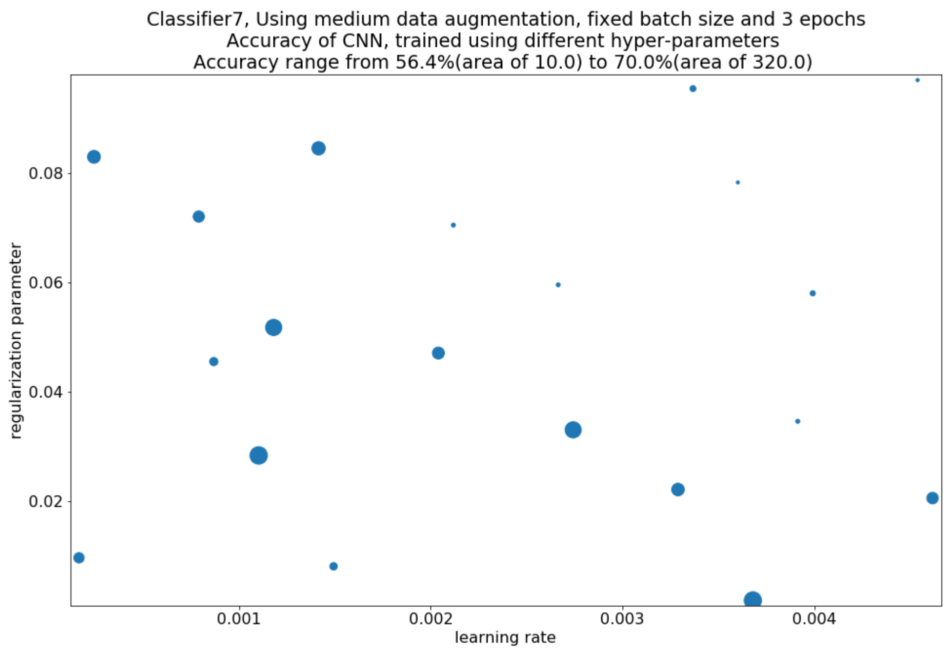


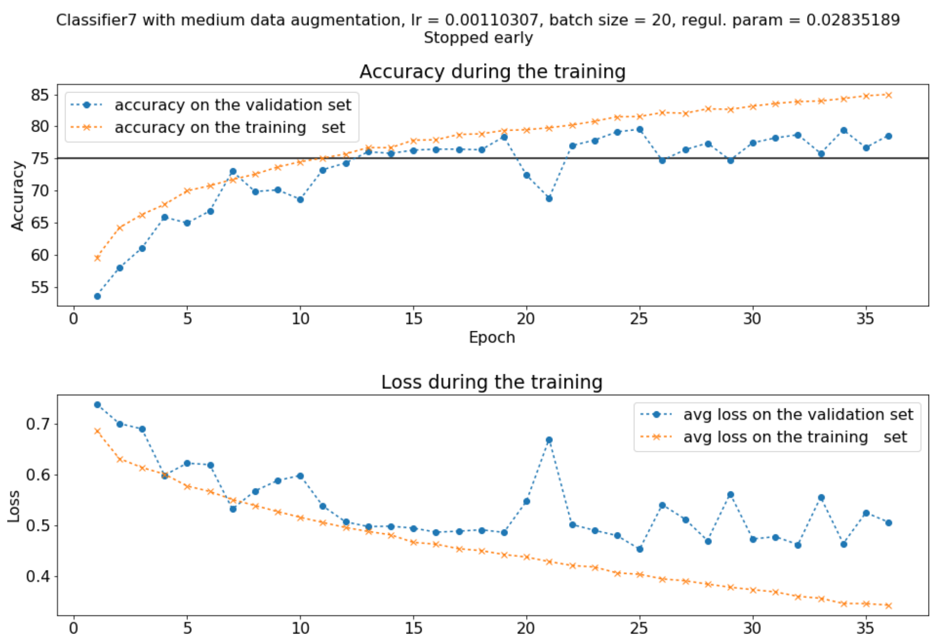



```
In [177]: # Here's what we add when we runned the notebook with low data augmentation :
          # and :
          # starting_point = 2030
          # nb_points      = 20
          # lr_interval    = [0.00001,0.01]
          # bs_interval    = [16,64]
          # using Classifier5, no regularization and low data augmentation :
          # lr = 0.0003392602539062500, batch size = 21
          loading_path = "./output/2019February14_PM01H40M.png"
          IPython.display.display(IPython.display.Image(filename=loading_path))
```



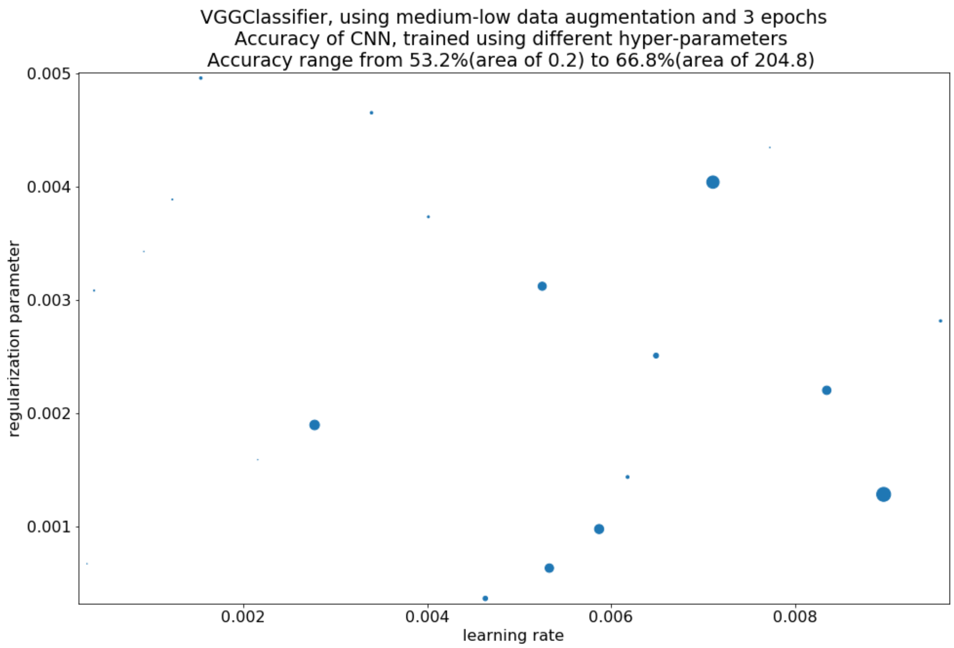
In [176]:
```
# Here's what we add when we runned the notebook with medium-low data augmentation :
# and :
# starting_point = 2030
# nb_points      = 20
# lr_interval    = [0.0001,0.01]
# re_interval    = [0.0001,0.03]
# bs_interval    = [20,20]
# using Classifier5, regularization and medium-low data augmentation :  HITLER
# lr = 0.00129663, batch size = 20, regul = 0.00378247
loading_path = "./output/2019February14_PM10H18M.png"
IPython.display.display(IPython.display.Image(filename=loading_path))
loading_path = "./output/2019February14_PM11H48M.png"
IPython.display.display(IPython.display.Image(filename=loading_path))
```

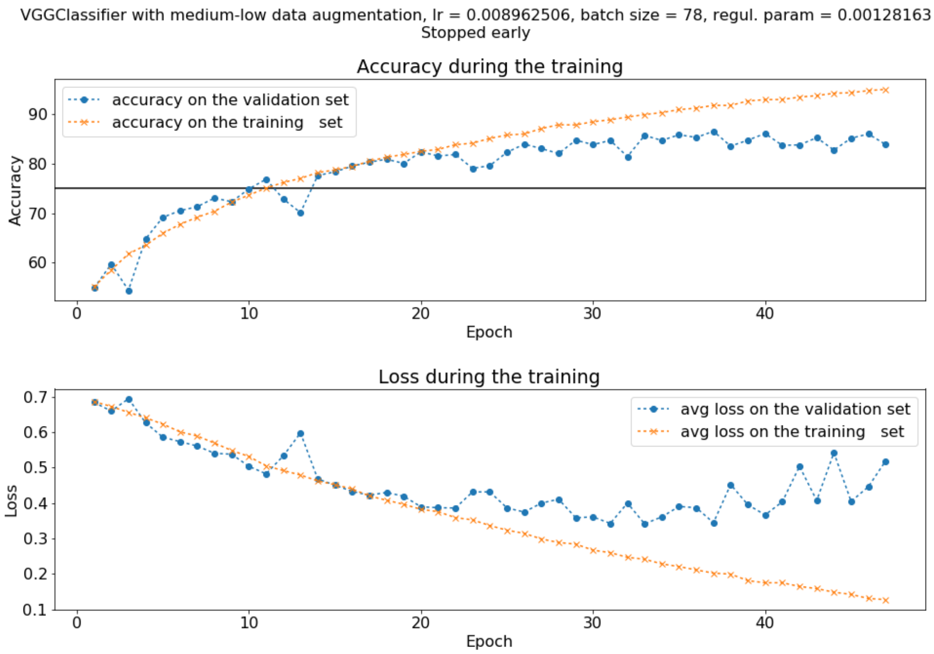




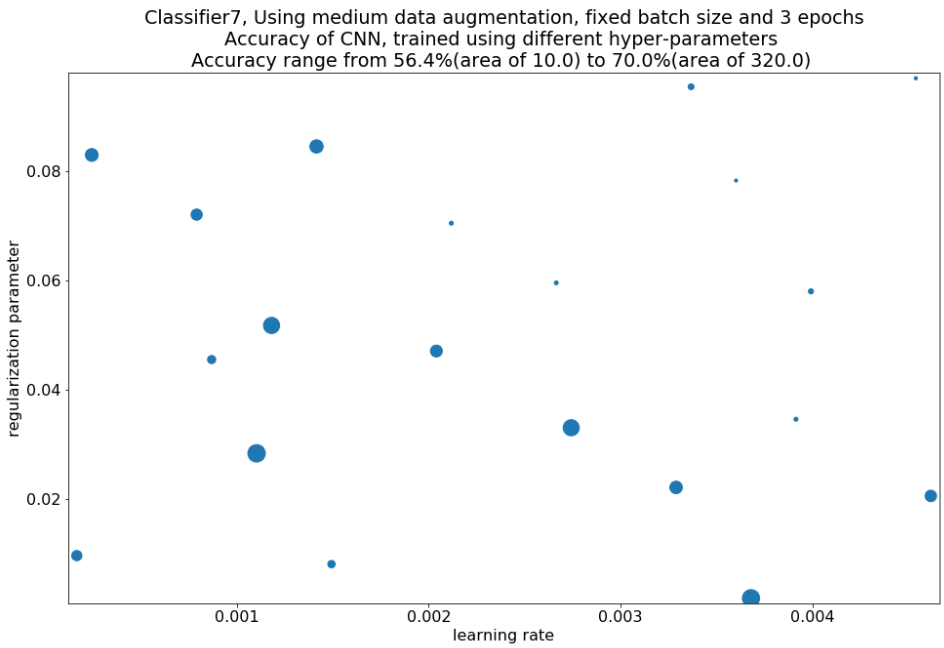

```
In [173]: # Here's what we add when we runned the notebook with low data augmentation :
          # and :
```

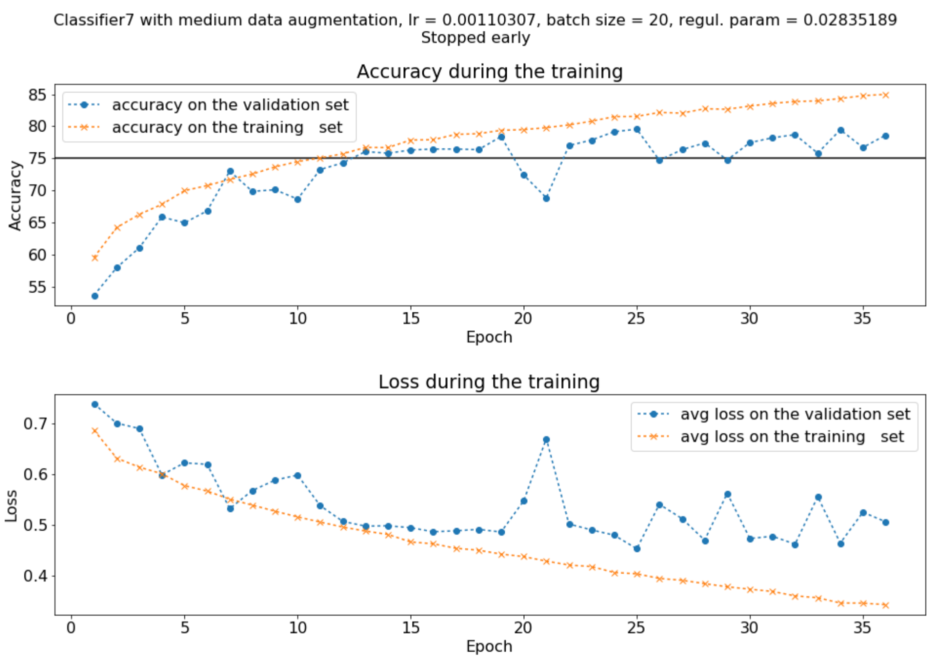
```python
# starting_point = 5030
# nb_points      = 20
# lr_interval    = [0.00001,0.01]
# re_interval    = [0.0001,0.01]
# bs_interval    = [16,64]
# using Classifier5, no regularization and low data augmentation :
# lr = 0.00236848, batch size = 20, regul = 0.00522644
# lr = 0.0003392602539062500, batch size = 21
loading_path = "./output/2019February14_PM03H35M.png"
IPython.display.display(IPython.display.Image(filename=loading_path))
loading_path = "./output/2019February14_PM05H01M.png"
IPython.display.display(IPython.display.Image(filename=loading_path))
```





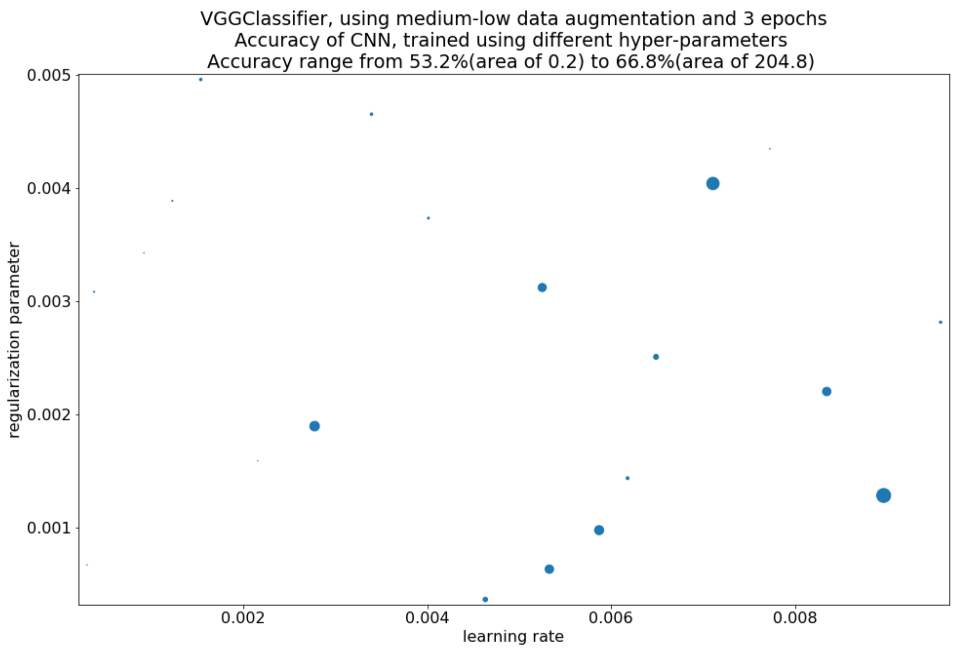

```
In [172]: # Here's what we add when we runned the notebook with Classifier7 and medium data au
          # and :
          # starting_point = 6030
          # nb_points      = 20
          # lr_interval    = [0.000001,0.005]
          # re_interval    = [0.00001,0.1]
          # bs_interval    = 20
          # using Classifier7, regularisation and medium data augmentation :
          # lr = 0.00110307, batch size = 20, regul = 0.02835189
          loading_path = "./output/2019February14_PM08H43M.png"
          IPython.display.display(IPython.display.Image(filename=loading_path))
          loading_path = "./output/2019February14_PM09H17M.png"
          IPython.display.display(IPython.display.Image(filename=loading_path))
```

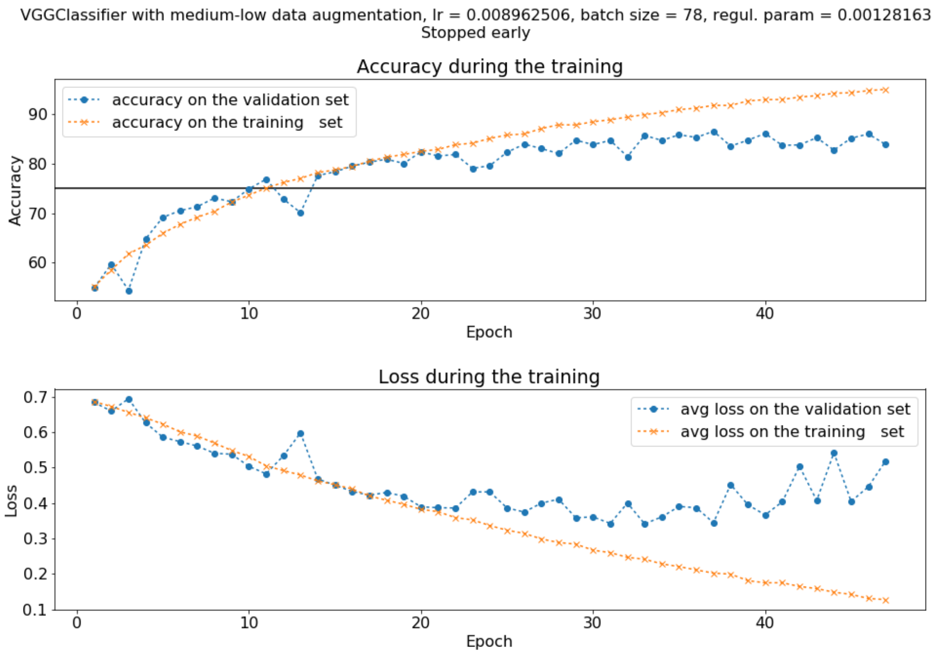





```
In [165]: # Here's what we add when we runned the notebook with VGGClassifier and medium-low d
          # and :
```

```python
# starting_point = 10030
# nb_points      = 20
# lr_interval    = [0.0001, 0.01]
# bs_interval    = [  1*64, 2*64]
# re_interval    = [0.0001,0.005]
# using VGGClassifier, regularisation, using med-low data augmentation we found :
# lr = 0.008962506103515625 , batch size = 78, regul = 0.00128163
# these 3 plots each represent a different hyper-plane of the search
# loading_path = "./output/2019February15_PM10H53M0.png"
loading_path = "./output/2019February15_PM10H53M1.png"
# loading_path = "./output/2019February15_PM10H53M2.png"
IPython.display.display(IPython.display.Image(filename=loading_path))
# the minimum loss on the validation dataset is at epoch 34
loading_path = "./output/2019February15_PM08H58M.png"
IPython.display.display(IPython.display.Image(filename=loading_path))
```





7 Our interpretation

Compare different hyperparameter settings The best type of data augmentation was determined using the Classifier5 model (with ~2 millions params). In order to be able to find what type of data augmentation works best, we had to settle to make the search using a 'small-but-not-too-small' model and stop at epoch 50. We could not afford to make the search using a very large model (i.e. VGGClassifier).

The plots show that the best performance (without regularization) was found with medium data augmentation. Higher than that, the net had not enough capacity to learn with the training dataset and was learning slowly. Lower than that, the net was quickly reaching a good accuracy on the training dataset and was overfitting.

So, we decided to implement regularization and compare low and medium-low data augmentation. Regularization improved the model performance by reducing the gap between training and validation dataset accuracy. Also, the gap between training and validation dataset accuracy was found reduced the most using medium-low data augmentation.

Then, we tried to use medium data augmentation with a bigger model : Classifier7 which has ~6 millions params. We wanted to see if its larger capacity would enable it to overfit the training dataset. The answer was negative so we concluded that medium data augmentation was making the learning task too difficult and we had to settle for a milder augmentation intensity for the next big run. Medium-low data augmentation was our best candidate.

The default VGGClassifier model (defined above) has ~13millions parameters. We picked a good combinason of hyper-parameters for it using the same search method as before. Then, we trained it with those hyper-parameters until it early stopped at epoch 47. We had saved its state at each epoch of the training and we loaded the state that was both minimizing average loss and close-to-maximizing accuracy for the validation dataset. The plots show that this model achieved the best accuracy over the validation dataset.

Report the final results of performance on your validation set : Our final results are : - training dataset accuracy = 91.838432 %
- validation dataset accuracy = 86.593300 %

With the following 95% confidence interval (c.i.) for the probability of finding the good label on the validation dataset (85.01%, 88.05%). The computation of this c.i. was explained earlier on the notebook. Seeing the gap between the two datasets accuracy indicates that we have to expect a lower accuracy on the test dataset. Especially since the model used for submission to kaggle was retrieved because of its good performance on the validation dataset.

How does your validation performance compare to the test set performance (that you can only get in Kaggle) On kaggle, we obtain 86.514% accuracy on the test set. This is numerically very close to the validation dataset accuracy and falls inside the 95% confidence interval for the probability of finding the good label on the validation dataset.

What techniques (you did not implement) could be useful to improve the validation performance. What we should talk about : - dropouts
- more data augmentation together with a bigger capacity model
- unsupervised pre-training - ...
- There are different techniques that are useful to explore further such as batch normalization and transfer learning.
- We also want to suggest that the model can become more robust if we could use some regularizations and learning rate tuning as the learning progresses.

8 Miscellaneous

Aside from quantitative results, also include some visual analysis such as :

- visualizing the feature maps or kernels, or
- showing examples where the images are :
  - (a) clearly misclassified and
  - (b) where the classifier predicts around 50% on both classes.

Explain yourobservation and/or suggest any improvements you think may help

8.0.1 Answer

In order to measure the model's performance we run the model on the validation set again and measure how confident (at what probability) the model predicts correctly or misclassifies.

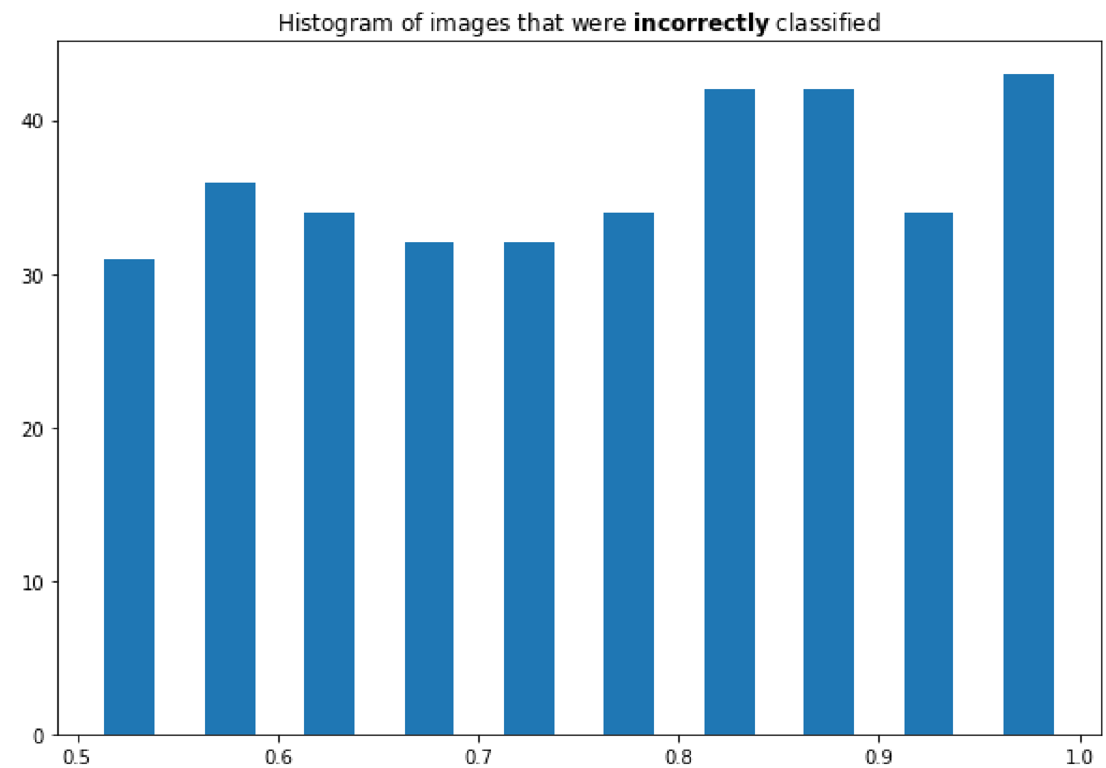
```
In [138]: # For this part, the neural network should be called : mynet
```

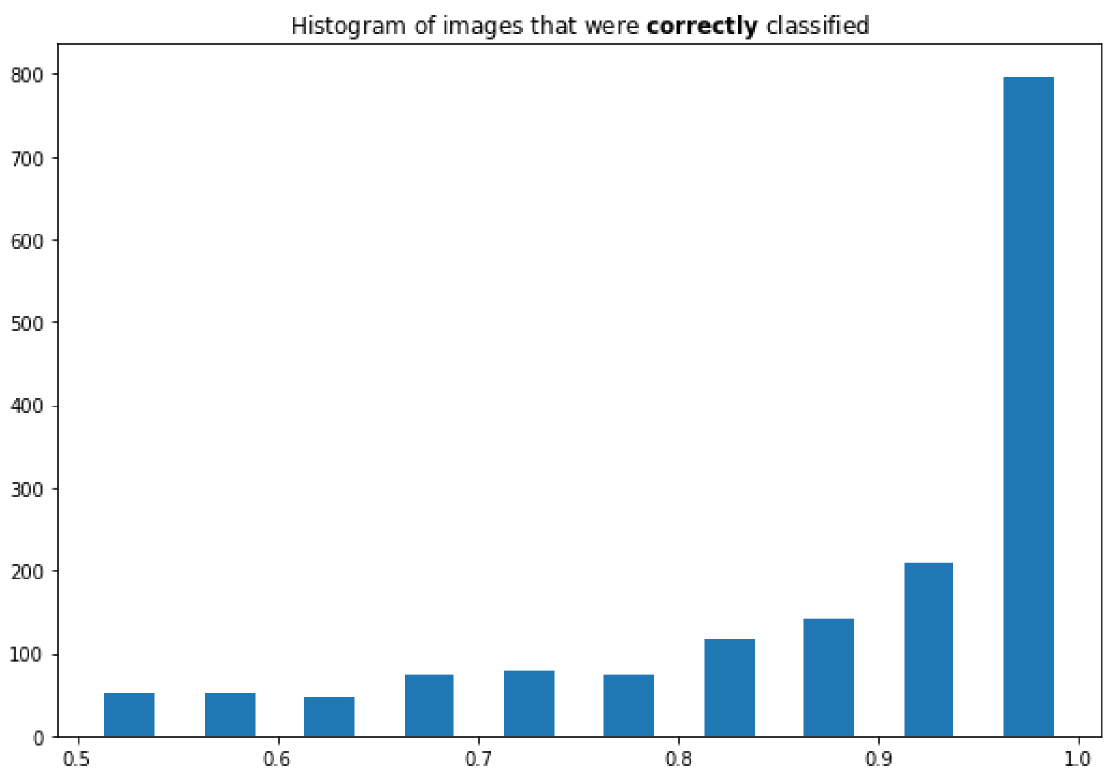
In [136]:
```
# set the number of pictures to display
max_nb_to_display = 32

worst_false_  = []
best_correct_ = []
positivehisto = []
negativehisto = []
from heapq import *

# class introduce to store 2 elements and only use the first for comparison purpose
class CostAndValue:
    def __init__(self, cost, value):
        self.cost  = cost
        self.value = value

    # do not compare values
    def __lt__(self, other):
        return self.cost < other.cost

    def get_cost_and_value(self) :
        return self.cost, self.value

#
def confidence(proba):
    pred = torch.softmax(proba,dim=-1)
    return (pred.max(1)[0] / pred.sum(1), pred.max(1)[1])

valid_batch_size=4*64
valid_loader = DataLoader(train_dataset_norm, batch_size=valid_batch_size,sampler=val

with torch.no_grad() :
    for img, lab in valid_loader:
        img = img.to(device)
        lab = lab.to(device)
        proba = mynet(img)
        confid, pred = confidence(proba)
        for i in range(img.size(0)) :
            img    = img.cpu()
            lab    = lab.cpu()
            confid = confid.cpu()
            pred   = pred.cpu()

            img_ = img[i]
            c    = confid[i].detach().item()
            if pred[i] != lab[i]:
                elem = CostAndValue(c,img_)
                if len(worst_false) > max_nb_to_display :
                    _ = heappushpop(worst_false_,elem)
```

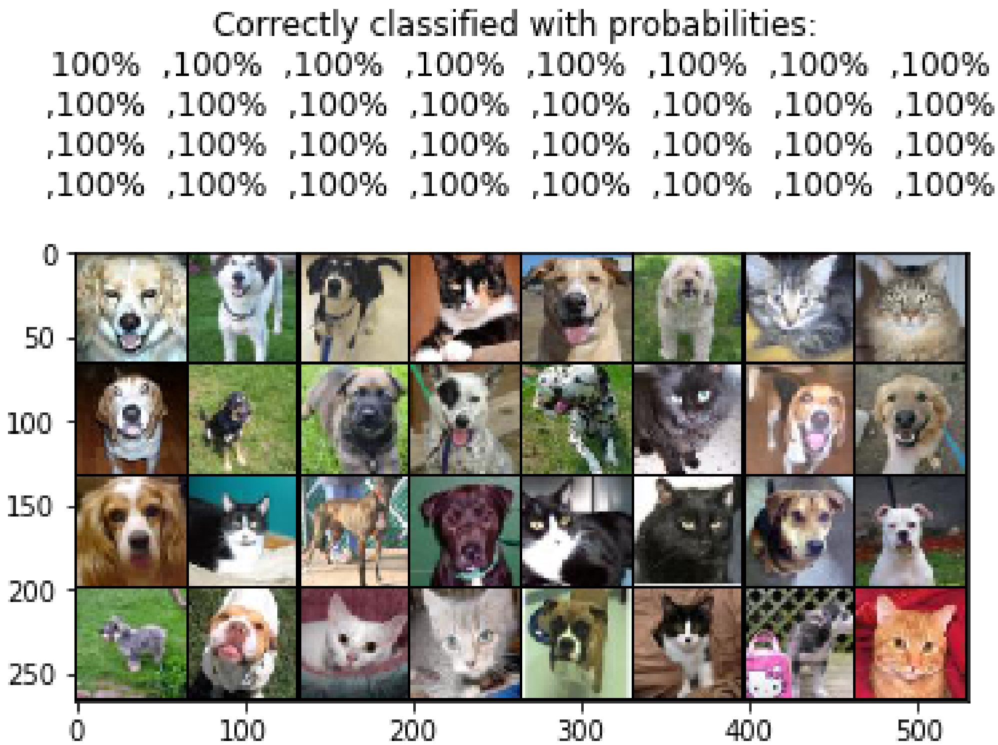
```
                else:
                    heappush(worst_false_,elem)
                negativehisto.append(c)
            else:
                elem = CostAndValue(-c,img_)
                if len(best_correct) > max_nb_to_display : # all end up having more 
                    _ = heappushpop(best_correct_,elem)
                else:
                    heappush(best_correct_,elem)
                positivehisto.append(c)

worst_false  = []
best_correct = []

for i in range(max_nb_to_display) :
    worst_false.append(worst_false_[i].get_cost_and_value())
    best_correct.append(best_correct_[i].get_cost_and_value())
```

Now by plotting the top k=32 most and least confident prediction we can see that the ones with highest probability are the ones where the animal is looking directly at the camera and create a more defined face parts whereas the ones that are highly doubted by the model have less color contrast on their faces or with the background. As we'll point out in the kernel, the model seems to be looking for elements in the image trying to

```
In [137]: def imshow(img):
              npimg = img.numpy()  / 255
              # npimg = img.numpy()
              plt.imshow(np.transpose(npimg, (1, 2, 0)))
              plt.show()

          plt.title('Misclassified with probabilities: \n'+ ",".join(["{c:.2f}%{end}".format(c
          imshow( torchvision.utils.make_grid([img.squeeze() for c,img in worst_false]) )

          plt.title('Correctly classified with probabilities: \n'+ ",".join(["{c:.0f}%{end}".fo
          imshow( torchvision.utils.make_grid([img.squeeze() for c,img in best_correct]) )
```

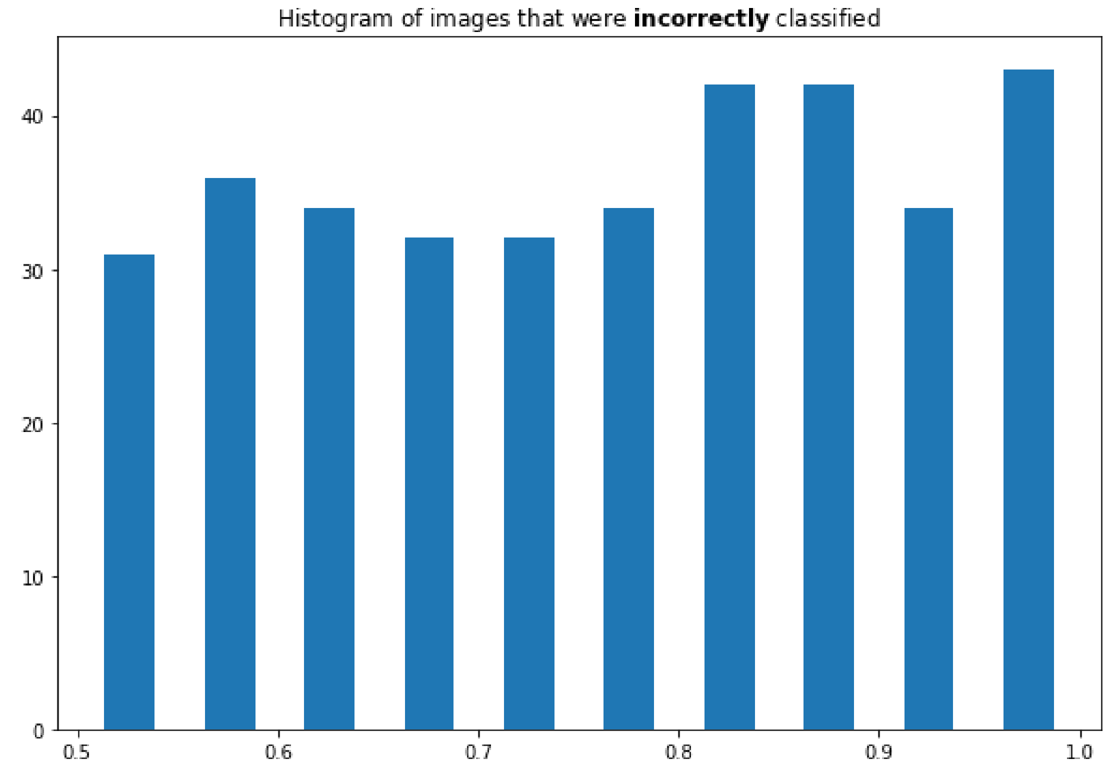

Histogram of images that were **incorrectly** classified
0
10
20
30
40
0.5
0.6
0.7
0.8
0.9
1.0

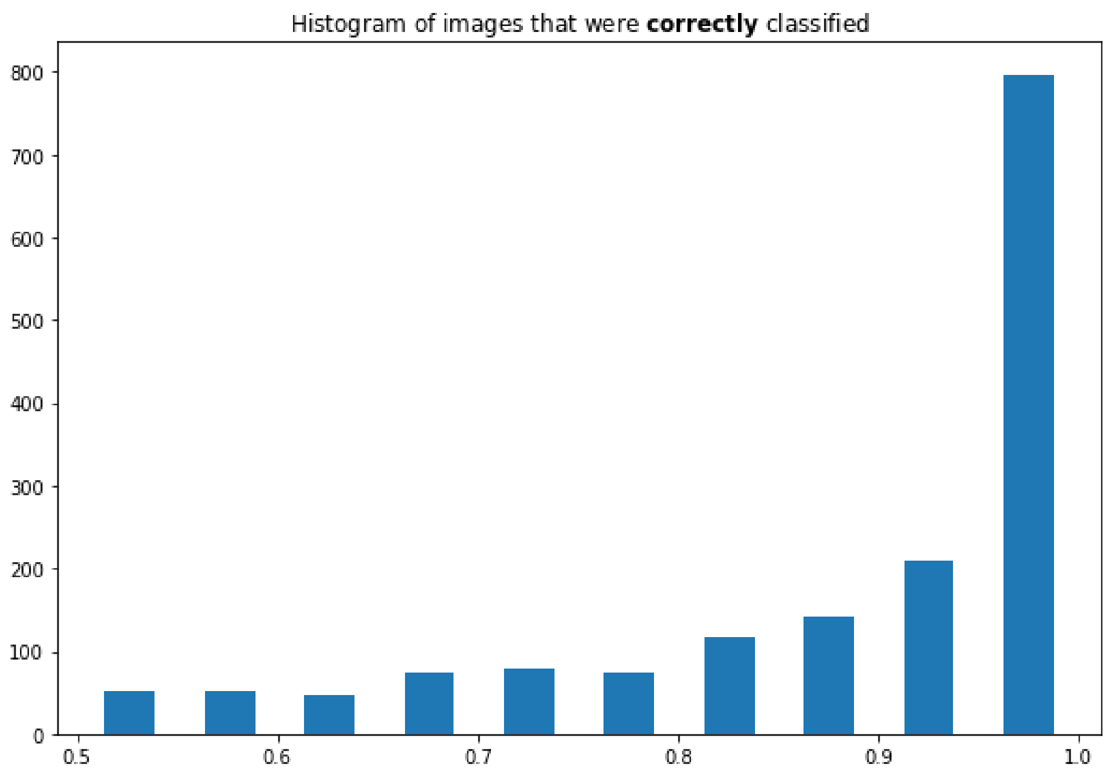

Histogram of images that were **correctly** classified
0
100
200
300
400
500
600
700
800
0.5
0.6
0.7
0.8
0.9
1.0



If we, in fact, plot the histograms of the misclassifications and correct classifications we can see that, on expectation, the model is far more confident when it predicts correct labels than misclassified cases. This is a good thing, it indicates that in a real-world application where it is acceptable to label a picture "i don't know" instead of just "cat" and "dog", one could set a threshold parameter that controls the confidence level below which the nets says "i don't know". The fact that the fraction of missclassified pictures increases as the confidence level of the net decreases render this threshold parameter meaningful. It could be useful in a context where we want to avoid false-positive (i.e. wrong labels) and are fine with not labeling all the pictures.

```
In [37]: plt.subplots(nrows=2, ncols=1, sharex=True, figsize=(10,15))
         plt.subplot(2, 1, 1)
         plt.title(r"Histogram of images that were $\bf{incorrectly}$ classified")
         plt.hist(torch.FloatTensor(negativehisto).numpy(),rwidth=0.5)
         plt.subplot(2, 1, 2)
         plt.title(r"Histogram of images that were $\bf{correctly}$ classified")
         plt.hist(torch.FloatTensor(positivehisto).numpy(),rwidth=0.5)
         plt.show()
```


Histogram of images that were **incorrectly** classified
40
30
20
10
0
0.5
0.6
0.7
0.8
0.9
1.0


Histogram of images that were **correctly** classified
800
700
600
500
400
300
200
100
0
0.5
0.6
0.7
0.8
0.9
1.0

8.0.2 Visualize feature maps

We further want to look into the kernels and feature maps and see if we can see any meaningful output of them. Interpreting the feature maps in the middle layers are no trivial task as the architecture is a continuous combination of weights that are not neccessarily in the same three layered regime of RGB channels. Zeiler et al., 2011 proposed a novel way of projecting back feature maps back to the input space through an architecture called deconvolutional networks (deconvnet). Deconvnet were originally proposed for unsupervised learning, but here they are only used to inspect the model's feature maps. They use rectification, unpooling, and transpose of the kernels (used in backpropagation of CNNs) corresponding to the original convnets (refer to page 52 of Lecture_3_convnets.pdf).

Loading the pretrained model:

This part was done to vizualise the feature maps of the classifier5 model, so we load one we have stored. The previous cells about missclassification statistics should be re-executed using the loaded model.

```
In [139]: # keep a reference to previous mynet
          mynet_old = mynet
```

```
In [140]: # load a trained Classifier5
          loading_path = "./save/export/dev1num3Classifier5_82.pth"    # Classifier5() with 82
          cudanet_tocpu = Classifier5()
          cudanet_tocpu.load_state_dict(torch.load(loading_path))
          mynet = copy.deepcopy( cudanet_tocpu ).cpu()
```

In the following we created a deconvnet of the chosen Classifier5 helping us examining the feature maps of our Classifier5 model. We initialize its parameters with the pretrained convnet and created a user interface to probe any arbitrary layer and unit. The only layers that we skipped implementing was rectification as per convenience. The program was inspired from the following link: https://github.com/csgwon/pytorch-deconvnet/blob/master/models/vgg16_deconv.py

The earlier featuremaps are showing how the model depicts more color detection with a subtle features encoding, and as it progresses the images despite being harder to interpret how the pieces com together, but it looks as if it is forming a more defined form of cat and dog.

```
In [141]: # for vizualisation purpose
          class Classifier5_extended(nn.Module):
              """
              Classifier5 extension for vizualisation of feature maps
              """
              def __init__(self):

                  kernel_sz = np.array([5,5,5,3,3,3,3,3])
                  pad = kernel_sz // 2
                  pad[7] = 0

                  super(Classifier5_extended, self).__init__()
                  self.conv = nn.Sequential(
                      # Layer, input size = 64^2
```

```
            nn.Conv2d(in_channels=3, out_channels=16, kernel_size= (kernel_sz[0],kern
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=(2, 2), stride=2, return_indices=True),

            # Layer 2, input size = 32^2
            nn.Conv2d(in_channels=16, out_channels=32, kernel_size= (kernel_sz[1],ker
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=(2, 2), stride=2, return_indices=True),

            # Layer 3, input size = 16^2
            nn.Conv2d(in_channels=32, out_channels=64, kernel_size= (kernel_sz[2],ker
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=(2, 2), stride=2, return_indices=True),

            # Layer 4, input size = 8^2
            nn.Conv2d(in_channels=64, out_channels=128, kernel_size= (kernel_sz[3],ke
            nn.ReLU(),

            # Layer 5
            nn.Conv2d(in_channels=128, out_channels=256, kernel_size= (kernel_sz[4],k
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=(2, 2), stride=2, return_indices=True),

            # Layer 6
            nn.Conv2d(in_channels=256, out_channels=256, kernel_size= (kernel_sz[5],
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=(2, 2), stride=2, return_indices=True),

            # Layer 7
            nn.Conv2d(in_channels=256, out_channels=512, kernel_size= (kernel_sz[6],
            nn.MaxPool2d(kernel_size=(2, 2), stride=2, return_indices=True)
        )
        #
        self.fct1b = nn.Linear(1*1*512, 2)
        self.feature_outputs = [0]*len(self.conv)
        self.pool_indices = dict()

    def initialize_weights_from(self, classifier5):
        # initializing weights using ImageNet-trained model from PyTorch
        for i, layer in enumerate(classifier5.conv):
            if isinstance(layer, torch.nn.Conv2d):
                self.conv[i].weight.data = layer.weight.data
                self.conv[i].bias.data = layer.bias.data
        self.fct1b.weight.data = classifier5.fct1b.weight.data
        self.fct1b.bias.data   = classifier5.fct1b.bias.data

    def forward_features(self, x):
        output = x
```

```
        for i, layer in enumerate(self.conv):
            if isinstance(layer, torch.nn.MaxPool2d):
                output, indices = layer(output)
                self.feature_outputs[i] = output
                self.pool_indices[i] = indices
            else:
                output = layer(output)
                self.feature_outputs[i] = output
        return output

    def forward(self, x):
        x = self.forward_features(x)
        x = x.view(x.size()[0], -1)
        x = self.fct1b(x)
        return x

class declassifier(nn.Module):
    """Convnet Classifier"""
    def __init__(self ):

        kernel_sz = np.array([5,5,3,3,3,3,3,3])
        pad = kernel_sz // 2
        pad[7] = 0

        self.conv2DeconvIdx = {0:12, 3:10, 6:8, 9:6, 11:5, 14:3, 17:1}
        self.conv2DeconvBiasIdx = {0:10, 3:8, 6:6, 9:5, 11:3, 14:1, 17:0}
        self.unpool2PoolIdx = {11:2, 9:5, 7:8, 4:13, 2:16, 0:18}

        super(declassifier, self).__init__()
        self.deconv_features = nn.Sequential(
            nn.MaxUnpool2d(kernel_size=(2, 2), stride=2),
            nn.ConvTranspose2d(in_channels=512, out_channels=256, kernel_size= (kerne
            nn.MaxUnpool2d(kernel_size=(2, 2), stride=2),
            nn.ConvTranspose2d(in_channels=256, out_channels=256, kernel_size= (kerne
            nn.MaxUnpool2d(kernel_size=(2, 2), stride=2),
            nn.ConvTranspose2d(in_channels=256, out_channels=128, kernel_size= (kerne
            nn.ConvTranspose2d(in_channels=128, out_channels=64, kernel_size= (kernel
            nn.MaxUnpool2d(kernel_size=(2, 2), stride=2),
            nn.ConvTranspose2d(in_channels=64, out_channels=32, kernel_size= (kernel_
            nn.MaxUnpool2d(kernel_size=(2, 2), stride=2),
            nn.ConvTranspose2d(in_channels=32, out_channels=16, kernel_size= (kernel_
            nn.MaxUnpool2d(kernel_size=(2, 2), stride=2),
            nn.ConvTranspose2d(in_channels=16, out_channels=3, kernel_size= (kernel_s
        )
        self.deconv_first_layers = nn.Sequential(
            nn.MaxUnpool2d(kernel_size=(2, 2), stride=2),
            nn.ConvTranspose2d(in_channels=1, out_channels=256, kernel_size= (kernel_
            nn.MaxUnpool2d(kernel_size=(2, 2), stride=2),
```

```
                nn.ConvTranspose2d(in_channels=1, out_channels=256, kernel_size= (kernel_
                nn.MaxUnpool2d(kernel_size=(2, 2), stride=2),
                nn.ConvTranspose2d(in_channels=1, out_channels=128, kernel_size= (kernel_
                nn.ConvTranspose2d(in_channels=1, out_channels=64, kernel_size= (kernel_s
                nn.MaxUnpool2d(kernel_size=(2, 2), stride=2),
                nn.ConvTranspose2d(in_channels=1, out_channels=32, kernel_size= (kernel_s
                nn.MaxUnpool2d(kernel_size=(2, 2), stride=2),
                nn.ConvTranspose2d(in_channels=1, out_channels=16, kernel_size= (kernel_s
                nn.MaxUnpool2d(kernel_size=(2, 2), stride=2),
                nn.ConvTranspose2d(in_channels=1, out_channels=3, kernel_size= (kernel_si
            )
            #

        def initialize_weights_from(self, classifier5):
            # initializing weights using ImageNet-trained model from PyTorch
            for i, layer in enumerate(classifier5.conv):
                if isinstance(layer, torch.nn.Conv2d):
                    self.deconv_features[self.conv2DeconvIdx[i]].weight.data = layer.weig
                    biasIdx = self.conv2DeconvBiasIdx[i]
                    if biasIdx > 0:
                        self.deconv_features[biasIdx].bias.data = layer.bias.data

        def forward(self, x, layer_number, map_number, pool_indices):
            start_idx = self.conv2DeconvIdx[layer_number]
            if not isinstance(self.deconv_first_layers[start_idx], torch.nn.ConvTranspose
                raise ValueError('Layer '+str(layer_number)+' is not of type Conv2d')
            # set weight and bias
            self.deconv_first_layers[start_idx].weight.data = self.deconv_features[start_
            self.deconv_first_layers[start_idx].bias.data = self.deconv_features[start_id
            # first layer will be single channeled, since we're picking a particular fil
            output = self.deconv_first_layers[start_idx](x)

            # transpose conv through the rest of the network
            for i in range(start_idx+1, len(self.deconv_features)):
                if isinstance(self.deconv_features[i], torch.nn.MaxUnpool2d):
                    output = self.deconv_features[i](output, pool_indices[self.unpool2Poo
                else:
                    output = self.deconv_features[i](output)
            return output
```

In [142]:
```
from math import sqrt, ceil
import numpy as np

def visualize_grid(Xs, ubound=255.0, padding=1):
    """
    Reshape a 4D tensor of image data to a grid for easy visualization.
    Inputs:
    - Xs: Data of shape (N, H, W, C)
```

```python
    - ubound: Output grid will have values scaled to the range [0, ubound]
    - padding: The number of blank pixels between elements of the grid
    """
    (N, H, W, C) = Xs.shape
    grid_size = int(ceil(sqrt(N)))
    grid_height = H * grid_size + padding * (grid_size - 1)
    grid_width = W * grid_size + padding * (grid_size - 1)
    grid = np.zeros((grid_height, grid_width, C))
    next_idx = 0
    y0, y1 = 0, H
    for y in range(grid_size):
        x0, x1 = 0, W
        for x in range(grid_size):
            if next_idx < N:
                img = Xs[next_idx]
                low, high = np.min(img), np.max(img)
                grid[y0:y1, x0:x1] = ubound * (img - low) / (high - low)
                # grid[y0:y1, x0:x1] = Xs[next_idx]
                next_idx += 1
            x0 += W + padding
            x1 += W + padding
        y0 += H + padding
        y1 += H + padding
    # grid_max = np.max(grid)
    # grid_min = np.min(grid)
    # grid = ubound * (grid - grid_min) / (grid_max - grid_min)
    return grid

def vis_grid(Xs):
    """ visualize a grid of images """
    (N, H, W, C) = Xs.shape
    A = int(ceil(sqrt(N)))
    G = np.ones((A*H+A, A*W+A, C), Xs.dtype)
    G *= np.min(Xs)
    n = 0
    for y in range(A):
        for x in range(A):
            if n < N:
                G[y*H+y:(y+1)*H+y, x*W+x:(x+1)*W+x, :] = Xs[n,:,:,:]
                n += 1
    # normalize to [0,1]
    maxg = G.max()
    ming = G.min()
    G = (G - ming)/(maxg-ming)
    return G

def vis_nn(rows):
    """ visualize array of arrays of images """
```

```
    N = len(rows)
    D = len(rows[0])
    H,W,C = rows[0][0].shape
    Xs = rows[0][0]
    G = np.ones((N*H+N, D*W+D, C), Xs.dtype)
    for y in range(N):
        for x in range(D):
            G[y*H+y:(y+1)*H+y, x*W+x:(x+1)*W+x, :] = rows[y][x]
    # normalize to [0,1]
    maxg = G.max()
    ming = G.min()
    G = (G - ming)/(maxg-ming)
    return G
```

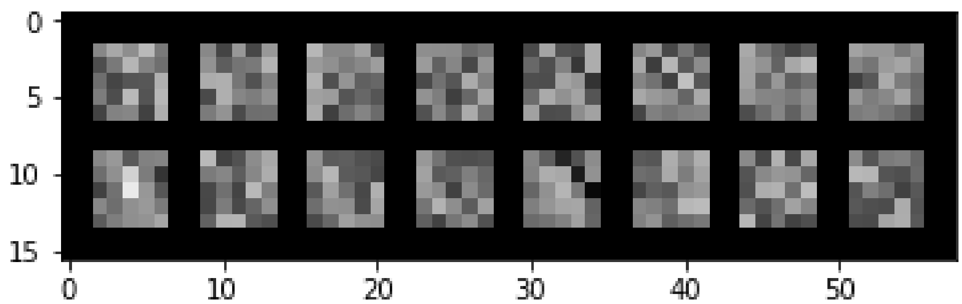
Display some feature maps We retrieve a sample that the net correctly classified and with high confidence and use it as input.

```
In [170]: import matplotlib.pyplot as plt
          from PIL import Image
          import numpy as np
          import sys

          def vis_layer(activ_map):
              plt.clf()
              plt.subplot(121)
              plt.imshow(activ_map[:,:,0], cmap='gray')

          def decon_img(layer_output):
              raw_img = layer_output.data.numpy()[0].transpose(1,2,0)
              img = (raw_img-raw_img.min())/(raw_img.max()-raw_img.min())*255
              img = img.astype(np.uint8)
              return img

          if __name__ == '__main__':
              if len(sys.argv) < 2:
                  print('Usage: '+sys.argv[0]+' img_file')
                  sys.exit(0)

              img_filename = sys.argv[1]

              n_classes = 1000 # using ImageNet pretrained weights

              #vgg16_c = VGG16_conv(n_classes)
              _ = mynet.cpu()
              mynet_extended = Classifier5_extended()
              mynet_extended.initialize_weights_from(mynet)
              cudanet_d = declassifier()
              cudanet_d.initialize_weights_from(mynet)
```

```python
            conv_layer_indices = list(cudanet_d.conv2DeconvIdx.keys())

            #img = np.asarray(Image.open(img_filename).resize((224,224)))
            img_var = best_correct[-1][1].unsqueeze(0)
            #img_var = torch.autograd.Variable(torch.FloatTensor(img.transpose(2,0,1)[np.new

            conv_out = mynet_extended(img_var)
            print('Classifier5 model:')
            print(mynet)

            plt.ion() # remove blocking
            plt.figure(figsize=(10,5))

            layer = int( input('Layer to view (0-17, -1 to exit): ') )

            activ_map = mynet_extended.feature_outputs[layer].data.numpy()
            activ_map = activ_map.transpose(1,2,3,0)
            activ_map_grid = vis_grid(activ_map)
            vis_layer(activ_map_grid)

            # only transpose convolve from Conv2d or ReLU layers
            conv_layer = layer
            if conv_layer not in conv_layer_indices:
                conv_layer -= 1
                if conv_layer not in conv_layer_indices:
                    raise ValueError('Invalid Layer Number')

            n_maps = activ_map.shape[0]

            map_idx = int( input('Take a map to view (0-{}): '.format(activ_map.shape[0]-1))

            decon = cudanet_d(mynet_extended.feature_outputs[layer][0][map_idx][None,None,:,
            img = decon_img(decon)
            plt.imshow(img)
```

```
Classifier5 model:
Classifier5(
  (conv): Sequential(
    (0): Conv2d(3, 16, kernel_size=(5, 5), stride=(1, 1), padding=(2, 2))
    (1): ReLU()
    (2): MaxPool2d(kernel_size=(2, 2), stride=2, padding=0, dilation=1, ceil_mode=False)
    (3): Conv2d(16, 32, kernel_size=(5, 5), stride=(1, 1), padding=(2, 2))
    (4): ReLU()
    (5): MaxPool2d(kernel_size=(2, 2), stride=2, padding=0, dilation=1, ceil_mode=False)
    (6): Conv2d(32, 64, kernel_size=(5, 5), stride=(1, 1), padding=(2, 2))
    (7): ReLU()
    (8): MaxPool2d(kernel_size=(2, 2), stride=2, padding=0, dilation=1, ceil_mode=False)
```

```
    (9): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (10): ReLU()
    (11): Conv2d(128, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (12): ReLU()
    (13): MaxPool2d(kernel_size=(2, 2), stride=2, padding=0, dilation=1, ceil_mode=False)
    (14): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (15): ReLU()
    (16): MaxPool2d(kernel_size=(2, 2), stride=2, padding=0, dilation=1, ceil_mode=False)
    (17): Conv2d(256, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (18): MaxPool2d(kernel_size=(2, 2), stride=2, padding=0, dilation=1, ceil_mode=False)
  )
  (fct1b): Linear(in_features=512, out_features=2, bias=True)
)
Layer to view (0-17, -1 to exit): 0
Take a map to view (0-15): 1
```

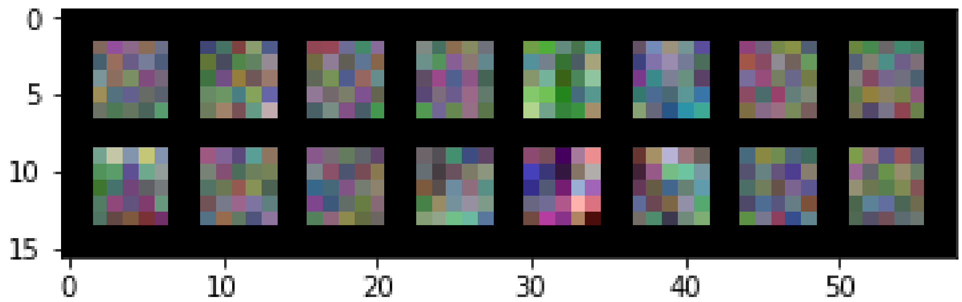


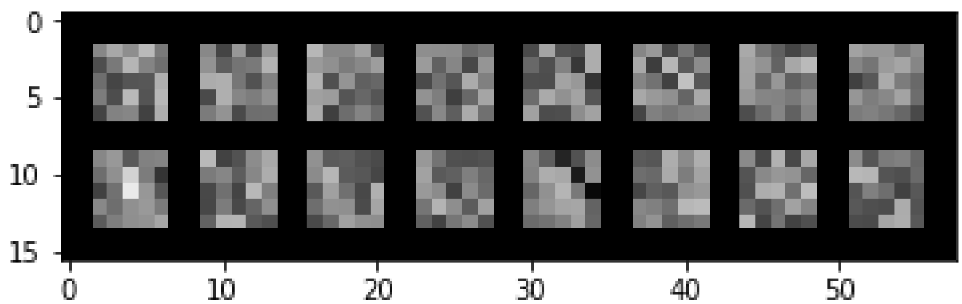
8.0.3 vizualize kernels

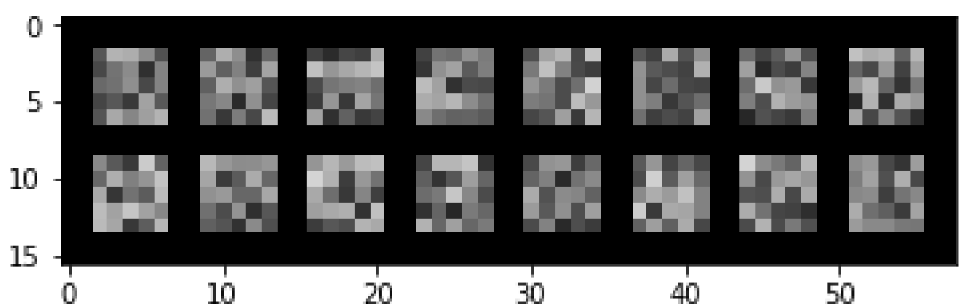
We display, a subset of kernels for each convolution layer. The kernel are small and they don't look like edge detector. There is not much else to be said.

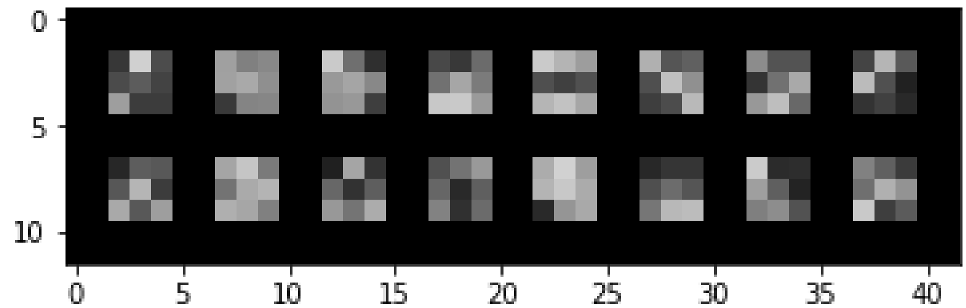
```
In [164]: for i,(name, kernels) in enumerate(mynet_extended.state_dict().items()) :
              # ou "conv"
              if not ((name.startswith("features") or name.startswith("conv"))and name.endswit
                  continue
              if i == 0 : # 3 input channels can be displayed in color
                   kernels = kernels.detach()
              else : # more than 3 input channels are displayed in greyscale
                  kernels = kernels.detach().view(-1,1,kernels.size()[-1],kernels.size()[-1])

              kernels = kernels - kernels.min()
              kernels = 255 * kernels / kernels.max()
              size = min(kernels.size()[0],16)
              # print( kernels.max() , kernels.min() )
```

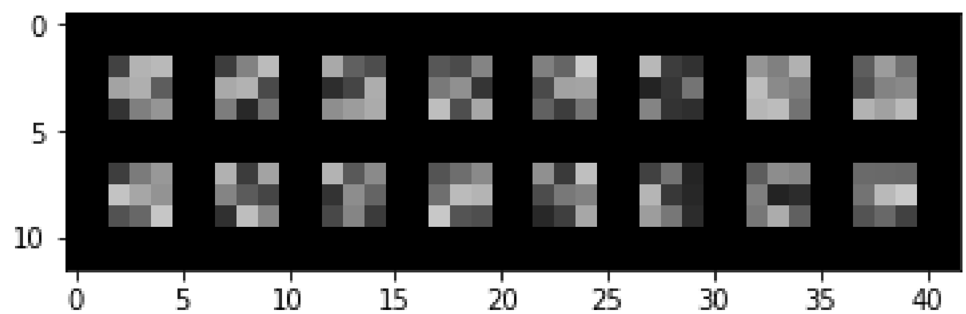
```
# print(kernels.size())
imshow(torchvision.utils.make_grid(kernels[0:size,:,:,:]))
```

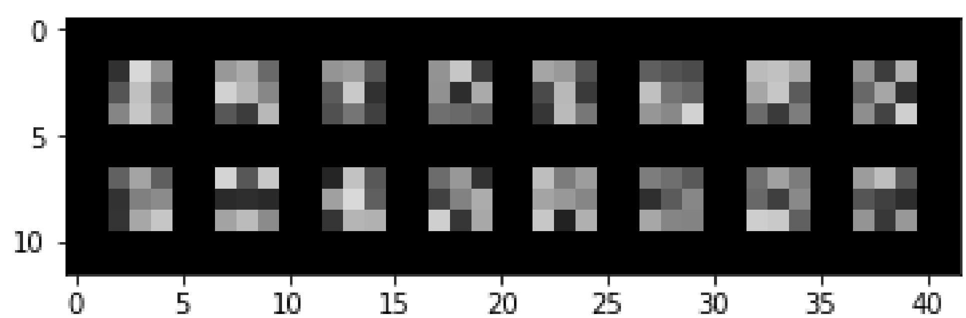


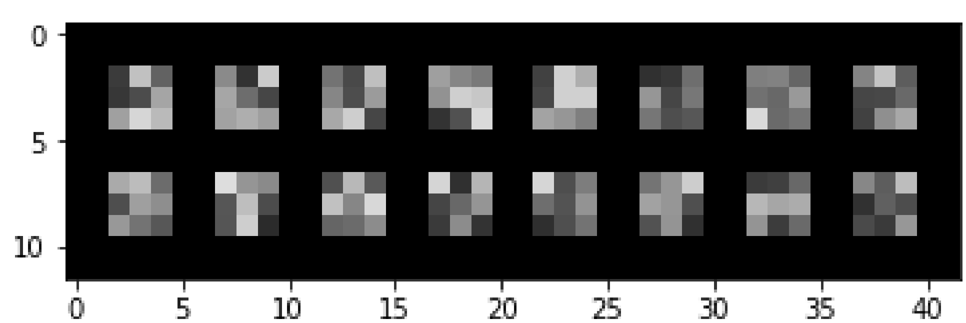





0
5
10
0
5
10
15
20
25
30
35
40


0
5
10
0
5
10
15
20
25
30
35
40


0
5
10
0
5
10
15
20
25
30
35
40


0
5
10
0
5
10
15
20
25
30
35
40

9 Submit

This part of the notebook is used for submission.

a) We define a dataset for the test samples

b) We load the test dataset, label all picture and produce a .csv file

In [137]:
```
class nonlabeledDataSet(torch.utils.data.Dataset):

    def __init__(self , nb_of_sample, root_dir ):
        """
        Args:
            label is either "Cat" or "Dog"
            load in the dataset picture no. idx_min to idx_max included
            root_dir(string): directory with all images with the same label
        """
        # super(labeledDataSet, self).__init__()
        self.root_dir = root_dir
        self.nb_of_sample = nb_of_sample
        self.load_data()

    def load_data(self) :
        size = self.__len__()

        self.data_tensor   = torch.empty(size,3,64,64,dtype=torch.float)

        for i in range(self.nb_of_sample) :
            j = i + 1
            img_path = self.root_dir +  "{index}.jpg".format(index=j)
            img = Image.open( img_path ).convert('RGB')
            image = torch.from_numpy( np.transpose( img , (-1,-3,-2) ) )
            image = image
            self.data_tensor[i,:,:,:] = image

    def __len__(self):
        return self.nb_of_sample

    def __getitem__(self, idx):
        return self.data_tensor[idx]
```

In [186]:
```
# Test the performance of mynet before using it
criterion = nn.CrossEntropyLoss()
batch_size = 4*64
train_loader = DataLoader(train_dataset_norm, batch_size=batch_size,sampler=train_sam
```

```
valid_loader = DataLoader(train_dataset_norm, batch_size=batch_size,sampler=valid_sam
a,b = measure_single_accuracy_and_loss( mynet , train_loader, criterion )
print(a.item(), "loss : " , b.item())
a,b = measure_single_accuracy_and_loss( mynet , valid_loader, criterion )
print(a.item(), "loss : " , b.item())
```

```
97.13873291015625 loss :  0.00036534047103486955
86.59329986572266 loss :  0.0013806667411699891
```

```
In [187]: testset_dir        = "./data_catdogs/testset/test/"
          batch_size         = 4*64
          total_nb_of_sample = 4999 # total number of total unlabelled test samples
          test_dataset = nonlabeledDataSet(total_nb_of_sample,testset_dir)
          test_loader  = DataLoader(test_dataset, batch_size=batch_size,shuffle=False, num_work

          def class_from_index(ind):
              return train_dataset_norm.classes[ind]

          remember_prediction = torch.empty(batch_size)
          with open('submission4.csv', mode='w') as submission:
              submission.write('id,label\n')
              i = 1
              for query in test_loader:
                  img = query
                  with torch.no_grad():
                      img          = img.to(device)
                      outputs      = mynet(img).squeeze()
                      _, predicted = torch.max(outputs.data, 1)
                      if i == 1 :
                          remember_prediction = copy.deepcopy(predicted).cpu()
                      for j in range(predicted.shape[0]) :
                          idx    = predicted[j]
                          label  = class_from_index(idx)
                          submission.write('{},{}\n'.format(i,label) )
                          i = i + 1
```

For sanity We have manually labeled the first 100 pictures to be certain that the data loader used was not feeding the pictures in the wrong order. Previously, we had this issue.

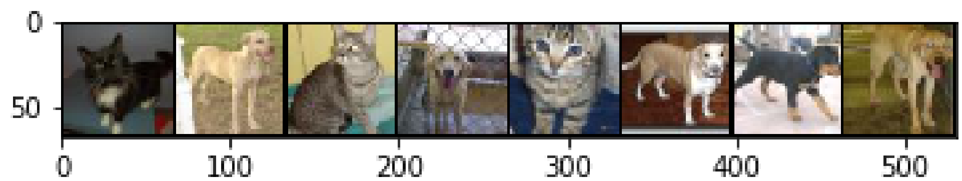
```
In [188]: good_test_answers = torch.zeros(100,dtype=torch.long)
          dog_idx = [2,4,6,7,8,14,16,17,19,20,22,24,26,29,31,32,39,41,43,45,53,58,61,
                     63,69,70,71,74,75,76,77,82,83,84,86,87,89,93,94,97,98,99]
          for i in dog_idx :
              good_test_answers[i-1] = 1

          count = 0
          prediction = remember_prediction[:100]
```

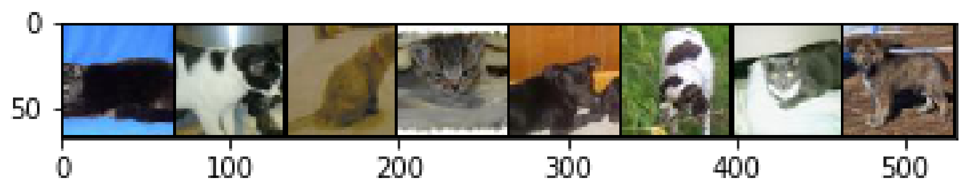
```
for i in range(100):
    if prediction[i] == good_test_answers[i] :
        count = count + 1
print("Number of good answer for first 100 samples : " , count)
```

```
Number of good answer for first 100 samples :  86
```

For sanity also Manually check that the loader loads the picture in the good order.

```
In [118]: test_pict_loader  = DataLoader(test_dataset, batch_size=8,shuffle=False, num_workers=
          for i, img in enumerate(test_pict_loader):
              if i > 1 :
                  break
              imshow(torchvision.utils.make_grid(img))
```





10 Save and load models

Load

```
In [81]: # On github
         loading_path = "./save/export/dev1num3Classifier5_82.pth"     # Classifier5() with 82%
         # loading_path = "./save/export/dev1num3VGGClassifier5_85.pth" # VGGClassifier() with
         # loading_path = "./save/export/dev1num3VGGClassifier_86.pth"  # VGGClassifier() with

         # Locally only
         # loading_path = "./save/classifier1_201to500/dev1num3model_for_epoch300.pth" # Class
         # loading_path = "./save/underfit201to300/dev1num3model_for_epoch100.pth" # Classifie
         # loading_path = "./save/classifier5wsm_nocrop_51to100/dev1num3model_for_epoch50.pth"
```

```
    # cudanet_tocpu = VGGClassifier()
    cudanet_tocpu = Classifier5()
    cudanet_tocpu.load_state_dict(torch.load(loading_path))
    mynet = copy.deepcopy( cudanet_tocpu ).to(device)
```

Save

```
In [189]: # save current state only
          # saving_path = "./save/export/dev1num3model.pth"
          saving_path = "./save/export/"
          saving_name = "dev1num3BLABLA.pth"
          _ = mynet.cpu()
          state_dict_to_disk = mynet.state_dict()
          torch.save( state_dict_to_disk , saving_path )
          _ = mynet.to(device)
```

Measure accuracy and average loss on training and validation dataset This is usefull is you load a previously saved model and want to measure its performance.

```
In [ ]: # mynet  = Classifier5()
        # mynet.load_state_dict(net1_state_dict_list[30])
        mynet = cudanet2
        _ = mynet.to(device)

        criterion_sum = nn.CrossEntropyLoss(reduction='sum')
        batch_size = 4*64
        # train_loader = DataLoader(train_dataset_norm, batch_size=batch_size,sampler=train_sa
        valid_loader = DataLoader(train_dataset_norm, batch_size=batch_size,sampler=valid_sampl
        a,b = measure_single_accuracy_and_loss( mynet , train_loader, criterion_sum )
        print("Training dataset")
        print("accuracy : " , a.item(), "loss : " , b.item())
        a,b = measure_single_accuracy_and_loss( mynet , valid_loader, criterion_sum )
        print("Validation dataset")
        print("accuracy : " , a.item(), "loss : " , b.item())
```

11 Other comments

11.0.1 Use majority vote

Use and odd number of net to find what they each think of a picture and take the majority vote among them.
This is usefull to see if multiple nets "are independant sources of information" or if "they all learnt the same things".
We used this method together with 3 different models achieving at least 80% accuracy on the validation dataset : - Classifier5 (trained using medium-low data augmentation) - Classifier7 (trained

using medium data augmentation) - VGGClassifier (trained using medium-low data augmentation) We found that this method could be used to improve the performance of the best of the 3 models by about 1%.

If we take the majority vote for yes-no questions using 3 independants voters that vote randomly with 80% accuracy each. The probability of the outcome of the vote to be right is :
- Prob(3 are right) + 3 Prob(2 are right)Prob(1 is wrong) = Prob(1 is right)^3 + 3 Prob(1 is right)^2 Prob(1 is wrong) = (0.8)^3 + 3(0.8)^2(0.2) = 0.896

This indicates that the three models we have tested cannot possibly be considered as independant. Even with different architectures, the 3 models have learnt very similar things about the classification task.

In [168]:
```
cudanet1 = Classifier5()
_ = cudanet1.to(device)
cudanet2 = Classifier5()
_ = cudanet2.to(device)
cudanet3 = Classifier5()
_ = cudanet3.to(device)
```

In [169]:
```
batch_size = 4*64

# with or without data augmentation
validation_loader = torch.utils.data.DataLoader(train_dataset_norm, batch_size=batch_
# validation_loader = torch.utils.data.DataLoader(train_dataset_augm, batch_size=bat

# If set to true, the answers of the
majority_by_confidence = False

correct = torch.tensor([0])
total = torch.tensor([0])

correct, total = correct.to(device) , total.to(device)
with torch.no_grad():
    for data in validation_loader:
        images, labels = data
        # if using BCE
        # labels = labels.float()
        images, labels = images.to(device), labels.to(device)

        if majority_by_confidence :
            outputs =  torch.softmax(cudanet1(images),dim=-1) + torch.softmax(cudane
            _, predicted = torch.max(outputs.data, 1)
        else :
            outputs = cudanet1(images)
            _, predicted1 = torch.max(outputs.data, 1)
            outputs = cudanet2(images)
            _, predicted2 = torch.max(outputs.data, 1)
            outputs = cudanet3(images)
            _, predicted3 = torch.max(outputs.data, 1)
```

```
                predicted , _ = torch.mode(torch.cat((predicted1.unsqueeze(1),predicted2
            # print(predicted1.shape)
            # print(predicted.shape)
            total += labels.size(0)
            correct += (predicted == labels).sum()

    print('Accuracy of the network on the' , total.item() , 'test images: %.2f %%'
               % ( (100 * correct.double()) / total.double()  )
         )
```

```
Accuracy of the network on the 1999 test images: 48.42 %
```

11.0.2 Find a good initialization

The following code is usefull to find a good initialization if finding one appears to be hard work.
We used this code to make sure that certain configurations did not work at all.
It works as follow :
Try different random init, train them for 3 epoch, repeat until you find one than has learnt something or the number of tries reach a certain threshold.

```
In [ ]: # del cudanet
        nb_epoch   = 1
        nb_try     = 10
        batch_size = 1*16
        train_loader = torch.utils.data.DataLoader(train_dataset_norm, batch_size=batch_size,sa

        state_dict_list = list()

        torch.cuda.synchronize()

        start = torch.cuda.Event(enable_timing=True)
        end   = torch.cuda.Event(enable_timing=True)
        start.record()

        for trial in range(nb_try) :
            cudanet = Classifier5()
            # cudanet = Classifier1b(sigmoid=True)
            cudanet.apply( glorot_init )
            _ = cudanet.to(device)
            criterion = nn.CrossEntropyLoss()
            # optimizer = optim.SGD(cudanet.parameters(), lr=0.00025, momentum=0, weight_decay
            optimizer = optim.SGD(cudanet.parameters(), lr=0.0001, momentum=0, weight_decay=0)
            correct = torch.tensor([0])
            total = torch.tensor([0])
            for epoch in range( nb_epoch ):  # loop over the dataset multiple times

                running_loss = 0.0
```

```
        for i, (inputs, labels) in enumerate(train_loader, 0):
            # if using BCE :
            # labels = labels.float()
            inputs, labels = inputs.to(device), labels.to(device)

            optimizer.zero_grad()
            outputs = cudanet(inputs).squeeze()
            loss = criterion(outputs, labels)
            loss.backward()
            optimizer.step()

            # print statistics
            with torch.no_grad() :
                running_loss += loss.item()
                _, predicted = torch.max(outputs.data, 1)
                total += labels.size(0)
                correct += (predicted == labels).sum()
        else : # print every epoch
            print('trial %d , epoch = %d, loss = %.8f' % (trial + 1, epoch + 1, running
            running_loss = 0.0
            torch.cuda.synchronize()
            tmp_state_dict = {}
            for k, v in cudanet.state_dict().items():
                tmp_state_dict[k] = v.cpu()
            state_dict_list.append( tmp_state_dict )
            torch.cuda.synchronize()
    accuracy = 100*correct.double()/total.double()
    print("Accuracy for trial %d : %.4f %%" % (trial+1 , accuracy) )
    if accuracy > 53 :
        print('Successful search')
        break
    del cudanet
else :
    print('Unsuccessful search')

end.record()
torch.cuda.synchronize()

print( "time required = " , start.elapsed_time(end)*0.001 , " s ")
if want_loud_warning :
    Audio(wave, rate=10000, autoplay=True)
```