Dev1num3

February 5, 2019

In [1]:
```
import torch
import torchvision
import torchvision.transforms as transforms #
import torchvision.datasets.mnist as mnist  # to import data

# we use torch.cuda.Event(enable_timing=True) to measure time
# from timeit import default_timer as timer
# import time

import torch.optim as optim
import torch.nn as nn
import torch.nn.functional as F

import collections           # for ordered_dictionnary
import torch.nn.init as init # to initialize model

import copy                  # for copy.deepcopy( ... )

import matplotlib.pyplot as plt
import numpy as np

from __future__ import print_function, division
import os
from PIL import Image
import torch
import pandas as pd
from skimage import io, transform
import numpy as np
import matplotlib.pyplot as plt
from torch.utils.data import Dataset, DataLoader
from torchvision import transforms, utils

import collections
import torch.nn.init as init
```

In [5]:
```
total_nb_of_sample = 9999 # total number of sample per class, this shouldn't be hardco
class labeledDataSet(torch.utils.data.Dataset):
```

```python
    def __init__(self, label, idx_min , idx_max , 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__()
        dic = {"Cat" : int(1) , "Dog" : int(0)}

        if dic.get(label , "not found" ) == "not found" :
            raise ValueError("label must either be Cat or Dog")

        if idx_max > total_nb_of_sample or idx_min < 0 :
            raise ValueError("min, max index error")

        self.label_name = label
        self.idx_min = idx_min
        self.idx_max = idx_max
        self.label = dic[label]
        self.root_dir = root_dir
        self.load_data()

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

        self.data_tensor = torch.empty(size,3,64,64,dtype=torch.float)
        self.target_tensor = torch.ones(size,dtype=torch.long) * self.label

        for i,j in enumerate(range( self.idx_min , self.idx_max , 1 ),0) :
            img_name = os.path.join(self.root_dir, "{index}.{Label}.jpg".format(index=
            # image = io.imread(img_name)
            # print( i , " : " , io.imread(img_name).shape )
            # img = io.imread(img_name)
            img = Image.open( img_name ).convert('RGB')
            """
            NOTE : There is at least one grey-scale picture of Einstein, manually remo
            the greyscale (1 channel) images have to be converted to 3 channels tensor
            """
            image = torch.from_numpy( np.transpose( img , (-1,-3,-2) ) )
            self.data_tensor[i,:,:,:] = image

    def __len__(self):
        # return len(self.name_frame)
        return (self.idx_max - self.idx_min + 1)

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

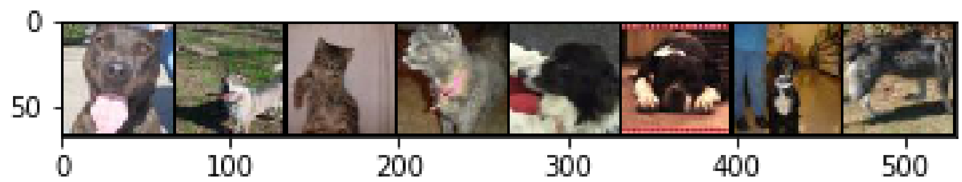
Setting the directory of the pictures

```
In [ ]: dog_dir = "./data_catdogs/trainset/Dog"
        cat_dir = "./data_catdogs/trainset/Cat"

        # picture no 1              to (idx_sep)            belong to the training dataset
        # picture no (idx_sep + 1) to (total_nb_of_sample) belong to the validation dataset
        idx_sep = 8000

        trainDogSet = labeledDataSet( "Dog", 1 , idx_sep , root_dir = dog_dir )
        trainCatSet = labeledDataSet( "Cat", 1 , idx_sep , root_dir = cat_dir )

        testsDogSet = labeledDataSet( "Dog", idx_sep + 1 , total_nb_of_sample , root_dir = dog_
        testsCatSet = labeledDataSet( "Cat", idx_sep + 1 , total_nb_of_sample , root_dir = cat_

In [6]: trainset = torch.utils.data.ConcatDataset( [ trainDogSet , trainCatSet ] )
        testsset = torch.utils.data.ConcatDataset( [ testsDogSet , testsCatSet ] )

In [7]: testing_dataset_size  = testsCatSet.__len__() + testsDogSet.__len__()
        training_dataset_size = trainCatSet.__len__() + trainDogSet.__len__()

        print( "training dataset size = " , training_dataset_size )
        print( "testing  dataset size = " , testing_dataset_size )
        print( trainDogSet.__doc__ )
        img, label =  trainDogSet.__getitem__(1)
        print( "img size = " , img.size() , "label size = " , label.size() )

training dataset size =  16000
testing  dataset size =  3998
None
img =  torch.Size([3, 64, 64]) label =  torch.Size([])
```

Display some samples

```
In [8]: nb_sample = 8

        trainloader = torch.utils.data.DataLoader(trainset , batch_size = nb_sample,  shuffle=
        testsloader  = torch.utils.data.DataLoader(testsset , batch_size = nb_sample, shuffle=

        # functions to show an image

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

        # get some random training images
        dataiter = iter( testsloader )
```

```
images, labels = dataiter.next()

# show images
imshow(torchvision.utils.make_grid(images))
# print labels
print(' '.join('%5s' % labels[j].item() for j in range(nb_sample)))
```




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

set the device

```
In [9]: device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
        print(device)
```

```
cuda:0
```

0.1 The model

architecture taken from : https://github.com/MaximumEntropy/welcome_tutorials/tree/pytorch/pytorch

```
In [10]: class Classifier(nn.Module):
             """Convnet Classifier"""
             def __init__(self, kernel_sz = 3 ):

                 if kernel_sz % 2 == 0 :
                     raise ValueError("kernel size must be odd")
                 pad = kernel_sz // 2

                 super(Classifier, self).__init__()
                 self.conv = nn.Sequential(
                     # Layer 1
                     nn.Conv2d(in_channels=3, out_channels=16, kernel_size=( kernel_sz , kernel
                     # nn.Dropout(p=0.5),
                     nn.ReLU(),
                     nn.MaxPool2d(kernel_size=(2, 2), stride=2),

                     # Layer 2
```

```
                nn.Conv2d(in_channels=16, out_channels=32, kernel_size=( kernel_sz , kerne
                # nn.Dropout(p=0.5),
                nn.ReLU(),
                nn.MaxPool2d(kernel_size=(2, 2), stride=2),

                # Layer 3
                nn.Conv2d(in_channels=32, out_channels=64, kernel_size=( kernel_sz , kerne
                # nn.Dropout(p=0.5),
                nn.ReLU(),
                nn.MaxPool2d(kernel_size=(2, 2), stride=2),

                # Layer 4
                nn.Conv2d(in_channels=64, out_channels=128, kernel_size=(kernel_sz , kerne
                # nn.Dropout(p=0.5),
                nn.ReLU(),
                nn.MaxPool2d(kernel_size=(2, 2), stride=2)
            )
            #
            self.fct = nn.Linear(4*4*128, 1)

        def forward(self, x):
            x = self.conv(x)
            x = x.view(-1, 4*4*128)
            x = torch.sigmoid(self.fct(x))
            # x = self.fct(x)
            # x = F.softmax(self.fct(x),dim=-1)
            return x
```

Print the number of parameters in each models and display the computation

```
In [11]: def number_of_params( net ) :
             nb_param  = 0
             param_lst = " "
             for i, (key, value) in enumerate( net.state_dict().items() ) :

                 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

        print( "number of params = " , nb_param , " = ", param_lst  )

mytestnet = Classifier( kernel_sz=9 )
number_of_params( mytestnet )
del mytestnet
```

```
number of params =  877089  =
 (conv.0.weight)          16*3*9*9
 (conv.0.bias)          + 16
 (conv.3.weight)        + 32*16*9*9
 (conv.3.bias)          + 32
 (conv.6.weight)        + 64*32*9*9
 (conv.6.bias)          + 64
 (conv.9.weight)        + 128*64*9*9
 (conv.9.bias)          + 128
 (fct.weight)           + 1*2048
 (fct.bias)             + 1
```

init method

In [12]:
```
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)
```

In [33]:
```
if True :
    del cudanet
```

In [34]:
```
cudanet = Classifier( kernel_sz = 9 )
cudanet.apply( glorot_init )
cudanet.to(device)
```

Out[34]:
```
Classifier(
  (conv): Sequential(
    (0): Conv2d(3, 16, kernel_size=(9, 9), stride=(1, 1), padding=(4, 4))
    (1): ReLU()
    (2): MaxPool2d(kernel_size=(2, 2), stride=2, padding=0, dilation=1, ceil_mode=Fal
    (3): Conv2d(16, 32, kernel_size=(9, 9), stride=(1, 1), padding=(4, 4))
    (4): ReLU()
    (5): MaxPool2d(kernel_size=(2, 2), stride=2, padding=0, dilation=1, ceil_mode=Fal
```

```
        (6): Conv2d(32, 64, kernel_size=(9, 9), stride=(1, 1), padding=(4, 4))
        (7): ReLU()
        (8): MaxPool2d(kernel_size=(2, 2), stride=2, padding=0, dilation=1, ceil_mode=Fals
        (9): Conv2d(64, 128, kernel_size=(9, 9), stride=(1, 1), padding=(4, 4))
        (10): ReLU()
        (11): MaxPool2d(kernel_size=(2, 2), stride=2, padding=0, dilation=1, ceil_mode=Fal
      )
      (fct): Linear(in_features=2048, out_features=1, bias=True)
    )
```

```
In [36]: criterion = nn.BCELoss() # Binary Cross Entropy
         optimizer = optim.SGD(cudanet.parameters(), lr=0.0001, momentum=0.0, weight_decay=0)
         nb_epoch  = 30
```

```
In [37]: if False :
             print( cudanet( torch.ones(1,3,64,64).to(device) ) )
             print( cudanet( torch.ones(1,3,64,64).to(device) ).dtype )

             with torch.no_grad() :
                 for i, data in enumerate(trainloader, 0):
                     # get the inputs
                     inputs, labels = data
                     labels = labels.float()
                     inputs, labels = inputs.to(device), labels.to(device)

                     # zero the parameter gradients
                     optimizer.zero_grad()

                     # forward + backward + optimize
                     outputs = cudanet(inputs).squeeze()
                     print( outputs.size() , labels.size() )
                     print( outputs )
                     loss = criterion(outputs, labels)
                     print( loss )

                     break
```

0.2 Training the model

Note : 30 epoch with lr=0.0001 are not enough, add more epoch, larger lr could be an issue for fine tuning the model

```
In [39]: trainloader = torch.utils.data.DataLoader(trainset, batch_size=4*64,shuffle=True, num_
         state_dict_list = list()

         torch.cuda.synchronize()

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

```python
        start.record()

        for epoch in range( nb_epoch ):  # loop over the dataset multiple times

            running_loss = 0.0
            for i, data in enumerate(trainloader, 0):
                # get the inputs
                inputs, labels = data
                labels = labels.float()
                inputs, labels = inputs.to(device), labels.to(device)

                # zero the parameter gradients
                optimizer.zero_grad()

                # forward + backward + optimize
                outputs = cudanet(inputs).squeeze()
                # if i == 0 : print( outputs )
                loss = criterion(outputs, labels)
                loss.backward()
                optimizer.step()

                # print statistics
                running_loss += loss.item()
            else : # print every epoch
                print('epoch = %d, loss = %.8f' % (epoch + 1, running_loss / (i*8*64))) # nb
                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()

        else :
            print('Finished Training')

        end.record()
        torch.cuda.synchronize()
        print( "time required = " , start.elapsed_time(end)*0.001 , " s ")
```

```
epoch = 1, loss = 0.00791041
epoch = 2, loss = 0.00150025
epoch = 3, loss = 0.00140869
epoch = 4, loss = 0.00135263
epoch = 5, loss = 0.00131762
epoch = 6, loss = 0.00128026
epoch = 7, loss = 0.00126457
epoch = 8, loss = 0.00125376
```

```
epoch = 9, loss = 0.00122598
epoch = 10, loss = 0.00122030
epoch = 11, loss = 0.00119520
epoch = 12, loss = 0.00118546
epoch = 13, loss = 0.00117974
epoch = 14, loss = 0.00116469
epoch = 15, loss = 0.00115254
epoch = 16, loss = 0.00115322
epoch = 17, loss = 0.00114271
epoch = 18, loss = 0.00113528
epoch = 19, loss = 0.00112319
epoch = 20, loss = 0.00111661
epoch = 21, loss = 0.00110833
epoch = 22, loss = 0.00110505
epoch = 23, loss = 0.00109424
epoch = 24, loss = 0.00109197
epoch = 25, loss = 0.00107874
epoch = 26, loss = 0.00108290
epoch = 27, loss = 0.00107191
epoch = 28, loss = 0.00106411
epoch = 29, loss = 0.00106355
epoch = 30, loss = 0.00104832
Finished Training
time required =  366.51428125  s
```

test accuracy of the current state on validation dataset

```
In [29]: testsloader = torch.utils.data.DataLoader(testsset, batch_size=8*64,shuffle=False, nu
         correct = torch.tensor([0])
         total = torch.tensor([0])

         correct, total = correct.to(device) , total.to(device)
         with torch.no_grad():
             for data in testsloader:
                 images, labels = data
                 images, labels = images.to(device), labels.to(device)
                 outputs = cudanet(images).squeeze()
                 predicted = torch.where(
                                 outputs > 0.5, torch.ones_like(labels, device=device) , torch
                             )
                 total += labels.size(0)
                 correct += (predicted == labels).sum()

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

```
Accuracy of the network on the 3998 test images: 70.19 %
```

accuracy across epoch

```
In [40]: trainloader = torch.utils.data.DataLoader(trainset , batch_size = 8*64 , shuffle=False
         testsloader = torch.utils.data.DataLoader(testsset , batch_size = 8*64, shuffle=False

         accuracy = torch.ones(nb_epoch,2, dtype=torch.float) * 100
         for epoch , tmp_state_dict in enumerate(state_dict_list,0) :
             if epoch % 1 != 0 :
                 continue

             cudaTOCPUnet = copy.deepcopy( cudanet )
             cudaTOCPUnet.load_state_dict( tmp_state_dict )
             cuda_test_net = copy.deepcopy(cudaTOCPUnet).to(device)

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

             correct, total = correct.to(device) , total.to(device)

             loader_list = [ testsloader , trainloader ]
             with torch.no_grad():
                 for i, loader in enumerate(loader_list,0) :
                     for data in loader:
                         images, labels = data
                         images, labels = images.to(device), labels.to(device)
                         outputs = cuda_test_net(images).squeeze()
                         predicted = torch.where(
                                         outputs > 0.5, torch.ones_like(labels, device=device)
                                     )
                         total[i] += labels.size(0)
                         correct[i] += (predicted == labels).sum()

             accuracy[epoch,:] = accuracy[epoch,:] * correct.type(torch.FloatTensor) / total.ty

             print('epoch %3d : Accuracy of the network on the test images: %.2f %% , training
                       % ( epoch+1, accuracy[epoch,0] , accuracy[epoch,1] )
                  )
```

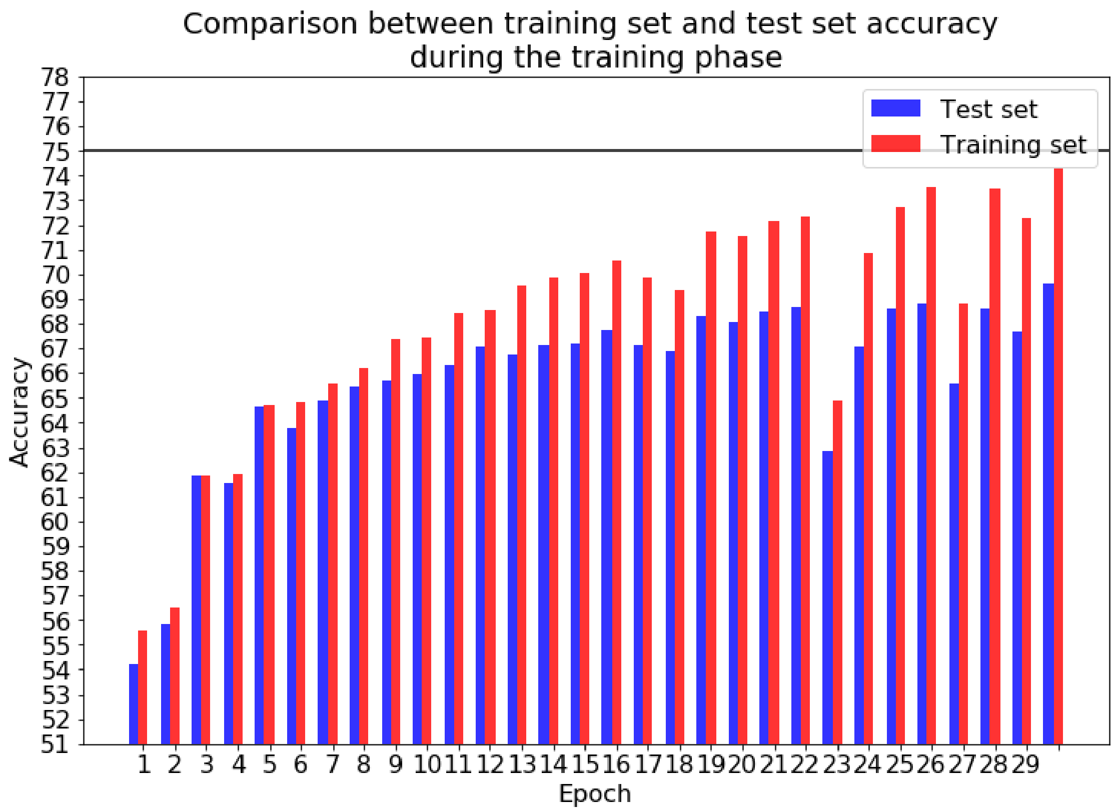
```
epoch   1 : Accuracy of the network on the test images: 54.23 % , training images 55.58 %
epoch   2 : Accuracy of the network on the test images: 55.85 % , training images 56.51 %
epoch   3 : Accuracy of the network on the test images: 61.83 % , training images 61.86 %
epoch   4 : Accuracy of the network on the test images: 61.56 % , training images 61.91 %
epoch   5 : Accuracy of the network on the test images: 64.66 % , training images 64.74 %
epoch   6 : Accuracy of the network on the test images: 63.78 % , training images 64.81 %
epoch   7 : Accuracy of the network on the test images: 64.88 % , training images 65.60 %
```

```
epoch   8 : Accuracy of the network on the test images: 65.48 % , training images 66.20 %
epoch   9 : Accuracy of the network on the test images: 65.71 % , training images 67.39 %
epoch  10 : Accuracy of the network on the test images: 65.96 % , training images 67.42 %
epoch  11 : Accuracy of the network on the test images: 66.33 % , training images 68.41 %
epoch  12 : Accuracy of the network on the test images: 67.06 % , training images 68.57 %
epoch  13 : Accuracy of the network on the test images: 66.78 % , training images 69.58 %
epoch  14 : Accuracy of the network on the test images: 67.13 % , training images 69.89 %
epoch  15 : Accuracy of the network on the test images: 67.21 % , training images 70.06 %
epoch  16 : Accuracy of the network on the test images: 67.76 % , training images 70.53 %
epoch  17 : Accuracy of the network on the test images: 67.11 % , training images 69.84 %
epoch  18 : Accuracy of the network on the test images: 66.88 % , training images 69.39 %
epoch  19 : Accuracy of the network on the test images: 68.28 % , training images 71.71 %
epoch  20 : Accuracy of the network on the test images: 68.08 % , training images 71.53 %
epoch  21 : Accuracy of the network on the test images: 68.48 % , training images 72.18 %
epoch  22 : Accuracy of the network on the test images: 68.66 % , training images 72.34 %
epoch  23 : Accuracy of the network on the test images: 62.83 % , training images 64.88 %
epoch  24 : Accuracy of the network on the test images: 67.06 % , training images 70.85 %
epoch  25 : Accuracy of the network on the test images: 68.63 % , training images 72.71 %
epoch  26 : Accuracy of the network on the test images: 68.83 % , training images 73.53 %
epoch  27 : Accuracy of the network on the test images: 65.56 % , training images 68.79 %
epoch  28 : Accuracy of the network on the test images: 68.61 % , training images 73.47 %
epoch  29 : Accuracy of the network on the test images: 67.68 % , training images 72.28 %
epoch  30 : Accuracy of the network on the test images: 69.63 % , training images 74.24 %
```

0.2.1 Plot accuracy

In [43]:
```
from matplotlib.pyplot import figure
# import warnings
# warnings.filterwarnings('ignore')

# data to plot
n_groups = nb_epoch
accuracy_toplot = accuracy.numpy()

tests_accuracy = accuracy_toplot[:,0]
train_accuracy = accuracy_toplot[:,1]

#
plt.rcParams.update({'font.size': 16})
plt.rcParams["figure.figsize"] = (12 ,8)
# create plot
fig, ax = plt.subplots()
index = np.arange(n_groups)
bar_width = 0.3
opacity = 0.8

rects1 = plt.bar(index, tests_accuracy, bar_width,
```

```
                 alpha=opacity,
                 color='blue',
                 label='Test set')

rects2 = plt.bar(index + bar_width, train_accuracy, bar_width,
                 alpha=opacity,
                 color='r',
                 label='Training set')

eps = 3
top = min(int( np.ceil(accuracy_toplot.max() + eps)) , 100)
bot = max(int(np.floor(accuracy_toplot.min() - eps)) , 0  )


plt.ylim(bot, top)     # set the ylim to bottom, top
plt.axhline(y=75,color="black")

plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.title('Comparison between training set and test set accuracy \nduring the training
plt.xticks(index + bar_width, range(1,n_groups,1) )
plt.yticks( range(bot,top+1,1) )
plt.legend()

# plt.tight_layout()
plt.show()
```

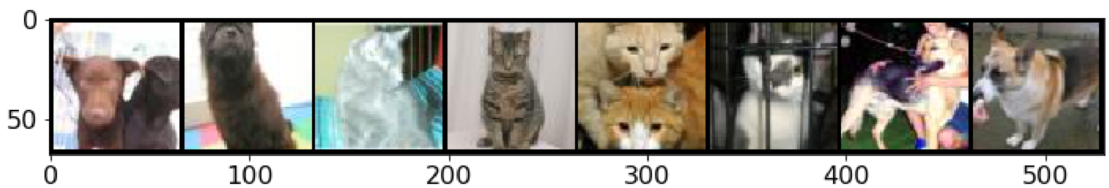


1 Misc

print some test sample that the net misclassifies

```
In [60]: testsloader = torch.utils.data.DataLoader(testsset , batch_size = 8*64, shuffle=True

         nb_of_error = torch.tensor([8])
         j = torch.tensor([0])
         errorimages  = torch.empty(8,3,64,64)
         errorlabels  = torch.empty(8)
         erroroutputs = torch.empty(8)
         for images, labels in testsloader :
             images, labels = images.to(device), labels.to(device)
             outputs = cuda_test_net(images).squeeze()
             predicted = torch.where(
                                 outputs > 0.5, torch.ones_like(labels, device=device) , torch.zer
                                 )
             if not (predicted == labels).sum() == labels.size()[0] :
                 comparison = (predicted == labels)
                 for i,b in enumerate( comparison ) :
                     if b == 0 :
```

```
                        errorimages[j,:,:,:] = copy.deepcopy(images[i,:,:,:]).cpu()
                        errorlabels[j] = labels[i].clone().detach().requires_grad_(False).cpu
                        erroroutputs[j] = outputs[i].clone().detach().requires_grad_(False).cp
                        j = j + 1
                        if j.item() >= nb_of_error.item() :
                            break
                else :
                    continue
                break

        if j.item() == 0 :
            print( "no error found")
        else :
            imshow( torchvision.utils.make_grid(errorimages) )

            print( "Probabilities goes from : 0 -> this is a dog for sure , to 1 -> cat for su
            print( "this should be          : " , ",".join( " %-4d" % nb.item() for nb in erro
            print( "net associated prob     : " , ",".join( "%5.2f" % nb.item() for nb in erro
```



```
Probabilities goes from : 0 -> this is a dog for sure , to 1 -> cat for sure
this should be          :   0    , 0    , 1    , 1    , 1    , 1    , 0    , 0
net associated prob     :   0.60, 0.85, 0.47, 0.25, 0.14, 0.41, 0.54, 0.76
```

1.0.1 Save and load models

Save the state_dict of the model for each epoch on a local directory

```
In [57]: local_path = "./save"
         for epoch , tmp_state_dict in enumerate(state_dict_list,1) :
             saving_path = local_path + "/dev1num3model_for_epoch{Epoch}.pth".format( Epoch = e
             torch.save( tmp_state_dict , saving_path)
             # print( saving_path )
```

```
./save/dev1num3model_for_epoch1.pth
./save/dev1num3model_for_epoch2.pth
./save/dev1num3model_for_epoch3.pth
./save/dev1num3model_for_epoch4.pth
./save/dev1num3model_for_epoch5.pth
```

```
./save/dev1num3model_for_epoch6.pth
./save/dev1num3model_for_epoch7.pth
./save/dev1num3model_for_epoch8.pth
./save/dev1num3model_for_epoch9.pth
./save/dev1num3model_for_epoch10.pth
./save/dev1num3model_for_epoch11.pth
./save/dev1num3model_for_epoch12.pth
./save/dev1num3model_for_epoch13.pth
./save/dev1num3model_for_epoch14.pth
./save/dev1num3model_for_epoch15.pth
./save/dev1num3model_for_epoch16.pth
./save/dev1num3model_for_epoch17.pth
./save/dev1num3model_for_epoch18.pth
./save/dev1num3model_for_epoch19.pth
./save/dev1num3model_for_epoch20.pth
./save/dev1num3model_for_epoch21.pth
./save/dev1num3model_for_epoch22.pth
./save/dev1num3model_for_epoch23.pth
./save/dev1num3model_for_epoch24.pth
./save/dev1num3model_for_epoch25.pth
./save/dev1num3model_for_epoch26.pth
./save/dev1num3model_for_epoch27.pth
./save/dev1num3model_for_epoch28.pth
./save/dev1num3model_for_epoch29.pth
./save/dev1num3model_for_epoch30.pth
```

load from file and set the load the state_dict of the last epoch on a object the files have to be located in "./save" and named "dev1num3model_for_epoch{j}.pth" for j from ... to ...

In [59]:
```python
local_path = "./save"
state_dict_list = list()

from_idx = 1
to_idx   = nb_epoch

for epoch in range( from_idx  , to_idx + 1 , 1 ):
    path = local_path + "/dev1num3model_for_epoch{Epoch}.pth".format( Epoch = epoch )
    tmp_dict = torch.load(path)
    state_dict_list.append(tmp_dict)
    # print( path )
else :
    cudanet = Classifier( kernel_sz = 9 )
    cudanet.load_state_dict(tmp_dict)
    cudanet.to(device)
    cudanet.eval()
```