```
#pip install pillow
```

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call
```

Download color images from the BSD dataset and storing to drive and getting from it:

```
# Get image names from a GDrive directory

import os

path = '/content/drive/MyDrive/image_ee610'

imageNames = []

for i in os.scandir(path):
  imageNames.append(i.path)

imageNames
```

```
['/content/drive/MyDrive/image_ee610/ee610-1.jpg',
 '/content/drive/MyDrive/image_ee610/ee610-2.jpg',
 '/content/drive/MyDrive/image_ee610/ee610-3.jpg',
 '/content/drive/MyDrive/image_ee610/ee610-4.jpg',
 '/content/drive/MyDrive/image_ee610/ee610-5.jpg',
 '/content/drive/MyDrive/image_ee610/ee610-6.jpg',
 '/content/drive/MyDrive/image_ee610/test_123.jpg',
 '/content/drive/MyDrive/image_ee610/ee610-7.jpg',
 '/content/drive/MyDrive/image_ee610/ee610test-8.jpg',
 '/content/drive/MyDrive/image_ee610/ee610test-9.jpg',
 '/content/drive/MyDrive/image_ee610/ee610-10.jpg']
```

```
len(imageNames)
```

```
11
```

Importing required libraries

```
import torch
#torch.cuda.memory_summary(device=None, abbreviated=False)
```

```
import numpy as np
import cv2
import matplotlib.pyplot as plt
from matplotlib import image
import PIL
```

```
from PIL import Image

# for creating validation set
from sklearn.model_selection import train_test_split

# for evaluating the model
from sklearn.metrics import accuracy_score
from tqdm import tqdm

#PyTorch libraries and modules
from torch.autograd import Variable
from torch.nn import Linear, ReLU, CrossEntropyLoss, Sequential, Conv2d, MaxPoo
from torch.optim import Adam, SGD

from torchvision import datasets, transforms
from torch.utils import data
```

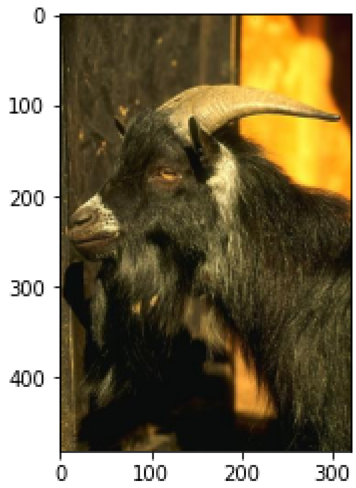
2. Prepare the training dataset:
   a. Select the largest odd window size W, e.g. 13 or 27
   b. Prepare a few blur kernels and noise models
   c. For each training image :-
   i. Degrade multiple times using different blur kernels and noise models
   ii. Display a few images to check if the degradation is realistic looking instead of too much or too little
   iii. For each degraded image version
      1. Mine and store degraded patches of size WxW and central pixel of original patch

```
orig_img = image.imread(imageNames[5])
test_img = image.imread(imageNames[10])
```

```
orig_img.dtype
```

```
dtype('uint8')
```

```
plt.figure(1)
plt.subplot(111)
plt.imshow(orig_img)
plt.show()
plt.subplot(111)
plt.imshow(test_img)
plt.show()
```

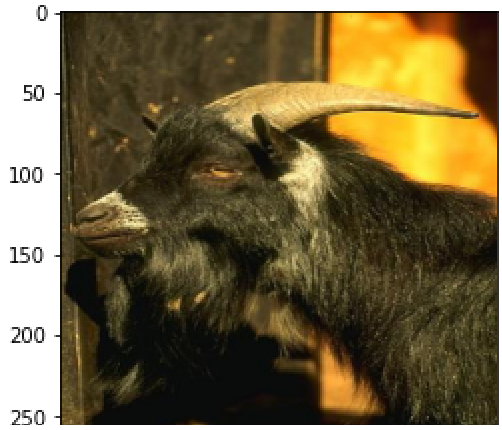


```
print(orig_img.shape)
print(test_img.shape)
```

```
(481, 321, 3)
(321, 481, 3)
```

```
orig_img = cv2.resize(orig_img,(270,270))
test_img = cv2.resize(test_img,(270,270))
```

```
plt.figure(2)
plt.subplot(111)
plt.imshow(orig_img)
plt.show()
plt.subplot(111)
plt.imshow(test_img)
plt.show()
```




```
img1 = orig_img
img2 = test_img
```

```
print(img1.shape)
print(img2.shape)
```

```
(270, 270, 3)
(270, 270, 3)
```

```
print(type(img1))
print(type(img2))
```

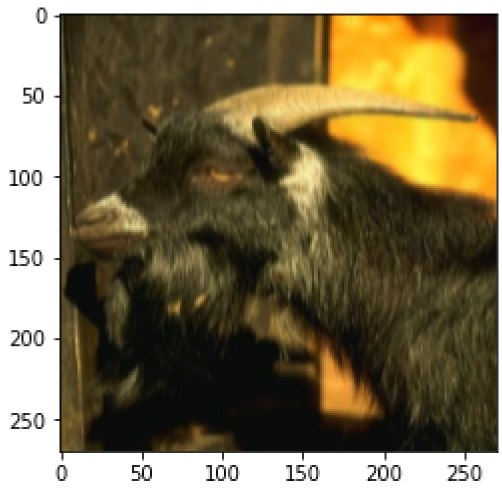
```
<class 'numpy.ndarray'>
<class 'numpy.ndarray'>
```

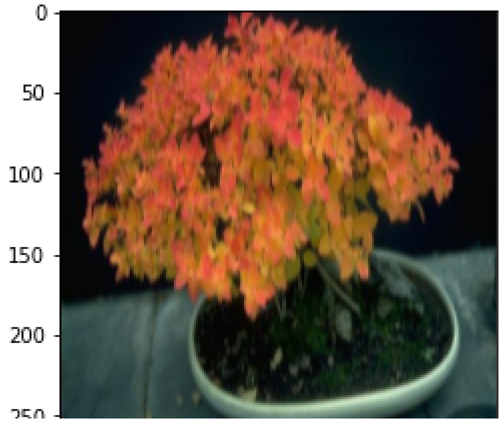
```
for i in range(2):
        blurred_img1 = cv2.GaussianBlur(img1,(27,27),0.01,0.010, cv2.BORDER_REPI
        blurred_img2 = cv2.GaussianBlur(img2,(27,27),0.01,0.010, cv2.BORDER_REPI
        gauss = np.random.normal(0,0.01,img1.size)
        #print(gauss.shape)     shape = (463203,)
        #print(gauss.dtype)     dtype = float64
        gauss = gauss.reshape(img1.shape[0],img1.shape[1],img1.shape[2]).astype
        img1 = cv2.add(blurred_img1,gauss)
        img2 = cv2.add(blurred_img2,gauss)

```

```
noisy_img1 = img1
noisy_img2 = img2
```

```
plt.figure(3)
plt.subplot(111)
plt.imshow(noisy_img1)
plt.show()
plt.subplot(111)
plt.imshow(noisy_img2)
plt.show()
```





```
from sklearn.feature_extraction import image
```

```
patchesO1 = image.extract_patches_2d(orig_img,(27,27),max_patches=12000)/255
patchesN1 = image.extract_patches_2d(noisy_img1, (27,27),max_patches=12000)/255
patchesO2 = image.extract_patches_2d(test_img,(27,27),max_patches=12000)/255
patchesN2 = image.extract_patches_2d(noisy_img2, (27,27),max_patches=12000)/255
numPatches = len(patchesO1)
center_pix1 = np.empty((numPatches,3),dtype=float)
center_pix2 = np.empty((numPatches,3),dtype=float)
#patches_img = np.empty((numPatches,13,13,1), dtype=float)

for i in range(numPatches):
   center_pix1[i] = patchesO1[i][14,14]
   #a.append(center_pix1[i])
   center_pix2[i] = patchesO2[i][14,14]
#print(center_pix)
```

```
patchesO1.shape
```

```
(12000, 27, 27, 3)
```

```
len(center_pix1)
```

```
12000
```

```
# b = []
# for i in range(numPatches):
```

```
#   diff = patchesO1[0][7,7] - center_pix1[0]
#   b.append(diff)
```

```
# center_pix1[0]
```

```
# center_pix1 = np.resize(center_pix1,(118,118,3))
# plt.imshow(center_pix1)
# plt.show()
```

```
# center_pix1 = np.resize(center_pix1,(1,1,3))
```

```
#center_pix1.shape
```

```
#center_pix = center_pix.astype('float')
```

```
patchesN1 = patchesN1.reshape(12000,3,27,27)
print(patchesN1.shape)
patchesN2 = patchesN2.reshape(12000,3,27,27)
print(patchesN2.shape)
```

```
(12000, 3, 27, 27)
(12000, 3, 27, 27)
```

```
center_pix1 = center_pix1.reshape(12000,3,1,1)
center_pix2 = center_pix2.reshape(12000,3,1,1)
print(center_pix1.shape)
print(center_pix2.shape)
```

```
(12000, 3, 1, 1)
(12000, 3, 1, 1)
```

```
# create validation set
train_x, val_x, train_y, val_y = train_test_split(patchesN1, center_pix1, test_
(train_x.shape, train_y.shape), (val_x.shape, val_y.shape)
```

```
(((9600, 3, 27, 27), (9600, 3, 1, 1)), ((2400, 3, 27, 27), (2400, 3, 1, 1)))
```

```
#  train_x = train_x[0:500]
#  train_y = train_y[0:500]
#  val_x = val_x[0:500]
#  val_y = val_y[0:500]
test_x = patchesN2
test_y = center_pix2
```

```
print(test_x.shape)
print(test_y.shape)
```

```
(12000, 3, 27, 27)
(12000, 3, 1, 1)
```

```
# train_x = train_x.astype('double')
# val_x = val_x.astype('double')
```

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

```
# converting training images into torch format
#train_x = train_x.reshape(54000, 1, 28, 28)
train_x  = torch.from_numpy(train_x)

# converting the target into torch format
#train_y = train_y.astype(int);
train_y = torch.from_numpy(train_y)

# shape of training data
train_x.shape, train_y.shape
```

```
(torch.Size([9600, 3, 27, 27]), torch.Size([9600, 3, 1, 1]))
```

```
val_x  = torch.from_numpy(val_x)
val_y = torch.from_numpy(val_y)
# shape of validation data
val_x.shape, val_y.shape
```

```
(torch.Size([2400, 3, 27, 27]), torch.Size([2400, 3, 1, 1]))
```

```
test_x  = torch.from_numpy(test_x)
test_y = torch.from_numpy(test_y)
# shape of validation data
test_x.shape, test_y.shape
```

```
(torch.Size([12000, 3, 27, 27]), torch.Size([12000, 3, 1, 1]))
```

```
train_x.dtype
```

```
torch.float64
```

```
print(type(test_x))
print(test_x.dtype)
```

```
<class 'torch.Tensor'>
torch.float64
```

```
train_x = train_x.double()
val_x  = val_x.double()
train_y = train_y.double()
```

```
val_y = val_y.double()
test_x = test_x.double()
test_y = test_y.double()
```

3. Train a regression model:
   a. Select a window size w less than or equal to the largest window size W.
   b. Select a machine learning model (nonlinear regression), e.g. support vector regression, random forest regression, neural network regression, or convolutional neural network.
   c. Write a function to read only the w×w central pixels as input, and (optionally) pre-process them (e.g. make it zero mean and unit variance, or work in HSI space).
   d. In python, train a regression model to predict the clean (optionally, normalized) central pixel.
   e. Monitor the normalized mean square error or mean absolute error for validation data.
   f. Observe if models over-fits. If so, then implement early stopping.
   g. Experiment with different choices, e.g. window size, machine learning models, capacity of models (e.g. tree depth, SVR penalty, number of hidden nodes in NN, number of layers and kernels in CNN, etc.) to find a reasonable model with small normalized RMSE, e.g. less than 1% or 2%.

```
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")

class Net(nn.Module):
  def __init__(self):
    super(Net,self).__init__()
    self.c1 = nn.Conv2d(3,16,13)
    self.bn1 = nn.BatchNorm2d(16)
    self.c2 = nn.Conv2d(16,32,9)
    self.bn2 = nn.BatchNorm2d(32)
    self.c3 = nn.Conv2d(32,64,5)
    self.bn3 = nn.BatchNorm2d(64)
    self.c4 = nn.Conv2d(64,128,3)
    self.bn4 = nn.BatchNorm2d(128)
    self.c5 = nn.Conv2d(128,256,1)
    self.c6 = nn.Conv2d(256,3,1)
    self.drop = nn.Dropout2d(p=0.25)
    self.double()

  def forward(self,x):

    x = self.bn1(F.relu(self.c1(x)))
    x = self.bn2(F.relu(self.c2(x)))
    x = self.bn3(F.relu(self.c3(x)))
    x = self.bn4(F.relu(self.c4(x)))
    x = F.relu(self.c5(x))
    x = self.c6(x)
    print(x.shape)
    return x
```

```
model = Net().to(device)
# image=torch.randn(1,3,27,27).to(device)
```

```
 #model = model.float()
```

```
# from torchsummary import summary
# model = Net().to(device)
# summary(model, (3, 13, 13))
```

```
  # defining the model
model = Net().to(device)
# defining the optimizer
optimizer = Adam(model.parameters(), lr=0.0001)
# defining the loss function
class RMSELoss(nn.Module):
    def __init__(self):
        super().__init__()
        self.mse = nn.MSELoss()

    def forward(self,yhat,y):
        return torch.sqrt(self.mse(yhat,y))
criterion = RMSELoss()
# checking if GPU is available
if torch.cuda.is_available():
    model = model.cuda()
    criterion = criterion.cuda()

print(model)
```

```
Net(
  (c1): Conv2d(3, 16, kernel_size=(13, 13), stride=(1, 1))
  (bn1): BatchNorm2d(16, eps=1e-05, momentum=0.1, affine=True, track_running_
  (c2): Conv2d(16, 32, kernel_size=(9, 9), stride=(1, 1))
  (bn2): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, track_running_
  (c3): Conv2d(32, 64, kernel_size=(5, 5), stride=(1, 1))
  (bn3): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_
  (c4): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1))
  (bn4): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running
  (c5): Conv2d(128, 256, kernel_size=(1, 1), stride=(1, 1))
  (c6): Conv2d(256, 3, kernel_size=(1, 1), stride=(1, 1))
  (drop): Dropout2d(p=0.25, inplace=False)
)
```

```
def train(s):
    model.train()
    tr_loss = 0
    # getting the training set
    x_train, y_train = Variable(train_x), Variable(train_y)
    # getting the validation set
    x_val, y_val = Variable(val_x), Variable(val_y)
    # getting the testing set
    # x_test, y_test = Variable(test_x), Variable(test_y)
    # converting the data into GPU format
```

```
    if torch.cuda.is_available():
        x_train = x_train.cuda()
        y_train = y_train.cuda()
        x_val = x_val.cuda()
        y_val = y_val.cuda()
        # x_test = x_test.cuda()
        # y_test = y_test.cuda()

    # clearing the Gradients of the model parameters
    optimizer.zero_grad()

    # prediction for training and validation set
    output_train = model(x_train)
    ot.append(output_train)
    output_val = model(x_val)
    ov.append(output_val)

    # computing the training and validation loss
    loss_train = criterion(output_train, y_train)
    loss_val = criterion(output_val, y_val)
    train_losses.append(loss_train)
    val_losses.append(loss_val)

    # computing the updated weights of all the model parameters
    loss_train.backward()
    optimizer.step()
    tr_loss = loss_train.item()

    #if epoch%2 ==0:
    print('Epoch : ',epoch+1, '\t', 'loss :', loss_val)

```

```
# defining the number of epochs
n_epochs = 45
# empty list to store training losses
train_losses = []
# empty list to store validation losses
val_losses = []
# empty list to store predicted value of training data
ot = []
ov = []
# training the model
for epoch in range(n_epochs):
    train(epoch)
# print(ot[0])
# print(ov[0])
```

```
torch.Size([9600, 3, 1, 1])
torch.Size([2400, 3, 1, 1])
Epoch :  1      loss : tensor(0.3809, device='cuda:0', dtype=torch.float64
torch.Size([9600, 3, 1, 1])
torch.Size([2400, 3, 1, 1])
Epoch :  2      loss : tensor(0.3439, device='cuda:0', dtype=torch.float64
torch.Size([9600, 3, 1, 1])
torch.Size([2400, 3, 1, 1])
Epoch :  3      loss : tensor(0.3222, device='cuda:0', dtype=torch.float64
torch.Size([9600, 3, 1, 1])
torch.Size([2400, 3, 1, 1])
Epoch :  4      loss : tensor(0.3072, device='cuda:0', dtype=torch.float64
torch.Size([9600, 3, 1, 1])
torch.Size([2400, 3, 1, 1])
Epoch :  5      loss : tensor(0.2952, device='cuda:0', dtype=torch.float64
torch.Size([9600, 3, 1, 1])
torch.Size([2400, 3, 1, 1])
Epoch :  6      loss : tensor(0.2848, device='cuda:0', dtype=torch.float64
torch.Size([9600, 3, 1, 1])
torch.Size([2400, 3, 1, 1])
Epoch :  7      loss : tensor(0.2762, device='cuda:0', dtype=torch.float64
torch.Size([9600, 3, 1, 1])
torch.Size([2400, 3, 1, 1])
Epoch :  8      loss : tensor(0.2696, device='cuda:0', dtype=torch.float64
torch.Size([9600, 3, 1, 1])
torch.Size([2400, 3, 1, 1])
Epoch :  9      loss : tensor(0.2645, device='cuda:0', dtype=torch.float64
torch.Size([9600, 3, 1, 1])
torch.Size([2400, 3, 1, 1])
Epoch :  10     loss : tensor(0.2608, device='cuda:0', dtype=torch.float64
torch.Size([9600, 3, 1, 1])
torch.Size([2400, 3, 1, 1])
Epoch :  11     loss : tensor(0.2581, device='cuda:0', dtype=torch.float64
torch.Size([9600, 3, 1, 1])
torch.Size([2400, 3, 1, 1])
Epoch :  12     loss : tensor(0.2560, device='cuda:0', dtype=torch.float64
torch.Size([9600, 3, 1, 1])
torch.Size([2400, 3, 1, 1])
Epoch :  13     loss : tensor(0.2542, device='cuda:0', dtype=torch.float64
torch.Size([9600, 3, 1, 1])
torch.Size([2400, 3, 1, 1])
Epoch :  14     loss : tensor(0.2527, device='cuda:0', dtype=torch.float64
torch.Size([9600, 3, 1, 1])
torch.Size([2400, 3, 1, 1])
Epoch :  15     loss : tensor(0.2514, device='cuda:0', dtype=torch.float64
torch.Size([9600, 3, 1, 1])
torch.Size([2400, 3, 1, 1])
Epoch :  16     loss : tensor(0.2501, device='cuda:0', dtype=torch.float64
torch.Size([9600, 3, 1, 1])
torch.Size([2400, 3, 1, 1])
Epoch :  17     loss : tensor(0.2490, device='cuda:0', dtype=torch.float64
torch.Size([9600, 3, 1, 1])
torch.Size([2400, 3, 1, 1])
Epoch :  18     loss : tensor(0.2479, device='cuda:0', dtype=torch.float64
torch.Size([9600, 3, 1, 1])
torch.Size([2400, 3, 1, 1])
Epoch :  19     loss : tensor(0.2470, device='cuda:0', dtype=torch.float64
```

```
# # plotting the training and validation loss
# plt.plot(train_losses, label='Training loss')
# plt.plot(val_losses, label='Validation loss')
# plt.legend()
# plt.show()
```

```
#SAVING FINAL MODEL

PATH2 = './sample_data/FinalModelCNN.pth'
torch.save(model.state_dict(), PATH2)
```

```
#loading ptocedure from path
model = Net().to(device)
model.load_state_dict(torch.load(PATH2))
```

Calculating the overall MSE Loss

```
# prediction for training set
with torch.no_grad():
    output = model(train_x.cuda())
predictions = output.cpu()

# accuracy on training set
print("MSE Loss is: ", criterion(train_y, predictions))

# prediction for validation set
with torch.no_grad():
    output = model(val_x.cuda())
predictions = output.cpu()

```