Keypoint(Patch) Description

This project will be all about defining and training a convolutional neural network to perform keypoint description. PyTorch tutorials are available at here: pytorch tutorials

Today we will go through:

1. Load and visualize the data

2. Build an example deep network

3. Train the deep network

4. Generate deep features

We will use below dataset in this project:

The Photo Tourism dataset

It is also available in PyTorch torchvision datasets: pytorch version

This dataset consists of 1024 x 1024 bitmap (.bmp) images, each containing a 16 x 16 array of image patches. Here are some examples:

For details of how the scale and orientation is established, please see the paper:

S. Winder and M. Brown. **Learning Local Image Descriptors**. To appear *International Conference on Computer Vision and Pattern Recognition (CVPR2007)* (pdf 300Kb)

Import packages

In [1]:

```
from __future__ import division, print_function
import glob
import os
import cv2
import PIL
import random
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
import torch
```

```python
import torch.nn.init
import torch.nn as nn
import torch.optim as optim
import torch.backends.cudnn as cudnn
import torch.nn.functional as F
import torchvision.datasets as dset
import torchvision.transforms as transforms
from tqdm import tqdm
from torch.autograd import Variable
from copy import deepcopy, copy
from config_profile import args
from Utils import cv2_scale36, cv2_scale, np_reshape, np_reshape64
from Utils import L2Norm, cv2_scale, np_reshape
```

Check GPU availability, using nvidia-smi

In [2]:

```python
# Since there are two GPUs on each pelican server, you can either select it as 0
os.environ["CUDA_VISIBLE_DEVICES"] = "1"
```

Load and visualize the data

In this section, we will

1. Define a PyTorch dataset

2. Define a PyTorch dataloader

3. Load data

4. Visualizaiton of the Training and Testing Data

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Define PyTorch dataset

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In [3]:

```python
class TripletPhotoTour(dset.PhotoTour):
    """
    From the PhotoTour Dataset it generates triplet samples
    note: a triplet is composed by a pair of matching images and one of
    different class.
    """
    def __init__(self, train=True, transform=None, batch_size = None,load_random
        super(TripletPhotoTour, self).__init__(*arg, **kw)
        self.transform = transform
        self.out_triplets = load_random_triplets
        self.train = train
        self.n_triplets = args.n_triplets
```

```python
        self.batch_size = batch_size
        self.triplets = self.generate_triplets(self.labels, self.n_triplets)

    @staticmethod
    def generate_triplets(labels, num_triplets):
        def create_indices(_labels):
            inds = dict()
            for idx, ind in enumerate(_labels):
                if ind not in inds:
                    inds[ind] = []
                inds[ind].append(idx)
            return inds

        triplets = []
        indices = create_indices(labels.numpy())
        unique_labels = np.unique(labels.numpy())
        n_classes = unique_labels.shape[0]
        # add only unique indices in batch
        already_idxs = set()

        for x in tqdm(range(num_triplets)):
            if len(already_idxs) >= args.batch_size:
                already_idxs = set()
            c1 = np.random.randint(0, n_classes)
            while c1 in already_idxs:
                c1 = np.random.randint(0, n_classes)
            already_idxs.add(c1)
            c2 = np.random.randint(0, n_classes)
            while c1 == c2:
                c2 = np.random.randint(0, n_classes)
            if len(indices[c1]) == 2:  # hack to speed up process
                n1, n2 = 0, 1
            else:
                n1 = np.random.randint(0, len(indices[c1]))
                n2 = np.random.randint(0, len(indices[c1]))
                while n1 == n2:
                    n2 = np.random.randint(0, len(indices[c1]))
            n3 = np.random.randint(0, len(indices[c2]))
            triplets.append([indices[c1][n1], indices[c1][n2], indices[c2][n3]])
        return torch.LongTensor(np.array(triplets))

    def __getitem__(self, index):
        def transform_img(img):
            if self.transform is not None:
                img = self.transform(img.numpy())
            return img

        t = self.triplets[index]
        a, p, n = self.data[t[0]], self.data[t[1]], self.data[t[2]]

        img_a = transform_img(a)
        img_p = transform_img(p)
        img_n = None
        if self.out_triplets:
            img_n = transform_img(n)
        # transform images if required
        if args.fliprot:
            do_flip = random.random() > 0.5
            do_rot = random.random() > 0.5
```

```
            if do_rot:
                img_a = img_a.permute(0,2,1)
                img_p = img_p.permute(0,2,1)
                if self.out_triplets:
                    img_n = img_n.permute(0,2,1)
            if do_flip:
                img_a = torch.from_numpy(deepcopy(img_a.numpy()[:,:,::-1]))
                img_p = torch.from_numpy(deepcopy(img_p.numpy()[:,:,::-1]))
                if self.out_triplets:
                    img_n = torch.from_numpy(deepcopy(img_n.numpy()[:,:,::-1]))
        return (img_a, img_p, img_n)


    def __len__(self):
        return self.triplets.size(0)
```

Define the dataloader

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In [4]:

```
def create_loaders(dataset_names, load_random_triplets = False, verbose=False):
    """
    For training, we use dataset 'liberty';
    For testing, we use dataset 'notredame' and 'yosemite'

    """
    test_dataset_names = copy(dataset_names)
    test_dataset_names.remove(args.training_set)

    kwargs = {'num_workers': args.num_workers, 'pin_memory': args.pin_memory} if

    np_reshape64 = lambda x: np.reshape(x, (64, 64, 1))
    transform_test = transforms.Compose([
            transforms.Lambda(np_reshape64),
            transforms.ToPILImage(),
            transforms.Resize(32),
            transforms.ToTensor()])
    transform_train = transforms.Compose([
            transforms.Lambda(np_reshape64),
            transforms.ToPILImage(),
            transforms.RandomRotation(5,PIL.Image.BILINEAR),
            transforms.RandomResizedCrop(32, scale = (0.9,1.0),ratio = (0.9,1.1)
            transforms.Resize(32),
            transforms.ToTensor()])
    transform = transforms.Compose([
            transforms.Lambda(cv2_scale),
            transforms.Lambda(np_reshape),
            transforms.ToTensor(),
            transforms.Normalize((args.mean_image,), (args.std_image,))])
    if not args.augmentation:
        transform_train = transform
        transform_test = transform
    train_loader = torch.utils.data.DataLoader(
            TripletPhotoTour(train=True,
                             load_random_triplets = load_random_triplets,
                             batch_size=args.batch_size,
                             root=args.dataroot,
```

```
                              name=args.training_set,
                              download=True,
                              transform=transform_train),
                              batch_size=args.batch_size,
                              shuffle=False, **kwargs)

    test_loaders = [{'name': name,
                     'dataloader': torch.utils.data.DataLoader(
             TripletPhotoTour(train=False,
                     batch_size=args.test_batch_size,
                     load_random_triplets = load_random_triplets,
                     root=args.dataroot,
                     name=name,
                     download=True,
                     transform=transform_test),
                        batch_size=args.test_batch_size,
                        shuffle=False, **kwargs)}
                    for name in test_dataset_names]

    return train_loader, test_loaders[0]
```

Load Data

Load the Photo Tourism dataset by PyTorch. Below line (function 'create_loader') will help you to download the dataset to your directory. The data dir and other configuration setings are specified in config_profile.py.

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In [5]:

```
dataset_names = ['liberty', 'notredame']

args.n_triplets = 100000    # for illustration, here we only use 5000 triples; i
args.epochs = 5             # in your experiment, set it as 60; For CNN1, it wil

train_loader, validation_loader = create_loaders(dataset_names, load_random_trip
```

```
/scratch/heli/miniconda3/envs/myenv/lib/python3.6/site-packages/torchvision/tran
sforms/transforms.py:1208: UserWarning: Argument interpolation should be of type
InterpolationMode instead of int. Please, use InterpolationMode enum.
  "Argument interpolation should be of type InterpolationMode instead of int. "
# Found cached data data/sets/liberty.pt
100%|██████████| 100000/100000 [00:01<00:00, 59961.54it/s]
# Found cached data data/sets/notredame.pt
100%|██████████| 100000/100000 [00:01<00:00, 60707.54it/s]
```

Visualizaiton of the Training and Testing Data

Below are some examples of patches in this dataset.

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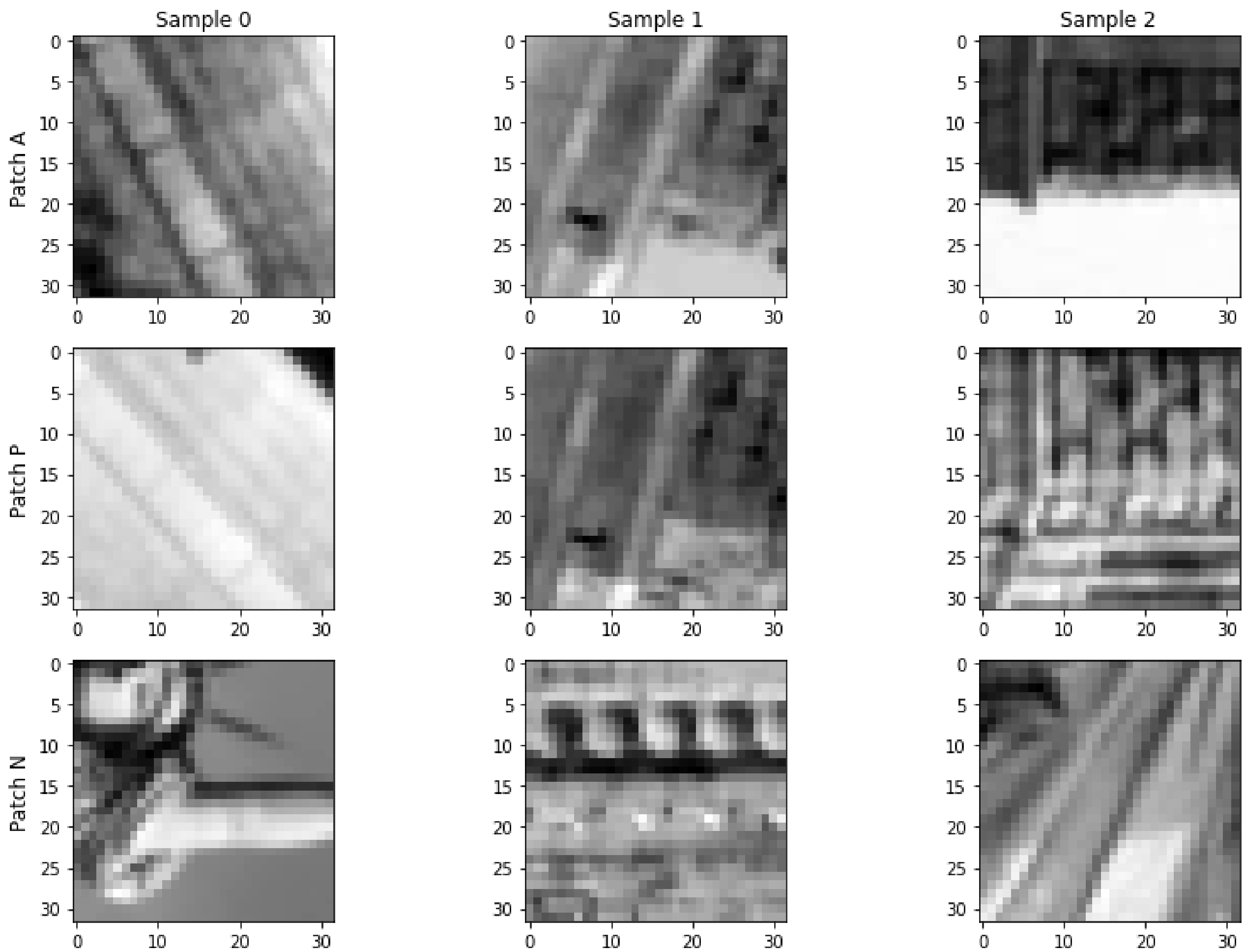
Data in Training

In the training phase, the input data is a batch of patch pairs: X = {(patch_a, patch_p)}, which represents the anchor patch and the positive patch, respectively.

In [6]:

```
def plot_examples(sample_batched, n_samples=3, labels=['A', 'P', 'N']):

    cols = ['Sample {}'.format(col) for col in range(0, n_samples)]
    rows = ['Patch {}'.format(row) for row in labels]
    nrow = len(rows)

    fig, axes = plt.subplots(nrows=len(rows), ncols=n_samples, figsize=(12, 8))
    for ax, col in zip(axes[0], cols):
        ax.set_title(col)

    for ax, row in zip(axes[:,0], rows):
        ax.set_ylabel(row, rotation=90, size='large')

#     for idx, img_tensor in enumerate(sample_batched):
    for idx in range(nrow):
        img_tensor = sample_batched[idx]
        for jdx in range(n_samples):
            img = img_tensor[jdx, 0]
            axes[idx][jdx].imshow(img, cmap='gray')

    fig.tight_layout()
    plt.show()

for i_batch, sample_batched in enumerate(train_loader):
    print("In training and validation, each data entry generates {} elements: an
    print("Each of them have the size of: {}".format(sample_batched[0].shape))
    print("Below we show in each column one triplet: top row shows patch a; mid

    if i_batch == 0:
        plot_examples(sample_batched, 3)
        break
```

```
In training and validation, each data entry generates 3 elements: anchor, positi
ve, and negative.
Each of them have the size of: torch.Size([1024, 1, 32, 32])
Below we show in each column one triplet: top row shows patch a; mid row shows p
atch p; and bot row shows patch n.
```



Build an exmaple deep network

In this section, we will:

1. [Build the deep network: DesNet]

2. [Setup optimization]

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Build the deep network: DesNet

The DesNet is a simple CNN network, which only contains two CNN blocks.

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In [7]:

```
# load network from the python file. You need to submit these .py files to TA
# from CNN1 import DesNet        # uncomment this line if you are using DesNet fr
# from CNN2 import DesNet       # uncomment this line if you are using DesNet fro
from CNN3 import DesNet      # uncomment this line if you are using DesNet from
```

```
model = DesNet()
# check model architecture

print(model)

if args.cuda:
    model.cuda()
```

```
DesNet(
  (features): Sequential(
    (0): Conv2d(1, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=F
alse)
    (1): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=False, track_running_st
ats=True)
    (2): ReLU()
    (3): Conv2d(32, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=
False)
    (4): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=False, track_running_st
ats=True)
    (5): ReLU()
    (6): Conv2d(32, 64, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=
False)
    (7): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=False, track_running_st
ats=True)
    (8): ReLU()
    (9): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=
False)
    (10): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=False, track_running_s
tats=True)
    (11): ReLU()
    (12): Conv2d(64, 128, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bia
s=False)
    (13): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=False, track_running_
stats=True)
    (14): ReLU()
    (15): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bi
as=False)
    (16): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=False, track_running_
stats=True)
    (17): ReLU()
    (18): Dropout(p=0.3, inplace=False)
    (19): Conv2d(128, 128, kernel_size=(8, 8), stride=(1, 1), bias=False)
    (20): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=False, track_running_
stats=True)
  )
)
```

Define optimization

We will use SGD, but you can change it to ADAM by modifying arg.lr in config_profile.py

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In [8]:

```
# define optimizer
def create_optimizer(model, new_lr):
    # setup optimizer
    if args.optimizer == 'sgd':
        optimizer = optim.SGD(model.parameters(), lr=new_lr,
                              momentum=0.9, dampening=0.9,
                              weight_decay=args.wd)
    else:
```

```
        raise Exception('Not supported optimizer: {0}'.format(args.optimizer))
    return optimizer
optimizer1 = create_optimizer(model.features, args.lr)
```

---

train the deep network

In this section, we will:

1. Define a training module

2. Define a testing module

3. Train and test on the validation data

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Define a training module

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In [9]:

```
def train(train_loader, model, optimizer, epoch, logger, load_triplets  = False)
    # switch to train mode
    model.train()
    pbar = tqdm(enumerate(train_loader))
    for batch_idx, data in pbar:
        data_a, data_p, data_n = data


        if args.cuda:
            data_a, data_p, data_n  = data_a.cuda(), data_p.cuda(), data_n.cuda(
            out_a = model(data_a)
            out_p = model(data_p)
            out_n = model(data_n)

        loss = loss_DesNet(out_a, out_p, out_n, anchor_swap = False, margin = 1.

        if args.decor:
            loss += CorrelationPenaltyLoss()(out_a)

        if args.gor:
            loss += args.alpha*global_orthogonal_regularization(out_a, out_n)

        optimizer.zero_grad()
        loss.backward()
        optimizer.step()
        adjust_learning_rate(optimizer)
        if batch_idx % args.log_interval == 0:
            pbar.set_description(
                'Train Epoch: {} [{}/{} ({:.0f}%)]\tLoss: {:.6f}'.format(
                    epoch, batch_idx * len(data_a), len(train_loader.dataset),
                           100. * batch_idx / len(train_loader),
                    loss.item()))
```

```
    if (args.enable_logging):
        logger.log_value('loss', loss.item()).step()

    try:
        os.stat('{}{}'.format(args.model_dir,suffix))
    except:
        os.makedirs('{}{}'.format(args.model_dir,suffix))

    torch.save({'epoch': epoch + 1, 'state_dict': model.state_dict()},
               '{}{}/checkpoint_{}.pth'.format(args.model_dir,suffix,epoch))


def adjust_learning_rate(optimizer):
    """Updates the learning rate given the learning rate decay.
    The routine has been implemented according to the original Lua SGD optimizer
    """
    for group in optimizer.param_groups:
        if 'step' not in group:
            group['step'] = 0.
        else:
            group['step'] += 1.
        group['lr'] = args.lr * (
        1.0 - float(group['step']) * float(args.batch_size) / (args.n_triplets *
    return
```

Define a testing module

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In [10]:

```
def test(test_loader, model, epoch, logger, logger_test_name):
    # switch to evaluate mode
    model.eval()

    losses = 0

    pbar = tqdm(enumerate(test_loader))

    for batch_idx, data in pbar:
        data_a, data_p, data_n = data


        if args.cuda:
            data_a, data_p, data_n  = data_a.cuda(), data_p.cuda(), data_n.cuda(
            out_a = model(data_a)
            out_p = model(data_p)
            out_n = model(data_n)

        loss = loss_DesNet(out_a, out_p, out_n, anchor_swap = False, margin = 1.
        losses = losses + loss.cpu().numpy()
    ave_loss = losses/len(test_loader)
    print('\33[91mLoss on validation: {:.8f}\n\33[0m'.format(ave_loss))

    if (args.enable_logging):
        logger.log_value(logger_test_name+' vloss', ave_loss)
    return
```

```
def ErrorRateAt95Recall(labels, scores):
    distances = 1.0 / (scores + 1e-8)
    recall_point = 0.95
    labels = labels[np.argsort(distances)]
    # Sliding threshold: get first index where recall >= recall_point.
    # This is the index where the number of elements with label==1 below the thr
    # 'recall_point' of the total number of elements with label==1.
    # (np.argmax returns the first occurrence of a '1' in a bool array).
    threshold_index = np.argmax(np.cumsum(labels) >= recall_point * np.sum(label

    FP = np.sum(labels[:threshold_index] == 0) # Below threshold (i.e., labelled
    TN = np.sum(labels[threshold_index:] == 0) # Above threshold (i.e., labelled
    return float(FP) / float(FP + TN)
```

Training

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In [11]:

```
start = args.start_epoch
end = start + args.epochs
logger, file_logger = None, None
triplet_flag = args.load_random_triplets
from Losses import loss_DesNet
TEST_ON_W1BS = True
LOG_DIR = args.log_dir
if(args.enable_logging):
    from Loggers import Logger, FileLogger
    logger = Logger(LOG_DIR)

suffix = '{}_{}_{}_as_fliprot'.format(args.experiment_name, args.training_set, a

res_fpr_liberty = torch.zeros(end-start,1)
res_fpr_notredame = torch.zeros(end-start, 1)
res_fpr_yosemite = torch.zeros(end-start, 1)

for epoch in range(start, end):

    # iterate over test loaders and test results
    train(train_loader, model, optimizer1, epoch, logger, triplet_flag)
    with torch.no_grad():
        test(validation_loader['dataloader'], model, epoch, logger, validation_l

    #randomize train loader batches
    train_loader, _ = create_loaders(dataset_names, load_random_triplets=triplet
```

```
Train Epoch: 0 [92160/100000 (92%)]     Loss: 0.407103: : 98it [00:51,  1.90it/
s]
98it [00:50,  1.93it/s]
/scratch/heli/miniconda3/envs/myenv/lib/python3.6/site-packages/torchvision/tran
sforms/transforms.py:1208: UserWarning: Argument interpolation should be of type
InterpolationMode instead of int. Please, use InterpolationMode enum.
  "Argument interpolation should be of type InterpolationMode instead of int. "
Loss on validation: 0.41001361

# Found cached data data/sets/liberty.pt
100%|██████████| 100000/100000 [00:01<00:00, 54349.16it/s]
# Found cached data data/sets/notredame.pt
100%|██████████| 100000/100000 [00:01<00:00, 57416.08it/s]
```

```
Train Epoch: 1 [92160/100000 (92%)]     Loss: 0.383148: : 98it [00:48,  2.02it/
s]
98it [00:49,  1.98it/s]
Loss on validation: 0.35937026

# Found cached data data/sets/liberty.pt
100%|██████████| 100000/100000 [00:01<00:00, 64396.35it/s]
# Found cached data data/sets/notredame.pt
100%|██████████| 100000/100000 [00:01<00:00, 60757.06it/s]
Train Epoch: 2 [92160/100000 (92%)]     Loss: 0.369258: : 98it [00:48,  2.04it/
s]
98it [00:50,  1.95it/s]
Loss on validation: 0.34224240

# Found cached data data/sets/liberty.pt
100%|██████████| 100000/100000 [00:01<00:00, 55745.16it/s]
# Found cached data data/sets/notredame.pt
100%|██████████| 100000/100000 [00:01<00:00, 60152.61it/s]
Train Epoch: 3 [92160/100000 (92%)]     Loss: 0.376284: : 98it [00:49,  1.98it/
s]
98it [00:49,  1.96it/s]
Loss on validation: 0.35268193

# Found cached data data/sets/liberty.pt
100%|██████████| 100000/100000 [00:01<00:00, 57026.34it/s]
# Found cached data data/sets/notredame.pt
100%|██████████| 100000/100000 [00:01<00:00, 61611.41it/s]
Train Epoch: 4 [92160/100000 (92%)]     Loss: 0.363426: : 98it [00:49,  1.96it/
s]
98it [00:50,  1.96it/s]
Loss on validation: 0.32906437

# Found cached data data/sets/liberty.pt
100%|██████████| 100000/100000 [00:01<00:00, 63733.27it/s]
# Found cached data data/sets/notredame.pt
100%|██████████| 100000/100000 [00:01<00:00, 60727.19it/s]
```

Select the best model, and save it as CNN.*pth;* can be 1, 2, or 3.

Generate deep features

In this section, we will use your trained network to generate deep features for each patch:

1. load weights

2. load patches

3. get deep features

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Load network weights

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In [12]:

```
trained_weight_path = "models/liberty_train/_liberty_min_as_fliprot/checkpoint_4
test_model = DesNet()
if args.cuda:
    test_model.cuda()
trained_weight = torch.load(trained_weight_path)['state_dict']
test_model.load_state_dict(trained_weight)
test_model.eval()
```

Out[12]:

```
DesNet(
  (features): Sequential(
    (0): Conv2d(1, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=F
alse)
    (1): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=False, track_running_st
ats=True)
    (2): ReLU()
    (3): Conv2d(32, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=
False)
    (4): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=False, track_running_st
ats=True)
    (5): ReLU()
    (6): Conv2d(32, 64, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=
False)
    (7): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=False, track_running_st
ats=True)
    (8): ReLU()
    (9): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=
False)
    (10): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=False, track_running_s
tats=True)
    (11): ReLU()
    (12): Conv2d(64, 128, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bia
s=False)
    (13): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=False, track_running_
stats=True)
    (14): ReLU()
    (15): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bi
as=False)
    (16): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=False, track_running_
stats=True)
    (17): ReLU()
    (18): Dropout(p=0.3, inplace=False)
    (19): Conv2d(128, 128, kernel_size=(8, 8), stride=(1, 1), bias=False)
    (20): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=False, track_running_
stats=True)
  )
)
```

Load raw patch files

Assume that the raw patch file is stored as patches.pth

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In [13]:

```
patches_dir = "patches.pth"            # these patches are from keypoint detecti
patches = torch.load(patches_dir)
print(patches.shape)                   # in your case, the shape should be [10, 2
num_imgs, num_pts, _, _, _ = patches.shape
```

```
patches = patches[0].view(-1, 1, 32, 32).cuda()
print(patches.shape)
```

```
torch.Size([1, 10, 1, 32, 32])
torch.Size([10, 1, 32, 32])
```

Get deep features

BackToSection

In [14]:

```
features = test_model(patches)
print(features.shape)
features = features.view(num_imgs, num_pts, 128).cpu().data
print(features.shape)                       # in your case, the shape should be [10,
```

```
torch.Size([10, 128])
torch.Size([1, 10, 128])
```

In [15]:

```
# save to file, with the name of *_features_CNN*.pth
features_dir = "features_CNN1.pth"
torch.save(features, features_dir)
```

In [ ]:

In [ ]:

In [ ]: