FinalProject

March 22, 2024

1 ECE 176: Introduction to Deep Learning & Applications

Final Project Option 2: Context Encoders: Feature Learning by Inpainting Author: ChaoYuan Lin Research Paper: https://arxiv.org/pdf/1604.07379.pdf Dataset: https://www.kaggle.com/datasets/arnaud58/landscape-pictures

1.0.1 Import packages

[1]:
```
import torch
import torch.nn as nn
from torch.utils.data import Dataset
import torchvision
import torchvision.transforms as transforms
import torchvision.datasets as dset
import torchvision.transforms as T
from torchvision.models import alexnet
import torch.nn.functional as F
import torch.optim as optim
from PIL import Image, ImageDraw
import numpy as np
import os
import matplotlib.pyplot as plt
import random
```

1.0.2 Building a Dataloader(code is from Assignment 6)

[2]:
```
class CMP_Facade_DB(Dataset):
    def __init__(self, data_list):
        self.data_list = data_list
        self.transform = transforms.Compose([
            transforms.Resize((227, 227)),
            transforms.ToTensor(),
            transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224,␣
↪0.225])
        ])

    def __len__(self):
```

```
        return len(self.data_list)


    def __getitem__(self, i):
        in_name = self.data_list[i]

        in_image = Image.open(in_name).convert('RGB')
        in_image_tensor = self.transform(in_image)

        mask = self.create_mask(in_image_tensor)

        whiteout_image_tensor = in_image_tensor * (1 - mask)

        return whiteout_image_tensor, in_image_tensor, mask


    def generate_mask(self, in_image):
        gray_image = in_image.convert('L')
        gray_np = np.array(gray_image)

        mask_np = gray_np > 240
        mask = torch.tensor(mask_np, dtype=torch.float32)
        mask = mask.unsqueeze(0)
        return mask


    def create_mask(self, image_tensor):
        mask = (image_tensor.mean(dim=0, keepdim=True) > 0.9).float()
        return mask


    def revert_input(self, img_tensor):
        img_tensor = img_tensor * torch.tensor([0.229, 0.224, 0.225]).view(3,␣
↪1, 1) + torch.tensor([0.485, 0.456, 0.406]).view(3, 1, 1)
        img_tensor = img_tensor.clamp(0, 1)
        img_np = img_tensor.permute(1, 2, 0).numpy()

        return img_np
```

1.0.3 Resize all the image to size 227 X 227

[3]:
```
img_names = [img_name for img_name in filter(lambda x: x.lower().endswith('.
↪jpg'), os.listdir("Dataset"))]



def resize_images(input_dir, output_dir, size):
```

```
    if not os.path.exists(output_dir):
        os.makedirs(output_dir)

        for img_name in img_names:
            img_path = os.path.join(input_dir, img_name)
            with Image.open(img_path) as img:
                img_resized = img.resize((size, size), Image.LANCZOS)
                output_path = os.path.join(output_dir, img_name)
                img_resized.save(output_path)

input_dir = "Dataset"
output_dir = "Dataset_resize"

resize_images(input_dir, output_dir, 227)
```

1.0.4 Image Visualization

[4]:
```
def visualize_5_images(directory):

    img_filenames = sorted(img_names)[:5]

    plt.figure(figsize=(20, 10))

    for i, img_filename in enumerate(img_filenames):

        img = Image.open(os.path.join(directory, img_filename))

        plt.subplot(1, 5, i+1)
        plt.imshow(img)
        plt.axis('off')
        plt.title(f'Image {i+1}')

    plt.show()

visualize_5_images(input_dir)
visualize_5_images(output_dir)
```

1.0.5 Process images into a list of the data that represent the images for model training(code is from Assignment 6)

[5]:
```python
def get_full_list(root_dir):
    data_list = []
    data_dir = os.path.join(root_dir)
    data_list += sorted(
        os.path.join(data_dir, img_name) for img_name in
            filter(
                lambda x: x[-4:] == '.jpg',
                os.listdir(data_dir)
            )
        )
    return data_list

TRAIN_SIZE = 1000
full_data_list = get_full_list(output_dir)

train_data_set = CMP_Facade_DB(full_data_list[: TRAIN_SIZE])

print("Training Set Size:", len(train_data_set))

train_loader = torch.utils.data.DataLoader(
    train_data_set, batch_size=1, shuffle=True
)

USE_GPU = True

dtype = torch.float32 # we will be using float throughout this tutorial

if USE_GPU and torch.cuda.is_available():
    device = torch.device('cuda')
else:
    device = torch.device('cpu')

# Constant to control how frequently we print train loss
print_every = 100
```

```
print('using device:', device)
```

```
Training Set Size: 1000
using device: cuda
```

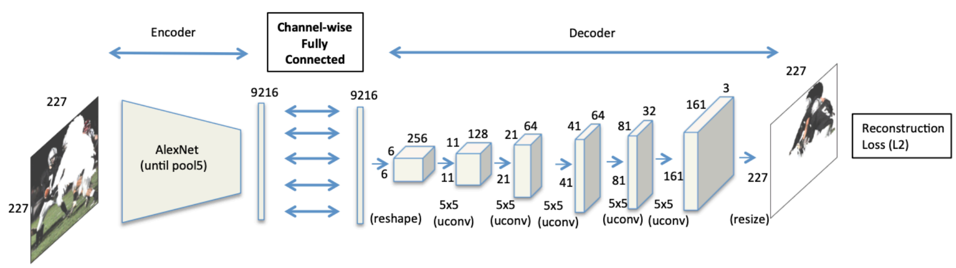
1.1 Context Encoder for image generation

1. Encoder: Given an input image of size 227×227, use the first five convolutional layers and the following pooling layer to compute an abstract $13 \times 13 \times 256$ dimensional feature representation.

2. Channel-wise fully-connected layer: a channel-wise fully-connected layer is used to connect the encoder features to the decoder.

3. Decoder: It generates pixels of the image using the encoder features from a channel-wise fully-connected layer between Encoder and Decoder.

4. Loss Function: Joint Loss Function = Reconstruction Loss + Adversarial Loss



(b) Context encoder trained with reconstruction loss for feature learning by filling in *arbitrary region dropouts* in the input.

Figure 9: Context encoder training architectures.

[6]:
```
class Discriminator(nn.Module):
    def __init__(self):
        super(Discriminator, self).__init__()
        self.main = nn.Sequential(
            nn.Conv2d(3, 64, 4, 2, 1, bias=False),
            nn.LeakyReLU(0.2, inplace=True),
            nn.Conv2d(64, 128, 4, 2, 1, bias=False),
            nn.BatchNorm2d(128),
            nn.LeakyReLU(0.2, inplace=True),
            nn.Conv2d(128, 256, 4, 2, 1, bias=False),
            nn.BatchNorm2d(256),
            nn.LeakyReLU(0.2, inplace=True),
            nn.Conv2d(256, 512, 4, 2, 1, bias=False),
            nn.BatchNorm2d(512),
            nn.LeakyReLU(0.2, inplace=True),
            nn.Conv2d(512, 1024, 4, 2, 1, bias=False),
            nn.BatchNorm2d(1024),
            nn.LeakyReLU(0.2, inplace=True),
```

```
            nn.Conv2d(1024, 1, 4, 1, 0, bias=False),
            nn.Flatten(),
            nn.Linear(4*4, 1),
            nn.Sigmoid()
        )

    def forward(self, input):
        return self.main(input)


# Context encoder using AlexNet until pool5
class ContextEncoder(nn.Module):
    def __init__(self):
        super(ContextEncoder, self).__init__()
        original_alexnet = alexnet(pretrained=True)
        self.encoder = nn.Sequential(*list(original_alexnet.features.
 ↪children())[:12])
        self.channelwise_fc = ChannelWiseFC(256, 13*13, 13*13)

    def forward(self, x):
        x = self.encoder(x)
        x = self.channelwise_fc(x)
        return x


# Channel Wise Fully Connected layer
class ChannelWiseFC(nn.Module):
    def __init__(self, num_channels, input_size, output_size):
        super(ChannelWiseFC, self).__init__()
        self.num_channels = num_channels
        self.fcs = nn.ModuleList([nn.Linear(input_size, output_size) for _ in␣
 ↪range(num_channels)])
        self.dropout = nn.Dropout2d(0.5)

    def forward(self, x):
        N, C, H, W = x.size()
        x_flat = x.view(N, C, -1)
        outputs = [self.fcs[i](x_flat[:, i, :]) for i in range(C)]
        output = torch.stack(outputs, dim=1).view(N, C, H, W)
        output = self.dropout(output)
        return output


# Decoder layer
class Decoder(nn.Module):
    def __init__(self):
        super(Decoder, self).__init__()
```

```
        self.decoder = nn.Sequential(
            nn.ConvTranspose2d(256, 256, kernel_size=5, stride=1),
            nn.ReLU(True),
            nn.ConvTranspose2d(256, 128, kernel_size=5, stride=1),
            nn.ReLU(True),
            nn.ConvTranspose2d(128, 64, kernel_size=5, stride=1),
            nn.ReLU(True),
            nn.ConvTranspose2d(64, 64, kernel_size=5, stride=1),
            nn.ReLU(True),
            nn.ConvTranspose2d(64, 32, kernel_size=5, stride=1),
            nn.ReLU(True),
            nn.ConvTranspose2d(32, 3, kernel_size=5, stride=1),
            nn.ReLU(True)
        )

    def forward(self, x):
        x = self.decoder(x)
        x = F.interpolate(x, size=(227, 227), mode='bilinear',␣
 ↪align_corners=False)
        return x


# Model for image inpainting
class ImageInpaintingModel(nn.Module):
    def __init__(self):
        super(ImageInpaintingModel, self).__init__()
        self.context_encoder = ContextEncoder()
        self.decoder = Decoder()
        self.loss_fn = nn.MSELoss()

    def forward(self, x, target, mask, discriminator=None):
        encoded_features = self.context_encoder(x * (1 - mask))
        decoded_image = self.decoder(encoded_features)
        inpainted_image = decoded_image * mask + x * (1 - mask)

        loss = self.loss_fn(inpainted_image * mask, target * mask)
        adversarial_loss = 0

        if discriminator:
            fake_preds = discriminator(inpainted_image)
            real_labels = torch.ones(fake_preds.size(), device=x.device)
            adversarial_loss = F.binary_cross_entropy(fake_preds, real_labels)

        return inpainted_image, loss, adversarial_loss


# Train Function
```

```python
def train_model(generator, discriminator, g_optimizer, d_optimizer, data_loader, num_epochs, device):
    generator.to(device)
    discriminator.to(device)
    adversarial_loss = torch.nn.BCELoss()

    for epoch in range(num_epochs):
        for batch_idx, (data, target, mask) in enumerate(data_loader):
            real_labels = torch.ones(data.size(0), 1, device=device)
            fake_labels = torch.zeros(data.size(0), 1, device=device)

            data, target, mask = data.to(device), target.to(device), mask.to(device)

            # Train Discriminator
            d_optimizer.zero_grad()
            real_preds = discriminator(target)
            real_loss = adversarial_loss(real_preds, real_labels)

            with torch.no_grad():
                inpainted_image, _, _ = generator(data, target, mask)
            fake_preds = discriminator(inpainted_image)
            fake_loss = adversarial_loss(fake_preds, fake_labels)

            d_loss = real_loss + fake_loss
            d_loss.backward()
            d_optimizer.step()

            # Train Generator
            g_optimizer.zero_grad()
            _, g_loss, g_adv_loss = generator(data, target, mask, discriminator)
            g_total_loss = g_loss + g_adv_loss
            g_total_loss.backward()
            g_optimizer.step()

            if (batch_idx + 1) % 1000 == 0:
                print(f'Epoch [{epoch+1}/{num_epochs}], Step [{batch_idx+1}/{len(data_loader)}], '
                      f'Discriminator Loss: {d_loss.item():.4f}, '
                      f'Generator Loss: {g_loss.item():.4f}, '
                      f'Adversarial Loss: {g_adv_loss.item():.4f}')


model = ImageInpaintingModel()
discriminator = Discriminator()
g_optimizer = optim.Adam(model.parameters(), lr=1e-5)
d_optimizer = optim.Adam(discriminator.parameters(), lr=1e-5)
```

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

train_model(model, discriminator, g_optimizer, d_optimizer, train_loader,
 ↪num_epochs=30, device=device)
```

```
/opt/conda/lib/python3.9/site-packages/torchvision/models/_utils.py:208:
UserWarning: The parameter 'pretrained' is deprecated since 0.13 and may be
removed in the future, please use 'weights' instead.
  warnings.warn(
/opt/conda/lib/python3.9/site-packages/torchvision/models/_utils.py:223:
UserWarning: Arguments other than a weight enum or `None` for 'weights' are
deprecated since 0.13 and may be removed in the future. The current behavior is
equivalent to passing `weights=AlexNet_Weights.IMAGENET1K_V1`. You can also use
`weights=AlexNet_Weights.DEFAULT` to get the most up-to-date weights.
  warnings.warn(msg)
```

```
Epoch [1/30], Step [1000/1000], Discriminator Loss: 0.5612, Generator Loss:
0.8222, Adversarial Loss: 1.0712
Epoch [2/30], Step [1000/1000], Discriminator Loss: 1.2217, Generator Loss:
0.6964, Adversarial Loss: 0.5264
Epoch [3/30], Step [1000/1000], Discriminator Loss: 0.1062, Generator Loss:
1.1305, Adversarial Loss: 2.6079
Epoch [4/30], Step [1000/1000], Discriminator Loss: 2.2261, Generator Loss:
0.0023, Adversarial Loss: 0.1596
Epoch [5/30], Step [1000/1000], Discriminator Loss: 0.9448, Generator Loss:
0.1240, Adversarial Loss: 2.2679
Epoch [6/30], Step [1000/1000], Discriminator Loss: 1.2413, Generator Loss:
0.0498, Adversarial Loss: 0.5463
Epoch [7/30], Step [1000/1000], Discriminator Loss: 1.0759, Generator Loss:
0.0434, Adversarial Loss: 0.9242
Epoch [8/30], Step [1000/1000], Discriminator Loss: 0.7757, Generator Loss:
0.4957, Adversarial Loss: 1.2635
Epoch [9/30], Step [1000/1000], Discriminator Loss: 1.4185, Generator Loss:
0.0157, Adversarial Loss: 1.3678
Epoch [10/30], Step [1000/1000], Discriminator Loss: 0.1897, Generator Loss:
0.4507, Adversarial Loss: 2.2311
Epoch [11/30], Step [1000/1000], Discriminator Loss: 0.5877, Generator Loss:
0.0292, Adversarial Loss: 2.2611
Epoch [12/30], Step [1000/1000], Discriminator Loss: 0.6651, Generator Loss:
0.0946, Adversarial Loss: 1.2554
Epoch [13/30], Step [1000/1000], Discriminator Loss: 0.3911, Generator Loss:
0.0618, Adversarial Loss: 1.2874
Epoch [14/30], Step [1000/1000], Discriminator Loss: 0.6543, Generator Loss:
0.0371, Adversarial Loss: 1.0863
Epoch [15/30], Step [1000/1000], Discriminator Loss: 0.3835, Generator Loss:
0.2501, Adversarial Loss: 1.9456
Epoch [16/30], Step [1000/1000], Discriminator Loss: 1.1999, Generator Loss:
0.1246, Adversarial Loss: 3.2886
```

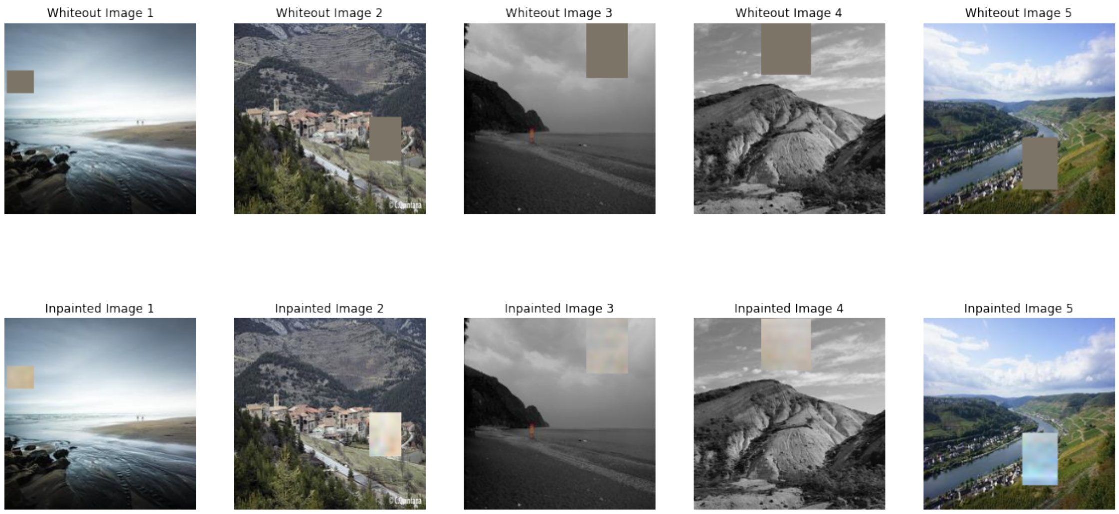
```
Epoch [17/30], Step [1000/1000], Discriminator Loss: 0.6327, Generator Loss:
0.0701, Adversarial Loss: 1.5948
Epoch [18/30], Step [1000/1000], Discriminator Loss: 0.4952, Generator Loss:
0.0827, Adversarial Loss: 1.7154
Epoch [19/30], Step [1000/1000], Discriminator Loss: 0.7964, Generator Loss:
0.1269, Adversarial Loss: 1.7339
Epoch [20/30], Step [1000/1000], Discriminator Loss: 2.5629, Generator Loss:
0.0796, Adversarial Loss: 2.8465
Epoch [21/30], Step [1000/1000], Discriminator Loss: 0.5560, Generator Loss:
0.0556, Adversarial Loss: 1.4693
Epoch [22/30], Step [1000/1000], Discriminator Loss: 0.3882, Generator Loss:
0.0996, Adversarial Loss: 2.1696
Epoch [23/30], Step [1000/1000], Discriminator Loss: 0.4012, Generator Loss:
0.1971, Adversarial Loss: 1.2118
Epoch [24/30], Step [1000/1000], Discriminator Loss: 0.1414, Generator Loss:
0.2189, Adversarial Loss: 4.4141
Epoch [25/30], Step [1000/1000], Discriminator Loss: 0.5093, Generator Loss:
0.0900, Adversarial Loss: 3.7129
Epoch [26/30], Step [1000/1000], Discriminator Loss: 0.0944, Generator Loss:
0.0995, Adversarial Loss: 2.6872
Epoch [27/30], Step [1000/1000], Discriminator Loss: 0.6387, Generator Loss:
0.0492, Adversarial Loss: 3.1747
Epoch [28/30], Step [1000/1000], Discriminator Loss: 0.3571, Generator Loss:
0.0121, Adversarial Loss: 1.4363
Epoch [29/30], Step [1000/1000], Discriminator Loss: 0.2320, Generator Loss:
0.0455, Adversarial Loss: 2.1805
Epoch [30/30], Step [1000/1000], Discriminator Loss: 2.6020, Generator Loss:
0.0001, Adversarial Loss: 0.1591
```

1.1.1 Compare the result with whiteout images and inpainting images

[44]:
```
def load_and_preprocess_image(image_path):
    transform = transforms.Compose([
        transforms.Resize((227, 227)),
        transforms.ToTensor(),
        transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.
↪225])
    ])
    image = Image.open(image_path).convert('RGB')
    return transform(image).unsqueeze(0)


def unnormalize(image_tensor):
    mean = torch.tensor([0.485, 0.456, 0.406]).view(1, 3, 1, 1)
    std = torch.tensor([0.229, 0.224, 0.225]).view(1, 3, 1, 1)
    if image_tensor.is_cuda:
        mean = mean.to(image_tensor.device)
```

```
        std = std.to(image_tensor.device)
    image_tensor = image_tensor * std + mean
    image_tensor = image_tensor.clamp(0, 1)
    return image_tensor


def create_white_mask(image_tensor, mask_height_range=(0.1, 0.3), mask_width_range=(0.1, 0.3)):

    if image_tensor.dim() == 4:
        _, _, H, W = image_tensor.size()
    else:
        _, H, W = image_tensor.size()


    mask_height = torch.randint(int(H * mask_height_range[0]), int(H * mask_height_range[1]), (1,)).item()
    mask_width = torch.randint(int(W * mask_width_range[0]), int(W * mask_width_range[1]), (1,)).item()


    x_top_left = torch.randint(0, W - mask_width, (1,)).item()
    y_top_left = torch.randint(0, H - mask_height, (1,)).item()


    mask = torch.zeros((H, W))


    mask[y_top_left:y_top_left+mask_height, x_top_left:x_top_left+mask_width] = 1


    mask = mask.unsqueeze(0)
    if image_tensor.dim() == 4:
        mask = mask.unsqueeze(0)

    return mask



def visualize_5_images(directory, model, device):
    img_filenames = sorted(os.listdir(directory))[:5]

    plt.figure(figsize=(20, 10))

    for i, img_filename in enumerate(img_filenames):
        img_path = os.path.join(directory, img_filename)
```

```
        image_tensor = load_and_preprocess_image(img_path)
        mask = create_white_mask(image_tensor)


        image_tensor, mask = image_tensor.to(device), mask.to(device)


        model.eval()
        with torch.no_grad():

            inpainted_tensor, _, _ = model(image_tensor, image_tensor, mask)


        whiteout_image = unnormalize(image_tensor * (1 - mask)).cpu().
↪squeeze(0).permute(1, 2, 0).numpy()
        inpainted_image = unnormalize(inpainted_tensor).cpu().squeeze(0).
↪permute(1, 2, 0).numpy()


        plt.subplot(2, 5, i+1)
        plt.imshow(whiteout_image)
        plt.axis('off')
        plt.title(f'Whiteout Image {i+1}')

        plt.subplot(2, 5, i+6)
        plt.imshow(inpainted_image)
        plt.axis('off')
        plt.title(f'Inpainted Image {i+1}')

    plt.show()


visualize_5_images(output_dir, model, device)
```


Whiteout Image 1
Whiteout Image 2
Whiteout Image 3
Whiteout Image 4
Whiteout Image 5
Inpainted Image 1
Inpainted Image 2
Inpainted Image 3
Inpainted Image 4
Inpainted Image 5

[ ]:

```

```