Visual Recognitionusing Deep Learning

Lab4 report

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My github

1. https://github.com/Potato-TW/visual_dl/tree/main

Introduction

In this lab, we are going to implement PromptIR to restore all-in-one blind images.
We use rainy and snowy masks on training data.
After 10 hours (400 epochs) training on 5070ti, we can get 30.23 PSNR on testing data.

Method

Dataset

For training data, we randomly pick out 20% of all data as validation data.

```
class HW4_REALSE_DATASET(Dataset):
    def get_img_list(self, img_dir: Path):
        a = sorted(img_dir.glob('*.png'))

        if self.shuffle_list is None:
            return a

        if self.mode == 'train':
            return [img for img, keep in zip(a, self.shuffle_list) if keep]
        elif self.mode == 'valid':
            return [img for img, keep in zip(a, self.shuffle_list) if not
keep]
        else:
            return a


class Training():
    def generate_shuffle_list(self):
        random.seed(self.seed)

        total = 3200
        true_count = int(total * self.train_ratio)  # 2560
        false_count = total - true_count  # 640

        # 創建初始列表
        bool_list = [True] * true_count + [False] * false_count

        # 隨機打亂順序
```

```
        random.shuffle(bool_list)

        return bool_list
```

We crop $64 * 64$ randomly on training data, and leave validation and testing data unchanging.

```
class HW4_REALSE_DATASET(Dataset):
    def get_trfm(self):
        if self.mode in ['train']:
            tfrm = T.Compose([
                T.RandomCrop(self.output_img_size),
                # T.RandomHorizontalFlip(p=0.5),
                # T.RandomVerticalFlip(p=0.5),
                # T.RandomRotation(30),
                # T.ColorJitter(brightness=0.2, contrast=0.5,
saturation=0.3, hue=0.1),
                T.ToTensor(),
                # T.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229,
0.224, 0.225])
            ])
        elif self.mode in ['valid']:
            tfrm = T.Compose([
                # T.Resize((self.output_img_size, self.output_img_size)),
                T.ToTensor(),
                # T.Normalize(mean = [0.485, 0.456, 0.406],
                #             std = [0.229, 0.224, 0.225])
            ])
        else:
            tfrm = T.Compose([
                # T.Resize((self.output_img_size, self.output_img_size)),
                T.ToTensor(),
                # T.Normalize(mean = [0.485, 0.456, 0.406],
                #             std = [0.229, 0.224, 0.225])
            ])

        return tfrm
```

And ensure input images and target images utilze the same tranforms in training process.

```
class HW4_REALSE_DATASET(Dataset):
    def __getitem__(self, idx):
        seed = np.random.randint(2147483647)
        if self.mode in ['train', 'valid']:
            degraded_img_path = self.degraded_imgs[idx]
            type_, num_ = degraded_img_path.stem.split('-')

            clean_img_path = self.img_dir_path / 'clean' / f'{type_}_clean-
{num_}.png'
            if clean_img_path not in self.clean_imgs:
```

```
                raise ValueError('Not found clean image')

            degraded_img = Image.open(degraded_img_path).convert('RGB')
            clean_img = Image.open(clean_img_path).convert('RGB')

            if self.transform:
                random.seed(seed)
                torch.manual_seed(seed)
                degraded_img = self.transform(degraded_img)
                random.seed(seed)
                torch.manual_seed(seed)
                clean_img = self.transform(clean_img)

            return degraded_img, clean_img
        else:
            degraded_img_path = self.degraded_imgs[idx]

            degraded_img = Image.open(degraded_img_path).convert('RGB')
            if self.transform:
                degraded_img = self.transform(degraded_img)

            img_name = degraded_img_path.stem
            return img_name, degraded_img
```

Model

For model structure, we refer to paper of PromptIR without any change.

Training

In training process, we refer to settings in paper.
Use AdamW, cosine annealing LR scheduler, and L1 loss.
Hyperparameter is mentioned later.

```
class Training():
    def __init__(self, args):
        self.model = PromptIR(decoder=True).to(self.device)

        self.optimizer = torch.optim.AdamW(self.model.parameters(),
lr=self.lr)
        self.lr_scheduler =
torch.optim.lr_scheduler.CosineAnnealingLR(optimizer=self.optimizer,

T_max=len(self.train_loader) * self.epochs,

last_epoch=-1,

eta_min=1e-9)

        self.loss_function = nn.L1Loss()
```

For every training epoch, similar to labs before, we record training loss and evaluation loss on Wandb.

```python
class Training():
    @torch.no_grad()
    def eval(self, dataloader=None):
        self.model.eval()

        eval_loss = []
        progress_bar = tqdm(dataloader, desc='Eval', ncols=100)
        for img, gt in progress_bar:
            img, gt = img.to(self.device), gt.to(self.device)

            output = self.model(img)

            loss = self.loss_function(output, gt)

            eval_loss.append(loss.item())
            progress_bar.set_postfix({"loss": np.mean(eval_loss)})
            progress_bar.update()

        return np.mean(eval_loss)

    def train_one_epoch(self):
        self.model.train()

        train_loss = []
        progress_bar = tqdm(self.train_loader, desc=f'Training', ncols=100)
        for i, (img, gt) in enumerate(progress_bar):
            img, gt = img.to(self.device), gt.to(self.device)

            output = self.model(img)

            loss = self.loss_function(output, gt)

            self.optimizer.zero_grad()
            loss.backward()
            self.optimizer.step()
            self.lr_scheduler.step()

            train_loss.append(loss.item())
            progress_bar.set_postfix({'loss': np.mean(train_loss)})
            progress_bar.update()

        return np.mean(train_loss)

    def run(self):
        for epoch in tqdm(range(self.epochs), desc="Epochs", ncols=100):
            loss = self.train_one_epoch()
            wandb.log({
                "Epoch": epoch,
                "Train loss": loss,
            })
```

```
            eval_loss = self.eval(dataloader=self.val_loader)
            wandb.log({
                "Epoch": epoch,
                "Eval loss": eval_loss,
            })

            if epoch % self.save_frequency == 0:
                self.save_ckpt(epoch)

        self.save_ckpt(-1)
```

Inference

After training, we load checkpoint and feed testing images.
And directly transform tensor to PIL images and save them.

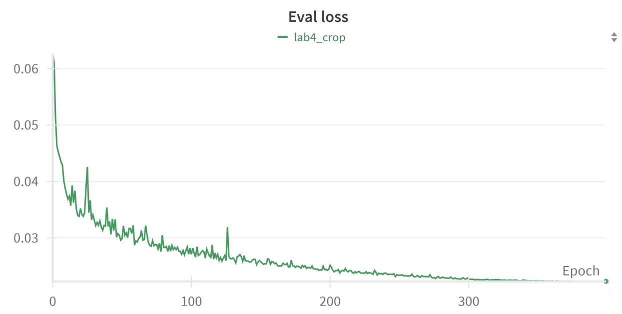
```
class Tester():
    def save_img(self, img_name, output: torch.tensor):
        img_name = img_name[0]
        output = output.detach().cpu()[0]
        output = output.numpy()

        ar = np.clip(output * 255, 0, 255).astype(np.uint8).transpose(1, 2,
0)

        from PIL import Image
        pil_image = Image.fromarray(ar)

        pil_image.save(f"{self.save_img_dir}/{img_name}.png")


    @torch.no_grad()
    def test(self):
        self.model.eval()

        # eval_loss = []
        progress_bar = tqdm(self.test_loader, desc='Test', ncols=100)
        for img_name, img in progress_bar:
            img = img.to(self.device)

            output = self.model(img)

            self.save_img(img_name, output)

            progress_bar.update()
```

Hyperparameter

HP	Value
lr	0.0004
batch size	10
Crop size	$64 * 64$

Results

We can see model converges starting from about 300^{th} epoch.

Training loss	Evaluation loss
	

References

[1] Potlapalli, V., Zamir, S. W., Khan, S., & Khan, F. S. (2023, June 22). ProMpTIR: Prompting for All-in-One Blind Image Restoration. arXiv.org. https://arxiv.org/abs/2306.13090

Additional experiments

Different dataset tranform

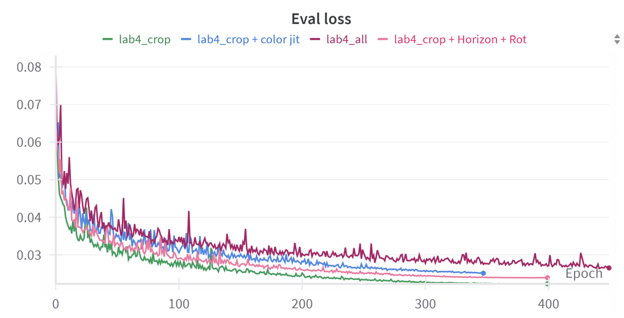
All the transform options are mentioned in Dataset part above.
Out of my expectation, we found out using original images produces the best results.

Term	Explanation
Crop	Random crop image size of $64 * 64$
Color jit	Color jitter enhances saturation, bright, hue
Rot	Random rotation within 30 degree
Horizon	Random horizon flip
Vertical	Random vertical flip
All	Crop + jit + Rot + Horizon + Vertical

Vertical flip and jitter causes worse results.

Training loss	Evaluation loss

Training loss	Evaluation loss



In addition, normalization may break the images, since normalization results in much worse outcome. Leave all the input images the same is the best methods.

Training loss	Evaluation loss