Visual Recognitionusing Deep Learning

Lab2 report

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My github

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

Introduction

In this lab, we implement Fast RCNN with different backbones to recognize digits in images.
We introduce Mobile V2 and V3, ResNet50 with several training strategies.
Finally, generate labels and boxes as json file, and also recognize the while number in images.

Method

1. Loading data
   For dataset, we extract image ID, bbox, and category ID as the dictionary $target$, and collect images to become one batch.

```
class DigitDataset(Dataset):
    def __init__(self, root, annotation_path, transforms=None):
        with open(annotation_path) as f:
            self.coco_data = json.load(f)
        self.root = root
        self.transforms = transforms
        self.image_info = {i['id']: i for i in
self.coco_data['images']}
        self.annotations = self._load_annotations()

    def _load_annotations(self):
        ann_dict = {}
        for ann in self.coco_data['annotations']:
            image_id = ann['image_id']
            if image_id not in ann_dict:
                ann_dict[image_id] = []
            ann_dict[image_id].append({
                'bbox': ann['bbox'],
                'category_id': ann['category_id'],
            })
        return ann_dict
```

   While loading each image and its annotation, we apply resizing transformation defined by ourselves. The transformation only makes images and their corresponding boxes resize to 224, and also turn boxes formattion from xywh to xyxy fed into model.

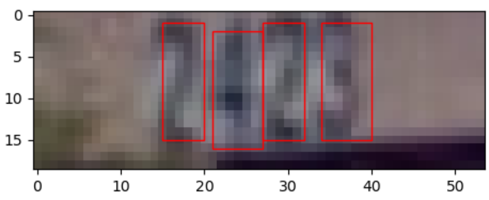
At final, images need normalized and turned into tensor data type, which is implemented by self.transforms.

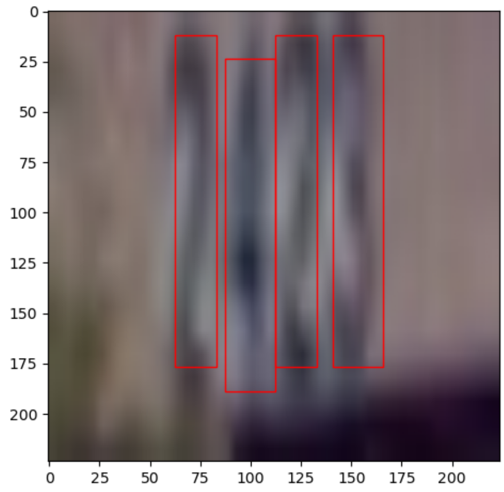
```
    def __getitem__(self, idx):
        image_id = list(self.image_info.keys())[idx]
        img_path = f"{self.root}/{self.image_info[image_id]
['file_name']}"
        image = Image.open(img_path)


        target = {}
        target['boxes'] = torch.as_tensor(
            [ann['bbox'] for ann in self.annotations[image_id]],
            dtype=torch.float32
        )
        target['labels'] = torch.as_tensor(
            [ann['category_id'] for ann in
self.annotations[image_id]],
            dtype=torch.int64
        )
        target['image_id'] = torch.tensor([image_id])

        image, target = ResizeWithBox((224, 224))(image, target)
# If need to validate transformation, comment this row

        if self.transforms:
            image = self.transforms(image)

        return image, target


    def __len__(self):
        return len(self.image_info)
```

This is how to resize image and targets (boxes).

```
class ResizeWithBox(object):
    def __init__(self, size=(224, 224)):
        self.size = size  # (height, width)

    def __call__(self, image, target):
        if isinstance(image, Image.Image):
            orig_w, orig_h = image.size
        else:
            orig_h, orig_w = image.shape[1], image.shape[2]

        # print(f'Original size: {orig_w}x{orig_h}')

        scale_w = self.size[1] / orig_w
        scale_h = self.size[0] / orig_h
```

```
        resized_image = F.resize(image, self.size)

        # print(f'Resized size: {resized_image}')

        # (COCO: [x, y, w, h])
        boxes = target['boxes'].clone()

        # print(f'Original boxes: {boxes}')
        if boxes.numel() > 0:
            boxes[:, 0] *= scale_w  # x
            boxes[:, 1] *= scale_h  # y
            boxes[:, 2] *= scale_w  # w
            boxes[:, 3] *= scale_h  # h

        # print(f'Resized boxes: {boxes}')

        from torchvision.ops import box_convert
        boxes = box_convert(boxes, in_fmt='xywh', out_fmt='xyxy')

        target['boxes'] = boxes
        return resized_image, target
```





2. Training
   For model, we use MobileNet v2 as model backbone, and use default settings of anchor, rpn provided by pyTorch.
   In dataset, we have 10 classes of digits to recognize, so thus we have to reserve one more class as background, totally 11 classes.

```
def build_model(num_classes=11):
    weights = torchvision.models.MobileNet_V2_Weights.DEFAULT
    backbone =
torchvision.models.mobilenet_v2(weights=weights).features
```

```
    backbone.out_channels = 1280

    anchor_generator = AnchorGenerator(
        sizes=((32, 64, 128, 256, 512),),
        aspect_ratios=((0.5, 1.0, 2.0),) * 5
    )

    model = FasterRCNN(
        backbone,
        num_classes=num_classes,
        rpn_anchor_generator=anchor_generator,
        box_score_thresh=0.8
    )

    return model
```

For hyperparameters:

1. Optimizer: AdamW
2. Scheduler: Cosine Annealing LR
3. Epoch: 50
4. Learning rate: 1e-3
5. Weight decay: 1e-4

```
def first_version_v2(model):
    optimizer = optim.AdamW(
        model.parameters(),
        lr=1e-3,
        weight_decay=0.0001,
        eps=1e-08
    )

    lr_scheduler = CosineAnnealingLR(
        optimizer,
        T_max=epochs*0.6,
        eta_min=1e-6
    )

    return optimizer, lr_scheduler
```

For each epoch

1. Extract batches from loader
2. Feed images, targets (boxes) in model to train
3. Update loss, optimizer, and scheduler
4. Record evaluate metrics

```
train_loss_list = []
for epoch in tqdm(range(epochs), desc="Epochs"):
    model.train()

    train_loss_iter = []
    bar = tqdm(train_data_loader, desc="Training", leave=False)
    for images, targets in train_data_loader:
        images = [img.to(device) for img in images]
        targets = [{k: v.to(device) for k,v in t.items()} for t in 
targets]

        loss_dict = model(images, targets)
        losses = sum(loss for loss in loss_dict.values())

        optimizer.zero_grad()
        losses.backward()
        optimizer.step()
        lr_scheduler.step()

        train_loss_iter.append(losses.detach().cpu().item())

        bar.set_postfix(loss=losses.detach().cpu().item() / 
len(train_data_loader))
        bar.update()

    mean_epoch_train_loss = np.mean(train_loss_iter)
    train_loss_list.append(mean_epoch_train_loss)
    bar.close()


    metrics['train_loss'].append(mean_epoch_train_loss)


    val_metrics = evaluate(model, val_data_loader, device)
    metrics['val_accuracy'].append(val_metrics['accuracy'])
    metrics['val_recall'].append(val_metrics['recall'])


    current_map = (val_metrics['accuracy'] + val_metrics['recall']) / 
2
    if current_map > metrics['best_map']:
        torch.save(model.state_dict(), f"ckpt/best_model.pth")
        metrics['best_map'] = current_map


    print(f"Epoch {epoch+1}/{epochs} | "
          f"Train Loss: {metrics['train_loss'][-1]:.4f} | "
          f"Val Acc: {val_metrics['accuracy']:.2%} | "
          f"Val Recall: {val_metrics['recall']:.2%}")


    torch.save(model.state_dict(), f"ckpt/model_epoch_{epoch}.pth")
```

3. For evaluation, this implementation features a dual-matching mechanism based on IoU threshold:

    1. IoU-based matching with -1 flag for missed detections
    2. Computes accuracy (matched samples) and recall (all truths)
    3. Returns {accuracy, recall, counts} with auto null-handling

```
def evaluate(model, data_loader, device, iou_threshold=0.5):
    model.eval()
    results = defaultdict(list)

    with torch.no_grad():
        for images, targets in tqdm(data_loader, desc="Evaluating", 
leave=False):
            images = [img.to(device) for img in images]

            # with autocast(device_type='cuda' if 'cuda' in device 
else 'cpu'):
            predictions = model(images)

            for pred, true in zip(predictions, targets):
                true_boxes = true['boxes'].to(device)
                true_labels = true['labels'].to(device)

                iou_matrix = box_iou(pred['boxes'], true_boxes)

                matched_true = set()
                for det_idx in range(len(pred['boxes'])):
                    if len(iou_matrix[det_idx]) == 0:
                        continue

                    best_true_idx = iou_matrix[det_idx].argmax()
                    if iou_matrix[det_idx][best_true_idx] >= 
iou_threshold:
                        if best_true_idx not in matched_true:

results['pred_labels'].append(pred['labels'][det_idx].item())

results['true_labels'].append(true_labels[best_true_idx].item())
                            matched_true.add(best_true_idx)

                for true_idx in range(len(true_boxes)):
                    if true_idx not in matched_true:
                        results['pred_labels'].append(-1)

results['true_labels'].append(true_labels[true_idx].item())

    pred_labels = np.array(results['pred_labels'])
    true_labels = np.array(results['true_labels'])

    valid_mask = pred_labels != -1
    accuracy = np.mean(pred_labels[valid_mask] == 
true_labels[valid_mask]) if any(valid_mask) else 0
```

```
    recall = len(matched_true) / len(true_labels) if len(true_labels)
> 0 else 0

    return {
        'accuracy': accuracy,
        'recall': recall,
        'matched_samples': len(matched_true),
        'total_samples': len(true_labels)
    }
```

4. For testing data, it's almost similar to how to load training data.
   The only different thing is testing data has no annotation to load in, which we can just use torch built-in compose to resize images.

```
class TestDataset(Dataset):
    def __init__(self, root, annotation_path=None, transforms=None):
        self.root = root
        self.transforms = transforms

        self.image_info = self._scan_directory()

    def _scan_directory(self):
        import re

        image_files = [f for f in os.listdir(self.root)
                       if f.lower().endswith(('png', 'jpg', 'jpeg'))]

        image_info = {}
        for f in sorted(image_files):
            match = re.search(r'^(\d+)', f)
            if match:
                img_id = int(match.group(1))
                image_info[img_id] = {'id': img_id, 'file_name': f}


        return image_info

    def __getitem__(self, idx):
        image_id = list(self.image_info.keys())[idx]
        img_path = f"{self.root}/{self.image_info[image_id]
['file_name']}"

        image = Image.open(img_path).convert('RGB')

        transform_chain = T.Compose([
            T.Resize((224, 224)),
            T.ToTensor(),
            T.Normalize(
                mean=[0.485, 0.456, 0.406],
                std=[0.229, 0.224, 0.225]
```

```
            )
        ])

        image_tensor = transform_chain(image)

        return image_tensor, {'image_id': torch.tensor([image_id])}

    def __len__(self):
        return len(self.image_info)

    def get_info(self):
        return self.image_info
```

Loading checkpoint model.

Like evaluation, model evaluating mode, feed images, and generate task 1 json file, task 2 csv file.

```
def test(model, test_data_loader):
    model.eval()

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

    task1 = []


    content = {
        "image_id": range(1, 13069),
        "pred_label": -1
    }

    import pandas as pd

    task2 = pd.DataFrame(content)

    test_bar = tqdm(test_data_loader, desc="Test", leave=False)
    with torch.no_grad():
        for images, images_id in test_data_loader:
            images = images.to(device)

            tmp = model(images)
            # print(tmp)

            coco = convert_to_coco_format(tmp, images_id['image_id'],
score_threshold=0.8)

            task1 = task1 + coco

            task2 = task2_do(tmp, images_id['image_id'], task2,
score_threshold=0.8)

            test_bar.update()
    test_bar.close()
```

```
    with open('./result/task1/pred.json', 'w') as f:
        json.dump(task1, f, indent=4)

    task2.to_csv('./result/task2/pred.csv', index=False)
```

In task 1, model will output boxes, category.
We need to de-normalize boxes back to original size and position.
Denormalization is mentioned in the next section.

```
def convert_to_coco_format(outputs, image_ids, score_threshold=0.8):
    coco_results = []

    for img_id, detections in zip(image_ids, outputs):
        boxes = detections['boxes'].cpu().detach()#.numpy()  # (N,4)
tensor -> numpy
        scores =
detections['scores'].cpu().detach().numpy().astype(float)  # (N,)
        labels =
detections['labels'].cpu().detach().numpy().astype(int)  # (N,)

        if boxes.shape[0] == 0:
            print(f'img_id: {img_id} no boxes')
            # continue

        for i in range(boxes.shape[0]):
            # if scores[i] < score_threshold:
            #     continue

            # from torchvision.ops import box_convert
            # new_box = box_convert(boxes[i], in_fmt='xyxy',
out_fmt='xywh')
            new_box = deNormalize_box(img_id, boxes[i])

            # (x1,y1,x2,y2) -> (x,y,width,height)
            # x1, y1, x2, y2 = boxes[i].tolist()
            # w = x2 - x1
            # h = y2 - y1

            output_dict = {
                "image_id": int(img_id.item()),
                "bbox": new_box,
                "score": float(scores[i]),
                "category_id": int(labels[i]),
            }

            coco_results.append(output_dict)

    return coco_results
```

We reload original images again to compare scale between outputs of model (normalized) and them (non-normalized).
Convert xyxy back to xywh.
Then we get original size box.

```
def deNormalize_box(image_id, xyxy_box):
    new_w, new_h = 224, 224

    from PIL import Image
    orig_img =
Image.open(f'./dataset/test/{int(image_id.item())}.png')
    orig_w, orig_h = orig_img.size

    from torchvision.ops import box_convert
    xywh_box = box_convert(xyxy_box, in_fmt='xyxy', out_fmt='xywh')

    xywh_box = xywh_box.tolist()

    scale_w = orig_w / new_w
    scale_h = orig_h / new_h

    x, y, w, h = xywh_box
    orig_x = x * scale_w
    orig_y = y * scale_h
    orig_w = w * scale_w
    orig_h = h * scale_h

    orig_box = [orig_x, orig_y, orig_w, orig_h]

    # print(f'orig box: {orig_box}')

    return orig_box
```

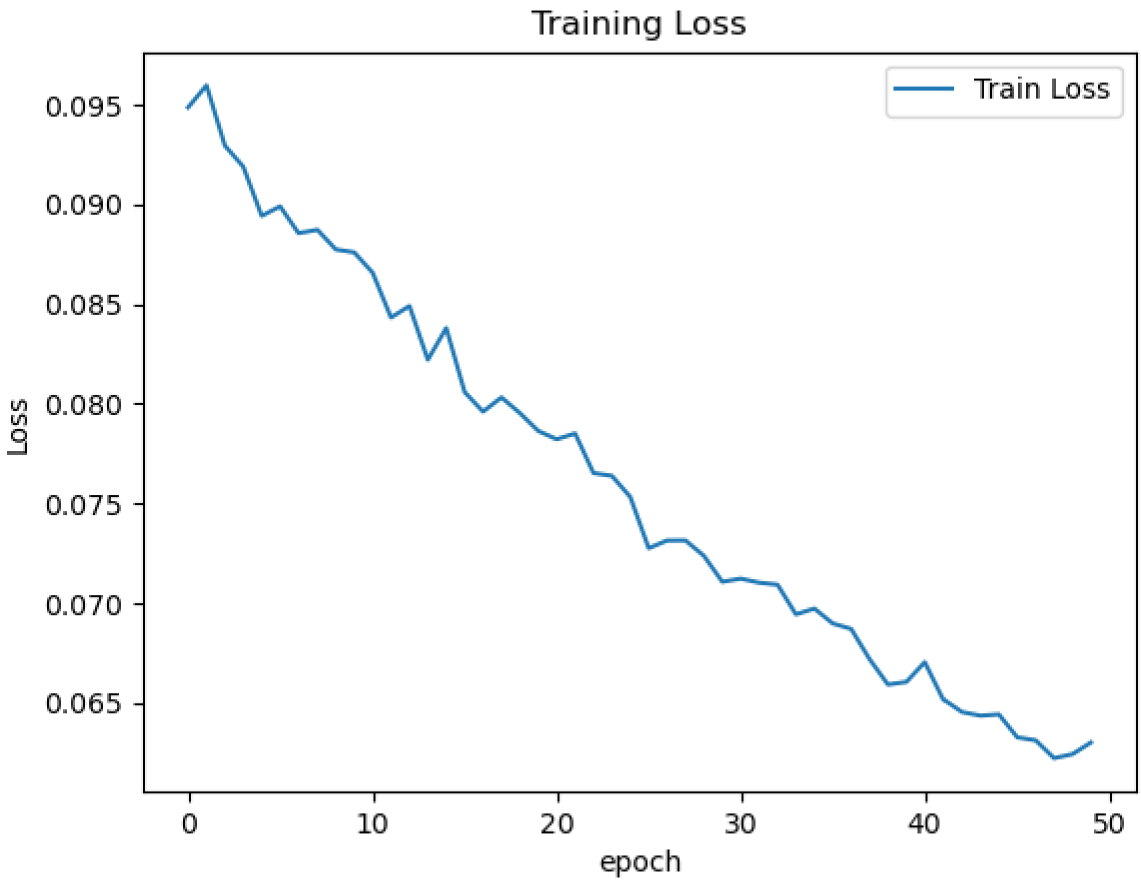
In task 2, we basically construct from task 1 that we make the leftmost box as the first digit and generate the number of those boxes consist.

```
def task2_do(outputs, image_ids, task2, score_threshold=0.8):
    import numpy as np
    # print(f'coco: {coco}')

    for img_id, detections in zip(image_ids, outputs):
        img_id = img_id.item()
        # print(f'img_id: {type(img_id), img_id}')
        boxes = detections['boxes'].cpu().detach().numpy()  # (N,4)
tensor -> numpy
        # print(f'boxes: {boxes, boxes.shape}')
        scores =
detections['scores'].cpu().detach().numpy().astype(float)  # (N,)
```

```
        if boxes.shape[0] == 0:
            continue

        labels_tmp =
detections['labels'].cpu().detach().numpy().astype(int)  # (N,)
        labels_tmp -= 1

        # print(f'labels_tmp: {labels_tmp}')

        new_boxes = []
        labels = []
        for i in range(boxes.shape[0]):
            # if scores[i] < score_threshold:
            #     continue
            new_boxes.append(boxes[i][0])
            labels.append(labels_tmp[i])


        new_boxes = np.array(new_boxes)
        labels = np.array(labels)


        sort_idx = np.argsort(new_boxes)

        # a_sorted = boxes[sort_idx]
        b_sorted = labels[sort_idx]

        # print(a_sorted)
        # print(b_sorted)

        pred = int(''.join(b_sorted.astype(str)))

        task2.loc[task2['image_id'] == img_id, 'pred_label'] = pred

    return task2
```

Results

With training MobileNet v2, here is training loss from epoch 50~100.
Though we can see loss is decreasing, however, both of 2 tasks have the same score from epoch 40, 50, 100, even getting worse.



We have tried MobileNet v3 and ResNet50 as additional experiments.

1. MobileNet v3 performs almost the same as v2.
2. ResNet50 doesn't converge at all, though training loss decreases, which ResNet can't recognize digits. We may try freeze some layers, or use lighter version of ResNet.

More content mentioned in ***Additional experiments***

References

1. DeepSeek R1
2. Sandler, M., Howard, A., Zhu, M., Zhmoginov, A., & Chen, L. (2018, January 13). MobileNetV2: Inverted residuals and linear bottlenecks. arXiv.org. https://arxiv.org/abs/1801.04381
3. https://github.com/Akikiii/FasterRcnn-MobilenetV2-Coconut/tree/main
4. Li, Y., Xie, S., Chen, X., Dollar, P., He, K., & Girshick, R. (2021, November 22). Benchmarking Detection Transfer Learning with Vision Transformers. arXiv.org. https://arxiv.org/abs/2111.11429

Additional experiments

1. Different backbones with AMP / GradScale:
   We tried 2 other pre-trained backbones provided by pyTorch, MobileNet v3 and ResNet50.

   Out of speeding up training process, we use torch.amp.
   Including MobileNet v2 we use above, we encounter non-convergence problem on these 3 models, nevertheless training loss is low and decreasing.

In addition, we find out Nan loss happens on V3, and both of Nan loss, loss explosion meanwhile happen on ResNet50.

We have tried several combinations of optimizers and schedulers like:

1. AdamW + Cosine Annealing
2. SGD + StepLR

It'd better apply bigger learning rate at first, which helps model to converge since v3 and ResNet are too big.

Interestingly, batch size also affects training loss.
The smaller batch size is, the lower loss we get.

Perhaps on ResNet, we can feed bigger batch size, and use gradient clip by norm to avoid explosion.