Lab 6: Object Localization with Fast R-CNN for Mobile Phone Detection

Objective

- the implementation of an object localization model using Fast R-CNN in PyTorch for detecting mobile phones. It involves:
  - Understanding object localization vs. classification.
  - Utilizing Fast R-CNN for bounding box predictions and class probabilities.
  - Applying evaluation metrics like mAP (mean Average Precision) and IoU (Intersection over Union).

Dataset Information

- Dataset: Mobile Phone Detection Dataset
- Format: COCO JSON annotations
- Classes: 1 (mobile-phone)

Splits:

- Training: 481 images (81%)
- Validation: 67 images (11%)
- Test: 49 images (8%)

Image Format: JPG

Annotation Format: COCO JSON with bounding boxes

Object Localization vs. Classification

Classification: Predicts only the class label of an object

Localization: Predicts both class label and object location (bounding box)

Output Format

- **Classification:** Class probabilities
- **Localization:** Class probabilities + Bounding box coordinates (x, y, width, height)

Mobile Phone Detection using Fast R-CNN

1. Environment Setup

Data Preparation

- Install necessary libraries:

  ```
  pip install torch torchvision pycocotools albumentations matplotlib numpy pandas
  ```

- Mount Google Drive to access datasets and annotations.

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2. Data Loading and Preparation

Custom Dataset Class:

- Implements PyTorch's `Dataset` for loading COCO annotations.
- Prepares image tensors and bounding box targets ([x1, y1, x2, y2]).
- Supports transformations (optional).

Key Methods:

- `__getitem__`: Loads images and bounding box annotations.
- `__len__`: Returns the size of the dataset.

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3. Model Setup

Fast R-CNN Architecture:

- **Base Model**: `fasterrcnn_resnet50_fpn_v2` (pre-trained).
- **Custom Head**:
  - Replaces the pre-trained classification layer.
  - Predicts bounding boxes and classes (background + mobile phones).

Key Function:

- `get_model(num_classes)`: Configures the model with a new head for custom classes.

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4. Training Pipeline

Tasks:

1. **Set Device**:
   - Use GPU if available:

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

2. **Load Datasets**:
   - Train and validation datasets.
   - Use `DataLoader` for batching and shuffling.
3. **Optimizer and Scheduler**:
   - **Optimizer**: SGD with a learning rate of 0.001.
   - **Scheduler**: `StepLR` to decay learning rate.
4. **Training Loop**:
   - Perform forward and backward passes.
   - Update weights using calculated loss.

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5. Evaluation

Metrics:

- **IoU (Intersection over Union)**: Measures overlap between predicted and ground truth bounding boxes.
- **mAP (Mean Average Precision)**: Evaluates detection performance across classes.

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6. Inference and Visualization

Tasks:

1. **Inference Function**:
   - Loads test images.
   - Uses the trained model to predict bounding boxes and confidence scores.
2. **Visualization Function**:
   - Draws bounding boxes on images with confidence scores.

Key Functionality:

- `detect_phones`: Runs inference.
- `visualize_detection`: Plots predictions.

---

run_inference('model_checkpoint.pth', 'test_image.jpg')

1. Environment Setup

```
# !pip install torch torchvision
# !pip install pycocotools
# !pip install albumentations
# !pip install matplotlib numpy pandas
```

```
# !pip install pycocotools
# !pip install albumentations
```

```
# Mount Google Drive
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
```

```
# Import necessary libraries
import torch
import torchvision
from torchvision.models.detection import fasterrcnn_resnet50_fpn_v2
from torchvision.models.detection.faster_rcnn import FastRCNNPredictor
import numpy as np
import matplotlib.pyplot as plt
import os
import json
from PIL import Image
from torchvision.transforms import functional as F
from pycocotools.coco import COCO
from torch.utils.data import Dataset, DataLoader
```

```
# Set random seeds for reproducibility
torch.manual_seed(42)
np.random.seed(42)
```

```
Start coding or generate with AI.
```

2. Data Loading and Preparation

```
class MobilePhoneDataset(Dataset):
    def __init__(self, root_dir, annotation_file, transforms=None):
        self.root_dir = root_dir
        self.transforms = transforms

        # Load COCO format annotations
        self.coco = COCO(annotation_file)
        self.ids = list(sorted(self.coco.imgs.keys()))

        # Filter for mobile phone class
        cat_ids = self.coco.getCatIds(catNms=['mobile-phone'])
        self.category_id_to_label = {cat_id: 1 for cat_id in cat_ids}  # Map to label 1

    def __getitem__(self, index):
        # Load image
        img_id = self.ids[index]
        img_info = self.coco.loadImgs(img_id)[0]
        image_path = os.path.join(self.root_dir, img_info['file_name'])
        image = Image.open(image_path).convert('RGB')

        # Convert PIL Image to tensor
        image = F.to_tensor(image)

        # Load annotations
        ann_ids = self.coco.getAnnIds(imgIds=img_id)
        anns = self.coco.loadAnns(ann_ids)

        boxes = []
        labels = []

        for ann in anns:
            boxes.append(ann['bbox'])  # [x, y, width, height]
            labels.append(1)  # 1 for mobile phone

        # Convert boxes to tensor
        boxes = torch.as_tensor(boxes, dtype=torch.float32)
        # Convert from [x, y, w, h] to [x1, y1, x2, y2]
        if len(boxes) > 0:
            boxes[:, 2] = boxes[:, 0] + boxes[:, 2]
            boxes[:, 3] = boxes[:, 1] + boxes[:, 3]

        # Prepare target
        target = {}
        target["boxes"] = boxes
        target["labels"] = torch.as_tensor(labels, dtype=torch.int64)
        target["image_id"] = torch.tensor([img_id])
        target["area"] = (boxes[:, 3] - boxes[:, 1]) * (boxes[:, 2] - boxes[:, 0])
        target["iscrowd"] = torch.zeros((len(boxes),), dtype=torch.int64)
```

```
        if self.transforms is not None:
            image = self.transforms(image)

        return image, target

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

3. Model Setup

```
def get_model(num_classes=2):  # 2 classes: background + mobile phone
    # Load pre-trained model
    model = fasterrcnn_resnet50_fpn_v2(pretrained=True)

    # Get number of input features
    in_features = model.roi_heads.box_predictor.cls_score.in_features

    # Replace the pre-trained head with a new one
    model.roi_heads.box_predictor = FastRCNNPredictor(in_features, num_classes)

    return model

def train_one_epoch(model, optimizer, data_loader, device):
    model.train()
    total_loss = 0

    for images, targets in data_loader:
        images = list(image.to(device) for image 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()

        total_loss += losses.item()

    return total_loss / len(data_loader)
```

4. Training Pipeline

```
# Set device
device = torch.device('cuda') if torch.cuda.is_available() else torch.device('cpu')
print(f"Using device: {device}")


# Dataset paths
train_root = '/content/drive/MyDrive/phone dataset/train'
train_annot = '/content/drive/MyDrive/phone dataset/train/_annotations.coco.json'
val_root = '/content/drive/MyDrive/phone dataset/valid'
val_annot = '/content/drive/MyDrive/phone dataset/valid/_annotations.coco.json'

# Create datasets
train_dataset = MobilePhoneDataset(train_root, train_annot)
val_dataset = MobilePhoneDataset(val_root, val_annot)

print(f"Number of training images: {len(train_dataset)}")
print(f"Number of validation images: {len(val_dataset)}")

# Create data loaders with smaller batch size for memory efficiency
train_loader = DataLoader(
    train_dataset,
    batch_size=2,
    shuffle=True,
    collate_fn=lambda x: tuple(zip(*x)),
    num_workers=2
)

val_loader = DataLoader(
    val_dataset,
    batch_size=1,
    shuffle=False,
    collate_fn=lambda x: tuple(zip(*x)),
    num_workers=2
)

# Initialize model
model = get_model(num_classes=2)  # background + mobile phone
model.to(device)

# Optimizer with lower learning rate
params = [p for p in model.parameters() if p.requires_grad]
optimizer = torch.optim.SGD(params, lr=0.001, momentum=0.9, weight_decay=0.0005)

# Learning rate scheduler
lr_scheduler = torch.optim.lr_scheduler.StepLR(optimizer, step_size=3, gamma=0.1)

# Training loop with try-except for debugging
num_epochs = 10
print("Starting training...")

try:
    for epoch in range(num_epochs):
        print(f"Epoch {epoch+1}/{num_epochs}")
        model.train()
        total_loss = 0
        num_batches = len(train_loader)

        for i, (images, targets) in enumerate(train_loader):
            # Move images and targets to device
            images = [image.to(device) for image in images]
            targets = [{k: v.to(device) for k, v in t.items()} for t in targets]

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

            # Backward pass
            optimizer.zero_grad()
            losses.backward()
            optimizer.step()

            total_loss += losses.item()
```

```
            if i % 10 == 0:  # Print every 10 batches
                print(f"  Batch {i+1}/{num_batches}, Loss: {losses.item():.4f}")

        # Step the scheduler
        lr_scheduler.step()

        avg_loss = total_loss / len(train_loader)
        print(f"Epoch {epoch+1} completed. Average Loss: {avg_loss:.4f}")

        # Save model checkpoint
        torch.save({
            'epoch': epoch,
            'model_state_dict': model.state_dict(),
            'optimizer_state_dict': optimizer.state_dict(),
            'loss': avg_loss,
        }, f'mobile_detector_epoch_{epoch+1}.pth')

except Exception as e:
    print(f"Error during training: {str(e)}")
    import traceback
    traceback.print_exc()
```

```
Epoch 5/10
  Batch 1/241, Loss: 0.0549
  Batch 11/241, Loss: 0.1368
  Batch 21/241, Loss: 0.0397
  Batch 31/241, Loss: 0.0179
  Batch 41/241, Loss: 0.0931
  Batch 51/241, Loss: 0.0755
  Batch 61/241, Loss: 0.0245
  Batch 71/241, Loss: 0.0419
  Batch 81/241, Loss: 0.0438
  Batch 91/241, Loss: 0.0281
  Batch 101/241, Loss: 0.0497
  Batch 111/241, Loss: 0.0536
  Batch 121/241, Loss: 0.1042
  Batch 131/241, Loss: 0.0338
  Batch 141/241, Loss: 0.0544
  Batch 151/241, Loss: 0.0540
  Batch 161/241, Loss: 0.0457
  Batch 171/241, Loss: 0.0258
  Batch 181/241, Loss: 0.1039
  Batch 191/241, Loss: 0.0364
  Batch 201/241, Loss: 0.0506
  Batch 211/241, Loss: 0.0326
  Batch 221/241, Loss: 0.0282
  Batch 231/241, Loss: 0.0875
  Batch 241/241, Loss: 0.0421
Epoch 5 completed. Average Loss: 0.0725
Epoch 6/10
  Batch 1/241, Loss: 0.1391
  Batch 11/241, Loss: 0.0395
  Batch 21/241, Loss: 0.0299
  Batch 31/241, Loss: 0.0306
  Batch 41/241, Loss: 0.1657
  Batch 51/241, Loss: 0.0424
  Batch 61/241, Loss: 0.0257
  Batch 71/241, Loss: 0.0828
  Batch 81/241, Loss: 0.2437
  Batch 91/241, Loss: 0.0260
  Batch 101/241, Loss: 0.0203
  Batch 111/241, Loss: 0.0444
  Batch 121/241, Loss: 0.1942
  Batch 131/241, Loss: 0.0339
  Batch 141/241, Loss: 0.0246
  Batch 151/241, Loss: 0.0509
  Batch 161/241, Loss: 0.0514
  Batch 171/241, Loss: 0.0476
  Batch 181/241, Loss: 0.1060
  Batch 191/241, Loss: 0.0890
  Batch 201/241, Loss: 0.0294
  Batch 211/241, Loss: 0.0588
  Batch 221/241, Loss: 0.0706
  Batch 231/241, Loss: 0.0666
  Batch 241/241, Loss: 0.0873
Epoch 6 completed. Average Loss: 0.0718
Epoch 7/10
  Batch 1/241, Loss: 0.0390
  Batch 11/241, Loss: 0.0588
  Batch 21/241, Loss: 0.0398
  Batch 31/241, Loss: 0.0280
```

5. Evaluation

```
from collections import defaultdict
from torchvision.ops import box_iou
from tqdm import tqdm
```

```
def get_model(num_classes=2):
    model = fasterrcnn_resnet50_fpn_v2(pretrained=True)
    in_features = model.roi_heads.box_predictor.cls_score.in_features
    model.roi_heads.box_predictor = FastRCNNPredictor(in_features, num_classes)
    return model

def evaluate_single_image(pred_boxes, pred_scores, target_boxes, iou_threshold=0.5):
    """
    Evaluate predictions for a single image
    """
    if len(pred_boxes) == 0:
        return {'precision': 0.0, 'recall': 0.0, 'f1': 0.0}
    if len(target_boxes) == 0:
        return {'precision': 0.0, 'recall': 0.0, 'f1': 0.0}

    # Calculate IoU between predicted and ground truth boxes
    iou_matrix = box_iou(pred_boxes, target_boxes)

    # Get maximum IoU for each predicted box
    max_ious, _ = iou_matrix.max(dim=1)

    # True positives: predicted boxes with IoU > threshold
    true_positives = (max_ious >= iou_threshold).sum().item()

    # Calculate metrics
    precision = true_positives / len(pred_boxes)
    recall = true_positives / len(target_boxes)
    f1 = 2 * (precision * recall) / (precision + recall + 1e-10)

    return {
        'precision': precision,
        'recall': recall,
        'f1': f1
    }
```

```python
def evaluate_model(model, data_loader, device, confidence_threshold=0.5):
    """
    Evaluate model performance on the validation set
    """
    model.eval()
    total_metrics = defaultdict(float)
    all_predictions = []
    all_targets = []
    num_images = 0

    print("\nEvaluating model...")
    with torch.no_grad():
        for images, targets in tqdm(data_loader):
            # Move images to device
            images = [image.to(device) for image in images]
            predictions = model(images)

            # Process each image in the batch
            for pred, target in zip(predictions, targets):
                # Filter predictions by confidence
                mask = pred['scores'] >= confidence_threshold
                pred_boxes = pred['boxes'][mask].cpu()
                pred_scores = pred['scores'][mask].cpu()
                target_boxes = target['boxes'].cpu()

                # Store predictions and targets for mAP calculation
                all_predictions.append((pred_boxes, pred_scores))
                all_targets.append(target_boxes)

                # Calculate metrics for this image
                metrics = evaluate_single_image(pred_boxes, pred_scores, target_boxes)
                for k, v in metrics.items():
                    total_metrics[k] += v
                num_images += 1

    # Calculate average metrics
    avg_metrics = {k: v / num_images for k, v in total_metrics.items()}

    # Calculate mAP
    mAP = calculate_map(all_predictions, all_targets)
    avg_metrics['mAP'] = mAP

    return avg_metrics

def calculate_map(all_predictions, all_targets, iou_thresholds=None):
    """
    Calculate mean Average Precision
    """
    if iou_thresholds is None:
        iou_thresholds = np.linspace(0.5, 0.95, 10)

    aps = []
    for iou_threshold in iou_thresholds:
        ap = calculate_ap_at_threshold(all_predictions, all_targets, iou_threshold)
        aps.append(ap)

    mAP = np.mean(aps)
    return mAP

def calculate_ap_at_threshold(all_predictions, all_targets, iou_threshold):
    """
    Calculate Average Precision at a specific IoU threshold
    """
    all_detections = []
    num_positives = sum(len(target_boxes) for target_boxes in all_targets)

    # Collect all detections
    for (pred_boxes, pred_scores), target_boxes in zip(all_predictions, all_targets):
        if len(pred_boxes) == 0:
            continue

        iou_matrix = box_iou(pred_boxes, target_boxes)
        max_ious, _ = iou_matrix.max(dim=1)

        for score, iou in zip(pred_scores, max_ious):
            all_detections.append({
                'score': score.item(),
                'tp': iou >= iou_threshold
            })

    # Sort detections by confidence
    all_detections.sort(key=lambda x: x['score'], reverse=True)

    # Calculate precision and recall
    precisions = []
    recalls = []
    num_correct = 0
    for i, detection in enumerate(all_detections):
        if detection['tp']:
            num_correct += 1
        precision = num_correct / (i + 1)
        recall = num_correct / num_positives
        precisions.append(precision)
        recalls.append(recall)

    if not precisions:
        return 0.0

    # Calculate AP using all points
    ap = np.trapz(precisions, recalls) if recalls else 0.0
    return ap

def visualize_predictions(model, dataset, device, num_images=5, confidence_threshold=0.5):
    """
    Visualize model predictions on sample images
    """
    model.eval()
    fig, axes = plt.subplots(1, num_images, figsize=(20, 4))

    with torch.no_grad():
        for i in range(num_images):
            # Get random image
            img, target = dataset[np.random.randint(len(dataset))]

            # Get prediction
            prediction = model([img.to(device)])
            pred = prediction[0]

            # Filter predictions by confidence
            mask = pred['scores'] >= confidence_threshold
            boxes = pred['boxes'][mask].cpu()
```

```
            scores = pred['scores'][mask].cpu()

            # Convert tensor image to numpy for plotting
            img = img.cpu().permute(1, 2, 0).numpy()

            # Plot image
            ax = axes[i]
            ax.imshow(img)

            # Draw predicted boxes
            for box, score in zip(boxes, scores):
                x1, y1, x2, y2 = box.tolist()
                rect = plt.Rectangle((x1, y1), x2-x1, y2-y1,
                                  fill=False, color='red', linewidth=2)
                ax.add_patch(rect)
                ax.text(x1, y1-5, f'{score:.2f}',
                       bbox=dict(facecolor='white', alpha=0.7))

            ax.axis('off')

    plt.tight_layout()
    plt.show()

def run_evaluation(model_path, val_loader, device):
    """
    Run complete model evaluation
    """
    # Load model
    model = get_model(num_classes=2)
    checkpoint = torch.load(model_path, map_location=device)
    model.load_state_dict(checkpoint['model_state_dict'])
    model.to(device)

    # Evaluate model
    metrics = evaluate_model(model, val_loader, device)

    # Print results
    print("\n=== Evaluation Results ===")
    print(f"Mean Average Precision (mAP): {metrics['mAP']:.4f}")
    print(f"Average Precision: {metrics['precision']:.4f}")
    print(f"Average Recall: {metrics['recall']:.4f}")
    print(f"Average F1 Score: {metrics['f1']:.4f}")

    # Visualize some predictions
    print("\nGenerating visualization of predictions...")
    visualize_predictions(model, val_loader.dataset, device)

    return metrics
```

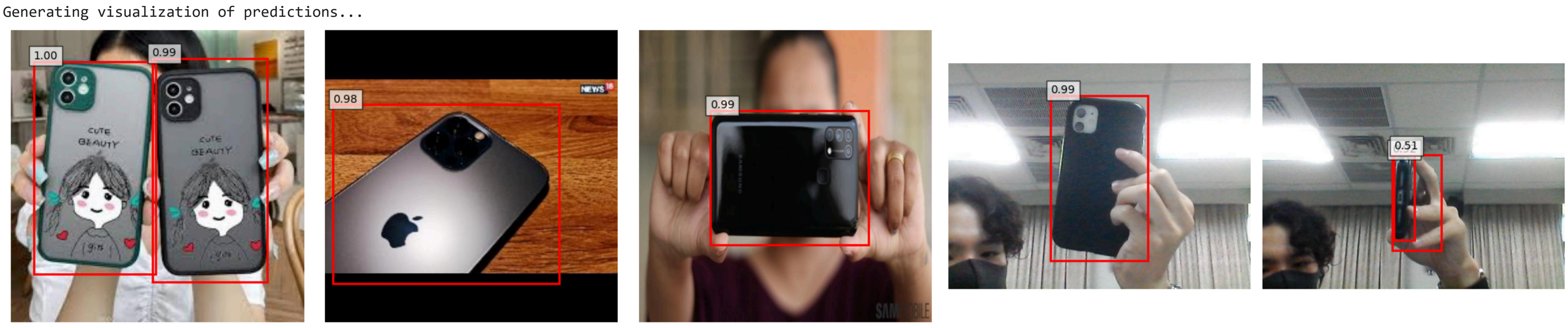
```
results = run_evaluation(
    model_path='/content/mobile_detector_epoch_10.pth',
    val_loader=val_loader,
    device=device
)
```

```
<ipython-input-48-d6730a283150>:186: FutureWarning: You are using `torch.load` with `weights_only=False` (the current default value), which uses the default pickle module implicitly.
  checkpoint = torch.load(model_path, map_location=device)

Evaluating model...
100%|██████████| 67/67 [00:12<00:00,  5.23it/s]

=== Evaluation Results ===
Mean Average Precision (mAP): 0.6545
Average Precision: 0.8893
Average Recall: 0.9739
Average F1 Score: 0.9143

Generating visualization of predictions...
```



6. Inference and Visualization

```
# Inference function
def detect_phones(model, image_path, device, conf_threshold=0.5):
    model.eval()
    image = Image.open(image_path).convert('RGB')
    image_tensor = F.to_tensor(image).unsqueeze(0).to(device)

    with torch.no_grad():
        prediction = model(image_tensor)

    # Filter predictions by confidence
    boxes = prediction[0]['boxes'][prediction[0]['scores'] > conf_threshold]
    scores = prediction[0]['scores'][prediction[0]['scores'] > conf_threshold]

    return image, boxes.cpu(), scores.cpu()

# Visualization function
def visualize_detection(image, boxes, scores):
    fig, ax = plt.subplots(1, figsize=(10, 10))
    ax.imshow(image)

    for box, score in zip(boxes, scores):
        x1, y1, x2, y2 = box
        rect = plt.Rectangle((x1, y1), x2-x1, y2-y1, fill=False, color='red', linewidth=2)
        ax.add_patch(rect)
        ax.text(x1, y1-5, f'{score:.2f}', bbox=dict(facecolor='white', alpha=0.7))

    plt.axis('off')
    plt.show()

# Function to run inference on a test image
def run_inference(model_path, image_path):
    # Load model
    model = get_model(num_classes=2)
```

```
    checkpoint = torch.load(model_path)
    model.load_state_dict(checkpoint['model_state_dict'])
    model.to(device)
    model.eval()

    # Run detection
    image, boxes, scores = detect_phones(model, image_path, device)
    visualize_detection(image, boxes, scores)

    return boxes, scores
```

```
run_inference('/content/mobile_detector_epoch_10.pth', '/content/drive/MyDrive/phone dataset/test/59381278d7b7ab85dfaa44e35c67a64a_jpg.rf.5b477cadcdafcdfaa3429691beceab11.jpg')
```

```
<ipython-input-40-90fb1b5ff341>:34: FutureWarning: You are using `torch.load` with `weights_only=False` (the current default value), which uses the default pickle module implicitly. I
  checkpoint = torch.load(model_path)
```


```
(tensor([[148.6618,  64.4105, 420.5332, 522.9233]]), tensor([0.9915]))
```

Start coding or generate with AI.

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