视听信息系统导论第二次编程作业报告

目录

1 实验任务

1.1 Task1

完成 model.py 文件中 ___init___ 函数。(完成代码即可，不用在报告中写文字说明)

代码如下:

```
    def __init__(self, in_dim=1280, hidden_dim=256, num_classes=20, \
              roi_output_w=2, roi_output_h=2, drop_ratio=0.3):
        super().__init__()

        assert(num_classes != 0)
        self.num_classes = num_classes
        self.roi_output_w, self.roi_output_h = roi_output_w, roi_output_h
        self.feat_extractor = FeatureExtractor()
        ##############################################################################
        # TODO: Declare the cls & bbox heads (in Fast R-CNN).             #
        # The cls & bbox heads share a sequential module with a Linear layer, #
        # followed by a Dropout (p=drop_ratio), a ReLU nonlinearity and another #
        # Linear layer.                                                   #
        # The cls head is a Linear layer that predicts num_classes + 1 (background). #
        # The det head is a Linear layer that predicts offsets(dim=4).    #
        # HINT: The dimension of the two Linear layers are in_dim -> hidden_dim and #
        # hidden_dim -> hidden_dim.                                       #
        ##############################################################################
        # Replace "pass" statement with your code
        self.shared_fc = nn.Sequential(
            nn.Linear(in_dim, hidden_dim),
            nn.Dropout(drop_ratio),
            nn.ReLU(),
            nn.Linear(hidden_dim, hidden_dim)
        )
        self.cls_head = nn.Linear(hidden_dim, num_classes + 1)
        self.bbox_head = nn.Linear(hidden_dim, 4)
        ##############################################################################
        #                          END OF YOUR CODE                       #
        ##############################################################################
```

1.2 Task2

完成 utils.py 文件中的 compute_iou 函数。(完成代码即可，不用在报告中写文字说明)

代码如下:

```
    def compute_iou(anchors, bboxes):
    """
    Compute the intersection-over-union between anchors and gts.

    Inputs:
    - anchors: Anchor boxes, of shape (M, 4), where M is the number of proposals
    - bboxes: GT boxes of shape (N, 4), where N is the number of GT boxes,
              4 indicates (x_{lr}^{gt}, y_{lr}^{gt}, x_{rb}^{gt}, y_{rb}^{gt})

    Outputs:
    - iou: IoU matrix of shape (M, N)
    """
    iou = None
    ##############################################################################
    # TODO: Given anchors and gt bboxes,                              #
    # compute the iou between each anchor and gt bbox.                #
    ##############################################################################
    x1 = torch.max(anchors[:, None, 0], bboxes[None, :, 0])
    y1 = torch.max(anchors[:, None, 1], bboxes[None, :, 1])
    x2 = torch.min(anchors[:, None, 2], bboxes[None, :, 2])
    y2 = torch.min(anchors[:, None, 3], bboxes[None, :, 3])
    inter = torch.clamp(x2 - x1, min=0) * torch.clamp(y2 - y1, min=0)
    area_anchors = (anchors[:, 2] - anchors[:, 0]) * (anchors[:, 3] - anchors[:, 1])
    area_bboxes = (bboxes[:, 2] - bboxes[:, 0]) * (bboxes[:, 3] - bboxes[:, 1])
    union = area_anchors[:, None] + area_bboxes[None, :] - inter
    iou = torch.zeros_like(union)
    non_zero_union = union > 0
    iou[non_zero_union] = inter[non_zero_union] / union[non_zero_union]
    ##############################################################################
    #                           END OF YOUR CODE                      #
    ##############################################################################

    return iou
```

1.3 Task3

阅读 utils.py 文件中的 assign_label 函数，并简要说明该函数如何判断正负样本框。

答：assign_label 函数用于在模型训练中将候选框（proposals）分配为正样本或负样本。如果某个候选框与任意一个 GT 框的 IoU 值是所有候选框中的最大值，或者当候选框与某个 GT 框的 IoU 大于正样本阈值（pos_thresh）时，则该候选框被标记为正样本。当候选框与所有 GT 框的 IoU 值都小于负样本阈值（neg_thresh）时，该候选框被标记为负样本，此外再随机采样负样本以平衡正负比例。

阅读 utils.py 文件中的 compute_offsets 函数，简要说明如何计算正样本框到真实框的偏移量。

答：compute_offsets 函数用于计算正样本框（anchors）相对于真实框（GT boxes）的偏移量，以便在模型训练中进行位置调整。

计算 GT 框和 anchor 框的宽高比例，通过 torch.log 函数取对数来得到宽高偏移量：

$$\Delta w = \log\left(\frac{w^{\text{gt}}}{w^{\text{anchor}}}\right), \quad \Delta h = \log\left(\frac{h^{\text{gt}}}{h^{\text{anchor}}}\right) \tag{1}$$

计算 GT 框与 anchor 框的中心坐标差异，并对 anchor 框的宽高进行归一化来得到中心坐标偏移量：

$$\Delta x = \frac{x^{\text{gt}}_{\text{center}} - x^{\text{anchor}}_{\text{center}}}{w^{\text{anchor}}}, \quad \Delta y = \frac{y^{\text{gt}}_{\text{center}} - y^{\text{anchor}}_{\text{center}}}{h^{\text{anchor}}} \tag{2}$$

随后将这四个偏移量拼接在一起，得到最终的偏移量。

$$\text{offsets} = (\Delta x, \Delta y, \Delta w, \Delta h) \tag{3}$$

1.4 Task4

完成 model.py 文件中的 forward 函数。(完成代码即可，不用在报告中写文字说明)

代码如下:

```python
def forward(self, images, bboxes, bbox_batch_ids, proposals, proposal_batch_ids):
    """
    Training-time forward pass for our two-stage Faster R-CNN detector.

    Inputs:
    - images: Tensor of shape (B, 3, H, W) giving input images
    - bboxes: Tensor of shape (N, 5) giving ground-truth bounding boxes
    and category labels, from the dataloader, where N is the total number
    of GT boxes in the batch
    - bbox_batch_ids: Tensor of shape (N, ) giving the index (in the batch)
    of the image that each GT box belongs to
    - proposals: Tensor of shape (M, 4) giving the proposals for input images,
    where M is the total number of proposals in the batch
    - proposal_batch_ids: Tensor of shape (M, ) giving the index of the image
    that each proposals belongs to

    Outputs:
    - total_loss: Torch scalar giving the overall training loss.
    """
    w_cls = 1 # for cls_scores
    w_bbox = 1 # for offsets
    total_loss = None
    ##############################################################################
    # TODO: Implement the forward pass of Fast R-CNN.                 #
    # A few key steps are outlined as follows:                        #
    # i) Extract image fearure.                                       #
    # ii) Perform RoI Align on proposals, then meanpool the feature in the #
    #    spatial dimension.                                           #
    # iii) Pass the RoI feature through the shared-fc layer. Predict  #
    #     classification scores ans box offsets.                      #
    # iv) Assign the proposals with targets of each image.            #
    # v) Compute the cls_loss between the predicted class_prob and GT_class #
    #   (For poistive & negative proposals)                           #
    #   Compute the bbox_loss between the offsets and GT_offsets      #
    #   (For positive proposals)                                      #
    #   Compute the total_loss which is formulated as:                #
    #   total_loss = w_cls*cls_loss + w_bbox*bbox_loss.               #
    ##############################################################################
    # Replace "pass" statement with your code
    B, _, H, W = images.shape

    # extract image feature
    features = self.feat_extractor(images)

```

```
        # perform RoI Pool & mean pool
        boxes = torch.cat((proposal_batch_ids.unsqueeze(1), proposals), dim=-1)
        roi_feat = torchvision.ops.roi_pool(features, boxes, (self.roi_output_w, self.roi_output_h))
        roi_feat = roi_feat.mean(dim=[2, 3])

        # forward heads, get predicted cls scores & offsets
        shared_feat = self.shared_fc(roi_feat)
        cls_scores = self.cls_head(shared_feat)
        bbox_offsets = self.bbox_head(shared_feat)

        # assign targets with proposals
        pos_masks, neg_masks, GT_labels, GT_bboxes = [], [], [], []
        for img_idx in range(B):
            # get the positive/negative proposals and corresponding
            # GT box & class label of this image
            proposals_img = proposals[proposal_batch_ids == img_idx]
            bboxes_img = bboxes[bbox_batch_ids == img_idx]
            pos_mask, neg_mask, GT_label, GT_bbox = assign_label(proposals_img, bboxes_img, self.num_classes)
            pos_masks.append(pos_mask)
            neg_masks.append(neg_mask)
            GT_labels.append(GT_label)
            GT_bboxes.append(GT_bbox)

        # compute loss
        cls_loss = 0
        bbox_loss = 0
        for img_idx in range(B):
            pos_mask = pos_masks[img_idx]
            neg_mask = neg_masks[img_idx]
            GT_label = GT_labels[img_idx]
            GT_bbox = GT_bboxes[img_idx]
            proposals_img = proposals[proposal_batch_ids == img_idx]
            cls_scores_img = cls_scores[proposal_batch_ids == img_idx]
            bbox_offsets_img = bbox_offsets[proposal_batch_ids == img_idx]
            cls_loss += ClsScoreRegression(cls_scores_img[pos_mask | neg_mask], GT_label[pos_mask | neg_mask], B)
            bbox_loss += BboxRegression(bbox_offsets_img[pos_mask], compute_offsets(proposals_img[pos_mask], GT_bbox), B)
        total_loss = w_cls * cls_loss + w_bbox * bbox_loss
        ##############################################################################
        #                             END OF YOUR CODE                               #
        ##############################################################################
        return total_loss
```

1.5 Task5

完成 utils.py 的 generate_proposal 函数。（完成代码即可，不用在报告中写文字说明）

代码如下：

```
def generate_proposal(anchors, offsets):
"""
```

```
Proposal generator.

Inputs:
- anchors: Anchor boxes, of shape (M, 4). Anchors are represented
by the coordinates of their top-left and bottom-right corners.
- offsets: Transformations of shape (M, 4) that will be used to
convert anchor boxes into region proposals. The transformation
offsets[m] = (tx, ty, tw, th) will be applied to the anchor
anchors[m].

Outputs:
- proposals: Region proposals of shape (M, 4), represented by the
coordinates of their top-left and bottom-right corners. Applying the
transform offsets[m] to the anchor[m] should give the
proposal proposals[m].

"""
proposals = None
##############################################################################
# TODO: Given anchor coordinates and the proposed offset for each anchor, #
# compute the proposal coordinates using the transformation formulas above. #
##############################################################################
# Replace "pass" statement with your code
xy_offsets = offsets[:, :2]
wh_offsets = offsets[:, 2:4]
proposals_minus = torch.exp(wh_offsets) * (anchors[:, 2:4] - anchors[:, :2])
proposals_plus = xy_offsets * (anchors[:, 2:4] - anchors[:, :2]) * 2 + (anchors[:, :2] + anchors[:, 2:4])
proposals = torch.cat(((proposals_plus - proposals_minus) / 2, (proposals_plus + proposals_minus) / 2), dim=-1)
##############################################################################
#                           END OF YOUR CODE                      #
##############################################################################

return proposals
```

1.6 Task6

完成 model.py 的 inference 函数。(完成代码即可，不用在报告中写文字说明)

代码如下：

```
def inference(self, images, proposals, proposal_batch_ids, thresh=0.5, nms_thresh=0.7):
    """
    Inference-time forward pass for our two-stage Faster R-CNN detector

    Inputs:
    - images: Tensor of shape (B, 3, H, W) giving input images
    - proposals: Tensor of shape (M, 4) giving the proposals for input images,
    where M is the total number of proposals in the batch
    - proposal_batch_ids: Tensor of shape (M, ) giving the index of the image
    that each proposals belongs to
    - thresh: Threshold value on confidence probability. HINT: You can convert the
```

```
        classification score to probability using a softmax nonlinearity.
        - nms_thresh: IoU threshold for NMS

        We can output a variable number of predicted boxes per input image.
        In particular we assume that the input images[i] gives rise to P_i final
        predicted boxes.

        Outputs:
        - final_proposals: List of length (B,) where final_proposals[i] is a Tensor
        of shape (P_i, 4) giving the coordinates of the final predicted boxes for
        the input images[i]
        - final_conf_probs: List of length (B,) where final_conf_probs[i] is a
        Tensor of shape (P_i, 1) giving the predicted probabilites that the boxes
        in final_proposals[i] are objects (vs background)
        - final_class: List of length (B,), where final_class[i] is an int64 Tensor
        of shape (P_i, 1) giving the predicted category labels for each box in
        final_proposals[i].
        """
        final_proposals, final_conf_probs, final_class = None, None, None
        ##############################################################################
        # TODO: Predicting the final proposal coordinates `final_proposals`, #
        # confidence scores `final_conf_probs`, and the class index `final_class`. #
        # The overall steps are similar to the forward pass, but now you cannot #
        # decide the activated nor negative proposals without GT boxes.    #
        # You should apply post-processing (thresholding and NMS) to all proposals #
        # and keep the final proposals.                                      #
        ##############################################################################
        # Replace "pass" statement with your code
        B = images.shape[0]

        # extract image feature
        features = self.feat_extractor(images)

        # perform RoI Pool & mean pool
        boxes = torch.cat((proposal_batch_ids.unsqueeze(1), proposals), dim=-1)
        roi_feat = torchvision.ops.roi_pool(features, boxes, (self.roi_output_w, self.roi_output_h))
        roi_feat = roi_feat.mean(dim=[2, 3])

        # forward heads, get predicted cls scores & offsets
        shared_feat = self.shared_fc(roi_feat)
        cls_scores = self.cls_head(shared_feat)
        bbox_offsets = self.bbox_head(shared_feat)

        # get predicted boxes & class label & confidence probability
        conf_probs = torch.softmax(cls_scores, dim=-1)
        pred_boxes = generate_proposal(proposals, bbox_offsets)

        final_proposals = []
        final_conf_probs = []
        final_class = []
        # post-process to get final predictions
        for img_idx in range(B):

            # filter by threshold
            img_proposals = pred_boxes[proposal_batch_ids == img_idx]
            img_conf_probs = conf_probs[proposal_batch_ids == img_idx]
            img_cls_scores = cls_scores[proposal_batch_ids == img_idx]
            keep = img_conf_probs[:, :self.num_classes].max(dim=1).values > thresh
            img_proposals = img_proposals[keep]
            img_conf_probs = img_conf_probs[keep]
            img_cls_scores = img_cls_scores[keep]
            conf_values, pred_classes = img_conf_probs[:, :self.num_classes].max(dim=1)

            # nms
            keep_idx = torchvision.ops.nms(img_proposals, conf_values, nms_thresh)
            final_proposals.append(img_proposals[keep_idx])
            final_conf_probs.append(conf_values[keep_idx].unsqueeze(1))
            final_class.append(pred_classes[keep_idx].unsqueeze(1))

        ##############################################################################
        #                           END OF YOUR CODE                                 #
        ##############################################################################
        return final_proposals, final_conf_probs, final_class
```

1.7 Task7

完成过拟合实验，在报告中给出训练损失曲线和测试样本可视化。

训练损失函数曲线和测试样本可视化如下：

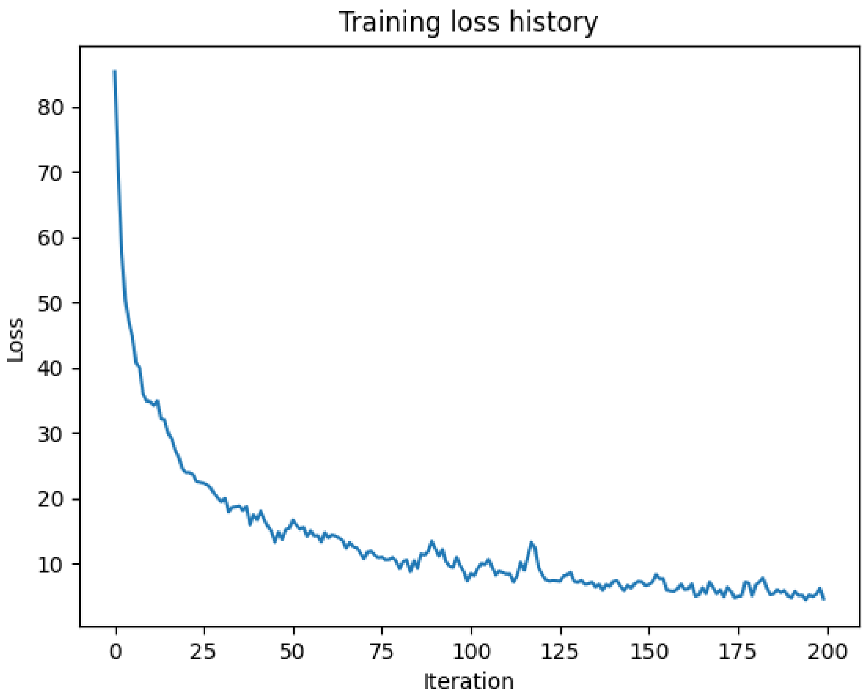
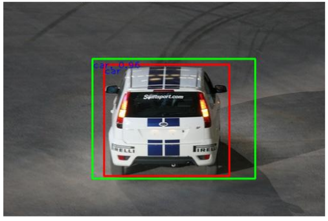
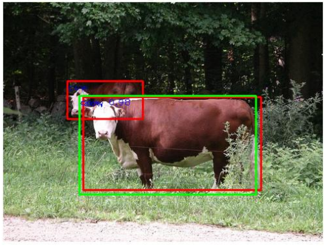


图 1: 训练损失曲线

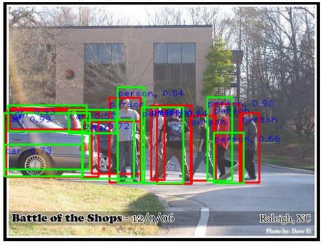
./exp/fast_rcnn_overfit_small/visualize/000012.jpg



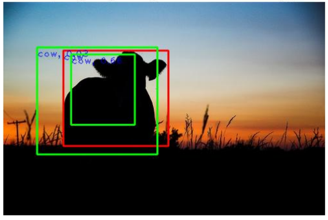
./exp/fast_rcnn_overfit_small/visualize/001182.jpg



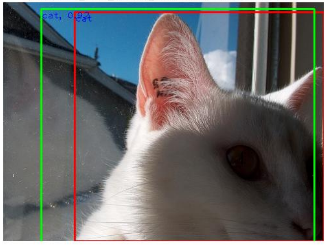
./exp/fast_rcnn_overfit_small/visualize/002241.jpg



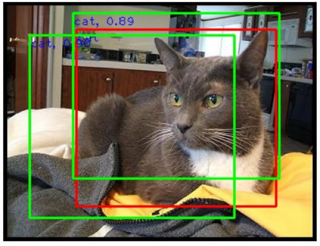
./exp/fast_rcnn_overfit_small/visualize/003354.jpg



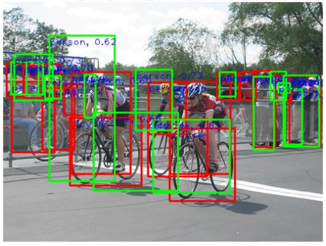
./exp/fast_rcnn_overfit_small/visualize/004376.jpg



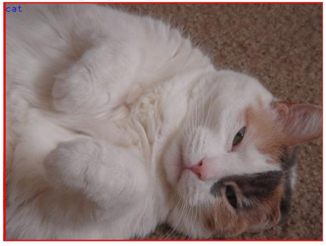
./exp/fast_rcnn_overfit_small/visualize/005455.jpg



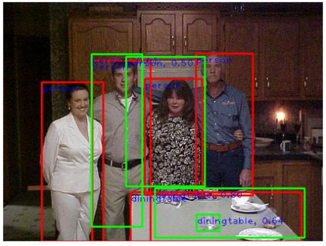
./exp/fast_rcnn_overfit_small/visualize/006551.jpg



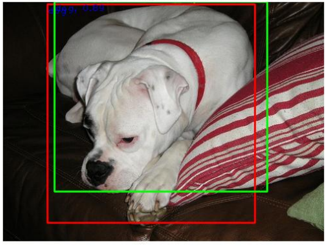
./exp/fast_rcnn_overfit_small/visualize/007753.jpg



./exp/fast_rcnn_overfit_small/visualize/008932.jpg



./exp/fast_rcnn_overfit_small/visualize/009961.jpg



注意到，训练损失函数曲线和“car”的测试样本与说明文档中的示例几乎完全一致，说明实验结果符合预期。

1.8 Task8

完成最终实验，在报告中给出训练损失曲线和评测情况。

训练损失曲线和评测情况如下：

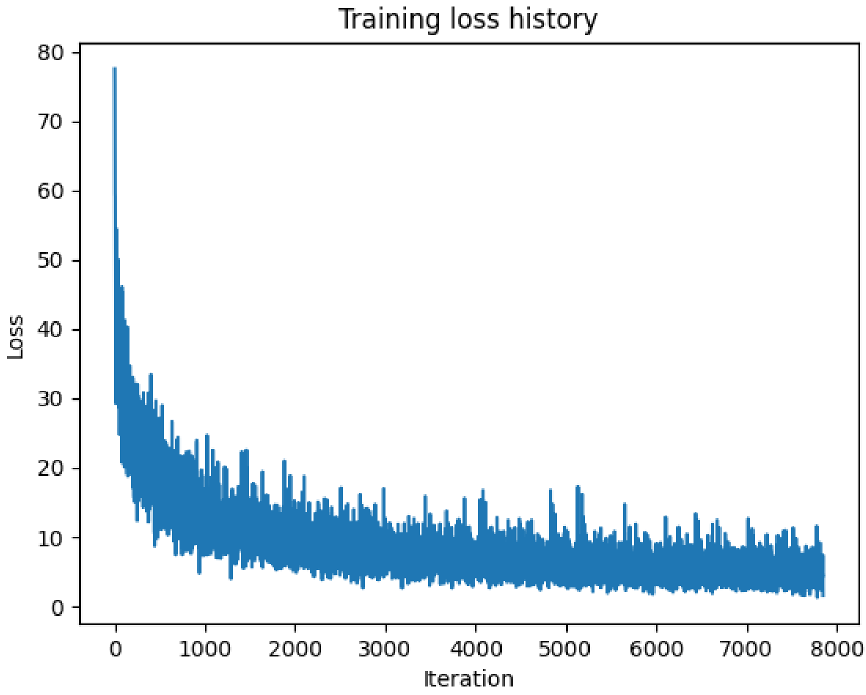
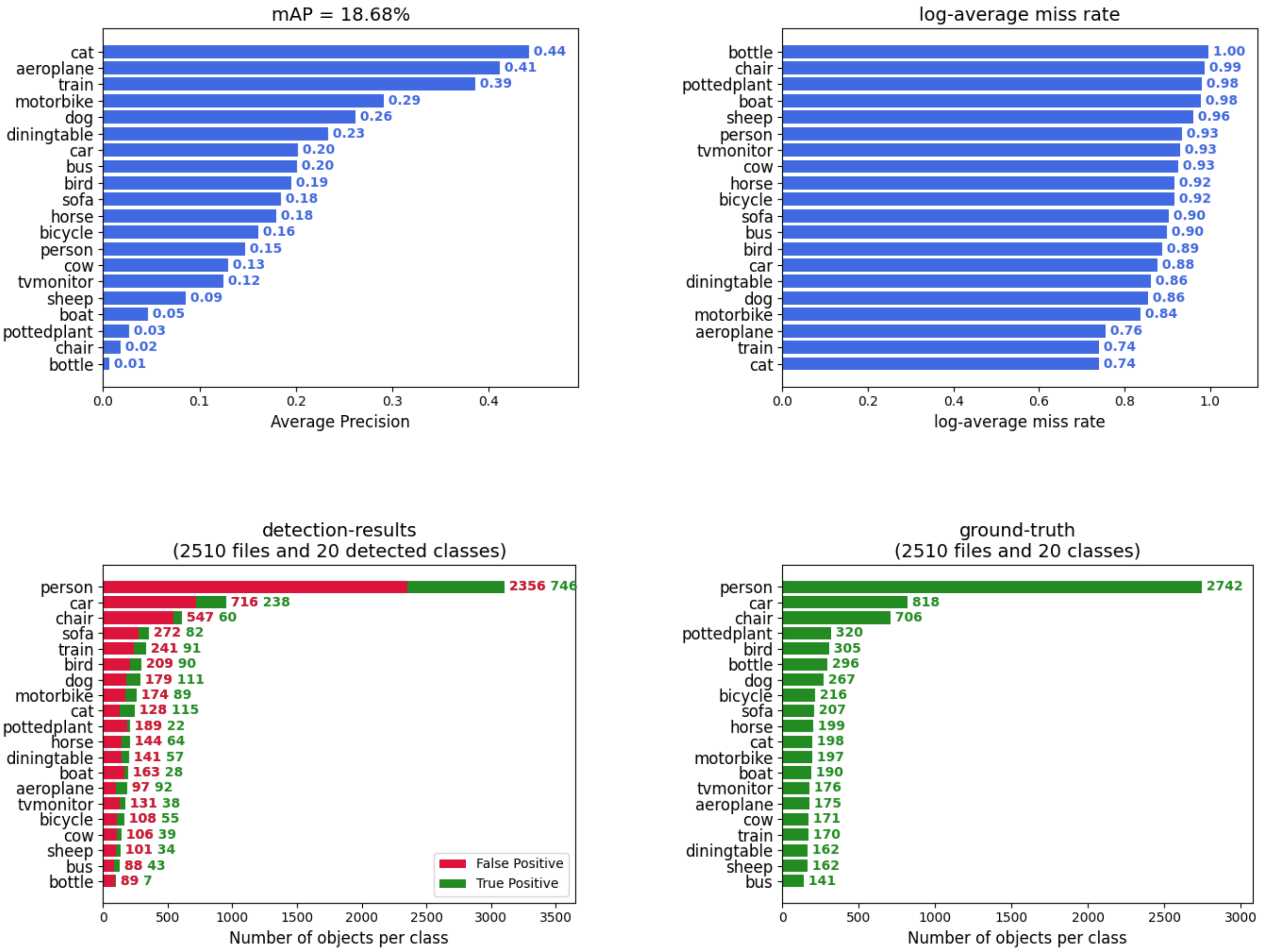
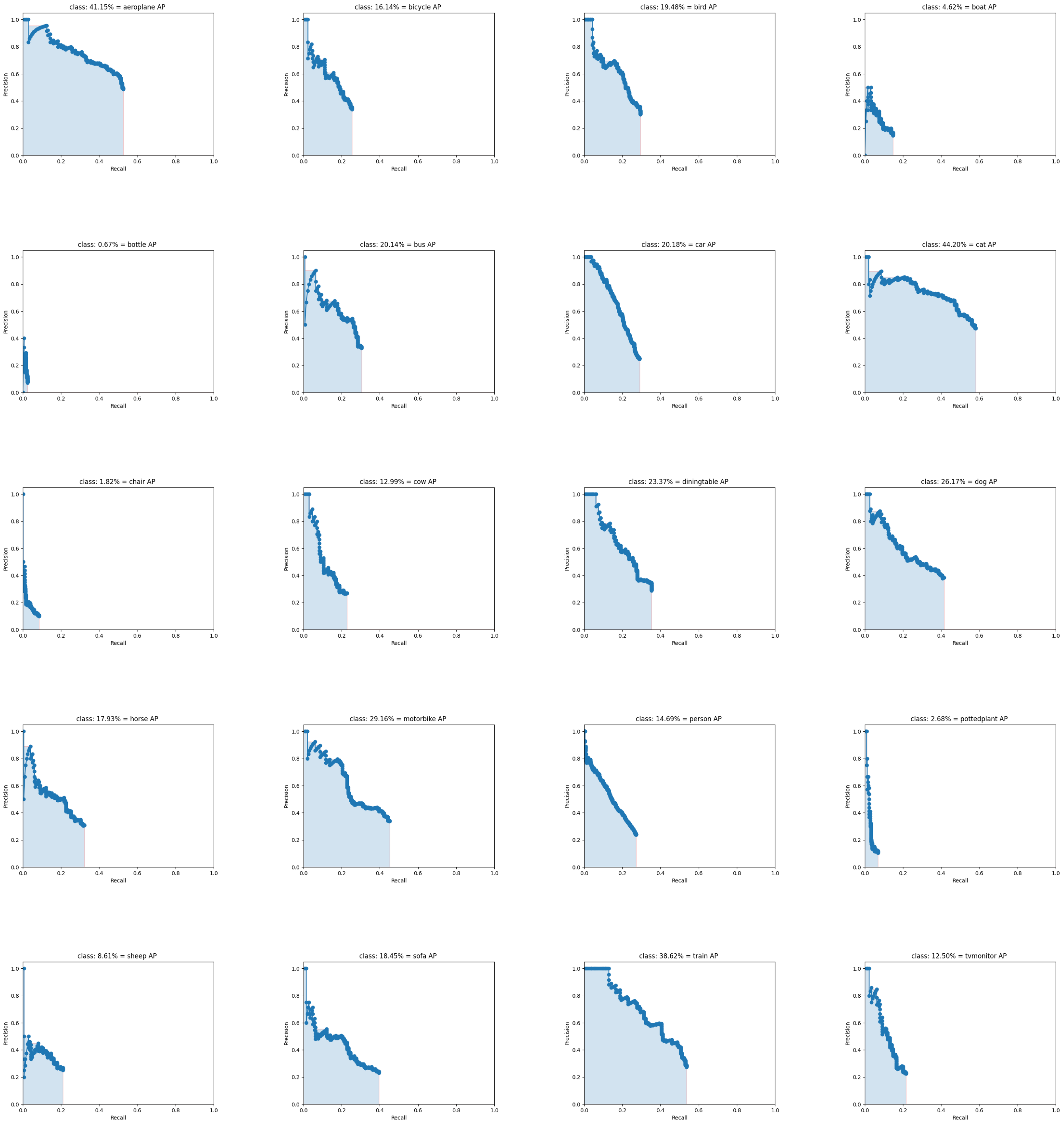

Training loss history
Loss
80
70
60
50
40
30
20
10
0
0
1000
2000
3000
4000
5000
6000
7000
8000
Iteration

图 2: 最终训练损失曲线


mAP = 18.68%
cat 0.44
aeroplane 0.41
train 0.39
motorbike 0.29
dog 0.26
diningtable 0.23
car 0.20
bus 0.20
bird 0.19
sofa 0.18
horse 0.18
bicycle 0.16
person 0.15
cow 0.13
tvmonitor 0.12
sheep 0.09
boat 0.05
pottedplant 0.03
chair 0.02
bottle 0.01
0.0
0.1
0.2
0.3
0.4
Average Precision
log-average miss rate
bottle 1.00
chair 0.99
pottedplant 0.98
boat 0.98
sheep 0.96
person 0.93
tvmonitor 0.93
cow 0.93
horse 0.92
bicycle 0.92
sofa 0.90
bus 0.90
bird 0.89
car 0.88
diningtable 0.86
dog 0.86
motorbike 0.84
aeroplane 0.76
train 0.74
cat 0.74
0.0
0.2
0.4
0.6
0.8
1.0
log-average miss rate
detection-results
(2510 files and 20 detected classes)
person 2356 746
car 716 238
chair 547 60
sofa 272 82
train 241 91
bird 209 90
dog 179 111
motorbike 174 89
cat 128 115
pottedplant 189 22
horse 144 64
diningtable 141 57
boat 163 28
aeroplane 97 92
tvmonitor 131 38
bicycle 108 55
cow 106 39
sheep 101 34
bus 88 43
bottle 89 7
False Positive
True Positive
0
500
1000
1500
2000
2500
3000
3500
Number of objects per class
ground-truth
(2510 files and 20 classes)
person 2742
car 818
chair 706
pottedplant 320
bird 305
bottle 296
dog 267
bicycle 216
sofa 207
horse 199
cat 198
motorbike 197
boat 190
tvmonitor 176
aeroplane 175
cow 171
train 170
diningtable 162
sheep 162
bus 141
0
500
1000
1500
2000
2500
3000
Number of objects per class



受限于算力和时间，最终评测得到的 mAP 为 18.68%，与说明文档中的预期（18% 左右）相符。