Unbiased Teacher for Semi-Supervised Object Detection笔记

- Paper: [Unbiased Teacher for Semi-Supervised Object Detection]
- Code: [facebookresearch/unbiased-teacher]

1. Introduction

1.1 Why

1.1.1 Motivation

- 海量数据能提升深度神经网络在不同任务中的表现；但是标注大量的数据很昂贵，半监督学习可作为一种减小标注代价的手段。

1.1.2 Challenges

- 目标检测中**类别不均衡**的特点阻碍了伪标签的使用。(The nature of **class-imbalance** in object detection tasks impedes the usage of pseudo-labeling.)
    - foreground-background imbalance
    - foreground classes imbalance

1.2 What

- **无偏老师**同时处理**伪标签问题**(标注数据中固有的类别不均衡引起的)和**过拟合问题**(标注数据稀缺引起的)。(We propose **Unbiased Teacher** to jointly address the pseudo-labeling bias issue and the overfitting issue in semi-supervised object detection, and our model performs favorably against existing works on COCO-standard, COCO-additional, and VOC.)
- 该方法以**互利**的方式同时训练学生和缓慢进步的老师，老师生成伪标签用于训练学生，学生通过指数滑动平均逐步更新老师。(**Unbiased Teacher**: an approach that jointly trains a Student and a slowly progressing Teacher in a mutually-beneficial manner, in which the Teacher generates pseudo-labels to train the Student, and the Student gradually updates the Teacher via Exponential Moving Average (EMA).)
- 分别老师和学生提供弱增广(为了生成可靠的伪标签)、强增广(为了提升学生模型的多样性)的输入。(The Teacher and Student are given weakly(to provide reliable pseudo-labels) and strongly(the diversity of Student models) augmented inputs, respectively.)

1.3 How

- 利用伪标签对RPN和ROIhead进行显式的监督学习，因此能减轻RPN和ROIhead的过拟合问题。(We utilize the pseudo-labels as explicit supervision for both RPN and ROIhead and thus alleviate the overfitting issues in both RPN and ROIhead.)
- 利用老师-学生互利模型来防止噪声伪标签产生的不利影响。(We also prevent detrimental effects due to noisy pseudo-labels by exploiting the Teacher-Student dual models.)
- 利用EMA training and Focal loss，解决因类别不均衡引起的伪标签偏差问题，提升伪标签的质量。(With the use of EMA training and the Focal loss (Lin et al., 2017b), we can address the pseudo-labeling bias problem caused by class-imbalance and thus improve the quality of pseudo-labels.)

1.4 Contributions

- 发现了目标检测任务中类别不均衡问题对半监督目标检测任务中伪标签方法的作用的限制。(By analyzing object detectors trained with limited-supervision, we identify that the nature of class-imbalance in object detection tasks impedes the effectiveness of pseudo-labeling method on SS-OD task.)
- 提出了无偏老师的方法，解决伪标签问题和过拟合问题。(We thus proposed a simple yet effective method, Unbiased Teacher, to address the pseudo-labeling bias issue caused by class-imbalance existing in ground-truth labels and the overfitting issue caused by the scarcity of labeled data.)
- 表现SOTA。(Our Unbiased Teacher achieves state-of-the-art performance on SS-OD across COCOstandard, COCO-additional, and VOC datasets. We also provide an ablation study to verify the effectiveness of each proposed component.)

2. Approach

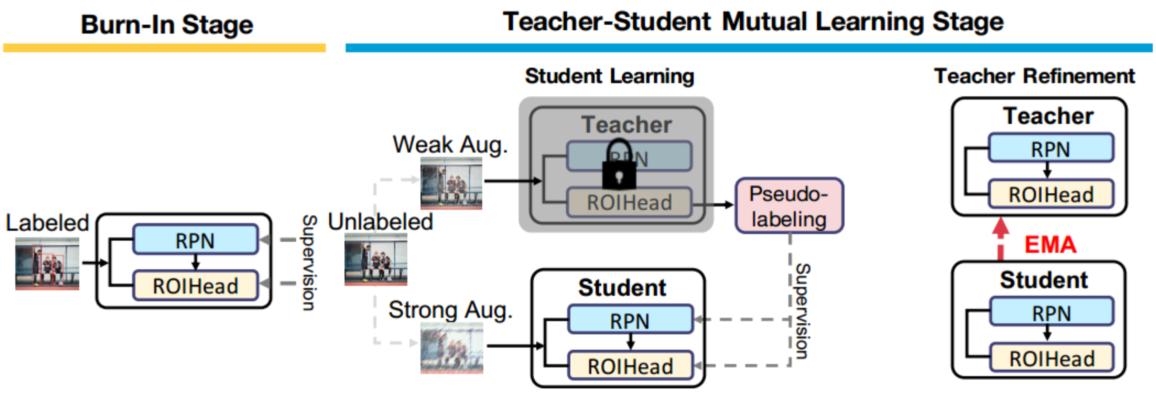

Figure 3: Overview of ***Unbiased Teacher***. Unbiased Teacher consists of two stages. ***Burn-In***: we first train the object detector using available labeled data. ***Teacher-Student Mutual Learning*** consists of two steps. **Student Learning**: the fixed teacher generates pseudo-labels to train the Student, while Teacher and Student are given weakly and strongly augmented inputs, respectively. **Teacher Refinement**: the knowledge that the Student learned is then transferred to the slowly progressing Teacher via exponential moving average (EMA) on network weights. When the detector is trained until converge in the Burn-In stage, we switch to the Teacher-Student Mutual Learning stage.

- 预热阶段，用标注数据进行监督学习来初始化老师模型。(In the Burn-In stage, we simply train the object detector using the available supervised data to initialize the detector.)
- 老师-学生相互学习阶段：(Our Teacher-Student Mutual Learning stage aims at evolving both Teacher and Student models via a mutual learning mechanism)
    - 老师教、学生学：老师生成伪标签来训练学生；(the Teacher generates pseudo-labels to train the Student)
    - 学生回馈、老师改善；(the Student updates the knowledge it learned back to the Teacher via exponential moving average (EMA))

2.1 BURN-IN

- 目的：**初始化检测模型**，用于生成可靠的伪标签供学生模型学习。该阶段模型收敛后，得到的模型在老师-学生相互学习阶段的开始时刻，会被复制给老师模型和学生模型。

$$\mathcal{L}_{sup} = \sum_i \mathcal{L}_{cls}^{rpn}(\boldsymbol{x}_i^s, \boldsymbol{y}_i^s) + \mathcal{L}_{reg}^{rpn}(\boldsymbol{x}_i^s, \boldsymbol{y}_i^s) + \mathcal{L}_{cls}^{roi}(\boldsymbol{x}_i^s, \boldsymbol{y}_i^s) + \mathcal{L}_{reg}^{roi}(\boldsymbol{x}_i^s, \boldsymbol{y}_i^s). \tag{1}$$

2.2 TEACHER-STUDENT MUTUAL LEARNING

- 目的：**提升伪标签生成的模型(improve the pseudo-label generation model)**

2.2.1 Student Learning with Pseudo-Labeling

- 目的：**the Student is optimized by using the pseudo-labels generated from the Teacher**

$$\theta_s \leftarrow \theta_s + \gamma \frac{\partial(\mathcal{L}_{sup} + \boldsymbol{\lambda}_u \mathcal{L}_{unsup})}{\partial \theta_s}, \quad \mathcal{L}_{unsup} = \sum_i \mathcal{L}_{cls}^{rpn}(\boldsymbol{x}_i^u, \hat{\boldsymbol{y}}_i^u) + \mathcal{L}_{cls}^{roi}(\boldsymbol{x}_i^u, \hat{\boldsymbol{y}}_i^u) \tag{2}$$

- 要点：
  - We first set a **confidence threshold** of predicted bounding boxes to **filter low-confidence predicted bounding boxes** to **prevent the consecutively detrimental effect of noisy pseudo-labels**.
  - We **remove the repetitive predictions** by applying **class-wise non-maximum suppression (NMS)** before the use of confidence thresholding as performed in STAC.
  - **Only the learnable weights of the Student model is updated** via back-propagation, because noisy pseudo-labels can affect the pseudo-label generation model (Teacher).
  - We do not apply unsupervised losses for the bounding box regression since the naive confidence thresholding is not able to filter the pseudo-labels that are potentially incorrect for bounding box regression.

2.2.2 Teacher Refinement via Exponential Moving Average

- 目的：**the Teacher is updated by gradually transferring the weights of continually learned Student model**
- 要点：The slowly progressing Teacher model can be regarded as the temporal ensemble of the Student models in different training iterations.

$$\theta_t \leftarrow \alpha\theta_t + (1 - \alpha)\theta_s. \tag{3}$$

2.3 BIAS IN PSEUDO-LABEL

- 目的：**解决生成的伪标签中的类别不均衡问题(address the crucial imbalance issue in generated pseudo-labels by Focal loss and EMA training)**
- 要点：
  - Multi-class Focal loss makes the model focus on hard samples
  - The EMA training can also alleviate the imbalanced pseudo-labeling biased issue due to the conservative property of the EMA training

$$\theta_t^i = \hat{\theta} - \gamma \sum_{k=1}^{i-1} (1 - \alpha^{-k+(i-1)}) \frac{\partial(\mathcal{L}_{sup} + \boldsymbol{\lambda}_u \mathcal{L}_{unsup})}{\partial \theta_s^k}, \tag{4}$$

3. Code

3.1 Training

- 以Train the Unbiased Teacher under 1% COCO-supervision为例：

```
python train_net.py \
      --num-gpus 8 \
      --config configs/coco_supervision/faster_rcnn_R_50_FPN_sup1_run1.yaml \
       SOLVER.IMG_PER_BATCH_LABEL 16 SOLVER.IMG_PER_BATCH_UNLABEL 16
```

3.2 Config

- 以configs/coco_supervision/faster_rcnn_R_50_FPN_sup1_run1.yaml为例：

```yaml
_BASE_: "../Base-RCNN-FPN.yaml"
MODEL:
  META_ARCHITECTURE: "TwoStagePseudoLabGeneralizedRCNN"
  WEIGHTS: "detectron2://ImageNetPretrained/MSRA/R-50.pkl"
  MASK_ON: False
  RESNETS:
    DEPTH: 50
  PROPOSAL_GENERATOR:
    NAME: "PseudoLabRPN"
  RPN:
    POSITIVE_FRACTION: 0.25
    LOSS: "CrossEntropy"
  ROI_HEADS:
    NAME: "StandardROIHeadsPseudoLab"
    LOSS: "FocalLoss"
SOLVER:
  LR_SCHEDULER_NAME: "WarmupMultiStepLR"
  STEPS: (179990, 179995)
  MAX_ITER: 180000  #论文第16页的A4中的Training部分有说明
  IMG_PER_BATCH_LABEL: 32  #论文第16页的A4中的Training部分有说明
  IMG_PER_BATCH_UNLABEL: 32  #论文第16页的A4中的Training部分有说明
  BASE_LR: 0.01  #论文第16页的A4中的Training部分有说明
DATALOADER:
  SUP_PERCENT: 1.0
  RANDOM_DATA_SEED: 1
DATASETS:
  CROSS_DATASET: False
  TRAIN: ("coco_2017_train",)
  TEST: ("coco_2017_val",)
SEMISUPNET:
  Trainer: "ubteacher"
  BBOX_THRESHOLD: 0.7  #论文第16页的A4中的Hyper-parameters部分有说明
  TEACHER_UPDATE_ITER: 1
  BURN_UP_STEP: 2000  #论文第16页的A4中的Training部分有说明
  EMA_KEEP_RATE: 0.9996  #论文第16页的A4中的Hyper-parameters部分有说明
  UNSUP_LOSS_WEIGHT: 4.0  #论文第16页的A4中的Hyper-parameters部分有说明
TEST:
  EVAL_PERIOD: 1000
  EVALUATOR: "COCOeval"
```

参考资料

1. 半监督目标检测SOTA: Unbiased Teacher(教学相长)
2. Unbiased Teacher for Semi-Supervised Object Detection论文解读

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