Semi-supervised Object Detection with Object-wise Contrastive learning and regression uncertainty

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1. Introduction

Semi-Supervised Object Detection
- Aims to boost detection performance by leveraging extra unlabeled data.
- Since the pseudo-labels are noisy, pseudo-label filtering is crucial.

Previous Works & Limitations
- Teacher-Student Framework [1] → Teacher network generates pseudo-labels for unlabeled data to assist the training of a student network.
- Previous Works ... → Adopted classification score to select pseudo-labels with confidence higher than a pre-defined threshold → Heuristic designs to measure the localization quality.
- Existing classification scores and localization optimization is suboptimal → Lack of labeled data makes classification scores less discriminative.
- Measurement of pseudo-labels’ localization quality is less investigated.

Key Ideas
- Object-wise Contrastive Learning (OCL) enhances the discriminativeness of the classification score.
- Regression-Uncertainty-guided Pseudo-Labeling (RUPL) models aleatoric uncertainty of object localization for label filtering.

2. Proposed Method

Framework Overview

Object-wise Contrastive Learning (OCL)

Object-wise Contrastive Loss

\[ \mathcal{L}_{\text{cont}} = -\sum_{i=1}^{N} \frac{1}{2} \left( 1 - \exp\left( \frac{\exp\left( \frac{1}{T} (s_i^p - s_i^m) \right)}{1 + \exp\left( \frac{1}{T} (s_i^p - s_i^m) \right)} \right) \right) \]

\[ w_{nm} = \begin{cases} 
1 & \text{if } n = m \\
\frac{p_n^p - p_m^m}{c_n^p - c_m^m} & \text{if } n \neq m \\
0 & \text{otherwise.}
\end{cases} \]

- Pseudo-label for Classification

\[ (x_i^{p}, y_i^{c}) \] if \( c_i^p \geq \frac{c_i^m}{p_i^m} \) \( \text{else, otherwise.} \)

Regression-Uncertainty-guided Pseudo-labeling (RUPL)

- Uncertainty-aware Regression Loss [2]

\[ \mathcal{L}_{\text{reg}} = \min(\frac{1}{\sigma_i^2} \mathcal{L}(\hat{y}_i, y_i^c)) + \text{smoothL1}(\hat{y}_i, y_i^c) + \text{log}\sigma_i^2 \]

- Pseudo-label for Regression

\[ (x_i^{p}, y_i^{c}) \] if \( \hat{y}_i^c \geq y_i^c \)

3. Experiments

Main Results

Ablation Study

4. Conclusion

- Propose a two-step pseudo-label filtering for SSOD.
- Deal with both classification and regression heads.
- OCL enhances discriminativeness of classification score.
- RUPL learns regression uncertainty to measure the localization quality.
- Achieve remarkable performance gain against our baseline and show competitive results compared to other SOTA.

References