Note: Weakly Supervised Semantic Segmentation using Out-of-Distribution Data[1]

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April 23, 2022

1 Introduction

This paper proposed to use out-of-distribution data to help to distinguish foreground and background pixels. OoD denotes data that do not contain any of the foreground classes od interest(i.e pure rail images). By subduing the recognition of foreground in OoD, model can better distinguish confusing cues.
OoDs are usually not a significant problem. Small amount of OoD data helps a lot.
And then authors proposed W-OoD.
Their contribution:
1, A new paradigm to utilize OoD to solve the problem of spurious correlations.
2, A dataset of hard OoDs will soon published.
3, W-OoD.

2 Method

2.1 Collecting the Hard OoD Data

Start from a candidate OoD set that that consists mostly of images without the foreground categories of interest. The aim is to refine it.

Where to get candidate OoDs Byproducts from the procedure of building a category-label image dataset.

Hard OoD samples via ranking and pruning Hard OoD samples: they are OoD samples confused by a classifier to be containing the foreground object. But the candidate OoDs may contain samples that is useless for training.
Method: we rank the candidate OoD data according to the prediction scores

$p(c)$ for the class c of interest. The classifier is trained on the images with foreground objects and the corresponding labels. Then prune OoD samples with $p(c) < 0.5$. This returns candidates for the hard OoD data.

Manual pruning of positive samples Many high rank OoDs may contain foreground samples. Manually check OoDs to prune those positive samples. (Need to Improve)

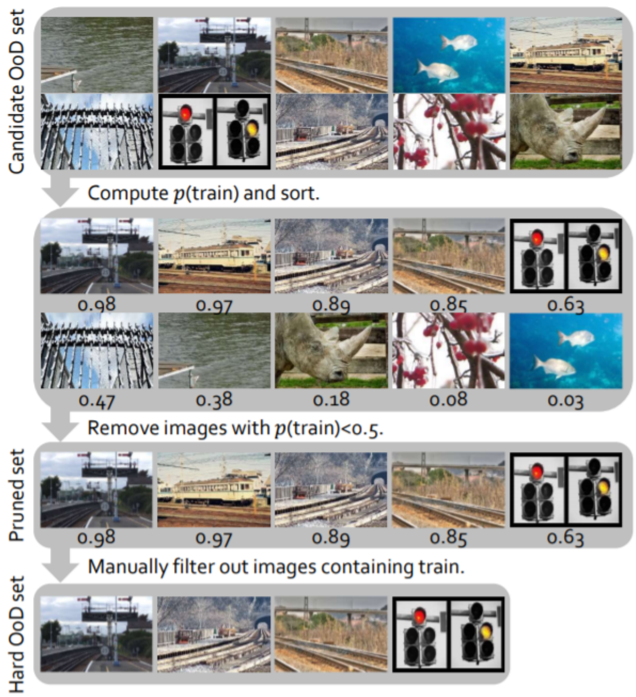

Figure 2. **Collecting hard OoD data**. Starting from the candidate OoD images at the top, we sequentially prune out easy OoDs and then false negatives for each foreground class $c \in \mathcal{C}$. The procedure results in the **hard OoD dataset**.

Surrogate source of OoD data How the authors construct their OoD dataset.

2.2 Learning with Hard OoD Dataset

To compute a metriclearning objective, use the penultimate feature z(?) of the in-distribution classifier F_{in} for an input x; we write z_{in} (resp. z_{ood}) as the

feature of $x_{in} \in D_{in}$ (resp. $x_{ood} \in D_{ood}$). We train a classifier F to ensure that z_{in} is significantly different from z_{ood}.
Let Z_{in} and Z_{ood} be the sets of z_{in} and z_{ood}, respectively. We first construct a set of clusters P_{in} (resp. P_{ood}) based onZ_{in} (resp. Z_{ood}). Each cluster in P_{in} contains features of x_{in} corresponding to each class $c \in C$, resulting in C clusters in P_{in}. Construct P_{ood} by using a K-means clustering algorithm on Z_{ood}.
To ensure that the distance between x and in-distribution clusters P min is s-mall, but the distance between x and OoD clusters P is large:

$$\mathcal{L}_{\mathrm{d}} = \sum_{c:y_c=1} d(x_{\mathrm{in}}, \mathcal{P}_c^{\mathrm{in}}) - \sum_{k \in \mathcal{K}} d(x_{\mathrm{in}}, \mathcal{P}_k^{\mathrm{ood}}),$$

where y is the one-hot code for classes in the image. K is the set of clusters in P_{ood} that are among the top-τ% closest from x_{in}.
The classification Loss:

$$\mathcal{L}_{\mathrm{cls}} = \frac{1}{|\mathcal{C}|} \sum_{c=1}^{|\mathcal{C}|} \left[\mathcal{L}_{\mathrm{BCE}}(\mathcal{F}^c(x_{\mathrm{in}}), y_c) + \mathcal{L}_{\mathrm{BCE}}(\mathcal{F}^c(x_{\mathrm{ood}}), 0) \right], \quad (3$$

Total loss is combines both loss aforementioned.

2.3 Training Segmentation Networks

The classifier F trained by total loss generates a localization map using the CAM technique and is refined with IRN framework.

3 Results

This method generates more precise maps around the actual foreground objects. Spuriously correlated background regions are effectively suppressed.
The pseudo ground-truth masks achieve an mIoU value of 72.1, which outperforms the previous state of the art by a large margin.

4 Summary

This paper proposed to utilize OoD as extra resource to suppress the prediction of the spurious background as foreground classes. And it also designed W-OoD and a new OoD dataset. The main idea is that utilizing the OoD actually gives an extra helpful information.

References

[1] J. Lee, S. J. Oh, S. Yun, J. Choe, E. Kim, and S. Yoon, "Weakly supervised semantic segmentation using out-of-distribution data," *arXiv preprint arXiv:2203.03860*, 2022. (document)