SELF-SUPERVISED ROBUST OBJECT DETECTORS FROM PARTIALLY LABELLED DATASETS

Mahdieh Abbasi, Denis Laurendeau, Christian Gagné

Department of Electrical and Computer Engineering, Université Laval, Québec, Canada

ABSTRACT

In the object detection task, merging various datasets from similar contexts but with different sets of Objects of Interest (OoI) is an inexpensive way (in terms of labor cost) for crafting a large-scale dataset covering a wide range of objects. Moreover, merging datasets allows us to train one integrated object detector, instead of training several ones, which in turn resulting in the reduction of computational and time costs. However, merging the datasets from similar contexts causes samples with partial labeling as each constituent dataset is originally annotated for its own set of OoI and ignores to annotate those objects that are become interested after merging the datasets. With the goal of training one integrated robust object detector with high generalization performance, we propose a training framework to overcome missing-label challenge of the merged datasets. More specifically, we propose a computationally efficient self-supervised framework to create on-the-fly pseudo-labels for the unlabelled positive instances in the merged dataset in order to train the object detector jointly on both ground truth and pseudo labels. We evaluate our proposed framework for training Yolo on a simulated merged dataset with missing rate $\approx 48\%$ using VOC2012 and VOC2007. We empirically show that generalization performance of Yolo trained on both ground truth and the pseudo-labels created by our method is on average $4\%$ higher than the ones trained only with the ground truth labels of the merged dataset.

Index Terms— Robust object detector, Self-supervised method, partially-labeled datasets, missing-label instances, Out-of-Distribution samples

1. INTRODUCTION

Modern CNN-based object detectors such as faster R-CNN [1] and Yolo [2] achieve remarkable performance when the training is done on fully labeled large-scale datasets, which include instance level annotations (i.e. bounding boxes around each object of interest) and image level (i.e. category of the object enclosed in a bounding box). Collecting a dataset with full annotations, especially bounding boxes, can be a tedious and costly process. However, object detectors such as R-CNN and Yolo show a dependency to such fully labeled datasets to achieve high performance. In other words, they suffer from a drop in generalization performance when trained on partially labeled datasets (i.e., containing instances with missing labels) [3, 4]. Datasets with missing label instances can occur in several situations, including unintentional errors occurring in the annotation process, partial annotation policy, and when datasets are merged. To reduce annotation cost of large-scale datasets (e.g. OpenImagev3 [5]), partial annotation policy considers annotation of only one instance of each object presented in a given image. For example, in an image containing a herd of sheeps, only one of them is annotated, instead of fully annotating all sheep instances. This policy causes some missing bounding box annotations but interestingly no missing image level labels, at least one instance of each existing object in the given image being annotated. For the case of merged datasets, we aim at combining several datasets from similar (or the same) contexts but with disjoint (or partially disjoint) sets of Objects-of-Interest (OoI), e.g. [6], in order to construct a larger dataset including a wider range of objects, of possibly more variations in their capture and nature (e.g. objects of different poses, illumi-
nations, styles, physical properties). For instance, Kitti [7] and German Traffic Signs [8] are datasets with two disjoint sets of OoI that could be merged to cover a wider spectrum of objects appearing on roads. However, merging datasets results in instances with missing labels, since some OoI in one dataset might be not be labeled in other datasets.

Furthermore, such merged datasets can facilitate the training of an integrated object detector, which in turn can potentially lead to a significant reduction of time and computational cost. This approach shows advantages over more direct approaches of creating several object detectors, trained on one of the base dataset. First, it circumvents the need to combine decisions made by the various networks, which can be tricky and lead to suboptimal solutions. It can also make a more efficient use of memory and computational resources with only one object detector having to be trained on the merged dataset instead of training a model for each constituting dataset. This is especially appealing for embedded devices with limited computational resources (e.g. self-driving cars) that need to make inference decisions in real-time. Finally, generating such merged datasets is a building block toward the development of universal object detectors (e.g. [2]).

Despite the great potential of the above strategies for the reduction of the computational cost and annotation burden, many modern object detectors trained on partially labeled datasets achieve inferior generalization performance than those trained with fully labeled datasets [3, 10]. Regardless the type of object detectors, the performance degradation is mostly rooted in the small size of training sets. However, in some object detectors such as faster R-CNN, performance can be impacted by incorrect training signals that is false negative signal arising from the Unlabeled Positive Instances (UPIs), the OoI instances without label [3]. A detector may incorrectly learn these UPIs as negative or background instances due to the lack of labels for them.

To augment the training size of such partially labeled datasets, Weakly Supervised Learning (WSL) methods [4, 10, 11, 12] have been proposed to generate pseudo-labels for some UPIs by leveraging the image-level labels available in sets following a partial annotation policy. In other words, according to this policy, it is known which image contains which objects (image-level labels), although there is no bounding box annotation to locate them. However, such WSL methods can not simply be exploited in the merged datasets scenario due to the absence of both image-level and instance-level annotations.

To mitigate the performance degradation in faster R-CNN trained on partially labeled datasets (e.g. OpenImagev3), Wu et al. [3] propose to ignore the false training signals arising from UPIs (i.e. false negative). To this end, they discard gradients created by the RoIs that have small or no overlap with any ground truth. Although this simple approach can remove the false negative training signals by UPIs, correcting them, instead of ignoring them, can further improve generalization performance, particularly for the merged dataset. In other words, to have a well-generalized object detector on a merged dataset consisting of diverse multiple datasets, it is important to train the model on positive instances, either the labeled ones or those unlabeled (UPIs). In [6], the authors proposed to generate pseudo-labels for UPIs in the merged dataset by using several object detectors trained separately on each individual dataset in the merged one. Finally, a unified object detector can be trained on the generated pseudo- and ground-truth labels. However, generating pseudo-labels requires significant computational resources for training and the use of several extra object detectors.

In this paper, we aim at enhancing generalization performance of the object detector, when it is trained on a merged dataset, through augmenting it with pseudo-labels of UPIs. For that purpose, we propose a general training framework for simultaneously training the detector (e.g. Yolo) while creating pseudo labels for UPIs. Fig. 1 demonstrates the pipeline of our proposed method. We use a pre-trained proxy neural CNN on Yolo-predicted bounding-boxes (b-boxes), which have small or no overlap with ground truth labels, in order to flag whether they are involving a positive instance or not. If the proxy network classifies them as one of the pre-defined positive objects (OoI), their pseudo-labels are created to being included in training phase of the object detector. Otherwise, they are discarded from contributing in training. Inspired by [13, 14], we use a Convolution Neural Network with an explicit rejection option as the proxy for either classifying a given RoI into one of the pre-defined OoI or reject it as a not-of-interest object. To train this proxy, we can leverage from readily accessible datasets that contain the samples from not-interested-objects (we call them Out-of-Distribution –OoD– samples) along with the labeled samples containing OoI (a.k.a. in-distribution samples). Recently, some promising results of OoD training have been reported for developing robust object recognition classifiers [13, 14] and semantic segmentation models [15], as well as for overcoming catastrophic forgetting [16].

2. PROPOSED METHOD

During training of Yolo, it is highly likely that some existing UPIs are localized correctly, but due to the lack of ground truth label for them, Yolo discard them during its training. the estimated RoIs by Yolo at training epoch $t$ are evaluated to check whether they actually contain a positive unlabeled object or not. To achieve this, our framework (see Algorithm 1) incorporates a pre-trained proxy network [13], denoted by $h(\cdot)$, into the training process of Yolo. Indeed, the proxy network maps the estimated RoI of a given image $I_j$ (denoted by $\hat{r}_j$), into a vector of probabilities over $K+1$ classes, i.e. $h(\hat{r}_j) \in [0, 1]^{K+1}$, where $\{1, \ldots, K\}$ denotes the class of $K$ positive objects (OoI) and $K+1$-th (extra) class is for any uninterested (negative) objects. Note that to enable $h$ for pro-
Fig. 2. Violet bounding boxes are our pseudo-labels generated during training of Yolo while the green bounding boxes are ground-truth labels in dataset \( D'_S \) (i.e. the merged dataset from VOC2007 and VOC2012 with disjoint sets of classes.)

Algorithm 1: Pseudo-label Generation Algorithm

Data: \( f^t(\cdot) \) object detector at training epoch \( t \); \( h(\cdot) \) pre-trained proxy network; \( I_j \) given input image with its associated ground-truth \( T_j = [R_j, Y_j] \) with \( R_j \) as instance-level labels (i.e. coordinate information) and \( Y_j \) as image-level labels (class of enclosed objects by bounding-boxes); \( \theta_1, \theta_2 \) and, \( \beta \) as hyper-parameters

Result: \( S^t_j \), pseudo-labels of \( I_j \) at time \( t \)

1. \( S^0_j = \emptyset \)
2. \( \tilde{R}^t, p_f, (\text{cls} | \tilde{R}^t), p_f, (\text{obj} | \tilde{R}^t) = f^t(I_j) \)
3. \( B = \{\emptyset\} \)
4. for \( \tilde{r} \in \tilde{R}^t_j \)
5. if \( \text{IoU}(\tilde{r}, R_j) \leq \theta_1 \)
6. \( B \leftarrow B \cup \{\tilde{r}\} \)
7. \( B \leftarrow \text{pre-processing step (} B \text{)} \)
8. for \( \tilde{r} \in B \)
9. \( \bar{h}(I_j^t) = \frac{1}{m+1} \left( h(I_j^t) + \sum_{i=1}^{m} h(I_j^t) \right) \)
10. if \( \arg \max \bar{h}(I_j^t) = K + 1 \& \max_{1 \cdots K} h(I_j^t) \geq \theta_2 \)
11. \( \bar{p}(\text{cls}|\hat{r}) = \beta \times p_f,(\text{cls}|\hat{r}) + (1 - \beta) \times \bar{h}(I_j^t) \)
12. \( \bar{p}(\text{obj}|\hat{r}) = \max_{1 \cdots K} \bar{h}(\hat{r}) \)
13. \( S^t_j \leftarrow S^t_j \cup \{\tilde{r}, \bar{p}(\text{cls}|\hat{r}), \bar{p}(\text{obj}|\hat{r})\} \)

2.1. Pre-processing Step

At the pre-processing step, we perform a transformation on the extracted RoIs to prepare them for \( h(\cdot) \). Training of \( h \) with mini-batch SGD on the input samples with different aspect ratio sizes is challenging since Python libraries such as Pytorch do not allow a batch of input samples with various sizes to be stacked. We can think of padding the inputs with the largest aspect ratio size in the batch, but this in turn can destroy the information of the smallest inputs (since these images are dominated by a large pad of zeros). To tackle this, in each training epoch of \( h \), we load the samples with similar (close) aspect ratio sizes in one batch and pad them with zeros to achieve a batch of samples with equal aspect ratio size. To implement this, all training samples are clustered by their widths and heights, using the \( k \)-means method. Then, the center of these clusters serves as the pre-defined aspect ratio sizes to load batches accordingly. In the pre-processing step, at test time, when needed, all input instances to \( h \) should be padded with zeros in order to keep their size equal to their nearest centers (line 7 of Algorithm 1).

2.2. Pseudo-label Generation

Inspired by [19], we make use of patch-drop at test time of \( h \) in order to estimate the true class of a given RoI more accurately. In patch-drop, we divide the given RoI into \( 3 \times 3 \) patches, then randomly drop one of the patches to create a new version of the RoI. In our experiments, We apply patch-drop \( m = 2 \) times on a given RoI to create \( m \) versions of \( I_j^t \) (i.e. \( \{I_j^{t1}, \ldots, I_j^{tm}\} \)). We feed them as well as \( I_j^t \) to the proxy network for estimating the conditional probability over \( K + 1 \) classes as follows:

\[
\bar{h}(I_j^t) = \frac{1}{m+1} \left( h(I_j^t) + \sum_{i=1}^{m} h(I_j^{t_i}) \right).
\] (1)

This trick leads to a lower confidence prediction for some hard-to-classify RoIs when \( h \) predicts each version of \( I_j^t \) (by drop-patch) differently (to different classes). This also leads to more accurate class prediction, which results in the creation of processing RoIs with different aspect ratios, we exploit a Spatial Pyramid Pooling (SSP) layer [17] after the proxy’s last convolution layer.

More precisely, using estimated coordinate information, compactly denoted as \( \tilde{R}_j^t \), which are estimated by Yolo at training time \( t \) for image \( I_j \), RoIs \( (\tilde{I}_j^t) \) are extracted from \( I_j \). To avoid re-labeling ground truths, only the RoIs that have a small or no overlap with any of ground truth annotations (line 4–6 of the algorithm) are processed. Before feeding these extracted RoIs to the proxy network, they should be pre-processed by the following procedure.
of accurate pseudo-labels. Using a threshold on confidence (i.e. $\theta_2$ in the algorithm), the RoIs with low confidence predictions are dropped to continue the pseudo-label generation procedure. If $h$ confidently classifies the given RoI into one of $K$ classes of interest, its pseudo conditional class probability $\hat{p}(cls|\vec{r})$ is computed as follows:

$$\hat{p}(cls|\vec{r}) = \beta * p_f(k|\vec{r}) + (1 - \beta) * \hat{h}(I^f_t),$$

where $p_f(k|\vec{r})$, $\hat{h}(\vec{r}) \in [0,1]^K$ are the respectively estimated class probabilities by Yolo at training epoch $t$ and the proxy network $h$ for given RoI $I^f_t$, note the $K + 1$ element of $\hat{h}$ is dropped and denoted by $\vec{r}$. Finally, we set the conditional probability of object given $\vec{r}$ as $\hat{p}(obj|\vec{r}) = \max_{k=1}^K \hat{h}(I^f_t)$.

To compute the loss between the pseudo-class label, i.e. $\hat{p}(cls|\vec{r}) \in [0,1]^K$ and the estimation by Yolo, i.e. $p_f(k|\vec{r})$, we use KL-divergent. We add $KL(\hat{p}(cls|\vec{r}) || p_f(k|\vec{r}))$ to the conventional loss functions, which is computed for the ground truth labels, including bounding-box loss (mean square error), object loss (binary cross-entropy), and class loss (categorical cross-entropy). Similar to object loss for ground-truths, the object loss for pseudo object labels $\hat{p}(obj|\vec{r})$ is computed by binary cross-entropy.

### 3. EXPERIMENTS

To simulate a merged dataset, we create two datasets with two disjoint sets of classes from VOC2007 with $S_A = \{\text{cat, cow, dog, horse, train, sheep}\}$ and VOC2012 with $S_B = \{\text{car, motorcycle, bicycle, aeroplane, bus, person}\}$. One dataset, called $D_{S_A}$, gathers the samples from VOC2007 that are containing one of the objects of interest in $S_A$ (dropping the annotations from other set of classes $S_B$, if there are any in $D_{S_A}$). Similarly, another dataset $D_{S_B}$ is made of the images from VOC2012 containing one of objects in $S_B$. Then, these two datasets are merged to produce a merged dataset $D'_S = D_{S_A} \cup D_{S_B}$ with total classes of $S = S_A \cup S_B$. In addition, a fully labeled dataset $D_S$ from the union of VOC2007 and VOC2012 are formed, where all the instances belonging to $S$ are fully annotated. The missing label rate of $D'_S$ (the merged dataset) with respect to $D_S$ is 48%.

As the proxy network, we adopt Resnet20 [19] by placing a SPP (Spatial Pyramid Pooling) layer after its last convolution layer to enable it to process the inputs with various aspect-ratio sizes. To train this network, we utilize MSCOCO [20] training set by extracting all the ground truth bounding boxes belonging to one of the classes in $S = S_A \cup S_B$, and all other ground truth bounding boxes not belonging to $S$ are used as OOD samples (labeled as class $K + 1$). The hyper-parameters of our algorithm are set to $\beta = 0$ (in Eq. [2]), $\theta_1 = 0.5$ (to remove RoIs having a large overlap with ground truth), line 4–6 of Algorithm), and $\theta_2 = 0.8$ (the threshold on the prediction confidence of the proxy network for given RoIs).

In Fig. [1] we demonstrate the pseudo labels generated by our proposed method for some UPIs in $D'_S$. In Table 1 we compare mAP@0.5 of three Yolos, where they are respectively trained on $D'_S$ (baseline), on augmented $D'_S$ by our pseudo-labels (Ours), and finally on fully labeled dataset $D_S$. As it can be seen, the Yolo trained on $D'_S$ (with a 48% rate of missing labels) leads to a $\approx 17\%$ drop in mAP@0.5, compared to the same Yolo when it trained on the fully-labeled dataset ($D_S$). Ours enhances mAP of Yolo trained on the merged dataset $D'_S$ by 4% (on average) as it achieves through augmenting $D'_S$ by pseudo-labels for some of UPIs.

### 4. CONCLUSION

With the goal of training an integrated object detector with the ability of detecting a wide range of OoIs, one can merge several datasets from similar context but with different sets of OoI. While merging multiple datasets to train an integrated object detector has attractive potential for reducing computational cost, many missing label instances (Unlabeled Positive Instances) in the merged dataset cause performance degradation of the object detector trained on it. To address this issue, we propose a general training framework for simultaneously training an object detector on the merged dataset while generating on-the-fly pseudo-labels for UPIs. Using a pre-trained proxy neural network, we generate a pseudo label for each estimated RoI if the proxy network confidently classifies it as one of its pre-defined interested classes. Otherwise, we exclude it from contributing in training of the object detector. By a simulated merged dataset using VOC2007 and VOC2012, We empirically show that Yolo trained by our framework achieve higher generalization performance, compared with the Yolo trained on the original merged dataset. This achievement is the result of augmenting the merged dataset with our generated pseudo-labels for UPIs.

### Table 1. Performance (i.e. mAP) of different Yolos on the test set of VOC2007 with fully labeled instances from classes $S = S_A \cup S_B$. Baseline is the trained Yolo on the merged dataset (voc2007+voc2012) with missing-label instances ($D'_S$), ours is Yolo trained on the augmented dataset $D'_S$ with our generated pseudo-labels, and the upper-bound is the Yolo trained on voc2007+voc2012 with fully annotated instances ($D_S$).

| Method (mAP@0.5) | Cat   | Cow   | Dog   | Horse | Train | Sheep | Car   | Motorbike | Bicycle | Aeroplane | Bus   | Person | Avg   |
|------------------|-------|-------|-------|-------|-------|-------|-------|------------|---------|------------|-------|--------|-------|
| Baseline         | 74.78 | 48.27 | 52.72 | 18.68 | 58.36 | 57.78 | 68.23 | 69.98      | 59.96   | 65.26      | 71.32 | 60.25   |       |
| Ours             | 77.21 | 55.60 | 62.0  | 23.72 | 57.70 | 65.11 | 78.34 | 72.41      | 72.10   | 62.64      | 71.26 | 72.0   | 64.2  |
| Upper-bound      | 82.05 | 69.71 | 78.70 | 82.51 | 79.18 | 72.45 | 83.88 | 79.01      | 71.30   | 78.83      | 78.302| 77.97  |       |
5. REFERENCES

[1] Shaoqing Ren, Kaiming He, Ross Girshick, and Jian Sun, “Faster r-cnn: Towards real-time object detection with region proposal networks,” in Advances in neural information processing systems, 2015, pp. 91–99.

[2] Joseph Redmon, Santosh Divvala, Ross Girshick, and Ali Farhadi, “You only look once: Unified, real-time object detection,” in Proceedings of the IEEE conference on computer vision and pattern recognition, 2016, pp. 779–788.

[3] Zhe Wu, Navaneeth Bodla, Bharat Singh, Mahyar Najibi, Rama Chellappa, and Larry S Davis, “Soft sampling for robust object detection,” arXiv preprint arXiv:1806.06986, 2018.

[4] Yongqiang Zhang, Yaicheng Bai, Mingli Ding, Yongqiang Li, and Bernard Ghanem, “Weakly-supervised object detection via mining pseudo ground truth bounding-boxes,” Pattern Recognition, vol. 84, pp. 68–81, 2018.

[5] Neil Alldrin Vittorio Ferrari Sami Abu-El-Haija Alina Kuznetsova Hassan Rom Jasper Uijlings Stefan Popov Andreas Veit Serge Belongie Victor Gomes Abhinav Gupta Chen Sun Gal Chechik David Cai Zheyun Feng Diyanesh Narayanan Ivan Krasin, Tom Duerig and Kevin Murphy, “Openimages: A public dataset for large-scale multi-label and multi-class image classification,” .

[6] Alexandre Rame, Emilien Garreau, Hedi Ben-Younes, and Charles Ollion, “Omnia faster r-cnn: Detection in the wild through dataset merging and soft distillation,” arXiv preprint arXiv:1812.02611, 2018.

[7] Andreas Geiger, Philip Lenz, Christoph Stiller, and Raquel Urtasun, “Vision meets robotics: The kitti dataset,” The International Journal of Robotics Research, vol. 32, no. 11, pp. 1231–1237, 2013.

[8] Sebastian Houben, Johannes Stallkamp, Jan Salmen, Marc Schlipsing, and Christian Igel, “Detection of traffic signs in real-world images: The German Traffic Sign Detection Benchmark,” in International Joint Conference on Neural Networks, 2013, number 1288.

[9] Xudong Wang, Zhaowei Cai, Dashan Gao, and Nuno Vasconcelos, “Towards universal object detection by domain attention,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2019, pp. 7289–7298.

[10] Mengmeng Xu, Yancheng Bai, Bernard Ghanem, Boxiao Liu, Yan Gao, Nan Guo, Xiaochun Ye, Fang Wan, Haihang You, Dongrui Fan, et al., “Missing labels in object detection,” in The IEEE Conference on Computer Vision and Pattern Recognition (CVPR) Workshops.

[11] Hakan Bilen and Andrea Vedaldi, “Weakly supervised deep detection networks,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2016, pp. 2846–2854.

[12] Ali Diba, Vivek Sharma, Ali Pazandeh, Hamed Pirsiavash, and Luc Van Gool, “Weakly supervised cascaded convolutional networks,” in Proceedings of the IEEE conference on computer vision and pattern recognition, 2017, pp. 914–922.

[13] Mahdieh Abbasi, Changjian Shui, Arezoo Rajabi, Christian Gagne, and Rakesh Bobba, “Toward metrics for differentiating out-of-distribution sets,” in WNeurIPS. Safety and Robustness in Decision Making, 2019.

[14] Dan Hendrycks, Mantas Mazeika, and Thomas G Dietterich, “Deep anomaly detection with outlier exposure,” Internation Conference on Representation Learning (ICLR), 2019.

[15] Petra Bevandić, Ivan Krešo, Marin Oršić, and Siniša Šegvić, “Discriminative out-of-distribution detection for semantic segmentation,” arXiv preprint arXiv:1808.07703, 2018.

[16] Kibok Lee, Kimin Lee, Jinwoo Shin, and Honglak Lee, “Overcoming catastrophic forgetting with unlabeled data in the wild,” in ICCV, 2019.

[17] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun, “Spatial pyramid pooling in deep convolutional networks for visual recognition,” IEEE transactions on pattern analysis and machine intelligence, vol. 37, no. 9, pp. 1904–1916, 2015.

[18] Krishna Kumar Singh and Yong Jae Lee, “Hide-and-seek: Forcing a network to be meticulous for weakly-supervised object and action localization,” in 2017 IEEE International Conference on Computer Vision (ICCV). IEEE, 2017, pp. 3544–3553.

[19] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun, “Deep residual learning for image recognition,” in Proceedings of the IEEE conference on computer vision and pattern recognition, 2016, pp. 770–778.

[20] Tsung-Yi Lin, Michael Maire, Serge Belongie, James Hays, Pietro Perona, Deva Ramanan, Piotr Dollár, and C Lawrence Zitnick, “Microsoft coco: Common objects in context,” in European conference on computer vision. Springer, 2014, pp. 740–755.