Discovery-and-Selection: Towards Optimal Multiple Instance Learning for Weakly Supervised Object Detection

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Abstract—Weakly supervised object detection (WSOD) is a challenging task that requires simultaneously learn object classifiers and estimate object locations under the supervision of image category labels. A major line of WSOD methods roots in multiple instance learning which regards images as bags of instance and selects positive instances from each bag to learn the detector. However, a grand challenge emerges when the detector inclines to converge to discriminative parts of objects rather than the whole objects. In this paper, under the hypothesis that optimal solutions are included in local minima, we propose a discovery-and-selection approach fused with multiple instance learning (DS-MIL), which finds rich local minima and select optimal solutions from multiple local minima. To implement DS-MIL, an attention module is designed so that more context information can be captured by feature maps and more valuable proposals can be collected during training. With proposal candidates, a re-rank module is designed to select informative instances for object detector training. Experimental results on commonly used benchmarks show that our proposed DS-MIL approach can consistently improve the baselines, reporting state-of-the-art performance.

Index Terms—Weakly Supervised Object Detection, Training Strategy, Self-supervised Attention

I. INTRODUCTION

Weakly supervised object detection (WSOD) has been attracted increasing attention, due to its effortless annotation that only needs indicator vectors to demonstrate the existence of each class [1]–[7]. Compared with fully supervised object detection which requires labor-intensive bounding-box annotations, WSOD significantly reduces the workload of data annotation. With WSOD, people can leverage rich images with tags on the internet to learn object-level models, and thereby convert human-supervised object detection to Webly supervised object modeling.

Multiple Instance Learning (MIL) [8] has been the cornerstone of many WSOD methods, either with hand-crafted features [9], [10] or deep learning pipelines [1], [3], [4], [6], [11]. With MIL, images are decomposed to bags of proposals (instances). Each image from the classes of interest has at least one positive instance and images from negative classes has no positive instance. WSOD is considered as an instance classification problem, where object detectors are constructed by alternates training the classifier and selecting positive candidate proposal.

MIL-based WSOD networks usually focus on classifier learning and feature learning, which roughly choose the high-scored candidate as positive samples for the object localization. Consequently, the detectors rely on classification score outputted by the MIL classifier, resulting in noisy proposals of poor localization. The noisy proposals are typically discriminative object parts instead of whole object extent.

To alleviate the impact of noisy proposals, one solution is re-training an object detector with pseudo ground-truths (top-scoring proposals) generated by weakly-supervised object detectors [3], [4], [6], [12]. However, because the number of the noisy proposals are usually greater than the optimal solution, the noisy proposal introduced in the training phase could seriously deteriorate the trained detectors.

The other solution is to explore sophisticated optimization strategies. The C-MIL method [6] recognized this problem by decomposing the complicated optimization problem to multiple sub-optimization problems which are easy to be solved. Nevertheless, as shown in Fig. 1(a), C-MIL remains getting stuck to the local minimum when the continuation parameters are not properly defined. In this paper, we introduce a discovery-and-selection training strategy in Fig. 1(b) to multiple instance learning network and thereby create DS-MIL. DS-MIL is implemented by introducing an instance discovery module and an instance selection module to the multiple instance learning network. It aims to discover multiple local minima and then select the best sample in these multiple local minima, alleviating the local minimum issue in WSOD in a simple-yet-effective fashion.

For the discovery term, inspired by non-local network [13], a self-attention module is designed so that the feature maps of CNN capture context information of the object proposals generated by Selective Search. In this manner, we can find rich local minima, which increases the probability to obtain optimal solutions during multiple instance learning. For the selection term, we take an Expectation-Maximization algorithm to re-rank the confidence of the object proposals, in which we explicitly model instance assignment as a hidden variable and derive the pseudo-label generation scheme to conduct the E and M steps respectively. The algorithm assign a high score to the proposals which lays a decisive role to determine an proposal bag whether belongs to positive.

The contributions of this study are summarized as follows:

1) We propose the discovery-and-selection training strategy for WSOD, solving the local minimum issue of multiple instance learning under the hypothesis that optimal solutions are included in local minima.
Fig. 1. Comparison of CMIL based approaches and our DS-MIL. (a) shows that C-MIL introduced the continuation method into WSOD, but still can not solve the non-convexity problem completely and localize only part of object (Red box). (b) shows our motivation which introduce a Discovering Module to find more local-minima and a Selection Module to choose in the found instances. This alleviates the non-convexity problem and localizes full object extent (Green box).

2) We design a proposal discovery module which leverages localization information from multiple locations and finds more reliable proposals. We propose a novel proposal selection module, which utilize self-supervised attention mechanism to optimize instance proposals.

3) Experimental results on commonly used benchmarks show our proposed DS-MIL approach can consistently improve the baselines, achieving state-of-the-art performance.

The rest of this paper is organized as follows: In Section II, we review related research. In Section III we describe the proposed approach in details. Experimental results are shown and discussed in Section IV, and we made a conclusion of our work in Section V.

II. RELATED WORK

WSOD is an attractive computer vision task in which a detector is trained only with image-level annotations. WSOD is usually solved with MIL based approach, especially significantly boosted with convolutional neural networks.

A. Multiple Instance Learning for WSOD.

MIL is effective to solve weakly supervised problem with coarse labels [8]. Positive and negative bags are used to train a instance-level classifier in MIL. A positive bag is a set of instances at least one of which is positive while a negative bag is a set of negative instances. The WSOD is natural to treat as a MIL problem. Supposing image is a bag with candidate instances which are generated by object proposal method [14]. The multi-fold MIL is proposed to solve large-scale training dataset by diving it to several parts [9]. In [10], full annotation of extra data is used to train a instance detector, improving the performance of MIL by transferring representation. However, the performance gap between weakly supervised and fully supervised task is insurmountable with traditional MIL approaches.

B. Deep Learning for WSOD

Recently, WSOD largely outperforms the previous State-of-the-arts by combining deep neural networks and MIL. The Weakly Supervised Deep Detection (WSDDN) [1] is firstly introduced to deal with WSOD, which is composed of a proposal classifier branch and a proposal selector branch inspired by MIL. WSDDN selects the positive samples by aggregating the score of the two branches and its effectiveness attracts lots of works to follow its framework. The WSDDN brings the WSOD into a new era.

Feature Learning based WSOD. [15] transfered tracked boxes from weakly-labeled videos to weakly-labeled images as pseudo ground-truth to train the detector directly on images. [16] proposed to fuse and filter object instances from different techniques and perform pixel labeling with uncertainty and they used the resulting pixel-wise labels to generate bounding boxes for object detection and attention maps for multi-label classification. Others are attempt to learn feature representation to gain better performance. [2] proposed an end-to-end cascaded convolutional network to perform weakly supervised object detection and segmentation in cascaded manner. [17] proposed to learn a context-aware CNN with contrast-based contextual modeling. [18] uses mask to hide the most discriminative part of a image to enforce the feature extractor to capture the integral extent of object. [19] leverage the complementary effects of WSOD and Weakly Supervised Semantic Segmentation to build detection-segmentation cyclic collaborative frameworks. Comprehensive Attention Self-Distillation (CASD) is proposed to balance feature learning among all object instances [7]. [5] inspired by a classical thermodynamic
principle, proposed a min-entropy latent model (MELM) and recurrent learning algorithm for weakly supervised object detection.

Proposal Refinement based WSOD. Several approaches focus on the refinement of proposal localization. [12] introduces domain adaptation into WSOD to fine-tune the network to collect class specific object proposals. In [3], Online Instance Classifier Refinement (OICR) alleviates the part domination problem by knowledge distillation. [4] is based on OICR, coming up with using proposal clustering to improve proposal generation and using proposal clusters as supervision. In order to generate more precise proposals for detection, [20] designed a weakly supervised region proposal network, [21] proposed a tight box mining method that leverages surrounding segmentation context derived from weakly supervised segmentation to suppress low quality distracting candidates and boost the high-quality ones. [10] proposed a multi-fold MIL detector by re-labeling proposals and retraining the object classifier iteratively to prevent the detector from being locked into inaccurate object locations. [22] proposed a pseudo label excavation algorithm and a pseudo label adaptation algorithm to refine the pseudo labels obtained by [3]. [11], [23], [24] integrate bounding box regressor into weakly-supervised detector. [25] leverage weakly supervised semantic segmentation to remove unprecise proposals.

Optimization Strategy for WSOD. [26] observes that the result of MIL based detector is unstable when use different initialization and utilizes the instability to improve the performance of the detector by fusing the results of differently initialized detectors. C-MIL [6] is proposed in order to alleviate the non-convexity problem by introducing continuation learning to WSOD to simplify the original MIL loss function. [27] proposed a self-taught learning approach to progressively harvest high-quality positive instances. [28] introduces a generative adversarial segmentation module interacts with the conventional detection module to avoid being trapped in local-minima.

C. Weakly Supervised Video Action Localization

Similar with the setting of WSOD, Weakly Supervised Video Action Localization aims to localize and classify the activities in an untrimmed video with only action label to identify the video has what kind of actions. [29], [30] uses attention in their methods to compute the importance of each clip. In order to localize complete activities, some adversarial methods [31], [32] mask the most conspicuous part of videos. [33] uses a prior that motionless video clips are unlikely to be actions to separate action clips from complex background. [34]–[36] try to use other weak labels such as scripts,images from web or action lists to train their model. [37] adopts Expectation-Maximization to make the video proposal selection more accuracy. Inspired by [37], we take the same selection strategy for object proposal selection, which also shows effectiveness for WSOD.

D. Attention in Object Detection.

Inspired by the process that humans selectively use an important part of the data to make a decision, attention mechanism was first proposed to solve natural language processing problems and then introduced to computer vision areas [38], [39]. For object detection, attention mechanism could be classified into two categories: features re-weighting [40]–[42] and loss regularizing [43], [44]. Attention is called self-attention when query is set as itself. Several previous works, i.e., non-local attention [13] and relation attention [45], indicate that self-attention is effective to learn the meaningful representation for conducting the given task. We attempt to optimizes the location and classification in WSOD by using both
self-attention to explore channel-wise feature re-weighting and normal attention for proposal-wise loss regularization.

It’s worth exploring how to effectively take the complementarity of the feature learning and proposal selection. By incorporating the attention mechanism, we propose discovering-and-selection strategy, which towards optimal multiple instance learning for weakly supervised object detection.

III. METHOD

A. Revisiting MIL-based WSOD

MIL-based WSOD model usually follows a two-phase learning procedure, i.e., Classification branch and Detection branch for refinement and regression. It denotes $I = \{I^1, I^2, ..., I^T\}$ as a dataset with $T$ images and $Y = \{Y^1, Y^2, ..., Y^T\}$ indicating object presence or not. Different from fully supervised object annotation with both location and category, the $Y^t = [y^t_1, y^t_2, ..., y^t_C] \in [0, 1]^C$ is a binary vector where $y^t_c = 1$ indicates the presence of at least one object of the $c$-th category, where $C$ indicates the total number of object categories in the dataset.

Suppose $R^t$ is the candidate proposals for the $t$-th image. Each image is pre-computed by Selective Search [14] to generate $N$ object proposals $R^t = \{R^t_1, R^t_2, ..., R^t_N\}$ for initialization. The selected proposals $r$ is a latent variable and $R^t$ can be regarded as the solution space. Denoting $\delta$ as the network parameters, the MIL model with proposal selection $r^*$ and features $\delta^*$ to be learned, can be defined as

$$r^*, \delta^* = \arg \min_{r, \delta} \mathcal{L}_{(1,Y)}(r, \delta)$$

where the image index $t$ are omitted for short and $\mathcal{L}_{cls}$ and $\mathcal{L}_{det}$ are the loss functions of instance classification and proposal detection respectively.

Initially, for instance classification term, the loss function is defined as

$$\mathcal{L}_{cls} = - \sum_{c=1}^{C} \{y_c \log p_c(r; \delta) + (1 - y_c) \log(1 - p_c(r; \delta))\},$$

where $p_c(r; \delta)$ is the joint probability of class $c$ and latent variable $r$, given learned network parameter $\delta$. It is calculated by a soft-max operation with the prediction score $s(r; \delta)$, as

$$p_c(r; \delta) = \frac{\exp(s(r; \delta))}{\sum_R \exp(s(r; \delta))}.$$ 

Pseudo label $\hat{y}$ for each selection branch is selected from the top-scoring proposals in previous stage.

Since we get pseudo labels, each proposal now has a bounding-box regression target and classification target. As a consequence, Selection Loss can be defined as:

$$\mathcal{L}_{det} = \mathcal{L}_{\text{refine}} + \lambda \mathcal{L}_{\text{regression}},$$

where $\mathcal{L}_{\text{refine}}$ is the refine classification loss; and $\mathcal{L}_{\text{regression}}$ is bounding box regression loss. $\lambda$ is used as a weight to balance the two losses. During the learning, a object detector is learned to generate instance bags by using the refine loss defined as:

$$\mathcal{L}_{\text{refine}} = - \sum_r \log p(r, \delta),$$

where $p(r, \delta)$ prediction score of the pseudo object with softmax operation. For bounding box regression loss, smooth-L1 loss is adopted:

$$\mathcal{L}_{\text{regression}} = \frac{1}{N} \sum_r \mathcal{L}_{\text{smooth-L1}}(\text{Target}(r), \text{Box}(r)),$$

where $\text{Box}(r)$ is the predicted box for proposal $r$, and $\text{Target}(r)$ is the regression target generated by pseudo label.

B. DS-MIL method

Optimizing the non-convex loss function and performing instance selection still remain to be elaborated in WSOD approaches. In C-MIL [6], a continuation strategy is used in MIL to alleviate these two problems. However, C-MIL is still easy to be stuck into local minima because the parameters are hard to choose and the optimization strategy is complex. As a consequence, we decide to propose a novel training strategy to solve these problems. We recognize WSOD as a Discovering-and-Selection process, and design the Discovering Module and Selection Module to model this process, as shown in Fig. 2.

1) Discover: Dealing with localization ambiguity under only classical Convolution layers is difficult, the high responses are focus on the most discriminative part, therefore only a few instances are mined. As a consequence, we propose to integrate a Discovering module into the network to capture more context information and enforce the feature learning to learn complete object feature. That means this module could help us discover more important instances. Following [13], the general self-attention mechanism is defined as:

$$v_m = \frac{1}{C(u_m)} \sum_{n} f(u_m, u_n) g(u_n) + u_m,$$

where $u$ and $v$ denote input and output feature, $m$ and $n$ are corresponding spatial position index. The output signal is normalized by $C(u_m) = \sum_{n} f(u_m, u_n)$. Function $g(u_n)$ gives a representation of input signal $u_n$ at each position and all of them are aggregated into position $m$ with the similarity weights given by $f(u_m, u_n) = \varphi(u_m)^T \varphi(u_n)$, which calculates the dot-product pixel affinity in an embedding space. Here, we take the inner-product to calculate the affinity between channels and integrate the similarity weights into Eq.13.

$$v_m = \frac{1}{C(u_m)} \sum_{n} \text{Softmax}(\varphi(u_m)^T \varphi(u_n)) \hat{v}_n,$$

where $\hat{v}_n$ is the original feature map. And the similarities are activated by Softmax. The final feature map is the weighted sum of the original feature map with normalized similarities. For the final feature map, because each part of it combines with other parts, more areas will be activated, part-domination could be improved. The self-attention module structure is illustrated in Fig. 2. Compared to other self-attention methods, our proposed self-attention method has two differences: Firstly, we implement self-attention module on instance-level, which can
avoid instance level feature map mixing other information and save a lot of computation capacity. Secondly, we cancel the residual connection to avoid changing the activation intensity.

2) Selection: Inaccurate classification score for proposals easily cause the localization ambiguity, e.g., Proposals cover only part of object have higher score. We propose a selection module to find the confident proposal from the proposal pool produced by Discovery Module, which is inspired by [37].

From the MIL setting, the proposals cover object determine the label of an image, while the proposals only cover background can not affect the label of an image. The proposal is regarded as key proposals when it covers the object in the image. A binary variable $h_i \in \{0, 1\}$ is used to indicate whether proposal $R_i$ cover the object. We use one estimator $\phi$ to estimate the probability of a proposal to be a key proposal and one predictor $\theta$ to predict the probability of a proposal belonging to different categories. The selection module is defined as

$$
\begin{align*}
0^*, h^* &= \arg \max_{\theta, h} p_\theta(y_c = 1 | R, h) \\
&= \arg \max_{\theta, h} p_\theta(y_{c,i} = 1 | R_i) \cdot [h_i = 1]
\end{align*}
$$

(9)

where the maximum operator select the most important proposal for the image, and $p_\theta(y_{c,i} = 1 | R_i)$ represents the probability that proposal $R_i$ is classified to the $c$-th category.

As $h$ is a latent variable, $p_\theta$ in Eq. 9 could be reformulated [37] as

$$
\log p_\theta(y_c | R) = KL(q_\phi(h|R) \parallel p_\theta(h|R, y_c)) + \\
+ \int q_\phi(h|R) \log \frac{p_\theta(h, y_c | R)}{q_\phi(h|R)} dh \\
\geq \int q_\phi(h|R) \log p_\theta(h, y_c | R) dh + H(q_\phi(h|R))
$$

(10)

We also use the EM algorithm [46] to optimize $q_\phi$ following [37]. Minimizing $KL(q_\phi(z | R) || p_\theta(z | R, y_c))$ to tighten the lower bound in E-step and maximize the lower bound to optimize $p_\theta$ in M-step, as shown in Fig. 3.

In E-step, in order to optimize $q_\phi$, we assume the posterior $p_\theta(z | R, y_c)$ is proportional to the proposal-level classification score $p_\theta(y_c | R_i)$. Therefore, a pseudo label is constructed by combining the classification score and the ground-truth class label. The pseudo-label is formulated as

$$
\hat{h}_i = \left\{ \begin{array}{ll} 
1, & \text{if } \sum_{c=1}^C \mathbb{I}(p_\theta(y_c | R_i) > \zeta) \text{ and } y_c = 1 \geq 0, \\
0, & \text{otherwise}
\end{array} \right.
$$

(11)

where $\zeta$ is a threshold. If an proposal has a classification score over the threshold for any ground-truth class within the image, the proposal is regarded as a positive proposal. Otherwise, it is regarded as a negative proposal. With the pseudo labels, $\phi$ is updated by the binary cross entropy (BCE) loss as

$$
L(\phi) = -\hat{h}_i \log q_\phi(h_i | x_i) - (1 - \hat{h}_i) \log (1 - q_\phi(h_i | x_i)).
$$

(12)

In M-step, as with regard to $\theta$, $H(q_\phi(h|R))$ is constant. We maximize $\int q_\phi(z | R) \log p_\theta(z, y_c | R) dz$, which can be achieved by optimizing the classification score $p_\theta(y_c | R_i)$ given proposal importance $q_\phi(z | R_i)$. As a result, we combine the proposal importance $q_\phi$ and the ground truth class labels to generate a pseudo label, as

$$
\hat{y}_{i,c} = \left\{ \begin{array}{ll} 
1, & \text{if } y_c = 1 \text{ and } q_\phi(z_i | R_i) > \xi, \\
0, & \text{otherwise}
\end{array} \right.
$$

(13)

where $\xi$ is a dynamic threshold, which is the mean of proposal importance. Proposals whose importance are higher than the threshold are recognized as positive, and the importance of negative proposals are lower than the threshold. With the pseudo labels, we also derive a BCE loss to optimize $\theta$ as

$$
L(\theta) = -\hat{y}_{i,c} \log p_\theta(y_c | R_i) - (1 - \hat{y}_{i,c}) \log (1 - p_\theta(y_c | R_i)).
$$

(14)
Fig. 4. Heatmaps of baseline and our method depict the effectiveness of Discovery Module. The heatmaps of baselines shows that baseline method only activate discriminative region for classification. The heatmaps of DS-MIL verify that DS-MIL could activate the full object region.

IV. EXPERIMENT

A.Datasets and Evaluation Metrics

| Method          | Dataset  | mAP  |
|-----------------|----------|------|
| MELM [5]        | VOC2007  | 47.3 |
| MELM+S          | VOC2007  | 48.5 |
| MELM+D          | VOC2007  | 47.8 |
| MELM+2D         | VOC2007  | 48.2 |
| MELM+S+2D       | VOC2007  | 49.5 |
| MELM+S+2D+Reg   | VOC2007  | 55.1 |

In experiment, we evaluate our approach on three popular datasets: PASCAL VOC 2007&2012 [47] and MS-COCO [48]. PASCAL VOC 2007&2012 datasets [47] have 9962 and 22531 images of 20 object classes respectively. Only image-level annotations are used as supervision in all experiments. For PASCALC VOC, we use the trainval set(5011 images for 2007 and 11540 for 2012) for training and test set for testing. For evaluation on PASCAL VOC, two metrics are used to evaluate our model. First, we evaluate detection performance using mean Average Precision (mAP) on the PASCAL VOC 2007 and 2012 test set. Second, we evaluate the localization accuracy using Correct Localization (CorLoc) on PASCAL VOC 2007 and 2012 trainval set. Based on the PASCAL criterion, a predicted box is considered positive if it has an IoU > 0.5 with a ground-truth bounding box. MS-COCO [48] contains 80 categories. We train on train2017 split and evaluate on val2017 split, which consists of 118287 and 5000 images, respectively. mAP0.5 (IoU threshold at 0.5) and mAP (averaged over IoU thresholds in [0.5 : 0.05 : 0.95]) on val2017 are reported.

B. Implementation Details

VGG16 [49] pre-trained on ImageNet [50] is used as the backbone in experiment. Selective Search [14] is used to generate about 2,000 proposals per-image for PASCAL VOC and MCG is used for MS-COCO. The maximum iteration numbers are set to be 150k, 160k and 300k for VOC 2007, VOC 2012 and MS-COCO respectively. For Selection Module, we alternate EM step every 3000 iterations in the first 30000 iterations, then we optimize them jointly. The whole WSOD network is by stochastic gradient descent (SGD) with a momentum of 0.9, an initial learning rate of 0.001 and a weight decay of 0.0005. The learning rate will decay with a factor of 10 at the 75kth, 80kth and 150kth iterations for VOC 2007, VOC 2012 and MS-COCO, respectively. The total number of refinement branches is set to be 3. For data augmentation, we use six image scales {480, 576, 688, 864, 1000, 1200} (resize the shortest side to one of these scales) and cap the longest image side to less than 2000 with horizontal flips for both training and testing.

C. Ablation Study

We conduct ablation experiments on PASCAL VOC 2007 to prove the effectiveness of our proposed DS-MIL approach from 4 perspectives.

For discovery module, we adopt MELM [5] as our baseline to verify its effectiveness. We add a single discovering module on the baselines, as shown in Table I. MELM+D improves
Compared to the baseline, DS-MIL shows great performance. In Table II, MELM with these modules gain a 2.2% improvement over C-MIL. As bounding box regressor is plugged into MELM by 1.2%. As the discovery module and selection module are plug and play, we conduct experiments with other two baselines besides MELM, i.e., OICR [3] and PCL [4]. The results verify that our method gain improvements in all of three baselines. For each baseline, 1 selection module and 2 discovery modules are added. In Table II, MELM with these modules gain a 2.2% improvement. In Table II, the mAP performance increases by 3.7% for OICR and 2.3% for PCL.

In Fig. 4, we provide some comparisons between the heatmaps of baseline and our approach. Obviously, the baseline activated the discriminated regions but ignore full object extent. Compared to the baseline, DS-MIL shows great performance to 47.8%, which indicates one discovering module is used. The performance is further improved by 0.9% when two discovery modules are used. To verify the effect of our newly proposed selection module, we also used MELM [5] as baseline, as shown in Table I. As Table I depicted, the selection module improves the performance of MELM by 1.2%. As bounding box regressor is plugged into several WSOD approach and illustrated that it’s effective for performance gain [24]. Following [24], we also add the regressor to the proposed approach, and we achieves 55.1% on PASCAL VOC 2007.

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Fig. 5. Visualization of DS-MIL results and the baseline (MELM). In upper part, the results of DS-MIL are shown in green boxes and the results of the baseline are shown in red boxes. In bottom part, some of failure cases of DS-MIL are shown.

...performance by activating more regions to cover the whole object. The main reason accounts for this result is our discovery module could capture more object extent and provide more accurate object localization information for detectors. On the contrary, baseline method only considers object classification and hardly optimizes object localization.

The number of detection branches determines how many times we refine the detection results. We also conduct some experiments on it. The number of branches is set to be K, and four different Ks: 1, 2, 3, 4 are adopted. While we change the value of K, the rest of the hyper-parameters are fixed. Table III shows the influence of K. We can find that when K is set to be 1, the mAP is only 50.9%. Then, the performance becomes better with the increasing of K. When K is set to be 3, it achieves the best performance which is 55.1%. And the result decreases when the K is equal to 4. The reason is those chosen proposals are too scattered for the 4th branch.

D. Comparison with Other Methods

VOC dataset In this comparison, we adopt MELM as our baseline, and add two discovery modules and one selection module to the baseline network. Besides, we use bounding box regressor to revise the location of the predicted boxes. In order to verify the effectiveness of DS-MIL, 12 state-of-the-art WSOD methods are compared with our method and most of the chosen methods are published in the last two years. To fully compare with these methods, we report both mAP results and Corloc results on VOC 2007 and VOC 2012 datasets are shown in Table IV, Table V, Table VI and Table VII. From the Table IV, we can see that our method outperforms all methods on VOC2007 dataset and achieves the highest mAP performance on 9 out of 20 categories. From Table V, the result is little lower than state-of-the-art methods, but our method also achieves best performance on bird, bottle, bus, car, cat and train. Table VI and Table VII shows the competitive results achieved by our method on VOC2012, it is noteworthy that our proposed method outperforms 4 previous methods and only little lower(0.4%) than the two-stage method C-MIDN+FRCNN [25].

MS-COCO dataset MS-COCO is larger dataset compared to PASCAL VOC, and only few previous approaches report results on it for the difficulty of obtaining good results on it. We report our results in Table VIII. We can find that our...
proposed approach achieves 12.3% for mAP and 24.5% for mAP0.5 which significantly outperforms previous works.

E. Visualization

In Fig. 5, we visualize some detection results of our proposed method and the baseline approach (MELM). The green boxes represent DS-MIL results and the red boxes represent the baseline, respectively. The first two rows of Fig. 5 prove that our proposed approach largely improves the part-dominant problem and the third row of Fig. 5 shows DS-MIL has the better capability to detect multiple objects. As a consequence, we can conclude that DS-MIL performs much better than the baseline. Moreover, the visualization results also shows that our approach tends to cover more extent of objects and avoid selecting incomplete proposals. And these are the effects of Selection Module and Discovering Module. In the last row of Fig. 5, we also show some failure cases of our method. As we can see, our detector will recognize multiple objects as single object or miss some objects. These failures are come from two factors: (1) The occlusion of objects. (2) The Selective Search algorithm [14] may not generate good proposal. And we believe these problems could be improved by applying network with stronger representation ability (e.g. transformer based network) or combining with Class Activation Map.

V. CONCLUSION

In this paper, We proposed an effective and novel method, referred to as DS-MIL, for weakly supervised object detection. DS-MIL targets alleviating the part-dominant problem of multiple instance learning using a new training strategy: discovering-and-selection. This strategy is achieved by introducing a self-supervised Discovering Module and a EM-based Selection Module. DS-MIL significantly improved performance of weakly supervised object detection on PASCAL VOC 2007 and MS-COCO datasets, and achieve competitive results on PASCAL VOC 2012 dataset.

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