Open Vocabulary Object Detection with Proposal Mining and Prediction Equalization

Peixian Chen†, Kekai Sheng†, Mengdan Zhang†§, Mingbao Lin†, Yunhang Shen†, Shaohui Lin†, Bo Ren†, Ke Li†,
† Tencent Youtu Lab ‡ East China Normal University

Abstract

Although learning from a pre-trained vision-language model is efficacious for open-vocabulary object detection (OVD) that identifies objects beyond the training vocabulary, two issues remain open, including proposal-level vision-language alignment and base-novel category prediction balance. In this paper, we introduce a novel proposal Mining and prediction Equalization framework for open-vocabulary object Detection (MEDet) to alleviate these issues. Specifically, we perform proposal mining by refining the inherited vision-semantic knowledge in a coarse-to-fine and online manner, allowing for detection-oriented proposal-level feature alignment. Meanwhile, we equalize prediction confidence by reinforcing novel category predictions with an offline class-wise adjustment, permitting the overall OVD performance gains. Extensive experiments demonstrate the superiority of MEDet over the state-of-the-art methods. In particular, we increase mAP of novel categories from 29.1% to 32.6% on MS COCO and obtain 22.4% mask AP on LVIS with gains of 1.4%. For the sake of reproducibility, code is anonymously released.

1. Introduction

Developing object detection is one of the most elementary missions in computer vision. Though efforts have been made [3, 30, 44], the remarkable success mostly relies on the permit of accessing fully annotated datasets. However, annotating datasets requires a time laborious and lavish process, which barricades their scalability in category size and further prevents their applicability in real-world applications. Fortunately, the recent prosperity of pre-trained vision-language models (VLMs) [26] opens a new horizon for open-vocabulary object detection (OVD) that expands the detection vocabulary beyond the training categories.

Typically, OVD methods [11, 41–43] are accomplished by first excavating an unbounded vocabulary of concepts as well as their general vision representations from image-caption pairs, and then transferring the general vision-language knowledge to the common detection learning process on the box-annotated data with base categories alone. Albeit their promising progress, we realize that two critical facts are sorely neglected in most existing methods including proposal-level vision-language alignment and base-novel category prediction equalization, which hamper the performance boost of existing OVD methods.

For the first issue, it is widely known that proposal annotations are the most beneficial hints for object detection. However, off-the-shelf studies dwell on weaker image-level vision-language annotations since most VLMs [10, 15, 26]
are pre-trained upon a whole caption text describing an entire image. Inaccurate proposal-concept pairs stem from a direct extension to excavate proposal-level vision-language annotations. Left of Fig. 1a illustrate an experiment w.r.t. CLIP [26] where two inaccurate proposal-concept pairs arise: (1) A big ambiguity stems from the matching between located proposals and concepts of “person” and “skis”. (2) The proposal of “person” only encloses part of the person within the image. Therefore, simply transferring the coarse vision-language knowledge to OVD models [41] or exploiting the noisy proposal-concept pairs for fine-grained detection model, even with distillation [11], may interfere with accurate object localization and degrade proposal-level vision-language alignment. We realize that opulent concepts describing proposal information are widely distributed in image-level caption texts. For example, Fig. 1a is in line with the caption “a person jumping a pair of skis in the air” where “person” and “skis” are indeed fine-grained proposal concepts. Exploiting these proposal concepts might help overcome inaccurate proposal-concept pairs and uphold accurate object localization. Recent Object Centric OVD [29] solves this issue by training on filtered proposal-concept pairs. However, the performance gains rely on a pre-trained MViT detector [22] upon large-scale box annotations.

As for the second problem, we empirically observe that existing optimized OVD models are prone to making imprecise predictions biased towards base categories. An illustrative example is given in Fig. 1b where we count instances w.r.t. the prediction score from Detic model [43] on COCO dataset [1]. As we can observe that Detic model can well distinguish base categories such as “person” and “car” with most instances being given a high prediction score. On the contrary, novel categories like “airplane” and “backpack” are often endowed with a very low prediction score which indicates a large amount of mispredicted instances. Moreover, we empirically find that most mispredicted novel instances are grouped into base categories. Thus, the performance of OVD is still far from satisfactory for real-world applications. Basically, we attribute the prediction bias issue to OVD training paradigm and class-imbalanced training datasets. For the training paradigm, as pointed out by previous works [41,42], the detectors in OVD are fine-tuned upon base categories, which often leads to catastrophic forgetting of the general vision-language knowledge in pre-trained VLMs, in particular to novel categories. As for class imbalance, OVD task requires abundant base training instances collected beforehand. Nonetheless, training samples for novel categories are scarcely excavated. Then, it causes insufficient learning of proposal-level vision-language knowledge for novel categories and the optimized detectors are biased towards base categories in inference.

In this paper, we present MEDet, a novel proposal Mining and prediction Equalization framework for open-vocabulary object Detection, to overcome the above two issues. Fig. 2 depicts the overall framework of our MEDet where proposal-level vision-language alignment and base-novel category prediction equalization are respectively accomplished via an online proposal mining (OPM) in the training and via an offline class-wise adjustment (OCA) in the inference. The OPM filters out low-qualified alignments in a three-step coarse-to-fine fashion. It first augments text embedding discrimination by online interacting with the corresponding image embedding information via a cross-modality-based transformer block [8]. Then, it further removes noisy proposal-concept pairs by building their semantic similarity distribution. Finally, to clean proposal fragments holding broken objects, OPM further merge two proposals if they are of high overlapping. Built upon OPM, an Iterative Matching with Recurrent Attention Memory (IMRAM) [5] is used to discover the full latent proposal-level vision-language alignments, resulting in more accurate proposal-concept pairs than common pre-trained VLMs, as shown in the right of Fig. 1a.

After training the OVD model, our OCA module further post-processes the trained OVD model for a better prediction. It performs density-based clustering [31] upon all dataset proposals in compliance with the same predicted concept. And then a de-bias term vector is offline computed based on the clustering density and online deployed to adjust the prediction of an incoming proposal. Experiments on COCO [1] and LVIS [12] benchmarks demonstrate that our method outperforms other cutting-edge OVD methods [11,41–43]. For example, MEDet reaches 32.6% AP50 for novel categories on the COCO dataset, which considerably suppresses the state-of-the-art approaches by 3.5%.

2. Related work

Open-Vocabulary Object Detection. Typically, researchers scale up the vocabulary size for object detection by exploiting rich knowledge within pre-trained VLMs [10,15,26]. OVR-CNN [41] first learned a projection layer behind the backbone of Faster R-CNN [30] to align visual space with textual space [15], and then fine-tuned the detector with only base categories. Distillation-based approaches [11,39] aligned the vision extractors with both image and text encoders of CLIP [26]. RegionCLIP [42] first leveraged CLIP model to match image regions with template captions, then pre-trained the model to align the region-concept pairs in the feature space and finally transferred the pre-trained model to downstream object detection. However, its training pipeline is complex, and the pseudo region-concept pairs are noisy. In this paper, we propose online proposal mining (OPM) within an end-to-end OVD network and simplify the training pipeline. Moreover, OPM provides more reliable region-concept pairs for acquiring rich proposal-level vision-language knowledge. Recently, Zhou et al. [43] applied additional image-level supervision
Debiasing Strategies in Object Detection. Real-world detection datasets [1,12,25] typically exhibit class-imbalance label distributions, making it difficult to learn generalized representation across classes. Existing debiasing approaches can be roughly categorized into four mainstreams: (1) re-weighting [4,12,34] to sample more instances of rare classes; (2) cost-sensitive learning [35,36,38] to spare more attention on hard examples; (3) knowledge transfer [16,17,20] to handle the confidence bias between the base and novel categories. The prediction bias also results from the training strategies of OVD models. Existing methods adopt model freezing [41] and focal scaling [42] to alleviate the catastrophic forgetting the general knowledge in the pre-trained VLMs when fine-tuning the detectors on the base categories.

3. Methodology

3.1. Preliminary

Considering a base dataset for object detection $D_{\text{bas}} = \{(I_{i}^{\text{bas}}, \{([b_i^k, c_i^k])_{k=1}^{K_i}\})_{i=1}^{N_{\text{bas}}}\} \in C_{\text{bas}}$ where $I_{i}^{\text{bas}}$ denotes the $i$-th image containing $K_i$ bounding box and class pairs $([b_i^k, c_i^k])$, and $C_{\text{bas}}$ denotes the base category set, OVD intends to learn a detector that recognizes well-unseen novel categories $C_{\text{nov}}$ with $C_{\text{nov}} \cap C_{\text{bas}} = \emptyset$. To this end, an image-caption dataset $D_{\text{cap}} = \{(I_{i}^{\text{cap}}, s_i, \{w_i^k\}_{k=1}^{K_i})|w_i^k \in C_{\text{cap}}\}_{i=1}^{N_{\text{cap}}}$ is introduced in VLMs-based OVD methods [41–43] in which $s_i$ is a caption sentence describing the image $I_{i}^{\text{cap}}$, $\{w_i^k\}_{k=1}^{K_i}$ is a set of word concepts (nouns) extracted from $s_i$, and $C_{\text{cap}}$ is the union of all concepts in $D_{\text{cap}}$. Then, the OVD models are trained upon both $D_{\text{bas}}$ and $D_{\text{cap}}$. Typically, the overall training loss in existing studies can be generally formulated as follows:

$$L_{\text{oqvd}} = \mathcal{L}_{\text{rpn}}(I_{i}^{\text{bas}}, \{([b_i^k, c_i^k])_{k=1}^{K_i}\}) + \mathcal{L}_{\text{cls}}(I_{i}^{\text{bas}}, \{([b_i^k, c_i^k])_{k=1}^{K_i}\}) + \mathcal{L}_{\text{reg}}(I_{i}^{\text{bas}}, \{([b_i^k, c_i^k])_{k=1}^{K_i}\}) + \mathcal{L}_{\text{bce}}(I_{i}^{\text{cap}}, s_i),$$

where $\mathcal{L}_{\text{rpn}}$ denotes the constraints for RPN, $\mathcal{L}_{\text{cls}}$ is the classification loss and $\mathcal{L}_{\text{reg}}$ regularizes the bounding box regression. These first three constraints are enforced upon the base dataset $D_{\text{bas}}$. As for $\mathcal{L}_{\text{bce}}$, it represents the binary-cross entropy (BCE) applied to model embedding similarity of image $I_{i}^{\text{cap}}$ and its caption sentence $s_i$.

3.2. Framework of MEDet

MEDet models proposal-level vision-language alignment in the training stage by an online proposal mining (OPM) mechanism in Sec. 3.3 and achieves base-novel category prediction equalization in the testing stage via an offline class-wise adjustment (OCA) in Sec. 3.4. Before diving into a detailed discussion, we first outline the framework of our MEDet, as illustrated in Fig. 2.

In the training stage, for incoming mini-batch data: First, we feed to a text encoder the category concepts of the base dataset and word concepts from current image-caption mini-
batch samples to obtain their text embeddings $T^{\text{bas}}$ and $T^{\text{cap}}$. Similarly, we have image embeddings $V^{\text{bas}}$ and $V^{\text{cap}}$ from an image encoder. **Second**, for the text embeddings $T^{\text{bas}}$ and $T^{\text{cap}}$, we boost their discriminative ability by injecting image information in Sec. 3.3, results of which are denoted as $T_{\text{aug}}^{\text{bas}}$ and $T_{\text{aug}}^{\text{cap}}$. **Third**, the base data ($T_{\text{aug}}^{\text{bas}}$, $V^{\text{cap}}$) are used for a standard two-stage detection training [30]. Considering the inaccessibility of bounding boxes, the image-caption pair ($T_{\text{aug}}^{\text{cap}}$, $V^{\text{cap}}$) further goes through a series of noise removal and fragment mergence in Sec. 3.3 to derive a concept set $T_i^0 = \{t_{i,q}\}_{q=1}^{Q_i}$ and a proposal set $E_i^0 = \{e_{i,j}\}_{j=1}^{J_i}$ for the $i$-th image $I_i^{\text{cap}}$. Here, the $q$-th concept $t_{i,q} \in T_{\text{aug}}^{\text{cap}}$ pairs with $J_q$ proposal embeddings $\{e_{i,j}\}_{j=1+J_0+j_1+...+J_{q-1}}$ where $J_0 = 0$. Also, we let $T_i^0$ and $E_i^0$ denote all concept sets and proposal sets in $D^{\text{cap}}$ except these from the $i$-th samples.

With this proposal-level vision-language knowledge, the most common way to align these pairs is through one-by-one contrastive loss [42], which however suffers from performance damage if mismatched pairs stem from the knowledge set. To avoid this obstacle, we adopt the Iterative Matching with Recurrent Attention Memory (IMRAM) [5] to mitigate the negative impact. IMRAM considers two independent concept sets and proposal sets in $D^{\text{cap}}$ except these from the $i$-th samples.

Here, $e_{i,j}$ is a reconstruction of $e_{i,j} \in E_i^0$ established upon the concept set $T_i^0$ and similar for $t_{i,q}$. The cross-modal cosine similarity is computed as:

$$S^{k}(\mathbf{e}_{i,j}^0, \mathbf{T}_i^0) = \mathbb{E}_i(\cos(e_{i,j}^0, e_{i,q}^0)) + \mathbb{E}_q(\cos(t_{i,q}^0, t_{i,q}^0)).$$

(3)

Here, $e_{i,j}$ is built upon the concept set $T_i^0$, therefore, the similarity is modeled between the proposal embedding $e_{i,j}$ and all the concepts, leading to a major difference to the one-by-one contrastive loss [42], details of which can be referred to [5]. The final similarity between the set $\mathbf{e}^0$ and $\mathbf{T}^0$ is:

$$S(\mathbf{e}_{i,j}^0, \mathbf{T}_i^0) = \sum_k S^{k}.\text{Similarly, we obtain the similarity of } S(\mathbf{e}_{i,j}^0, \mathbf{T}_i^0) \text{ and } S(\mathbf{e}_{i,j}^0, \mathbf{T}_i^0), \text{ both of which play as negative factors to raise up positive factor of } (\mathbf{e}_{i,j}^0, \mathbf{T}_i^0) \text{ in a contrastive style:}$$

$$\mathcal{L}_{\text{ram}} = \sum_{i=1}^{B} [\delta - S(\mathbf{e}_{i,j}^0, \mathbf{T}_i^0) + S(\mathbf{e}_{i,j}^0, \mathbf{T}_i)]_+$$

(4)

$$+ \sum_{i=1}^{B} [\delta - S(\mathbf{e}_{i,j}^0, \mathbf{T}_i^0) + S(\mathbf{e}_{i,j}^0, \mathbf{T}_i^0)]_+,$$

where $[x]_+ = \max(x,0)$, $\delta$ is the margin, and $B$ is the training batch size. Combining Eq. (1) and Eq. (4) leads to our final training objective:

$$\mathcal{L} = \mathcal{L}_{\text{ovd}} + \mathcal{L}_{\text{ram}}.$$  

As for the inference stage, we devise an offline class-wise adjustment in Sec. 3.4 to accomplish the goal of base-novel category prediction equalization.

### 3.3. Online Proposal Mining

In this subsection, we formally introduce our online proposal mining (OPM) that extracts fine-grained proposal-level vision-language knowledge from the image-caption dataset $D^{\text{cap}}$ to promote detection performance. Our OPM is a three-step pipeline including concept augmentation, noisy removal and fragment mergence.

**Concept Augmentation.** Current OVD implementations [11, 42, 43] train detectors by embedding a concept as the results of a prompt template, e.g., *It is a photo of [concept]*. The shared prompt templates lead to less discriminative text features since images are much more diverse [13] compared to highly-semantic and information-dense texts. Though prompt ensemble [11] or prompt design [9] might be an alternative, they cannot eliminate the information variance between texts and images. To mitigate this issue, at the end of the backbone, we append a cross-modality attention-based transformer block [8] to enhance the text embedding discrimination by injecting image embedding information.

Giving text embeddings $T = \{T_{\text{bas}}, T_{\text{cap}}\}$ in a batch, the augmentation is dynamically adopted for each image $V_i \in V = \{V^{\text{bas}}, V^{\text{cap}}\}$:

$$T_{\text{aug}}^i = T + \text{CA}(W^vT, W^kV_i, W^vV_i),$$

$$T_{\text{aug}}^i \cap T_{\text{cap}}^i = T_{\text{aug}}^i + \text{FFN}(T_{\text{aug}}^i),$$

(6)

where CA denotes cross attention of different modalities; FFN is the feed-forward network consisting of two linear layers; $W^v$, $W^k$ and $W^v$ represent projection matrices. For a brief description, we omit the subscript $i$ for each image. Given that the base image-category pair $(T_{\text{aug}}^{\text{bas}}, V^{\text{cap}})$ are accomplished with bounding box information, they are directly used for a standard two-stage detection training as stated in Sec. 3.2. Differently, we further refine image-caption $(T_{\text{aug}}^{\text{cap}}, V^{\text{cap}})$ by noise removal and fragment mergence due to their invisibility of bounding boxes.

**Noise Removal.** Considering an image $I_i^{\text{cap}}$, we have its augmented concept embedding set $\{t_{i,n}\}_{n=1}^{P_i} \in T_{\text{aug},i}$ and image-level embedding $V^{\text{cap}} \in V^{\text{cap}}$. Then, as shown in Fig. 2, $V^{\text{cap}}_i$ is sent to the RPN to derive a proposal set $\{(e_{i,m}, p_{i,m}, o_{i,m})\}_{m=1}^{M_i}$ where $e_{i,m}$ is the feature embedding of the $m$-th proposal, $p_{i,m} \in \mathbb{R}^4$ and $o_{i,m}$ are its coordinates and objectness score. To match a proposal $t_{i,n}$ with an accurate feature embedding $e_{i,m}$, one naive approach is to consider the cosine similarity. However, as shown in Fig. (1a), highly-overlapped proposals are often identified as
different categories due to semantic confusion. Instead, we introduce a similarity entropy measurement.

We first measure the semantic similarity between \( t_{i,n} \) and \( e_{i,m} \) in relation to their cosine similarity and objectiveness score of \( e_{i,m} \) as:

\[
SC_{n,m} = \cos(t_{i,n}, e_{i,m}) \cdot o_{i,m},
\]

which is then normalized by the softmax function to obtain the similarity entropy for the proposal embedding \( e_{i,m} \) as:

\[
E_m = \text{entropy}(\text{softmax}(SC_{n,m})).
\]

Here, we would like to stress the efficacy of \( E_m \). A large \( E_m \) value manifests the proposal embedding \( e_{i,m} \) is almost equally matched with every concept embedding, which in turn indicates poor proposal mining. On the contrary, a small \( E_m \) means \( e_{i,m} \) is well matched with some particular concept, in which case \( e_{i,m} \) should be preserved.

To this end, we regard the entire image as a proposal and first discard these proposals whose similarity entropy is larger than that of the image proposal since an entire image is a very rough proposal therefore any poorer proposal can be safely removed. Next, we match each concept embedding \( t_{i,n} \) with proposals of the top-3 largest semantic similarity to form positive proposal-level vision-language pairs. Lastly, we further filter out pairs for each concept whose largest semantic similarity is smaller than that between the concept and the image proposal. Note that, we do not calculate the similarity entropy for each concept like that for each proposal in Eq. (8) to delete unreliable proposal-concept pairs, mostly because each concept often matches several different proposals in the OVD task. Therefore, the value of similarity entropy fails to reflect the quality of concepts.

**Fragment Mergence.** Albeit the removal of noisy proposal-concept pairs, it remains some fragments that merely contain part of an object. Therefore, we propose to merge these fragments in compliance with their spatial relationships. For each concept \( t_{i,n} \), we compute the IoU \( \cap \) \( t \) \( \cup \) \( t_{i,n} \) (intersection over union) between its two matched proposals \( p_j \) and \( p_t \) as the similarity evaluation. These two proposals are retained if \( \text{IoU} \geq 0.7 \) and merged into a larger one otherwise. We repeat these steps until no proposals can be merged, obtaining the final concept set \( \tilde{T}^n = \{t_{i,q}\}^Q_{q=1} \) and proposal set \( \tilde{E}^n = \{e_{i,j}\}^J_{j=1} \) for the i-th image \( \tilde{T}^n \) as utilized in Sec. 3.2.

### 3.4. Offline Class-wise Adjustment

Suppose a total of \( Q \) concept embeddings are obtained upon the whole training set, denoted as \( \mathcal{T} = \{t_q\}^Q_{q=1} \). For an incoming proposal embedding \( e \) in inference, OVD performs a linear projection from visual features to concept embeddings and prediction scores of \( e \) are obtained as:

\[
P(\mathcal{T}|e) = \mathcal{T} \cdot e^T.
\]

Nevertheless, as analyzed in Sec. 1, the training paradigm and class-imbalanced datasets cause immediate reliance of OVD models on the base dataset and damage the performance. Such OVD settings as well as the scarcity of information (e.g., the class name and frequency) of \( C^{\text{nov}} \) to test in inference, hinder the deployment of debiasing methods [4, 18, 36] for a better training paradigm.

Inspired by [23] where the Bayes-optimal problem is analyzed in a post-hoc adjustment manner, we propose an offline class-wise adjustment (OCA) to post-process the trained OVD model for a better prediction. For easy understanding, we first give our refined concept prediction of \( e \) as:

\[
P(\mathcal{T}|e) = \mathcal{T} \cdot e^T - \gamma \cdot \beta,
\]

where \( \beta = \{\beta_t\}^Q_{t=1} \) denotes our de-bias term and \( \gamma \) is a scalar to control de-bias degree.

After training, for the \( q \) \( \text{-th concept} \( t_q \) associated with its proposal embedding set \( \{e_{i,t}^q\}^N_{i=1} \) extracted from the entire training set, we perform density-based clustering [31] which automatically forms \( K_q \) cluster centers upon these proposals \( \{e_{i,q}^t\}^N_{i=1} \), leading to an average of \( \rho_q = \bar{N}_q/K_q \) proposal density for each cluster where \( \bar{N}_q \leq N_q \) since some outlier proposals will be removed by [31].

Then, the \( q \) \( \text{-th de-bias term} \( \beta_q \) for concept \( t_q \) is computed:

\[
\beta_q = \sqrt{K_q \cdot \rho_q}.
\]

We observe many common concepts such as “dog” and “person”, embrace diverse images and result in a very large \( K_q \) than others. The square root operation well prevents these illegitimate clustering. Our de-bias design is built upon a simple posterior truth: a large number of proposals will be mistakenly attributed to concept \( t_q \) to which we suppose the trained OVD model is prone, leading to either a large \( K_q \) or \( \rho_q \) and finally a stronger \( \beta_q \). Therefore, our design in Eq. (10) decreases the tendency of mistaken predictions.

Notice we do not conduct any optimization, thus our OCA is flexible for any novel categories. Besides, the estimation of de-bias term \( \beta \) can be offline implemented once-for-all. Thus, it does not increase any computation burden in inference. Importantly, we find the calculated \( \beta \) can be well reused on other OVD methods as listed in Tab. 6.

### 4. Experiments

#### 4.1. Setup

**Datasets & Metric.** We evaluate our method on two standard open-vocabulary detection benchmarks modified from COCO [19] and LVIS [12]. COCO Caption [6] and Conceptual Caption (CC) [33] are used respectively for OVD datasets [4, 18, 36] for a better training paradigm.

COCO Caption has the same images and train/test split as the COCO Object dataset, which has 118, 287 images...
Table 1. Results of OVD on COCO dataset [1]. MEDet equipped with online proposal mining and offline class-wise adjustment outperforms other methods on the novel categories.

| Method          | Detector Training Backbone Box generator | COCO Generalized (48+17) Novel Base All |
|-----------------|------------------------------------------|----------------------------------------|
| Base-only (CLIP)| -                                        | 2.4                                    |
| WSDDN [2]       | -                                        | 20.5                                   |
| Cap2Det [40]    | -                                        | 2.01                                   |
| PL [28]         | RN50-FPN                                 | 1.3                                    |
| OVR-CNN [41]    | RN50-C4                                 | 1.3                                    |
| HierKD [21]     | RN50-C4                                 | 20.3                                   |
| ViLD [11]       | RN50-FPN                                 | 20.3                                   |
| RegionCLIP [42] | RN50-C4                                 | 20.3                                   |
| Detic [43]      | RN50-C4                                 | 20.3                                   |

MEDet (Ours) RN50-C4 COCO Base (48) | 32.6 |

We adopt the standard object detection metrics: mean Average Precision (mAP) and AP50. On COCO, we mimic the generalized setting [27] and report AP50s for base and novel categories. On LVIS, we use a standard class-agnostic mask head [14] to produce segmentation masks for boxes. Following [43], the mask mAPs for novel categories and all categories are used for evaluation.

Implementation Details. We leverage the CLIP text-encoder [26] on ViT-B-32 [7] to convert concepts to text embeddings. For COCO, we use Faster R-CNN [30] with the RN50-C4 configuration and train 40,000 iterations of batch size 4 for the detection data and batch size 16 for the caption data on 8 V100 GPUs. The learning rate is initially 0.02 and multiplied by 0.1 at the 25,000 and 35,000 steps. For LVIS, we use CenterNet2 [44] with the RN50-FPN architecture and the same data augmentation and learning schedules. All models are pre-trained for 30,000 iterations on the detection dataset and the caption dataset using loss $L_{all}$ in Eq. (1).

To merge fragmented proposals, we set $\theta_{iou}$ to 0.6. And we set the margin $\sigma$ of $L_{ram}$ to 0.2. In OCA, we set $\gamma$ as 0.4. For the detailed ablation results, please refer to Sec. 4.3.

4.2. Main Results

OVD on COCO. The comparisons of OVD results on the COCO dataset are shown in Tab. 1. “Base-only” means training Faster R-CNN only on the detection data of base categories, and using text embeddings of class names from CLIP to replace the classifier’s weights. Compared with weakly supervised methods such as WSDDN [2] and Cap2Det [40], and 5x captions. We parse the captions by Scene-Graph-Parser [32] and get 62,682 noun concepts for COCO Caption and 76,311 noun concepts for CC. On COCO, we follow the data split of [41] with 48 base categories $C_{bas}$ and 17 novel categories $C_{nov}$, which are subsets of 80 COCO object classes. The rest 15 categories $C_{ret}$ are also evaluated to further investigate the generalization of OVD models. On LVIS, following [11], we use the training/validation images and adopt the category split with 800 base categories (common and frequent objects) and 337 novel categories (rare objects). We adopt the standard object detection metrics: mean Average Precision (mAP) and AP50. On COCO, we mimic the generalized setting [27] and report AP50s for base and novel categories. On LVIS, we use a standard class-agnostic mask head [14] to produce segmentation masks for boxes. Following [43], the mask mAPs for novel categories and all categories are used for evaluation.

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4.2. Main Results

OVD on COCO. The comparisons of OVD results on the COCO dataset are shown in Tab. 1. “Base-only” means training Faster R-CNN only on the detection data of base categories, and using text embeddings of class names from CLIP to replace the classifier’s weights. Compared with weakly supervised methods such as WSDDN [2] and Cap2Det [40], and 5x captions. We parse the captions by Scene-Graph-Parser [32] and get 62,682 noun concepts for COCO Caption and 76,311 noun concepts for CC. On COCO, we follow the data split of [41] with 48 base categories $C_{bas}$ and 17 novel categories $C_{nov}$, which are subsets of 80 COCO object classes. The rest 15 categories $C_{ret}$ are also evaluated to further investigate the generalization of OVD models. On LVIS, following [11], we use the training/validation images and adopt the category split with 800 base categories (common and frequent objects) and 337 novel categories (rare objects). We adopt the standard object detection metrics: mean Average Precision (mAP) and AP50. On COCO, we mimic the generalized setting [27] and report AP50s for base and novel categories. On LVIS, we use a standard class-agnostic mask head [14] to produce segmentation masks for boxes. Following [43], the mask mAPs for novel categories and all categories are used for evaluation.

Implementation Details. We leverage the CLIP text-encoder [26] on ViT-B-32 [7] to convert concepts to text embeddings. For COCO, we use Faster R-CNN [30] with the RN50-C4 configuration and train 40,000 iterations of batch size 4 for the detection data and batch size 16 for the caption data on 8 V100 GPUs. The learning rate is initially 0.02 and multiplied by 0.1 at the 25,000 and 35,000 steps. For LVIS, we use CenterNet2 [44] with the RN50-FPN architecture and the same data augmentation and learning schedules. All models are pre-trained for 30,000 iterations on the detection dataset and the caption dataset using loss $L_{all}$ in Eq. (1).

To merge fragmented proposals, we set $\theta_{iou}$ to 0.6. And we set the margin $\sigma$ of $L_{ram}$ to 0.2. In OCA, we set $\gamma$ as 0.4. For the detailed ablation results, please refer to Sec. 4.3.

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onomy. The comparisons demonstrate the effectiveness and flexibility of the proposed MEDet in the OVD scenario.

**Generalization of MEDet.** Besides the evaluation experiments on $C^{bas}$ and $C^{nov}$, we also analyze the performance on the retained 15 classes $C^{ret}$ in the COCO dataset [1] to further investigate the generalization ability of OVD models. Tab. 3 lists the results. Note that, when using COCO Caption, Detic [43] requires a hand-crafted taxonomy to map each concept to one class in a set $C^T$. “Detic-80” uses $C^{bas} \cup C^{nov} \cup C^{ret}$ (80 classes) as $C^T$ and works well on $C^{nov}$. But when $C^T$ is $C^{bas} \cup C^{nov}$ (65 classes), “Detic-65” performs worse in novel categories. In contrast, our MEDet works better on both $C^{nov}$ and $C^{ret}$. The results ensure that the proposed method utilizes the caption dataset more effectively for generalization toward the OVD setting.

### 4.3. Ablation Studies

**Components of MEDet.** Tab. 4 shows the ablation studies of components in MEDet. The pre-trained model only uses constraints $L_{all}$, and is trained 30,000 steps without Online Proposal Mining (OPM) and Offline Class-wise Adjustment (OCA). When we apply OPM, the AP50 on novel categories reaches 32.0% (+14.4%). The performance is also higher than other OVD methods in Tab. 1. It means that OPM effectively explores proposal-level vision-language knowledge. In the third row, the OCA handles the confidence bias and thus boosts the performance on novel categories by 0.6%. Lastly, we replace the matching loss [5] (i.e., Eq. (4)) with a common grounding loss used by [41] to verify the rationality of $L_{ram}$. Although the performance on novel categories drops by 1.8% (32.6% vs. 30.8%), it is also competitive compared with the other methods in Tab. 1.

**Effectiveness of OPM.** In Tab. 5, we remove the OCA module to verify the rationality of OPM. The result shows that Concept Augmentation can effectively consider the semantic relationship among different concepts and the image embedding to adapt the text embeddings online. When used, the result on novel categories is increased by 1.0%. When removing the Noise Removal step, we directly use proposals of the top-100 objectness scores to align with concepts. The result on novel categories is only 29.3% (−1.7%) due to noisy proposals. And disabling merging fragmented proposals may lose some large proposals, thus the performance decreases by 0.6% (30.4% vs. 31.0%).

In order to further demonstrate the effectiveness of the OPM, we show the qualitative results of each step in OPM. Fig. 3b shows the result after proposal filtering via similarity entropy (Eq. (8)). The gray proposals are obtained according to the top-100 objectness scores from RPN. The green proposals are retained after removing incorrect proposals. Fig. 3c shows proposals of the TOP-3 SC scores (Eq. (7)) for every concept. Actually, we can select proposals for objects of different sizes and types. Fig. 3d shows the refined proposals after fragment merging. In a word, our OPM removes the most noise and obtains more reliable proposal-level vision-language knowledge.

**Effectiveness of OCA.** Tab. 6 shows the improvement of OCA when it is used in different OVD models. As the results of rows 2–4 (+ OCA), the improvements in both novel and base categories are generally higher than 1%. Notably, in the OCA experiment, we don’t recalculate the bias according to different models. Instead, the bias $\beta$ obtained from our MEDet model is reused directly to the inference stage of OVR-CNN and Detic, which fully demonstrates that the bias of concepts obtained from OCA can be reused by other OVD methods when training on the same caption dataset.

To further understand the rationale and effectiveness of the proposed OCA, we analyze the AR, and AP, and estimate $\beta$ for each category. The results are shown in Fig. 4. As we observe that: for the category with lower $\beta$, such as umbrella (id 21, 9.0% AP50, 18% AR, $\beta = 9.01$) and scissors (id 63, 4.5% AP50, 16% AR, $\beta = 4.93$), the optimized model generates under-confident predictions, and generally has suboptimal AP or AR performance, thus we should conduct less debiasing adjustment $\beta$ on it. After adjusting by OCA, the AP and AR on novel categories are improved, especially AR. On the other hand, for the category with higher $\beta$, such as “person” (id 0, 76.8% AP50, 53% AR, $\beta = 23.9$), the
Figure 3. Qualitative results of each step in OPM. (b) **Noise Removal**: Filter top-100 proposals from RPN by similarity entropy, where green and gray boxes are preserved and removed proposals, respectively. (c) **Noise Removal**: Select proposals with top-3 SC scores for every concept. (d) **Fragment Mergence**: Merge proposals to eliminate fragmented proposals.

Figure 4. The AP, AR, and $\beta$ for each category on COCO [1] when (a) we don’t apply OCA or (b) we apply OCA. The results indicate the positive contribution from OCA to the OVD task.

model produces over-confidence outputs, and thus has higher AR performance but inferior AP performance. So we need to conduct more debiasing adjustments on it. After using OCA, the AP and AR on base categories are also improved. With the help of our OCA, we handle the confidence bias well and promote the overall OVD result.

4.4. Hyper-parameter Analysis

**Different $\theta_{iou}$ in OPM.** To investigate the $\theta_{iou}$ in OPM, we analyze the AP50 results on COCO dataset with varied $\theta_{iou}$ in Tab. 7. The observations show that a small threshold ($\theta_{iou} = 0.2$) causes too many proposals to be merged and the accuracy is reduced. And a high threshold ($\theta_{iou} = 0.8$) makes only a few (or no) proposals be merged.

**Different $\gamma$ in OCA.** To investigate the optimal $\gamma$ of Eq.(11) in OCA, we analyze the OVD performance with varied $\gamma$. The AP50 results on COCO dataset [1] are listed in Tab. 8. The observations show the optimal $\gamma$ and indicate that the positive effect of OCA is relatively insensitive to $\gamma$.

Table 7. The results of various $\theta_{iou}$ in OPM on COCO.

| $\theta_{iou}$ | w/o | 0.2 | 0.4 | 0.6 | 0.8 |
|---------------|-----|-----|-----|-----|-----|
| Novel         | 30.4| 30.5| 30.8| 31.0| 30.4|
| Base          | 52.8| 52.6| 52.6| 52.9| 52.0|

Table 8. The results of various $\gamma$ in OCA on COCO.

| $\gamma$ | 0.0 | 0.2 | 0.4 | 0.6 | 0.8 | 1.0 |
|----------|-----|-----|-----|-----|-----|-----|
| Novel    | 32.0| 32.5| 32.6| 32.6| 32.6| 32.4|
| Base     | 53.1| 53.3| 53.4| 53.5| 53.4| 53.3|

5. Conclusion

In this paper, we present MEDet, a novel and effective framework to solve the two observable challenges for better OVD results. To sharpen the vision-language knowledge of caption datasets from image-level to proposal-level and learn an unbounded vocabulary of concepts, we devise an online proposal mining scheme in an end-to-end network to fully explore the knowledge of caption data. Moreover, we propose an offline class-wise adjustment to generate accurate predictions on both base and novel categories with less bias. Experiments on popular COCO and LVIS benchmarks verify that our MEDet outperforms the counterpart approaches in detecting objects of novel categories.
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