Towards Open Vocabulary Object Detection without Human-provided Bounding Boxes

Mingfei Gao*, Chen Xing*, Juan Carlos Niebles, Junnan Li, Ran Xu, Wenhao Liu, Caiming Xiong
Salesforce Research, Palo Alto, USA
{mingfei.gao,cxing,jniebles,junnan.li,ran.xu,wenhao.liu,cxiong}@salesforce.com

Abstract

Despite great progress in object detection, most existing methods are limited to a small set of object categories, due to the tremendous human effort needed for instance-level bounding-box annotation. To alleviate the problem, recent open vocabulary and zero-shot detection methods attempt to detect object categories not seen during training. However, these approaches still rely on manually provided bounding-box annotations on a set of base classes. We propose an open vocabulary detection framework that can be trained without manually provided bounding-box annotations. Our method achieves this by leveraging the localization ability of pre-trained vision-language models and generating pseudo bounding-box labels that can be used directly for training object detectors. Experimental results on COCO, PASCAL VOC, Objects365 and LVIS demonstrate the effectiveness of our method. Specifically, our method outperforms the state-of-the-arts (SOTA) that are trained using human annotated bounding-boxes by 3% AP on COCO novel categories even though our training source is not equipped with manual bounding-box labels. When utilizing the manual bounding-box labels as our baselines do, our method surpasses the SOTA largely by 8% AP.

1. Introduction

Object detection [11, 19, 20, 27] is a core task in computer vision that has considerably advanced with the adoption of deep learning and continues to attract significant research effort [26, 33, 35]. Current deep object detection methods achieve astonishing performance when learning a pre-defined set of object categories that have been annotated in a large number of training images (PASCAL VOC [6], COCO [17]). Unfortunately, their success is still limited to detecting a small number of object categories (e.g., 80 categories in COCO). One reason is that most detection methods rely on supervision in the form of instance-level bounding-box annotations, hence requiring very expensive human labeling efforts to build training datasets. Furthermore, when we need to detect objects from a new category, one has to further annotate a large number of bounding-boxes in images for this new object category.

Two families of recent work have attempted to reduce the need of human-provided bounding-box annotations for detecting new object categories: zero-shot object detection and open-vocabulary object detection. In zero-shot detec-
tion methods [1, 22], object detection models are trained on base object categories with bounding box annotations to promote their generalization ability on novel object categories which do not have annotations. These methods can alleviate the need for large amounts of human labeled data to some extent. Building on top of such methods, open vocabulary object detection [36] aims to improve the detection performance of novel objects via knowledge transfer from pre-trained vision-language models. It initializes the detector with parameters of a pre-trained vision-language model, before training the detector on base object categories. Such initialization implicitly transfers knowledge related to novel objects from the training image-caption pairs of the pre-trained model, which boosts detection performance on novel objects. However, both zero-shot and open vocabulary object detection methods still require bounding-box annotations on base object categories during training. The broader the base category set covers, the better a detector performs on novel objects [31, 32]. As a result, human bounding-box annotation costs cannot be avoided for the detector to perform well on new objects.

Can we avoid such manual bounding-box labels when we want to detect arbitrary objects of new categories, and train a more universal object detector with no human-provided instance-level annotations? The most recent progress on vision-language pre-training gives us some hope. Vision-language models [12, 15, 16, 21, 28] are pre-trained with large scale weakly-aligned image-caption pairs from the web. They show amazing zero-shot performance on image classification, as well as promising results on tasks related to text-visual region alignment, such as referring expressions, which implies a strong localization ability.

Motivated by these observations, we propose an open vocabulary object detection framework that can be trained without human-provided bounding-box annotations, by taking advantage of the localization ability of pre-trained vision-language models. As shown in Figure 1, we design a pseudo bounding-box label generation strategy to automatically obtain pseudo box annotations of a diverse set of objects from large-scale image-caption dataset. Specifically, given a pre-trained vision-language model and an image-caption pair, we compute an activation map (Grad-CAM [24]) in the image that corresponds to an object of interest mentioned in the caption. We then convert the activation map into a pseudo bounding-box label for the corresponding object category. Our open vocabulary detector is then directly supervised by these pseudo box-labels, which enables training object detectors with no human-provided bounding-box annotations. Since our method for generating pseudo bounding-box labels is fully automated with no manual intervention, the size of training data and the number of training object categories can be largely increased. This enables our approach to outperform existing zero-shot/open vocabulary detection methods trained with a limited set of base categories, even though our method does not rely on human-provided bounding boxes.

We evaluate the effectiveness of our method by comparing with the state-of-the-art (SOTA) on four widely used datasets: COCO, PASCAL VOC, Objects365 and LVIS. Experimental results show that our method outperforms the best open-vocabulary detection method trained with human-annotated bounding boxes by 3% mAP on novel objects on COCO, even though our method does not require human-provided bounding boxes during training. When fine-tuned with COCO base categories, our method improves existing performance largely by 8% mAP. We also evaluate the generalization performance of our method to other datasets. Experimental results show that under this setting, our method improves existing approaches by 6.3%, 2.3% and 2.8% on PASCAL VOC, Objects365 and LVIS, respectively.

Our contributions are summarized as follows: (1) We propose an open vocabulary object detection method that can be trained without human-provided bounding-box annotations. To the best of our knowledge, this is the first work which enables open vocabulary object detection using pseudo labels during training. (2) We introduce a pseudo label generation strategy using the existing pre-trained vision-language models. The generated pseudo labels could benefit object detection in general beyond the open vocabulary task. (3) Although with only pseudo labels, our method largely improves the SOTA methods that rely on training with manual bounding-box annotations.

2. Related Work

Object detection aims at localizing objects in images. Traditional detection methods are supervised using human-provided bounding box annotations. Two-stage detection methods [8, 11, 23] are one of the most popular frameworks. These methods generate object proposals in the first stage and classify these proposals to different categories in the second stage. Weakly supervised object detectors seek to relieve such heavy human annotation burden by using image-level labels such as image-level object categories [2, 29], captions [34] and object counts [7] for training. Although these approaches show promising performance, they only support objects in a fixed set of categories. Whenever one needs to detect objects from a new category, we have to collect and manually annotate instances from the new category and retrain the detector.

Open vocabulary and zero-shot object detection target at training an object detector with annotations on base object classes to generalize to novel object classes during inference. Most zero-shot detection methods achieve this level of generalization by aligning the visual and the text representation spaces for objects from base classes during
training [1, 22, 38]. Recent methods encourage the visual-semantic alignment for novel objects by different strategies such as synthesizing visual representations of novel classes [37, 38] or utilizing existing object names semantically similar to their names [22]. Joseph et al. introduce OREO [13] to incrementally learn unknown objects based on contrastive clustering and energy based unknown identification. To further improve the zero-shot performance on novel object categories, Zareian et al. [36] proposes open vocabulary object detection which takes advantage of pre-trained vision-language models by initializing their detector with parameters of the vision-language model. This strategy improves the state-of-the-art by a large margin. Gu et al. [9] propose ViLD which achieves great zero-shot performance by distilling knowledge from a large-scale vision-language model (CLIP [21]). However, all these methods still rely on human-provided bounding box annotations of base classes during training. In contrast, our method generates pseudo box labels for all objects of interest and use them to train the detector. When human-provided annotations are available, our framework has the flexibility to utilize them as well.

Vision-language pre-training models are trained with large-scale weakly-aligned image-caption pairs from the web. They have been successful not only in image-language tasks such as image retrieval, VQA and referring expression [12, 15, 16, 28], but also in pure image tasks such as zero-shot image classification [21]. Recent methods typically utilize a multi-modal module to encourage the interaction between the vision and language modalities [15,16,28], which may implicitly encode the word-to-region localization information inside the model. In this paper, we take advantage of their localization ability and design a strategy to obtain pseudo bounding-box labels of a large and diverse set of objects from the large-scale image-caption datasets. With this strategy, we successfully train an object detector that enables open vocabulary object detection without requiring human-provided bounding boxes.

3. Our Approach

Our framework contains two components: a pseudo bounding-box label generator and an open vocabulary object detector. Our pseudo label generator automatically generates bounding-box labels for a diverse set of objects by leveraging a pre-trained vision-language model. We then train our detector directly with the generated pseudo labels and perform open vocabulary detection during inference.

3.1. Generating Pseudo Box Labels

Figure 2 illustrates the overall procedure of our pseudo label generation. Our goal is to generate pseudo bounding-box annotations for objects of interest in an image, by leveraging the implicit alignment between regions in the image and words in its corresponding caption in a pre-trained vision-language model. Before diving into our method, we first briefly introduce the general structure of the recent vision-language models.

An image $I$ and its corresponding caption, $X = \{x_1, x_2, ..., x_{N_T}\}$, are the inputs to the model, where $N_T$ is the number of words in the caption (including [CLS] and [SEP]). An image encoder is used to extract image features $V \in \mathbb{R}^{N_V \times d}$ and a text encoder is utilized to get text representations $T \in \mathbb{R}^{N_T \times d}$. $N_V$ is the number of region representations of the image. Moreover, a multi-modal encoder with $L$ consecutive cross-attention layers is often employed to fuse the information from both image and text encoders. In the $l$-th cross-attention layer, the interaction of an object
of interest $x_t$ in the caption with the image regions is shown in Equation 1, where $A^l_t$ denotes the corresponding visual attention scores at the $l$-th cross-attention layer. $h^l_{t-1}$ indicates the hidden representations obtained from the previous $(l-1)$-th cross-attention layer and $h^0_t$ is the representation of $x_t$ from the text encoder.

$$A^l_t = \text{Softmax} \left( \frac{h^l_{t-1} V^T}{\sqrt{d}} \right), \quad (1)$$

$$h^l_t = A^l_t \cdot V. \quad (2)$$

From these equations, a cross-attention layer measures the relevance of the visual region representations with respect to a token in the input caption, and calculates the weighted average of all visual region representations accordingly. As a result, the visual attention scores $A^l_t$ can directly reflect how important the visual regions are to token $x_t$. Therefore, we visualize the activation maps of such attention scores to locate an object in an image given its name in the caption.

We use Grad-CAM [24] as the visualization method and follow its original setting to take the final output $s$ from the multi-modal encoder, and calculate its gradient with respect to the cross-attention scores. $s$ is a scalar that represents the similarity between the image and its caption. Specifically, the final activation map $\Phi_t$ of the image given an object name $x_t$ is calculated as

$$\Phi_t = A^l_t \cdot \text{max} \left( \frac{\partial s}{\partial A^l_t}, 0 \right). \quad (3)$$

In practice, if there are multiple attention heads in one cross-attention layer, we average the activation map $\Phi_t$ from all attention heads as the final activation map.

After we get an activation map of an object of interest in the caption using this strategy, we draw a bounding box covering the activated region as the pseudo label of the category. We adopt existing proposal generators to generate proposal candidates $B = \{b_1, b_2, ..., b_K\}$ and select the one that overlaps the most with $\Phi_t$.

$$\hat{b} = \arg \max_i \sum_{b_i} \frac{\Phi_t(b_i)}{\sqrt{|b_i|}}, \quad (4)$$

where $\sum_{b_i} \Phi_t(b_i)$ indicates summation of the activation map within a box proposal and $|b_i|$ indicates the proposal area. In practice, we maintain a list of objects of interest (referred as object vocabulary) during training and get pseudo bounding-box annotations for all objects in the training vocabulary (see Sec. 4.1 for details). Qualitative and quantitative experiments show that our generated bounding boxes are of surprisingly good quality (see Sec. 4.4 for details) and therefore can be directly used to train an object detector.

![Diagram](image)

**Figure 3. Illustration of our detector.** An image is processed by a feature extractor followed by a region proposal network. Region-based features are then calculated by applying RoI pooling/RoI align over region proposals and the corresponding visual embeddings are obtained. Similarity of the visual and text embeddings of the same object are encouraged during training.

### 3.2. Open vocabulary Object Detection with Pseudo Labels

After we get pseudo bounding-box labels, we can use them to train an object detector. Since our pseudo-label generation is disentangled from detector training process, our framework can accommodate detectors with any architecture. In this work, we focus on the open-vocabulary scenario where a detector aims at detecting arbitrary objects during inference.

A general open vocabulary detection system [36] is shown in Fig. 3. A feature map is extracted from an input image using a feature extractor based on which object proposals are generated. Then, region-based visual embeddings, $R = \{r_1, r_2, ..., r_{N_r}\}$, are obtained by RoI pooling/RoI align [11] followed by a fully connected layer, where $N_r$ denotes the number of regions. In the meanwhile, text embeddings, $C = \{bg, c_1, c_2, ..., c_{N_c}\}$, of object candidates from the object vocabulary are acquired by a pretrained text encoder, where $N_c$ is the training object vocabulary size and $bg$ indicates “background” that matches irrelevant visual regions. The goal of the open vocabulary object detector is to pull close the visual and text embeddings of the same objects and push away those of different objects. The probability of $r_i$ matches $c_j$ is calculated as

$$p(r_i \text{ matches } c_j) = \frac{\exp(r_i \cdot c_j)}{\exp(r_i \cdot bg) + \sum_k \exp(r_i \cdot c_k)}, \quad (5)$$

where text embeddings $C$ is fixed during training. The cross entropy loss is used to encourage the matching of positive pairs and discourage the negative ones.

During inference, given a group of object classes of interest, a region proposal will be matched to the object class if its text embedding has the smallest distance to the visual embedding of the region compared to all object names in the vocabulary. This strategy is similar to other zero-shot/open...
vocabulary detection methods. To perform a fair comparison to prior work, we also adopt Mask-RCNN as the base of our open vocabulary detector. We set \( bg = 0 \) and include objectness classification, objectness box regression and class-agnostic box regression losses following [36].

4. Experiments

4.1. Datasets and Object Vocabulary for Training

Training Datasets. Unlike prior object detection work that requires training datasets with human-provided bounding boxes for objects, our method only needs datasets with annotations of image-caption pairs. Therefore, we use a combination of existing image-caption datasets including COCO Caption [3], Visual-Genome [14], and SBU Caption [18]. Our final dataset for pseudo label generation and detector training contains about 1M images.

Object Vocabulary. When we generate pseudo labels for object categories from the aforementioned dataset, our default object vocabulary for pseudo label generation is constructed by the union of all the object names in COCO, PASCAL VOC, Objects365 and LVIS, resulting in 1,582 categories. We would also like to note that since our method doesn’t require extra human annotation efforts, the object vocabulary that our method support can be easily augmented. In Sec. 4.6, we also investigate the effect of expanding/shrinking this vocabulary.

4.2. Evaluation Benchmarks

Our method is evaluated in the following two settings, Setting 1: Training without human-provided bounding boxes. The major difference between our method and existing detection methods is that our method can be trained solely with our generated pseudo labels. Therefore, we mainly demonstrate the effectiveness of our framework in this setting.

Setting 2: Fine-tuning with existing base object categories. We are also curious about how our method will perform after further fine-tuned on existing object categories with human-provided bounding-box labels. Therefore, following existing zero-shot/open vocabulary works [1, 22, 36, 38], we show the performance of our method when it is fine-tuned using COCO base categories after trained with our pseudo box labels. Following the setting proposed in [1], COCO detection training set is split to base set containing 48 base/seen classes and target set including 17 novel/unseen classes. All methods are trained on base classes. Two evaluation settings are used during inference [36]. In the generalized setting, models predict object categories from the union of base and novel classes and in the non-generalized setting, models detect an object from only the list of novel classes.

Baselines. Because there are no existing open vocabulary detection methods that can be trained without manual bounding-box annotations, we compare with recent zero-shot/open-vocabulary methods [1, 22, 36, 38] that require human-provided bounding boxes for base categories during training. Among the baselines, Zareian et al. [36] is the SOTA method, thus, is treated as our major baseline.

Evaluation Datasets. To perform a fair comparison with previous work, we first evaluate on the COCO target set. Besides, we are interested in measuring the performance of all models to other datasets that models are not trained on. Therefore, we also evaluate our method and the strongest baseline on PASCAL VOC [5] test set, Objects365 v2 [25] validation set and LVIS [10] validation set. PASCAL VOC is a widely used dataset by traditional object detection methods which contains 20 object categories. Objects365 and LVIS are datasets include 365 and 1,203 object categories, respectively, which makes them very challenging in practice. When evaluating on each of these datasets (PASCAL VOC, Objects365 and LVIS), visual regions will be matched to one of the object categories (including background) of the dataset during inference.

Evaluation Metric. We use the mean average precision over classes and set the IoU threshold to 0.5.

4.3. Implementation Details

In our pseudo label generator, we use the ALBEF model pre-trained with 12M data as our vision-language model. We follow the default setting of ALBEF, unless otherwise noted. The cross-attention layer used for Grad-CAM visualization is set to \( l = 8 \) in Eq. 3. We conduct our main experiments using ALBEF because it has reasonable object grounding performance when image captions are present. Note that other pre-trained vision-language models can also fit our framework without major modifications or adding additional constraints on detector training. As a default option, we use a off-the-shelf Mask-RCNN with ResNet-50 trained on COCO 2017 train set as our proposal generator. To ensure there is no labels of novel categories leaking to our model, we have excluded the novel categories when training the proposal generator. Although a small amount of box annotations are used for training the proposal generator, it is used to generate proposals for thousands of categories in all the datasets. Besides, we also show our performance using an unsupervised proposal generator, selective search [30], in Sec. 4.6.

We use Mask-RCNN with ResNet-50 as the base of our open vocabulary detector and keep following the default set-

---

1 We use LVIS v0.5, since the validation set of LVIS v1.0 contains images from COCO train 2017 which our method may finetune on in some experiments.

2 We use the model provided in https://github.com/salesforce/ALBEF (BSD-3-Clause License)
Table 1. Performance on COCO dataset compared with existing methods. Our method (No fine-tune with box annotations) outperforms all the previous approaches (fine-tune with box annotations).

| Method                | Fine-tuned with Box Anno. on COCO Base Categories | Generalized Setting |
|-----------------------|---------------------------------------------------|---------------------|
|                       | Novel AP | Base AP | Overall AP |
| Bansal et al. [1]     | Yes      | 0.3     | 29.2       | 24.9       |
| Zhu et al. [38]       | Yes      | 3.4     | 13.8       | 13.0       |
| Rahman et al. [22]    | Yes      | 4.1     | 35.9       | 27.9       |
| Zareian et al. [36]   | Yes      | 22.8    | 46.0       | 39.9       |
| Our method            | No       | 25.8    |             |             |
|                       | Yes      | 30.8    | 46.1       | 42.1       |

Table 2. Generalization performances to other datasets. In general, our method has better generalization performance to other datasets compared to Zareian et al., even though our method is not fine-tuned using box annotations.

Table 3. Effect of proposal quality. All models are not fine-tuned. Better proposals lead to better detection performance.

4.4. Quality of Pseudo Bounding-box Annotations

Replacing manual annotations with our pseudo labels (Plabels) when training a detector is the core of our method. Therefore, before describing results of the experiments illustrated in Sec. 4.2, we first evaluate the quality of our generated pseudo bounding-box annotations both qualitatively and quantitatively.

**Qualitative analysis.** We visualize some examples of our generated pseudo bounding boxes in Figure 4. As we can see, the generated pseudo labels show promising performance (see red boxes) in localizing objects and are able to cover categories, e.g., pot, slippers and pie, that are not in the original object list of COCO’s ground-truth annotations. However, we observe that if there are multiple instances of the same object are present in an image, our pseudo label generator often fails to capture all of them (see the yellow box in the third column). Moreover, an object of interest will be missed if it is not in the caption (see the yellow box in the last column). Therefore, we train a standard open vocabulary object detector with such pseudo labels to support multi-instance detection with no dependency on captions.

**Quantitative evaluation.** We quantitatively evaluate our pseudo labels on the COCO validation set. Since our generator requires captions as inputs, we use the caption annotation of COCO and only evaluate on a subset (referred as COCO\(N\)) of images whose caption include the name of at least one novel object (resulting in 890 images in total). The Novel AP of our pseudo box generator under this setting reaches a surprising 18.7, which indicates that the pseudo labels have decent quality. However, if we don’t use the caption context and only use text prompt “a photo of a \{category\}” given a novel category, the performance is only 0.8 AP on COCO\(N\). This suggests that it is not wise to use our pseudo-label generator as a standalone detector, because it requires caption context to perform well. While in the default detection task, a caption is usually not available during inference. As a result, we use the large-scale pseudo labels to train an open-vocabulary object detector that enables great generalization ability to novel classes without any dependency on captions during inference. In the following we show the effectiveness of the open-vocabulary object detector trained with the pseudo box labels.

4.5. Experimental Results

When only trained using the generated pseudo labels, our method outperforms all the baseline methods even though the baseline methods are fine-tuned on the COCO base categories with manual bounding-box annotations. As we can...
A room with a small bed, slippers and a pot.

A giraffe stares at a woman standing close to it.

A tree with two umbrellas

A fire hydrant sitting on the side of the road.

Figure 4. Visualization of our generated pseudo bounding-box annotations on COCO. The red boxes indicate successful cases and the yellow ones denote failure cases. Our pseudo label generator can generate objects (slippers, pot and pie) that are not covered by COCO’s category list. The generator can fail when there are multiple object instances of the same category are present (e.g., the umbrellas in the third column) and cannot capture an object if its not is not shown in the caption (e.g. the car in the last column).

see in Table 1, our method achieves 25.8 AP on the novel categories which significantly improves our strongest baseline (Zareian et al.) by 3%. When also fine-tuned using COCO base categories as our baselines do, our method outperforms Zareian et al. even further by 8%.

Generalization ability to a wide range of datasets is also important for an open-vocabulary object detector, since it makes a detector directly usable as a out-of-the-box method in the wild. Table 2 shows the generalization performance of detectors to different datasets, where both our method and our baseline are not trained using these datasets. Object365 and LVIS have a large set of diverse object categories, so evaluation results on these datasets would be more representative to demonstrate the generalization ability. The results suggest that our method (without fine-tune) has already shown better performance than Zareian et al. (with finetune) on Object365 and LVIS. When fine-tuned using COCO base set, our method further improves the results surpassing our baseline by 2.3% in Object365 and 2.8% on LVIS. Besides, our fine-tuned method beats the SOTA largely by 6.3% on PASCAL VOC. When not fine-tuned, our performance drops significantly on PASCAL VOC. It is very likely that there is a large semantic overlap between the COCO base categories and PASCAL VOC object categories. Therefore, fine-tuning on COCO base set helps the model’s transfer ability to PASCAL VOC.

4.6. Ablation Study

How does quality of bounding-box proposals affect performance? Our pseudo label generator combines object proposals and the activation map to select boxes. Generally, the better the proposals are, the more accurate our pseudo bounding-box annotations would be. To analyze the effect of proposal quality, we run experiments with three proposal generators and summarize results in Table 3. First, PG is a supervised Mask-RCNN trained on COCO excluding the novel/unseen categories. This is the default proposal generator in all other experiments. Second, PG+ is a supervised Mask-RCNN trained on the full COCO train set with annotations from all 80 categories which should produce better quality proposals. Finally, Selective Search [30] is an unsupervised proposal generator, which means no bounding-box annotations are involved in any phase of our framework. Using these three proposal approaches, we evaluate our performance on PASCAL VOC, Object365 and LVIS without any fine-tuning. The results show that the supervised proposal generators can significantly improve performance over fully unsupervised proposals. Among the supervised proposals, we see that training them with more annotated categories can also be slightly beneficial. Although we default to use the supervised proposal PG+ for better performance, our framework can also work with unsupervised proposal generators. Besides, we utilize a rather small number of annotated categories for training the proposal generator (63 categories) particularly in comparison to the size of our training vocabulary (1582 categories).

| Methods       | Petrain Source             | Novel (17) | Base (48) | All (65) |
|---------------|----------------------------|------------|-----------|----------|
| Zareian [36]  | COCO Cap                  | 27.5       | 46.8      | 39.9     |
|               | COCO Cap, VG, SBU (1M)    | 23.3       | 45.6      | 38.0     |
|               | COCO Cap, CC (3M)         | 16.7       | 43.0      | 34.3     |
| Ours          | COCO Cap                  | 30.5       | 45.1      | 40.4     |
|               | COCO Cap, VG, SBU (1M)    | 32.3       | 46.9      | 42.1     |

Table 4. Comparison with the SOTA when pre-trained using different sources. All models are fine-tuned using COCO base categories. For Zareian et al., results in the first and third rows are copied from their original paper. The performance of Zareian et al. drops when pre-training with more data.
pairs, a natural question could be “does the large performance gap simply come from the larger image-caption dataset that our method is trained on?”. To answer this question, we show the performance of our baseline [36] pre-trained using different amounts of image-caption data in Table 4. As we can see, increasing the data amount does not improving the performance of the baseline. Specifically, their novel AP drops significantly by 4.2% and 10.8% when the pre-trained source is increased to 1M and 3M images. This may be because of the large domain gap of the additional data from the evaluation data. In contrast, our method can benefit from a larger dataset. Our performance is improved by ~2% on the target set when using more data. Moreover, our method achieves 3% more AP compared to our baseline even when trained using COCO Caption only.

What is the effect of the text encoder? We evaluate our method using two text encoders. Our default choice is the CLIP text encoder. Besides, we also experiment with Bert (base) [4] which is a widely used language model that is trained using text data only. The comparison results are shown in Table 6. The results suggest that Bert encoder achieves slightly better results on COCO target set, but much worse performance on PASCAL VOC. This may due to the fact that CLIP text encoder is trained using image-caption pairs which results in better generalization performance for image-related tasks.

### 5. Closing Remarks

We propose an open vocabulary object detection framework that can be trained without human-provided bounding-box annotations. We introduce a pseudo label generator that leveraging the localization ability of a pre-trained vision-language model to generate pseudo bounding-box annotations from large-scale image-caption datasets. The generated pseudo labels are used to train an open vocabulary object detector. Experimental results show that our method outperforms the state-of-the-arts which rely on training with base classes of a dataset even though our method only trains using the pseudo labels.

**Limitations.** Our pseudo label generator utilizes a proposal generator that is trained with human-provided bounding-box annotations in the main experiments. However, our method is not constrained to use supervised proposal generator; we argue that this is a rather small amount of annotations given the much larger amount of annotations that we can save in the base and novel categories. Ideally, it would be the best if a purely unsupervised method is available to generate high-quality proposals. Addressing this limitation will be future work.

**Potential Negative Societal Impact.** Our method generates pseudo bounding-box annotations to alleviate human labeling efforts. Since our pseudo label generator mines annotations of objects from the input captions without human intervention, our pseudo labels might be biased because of the bias embedded in the language descriptions. Manually filtering out the biased object names in the vocabulary could be an effective solution.

---

**Table 5. Performance of our method when using vocabularies of different sizes. Models are not fine-tuned. \( V^- \), \( V \) and \( V^+ \) contain 65, 1.5k+ and 8k+ categories, respectively.**

| Vocab. (Size) | Generalized COCO Novel | PASCAL VOC | Objects365 | LVIS |
|--------------|-------------------------|------------|------------|------|
| \( V^- \) (65) | 25.5                    | 45.6       | 3.1        | 4.5 |
| \( V^+ \) (8k+) | 23.0                    | 43.8       | 4.2        | 5.1 |
| \( V \) (1.5k+) | **25.8**                | **44.4**   | **5.1**    | **6.5** |

**Table 6. Performance of our method with different text encoders.**

| Text Encoder | Generalized COCO Novel | PASCAL VOC |
|--------------|-------------------------|------------|
| Bert         | **26.5**                | 38.8       |
| CLIP         | 25.8                    | **44.4**   |
References

[1] Ankan Bansal, Karan Sikka, Gaurav Sharma, Rama Chellappa, and Ajay Divakaran. Zero-shot object detection. In ECCV. 2, 3, 5, 6
[2] Hakan Bilen and Andrea Vedaldi. Weakly supervised deep detection networks. In CVPR. pages 2846–2854, 2016. 2
[3] Xinlei Chen, Hao Fang, Tsung-Yi Lin, Ramakrishna Vedantam, Saurabh Gupta, Piotr Dollar, and C Lawrence Zitnick. Microsoft coco captions: Data collection and evaluation server. arXiv preprint arXiv:1504.00325, 2015. 5
[4] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding. arXiv preprint arXiv:1810.04805, 2018. 8
[5] Mark Everingham. The pascal visual object classes challenge.(voc2007) results. http://pascallin.ecs.soton.ac.uk/challenges/VOC/voc2007/index.html., 2007. 5
[6] Mark Everingham, SM Ali Eslami, Luc Van Gool, Christopher KI Williams, John Winn, and Andrew Zisserman. The pascal visual object classes challenge: A retrospective. International journal of computer vision, 111(1):98–136, 2015. 1
[7] Mingfei Gao, Ang Li, Ruichi Yu, Vlad I Morariu, and Larry S Davis. C-wsl: Count-guided weakly supervised localization. In Proceedings of the European conference on computer vision (ECCV), pages 152–168, 2018. 2
[8] Ross Girshick. Fast r-cnn. In Proceedings of the IEEE international conference on computer vision, pages 1440–1448, 2015. 2
[9] Xiuye Gu, Tsung-Yi Lin, Weicheng Kao, and Yin Cui. Zero-shot detection via vision and language knowledge distillation. arXiv preprint arXiv:2104.13921, 2021. 3, 6
[10] Agrim Gupta, Piotr Dollar, and Ross Girshick. LVIS: A dataset for large vocabulary instance segmentation. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2019. 5
[11] Kaiming He, Georgia Gkioxari, Piotr Dollár, and Ross Girshick. Mask r-cnn. In Proceedings of the IEEE international conference on computer vision, pages 2961–2969, 2017. 1, 2, 4
[12] Chao Jia, Yinfei Yang, Ye Xia, Yi-Ting Chen, Zarana Parekh, Hieu Pham, Quoc V Le, Yunhuan Sung, Zhen Li, and Tom Duerig. Scaling up visual and vision-language representation learning with noisy text supervision. arXiv preprint arXiv:2102.05918, 2021. 2, 3
[13] KJ Joseph, Salman Khan, Fahad Shabbaz Khan, and Vinneeth N Balasubramanian. Towards open world object detection. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 5830–5840, 2021. 3
[14] Ranjay Krishna, Yuke Zhu, Oliver Groth, Justin Johnson, Kenji Hata, Joshua Kravitz, Stephanie Chen, Yannis Kalantidis, Li-Jia Li, David A Shamma, et al. Visual genome: Connecting language and vision using crowdsourced dense image annotations. International journal of computer vision, 123(1):32–73, 2017. 5
[15] Junman Li, Ramprasaath R Selvaraju, Akhilesh Deepak Gotmare, Shafiq Joty, Caiming Xiong, and Steven Hoi. Align better fuse: Vision and language representation learning with momentum distillation. In NeurIPS, 2021. 2, 3
[16] Liunian Harold Li, Mark Yatskar, Da Yin, Cho-Jui Hsieh, and Kai-Wei Chang. Visualbert: A simple and performant baseline for vision and language. arXiv preprint arXiv:1908.03557, 2019. 2, 3
[17] Tsung-Yi Lin, Michael Maire, Serge Belongie, James Hays, Pietro Perona, Deva Ramanan, Piotr Dollar, and C Lawrence Zitnick. Microsoft coco: Common objects in context. In European conference on computer vision, pages 740–755. Springer, 2014. 1
[18] Vicente Ordonez, Girish Kulkarni, and Tamara Berg. Im2text: Describing images using 1 million captioned photographs. Advances in neural information processing systems, 24:1143–1151, 2011. 5
[19] Constantine Papageorgiou and Tomaso Poggio. A trainable system for object detection. International journal of computer vision, 38(1):15–33, 2000. 1
[20] Constantine P Papageorgiou, Michael Oren, and Tomaso Poggio. A general framework for object detection. In Sixth International Conference on Computer Vision (IEEE Cat. No. 98CH36271), pages 555–562. IEEE, 1998. 1
[21] Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, et al. Learning transferable visual models from natural language supervision. arXiv preprint arXiv:2103.00020, 2021. 2, 3
[22] Shafin Rahman, Salman Khan, and Nick Barnes. Improved visual-semantic alignment for zero-shot object detection. In AAAI, volume 34, pages 11932–11939, 2020. 2, 3, 5, 6
[23] Shaoqing Ren, Kaiming He, Ross Girshick, and Jian Sun. Faster r-cnn: Towards real-time object detection with region proposal networks. Advances in neural information processing systems, 28:91–99, 2015. 2
[24] Ramprasaath R Selvaraju, Michael Cogswell, Abhishek Das, Ramakrishna Vedantam, Devi Parikh, and Dhruv Batra. Grad-cam: Visual explanations from deep networks via gradient-based localization. In Proceedings of the IEEE international conference on computer vision, pages 618–626, 2017. 2, 4
[25] Shuai Shao, Zeming Li, Tianyuan Zhang, Chao Peng, Gang Yu, Xiangyu Zhang, Jing Li, and Jian Sun. Objects365: A large-scale, high-quality dataset for object detection. In Proceedings of the IEEE/CVF International Conference on Computer Vision, pages 8430–8439, 2019. 5
[26] Peiye Sun, Rufeng Zhang, Yi Jiang, Tao Kong, Chenfeng Xu, Wei Zhan, Masayoshi Tomizuka, Lei Li, Zehuan Yuan, Changhu Wang, et al. Sparse r-cnn: End-to-end object detection with learnable proposals. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 14454–14463, 2021. 1
[27] Christian Szegedy, Alexander Toshev, and Dumitru Erhan. Deep neural networks for object detection. 2013. 1
[28] Hao Tan and Mohit Bansal. Lxmert: Learning cross-modality encoder representations from transformers. arXiv preprint arXiv:1908.07490, 2019. 2, 3
[29] Peng Tang, Xinggang Wang, Song Bai, Wei Shen, Xiang Bai, Wenyu Liu, and Alan Yuille. Pcl: Proposal cluster learning
for weakly supervised object detection. *IEEE transactions on pattern analysis and machine intelligence*, 42(1):176–191, 2018.

[30] Jasper RR Uijlings, Koen EA Van De Sande, Theo Gevers, and Arnold WM Smeulders. Selective search for object recognition. *IJCV*, 104(2):154–171, 2013.

[31] Yongqin Xian, Tobias Lorenz, Bernt Schiele, and Zeynep Akata. Feature generating networks for zero-shot learning. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 5542–5551, 2018.

[32] Yongqin Xian, Bernt Schiele, and Zeynep Akata. Zero-shot learning-the good, the bad and the ugly. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 4582–4591, 2017.

[33] Enze Xie, Jian Ding, Wenhai Wang, Xiaohang Zhan, Hang Xu, Peize Sun, Zhenguo Li, and Ping Luo. Detco: Unsupervised contrastive learning for object detection. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 8392–8401, 2021.

[34] Keren Ye, Mingda Zhang, Adriana Kovashka, Wei Li, Dafeng Qin, and Jesse Berent. Cap2det: Learning to amplify weak caption supervision for object detection. In *ICCV*, pages 9686–9695, 2019.

[35] Tianwei Yin, Xingyi Zhou, and Philipp Krahenbuhl. Center-based 3d object detection and tracking. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 11784–11793, 2021.

[36] Alireza Zareian, Kevin Dela Rosa, Derek Hao Hu, and Shih-Fu Chang. Open-vocabulary object detection using captions. In *CVPR*, pages 14393–14402, 2021.

[37] Pengkai Zhu, Hanxiao Wang, and Venkatesh Saligrama. Zero-shot detection. *IEEE Transactions on Circuits and Systems for Video Technology*, 30(4):998–1010, 2019.

[38] Pengkai Zhu, Hanxiao Wang, and Venkatesh Saligrama. Don’t even look once: Synthesizing features for zero-shot detection. In *CVPR*, pages 11693–11702, 2020.