

Region-centric Image-Language Pretraining for Open-Vocabulary Detection

Dahun Kim Anelia Angelova Weicheng Kuo

Google DeepMind

Abstract. We present a new open-vocabulary detection approach based on region-centric image-language pretraining to bridge the gap between image-level pretraining and open-vocabulary object detection. At the pretraining phase, we incorporate the detector architecture on top of the classification backbone, which better serves the region-level recognition needs of detection by enabling the detector heads to learn from large-scale image-text pairs. Using only standard contrastive loss and no pseudo-labeling, our approach is a simple yet effective extension of the contrastive learning method to learn emergent object-semantic cues. In addition, we propose a shifted-window learning approach upon window attention to make the backbone representation more robust, translation-invariant, and less biased by the window pattern. On the popular LVIS open-vocabulary detection benchmark, our approach sets a new state of the art of 37.6 mask AP_r using the common ViT-L backbone and public LAION dataset, and 40.5 mask AP_r using the DataComp-1B dataset, significantly outperforming the best existing approach by +3.7 mask AP_r at system level. On the COCO benchmark, we achieve very competitive 39.6 novel AP without pseudo labeling or weak supervision. In addition, we evaluate our approach on the transfer detection setup, where it demonstrates notable improvement over the baseline. Visualization reveals emerging object locality from the pretraining recipes compared to the baseline.¹

1 Introduction

To understand and localize all objects and entities in the visual world has been a foundational problem in computer vision and machine learning. This capability unlocks a broad array of compelling applications from self-driving cars to search and recommendation. However, existing object detectors typically rely on human-annotated regions and class labels. These annotations are costly and unscalable in terms of the number of categories *e.g.* O(1K) and the number of images *e.g.* O(100K).

The open-vocabulary detection (OVD) task [43] has been introduced to overcome both limitations by pretraining on larger-scale image-text data before finetuning for detection tasks. In particular, recent open-vocabulary detection approaches are mostly based on Contrastive Language-Image Pretraining (CLIP) [30], representing each category as a text embedding rather than a discrete label. This enables the detectors to localize objects based on any user-provided text queries unavailable during training.

Most existing open-vocabulary detection works assume the pretrained CLIP backbone is given, and focus on techniques such as knowledge distillation [6, 11], weak

¹ project page: github.com/google-research/google-research/tree/master/fvlm/dito

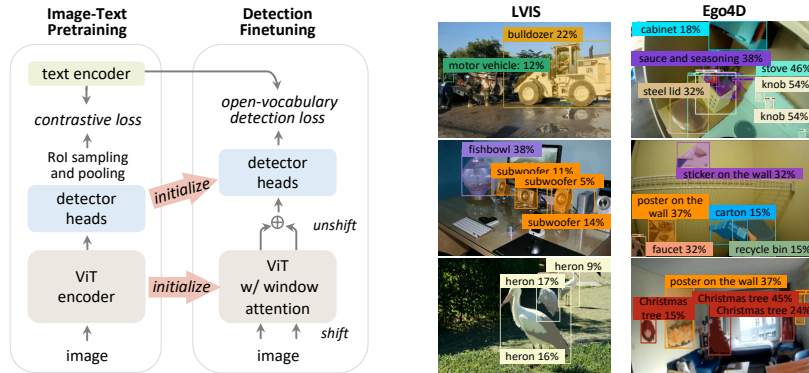


Fig. 1: DITO overview (left): Existing image-text pretraining methods for open-vocabulary detection [17, 18] only update the vision transformer backbone and finetune detector heads from scratch. We propose to pretrain both backbone and detector heads directly from the large-scale image-text paired data, without a need for pseudo labeling or box annotations. In open-vocabulary detection finetuning, we introduce a simple shifted-window learning method to produce more robust representations from the pretrained vision transformer. **DITO prediction (right):** LVIS results only show the novel categories (e.g., *bulldozer*, *fishbowl*, *subwoofer*, *heron*). While Ego4D is a real-world and out-of-distribution data, many unseen objects are detected (e.g., *steel lid*, *sticker on the wall*, *recycle bin*). Best viewed with zoom in.

supervision [48], pseudo labeling [14, 31, 45, 46], and frozen backbone application [19], using the pretrained backbone. Consequently, during detection finetuning, the detector heads often need to be trained from scratch. This tends to result in sub-optimal generalization because the detector heads are trained on the limited vocabulary of detection datasets, while only the backbone contains the knowledge of open-vocabulary concepts.

Several studies have integrated detection models into CLIP pretraining. For instance, RegionCLIP [46] employs an off-the-shelf detector during CLIP pretraining to obtain proposals on the image-text data and subsequently generate pseudo region-text labels. However, their pretraining only updates the image backbone, with the detector heads exclusively trained on detection data. These pseudo labeling-based pretraining methods [26, 46] require multi-stage training and handcrafted processing to generate high-quality pseudo labels, and results in increased complexity and cost of training. Similarly, other approaches such as GLIP [20, 44], Grounding DINO [23], CoDet [25] and DetCLIP [40, 41] integrate detector architectures in CLIP training. However, their joint training requires additional detection and visual grounding datasets and complex multitask learning setups.

In this paper, we propose a simple yet effective solution, Region-centric Pretraining approach, which incorporates detector modules into CLIP pretraining without the need for pseudo labeling or box annotations. This method involves generating random box regions across feature pyramid levels, followed by feature pooling over these regions. Subsequently, an image-text contrastive loss is applied, encouraging text-aligned region features to contribute more to the whole image representation. Our approach not only facilitates the warm-starting of detector heads in finetuning, but also leads to emergent representations with more localized semantic information compared to the

baseline CLIP backbone, as demonstrated in our experiments. Compared to pseudo-labeling techniques [37, 46–48], our approach can be viewed as an extension of contrastive models to bypass the need for offline object proposal generation, which could be cumbersome for large-scale image-text data.

In addition, we focus on the Vision Transformer (ViT) based CLIP models. While CLIP ViTs excel in zero-shot recognition, their direct integration to open-vocabulary detector has gained less traction compared to their ConvNet counterparts [19, 38, 46]. The typical pretraining of CLIP ViT backbones on lower resolutions, followed by adaptation to higher resolution detection images, presents challenges due to increased computational demands and the risks of breaking locality structure in pretrained features. Although the windowed attention technique of ViTDet [18, 21] can reduce computation and preserve locality structure, it introduces bias from the fixed window patterns at the same time. To address this, we propose Shifted-Window Learning (SWL) approach to enhance information mixing across fixed windows and mitigate grid pattern bias. Unlike the Swin Transformer [24], which applies shifted window layer by layer, SWL applies shifted windowed attention as a separate forward pass using the same ViT backbone. This simple strategy enhances the windowed attention representation when applied low-res trained ViT backbone to high-res images, ensuring compatibility with vanilla ViT backbones pretrained without shifted windows. Apart from improving windowed attention, SWL better preserves the open-vocabulary knowledge of pretrained features compared to full-attention ViT perhaps due to its emphasis on local cues.

Incorporating both region-centric pretraining and shifted-window learning, our approach is called DITO (Detection-aligned Image-Text pretraining for Open-vocabulary detection). DITO serves to narrow the gap between image-text pretraining and open-vocabulary detection, and obtain better generalization. The best DITO model achieves 37.6 mask AP_r on the widely used LVIS open-vocabulary detection benchmark, surpassing the previous best approach by +3.7 AP_r . It achieves the state-of-the-art 40.5 mask AP_r when pretrained on the DataComp-1B dataset. On the COCO benchmark, DITO achieves a very competitive 39.6 novel AP without using pseudo-labels or joint training. In summary, our contributions are:

- We present a novel region-centric pretraining approach for open-vocabulary detection by integrating detector heads on top of the image backbone into CLIP pretraining. This learns better detection-oriented features from large-scale image-text data without a need for pseudo labeling or extra box annotations.
- We propose the Shifted-Window Learning technique to produce more robust and translation-invariant representation from pretrained CLIP ViT for open-vocabulary detection.
- Our approach significantly outperforms the state-of-the-art methods on LVIS open-vocabulary detection benchmark, including larger models and pseudo labeling-based approaches, and achieves very competitive performance on COCO benchmark and transfer detection to Objects365.

2 Related Work

Open-vocabulary detection. Conventional closed-set object detectors exhibit great performance but are limited in their vocabulary size. Motivated by the strong zero-

shot abilities of Vision-Language Models (VLMs) like CLIP [30], open-vocabulary detection has shown notable progress in recent years. Efforts have been directed towards leveraging pretrained CLIP models for detection, with various techniques such as knowledge distillation [11] and prompt optimization [6]. Also, there are works that directly utilize the pretrained CLIP backbone by adding new detection heads either by setting the backbone frozen [19, 38] or finetunable [18, 27]. Many top-performing approaches [7, 9, 20, 26, 46] rely on pseudo labeling techniques which aim to mitigate the issue of catastrophic forgetting in detection finetuning. However, these self-training methods often necessitate multi-stage detection training [37, 46], extra steps for generating high-quality pseudo labels [26], or the use of off-the-shelf detector modules [31, 46]. Unlike these approaches, our method focuses on both upstream image-text pretraining and downstream open-vocabulary detection without the need for pseudo labeling techniques. We demonstrate significant improvements in open-vocabulary detection.

Region-aligned Vision-Language Models. Driven by the progress in aligning image-text representations [30, 33], several studies have aimed to integrate region-level alignment into CLIP pretraining. For instance, RegionCLIP [46] learns region-word alignment by generating pseudo region-text pairs. However, their pretraining requires an off-the-shelf detector for the pseudo labeling, and it solely focuses on training the image backbone, relying on the off-the-shelf detector during inference. Other approaches like GLIP [20, 44], Grounding DINO [23], DetCLIP [40, 41], CoDet [25] integrate detector architectures in CLIP training to explicitly align regions with words. However, they require additional detection or visual grounding annotations for explicit region-level supervision, resulting in complex multitask learning. To our knowledge, our approach is the first work that incorporates detector modules in image-text pretraining without relying on any box annotations.

Vision Transformers in open-vocabulary detection. Regarding backbone architecture, ConvNet, ViT or hybrid models [24] have been used in open-vocabulary detection. While ViT-based CLIP models exhibit superior capability in zero-shot recognition, their adaptation to open-vocabulary detection is relatively less explored compared to ConvNet-based CLIP models. A notable example is OWL-ViT [26, 27], which finetunes the pretrained ViT on higher-resolution detection images while maintaining fully global attentions. However, employing full attention models can be computationally demanding for large images. RO-ViT [18] proposes region-aware positional embeddings that aid in the generalization of CLIP ViT onto detection finetuning. These methods [17, 18] adopt windowed attention from ViTDet [21] for adaptation to detection. In this paper, to further enhance information mixing across fixed windows while preserving the locality structure of the pretrained lower-resolution features, we propose shifted-window learning to mitigate the window-induced bias and improve open-vocabulary detection.

Self-supervised pretraining for visual tasks. Self-supervised learning has emerged as a promising paradigm to learn object features for complex visual tasks such as detection, given the challenge of scaling up human annotations. Most relevant direction is contrastive learning, where the contrastive samples can take the forms of augmented images [3], sliding windows [39], object proposals [36], or point samples [1]. Some alternative strategies like pseudo-labeling [47] and pixel reconstruction [12] have also proven effective. While the majority of these methods have focused on learning from

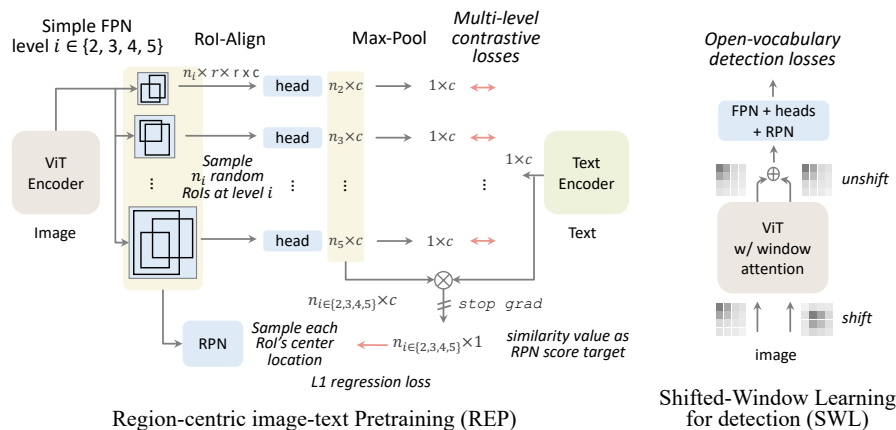


Fig. 2: DITO method. Region-centric image-text pretraining (left): We train the detector heads (e.g. FPN [21, 22], Faster RCNN head [32], and RPN [32]) upon a ViT encoder backbone with multi-level image-text contrastive loss to bridge the gap between image-text pretraining and open-vocabulary detection. Shifted-window learning for detection (right): We roll the image and combines the shifted features with the original features to mitigate the bias of windowed attention grid [21], and produce more robust semantic representation.

images without textual context, and applying to closed-vocabulary detection, DITO leverages large image-text data to tackle the more demanding open-vocabulary detection task, without a need for offline proposal generation [36, 47].

3 Method

We address the problem of open-vocabulary object detection. At training time, the model can access the class and box labels of base categories (C_B). At test time, the model is tasked with detecting objects from a set of novel categories (C_N) not present in the training set. To achieve this, we leverage pretrained vision and language models (VLMs) as in prior studies [11, 18, 19, 46].

More specifically, we leverage recent advances in ViT-based detectors [18, 21] for their promising results. However, instead of solely taking the pretrained ViT backbone, we demonstrate how to enhance the VLMs by integrating detector heads into the CLIP pretraining process, referred to as Region-centric image-text Pretraining (REP). Additionally, for detection finetuning, we propose a Shifted-Window Learning (SWL) strategy to enhance the adaptation of the pretrained ViT model to open-vocabulary detection task. By combining these approaches, DITO achieves significant improvements in open-vocabulary detection over prior arts.

3.1 Preliminaries

Baseline. Our baseline approach is RO-ViT [18], a state-of-the-art ViT-based method for open-vocabulary detection. RO-ViT introduces CLIP pretraining with a new positional embedding scheme called cropped positional embedding (CPE). CPE involves randomly cropping and resizing the standard whole-image positional embedding during pretraining to enhance the ViT's generalization onto region-level recognition task

and higher resolution detection inputs downstream. For detection finetuning, it adopts ViTDet [21] architecture, initialized with the pretrained ViT backbone. In the following, we describe the image-text pretraining and the downstream open-vocabulary detection.

Image-text pretraining. We adopt dual-encoder CLIP pretraining widely used in existing works [30, 33]. The image embeddings $\{v\}$ and text embeddings $\{l\}$ are the average-pooled outputs from the image and text encoders, respectively. As in previous works, we compute the dot product of the embeddings in batch B , and scale it by a learnable temperature τ before applying the InfoNCE loss [28, 30]. Mathematically, the image-to-text (I2T) loss can be expressed as:

$$L_{I2T} = -\frac{1}{B} \sum_{i=1}^B \log\left(\frac{\exp(v_i l_i / \tau)}{\sum_{j=1}^B \exp(v_i l_j / \tau)}\right). \quad (1)$$

The text-to-image (T2I) loss is symmetrical by exchanging the inner/outer summation loops. The total contrastive loss L_{con} is obtained by $L_{con} = (L_{I2T} + L_{T2I})/2$. As mentioned above, we adopt the cropped positional embeddings (CPE) following [18].

Open-vocabulary detection finetuning. At the fine-tuning stage, our detection finetuning recipe follows previous studies [11, 18, 19, 43]. During the training phase, we use the RoI-Align [13] feature as the detection embedding for each detected region. We replace the fixed-size classifier layer with the text embeddings of base categories (C_B). The detection score p_i is determined by calculating the cosine similarity between the region embedding r_i and text embeddings of base categories (C_B) followed by a softmax operation. We prepend an additional background class embedding to C_B and use the term ‘‘background’’ to represent the background category. Any proposals that do not match to any base category annotations are treated as background during training. It is important that the text embeddings are computed from the same text encoder as from the image-text pretraining. During testing, we expand the text embeddings to include the novel categories ($C_B \cup C_N$), resulting in $(C_B \cup C_N + 1)$ categories including the background. We calculate the detection scores (p_i) as the cosine similarity between the region embeddings (r_i) and the expanded text embeddings. Apart from the detection embedding (r_i), we extract the VLM embedding [19] of region i by RoI-Align at the last ViT backbone feature map. The VLM score (z_i) is calculated as the cosine similarity with the text embeddings of the combined categories ($C_B \cup C_N$).

To compute the open-vocabulary detection score (s_i^{ens}), we ensemble the detection and VLM scores by geometric means [11, 19]. The formula is as follows:

$$s_i^{ens} = \begin{cases} z_i^{(1-\alpha)} \cdot p_i^\alpha & \text{if } i \in C_B \\ z_i^{(1-\beta)} \cdot p_i^\beta & \text{if } i \in C_N \end{cases} \quad (2)$$

Here, α, β are floats $\in [0, 1]$ that control the weighting of base versus novel categories. The background score comes from the detection score (p_i) alone, because we observe the VLM score of ‘‘background’’ class is often less reliable.

3.2 Region-centric Image-Text Pretraining

Standard image-text pretraining uses classification architectures (*e.g.* ViT backbone followed by global pooling) as the language supervision occurs at the image level rather

than the region level. Subsequently, for downstream detection, new detection heads are introduced and trained from scratch on a limited set of detection categories [17–19]. To fully utilize the knowledge embedded in large-scale image-text data, we propose Region-centric Pretraining (REP) which integrates the detector modules during the CLIP pretraining phase. Specifically, given access to image-text paired data but lacking box labels, our pretraining focuses on the *region-recognition pathway* of a detector, encompassing components like the backbone, FPN [21, 22], RoI-Align [13], RPN-objectness [32], and Faster RCNN-classifier [32]. Consequently, the detector heads can be warm-started from the knowledge of large image-text data, thereby improving the generalization capability. To our knowledge, we are the first to integrate detector modules in image-text pretraining without box labels, and our experiments demonstrate clear benefits of our approach in open-vocabulary detection.

Detector head learning from random regions. Fig. 2 (left) illustrates our region-centric pretraining system. Following existing works [17, 18], we adopt SimpleFPN [21] and Faster R-CNN [32] models to remove the detector differences and study the benefits of our region-centric pretraining. Specifically, the multi-level feature pyramid is computed from the ViT backbone. Then, RoI-Align [13] and Faster R-CNN classifier head are applied to these feature maps to match the classification pathway in pretraining with the region-recognition pathway in detection finetuning (see Table 4b for ablations).

For each level i of the feature pyramid, we randomly generate n_i box regions uniformly over the image by sampling the box size $h, w \sim \text{Uniform}(0.2, 0.5)$ and aspect ratio $h/w \sim \text{Uniform}(0.5, 2.0)$. The n_i value is set proportional to the size of the i -th feature map so that larger feature map would be covered by more regions. We extract the RoI-features of each region by RoI-Align, and feed them through the region classifier head [32] to obtain the RoI embeddings.

Multi-level image-text supervision. After computing the RoI embeddings across pyramid levels, we perform a max pooling over the RoI embeddings per-level to obtain an image embedding for each pyramid level. Intuitively, max pooling allows the representation to focus on salient regions and discriminative features, thereby learning region-level information without explicit supervision. Then we apply the standard image-text contrastive loss (see Eqn. (1)) on each feature level separately, which aids the learning of rich semantic and object knowledge within every feature map (see Table 4c for ablations). The losses from all levels are weighted equally and summed together. Without explicit region-level supervision, the max pooling over regions encourages the more salient, text-aligned region features to contribute more to the whole image representation in the contrastive loss. Our experiments show emergent region-text alignments from the multi-level training, where the feature maps possess more localized semantic information compared to the baseline CLIP [18] backbone (see Fig. 3).

Different from pseudo-labeling techniques [7, 14, 36, 37, 46] that require additional steps to generate and store annotations, our approach learns the detector heads on the fly without a need to compute or store object proposals.

Region proposal network learning. Fig. 3 shows that the learnt multi-level representations exhibit localized semantics well-aligned with the text query, *i.e.* the salient regions have higher similarity with the text relative to the background. Motivated by this observation, we employ the multi-level visual-text similarity as a supervisory signal for

training the Region Proposal Network (RPN) [32]. Specifically, we compute the cosine similarity between each RoI embedding and the text, and use it as the target RPN score for the center location of each RoI. Any negative dot product value is mapped to zero to keep the target score in range $[0, 1]$. We use L1 regression loss and set the loss weight equal to the multi-level contrastive loss (see Sec. A in supp.) The losses are propagated only through the RoI centers and other pixels are ignored. Note that the box regression of the RPN is *not* trained here but learnt later through the detection finetuning, as we only use the image-text paired data without any box annotations.

3.3 Shifted-Window Learning for Detection

The CLIP ViT backbones are typically pretrained on lower resolutions (*e.g.* 224×224) and then adapted to higher resolution detection images (*e.g.* 1024×1024). While the detection task benefits from global information, directly applying the pretrained ViT on high-resolution inputs is not only computationally intensive but can also compromise the preservation of the locality structure of the pretrained lower-resolution features.

The adaptation such as windowed attention in ViTDet [21] effectively reduces the computation and is thus also adopted by our baseline RO-ViT [18] detector. However, we observed that the backbone representation is still biased by the fixed-size grid pattern of the windowed attention, compromising the representation power of the pretrained ViT. To improve information mixing across the fixed windows and mitigate the bias of the grid pattern, we propose the Shifted-Window Learning (SWL) approach.

Network architecture. Fig. 2 (right) and Algorithm 1 describe the SWL algorithm. The standard ViT consists of a patchifying layer and a set of transformer layers. After feeding the image through the patchifying layer, we obtain a feature map x of shape (h, w, d) . This feature map x is fed through the rest of the ViT with windowed attention layers on a grid $K \times K$, and L global attention layers evenly spaced throughout the ViT (where $L = 4$) following [21], resulting in output y . In parallel, we create another copy of x , which is rolled along both h and w axes by s pixels. The elements that roll beyond the last position are reintroduced from the first. We carefully design the attention masks such that the rolled around patches would not attend to the patches on the other side of the image (see the right figure of Algorithm 1). The shift size s is set as the half of the attention window size M (*i.e.* $s = M/2$). Empirically, the window size $M = 16$ equals the image size (*e.g.* 1024) divided by the product of patch size (*e.g.* $P = 16$) and the grid size (*e.g.* $K = 4$). The shifted feature map x' is then processed through the rest of the ViT in the same manner, resulting in output y' in the same shape (h, w, d) as y . We then unshift y' and combine it with y by averaging. We apply the above shifted window operations in detection finetuning and inference times.

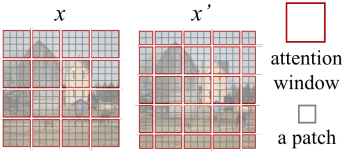
Comparison with Swin Transformer. Compared to the Swin Transformer [24], we apply the shifted-window ideas as separate forward passes, while Swin Transformer applies similar ideas in an alternating manner layer by layer. Our approach requires no change to the vanilla transformer architecture and is compatible with any ViT backbones pretrained without shifted windows (*e.g.* [30]), whereas Swin Transformer requires specialized pretraining on the same architecture. Compared to the full-attention ViT [5], we observe that shifted-window ViT taps more effectively into the semantic

Algorithm 1 Shifted Window backbone

```

x: image patch tokens + positional embeddings.      # [h, w, d]
M: attention window size.
s = M // 2
y = forward_vit_with_win_attn(x, M)
x' = np.roll(x, shift=[s, s], axis=[0, 1])        # shift
y' = forward_vit_with_win_attn(x', M)
y'' = np.roll(y', shift=[-s, -s], axis=[0, 1])    # unshift
return (y + y'') / 2                               # SWL backbone output

```



knowledge of pretrained backbone than full global attention, perhaps because the window helps the model focus more on local cues and ignore the noises farther away.

3.4 Distillation from Frozen ViT Backbone

While the ViT backbone adapts to the detection tasks, it may lose some of its pre-trained open-vocabulary knowledge. Therefore, we propose a simple distillation approach which uses a separate frozen ViT to teach the finetuned ViT backbone during the detection finetuning. We use a cosine distance loss that aligns the RoI-Align embeddings extracted from the feature maps of both backbones. The cosine distance is computed for each RoI then averaged over all RoIs. Empirically, we find it advantageous to add a 1×1 Conv projection layer to the finetuned ViT backbone before the RoI-Align, allowing some flexibility in distillation when jointly trained with other detection objectives. The auxiliary distillation loss is then added to other detection losses, with a loss weight $\gamma = 1$ (see Sec. A in supp.) At inference, the ViT backbone features after the projection are used to compute the region VLM score z_i (Sec. 3.1). It is worth noting that the frozen ViT backbone is only used during training for distillation purposes and is removed at inference.

While previous studies [2, 11] have utilized knowledge distillation from the CLIP models, their teacher CLIP models mostly operate on image crops in an offline process, thus needing multiple forward passes through the backbone for all RoIs. In contrast, our distillation operates efficiently on RoIs cropped from dense feature maps in a single forward pass during the detection finetuning with minimal overhead.

4 Experimental Results

Baseline reproduction. As discussed in Sec. 3.1, our baseline method is RO-ViT [18], a leading ViT-based approach for open-vocabulary detection. RO-ViT introduces cropped positional embedding (CPE) in CLIP pretraining to enhance the generalization of the pretrained ViT onto the downstream detection. Additionally, it adopts global average pooling of the ViT features instead of CLS-token pooling, which simplifies the adaptation onto higher resolution inputs, and the extraction of region features (*e.g.* RoI-Align) at the final layer. We reproduce the CLIP pretraining of RO-ViT [18] using the widely adopted LAION-2B dataset [33], as the OpenAI CLIP’s WIT [30] and ALIGN [15] datasets are not publicly available. We trained the CLIP models from scratch, following the same pretraining protocol and hyperparameters, including 500k iterations and 16k batch size (*i.e.* 8B samples seen in training), 224×224 image size, global average pooling, and cropped positional embedding. We use the standard InfoNCE loss (Eqn. (1))

instead of their focal constrastive loss [18]. The following compares our reproduced CLIP with OpenAI CLIP [30] and OpenCLIP [33]:

method	dataset	# samples seen	backbone	ImageNet Top-1 Acc.
CLIP [30]	WIT-400M	13B	ViT-L/14	75.5
OpenCLIP [33]	LAION-2B	32B	ViT-L/14	75.2
RO-ViT CLIP [18] <i>our repro.</i>	LAION-2B	8B	ViT-L/16	73.9

On the popular zero-shot ImageNet classification benchmark, the LAION-2B pretraining matches or slightly underperforms the OpenAI CLIP with WIT-400M.

Pretraining setup. After the above-mentioned baseline CLIP training, we apply our region-centric pretraining (REP) where we freeze the image and text encoders trained in the first phase and introduce the detector heads. We use the Simple FPN [21], and classification layers of Faster R-CNN and RPN [32], where we replace the batch normalization with layer normalization. At the i -th pyramid level $i \in \{2, 3, 4, 5\}$, we randomly sample $n_i \in \{400, 200, 100, 50\}$ box regions and compute their RoI-Align features. We use a short training cycle of 30k iterations, 4k batch size, 256×256 image size, AdamW optimizer with an initial learning rate of $1e-4$ with linear decay. For both phases of image-text pretraining, we use the publicly available LAION-2B [33] dataset.

Detection finetuning setup. As noted in Sec. 3.2, we adopt the ViTDet [21] with SimpleFPN as our detector following the baseline works [17, 18]. We follow the same finetuning settings of [18]. Specifically, we train the detector with image size 1024×1024 and use windowed attention in the backbone with grid size 4×4 . The learning rate for the backbone is set lower as $0.6 \times$ of the detector head layers. We use $\alpha=0.3$, $\beta=0.65$ for score combination in Eqn. (2). The text embedding of each category is calculated as the average over the CLIP prompt templates. We use the batch size 128, the SGD optimizer with momentum 0.9. The initial learning rate and iterations are set to 0.18 and 36.8k for LVIS, and 0.02 and 11.3k for COCO datasets.

4.1 Main Results

LVIS Benchmark. In Table 1, we report the comparison with existing methods on the challenging LVIS benchmark. The ‘frequent’ and ‘common’ classes of the dataset belong to the base categories C_B , and the ‘rare’ classes are the novel categories C_N . The primary metric is the mask AP on rare classes (mask AP_r). The DITO model achieves the performance of 37.6 mask AP_r , which significantly outperforms the state-of-the-art approach RO-ViT [18] with the same ViT-L backbone by +5.1 points using the same pretraining data LAION-2B [33]. We also outperform the state-of-the-art CFM-ViT [17] by +3.6 points. Our best performance sets a new state-of-the-art 40.9 mask AP_r when using DataComp-1B [8] in pretraining. With the ViT-B backbone, DITO maintains a healthy margin of around +2.5 AP_r above existing ViT-B based approaches.

COCO Benchmark. We present the comparison on COCO benchmark in Table 2. The main metric is AP50 of novel categories (novel AP). Without using pseudo labeling [7, 14, 45, 46], weak supervision [48], or externally trained detector modules [31, 37], our model demonstrates competitive results of 39.6 novel AP with LAION-2B and 40.2 with DataComp-1B. Among the ViT-based methods, DITO outperforms recent works RO-ViT [18] and CFM-ViT [17] by a clear margin of +6.3 and +5.3 points, respectively.

method	pretraining model	pretraining data	detector backbone	w/ pseudo box labels	mask AP _r	mask AP
ConvNet based:						
OV-DETR [42]	ViT-B/32	CLIP-400M	R-50	-	17.4	26.6
Kaul <i>et al.</i> [16]	ViT-B/32	CLIP-400M	R-50	-	19.3	30.6
DetPro-Cascade [6]	ViT-B/32	CLIP-400M	R-50	-	20.0	27.0
Rasheed [31]	ViT-B/32	CLIP-400M	R-50	-	21.1	25.9
BARON [37]	ViT-B/32	CLIP-400M	R-50	-	22.6	27.6
CoDet [25]	R-50	CLIP-400M + CC3M	R-50	-	23.4	30.7
EdaDet [34]	R-50	CLIP-400M	R-50	-	23.7	27.5
VL-PLM [45]	ViT-B/32	CLIP-400M	R-50	✓	17.2	27.0
PromptDet [7]	ViT-B/32	CLIP-400M	R-50	✓	21.4	25.3
OADB [35]	ViT-B/32	CLIP-400M	R-50	✓	21.7	26.6
RegionCLIP [46]	R-50x4	CLIP-400M + CC3M	R-50x4	✓	22.0	32.3
CORA [38]	R-50x4	CLIP-400M	R-50x4	✓	22.2 ^{box}	-
Detic-CN2 [48]	ViT-B/32	CLIP-400M + INet-21K	R-50	WS	24.6	32.4
ViLD-Ens [11]	EffNet-B7	ALIGN-1.8B	EffNet-B7	-	26.3	29.3
F-VLM [19]	R-50x64	CLIP-400M	R-50x64	-	32.8	34.9
ViT based:						
OWL-ViT [27] ^{O365+VG}	ViT-L/14	CLIP-400M	ViT-L/14	-	25.6 ^{box}	34.7 ^{box}
OWL-ViT v2 [26] ^{O365+VG}	ViT-L/14	WebLI-10B	ViT-L/14	✓	45.9 ^{box}	50.4 ^{box}
RO-ViT [18]	ViT-B/16	ALIGN-1.8B	ViT-B/16	-	28.0	30.2
RO-ViT [18] †	ViT-L/16	LAION-2B	ViT-L/16	-	32.4	32.9
CFM-ViT [17]	ViT-B/16	ALIGN-1.8B	ViT-B/16	-	28.8	32.0
CFM-ViT [17]	ViT-L/16	ALIGN-1.8B	ViT-L/16	-	33.9	36.6
CFM-ViT [17] *	ViT-L/16	LAION-2B	ViT-L/16	-	33.8	36.4
DITO (ours)	ViT-S/16	LAION-2B	ViT-S/16	-	26.2	28.8
DITO (ours)	ViT-B/16	LAION-2B	ViT-B/16	-	31.5	32.4
DITO (ours)	ViT-L/16	LAION-2B	ViT-L/16	-	37.6	36.2
DITO (ours)	ViT-L/16	DataComp-1B	ViT-L/16	-	40.5	38.0

Table 1: LVIS open-vocabulary detection (mask AP). DITO outperforms the best existing approach by +3.7 mask AP_r. WS: uses weak supervision from ImageNet-21K. †: reports LAION-2B results in arXiv version. *: our reproduced result using LAION-2B. O365+VG: uses extra Objects365 and Visual Genome data.

Transfer detection. We further evaluate DITO in the transfer detection setting, where the open-vocabulary detector trained on one dataset (LVIS_{base}) is tested on another dataset (Objects365) without any finetuning. By simply replacing the text embeddings, Table 3 shows that DITO achieves 20.0 AP, outperforming previous methods using ConvNet or ViT backbones of similar size.

4.2 Ablation Studies

For ablation study, we use the ViT-L/16 model pretrained with LAION-2B, and evaluate on the LVIS benchmark and report mask AP_r.

DITO overall framework. Table 4a summarizes the benefits of each DITO components. The region-centric pretraining (REP) improves the contrastive model baseline by +2.6 AP_r and shifted window learning (SWL) improves the baseline by +2.8 points. Combining both strategies brings a significant gain of +4.1 AP_r. Lastly, we observe that incorporating the frozen backbone distillation leads to an additional boost of +1.2 points. In the following, we provide ablations for each components.

Region-centric Pretraining. In Table 4b, we ablate our region-centric image-text pretraining by progressively adding the FPN, Faster R-CNN head, and RPN into the pretraining. Our ‘baseline’ is the contrastive image-text pretraining with cropped positional embedding [18]. On top of this, ‘w/ FPN’ introduces the FPN into the pretraining,

method	pretraining model	pretraining data	detector backbone	w/ pseudo box labels	novel AP	AP
<i>ConvNet based:</i>						
OVR-CNN [43]	R-50	CLIP-400M + COCO-Cap	R-50	-	22.8	39.9
ViLD [11]	ViT-B/32	CLIP-400M	R-50	-	27.6	51.3
F-VLM [19]	R-50	CLIP-400M	R-50	-	28.0	39.6
OV-DETR [42]	ViT-B/32	CLIP-400M	R-50	-	29.4	52.7
CoDet [25]	R-50	CLIP-400M + COCO-Cap	R-50	-	30.6	46.6
PromptDet [7]	ViT-B/32	CLIP-400M	R-50	✓	26.6	50.6
XPM [14]	R-50	CLIP-400M	R-50	✓	27.0	41.2
OADB [35]	ViT-B/32	CLIP-400M + COCO-Cap	R-50	✓	30.0	47.2
VL-PLM [45]	ViT-B/32	CLIP-400M	R-50	✓	34.4	53.5
RegionCLIP [46]	R-50x4	CLIP-400M + CC3M + COCO-Cap	R-50x4	✓	39.3	55.7
EdaDet [34]	R-50	CLIP-400M	R-50	✓	40.2	52.5
CORA [38]	R-50x4	CLIP-400M	R-50x4	✓	41.7	43.8
Detic-CN2 [48]	ViT-B/32	CLIP-400M + INet-21K	R-50	WS	27.8	45.0
<i>ViT based:</i>						
RO-ViT [18]	ViT-B/16	ALIGN-1.8B	ViT-B/16	-	30.2	41.5
RO-ViT [18]	ViT-L/16	ALIGN-1.8B	ViT-L/16	-	33.0	47.7
RO-ViT [18] *	ViT-L/16	LAION-2B	ViT-L/16	-	33.3	47.9
CFM-ViT [17]	ViT-B/16	ALIGN-1.8B	ViT-B/16	-	30.8	42.4
CFM-ViT [17]	ViT-L/16	ALIGN-1.8B	ViT-L/16	-	34.1	46.0
CFM-ViT [17] *	ViT-L/16	LAION-2B	ViT-L/16	-	34.3	46.4
DITO (ours)	ViT-S/16	LAION-2B	ViT-S/16	-	32.3	44.4
DITO (ours)	ViT-B/16	LAION-2B	ViT-B/16	-	36.6	48.8
DITO (ours)	ViT-L/16	LAION-2B	ViT-L/16	-	39.6	54.4
DITO (ours)	ViT-L/16	DataComp-1B	ViT-L/16	-	40.2	54.6

Table 2: COCO open-vocabulary detection (box AP50). DITO demonstrates a very competitive novel category AP without using pseudo labeling or weak supervision (WS). *: our reproduced result using LAION-2B.

method	backbone	AP	AP ₅₀	AP ₇₅
Supervised [11]	R-50	25.6	38.6	28.0
ViLD [11]	R-50	11.8	18.2	12.6
DetPro [6]	R-50	12.1	18.8	12.9
BARON [37]	R-50	13.6	21.0	14.5
F-VLM [19]	R-50x16	16.2	25.3	17.5
F-VLM [19]	R-50x64	17.7	27.4	19.1
RO-ViT [18]	ViT-L/16	17.1	26.9	18.5
CFM-ViT [17]	ViT-L/16	18.7	28.9	20.3
DITO (ours)	ViT-L/16	20.0	31.8	21.5

Table 3: Zero-shot transfer detection from LVIS_{base} to Objects365 (box AP). All models are tested on Objects365 dataset following the setup of [11].

where each pyramid level (whole image) map is mean-pooled into an image embedding, followed by the image-text contrastive loss per level. It improves the baseline by +1.0 AP_r. Adding the Faster R-CNN head further improves the alignment between the pretraining and detection finetuning, showing a gain of +2.0 AP_r. Incorporating all components *i.e.* the FPN, Faster R-CNN and RPN heads achieves the best 34.8 AP_r, a significant gain of +2.6 points over the baseline.

Table 4c shows that both global avg- and max-pooling are sub-optimal due to the lack of saliency map (avg-pool), and the limited capacity of a single pixel to represent semantic concepts for contrastive learning (max-pool), respectively. Our approach combines the best of both worlds, by first avg-pooling within each RoI, and then max-pooling over these RoI embeddings. Each embedding represents a proper RoI and the global representation captures the saliency map through max-pooling. Pooling per pyramid level (*i.e.* multi-level image-text supervision) outperforms pooling over all levels.

method	AP _r	AP	pretraining method	AP _r	AP	RoI embedding	AP _r	AP
RO-ViT [18]	32.4	32.9	RO-ViT <i>our repro.</i>	32.2	33.0	global avg / lvl	34.0	33.9
RO-ViT <i>our repro.</i>	32.2	33.0	w/ FPN	33.2 (+1.0)	33.7	global max / lvl	33.7	33.5
w/ REP	34.8 (+2.6)	34.9	w/ FPN +Head	34.2 (+2.0)	34.2	multi RoIs, avg / lvl	33.8	34.0
w/ SWL	35.0 (+2.8)	35.2	w/ FPN +Head +RPN	34.8 (+2.6)	34.9	multi RoIs, max / lvl	34.8	34.9
w/ REP +SWL	36.3 (+4.1)	35.8				multi RoIs, max all	34.1	34.3
w/ REP +SWL +FD	37.6 (+5.4)	36.2						

(a) DITO framework.

(b) Detector components in pretraining.

(c) RoI sampling and pooling.

Table 4: Ablation on overall DITO framework and Region-centric Pretraining (Sec. 3.2). REP: Region-centric Pretraining, SWL: Shifted-Window Learning, FD: Frozen backbone Distillation. Best setting is in gray.

backbone	AP _r	AP	# global attn. layer	base	w/ SWL
fully global attn.	33.4	33.8	0	30.7	34.6 (+3.9)
baseline window attn. [18]	32.2	33.0	4	32.2	35.0 (+2.8)
Swin [24] style	31.3	33.1	12	32.4	34.2 (+1.8)
shifted window	35.0	35.2	24 (all layers)	33.4	33.4 (+0.0)

(a) Shifted-window learning.

(b) Effect of SWL w.r.t. # global attention layers.

Table 5: Ablation on Shifted-Window Learning (SWL - Sec. 3.3). Best setting is in gray.

Shifted-Window Learning for detection. The CLIP ViT backbones are initially pre-trained on lower resolutions and then adapted to higher resolution detection images. In Table 5a, we assess the efficacy of the shifted-window backbone in open-vocabulary detection training. Although the fully global attention model improves the detection task compared to the baseline windowed attention model [18], directly applying the pre-trained ViT on high-resolution inputs may not be optimal, potentially compromising the locality structure of the pretrained lower-resolution features. Our shifted-window learning approach achieves 35.0 AP_r by preserving the locality structure from windowed attention as well as integrating information across fixed windows, outperforming the fully global attention model (33.4 AP_r) which is computationally intensive. Notably, OWL-ViT [26, 27] adopts the fully global attention model. In addition, naively applying the layer-alternating shifted window as in Swin [24] leads to a performance drop (see Sec. 3.3). Table 5b delves deeper into the behavior of SWL. The advantage of SWL diminishes steadily with increasing number of global attention layers in the windowed attention backbone, validating its better information mixing enabled by the SWL.

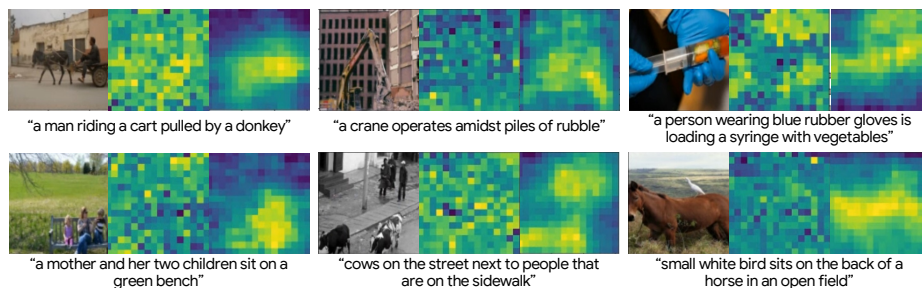


Fig. 3: Visual-text similarity map. For each example, we show the paired image (left) and text (bottom) input, and the visual-text similarity map using the contrastive model baseline [18] backbone features (middle) or our region-centric pretraining features (right). We use Flickr30K (top row) and COCO Captions (bottom row) datasets.

backbone	AP	AP _r	AP _c	AP _f	method	AP _r	AP
<i>GT boxes given (region classification):</i>							
before detection training	48.7	56.8	51.5	42.1	RO-ViT <i>our repro.</i>	32.2	33.0
after detection training	53.7	54.2	53.7	53.5	RO-ViT <i>our repro.</i> + FD	34.0 (+1.8)	33.6
after detection training w/ FD	54.8	57.7	54.3	53.2	w/ REP + SWL	36.3	35.8
					w/ REP + SWL + FD	37.6 (+1.3)	36.2

(a) Frozen backbone distillation (GT region recognition).

(b) Effect of frozen backbone distillation.

Table 6: Ablation on frozen backbone distillation (FD - Sec. 3.4). Best setting is in gray.

Frozen backbone distillation. Table 6a studies the region classification capability of the CLIP ViT backbone before and after the detection finetuning. We use the ground truth boxes and measures AP scores to evaluate the zero-shot region classification of the base (‘frequent’ + ‘common’) and novel (‘rare’) categories. We observe that the finetuned backbone indeed shows a notable drop of -2.6 AP_r on novel classes, while overfitting to the base classes. The frozen backbone distillation (‘w/ FD’) leads to a significant improvement of +3.5 AP_r even surpassing the frozen pretrained backbone (before detection finetuning), while maintaining performance on the base classes (AP_c and AP_f). Table 6b presents the open-vocabulary detection results where the frozen backbone distillation brings a clear gain of +1.3~1.8 AP_r. These results highlight the efficacy of our frozen backbone distillation in detection finetuning (Sec. 3.4), as it effectively preserves the pretrained open-vocabulary knowledge while acquiring explicit region-text alignment through detection supervision.

4.3 Visualization

In Fig. 3, we visualize the similarity map between the image features and a query text embedding using the Flickr30K [29] and COCO Captions [4] datasets. For each sample, we compare the baseline contrastive model [18] backbone features (middle) and region-centric pretrained features (right). We select pyramid level 4 which has the same resolution as the backbone features and apply the Faster R-CNN head in a sliding window manner to obtain the dense feature map. We observe that region-centric pretraining captures more localized semantic information on the image-text pairs.

In Fig. 1, we visualize the DITO outputs on LVIS novel categories and Ego4D [10] which is real-world and out-of-distribution data. We use the same DITO detector trained on LVIS_{base}. The categories for Ego4D are provided by the user based on visual inspection of the video. We observe that DITO is able to capture many novel and unseen objects even under the significant domain shift.

5 Conclusion

We introduce DITO, a region-centric approach for open-vocabulary detection using large-scale image-text pairs. By integrating detection architecture onto the image backbone in CLIP pretraining, it learns locality-sensitive information without requiring pseudo labeling or box annotations. Furthermore, we propose a shifted-window learning method to mitigate the bias of the window attention pattern in CLIP ViT detectors. Experiments show that DITO outperforms the state-of-the-art by large margins on the LVIS benchmark, and is very competitive on the COCO benchmark and transfer detection. We hope this work would inspire the community to explore region-centric image-language pretraining for open-vocabulary localization tasks.

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