
OneRef: Unified One-tower Expression Grounding and Segmentation with Mask Referring Modeling

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Abstract

Constrained by the separate encoding of vision and language, existing grounding and referring segmentation works heavily rely on bulky Transformer-based fusion en-/decoders and a variety of early-stage interaction technologies. Simultaneously, the current mask visual language modeling (MViLM) fails to capture the nuanced referential relationship between image-text in referring tasks. In this paper, we propose **OneRef**, a minimalist referring framework built on the modality-shared one-tower transformer that unifies the visual and linguistic feature spaces. To modeling the referential relationship, we introduce a novel MViLM paradigm called **Mask Referring Modeling (MRefM)**, which encompasses both referring-aware mask image modeling and referring-aware mask language modeling. Both modules not only reconstruct modality-related content but also cross-modal referring content. Within MRefM, we propose a referring-aware dynamic image masking strategy that is aware of the referred region rather than relying on fixed ratios or generic random masking schemes. By leveraging the unified visual language feature space and incorporating MRefM’s ability to model the referential relations, our approach enables direct regression of the referring results without resorting to various complex techniques. Our method consistently surpasses existing approaches and achieves SoTA performance on both grounding and segmentation tasks, providing valuable insights for future research. Our code and models are available at <https://github.com/linhuixiao/OneRef>.

1 Introduction

Visual Grounding (VG) aims to ground a region referred by a expression query text in a specific image. The generalized VG / referring tasks include Referring Expression Comprehension (REC) [69, 62, 101, 31, 14, 91, 90, 48], Phrase Grounding (PG) [1, 74], and Referring Expression/Image Segmentation (RES/RIS) [69, 94, 89]. In REC/PG, the grounding region is represented by a rectangular boundary box, while in RES/RIS, it is represented by an irregular fine-grained segmented mask of the referred object. Unlike object detection [57, 58] or instance segmentation [26], which usually relies on a close-set of categories to detect or segment multiple regions that satisfy the object label, visual grounding is not limited to fixed categories. It requires understanding the semantics of the query text and then grounding or segmenting specific areas. Therefore, visual grounding is a task that strongly relies on the multimodal interaction and alignment of visual and linguistic features.

Since the introduction of BERT [16] and ViT [19, 7], the state-of-the-art (SoTA) grounding works have widely adopted a pre-training and fine-tuning paradigm. As illustrated in Fig. 1, existing studies

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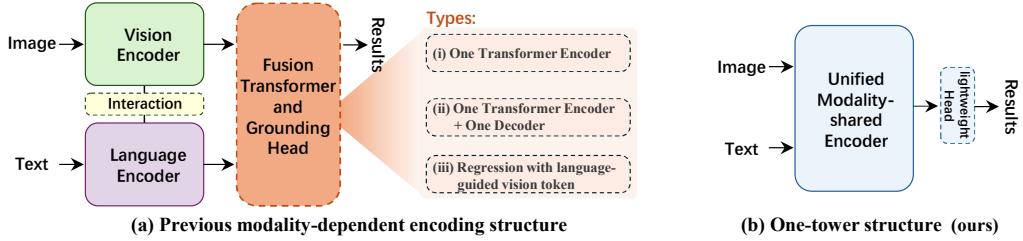


Figure 1: Comparison between our proposed approach and the mainstream REC/RES architectures.

employing pre-trained models, either utilizing uni-modal pre-trained models to separately transfer visual and language knowledge [14, 15, 98, 33, 55] or utilizing multimodal pre-trained models [91, 77, 89, 35], primarily fall into three typical architectures: (i) two modality encoders combined with a cross-modal fusion encoder, exemplified by TransVG *etc.* [11, 14, 98, 89, 91, 35, 92]; (ii) additionally incorporating a decoder, exemplified by MDETR *etc.* [33, 45, 97, 85, 54, 53, 77, 55]; (iii) direct regression based on language-guided visual features, such as LAVT, TransVG++, *etc.* [94, 15, 79, 99]. However, incorporating modality-dependent encoders in these studies presents a challenge for seamlessly integrating the two modalities into a unified feature space. Consequently, these works not only require an additional cross-modal Transformer-based [82] en-/decoder ((i) and (ii)), but also propose a variety of careful-designed interaction structures for modality-dependent encoders to facilitate early-stage fine-grained cross-modal alignment [15, 98, 92, 79, 54, 35, 55, 59], such as adapter [15, 35], cross-modal bridge [92], weight generation [79], image-text cross-attention [55, 54], *etc.* Therefore, these methods not only entail a large number of parameters but also involve intricate processes. Considering these critical limitations, we aim to explore simpler modality-shared grounding frameworks that can unify vision and language within a unified feature space, thereby obviating the necessity of the elaborate interaction modules, bulky fusion Transformer en-/decoders, as well as the special grounding tokens.

With the advancement of pre-training [70, 66], several studies have been conducted to explore unified modality-shared multimodal frameworks. YORO [29] implemented a shared encoder based on ViLT [37]. However, its modeling approach tends to overshadow the uni-modal knowledge and requires the encoder to incorporate additional query anchors, limiting its applicability for transfer with common pre-trained models. ONE-PEACE [86] has designed seven expert branches based on Mix-of-Expert (MoE) [5, 76, 22] to construct a three-modality foundation model to realize the integration of image, text, and audio modalities. However, their research employed extensive tri-modal data without exploring the potential utilization of MVLM for modeling the referring tasks. BEiT-3 [87] is built upon multi-way Transformer [5, 80], which adopts three MoE heads (*i.e.*, vision, language, vision-language) and a modality-shared structure that effectively unifies vision and language within a shared feature space. It demonstrates notable advantages across various classification-like cross-modal fields (*e.g.*, Retrieval, VQA *etc.*). However, no prior research has explored the utilization of BEiT-3 for achieving transfer in referring tasks. Consequently, our objective is to explore more concise and efficient referring grounding and segmentation transfer within a unified feature space on the one-tower model of BEiT-3. However, BEiT-3 model is pre-trained utilizing a generic Mask Vision Language Modeling (MVLM) approach, and this masking paradigm lacks fine-grained cross-modal referring ability and cannot effectively model the intricate referential relationship between images and text. As a result, there exists a significant gap when applying BEiT-3 to the regression-like referring tasks. Therefore, exploring how to incorporate fine-grained cross-modal referring capability into the mask modeling paradigm becomes an important research issue that has not been addressed yet.

In this paper, we propose a novel paradigm called ***Mask Referring Modeling (MRefM)***, as well as a unified and extremely concise grounding and referring segmentation framework named ***OneRef*** that no longer requires the fusion or interaction Transformer structure and the special grounding tokens.

Firstly, we propose MRefM paradigm to enhance the referring capability of BEiT-3 in a flexible manner. MRefM consists of two components: Referring-aware Mask Image Modeling (**Referring MIM**) and Referring-aware Mask Language Modeling (**Referring MLM**). The conventional MVLM is typically trained alternately or randomly with uni-modal MIM and MLM. In contrast, Referring MIM and Referring MLM are required to reconstruct two distinct types of content: their own modality-related content and cross-modal referring information. Specifically, (i) **Referring MIM** employs visual tokens after the dot product operation with the aggregated text token for reconstruction purposes. This not only entails reconstructing masked visual features itself but also necessitates

reconstructing the visual target-relation score, which indicates the distance between the current token and the grounding region. The score encompasses four dimensions: horizontal and vertical distance to the grounding center, as well as width and height of the grounding region. In order to enhance the model’s understanding capability for referred regions, we propose a referring-aware dynamic image masking strategy that replaces traditional ratio-fixed random masking so that referred regions are reconstructed with a relatively high mask ratio. **(ii) Referring MLM** employs text tokens after the dot product operation with the aggregated visual token for reconstruction purposes. This not only involves reconstructing masked text itself but also requires reconstructing semantic target-relation scores that represent the correlation degrees between current text tokens and referred image regions.

Secondly, existing grounding and segmentation models commonly employ a [Region] token and multiple query anchors to regress results. However, embedding the region token in backbone will disrupt the pre-trained model [15], and the query anchor also depends on the decoder [33]. With the unified feature space established by modality-shared encoder, we no longer need additional cross-modal en-/decoders to fuse uni-modal features, enabling us to more effectively leverage the knowledge acquired by pre-trained backbone. Benefiting from MRefM paradigm, the visual token inherently contains referring information. Consequently, we can discard special grounding token/anchors and directly construct lightweight and highly concise grounding and segmentation task heads based on the dot product operation within Referring MIM to unify the referring framework.

Contributions: Our contributions are threefold: **(i)** We pioneer the application of mask modeling to referring tasks by introducing a novel paradigm called mask referring modeling. This paradigm effectively models the referential relation between visual and language. **(ii)** Diverging from previous works, we propose a remarkably concise one-tower framework for grounding and referring segmentation in a unified modality-shared feature space. Our model eliminates the commonly used modality interaction modules, modality fusion en-/decoders, and special grounding tokens. **(iii)** We extensively validate the effectiveness of MRefM in three referring tasks on five datasets. Our method consistently surpasses existing approaches and achieves SOTA performance across several settings, providing a valuable new insights for future grounding and referring segmentation research.

2 Related work

2.1 Referring expression comprehension (REC) and segmentation (RES)

(i) REC. The recent supervised REC task, also known as visual grounding in a narrow sense, can be broadly categorized into **five main approaches**: **(1)** Fine-tuning with a uni-modal pre-trained language model and a closed-set detector. This setting is exemplified by TransVG [14], which builds upon the two-stage [102, 56, 52, 30] and one-stage [96, 95, 106] methods from the CNN era. It is considered the most conventional and extensively studied approach. **(2)** Fine-tuning with a pre-trained uni-modal language model and an open-set detection model pre-trained on box-level datasets mixed with multiple data sources. MDETR [33] represents this type of setting, where Fig. 1-(a)-(ii) plays a dominant role in its model structure. **(3)** Fine-tuning with multimodal self-supervised pre-trained models. CLIP-VG [91] serves as an example for this category, introduced primarily through the proposal of CLIP [70]. **(4)** Multimodal and multi-task mix-supervised pre-trained models. These methods typically combine multiple tasks while mixing datasets from each downstream task, employing mixed pre-training that incorporates both self-supervision and fine-grained supervision. UniTAB [97], OFA[85], etc., represent such approaches where visual grounding often acts as one of the pre-training tasks. **(5)** Grounding multimodal large language models (GMLLMs). These methods influenced by works like GPT [6] or LLAMA [81] etc. These models integrate visual backbones into Large Language Models (LLMs) to generate grounding results rather than relying on regression techniques. Our approach mainly falls under type (3). **(ii) RES.** The development and approach categories of RES [49, 13, 35, 89, 79, 94, 93, 88] are generally similar to those of REC. However, the key distinction lies in the finer granularity of RES’s output, which necessitates separate study from REC. In terms of model architecture, RES works predominantly employ two modality-dependent encoders and a decoder to generate the segmentation mask. Our work stands out as the first endeavor to explore RES within a unified multimodal feature space under a one-tower structure.

2.2 Mask vision language modeling

Motivated by the success of MLM [82] in BERT [16], MAE [27] and BEiT [4] have primary shifted their attention to MIM [21, 83, 3]. Subsequently, exemplified by BEiT-3 [87], numerous MVLM

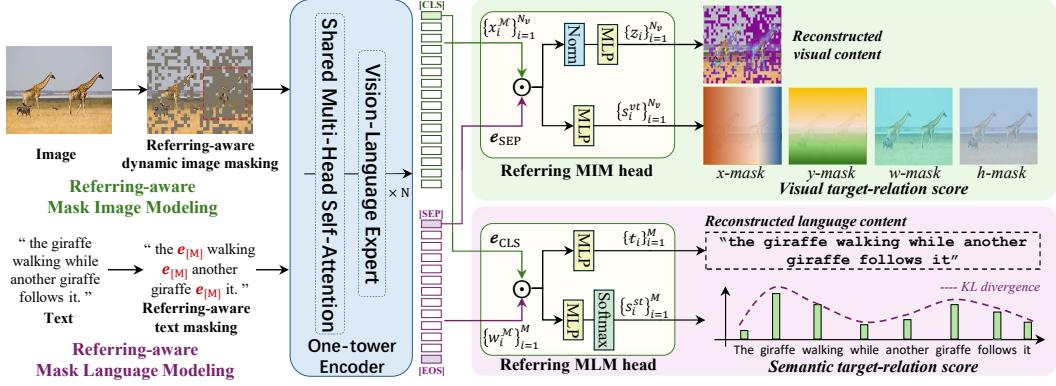


Figure 2: Illustration of our multimodal Mask Referring Modeling (MRefM) paradigm, which includes Referring-aware mask image modeling and Referring-aware mask language modeling.

works [61, 47, 36, 104, 2] have emerged, with most of these works implementing randomly alternating uni-modal MIM and MLM. Most relevant to our work are mask region modeling (known as MRM) [64, 83], which can be either unimodal MIM (*e.g.*, R-MAE [64]) or employ more fine-grained regional data and contrastive learning to reconstruct the alignment between regions and object labels (*e.g.*, ConLIP [61], VLT [17, 18] *etc.*). However, our work focuses on modeling the fine-grained referential relationship within image and text, so as to enhance the cross-modal referring capability, which is significantly different from these works.

3 Methodology

In this section, we propose our multimodal Mask Referring Modeling (**MRefM**) paradigm, which includes Referring MIM and Referring MLM, as well as a feature space unified grounding and segmentation framework **OneRef**. We will introduce these methods in the following sections.

Following BEiT-3 [87], we employ a multimodal modality-shared Transformer [5] as the underlying backbone network. Initially, we perform mask-then-predict MRefM pre-training, and followed by transfer fine-tuning on the referring tasks. As shown in Fig. 2, the MRefM pre-training stage consists of two components: Referring-aware Mask Image Modeling (**Referring MIM**) and Referring-aware Mask Language Modeling (**Referring MLM**). Both modules aim to reconstruct two types of content: modality-related content within each modality and cross-modal fine-grained referring content.

3.1 Preliminaries

BEiT-3 [87] utilizes MIM, MLM, and MVLM for processing image, text, and image-text pairs respectively to facilitate the acquisition of general representations through MoE heads and shared multi-head self-attention. Notably, MVLM involves alternate training of MIM and MLM. Specifically:

(i) Vanilla mask image modeling. We denote $\mathbf{x} \in \mathbb{R}^{H \times W \times 3}$ as the input image, and it is tokenized by a convolution projection to $N_v = HW/P^2$ patches $\{\mathbf{x}_i^p\}_{i=1}^{N_v}$, where $\mathbf{x}^p \in \mathbb{R}^{N_v \times D}$, H, W are the image size, and P is the patch size, D is the hidden dimension of the unified feature space. Then, we leverage a specific masking strategy to mask a specific number of image patches. The masked position is termed as \mathcal{M}_v . Thus, a shared learnable embedding $e_{[M]}$ is used to replace the masked image patch embeddings \mathbf{x}_i^p if $i \in \mathcal{M}_v$. Subsequently, we prepend a learnable [CLS] token to the input, *i.e.*, $[e_{\text{CLS}}, \{\mathbf{x}_i^p\}_{i=1}^{N_v}]$, and feed them to the one-tower Transformer. Next, we utilize a MIM head which consists of a linear projection and a softmax classifier to predict the visual tokens of the masked positions based on the corrupted image \mathbf{x}^M . The visual tokens are obtained by the image tokenizer VQ-KD_{CLIP} proposed in BEiT v2 [67], which provides supervisions for the MIM self-supervised learning procedure. The visual tokens of the original image are denoted as $\{\mathbf{z}_i\}_{i=1}^{N_v}$, and \mathcal{I} denotes the pre-training images. Then, the training loss of MIM is defined as:

$$\mathcal{L}_{\text{MIM}} = - \sum_{\mathbf{x} \in \mathcal{I}} \sum_{i \in \mathcal{M}_v} \log p(\mathbf{z}_i | \mathbf{x}_i^M). \quad (1)$$

(ii) Vanilla mask language modeling. The input text is tokenized and projected to the word embeddings $\{\mathbf{w}_i\}_{i=1}^M$ by a SentencePiece tokenizer [41] with vocabulary size of 64010, where $\mathbf{w} \in \mathbb{R}^{M \times D}$, M is the length of tokenized text sequence. Then, following BEiT-3 [87], we randomly mask the text tokens with a fixed masking ratio δ . The masked position is termed as \mathcal{M}_w . Thus, a shared learnable embedding $\mathbf{w}_{[M]}$ is used to replace the masked word tokens \mathbf{w}_i if $i \in \mathcal{M}_w$. We prepend a learnable special tokens [SEP] and an end-of-sequence token [EOS] to the sequence, *i.e.*, $[\mathbf{e}_{\text{SEP}}, \{\mathbf{w}_i\}_{i=1}^M, \mathbf{e}_{\text{EOS}}]$, and feed them to the one-tower Transformer. Similarly, we utilize a MLM head which consists of a linear projection to predict the text tokens of masked positions based on the corrupted text data $\mathbf{w}^{\mathcal{M}}$. The original textual tokens are denoted as $\{\mathbf{t}_i\}_{i=1}^M$, and \mathcal{T} denotes the pre-training text sequences. Then, the training loss of MLM is defined as:

$$\mathcal{L}_{\text{MLM}} = - \sum_{\mathbf{x} \in \mathcal{T}} \sum_{i \in \mathcal{M}_w} \log p(\mathbf{t}_i | \mathbf{w}_i^{\mathcal{M}}). \quad (2)$$

3.2 Referring-aware mask image modeling

After concatenating the visual and text tokens and feeding them into the modality-shared encoder, the vanilla MVLM is commonly implemented through the alternating use of MIM and MLM [87]. Despite the multimodal features are interact within the modality-shared encoder, it fundamentally remains a unimodal information reconstruction. Additionally, MVLM acquires general knowledge by randomly masking images and texts, it fails to effectively model the referential relationship. Hence, we propose Referring MIM and Referring MLM methods. Specifically, as shown in Fig. 2, our proposed Referring MIM incorporates two additional components: the reconstruction of visual target-relation score and a referring-aware dynamic masking strategy.

In Referring MIM (Fig. 2), instead of using uni-modal visual tokens [87, 47, 2], we propose to employ visual tokens that dot product with the aggregated text token $\mathbf{e}_{\text{SEP}} \in \mathbb{R}^{1 \times D}$ for the reconstruction purpose. The reconstruction of Referring MIM involves not only the modality-related content $\{\mathbf{z}_i\}_{i \in \mathcal{M}_v}$, but also the visual target-relation scores $\{\mathbf{s}_i^{vt}\}_{i=1}^{N_v} \in \mathbb{R}^{N_v \times 4}$. We utilize a visual target-relation head which consists of a three-layer perceptron (MLP) to predict the scores. The scores represent the distance between each patch token $\{\mathbf{x}_i^{\mathcal{M}}\}_{i=1}^{N_v}$ and the referred region $\mathcal{B} = (x_c, y_c, w_r, h_r)$, where (x_c, y_c, w_r, h_r) denote the center coordinate and the width and height of the referred region. It encompasses four masks, *i.e.*, x -, y -, w -, h - masks, which represent the normalized horizontal and vertical distances from the referred center, *i.e.*, $((x - x_c)/W, (y - y_c)/H)$, and the proportion of width and height on the the referred region, *i.e.*, $(P/w_r, P/h_r)$, respectively, where (x, y) denote the center coordinate of each patch. We denote \odot as dot product operation. Finally, the training loss of Referring MIM is defined as:

$$\mathcal{L}_{\text{Referring MIM}} = - \sum_{\mathbf{x} \in \mathcal{T}} \sum_{i \in \mathcal{M}_v} \log p(\mathbf{z}_i | (\mathbf{x}_i^{\mathcal{M}} \odot \mathbf{e}_{\text{SEP}})) - \sum_{\mathbf{x} \in \mathcal{T}} \sum_{i \in [1, N_v]} \log p(\mathbf{s}_i^{vt} | (\mathbf{x}_i^{\mathcal{M}} \odot \mathbf{e}_{\text{SEP}})). \quad (3)$$

Referring-aware dynamic image masking strategy. As shown in Fig. 4, among the existing masking strategies, MAE [27] adopts a high-ratio random masking while BEiT-3 [87] uses a low-ratio block-wise random masking, neither of which effectively directs attention to the referred region. SemMAE [43] proposes a semantic-guided masking that requires additional bulky semantic models and limits its generality. To enhance the model’s understanding of the referred region through surrounding visual context and text semantics, we propose a referring-aware dynamic masking strategy as shown in Algo. 1.

The strategy avoids the drawbacks of the aforementioned methods and directs the model’s attention to the referred region. Specifically, we denote the shape after patch reshaping of the image as (h, w) , where $h = H/P$, $w = W/P$, and $N_v = h \times w$. To maximize the masking of the

Algorithm 1 Referring-aware Dynamic Masking

Input: N_v image patches, N_r ($h_{rp} \times w_{rp}$) referred patches.
Output: Dynamic masked positions \mathcal{M} .

```

 $c \leftarrow \text{Rand Select } \beta \cdot N_v \text{ numbers in } [1, N_v]$ 
New  $\mathcal{M} \in \mathbb{R}^{1 \times N_v}$ ,  $\{\{\mathcal{M}_i\}_{i=1}^{N_v} \mid \mathcal{M}_i = 1 \text{ if } i \in c, \text{ else } 0\}$ 
 $\mathcal{M} \leftarrow \mathcal{M}$  reshape as  $\mathcal{M} \in \mathbb{R}^{h \times w}$   $\triangleright$  In-context masking
New  $\mathcal{M}_r \in \mathbb{R}^{h_{rp} \times w_{rp}}$  with all as 0  $\triangleright$  Referred masking
while  $|\mathcal{M}_r| \leq \gamma \cdot N_r$  do
     $s \leftarrow \text{Rand}(1, \gamma \cdot N_r - |\mathcal{M}_r|)$   $\triangleright$  Block size
     $r \leftarrow \text{Rand}(a, \frac{1}{a})$   $\triangleright$  Aspect ratio of block
     $w_b \leftarrow \sqrt{s/r}; h_b \leftarrow \sqrt{s \cdot r}$   $\triangleright$  Width, height of block
     $l \leftarrow \text{Rand}(0, w_{rp} - w_b); t \leftarrow \text{Rand}(0, h_{rp} - h_b)$ 
     $\{\mathcal{M}_r(i, j) = 1 \mid i \in [l, l + w_b], j \in [t, t + h_b]\}$ 
end
 $\mathcal{M}(x_{sp} : x_{sp} + w_{rp}, y_{sp} : y_{sp} + h_{rp}) = \mathcal{M}_r$ 
return  $\mathcal{M}$ .
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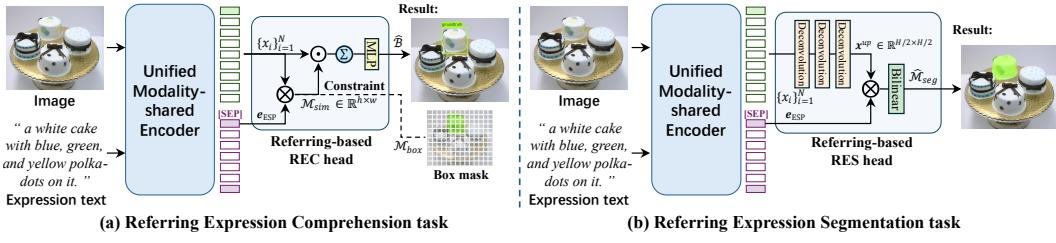


Figure 3: Illustration of the referring-based grounding and segmentation transfer.

referred region (x_s, y_s, w_r, h_r) , where x_s, y_s represent the starting coordinates of the referred region, we introduce a margin m to its surroundings and denote its patch coordinates as $(x_{sp}, y_{sp}, w_{rp}, h_{rp})$, *i.e.*, $x_{sp} = \lfloor x_s/P \rfloor - m$, $w_{rp} = \lfloor w_r/P \rfloor + m$, y_{sp} and h_{rp} are similar to that of x_{sp} and w_{rp} , where $\lfloor \cdot \rfloor$ indicates rounding down to an integer. Thus, the number of referred patches is denote as $N_r = h_{rp} \times w_{rp}$. Then, as shown in Algo. 1, to ensure that the model allocates appropriate attention to the in-contextual information around the referred region, we utilize a random masking with a relatively low ratio β for its surroundings. Simultaneously, we employ a block-wise masking approach with a high ratio γ in the extended area of the region. Since referred regions vary across different image-text pairs, each sample’s entire masking ratio α is dynamically determined:

$$\alpha = [\beta \cdot (N_v - N_r) + \gamma \cdot N_r]/N_v. \quad (4)$$

3.3 Referring-aware mask language modeling

Similarly, in Referring MLM, instead of using uni-modal linguistic tokens [87, 47, 2], we propose to employ linguistic tokens that dot product with the aggregated visual token $e_{CLS} \in \mathbb{R}^{1 \times D}$ for the reconstruction purpose. The reconstruction of Referring MLM involves not only the modality-related content $\{t_i\}_{i \in \mathcal{M}_w}$ but also the semantic target-relation scores $\{s_i^{st}\}_{i=1}^M$. The score represents the correlation between the referred target and the language token, which is obtained by a teacher model (*i.e.*, a BEiT-3 model with performed image-text contrastive intermediate tuning) with calculating the weighted sum of the normalized similarity between the language token $\{w_i\}_{i=1}^M$ and the aggregated visual token e_{CLS}^{reg} of referred region, as well as the aggregated visual token e_{CLS}^{img} of entire image:

$$s^{st} = \lambda_{reg} \cdot \sigma(\langle e_{CLS}^{reg \top}, \{w_i\}_{i=1}^M \rangle) + \lambda_{img} \cdot \sigma(\langle e_{CLS}^{img \top}, \{w_i\}_{i=1}^M \rangle), \quad (5)$$

where $\langle \cdot, \cdot \rangle$ denotes cosine similarity operation, σ denotes the softmax normalization. As shown in Fig. 2, we utilize a semantic target-relation head which consists of a three-layer MLPs and a softmax normalization to predict the scores. Finally, the training loss of Referring MLM is defined as:

$$\mathcal{L}_{\text{Referring MLM}} = - \sum_{w \in \mathcal{T}} \sum_{i \in \mathcal{M}_w} \log p(t_i | (w_i^M \odot e_{CLS})) - \sum_{w \in \mathcal{T}} \sum_{i \in [1, M]} \log p_{kl}(s_i^{st} | (w_i^M \odot e_{CLS})), \quad (6)$$

where p_{kl} represents a probabilistic prediction with Kullback-Leibler divergence [28].

3.4 Referring-based grounding and segmentation transfer

The modeling of visual and language in a unified feature space eliminates the need for the commonly-used Transformer-based fusion en-/decoder [14, 54, 55] and various early-stage interaction techniques [15, 79, 92] to further uniform the visual and language features. Additionally, since the referential relationship is modeled by MRefM during pre-training, we can accurately regress the results of grounding and referring segmentation using the output tokens, without relying on the widely-used special grounding tokens (*e.g.*, [Region] token [14, 15, 98, 91, 92], query anchors [55, 54]).

Referring expression comprehension. As illustrated in Fig. 3-(a), based on Referring MIM, we initially perform a similarity operation between visual tokens $\{x_i\}_{i=1}^{N_v} \in \mathbb{R}^{N_v \times D}$ and aggregated language token $e_{SEP} \in \mathbb{R}^{1 \times D}$ to obtain a softmax-normalized similarity mask $M_{sim} \in \mathbb{R}^{h \times w}$. This mask is then replicated and multiplied back to each hidden dimension of the visual tokens. Subsequently, the visual tokens are summed to yield reduced tokens, which are finally subjected to regress the prediction box $\hat{B} = (\hat{x}_c, \hat{y}_c, \hat{w}_r, \hat{h}_r)$ using a 3-layer MLPs:

$$\hat{B} = \text{MLP} \left(\sum_{i \in [1, N_v]} (\text{Repeat}(\sigma(\langle e_{ESP}^\top, \{x_i\}_{i=1}^{N_v} \rangle)) \odot \text{MLP}(\{x_i\}_{i=1}^{N_v}))) \right). \quad (7)$$

To enhance the accuracy of cross-modal similarity, we propose treating the similarity as a coarse-grained downsampling bounding box mask $M_{box} \in \mathbb{R}^{h \times w}$ and imposing segmentation loss (*i.e.*,

Table 1: Comparison with **latest** SoTA methods on the five datasets for **REC/PG** tasks with single-dataset fine-tuning setting. We highlight best result of base model in **red** and **bold** for large model.

Methods	Venue	Visual Backbone	Language Backbone	RefCOCO	RefCOCO+	RefCOCOg	ReferIt	Flickr
val testA testB val testA testB val test								
Single-dataset fine-tuning setting w. uni-modal pre-trained close-set detector and language model: (traditional setting)								
TransVG [14]	ICCV'21	RN101+DETR	BERT-B	81.02	82.72	78.35	64.82	70.70
Word2Pic [103]	TNNLS'22	RN101+DETR	BERT-B	81.20	84.39	78.12	69.74	76.11
QRNet [98]	CVPR'22	Swin-S [60]	BERT-B	84.01	85.85	82.34	72.94	76.17
VG-LAW [79]	CVPR'23	ViT-Det [46]	BERT-B	86.06	88.56	82.87	75.74	80.32
TransVG++ [15]	TPAMI'23	ViT-Det [46]	BERT-B	86.28	88.37	80.97	75.39	80.45
Single-dataset fine-tuning setting w. vision-language self-supervised pre-trained model:								
CLIP-VG [91]	TMM'23	CLIP-B	CLIP-B	84.29	87.76	78.43	69.55	77.33
JMRI [108]	TIM'23	CLIP-B	CLIP-B	82.97	87.30	74.62	71.17	79.82
Dynamic-MDETR	TPAMI'23	CLIP-B	CLIP-B	85.97	88.82	80.12	74.83	81.70
HiVG-B [92]	ACMMM'24	CLIP-B	CLIP-B	87.32	89.86	83.27	78.06	83.81
HiVG-L [92]	ACMMM'24	CLIP-L	CLIP-L	88.14	91.09	83.71	80.10	86.77
OneRef-B (ours)	NeurIPS'24	BEiT3-B	BEiT3-B	88.75	90.95	85.34	80.43	86.46
OneRef-L (ours)	NeurIPS'24	BEiT3-L	BEiT3-L	92.87	94.01	90.19	87.98	91.57
							83.73	88.11
							83.52	89.29
							83.61	84.75

Table 2: Comparison with **latest** SoTA methods for **REC** task with dataset-mixed intermediate pre-training setting. ‘RefC’ represents the mixup of RefCOCO/+g training data. \dagger indicates RefC has been used during pre-training. ‘G-DINO-L*’ denotes ‘O365, OI, GoldG, Cap4M, COCO, RefC’.

Methods	Venue	Visual/Language Backbone	Intermediate pre-trained model	Data size	RefCOCO	RefCOCO+	RefCOCOg
val testA testB val test							
Dataset-mixed intermediate pre-training setting (w. box-level dataset-open-set detection pre-trained model)							
MDETR \dagger [33]	ICCV'21	RN101/RoBERT-B	GoldG,RefC	6.5M	86.75	89.58	81.41
YORO \dagger [29]	ECCV'22	ViLT [37] / BERT-B	GoldG,RefC	6.5M	82.90	85.60	77.40
DQ-DETR \dagger [54]	AAAI'23	RN101 / BERT-B	GoldG,RefC	6.5M	88.63	91.04	83.51
Grounding-DINO-B \dagger	arXiv'23	Swin-T / BERT-B	O365,GoldG,RefC	7.2M	89.19	91.86	85.99
Grounding-DINO-L \dagger	arXiv'23	Swin-L / BERT-B	G-DINO-L*	>120M	90.56	93.19	88.24
CyCo [84]	AAAI'24	ViT19 \dagger / BERT-B	VG,SBU,CC3M,etc.	21.4M	89.47	91.87	85.33
HiVG-B \dagger [92]	ACMMM'24	CLIP-B / CLIP-B	RefC,ReferIt,Flickr	0.8M	90.56	92.55	87.23
HiVG-L \dagger [92]	ACMMM'24	CLIP-L / CLIP-L	RefC,ReferIt,Flickr	0.8M	91.37	93.64	88.03
Fine-tuning setting w. dataset-mixed multi-task mix-supervised pre-trained model:							
UnitAB \dagger [97]	ECCV'22	RN101/RoBERT-B	VG,COCO,etc.	>20M	88.59	91.06	83.75
OFA-B \dagger [85]	ICML'22	OFA-B / OFA-B	–	–	88.48	90.67	83.30
OFA-L \dagger [85]	ICML'22	OFA-L / OFA-L	–	–	90.05	92.93	85.26
Fine-tuning setting w. grounding multimodal large language model (GMLLM):							
Shikra-7B \dagger [10]	arXiv'23	CLIP-L / Vicuna-7B[12]	RefC,VG	0.5M	87.01	90.61	80.24
Fernet-7B \dagger [100]	ICLR'24	CLIP-L / Vicuna-7B[12]	GRIT [100]	>8M	87.49	91.35	82.45
LION-4B \dagger [9]	CVPR'24	EVA-G[21]/FlanT5-3B	VG,COCO,etc.	3.6M	89.73	92.29	84.82
LION-12B \dagger [9]	CVPR'24	EVA-G[21]/FlanT5-11B	VG,COCO,etc.	3.6M	89.80	93.02	85.57
OneRef-B\dagger (unsupervised)	BEiT3-B / BEiT3-B	RefC,ReferIt	0.5M	89.16	92.03	87.26	83.18
OneRef-B\dagger (0.2B)	NeurIPS'24	BEiT3-B / BEiT3-B	RefC,ReferIt	0.5M	91.89	94.31	88.58
OneRef-L\dagger (0.6B)	NeurIPS'24	BEiT3-L / BEiT3-L	RefC,ReferIt	0.5M	93.21	95.43	90.11
					88.35	92.11	82.70
						79.47	86.82
							87.32
							87.81
							88.83

Focal loss [51] and Dice/F-1 loss [63]) on the sigmoid activated similarity mask $\mathcal{M}_{sim} \in \mathbb{R}^{h \times w}$ with coefficient λ_{f_box} and λ_{d_box} as the box mask constraints:

$$\mathcal{L}_{box_mask_constraints} = \lambda_{f_box} \mathcal{L}_{focal}(\mathcal{M}_{sim}, \mathcal{M}_{box}) + \lambda_{d_box} \mathcal{L}_{dice}(\mathcal{M}_{sim}, \mathcal{M}_{box}). \quad (8)$$

Consequently, the loss function for the REC task can be reformulated as the weighted sum of vanilla grounding loss (*i.e.*, smooth L1 loss [25] and Giou loss [73]) and box mask constraints:

$$\mathcal{L}_{REC} = \lambda_{L1} \mathcal{L}_{L1}(\hat{\mathcal{B}}, \mathcal{B}) + \lambda_{giou} \mathcal{L}_{giou}(\hat{\mathcal{B}}, \mathcal{B}) + \mathcal{L}_{box_mask_constraints}. \quad (9)$$

Referring expression segmentation. As illustrated in Fig. 3-(b), the implementation of referring segmentation can be regarded as a simplified version of grounding. Initially, we employ a 3-layer deconvolution to up-sample the visual token to $\mathcal{X}^{up} \in \mathbb{R}^{H/2 \times W/2}$. Subsequently, cosine similarity operations are performed on the up-sampled visual tokens and the aggregated language token. The resulting similarity mask is then utilized as the final predicted mask $\hat{\mathcal{M}}_{seg} \in \mathbb{R}^{H \times W}$ after applying 1-layer bilinear interpolation. We denote the ground truth segmentation mask as $\mathcal{M}_{seg} \in \mathbb{R}^{H \times W}$, then the loss function for RES is defined as follows:

$$\mathcal{L}_{RES} = \lambda_{f_seg} \mathcal{L}_{focal}(\hat{\mathcal{M}}_{seg}, \mathcal{M}_{seg}) + \lambda_{d_seg} \mathcal{L}_{dice}(\hat{\mathcal{M}}_{seg}, \mathcal{M}_{seg}). \quad (10)$$

4 Experiments

4.1 Experimental setups

Datasets and evaluation metrics. Our method is validated in the REC, RES, and PG tasks with five widely used datasets, namely three REC/RES datasets (RefCOCO/+g [101, 62]), as well as two PG datasets (ReferItGame [34] and Flickr30k Entities [68]). In PG, the query pertains to a specific phrase,

Table 3: Comparison with latest SoTA methods (**mIoU** metric) on the three datasets for **RES** task with both single-dataset fine-tuning setting and dataset-mixed intermediate pre-training setting.

Methods	Venue	Visual/Language Backbone	Intermediate pretrain data	RefCOCO			RefCOCO+			RefCOCOg	
				val	testA	testB	val	testA	testB	val	test
Single-dataset fine-tuning setting w. uni-modal pre-trained close-set segmentation model: (traditional setting)											
RefTR [45]	NIPS'21	RN101 / BERT-B	—	74.34	76.77	70.87	66.75	70.58	59.40	66.63	67.39
SeqTR [107]	ECCV'22	DN53[72]/Bi-GRU	—	71.70	73.31	69.82	63.04	66.73	58.97	64.69	65.74
LAVT [94]	CVPR'22	Swin-B / BERT-B	—	74.46	76.89	70.94	65.81	70.97	59.23	63.34	63.62
VG-LAW [79]	CVPR'23	ViT-Det / BERT-B	—	75.05	77.36	71.69	66.61	70.30	58.14	65.36	65.13
Single-dataset fine-tuning setting w. vision-language self-supervised pre-trained model:											
CRIS [89]	CVPR'22	CLIP-L / CLIP-L	—	70.47	73.18	66.10	62.27	68.06	53.68	59.87	60.36
JMCELN[32]	EMNLP'23	CLIP-B / CLIP-B	—	74.40	77.69	70.43	66.99	72.69	57.34	64.08	64.99
RISCLIP-B [35]	NAACL'24	CLIP-B / CLIP-B	—	75.68	78.01	72.46	69.16	73.53	60.68	67.62	67.97
RISCLIP-L [35]	NAACL'24	CLIP-L / CLIP-L	—	78.87	81.46	75.41	74.38	78.77	66.84	71.82	71.65
OneRef-B (ours)	NeurIPS'24	BEiT3-B / BEiT3-B	—	77.57	79.05	75.11	71.25	75.41	65.45	69.37	69.70
OneRef-L (ours)	NeurIPS'24	BEiT3-L / BEiT3-L	—	80.09	82.19	77.51	75.17	79.38	70.17	73.18	73.76
Dataset-mixed intermediate pre-training setting:											
PolyFormer-B [†] [53]	CVPR'23	Swin-B / BERT-B	RefC	75.96	77.09	73.22	70.65	74.51	64.64	69.36	69.88
RISCLIP-B [†] [35]	NAACL'24	CLIP-B / CLIP-B	RefC	75.68	78.01	72.46	72.46	74.30	61.37	69.49	69.53
RISCLIP-L [†] [35]	NAACL'24	CLIP-L / CLIP-L	RefC	79.53	81.78	75.78	74.88	78.88	68.09	73.45	74.52
OneRef-B[†] (unsupervised)		BEiT3-B / BEiT3-B	RefC	78.20	79.26	75.92	72.54	75.54	67.39	71.28	71.13
OneRef-B[†] (ours)	NeurIPS'24	BEiT3-B / BEiT3-B	RefC	79.83	81.86	76.99	74.68	77.90	69.58	74.06	74.92
OneRef-L[†] (ours)	NeurIPS'24	BEiT3-L / BEiT3-L	RefC	81.26	83.06	79.45	76.60	80.16	72.95	75.68	76.82

Table 4: Ablation of MRefM on mixup pre-training setting.

MIM	MLM	image masking strategy	RefCOCO+			RefCOCOg		
			val	testA	testB	val	test	
✗	✗	✗	78.56	83.36	71.72	80.41	80.52	
vanilla	vanilla	random	79.68	84.59	72.11	81.35	81.11	
vanilla	vanilla	referring-aware	80.06	85.77	73.96	81.96	82.17	
Ref MIM	vanilla	referring-aware	83.64	88.26	76.58	83.55	85.86	
Ref MIM	Ref MLM	referring-aware	81.52	86.87	75.93	82.88	84.32	
Ref MIM	Ref MLM	random	85.08	89.12	78.56	85.57	86.89	
Ref MIM	Ref MLM	referring-aware	86.38	90.38	79.47	86.82	87.32	

Table 5: Ablation of the task heads.

Architecture (Fine-tuning setting)	RefCOCOg	
	val	test
full model in REC	83.68	83.52
full model w/o box mask loss	82.54	82.02
w. fusion encoder + region token	78.93	78.51
full model in RES	69.37	69.70
deconv after similarity operation	67.98	68.62
4-layer deconv w/o linear upsample	68.33	68.96
2-layer deconv w. 2-layer upsample	67.51	67.65

while in REC and RES, the query refers to a reference expression. The text of RefCOCO+/g exhibits greater length and complexity in comparison to that of RefCOCO. In REC/PG, we follow previous works [14, 96] that employs Intersection-over-Union (IoU) as the evaluation metric, *i.e.*, a prediction is deemed accurate only when its IoU exceeds or equals 0.5. We compute the prediction accuracy for each dataset as a performance indicator. While in RES, we follow previous works [79, 35] that employs mean IoU (mIoU) and overall IoU (oIoU) for each dataset as the indicators. The detailed statistics information regarding these five datasets are provided in the Appendix B.

Experimental details. Since MRefM is proposed on the basis of the traditional MVLM, considering the pre-training cost of MVLM, we adopt BEiT-3 [87] base and large model as our initial weights and then perform intermediate MRefM pre-training on the task-relevant dataset. Such intermediate pre-training is common in existing grounding works [55, 54, 33]. As described in Sec. 2.1, to verify the effectiveness of our MRefM approaches, we conduct extensive experiments on three settings: **(1) The basic single-dataset fine-tuning setting.** This setting does not require additional training data and aligns with existing supervised and self-supervised transfer approaches [91, 92, 89, 35]. In this setting, we perform supervised single-dataset intermediate MRefM pre-training before fine-tuning. **(2) The setting of fine-tuning with supervised dataset-mixed intermediate pre-training.** This setting aligns with existing grounded pre-trained approaches, such as Grounding-DINO [55], DQ-DETR [54] *etc.* we perform an MRefM intermediate pre-training before fine-tuning. **(3) To verify the generality of MRefM, we perform the setting of fine-tuning with unsupervised intermediate MRefM pre-training.** There are several ways to obtain the regions in the regional masking modeling works [64, 24, 78], such as Felzenswalb-Huttenlocher (FH) algorithm [23], SAM [38] *etc.* Thus, we adopt the unsupervised, fast, image-computable FH algorithm [23] to generate regions following R-MAE [64]. We then select the referred one using a BEiT-3 model with performed image-text contrastive intermediate tuning. More details about the selection of the unsupervised regions, network architecture, training and inference, model hyperparameters *etc.* are provided in the Appendix C.

4.2 Comparison with state-of-the-art methods

Referring expression comprehension. As shown in Tab. 1 and Tab. 2, we conducted experiments for the REC and PG tasks across three settings. **(1)** In the single-dataset fine-tuning setting, our base model surpasses the current SoTA method HiVG [92] by 2.07%(testB), 6.15%(testB), 4.73%(test),

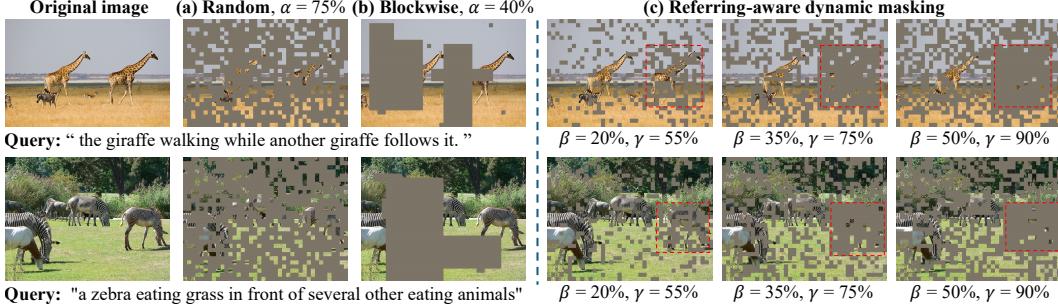


Figure 4: Illustrations of random masking (MAE) [27], block-wise masking (BEiT) [4], and our referring-aware dynamic masking. α denotes the entire masking ratio, while β and γ denote the masking ratio beyond and within the referred region.

Table 6: Generality study of MRefM on RefCOCOg.

Architecture	Backbone	Single-dataset		Mixup pretrain	
		val	test	val	test
TransVG	DETR / BERT-B	68.67	67.73	75.73	75.86
MRefM-TransVG	DETR / BERT-B	71.51	70.84	78.71	78.69
CLIP-VG	CLIP-B / CLIP-B	73.18	72.54	78.67	78.54
MRefM-CLIP-VG	CLIP-B / CLIP-B	74.22	74.50	80.48	80.83

Table 7: Generality of the task heads.

Architecture (Fine-tuning setting)	RefCOCOg	
	val	test
TransVG++ (Reproduced by us)	75.04	75.55
TransVG++ w. our REC head	76.65	77.09
LAVT [94]	63.34	63.62
LAVT w. our RES head	64.84	65.35

1.95%(test), and 1.50%(test) on the five datasets respectively, while also significantly outperforming the traditional uni-modal detector-based approach TransVG++ [15] by 4.37%(testB), 7.98%(testB), 7.22%(test), 2.47%(test), and 2.12%(test), respectively. (2) In dataset-mixed pre-training setting, our base model outperforms HiVG [92] by 1.35%, 2.79%, and 2.63% on RefCOCO/+/g testB/testB/test splits, outperforms Grounding-DINO [55] by 2.59%, 4.76%, and 2.38%, exceeds OFA by 5.28%, 5.18%, and 5.01%, and even surpasses LION [9] - a GMLLM model that is 20-60 times larger than ours - by 3.76%, 2.13%, and 1.69%. Note that among these works, UnitAB [97], OFA[85], LION [9] also utilize the MVLM on the pre-training stage. (3) Furthermore, we achieve competitive performance in the unsupervised setting, which shows the generality of MRefM paradigm. Additionally, our large-size model exhibits remarkable scalability with further substantial improvements in performance. More detailed results are provided in the Appendix E.

Referring expression segmentation. As presented in Tab. 3 (mIoU metric), we conducted experiments for RES task under **three settings**. (1) In the single-dataset fine-tuning setting, our base model surpasses the SoTA self-supervised method RISCLIP [35] by 2.65%, 4.77%, and 1.73% on RefCOCO/+/g testB/testB/test splits, respectively, while also significantly outperforming the traditional uni-modal detector-based approach VG-LAW [79] by 3.42%, 7.31%, and 4.57%, respectively. (2) In the dataset-mixed pre-training setting, our base model achieves superior performance compared to the SoTA method RISCLIP [35] with improvements of 4.53%, 8.21%, and 5.39%. (3) In the unsupervised pre-training setting, we also achieve competitive performance. Additionally, our large-size model also exhibits remarkable scalability and demonstrates a substantial improvement in performance. For oIoU metric, the results are presented in Appendix E.2 (Tab. 13).

4.3 Ablation study

The Mask Referring Modeling. In Tab. 4, we conducted ablation studies on MRefM, which included Referring MIM ('Ref MIM'), Referring MLM ('Ref MLM'), and referring-aware dynamic image masking ('referring-aware'). The 'vanilla' denotes the vanilla MVLM described in Sec. 3.1. As shown in Tab. 4, referring MIM, referring MLM, and dynamic masking strategy resulted in improvements of 3.70%, 2.16%, and 1.05% on the RefCOCOg-test dataset, and with an overall improvement of 6.21%, demonstrates the effectiveness of our methods. More results are provided in the Appendix E.4.

The referring-aware dynamic masking strategy. Fig. 4 presents a schematic of the three masking strategies. In our experiments, as illustrate in Fig. 4-(c), β and γ demonstrate optimal performance at values of 0.35 and 0.75, respectively. More detailed results are provided in the Appendix E.5.

The referring-based task heads. We conducted ablation studies on the design of two referring-based task heads. Tab. 5 reveals that our modeling method effectively captures referring information at the backbone stage, benefiting from the one-tower structure. This approach is significantly more efficient

than the traditional fusion encoder and special token-based method. Additionally, our proposed box mask loss also contributes to a performance gain of 1.50% (test).

4.4 Generality study

The generality of MRefM. Firstly, we perform an unsupervised MRefM pre-training in Tab. 2 and Tab. 3, both of which achieve competitive performance. Secondly, we replace the backbone and apply MRefM on DETR and CLIP by using TransVG [14] and CLIP-VG [91] under the two settings. Since the two frameworks do not interact at backbone stage, we build MRefM on the fusion encoder. In Tab. 6, MRefM can effectively learn referring representation, resulting in an overall performance gain of about 2.0%. All these findings demonstrate the validity and generality of the MRefM paradigm.

The generality of referring-based task heads. Since both TransVG++ [15] and LAVT [94] have modality interactions at backbone stage, we attempted to apply our task heads to both frameworks. TransVG++ is reproduced by us since its code is not available. Tab. 7 shows that our proposed task heads achieve a 1.5+% improvement in both REC and RES, offering a new avenue for future research.

5 Conclusion

In this paper, we propose a novel, highly concise, and feature space unified one-tower referring framework. Additionally, we pioneer the exploration of mask modeling in referring tasks by introducing MRefM paradigm to capture the referential relationships between vision and text. We demonstrate the effectiveness and generality of MRefM across three settings on REC, PG, and RES tasks, consistently achieving groundbreaking results. Furthermore, leveraging unsupervised methods enables potential large-scale pre-training of MRefM in the future, presenting a new direction for referring tasks.

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Appendix

We provide an overview of the Appendix below:

- **Appendix A: Explanation of the task definition**
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- **Appendix E: Extra experimental results**
 - Appendix E.1 The results on phrase grounding task under mixup pre-training setting.
 - Appendix E.3 Computational costs analysis compared with SoTA methods.
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- **Appendix F: Visualization of the results**
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A Explanation of the task definition

As explained in Sec. 1 of the main text, Visual Grounding (VG) aims to grounding a region referred by a query text in a specific image. The generalized visual grounding includes Referring Expression Comprehension (REC), Phrase Grounding (PG), and Referring Expression Segmentation (RES) tasks. However, in recent years, REC and RES have often been studied separately. Therefore, in numerous works [14, 15, 79, 92, 91, 98], visual grounding specifically refers to REC and PG tasks, which involve grounding a rectangular region. In this paper, we follow the mainstream and have not clearly separated the “grounding” from “generalized visual grounding” and “REC and PG tasks”. When expressing the experimental task, “grounding” usually refers to REC or PG tasks, so as to discuss it parallelly with the RES task.

B Introduction of the datasets

B.1 The five referring datasets

We present the detailed descriptions of the five referring datasets used in our experimental study on the REC, PG, and RES tasks. Tab. 8 presents the detailed statistics.

RefCOCO/RefCOCO+/RefCOCOg. These three datasets belong to the Referring Expression Comprehension (REC) and Referring Expression Segmentation (RES) tasks, and the images of these three datasets derived from MSCOCO [50]. Expressions in RefCOCO [101] and RefCOCO+ [101] are collected by the two-player game proposed in ReferitGame [34]. There are two test splits called “testA” and “testB”. Images in “testA” only contain multiple people annotation. In contrast, images in “testB” contain all other objects. Expressions in RefCOCOg [62] are collected on Amazon Mechanical Turk in a non-interactive setting. Thus, the expressions in RefCOCOg are longer and more complex. RefCOCOg has “google” and “umd” splits. **The “google” split** does not have a public test set,

Table 8: The detailed statistics of RefCOCO [101], RefCOCO+ [101], RefCOCOg [62], ReferItGame [34] and Flickr30K Entities [68] datasets. We represent test split and testA split in the same column.

Dataset	Images	Instances	total queries	train queries	val queries	test(A) queries	testB queries
RefCOCO [101]	19,994	50,000	142,210	120,624	10,834	5,657	5,095
RefCOCO+ [101]	19,992	49,856	141,564	120,191	10,768	5,726	4,889
RefCOCOg [62]	25,799	49,822	95,010	80,512	4,896	9,602	—
ReferItGame [34]	20,000	19,987	120,072	54,127	5,842	60,103	—
Flickr30k [68]	31,783	427,000	456,107	427,193	14,433	14,481	—

Table 9: Comparison of datasets used in the pre-trained models of the comparable methods.

Pretrained model	Uni-modal image / Data size	Uni-modal text / Data size	Image-text pairs / Data size	Total
CLIP [70]	—	—	LAION-400M [75] / 400M	400M
UniTAB [86]	image-text pairs: CC3M[8], etc. ; image-text-box pairs: COCO, VG, RefC, O365, SBU, etc. from multiple downstream task	—	—	>20M
OFA [85]	ImageNet-21K, etc. / 40M	filtered BookCorpus[109]etc. / 140GB	CC12M[8], SBU[65], COCO[50], VG[39], etc. / 21M	40M+140GB+21M
EVA-G [21]	—	—	Merged-2B(LAION-2B [75]+COYO-700M) / >2B	>2000M
FlanT5 [21]	—	filtered crawl data / >750GB	—	>750GB
ONE-PEACE [86]	image-text pairs: LAION-2B [75]; audio-text pairs: 2.4M + 8000 hours	—	—	>2000M
BEiT-3 [87]	ImageNet-21K[40] / 14M	BookCorpus[109],etc. / 160GB	CC12M[8], SBU[65], COCO[50], VG[39], etc. / 21M	14M+160GB+21M

and **exists an overlap between the training and validation image sets**. The “umd” split does not have this overlap. Therefore, **to prevent data leakage of the test set** and following previous studies [79, 102], **we exclude the “google” split in the fine-tuning setting and dataset-mixed pre-training setting**. Thus, we trained and tested the RefCOCOg dataset only on the “umd” split.

ReferItGame. ReferItGame [34] (short as ReferIt) belongs to the Phrase Grounding (PG) task, which contains images from SAIAPR12 [20] and collects expressions through a two-player game. In this game, the first player is shown an image with an object annotation and is asked to write a natural language expression referring to the object. The second player is then shown the same image along with the written expression and is asked to click on the corresponding area of the object. If the clicking is correct, both players receive points and swap roles. If not, a new image will be presented.

Flickr30k Entities. Flickr30k Entities (short as Flickr30k) [68] belongs to the phrase grounding task, which contains images in Flickr30k dataset. The query sentences are short noun phrases in the captions of the image. The queries are simpler and easier to understand compared to RefCOCO/+g. Therefore, the ambiguity of the expression is heightened simultaneously, resulting in a relative increase in noise.

B.2 Explanation of the dataset abbreviations

In Tab. 2 of the main text, we provide abbreviations for the datasets used in intermediate pre-training. Specifically, ‘GoldG’ (proposed in MDETR [33]) is a mixed region-level fine-grained dataset created by combining three datasets - Flickr30k [68], MS COCO [50], and Visual Genome [39] - along with annotated text data for detection, REC and QGA tasks. It has a size of approximately 6.2M. ‘O365’ refers to the Object365 [105] dataset, ‘SBU’ stands for SBU caption [65], ‘VG’ represents the Visual Genome [39] dataset, and ‘OI’ stands for OpenImage [42] dataset.

B.3 Comparison of datasets used in the pre-trained models

As presented in Tab. 9, we conducted an analysis of the datasets employed by the backbone models compared in Tab. 2 within the dataset-mixed pre-training setting. From the Tab. 9, it is evident that BEiT-3 and OFA utilize comparable datasets for pre-training. Conversely, other compared works in Tab. 2, such as Shikra [10], Ferret [100], LION [9], and other models, such as ONE-PEACE [86] (a tri-modality foundation model), employ significantly larger amounts of data than BEiT-3. Consequently, our method does not possess any advantage concerning the volume of data used in pre-training.

C Implementation details

Network Architecture. The detailed network structure of our framework is shown in Tab. 10. We employ BEiT-B/16 and BEiT-L/16 as the backbone for our OneRef base and large version,

Table 10: Network structure of our proposed OneRef framework.

Model	Backbone	Input resolution	One-tower Transformer layers	dimension	heads	All parameters (include all MoE heads)
OneRef-B	BEiT-B/16	384	12	768	12	234M (REC), 267M (RES)
OneRef-L	BEiT-L/16	384	24	1024	16	639M (REC), 679M (RES)

Table 11: Hyperparameters of our framework during training. lr : denotes the learning rate.

Item	Value	
	base model	large model
optimizer	AdamW	
Epoch for MRefM pre-training	110	
lr for MRefM pre-training	0.5×10^{-4}	
weight decay	0.5×10^{-5}	
patch size	16×16	
Initial value of aspect ratio a in MIM	0.3	
mask ratio β in Referring MIM	0.75	
mask ratio γ in Referring MIM	0.35	
mask ratio δ in Referring MLM	0.40	
λ_{reg} and λ_{img} in Referring MLM	1, 1	
batch size for MRefM pre-training	32	8
Epoch for REC/RES transfer	20	
lr for REC/RES transfer	0.3×10^{-4}	
$\lambda_{l_1}, \lambda_{giou}$ in REC	2, 2	
λ_f, λ_d in REC	20, 2	
$\lambda_{seq_f}, \lambda_{seq_d}$ in RES	20, 2	
batch size for REC/RES transfer	32 / 16	8 / 6

respectively. In the structure of OneRef-B, the one-tower encoder are 12-layer Transformers with the hidden embedding dimension of 768. In the structure of OneRef-L, the one-tower encoder is 24-layer Transformers with the hidden embedding dimension of 1024. The one-tower encoder encodes both textual and visual modalities. Due to the utilization of a 3-layer deconvolution, RES exhibits a slightly higher number of model parameters compared to the REC task.

Training Details. The batch size for pre-training the base model and large model are (32, 8), while they are (32, 8) and (16, 6) for transferring to the REC and RES tasks, respectively. Our model is optimized end-to-end by using the AdamW optimizer and a cosine learning scheduler with an initial learning rate of 0.5×10^{-4} for 110 epochs during the pre-training stage. During REC/RES transfer stage, the learning rates is 0.3×10^{-4} with 20 epochs. The framework and experiments in our study were conducted using PyTorch. For MRefM pre-training, the base model took 15 hours on 32 NVIDIA A100 GPUs, while the large model took 50 hours on the same number of GPUs. As for REC/RES transfer fine-tuning training, it took an average of 3 hours for the base model and 8 hours for the large model to process one dataset on 8 A100 GPUs.

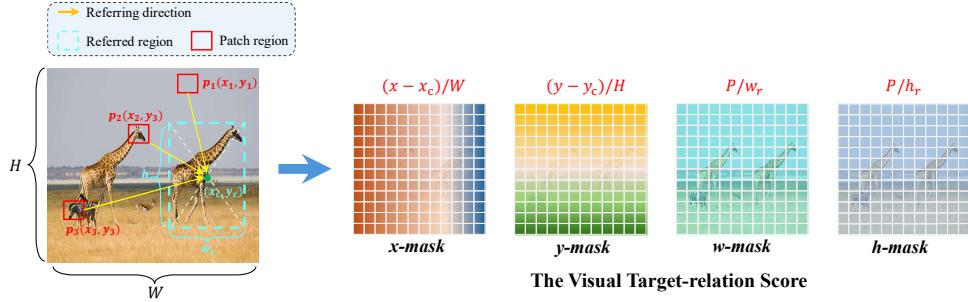
Inference Details. Unlike previous methods, such as TransVG++ [15], QRNet [98], etc. , which heavily rely on high-resolution images like 640×640 , we adopt smaller resolution of 384×384 . To ensure compatibility, we employ a long edge alignment and short edge pad filling scheme to the image. We include [SEP] and [EOS] token at the beginning and the end of the input text, and align it to a fixed length of 64 by padding empty tokens.

Model Hyperparameters. We summarize and report the hyperparameter settings of the OneRef framework in Tab. 11.

D Technical remarks

D.1 Further explanation for the effectiveness mechanism of the visual target-relation score

(1) The purpose of designing the Referring MIM algorithm. In the existing MIM paradigm, reconstruction is limited to solely relying on the visual features within the image. To enhance content reconstruction by leveraging cross-modal information as much as possible, our Referring MIM approach incorporates visual target-relation scores alongside visual modality content during reconstruction. This modeling approach presents increased difficulty as it necessitates reliance on



Referring text: “ the giraffe walking while another giraffe follows it. ”

Figure 5: The reconstruction of the visual target-relation score $s^{vt} \in \mathbb{R}^{N_v \times 4}$. (x, y) represents the coordinates of a general image patch, and P is the patch size. By slicing the predicted score, four masks can be derived. The score represents the spatial distance and the relative size between the current patch region and the referred region.

textual information for reconstructing the two visual branch. Consequently, our model achieves a more comprehensive understanding of both visual and textual information. In this way, the model not only can perceive the information of the image modality itself but also have a more accurate understanding of the location and correlation of the key object features in different regions.

(2) How and why the visual target-relation score (i.e., the x -, y -, w -, and h -masks) works. We provide a clearer illustration in Fig. 5 for further explanation. As mentioned in Sec. 3.2, this score represents the spatial distance between the current patch region and the referred region, it enables implicit deployment of grounding capability within each token of the model. When reconstructing the visual features and target-relation score of each local patch, the model actually needs to have a global and comprehensive understanding of the text modality information and the visual information. On this basis, the model needs to rely on the reconstructed visual features of the local patch to implicitly predict the specific location and size of the referred object, and then accurately predict the visual target-relation score. Finally, Referring MIM can enhance the model’s global and multimodal understanding of textual and visual information, and then learn more general visual representations, which can have better generalization ability when deployed to downstream referring tasks.

The proposed Referring MIM is our own design, which is mainly used to improve the defects existing in MAE [27]/BEiT [4]. We can find the rationale of our method in some classic computer vision works, such as the YOLO series works [71], which predicts the location, size, confidence, and category of the object box corresponding to each grid cell based on the global understanding of the image. YOLO etc. [71] also confirmed that the object detection model obtained in this way has stronger generalization ability when transfer to detection tasks that differ greatly from the training data compared with other detectors.

D.2 The selection of the unsupervised regions

The process of selecting unsupervised regions bears resemblance to weakly-supervised visual grounding. Drawing inspiration from ALBEF’s method [44] for weakly-supervised grounding, we employ a BEiT-3 model with performed image-text contrastive tuning to encode both the image and text, thereby obtaining a cross-modal text-to-image attention map for selection. Subsequently, leveraging the cross-modal attention and modular parsing of textual sentences provided by MAttNet [102] enables us to derive scores for each proposal. Finally, we select the region with the highest score as our objective in Referring MRefM.

D.3 Referring-aware text masking

In referring MLM, we utilize a referring-aware text masking strategy. Specifically, we preferentially mask out the referential subject of the expression text on the basis of a random mask, and the subject is obtained by the NLP parsing tool (e.g., spaCy). Since this small technical point does not observe a significant performance gain as the referring-aware dynamic image masking strategy, we do not provide additional ablation experiments.

Table 12: Comparison with **latest** SoTA methods for PG task with dataset-mixed intermediate pre-training setting. ‘RefC’ represents the mixup of RefCOCO/+g training data. \dagger indicates RefC has been used during pre-training.

Methods	Venue	Visual/Language Backbone	Intermediate pretrain data	Data size	ReferIt test	Flickr test
Dataset-mixed intermediate pre-training setting						
MDETR \dagger [33]	ICCV’21	RN101/RoBERT-B	GoldG,RefC	6.5M	–	83.80
YORO \dagger [29]	ECCV’22	ViLT [37] / BERT-B	GoldG,RefC	6.5M	71.90	–
UniTAB \dagger [97]	ECCV’22	RN101/RoBERT-B	VG,COCO, <i>etc.</i>	>20M	–	79.38
HiVG-B \dagger [92]	ACMMM’24	CLIP-B / CLIP-B	RefC,ReferIt,Flickr	0.8M	77.75	82.08
HiVG-L \dagger [92]	ACMMM’24	CLIP-L / CLIP-L	RefC,ReferIt,Flickr	0.8M	78.16	82.63
OneRef-B\dagger (0.2B)	NeurIPS’24	BEiT3-B / BEiT3-B	RefC,ReferIt	0.5M	79.66	84.01
OneRef-L\dagger (0.6B)	NeurIPS’24	BEiT3-L / BEiT3-L	RefC,ReferIt	0.5M	83.22	85.13

Table 13: Comparison with **latest** SoTA methods (**oIoU** metric) on the three datasets for **RES** task with both single-dataset fine-tuning setting and dataset-mixed intermediate pre-training setting. \dagger indicates RefC has been used during pre-training.

Methods	Venue	Visual/Language Backbone	Intermediate pretrain data	RefCOCO	RefCOCO+	RefCOCOg	
				val	testA	testB	
Single-dataset fine-tuning setting w. uni-modal pre-trained close-set segmentation model: (traditional setting)							
LAVT [94]	CVPR’22	Swin-B / BERT-B	–	72.73	75.82	68.79	62.14
RISCLIP-B [35]	NAACL’24	CLIP-B / CLIP-B	–	73.57	76.46	69.76	65.53
RISCLIP-L [35]	NAACL’24	CLIP-L / CLIP-L	–	76.92	80.99	73.04	71.24
OneRef-B (ours)	NeurIPS’24	BEiT3-B / BEiT3-B	–	77.55	80.96	73.53	70.82
OneRef-L (ours)	NeurIPS’24	BEiT3-L / BEiT3-L	–	80.48	82.78	78.27	74.25
Dataset-mixed intermediate pre-training setting:							
HIPIE \dagger [88]	NeurIPS’23	RN50,CLIP / BERT-B	RefC,O365,PACO	78.30	–	–	66.20
UNINEXT \dagger [93]	CVPR’23	RN50 / BERT-B	RefC,O365,SOT	77.90	79.68	75.77	66.20
PolyFormer-B \dagger [53]	CVPR’23	Swin-B / BERT-B	RefC	74.82	76.64	71.06	67.64
PolyFormer-L \dagger [53]	CVPR’23	Swin-L / BERT-B	RefC	75.96	78.29	73.25	69.33
OneRef-B\dagger (ours)	NeurIPS’24	BEiT3-B / BEiT3-B	RefC	81.06	83.05	77.80	72.24
OneRef-L\dagger (ours)	NeurIPS’24	BEiT3-L / BEiT3-L	RefC	81.95	83.62	79.57	74.55
					79.54	79.54	70.65
						76.53	79.18

D.4 The difference of the task heads between ours with other frameworks

Recently, several multi-task visual grounding studies [79, 45] have incorporated both grounding and segmentation task heads into their frameworks. Most relevance to our work is VG-LAW [79], which simplifies the implementation of grounding and segmentation heads by eliminating Transformer-based fusion encoders through visual adaptive weights generation. In contrast, for REC headers, we propose a box mask constraint based on cross-modal cosine similarity that significantly enhances the accuracy of such grounding approach. For the RES head, instead of employing adaptive weights generation, we directly obtain segmentation masks using cosine similarity for the visual tokens upsampled by a 3-layer deconvolution.

E Extra experimental results

E.1 The results on ReferIt and Flickr30k dataset under mixup pre-training setting

The results of our framework on the PG task (*i.e.*, ReferIt [34] and Flickr30k [68] datasets) under the mixup pre-training setting are presented in Tab. 12. It is worth noting that a majority of studies conducted under this setting have not provided these results, thus only several works are included in the table. As shown in Tab. 12, our base model outperforms HiVG by 1.91% and 1.93% on the two datasets, and also achieves SoTA performance.

E.2 The results for RES task under oIoU metric

The results for RES task under oIoU metric are presented in Tab. 13. oIoU is calculated as the ratio between the total intersection area and the total union area of all test samples, each of which consists of both a text query and an image. This metric particularly favors larger objects. As indicated in Tab. 13, (1) in the single-dataset fine-tuning setting, our base model outperforms RISCLIP [35] by 3.77%, 8.87%, and 5.52% on RefCOCO/+g testB/testB/test split, respectively. (2) Similarly, in the

Table 14: Comparison of the computational cost in REC task. The results are obtained on RefCOCO dataset. The testing environment is 1 NVIDIA A100 GPU. \dagger indicates that the model’s code is not publicly available, and the replicated estimation results are shown. The backbone parameters of our UniRef model only include the actual calculated parameters, specifically those of the V-L expert head in MoE, while excluding the parameters of unused visual and language expert heads and their uni-modal branches. We highlight the best result in **bold**. (FPS: $\text{images} / (\text{GPU} \cdot \text{second})$)

Model	Backbone param. \downarrow	Fusion+head param. \downarrow	Total param. \downarrow	FLOPs (G) \downarrow	Fine-tune FPS \uparrow	Test FPS \uparrow	testA time \downarrow	testA Acc. \uparrow
TransVG [14]	150M	21M	171M	214	22.8	59.6	95s	82.7
QRNet [98]	252M	21M	273M	540	9.4	50.9	111s	85.9
TransVG++ \dagger [15]	161M	10M	171M	396	2.6	8.7	644s	88.4
MDETR [33]	150M	135M	185M	642	4.7	19.9	283s	89.6
Grounding-DINO [55]	156M	15M	172M	464	—	8.3	681s	91.8
UniRef (Ours)	147M	1.7M	149M	162	55.8	83.2	68s	94.3

Table 15: Complete ablation study of MRefM using our OneRef-base model in REC task on both single-dataset fine-tuning setting and mixup intermediate pre-training setting.(Acc@0.5(%))

MIM	MLM	image masking strategy	RefCOCO			RefCOCO+ testA testB			RefCOCOg val test	
			val	testA	testB	val	testA	testB	val	test
Single-dataset fine-tuning setting:										
\times vanilla	\times vanilla	\times block-wise	85.23	88.13	83.82	78.56	83.36	71.72	80.41	80.52
Ref MIM	Ref MLM	referring-aware	85.75	88.86	83.43	78.47	84.27	71.66	81.06	81.19
			88.75	90.95	85.34	80.43	86.46	74.26	83.68	83.52
Dataset-mixed intermediate pre-training setting: (main)										
\times vanilla	\times vanilla	\times random	85.23	88.13	83.82	78.56	83.36	71.72	80.41	80.52
vanilla	vanilla	referring-aware	86.60	89.86	84.96	79.68	84.59	72.11	81.35	81.11
Ref MIM	vanilla	referring-aware	86.71	90.58	85.33	80.06	85.77	73.96	81.96	82.16
vanilla	Ref MLM	referring-aware	88.86	92.12	86.89	83.64	88.26	76.58	83.55	85.86
Ref MIM	Ref MLM	referring-aware	87.26	91.68	86.37	81.52	86.87	75.93	82.88	84.32
Ref MIM	Ref MLM	random	90.56	93.55	88.23	85.08	89.12	78.56	85.57	86.89
Ref MIM	Ref MLM	block-wise	90.07	93.32	88.21	84.55	88.83	77.98	84.71	86.69
Ref MIM	Ref MLM	referring-aware	91.89	94.31	88.58	86.38	90.38	79.47	86.82	87.32

dataset-mixed intermediate pre-training setting, our base model surpasses UNINEXT [93] by 2.03%, 8.07%, and 6.69% on RefCOCO/+g testB/testB/test split, respectively. Furthermore, our large model exhibits remarkable scalability with additional performance enhancements.

E.3 Computational costs analysis compared with SoTA methods

In this paper, we highlight two significant advantages of our model architecture over other frameworks: (a) Instead of using a Transformer to fuse visual and language features, we only employ a simple lightweight task head; (b) Our one-tower architecture eliminates the need for early interaction techniques in the backbone network, thereby reducing the computational complexity of the model.

We compare the energy efficiency of our model with several well-known SoTA works on the REC task from various perspectives, including the number of parameters, computational complexity (FLOPs), inference speed (FPS), and test time (s). As can be seen from Tab. 14, due to the simplification of our model’s structure, the number of parameters and the calculation complexity are significantly lower than other well-known models. Specifically, our feature fusion and grounding head module only require 1.7M parameters, while other methods use 20M, meaning we only have about 8.5% of their parameter count. Additionally, our computation is only 34.9% of Grounding-DINO and 25.2% of MDETR. Moreover, our inference speed is $10 \times$ faster than Grounding-DINO and TransVG++ (the speed also related to the image size used by the model). Despite these advantages, thanks to the modality-shared feature space, we outperform all these well-known works.

E.4 Complete ablation study of MRefM on single-dataset fine-tuning and mixup pretrain settings

The complete ablation results of MRefM on both single-dataset fine-tuning and mixup pretrain settings are provided in Tab. 15, which serves as a supplement to Tab. 4 in the main text. In the table, the masking ratio is set to 0.4 when using block-wise or random masking strategies.

Table 16: Ablation study of the mask ratio in referring-aware dynamic masking strategy on RefCOCOg(val) dataset.

mask ratio			RefCOCOg		mask ratio			RefCOCOg	
β	γ	Acc@0.5(%)	β	γ	Acc@0.5(%)	β	γ	Acc@0.5(%)	
0.20	0.75	83.40	0.35	0.50	85.98				
0.30	0.75	85.01	0.35	0.60	86.32				
0.35	0.75	86.82	0.35	0.70	86.62				
0.40	0.75	86.62	0.35	0.75	86.82				
0.50	0.75	86.23	0.35	0.80	86.19				
0.60	0.75	84.72	0.35	0.85	85.56				
0.70	0.75	83.39	0.35	0.90	84.87				

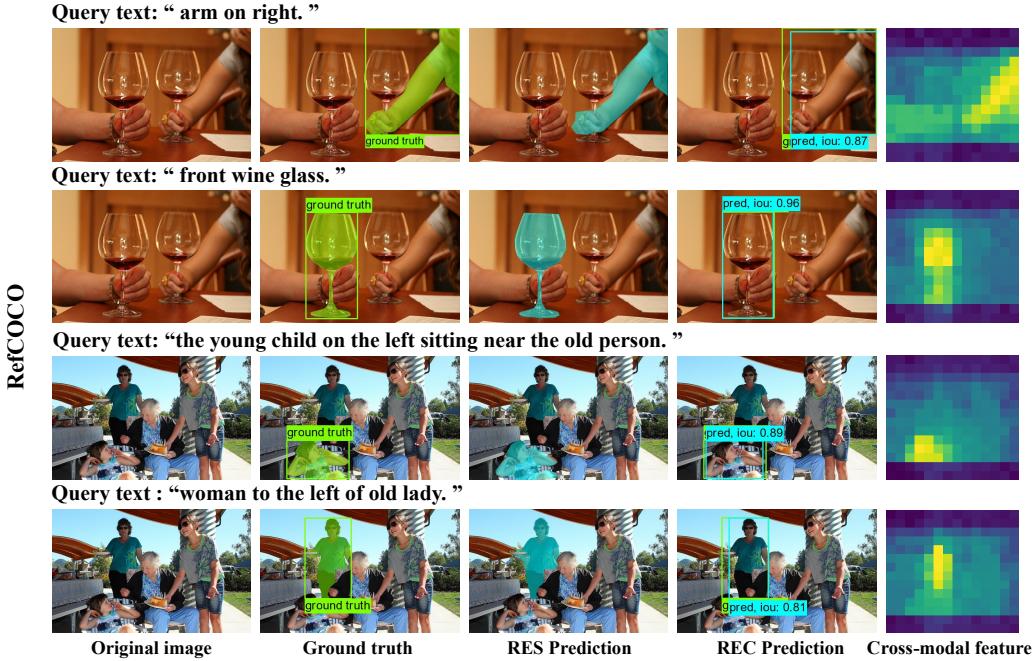


Figure 6: Qualitative results of our OneRef framework on the RefCOCO-val split. Each example shows two different query texts. From left to right: the original input image, the ground truth with box and segmentation mask (in green), the RES prediction of OneRef (in cyan), the REC prediction of OneRef (in cyan), and the cross-modal feature.

E.5 Ablation study of the mask ratio in referring-aware dynamic masking strategy

As depicted in Tab. 16, we conducted ablation experiments on the mask ratio within our proposed referring-aware dynamic image masking strategy. It is observed that while a high mask ratio of 0.75 is employed for the pixel reconstruction of MAE [27], achieving better results for BEiT’s feature reconstruction requires a mask ratio ranging from approximately 0.4 to 0.45. In our proposed approach, favorable outcomes can be attained by setting β and γ to 0.35 and 0.75, respectively; where β represents the mask ratio beyond the referred region and γ denotes the mask ratio within it. Experimental statistics show that our entire mask rate α in each sample is about $0.4 \sim 0.5$.

F Visualization of the results

As shown in Fig. 6, Fig. 7, and Fig. 8, we present the qualitative grounding and referring segmentation results with several relatively challenging examples. Each example shows two different query texts. The cross-modal features are obtained by the cosine similarity between the [SEP] language token and the vision tokens on REC transfer model of OneRef-B. These results demonstrate the strong semantic comprehension capability of our OneRef model in complex text understanding and cross-modal grounding.

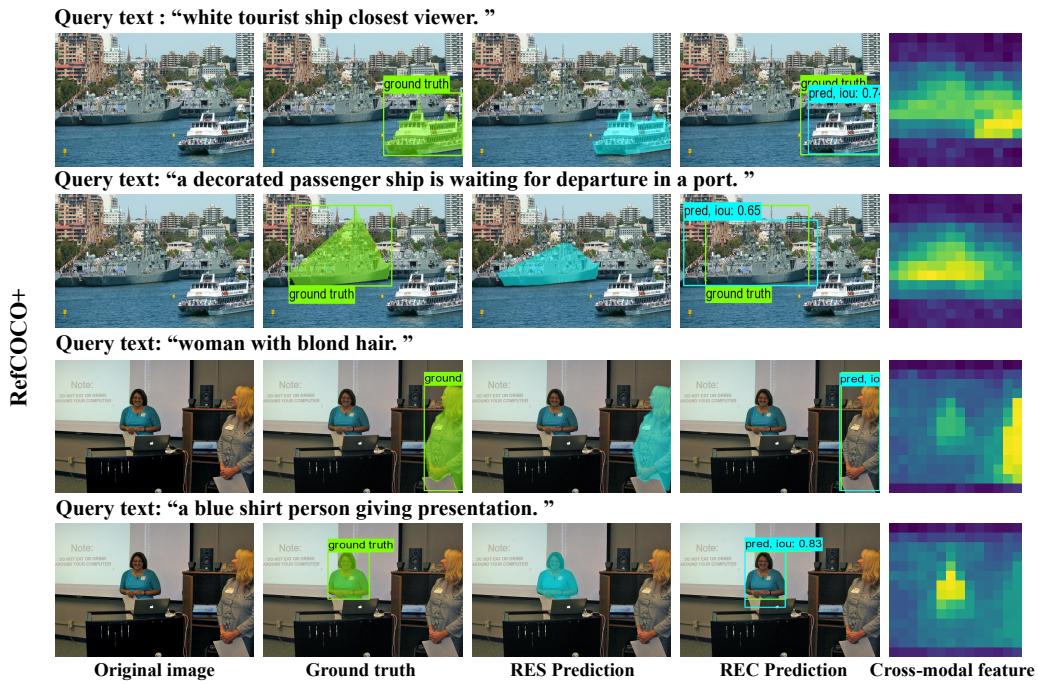


Figure 7: Qualitative results on the RefCOCO+ -val dataset. The annotation is the same as Fig. 6.

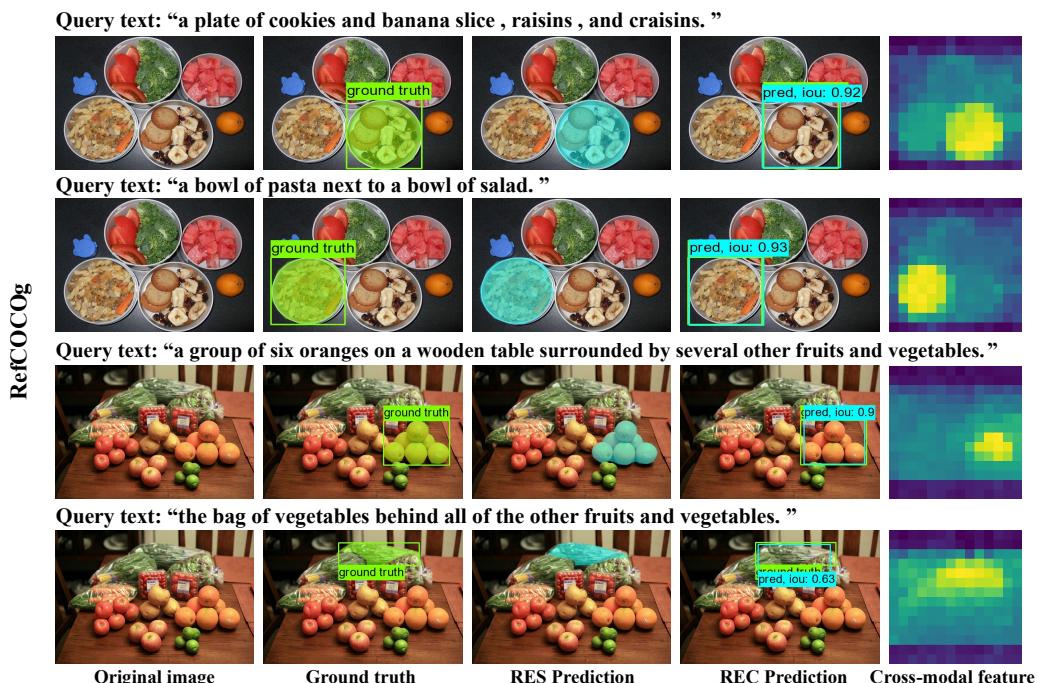


Figure 8: Qualitative results on the RefCOCOg -val dataset. The annotation is the same as Fig. 6.

G Further discussions

G.1 Limitations

Firstly, despite achieving remarkable grounding and segmentation results, the pre-training in this paper solely relies on the comparatively limited RefC dataset, as opposed to other studies with larger datasets.

Secondly, the MRefM paradigm necessitates additional referential bounding boxes as supervised data compared to self-supervised pre-training. Therefore, we explore the potential of unsupervised pre-training for MRefM. However, when utilizing image-text pairs obtained from web crawling, there is no guarantee that the referred regions will exhibit strong correlation with the text due to many texts describing the entire image. This aspect introduces certain challenges and biases during large-scale pre-training of MRefM. Consequently, this paper should serve as an inspiration for subsequent researchers to propose more convenient plug-and-play modeling methods.

G.2 Broader impacts

OneRef demonstrates strong grounding and referring segmentation capabilities, while MRefM represents a novel modeling paradigm for referential relationship. This facilitates users to easily utilize our model (*e.g.*, OneRef-L) for their own needs by simply providing some appropriate text queries. However, this also raises concerns about how our OneRef models with a strong understanding capabilities could be used inappropriately in the community, such as for large-scale illegal video surveillance. The open-set grounding capabilities could be manipulated through specialized textual cues to facilitate targeted detection or human tracking instead of generic ones. This manipulation could introduce biases in the detector and result in unfair predictions.

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