

# Language Adaptive Weight Generation for Multi-task Visual Grounding

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## Abstract

Although the impressive performance in visual grounding, the prevailing approaches usually exploit the visual backbone in a passive way, i.e., the visual backbone extracts features with fixed weights without expression-related hints. The passive perception may lead to mismatches (e.g., redundant and missing), limiting further performance improvement. Ideally, the visual backbone should actively extract visual features since the expressions already provide the blueprint of desired visual features. The active perception can take expressions as priors to extract relevant visual features, which can effectively alleviate the mismatches. Inspired by this, we propose an active perception Visual Grounding framework based on Language Adaptive Weights, called VG-LAW. The visual backbone serves as an expression-specific feature extractor through dynamic weights generated for various expressions. Benefiting from the specific and relevant visual features extracted from the language-aware visual backbone, VG-LAW does not require additional modules for cross-modal interaction. Along with a neat multi-task head, VG-LAW can be competent in referring expression comprehension and segmentation jointly. Extensive experiments on four representative datasets, i.e., RefCOCO, RefCOCO+, RefCOCOg, and ReferItGame, validate the effectiveness of the proposed framework and demonstrate state-of-the-art performance.

## 1. Introduction

Visual grounding (such as referring expression comprehension [4, 23, 42, 45, 46, 48, 50], referring expression segmentation [6, 14, 17, 23, 32, 33, 44], and phrase grounding [4, 23, 50]) aims to detect or segment the specific object

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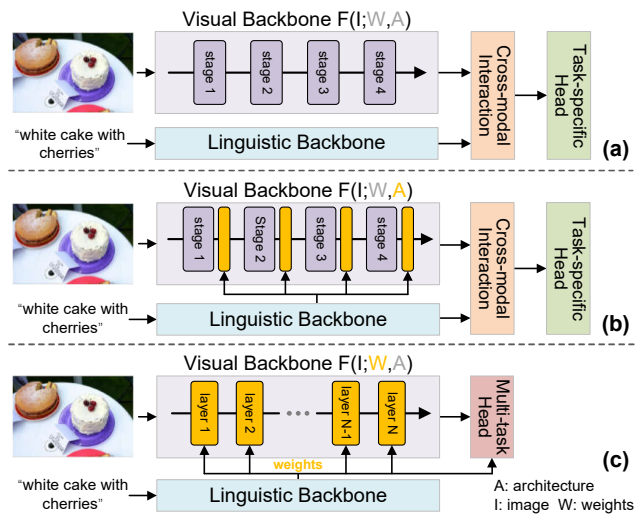


Figure 1. The comparison of visual grounding frameworks. (a) The visual and linguistic backbone independently extracts features, which are fused through cross-modal interaction. (b) Additional designed modules are inserted into the visual backbone to modulate visual features using linguistic features. (c) VG-LAW can generate language-adaptive weights for the visual backbone and directly output referred objects through our designed multi-task head without additional cross-modal interaction modules.

based on a given natural language description. Compared to general object detection [38] or instance segmentation [11], which can only locate objects within a predefined and fixed category set, visual grounding is more flexible and purposeful. Free-formed language descriptions can specify specific visual properties of the target object, such as categories, attributes, relationships with other objects, relative/absolute positions, and *etc.*

Due to the similarity with detection tasks, previous visual grounding approaches [23, 33, 46, 50] usually follow the general object detection frameworks [1, 11, 37], and pay

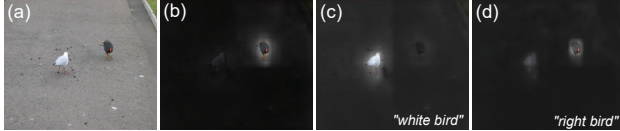


Figure 2. Attention visualization of the visual backbone with different weights. (a) input image, (b) visual backbone with fixed weights, (c) and (d) visual backbone with weights generated for “white bird” and “right bird”, respectively.

attention to the design of cross-modal interaction modules. Despite achieving impressive performance, the visual backbone is not well explored. Concretely, the visual backbone passively extracts visual features with fixed architecture and weights, regardless of the referring expressions, as illustrated in Fig. 1 (a). Such passive feature extraction may lead to mismatches between the extracted visual features and those required for various referring expressions, such as missing or redundant features. Taking Fig. 2 as an example, the fixed visual backbone has an inherent preference for the image, as shown in Fig. 2 (b), which may be irrelevant to the referring expression “white bird”. Ideally, the visual backbone should take full advantage of expressions, as the expressions can provide information and tendencies about the desired visual features.

Several methods have noticed this phenomenon and proposed corresponding solutions, such as QRNet [45], and LAVT [44]. Both methods achieve the expression-aware visual feature extraction by inserting carefully designed interaction modules (such as QD-ATT [45], and PWAN [44]) into the visual backbone, as illustrated in Fig. 1 (b). Concretely, visual features are first extracted and then adjusted using QD-ATT (channel and spatial attention) or PWAM (transformer-based pixel-word attention) in QRNet and LAVT at the end of each stage, respectively. Although performance improvement with adjusted visual features, the extract-then-adjust paradigm inevitably contains a large number of feature-extraction components with fixed weights, *e.g.*, the components belonging to the original visual backbone in QRNet and LAVT. Considering that the architecture and weights jointly determine the function of the visual backbone, this paper adopts a simpler and fine-grained scheme that modifies the function of the visual backbone with language-adaptive weights, as illustrated in Fig. 1 (c). Different from the extract-then-adjust paradigm used by QRNet and LAVT, the visual backbone equipped with language-adaptive weights can directly extract expression-relevant visual features without additional feature-adjustment modules.

In this paper, we propose an active perception Visual Grounding framework based on Language Adaptive Weights, called VG-LAW. It can dynamically adjust the behavior of the visual backbone by injecting the informa-

tion of referring expressions into the weights. Specifically, VG-LAW first obtains the specific language-adaptive weights for the visual backbone through two successive processes of linguistic feature aggregation and weight generation. Then, the language-aware visual backbone can extract expression-relevant visual features without manually modifying the visual backbone architecture. Since the extracted visual features are highly expression-relevant, cross-modal interaction modules are not required for further cross-modal fusion, and the entire network architecture is more streamlined. Furthermore, based on the expression-relevant features, we propose a lightweight but neat multi-task prediction head for jointly referring expression comprehension (REC) and referring expression segmentation (RES) tasks. Extensive experiments on RefCOCO [47], RefCOCO+ [47], RefCOCOg [36], and ReferItGame [19] datasets demonstrate the effectiveness of our method, which achieves state-of-the-art performance.

The main contributions can be summarized as follows:

- We propose an active perception visual grounding framework based on the language adaptive weights, called VG-LAW, which can actively extract expression-relevant visual features without manually modifying the visual backbone architecture.
- Benefiting from the active perception of visual feature extraction, we can directly utilize our proposed neat but efficient multi-task head for REC and RES tasks jointly without carefully designed cross-modal interaction modules.
- Extensive experiments demonstrate the effectiveness of our framework, which achieves state-of-the-art performance on four widely used datasets, *i.e.*, RefCOCO, RefCOCO+, RefCOCOg, and ReferItGame.

## 2. Related Work

### 2.1. Referring Expression Comprehension

Referring expression comprehension (REC) [4, 13, 30, 42, 43, 46, 48–50] aims to generate a bounding box in an image specified by a given referring expression. Early researchers explore REC through a two-stage framework [13, 29, 30, 46], where region proposals [38] are first extracted and then ranked according to their similarity scores with referring expressions. To alleviate the speed and accuracy issues of the region proposals in the two-stage framework, simpler and faster one-stage methods [42, 43, 49] based on dense anchors are proposed. Recently, transformer-based methods [4, 12, 18, 48, 50] can effectively capture intra- and inter-modality context and achieve better performance, benefiting from the self-attention mechanism [40].

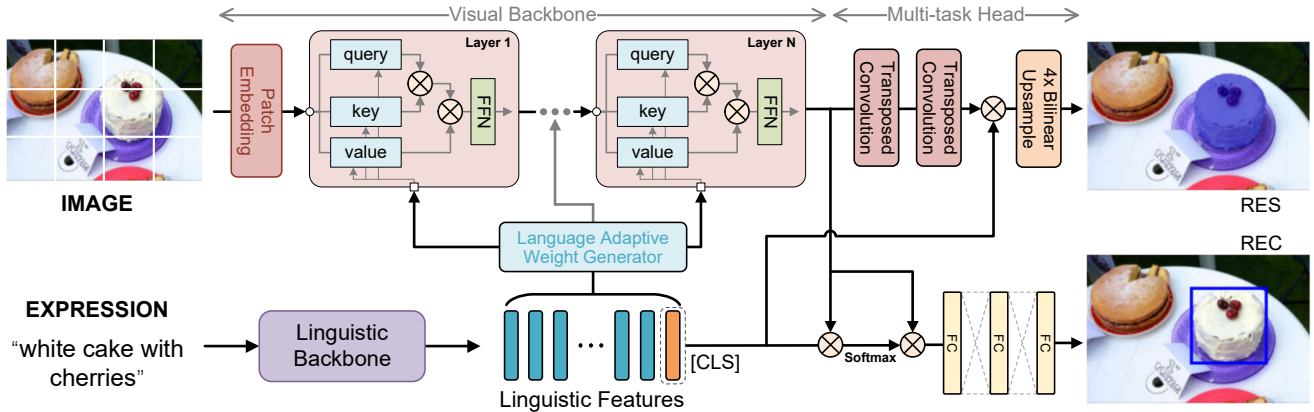


Figure 3. The overall architecture of our proposed VG-LAW framework. It consists of four components: (1) Linguistic Backbone, which extracts linguistic features from free-formed referring expressions, (2) Language Adaptive Weight Generator, which generates dynamic weights for the visual backbone conditioned on specific expressions, (3) Visual Backbone, which extracts visual features from the raw image and its behavior can be modified by language-adaptive weights, and (4) Multi-task Head, which predicts the bounding box and mask of referred object jointly.  $\otimes$  represents the matrix multiplication.

## 2.2. Referring Expression Segmentation

Similar to REC, referring expression segmentation (RES) [6, 9, 14, 15, 17, 20, 23, 32, 44, 50] aims to predict a precise pixel-wise binary mask corresponding to the given referring expression. The pioneering work [14] proposes to generate segmentation masks for natural language expressions by concatenating the visual and linguistic features and mixing these two modal features with fully convolutional classifiers. Follow-up solutions [9, 15, 17, 32] propose various attention mechanisms to perform cross-modal interaction to generate a high-resolution segmentation map. Recent studies [6, 20, 23, 44, 50], like REC, leverage transformer [40] to realize cross-modal interaction and achieve excellent performance. All these methods achieve cross-modal interaction by either adjusting the inputs or modifying the architectures with fixed network weights.

## 2.3. Dynamic Weight Networks

Several works [3, 10, 16, 24, 41] have investigated dynamic weight networks, where given inputs adaptively generate the weights of the network. According to the way of dynamic weight generation, the current methods can be roughly divided into three categories. (1) Dynamic weights are directly generated using fully-connected layers with learnable embeddings [10] or intermediate features [16] as input. (2) Weights are computed as the weighted sum of a set of learnable weights [3, 22, 41], which can also be regarded as the mixture-of-experts and may suffer from challenging joint optimization. (3) The weights are analyzed from the perspective of matrix decomposition [24], and the final dynamic weights are generated by calculating the multiplication of several matrices.

## 3. Method

In this section, we will introduce the active perception framework for multi-task visual grounding, including the language-adaptive weight generation, multi-task prediction head, and training objectives.

### 3.1. Overview

The extraction of visual features by the visual backbone in the manner of passive perception may cause mismatch problems, which can lead to suboptimal performance despite subsequent carefully designed cross-modal interaction modules. Considering that expressions already provide a blueprint for the desired visual features, we propose an active perception visual grounding framework based on the language adaptive weights, called VG-LAW, as illustrated in Fig. 3. In this framework, the visual backbone can actively extract expression-relevant visual features using language-adaptive weights, without needing to manually modify the visual backbone architecture or elaborately design additional cross-modal interaction modules.

Specifically, the VG-LAW framework consists of four components, *i.e.*, linguistic backbone, language adaptive weight generator, visual backbone, and multi-task head. Given a referring expression, the  $N$ -layer BERT-based [5] linguistic backbone tokenizes the expressions, prepends a [CLS] token, and extracts linguistic features  $F_l \in \mathbb{R}^{L \times d_l}$ , where  $L$  and  $d_l$  represent the token numbers and dimension of linguistic features, respectively. The linguistic features  $F_l$  are then fed to the language adaptive weight generator to generate weights for the transformer-based visual backbone. Next, given an image  $I \in \mathbb{R}^{3 \times H \times W}$ , the expression-aware visual features  $F_v \in \mathbb{R}^{C \times \frac{H}{s} \times \frac{W}{s}}$  can be extracted by

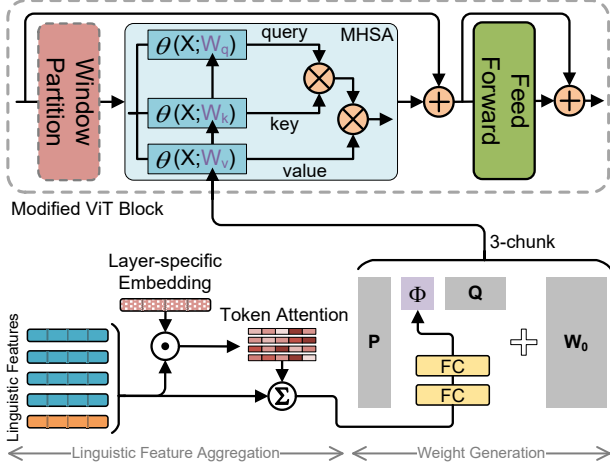


Figure 4. The detailed architecture for language adaptive weight generation. The upper part shows the architecture of the adapted ViT block in the visual backbone, and the lower part shows the linguistic feature aggregation and weight generation.

the visual backbone, where  $C$  and  $s$  represent the channel number and stride of the visual features, respectively. Finally, we pass the linguistic features  $F_l^1 \in \mathbb{R}^{d_l}$  represented by the [CLS] token and the visual features to the multi-task head, which predicts the bounding box and mask of the referred object for REC and RES, respectively.

### 3.2. Language Adaptive Weight Generation

After extracting linguistic features, language-adaptive weights are generated to guide the active perception of the visual backbone. The process of language adaptive weight generation has two stages, *i.e.*, the layer-wise linguistic feature aggregation and the weight generation.

**Linguistic Feature Aggregation.** Considering the referring expressions correspond to a different number of linguistic tokens and each layer of the visual backbone may prefer different linguistic tokens, we try to aggregate linguistic features with fixed sizes for each layer independently. Inspired by the multi-head attention mechanism [40], we introduce a learnable layer-specific embedding  $e_i \in \mathbb{R}^{d_l}$  for each layer  $i$  of the visual backbone to extract layer-specific linguistic features dynamically, which can improve the model flexibility at negligible cost. The calculation is performed on  $G$  groups. For each group  $g$ , the token-wise attention  $\alpha_i^g \in [0, 1]^L$  is assigned to the normalized dot product of  $e_i^g$  and  $F_l^g$ , which is denoted as:

$$\alpha_i^g = \text{Softmax}([e_i^g \cdot F_l^{g,1}, e_i^g \cdot F_l^{g,2}, \dots, e_i^g \cdot F_l^{g,L}]). \quad (1)$$

Then, the aggregated linguistic feature  $h_0^i \in \mathbb{R}^{d_l}$  can be derived by concatenating  $h_0^{i,g} = \sum_{j=1}^L \alpha_i^{g,j} F_l^{g,j}$ .

Finally, we use a fully-connected layer (FC) to reduce the dimension of the aggregated linguistic features for the  $i$ -th layer of the visual backbone, which is indicated as:

$$h_1^i = \delta(W_1^i h_0^i), \quad (2)$$

where  $W_1^i \in \mathbb{R}^{d_l \times d_h}$  is used to reducing the dimension to  $d_h = d_l/r$ , and  $r$  is the reduction ratio.  $\delta$  refers to the GeLU activation function.

**Weight Generation.** To guide the active perception of the visual backbone, we generate language-adaptive weights for producing the query  $X_q$ , key  $X_k$ , and value  $X_v$  in the visual backbone conditioned on referring expressions, which can be represented as:

$$X_q = \theta(X; W_q), X_k = \theta(X; W_k), X_v = \theta(X; W_v), \quad (3)$$

where  $\theta(\cdot; W)$  indicates the linear projection operation parameterized by  $W$ , and  $X$  represents the input visual features.  $W_q, W_k, W_v \in \mathbb{R}^{d_{out} \times d_{in}}$  are the dynamic projection weights used to generate the query, key, and value, respectively.  $d_{in}$  and  $d_{out}$  are the dimension of feature  $X$  and query/key/value, respectively.

Considering the large number  $d_{out} \times d_{in}$  of the dynamic weights, it is unaffordable to directly generate weights using fully-connected layers like Hypernetworks [10]. The DynamicConv [3] and CondConv [41] can alleviate this problem by generating weights with weighted summation of  $K$  static kernels but can increase the parameter number by  $K$ -times and suffer from challenging joint optimization. Inspired by the dynamic channel fusion [24], we try to generate dynamic weights following the matrix decomposition paradigm. Taking the  $i$ -th ViT block as an example, which can be formulated as:

$$[W_q^i, W_k^i, W_v^i] = W_0^i + P\Phi(h_1^i)Q^T, \quad (4)$$

where  $W_0^i \in \mathbb{R}^{d_{out} \times d_{in}}$  is the layer-specific static learnable weights.  $P \in \mathbb{R}^{d_{out} \times d_w}$  and  $Q \in \mathbb{R}^{d_{in} \times d_w}$  are also static learnable weights, but sharable across all ViT blocks to reduce the parameter numbers and prevent the model from overfitting.  $\Phi(h_1^i)$  is a fully-connected layer, which produces a dynamic matrix of shape  $d_w \times d_w$  with aggregated linguistic features  $h_1^i$  as input.

### 3.3. Multi-task Head

Different from the previous methods [6, 23, 42, 45, 46, 49, 50], which require carefully designed cross-modal interaction modules, VG-LAW can obtain expression-relevant visual features extracted by the language-aware visual backbone without additional cross-modal interaction modules. Through our proposed neat but efficient multi-task head, we can utilize the visual and linguistic features to predict

the bounding box for REC and the segmentation mask for RES. Concretely, there are two branches in the multi-task head for REC and RES, respectively.

For the REC branch, we apply direct coordinate regression to predict the bounding box of referred object. To pool the 2- $d$  visual features along the spatial dimension, we propose a language adaptive pooling module (LAP), which aggregates visual features using language-adaptive attention. Specifically, the visual features  $\{F_v^{i,j}\} \in \mathbb{R}^{C \times \frac{H}{s} \times \frac{W}{s}}$  and linguistic feature  $F_l^1 \in \mathbb{R}^{d_l}$  are firstly projected to the lower-dimension space  $\mathbb{R}^k$ , and the attention weights  $A \in \mathbb{R}^{\frac{H}{s} \times \frac{W}{s}}$  are calculated as dot-product similarity followed by Softmax normalization. Then, the visual features are aggregated by calculating the weighted sum with attention weights  $A$ . Finally, the aggregated visual features are fed to a three-layer fully-connected layer, and the Sigmoid function is used to predict the referred bounding box  $\hat{b} = (\hat{x}, \hat{y}, \hat{w}, \hat{h})$ .

For the RES branch, we apply binary classification to each visual feature along the spatial dimension to predict segmentation masks for referred objects. Specifically, the visual features  $F_v$  are first up-sampled to  $\hat{F}_v \in \mathbb{R}^{d_l \times \frac{H}{4} \times \frac{W}{4}}$  with successive transposed convolutions. Then, the intermediate segmentation map  $\bar{s} \in \mathbb{R}^{\frac{H}{4} \times \frac{W}{4}}$  can be obtained by using linear projection  $\theta(\cdot; W)$  on each visual feature. Following the language adaptive weight paradigm, we also use dynamic rather than fixed weights by simply setting  $W = F_l^1$ . Finally, the full-resolution segmentation mask  $\hat{s} \in \mathbb{R}^{H \times W}$  is derived by simply up-sample  $\bar{s}$  using bilinear interpolation, followed by the Sigmoid function.

### 3.4. Training Objectives

The VG-LAW framework can be optimized end-to-end for multi-task visual grounding. For REC, given the predicted bounding box  $\hat{b} = (\hat{x}, \hat{y}, \hat{w}, \hat{h})$  and the ground truth  $b = (x, y, w, h)$ , the detection loss function is defined as follows:

$$\mathcal{L}_{det} = \lambda_{L1} \mathcal{L}_{L1}(b, \hat{b}) + \lambda_{giou} \mathcal{L}_{giou}(b, \hat{b}), \quad (5)$$

where  $\mathcal{L}_{L1}(\cdot, \cdot)$  and  $\mathcal{L}_{giou}(\cdot, \cdot)$  represent L1 loss and Generalized IoU loss [39], respectively, and  $\lambda_{L1}$  and  $\lambda_{giou}$  are the relative weights to control the two detection loss functions. For RES, given the predicted mask  $\hat{s}$  and the ground-truth  $s$ , the segmentation loss function is defined as follows:

$$\mathcal{L}_{seg} = \lambda_{focal} \mathcal{L}_{focal}(s, \hat{s}) + \lambda_{dice} \mathcal{L}_{dice}(s, \hat{s}), \quad (6)$$

where  $\mathcal{L}_{focal}(\cdot, \cdot)$  and  $\mathcal{L}_{dice}(\cdot, \cdot)$  represent focal loss [27] and DICE/F-1 loss [35], respectively, and  $\lambda_{focal}$  and  $\lambda_{dice}$  are the relative weights to control the two segmentation loss functions. Our framework can be seamlessly used for joint training of REC and RES, and its joint training loss function is defined as follows:

$$\mathcal{L}_{total} = \mathcal{L}_{det} + \mathcal{L}_{seg}. \quad (7)$$

The trained model performs well for language-guided detection and segmentation. The experimental analysis of the whole framework will be elaborated in Sec. 4.

## 4. Experiments

In this section, we will give a detailed experimental analysis of the whole framework, including the datasets, evaluation protocol, implementation details, comparisons with the state-of-the-art methods, and ablation analysis.

### 4.1. Datasets and Evaluation Protocol

**Datasets.** To verify the effectiveness of our method, we conduct experiments on the widely used RefCOCO [47], RefCOCO+ [47], RefCOCOg [34], and ReferItGame [19] datasets. RefCOCO, RefCOCO+, and RefCOCOg are collected from MS-COCO [28]. RefCOCO and RefCOCO+, which are collected in interactive games, can be divided into train, val, testA, and testB sets. Compared to RefCOCO, the expressions of RefCOCO+ contain more attributes than absolute locations. Unlike RefCOCO and RefCOCO+, RefCOCOg collected by Amazon Mechanical Turk has a longer length of 8.4 words, including the attribute and location of referents. Following a common version of split [36], RefCOCOg has train, val, and test sets. In addition, ReferItGame collected from SAIAPR-12 [8] contains train and test sets. Each sample in the above datasets contains its corresponding bounding box and mask.

**Evaluation Protocol.** Following the previous works [23, 33, 50], we use  $Prec@0.5$  and  $mIoU$  to evaluate the performance of REC and RES, respectively. For  $Prec@0.5$ , the predicted bounding box is considered correct if the intersection-over-union (IoU) with the ground-truth bounding box is greater than 0.5.  $mIoU$  represents the IoU between the prediction and ground truth averaged across all test samples.

### 4.2. Implementation Details

**Training.** The resolution of the input image is resized to  $448 \times 448$ . ViT-Base [7] is used as the visual backbone, and we follow the adaptation introduced by ViTDet [25] to adapt the visual backbone to higher-resolution images. The visual backbone is pre-trained using Mask R-CNN [11] on MS-COCO [28], where overlapping images of the val/test sets are excluded. The  $W_0^i$  and  $\Phi(h_1^i)$  in Eq. (4) are initialized with the corresponding pre-trained weights of the visual backbone and zeros, respectively. The maximum length of referring expression is set to 40, and the uncased base of six-layer BERT [5] as the linguistic backbone is used to generate linguistic features.  $\lambda_{L1}$  and  $\lambda_{giou}$  are set to 1.  $\lambda_{focal}$  and  $\lambda_{dice}$  are set to 4. The reduction ratio  $r$  is set to 16. The initial learning rate for the visual and linguistic backbone is  $4e-5$ , and the initial learning rate for the

Methods	Venue	Visual Backbone	Multi-task	RefCOCO			RefCOCO+			RefCOCOg		ReferItGame test
				val	testA	testB	val	testA	testB	val	test	
<b>Two-stage:</b>												
MAttNet [46]	CVPR18	RN101	✗	76.65	81.14	69.99	65.33	71.62	56.02	66.58	67.27	29.04
RvG-Tree [13]	TPAMI19	RN101	✗	75.06	78.61	69.85	63.51	67.45	56.66	66.95	66.51	-
CM-A-E [30]	CVPR19	RN101	✗	78.35	83.14	71.32	68.09	73.65	58.03	67.99	68.67	-
Ref-NMS [2]	AAAI21	RN101	✗	80.70	84.00	76.04	68.25	73.68	59.42	70.55	70.62	-
<b>One-stage:</b>												
FAOA [43]	ICCV19	DN53	✗	72.54	74.35	68.50	56.81	60.23	49.60	61.33	60.36	60.67
ReSC-Large [42]	ECCV20	DN53	✗	77.63	80.45	72.30	63.59	68.36	56.81	67.30	67.20	64.60
MCN [33]	CVPR20	DN53	✓	80.08	82.29	74.98	67.16	72.86	57.31	66.46	66.01	-
RealGIN [49]	TNNLS21	DN53	✗	77.25	78.70	72.10	62.78	67.17	54.21	62.75	62.33	-
PLV-FPN* [26]	TIP22	RN101	✗	81.93	84.99	76.25	71.20	77.40	61.08	70.45	71.08	71.77
<b>Transformer-based:</b>												
TransVG [4]	ICCV21	RN101	✗	81.02	82.72	78.35	64.82	70.70	56.94	68.67	67.73	70.73
RefTR* [23]	NeurIPS21	RN101	✓	82.23	85.59	76.57	71.58	75.96	62.16	69.41	69.40	71.42
SeqTR [50]	ECCV22	DN53	✗	81.23	85.00	76.08	68.82	75.37	58.78	71.35	71.58	69.66
Word2Pix [48]	TNNLS22	RN101	✗	81.20	84.39	78.12	69.74	76.11	61.24	70.81	71.34	-
YORO [12]	ECCV22	-	✗	82.90	85.60	77.40	73.50	78.60	64.90	73.40	74.30	71.90
QRNet [45]	CVPR22	Swin-S	✗	84.01	85.85	82.34	72.94	76.17	63.81	71.89	73.03	74.61
<b>Ours:</b>												
VG-LAW	-	ViT-B	✗	86.06	88.56	82.87	75.74	80.32	66.69	75.31	75.95	76.60
VG-LAW	-	ViT-B	✓	86.62	89.32	83.16	76.37	81.04	67.50	76.90	76.96	77.22

Table 1. Comparison with state-of-the-art methods on RefCOCO [47], RefCOCO+ [47], RefCOCOg [36] and ReferItGame [19] for REC task. The visual backbone is pre-trained on MS-COCO [28], where overlapping images of the val/test sets are excluded. \* represents ImageNet [21] pre-training. RN101, DN53, Swin-S, and ViT-B are shorthand for the ResNet101, DarkNet53, Swin-Transformer Small, and ViT Base, respectively. We highlight the best and second best performance in the red and blue colors.

Methods	Venue	Visual Backbone	Multi-task	RefCOCO			RefCOCO+			RefCOCOg		
				val	testA	testB	val	testA	testB	val	test	
CGAN [32]	MM20	DN53	✗	64.86	68.04	62.07	51.03	55.51	44.06	54.40	54.25	
MCN [33]	CVPR20	DN53	✓	62.44	64.20	59.71	50.62	54.99	44.69	49.22	49.40	
LTS [17]	CVPR21	DN53	✗	65.43	67.76	63.08	54.21	58.32	48.02	54.40	54.25	
VLT [50]	ICCV21	DN53	✗	65.65	68.29	62.73	55.50	59.20	49.36	52.99	56.65	
RefTR* [23]	NeurIPS21	RN101	✓	70.56	73.49	66.57	61.08	64.69	52.73	58.73	58.51	
SeqTR [50]	ECCV22	DN53	✗	67.26	69.79	64.12	54.14	58.93	48.19	55.67	55.64	
LAVT* [44]	CVPR22	Swin-B	✗	74.46	76.89	70.94	65.81	70.97	59.23	63.62	63.66	
<b>Ours:</b>												
VG-LAW	-	ViT-B	✗	75.05	77.36	71.69	66.61	70.30	58.14	65.36	65.13	
VG-LAW	-	ViT-B	✓	75.62	77.51	72.89	66.63	70.38	58.89	65.63	66.08	

Table 2. Comparison with state-of-the-art methods on RefCOCO [47], RefCOCO+ [47], and RefCOCOg [36] for RES task. The visual backbone is pre-trained on MS-COCO [28], where overlapping images of the val/test sets are excluded. \* represents ImageNet [21] pre-training. RN101, DN53, Swin-B, and ViT-B are shorthand for the ResNet101, DarkNet53, Swin-Transformer Base, and ViT Base, respectively. We highlight the best and second best performance in the red and blue colors.

remaining components is  $4e-4$ . The model is end-to-end optimized by AdamW [31] for 90 epochs with a batch size of 256, where weight decay is set to  $1e-4$ , and the learning rate is reduced by a factor of 10 after 60 epochs. Data augmentation operation includes random horizontal flips. We implement our framework using PyTorch and conduct experiments with NVIDIA A100 GPUs.

**Inference.** At inference time, the input image is resized to  $448 \times 448$ , and the maximum length of referring expressions is set to 40. Following the previous method [33], We set the threshold to 0.35 to realize the binarization of the RES prediction. Without any post-processing operation, our framework directly outputs bounding boxes and segmentation maps specified by referring expressions.

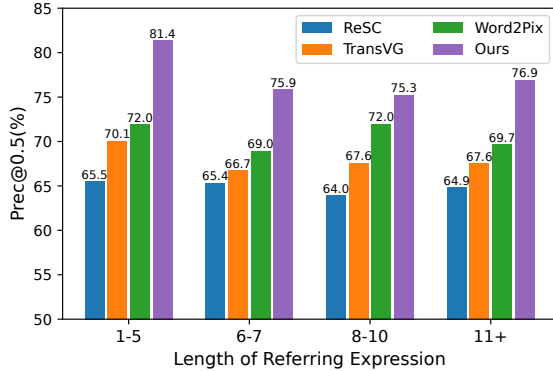


Figure 5. Comparison of accuracy under different lengths of referring expression on RefCOCOg-test. ReSC [42], TransVG [4], Word2Pix [48], and the proposed VG-LAW are compared.

### 4.3. Comparisons with State-of-the-art Methods

To estimate the effectiveness of the proposed VG-LAW framework, we conduct quantitative experiments on four widely used datasets, *i.e.*, RefCOCO [47], RefCOCO+ [47], RefCOCOg [34], and ReferItGame [19].

**REC Task.** For the REC task, we compare the performance with state-of-the-art REC methods, including the two-stage methods [2, 13, 30, 46], one-stage methods [26, 33, 42, 43, 49], and transformer-based methods [4, 12, 23, 45, 48, 50]. The main results are summarized to Tab. 1. It can be observed that VG-LAW achieves a significant performance improvement compared to the state-of-the-art two-stage method Ref-NMS [2] and one-stage method PLV-FPN [26]. When comparing to the transformer-based method QRNet [45], which modified the visual backbone by inserting language-aware spatial and channel attention modules, our method has better performance with +2.62%/ +3.47%/ +0.82% on RefCOCO, +3.43%/ +4.87%/ +3.69% on RefCOCO+, +5.01%/ +3.93% on RefCOCOg, and +2.61% on ReferItGame. QRNet [45] follows the TransVG [4] framework, both of which use the transformer encoder-based cross-modal interaction module. Compared to them, VG-LAW achieves better performance without complex cross-modal interaction modules. Furthermore, our method significantly outperforms MCN [33] and RefTR [23] based on joint training of REC and RES.

**RES Task.** For the RES task, we compare the performance with state-of-the-art methods [6, 17, 23, 32, 33, 44, 50], and the main results are summarized to Tab. 2. Compared with state-of-the-art RES method LAVT [44], VG-LAW achieves better *mIoU* with +1.16%/ +0.62%/ +1.95% on RefCOCO, +2.01%/ +2.42% on RefCOCOg, and comparable *mIoU* with +0.82%/ -0.59%/ -0.34% on RefCOCO+.

LAWG	LAP	MTH	Prec@0.5(%)
✓			74.89
	✓		74.37
✓	✓		76.60
✓	✓	✓	77.22

Table 3. Ablation experiments on ReferItGame [19] to evaluate the proposed language adaptive weight generation (LAWG), language adaptive pooling (LAP), and multi-task head (MTH).

When comparing the models trained with or without multi-task settings, it can also be observed that consistent performance gains are achieved across all the datasets and splits. As REC can provide localization information of the referred object, such coarse-grained supervision can slightly improve the segmentation accuracy in RES.

**Analysis of Referring Expression Length.** As the visual backbone in VG-LAW extracts features purely perceptually, it is of concern whether it can handle long and complex referring expressions. ReSC [42] reveals that one-stage methods may ignore detailed descriptions in complex referring expressions and lead to poor performance. Following that, we evaluate the REC performance on referring expressions of different lengths, as illustrated in Fig. 5. VG-LAW performs better than ReSC, TransVG [4] and Word2Pix [48], with no significant performance degradation when the length of referring expressions varies from 6-7 to 11+.

### 4.4. Ablation Analysis

To validate the effectiveness of our proposed modules, *i.e.* language-adaptive weight generation, language-adaptive pooling, and multi-task head, we conduct ablation experiments on the REC dataset of ReferItGame, which is summarized in Tab. 3. When only using the LAWG, the visual features are pooled with global average pooling, and when only using the LAP, the visual backbone has fixed architecture and weights. When only using the LAWG or the LAP, it can be observed that the model already achieves 74.89% and 74.37%, respectively, which is close to the 74.61% reported by QRNet [45]. When combined with the LAWG and LAP, further improvements can be brought by LAWG and LAP with +2.23% and +1.71%, respectively. Benefiting from the auxiliary supervision of RES, our model equipped with the multi-task head can localize the referred objects better and achieve 77.22%.

### 4.5. Qualitative Results

The qualitative results of the four datasets are shown in Fig. 6. It can be observed that our model can successfully locate and segment the referred objects, and the attention of



Figure 6. Qualitative results on the RefCOCO [47], RefCOCO+ [47], RefCOCOg [34], and ReferItGame [19] datasets. Each dataset shows two examples. From left to right: the input image, the ground truth of REC and RES, the prediction of VG-LAW, and the attention of the visual backbone with language-adaptive weights.

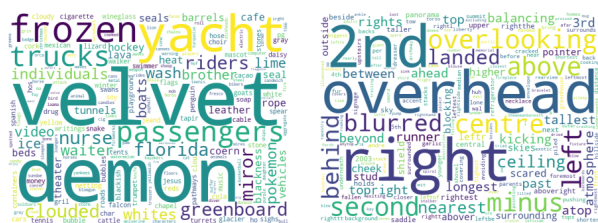


Figure 7. Wordcloud visualization of words assigned to the first and second halves of the visual backbone.

the visual backbone can focus on the most relevant image regions, demonstrating the effectiveness of using language adaptive weights. Taking the results on ReferItGame as an example, the visual backbone can dynamically filter out irrelevant regions for different expressions. For instance, when the “purple curtain” is referred to, the regions related to the “the painting/photo on the wall” are ignored.

In addition, we count the scores of words assigned to the first and second halves of the visual backbone, as shown in Fig. 7. The scores are calculated by averaging attention score  $\alpha_i$  in Eq. (1) for each word, followed by softmax normalization along the layer dimension. It can be observed that the shallow layers tend to the words describing individuals, such as the categories “velvet” and “yacht”, and the deep layers tend to the words about contexts, such as the ordinal number “2nd” and the position “right”.

## 5. Conclusions and Liminations

In this paper, we propose an active perception framework VG-LAW for visual grounding, based on the language adaptive weights. VG-LAW can directly inject the information of referring expressions into the weights of the visual backbone without modifying its architecture. Equipped with the proposed neat yet efficient multi-task head, VG-LAW achieves state-of-the-art performance for REC and RES tasks on widely used datasets. The limitations of our method are two-fold: (1) VG-LAW is weak in interpretability, and the entire reasoning process is implicit, which makes it difficult to understand how the reasoning process works, and (2) the multi-task head predicts one instance at a time, which limits its application in phrase grounding.

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