Towards Robust Referring Image Segmentation

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Abstract

Referring Image Segmentation (RIS) is a fundamental vision-language task that outputs object masks based on text descriptions. Many works have achieved considerable progress for RIS, including different fusion method designs. In this work, we explore an essential question, “What if the text description is wrong or misleading?” For example, the described objects are not in the image. We term such a sentence as a negative sentence. However, existing solutions for RIS cannot handle such a setting. To this end, we propose a new formulation of RIS, named Robust Referring Image Segmentation (R-RIS). It considers the negative sentence inputs besides the regular positive text inputs. To facilitate this new task, we create three R-RIS datasets by augmenting existing RIS datasets with negative sentences and propose new metrics to evaluate both types of inputs in a unified manner. Furthermore, we propose a new transformer-based model, called RefSegformer, with a token-based vision and language fusion module. Our design can be easily extended to our R-RIS setting by adding extra blank tokens. Our proposed RefSegformer achieves state-of-the-art results on both RIS and R-RIS datasets, establishing a solid baseline for both settings. Our project page is at https://github.com/jianzongwu/robust-ref-seg.

1. Introduction

Referring Image Segmentation (RIS) requires the model to output object masks in an image based on a given text expression. Many previous works [41, 38, 10, 12, 9, 60] have proposed various methods and achieved significant improvements in this field. There are also related works on video-level referring segmentation [22, 2, 54, 50, 34], which extend RIS to the temporal domain.

However, the RIS task assumes that the referred object always exists in the image. Under that concern, a RIS model only needs to locate and segment the objects without verifying whether the text description matches the image content. This may limit RIS models’ robustness and interpretability. Moreover, several works [14, 45, 47, 20, 67] explore the robustness and interpretability of vision models for image classification and segmentation. Motivated by that, we argue that a better RIS task should be able to handle both matching and mismatching image-text pairs.

In this work, we rethink the RIS setting by asking an essential question: “what are the segmentation results given a text description that refers to a non-existing object or even a wrong object?”. We argue that a robust RIS model should not output any masks for such text descriptions. However,
existing two-stage methods, e.g., MATTNet [62], acquire segmentation masks from an off-the-shelf image segmentation model and use the text description to select the best matching one, thus can not produce the correct result (no mask) for a reference that describes a non-existing object. One-stage methods [9, 60] also suffer from data bias (referred objects always exist). They tend to output masks even if no such object exists in the image. As shown in Fig. 1 (a), there are several failure cases for existing methods. A person is segmented as a cat, while a non-existing black hat man is also segmented as a false positive example.

To address these issues, we redefine the RIS task with a concept: Robust Referring Image Segmentation (R-RIS). It considers the cases where the given expression may refer to objects not in the images. As shown in Fig 1 (b), compared with the previous RIS, R-RIS requires the model to output blank masks for non-existing objects and regular masks for existing objects. Thus, the R-RIS covers both regular and noisy text inputs. To facilitate the R-RIS research, we build new R-RIS benchmarks based on the existing RIS datasets, including RefCOCO [63], RefCOCO+ [63], and RefCOCOg [43, 44]. In particular, we present five ways to generate false text descriptions, including randomly replacing sentences, replacing names, changing the target objects, changing the attributes, and changing the relationships. Moreover, we present two metrics: robust IoU (rIoU) and mean Robust Recall (mRR). The former measures the robustness and accuracy of R-RIS models at the pixel level, while the latter measures the instance-level robustness for negative text inputs.

To address the R-RIS task, a naive solution is to use a two-stage approach that combines a standard RIS model with an additional binary classifier to determine the existence of the referred object in the image. The model produces a mask only if the classifier predicts a positive result. However, this simple baseline, which relies on existing RIS models not tailored for negative inputs, performs poorly on the R-RIS task. To overcome this limitation, we propose RefSegformer, a transformer-based model designed explicitly for the R-RIS task and can serve as a strong baseline for future work.

We introduce RefSegformer, a Transformer-based model that consists of a language encoder, a vision encoder, and an encoder-fusion meta-architecture. The key component of our model is the Vision-Language Token Fusion (VLTF) module, which dynamically selects the most relevant language information using memory tokens and fuses it with the vision encoder using Multi-Head Cross Attention (MHCA). To handle the R-RIS task, we propose a blank token design to indicate the presence or absence of the referred object in the image. The blank tokens are not involved in the MHCA fusion with language inputs, thus avoiding the over-fitting to either positive or negative inputs. RefSegformer achieves state-of-the-art results on both RIS and R-RIS datasets. We conduct extensive experiments and analyses to demonstrate the effectiveness of RefSegformer.

Our main contributions are summarized as follows:

- We introduce the R-RIS task, the first robust-based RIS, which extends the RIS task to account for the possibility of incorrect referring expressions.
- We construct three benchmarks for the R-RIS task and propose new metrics to evaluate R-RIS models. We also benchmark five baseline methods for R-RIS.
- We develop RefSegformer, a Transformer-based model incorporating VLTF modules specially designed for the R-RIS task.
- RefSegformer achieves state-of-the-art performance on six datasets from both RIS and R-RIS tasks, demonstrating its effectiveness and robustness.

2. Related Work

Referring Image Segmentation. This task aims to segment an object that matches a given reference expression. There are mainly two approaches: decoder-fusion and encoder-fusion. The former [62, 38, 42, 59, 41, 9, 53, 17, 18] extracts vision and language features separately and fuses them in a multi-modal decoder. For instance, MAttNet [62] uses a two-stage framework that first generates candidate proposals using a Mask R-CNN model [15], then selects the most relevant one based on the linguistic feature of the expression. CMPC [38] adopts a progressive strategy based on informative words in the expression. The encoder fusion approaches [12, 60, 32, 33] fuse language features into vision features early in the vision encoder, which is more prevalent in recent works. Specifically, EFN [12] transforms a CNN backbone into a multi-modal network that uses language to refine the multi-modal features. LAVT [60], inspired by the success of vision Transformers, designs pixel-word attention and a language pathway module to fuse linguistic features into a vision Transformer backbone and adopt various feature fusion methods [39, 11, 56, 29, 31, 28] in the encoder stage. To summarize, the vision and language encoders can have different designs. However, a common assumption is that the text description refers to an object in the image. In this paper, we challenge this assumption and introduce a new R-RIS task, which requires models to handle both positive and negative information effectively in a more realistic and difficult setting.

Robustness In Segmentation and Classification. Robustness studies on CNNs have been conducted in various benchmarks [14, 45]. Recent works also investigated how to evaluate and improve the robustness of CNNs against different weather conditions [4, 48, 49], and proposed other
word generation.

**Motivation and Concepts.** To evaluate our R-RIS model, we create datasets that contain negative referring expressions, which are text descriptions of objects that do not exist or are incorrectly described in the image. The default RIS expressions are positive sentences. Given an input image with a negative sentence as the referring expression, an R-RIS model is expected to output an empty mask, which indicates that no object matches the description.

**Generating Negative Sentences.** We propose five different methods to generate negative sentences. We describe these methods in detail below:

1. **Randomly select a sentence from another reference in the RIS dataset that does not describe any object in the image.** Since all the images come from COCO dataset [35], we use COCO annotations to filter out sentences that match any of the object categories in the image. However, some sentences are too vague to be filtered out, such as “Left one”, “Second from left”, or “The black”. These sentences may refer to different objects depending on the image context. To avoid these false negative sentences, we create a list of vague words and exclude sentences that only contain words from this list.

2. **Randomly choose a category name in COCO as a target object.** We ensure the image does not contain any object of this category by using the COCO annotations.

3. **Replace the target object in the positive sentence with a randomly chosen category name.** For example, “Man in the left” becomes “Cat in the left” while there is no cat in the image. We use the Natural Language Toolkit (NLTK) to identify nouns in positive sentences and take the first noun as the target object.

4. **Change adjective words of the target object.** For example, “Man in blue hat” becomes “Man in black hat”. We mainly focus on two types of adjective words: positions and colors, the most common features mentioned in the referring expressions. If the original positive sentence does not have adjective words, we add a random position and color for them.

5. **Change the related objects of the target object.** For example, the original sentence is “Man standing”. We transform the sentence to “Man standing left to the cat” to add some constraints to this object by adding a related object. We use COCO annotations to check the existence of the related object, as in the methods above. If the original sentence has two or more nouns, we use the first noun as the target object and change the second to a different, non-exist category name.

**Visual Example.** Fig. 2 shows a visual example of the...
We build our benchmark based on existing RIS datasets. Specifically, we expand RefCOCO [63], RefCOCO+ [43], and RefCOCOg [44] to form R-RefCOCO, R-RefCOCO+, and R-RefCOCOg. As negative sentences are not limited in number (non-existing objects can be anything), we generate negative sentences as many as possible. In detail, for each reference, we generate ten negative sentences by default. Tab. 1 summarizes the statistics of the datasets.

**Proposed R-RIS Datasets.** We build our benchmark based on existing RIS datasets. Specifically, we expand RefCOCO [63], RefCOCO+ [43], and RefCOCOg [44] to form R-RefCOCO, R-RefCOCO+, and R-RefCOCOg. As negative sentences are not limited in number (non-existing objects can be anything), we generate negative sentences as many as possible. In detail, for each reference, we generate ten negative sentences by default.

**New Metrics.** The existing RIS setting adopts Intersection over Union (IoU) metrics such as mean IoU (mIoU) and overall IoU (oIoU) to evaluate the pixel-level performance. However, they are inadequate in handling negative inputs. Therefore, it is necessary to establish appropriate metrics to validate the R-RIS model’s performance.

We propose robust Intersection over Union (rIoU) to consider the negative input jointly. In both RIS and R-RIS settings, data are sampled by reference. Each reference consists of one image, several positive referring expressions, and multiple negative inputs (take R-RIS for examples). Supposing the $i$-th reference $R_i$ has $p_i$ positive sentences and $n_i$ negative sentences, an R-RIS model predicts masks for these language inputs. It gets $M_i = \{\hat{m}_{i1}, \hat{m}_{i2}, ..., \hat{m}_{ip_i}, \hat{m}_{i1}, \hat{m}_{i2}, ..., \hat{m}_{in_i}\}$. There are ground-truth masks $M_i = \{m_{i1}, m_{i2}, ..., m_{ip_i}\}$ for positive inputs. rIoU is calculated as follows:

$$\text{rIoU} = \frac{1}{|R|} \sum_{i=1}^{|R|} \frac{\sum_{j=1}^{p_i} |\hat{m}_{ij} \cap m_{ij}|}{\sum_{j=1}^{p_i} |\hat{m}_{ij} \cup m_{ij}| + \sum_{k=1}^{n_i} |\hat{m}_{ik}|}$$

where $|R|$ represents number of references in the validation set, and $|m|$ denotes the number of pixels in mask $m$. $\cap$ and $\cup$ refer to the intersection and union operations. However, the denominator includes the mask predicted by the model for negative inputs, which can also be expressed as $|\hat{m}_{ik} \cup \emptyset|$ since the ground truth for negative inputs is always $\emptyset$. This aspect treats the mask predicted for negative inputs as the union component, thereby penalizing the model for incorrect outputs for negative inputs. Figure 3 illustrates the rIoU metric.

Despite rIoU being a metric for R-RIS, there is a need for a more precise assessment of the model’s discriminative ability on negative inputs. In most cases, an R-RIS model is expected to generate small masks for negative inputs and an exact 0-pixel mask, indicating no mask. Therefore, we adopt an instance-level metric, mean Robust Recall (mRR), to evaluate the R-RIS model’s performance.

For the input reference $R_i$, the Robust Recall is computed as $\text{RR}_i = \frac{1}{n_i} \sum_{k=1}^{n_i} \mathbb{1}(\hat{m}_{ik} = 0)$, where $\mathbb{1}(\cdot)$ is the indicator function, which equals 1 if the input is an exact 0-pixel mask and 0 otherwise. mRR is then defined as the mean RR across all references in the validation set, as shown below:

$$\text{mRR} = \frac{1}{|R|} \sum_{i=1}^{|R|} \text{RR}_i .$$

Since R-RIS is still a pixel-level prediction task, we use rIoU as the main metric. Moreover, only using mRR can not well judge the extreme cases where the R-RIS models treat all inputs as negative examples.

### 4. Method

In this section, we provide a detailed account of the RefSegformer. Initially, we introduce a two-stage baseline for the R-RIS task and subsequently delve into the architecture of RefSegformer. The proposed model incorporates a novel module called Vision-Language Token Fusion (VLTF). To better handle the R-RIS task, our framework also introduces a negative token modeling technique, which offers a simple yet effective baseline for R-RIS.

#### 4.1. RefSegformer Architecture

**Two-Stage Baseline.** To tackle the R-RIS task, it is intuitive to develop a two-stage model that integrates a standard RIS model and an extra binary classifier to verify whether the referring expression is correct. The model generates a mask only when the classification result is true. Drawing
inspiration from prior studies [12, 60], we establish our RefSegformer from a two-stage baseline by fusing vision and language features early in the encoding stage. **Encoder Fusion Framework.** Given input containing a pair of an image and a referring expression, we leverage a language encoder [8] to extract the features of the expression, denoted as $L \in \mathbb{R}^{T \times C_L}$, where $T$ is the number of words, and $C_L$ is the number of channels. These language features are inserted into the vision encoder and fused with vision features through our proposed Vision-Language Token Fusion module (VLTF) between each vision stage. Specifically, we adopt Swin Transformer [39] as our vision encoder. The four stages of the vision encoder are denoted as $\{v_i|i \in \{1, 2, 3, 4\}\}$, while VLTF modules are $\{f_i|i \in \{2, 3, 4\}\}$. The whole encoding process can be formulated as follows:

$$\begin{align*}
V_1 &= v_1(I) \\
V_2 &= v_2(V_1) \\
F_i &= f_i(V_i, L), i \in \{2, 3, 4\} \\
V_i &= V_{i-1} + \sigma(F_i), i \in \{3, 4\},
\end{align*}$$

(3)

where $I$ denotes the input image, $\{V_i|i \in \{1, 2, 3, 4\}\}$ represents vision features from four stages in Swin Transformer, and $\{F_i|i \in \{2, 3, 4\}\}$ denotes the fused multi-modal features. $\sigma$ is a normalization function. Following each stage in Swin Transformer, except for stage 1, a VLTF module combines vision and language features, fusing them to obtain a multi-modal feature $F_i$. Subsequently, the multi-modal feature is fed as input to the next stage. Ultimately, we obtain three hierarchical multi-modal features $\{F_i|i \in \{2, 3, 4\}\}$ and one vision feature $V_4$ with high resolution, which we feed into an FPN-like decoder to extract the hierarchical mask features. We utilize a stack of $1 \times 1$ convolution layers to produce the final mask.

**FPN-like Decoder.** To generate the final masks, we use an FPN-like decoder that takes the hierarchical features of $V_1$ and $\{F_i|i \in \{2, 3, 4\}\}$ as input. The decoder outputs $\{S_i|i \in \{1, 2, 3, 4\}\}$, which are then passed to $1 \times 1$ convolutional layers, separately, to obtain coarse-to-fine segmentation masks.

$$\begin{align*}
S &= \phi(V_1, F_2, F_3, F_4) \\
M &= \rho(S_i), i \in \{1, 2, 3, 4\},
\end{align*}$$

(4)

where $S = \{S_i|i \in \{1, 2, 3, 4\}\}$ represents the segmentation features, $M = \{M_i|i \in \{1, 2, 3, 4\}\}$ represents the hierarchical output masks, $\phi$ denotes the FPN-like decoder, and $\rho$ denotes the $1 \times 1$ convolutions that project the segmentation features into two-dimensional mask score maps. Finally, we calculate the cross-entropy loss, shown as follows:

$$L_s = \text{CELoss}(y, M_1) + \lambda \cdot \sum_{i=2}^{4} \text{CELoss}(y, M_i),$$

(5)

where $\lambda$ is a hyperparameter between 0 and 1 that reduces the impact of coarse-grained masks.

**Binary Classification Head.** We add a binary classification head upon the outputs of the FPN-like decoder and the tokens from a VLTF module. Specifically, we utilize the mask feature $M_1$ with the highest resolution to interact with the conditional and blank tokens from the last VLTF using an MHCA. Subsequently, we feed the output into a linear layer and obtain the predicted probability of the existence:

$$\hat{c} = \mu(\text{MHCA}(M_1, T_4, T_4)),$$

(6)

where $T_4$ refers to the tokens from the last VLTF module, and $\mu$ denotes a linear layer. By default, $M_1$ is used as the query, while $T_4$ serves as the key and value. In our experiments, we test the opposite approach and find that using the high-resolution features as the query yield superior results.
An additional existing loss is applied to optimize the binary classification head.

\[ L_c = (e \log(\hat{e}) + (1 - e) \log(1 - \hat{e})) \]

where \( e \) is the ground truth about the existence of the referred object. Finally, the complete loss function in our training procedure for the R-RIS task is:

\[ L = L_s + \gamma \cdot L_c, \]

where \( \gamma \) is a hyperparameter balancing segmentation loss and existing loss. We set \( \gamma \) to 1.0 in our experiments.

### 4.2. Vision-Language Token Fusion Module

As shown in Fig 4(b), the Vision-Language Token Fusion module (VLTF) is the key component for RefSegformer. It contains several attention operations to fuse vision and language features via learnable memory tokens.

Given an input vision feature \( V_i \in \mathbb{R}^{N \times HW \times C_v} \) of stage \( i \) and language feature \( L \in \mathbb{R}^{N \times F \times C_l} \), we first transform them into a common dimension \( C_i \) using two separate \( 1 \times 1 \) convolution layers. The transformed vision and language features are then passed through an MHCA module, with the language features serving as the query and the vision features as key and value. This process produces a vision-aware language-shaped feature. We then introduce a set of randomly initialized vectors known as memory tokens to perform the second MHCA operation. This results in the generation of conditional tokens, which contain multi-modal information. The conditional tokens are further processed using the third MHCA module and the transformed vision features. At this time, the transformed vision features serve as the query, projecting the language information into the vision features. Finally, through a \( 1 \times 1 \) convolution, the output feature of VLTF is of the same shape as the input vision features but is now fused with the information of language, resulting in a multi-modal fused feature. Unlike previous works [12, 60] that adopt pixel-wised cross-modal attention, our framework adopts memory tokens to dynamically select relevant language information, which is flexible to extend into the R-RIS setting.

### 4.3. Extension to Robust Referring Segmentation

#### Blank Tokens Design.

In the second MHCA of VLTF, it takes randomly initialized memory tokens and vision-aware language-shaped features as input and outputs a set of vectors \( T_{ic} \in \mathbb{R}^{N \times K \times C_l} \). We call them conditional tokens.

To further handle the R-RIS task, we use a new set of blank tokens, represented as \( T_{ic} \in \mathbb{R}^{N \times K \times C_l} \). These blank tokens are concatenated with the set of conditional tokens \( T_{ic} \), as depicted in Fig 4(b). Notably, the blank tokens are randomly initialized and are not fused with the language features. When fed to the third MHCA, the blank tokens interact with vision features and are expected to attend to linguistically unrelated regions. This approach effectively decouples the effectiveness of conditional and blank tokens, enabling the former to learn the alignments between vision and language, while the latter serves as an unrelated linguistic learner. Thus expanding our model to the R-RIS task.

### R-RIS Training Pipeline

We train the R-RIS models by adding negative sentences into the training set. The model is trained to learn to distinguish them by setting the ground-truth segmentation mask of negative sentences to all-0. We set the ratio between positive and negative sentences to 1:1. Our proposed training pipeline requires no changes to most RIS models’ architecture or loss functions, making it a straightforward and practical solution for R-RIS model training.

### 5. Experiment

#### 5.1. Dataset and Settings

**Dataset and Metrics** We build our benchmark based on three standard RIS datasets, RefCOCO [63], RefCOCO+ [63], and RefCOCOg [43, 44], formulating R-RefCOCO, R-RefCOCO+, and R-RefCOCOg. We abandon the words about absolute positions when generating R-RefCOCO+ following [63]. We conduct our robust benchmark on the UNC/UMD partitions and target only the validation set. The three robust validation sets can be called as ‘rval’ set if referred to in future works. For our proposed R-RIS setting, we adopt robust Intersection-over-Union (rIoU) and mean Robust Recall (mRR) as the main metrics. In addition, we report standard metrics, including mean intersection-over-union (mIoU), overall intersection-over-union (oIoU), and precision at the different thresholds. Precision means the percentage of test samples that IoU number is higher than the threshold.

**Implementation Details.** We use PyTorch to implement our model. The language encoder is an officially pre-trained BERT model [8]. For the vision encoder, we adopt Swin Transformer [39] as the architecture and initialize it with the pre-trained weights on ImageNet [7]. Other modules, such as VLTF and the segmentation decoder, are trained from scratch. We set the hyperparameter \( \lambda \) to 0.4. The numbers of conditional and blank tokens are set to 20 and 10, respectively. The maximum length of input referring expressions is set to 20 for all datasets. We use the AdamW
optimizer [40] with a weight decay of 0.02. The learning rate is initialized as 3e-5 and scheduled by polynomial learning rate decay with a power of 0.9. Following [23, 60], input images are resized to 480x480 without any other data augmentations. All the models are trained for 50 epochs with batch size 64 on 8 Nvidia RTX-3090 GPUs.

5.2. Benchmark Results

Results on R-RIS datasets. We benchmark five different methods on our proposed datasets using the same training setting for a fair comparison. Tab. 2 presents the results of the R-RIS task for RefSegFormer and these models, including CRIS [53], EFN [12], VLT [9], LAVT [60] and LAVT+ [60]. We denote LAVT+ as LAVT [60] combined with our binary classification head, which is a strong baseline for reference. All models are trained using the pipeline described in Sec. 4.3. RefSegFormer outperforms all baseline models in our proposed rIoU metric. Furthermore, compared to most baseline models, RefSegFormer achieves a better balance between mIoU and the mean Robust Recall mRR. Although LAVT+ performs well in mRR, it still has much lower rIoU. This is because the model cannot effectively disentangle between positive and negative inputs, leading to a trivial output of mostly negative. That means all examples may be negative ones. We will provide more examples in the appendix. In contrast, our method can achieve much better results (6% rIoU better than LAVT+) to balance both positive and negative inputs.

Results on RIS datasets. We further present the performance of RefSegFormer in the regular RIS task. As depicted in Tab. 3, although RefSegFormer is primarily designed to excel in the proposed R-RIS task, without further extra design, it achieves strong performance in regular RIS as well. Notably, our method achieves eight out of nine best results on these datasets without specific modifications. RefSegFormer outperforms the previous state-of-the-art method, LAVT [60]. The most notable improvement of 1.38 is observed in the val split of RefCOCO+. An average improvement of 0.43 is achieved across all nine validation sets. This result underlines the exceptional generalization ability of RefSegformer.

5.3. Ablation Study and Analysis

Blank Tokens Design. We investigate the impact of blank tokens on the performance of VLTF. We conduct experiments by training our model with 0, 5, and 10 blank tokens and report the results in Tab. 4. Compared to the no blank tokens setting, the default setting of RefSegFormer, which uses 10 blank tokens, yields an improvement of 4.07 total points in rIoU. Increasing the number of blank tokens from 0 to 5 also improves rIoU by 3.54, and increasing it to 10 results in the most significant effect.

Binary Classification Head. We discuss the importance of the binary classification head in RefSegformer for the R-RIS task. As shown in Tab. 2, when without this explicit exist-or-not classification head, the performance experiences a significant drop with an average decay point around 6. Once added, the model’s performance significantly improves, regardless of whether we input tokens or vision features as the query. This result underscores the importance of explicitly predicting whether the referred object occurs in the image. Moreover, our experiments demonstrate that vision features outperform tokens in all settings for choosing MHCA input queries. This result is because a multi-modal fused feature map contains richer information than a set of embeddings.

Effectiveness of VLTF. We evaluate the effectiveness of the VLTF module in RefSegformer. We vary the number of VLTF modules and show the results in Tab. 5. Our experiments demonstrate that the model’s performance decreases as we use fewer VLTFs, indicating that the proposed multi-modal fusion network on multi-stage is essential and effective for the R-RIS task. Specifically, the performance declines from 46.08 to 39.40 in terms of rIoU when using only one VLTF module, while the performance drops from 46.08 to 43.33 when using two VLTF modules.

Number of Memory Tokens. We explore the number of memory tokens for the RIS dataset. When increasing the number of memory tokens in VLTF, the oIoU metrics increase initially and then become saturated. This is because the relevant language semantics are limited in the RIS dataset. We choose \( K_c = 20 \) as the default setting.

Deformable FPN and Text Prompt. To generate more precise results, we adopt the recently proposed deformable pixel decoder [68] to decode the multi-modal features \( F \) dynamically. By comparing with the plain FPN architecture, we improve 1.2% in oIoU, as demonstrated in Tab. 6. Moreover, we utilize prompting methods by concatenating multiple referring expressions into one sentence [37]. For example, “woman on the right”, and “woman in black” are concatenated as “woman on the right woman in black”. As shown in Tab. 6, text prompt leads to a significant increase of 3.7 in the oIoU value, albeit with a decreased precision.
Table 3: Comparison with state-of-the-art methods in RIS task. U: The UMD partition. G: The Google partition. We refer to the language model of each reference method. * means with text prompt.

| Method          | Language Model | RefCOCO  | RefCOCO+ | RefCOCOg |
|-----------------|----------------|----------|----------|----------|
|                | val | test A | test B | val | test A | test B | val (U) | test (U) | val (G) |
| MAttNet [62]    | Bi-LSTM | 56.51 | 62.37 | 51.70 | 46.67 | 32.39 | 40.08 | 47.64 | 48.61 |
| CMSA [61]       | None | 58.32 | 60.61 | 55.09 | 43.76 | 47.60 | 37.89 | - | - |
| CAC [3]         | Bi-LSTM | 58.90 | 61.77 | 53.81 | - | - | - | 46.37 | 46.95 |
| LSCM [17]       | LSTM | 61.47 | 64.99 | 59.55 | 49.34 | 53.12 | 43.50 | - | - |
| CMP+ [38]       | LSTM | 62.47 | 65.08 | 60.82 | 50.25 | 54.04 | 43.47 | - | - |
| MCN [12]        | Bi-GRU | 62.44 | 64.20 | 59.71 | 50.62 | 54.99 | 44.69 | 49.22 | 49.40 |
| EFN [32]        | Bi-GRU | 62.76 | 65.69 | 56.67 | 51.50 | 55.24 | 43.01 | - | - |
| BUSNet [59]     | Self-Att | 63.27 | 66.41 | 61.39 | 51.76 | 56.87 | 44.13 | - | - |
| CGAN [44]       | Bi-GRU | 64.86 | 68.04 | 62.07 | 51.03 | 55.51 | 44.06 | 51.01 | 51.69 |
| ISFP [36]       | Bi-GRU | 65.19 | 68.45 | 62.73 | 52.70 | 56.77 | 46.39 | 52.67 | 53.00 |
| LTS [19]        | Bi-GRU | 65.43 | 67.76 | 63.08 | 54.21 | 58.32 | 48.02 | 54.40 | 54.25 |
| VLT [9]         | Bi-GRU | 65.65 | 68.29 | 62.73 | 55.50 | 59.20 | 49.36 | 52.99 | 56.65 |
| ReSTR [23]      | Transformer | 67.22 | 69.30 | 64.45 | 55.78 | 60.44 | 48.27 | 54.48 | - |
| CRIS [53]       | Transformer | 70.47 | 73.18 | 66.10 | 62.27 | 68.08 | 53.68 | 59.87 | 60.36 |
| LAVT [60]       | BERT | 72.73 | 75.82 | 68.79 | 62.14 | 68.38 | 55.10 | 61.24 | 62.09 |
| RefSegformer*   | BERT | 73.22 | 75.64 | 70.09 | 63.50 | 68.69 | 55.44 | 62.56 | 63.07 |
| RefSegformer    | BERT | 76.92 | 79.31 | 74.25 | 63.69 | 69.24 | 55.91 | 62.19 | 62.42 |

Table 4: Ablation studies on the R-RefCOCO dataset for R-RIS. In the second column, “None” means without binary classification head, “T” means VLTF tokens as the query, and “V” means vision features as the query.

| # Blank Tokens | Binary Head | mlOu | eloU | mRR | rloU | GFLOPs | Params |
|----------------|-------------|------|------|-----|------|--------|--------|
| 0              | None        | 69.52 | 70.25 | 58.50 | 31.67 |        |        |
|                | T           | 69.57 | 70.29 | 68.63 | 38.10 |        |        |
|                | V           | 68.96 | 70.38 | 62.01 |      |        |        |
| 5              | None        | 70.14 | 70.66 | 58.46 | 35.40 |        |        |
|                | T           | 69.01 | 69.93 | 60.57 | 41.81 |        |        |
|                | V           | 68.93 | 69.35 | 70.86 | 45.65 |        |        |
| 10             | None        | 70.50 | 70.63 | 58.80 | 38.78 |        |        |
|                | T           | 69.01 | 69.26 | 68.40 | 44.12 |        |        |
|                | V           | 68.78 | 69.78 | 73.73 |      |        |        |

Table 5: Ablation study on the effectiveness and computational cost of VLQFs.

| # VLQFs | mlOu | eloU | mRR | rloU | GFLOPs | Params |
|---------|------|------|-----|------|--------|--------|
| 1       | 68.33 | 68.46 | 72.90 | 43.33 | 130.40 | 233.27M |
| 2       | 68.78 | 69.78 | 73.73 | 46.08 | 132.86 | 234.39M |

Table 6: Ablations about components of RefSegFormer for RIS task. Evaluated in val split, RefCOCO dataset.

| Deformable FPN | Text Prompt | P@0.5 | P@0.7 | P@0.9 | eloU |
|----------------|-------------|-------|-------|-------|------|
| ✓              |             | 90.71 | 84.42 | 68.76 | 72.02 |
| ✓              | ✓           | 91.66 | 87.05 | 71.40 | 73.22 |
| ✓              | ✓           | 87.84 | 76.73 | 38.57 | 76.92 |

This is because adding more text can improve recognition ability while decreasing localization ability since more localization text noises become the inputs.

**GFLOPs and Parameter Analysis.** To analyze the computational cost of RefSegformer, we evaluate the GFLOPs and parameters at varying numbers of VLQFs, as presented in Tab. 5. We observe that as the number of VLQFs increases from 1 to 3, the GFLOPs show a slight increment of 5%. Similarly, the parameters increase by 4.2M. Nevertheless, these increases are negligible compared to the overall computational cost of the model.

**Visualization Analysis.** Fig. 6 (a) shows RefSegformer can perform correct segmentation results given various language expressions. In Fig. 6 (b) and (c), we visualize the attention maps between conditional/blank tokens and the visual features for positive sentences. (c) Attention maps for negative sentences.

![Image-token attention visualization](image-url)
6. Conclusion

We propose a novel task called Robust Referring Image Segmentation (R-RIS), which takes both positive and negative text inputs into consideration to achieve a robust and explainable machine learning approach. To build robust referring image segmentation datasets, five different ways of selecting negative texts have been presented. We also introduce new metrics, named rIoU and mRR, that effectively evaluate the R-RIS models. In order to solve the R-RIS problem, we propose a transformer-based baseline, RefSegformer. It connects the image and text features through learnable tokens, and the token-based approach can be easily extended to R-RIS by adding blank tokens. The proposed RefSegformer achieves state-of-the-art results on both RIS datasets and R-RIS datasets, thereby serving as a new baseline for future research in this area. We believe these works will inspire further studies in this field.

Future Works. Two potential research directions on R-RIS can be: 1, train only one model for both R-RIS and RIS settings. 2, a better model to balance mRR and rIoU.

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A. Appendix

Overview As mentioned in the main paper, we provide the following parts: 1, More building benchmark details. 2, More implementation details. 3, More ablation studies and comparative analysis of the proposed baseline RefSegformer, including more comparison, visual examples, and analysis. 4, Comparison with recent co-current work, R2VOS [25].

Table 7: Five approaches to generate negative sentences and the test results of a state-of-the-art RIS model [60]. The mask ratio is the average size of the output masks over the entire image. “Origin” means the results on the origin RIS dataset.

| Method       | Description                          | Mask Ratio |
|--------------|--------------------------------------|------------|
| Sentence     | Replace the entire sentence with another sentence | 7.93       |
| Category     | Replace the entire sentence with a random category name | 11.37      |
| Target Obj.  | Replace the target object with a random category name | 9.48       |
| Attribute    | Change the attribute words of the target object | 9.64       |
| Relation Obj.| Change the relation object            | 10.26      |
| Origin       | No negative sentence                  | 10.97      |

Table 7: Five approaches to generate negative sentences and the test results of a state-of-the-art RIS model [60]. The mask ratio is the average size of the output masks over the entire image. “Origin” means the results on the origin RIS dataset.

Figure 8: An example of text prompt in evaluation for illustration.

A.1. More Benchmark Details

RIS Model on Negative Sentences. We conduct an experiment that uses a previous model [60] trained on the RIS datasets for the evaluation of negative sentences. We report the average size of the output masks over the size of the whole image. Tab. 7 shows LAVT outputs masks with an average of around 1/10 of the image size for the RIS task, originally. When given negative sentences as input, the ratios decrease slightly. For the “Category” generation method, the number is even higher. The results demonstrate that a RIS model trained only with positive sentences cannot be directly transferred to the proposed R-RIS task.

A.2. More Implementation Details

Text Prompt. In RefCOCO+/+/g, there are usually several sentences describing the same object in an image. As shown in Fig. 8, a zebra can be described in three different sentences. When evaluating the traditional RIS task, we propose a setting called ‘with prompt.’ The details are also shown in Fig. 8. Instead of evaluating the same reference several times with three sentences and averaging the IoU value for the final metric, we alternatively concatenate all three sentences into one long sentence (bottom in Fig. 8). Doing so can reduce the validating time because the model only needs to forward once for one reference. At the same time, we observe a result increase in the final oIoU metric (See Sec. 5). That is probably because a concatenated
A.4. Comparison With R2VOS

In this section, we present the differences between our proposed R-RIS task and the recent R2VOS [25] work, which proposes a robust setting for video referring segmentation.

**Different Settings.** Unlike our proposed R-RIS, which is an extension on Referring Image Segmentation, R2VOS proposes a robust setting upon Referring Video Segmentation. The two tasks share certain similarities because they both focus on the problem that referring expressions may describe objects not existing in the image. However, the two tasks have no intersections since one is applied on the image level, while another is on the video level, like Referring Image Segmentation and Referring Video Segmentation. Moreover, our method is a generalized RIS task and mainly focus on the robustness of current RIS models.

**Different Datasets.** We build three validation datasets, in-cluding R-RefCOCO, R-RefCOCO+, and R-RefCOCOg, to evaluate an R-RIS model’s performance. Each is built upon existing RIS datasets (RefCOCO, etc.) along with carefully generated negative sentences as negative inputs. We believe a dataset that contains multiple negative sentences for one reference can better test the robust ability of an R-RIS model. Thus, we generate 10 negative sentences for each reference, using a total of 5 generating methods (Details are in Sec. A.3). In R2VOS, the proposed model is validated on the original RVOS datasets, with only one negative sentence added per reference. The negative sentence is obtained by shuffling the original video set and constraining all negative text-video pairs unrelated, which is close to the “Sentence” method of our generating methods.

**Different Metric.** We propose two evaluation metrics for R-RIS, named rIoU and mRR. The rIoU metric measures the mask outputs of positive and negative sentences at the same time, and the mRR metric describes instance-level results of an R-RIS model. R2VOS introduces its metric for its task, named R. \[ R = 1 - \frac{\sum_{M \in V_{neg}} |M|}{\sum_{M \in V_{pos}} |M|} \]

According to the formula, \( R \) becomes bigger when the model predicts smaller masks for the negative inputs compared to the positive inputs. It measures the robustness but can not measure the segmentation quality for positive inputs.

**Table 8**: Comparison between our proposed multi-modal fusion module VLTF and PWAN + LP in LAVT [60]. Both modules are applied in RefSegformer.

| fusion module | mIoU | oIoU | mRR | rIoU |
|---------------|------|------|-----|------|
| VLTF          | 68.78| 66.30| 73.73| 46.08|
| PWAN + LP     | 69.72| 70.40| 66.58| 44.58|

Table 8: Comparison between our proposed multi-modal fusion module VLTF and PWAN + LP in LAVT [60]. Both modules are applied in RefSegformer.

Figure 9: Visualization comparison between RefSegformer and EFN [12]. All the expressions are positive.

long sentence contains more information than a separate one does individually.

**A.3. More Experimental Results**

**Comparison of fusion modules with LAVT.** We compare VLTF with PWAN + LP (LAVT [60]) in the architecture of RefSegformer. Results are shown in Tab. 8. RefSegformer adopting PWAN + LP achieves higher mIoU and oIoU metrics, while RefSegformer with VLTF module is higher in the mRR and rIoU metric. The reason is VLTF module contains blank tokens that do not interact with text features, thus dis-entangling the identification of positive and negative inputs. The results demonstrate VLTF is more suitable than PWAN + LP for the proposed R-RIS task.

**Visualization Comparison with EFN.** We present visualization results and compare the proposed RefSegformer with a previous work, EFN [12]. Fig. 9 shows that the EFN model predicts no masks for positive sentence inputs, while RefSegformer predicts correct outputs. Both models are trained in the R-RIS task with negative inputs. EFN does not have modules designed specifically for the R-RIS task, thus the negative training samples harm the original architecture for the aligning of visual and linguistic features.

**More Visual Results.** We present more visualization results in Fig. 10. Our proposed RefSegformer can segment correct masks in RIS while identifying which sentence is wrong in R-RIS.

**Failure Cases Analysis.** We visualize some failure cases in Fig. 11. For negative inputs, when the object described by the input sentence is close to the objects in the image, the R-RIS model may incorrectly output masks. For example, in Fig. 11, “zebra” is identified as a “swan”, and “sandwich” is considered as a piece of “pizza”. For positive sentences, if the expressions are too complicated and contain infrequently used words like “bottom left station wagon out of picture frame”, the model tends to output no masks, i.e., takes the input as negative. These results indicate that a better R-RIS model should be less sensitive to the localization words and more robust to the concepts with the similar shapes for the negative sentence.

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Figure 10: Visualization results of RefSegformer. Sentences in italics are negative sentences.

Figure 11: Visualization of failure cases.
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