

Real-Time Referring Expression Comprehension by Single-Stage Grounding Network

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Abstract

In this paper, we propose a novel end-to-end model, namely Single-Stage Grounding network (SSG), to localize the referent given a referring expression within an image. Different from previous multi-stage models which rely on object proposals or detected regions, our proposed model aims to comprehend a referring expression through one single stage without resorting to region proposals as well as the subsequent region-wise feature extraction. Specifically, a multimodal interactor is proposed to summarize the local region features regarding the referring expression attentively. Subsequently, a grounder is proposed to localize the referring expression within the given image directly. For further improving the localization accuracy, a guided attention mechanism is proposed to enforce the grounder to focus on the central region of the referent. Moreover, by exploiting and predicting visual attribute information, the grounder can further distinguish the referent objects within an image and thereby improve the model performance. Experiments on RefCOCO, RefCOCO+, and RefCOCOg datasets demonstrate that our proposed SSG without relying on any region proposals can achieve comparable performance with other advanced models. Furthermore, our SSG outperforms the previous models and achieves the state-of-art performance on the ReferItGame dataset. More importantly, our SSG is time efficient and can ground a referring expression in a 416×416 image from the RefCOCO dataset in 25ms (40 referents per second) on average with a Nvidia Tesla P40, accomplishing more than 9 \times speedups over the existing multi-stage models.

1. Introduction

The referring expression comprehension [32, 33, 34, 35], also known as referring expression grounding, is a fun-

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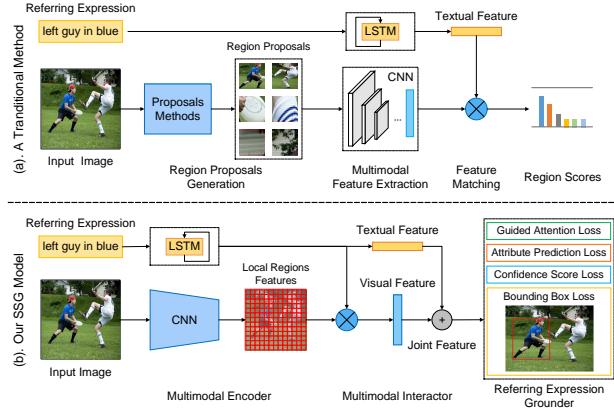


Figure 1. A comparison between our SSG model and a traditional multi-stage method. By completely discarding the region proposal generation stage and directly predicting the bounding box for the referring expression, our SSG model runs faster by design.

damental research problem which has received increasing attention from both computer vision and natural language processing research communities. Given an image as well as a referring expression, which describes a specific referent within the image, the referring expression comprehension aims to localize the referent corresponding to the semantic meaning of the referring expression. This is a general-purpose yet challenging vision plus language task, since it requires not only localization of the referent, but also high-level semantic comprehension of the referring and relationships (e.g. “left” in Fig. 1) that help distinguish the correct referent from the other unrelated ones in the same image.

Previous referring expression comprehension models can be regarded as multi-stage methods which comprise three stages [7, 14, 16, 24, 32, 33, 34, 35], as illustrated in Fig. 1 (a). First, the conventional object proposal generation methods, such as EdgeBox [36], Selective Search [28], or off-the-shelf object detectors such as Faster R-CNN [23], SSD [12], and mask R-CNN [4], are utilized to extract a set of regions as the candidates for

matching the referring expression. Second, convolutional neural networks (CNNs) [26, 27] and recurrent neural networks (RNNs) [2, 5] are used to encode the image regions and the referring expression, respectively. Finally, a ranking model is designed to select the region with the highest matching score as the referent. These multi-stage models have achieved remarkable performance over related datasets on the referring expression comprehension task [32, 34, 35].

However, these multi-stage models are very computationally expensive, with high time cost taken in each stage, especially region proposal generation and region-wise feature extraction, as illustrated in Table 3. As such, these models are not applicable to the practical scenarios with real-time requirements. Therefore, this new challenge motivates and inspires us to design a grounding model which can localize the referent within an image both effectively and efficiently. To this end, in this paper, we propose a Single-Stage Grounding network (SSG) to achieve the real-time grounding results as well as the favorable performance without resorting to region proposals. More specifically, as shown in Fig. 1 (b), our SSG model consists of three components, namely multimodal encoder, multimodal interactor, and referring expression grounder. The multimodal encoder (Sec. 3.1) is leveraged to encode the given image and the referring expression, respectively. The multimodal interactor (Sec. 3.2) aims to attentively summarize the image local representations conditioned on the textual representation. Finally, based on the joint representation, the referring expression grounder (Sec. 3.3) is responsible for directly predicting the coordinates of the bounding box corresponding to the referring expression. In addition to the bounding box regression loss, additional three auxiliary losses are introduced to further improve the performance of SSG. They are the confidence score loss (Sec. 3.3.1) reflecting how accurate the bounding box is, the attention weight loss (Sec. 3.3.2) enforcing the grounder to focus on the useful region by using the central point of the ground-truth bounding box as the target, and the attribute prediction loss (Sec. 3.3.3) benefiting to distinguish the referring objects in the same image. As such, our proposed SSG performs in one single stage for tackling the referring expression comprehension task, thus leading to the comparable model performance as well as more than 9 \times speedups over the existing multi-stage models.

In summary, the main contributions of our work are as follows:

- We propose a novel end-to-end model, namely Single-Stage Grounding network (SSG) for addressing the referring expression comprehension task, which directly predicts the coordinates of the bounding box within the given image corresponding to the referring expression without relying on any region proposals.

- We propose a guided attention mechanism with the object center-bias to encourage our SSG to focus on the central region of a referent. Moreover, our proposed SSG can further distinguish referent objects, by exploiting and predicting the visual attribute information.
- Our SSG can carry out the referring expression comprehension task both effectively and efficiently. Specifically, our SSG achieves comparable results with the state-of-the-art models, while taking more than 9 \times faster under the same hardware environment.

2. Related Work

2.1. Referring Expression Comprehension

The referring expression comprehension task is to localize a referent within the given image, which semantically corresponds to the given referring expression. This task involves comprehending and modeling the different spatial contexts, such as spatial configurations [14, 33], attributes [11, 32], and the relationships between regions [16, 33]. In previous work, this task is generally formulated as a ranking problem over a set of region proposals from the given image. The region proposals are extracted from the proposal generation methods such as EdgeBoxes [36], or advanced object detection methods such as SSD [12], Faster RCNN [23], and Mask R-CNN [4]. Earlier models [14, 33] scored region proposals according to visual and spatial feature representations. However, these methods fail to incorporate the interactions between objects because the scoring process of each region is isolated. Nagaraja et al. [16] improved the performance with the help of modeling the relationships between region proposals. Yu et al. [34] proposed a joint framework that integrates referring expression comprehension and generation tasks together. The visual features from the region proposals and the semantic information from the referring expressions are embedded into a common space. Zhang et al. [35] developed a variational Bayesian framework to exploit the reciprocity between the referent and context. In spite of these models and their variants have achieved remarkable performance improvements on the referring comprehension task [32], these multi-stage methods could be computationally expensive for practical applications.

2.2. Object Detection

Our proposed SSG also benefits from the state-of-art object detectors, especially YOLO [20], YOLO-v2 [21], and YOLO-v3 [22]. YOLO [20] divides an input image into 7 \times 7 grid cells and directly predicts both the confidence values for multiple categories and coordinates of the bounding boxes. Similar to YOLO, YOLO-v2 [21] also divides an input image into a set of grid cells. However, it places 5 anchor boxes at each grid cell and predicts corrections of the

anchor boxes. Furthermore, YOLO-v3 takes a deeper network with 53 convolutional layers as the backbone which is more powerful. In order to localize small objects, YOLO-v3 [22] also introduces the additional pass-through layer to obtain more fine-grained features.

3. Architecture

Given an image I and a referring expression $E = \{e_t\}_{t=1}^T$, where e_t is the t -th word and T denotes the total number of words, the goal of referring expression comprehension is to localize one sub-region I_b within the image I , which corresponds to the semantic meaning of the referring expression E .

We propose a novel model free of region proposals, namely SSG, to tackle the referring expression comprehension task. As illustrated in Fig. 2, our proposed SSG is a single-stage model and consists of three components. More specifically, the multimodal encoders generate the visual and textual representations for the image and referring expression, respectively. Afterward, the multimodal interactor performs a visual attention mechanism which aims to generate an aggregated visual vector by focusing on the useful region of the input image. Finally, the referring expression grounder performs the localization to predict the bounding box corresponding to the referring expression.

3.1. Multimodal Encoder

The multimodal encoder in our SSG is used to generate the semantic representation of the input data, *i.e.*, both image and text, as shown in Fig. 2.

3.1.1 Image Encoder

We take an advanced CNN architecture — YOLO-v3¹ [22] — pretrained on the MSCOCO-LOC dataset [10] as the image encoder. Specifically, we first resize the given image I to the size as $3 \times 416 \times 416$, and then feed it into the encoder network. The output vectors $s = \{\mathbf{s}_n\}_{n=1}^N$, $\mathbf{s}_n \in \mathbb{R}^{D_I}$, from the 58-th convolutional layer are used as the feature representations which denote different local regions for the image. According to the network structure of YOLO-v3, \mathbf{s}_n is a vector with dimension size $D_I = 1024$, and the total number of local regions $N = 169$.

3.1.2 Text Encoder

Given a referring expression $E = \{e_t\}_{t=1}^T$, where e_t denotes the t -th word. First, each word in the referring expression needs to be initialized by the recent advanced word embedding models, such as Word2Vec [15], GloVe [18], and ELMo [19]. In this paper, we take the ELMo model

¹<https://pjreddie.com/media/files/yolov3.weights>

pre-trained on a dataset of 5.5B tokens to generate the corresponding word embedding vectors $w = \{\mathbf{w}_t\}_{t=1}^T$, $\mathbf{w}_t \in \mathbb{R}^{D_w}$, where the dimension size is $D_w = 3072$. Afterwards, each word embedding vector \mathbf{w}_t of the referring expression is fed into an RNN encoder sequentially to generate a fixed-length semantic vector as its textual feature.

In order to adequately capture long-term dependencies between words, Long Short-Term Memory (LSTM) [5] with specifically designed gating mechanisms is employed as the RNN unit to encode the referring expression. Moreover, the bidirectional LSTM (Bi-LSTM) [25, 32] can capture the past and future context information for the referring expression, which thereby outperforms both traditional LSTMs and RNNs. In this paper, the text encoder is realized by stacking two Bi-LSTM layers together, with hidden size being $H = 512$ and initial hidden and cell states setting to zeros. The semantic representation of the reference expression is thus obtained by concatenating the forward and backward outputs of the two stacked layers:

$$\mathbf{v}_E = [\mathbf{h}_T^{(1,fw)}; \mathbf{h}_T^{(1,bw)}; \mathbf{h}_T^{(2,fw)}; \mathbf{h}_T^{(2,bw)}], \quad (1)$$

where $\mathbf{h}_T^{(1,fw)}$ and $\mathbf{h}_T^{(2,fw)}$ indicate the forward outputs of the first and second layers of Bi-LSTM, respectively. And $\mathbf{h}_T^{(1,bw)}$ and $\mathbf{h}_T^{(2,bw)}$ indicate the corresponding backward outputs of the first and second layers of Bi-LSTM. $\mathbf{v}_E \in \mathbb{R}^{D_E}$, with the dimension size being $D_E = 2048$, denotes the finally obtained textual feature.

3.2. Multimodal Interactor

Based on the local visual features s and textual feature \mathbf{v}_E , a multimodal teractor is proposed to attentively exploit and summarize their complicated relationships. Specifically, we take the attention mechanism [29] to aggregate the visual local features $s = \{\mathbf{s}_n\}_{n=1}^N$, $\mathbf{s}_n \in \mathbb{R}^{D_I}$ and generate the aggregated visual feature $\mathbf{v}_I \in \mathbb{R}^{D_I}$ conditioned on the textual feature $\mathbf{v}_E \in \mathbb{R}^{D_E}$ of the referring expression:

$$\mathbf{v}_I = f_{att}(s, \mathbf{v}_E) = \sum_{i=1}^{|s|} \frac{\exp(\alpha(\mathbf{s}_i, \mathbf{v}_E))}{\sum_{j=1}^{|s|} \exp(\alpha(\mathbf{s}_j, \mathbf{v}_E))} \mathbf{s}_i, \quad (2)$$

where f_{att} denotes the attention mechanism. $\alpha(\mathbf{s}_i, \mathbf{v}_E)$ determines the attentive weight for the i -th visual local feature \mathbf{s}_i with regard to the expression representation \mathbf{v}_E , which is realized by a Multi-Layer Perceptron (MLP):

$$\alpha(\mathbf{s}_i, \mathbf{v}_E) = \mathbf{W}_{s_i, v_E} \tanh(\mathbf{W}_{s_i} \mathbf{s}_i + \mathbf{W}_{v_E} \mathbf{v}_E), \quad (3)$$

where $\mathbf{W}_{s_i, v_E} \in \mathbb{R}^{H \times N}$, $\mathbf{W}_{s_i} \in \mathbb{R}^{D_I \times H}$, and $\mathbf{W}_{v_E} \in \mathbb{R}^{D_E \times H}$ are the trainable parameters of the MLP.

Such an attention mechanism enables each local visual feature to meet and interact with the referring expression representation, therefore attentively summarizing the visual local features together and yielding the aggregated visual context feature. Finally, by concatenating the aggregated

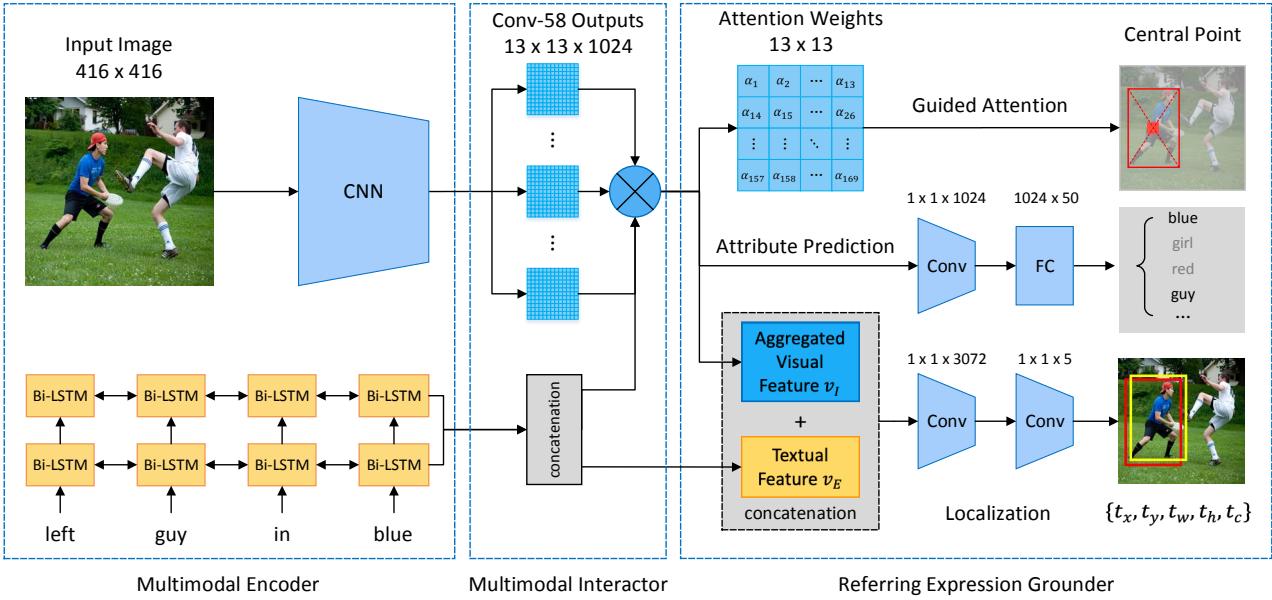


Figure 2. An overview of our proposed SSG model. The input image is encoded by a CNN to generate the local visual features representing different regions. An RNN encoder realized by a two-layer bidirectional LSTM (Bi-LSTM) is employed to process the referring expression sequentially and yield the textual feature. The multimodal interactor attentively exploits and summarizes the complicated relationships between the visual and textual features. In the referring expression grounder, the localization module relies on the joint context representations to yield the coordinates and the confidence score of the bounding box. Moreover, a novel guided attention mechanism by relating the attention weights to the referring region, enforces the visual attention to focus on the central region of the referent. Furthermore, the attribute prediction module is introduced to reproduce the attribute information contained in the referring expression. Please note that we only use the localization module to generate the bounding box for the referring expression during the inference stage.

visual context feature and the textual feature together, we can obtain the joint representation $\mathbf{v}_{I,E} \in \mathbb{R}^{D_{I,E}}$ for the image and referring expression:

$$\mathbf{v}_{I,E} = [\mathbf{v}_I; \mathbf{v}_E], \quad (4)$$

where the dimension size is $D_{I,E} = 3072$. Based on $\mathbf{v}_{I,E}$, our proposed referring expression grounder is proposed to localize the image region for the referring expression.

Discussion. Note that our multimodal interactor is different from the maximum attention module proposed in GroundR [24]. The local regions for attention in GroundR are first extracted by Selective Search [28] or EdgeBoxes [36], and then encoded by the VGG [26] model. Moreover, the “in-box” attention module proposed in [32] is used to localize the relevant region within a region proposal without any auxiliary guided attention loss (Sec. 3.3.2).

3.3. Referring Expression Grounder

As illustrated in Fig. 2, the referring expression grounder consists of three modules, namely localization, guided attention, and attribute prediction. We first introduce the localization module for predicting the bounding box as well as the confidence score, which relies on the coordinate information of the ground-truth referents for training. Subsequently, we introduce the guided attention mechanism and

the attribute prediction modules to further improve the localization accuracy by exploiting the hidden information contained in the image as well as the referring expression.

3.3.1 Localization

We rely on the joint representation $\mathbf{v}_{I,E}$ to predict the referring region within the image I , indicated by a bounding box b_{pred} , which semantically corresponds to the referring expression E . As illustrated in Fig. 2, the joint representation $\mathbf{v}_{I,E}$ undergoes one convolutional layer with 3072 filters and stride 1×1 . Afterwards, another convolutional layer with 5 filters and stride 1×1 followed by a sigmoid function is stacked to predict the coordinate information, which consists of 4 values $\{t_x, t_y, t_w, t_h\}$ and the confidence score t_c for the predicted bounding box b_{pred} . Here, a convolutional layer consists of a convolution operation and an activation process, specifically the Leaky ReLU [13].

Coordinates. The four coordinates are real values between 0 and 1 relative to the width and height of the image. More specifically, t_x and t_y denote the top-left coordinates, while t_w and t_h indicate the width and height of the bounding box. In order to reflect that small deviations in large bounding boxes matter less than those in small boxes, similar to [20], we predict the square root of the bounding

box width and height instead of the actual width and height. As such, the coordinates of the predicted bounding box are computed:

$$\begin{aligned} b_x &= t_x * p_w, & b_y &= t_y * p_h, \\ b_w &= t_w^2 * p_w, & b_h &= t_h^2 * p_h, \end{aligned} \quad (5)$$

where p_w and p_h represent the width and the height of the input image, respectively. $\{b_x, b_y\}$, b_w , and b_h denote the top-left coordinates, width, and height of the predicted bounding box b_{pred} , respectively. During the training, the mean squared error (MSE) is used as the objective function:

$$\begin{aligned} \mathcal{L}_{loc} = & \left(t_x - \frac{\hat{b}_x}{p_w} \right)^2 + \left(t_y - \frac{\hat{b}_y}{p_h} \right)^2 \\ & + \left(t_w - \sqrt{\frac{\hat{b}_w}{p_w}} \right)^2 + \left(t_h - \sqrt{\frac{\hat{b}_h}{p_h}} \right)^2, \end{aligned} \quad (6)$$

where $\hat{b}_x, \hat{b}_y, \hat{b}_w, \hat{b}_h$ are the coordinate information of the ground-truth bounding box b_{gt} .

Confidence Score. As aforementioned, besides the coordinate information, the localization module will also generate a confidence score t_c , reflecting the accuracy of the predicted box. During the evaluation, a predicted bounding box is regarded as a correct comprehension result if the intersection-over-union (IoU) of the box with the ground-truth bounding box is larger than a threshold η . Usually, the threshold is set to $\eta = 0.5$. Therefore, we naturally realize the confidence score prediction as a binary classification problem rather than a regression problem as YOLO [20]. Hence the target confidence score \hat{b}_c is defined as:

$$\hat{b}_c = \begin{cases} 1, & \text{if } IoU(b_{pred}, b_{gt}) \geq \eta \\ 0, & \text{otherwise} \end{cases} \quad (7)$$

The objective function regarding the confidence score is defined as a binary cross-entropy:

$$\mathcal{L}_{conf} = \hat{b}_c * \log(t_c) + (1 - \hat{b}_c) * \log(1 - t_c). \quad (8)$$

Please note that the objective function regarding confidence score is different from the definition in [20, 21], which is considered as a regression problem and formulated as $Pr(b_{gt}) * IoU(b_{pred}, b_{gt})$, where $Pr(b_{gt})$ is equal to 1 when there is an object in the cell, and 0 otherwise.

3.3.2 Guided Attention

For further boosting the grounding accuracy, we propose a guided attention mechanism to encourage our model to pay more attention to the central region of the correct referent. As introduced in Sec. 3.2, a set of attention weights $\alpha = \{\alpha_n\}_{n=1}^N, \alpha_n \in \mathbb{R}$ are computed conditioned on the textual feature for different visual local features, with each

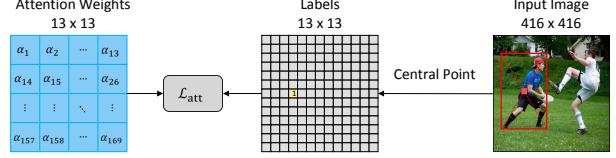


Figure 3. The illustration of our proposed guided attention loss. We formulate the guided attention process as a classification problem with the local region, where the central point falls into being labeled as 1 and the rest labeled as 0.

representing its relevance to the referring expression. We notice that there exists one piece of hidden information, namely *object center bias* [1], which we can make full use of. The central region of the ground-truth bounding box should produce the maximum attention weight since the visual feature related to the central region is more important for grounding the referring expression. To this end, as illustrated in Fig. 3, we first identify the position of the center point using the ground-truth bounding box, and encode it into a one-hot vector as the label \hat{y} , which means that only the region cell, where the central point of the referent falls into, is labeled as 1 with all the rest labeled as 0. The coordinates of the central point after rescaling to the size of the attention weight map are given by:

$$\left(\left\lfloor \frac{\hat{b}_x + 0.5 \times \hat{b}_w}{m} \right\rfloor, \left\lfloor \frac{\hat{b}_y + 0.5 \times \hat{b}_h}{m} \right\rfloor \right). \quad (9)$$

As mentioned in Sec. 3.1.1, the sizes of the attention weight map and the input image are 13×13 and 416×416 , respectively. Therefore, the rescaling factor m is set to $416/13 = 32$. Finally, we use the cross-entropy loss as the objective function to measure the difference between the visual attention weights and the obtained one-hot label \hat{y} :

$$\mathcal{L}_{att} = - \sum_i^N \hat{y}_i \log \alpha_i, \quad (10)$$

where \hat{y}_i denotes the i -th entry of the label vector \hat{y} . N denotes the number of attention weights, which is equal to $13 \times 13 = 169$. Such auxiliary loss can help our model learn to discriminate the target region with the other ones and encourage the attentive visual feature to embed more important information for predicting the bounding box.

3.3.3 Attribute Prediction

Additionally, visual attributes are usually used to distinguish referent objects of the same category and have shown impressive performance on many multimodal tasks, such as image captioning [8, 30, 31], video captioning [17], and referring expression comprehension [11, 32]. Inspired by the previous work [32], we introduce an attribute prediction module to further boost the performance of our grounder.

Table 1. The performance comparisons (Acc%) of different methods on RefCOCO, RefCOCO+, and RefCOCOg datasets. The best results among all models are marked with boldface.

Line	Models	RefCOCO		RefCOCO+		RefCOCOg	RefCOCOg
		test A	test B	test A	test B	val (<i>google</i>)	val (<i>umd</i>)
1	MMI [14]	64.90	54.51	54.03	42.81	45.85	-
2	Vis-Diff + MMI [33]	67.64	55.16	55.81	43.43	46.86	-
3	Neg-Bag [16]	58.70	56.40	-	-	-	49.50
4	Attr + MMI + Vis-Diff [11]	72.08	57.29	57.97	46.20	52.35	-
5	CMN [6]	71.03	65.77	54.32	47.76	57.47	-
6	Speaker + Listener + MMI [34]	72.95	62.43	58.58	48.44	57.34	-
7	Speaker + Listener + Reinforcer + MMI [34]	72.94	62.98	58.68	47.68	57.72	-
8	Variational Context [35]	73.33	67.44	58.40	53.18	62.30	-
9	MAttNet [32]	80.43	69.28	70.26	56.00	-	66.67
10	SSG (λ_{loc})	72.90	63.97	23.00	16.51	17.64	18.83
11	SSG ($\lambda_{loc+conf}$)	73.44	64.39	58.16	43.55	42.10	51.97
12	SSG ($\lambda_{loc+conf+att}$)	75.20	65.77	61.39	46.50	43.90	56.63
13	SSG ($\lambda_{loc+conf+att+attr}$)	76.51	67.50	62.14	49.27	47.78	58.80

As illustrated in Fig. 2, the attentively aggregated visual feature \mathbf{v}_I undergoes an additional convolutional layer with 1024 filters and stride 1×1 . A fully connected layer is subsequently stacked to predict the probabilities $\{p_i\}_{i=1}^{N_{attr}}$ for all N_{attr} attributes, where N_{attr} is the number of the most frequent attribute words extracted from the training dataset². In this paper, we empirically set $N_{attr} = 50$ as [33]. As such, the attribute prediction can be formulated as a multi-label classification problem, whose objective function is defined as:

$$\mathcal{L}_{attr} = \sum_{i=1}^{N_{attr}} w_i^{attr} (\hat{y}_i \log(p_i) + (1 - \hat{y}_i) \log(1 - p_i)), \quad (11)$$

where $w_i^{attr} = 1/\sqrt{\text{freq}_{attr}}$ is used to balance the weights of different attributes. \hat{y}_i is set to 1 when the i -th attribute word exists in the referring expression, and 0 otherwise. During training, the loss value of attribute prediction is set to zero if there is no attribute word existing in the referring expression.

3.4. Training Objective

The objective function of our SSG model for a single training sample (*image*, *referring expression*, *bounding box*) is defined as a weighted sum of the aforementioned localization loss, the confidence score loss, the guided attention loss, and the attribute prediction loss:

$$\mathcal{L}_{sum} = \lambda_{loc}\mathcal{L}_{loc} + \lambda_{conf}\mathcal{L}_{conf} + \lambda_{att}\mathcal{L}_{att} + \lambda_{attr}\mathcal{L}_{attr}, \quad (12)$$

where λ_{loc} , λ_{conf} , λ_{att} , and λ_{attr} are the weight factors to balance the contributions of different losses for model training.

3.5. Inference

During the inference phase, only the localization module is enabled to predict the bounding box, which corresponds

to the referring expression, with the guided attention and attribute prediction modules deactivated. For one given image I and the corresponding referring expression E , these modules, namely the multimodal encoder (including image and text encoders), multimodal interactor, and localization, fully couple with each other and accordingly predict the bounding box b_{pred} in one single stage. As such, our SSG performs more efficiently for referring expression comprehension compared with the existing multi-stage models, which will be further demonstrated in Sec. 4.5.

4. Experiments

4.1. Datasets

We evaluate and compare our proposed SSG with existing approaches comprehensively on the four popular datasets, namely RefCOCO [33], RefCOCO+ [33], RefCOCOg [14], and ReferItGame [9].

RefCOCO, RefCOCO+, and RefCOCOg were all collected from the MSCOCO [10] dataset, but with several differences. (1). The expressions in RefCOCO contain many location words (*e.g.* “left”, “corner”). While RefCOCO+ was collected to encourage the expressions to focus on the appearance of the referent without using location words. RefCOCOg contains longer referring expressions on average than RefCOCO and RefCOCO+ (8.4 vs. 3.5) and provides more embellished expressions than RefCOCO and RefCOCOg. (2). Both RefCOCO and RefCOCO+ are divided into train, validation, test A containing person referents, and test B containing common object referents. While RefCOCOg has two types of data partitions. The first split is denoted as *google* which was used in [14]. Since the testing set has not been released, recent work [6, 11, 14, 32, 33, 34, 35] reported their results on the validation set. The second split is denoted as *umd* which was used in [16, 32]. In this paper, we evaluate our model

²<https://github.com/lichengunc/refer-parser2>

Table 2. The performance comparisons (Acc%) of different methods on the ReferItGame dataset.

Line	Models	Proposal	ReferItGame
1	SCRC [7]	EdgeBoxes	17.93
2	GroundR [24]		26.93
3	CMN [6]		28.33
4	Variational Context [35]		31.13
5	MAttNet		29.04
6	Oracle		59.45
7	SSG (λ_{loc})	—	49.68
8	SSG ($\lambda_{loc+conf}$)		49.97
9	SSG ($\lambda_{loc+conf+att}$)		54.14
10	SSG ($\lambda_{loc+conf+att+attr}$)		54.24

on both types of data splits for RefCOCOg.

ReferItGame also named as RefCLEF was collected from the segmented and annotated extension of the Image-CLEF IAPR TC-12 dataset (SAIAPR TC-12) [3]. Note that the annotated expressions provided by this dataset exist some equivocal words and erroneous annotations, such as *anywhere* and *don't know*. In this paper, we use the same data split as [6, 7, 24, 35] for fair comparison.

4.2. Experiment Settings

Preprocessing. As aforementioned, we initialize the word embedding layers in our model with EMLo [19], which is a character-based embedding model. Special characters are removed, resulting in a vocabulary size of 10,342, 12,227, 12,679, and 9,024 for RefCOCO, RefCOCO+, RefCOCOg, and ReferItGame, respectively. We truncate all the referring expressions longer than 15 words and use zero padding for the expressions shorter than 15 words.

Training. To balance the contribution of each loss for optimal model training in Eq. 12, we empirically set λ_{loc} , λ_{conf} , λ_{att} and λ_{attr} to 20.0, 5.0, 1.0, and 5.0, respectively. The SGD optimizer with an initial learning rate of 1×10^{-3} and the momentum setting as 0.9 is employed to train our model. The learning rate is decreased by 0.8 every 5 epochs. All the expressions for the same referent are tied into one single batch samples for training. Early stopping is used to prevent overfitting if the performance on the validation set does not improved over the last 10 epochs. Our SSG is implemented with PyTorch and can be trained within 100 hours on a single Tesla P40 and CUDA 9.0 with Intel Xeon E5-2699v4@2.2GHz.

Evaluation Metric. Same as the previous work [7, 16, 32, 35], we evaluate the performance of our model using the ratio of Intersection over Union (IoU) between the ground truth and the predicted bounding box. If the IoU is larger than 0.5, we treat this predicted bounding box as a true positive. Otherwise it is a false positive. The fraction of the true positive expressions are denoted as the final accuracy.

Table 3. The inference time (seconds per referent) comparisons on the RefCOCO dataset between our SSG, SCRC, and MAttNet. Env. means the hardware environment.

Models	Env.	Stage I	Stage II	Stage III	Total
SCRC	CPU	0.353	0.511	10.781	11.645
		14.907	0.849	0.157	15.913
		-	-	-	1.373
SCRC	GPU	0.353	0.025	0.272	0.650
		0.183	0.043	0.010	0.236
		-	-	-	0.025

4.3. Performance Comparisons

We compare our SSG with existing multi-stage methods comprehensively. For the fair comparison, we directly copy the results from their papers.

The results on RefCOCO, RefCOCO+, and RefCOCOg are shown in Table 1. Although it is more challenge to localize the referent without resorting to region proposals directly, the results of our SSG (Line 13) on the test A and test B split of RefCOCO outperform most of the previous models, except MAttNet [34]. RefCOCO+ is more challenge than RefCOCO since the referring expressions in RefCOCO+ are annotated with appearance words without location information. Nevertheless, our SSG can take the second and third place on the test A and test B split of RefCOCO+, respectively. On the validation set of RefCOCOg split by *google*, our model achieves favorable results which is better than [14, 33]. Furthermore, although the performance of SSG on the validation set of RefCOCOg split by *umd* is worse than the best model MAttNet, it still outperforms [16]. One reason may be that the language used in RefCOCOg tend to be more flowery than the expressions in RefCOCO and RefCOCO+ [33].

The performance comparisons on ReferItGame of different models are shown in Table. 2. The upper-bound result of the region proposals extracted by EdgeBoxes [36] is only 59.45% (Line 6), which is denoted by “Oracle” as in SCRC [7]. We use the released code as well as off-the-shelf proposals provided by the authors³ [32] to evaluate the performance of MAttNet on the ReferItGame dataset (Line 5). It can be observed that our SSG outperforms all the previous models. One reason may be attributed to the low-quality proposals providing for the ReferItGame dataset, which constraint the performance of the previous multi-stage models. In contrast, the result of MAttNet evaluated by ourselves using the ground-truth bounding boxes of ReferItGame as region proposals is 81.29%. Our model achieves the much better performance than the existing methods since it can be trained and optimized end-to-end without resorting to region proposals.

Fig. 4 shows some qualitative results of referring expression comprehension using our proposed SSG, as well as the

³<https://github.com/lichengunc/MAttNet>

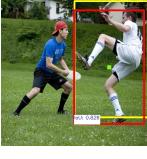
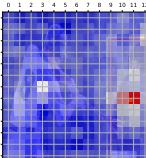
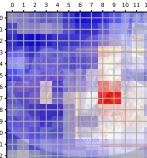
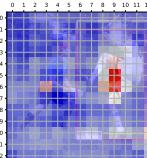
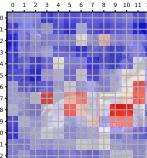
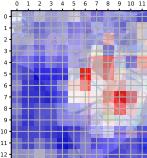
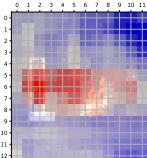
	RefCOCO		RefCOCO+		RefCOCOg	ReferItGame
Exps	right guy in blue	half sandwich front right	white man	smallest lamb	a green and white small laptop	person on left
Predictions						
Visual Attention						
Top-5 Attributes	1. blue (0.83) 2. guy (0.52) 3. shirt (0.15) 4. black (0.08) 5. purple (0.04)	1. half (0.80) 2. food (0.17) 3. white (0.05) 4. side (0.05) 5. woman (0.03)	1. white (0.99) 2. shirt (0.95) 3. woman (0.01) 4. guy (0.01) 5. player (0.01)	1. white (0.93) 2. boy (0.04) 3. woman (0.03) 4. guy (0.03) 5. animal (0.03)	1. green (0.90) 2. white (0.26) 3. table (0.09) 4. black (0.06) 5. computer (0.03)	1. path (0.64) 2. boy (0.64) 3. hand (0.61) 4. van (0.60) 5. wave (0.59)

Figure 4. Qualitative results of the referring expression comprehensions with the corresponding visual attention heat maps and top-5 predicted attributes. The red rectangles denote the ground-truth bounding boxes, while the yellow ones denote the predicted boxes by our SSG. The green dots indicate the center points of the ground-truth bounding boxes.

visualizations of attention weights and top-5 predicted attributes⁴. First, our SSG can accurately ground the referents in the images. Second, by visualizing the attention weights, we can observe that our guided attention mechanism can enforce the visual attention mechanism to focus on the meaningful region of the image. And the top-5 predicted attribute words can accurately characterize the attribute information of the referents, such as “blue”, “white”, and “food”.

4.4. Ablation Study

We perform ablation studies to examine the contribution of each component of SSG. The results are shown in Table 1 (Line 10 - 13) and Table 2 (Line 7 - 10). As a baseline, the performance of SSG (λ_{loc}) trained with localization loss only is illustrated in Table 1 and Table 2. By incorporating the confidence score loss, the performance of SSG ($\lambda_{loc} + conf$) can be improved obviously. The performance of SSG ($\lambda_{loc} + conf + att$) by adding the guided attention loss can be further improved. By further introducing the attribute prediction loss, the performance of SSG ($\lambda_{loc} + conf + att + attr$) can be boosted consistently.

4.5. Efficiency

We measure the speed by calculating the average time per referent (*image, referring expression*) at inference stage on the RefCOCO dataset running on the GPU-enabled and

CPU-only environments. Table 3 shows the comparisons between SSG, SCRC [7], and MAttNet [32]. Please note that the computation time of EdgeBoxes⁵ [36], SCRC⁶ [7], and MAttNet [32] are all obtained by using the author-released code under the same hardware environment. We can observe that all the models with GPU-enabled achieve significant speedups compared with the CPU implementations. When we activate the GPU for acceleration, SCRC takes the longest time due to the computation time cost by EdgeBoxes at the proposal extraction stage. MAttNet uses Faster R-CNN [23] for proposal extraction and takes shorter computation time at 0.236s. However, our SSG can significantly reduce the computation time to 0.025s for a referring expression along with an image, running at 40 referents per second, which is more than 9× faster than MAttNet.

5. Conclusion

In this paper, we proposed a novel grounding model, namely Single-Stage Grounding network (SSG), to directly localize the referent within the given image semantically corresponding to a referring expression without resorting to region proposals. To encourage the multimodal interactor to focus on the useful region for grounding, a guided attention loss based on the object center-bias is proposed. Furthermore, by introducing attribute prediction loss, the performance can be improved consistently. Experiments on

⁵<https://github.com/pdollar.edges>

⁶<https://github.com/ronghanghu/natural-language-object-retrieval>

four public datasets show that our SSG model can achieve favorable performance, especially achieving the state-of-art performance on the ReferItGame dataset. Most importantly, our model is fast by design and able to run at 40 referents per second averagely on the RefCOCO dataset.

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A. Appendix

A.1. Datasets

For the referring expression comprehension task, a number of datasets have been used in the previous work [14, 7, 33, 24, 16, 11, 6, 34, 35, 32], which are summarized in Table 4. For comparing our SSG with the previous methods comprehensively, we take the four commonly used datasets for our experiments, which are RefCOCO, RefCOCO+, RefCOCOg, and ReferItGame. Please note that the RefCOCOg dataset has two types of data splits.

Table 4. The datasets used for referring expression comprehension.

Models	RefCOCO	RefCOCO+	RefCOCOg	ReferItGame	Flickr30K	Visual Genome	Kitchen
MMI [14]	✓		✓				
SCRC [7]				✓	✓		✓
VisDiff + MMI [33]	✓	✓	✓				
GroundR [24]				✓	✓		
Neg-Bag [16]	✓		✓				
Attribute + VisDiff [11]	✓	✓	✓				
CMN [6]			✓				✓
Speaker-Listener-Reinforcer [34]	✓	✓	✓				
Variational Context [35]	✓	✓	✓	✓			
MAttNet [32]	✓	✓	✓				
Our SSG	✓	✓	✓	✓			

A.2. Effect of End-to-end Training

Our proposed SSG is an end-to-end model. The parameters in all components can be optimized jointly by stochastic gradient descent methods. As illustrated in Table 5, we report the results when freezing the parameters of the image encoder and compare them to the results with the fine-tuning strategy. The performance can be consistently improved by fine-tuning the image encoder, demonstrating the advantage of the end-to-end training strategy.

Table 5. Ablation study of SSG with and without fine-tuning strategy on the four datasets, which are RefCOCO, RefCOCO+, RefCOCOg, and ReferItGame.

Models	Fine-tuning	RefCOCO		RefCOCO+		RefCOCOg val (google)	RefCOCOg val (umd)	ReferItGame test
		test A	test B	test A	test B			
SSG ($\lambda_{loc+conf+att+attr}$)	No	52.88	48.26	35.88	30.36	33.25	37.00	40.05
SSG ($\lambda_{loc+conf+att+attr}$)	Yes	76.51	67.50	62.14	49.27	47.78	58.80	54.24

A.3. More Examples

We show more qualitative examples of our SSG ($\lambda_{\text{loc+conf+att+attr}}$) in Fig. 5, Fig. 6, Fig. 7, and Fig. 8. As comparison, we also show some failure cases in Fig. 9 and Fig. 10.

A.3.1 Qualitative Results

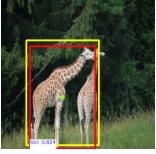
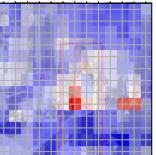
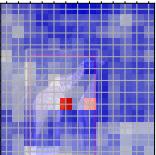
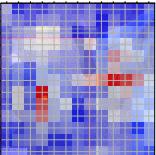
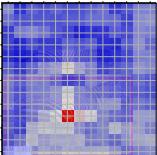
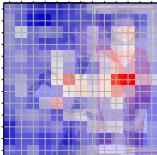
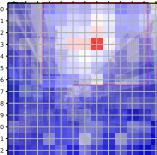
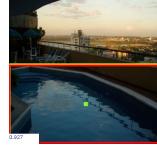
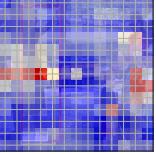
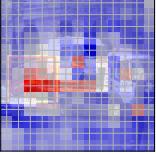
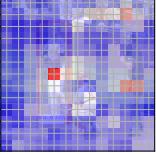
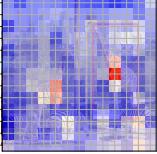
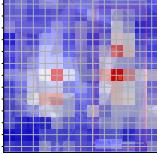
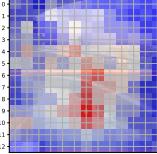
	RefCOCO		RefCOCO+		RefCOCOg		ReferItGame	
Exps	lady in white	giraffe on the left	darker jeans	closest zebra	standing woman in a red dress	the sky		
Predictions								
Top-5 Attributes	Visual Attention	Visual Attention	Visual Attention	Visual Attention	Visual Attention	Visual Attention		
Top-5 Attributes								
Top-5 Attributes	1. woman (0.74) 2. lady (0.56) 3. girl (0.43) 4. white (0.07) 5. black (0.06)	1. animal (0.28) 2. guy (0.14) 3. red (0.13) 4. white (0.11) 5. baby (0.09)	1. blue (0.99) 2. shirt (0.10) 3. guy (0.09) 4. brown (0.11) 5. woman (0.01)	1. animal (0.36) 2. white (0.14) 3. guy (0.09) 4. black (0.02) 5. woman (0.01)	1. woman (0.80) 2. girl (0.52) 3. black (0.06) 4. red (0.03) 5. shirt (0.01)	1. biker (0.54) 2. van (0.47) 3. people (0.45) 4. walkway (0.43) 5. brick (0.21)		
Exps	woman in black	red van	man with bat	tallest giraffe	man standing with back toward camera	the pool		
Predictions								
Top-5 Attributes	Visual Attention	Visual Attention	Visual Attention	Visual Attention	Visual Attention	Visual Attention		
Top-5 Attributes								
Top-5 Attributes	1. guy (0.54) 2. black (0.30) 3. shirt (0.17) 4. boy (0.06) 5. dark (0.05)	1. red (0.98) 2. brown (0.02) 3. shirt (0.01) 4. white (0.01) 5. yellow (0.01)	1. batter (0.99) 2. player (0.63) 3. white (0.04) 4. shirt (0.01) 5. black (0.01)	1. white (0.10) 2. whole (0.08) 3. guy (0.07) 4. shirt (0.01) 5. black (0.01)	1. boy (0.61) 2. white (0.03) 3. blue (0.03) 4. part (0.05) 5. shirt (0.04)	1. pool (0.16) 2. sea (0.10) 3. pavement (0.06) 4. sand (0.05) 5. sign (0.03)		

Figure 5. Qualitative results of the referring expression comprehensions with the corresponding visual attention heat maps and top-5 predicted attributes. The red rectangles denote the ground-truth bounding boxes, while the yellow ones denote the predicted boxes by our SSG. The green dots indicate the center points of the ground-truth bounding boxes.

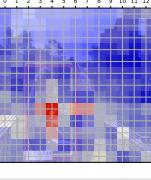
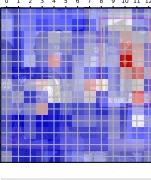
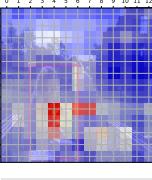
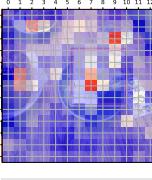
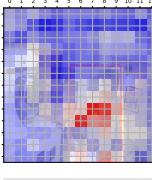
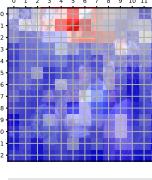
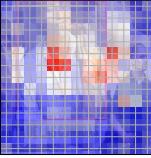
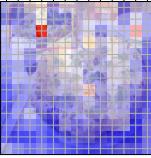
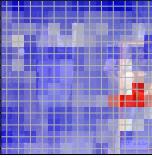
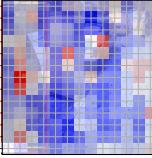
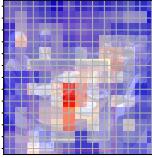
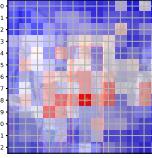
	RefCOCO		RefCOCO+		RefCOCOg	ReferItGame	
Exps	woman sitting down	suitcase back right	the girl wearing shorts	beverage tan in color	the guy in the grey shirt	sky white top	
Predictions							
Top-5 Attributes	Visual Attention	 1. woman (0.81) 2. girl (0.64) 3. lady (0.33) 4. shirt (0.09) 5. guy (0.03)	 1. bag (0.57) 2. black (0.32) 3. gray (0.18) 4. side (0.07) 5. green (0.06)	 1. woman (0.98) 2. girl (0.79) 3. white (0.02) 4. side (0.07) 5. green (0.06)	 1. white (0.38) 2. blue (0.12) 3. glass (0.03) 4. brown (0.01) 5. shirt (0.01)	 1. boy (0.78) 2. white (0.48) 3. guy (0.32) 4. kid (0.03) 5. back (0.01)	 1. ceiling (0.76) 2. people (0.24) 3. brick (0.09) 4. stair (0.07) 5. girl (0.06)
Exps	dude eating pizzas face	pizza in back	guy in the black shirt and jeans	partial end of vehicle	a dinner table filled with meals	man middle red	
Predictions							
Top-5 Attributes	Visual Attention	 1. white (0.41) 2. guy (0.37) 3. woman (0.27) 4. lady (0.17) 5. shirt (0.07)	 1. food (0.87) 2. plate (0.4) 3. white (0.11) 4. corner (0.06) 5. guy (0.05)	 1. black (0.99) 2. shirt (0.67) 3. guy (0.62) 4. blue (0.005) 5. girl (0.004)	 1. guy (0.02) 2. white (0.02) 3. gray (0.02) 4. black (0.02) 5. girl (0.004)	 1. table (0.89) 2. wooden (0.40) 3. brown (0.17) 4. green (0.08) 5. yellow (0.02)	 1. girl (0.41) 2. guy (0.39) 3. people (0.03) 4. anyone (0.02) 5. sign (0.02)

Figure 6. Qualitative results of the referring expression comprehensions with the corresponding visual attention heat maps and top-5 predicted attributes. The red rectangles denote the ground-truth bounding boxes, while the yellow ones denote the predicted boxes by our SSG. The green dots indicate the center points of the ground-truth bounding boxes.

	RefCOCO		RefCOCO+		RefCOCOg	ReferItGame
Exps	man in black on skis	bananas front row third from left	white shirt	fuzzy food	a clock on the tower	building on the left
Predictions						
Top-5 Attributes	Visual Attention	Visual Attention				
Exps	bro on the right in the air	back of chair on right with bag on it	guy in back	partial doughnut alone	a dark brown chair under a shelf	middle of lake
Predictions						
Top-5 Attributes	Visual Attention	Visual Attention				
Exps	leg (0.38)	white (0.23)	black (0.96)	red (0.02)	brown (0.63)	wave (0.75)
Predictions	guy (0.31)	side (0.08)	guy (0.85)	black (0.01)	wooden (0.41)	sea (0.30)
Top-5 Attributes	Visual Attention	Visual Attention				
Exps	black (0.26)	red (0.07)	shirt (0.22)	brown (0.01)	white (0.05)	step (0.10)
Predictions	girl (0.05)	girl (0.05)	white (0.01)	guy (0.01)	girl (0.01)	foreground (0.08)
Top-5 Attributes	Visual Attention	Visual Attention				
Exps	woman (0.03)	brown (0.04)	woman (0.001)	half (0.004)	black (0.01)	walkway (0.07)

Figure 7. Qualitative results of the referring expression comprehensions with the corresponding visual attention heat maps and top-5 predicted attributes. The red rectangles denote the ground-truth bounding boxes, while the yellow ones denote the predicted boxes by our SSG. The green dots indicate the center points of the ground-truth bounding boxes.

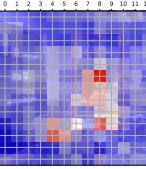
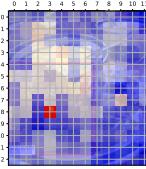
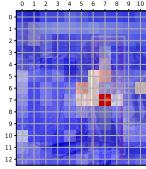
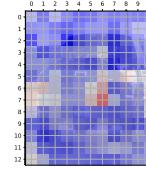
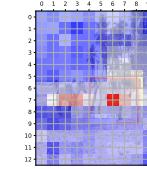
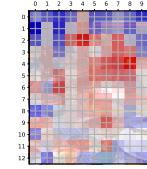
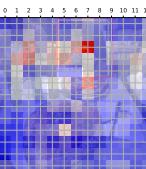
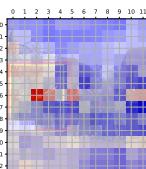
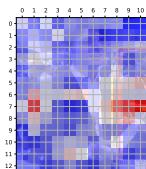
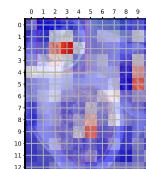
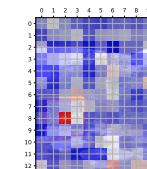
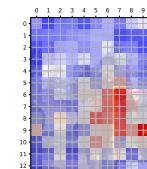
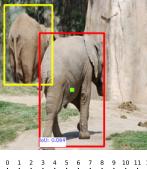
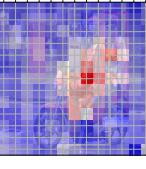
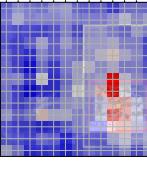
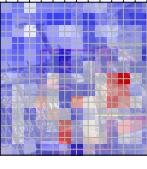
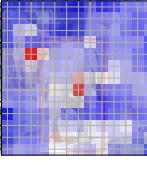
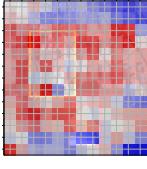
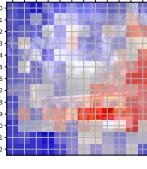
	RefCOCO		RefCOCO+		RefCOCOg		ReferItGame	
Exps	guy in gray shirt standing	left half of sandwich	red jacket	yellow car	a beige horse with a black and yellow saddle	girl		
Predictions								
Top-5 Attributes	Visual Attention							
Top-5 Attributes	Predictions	<ul style="list-style-type: none"> 1. guy (0.91) 2. shirt (0.07) 3. old (0.05) 4. black (0.02) 5. white (0.02) 	<ul style="list-style-type: none"> 1. half (0.80) 2. food (0.15) 3. brown (0.09) 4. black (0.05) 5. woman (0.04) 	<ul style="list-style-type: none"> 1. jacket (0.99) 2. red (0.97) 3. coat (0.71) 4. guy (0.06) 5. woman (0.03) 	<ul style="list-style-type: none"> 1. yellow (0.37) 2. brown (0.17) 3. red (0.11) 4. guy (0.03) 5. white (0.03) 	<ul style="list-style-type: none"> 1. brown (0.61) 2. white (0.37) 3. black (0.04) 4. young (0.03) 5. girl (0.01) 	<ul style="list-style-type: none"> 1. girl (0.56) 2. lady (0.32) 3. face (0.24) 4. guy (0.22) 5. people (0.06) 	
Exps	man with watch	elephant at far left	hoodie black near orange shirt	bowl of salad	black and white floral pattern patio chair	man in white shirt		
Predictions								
Top-5 Attributes	Visual Attention							
Top-5 Attributes	Predictions	<ul style="list-style-type: none"> 1. guy (0.70) 2. shirt (0.53) 3. blue (0.44) 4. old (0.14) 5. gray (0.09) 	<ul style="list-style-type: none"> 1. baby (0.29) 2. partial (0.14) 3. red (0.13) 4. shirt (0.12) 5. guy (0.11) 	<ul style="list-style-type: none"> 1. black (0.99) 2. shirt (0.68) 3. guy (0.54) 4. white (0.18) 5. woman (0.02) 	<ul style="list-style-type: none"> 1. white (0.84) 2. green (0.79) 3. food (0.05) 4. yellow (0.02) 5. black (0.01) 	<ul style="list-style-type: none"> 1. black (0.88) 2. white (0.10) 3. blue (0.02) 4. woman (0.01) 5. monitor (0.01) 	<ul style="list-style-type: none"> 1. people (0.64) 2. lady (0.17) 3. guy (0.16) 4. girl (0.10) 5. face (0.02) 	

Figure 8. Qualitative results of the referring expression comprehensions with the corresponding visual attention heat maps and top-5 predicted attributes. The red rectangles denote the ground-truth bounding boxes, while the yellow ones denote the predicted boxes by our SSG. The green dots indicate the center points of the ground-truth bounding boxes.

A.3.2 Failure Cases

	RefCOCO		RefCOCO+		RefCOCOg		ReferItGame	
Exps	woman on bike	right cake	girl with hand on her side	gray elephant	green color kite holding the man	door 2nd right		
Predictions								
Visual Attention								
Top-5 Attributes	1. guy (0.56) 2. bike (0.20) 3. old (0.10) 4. woman (0.08) 5. brown (0.07)	1. part (0.35) 2. side (0.24) 3. brown (0.18) 4. corner (0.10) 5. area (0.08)	1. woman (0.93) 2. black (0.71) 3. girl (0.60) 4. shirt (0.13) 5. blue (0.04)	1. animal (0.81) 2. white (0.09) 3. girl (0.04) 4. full (0.03) 5. blue (0.03)	1. green (0.37) 2. dark (0.04) 3. blue (0.03) 4. plant (0.02) 5. black (0.03)	1. face (0.63) 2. stair (0.39) 3. doorway (0.18) 4. building (0.16) 5. step (0.14)		

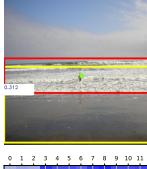
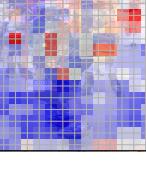
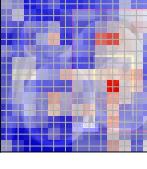
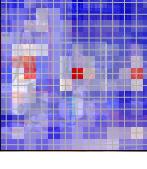
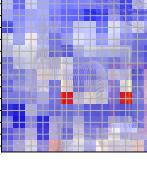
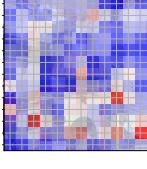
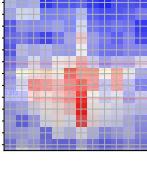
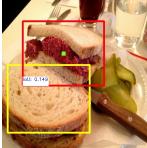
	white mask		rightmost plate		woman in blue		zebra at tree		a brick oven with boxes under it		ocean waves	
Exps	white mask	rightmost plate	woman in blue	zebra at tree	a brick oven with boxes under it	ocean waves						
Predictions												
Visual Attention												
Top-5 Attributes	1. white (0.59) 2. guy (0.59) 3. shirt (0.57) 4. woman (0.09) 5. black (0.08)	1. food (0.86) 2. part (0.10) 3. corner (0.07) 4. guy (0.06) 5. woman (0.03)	1. woman (0.97) 2. girl (0.95) 3. lady (0.13) 4. pink (0.13) 5. shirt (0.02)	1. full (0.80) 2. whole (0.05) 3. woman (0.04) 4. black (0.03) 5. number (0.03)	1. white (0.37) 2. glass (0.07) 3. woman (0.07) 4. empty (0.07) 5. black (0.03)	1. sea (0.28) 2. sand (0.06) 3. wave (0.05) 4. people (0.03) 5. pool (0.02)						

Figure 9. Some failure cases of the referring expression comprehensions with the corresponding visual attention heat maps and top-5 predicted attributes. The red rectangles denote the ground-truth bounding boxes, while the yellow ones denote the predicted boxes by our SSG. The green dots indicate the center points of the ground-truth bounding boxes.

	RefCOCO		RefCOCO+		RefCOCOg	ReferItGame
Exps	man back of lady	white board	row 2 glasses head turned	half cut sandwich	a yellow bus	blue building near right of statue
Predictions						
Top-5 Attributes	Visual Attention	Visual Attention	Visual Attention	Visual Attention	Visual Attention	Visual Attention
Top-5 Predictions	<p>1. guy (0.72) 2. old (0.13) 3. woman (0.12) 4. shirt (0.08) 5. glass (0.04)</p>	<p>1. board (0.58) 2. white (0.28) 3. red (0.17) 4. yellow (0.11) 5. pink (0.03)</p>	<p>1. guy (0.71) 2. black (0.10) 3. white (0.09) 4. jacket (0.09) 5. woman (0.01)</p>	<p>1. half (0.87) 2. slice (0.02) 3. guy (0.02) 4. part (0.01) 5. red (0.01)</p>	<p>1. white (0.33) 2. black (0.05) 3. green (0.04) 4. grey (0.01) 5. red (0.003)</p>	<p>1. stair (0.57) 2. building (0.37) 3. doorway (0.33) 4. people (0.33) 5. yup (0.28)</p>

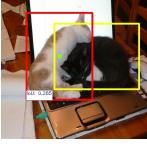
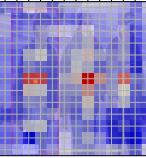
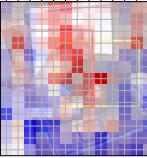
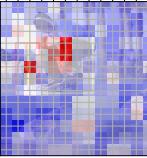
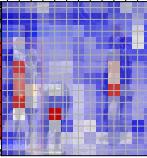
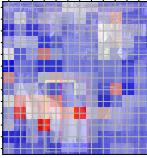
	girl carrying board	top kitty	guy walking to skater	horse under man in blue shirt	a goat stand near security	man on right with hat
Exps						
Predictions						
Top-5 Attributes	Visual Attention	Visual Attention	Visual Attention	Visual Attention	Visual Attention	Visual Attention
Top-5 Predictions	<p>1. guy (0.85) 2. black (0.16) 3. hand (0.05) 4. boy (0.04) 5. kid (0.03)</p>	<p>1. black (0.58) 2. gray (0.18) 3. part (0.15) 4. white (0.15) 5. guy (0.05)</p>	<p>1. guy (0.91) 2. kid (0.10) 3. shirt (0.06) 4. boy (0.06) 5. white (0.02)</p>	<p>1. black (0.99) 2. white (0.01) 3. guy (0.01) 4. kid (0.004) 5. animal (0.003)</p>	<p>1. white (0.99) 2. grey (0.01) 3. brown (0.01) 4. young (0.003) 5. black (0.003)</p>	<p>1. people (0.66) 2. girl (0.22) 3. lady (0.14) 4. sand (0.13) 5. step (0.06)</p>

Figure 10. Some failure cases of the referring expression comprehensions with the corresponding visual attention heat maps and top-5 predicted attributes. The red rectangles denote the ground-truth bounding boxes, while the yellow ones denote the predicted boxes by our SSG. The green dots indicate the center points of the ground-truth bounding boxes.