Advancing Visual Grounding with Scene Knowledge: Benchmark and Method

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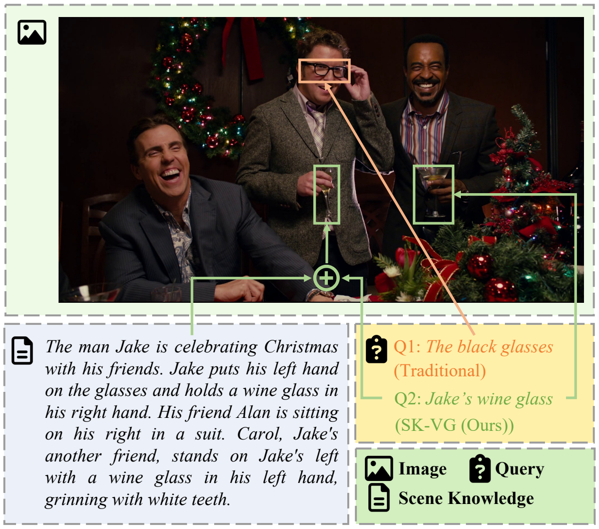
Abstract

Visual grounding (VG) aims to establish fine-grained alignment between vision and language. Ideally, it can be a testbed for vision-and-language models to evaluate their understanding of the images and texts and their reasoning abilities over their joint space. However, most existing VG datasets are constructed using simple description texts, which do not require sufficient reasoning over the images and texts. This has been demonstrated in a recent study [27], where a simple LSTM-based text encoder without pretraining can achieve state-of-the-art performance on mainstream VG datasets. Therefore, in this paper, we propose a novel benchmark of Scene Knowledge-guided Visual Grounding (SK-VG), where the image content and referring expressions are not sufficient to ground the target objects, forcing the models to have a reasoning ability on the long-form scene knowledge. To perform this task, we propose two approaches to accept the triple-type input, where the former embeds knowledge into the image features before the image-query interaction; the latter leverages linguistic structure to assist in computing the image-text matching. We conduct extensive experiments to analyze the above methods and show that the proposed approaches achieve promising results but still leave room for improvement, including performance and interpretability. The dataset and code are available at https://github.com/zhjohnchan/SK-VG.

1. Introduction

Visual grounding (VG), aiming to locate an object referred to by a description phrase/text in an image, has emerged as a prominent attractive research direction. It can be applied to various tasks (e.g., visual question answering [4, 13, 38, 51] and vision-and-language navigation [1, 11, 35]) and also be treated as a proxy to evaluate machines for open-ended scene recognition. Typically, VG requires models to reason over vision and language and build connections through single-modal understanding and cross-modal matching. Yet, current VG benchmarks (e.g., RefCOCO [47], RefCOCO+ [47], RefCOCOg [29], ReferItGame [17], and CLEVR-Ref+ [23]) can not serve as a good test bed to evaluate the reasoning ability since they only focus on simple vision-language alignment. In addition to the simple nature of constructed referring expressions, this can be reflected in the recent state-of-the-art study [27], where they showed that *VG models are less affected by language modeling through extensive empirical analyses*.



The man Jake is celebrating Christmas with his friends. Jake puts his left hand on the glasses and holds a wine glass in his right hand. His friend Alan is sitting on his right in a suit. Carol, Jake's another friend, stands on Jake's left with a wine glass in his left hand, grinning with white teeth.

Q1: *The black glasses* (Traditional)
Q2: *Jake's wine glass* (SK-VG (Ours))
Image
Query
Scene Knowledge

Figure 1. An example from the proposed SK-VG dataset for scene knowledge-guided visual grounding. The task requires a model to reason over the (image, scene knowledge, query) triple to locate the target object referred to by the query.

In this paper, we believe that the intrinsic difficulty of VG lies in the difference between perceptual representations of images and cognitive representations of texts. Specifically, visual features are obtained through perceptual learning, which

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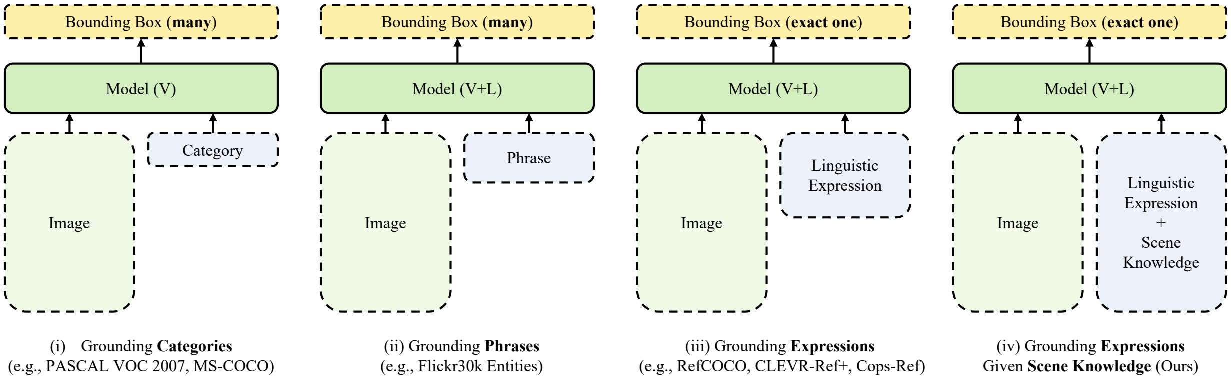


Figure 2. Illustrations of four categories of grounding tasks, including categories, phrases, linguistic expressions, and linguistic expression+scene knowledge. The height of the input green and blue rectangles denotes its relative information.

only maps visual appearances in images to semantic concepts. However, open-ended queries might require VG models to understand the whole scene knowledge before performing reasoning to locate the target object. As shown in Figure 1, the perceptual features can encode the information about "*a wine glass*", but it would struggle to locate "*Jake's wine glass*" without the scene knowledge about "*who is Jake?*". This is a challenging task owing to two facts: (i) From the dataset perspective, there are no relevant benchmarks for the VG researchers to evaluate their models; (ii) From the model/algorithm perspective, it is not easy to design models to perform reasoning among images, scene knowledge, and open-ended querying texts.

Therefore, we propose to break this limitation of current VG research and construct a new benchmark requiring VG to perform reasoning over Scene Knowledge (i.e., text-based stories). The benchmark named SK-VG contains ~40,000 referring expressions and 8,000 scene stories from 4,000 images, where each image contains 2 scene stories with 5 referring expressions for each story. Moreover, to evaluate the difficulty levels of queries, we curate the test set by splitting the samples into easy/medium/hard categories to provide a detailed evaluation of the vision-language models. Under this new setting, we develop a one-stage approach (i.e., Knowledge-embedded Vision-Language Interaction (KeViLI)) and a two-stage approach (i.e., Linguistic-enhanced Vision-Language Matching (LeViLM)). In KeViLI, the scene knowledge is firstly embedded into the image features, and then the interaction between the image and the query is performed; In LeViLM, the image features and the text features are first extracted, and then the matching between the (image) regions and the (text) entities are computed, assisted by the structured linguistic information. Through extensive experiments, we show that the proposed approaches can achieve the best performance but still leave room for improvement, especially in the hard split. It challenges the models from three perspectives: First, it is an open-ended grounding task; Second, the scene stories are long narratives consisting of multiple sentences; Third, it might require the multi-hop reasoning ability of the models. In summary, the contributions of this paper are three-fold:

- We introduce a challenging task that requires VG models to reason over (image, scene knowledge, query) triples and build a new dataset named SK-VG on top of real images through manual annotations.
- We propose two approaches to enhance the reasoning in SK-VG, i.e., one one-stage approach KeViLI and one two-stage approach LeViLM.
- Extensive experiments demonstrate the effectiveness of the proposed approaches. Further analyses and discussions could be a good starting point for future study in the vision-and-language field.

2. Background

2.1. Taxonomy of Visual Grounding Datasets

In the past few years, a variety of datasets have been proposed for visual grounding. We propose a taxonomy of existing (generalized) VG datasets along with the proposed dataset based on types of queries, as shown in Figure 2.

The datasets of the first type use fixed categories as queries.[1] Grounding categories in images are a fundamental task in computer vision and has attracted much attention. One of the most representative examples is the MS-COCO dataset [20], which contains 80 categories. Besides, PASCAL VOC 2007 [12], Visual Genome [18], and Object365 [34] are also popular datasets of this type.

The Flickr30K Entities dataset[2] [30] belongs to the second type, where the queries are short phrases. Similar to the

[1] Generally, it is called object detection. We generalize it to visual grounding to summarize and classify existing grounding datasets better.

[2] Although there are some studies locating the entities using the context provided by the dataset, we refer in particular to those using only the phrases as in [27].

first type, an image might contain multiple objects referred to by a phrase following the one-to-many mappings. The most distinct characteristic of this type from the first type is that it is an open-vocabulary grounding problem instead of using fixed categories. Most recently, researchers constructed relevant datasets of this type, i.e., PhraseCut [39] and LVIS [14], with a larger scale.

The third type aims at localizing a specific object in the image based on an expression in the form of natural language. In the narrow sense, the term *visual grounding* refers to this type of dataset in previous studies. Various benchmark datasets (e.g., RefCOCO [47], RefCOCO+ [47], RefCOCOg [29], and CLEVR-Ref+ [23]) have been constructed to test the ability to refer expression comprehension of existing vision-language models. In general, expressions in these datasets are written according to the visual appearance and spatial location of an object, where the visual appearance includes visual categories, color, and other visual attributes, and the spatial location describes the absolute or relative location. Different from the aforementioned two types, an expression in this type of dataset points to a unique object in the image following the one-to-one mapping.

Our proposed SK-VG is the first dataset of the fourth type, where for each image, we provide human-written scene knowledge to describe its content. By doing so, the VG models need to have a good understanding of the scene stories and then locate the queried object in the image according to both querying expressions and scene stories. Although there exists a dataset [36] introducing knowledge to the visual grounding model, it only focuses on the commonsense knowledge, which interprets the concept in the referring expressions, e.g., the interpretation of the target object 'banana'. There are also some datasets on grounding complex/compositional visual description, e.g., the human-centric HumanCog dataset [45] and the Cops-Ref dataset [5]. HumanCog requires the model to understand human-centric commonsense (e.g., the mental aspect), and Cops-Ref proposed a difficult task to require a model to identify an object described by a compositional referring expression from a curated set of images. We can still classify them into the first three categories since the knowledge is more about referring expressions, while the knowledge in our dataset is a comprehensive description of the scene.

2.2. Visual Grounding Models

Existing methods can be categorized into two classes: (i) two-stage methods [2, 21, 25, 37, 46] and (ii) one-stage methods [8, 15, 28, 42, 44, 50].[3] The former generates region proposals first and then exploits the language expression to select the best-matching region; The latter directly predicts the bounding boxes through vision-and-language interaction to avoid the computation-intensive object proposal generation and region feature extraction in the two-stage paradigm. Among these methods, some work [6, 10, 37, 40, 41] perform explicit reasoning by modeling the attributes of objects and the relations between objects to improve interpretability. However, limited by the simplicity of existing datasets, they can not take full advantage of their algorithms and do not model complicated semantic relations in images and texts. Besides, pretraining-based methods [16,19,43,49] have been applied to VG to improve the open-vocabulary grounding ability.

3. Dataset Construction

In this section, we present the SK-VG dataset. Compared to existing VG tasks, the key difference is that each image is paired with scene knowledge to describe its content. We detail the image collection, the annotation process, the dataset statistics, and splits in the following subsections.

3.1. Image Collection

To facilitate and ease the writing of a text story, we identify three significant aspects a qualified image should fulfill:

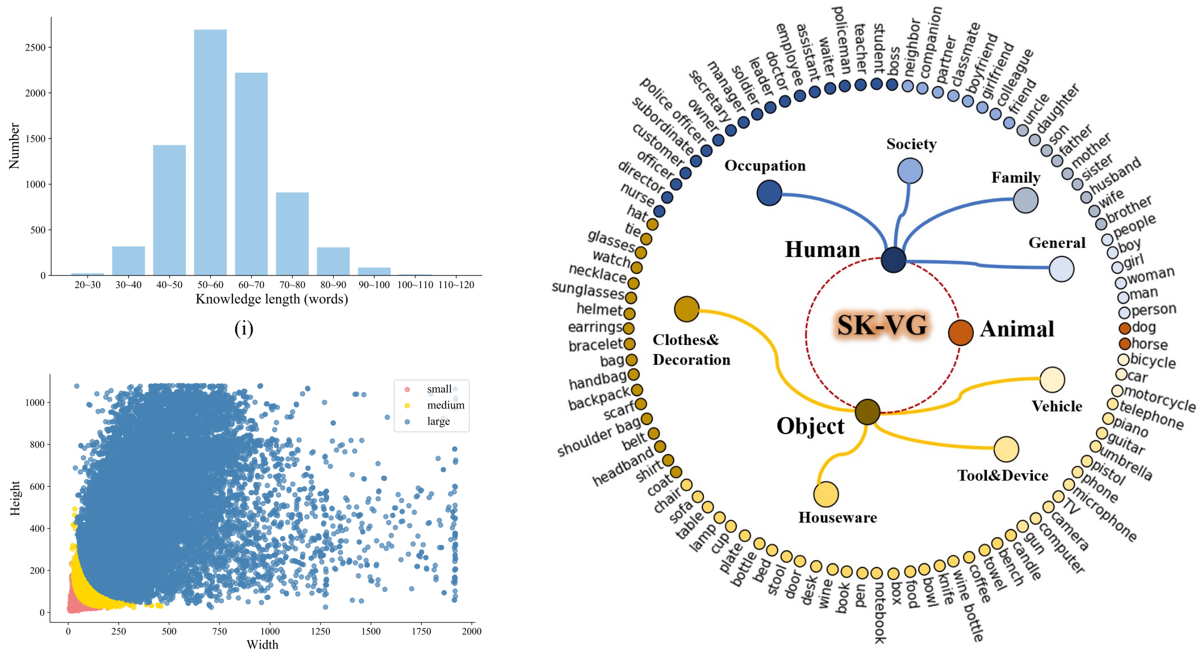
- **Humans** are the main body of a story. A satisfying image is better full of multiple characters with interactions to create complex and dramatic stories.
- **Objects** are also essential and necessary to complement the details of a story. The number and category of objects also impact our SK-VG task, making it more challenging and interesting.
- **Scenes** are the third factors we can not ignore since the scenes determine the background and starting point of stories. Complex and real scenes (e.g., theaters, classrooms, and parks) can inspire diverse stories.

Based on the above consideration, we select the existing Visual Commonsense Reasoning dataset [48], which is designed for the visual question answering task and contains more than 110,000 movie scene images. Thanks to the movie attribute of these images, they are more likely to meet our requirements and are suitable for our task. Therefore, through careful manual filtering and selection, 4,000 images serve as the ingredients of our SK-VG dataset.

3.2. Image Annotation

To facilitate the annotation process, we develop software. For each image, the annotation mainly includes two phases: (i) Annotators are asked to create two different story descriptions based on a given image; (ii) Given each story, the annotators are asked to write five referring expressions related to the given image and story and annotate the corresponding object bounding boxes as the ground truth. The required rules for each step are detailed as follows: (i) Knowledge

[3] Grounding categories is a very hot topic, where there are many research works [22, 24, 31, 32]. Yet we mainly discuss existing studies of grounding phrases/expressions, which are more related to this work.



(i)

(ii)

(iii)

Figure 3. Statistics of the proposed SK-VG dataset: (i) the length distribution of the knowledge description; (ii) the referred objects of high-frequency; (iii) the size distribution of referred objects.

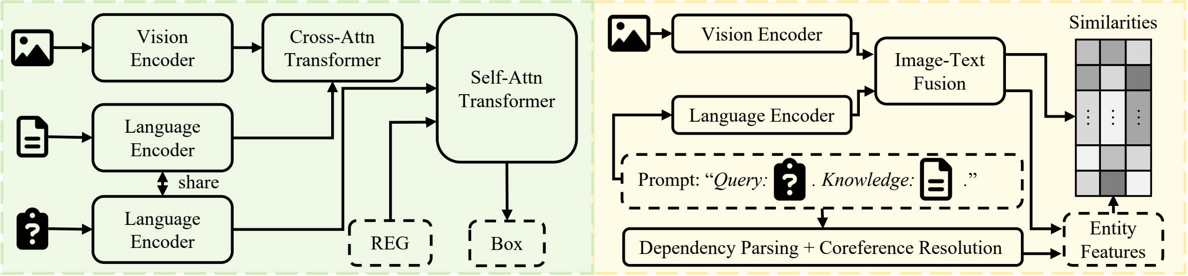
Annotation serves as a foundation stone of our annotation, determining the scope and quality of query sentences. A satisfying story should be related but beyond the image content. Specifically, the story should cover the person who occurred in one image with accurate visual descriptions, thus providing significant clues and evidence to match the image object and knowledge entity. Besides, the story is required to contain more context beyond the image, such as background, character relationship, mental state, and emotion, so as to promote the design of more challenging and flexible query expression. (ii) Query Expression Annotation plays an essential role in our task and ought to obey the following criteria:

- **Knowledge Relevance:** The main insight of our SK-VG task is to advance the traditional VG task by introducing extra scene knowledge descriptions. Based on this consideration and prospect, the first principle is that query sentences must be highly relevant to knowledge instead of directly visually distinguishable. Taking Figure 1 as an example, "*The black glasses*" is not qualified since it does not involve knowledge information.
- **Uniqueness:** To give a unique bounding box of the referred object, the query should be clear and unambiguous. For instance, queries like "*The person holding a wine glass*" or "*Jake's friend*" are not satisfied in Figure 1 since they involve several objects in the image.
- **Diversity:** For one thing, the referring objects should be diverse; For another, the lexical expression of the query sentence is also required to be diversified. For example, the general terms (e.g., "*person*") could be replaced by other specific alternatives (e.g., "*colleague*").

3.3. Dataset Statistics

To further dive into the proposed SK-VG dataset, we demonstrate its characteristics from three aspects:

- **Length of scene knowledge**: As shown in Figure 3(i), the word-based length of most stories ranges from 50 to 70. This puts high demands on models to capture long-range dependency to understand text content.
- **Categories of referred objects**: As an open-world task, referred objects of our dataset are not limited to a fixed number of categories. Figure 3(ii) exhibits 100 referred object classes with the highest frequency. Benefiting from the diverse stories and scenes, we introduce extensive referred targets with various expressions, increasing the difficulty of recognition and localization.
- **Size of referred objects**: We report the size of referred objects in Figure 3(iii), which indicates that the objects in our dataset fall into a wide range of sizes. Further, we define small, medium, and large concepts according to the area of the objects, following the boundary of 64×64 and 128×128. We can observe that large objects dominate our dataset, while small and medium instances hold a small proportion.



(i) Knowledge-embedded Vision-Language Interaction

(ii) Linguistic-enhanced Vision-Language Matching

Figure 4. Illustration of the proposed approaches: (i) the one-stage algorithm, where the knowledge is embedded into the image features before the image-query interaction; (ii) the two-stage algorithm, where the image features and text features are firstly extracted, and then the structured linguistic information is leveraged to assist in computing the region-entity similarities.

3.4. Dataset Splits

We randomly sample 60% of images and their annotations as the training set. For the remaining (image, scene knowledge, query) triples, we sample parts of them for annotating their difficulty levels and use them as the test set while the remaining triples are used as the validation set.[4] We follow the following rule to annotate the difficulty level. The core principle is that more knowledge-related but less visual-distinguishable expressions deserve a higher difficulty level: (i) Easy: The referring expression contains obvious appearance, object relationship, or other visual clues; (ii) Medium: The expression only mentions weak visual information; (iii) Hard: The answer is required to be entirely derived from the scene knowledge without visual bias. We show examples of different difficulty levels in §4.5.

4. Algorithmic Analysis

4.1. Algorithm 1: KeViLI

To perform SK-VG, we introduce a one-stage algorithm: Knowledge-embedded Vision-Language Interaction (KeViLI). Given an image I and its corresponding scene knowledge K, the goal is to locate the object referred to by a querying text T by predicting the coordinates of its corresponding bounding box directly.

In detail, given I, we use an image encoder to encode I to the image patch features H_I; given K and T, we use a language encoder to encode them to the knowledge features H_K and the text subword features H_T, respectively. Afterward, we embed the scene knowledge into the image features before the image-query interaction. As an intuitive illustration, in Figure 1, the visual features of "*person*" in the image is not only about the concept "*person*" but also about the specific refer "*Jake*" after embedding knowledge, which can assist in grounding "*Jake's wine glasses*". The embedding procedure is implemented using a cross-attention Transformer, which is stacked by self-attention, cross-attention, and feed-forward sub-layers. The attention mechanism is applied in the self-attention and cross-attention sub-layers and is defined as

$$\mathrm{ATTN}(\boldsymbol{Q},\boldsymbol{K},\boldsymbol{V}) = \mathrm{Softmax}\left(\boldsymbol{Q}\boldsymbol{K}^{\top}/\sqrt{D_k}\right)\cdot\boldsymbol{V}, \tag{1}$$

In the self-attention sub-layer, the patch features interact with each other through $H^I = \mathrm{ATTN}(H^I, H^I, H^I)$; In the cross-attention sub-layer, the knowledge is embedded into the image features by $H^I = \mathrm{ATTN}(H^I, H^K, H^K)$.[5] Subsequently, H_I and H_T are input to a Transformer with a learnable regression token `[REG]` to perform the image-query interaction. The output of `[REG]` is input to a two-layer multilayer perceptron (MLP) to produce to predict the coordinates directly without region proposals. The model is trained to minimize the generalized IoU loss [33] (GIoU loss):

$$L = L_{\text{smooth\_l1}}(b, \hat{b}) + L_{\text{giou}}(b, \hat{b}), \tag{2}$$

where b and $\hat{b}$ refer to the ground-truth and prediction boxes, respectively and $L_{\text{smooth\_l1}}(\cdot)$ and $L_{\text{giou}}(\cdot)$ are the smooth L1 loss and GIoU loss, respectively.

4.2. Algorithm 2: LeViLM

We further introduce a two-stage algorithm: Linguistic-enhanced Vision-Language Matching (LeViLM). In LeViLM, we follow GLIP [19] to initialize the backbone model, which had been trained from large-scale datasets to detect objects of open-vocabulary classes.

In detail, the grounding process is disentangled into two stages, i.e., region proposal and scoring, where the former aims to find all the objects in the image, and the latter aims to score the proposal regions. In the region proposal stage, given the scene knowledge K and the query T, we construct a manual prompt text P: "`Query:` T`.` `Knowledge:` K`.`". Then we use a language encoder to

[4] The images in the training set have no overlap with those in the validation and test sets.

[5] We overload the notations here for simplicity.

encode P into the prompt features H_P and an image encoder to encode I to the image features H_I. Afterward, we perform the image-text fusion using a stack of L layers. In each layer, there is one self-attention layer for text encoding and one Dynamic Head layer [7] for image encoding, and two cross-attention layers for cross-modal fusion. The text encoding and image encoding process can be formulated as $H_P = \mathrm{ATTN}(H_P, H_P, H_P)$ and $H_I = \mathrm{DynamicHead}(H_I)$, respectively. The cross-modal information fusion process can be formalized as $H_P = \mathrm{ATTN}(H_P, H_I, H_I), H_I = \mathrm{ATTN}(H_I, H_P, H_P)$, where the cross-attention mechanism is applied to exchange the image and text information. Subsequently, a region proposal layer is applied to H_I to obtain the region features. For simplicity, we denote the after-fusion image (region) features and text (subword) features as $Z_I \in \mathrm{R}^{N\times d}$ and $Z_P \in \mathrm{R}^{M\times d}$, where N refers to the number of proposed regions and M represents the number of subwords. In the region scoring stage, we extract structured linguistic information from the query T and the scene knowledge K. Specifically, given T, we perform syntactic dependency parsing to obtain its dependency tree and apply a set of rules to extract the subject of T, which we denote as the head entity E_h. Besides, we also build the connection between T and K through coreference resolution to find all mentions E_m in K refer to the same underlying entity E_h. Therefore, during the training procedure, we have the bounding box annotation for E_h and its co-referred E_m since E_h and E_m share the same object. Then we can take the representations of E_h and E_m from Z_P, denoted as $Z_E \in \mathrm{R}^{(E+1)\times d}$, where E represents the number of co-referred mentions. Afterward, we can compute the alignment scores between the image regions and the entities in the prompt:

$$Score = Z_I Z_e^\top, \tag{3}$$

where $Score \in \mathrm{R}^{N\times(E+1)}$. Finally, the model is trained to minimize the following loss:

$$L = L_{xe}(Score, Target), \tag{4}$$

where L_{xe} is the cross entropy loss and $Target \in \mathbb{R}^{N\times(E+1)}$, where each element indicates if a region and an entity are matched or not.

4.3. Implementation Details

For KeViLI, the input image is resized to 640 × 640, and the max (token-based) length for T and K are set to 32 and 256, respectively. During training, the model is optimized with the batch size set to 64 using AdamW optimizer [26], where the initial learning rate of the vision encoder and language encoder is set to 10^{-5} and the learning rate of the remaining parameters are set to 10^{-4}. Similar to [8], the vision encoder is initialized from the DETR model [3], and the language encoder is initialized with the BERT model [9]. The model is trained for 90 epochs with a learning rate dropped by a factor of 10 after the 60th epoch. For LeViLM, we initialize the backbone model from [19]. We train the model with the batch size set to 32. Similarly, the learning rate is set to 10^{-5} for the text encoder and 10^{-4} for the remaining parameters. During training, the learning rate is decayed at 67% and 89% of the total training steps.

Method	[46]	[21]	[25]	[44]	[42]	KeViLI	LeViLM
Acc	25.28	25.24	26.08	16.3	36.68	30.01	72.57

Table 1. Comparisons of our approaches with existing studies.

To evaluate LeViLM on the SK-VG dataset, we testify different experimental settings:

- **Data**: Query-only (Q), Query-knowledge (Q+K), and Query-knowledge-linguistic-structure (Q+K+S);
- **Training**: (i) Zero-shot (ZS): We directly evaluated the pre-trained model without finetuning; (ii) Linear-probing (LP): We fixed the backbone model; (iii) Fine-tuning (FT): We tuned all the parameters of the model.
- **Evaluation**[6]: (i) Selecting the prediction with the highest score (H), (ii) Randomly picking the prediction whose score is over 0.5 (R), (iii) Selecting the ground-truth one if its score is larger than 0.5 (U).[7]

For the evaluation metric, we adopt Intersection-over-Union (IoU), which measures the overlap degree between the prediction and the ground truth. Following previous studies [8, 29, 47], we use IOU@0.5 as the prediction accuracy.

4.4. Experimental Results and Analyses

To analyze the performance of different baselines, we consider the following questions and conduct analyses to answer them with the results reported in Table 1 and 2.

Q1: Is SK-VG a hard task for traditional VG models? As shown in Table 1, existing models did not achieve promising results An interesting finding is that ReSC, which uses texts to recursively refine the text-conditional visual features, achieved the best result (∼36%) among these existing models, which matches our intuition that it can better use long-form story information.

Q2: Which one is better, KeViLI or LeViLM? It can be observed in Table 2 that the performance of LeViLM (ID 3-26) is consistently better than KeViLI (ID 1-2), even without any finetuning (ID 3-4). We can explain this by the reason that the task's inherent difficulty is understanding open-ended stories, queries, and their relations with the images. For KeViL, the one-stage optimization to directly output bounding boxes of such open-ended target objects could be difficult. Instead,

[6] Since the LeViLM model might predict multiple bounding boxes, we adapt different evaluation strategies for analysis.

[7] The U strategy is adopted to analyze the reasoning error of the model.

Method	Text	Criteria	ID	Overall Acc	Difficulty-level			Area-level		
					Acc$_{de}$	**Acc**$_{dm}$	**Acc**$_{dh}$	**Acc**$_{as}$	**Acc**$_{am}$	**Acc**$_{al}$
KeViLI	Q	-	1	28.71	32.53	25.23	25.70	0.80	14.44	34.02
	Q + K	-	2	30.01	33.75	26.55	27.14	1.20	12.85	35.94
LeViLM (ZS)	Q	H	3	29.75	49.97	18.23	6.71	24.20	33.33	29.64
		R	4	29.77	48.28	18.88	9.01	23.20	33.12	29.79
		U	5	38.13	54.23	29.56	19.16	30.20	39.38	38.67
	Q + K	H	6	7.55	13.08	4.38	1.26	2.20	5.94	8.36
		R	7	7.78	12.88	4.71	2.12	2.20	5.73	8.69
		U	8	8.79	13.34	6.02	3.79	2.20	6.05	9.93
LeViLM (LP)	Q	H	9	44.97	72.03	31.86	11.70	50.60	57.54	42.13
		R	10	44.82	66.91	32.68	19.16	48.20	56.48	42.36
		U	11	63.09	77.51	54.90	46.64	52.60	64.86	63.79
	Q + K	H	12	35.71	60.40	25.07	3.96	41.20	48.51	32.84
		R	13	35.89	57.00	24.41	11.24	39.40	47.13	33.49
		U	14	47.71	64.40	41.43	25.30	43.20	55.52	46.72
	Q + K + S	H	15	37.25	62.09	26.98	4.88	42.20	49.47	34.54
		R	16	36.91	58.03	25.83	11.82	40.20	46.92	34.76
		U	17	50.47	66.61	44.77	28.40	44.40	56.69	49.92
LeViLM (FT)	Q	H	18	57.18	80.35	46.80	27.83	65.00	66.77	54.67
		R	19	57.29	80.15	46.63	28.74	65.00	65.39	55.06
		U	20	63.79	83.45	55.17	38.67	68.60	71.23	61.97
	Q + K	H	21	70.70	84.51	63.16	54.62	68.20	72.51	70.62
		R	22	70.49	84.28	62.67	54.73	68.80	72.51	70.29
		U	23	74.95	86.49	68.20	61.96	71.00	76.11	75.12
	Q + K + S	H	24	72.57	84.08	65.52	59.95	70.00	71.02	73.10
		R	25	71.93	83.72	64.97	58.75	70.00	71.44	72.21
		U	26	77.31	86.59	71.59	67.18	72.60	76.96	77.83

Table 2. The performance of two proposed approaches. In the text column, Q, K, and S represent query, knowledge, and linguistic structure, respectively. In the criteria column, H, R, and U represent the criteria to pick the detected bounding boxes by adopting the boxes with the highest scores, the random boxes, and the upper-bound scores that can be achieved, respectively. For the metrics, the overall accuracy, the difficulty-level accuracy, and the area-level accuracy are shown.

for LeViLM, after dividing and conquering the process (i.e., region proposing and scoring), it is easier to ensure each stage works well, e.g., to guarantee its basic detection ability before complex grounding using a pre-trained VG backbone.

Q3: Are linear-probing or finetuning necessary for LeViLM? We can investigate the effects of linear probing and finetuning by comparing the results (ID 3-8, ID 9-14, and ID 18-23). When adapting LeViLM on this dataset, the performance follows this pattern: finetuning $>$ linear-probing $>$ zero-shot. The reason behind this is that finetuning can guide the model to use the scene knowledge in a better way.

Q4: Is the scene knowledge critical for accurate prediction? To answer this question, we need to take the different evaluation strategies into account. Specifically, in the ZS and LP setting, it can be observed that the knowledge is harmful to the model performance by comparing ID 3-5 and ID 6-8 (or comparing ID 9-11 and ID 12-17). This is due to two reasons: (i) The texts of the pretraining datasets of LeViLM are relatively short, yet the length of scene knowledge in our dataset is much longer than that; (ii) The majority of the LeViLM pretraining datasets are about perception, i.e., detecting all the objects in the images instead of reasoning over the images and texts. Therefore, it is not enough to exploit the knowledge under the zero-shot and linear-probing settings. On the contrary, the knowledge has a considerably positive effect when full-finetuning LeViLM on the proposed dataset, which can be explained by the fact that LeViLM learns to reason over the images, knowledge, and querying texts after adaptation. Besides, bridging the scene knowledge and the queries in an appropriate way (ID 24-25) can further promote performance. The conclusion is that knowledge is critical for finetuning but can not be exploited appropriately in the zero-shot and linear-probing settings.

Q5: What is the advantage of exploiting the knowledge? For this question, there are two interesting observations from the results. First, when using the knowledge, the model can achieve a higher upper-bound result (comparing ID 20, 23, and 26), which means that the model can detect more objects in the images. We can explain this phenomenon by one of the possible instances: the querying text might contain different names of persons, and the model might not know the name refers to a person, which can be inferred from the

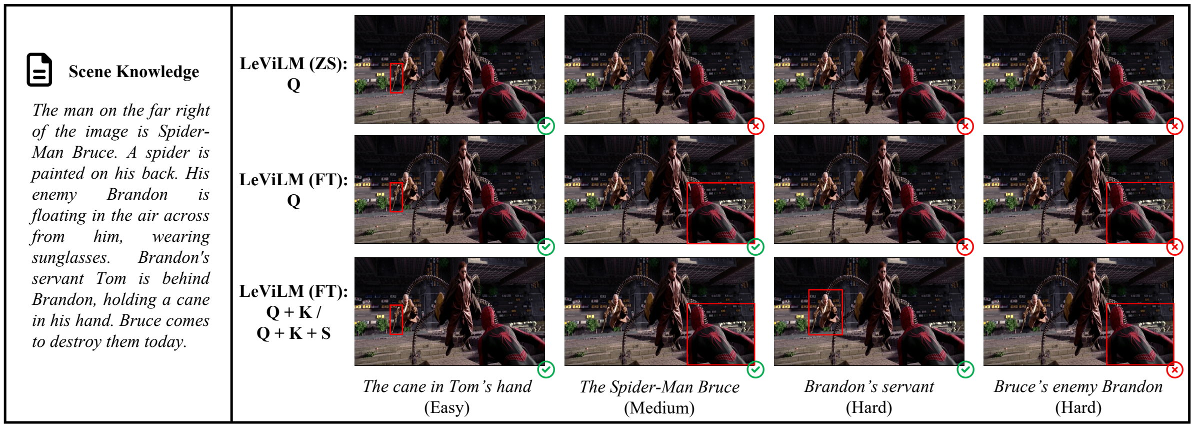

Scene Knowledge
The man on the far right of the image is Spider-Man Bruce. A spider is painted on his back. His enemy Brandon is floating in the air across from him, wearing sunglasses. Brandon's servant Tom is behind Brandon, holding a cane in his hand. Bruce comes to destroy them today.
LeViLM (ZS): Q
LeViLM (FT): Q
LeViLM (FT): Q + K / Q + K + S
The cane in Tom's hand (Easy)
The Spider-Man Bruce (Medium)
Brandon's servant (Hard)
Bruce's enemy Brandon (Hard)

Figure 5. The illustration of samples from the proposed SK-VG dataset, where a scene story and its four referring expressions are shown with the grounding results from four baseline methods.

knowledge. Second, with the knowledge, the model is able to perform more accurate reasoning, which can be observed by comparing the reasoning errors (the results of $U - H$) of Q and Q+K (or Q+K+S). This is because the knowledge can alleviate the reasoning uncertainty when grounding the objects. The answer is that scene knowledge can not only assist in detecting more objects but also reduce the uncertainty of locating/reasoning the target objects.

Q6: What do the approaches still struggle to do? Before answering this question, we can investigate the effects of the area of objects. As shown in Table 2, it is not challenging for LeViLM to detect small objects. By observing the difficulty-level accuracy, we can obtain the message that LeViLM is not capable of performing complicated (multi-hop) reasoning over the scene knowledge and producing accurate predictions. Besides, the prediction process is black-box and can not be explainable, which can be further studied in the future. The answer is that (i) The current baselines can only achieve strong results on easy or medium tasks and are unable to perform well on the hard task; (ii) The interpretability of the baselines is poor.

4.5. Case Study

To further investigate the effects of knowledge, we perform qualitative analysis on four cases in the SK-VG dataset. Figure 5 shows the grounding results of four baselines on four referring expressions. It is observed that in the first case, all the baselines can ground the "*cane*" in the image even without the knowledge since there is only one cane presented. In the second case, the finetuned LeViLM can detect the target object even without knowledge, while it can not detect the "*Brandon's servant*" without knowledge in the third case. In the last case, all the baselines can not ground the referred object correctly, and the last three baselines all treat the "*Spider-Man*" as the "*enemy*". This shows that the baseline models can not perform accurate reasoning in some complicated cases, demonstrating the challenges.

5. Concluding Remarks

The visual grounding field has emerged as a prominent attractive research direction, where the models are required to reason over vision and language to ground the target objects. Yet, the language part of the existing VG benchmarks is only simple description texts, which can not evaluate the reasoning capability of the models comprehensively. To take a step in this direction, we propose a new benchmark dataset called SK-VG, which requires models to reason over the (image, scene knowledge, query) triples to perform accurate reasoning. We propose two approaches to perform this new task: Knowledge-embedded Vision-Language Interaction and Linguistic-enhanced Vision-Language Matching. Experimental results confirm the validity of the proposed approaches but also show that there is still substantial room for improvement, e.g., reasoning and interpretability.

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