Interaction-Centric Knowledge Infusion and Transfer for Open-Vocabulary Scene Graph Generation

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https://github.com/HKUST-LongGroup/ACC

Abstract

Open-vocabulary scene graph generation (OVSGG) extends traditional SGG by recognizing novel objects and relationships beyond predefined categories, leveraging the knowledge from pre-trained large-scale models. Existing OVSGG methods always adopt a two-stage pipeline: 1) *Infusing knowledge* into large-scale models via pre-training on large datasets; 2) *Transferring knowledge* from pre-trained models with fully annotated scene graphs during supervised fine-tuning. However, due to a lack of explicit interaction modeling, these methods struggle to distinguish between interacting and non-interacting instances of the same object category. This limitation induces critical issues in both stages of OVSGG: it generates noisy pseudo-supervision from mismatched objects during knowledge infusion, and causes ambiguous query matching during knowledge transfer. To this end, in this paper, we propose an inter**AC**tion-**C**entric end-to-end OVSGG framework (**ACC**) in an interaction-driven paradigm to minimize these mismatches. For *interaction-centric knowledge infusion*, ACC employs a bidirectional interaction prompt for robust pseudo-supervision generation to enhance the model's interaction knowledge. For *interaction-centric knowledge transfer*, ACC first adopts interaction-guided query selection that prioritizes pairing interacting objects to reduce interference from non-interacting ones. Then, it integrates interaction-consistent knowledge distillation to bolster robustness by pushing relational foreground away from the background while retaining general knowledge. Extensive experimental results on three benchmarks show that ACC achieves state-of-the-art performance, demonstrating the potential of interaction-centric paradigms for real-world applications.

1 Introduction

Scene graph generation (SGG) [55] aims to map an image into a structured semantic representation, where objects are expressed as nodes and their relationships are as edges within the graph. Recently, with the burgeoning of large-scale models, *e.g.*, vision-language models (VLMs) and multimodal large language models (MLLMs), OVSGG [14, 29, 9] has emerged as a promising area. It pushes beyond predefined categories to support the recognition and generation of novel objects and relationships, holding great potential for real-world applications.

Generally, an end-to-end VLM-based[2] OVSGG pipeline consists of two phases: **Knowledge Infusion** and **Knowledge Transfer**. The **former** infuses knowledge from large-scale datasets into VLMs via pre-training. This process aims to achieve visual-concept alignment via caption-region comparison. Specifically, due to the lack of region-level information (*e.g.*, bounding box annotations), recent work [14, 63, 9] adopts a weakly-supervised strategy to generate $\langle$`subject`, `predicate`, `object`$\rangle$

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[2]We primarily discuss VLM-based models due to the high resource demands of MLLM-based approaches.

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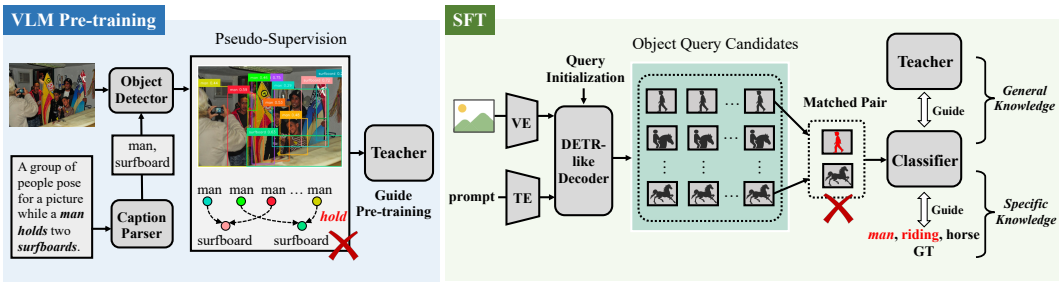

(a) Knowledge Infusion **(b) Knowledge Transfer**

Figure 1: Overview of the end-to-end OVSGG framework challenges. a) Knowledge Infusion, using solely object categories for detection causes ambiguity in associating object pairs (*e.g.*, identifying the correct "`man-surfboard`" for the "`hold`"). b) Knowledge Transfer, vast object query[3] candidates make misaligned non-interacting objects (*e.g.*, "`man` 🚶") with interacting training target "`man`" in ⟨`man`, `riding`, `horse`⟩.

triplets with bounding boxes as pseudo-supervisions. As displayed in Figure 1(a), this framework first extracts semantic graphs from image captions using SGG parsers [41], then grounds objects in the graphs with off-the-shelf object detectors (*e.g.*, Faster R-CNN [39], GLIP [27] and Grounding DINO [35]). The **latter** transfers knowledge from pre-trained VLMs by refining with task-specific objectives and high-quality annotations during supervised fine-tuning (SFT). Concretely, for specific knowledge, it finetunes part of VLM's parameters [9] or adapts prompt-tuning [14] on SGG dataset with fully-supervised triplet annotations (*c.f.* Figure 1(b)). Leveraging these bounding box annotations, a DETR-like structure [4, 66, 62] with bipartite graph matching is typically used to align predicted object queries[3] with ground-truths. Moreover, knowledge distillation (KD) [13, 60, 9] is widely used during SFT, where a generalist VLM (teacher) guides the target model (student) to retain general knowledge, allowing robust adaptation to unseen categories in open-world scenarios.

Despite notable advancements, prevailing OVSGG frameworks exhibit an *object-centric paradigm* in both knowledge infusion and transfer, *i.e.*, lack of interaction differentiation between instances within the same object category. For example, the `man` involved in a holding action and the `man` without any action are represented in an indistinguishable manner. It can amplify ***mismatches in relation pairs*** across both pre-training stage (*i.e.*, knowledge infusion) and SFT stage (*i.e.*, knowledge transfer), which induces the following drawbacks: ❶ *Bringing noisy supervision in pre-training*. As illustrated in Figure 1(a), relying solely on entity categories (*e.g.*, `man` and `surfboard`) to detect objects generates a large number of candidate pairs. This ambiguity makes it hard to associate relation (*e.g.*, "`hold`") to the proper object pair (*e.g.*, "`man-surfboard`"). Using mismatched triplets (*e.g.*, `man` in red and `surfboard` in pink) further exacerbates the confusion, hindering the training of robust SGG models. ❷ *Leading mismatched objects during SFT*. Due to the vast object query candidates, a non-interacting "`man` 🚶" query can be mistakenly associated with `man` in the triplet annotation ⟨`man`, `riding`, `horse`⟩ during bipartite graph matching, as displayed in Figure 1(b). However, the real target is another "`man` 🐎" engaged in riding. This mismatch further complicates the relation classification task, making it harder to predict correct interactions.

In this paper, we propose the inter**AC**tion-**C**entric end-to-end OVSGG framework (**ACC**), which fundamentally rethinks knowledge infusion and transfer through an interaction-driven paradigm. Unlike conventional object-centric approaches that treat all instances uniformly, ACC explicitly models relational dynamics at both pre-training and SFT stages to reduce the pervasive mismatch between interacting/non-interacting object pairs. For **interaction-centric knowledge infusion**, we devise a bidirectional interaction prompt to facilitate visual triplet pseudo-supervision generation, thereby infusing more robust interaction knowledge into pre-trained VLMs. These prompts incorporate interaction tokens that capture contextual dependencies and relational semantics, enabling the grounding model to distinguish interacting objects (*e.g.*, `man` involved in holding action) from non-interacting ones through the attention mechanism [49]. For **interaction-centric knowledge transfer**, to achieve the paradigm shift from object-centric to interaction-centric knowledge transfer, we first establish *interaction-guided query selection*, a two-step mechanism to prioritize interacting objects and incorporate relational context into the query selection process, mitigating interference of

[3]Object queries are learnable embeddings input to its Transformer decoder, each specializing through attention to global image features to predict a unique object's localization and classification.

inactive objects and reducing mismatches in bipartite graph matching. To preserve general knowledge, we further incorporate *interaction-consistent KD* to realize both point-wise semantic alignment and inter-pair relational consistency among teacher and student. By explicitly modeling the relative dependencies between interaction-based and non-interaction pairs, this KD strategy enhances the model's robustness in handling novel triplet combinations and background and avoiding catastrophic general knowledge forgetting [13, 9].

To evaluate ACC, we conducted comprehensive experiments on the benchmark Visual Genome (VG) [19], GQA [16], and PSG [56] datasets to validate its effectiveness in addressing the key challenges of OVSGG. In summary, our contributions are threefold:

- We reveal key limitations in existing OVSGG frameworks, *i.e*., the neglect of interaction-specific characteristics among instances of the same object category during knowledge infusion and transfer, which leads to widespread relation pair mismatches.
- We propose an interaction-centric end-to-end OVSGG framework ACC, shifting the paradigm from object-level representations to interaction-driven learning. By explicitly encoding interactions during both knowledge infusion and transfer, ACC enables more accurate scene graph generation and robust generalization to unseen categories.
- Extensive experiments on three prevalent SGG benchmarks demonstrate the effectiveness and generalizability of ACC.

2 Related Work

Open-Vocabulary SGG (OVSGG). This task bridges the gap between closed-set SGG and real-world requirements by leveraging VLMs or MLLMs to generalize beyond predefined categories [38, 35, 22, 57]. Current approaches fall into two main groups: 1) *VLM-based Methods.* They primarily rely on contrastive pre-training to align visual and textual embeddings. By comparing visual features of unseen objects/relations and their semantics in common spaces, these models (*e.g*., CLIP [38] and Grounding DINO [35]) enable zero-shot generalization. Recent advancements, such as He *et al*. [14], explore visual-relation pre-training and prompt fine-tuning for OVSGG. Yu *et al*. [59] leverage CLIP to align relational semantics in multimodal spaces, while Chen *et al*. [9] use a student-teacher framework to improve open-set relation prediction. Besides, other methods integrate class-level descriptions [25, 20] or scene-level descriptions [6] to enrich the semantic context and enhance the discrimination among different relationships. 2) *MLLM-based Methods.* They extend the capabilities of VLMs by incorporating auto-regressive language models, predicting objects and relations in an open-ended manner. Specifically, they use the sequential prediction capabilities of MLLMs, *e.g*., BLIP [21] and LLaVA [33], to model scene graphs as structured sequences [24]. For example, PGSG [29] and OpenPSG [65] employ auto-regressive models to iteratively predict open-ended objects and relations. ASMv2 [51] builds on LLaVA [33] with instruction tuning [52], unifying both object localization [42, 43] and relation comprehension [23, 26]. Despite their power, MLLM-based methods typically require huge computing resources. This work focuses on VLM-based methods and proposes an interaction-centric framework that explicitly models interactions and enhances generalization to novel categories.

Knowledge Infusion and Transfer for Open-Vocabulary Learning. Recent VLM advancements unlock open-vocabulary downstream tasks via two main steps: 1) Knowledge infusion into VLMs (*e.g*., CLIP [38]) via contrastive learning on large image-text pairs for aligned visual-textual representations. 2) Knowledge transfer by SFT of pre-trained VLMs with task-specific objectives and high-quality annotations for adaptation to tasks like open-vocabulary object detection/segmentation. Within this framework, effectively mining semantic knowledge and leveraging transferable representations has emerged as a key research area to improve generalization in open-world settings while reducing computational/annotation costs. For instance, Wu *et al.* [54] replace the DETR-style encoder with CLIP's visual encoder and employ prompt tuning [30] to adapt image-level representations to region-level tasks for OV object detection. Similarly, Cho *et al.* [10] fine-tune CLIP for open-vocabulary segmentation by incorporating cost aggregation techniques [15]. Besides, Chen *et al.* [9] extend this framework to OVSGG and build upon the GroundingDINO [35] with knowledge distillation to preserve learned knowledge, but still under an object-centric paradigm. Conversely, this work emphasizes interaction-centric knowledge infusion and transfer for robust OVSGG.

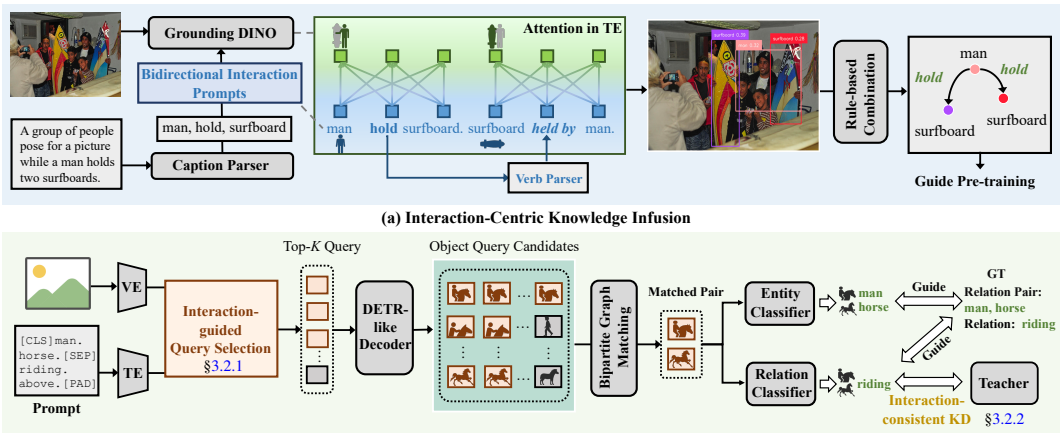

Figure 2: Overview of ACC for OVSGG. (a) Interaction-Centric Knowledge Infusion: Employs bidirectional interaction prompts and rule-based bounding box combinations for robust pseudo-supervision, empowering the model's grasp of relational knowledge. (b) Interaction-Centric Knowledge Transfer: Uses interaction-guided query selection to prioritize learning on interacting objects, and interaction-consistent KD transfers comprehensive relational insights from the pre-trained VLM to ensure robust generalization to novel categories.

Knowledge Distillation (KD). This strategy trains a smaller "student" model to replicate the outputs of a larger "teacher" model, commonly used in open-vocabulary learning to transfer knowledge from VLMs. It encourages the student to mimic the teacher's enriched hidden space, enabling generalization from base to novel concepts. Prior work [13, 60] explores KD in open-vocabulary object detection by using L1/MSE loss to align the student detector's features with the teacher VLM's regional visual features. However, this hard alignment may fail to capture complex feature structures. Later work [2, 37] aligns the similarity of inter-embeddings, aiding in the acquisition of structured knowledge. Recent work extends to multi-scale level [50] or bags-of-region level [53], contrasting with InfoNCE loss. This paper adopts an interaction-consistent KD that combines point-to-point concept retention and structure-aware interaction retention distillation, preserving teacher's knowledge and identifying novel relationships beyond backgrounds.

3 ACC: Interaction-Centric End-to-end OVSGG Framework

Formulation. Given an image I, SGG aims to construct a structured semantic graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$. Each node $v_i \in \mathcal{V}$ is defined by its bounding box (bbox) and category, while each edge $e_{ij} \in \mathcal{E}$ represents the relationship between v_i and v_j. In **open-vocabulary settings**, the label set $\mathcal{C}$ for nodes and edges is divided into *base classes* $\mathcal{C}_B$ and *novel classes* $\mathcal{C}_N$, such that $\mathcal{C}_B \cup \mathcal{C}_N = \mathcal{C}$ and $\mathcal{C}_B \cap \mathcal{C}_N = \emptyset$. $\mathcal{C}_B$ contains seen classes during training, while $\mathcal{C}_N$ includes unseen classes that the model is expected to generalize to during inference.

Baseline End-to-End OVSGG Architecture. As illustrated in Figure 2(b), an end-to-end OVSGG framework [9, 36] typically follows a dual-encoder-single-decoder architecture [35], involving three main components:

- **Visual and Text Encoders.** Visual encoder (VE) extracts multi-scale visual features $\mathbf{V} \in \mathbb{R}^{N_v \times d}$. Text encoder (TE) processes textual prompts that concatenate all predefined object and relation categories [63, 9], *e.g.*, "`[CLS] man. horse. [SEP] riding. above. [PAD]`" to derive semantic embeddings for objects $\mathbf{T}_o \in \mathbb{R}^{N_o \times d}$ and relation $\mathbf{T}_r \in \mathbb{R}^{N_r \times d}$. Here, N_v, N_o, and N_r denote the numbers of image, object, and relation tokens, respectively. d is the feature dimension.
- **DETR-like Decoder.** It refines the representations of K object queries $\{\mathbf{q}_i\}_{i=1}^{K}$ through self-attention and cross-attention mechanisms, leveraging both visual and text features, ultimately predicting object bounding box coordinates. Besides, a global relation query $\mathbf{q}_{rel}$ is often utilized to capture spatial and semantic dependencies among objects [44, 9].
- **Entity and Relation Classifiers.** For open-vocabulary recognition, node features $\{\mathbf{e}_o\}$ (derived from refined object queries) and edge features $\{\mathbf{e}_{ij}\}$ (constructed by combining features of paired

objects, potentially augmented with global relation embeddings) are compared against the textual object/relation class embeddings.

The training of such models conventionally relies on *bipartite graph matching* to align object queries with ground-truth annotations, minimizing a cost function based on semantic and spatial criteria [4]. Optimization objectives usually include bbox regression loss (L1 $\mathcal{L}_{reg}$ and GIoU loss $\mathcal{L}_{giou}$ [40]), cross-entropy based entity and relation classification losses ($\mathcal{L}_{obj}$ and $\mathcal{L}_{rel}$)[4]. However, the efficacy of this process is undermined if the supervision is noisy (due to object-centric pre-training) or if query-to-target alignment is confounded by non-interacting distractors (due to object-centric SFT). To surmount the limitations imposed by current end-to-end OVSGG designs, ACC introduces a fundamental shift towards an *interaction-driven* paradigm. As illustrated in Figure 2, ACC incorporates interaction-centric knowledge infusion and transfer.

3.1 Interaction-Centric Knowledge Infusion

Addressing the challenge of noisy supervision from object-centric pseudo-labeling (issue ❶ in §1), ACC's knowledge infusion stage fundamentally alters how training targets are generated for VLM pre-training. To ensure that pseudo-supervision effectively captures interaction distinctiveness, especially within weakly annotated data, ACC conditions the object detection process on interactional context rather than relying on prompts based on isolated object classes (*e.g.*, "`man. surfboard.`").

To be specific, after the semantic graph parsing process, which extracts initial subject-predicate-object triplets from image captions with a language parser [41], we employ Grounding DINO [35] as the object detector and design **bidirectional interaction prompt** to guide the object localization. The bidirectional interaction prompt is constructed by combining two perspectives for each interaction triplet: one reflecting the action from the subject's viewpoint (*e.g.*, "`man hold surfboard`") and another from the object's perspective (*e.g.*, `surfboard held by man`"). The former is directly derived from the components of the interaction triplet, while the latter converses the subject and object with a *counter-action* (*e.g.*, "`held by`") generated by the verb parser. This verb parser is typically an LLM[5] (*e.g.*, Llama2 [48] and Qwen [1]) or Python Library.

The dual-perspective construction process brings two key advantages: 1) *Modeling Context Information*: Through the attention mechanism in the text encoder of Grounding DINO, the bidirectional interaction prompt integrates contextual interaction information into object tokens. As shown in Figure 2(a), the attention mechanism enables the token "`man`" to absorb relevant interaction semantics, such as "`hold surfboard`", ensuring that the grounded object "`man`" is correctly aligned with its interaction context. 2) *Enhancing Object Role Awareness*: By reversing operation, the object (*e.g.*, "`surfboard`") of given triplet becomes the syntactic subject of the whole sentence (*e.g.*, "`surfboard held by man`"). As the central of the rephrased sentence, the syntactic subject receives heightened attention, improving its accuracy in localization.

Furthermore, inspired by [31, 17], we adopt a *rule-based combination* that combines overlapping subject and object bounding boxes to form triplet supervision by Intersection over Union (IoU) score.

3.2 Interaction-Centric Knowledge Transfer

The interaction-centric knowledge infused during pre-training (§3.1) provides a strong foundation. Nevertheless, it still faces a mismatch problem during SFT (issue ❷ in §1). ACC's interaction-centric knowledge transfer is designed to ensure that 1) the selection and refinement of object queries are explicitly guided by interaction potential, and 2) the rich, interaction-focused knowledge from the pre-trained model is adequately transferred and further enhanced to discriminate between genuine interactions and non-interacting background. This is achieved through interaction-guided query selection and interaction-consistent knowledge distillation.

3.2.1 Interaction-Guided Query Selection

To mitigate mismatched object pairs during SFT, interaction-guided query selection instills an interaction prior into the two-step query generation process to reduce non-interacting candidates.

[4]Detailed formulations are left in appendix §B.

[5]The generation process of counter-action is in the appendix §C.

Step I. This step aims to directly identify the most relevant visual tokens likely to participate in object interactions. Intuitively, the visual features of interacting objects should exhibit strong correlations with both object and relation semantics. To achieve this, for each visual token $\mathbf{v}_i \in \mathbf{V}_v$, a relevance score s_i is computed by combining its maximum similarity with object and relation class tokens:

$$s_i = \left(\max(\mathbf{v}_i \mathbf{T}_o^\top)\right)^\gamma \cdot \left(\max(\mathbf{v}_i \mathbf{T}_r^\top)\right)^{1-\gamma}, \tag{1}$$

where $\max(\mathbf{v}_i \mathbf{T}_o^\top)$ computes the maximum similarity between the visual token $\mathbf{v}_i$ and all object class tokens in $\mathbf{T}_o$, while $\max(\mathbf{v}_i \mathbf{T}_r^\top)$ computes the maximum similarity between $\mathbf{v}_i$ and all relation class tokens in $\mathbf{T}_r$. The parameter $\gamma \in [0, 1]$ balances their contributions. Based on the relevance scores, the top K query indices, denoted as $\mathcal{I}_K$, are selected by the following procedure:

$$\mathcal{I}_K = \text{Top}_K(\{s_i \mid i = 1, 2, \ldots, N_v\}). \tag{2}$$

The visual features and the position embedding [62, 35] corresponding to the selected indices $\mathcal{I}_K$ are used to initialize queries for further decoding operations.

Step II. Nevertheless, Step I's individual encoding of object and relation tokens struggles to capture deeper interaction semantics and distinguishes among objects. Thus, Step II explicitly models interaction semantics by integrating relational context into the object tokens. Specifically, after the initial forward pass, the model predicts a set of visual relation triplets. These triplets are decomposed into interaction pairs $\langle$`subject`, `predicate`$\rangle$ and $\langle$`predicate`, `object`$\rangle$, which serve as *interaction-guided prompts*. These prompts are encoded via the TE of VLM to get interaction tokens embeddings $\mathbf{T}_{in}$. The decomposition process has dual advantages: First, the predicates within prompts guide the TE's attention to infuse object tokens with interaction information, enabling the model to capture contextual dependencies and enhance its understanding of relationships. For instance, the token "`man`" can incorporate the semantic meaning of the interaction "`riding`" to obtain "`man` 🏇" in Figure 2(b). Second, decomposing triplets into pairs avoids direct interference between object tokens, effectively preserving their unique characteristics. As illustrated in Figure 2(b), "`man` 🏇" and "`horse` 🐎" are independently processed, preventing unnecessary dependencies across unrelated categories and maintaining the individual semantics of each object.

For each visual token $\mathbf{v}_i$, the interaction relevance score s_i^{in} is calculated by measuring the maximum similarity with interaction tokens:

$$s_i^{in} = \max(\mathbf{v}_i \mathbf{T}_{in}^\top). \tag{3}$$

The query indices set prioritizes the top L tokens with the highest interaction relevance:

$$\mathcal{I}_L^{in} = \text{Top}_L(\{s_i^{in} \mid i = 1, 2, \ldots, N_v\}). \tag{4}$$

However, relying solely on interaction relevance may fail to identify objects absent from the initially predicted triplets yet crucial for comprehensive scene understanding. To address this, the object relevance score s_i^o is computed similarly, but using object tokens $\mathbf{T}_o$. The remaining $K - L$ query indices are selected based on object relevance, excluding those already chosen:

$$\mathcal{I}_{K-L}^o = \text{Top}_{K-L}(\{s_i^o \mid i \notin \mathcal{I}_L^{in}, i = 1, 2, \ldots, N_v\}). \tag{5}$$

The final query indices set combines these two subsets $\mathcal{I}_K = \mathcal{I}_L^{in} \cup \mathcal{I}_{K-L}^o$. This two-step strategy effectively reduces non-interacting candidates and mitigates bipartite graph mismatches. Pseudo-code detailing this process is in appendix §D for clarity.

3.2.2 Interaction-Consistent Knowledge Distillation

Beyond localization and classification objectives, we adopt interaction-consistent KD to enhance the model's ability to distinguish interacting pairs from background and address catastrophic forgetting of learned relational semantics [9]. Specifically, it uses the VLM pre-trained in the first stage as the teacher model. The student network is designed as a pseudo-siamese structure of the teacher, initialized with its parameters.

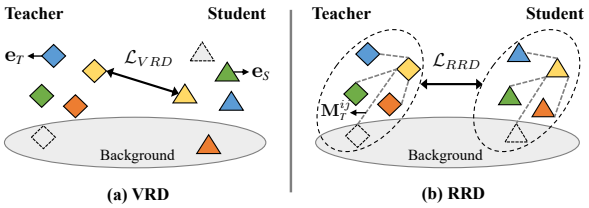

Figure 3: Illustration of interaction-consistent KD.

This KD combines *visual-concept retention distillation* (VRD) and *relative-interaction retention distillation* (RRD) to align the student model with the teacher's semantic space while maintaining inter-pair relational consistency. The entire loss function contains two complementary objectives:

VRD. The first objective draws from [9] ensures that the student's edge features remain point-wise consistent with the teacher's semantic space for negative samples. The loss is defined as:

$$\mathcal{L}_{VRD} = \frac{1}{|\mathcal{N}|} \sum_{\mathbf{e} \in \mathcal{N}} \|\mathbf{e}_S - \mathbf{e}_T\|_1, \tag{6}$$

where $\mathbf{e}_S$ and $\mathbf{e}_T$ represent student and teacher's edge features, and $\mathcal{N}$ is the set of negative samples.

RRD. While VRD effectively preserves point-wise semantic consistency, it fails to ensure the relative relationships between triplets, *i.e.*, distinguishing interaction pairs from backgrounds (*c.f.* Figure 3(a)). RRD explicitly models inter-pair relativity [2, 37] by aligning the structure similarity of triplet embeddings between the teacher and student models. The structure similarity matrices for the teacher and student models, $\mathbf{M}_T$ and $\mathbf{M}_S$, are normalized by L2 norm:

$$\mathbf{M}_T^{ij} = \frac{\mathbf{e}_T^i \cdot \mathbf{e}_T^{j\top}}{\|\mathbf{e}_T^i \cdot \mathbf{e}_T^{j\top}\|_2}, \quad \mathbf{M}_S^{ij} = \frac{\mathbf{e}_S^i \cdot \mathbf{e}_S^{j\top}}{\|\mathbf{e}_S^i \cdot \mathbf{e}_S^{j\top}\|_2}. \tag{7}$$

RRD then aligns these similarity matrices by minimizing the Frobenius norm $\|\cdot\|_F$ between them:

$$\mathcal{L}_{RRD} = \frac{1}{|\mathcal{N}|^2} \|\mathbf{M}_S - \mathbf{M}_T\|_F^2. \tag{8}$$

Final Objectives: Combine localization and classification losses with above complementary objectives to achieve point-wise semantic alignment and relational consistency:

$$\mathcal{L} = \mathcal{L}_{reg} + \mathcal{L}_{giou} + \mathcal{L}_{obj} + \mathcal{L}_{rel} + \beta_1 \mathcal{L}_{VRD} + \beta_2 \mathcal{L}_{RRD}. \tag{9}$$

The weights β_1 and β_2 control the importance of semantic alignment and relational consistency.

4 Experiments

4.1 Experiment Setup

Datasets. We evaluated ACC on three SGG benchmarks: 1) **VG** [19] contains annotations for 150 object categories and 50 relation categories across 108,777 images. Following standard setup [55], 70% of the images are used for training, 5,000 for validation, and the remaining for testing. For a fair comparison, we excluded images overlapping with the pre-training dataset of Grounding DINO [35], retaining 14,700 test images as in [63]. 2) **GQA** [16] uses the GQA200 split [12, 45], including 200 object categories and 100 predicate categories. We randomly sampled 70% of the object and predicate categories as the base, and more details can be found in the appendix §A. 3) **PSG** [56] offers 44,967 training, 1,000 test, and 3,000 validation images (sampled from training), with 133 object and 56 predicate categories. We adopted the same base and novel class splitting in [29].

Settings. Following [9], we compared ACC under two settings: 1) **OvR-SGG**: Evaluates generalization to unseen relations while retaining original object categories. Fifteen of 50 relation categories in VG150 are removed during training, with performance measured on "Base+Novel (Relation)" and "Novel (Relation)". 2) **OvD+R-SGG**: Assesses handling of unseen objects and relations simultaneously. Both novel objects and relations are excluded during training, evaluated on "Joint Base+Novel", "Novel (Object)", and "Novel (Relation)".

Metrics. We conducted experiments under the challenging Scene Graph Detection (**SGDET**) protocol [55, 19], which requires detecting objects and identifying relationships between object pairs without GT object labels or bounding boxes. We reported: 1) **Recall@K** (**R@K**): The proportion of ground-truth triplets correctly predicted within the top-K confident predictions. 2) **Mean R@K** (**mR@K**): The average R@K across all categories.

Implementation Details. Due to space constraints, details are provided in the appendix §A.

4.2 Comparison with State-of-the-Art Methods

We compared ACC with existing state-of-the-art methods, *i.e.*, **VS**^{3} [63], **OvSGTR** [9], and **RAHP** [36]. The experimental results on the VG dataset [19] under both the OvR-SGG and OvD+R-SGG setups are shown in Table 1 and Table 2, respectively. Notably, ACC consistently outperforms the latest SOTA methods across all metrics. In the OvR-SGG setup, ACC surpasses the RAHP (Swin-T) by **+1.78**% R@100 within the novel relation categories, demonstrating superior generalization

Table 1: Experimental results of OvR-SGG setting on VG [19] test set.

Method		Backbone	Base+Novel (Relation)			Novel (Relation)		
			R@20	R@50	R@100	R@20	R@50	R@100
IMP [55]	CVPR'17	-	-	12.56	14.65	-	0.00	0.00
MOTIFS [61]	CVPR'18	-	-	15.41	16.96	-	0.00	0.00
VCTREE [47]	CVPR'19	-	-	15.61	17.26	-	0.00	0.00
TDE [46]	CVPR'20	-	-	15.50	17.37	-	0.00	0.00
OpenSGen [18]	ICMR'25	-	-	18.00	20.50	-	15.70	17.90
VS^3 [63]	CVPR'23	Swin-T	-	15.60	17.30	-	0.00	0.00
OvSGTR [9]	ECCV'24		-	20.46	23.86	-	13.45	16.19
RAHP [36]	AAAI'25		-	20.50	25.74	-	15.59	19.92
ACC (Ours)			**17.49**	**23.22**	**27.40**	**12.90**	**17.89**	**21.70**
OvSGTR [9]	ECCV'24	Swin-B	-	22.89	26.65	-	16.39	19.72
ACC (Ours)			**18.77**	**24.81**	**29.28**	**14.72**	**20.04**	**24.66**

Table 2: Experimental results of OvD+R-SGG setting on VG [19] test set.

Method		Backbone	Joint Base+Novel			Novel (Obj)			Novel (Rel)		
			R@20	R@50	R@100	R@20	R@50	R@100	R@20	R@50	R@100
IMP [55]	CVPR'17	-	-	0.77	0.94	-	0.00	0.00	-	0.00	0.00
MOTIFS [61]	CVPR'18	-	-	1.00	1.12	-	0.00	0.00	-	0.00	0.00
VCTREE [47]	CVPR'19	-	-	1.04	1.17	-	0.00	0.00	-	0.00	0.00
TDE [46]	CVPR'20	-	-	1.00	1.15	-	0.00	0.00	-	0.00	0.00
VS^3 [63]	CVPR'23	Swin-T	-	5.88	7.20	-	0.00	0.00	-	0.00	0.00
OvSGTR [9]	ECCV'24		10.02	13.50	16.37	10.56	14.32	17.48	7.09	9.19	11.18
ACC (Ours)			**12.61**	**17.43**	**21.27**	**12.48**	**17.16**	**21.10**	**11.38**	**15.90**	**19.46**
OvSGTR [9]	ECCV'24	Swin-B	12.37	17.14	21.03	12.63	17.58	21.70	10.56	14.62	18.22
ACC (Ours)			**13.50**	**18.88**	**23.19**	**13.46**	**18.84**	**23.29**	**12.37**	**17.50**	**21.73**

and reduced overfitting. With the Swin-B backbone, ACC achieves 29.28% R@100, which is higher than OvSGTR across both base and novel relations, further emphasizing its robustness. In the more challenging OvD+R-SGG scenario, ACC continues to outperform the competition. Specifically, on the joint base and novel classes, ACC gains **+4.90**% and **+2.16**% R@100 over OvSGTR with the Swin-T and Swin-B backbones, respectively. These results validate ACC's superior performance and robust generalization across both relation and object domains.

4.3 Diagnostic Experiment

To ensure a comprehensive evaluation, we performed a series of ablation studies on the VG dataset [19] in the challenging OvD+R-SGG scenario. More experimental analyses are left in the appendix.

Knowledge Infusion Part. We analyzed the effectiveness of ACC's bidirectional interaction prompt (BIP) for pseudo-supervision generation (§3.1) in Table 3. It can be seen that BIP leads to consistent improvements across all metrics. Notably, when compared to the configuration without BIP, it achieves R@100 gains of **1.73**% on the joint base and novel classes, **1.45**% on novel object classes, and **1.63**% on novel relation classes, respectively. This demonstrates that BIP effectively improves performance by considering interaction contexts in supervision generation.

Table 3: Ablation studies (§4.3) on BIP.

Method	Split	R@20	R@50	R@100
Ours	`Joint Base+Novel`	**12.61**	**17.43**	**21.27**
w/o BIP		11.84	16.17	19.55
Ours	`Novel (Obj)`	**12.48**	**17.16**	**21.10**
w/o BIP		12.36	16.09	19.65
Ours	`Novel (rel)`	**11.38**	**15.90**	**19.46**
w/o BIP		10.73	14.40	17.83

Knowledge Transfer Part. We evaluated the efficacy of ACC's interaction-guided query selection (IGQS §3.2.1) and interaction-consistent KD (ICKD §3.2.2) in the knowledge transfer phase. The results are summarized in Table 4, with the first row representing the baseline OVSGG pipeline with *visual-concept retention distillation* from [9]. From this analysis, three key conclusions can be drawn: **First**, IGQS refines the query selection process. By prioritizing interacting objects and minimizing mismatched assignments, IGQS achieves notable improvements, such as **3.00**% R@100 gains, highlighting its ability to enhance precision by focusing on interacting object pairs. **Second**,

Table 4: Ablation studies (§ 4.3) on IGQS and ICKD.

Components		Joint Base+Novel			Novel (Obj)			Novel (Rel)		
IGQS	ICKD	R@20	R@50	R@100	R@20	R@50	R@100	R@20	R@50	R@100
		10.02	13.50	16.37	10.56	14.32	17.48	7.09	9.19	11.18
✓		11.37	15.71	19.37	11.43	15.80	19.61	9.84	13.92	17.38
	✓	11.43	15.67	19.20	11.57	15.65	19.32	10.07	14.00	17.32
✓	✓	11.84	16.17	19.55	12.36	16.09	19.65	10.73	14.40	17.83

Table 5: Comparison with pre-training methods. All models are **pre-trained** on image-caption data and tested on VG150 [19] test set directly. Our models trained on COCO captions are used as pre-trained models.

SGG model		Backbone	Grounding	R@20	R@50	R@100
LSWS [58]	CVPR'21	-	-	-	3.28	3.69
MOTIFS [61]	CVPR'18	-	Li *et al*. [31]	5.02	6.40	7.33
Uniter [8]	ECCV'20	-	SGNLS [64]	-	5.80	6.70
Uniter [8]	ECCV'20	-	Li *et al*. [31]	5.42	6.74	7.62
VS^3 [63]	CVPR'23	Swin-T	GLIP-L [27]	5.59	7.30	8.62
OvSGTR [9]	ECCV'24	Swin-T	Grounding DINO [35]	6.61	8.92	10.90
ACC (Ours)		Swin-T	Grounding DINO [35]	**7.86**	**10.81**	**13.31**
OvSGTR [9]	ECCV'24	Swin-B	Grounding DINO [35]	6.88	9.30	11.48
ACC (Ours)		Swin-B	Grounding DINO [35]	**8.28**	**11.61**	**14.33**

leveraging interaction-consistent KD with *relative-interaction retention distillation* ensures relational consistency during training, resulting in significant performance boosts. It contributes **2.83**% R@100 gains, improving the model's ability to handle novel classes effectively. **Third**, the integration of two components yields the best overall performance, with **1.80**%∼**6.65**% improvements across all evaluation metrics. However, the improvement is less pronounced than expected, since each strategy prioritizes interacting objects, which may lead to diminishing returns by progressively reducing non-interacting objects. Despite this, the combined results still demonstrates enhanced relational understanding and serve as a valuable tool for improving performance in complex scenarios.

Supervision Analysis. We investigated ACC's impact in the pre-training process (*c.f*. Table 5). As seen, models pre-trained on COCO [7] captions with ACC variants consistently outperform others, achieving **13.31**% R@100 with Swin-T and **14.22**% R@100 with Swin-B. These results demonstrate the effectiveness of ACC in the VLM pre-training process.

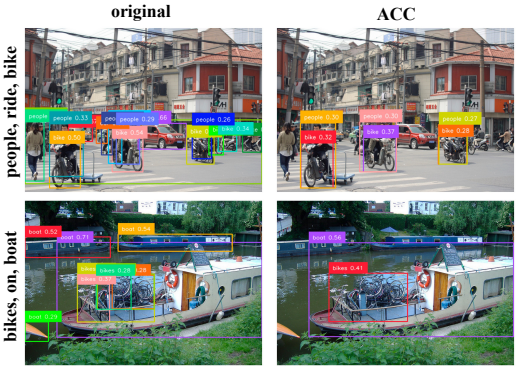

Figure 4: Pseudo supervision generation in ACC.

In addition, we visualized the object detection results from ACC and the original methods that solely use object categories for detection. As displayed in Figure 2, the original method produces redundant objects, complicating the identification of subject-object interactions. For instance, given the "⟨`people`, `ride`, `bike`⟩" triplet, the baseline detects multiple instances of "`people`" and "`bike`", obscuring the interaction. In contrast, ACC leverages bidirectional interaction prompts and attention mechanisms to accurately localize the interaction-relevant objects. A similar enhancement is observed in the "⟨`bikes`, `on`, `boat`⟩" triplet, where ACC focuses on interaction-relevant entities.

Query Visualization. To demonstrate the effectiveness of IGQS, we visualized the top-50 selected queries in Figure 5. As seen, the original approach makes no distinction between instances within the same category, such as "`man`" or "`zebra`", resulting in both interacting and non-interacting instances receiving a similar number of queries. This indiscriminate query generation increases the likelihood of incorrect matches during bipartite graph matching, as irrelevant regions compete with interaction-relevant instances. Conversely, IGQS prioritizes interacting queries ("man holding" or "zebra laying on" in Figure 5), increasing discrimination among objects with the same categories.

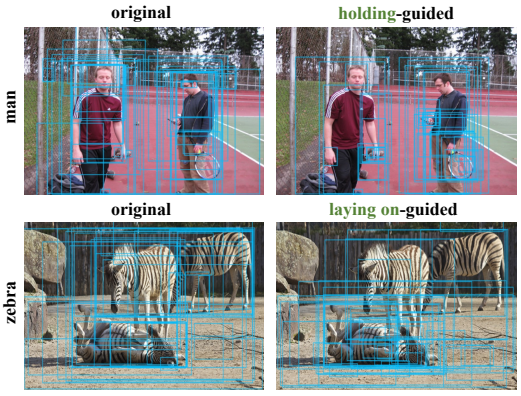

Figure 5: Interaction-guided query selection.

5 Conclusion

This work presented ACC, an interaction-centric OVSGG framework. ACC alleviates current paradigms' failure to distinguish interacting from non-interacting instances by adopting interaction-

centric principles in two key phases. Knowledge infusion uses a bidirectional interaction prompt for robust pseudo-supervision, enhancing interaction understanding; knowledge transfer combines interaction-guided query selection with interaction-consistent knowledge distillation to mitigate mismatches and irrelevant object interference. ACC shows significant improvements on three main benchmarks. We anticipate that ACC will not only set new standard for OVSGG but also inspire further exploration of interaction-driven strategies in VLMs for more accurate scene understanding.

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References

[1] Jinze Bai, Shuai Bai, Yunfei Chu, Zeyu Cui, Kai Dang, Xiaodong Deng, Yang Fan, Wenbin Ge, Yu Han, Fei Huang, et al. Qwen technical report. *arXiv preprint arXiv:2309.16609*, 2023.

[2] Hanoona Bangalath, Muhammad Maaz, Muhammad Uzair Khattak, Salman H Khan, and Fahad Shahbaz Khan. Bridging the gap between object and image-level representations for open-vocabulary detection. In *NeurIPS*, volume 35, pages 33781–33794, 2022.

[3] Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. Language models are few-shot learners. In *NeurIPS*, 2020.

[4] Nicolas Carion, Francisco Massa, Gabriel Synnaeve, Nicolas Usunier, Alexander Kirillov, and Sergey Zagoruyko. End-to-end object detection with transformers. In *ECCV*, pages 213–229, 2020.

[5] Yu-Wei Chao, Yunfan Liu, Xieyang Liu, Huayi Zeng, and Jia Deng. Learning to detect human-object interactions. pages 381–389. IEEE, 2018.

[6] Guikun Chen, Jin Li, and Wenguan Wang. Scene graph generation with role-playing large language models. *NeurIPS*, 2024.

[7] Xinlei Chen, Hao Fang, Tsung-Yi Lin, Ramakrishna Vedantam, Saurabh Gupta, Piotr Dollár, and C. Lawrence Zitnick. Microsoft COCO captions: Data collection and evaluation server. *CoRR*, abs/1504.00325, 2015.

[8] Yen-Chun Chen, Linjie Li, Licheng Yu, Ahmed El Kholy, Faisal Ahmed, Zhe Gan, Yu Cheng, and Jingjing Liu. UNITER: universal image-text representation learning. In *ECCV*, pages 104–120, 2020.

[9] Zuyao Chen, Jinlin Wu, Zhen Lei, Zhaoxiang Zhang, and Changwen Chen. Expanding scene graph boundaries: Fully open-vocabulary scene graph generation via visual-concept alignment and retention. In *ECCV*, 2024.

[10] Seokju Cho, Heeseong Shin, Sunghwan Hong, Anurag Arnab, Paul Hongsuck Seo, and Seungryong Kim. Cat-seg: Cost aggregation for open-vocabulary semantic segmentation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 4113–4123, 2024.

[11] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. BERT: pre-training of deep bidirectional transformers for language understanding. In *NAACL-HLT*, pages 4171–4186, 2019.

[12] Xingning Dong, Tian Gan, Xuemeng Song, Jianlong Wu, Yuan Cheng, and Liqiang Nie. Stacked hybrid-attention and group collaborative learning for unbiased scene graph generation. In *CVPR*, pages 19427–19436, 2022.

[13] Xiuye Gu, Tsung-Yi Lin, Weicheng Kuo, and Yin Cui. Open-vocabulary object detection via vision and language knowledge distillation. *arXiv preprint arXiv:2104.13921*, 2021.

[14] Tao He, Lianli Gao, Jingkuan Song, and Yuan-Fang Li. Towards open-vocabulary scene graph generation with prompt-based finetuning. In *ECCV*, pages 56–73, 2022.

[15] Sunghwan Hong, Jisu Nam, Seokju Cho, Susung Hong, Sangryul Jeon, Dongbo Min, and Seungryong Kim. Neural matching fields: Implicit representation of matching fields for visual correspondence. *Advances in Neural Information Processing Systems*, pages 13512–13526, 2022.

[16] Drew A Hudson and Christopher D Manning. Gqa: A new dataset for real-world visual reasoning and compositional question answering. In *CVPR*, pages 6700–6709, 2019.

[17] Kibum Kim, Kanghoon Yoon, Jaehyeong Jeon, Yeonjun In, Jinyoung Moon, Donghyun Kim, and Chanyoung Park. Llm4sgg: Large language models for weakly supervised scene graph generation. In *CVPR*, pages 28306–28316, 2024.

[18] Zihan Kong and Haiwei Zhang. Opensgen: Fine-grained relation-aware prompt for open-vocabulary scene graph generation. pages 634–643, 2025.

[19] Ranjay Krishna, Yuke Zhu, Oliver Groth, Justin Johnson, Kenji Hata, Joshua Kravitz, Stephanie Chen, Yannis Kalantidis, Li-Jia Li, David A Shamma, et al. Visual genome: Connecting language and vision using crowdsourced dense image annotations. *IJCV*, 123:32–73, 2017.

[20] Jiaming Lei, Lin Li, Chunping Wang, Jun Xiao, and Long Chen. Seeing beyond classes: Zero-shot grounded situation recognition via language explainer. In *ACM MM*, pages 1602–1611, 2024.

[21] Junnan Li, Dongxu Li, Silvio Savarese, and Steven Hoi. Blip-2: Bootstrapping language-image pre-training with frozen image encoders and large language models. In *International conference on machine learning*, pages 19730–19742. PMLR, 2023.

[22] Lin Li, Guikun Chen, Jun Xiao, and Long Chen. Compositional zero-shot learning via progressive language-based observations. In *ACM MM*, 2025.

[23] Lin Li, Long Chen, Yifeng Huang, Zhimeng Zhang, Songyang Zhang, and Jun Xiao. The devil is in the labels: Noisy label correction for robust scene graph generation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 18869–18878, 2022.

[24] Lin Li, Wei Chen, Jiahui Li, Kwang-Ting Cheng, and Long Chen. Relation-r1: Progressively cognitive chain-of-thought guided reinforcement learning for unified relation comprehension. *arXiv preprint arXiv:2504.14642*, 2025.

[25] Lin Li, Jun Xiao, Guikun Chen, Jian Shao, Yueting Zhuang, and Long Chen. Zero-shot visual relation detection via composite visual cues from large language models. *NeurIPS*, 36, 2024.

[26] Lin Li, Jun Xiao, Hanrong Shi, Hanwang Zhang, Yi Yang, Wei Liu, and Long Chen. Nicest: Noisy label correction and training for robust scene graph generation. 46(10):6873–6888, 2024.

[27] Liunian Harold Li, Pengchuan Zhang, Haotian Zhang, Jianwei Yang, Chunyuan Li, Yiwu Zhong, Lijuan Wang, Lu Yuan, Lei Zhang, Jenq-Neng Hwang, Kai-Wei Chang, and Jianfeng Gao. Grounded language-image pre-training. In *CVPR*, pages 10955–10965, 2022.

[28] Rongjie Li, Songyang Zhang, and Xuming He. Sgtr: End-to-end scene graph generation with transformer. In *CVPR*, pages 19464–19474, 2022.

[29] Rongjie Li, Songyang Zhang, Dahua Lin, Kai Chen, and Xuming He. From pixels to graphs: Open-vocabulary scene graph generation with vision-language models. In *CVPR*, pages 28076–28086, 2024.

[30] Xiang Lisa Li and Percy Liang. Prefix-tuning: Optimizing continuous prompts for generation. *arXiv preprint arXiv:2101.00190*, 2021.

[31] Xingchen Li, Long Chen, Wenbo Ma, Yi Yang, and Jun Xiao. Integrating object-aware and interaction-aware knowledge for weakly supervised scene graph generation. In *ACMMM*, pages 4204–4213, 2022.

[32] Tsung-Yi Lin, Priya Goyal, Ross B. Girshick, Kaiming He, and Piotr Dollár. Focal loss for dense object detection. In *ICCV*, pages 2999–3007, 2017.

[33] Haotian Liu, Chunyuan Li, Qingyang Wu, and Yong Jae Lee. Visual instruction tuning. *NeurIPS*, 36, 2024.

[34] Jiachang Liu, Dinghan Shen, Yizhe Zhang, Bill Dolan, Lawrence Carin, and Weizhu Chen. What makes good in-context examples for gpt-3? *arXiv preprint arXiv:2101.06804*, 2021.

[35] Shilong Liu, Zhaoyang Zeng, Tianhe Ren, Feng Li, Hao Zhang, Jie Yang, Chunyuan Li, Jianwei Yang, Hang Su, Jun Zhu, and Lei Zhang. Grounding DINO: marrying DINO with grounded pre-training for open-set object detection. *CoRR*, abs/2303.05499, 2023.

[36] Tao Liu, Rongjie Li, Chongyu Wang, and Xuming He. Relation-aware hierarchical prompt for open-vocabulary scene graph generation. In *AAAI*, 2025.

[37] Wonpyo Park, Dongju Kim, Yan Lu, and Minsu Cho. Relational knowledge distillation. In *CVPR*, pages 3967–3976, 2019.

[38] Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, Gretchen Krueger, and Ilya Sutskever. Learning transferable visual models from natural language supervision. In *ICML*, pages 8748–8763, 2021.

[39] Shaoqing Ren, Kaiming He, Ross Girshick, and Jian Sun. Faster r-cnn: Towards real-time object detection with region proposal networks. *NeurIPS*, 28, 2015.

[40] Hamid Rezatofighi, Nathan Tsoi, JunYoung Gwak, Amir Sadeghian, Ian D. Reid, and Silvio Savarese. Generalized intersection over union: A metric and a loss for bounding box regression. In *CVPR*, pages 658–666, 2019.

[41] Sebastian Schuster, Ranjay Krishna, Angel Chang, Li Fei-Fei, and Christopher D Manning. Generating semantically precise scene graphs from textual descriptions for improved image retrieval. In *Proceedings of the fourth workshop on vision and language*, pages 70–80, 2015.

[42] Feifei Shao, Long Chen, Jian Shao, Wei Ji, Shaoning Xiao, Lu Ye, Yueting Zhuang, and Jun Xiao. Deep learning for weakly-supervised object detection and localization: A survey. *Neurocomputing*, 496:192–207, 2022.

[43] Feifei Shao, Yawei Luo, Fei Gao, Yi Yang, and Jun Xiao. Knowledge-guided causal intervention for weakly-supervised object localization. 36(11):6477–6489, 2024.

[44] Suprosanna Shit, Rajat Koner, Bastian Wittmann, Johannes Paetzold, Ivan Ezhov, Hongwei Li, Jiazhen Pan, Sahand Sharifzadeh, Georgios Kaissis, Volker Tresp, et al. Relationformer: A unified framework for image-to-graph generation. In *ECCV*, pages 422–439. Springer, 2022.

[45] Gopika Sudhakaran, Devendra Singh Dhami, Kristian Kersting, and Stefan Roth. Vision relation transformer for unbiased scene graph generation. In *ICCV*, pages 21882–21893, 2023.

[46] Kaihua Tang, Yulei Niu, Jianqiang Huang, Jiaxin Shi, and Hanwang Zhang. Unbiased scene graph generation from biased training. In *CVPR*, pages 3713–3722, 2020.

[47] Kaihua Tang, Hanwang Zhang, Baoyuan Wu, Wenhan Luo, and Wei Liu. Learning to compose dynamic tree structures for visual contexts. In *CVPR*, pages 6619–6628, 2019.

[48] Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, et al. Llama 2: Open foundation and fine-tuned chat models. *arXiv preprint arXiv:2307.09288*, 2023.

[49] A Vaswani. Attention is all you need. *NeurIPS*, 2017.

[50] Luting Wang, Yi Liu, Penghui Du, Zihan Ding, Yue Liao, Qiaosong Qi, Biaolong Chen, and Si Liu. Object-aware distillation pyramid for open-vocabulary object detection. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 11186–11196, 2023.

[51] Weiyun Wang, Yiming Ren, Haowen Luo, Tiantong Li, Chenxiang Yan, Zhe Chen, Wenhai Wang, Qingyun Li, Lewei Lu, Xizhou Zhu, et al. The all-seeing project v2: Towards general relation comprehension of the open world. In *ECCV*, pages 471–490. Springer, 2025.

[52] Zhen Wang, Lin Li, and Long Chen. Recent advances in finetuning multimodal large language models. *AI Magazine*, 46(3):e70025, 2025.

[53] Size Wu, Wenwei Zhang, Sheng Jin, Wentao Liu, and Chen Change Loy. Aligning bag of regions for open-vocabulary object detection. In *CVPR*, pages 15254–15264, 2023.

[54] Xiaoshi Wu, Feng Zhu, Rui Zhao, and Hongsheng Li. Cora: Adapting clip for open-vocabulary detection with region prompting and anchor pre-matching. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 7031–7040, 2023.

[55] Danfei Xu, Yuke Zhu, Christopher B. Choy, and Li Fei-Fei. Scene graph generation by iterative message passing. In *CVPR*, pages 3097–3106, 2017.

[56] Jingkang Yang, Yi Zhe Ang, Zujin Guo, Kaiyang Zhou, Wayne Zhang, and Ziwei Liu. Panoptic scene graph generation. In *ECCV*, pages 178–196. Springer, 2022.

[57] Gefan Ye, Lin Li, Kexin Li, Jun Xiao, and Long Chen. Zero-shot compositional action recognition with neural logic constraints. In *ACM MM*, 2025.

[58] Keren Ye and Adriana Kovashka. Linguistic structures as weak supervision for visual scene graph generation. In *CVPR*, pages 8289–8299, 2021.

[59] Qifan Yu, Juncheng Li, Yu Wu, Siliang Tang, Wei Ji, and Yueting Zhuang. Visually-prompted language model for fine-grained scene graph generation in an open world. In *ICCV*, pages 21560–21571, 2023.

[60] Yuhang Zang, Wei Li, Kaiyang Zhou, Chen Huang, and Chen Change Loy. Open-vocabulary detr with conditional matching. In *ECCV*, pages 106–122. Springer, 2022.

[61] Rowan Zellers, Mark Yatskar, Sam Thomson, and Yejin Choi. Neural motifs: Scene graph parsing with global context. In *CVPR*, pages 5831–5840, 2018.

[62] Hao Zhang, Feng Li, Shilong Liu, Lei Zhang, Hang Su, Jun Zhu, Lionel Ni, and Heung-Yeung Shum. Dino: Detr with improved denoising anchor boxes for end-to-end object detection. In *ICLR*, 2022.

[63] Yong Zhang, Yingwei Pan, Ting Yao, Rui Huang, Tao Mei, and Chang Wen Chen. Learning to generate language-supervised and open-vocabulary scene graph using pre-trained visual-semantic space. In *CVPR*, pages 2915–2924, 2023.

[64] Yiwu Zhong, Jing Shi, Jianwei Yang, Chenliang Xu, and Yin Li. Learning to generate scene graph from natural language supervision. In *ICCV*, pages 1823–1834, 2021.

[65] Zijian Zhou, Zheng Zhu, Holger Caesar, and Miaojing Shi. Openpsg: Open-set panoptic scene graph generation via large multimodal models. In *ECCV*, pages 199–215. Springer, 2025.

[66] Xizhou Zhu, Weijie Su, Lewei Lu, Bin Li, Xiaogang Wang, and Jifeng Dai. Deformable detr: Deformable transformers for end-to-end object detection. In *ICLR*, 2020.

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Summary of the Appendix

To facilitate a deeper understanding of the main paper, we present supplementary material with additional details, organized as follows:

- §A elaborates on the implementation details.
- §B introduces the formulations of training objectives.
- §C introduces the counter-action generation prompt.
- §D provides the pseudo-code for interaction-guided query selection.
- §E offers additional experimental results.
- §F presents further qualitative results.
- §G discusses our limitations, broader impact, and directions of future work.

A Implementation Details

Pre-training. Our models are trained with a batch size of 3, utilizing four/eight RTX 3090 GPUs for computation. During the supervision generation phase (*c.f.* §3.1), we employ Llama2-7B [48] to generate counter-actions based on the prompts described in §C. A pseudo-triplet class is annotated when the confidence of the grounding object class exceeds 0.25, and the intersection over union (IoU) between the subject and object is greater than 0.0. During pre-training, we initialize our model using the pre-trained Grounding DINO checkpoints provided by [9], keeping the visual backbone (Swin-T or Swin-B) and the text encoder (BERT-base [11]) frozen. The remaining modules, such as the relation-aware embedding, are initialized randomly. In line with [9], we select 100 object detections per image for pairwise relation recognition during training.

Supervised Fine-Tuning. The supervised fine-tuning process is conducted using the same computational resources as pre-training. For interaction-guided query selection (*c.f.* §3.2.1), we adopt the settings from [35, 9], where the total number of selected visual tokens K is set to 900, and the top-ranked interaction tokens L is fixed at 200. The models after the pre-training process are leveraged as the teacher model and serve as the initialization for the student model. The weights β_1 and β_2 of the loss function $\mathcal{L}_{VRD}$ and $\mathcal{L}_{RRD}$ are set to 0.1 and 0.5, respectively, to balance different optimization objectives.

Dataset Splits. All entity and relation categories for the GQA dataset [16] are listed in Table S1. For the VG dataset [19], we adopted the splitting protocol from [9]. As for the PSG dataset [56], we followed the splits utilized in [29].

B Training Objectives

As mentioned in §3, the model is guided by the bounding box regression loss, entity classification loss, and relation classification loss. This section details their corresponding formulations.

Bounding Box Regression Loss: The primary objective of object localization is to accurately predict the positions and sizes of objects within an image. To achieve this, the model utilizes a combination of L1 loss ($\mathcal{L}_{reg}$) and GIoU loss ($\mathcal{L}_{giou}$) [40], ensuring both precise positioning of the bounding boxes and effective handling of overlaps. The corresponding loss functions are defined as:

$$\begin{aligned} \mathcal{L}_{reg} &= \frac{1}{N_b}\sum_{i=1}^{N_b}\|\hat{\mathbf{b}}_i - \mathbf{b}_i\|_1, \\ \mathcal{L}_{giou} &= 1 - \frac{A_{inter}}{A_{union}} + \frac{(A_{min} - A_{union})}{A_{min}}, \end{aligned} \tag{10}$$

where $\hat{\mathbf{b}}_i$ and $\mathbf{b}_i$ denote the predicted bounding box and GT bounding box, respectively. N_b is the number of the object's bounding boxes. A_{inter} represents the area of intersection between the predicted and ground truth bounding boxes, A_{union} is the union area of the bounding boxes, and A_{min} is the area of the smallest enclosing box covering both.

Entity Classification Loss: To address the class imbalance in the object classification task, the model employs Focal Loss ($\mathcal{L}_{obj}$) [32], which emphasizes difficult-to-classify and underrepresented

Table S1: The categories spitting of GQA [16].

Split	Relation Categories	Object Categories
Base	parked on, growing on, standing in front of, wearing, standing on, with, looking at, under, carrying, near, above, covered in, behind, at, using, hanging from, sitting on, flying in, watching, covering, mounted on, in front of, lying on, standing next to, grazing in, holding, beside, on the back of, catching, running on, swimming in, playing on, on top of, floating in, talking on, on the bottom of, standing behind, leaning against, covered by, facing, filled with, attached to, sitting next to, next to, worn on, in, on the side of, driving, close to, surrounded by, lying in, hitting, pulling, swinging, touching, eating, throwing, skiing on, driving on, hang on, riding, playing in, crossing, walking with, on, growing in, sitting in, cutting, feeding, leaning on	mountain, cow, people, face, number, pizza, tire, player, pillow, screen, truck, kite, trunk, sock, neck, glove, coat, letter, roof, windshield, desk, paw, leaf, flower, plant, counter, paper, eye, book, branch, lamp, cup, phone, toilet, skateboard, logo, laptop, vehicle, motorcycle, hill, curtain, nose, sheep, bowl, wire, bear, banana, mouth, drawer, shelf, cap, animal, bottle, box, airplane, finger, room, flag, seat, tower, wing, fruit, rock, house, pot, bird, umbrella, surfboard, lady, tie, fork, vase, bag, orange, clock, sidewalk, food, sink, cabinet, beach, boat, basket, helmet, child, racket, post, guy, towel, arm, napkin, bush, bench, person, cone, apple, jacket, fur, air, sign, bus, wrist, frame, floor, dress, street, shoe, ball, girl, ear, boy, broccoli, fence, uniform, hair, sneakers, blanket, zebra, train, camera, sticker, license plate, lid, tomato, pants, giraffe, watch, wall, leg, bed, t-shirt, shorts, horse, spots, arrow, field, bread, bicycle, knife, couch, ceiling
Novel	on the front of, reaching for, flying, of, parked along, talking to, sitting at, standing by hanging on, covered with, standing near, full of, surrounding, walking in, reflected in, walking down, walking on, contain, below, printed on, driving down, waiting for, resting on, playing with, standing in, grazing on, by, around, pulled by, beneath	ocean, car, picture, hand, snow, horn, woman, sweater, container, paint, feet, clouds, foot, dirt, faucet, chair, sand, tail, stone, cat, tag, traffic light, keyboard, tree, leaves, elephant, ground, glass, frisbee, trash can, word, man, jeans, door, building, sky, table, wheel, pole, collar, hat, cheese, mane, shirt, dog, cord, cake, donut,plate, backpack, mirror, street light, skis, window, grass, water, bike, road, head, cell phone

categories. Focal Loss modifies the standard cross-entropy loss by down-weighting easy examples, focusing the model's attention on challenging ones. The formulation is as follows:

$$\mathcal{L}_{obj} = -\alpha(1 - y_c)^{\gamma} \log(y_c), \tag{11}$$

where y_c denotes the predicted probability of the true object class c, α is a balancing factor, and γ is a focusing parameter that adjusts the emphasis on hard examples.

Relation Classification Loss: The model's objective is to predict the relationships between objects, aligning predicted relation scores with ground-truth annotations. This is achieved using BCE loss ($\mathcal{L}_{rel}$), which measures the discrepancy between predicted and true relationship probabilities. The BCE loss function is expressed as:

$$\mathcal{L}_{rel} = -\frac{1}{N_{rel}} \sum_{i=1}^{N_{rel}} \left[y_{ij} \log(\hat{y}_{ij}) + (1 - y_{ij}) \log(1 - \hat{y}_{ij}) \right], \tag{12}$$

where y_{ij} denotes the GT relation label between the i-th object and j-th object, $\hat{y}_{ij}$ is the predicted relation probability.

C Counter-action Generation Prompt

In this section, we present the prompt used for counter-action generation (*c.f.* §3.1) in Figure S1 with LLMs, *i.e.*, Llama2 [48]. The prompt is structured into two key components: the example and the question. **Example:** The example, such as the instance of "ride", serves as a reference for the model to produce contextually relevant outputs in an in-context learning framework [3, 34]. This part of the prompt is also generated by the LLM, providing a model-driven demonstration of the expected output format. **Question:** The question, *i.e.* "please generate...", prompts the model to produce a corresponding counter-action or a related output. This structure ensures that the

Question: Given the action 'ride', please generate its corresponding counter-action.
Answer: 'be ridden by'.
Question: Given the action 'eat', please generate its corresponding counter-action.
Answer: 'be eaten by'.

Question: Given the action '{**relation**}', please generate its corresponding counter-action.
Answer:

Figure S1: Counter-action generation prompt.

Algorithm S1 Pseudo-code for Step I in Interaction-Guided Query Selection.

```
X_v: visual features of all tokens.
X_o: object class tokens.
X_r: relation class tokens.
gamma: balancing parameter.

def Step1_QuerySelection(X_v, X_o, X_r, gamma):
    scores = []
    for i in range(len(X_v)):
        # Calculate the relevance score for each visual token.
        sim_o = max(X_v[i] @ X_o.T) # max similarity with object class tokens
        sim_r = max(X_v[i] @ X_r.T) # max similarity with relation class tokens
        score = (sim_o ** gamma) * (sim_r ** (1 - gamma)) # Eq. (1)
        scores.append(score)

    # Select top K visual tokens based on relevance score.
    I_K = top_K(scores, K)

    return I_K
```

Algorithm S2 Pseudo-code for Step II in Interaction-Guided Query Selection.

```
X_v: visual features of all tokens.
X_in: interaction tokens from text encoder.
X_o: object class tokens.

def Step2_QuerySelection(X_v, X_in, X_o):
    interaction_scores = []
    for i in range(len(X_v)):
        # Compute interaction relevance score based on interaction tokens.
        sim_in = max(X_v[i] @ X_in.T) # max similarity with interaction tokens
        interaction_scores.append(sim_in)

    # Select top L visual tokens based on interaction relevance score.
    I_L_in = top_L(interaction_scores, L)

    # Compute object relevance for remaining tokens.
    object_scores = []
    for i in range(len(X_v)):
        if i not in I_L_in:
            sim_o = max(X_v[i] @ X_o.T) # max similarity with object class tokens
            object_scores.append(sim_o)

    # Select top (K-L) tokens based on object relevance.
    I_K_L_o = top_K_minus_L(object_scores, K - L, I_L_in)

    # Final query set is the union of both sets.
    I_K = I_L_in + I_K_L_o

    return I_K
```

model can generate responses specific to the action at hand, supporting more relevant and consistent counter-action generation.

D Pseudo Code

To make the interaction-guided query selection (§3.2.1) process easier to understand, we provide pseudo-code for Step I and Step II in Algorithm S1 and Algorithm S2, respectively.

E More Experimental Results

E.1 Comparison with State-of-the-Arts on GQA dataset

In Table S2, we compared our ACC with the existing SOTA method (*i.e.*, OvSGTR [9]) on the GQA [16] dataset under the more challenging OvD+R-SGG setting. The backbones are uniformly set to Swin-T. Notably, ACC consistently outperforms OvSGTR across all metrics, demonstrating the universality and effectiveness of our approach.

Table S2: Experimental results of OvD+R-SGG setting on GQA [16] test set.

Method	Joint Base+Novel			Novel (Obj)			Novel (Rel)		
	R@20	R@50	R@100	R@20	R@50	R@100	R@20	R@50	R@100
OvSGTR [9] ECCV'24	11.21	15.80	19.14	10.32	14.92	18.76	2.59	5.21	7.40
ACC (Ours)	**12.30**	**16.88**	**20.63**	**11.51**	**16.16**	**20.57**	**3.41**	**6.60**	**9.80**

Table S3: Experimental results of OvR-SGG setting on PSG [56] test set.

Method		Joint Base+Novel			Novel (Rel)		
		R@20	R@50	R@100	R@20	R@50	R@100
SGTR [28]	CVPR'22	-	14.2	18.2	-	-	-
PGSG [29]	CVPR'24	-	18.0	20.2	-	-	-
OvSGTR [9]	ECCV'24	15.14	17.76	19.50	5.32	6.93	8.08
ACC (Ours)		**16.69**	**20.01**	**21.71**	**6.78**	**8.78**	**9.70**

Table S4: Extra metrics of OvD+R-SGG setting on VG150 [19] test set.

Method	Base (Obj)			Base (Rel)			Novel (Obj)			Novel (Rel)		
	R@20	R@50	R@100	R@20	R@50	R@100	mR@20	mR@50	mR@100	mR@20	mR@50	mR@100
OvSGTR [9]	8.78	11.95	14.79	12.07	16.47	20.09	1.69	2.44	3.06	0.82	1.13	1.47
ACC (Ours)	11.66	16.46	20.35	12.20	16.67	20.57	1.93	2.84	3.61	1.64	2.59	3.38

E.2 Comparison with State-of-the-Arts on PSG dataset

Given that the PSG dataset split proposed by [29] exclusively addresses novel relation categories, our evaluation consequently focused on the OVD-R-SGG setting. As detailed in Table S3, when compared with other prominent state-of-the-art methods (*e.g.*, SGTR [28], PGSG [29], and OvSGTR [9]), our ACC framework also demonstrates superior performance across all reported metrics.

E.3 Evaluation with More Metrics

We reported both recall of base classes and mean Recall (m@R) in S4. It can be seen that our ACC outperforms the previous SOTA method (*i.e.*, OvSGTR [9]) in both metrics. This demonstrates that our approach provides a more comprehensive and powerful generalization capability, enhancing performance across the board, not just for unseen classes.

E.4 Ablation Study on Interaction-Centric Knowledge Infusion

Effectiveness of bidirectional interaction prompt. To investigate the bidirectional interaction prompt's sensitivity to the choice of verb parser for counter-action generation, we replaced the default Llama2 parser with two alternatives: a smaller Large Language Model (LLM), Qwen2.5-0.5B [1], and the Pattern (a Python library) under OvD+R-SGG setting on VG test set (Swin-B as backbone). As shown in Table S5, ACC sustains high performance even when utilizing a smaller LLM or a non-LLM parser for this task. This demonstrates the robustness of our bidirectional interaction prompt in generating effective pseudo-supervision across various verb parsing mechanisms.

Table S5: Ablation study on the verb parser in counter-action generation.

Method	Verb Parser	Size	Joint Base+Novel		
			R@20	R@50	R@100
ACC (Ours)	Llama2	7B	13.50	18.88	23.19
ACC (Ours)	Qwen2.5	0.5B	13.64	18.99	23.43
ACC (Ours)	Pattern (Python Lib)	-	13.36	18.56	22.64

E.5 Ablation Study on Interaction-Centric Knowledge Transfer

Effectiveness of query selection. We performed an ablation study of the two-step query selection in IGQS (*c.f.* §3.2.1), as shown in Table S6. The general end-to-end OVSGG pipeline with visual-concept retention distillation as the baseline. The results demonstrate that using a single step also yields performance improvements over the baseline, with the best performance achieved by employing both steps simultaneously.

Table S6: Ablation on two-step query selection in IGQS on OvD+R-SGG setting of VG150 [19] test set.

IGQS		Joint Base+Novel		
Step I	Step II	R@20	R@50	R@100
		10.02	13.50	16.37
✓		11.30	15.71	19.16
	✓	11.32	15.70	19.29
✓	✓	11.37	15.71	19.37

Table S7: Experimental results of HICO-DET [5] dataset under the OvR-SGG setting.

Method	Joint Base+Novel			Novel (Rel)		
	R@20	R@50	R@100	R@20	R@50	R@100
OvSGTR [9] ECCV'24	34.62	37.39	39.04	22.94	28.48	31.84
ACC (Ours)	35.74	38.58	40.19	24.44	30.77	34.38

Table S8: Inference costs on the VG150 [19] test set.

Method	Training costs (min)	Inference costs (s/I)
OvSGTR [9] ECCV'24	68	0.3871220016479492
ACC	71	0.3896771125793457
ACC w/ Step II	94	0.6402182579040527

Hyperparameters in ICKD. We conducted an ablation study on the hyperparameters (β_1 and β_2) in the ICKD (visual-concept retention distillation and relative-interaction retention distillation). Results in Figure S2 show that increasing β_1 (*e.g.*, raising VRD weight) decreases overall performance, consistent with results in [9]. RRD demonstrates robustness for different hyperparameters. The best performance can be achieved with β_1= 0.1 and β_2 = 0.5, respectively.

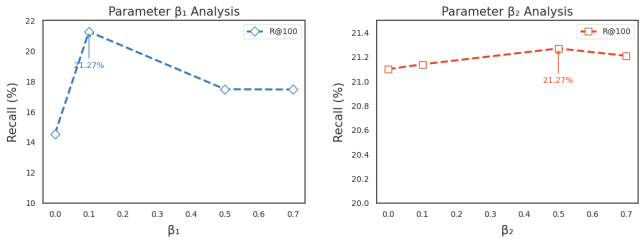

Figure S2: Ablation on β_1 and β_2 in VRD and RRD loss function under OvD+R-SGG setting on VG test set.

E.6 Comparison on Human-Object Interaction Detection Tasks

Human-Object Interaction (HOI) detection, particularly on benchmarks like HICO-DET [5], is primarily a detection task over a set of specific human-centric interactions (*i.e.*, <action, object> pairs). In contrast, SGG addresses a more general and compositional challenge: generating <subject, action, object> triplets between any pair of objects. To empirically validate the effectiveness of the proposed ACC, we evaluated ACC and OvSGTR [9] on the HICO-DET benchmark. As shown in Table S7, ACC consistently outperforms OvSGTR, achieving 2.54% absolute improvement in R@100 of novel classes. This result is significant: it demonstrates that our model's core principles are so robust. They excel not only on the general OVSGG task they were designed for, but also on the specialized HOI task.

E.7 Computational Overhead

We conducted a time analysis on VG [19], with training on the entire dataset and testing on 20 images. We report the mean value in Table S8 of our ACC (w/o and with Step II in IGQS). We would like to claim that: 1) Our Step I in IGQS just introduces minor computational complexity in elementary matrix operations (*c.f.*, Eq. 1). 1) Due to the requirement of forward prediction for self-enhancement, Step II will induce extra computational overhead, but the performance gain brought by Step II is optional.

F More Qualitative Comparison Results

F.1 Grounded Entity Visualization

To evaluate the effectiveness of the proposed bidirectional interaction prompt (§3.1), we visualized the entity grounding results for various types of prompts during the pre-training process in Figure S3:

Object Prompt. Prior methods [9] often rely on concatenating the subject and object entities extracted from a scene graph parser, such as "`man. knife`".

Interaction Prompt. It incorporates relation triplets into a phrase, *e.g.*, "`man hold knife`."

Figure S3: Entity grounding results of different prompts.

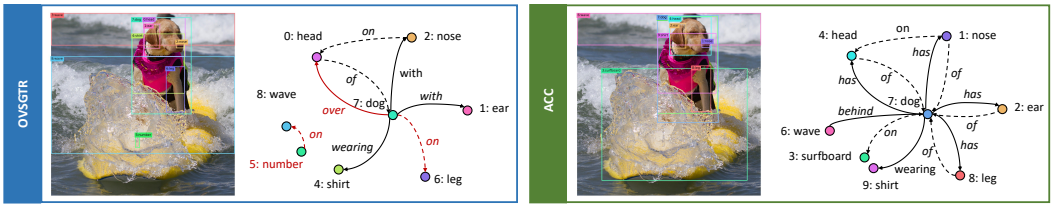

Figure S4: Qualitative Results of OvSGTR and ACC on the SGDet task and VG dataset [19]. The dashed line represents the predicted novel categories, and the **red** represents the unreasonable predictions.

Bidirectional Interaction Prompt. This proposed prompt further integrates relation triplets with their corresponding counter-action, forming phrases like "`man hold knife. knife held by man.`".

From the visualization results, the following observations can be made: 1) Directly adopting object prompts tends to generate redundant bounding box candidates (*e.g.*, multiple instances of "`man`" and "`kid`" in Figure S3). This redundancy complicates the identification of interacting object pairs. Additionally, some interacting object boxes are missing. For example, the imperceptibly held "`knife`" is not detected, while the non-interacting "`knife`" is identified. These limitations result in mismatched relational pairs, which ultimately mislead the subsequent training process. 2) While incorporating interaction prompts significantly reduces the number of redundant object boxes, it often over-focuses on the subject (*e.g.*, detecting only the "`man`" subject bounding box), leading to the omission of critical object boxes. 3) By leveraging bidirectional interaction prompts, both the subject and object bounding boxes are accurately detected under the given relation triplet. This approach not only resolves the redundancy issue but also ensures the inclusion of subtle yet crucial interactions (*e.g.*, correctly identifying the "`knife`" being held). Consequently, it provides a more comprehensive and precise grounding for subsequent training stages.

F.2 Mismatched Examples Visualization.

To intuitively illustrate the challenges stemming from current paradigms, Figure S5 visualizes representative examples of mismatched relational triplets. As depicted, a common error involves triplets such as ⟨`man`, `riding`, `horse`⟩ being incorrectly assigned. This type of mis-

Figure S5: Mismatched relation triplets examples.

assignment frequently occurs because models lacking explicit interaction modeling struggle to distinguish the specific "man" instance actively engaged in the "riding" interaction from other, non-interacting "man" instances that may be present in the scene. Such visualizations highlight the critical need for interaction-centric approaches to achieve more precise relation recognition.

F.3 Scene Graph Visualization

Figure S4 displays the scene graph predictions generated by OvSGTR and ACC on the Swin-T backbone using the VG dataset. Apparently, the scene graph produced by OvSGTR includes several incorrect and redundant relationships, such as "⟨number, on, wave⟩" and "⟨dog, on, leg⟩". Instead, our ACC eliminates such unreasonable predictions and can generate easily missing the relationship triplet, such as "⟨wave, behind, dog⟩". Even interactive relationships, like "⟨dog, has, head⟩" and "⟨head, of, dog⟩", are accurately captured, showcasing ACC's enhanced capacity to reason over subject-object interactions and identify precise and semantically coherent relationships in complex scenes.

F.4 Failure Cases Analysis

We analyzed the examples in Figure S6 where ACC misidentifies non-interacting object pairs, and find that: 1) For Interaction-Centric Knowledge Infusion, it is difficult to correctly match small objects (*e.g.*, hat in background) and their related objects through bidirectional interaction prompts. 2) For Interaction-Centric Knowledge Transfer, when multiple subject-object pairs with the same relational triplet categories (*e.g.*, ⟨person, riding, horse⟩) appear in the same image, the model might mistakenly match the subject in one triplet to the object in another triplet.

Figure S6: Failure cases.

G Discussion

Limitation Analysis. Our approach employs a knowledge infusion and transfer framework §2 for open-vocabulary scene graph generation. While this framework reduces annotation costs and effectively leverages transferable representations from pre-trained vision-language models, it also inherits inductive biases from the teacher model. Like two sides of a coin, any biases in the vision-language model toward specific feature traits or classes may propagate to our model. Besides, our method can alleviate mismatched relational pairs, but cannot avoid all mismatches.

Potential Broader Impact. This paper presents work aimed at advancing the field of open vocabulary scene graph generation. By introducing interaction-aware mechanisms, our approach enhances the model's ability to recognize novel objects and relationships, improving the robustness and accuracy of scene understanding in real-world applications such as robotics, autonomous systems, and augmented reality. While our work has the potential to drive innovation in these fields, ethical considerations must be taken into account, particularly regarding the fairness and representativeness of the training data used. Ensuring that our models are inclusive and minimize bias will be crucial to preventing harmful misinterpretations or exclusions in practical applications.

Future Work. Our current algorithm is tailored for open-vocabulary scene graph generation, adopting a dual-encoder-single-decoder architecture as proposed in [9, 36]. It prioritizes base-novel generalization over real-time performance, which may not fully meet the timeliness requirements of real-world applications. In future work, we aim to enhance the computational efficiency of our approach to better address these practical demands.