Robust Cross-modal Alignment Learning for Cross-Scene Spatial Reasoning and Grounding

Yanglin Feng[1], **Hongyuan Zhu**[2], **Dezhong Peng**[1,3], **Xi Peng**[1], **Xiaomin Song**[4], **Peng Hu**[1]*
[1]College of Computer Science, Sichuan University, Chengdu, China.
[2]Institute for Infocomm Research (I^{2}R), A*STAR, Singapore.
[3]Tianfu Jincheng Laboratory, Chengdu, China.
[4]Sichuan National Innovation New Vision UHD Video Technology Co., Ltd., Chengdu, China.
fcyzfyl@163.com, hongyuanzhu.cn@gmail.com, pengdz@scu.edu.cn,
pengx.gm@gmail.com, songxiaomin@uptcsc.com, penghu.ml@gmail.com

Abstract

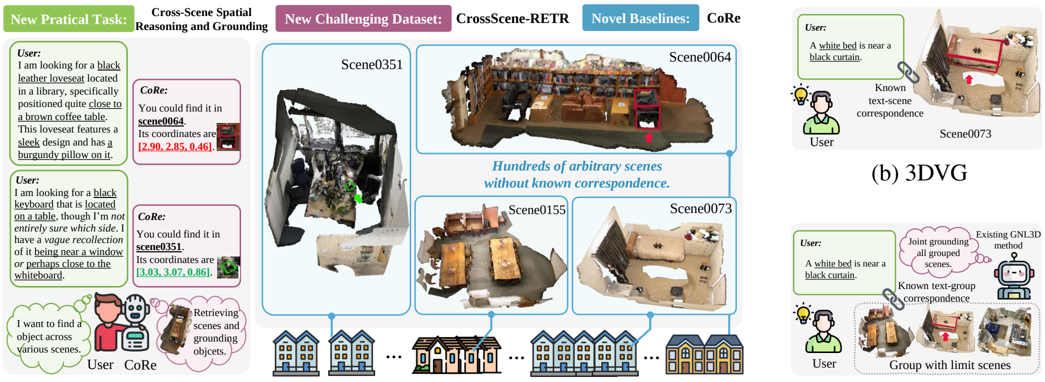
Grounding target objects in 3D environments via natural language is a fundamental capability for autonomous agents to successfully fulfill user requests. Almost all existing works typically assume that the target object lies within a known scene and focus solely on in-scene localization. In practice, however, agents often encounter unknown or previously visited environments and need to search across a large archive of scenes to ground the described object, thereby invalidating this assumption. To address this, we reveal a novel task called Cross-Scene Spatial Reasoning and Grounding (CSSRG), which aims to locate a described object anywhere across an entire collection of 3D scenes rather than predetermined scenes. Due to the difference from existing 3D visual grounding, CSSRG poses two challenges: the prohibitive cost of exhaustively traversing all scenes and more complex cross-modal spatial alignment. To address the challenges, we propose a **Cr**o**ss**-Scene 3D Object **Re**asoning Framework (CoRe), which adopts a matching-then-grounding pipeline to reduce computational overhead. Specifically, CoRe consists of i) a Robust Text-Scene Aligning (RTSA) module that learns global scene representations for robust alignment between object descriptions and the corresponding 3D scenes, enabling efficient retrieval of candidate scenes; and ii) a Tailored Word-Object Associating (TWOA) module that establishes fine-grained alignment between words and target objects to filter out redundant context, supporting precise object-level reasoning and alignment. Additionally, to benchmark CSSRG, we construct a new CrossScene-RETR dataset and evaluation protocol tailored for cross-scene grounding. Extensive experiments across four multimodal datasets demonstrate that CoRe dramatically reduces computational overhead while showing superiority in both scene retrieval and object grounding. Code is available at `https://github.com/Yangl1nFeng/CoRe`.

1 Introduction

Grounding objects in 3D environments with natural language has emerged as a pivotal advancement in multimodal artificial intelligence, enhancing object understanding and interaction of autonomous agents. Building on this progress, recent developments in 3D Visual Grounding (3DVG) [1, 2, 3] and Group-wise 3D Object Grounding (GNL3D) [4] have further demonstrated the capability of agents to locate objects accurately within several given scenes using linguistic cues. However, in real-world scenarios, users may inquire about where specific events occurred or seek to distinguish

*Corresponding author.

39th Conference on Neural Information Processing Systems (NeurIPS 2025)



User: I am looking for a black leather loveseat located in a library, specifically positioned quite close to a brown coffee table. This loveseat features a sleek design and has a burgundy pillow on it.

CoRe: You could find it in **scene0064**. Its coordinates are [2.90, 2.85, 0.46].

User: I am looking for a black keyboard that is located on a table, though I'm *not entirely sure which side*. I have a *vague recollection* of it being near a window *or* perhaps close to the whiteboard.

CoRe: You could find it in **scene0351**. Its coordinates are [3.03, 3.07, 0.86].

I want to find a object across various scenes.

Retrieving scenes and grounding objcets.

(a) CSSRG

User: A white bed is near a black curtain.

(b) 3DVG

User: A white bed is near a black curtain.

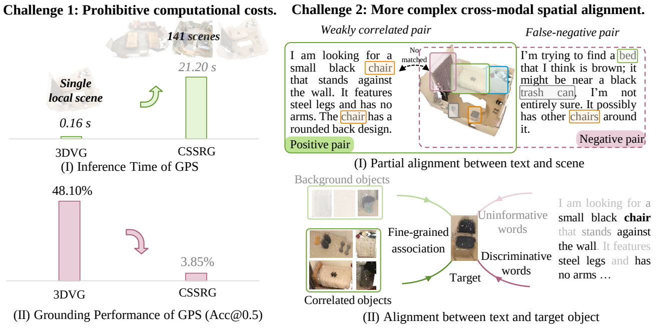
Joint grounding all grouped scenes.
Existing GNL3D method
Known text-group correspondence
User
Group with limit scenes

(c) GNL3D

Figure 1: Overview of our proposed Cross-Scene Spatial Reasoning and Grounding (CSSRG) and comparisons with similar tasks. (a) illustrates our CSSRG. (b) and (c) show the illustrations of 3D Visual Grounding (3DVG) and Group-wise 3D Object Grounding (GNL3D), respectively.

objects across various places. Addressing such queries requires agents to reason over numerous memory scenes from their long deployment history. To concretize this requirement, we propose and study a more general task, Cross-Scene Spatial Reasoning and Grounding (CSSRG), which requires locating described objects anywhere across an entire collection of 3D scenes. The scene archive is not a collection of disjoint scenes, but rather represents the locations traversed by agents within a large-scale continuous map [5]. In contrast to 3DVG and GNL3D, which assume the availability of predefined corresponding scenes, CSSRG seeks to unlock the text-scene correspondence for general object localization, as shown in Figure 1. Benefiting from this, CSSRG would serve as a technical foundation for building-scale indoor navigation [6, 7] and task planning [8, 9], thereby enabling broader applications in smart homes and robotics.

However, directly applying existing methods to tackle CSSRG is infeasible and would face substantial challenges of high computational costs and low performance, as shown in Figure 2. Specifically, although existing 3DVG and GNL3D approaches can ground objects within known scenes, they either require meticulous scene-by-scene reasoning or concatenating all scenes for joint grounding, resulting in prohibitive computational and memory costs. To address this, an intuitive alternative is to use efficient cross-modal matching methods to retrieve the most relevant scenes and then apply 3DVG within them, reducing the scene traversal time remarkably. It requires cross-modal spatial alignment of the query texts with both relevant scenes and target objects, which is by no means an easy task. To be specific, object descriptions typically focus on target objects instead of an entire scene, resulting in a partial alignment problem.



I am looking for a small black chair that stands against the wall. It features steel legs and has no arms. The chair has a rounded back design.

I'm trying to find a bed that I think is brown; it might be near a black trash can, I'm not entirely sure. It possibly has other chairs around it.

I am looking for a small black **chair** that stands against the wall. It features steel legs and has no arms …

Figure 2: Task-specific challenges faced by CSSRG are illustrated with the VisTA method [10] on the ScanRefer dataset.

To overcome these challenges, we propose a **Cr**oss-Scene 3D Object **Re**asoning Framework (CoRe), which efficiently handles CSSRG via two key modules: a Robust Text-Scene Aligning module (RTSA) for scene matching and a Tailored Word-Object Associating module (TWOA) for object grounding. More specifically, our RTSA first aggregates multimodal fine-grained features into global representations, facilitating convenient text-scene alignment. However, the partial alignment between texts and scenes implies the presence of a certain number of mismatched pairs, leading to degradation of alignment performance. To address this issue, our RTSA adopts an innovative complementary learning paradigm that adaptively pushes apart negative pairs in the common space to robustly establish text-scene alignment, thereby achieving reliable scene matching. Moreover, our TWOA presents a novel Screening Attention mechanism (ScA) to construct the association between target objects and text words, enabling spatial reasoning from text to objects within the scenes. Specifically, ScA progressively prunes low-attention word-object associations in a coarse-to-fine manner and dynamically integrates the contextually relevant retentions, seeking non-redundant alignment between textual descriptions and target objects.

Our CoRe outperforms existing methods in CSSRG, achieving superior scene-matching and object-grounding performance compared to general baselines, as demonstrated in Table 4. These results confirm that achieving complex cross-modal spatial alignment remains a significant challenge under the constraints of existing datasets. To further address this issue, we present a CrossScene-RETR benchmark, which includes discriminative object descriptions and a tailored evaluation protocol specifically designed for CSSRG. As demonstrated in Table 2, the use of comprehensive descriptions brings robust performance gains for CSSRG, supporting a more reliable evaluation and embracing practical applicability. In summary, our contributions are as follows:

- We extend the 3D visual grounding task to the more general Cross-Scene Spatial Reasoning and Grounding (CSSRG) task, which aims to ground a described object anywhere across an entire collection of 3D scenes instead of predetermined scenes.
- We propose the novel two-stage **Cro**ss-Scene 3D Object **Re**asoning Framework (CoRe), following a matching-then-grounding paradigm to effectively mitigate computational costs. CoRe includes a Robust Text-Scene Aligning module (RTSA) for robust scene matching and a Tailored Word-Object Associating module (TWOA) for object grounding.
- We present the CrossScene-RETR dataset to facilitate complex cross-modal spatial alignment in the data aspect, offering a comprehensive evaluation for CSSRG.
- Extensive experiments on four multimodal datasets demonstrate the superiority and effectiveness of our CoRe in CSSRG, remarkably outperforming state-of-the-art baselines.

2 Related Works

2.1 3D Visual Grounding

In recent years, the application potential of vision and language has been constantly explored, attracting significant attention [2, 10, 11]. As one of the primary tasks, 3D Visual Grounding (3DVG) has also gained considerable interest. More specifically, numerous methods [12, 13, 14, 15, 16] attempt to fully explore the specific information (*e.g.*, viewpoints, text graphs, *etc.*) from two modalities to boost the performance. Others [17, 18] attempt to introduce 2D pre-trained knowledge to achieve more comprehensive scene understanding by employing multi-view images. In addition, several approaches [10, 19, 20] proposed general frameworks to tackle multiple 3D vision and language tasks, aiming to break down the barriers between tasks and achieve complementary performance gains. Recently, a study [4] has attempted to expand the scope of grounding to point-cloud groups composed of a limited number of scenes. However, it remains limited to scene-by-scene inference, rendering object reasoning across a large-scale scene set challenging. To address this issue, this paper proposes a general approach to reason target objects from numerous scenes efficiently.

2.2 Cross-modal Matching

Cross-Modal Matching (CMM) [21, 22, 23] has received widespread attention in recent years, which aims to match the relevant results for given queries across different modalities. Due to its substantial role in multi-modal data management and pattern discovery, it is widely applied across various modalities and achieves notable success, *e.g.*, image-text matching [24, 25, 26, 27, 28], text-video matching [29], Infrared-visible matching [30], *etc*. Typically, most CMM methods focus on mapping heterogeneous data into common representations for modality-invariant matching. Specifically, CMM methods could be grouped into fine-grained and coarse-grained methods. 1) Fine-grained approaches [31, 32] aim to capture more nuanced cross-modal semantic associations by focusing on fine-grained features, such as image regions, text words, *etc*. 2) Coarse-grained methods [33, 34] aggregate fine-grained features into holistic representations, seeking straightforward alignment by employing the cross-modal contrast constraints [35, 36, 37]. However, existing methods aim at establishing correspondence between instances, making it difficult to precisely align fine-grained objects with whole texts in the Cross-Scene Spatial Reasoning and Grounding task.

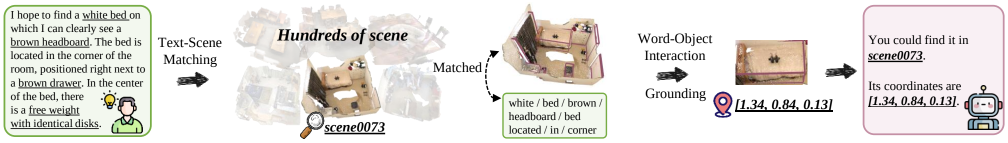

I hope to find a white bed on which I can clearly see a brown headboard. The bed is located in the corner of the room, positioned right next to a brown drawer. In the center of the bed, there is a free weight with identical disks.
Text-Scene Matching
Hundreds of scene
scene0073
Matched
white / bed / brown / headboard / bed located / in / corner
Word-Object Interaction
Grounding
[1.34, 0.84, 0.13]
You could find it in scene0073.
Its coordinates are [1.34, 0.84, 0.13].

Figure 3: The solution pipeline for the Cross-Scene Spatial Reasoning and Grounding (CSSRG) task.

3 Task: Cross-Scene Spatial Reasoning and Grounding

In this paper, we present a Cross-Scene Spatial Reasoning and Grounding (CSSRG) task, with its pipeline illustrated in Figure 3. This task involves grounding a 3D object from a scene archive that relies only on a query description. More specifically, CSSRG requires efficiently retrieving the most relevant scene containing the target 3D object from hundreds of scene candidates based on a user description. Subsequently, all objects in the matched scene and all words in the description must undergo fine-grained fusion to ultimately reason about the target object. During the abovementioned process, CSSRG introduces task-specific challenges, as illustrated in Figure 2, which could be summarized as follows:

1) *Prohibitive computational costs.* Existing methods are constrained to grounding objects within a well-matched local 3D scene, whereas CSSRG requires the traversal of numerous scenes, inevitably resulting in an inescapable crisis in both efficiency and performance. When 3DVG methods (*i.e.*, VisTA [10]) are extended from a single local scene to reasoning across 141 ScanRefer rooms [2], the inference time catastrophically increases by nearly 75 times, while performance declines to only 11.7% of the original.

2) *Complex cross-modal spatial alignment.* In contrast to 3DVG, which presumes a predefined text-scene correspondence, CSSRG requires achieving more challenging cross-modal alignment of the query texts with both relevant scenes and target objects. However, existing brief object descriptions fail to align comprehensively with the relevant complex scenes (*i.e.*, weakly correlated positives) and may resemble local parts of unrelated scenes (*i.e.*, false negatives), called the partial alignment problem. For example, a description text aiming to locate a *bed* typically focuses only on the *bed*'s attributes and its placement, while ignoring other scene-level salient information, leading to the partial alignment problem [38, 39].

4 Baseline: CoRe

Give a dataset $\mathcal{D} = \{\mathcal{T}, \mathcal{S}\}$, where $\mathcal{T} = \{X_i^t\}_{i=1}^M$ and $\mathcal{S} = \{X_j^s\}_{j=1}^N$ are the text and 3D scene sets with M and N samples, respectively. CSSRG task requires establishing the positive correspondence (*i.e.*, , $y_{ij} = 1$, with the rest negative pairs $y_{i\cdot} = 0$) between text X_i^t and corresponding scene X_j^s, and grounding the target object y_i^t.

To tackle this challenging task, we propose a novel Cross-Scene 3D Object Reasoning Framework (CoRe), as illustrated in Figure 4. To be specific, our CoRe incorporates an innovative Robust Text-Scene Aligning module (RTSA) and Tailored Word-Object Associating module (TWOA), realizing a matching-then-grounding pipeline to handle the task-specific challenges. The model can be optimized via gradient descent based on the overall objective function of the batch, as shown below:

$$\mathcal{L} = \mathcal{L}_c + \lambda_m \mathcal{L}_m + \lambda_g \mathcal{L}_g, \tag{1}$$

where $\mathcal{L}_c$ is the loss for object semantic aligning in CoRe, $\mathcal{L}_m$ and $\mathcal{L}_g$ are the loss terms employed by the RTSA and TWOA, λ_m and λ_g are the trade-off parameters, respectively. In the following sections, we will elaborate on the framework and two novel modules of CoRe.

4.1 Cross-Scene 3D Object Reasoning Framework

In CoRe, we innovatively introduce a matching-then-grounding pipeline for CSSRG. More specifically, we first perform feature encoding. On the one hand, the text X_i^t is encoded into d-dimension features $Z_i^w \in \mathbb{R}^{M_i \times d}$ via a pre-trained BERT [40], where M_i is the number of words in i-th text. On the other hand, the collection of scene objects X_j^s segmented through the pre-trained Mask3D [41] is encoded by the pre-trained PointNet++ [42], obtaining the object embedding set $\bar{Z}_j^o$. Then, these

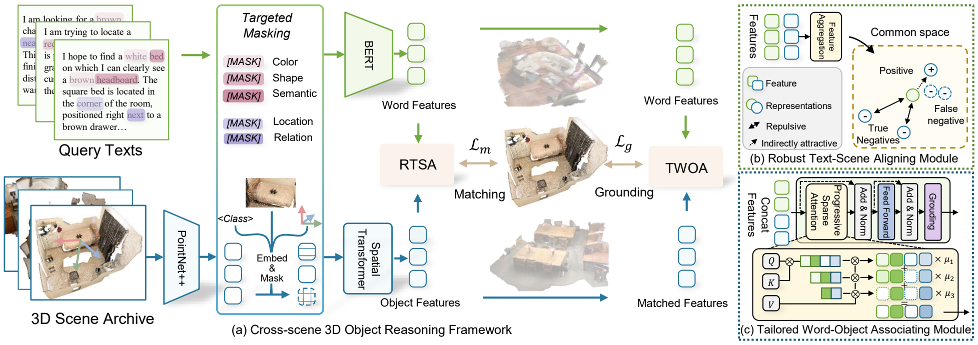


Figure 4: The pipeline of CoRe. First, modality-specific networks extract fine-grained features with a targeted masking strategy applied in each modality. Second, a Robust Text-Scene Aligning module (RTSA) adaptively aggregates multimodal features into common representations and ensures robust text-scene matching by only using negative pairs. Finally, a Tailored Word-Object Associating module (TWOA) adopts a Screening Attention mechanism for word-object association in a stepwise manner, performing object grounding. $\mathcal{L}_m$ and $\mathcal{L}_g$ are the losses employed by RTSA and TWOA.

embeddings are fed into Spatial Transformer [43] with spatial relation and class semantics, obtaining object features $Z_j^o \in \mathbb{R}^{N_j \times d}$, where N_j is the number of objects in j-th scene.

To enhance our CoRe's perception within 3D scenes, we introduced a targeted masking strategy during encoding, focusing on visual attributes (*e.g.*, class semantics, color, shape) and spatial details. Specifically, for text modality, we mask the original text by replacing words in predefined attributive and spatial vocabularies with *[MASK]* at a specified probability. For point-cloud modality, we selectively mask the object, class-semantic, and positional embeddings.

After feature encoding, the fine-grained features of two modalities are aggregated into common representations for text-scene matching in our RTSA, which aligns description texts with the corresponding scenes. TWOA performs feature association between words and objects only within the matched scenes, which obtains fused features $\tilde{Z}_j^o \in \mathbb{R}^{N_j \times d}$ for efficient object reasoning. To maintain the discrimination of objects, we follow VisTA [10] to bridge the feature space and semantic space of the objects throughout the pipeline. This could be formulated as:

$$\mathcal{L}_c = \frac{1}{K} \sum_{j=1}^{K} \left(\mathcal{H}(\bar{\boldsymbol{p}}_j^o; \boldsymbol{y}_j^o) + \mathcal{H}(\boldsymbol{p}_j^o; \boldsymbol{y}_j^o) + \mathcal{H}(\tilde{\boldsymbol{p}}_j^o; \boldsymbol{y}_j^o) \right), \tag{2}$$

where $\mathcal{H}$ is Cross Entropy (CE), K is size of the mini-batch, $\boldsymbol{y}_j^o$ is class label of the j-th scene objects corresponding to i-th text, $\bar{\boldsymbol{p}}_j^o$, $\boldsymbol{p}_j^o$, $\tilde{\boldsymbol{p}}_j^o$ are class semantic predictions of $\bar{Z}_j^o$, Z_j^o, $\tilde{Z}_j^o$.

4.2 Robust Text-Scene Aligning module

To facilitate text-scene Cross-Modal Matching (CMM), following [44], we first aggregate fine-grained object and word features into global text and scene representations with two different focuses: one emphasizes discriminative tokens (*i.e.*, words and objects), and the other focuses on informative feature dimensions. To effectively leverage their complementary focuses, we adaptively combine them, ultimately obtaining common representations of two modalities (*i.e.*, $\boldsymbol{z}_i^t$ and $\boldsymbol{z}_j^s$).

After obtaining the representations, we try to establish cross-modal alignment in the common space to facilitate matching from text to scene. To tackle the partial alignment between scenes and texts in CSSRG, we first employ the complementary learning paradigm [45] with GCE [46] expansion for a robust solution, as shown below:

$$\mathcal{L}_m = \tfrac{1}{K} \textstyle\sum_{i,j}^{K} (1 - y_{ij}) \left(\tfrac{1-(1-\overrightarrow{s_{ij}})^q}{q} + \tfrac{1-(1-\overleftarrow{s_{ij}})^q}{q} \right), \tag{3}$$

where $\overrightarrow{s_{ij}} = \frac{\exp(\boldsymbol{z}_i^{t\top} \boldsymbol{z}_j^s / \tau)}{\sum_k^K \exp(\boldsymbol{z}_i^{t\top} \boldsymbol{z}_k^s / \tau)}$, $\overleftarrow{s_{ij}} = \frac{\exp(\boldsymbol{z}_i^{s\top} \boldsymbol{z}_j^t / \tau)}{\sum_k^K \exp(\boldsymbol{z}_i^{s\top} \boldsymbol{z}_k^t / \tau)}$ is the similarity between the i-th scene/text feature and the j-th text/scene feature, q is a hyper-parameter, $\tau \in (0, 1]$ is the temperature parameter. Minimizing the Equation (3) would reduce the similarity of negative pairs, embracing discrimination without employing partially aligned positive pairs that prone to be noisy.

Subsequently, to mitigate the impact of false-negative pairs, we set the fixed q as a variable that adaptively controls the loss robustness for each pair. Specifically, we aim to associate the loss robustness with the reliability of negative pairs, enhancing the robustness of the loss for unreliable pairs while preserving discrimination for reliable ones. In simple terms, we empirically set $q = \overleftarrow{s_{ij}}$, where the similarity of pairs serves as a proxy for their reliability, with pairs exhibiting higher similarity being prone to constitute false negatives. For more aggregation details of the feature aggregation and the analysis on proposed $\mathcal{L}_m$, please refer to our Supplementary Material.

4.3 Tailored Word-Object Associating module

Although RTSA has established robust text-scene alignment by aligning rich global representations, reasoning from the redundant context to the target objects requires precise finer-grained alignment. However, dense attention mechanisms (*e.g.*, Self-Attention [47], Cross-Attention), commonly used for fine-grained information fusion, force associations across all input features. It would make the model inevitably pay attention to numerous irrelevant features. In contrast, sparsity control in sparse attention mechanisms relies on prior knowledge, potentially leading to the loss of crucial information.

To address the issues, we propose a Tailored Word-Object Associating module (TWOA) incorporated with a novel Screening Attention mechanism (ScA), built on the Transformer encoder architecture. Specifically, it calculates attention across word and object features based on the *Query* and *Key*, then evenly divides the attention into L segments based on the L-Quantile[48], from high to low. Assuming the i-th text matches j-th scene, it is written as:

$$A_i = \text{Sort}\left(W_q Z_i^c (W_k Z_i^c)^\top\right) = [A_{i1}; \cdots; A_{iL}], \tag{4}$$

where $A_i \in \mathbb{R}^{(M_i+N_j)\times(M_i+N_j)}$ is the attention scores across the word-object features, W_q and W_k is projection matrices to map Z_i^c to *Query* and *Key*, $Z_i^c = [Z_i^w; Z_j^o] \in \mathbb{R}^{(M_i+N_j)\times d}$ is the i-th word-object concatenated feature, and $A_{ik} \in \mathbb{R}^{(M_i+N_j)\times(M_i+N_j)/L}$ is the k-th attention segment of the i-th sample. Attention across segments varies in effectiveness, with top segments exhibiting greater weighting efficacy. Subsequently, we progressively screen the attention segments from low to high, resulting in L distinct degrees of attention retention. We dynamically combine these attentions with the *Value* in a stepwise accumulation manner, enabling a progressive refinement of fine-grained feature associations through the flexible attention screening, which is written as:

$$\tilde{Z}_i^c = f_u\Big(\sum_{j=1}^{L} \mu_j \tilde{A}_{ij} (W_v Z_i^c)^\top; \theta_u\Big), \tag{5}$$

where $\tilde{Z}_i^c = [\tilde{Z}_i^w; \tilde{Z}_j^o]$ is the multimodal feature after applying ScA (*i.e.*, $\tilde{Z}_i^w$ and $\tilde{Z}_j^o$ are the word and object features, respectively), $\{\mu_j\}_{j=1}^L$ is the learnable coefficients, $\tilde{A}_{ij} = \text{Softmax}([A_{i1}; \cdots; A_{ij}; 0; \cdots; 0])$ is top-j accumulative screened attention, where attention after the j-th segment is masked. W_v is projection matrices to map Z_i^c to *Value*, and $f_u(\cdot; \theta_u)$ represents the Transformer fusion function. With ScA, TWOA could gradually adjust the volume of features involved in the fine-grained association, filtering out excessive information and achieving precise fine-grained alignment between textual descriptions and target objects.

Finally, we can calculate the grounding scores of each object feature to infer the target object through a grounding layer with a weight matrix W_g, and we supervise it with CE loss:

$$\mathcal{L}_g = \frac{1}{K} \sum_{i}^{K} \mathcal{H}(W_g \tilde{Z}_i^o, y_i^t). \tag{6}$$

5 Dataset: CrossScene-RETR

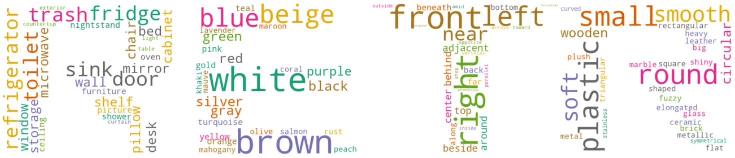


Figure 5: Word clouds of the proposed CrossScene-RETR dataset.

To the best of our knowledge, the descriptions in existing 3DVG datasets (*e.g.*, ScanRefer [2], *etc.*) provide fewer than 5 information points (*e.g.*, object class, colors, positions, *etc.*) and only cover 1.8 objects, as shown in Table 1. Such limited informational texts, when applied to CSSRG, undoubtedly intensify the challenges and complexity of the cross-modal spatial alignment.

To tackle the issues, we establish a discrimination benchmark dataset specific to CSSRG, namely CrossScene-RETR. In CrossScene-RETR, the 3D point-cloud data and object annotations are sourced from the widely used ScanNet dataset [49]. Query descriptions of objects with cross-scene discrimination are generated through our spatial analysis texts of scenes and corresponding corpora from existing text datasets (*i.e.*, ScanRefer [2], Nr3D [50], Sr3D [50], and ScanQA [51]). We will elaborate on its construction and statistics in the following.

5.1 Dataset Construction

We establish description texts of our CrossScene-RETR in four phases, with the pipeline shown in Figure 6.

1) *Scene Analysis Phase*: We first conduct an intra-scene analysis to assess object discrimination and localization within scenes. In addition, inter-scene analysis is performed to determine whether similar objects frequently appear across various scenes. Based on these, we gather extensive spatial information about objects and divide objects into *conspicuous*, *regular*, and *confusing* subsets to reflect the challenge level of each object in CSSRG, guiding text generation and model evaluation.

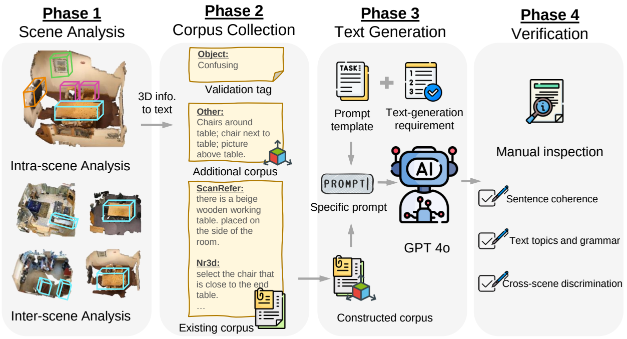


Figure 6: Construction pipeline of CrossScene-RETR.

2) *Corpus Collection Phase*: We gather available descriptions from ScanRefer, Nr3D, Sr3D, and ScanQA related to every object, covering attributes such as color, shape, position information, *etc.* Additionally, we enriched these preliminary texts on object positions and relative spatial relationships based on the *Scene Analysis Phase*. Based on these, we construct a rich corpus for scene objects.

3) *Text Generation Phase*: We utilize GPT-4o as the generation model and design a prompt template tailored to the task requirements. To ensure relevance for real-world applications, we switch four generation requirements in the template to generate four style description subsets: *characteristic-focused*, *spatial-information-focused*, *comprehensive*, and *fuzzy* subsets.

4) *Verification Phase*: We manually assess the generated descriptions for linguistic coherence and grammatical accuracy. In addition, we employ several staff to remove erroneous descriptions and eliminate ambiguous descriptions, ensuring the cross-scene discrimination of descriptions.

5.2 Brief Statistics

To comprehensively understand our proposed CrossScene-RETR, we provide a statistical comparison of it, as shown in Table 1. The results show that our descriptions are richer and more discriminative, which ensures that they are unambiguous for CSSRG applications. Due to space limitations, more comprehensive construction details and statistical analysis of CrossScene-RETR are provided in our Supplementary Material.

Table 1: Statistics comparison among four datasets.

Statistical indicators		ScanRefer	Nr3D	Sr3D	RETR
Overall	Average length	17.9	11.4	9.7	77.7
	Number of samples	46,173	41,503	83,572	39,526
	Vocabulary size	6,919	6,951	196	22,485
	Free-form	√	√	×	√
Richness of description	Number of objects per text	1.8	1.7	1.8	11.4
	Number of characteristics per text	1.5	1.6	0.0	5.9
	Number of Spatial info. per text	1.2	1.1	0.6	6.3
	Number of info. points per text	4.5	4.4	2.4	23.2
	Text with Spatial info. (%)	69.8	47.5	55.6	97.5
	Text with color description (%)	58.2	29.7	0.0	81.2
	Text with shape description (%)	20.3	6.5	0.0	45.0
	Text with material description (%)	13.0	2.1	0.7	38.5

Table 4: Scene matching and Object Grounding (OG) performance comparison on four datasets in terms of R@1, R@5, R@10, and Acc@0.25. The top of the table shows the results of fine-grained CMM methods, and the bottom shows the coarse-grained methods results. The highest results are shown in **bold** and the second highest results are underlined.

Method	ScanRefer				Nr3D				Sr3D				CrossScene-RETR				T
	Scene matching			OG	Scene matching			OG	Scene matching			OG	Scene matching			OG	
	R@1	R@5	R@10	Acc@0.25	R@1	R@5	R@10	Acc@0.25	R@1	R@5	R@10	Acc@0.25	R@1	R@5	R@10	Acc@0.25	
NAAF	9.17	35.05	54.17	2.17	10.35	34.32	50.63	1.48	3.36	12.76	24.83	0.37	28.72	66.34	78.03	2.05	58 *ms*
CHAN	10.14	38.03	55.35	3.15	14.03	40.06	59.42	2.06	5.36	21.34	34.78	1.04	30.35	67.51	78.35	4.01	63 *ms*
CRCL-F	10.05	37.61	56.13	2.08	13.95	41.42	**59.50**	1.88	5.34	**24.16**	**35.44**	1.13	28.35	65.45	78.17	3.47	63 *ms*
VSE∞	9.32	37.53	55.78	-	12.73	38.56	56.77	-	5.71	21.99	35.29	-	30.31	67.07	77.59	-	13 *ms*
HREM	9.13	38.35	54.38	-	12.81	39.86	57.31	-	5.42	21.92	33.57	-	29.13	66.16	78.73	-	18 *ms*
ESA	10.13	37.41	55.63	-	13.74	39.25	58.74	-	5.52	21.25	34.44	-	29.24	67.08	79.78	-	18 *ms*
CRCL-C	10.78	38.05	54.29	-	13.08	39.90	58.69	-	4.94	19.49	31.90	-	28.31	65.63	76.97	-	14 *ms*
Ours	**13.29**	**38.84**	**56.20**	**6.24**	**14.56**	**43.54**	58.23	**5.86**	**5.95**	23.22	34.79	**3.52**	**36.48**	**68.53**	**81.44**	**22.99**	54 *ms*

6 Experiments

In the experiments, we adopt the 3D set along with CrossScene-RETR, ScanRefer, Nr3D, and Sr3D text sets for CSSRG evaluation. We compare our CoRe with 13 state-of-the-art methods, which include: 3DVG methods (*i.e.*, ScanRefer [2], 3D-BUTD [52], EDA [53], VisTA [10], GPS [3], and TSP3D [54]) and CMM methods (*i.e.*, NAAF [32], CHAN [55], VSE∞ [33], HREM [56], ESA [57], coarse-grained CRCL-C and fine-grained CRCL-F [58]). In addition, we integrate advanced CMM and 3DVG methods to construct matching-then-grounding baselines (*i.e.*, HREM+VisTA, ESA+GPS) for comparison. We report the following metrics for CSSRG evaluation: **1)** Acc@k ($k \in \{0.25, 0.5\}$): The reasoning accuracy which requires matching the correct scene while the predicted box overlaps the ground truth with IoU $> k$. **2)** R@K ($K \in \{1, 5, 10\}$): Scene retrieval recall at K, following the CMM metrics [21]. **3)** T: Average inference time per query. Due to space limitations, the introduction to the adopted datasets, implementation details of the methods, could be found in our Supplementary Material.

Table 2: Performance comparison on CrossScene-RETR in terms of Acc@0.25 (0.25) and Acc@0.5 (0.5). The highest results are shown in **bold** and the second highest are underlined.

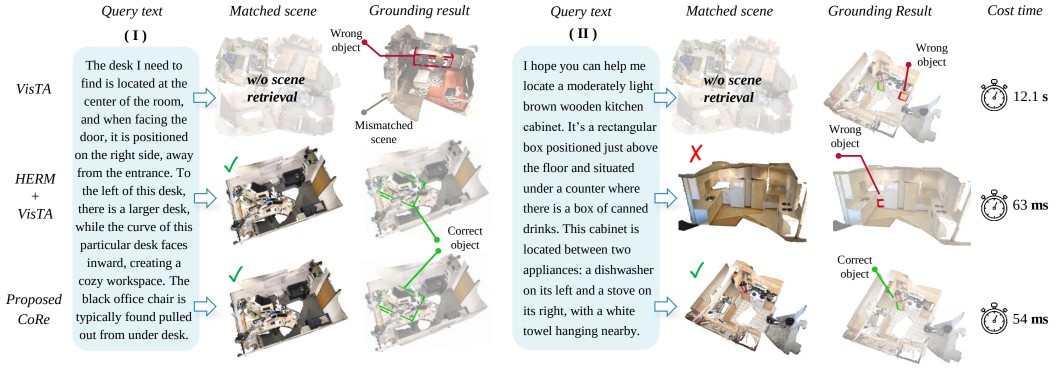
Method	Conspicuous		Regular		Confusing		Overall		T
	0.25	0.5	0.25	0.5	0.25	0.5	0.25	0.5	
CRCL-F	2.35	2.35	2.54	2.22	2.69	2.58	2.54	2.34	63 *ms*
Vista	7.06	4.57	8.70	6.26	7.38	5.08	8.04	5.62	14.2 *s*
GPS	5.54	5.31	5.30	5.27	5.27	5.17	5.34	5.24	27.2 *s*
TSP3D	4.85	4.36	4.61	4.21	4.32	3.74	4.58	4.12	14.3 *s*
HREM+VisTA	20.41	19.46	16.88	15.43	14.13	12.88	17.25	15.96	(18 + 45) *ms*
ESA+GPS	21.26	20.08	14.34	13.18	13.98	12.82	15.60	14.44	(18 + 171) *ms*
Ours	**28.67**	**26.52**	**22.45**	**20.82**	**19.83**	**18.20**	**22.99**	**21.26**	54 *ms*

6.1 Comparison with the State-of-the-Arts

The performance comparison results between CoRe, 3DVG, and constructed matching-then-grounding methods are reported in Tables 2 and 3, and the scene matching comparison results between our CoRe and the CMM methods are presented in Table 4. These results could yield the following observations: **1)** Compared to the inferior performance in existing datasets, the performance in our CrossScene-RETR shows a substantial improvement. This demonstrates that it encapsulates greater discrimination, addressing the complex cross-modal spatial alignment challenge. **2)** Our CoRe achieves inference efficiency comparable to CMM methods, outperforming 3DVG methods by a factor of 250. This validates the effectiveness of our two-stage framework for CSSRG. **3)** Our CoRe achieves better results both in scene matching and in object grounding compared with baselines, showing its superiority in overcoming the specific challenges. **4)** The performance on CSSRG is relatively low, indicating that the methods still face difficulties in handling CSSRG, and call for more advanced solutions.

Table 3: Performance comparison on ScanRefer, Nr3D, and Sr3D using Acc@0.25/0.5 (0.25/0.5). Best results are in **bold**, second-best are underlined.

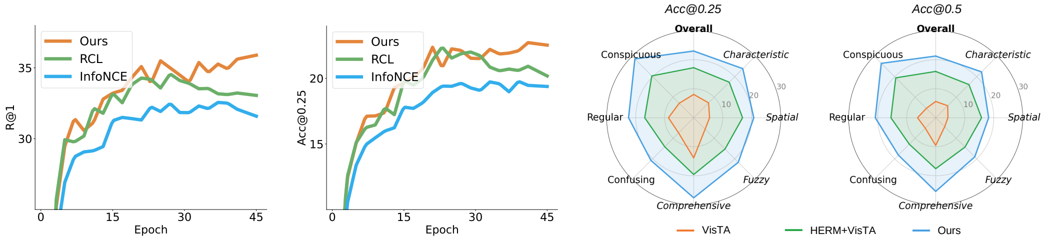
Method	ScanRefer						Nr3D	Sr3D	T
	Unique		Multiple		Overall		Overall	Overall	
	0.25	0.5	0.25	0.5	0.25	0.5	0.25	0.25	
3D-BUTD	6.14	2.90	2.17	2.03	2.90	2.19	0.00	0.20	13.2 *s*
EDA	3.31	0.00	0.40	0.00	0.70	0.00	2.50	0.66	23.1 *s*
VisTA	5.63	5.44	5.16	5.34	5.23	5.36	0.63	0.25	12.1 *s*
GPS	5.04	4.11	3.84	3.80	4.04	3.85	0.20	0.35	21.2 *s*
TSP3D	3.17	2.82	1.53	1.32	1.78	1.55	1.14	-	14.3 *s*
HREM+VisTA	6.14	5.34	4.74	4.14	5.00	4.36	4.57	2.14	(18 + 42) *ms*
ESA+GPS	6.60	5.86	5.21	4.91	5.43	5.06	4.78	2.97	(18 + 164) *ms*
Ours	**7.39**	**6.88**	**5.98**	**5.54**	**6.24**	**5.79**	**5.86**	**3.52**	51 *ms*



The desk I need to find is located at the center of the room, and when facing the door, it is positioned on the right side, away from the entrance. To the left of this desk, there is a larger desk, while the curve of this particular desk faces inward, creating a cozy workspace. The black office chair is typically found pulled out from under desk.

I hope you can help me locate a moderately light brown wooden kitchen cabinet. It's a rectangular box positioned just above the floor and situated under a counter where there is a box of canned drinks. This cabinet is located between two appliances: a dishwasher on its left and a stove on its right, with a white towel hanging nearby.

Figure 7: Some CSSRG instances on CrossScene-RETR among VisTA, HREM+VisTA, and CoRe. Correctly matched scenes are marked with a **green** tick, otherwise the **red** cross. Correctly located objects are highlighted with **green** boxes, otherwise the **red** boxes.



(a) Scene matching (b) Object grounding (c) Grounding performance across dataset subsets

Figure 8: (a) and (b) show matching and grounding performance comparison of our CoRe and its variants using contrastive learning (InfoNCE) and complementary learning (RCL), evaluated by R@1 and Acc@0.25. (c) shows object grounding performance of CoRe across different subsets of CrossScene-RETR, in terms of Acc@0.25 and Acc@0.5. Overall performance is highlighted in **bold**, and subsets with varying challenge levels and description styles are shown in *italics* and normal font.

6.2 Ablation Study

Table 5: Ablation studies for components of our CoRe on CrossScene-RETR. R@Sum is the sum of R@1, R@5, R@10. ✓ stands for use.

Mask	RTSA	TWOA	R@Sum	Acc@0.25	Acc@0.5
✓	✓	✓	186.45	22.99	21.26
	✓	✓	183.26	21.37	20.29
✓		✓	5.25	1.03	0.72
✓	$\mathcal{L}_m^{\bar{q}}$	✓	177.94	21.18	20.29
✓	✓	SA	185.72	19.76	18.38
✓	✓	CA	177.43	17.53	16.47

In this section, we investigate the contribution of each adopted component to CSSRG. For a comprehensive comparison, we ablate or substitute each component and conduct the variants with the same experimental setting on the CrossScene-RETR dataset. Specifically, we ablate the Targeted Masking and RTSA from our framework. In addition, we replace the matching loss with its fixed q variant (*i.e.*, $\mathcal{L}_m^{\bar{q}}$) in the RTSA, and the ScA with dense Self-/Cross-Attention (SA/CA) in our TWOA. The results in Table 5 lead to the following observation: **1)** Removing or replacing any component from CoRe results in performance degradation, highlighting the contribution of each component. **2)** The performance brought by the matching loss we use in RTSA is superior to the vanilla alternatives, demonstrating its contribution to robust text-scene matching in CSSRG. **3)** The replacement with dense attention degrades performance, proving that ScA alleviates the impact of redundant information on word-object association.

6.3 Visualization Analysis

To provide a comprehensive understanding of our proposed CrossScene-RETR dataset and CoRe baseline, we conduct visualization experiments. Specifically, we visualize the CSSRG result instances of VisTA, HREM+VisTA, and our CoRe, as shown in Figure 7. Additionally, we present the CSSRG performance comparisons between VisTA, HREM+VisTA and CoRe within varying challenge levels and description styles subsets in the proposed CrossScene-RETR. We present the performance comparison in scene matching and object grounding between CoRe and its variants based on contrastive and complementary learning. Both are presented together in Figure 8. The following observations can be drawn from the results: **1)** Our CoRe achieves more accurate results and reasoning efficiency, demonstrating its ability to address the specific challenges of CSSRG. **2)** Diverse descriptions and scene objects in CrossScene-RETR pose various practical challenges to methods. Experimental results demonstrate that our CoRe achieves an extensive understanding and superior grounding performance of diverse texts and objects. **3)** Throughout the learning process, it is evident that non-robust variants exhibit suboptimal matching and grounding performance compared to our CoRe, highlighting the ability to mitigate partial text-scene alignment issue of CoRe.

7 Conclusion

In this paper, we introduce a new task, Cross-Scene Spatial Reasoning and Grounding (CSSRG), which extends 3D visual grounding to a broader, more practical, and more complex setting. To effectively tackle this task, we propose the **Cro**ss-Scene 3D Object **Re**asoning Framework (CoRe), integrating two novel modules: the Robust Text-Scene Aligning module (RTSA) and the Tailored Word-Object Associating module (TWOA). Specifically, CoRe adopts a matching-then-grounding pipeline, enabling efficient cross-scene grounding. RTSA mitigates the issue of partial alignment by refining text-scene association, while TWOA enhances non-redundant word-object association, improving object grounding precision. Additionally, we introduce the CrossScene-RETR dataset, designed to evaluate the challenges of CSSRG more effectively. Extensive experiments on four datasets demonstrate the superiority and effectiveness of our CoRe, highlighting its potential for advancing cross-scene 3D reasoning and multimodal understanding.

Acknowledgments

This work was supported in part by NSFC under Grant 62472295, 62176171, 62372315, U24B20174; in part by the National Key R&D Program of China under Grant 2024YFB4710604; in part by the Fundamental Research Funds for the Central Universities under Grant CJ202303, CJ202403; in part by Sichuan Science and Technology Planning Project under Grant 24NSFTD0130, 2024ZDZX0004, 2024NSFTD0049; in part by the Chengdu Science and Technology Project under Grant 2023-XT00-00004-GX; in part by System of Systems and Artificial Intelligence Laboratory pioneer fund grant under Grant HLJGGG20240327517-15, and in part by TCL science and technology innovation fund.

References

[1] Zhihao Yuan, Xu Yan, Yinghong Liao, Ruimao Zhang, Sheng Wang, Zhen Li, and Shuguang Cui. Instancerefer: Cooperative holistic understanding for visual grounding on point clouds through instance multi-level contextual referring. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 1791–1800, 2021.

[2] Dave Zhenyu Chen, Angel X Chang, and Matthias Nießner. Scanrefer: 3d object localization in rgb-d scans using natural language. In *European conference on computer vision*, pages 202–221. Springer, 2020.

[3] Baoxiong Jia, Yixin Chen, Huangyue Yu, Yan Wang, Xuesong Niu, Tengyu Liu, Qing Li, and Siyuan Huang. Sceneverse: Scaling 3d vision-language learning for grounded scene understanding. In *European Conference on Computer Vision*, pages 289–310. Springer, 2025.

[4] Wencan Huang, Daizong Liu, and Wei Hu. Advancing 3d object grounding beyond a single 3d scene. In *Proceedings of the 32nd ACM International Conference on Multimedia*, pages 7995–8004, 2024.

[5] Jiaqi Chen, Daniel Barath, Iro Armeni, Marc Pollefeys, and Hermann Blum. “where am i?” scene retrieval with language. In *European Conference on Computer Vision*, pages 201–220. Springer, 2024.

[6] Binbin Xu, Allen Tao, Hugues Thomas, Jian Zhang, and Timothy D Barfoot. Makeway: Object-aware costmaps for proactive indoor navigation using lidar. *arXiv preprint arXiv:2408.17034*, 2024.

[7] Yanglin Feng, Yang Qin, Dezhong Peng, Hongyuan Zhu, Xi Peng, and Peng Hu. Pointcloud-text matching: Benchmark dataset and baseline. *IEEE Transactions on Multimedia*, 2025.

[8] Qiao Gu, Ali Kuwajerwala, Sacha Morin, Krishna Murthy Jatavallabhula, Bipasha Sen, Aditya Agarwal, Corban Rivera, William Paul, Kirsty Ellis, Rama Chellappa, et al. Conceptgraphs: Open-vocabulary 3d scene graphs for perception and planning. In *2024 IEEE International Conference on Robotics and Automation (ICRA)*, pages 5021–5028. IEEE, 2024.

[9] Duo Zheng, Shijia Huang, Lin Zhao, Yiwu Zhong, and Liwei Wang. Towards learning a generalist model for embodied navigation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 13624–13634, June 2024.

[10] Ziyu Zhu, Xiaojian Ma, Yixin Chen, Zhidong Deng, Siyuan Huang, and Qing Li. 3d-vista: Pre-trained transformer for 3d vision and text alignment. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 2911–2921, 2023.

[11] Chao Su, Zhi Li, Tianyi Lei, Dezhong Peng, and Xu Wang. Metavg: A meta-learning framework for visual grounding. *IEEE Signal Processing Letters*, 31:236–240, 2023.

[12] Shijia Huang, Yilun Chen, Jiaya Jia, and Liwei Wang. Multi-view transformer for 3d visual grounding. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 15524–15533, 2022.

[13] Lichen Zhao, Daigang Cai, Lu Sheng, and Dong Xu. 3dvg-transformer: Relation modeling for visual grounding on point clouds. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 2928–2937, 2021.

[14] Zhihao Yuan, Jinke Ren, Chun-Mei Feng, Hengshuang Zhao, Shuguang Cui, and Zhen Li. Visual programming for zero-shot open-vocabulary 3d visual grounding. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 20623–20633, 2024.

[15] Zhipeng Qian, Yiwei Ma, Zhekai Lin, Jiayi Ji, Xiawu Zheng, Xiaoshuai Sun, and Rongrong Ji. Multi-branch collaborative learning network for 3d visual grounding. In *European Conference on Computer Vision*, pages 381–398. Springer, 2024.

[16] Chun-Peng Chang, Shaoxiang Wang, Alain Pagani, and Didier Stricker. Mikasa: Multi-key-anchor & scene-aware transformer for 3d visual grounding. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 14131–14140, 2024.

[17] Zhengyuan Yang, Songyang Zhang, Liwei Wang, and Jiebo Luo. Sat: 2d semantics assisted training for 3d visual grounding. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 1856–1866, 2021.

[18] Yuqi Zhang, Han Luo, and Yinjie Lei. Towards clip-driven language-free 3d visual grounding via 2d-3d relational enhancement and consistency. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 13063–13072, 2024.

[19] Yining Hong, Haoyu Zhen, Peihao Chen, Shuhong Zheng, Yilun Du, Zhenfang Chen, and Chuang Gan. 3d-llm: Injecting the 3d world into large language models. *Advances in Neural Information Processing Systems*, 36:20482–20494, 2023.

[20] Zhenyang Liu, Yikai Wang, Sixiao Zheng, Tongying Pan, Longfei Liang, Yanwei Fu, and Xiangyang Xue. Reasongrounder: Lvlm-guided hierarchical feature splatting for open-vocabulary 3d visual grounding and reasoning. *arXiv preprint arXiv:2503.23297*, 2025.

[21] Kuang-Huei Lee, Xi Chen, Gang Hua, Houdong Hu, and Xiaodong He. Stacked cross attention for image-text matching. In *Proceedings of the European conference on computer vision (ECCV)*, pages 201–216, 2018.

[22] Ruitao Pu, Yuan Sun, Yang Qin, Zhenwen Ren, Xiaomin Song, Huiming Zheng, and Dezhong Peng. Robust self-paced hashing for cross-modal retrieval with noisy labels. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 39, pages 19969–19977, 2025.

[23] Yongxiang Li, Yang Qin, Yuan Sun, Dezhong Peng, Xi Peng, and Peng Hu. Romo: Robust unsupervised multimodal learning with noisy pseudo labels. *IEEE Transactions on Image Processing*, 2024.

[24] Yongxiang Li, Dezhong Peng, Haixiao Huang, Yizhi Liu, Huiming Zheng, and Zheng Liu. Multi-granularity confidence learning for unsupervised text-to-image person re-identification with incomplete modality. *Knowledge-Based Systems*, 315:113304, 2025.

[25] Yang Qin, Yingke Chen, Dezhong Peng, Xi Peng, Joey Tianyi Zhou, and Peng Hu. Noisy-correspondence learning for text-to-image person re-identification. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 27197–27206, 2024.

[26] Ruitao Pu, Yang Qin, Dezhong Peng, Xiaomin Song, and Huiming Zheng. Deep reversible consistency learning for cross-modal retrieval. *IEEE Transactions on Multimedia*, 2025.

[27] Yang Qin, Yuan Sun, Dezhong Peng, Joey Tianyi Zhou, Xi Peng, and Peng Hu. Cross-modal active complementary learning with self-refining correspondence. *Advances in neural information processing systems*, 36:24829–24840, 2023.

[28] Siyuan Duan, Yuan Sun, Dezhong Peng, Zheng Liu, Xiaomin Song, and Peng Hu. Fuzzy multimodal learning for trusted cross-modal retrieval. In *Proceedings of the Computer Vision and Pattern Recognition Conference*, pages 20747–20756, 2025.

[29] Kaixiang Ji, Jiajia Liu, Weixiang Hong, Liheng Zhong, Jian Wang, Jingdong Chen, and Wei Chu. Cret: Cross-modal retrieval transformer for efficient text-video retrieval. In *Proceedings of the 45th international ACM SIGIR conference on research and development in information retrieval*, pages 949–959, 2022.

[30] Yongxiang Li, Yuan Sun, Yang Qin, Dezhong Peng, Xi Peng, and Peng Hu. Robust duality learning for unsupervised visible-infrared person re-identification. *IEEE Transactions on Information Forensics and Security*, 2025.

[31] Haiwen Diao, Ying Zhang, Lin Ma, and Huchuan Lu. Similarity reasoning and filtration for image-text matching. In *Proceedings of the AAAI conference on artificial intelligence*, volume 35, pages 1218–1226, 2021.

[32] Kun Zhang, Zhendong Mao, Quan Wang, and Yongdong Zhang. Negative-aware attention framework for image-text matching. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 15661–15670, 2022.

[33] Jiacheng Chen, Hexiang Hu, Hao Wu, Yuning Jiang, and Changhu Wang. Learning the best pooling strategy for visual semantic embedding. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 15789–15798, 2021.

[34] Zheren Fu, Zhendong Mao, Yan Song, and Yongdong Zhang. Learning semantic relationship among instances for image-text matching. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 15159–15168, 2023.

[35] Aaron van den Oord, Yazhe Li, and Oriol Vinyals. Representation learning with contrastive predictive coding. *arXiv preprint arXiv:1807.03748*, 2018.

[36] Kaiming He, Haoqi Fan, Yuxin Wu, Saining Xie, and Ross Girshick. Momentum contrast for unsupervised visual representation learning. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 9729–9738, 2020.

[37] Shilin Xu, Yuan Sun, Xingfeng Li, Siyuan Duan, Zhenwen Ren, Zheng Liu, and Dezhong Peng. Noisy label calibration for multi-view classification. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 39, pages 21797–21805, 2025.

[38] Zhenyu Huang, Guocheng Niu, Xiao Liu, Wenbiao Ding, Xinyan Xiao, Hua Wu, and Xi Peng. Learning with noisy correspondence for cross-modal matching. *Advances in Neural Information Processing Systems*, 34:29406–29419, 2021.

[39] Yuan Sun, Yongxiang Li, Zhenwen Ren, Guiduo Duan, Dezhong Peng, and Peng Hu. Roll: Robust noisy pseudo-label learning for multi-view clustering with noisy correspondence. In *Proceedings of the Computer Vision and Pattern Recognition Conference*, pages 30732–30741, 2025.

[40] Jacob Devlin. Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805*, 2018.

[41] Jonas Schult, Francis Engelmann, Alexander Hermans, Or Litany, Siyu Tang, and Bastian Leibe. Mask3d: Mask transformer for 3d semantic instance segmentation. In *2023 IEEE International Conference on Robotics and Automation (ICRA)*, pages 8216–8223. IEEE, 2023.

[42] Charles Ruizhongtai Qi, Li Yi, Hao Su, and Leonidas J Guibas. Pointnet++: Deep hierarchical feature learning on point sets in a metric space. *Advances in neural information processing systems*, 30, 2017.

[43] Shizhe Chen, Pierre-Louis Guhur, Makarand Tapaswi, Cordelia Schmid, and Ivan Laptev. Language conditioned spatial relation reasoning for 3d object grounding. *Advances in neural information processing systems*, 35:20522–20535, 2022.

[44] Kun Zhang, Bo Hu, Huatian Zhang, Zhe Li, and Zhendong Mao. Enhanced semantic similarity learning framework for image-text matching. *IEEE Transactions on Circuits and Systems for Video Technology*, 2023.

[45] Peng Hu, Zhenyu Huang, Dezhong Peng, Xu Wang, and Xi Peng. Cross-modal retrieval with partially mismatched pairs. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, pages 1–15, 2023.

[46] Zhilu Zhang and Mert Sabuncu. Generalized cross entropy loss for training deep neural networks with noisy labels. *Advances in neural information processing systems*, 31, 2018.

[47] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is all you need. *Advances in neural information processing systems*, 30, 2017.

[48] Frederik Michel Dekking. *A Modern Introduction to Probability and Statistics: Understanding why and how*. Springer Science & Business Media, 2005.

[49] Angela Dai, Angel X Chang, Manolis Savva, Maciej Halber, Thomas Funkhouser, and Matthias Nießner. Scannet: Richly-annotated 3d reconstructions of indoor scenes. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 5828–5839, 2017.

[50] Panos Achlioptas, Ahmed Abdelreheem, Fei Xia, Mohamed Elhoseiny, and Leonidas Guibas. Referit3d: Neural listeners for fine-grained 3d object identification in real-world scenes. In *Computer Vision–ECCV 2020: 16th European Conference, Glasgow, UK, August 23–28, 2020, Proceedings, Part I 16*, pages 422–440. Springer, 2020.

[51] Daichi Azuma, Taiki Miyanishi, Shuhei Kurita, and Motoaki Kawanabe. Scanqa: 3d question answering for spatial scene understanding. In *proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 19129–19139, 2022.

[52] Ayush Jain, Nikolaos Gkanatsios, Ishita Mediratta, and Katerina Fragkiadaki. Bottom up top down detection transformers for language grounding in images and point clouds. In *European Conference on Computer Vision*, pages 417–433. Springer, 2022.

[53] Yanmin Wu, Xinhua Cheng, Renrui Zhang, Zesen Cheng, and Jian Zhang. Eda: Explicit text-decoupling and dense alignment for 3d visual grounding. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 19231–19242, 2023.

[54] Wenxuan Guo, Xiuwei Xu, Ziwei Wang, Jianjiang Feng, Jie Zhou, and Jiwen Lu. Tsp3d: Text-guided sparse voxel pruning for efficient 3d visual grounding. *arXiv preprint arXiv:2502.10392*, 2025.

[55] Zhengxin Pan, Fangyu Wu, and Bailing Zhang. Fine-grained image-text matching by cross-modal hard aligning network. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 19275–19284, 2023.

[56] Zheren Fu, Zhendong Mao, Yan Song, and Yongdong Zhang. Learning semantic relationship among instances for image-text matching. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 15159–15168, June 2023.

[57] Hongguang Zhu, Chunjie Zhang, Yunchao Wei, Shujuan Huang, and Yao Zhao. Esa: External space attention aggregation for image-text retrieval. *IEEE Transactions on Circuits and Systems for Video Technology*, 33(10):6131–6143, 2023.

[58] Yang Qin, Yuan Sun, Dezhong Peng, Joey Tianyi Zhou, Xi Peng, and Peng Hu. Cross-modal active complementary learning with self-refining correspondence. *Advances in Neural Information Processing Systems*, 36, 2024.

NeurIPS Paper Checklist

1. **Claims**

   Question: Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope?

   Answer: [Yes]

   Justification: The abstract and introduction clearly state the claims made.

   Guidelines:

   - The answer NA means that the abstract and introduction do not include the claims made in the paper.
   - The abstract and/or introduction should clearly state the claims made, including the contributions made in the paper and important assumptions and limitations. A No or NA answer to this question will not be perceived well by the reviewers.
   - The claims made should match theoretical and experimental results, and reflect how much the results can be expected to generalize to other settings.
   - It is fine to include aspirational goals as motivation as long as it is clear that these goals are not attained by the paper.

2. **Limitations**

   Question: Does the paper discuss the limitations of the work performed by the authors?

   Answer: [Yes]

   Justification: The limitations are discussed in the Supplementary Material.

   Guidelines:

   - The answer NA means that the paper has no limitation while the answer No means that the paper has limitations, but those are not discussed in the paper.
   - The authors are encouraged to create a separate ”Limitations” section in their paper.
   - The paper should point out any strong assumptions and how robust the results are to violations of these assumptions (e.g., independence assumptions, noiseless settings, model well-specification, asymptotic approximations only holding locally). The authors should reflect on how these assumptions might be violated in practice and what the implications would be.
   - The authors should reflect on the scope of the claims made, e.g., if the approach was only tested on a few datasets or with a few runs. In general, empirical results often depend on implicit assumptions, which should be articulated.
   - The authors should reflect on the factors that influence the performance of the approach. For example, a facial recognition algorithm may perform poorly when image resolution is low or images are taken in low lighting. Or a speech-to-text system might not be used reliably to provide closed captions for online lectures because it fails to handle technical jargon.
   - The authors should discuss the computational efficiency of the proposed algorithms and how they scale with dataset size.
   - If applicable, the authors should discuss possible limitations of their approach to address problems of privacy and fairness.
   - While the authors might fear that complete honesty about limitations might be used by reviewers as grounds for rejection, a worse outcome might be that reviewers discover limitations that aren't acknowledged in the paper. The authors should use their best judgment and recognize that individual actions in favor of transparency play an important role in developing norms that preserve the integrity of the community. Reviewers will be specifically instructed to not penalize honesty concerning limitations.

3. **Theory assumptions and proofs**

   Question: For each theoretical result, does the paper provide the full set of assumptions and a complete (and correct) proof?

   Answer: [Yes]

   Justification: The Analysis and proof are provided in the supplementary material.

Guidelines:

- The answer NA means that the paper does not include theoretical results.
- All the theorems, formulas, and proofs in the paper should be numbered and cross-referenced.
- All assumptions should be clearly stated or referenced in the statement of any theorems.
- The proofs can either appear in the main paper or the supplemental material, but if they appear in the supplemental material, the authors are encouraged to provide a short proof sketch to provide intuition.
- Inversely, any informal proof provided in the core of the paper should be complemented by formal proofs provided in appendix or supplemental material.
- Theorems and Lemmas that the proof relies upon should be properly referenced.

4. **Experimental result reproducibility**

   Question: Does the paper fully disclose all the information needed to reproduce the main experimental results of the paper to the extent that it affects the main claims and/or conclusions of the paper (regardless of whether the code and data are provided or not)?

   Answer: [Yes]

   Justification: The implementation and training details are clearly described for reproduction in our main paper and supplementary material.

   Guidelines:

   - The answer NA means that the paper does not include experiments.
   - If the paper includes experiments, a No answer to this question will not be perceived well by the reviewers: Making the paper reproducible is important, regardless of whether the code and data are provided or not.
   - If the contribution is a dataset and/or model, the authors should describe the steps taken to make their results reproducible or verifiable.
   - Depending on the contribution, reproducibility can be accomplished in various ways. For example, if the contribution is a novel architecture, describing the architecture fully might suffice, or if the contribution is a specific model and empirical evaluation, it may be necessary to either make it possible for others to replicate the model with the same dataset, or provide access to the model. In general. releasing code and data is often one good way to accomplish this, but reproducibility can also be provided via detailed instructions for how to replicate the results, access to a hosted model (e.g., in the case of a large language model), releasing of a model checkpoint, or other means that are appropriate to the research performed.
   - While NeurIPS does not require releasing code, the conference does require all submissions to provide some reasonable avenue for reproducibility, which may depend on the nature of the contribution. For example
     (a) If the contribution is primarily a new algorithm, the paper should make it clear how to reproduce that algorithm.
     (b) If the contribution is primarily a new model architecture, the paper should describe the architecture clearly and fully.
     (c) If the contribution is a new model (e.g., a large language model), then there should either be a way to access this model for reproducing the results or a way to reproduce the model (e.g., with an open-source dataset or instructions for how to construct the dataset).
     (d) We recognize that reproducibility may be tricky in some cases, in which case authors are welcome to describe the particular way they provide for reproducibility. In the case of closed-source models, it may be that access to the model is limited in some way (e.g., to registered users), but it should be possible for other researchers to have some path to reproducing or verifying the results.

5. **Open access to data and code**

   Question: Does the paper provide open access to the data and code, with sufficient instructions to faithfully reproduce the main experimental results, as described in supplemental material?

   Answer: [Yes]

Justification: The code will be released publicly after in-peer review.

Guidelines:

- The answer NA means that paper does not include experiments requiring code.
- Please see the NeurIPS code and data submission guidelines (`https://nips.cc/public/guides/CodeSubmissionPolicy`) for more details.
- While we encourage the release of code and data, we understand that this might not be possible, so "No" is an acceptable answer. Papers cannot be rejected simply for not including code, unless this is central to the contribution (e.g., for a new open-source benchmark).
- The instructions should contain the exact command and environment needed to run to reproduce the results. See the NeurIPS code and data submission guidelines (`https://nips.cc/public/guides/CodeSubmissionPolicy`) for more details.
- The authors should provide instructions on data access and preparation, including how to access the raw data, preprocessed data, intermediate data, and generated data, etc.
- The authors should provide scripts to reproduce all experimental results for the new proposed method and baselines. If only a subset of experiments are reproducible, they should state which ones are omitted from the script and why.
- At submission time, to preserve anonymity, the authors should release anonymized versions (if applicable).
- Providing as much information as possible in supplemental material (appended to the paper) is recommended, but including URLs to data and code is permitted.

6. **Experimental setting/details**

   Question: Does the paper specify all the training and test details (e.g., data splits, hyper-parameters, how they were chosen, type of optimizer, etc.) necessary to understand the results?

   Answer: [Yes]

   Justification: The experiment settings are clearly presented in the paper and supplementary material.

   Guidelines:

   - The answer NA means that the paper does not include experiments.
   - The experimental setting should be presented in the core of the paper to a level of detail that is necessary to appreciate the results and make sense of them.
   - The full details can be provided either with the code, in appendix, or as supplemental material.

7. **Experiment statistical significance**

   Question: Does the paper report error bars suitably and correctly defined or other appropriate information about the statistical significance of the experiments?

   Answer: [No]

   Justification: Error bars are not reported because it would be too computationally expensive for experiments involving LLMs.

   Guidelines:

   - The answer NA means that the paper does not include experiments.
   - The authors should answer "Yes" if the results are accompanied by error bars, confidence intervals, or statistical significance tests, at least for the experiments that support the main claims of the paper.
   - The factors of variability that the error bars are capturing should be clearly stated (for example, train/test split, initialization, random drawing of some parameter, or overall run with given experimental conditions).
   - The method for calculating the error bars should be explained (closed form formula, call to a library function, bootstrap, etc.)
   - The assumptions made should be given (e.g., Normally distributed errors).
   - It should be clear whether the error bar is the standard deviation or the standard error of the mean.

- It is OK to report 1-sigma error bars, but one should state it. The authors should preferably report a 2-sigma error bar than state that they have a 96% CI, if the hypothesis of Normality of errors is not verified.
- For asymmetric distributions, the authors should be careful not to show in tables or figures symmetric error bars that would yield results that are out of range (e.g. negative error rates).
- If error bars are reported in tables or plots, The authors should explain in the text how they were calculated and reference the corresponding figures or tables in the text.

8. **Experiments compute resources**

   Question: For each experiment, does the paper provide sufficient information on the computer resources (type of compute workers, memory, time of execution) needed to reproduce the experiments?

   Answer: [Yes]

   Justification: The compute resources are reported in the experiment settings.

   Guidelines:

   - The answer NA means that the paper does not include experiments.
   - The paper should indicate the type of compute workers CPU or GPU, internal cluster, or cloud provider, including relevant memory and storage.
   - The paper should provide the amount of compute required for each of the individual experimental runs as well as estimate the total compute.
   - The paper should disclose whether the full research project required more compute than the experiments reported in the paper (e.g., preliminary or failed experiments that didn't make it into the paper).

9. **Code of ethics**

   Question: Does the research conducted in the paper conform, in every respect, with the NeurIPS Code of Ethics `https://neurips.cc/public/EthicsGuidelines`?

   Answer: [Yes]

   Justification: The research conducted in the paper conform with the NeurIPS Code of Ethics in every respect.

   Guidelines:

   - The answer NA means that the authors have not reviewed the NeurIPS Code of Ethics.
   - If the authors answer No, they should explain the special circumstances that require a deviation from the Code of Ethics.
   - The authors should make sure to preserve anonymity (e.g., if there is a special consideration due to laws or regulations in their jurisdiction).

10. **Broader impacts**

    Question: Does the paper discuss both potential positive societal impacts and negative societal impacts of the work performed?

    Answer: [Yes]

    Justification: The broader impacts are discussed with the limitations in our Supplemental Material.

    Guidelines:

    - The answer NA means that there is no societal impact of the work performed.
    - If the authors answer NA or No, they should explain why their work has no societal impact or why the paper does not address societal impact.
    - Examples of negative societal impacts include potential malicious or unintended uses (e.g., disinformation, generating fake profiles, surveillance), fairness considerations (e.g., deployment of technologies that could make decisions that unfairly impact specific groups), privacy considerations, and security considerations.
    - The conference expects that many papers will be foundational research and not tied to particular applications, let alone deployments. However, if there is a direct path to any negative applications, the authors should point it out. For example, it is legitimate

to point out that an improvement in the quality of generative models could be used to generate deepfakes for disinformation. On the other hand, it is not needed to point out that a generic algorithm for optimizing neural networks could enable people to train models that generate Deepfakes faster.

- The authors should consider possible harms that could arise when the technology is being used as intended and functioning correctly, harms that could arise when the technology is being used as intended but gives incorrect results, and harms following from (intentional or unintentional) misuse of the technology.
- If there are negative societal impacts, the authors could also discuss possible mitigation strategies (e.g., gated release of models, providing defenses in addition to attacks, mechanisms for monitoring misuse, mechanisms to monitor how a system learns from feedback over time, improving the efficiency and accessibility of ML).

11. **Safeguards**

Question: Does the paper describe safeguards that have been put in place for responsible release of data or models that have a high risk for misuse (e.g., pretrained language models, image generators, or scraped datasets)?

Answer: [NA]

Justification: All datasets and models used in this paper are publicly available.

Guidelines:

- The answer NA means that the paper poses no such risks.
- Released models that have a high risk for misuse or dual-use should be released with necessary safeguards to allow for controlled use of the model, for example by requiring that users adhere to usage guidelines or restrictions to access the model or implementing safety filters.
- Datasets that have been scraped from the Internet could pose safety risks. The authors should describe how they avoided releasing unsafe images.
- We recognize that providing effective safeguards is challenging, and many papers do not require this, but we encourage authors to take this into account and make a best faith effort.

12. **Licenses for existing assets**

Question: Are the creators or original owners of assets (e.g., code, data, models), used in the paper, properly credited and are the license and terms of use explicitly mentioned and properly respected?

Answer: [Yes]

Justification: Proper citations are provided throughout the document and the licenses will be included with the code when it is released.

Guidelines:

- The answer NA means that the paper does not use existing assets.
- The authors should cite the original paper that produced the code package or dataset.
- The authors should state which version of the asset is used and, if possible, include a URL.
- The name of the license (e.g., CC-BY 4.0) should be included for each asset.
- For scraped data from a particular source (e.g., website), the copyright and terms of service of that source should be provided.
- If assets are released, the license, copyright information, and terms of use in the package should be provided. For popular datasets, `paperswithcode.com/datasets` has curated licenses for some datasets. Their licensing guide can help determine the license of a dataset.
- For existing datasets that are re-packaged, both the original license and the license of the derived asset (if it has changed) should be provided.
- If this information is not available online, the authors are encouraged to reach out to the asset's creators.

13. **New assets**

Question: Are new assets introduced in the paper well documented and is the documentation provided alongside the assets?

Answer: [Yes]

Justification: The document will accompany the code upon its release.

Guidelines:

- The answer NA means that the paper does not release new assets.
- Researchers should communicate the details of the dataset/code/model as part of their submissions via structured templates. This includes details about training, license, limitations, etc.
- The paper should discuss whether and how consent was obtained from people whose asset is used.
- At submission time, remember to anonymize your assets (if applicable). You can either create an anonymized URL or include an anonymized zip file.

14. **Crowdsourcing and research with human subjects**

    Question: For crowdsourcing experiments and research with human subjects, does the paper include the full text of instructions given to participants and screenshots, if applicable, as well as details about compensation (if any)?

    Answer: [NA]

    Justification: The paper does not research with human subjects.

    Guidelines:

    - The answer NA means that the paper does not involve crowdsourcing nor research with human subjects.
    - Including this information in the supplemental material is fine, but if the main contribution of the paper involves human subjects, then as much detail as possible should be included in the main paper.
    - According to the NeurIPS Code of Ethics, workers involved in data collection, curation, or other labor should be paid at least the minimum wage in the country of the data collector.

15. **Institutional review board (IRB) approvals or equivalent for research with human subjects**

    Question: Does the paper describe potential risks incurred by study participants, whether such risks were disclosed to the subjects, and whether Institutional Review Board (IRB) approvals (or an equivalent approval/review based on the requirements of your country or institution) were obtained?

    Answer: [NA]

    Justification: This work does not involve crowdsourcing nor research with human subjects.

    Guidelines:

    - The answer NA means that the paper does not involve crowdsourcing nor research with human subjects.
    - Depending on the country in which research is conducted, IRB approval (or equivalent) may be required for any human subjects research. If you obtained IRB approval, you should clearly state this in the paper.
    - We recognize that the procedures for this may vary significantly between institutions and locations, and we expect authors to adhere to the NeurIPS Code of Ethics and the guidelines for their institution.
    - For initial submissions, do not include any information that would break anonymity (if applicable), such as the institution conducting the review.

16. **Declaration of LLM usage**

    Question: Does the paper describe the usage of LLMs if it is an important, original, or non-standard component of the core methods in this research? Note that if the LLM is used only for writing, editing, or formatting purposes and does not impact the core methodology, scientific rigorousness, or originality of the research, declaration is not required.

Answer: [Yes]

Justification: We have fully disclosed the details of the use of the adopted LLMs in our supplementary material.

Guidelines:

- The answer NA means that the core method development in this research does not involve LLMs as any important, original, or non-standard components.
- Please refer to our LLM policy (https://neurips.cc/Conferences/2025/LLM) for what should or should not be described.