Voxel-informed Language Grounding

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Abstract

Even when applied to 2D images, natural language describes a fundamentally 3D world. We present the Voxel-informed Language Grounder (VLG), a language grounding model that leverages 3D geometric information in the form of voxel maps derived from the visual input using a volumetric reconstruction model. We show that VLG significantly improves grounding accuracy on SNARE (Thomason et al., 2021), an object reference game task. At the time of writing, VLG holds the top place (anonymized) on the SNARE leaderboard, achieving SOTA results with a 1.7% overall improvement on all descriptions.

1 Introduction

Embodied robotic agents hold great potential for providing assistive technologies in home environments (Pineau et al., 2003), and natural language provides an intuitive interface for users to interact with such systems (Andreas et al., 2020). For these systems to be effective, they must be able to reliably ground language in perception (Bisk et al., 2020; Bender and Koller, 2020).

Despite typically being paired with 2D images, natural language that is grounded in vision describes a fundamentally 3D world. For example, consider the grounding task in Figure 1, where the agent must select a target chair against a distractor given the description “the swivel chair with 6 wheels.” Although the agent is provided with multiple images revealing all of the wheels on each chair, it must be able to properly aggregate information across images to successfully differentiate them, something that requires reasoning about their 3D geometry at some level.

In this work we show how language grounding performance may be improved by leveraging 3D prior knowledge. Our model, Voxel-informed Language Grounder (VLG), extracts 3D voxel maps using a pre-trained volumetric reconstruction model, which it fuses with multimodal features from a large-scale vision and language model in order to reason jointly over the visual and 3D geometric properties of objects.

We focus our investigation within the context of SNARE (Thomason et al., 2021), an object reference game where an agent must ground natural language describing common household objects by their geometric and visual properties, showing that grounding accuracy significantly improves by incorporating information from predicted 3D volumes of objects. At the time of writing, VLG achieves SOTA performance on SNARE, attaining an absolute improvement of 1.7% over the next closest baseline.

2 Related Work

Prior work has studied deriving structured representations from images to scaffold language grounding. However, a majority of systems use representations such as 2D regions of interest (Anderson et al., 2018; Wang et al., 2020) or symbolic graph-based representations (Hudson and Manning, 2019; Kulkarni et al., 2013), which do not encode 3D geometry.
properties of objects.

Most prior work tying language to 3D representations has largely focused on generating 3D structures conditioned on language, either at the scene (Chang et al., 2014, 2015a), pose (Ahuja and Morency, 2019; Lin et al., 2018), or object (Chen et al., 2018) level. In contrast, in this work we focus on augmenting language grounding using structured 3D representations derived from 2D images. For the task of visual language navigation, prior work has shown how a persistent 3D semantic map may be used as an intermediate representation to aid in selecting navigational waypoints (Chaplot et al., 2020; Blukis et al., 2021). The semantic maps, however, represent entire scenes with voxels representing object categories, rather than their geometric properties. In this work, we show how a more granular occupancy map representing objects’ geometry can improve language grounding.

Closest to our work is that of Prabhudesai et al. (2020), which presents a method for mapping language to 3D features within scenes from the CLEVR (Johnson et al., 2017) dataset. Their system generates 3D feature maps inferred from images and then grounds language directly to 3D bounding boxes or coordinates. Their system assumes, however, that dependency trees are provided for the natural language, and it is trained with supervised alignments between tree constituents and the 3D representations.

3 Voxel-informed Language Grounder

We consider a task where an agent must correctly predict a target object $v^t$ against a distractor $v^c$ given a natural language description $w^d = \{w_1, \ldots, w_m\}$ of the target. For each object, the agent is provided with $n$ 2D views $v = \{x_1, \ldots, x_n\}$, $x_i \in \mathbb{R}^{3 \times W \times H}$.

An agent for this task is represented by a scoring function $s(v, w) \in [0, 1]$, computing the compatibility between the target description and the 2D views of an object. We first use unimodal encoders to encode the language description into $e_w = h(w)$ and the object view images into a single aggregate visual embedding $e_v = g(v)$ before fusing them with a visiolinguistic module $e_{vw} = f_{vw}([e_v; e_w])$. Prior approaches to this problem directly input this fused representation to a scoring module to produce a score $s(e_{vw})$. They do not explicitly reason about the 3D properties of the observed objects, requiring the models to learn them implicitly.

In contrast, our Voxel-informed Language Grounder augments the scoring function $s$ with explicit 3D volumetric information $e_o = o(v)$ extracted from a pre-trained multiview reconstruction model $o(v)$. The volumetric information (in the form of a voxel occupancy map in $\mathbb{R}^{W \times H \times D}$) is first fused into a joint representation with the language using a multimodal voxel-language module $e_{ow} = f_{ow}([e_o; e_w])$. The scoring function then produces a score based on all three modalities $s([e_{vw}; e_{ow}])$.
3.1 Model Architecture

**Visiolinguistic Module.** The architecture of our visiolinguistic module $f_{vu}$ (on left panel, Figure 2) largely mirrors the architecture of MATCH from (Thomason et al., 2021). A pre-trained CLIP-ViT (Radford et al., 2021) model is used to encode the language description and view images into vectors in $\mathbb{R}^{512}$. The image embeddings are max-pooled and concatenated to the description embedding before being passed into an MLP which generates a fused representation.

**Voxel-Language Module.** We use representations extracted from a ShapeNet (Chang et al., 2015b; Wu et al., 2015) pre-trained LegoFormerM (Yagubbayli et al., 2021), a multi-view 3D volumetric reconstruction model, as input to our voxel-language module $f_{ov}$. LegoFormer is a transformer (Vaswani et al., 2017) based model whose decoder generates volumetric maps factorized into 12 parts. Each object factor is represented by a set of three vectors $x, y, z \in \mathbb{R}^{32}$, which we concatenate to use as input tokens for our voxel-language module. A triple cross-product over $x, y, z$ may be used to recover a 3D volume $V \in \mathbb{R}^{32 \times 32 \times 32}$ for each factor. The full volume for the object is generated by aggregating the factor volumes through a sum operation. For more details on LegoFormer, we refer the reader to (Yagubbayli et al., 2021).

We use a cross-modal transformer (Vaswani et al., 2017) encoder to fuse the language and object factors (Figure 2, right). The cross-modal transformer takes as input language tokens, in the form of CLIP word embeddings, and the 12 object factors output by the LegoFormer decoder, which contain the inferred geometric occupancy information of the object. We use a CLS token as an aggregate representation of the language and object factors.

The final scoring layer of our model is represented by an MLP which takes as input the concatenation of the visiolinguistic model output and the cross-modal transformer’s CLS token.

4 Language Grounding Evaluation

We test our method on the SNARE benchmark (Thomason et al., 2021). SNARE is a language grounding dataset which augments ACRONYM (Eppner et al., 2021), a grasping dataset built off of ShapeNetSem (Savva et al., 2015; Chang et al., 2015a), with natural language annotations of objects.

SNARE presents an object reference game where an agent must correctly guess a target object against a distractor. In each instance of the game, the agent is provided with a language description of the target as well as multiple 2D views of each object. SNARE differentiates between visual and blind object descriptions. For visual descriptions, AMT workers were primed to describe objects by name, shape, and color (e.g. “classic armchair with white seat”). In contrast, for blind descriptions workers were primed to describe objects by shape and parts (e.g. “oval back and vertical legs”) in order to get descriptions biased towards objects’ geometric properties. The train/validation/test sets were generated by splitting over (207 / 7 / 48) ShapeNetSem object categories, respectively containing (6,153 / 371 / 1,357) unique object instances and (39,104 / 2,304 / 8,751) object pairings with referring expressions. Renderings are provided for each object.

| Model     | Visual | Blind | All  | Visual | Blind | All  |
|-----------|--------|-------|------|--------|-------|------|
| ViLBERT   | 89.5   | 76.6  | 83.1 | 80.2   | 73    | 76.6 |
| MATCH     | 89.2 (0.9) | 75.2 (0.7) | 82.2 (0.4) | 83.9 (0.5) | 68.7 (0.9) | 76.5 (0.5) |
| MATCH*    | 90.6 (0.004) | 75.7 (0.01) | 83.2 (0.006) | -     | -     | -    |
| LAGOR     | 89.8 (0.4) | 75.3 (0.7) | 82.6 (0.4) | 84.3 (0.4) | 69.4 (0.5) | 77.0 (0.5) |
| LAGOR*    | 89.6 (0.003) | 74.9 (0.003) | 82.3 (0.0) | -     | -     | -    |
| VLG (Ours)| **91.6 (0.008)** | **78.5 (0.002)** | **85.2 (0.004)** | **85.8** | 71.3 | **78.7** |

Table 1: SNARE Benchmark Performance. Object reference game accuracy on the SNARE task across validation and test sets. Performance on models with an asterisk are our replications of the baselines in (Thomason et al., 2021). MATCH*, LAGOR*, and VLG performances are averaged over 3 seeds. Standard deviations are shown in parentheses. Our VLG model achieves the best overall performance. Due to leaderboard submission restrictions, we were not able to get test set results for the MATCH* and LAGOR* replications. † denotes statistical significance in improvement over the next best model (with $p < 0.05$).

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2https://github.com/faridyagubbayli/LegoFormer
Table 2: Ablation Study. SNARE reference game accuracy across ablations of our model on the validation set. Performance is averaged over 3 seeds for each condition, with standard deviations in parentheticals.

| Model    | Visual     | Blind      | All        |
|----------|------------|------------|------------|
| VGG16    | 91.6 (0.004) | 75.9 (0.005) | 83.3 (0.006) |
| MLP      | 91.2 (0.007) | 77.7 (0.007) | 84.6 (0.007) |
| no-CLIP  | 67.7 (0.006) | 69.0 (0.007) | 68.8 (0.002) |
| VLG      | 91.6 (0.008) | 78.5 (0.002) | 85.2 (0.004) |

We present a variety of ablations on the validation set. The performance of the SNARE baselines was provided with SNARE. At the time of writing, these were the only available models for the task. All SNARE baselines except ViLBERT use a CLIP-ViT (Radford et al., 2021) backbone for encoding both images and language descriptions. We refer the reader to Appendix A.1 for details.

5 Results

We present average performance for trained models over 3 seeds with standard deviations on the validation set. We also present test set performance for VLG and the performance of the SNARE baselines reported by Thomason et al. (2021) (See Appendix A.2 for details on training procedures).

5.1 Comparison to SOTA

In Table 1 we can observe reference game performance for all models. VLG achieves SOTA performance with an absolute improvement on the test set of 1.7% over LAGOR, the next best leaderboard model. Although there is a general improvement of 1.5% in visual reference grounding, there is an improvement of 1.9% in blind reference grounding. This suggests that the transformer is better able at disambiguating between examples referring to geometric properties of the referred objects. Improvements on the Blind and All conditions of the validation set are statistically significant (with p < 0.05) under a Welch’s two-tailed t-test.

5.2 Ablation Study

We present a variety of ablations on the validation set to investigate the contributions of each piece of our model. All results can be observed in Table 2. VGG16 Embeddings. LegoFormer uses an ImageNet (Deng et al., 2009) pre-trained VGG16 (Simonyan and Zisserman, 2014) as a backbone for extracting visual representations, which is a different dataset and pre-training task than what the CLIP-ViT image encoder is trained on. This presents a confounding factor which we ablate by performing an experiment where we feed our model’s scoring function VGG16 features directly instead of LegoFormer object factors (VGG16 in Table 2).

Architecture. We ablate the contribution of our cross-modal transformer branch by comparing it against an MLP mirroring the structure of the SNARE MATCH baseline. This model (MLP in Table 2) max-pools the LegoFormer object factors and concatenates the result to the CLIP visual and language features before passing them to an MLP scoring function. The MLP model overall outperforms the SNARE baselines from Table 1, corroborating the usefulness of the 3D information for grounding, but does not result in as large an improvement as the cross-modal transformer. This suggests that the transformer is better able at integrating information from the multi-view input.

CLIP Visual Embeddings. Finally, we evaluate the contribution of the visiolinguistic branch of the model by removing it and only using the cross-modal transformer over language and object factors. As may be observed, there is a large drop in performance, particularly for visual references. These results suggest that maintaining visual information such as color and texture is critical for good performance on this task, since the LegoFormer outputs contain only volumetric occupancy information.

6 Discussion

We have presented the Voxel-informed Language Grounder, a model which leverages explicit 3D information from predicted volumetric voxel maps to improve language grounding performance. VLG achieves SOTA results on SNARE, and ablations corroborate the effectiveness of using this 3D information for grounding. We hope this paper may encourage further work on integrating structured 3D representations into language grounding tasks.
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MATCH uses a learned MLP to produce a score over CLIP-ViT language and pooled image embeddings.

ViLBERT fine-tunes a 12-in1 (Lu et al., 2020) pre-trained ViLBERT (Lu et al., 2019). This baseline is additionally provided with ground-truth image bounding boxes during training.

LAGOR. LAGOR’s (Language Grounding through Object Rotation) scoring function mirrors the architecture of the MATCH module. During training, LAGOR is augmented with an auxiliary view-prediction loss, which tasks the agent with predicting the canonical view angle for each image given its embedding. LAGOR uses a separate MLP to produce view-predictions.

A.2 Training Procedure
We train each model for 75 epochs, reporting performance of the best performing checkpoint on the validation set. For the SNARE MATCH∗ and LAGOR∗ baselines we use the hyperparameters reported by Thomason et al. (2021). For all variants of our VLG model we use the AdamW (Loshchilov and Hutter, 2017) optimizer with a learning rate of 1e-3, linear learning rate warmup of 10K steps, and a smoothed binary cross-entropy loss (Achlioptas et al., 2019). We use a computing cluster with RTX 2080 GPUs to run our experiments. All code to replicate our results will be made publicly available.

A Appendix
A.1 SNARE Baselines
Here we briefly describe the baselines provided by SNARE. For more details, we refer the reader to (Thomason et al., 2021).