3D Visual Grounding with Transformers

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Abstract

3D visual grounding lies at the intercept of 3D object detection and natural language understanding. This work focuses on developing a transformer architecture for bounding box prediction around a target object that is described by a natural language description. Transformers are the natural choice since they are permutation invariant and thus able to operate on 3D point clouds scenes. Additionally they have become the default choice for natural language processing. Our method achieves around 2.5% improvement over the ScanRefer architecture by replacing the object detection with 3DETR-m and adding to the matching module a vanilla transformer encoder.

1. Introduction

3D visual grounding is the task of localizing a target object in a 3D scene given a natural language description. Performing accurately this task will be beneficial for many real-world applications such as AR/VR, autonomous robots, etc. 3D scenes can be represented by point clouds which encode both geometrical and other point features. This makes the 3D scene understanding challenge radically different from 2D where the data is ordered on a grid and higher-level features can be learned by convolutions. One way to address this is to use transformers since they can operate on variable-sized inputs and encode relational aspects in scenes that enrich the visual grounding task. In this work, we focus on implementing a transformer-based architecture for 3D visual grounding. The model takes as input a point cloud and a natural language description of an object and outputs a bounding box around the described object. The architecture of our model consists of three main parts:

1. Language encoder module: encodes the textual description into a language feature vector
2. Object detection module: generates object proposals alongside their feature vectors
3. Multimodal fusion module: combines the textual and visual representation to detect the target object

Our contributions are the following:

1. Extensive testing of the transformers architecture for the different parts of the architecture.
2. Improvement of 2.5% IoU 0.5 accuracy over the ScanRefer baseline. Proofing thereby the usefulness of a transformer-based architecture.

2. Related work

2.1. 3D object detection

Point cloud based 3D object detection is a well-studied field. PointNet [6] and PointNet++ [7] have been used as the backbone for several 3D object detection and 3D object segmentation. VoteNet [1] is a 3D object detection that uses Hough Voting on sparse point cloud input. Misra et al. [5] introduced 3DETR, an end-to-end 3D object detection transformer-based model that achieves competitive results on the ScanNetV2 [3] and SUN RGB-D-v1 [8] datasets. Our object detection model is based on the 3DETR model.

2.2. 3D visual grounding

Chen et al. introduced the ScanRefer dataset [2] and proposed a 3D grounding framework with the identical name. As a first step, object proposals are generated as well as features for the description and the proposed objects. Afterwards, the object and textual features are fused to predict the target object. Zhao et al. introduced 3DVG [10], a model that follows the same paradigm but relies partly on a transformer architecture to better utilize the contextual clues.

3. Method

3.1. Network architecture

Our architecture is based on the ScanRefer paper. We experiment with the replacement of each sub module (object detection, language encoding, multimodal fusion) with an attention-based model and also the combination of these.

For the language encoding module, we tested the well-known Bert [4] architecture to get richer language features than the GRU module from ScanRefer that is based on GloVE embeddings. Notably, the Bert model was not employed as a final language encoder, since we found that it hurts the performance while increasing the training time. A detailed ablation study of the language encoder can be found in section 4. In the object detection part we rely on the transformer-based 3DETR [5] architecture instead of VoteNet [1]. Similar to VoteNet 3DETR uses a PointNet++ backbone to get the number of points to a manageable level. This is especially important since 3DETR is an attention-based architecture with a quadratic runtime in the number of points. For details on the 3DETR architecture the reader may refer to Misra et. al. [5]. In the fusion and localization module, we utilize a vanilla transformer encoder architecture as it was proposed by Vaswani et. al. [9]. It is applied after the concatenation of the features to better represent dependencies between the features using the self-attention within the encoder. This is then followed by an MLP from ScanRefer. We found that the best results where achieved with 5 encoder layers with 8 self-attention heads each. The final architecture can be observed in figure 1.

3.2. Loss Function

We adjusted the loss function from ScanRefer to accommodate the 3DETR object detection part. In addition, we increased the loss weight of the localization loss in order to stronger emphasize the localization task. For more details on the object detection loss we refer to the Misra et. al. [5] and for the language classification loss as well as the localization loss to Chen et al. [2]. The final loss of our method is then built as follow:

$$\mathcal{L}_{final} = 1 \cdot \mathcal{L}_{obj} + 0.1 \cdot \mathcal{L}_{cls} + 1 \cdot \mathcal{L}_{loc}$$

3.3. Training

The architecture is implemented on top of ScanRefer with PyTorch. The transformer-based submodules require a lower learning rate than the language module. The 3DETR-m and the multimodel fusion module were trained with 2e-4 while the language encoding part was trained with 1e-3. For data augmentation we refer to Zhao et al. for a technique called Word Drop [10].

Chunking We implemented a chunking mechanism for the ScanRefer architecture following Zhao et. al. [10] to reduce the training time for the larger models to a more manageable level. Chunking exploits the fact that in the ScanRefer dataset there are multiple objects in one 3D scene. So the object detection part in theory only has to run once per scene. In practice the chunk size determines how many objects are simultaneously predicted. With a chunk size of 8 the training time for 50 epochs could be reduced by more than 500% from 25 hours to 4 hours and 17 minutes on one current GPU (NVIDIA Tesla T4), while losing 1-2% IoU 0.5 accuracy. The detailed results of the experiment can be observed in table 1.

Model	Acc@0.25	Acc@0.5	Duration 50 epochs
ScanRefer	**36.65**	**23.71**	25h
ScanRefer chunking 8	35.66	22.01	4h 17min
ScanRefer chunking 16	33.08	18.08	**3h 11min**

Table 1. ScanRefer training duration and accuracy with different chunk sizes.

Model	AP@0.25	AP@0.5
VoteNet	52.29	26.27
3DETR-m	**56.36**	**31.67**

Table 2. Pretraining 3D Object Detection on 3D scans in ScanRefer dataset with xyz + rgb as input.

Pre-training We believe that the loss in accuracy while doing chunking stems from the fact that the object detection part is trained less often than regular training. We mitigate this loss by using a pre-trained object detection model. The pre-training of the object detection part was performed by training solely on the 3D scans in the ScanRefer dataset using the corresponding settings from Misra et al. [5] for 3DETR-m and Qi et al. [1] for VoteNet. The comparison hereby showed that 3DETR-m clearly outperforms VoteNet as can be seen in table 2.

4. Experiments

All our results are reported on the validation set of the ScanRefer dataset following Chen et. al [2].

Bert The Bert architecture as a language encoder was extensively tested to check whether Bert can produce richer language features than the baseline GRU. We performed tests on the optimal number of layers for Bert, which can be observed in the table 3. Bert did not improve the quality of the overall predictions while increasing the training time significantly. Our hypothesis is that Bert focuses too much on the semantic meaning rather than on the relationship between objects. We tested the performance if there is a single object of its class in the scene compared to if there are multiple objects of the same class in the scene. The results from table 4 seem to confirm the hypothesis since Bert outperformed GRU in the unique object category while failing multiple object cases.

3DETR-m The following section provides an overview over the best results when using 3DETR-m as the object detection module. The comparison between 3DETR-m and VoteNet for different input features shows that 3DETR-m helps to provide slightly better bounding boxes as it's re-

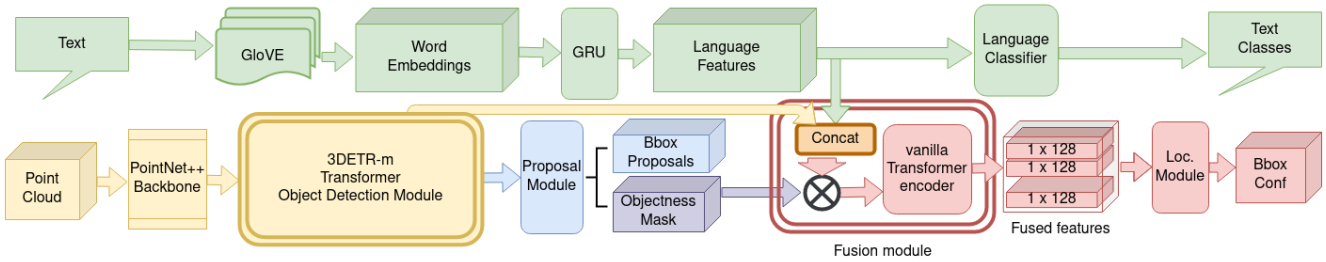

Figure 1. Our final architecture: The PointNet++ [7] aggregates the pointcloud to higher level features that are then passed to the 3DETR-m [5] object detection module. The object detection module passes high level features to the proposal module, which essentially is a set of MLP's that output bounding box proposals and an objectness mask. The descriptions are first passed through a pretrained GloVE and are then processed by a GRU to obtain the language features like in ScanRefer [2]. The language features and the object features are then concatenated, masked by the objectness mask and then run through a vanilla transformer encoder [9] to get the fused features. As a last step a MLP is applied to the fused features in the localization module to output confidence scores.

Model	Acc@0.25	Acc@0.5	Duration 50 epochs
ScanRefer (VoteNet + **GRU** + concat)	**35.66**	**22.01**	**4h 17min**
VoteNet + **Bert layer 3** + concat	34.45	20.93	8h 50min
VoteNet + **Bert layer 5** + concat	34.75	21.06	10h 50min
VoteNet + **Bert layer 12** + concat	34.22	21.10	18h

Table 3. Comparison of accuracy and training time for different numbers of Bert layers. All results are reported with chunk size 8 and learning rate 1e-3. Only the Bert language encoder was trained with a learning rate of 5e-5 in every case.

Model	unique		multiple		overall	
	Acc@0.25	Acc@0.5	Acc@0.25	Acc@0.5	Acc@0.25	Acc@0.5
pretrained VoteNet + **GRU** + concat	62.71	41.84	**30.22**	**19.57**	**36.53**	**23.90**
pretrained VoteNet + **BERT layer 12** + concat	**63.79**	**42.16**	28.57	17.80	35.40	22.53

Table 4. Comparison of accuracy for one unique object of one category in the scene with multiple objects of one category.

sults show some improvements on the validation set as can be seen in table 5. The improvement of 3DETR-m over VoteNet is smaller than predicted especially considering the promising results from table 2.

Matching Module Finally, via intensive experiments found that adding a vanilla transformer encoder after the concatenation and before the localization module, helped to get better final confidence scores than without. The intuition here is that the self-attention within the encoder helps to get better fused features due to the stronger emphasize on the dependency relations between the features.

Final Model Table 7 depicts that our architecture improves the baseline ScanRefer by almost 2.5% on the IoU 0.5 accuracy indicating that a transformer architecture helps the 3D visual grounding task.

Model	Acc@0.25	Acc@0.5
Input: xyz		
pre-trained **VoteNet** + GRU + concat	**37.77**	24.69
pre-trained **3DETR-m** + GRU + concat	35.53	**25.25**
Input: xyz + rgb		
pre-trained **VoteNet** + GRU + concat	**37.11**	25.21
pre-trained **3DETR-m** + GRU + concat	35.00	**25.50**

Table 5. Ablation study with pre-trained 3DETR-m and VoteNet in comparison

Model	Acc@0.25	Acc@0.5
pre-trained 3DETR-m + GRU + **concat**	35.00	25.50
pre-trained 3DETR-m + GRU + **vTransformer 2 Layers**	36.59	26.23
pre-trained 3DETR-m + GRU + **vTransformers 4 Layers**	36.57	26.23
pre-trained 3DETR-m + GRU + **vTransformer 5 Layers**	37.08	**36.34**
pre-trained 3DETR-m + GRU + **vTransformer 6 Layers**	**37.11**	26.15

Table 6. Ablation study with vanilla transformer using xyz + rgb as input

5. Qualitative Analysis

Figure 2 shows our qualitative analysis for the ScanRefer baseline model, the optimized baseline namely ScanRefer with pre-trained VoteNet as well as our final model. The blue bounding boxes under the section "Ours" show that

Model	Acc@0.25	Acc@0.5
ScanRefer	37.05	23.93
pre-trained VoteNet + GRU + concat	**37.11**	25.21
pre-trained 3DETR-m + GRU + concat	35.00	25.50
Ours (pre-trained 3DETR-m + GRU + vTransformer)	37.08	**26.34**

Table 7. Model comparison on ScanRefer dataset with xyz + rgb as input

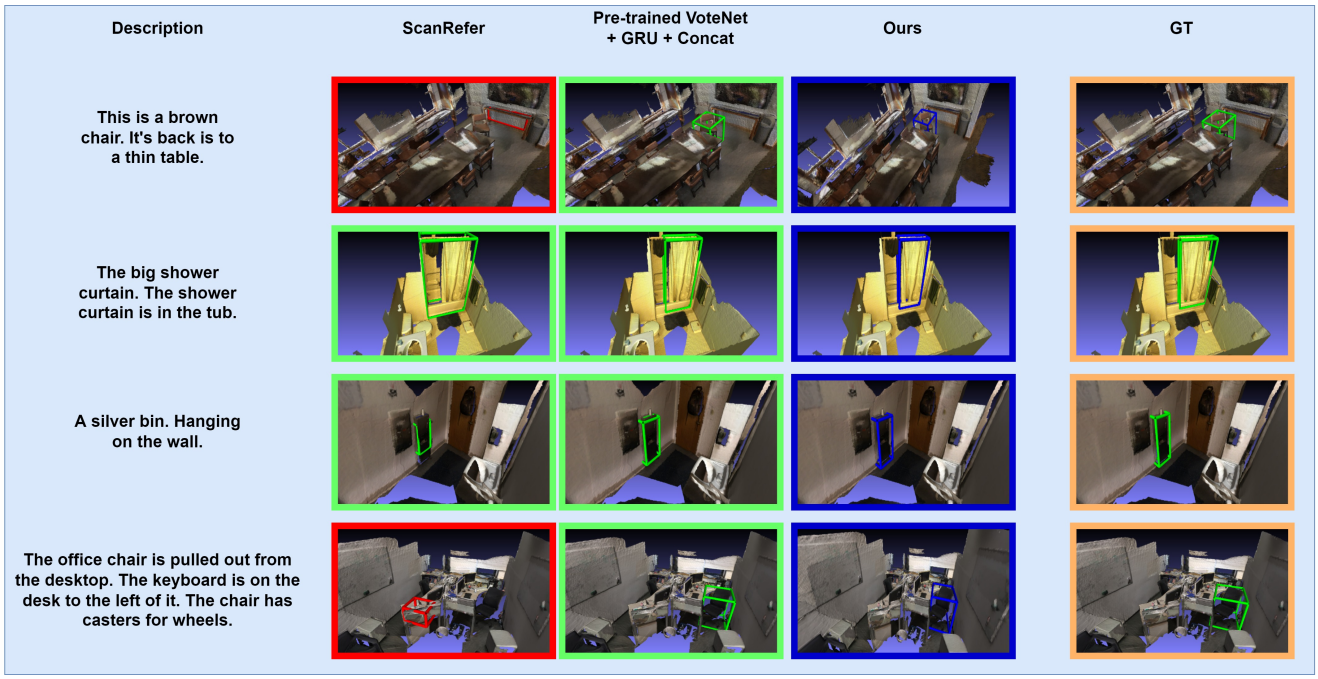

Figure 2. Qualitative Analysis for baseline model ScanRefer, pre-trained VoteNet with chunking and our final transformer architecture. The predicted bounding boxes are marked green if they predict the correct object, red if they predict a wrong object, and blue if it is the best prediction out of all three predictions.

our model not only managed to predict the correct objects, but also managed to produce the best bounding boxes in comparison to the other models in each scenario displayed.

6. Conclusion

In this project we showed that a transformer-based architecture for object detection as well as the matching module helps to achieve better results in 3D visual grounding task. We could also significantly decrease the duration of training with the help of chunking. The performance loss of chunking could be eliminated by employing pretrained object detection models. The replacement of VoteNet with 3DETR-m for the object detection part and the addition of a vanilla transformer encoder for the matching module improved the overall performance on the ScanRefer dataset compared to the original ScanRefer model by more than 2.5%.

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