Project Report: Scan2Cap

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Abstract

In this work, we investigate the task of generating a description for a target object in context to its environment in the 3D domain. To this end, we propose a pipeline which combines concepts from 3D object detection and visual attention-based captioning. The proposed pipeline first uses VoteNet to extract feature vectors of the scene. It then combines this information with the features of the object of interest, which are extracted by PointNet++, and feeds this data into an LSTM captioning mechanism, that generates a caption of the object in context of the scene.

1. Problem Statement & Motivation

Extracting a detailed and semantic correct understanding of the layout of a 3D scene is crucial for many tasks, e.g. in robotics for navigation and interaction with objects. This includes relating the 3D positions of the objects and their spatial extent, so that a semantically correct description of the objects' environment is generated. However, to the best of our knowledge, there has been no work so far to generate a description of an object representation in point clouds or 3D data.

Therefore, we are interested in implementing a pipeline to obtain a description for a given object in a 3D scan, using state-of-the-art point cloud feature extractors, object detectors, and a captioning mechanism to generate a semantic description for a given object in the 3D scene. This allows the object to be placed in a global semantic context within its environment.

2. Related Work

Our work will be based on the ScanRefer dataset [2]. This dataset consists of 1513 RGB-D scans of ScanNet [3] and contains approximately 5 unique object descriptions for each object in each scene. The work of [2] will also be used as guideline in this project.

The extraction of features on point clouds is presented by [10], who apply the feature extraction directly on the point cloud on a hierarchical level, allowing the extraction of local features in a global context. The task of object detection on point clouds is studied by [9].

Methods for image captioning using visual attention are described by [13], [6] and [1]. These methods have in common, that they generate a caption for the entire image. Since our goal includes using a bounding box for the object to be set in context to the scene, the work of [11] is also of interest for this project.

3. Architecture

Given a point cloud $p \in R^{N \times (d+C)}$ and an object in that scene, which is described by a target bounding box $b_{target} \in R^6$, our goal is to generate a meaningful caption for the object embedded in the context of the scene. To this end, we used three different pipelines, which are described in the following.

3.1. Baseline

To extract information from the point cloud, we use a PointNet++ [10] model. To give the network information about which object we are interested in, we add a new feature channel to each point that masks all points that lay within the bounding box of the object. To ensure that we receive meaningful features, we use weights pretrained for classification of the masked object. The idea behind this is that classification will not only use information from the masked objects, but also global features, for example from close-by objects.

To generate the caption, we use a classical LSTM with an appended fully-connected layer. The fully-connected layer acts as a word classifier and maps the hidden state h_t of the LSTM to our vocabulary. As input, the LSTM receives the feature vector extracted from the point cloud and the word embedding vector of the previously generated word. The word embedding is taken from a pre-computed GloVe [8] word embedding matrix. This structure of the iterative caption generation is similar to [13].

3.2. Better Feature Extraction with VoteNet

Because PointNet++ is pretrained to classify the object of interest there is no guarantee that the feature vector will give high-quality information about the global context, thus limiting the baseline approach. In the second architecture iteration, we therefore employ a VoteNet [9] network, which computes a fixed number of object proposals and according feature vectors for our point cloud. Those feature vectors nicely describe the context of our scan and help the network to understand the surroundings of the object we want to describe. Because the number of proposals may vary and the proposals are not in a fixed order, we average pool them to obtain a concise representation of the information. This pooled feature vector is finally concatenated with the feature vector from PointNet++ and the embedding vector of the previously predicted word to then be passed into the LSTM.

3.3. Better Captioning with Attention

Average pooling the feature vectors from VoteNet is not ideal as often only a small number of the object proposals is relevant for the final caption. Therefore, in the third model iteration we replace the average pooling step from before with an attention mechanism, as it is described in [13]. The attention mechanism receives the hidden state of the captioning LSTM from the previous iteration and the feature vectors of the object proposals. It then uses a series of fully-connected layers to predict relevancy scores for the different object proposals that are turned into probabilities using the softmax function. Instead of average pooling, we can now multiply all feature vectors with their respective probability and sum over all of them. This approach allows our model to select the most relevant object for each token in the caption and make word predictions that better match the the context of the scene.

Figure 1 summarizes the project architectures.

4. Experiments & Results

To have a quantitative comparison between the proposed architectures, we have constructed the same training pipeline for the three models. As mentioned input the models get the pointcloud of a scene, the ground truth bounding box of the target object and the tokenized description.

Similar to [13] all architectures make use of teacher forcing during training time. Instead of inserting the previous predicted word, the captioning LSTM gets the previous ground truth word as input together with the encoded feautre vectors of the scene. This allows to get a faster convergences as the drift between ground truth token and predicted word is minimized in training time. In evaluation time the networks takes the previous predicted word as input.

As metrics for the evaluation of performance we make us of BLEU [7], ROUGE-L [5], METEOR [4] and CIDEr [12]. All metrics sets the predicted In this work we focus on the BLEU score for determining the best models as in [13].

For our models including the VoteNet we filter out objects that have an objectness score below 0.75. We also consider just the 8 closest objects as these thresholds lead to better resuts representing the local scene context.

4.1. Quantitative Improvements

In this experiment we want to investigate the influence of our proposed architecture improvements. ALl models integrate the same pretrained masked PointNet++ feature extractor. Table X shows the quantitative results.

As first result we can observe that the baseline model achieves reasonable good results that are not far off from the improved architectures. Comparing the BLEU-4 Score against the results of the COCO Image Captioning Challenge 2015 ”Zitat”, our models outperform the best performing architecture. Of course the quesiton reamains, whether our task and the COCO Image Captioning tasks are comparable, as we argue that our vocaabulary and the gt sentence structure is a lot simpler.

Secondly, the results show that improving the feature extractor (improved architecture) and improving the captioning part (attention) lead to higher scores. The best results are achieved by the attention model except for the BLEU-4 score, where the improved architecture is slightly better.

4.2. Qualitative Analysis

In this experiment we want to analyze the quality of the predicted descriptions. To this end we compare two example ground truth and predicted description pairs depicted in picture X. The first pair shows the comparison between ground truth and the predictions given by our 3 architectures.The result shows that the three models predict a correct description that sets the object in context of its environment. There are slight difference in the context that the models use, especially for the attention model. This indicates that the attention meachnism is able to generate a description that is more unusal. The baseline and the improved architecture were able to predict a chair near a table, which is quite a common scenario. The second pair illustrating a long ground truth description and the prediction of the atttention model shows the correctness of the prediction even if is quite short.

For all predicted descriptions we can observe a simple two sentence structure. As an explanation for this we claim that the statistics of the ScanRefer Dataset influences this behaviour. Therefore we analzed the number of tokens per description and number of sentences in per description. Figures Z and Y support this claim showing the hsitograms of

number of tokens and sentence lengths for the our predictions and for the ScanRefer Dataset respectively.

4.3. Inference without GT

5. Coclusion

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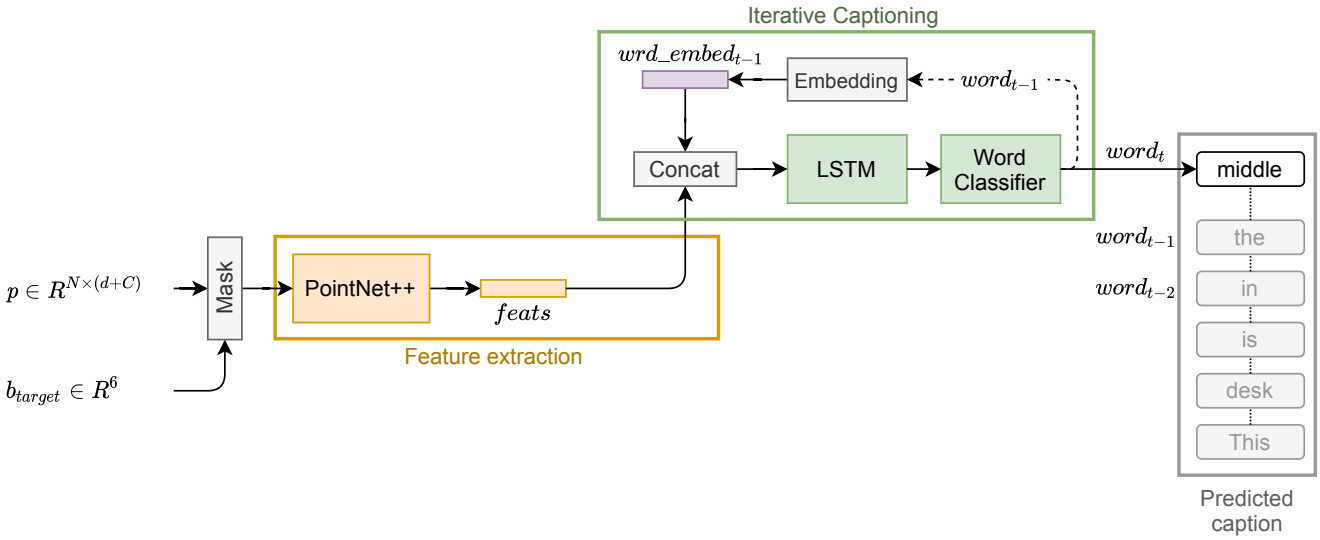
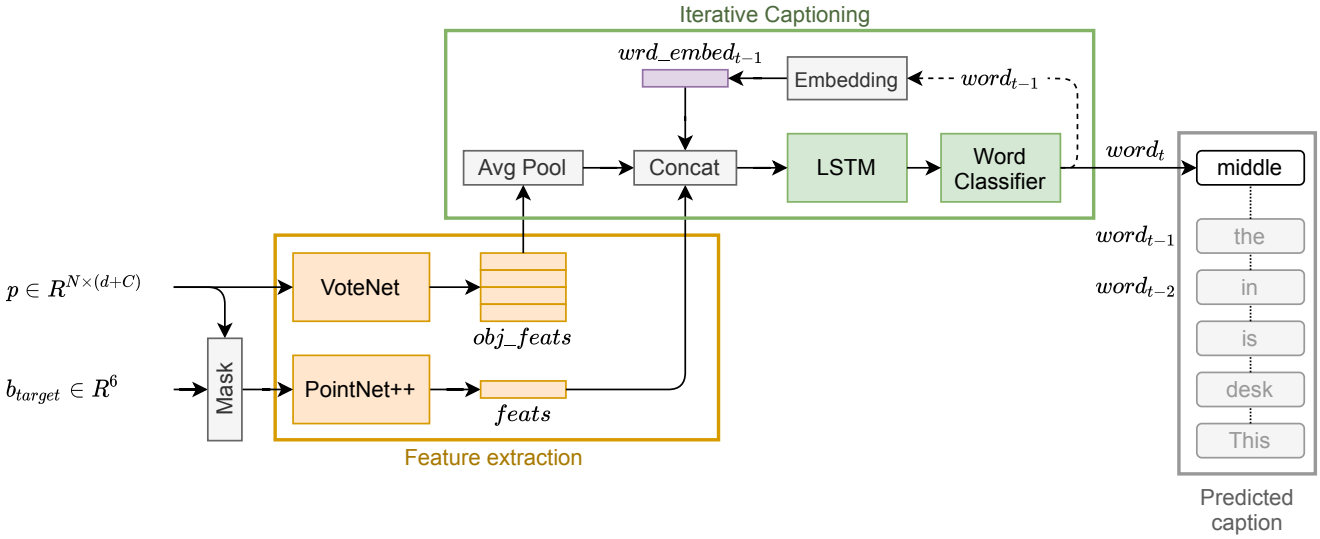
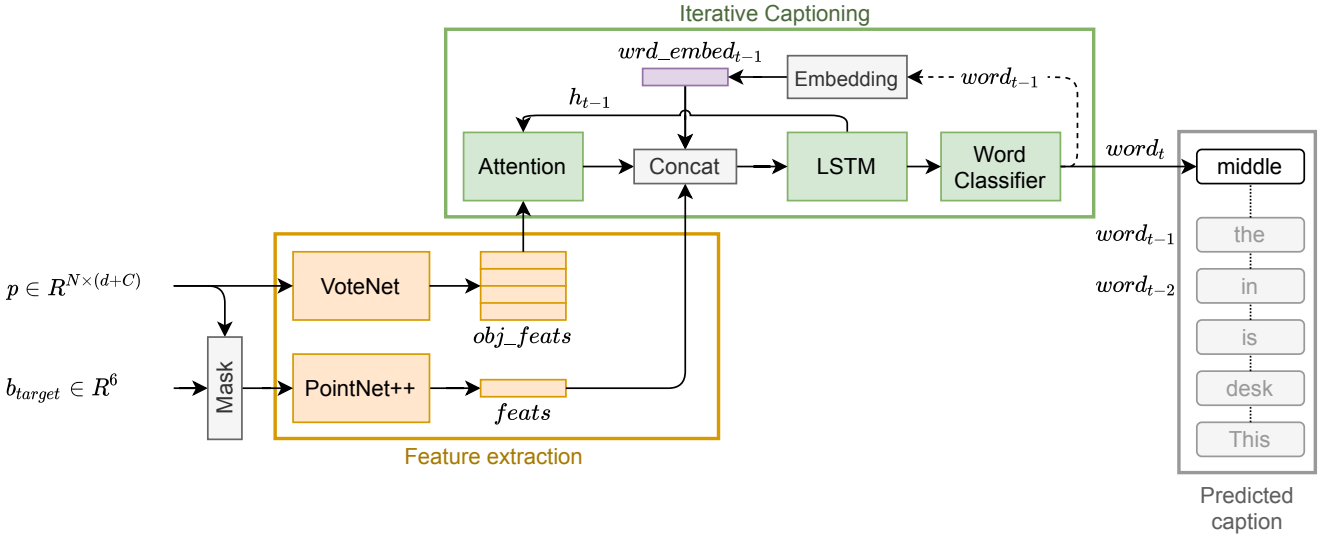


(a) Baseline model



(b) Better feature extraction with VoteNet



(c) Better captioning with attention

Figure 1: Model architectures for project