Unified Questioner Transformer for Descriptive Question Generation in Goal-Oriented Visual Dialogue

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Abstract

Building an interactive artificial intelligence that can ask questions about the real world is one of the biggest challenges for vision and language problems. In particular, goal-oriented visual dialogue, where the aim of the agent is to seek information by asking questions during a turn-taking dialogue, has been gaining scholarly attention recently. While several existing models based on the GuessWhat?! dataset [10] have been proposed, the Questioner typically asks simple category-based questions or absolute spatial questions. This might be problematic for complex scenes where the objects share attributes, or in cases where descriptive questions are required to distinguish objects. In this paper, we propose a novel Questioner architecture, called Unified Questioner Transformer (UniQer), for descriptive question generation with referring expressions. In addition, we build a goal-oriented visual dialogue task called CLEVR Ask. It synthesizes complex scenes that require the Questioner to generate descriptive questions. We train our model with two variants of CLEVR Ask datasets. The results of the quantitative and qualitative evaluations show that UniQer outperforms the baseline.

1. Introduction

Information seeking through interaction is one of the most vital abilities for artificial intelligence. This is particularly true in the human-agent interaction scenario [24, 17]. For example, task-oriented agents need to understand what the users are thinking, i.e., beliefs, preferences, and intentions, in order to correctly interpret their instructions [14, 39]. In most cases, such information is not provided prior to the interaction, so the agents have to elicit it by asking questions on the fly.

To build effective information-seeking agents, several studies in the vision and language community have tackled the goal-oriented visual dialogue task [10, 28]. This task consists of two agents, called a Questioner and an Oracle, and the goal is to train the Questioner to guess the Oracle’s reference object by asking yes-no questions during a turn-taking dialogue. The Oracle then needs to provide an answer given the question and the target object.

In goal-oriented visual dialogue, deciding which objects and how to address will depend on the complexity of the presented image. For example, in simple scenes, where each object has different attributes and thus is easy to distinguish, the Questioner only needs to ask category-based questions such as “Is it a car?”. In a more complex scene, on the other hand, the Questioner needs to ask descriptive questions with referring expressions [7, 31] to narrow down
the candidates, such as “Is it behind a tree?” or “Is it a red car?” In this paper, we particularly focus on building an agent that can facilitate such descriptive questions in goal-oriented visual dialogue.

Several models based on GuessWhat?! [10] have been published, most of which leveraged reinforcement learning aimed at maximizing the success reward by generating a word token as an action [28, 35, 37, 26, 27, 2, 22, 1]. However, the Questioners in these models typically generate only simple category-based questions, such as “Is it a person?” or “Is it a computer?”, or absolute spatial questions, such as “Is it in front?” or “Is it on the left side of the image?”, which is not effective when a large number of similar-looking candidates is presented in the same place.

In response to the above issues, we propose Unified Questioner Transformer (UniQer) and a task called CLEVR Ask for descriptive question generation in goal-oriented visual dialogue (Fig. 1). In UniQer, the question generator (QGen) and the Guesser are unified into a single transformer architecture. By utilizing such architecture, both the QGen and the Guesser can make use of the same object features, and the Guesser can consider object relations more effectively thanks to the self-attention structure. We also introduce an object-targeting module, inspired by the notion of which similar-looking objects are presented; therefore, the image?, which is not effective when a large number of similar-looking candidates is presented in the same place.

To summarize, our contributions are three-fold:

- We proposed a novel unified transformer architecture for the Questioner. To the best of our knowledge, this is the first study that introduces a unified transformer architecture to goal-oriented visual dialogue.

- To address the limitations of GuessWhat?! dataset, we constructed a novel goal-oriented visual dialogue task, namely CLEVR Ask, which requires the Questioner to ask descriptive questions.

- We evaluated UniQer with two variants of CLEVR Ask datasets and found that our model outperformed the baseline and was able to ask descriptive questions with referring expressions, given complex scenes where the objects were hard to distinguish.

2. Related Works

Visual Question Answering. Visual Question Answering (VQA) [3, 15, 13] lies at the intersection of computer vision and natural language processing (NLP). Compared with image captioning tasks [12], VQA requires a comprehensive understanding of the visual object elements and the relationships between them. [15] proposed CLEVR, a synthetic VQA dataset, aiming to remove the difficulties in image recognition and creates a balanced dataset that requires reasoning abilities without shortcuts. Besides, extending VQA to dialogues has been challenged in Visual Dialogue [9, 25].

Transformer Architecture. Transformer architecture [30] was recently introduced in NLP tasks showing the effectiveness of the self-attention structure in language modeling, followed by large-scale pre-trained models such as BERT [11] and its successive models [20, 32]. Several studies have imported transformer architecture to the aforementioned vision and language tasks, such as Image BERT [23], Meshed Memory Transformer [6], and UNITER [4].

Referring Expression Generation. Referring expressions are language constructions used to identify specific objects in a scene [31, 7]. These specific objects here are called the targets, and a set of objects that are to be isolated from the target set is called the distractor group [8]. Various datasets have been proposed recently including both synthetic [19] and natural image datasets [21, 33] to generate and comprehend referring expressions.

Goal-oriented Visual Dialogue. Our task is grounded on the goal-oriented visual dialogue framework. This test-bed was first implemented in GuessWhat?! [10], which is composed of 155K goal-oriented dialogues, collected via the Amazon Mechanical Turk, and includes 822K questions, with a unique vocabulary size of 5K. The images were borrowed from the MSCOCO dataset and consist of up to 67k images and 134K objects.

The GuessWhat?! task was originally designed for supervised learning, but it was extended to fit into the reinforcement learning framework [28]. Ongoing works promote various approaches to GuessWhat?! One is the rewarding in reinforcement learning, where [36] used two intermediate rewards, while another, proposed by [27], makes use of an informativeness reward based on regularized information gain. [37] improved the RL optimization by extending a policy gradient method using a temperature for each action based on action frequencies. Moreover, other studies focus on improving the model’s architecture. [2] introduced a Bayesian approach to quantify the uncertainty in the model. [22] proposed dialogue state tracking module to make use of the belief of the Guesser. [27] proposed single visually grounded dialogue encoder shared by both the Guesser and the QGen, trained with cooperative learning.

Limitations. Among such models proposed on GuessWhat?! there are two major limitations. (1) First is the...
separated learning approach that previous methods adopt. In most of the previous methods, a Questioner has two major components: the QGen which generates questions based on the image presented and the current dialogue history and the Guesser which guesses the target object of the Oracle. Ideally, the object’s features obtained during the training should be shared with both module, but these two components are often learning separately. Additionally, the Guesser in the previous studies only looks at a single object at a time to determine the probability of it being the target object and does not consider the relation between objects. This will be problematic for processing questions that refer to the other objects, i.e. referring expressions. (2) Another problem comes from the fact that the QGen was too heavily burdened. The QGen in the previous models needs to decide on which objects to refer to and how to refer to in the same architecture. Coupled with the difficulties of tuning generator with reinforcement learning, this will degrade the final performance of the task, such as losing the lexical diversity of the questions as reported in [26].

While GuessWhat?! has pioneered the frontier of the goal-oriented visual dialogue, it has several issues yet to be resolved in order to build a Questioner that can ask descriptive questions. The major issue of the GuessWhat?! dataset is the poor performance of the Oracle [10]. Since the Oracle is solving a 3-class classification problem—yes, no, and not applicable—, this accuracy causes substantial errors in the Questioner’s learning process. Another problem is that the Oracle generates answers to the questions without having been given the visual features; only the categorical information and spatial information of the objects are given. This means that the Oracle is incapable of understanding descriptive questions with referring expressions that include visual attributes.

3. CLEVR Ask Specifications

Notation. CLEVR Ask is defined by the tuple \((I, S, \mathcal{O}, o^*, \mathcal{D})\), where \(I\) is the image, \(S\) is the scene meta-data for the image, \(\mathcal{O}\) is the set of objects appearing in the scene, \(o^*\) is the goal reference object of the Oracle, and \(\mathcal{D}\) is the dialogue between the Oracle and the Questioner.

Formally, \(I \in \mathbb{R}^{H \times W}\) is the current observed image, with height \(H\) and width \(W\). Corresponding to the image, the scene meta-data \(S\) provides the information of the scene, including the collections of the objects attributes (shape, size, color, and material) and position on the ground-plane. These are represented by a scene graph [16] of CLEVR, which provides a complete view of the environment. The objects in the scene are represented by \(\mathcal{O} = \{o_i\}_{i=1}^N\), where \(o_i\) is the \(i\)-th object and \(N\) is the number of the objects within the scene. For each session, the goal object \(o^* \in \mathcal{O}\) is arbitrarily chosen. The dialogue, where the Questioner seeks to identify the goal object \(o^*\), consists of question-answer pairs \(\mathcal{D} = (q^t, a^t)_{t=1}^T\), \(T\) denotes the number of such pairs. Each question is composed of word tokens \(q^t = (w^t_0)_{0 \leq t \leq W}\), that were sampled from the vocabulary \(\mathcal{V}\). Finally, the answer to the question is restricted to yes, no or invalid question, that is, \(a^t \in \{<yes>, <no>, <invalid>\}\).

Oracle. The central role of the Oracle is to provide an answer to each question generated by the Questioner based on the current scene. Since its performance will directly affect the learning process of the Questioner, the Oracle needs to be perfect, as the name implies.

To satisfy this demand, we built a robust Oracle function that meets the following two requirements. First, the Oracle needs to understand the scene completely to answer questions. For this purpose, we take advantage of the fully structured environment of CLEVR. Since the CLEVR world is built on a structured ground-truth representation [16], the complete and exhaustive information about the image is available in the scene file. We introduced such information to the Oracle so that it can answer any kind of detailed expressions. Second, the Oracle is required to completely understand what the Questioner says. Here, we standardized the language used by the Questioner to a pseudo-language that can be directly interpreted by the Oracle. This language is an executable functional program; given the scene-file, it yields the objects that match the query in a deterministic manner, which enables the Oracle to deduce the answer to the question. These settings will liberate the Oracle from having to interpret the question based on the model obtained via learning, which is likely to produce some errors.

Dataset Generation. The CLEVR Ask dataset consists of images including scene files and questions that are bound to images. In the original CLEVR dataset, the object attributes are three object shapes, two absolute sizes, two materials, and eight colors. Notably, the numbers of entities in each attribute in the CLEVR dataset are not the same. This will likely cause undesirable shortcuts for the goal-oriented visual dialogue task; for example, only asking questions about attributes with fewer entities, (e.g., sizes and materials) can result in the candidate objects being bisected.

To circumvent this issue, we prepared two new balanced datasets, Ask3 and Ask4, which contain three and four entities for each attribute, respectively. Both Ask3 and Ask4 datasets consist of 70K training, 7.5K validation, and 7.5K test images. All images were generated by randomly sampling a scene graph and rendered by Blender [5]. We followed the original sampling procedure in CLEVR except that for each generation step we randomly chose either to copy the existing object or to create a new object by sampling attributes. This enables us to intentionally place an identical object in the scene.

As presented in [26], the questions that appear in goal-oriented visual dialogue can be roughly categorized into the following question types and its combinations thereof: en-
Figure 2. Network structure of UniQer. Given the cropped image features, geometrical features, [CLS] token, and past question and answer tokens, with the segment and sequence position embedding injected, embedding vectors are fed into OET. By comparing the encoded [CLS] token with the encoded objects and passing them to softmax, goal object probability $P_h$ is obtained. The top-k objects with high $P_h$ are encoded and input to the OTM module along with the image features and geometrical features, and each object is assigned a group ID. Finally, QDT takes [BOS] as an input, generates the next question by taking the sum of the encoded objects and the group vector as memory, and the Oracle answers to the question.

4. Unified Questioner Transformer

We propose Unified Questioner Transformer (UniQer) as a Questioner model for goal-oriented visual dialogue tasks. Conceptually, UniQer can be divided into the following three major components:

- Object Encoder Transformer (OET)
- Object Targeting Module (OTM)
- Question Decoder Transformer (QDT)

as shown in Fig. 2. The OET encodes objects and serves as a Guesser, which infers the goal object $o^*$. The OTM is trained to learn which object should be addressed in the next question based on the OET’s current inference. The QDT decodes object features and generates questions, by addressing the object to set apart from the other objects that have different group IDs from the OTM. When it is confident enough, the OTM decides to submit its answer to the oracle. Both the OET and QDT are trained jointly in a supervised manner, and thus they can benefit from each other. The OET is trained with reinforcement learning.

4.1. Embedding Preparation

The input of the UniQer is the cropped object images and dialogue history. The embedding layer prepares the feature vectors for both inputs by

$$x_c(i) = x_h(i) + x_{seg}(i) + x_{pos}(i),$$

where $i$ denotes the index of the object, $x_h(i)$ is either the object feature embedding $x_c(i)$ or the dialog token embedding $x_d(i)$, $x_{seg}(i)$ is a segment embedding, and $x_{pos}(i)$ is a sequence position embedding.

Object Feature Embedding. Each cropped image corresponding to the objects in the scenes is first processed to $o_c(i)$ using an arbitrary image feature extractor. As in [34], two types of 5D geometric feature for each object are introduced as well: a source geometric feature represented by
The OTM has two roles; it determines which objects should be addressed by QDT and it decides when to submit the answer, the OET’s prediction, to the Oracle.

The OTM determines which objects should be addressed in the question by assigning any of the following three types of property to each object: a target object property for the object to be addressed, a distracter object property for an object that will not be addressed but is distinguishable from the target objects, and a masked object property for objects that do not exist or will be ignored.

The OTM only pays attention to top-k high-scored candidate objects calculated from the object probability $P_o$, and ignores the others. More specifically, the input of the OTM is the set of top-k feature vectors $\{x_k(i)\}_{i \in K}$, where $K$ is the set of top-k object indices and $x_k(i) = [F_A(o_k(i)), F_B(o_k(i)), F_C(P_o(i))]$, where $F_A, F_B$, and $F_C$ are different linear layers. Given such an input, the OTM will decide how to assign these properties to each top-k objects by producing a targeting action $\hat{g}_k$ as

$$\hat{g}_k \sim \mathcal{F}_{RL}(\{x_k(i)\}_{i \in K}),$$

where $\hat{g}_k$ is an integer ranging from zero to $3^k - 1$, which corresponds to the number of combinations to respectively allot the three property groups to $k$ objects. $\mathcal{F}_{RL}$ is a parameterized function trained with RL defined as

$$\mathcal{F}_{RL} = \text{softmax}(\mathcal{F}_I(\mathcal{F}_{GRU}(\{x_k(i)\}_{i \in K}))),$$

where $\mathcal{F}_{GRU}$ is the two-layered bi-directional GRU to encode input vectors and $\mathcal{F}_I$ is the linear transformation function with the ReLU activation.

To make the OTM’s output compatible with the QDT’s input, the targeting action $\hat{g}_k$ is then reformatted with base-10 to base-3 conversion to a top-k group vector $g_k \in \mathbb{R}^{k \times 3}$, whose elements each represent the group ID – zero, one, or two – assigned to an object. Finally, a group vector $g \in \mathbb{R}^{N_{max} \times 3}$ is obtained by filling the masked property group ID to the index for the ignored objects on top-k.

We treat the cases $g_k = 0$ and $g_k = 3^k - 1$ as a submission action, which submits the current answer $\hat{o} = \text{argmax}(P_o)$ to the oracle. Examples of the OTM are demonstrated in the appendix section.
4.4. Question Decoder Transformer

The role of the QDT is to generate a question that will distinguish the target objects from the distracter objects as specified by the group vector $g$ produced by the OTM. The QDT consists of a standard transformer decoder [30]. The input of the QDT is the beginning of sentence token ([BOS]) and as a memory we put the element-wise sum of the object embeddings $\hat{X}_o$ and the embeddings of group vector $g$, described as:

$$\mathcal{M} = \{ \hat{X}_o^{(i)} + F_s(g^{(i)}) \}_{i \in \mathcal{N}}, \quad (7)$$

where $F_s$ is an embedding function and $g^{(i)}$ is the i-th element of $g$, which represents the property group of the object $o_i$. Given [BOS] token and $\mathcal{M}$, the QDT generates a tokenized word in an auto-regressive manner.

5. Training Process

5.1. Supervised Learning.

Both the OET and the QDT are jointly trained with supervised learning to predict the goal object and generate questions. For this purpose, the overall loss function can be expressed as the sum of the object prediction loss and the target-wise question generation loss, as $L = \alpha L_{\text{pred}} + L_{\text{gen}}$, where $\alpha$ is a constant that modifies the ratio between the two loss functions.

Object Prediction Loss. To predict the goal object, we can simply classify each object as to whether or not it is a candidate at the end of each question and answer pair. By applying the softmax function during reinforcement learning, we can acquire the goal object probability. Therefore, the loss for candidate object prediction is formalized as a multi-label classification problem, where the binary cross-entropy is applied to the sigmoid-activated result in Eq. (3) as follows:

$$L_{\text{pred}} = \sum_{t=1}^{T} - y_t^o \log(\sigma_o^t) - (1 - y_t^o) \log(1 - \sigma_o^t), \quad (8)$$

where $T$ is the number of questions in a dialogue, $y_t^o$ represents the ground-truth binary labels for the object in the $t$-th question.

Target-Wise Question Generation Loss. Question generation loss is defined as the negative log-likelihood, as

$$L_{\text{gen}} = - \sum_{t=1}^{T} \sum_{i=1}^{W_t} \log p(w_{t+1}^t | w_1^t, \ldots, w_t^t, w_1^t, \mathcal{M}), \quad (9)$$

where $W_t$ is the number of tokens included in the $t$-th question and $\mathcal{M}$ is expressed as $\{ \hat{X}_o^{(i)} + F_s(g^{(i)}) \}_{i \in \mathcal{N}}$. During supervised learning, the $g$ is computed from the ground-truth question. Here, the target group is assigned to the object that matches with the question when the answer to it is true, otherwise the distracter group is assigned. Note that, $N_{\text{max}} - k$ objects are assigned to a masked group in order to reproduce the reinforcement training conditions, where $k$ is a pre-defined constant for top-k objects.

5.2. Reinforcement Learning

The OTM is trained with reinforcement learning to generate the group vector $g$ and decide when to submit its answer. During RL, the OET and the QDT are frozen.

We formalize CLEVR Ask as an MDP problem given the tuple $(S, A, P, R, \gamma)$, where $S$ is the set of states, $A$ is the finite set of actions, $P$ is the state transition function, $R$ is the reward function, and $\gamma$ is the discount factor. We define each state, action, and reward on the timestep $t$. The set of actions $A$ corresponds to $\hat{g}_t$ produced by an action function $F_{RL}$ defined in Eqs. (5, 6). The states of the game are defined as $S_t = (I, \{(q_i^t, a_i^t)\}_{i=1:t-1})$. Agent chooses actions until the number of questions reaches the pre-defined limit question count, $T$. Among the $3^k$ actions, we treat $A_t = 0$ or $A_t = 3^k - 1$ as end of dialogue (EOD) cases. If one of these actions is selected, the dialogue is considered finished and the object with the highest probability $P_o$ at that time is submitted to the Oracle as the final prediction. The Oracle compares the Questioner’s prediction with the ground truth $o^*$ and returns the reward. The model is trained with policy gradient optimization using REINFORCE algorithm [29].

6. Experiments

6.1. Settings

Datasets. We trained and evaluated our model with two different datasets: CLEVR Ask3 and CLEVR Ask4.

Baseline model. We compared the proposed model with a model proposed in [28]. This baseline model consists of a Guesser-QGen architecture connected with a dialogue state encoder, where the Guesser is a multi-label classifier with a single weight-shared MLP and the QGen is a recurrent neural network. As in the previous studies, the QGen and Guesser are pre-trained separately and then tuned with reinforcement learning using policy gradient optimization. Details of the baseline model can be found in the appendix.

Implementation details. Supervised learning was early-stopped with 50-epoch patience using the AdaBelief optimizer [38] with the learning rate 1e-4, and 20 epochs for the warmup, and a batch size of 1024. As for the reinforcement learning, all experiments were trained for 150 epochs using the Adam optimizer [18] with the learning rate 5e-4, and a batch size of 1024. Additional details are available in the appendix.

6.2. Supervised Learning

Metrics. In supervised learning, we evaluated the OET and the QDT with three metrics: F1 score, perfect address ratio,
and correct address ratio.

F1 score was used to evaluate if the OET can find out candidate objects that match a dialogue \( D \). The F1 score was computed from predicted candidate objects \( \hat{O}_D \) and ground-truth candidate objects \( O_D \). We obtained \( \hat{O} \) from the result of \( \sigma_t \) in Eq. (3) as \( \hat{O} = \{ \hat{o}_i | i \in \mathcal{N} \land 0.5 < \sigma_t \} \).

Perfect address ratio and correct address ratio were used to evaluate the QDT’s ability to generate questions that will distinguish the target objects from the distractor objects as instructed by a group vector \( g \). The group vector \( g \) groups objects \( O \) into three groups: the target object group \( O_t \), the distractor object group \( O_d \), and the masked object group \( O_m \). If the generated question succeeds to distinguish \( O_t \) from \( O_d \), it is perfect. If it succeeds to do so but mixes \( O_m \) with \( O_t \), it is only deemed correct. The detailed definition of these metrics is available in the appendix section.

**Results.** The results of supervised learning are summarized in Tab. 1. For both Ask3 and Ask4 datasets, the F1 scores yield a near-perfect 0.994. The question generation achieved a fairly high probability, almost 87%, of generating correct questions in Ask3 and even in Ask4, which has an increased dataset complexity, as it is still able to generate nearly 70% of the questions correctly. The scores on perfect address were around 58% and 43% for Ask3 and Ask4 respectively. Although they were lower then the scores of correct address, the model still shows the capability of addressing the target objects considering the irrelevant masked objects.

### 6.3. Reinforcement Learning

**Metrics and Conditions.** Following [28], we used the task success ratio, defined as the rate of correct predictions submitted by a questioner, as our primary metric. The training was conducted in two different settings: new image and new object. In the new image setting, both the image and the goal object are completely new and have not been presented before. In the new object setting, the goal object is new but the image has already been presented in the training. We conducted five experimental runs across different seeds.

**Reward function.** The basic reward for reinforcement learning is the zero-one task success reward \( r_c \), similar to [28], which is given when the stop-action is produced and the predicted goal object is correct. Note well that submitting the answer at the first action step is treated as invalid and the success reward will not be given, so as to prevent the random predictions without asking questions. We also introduced a turn discount factor \( r_d \), similar to the goal-achieved reward proposed by [35], which will give a discount to the success reward depending on the number of questions asked to reach the answer.

**Ablation Studies.** Ablation studies were conducted to determine the effectiveness of UniQer. We performed testing using the following three ablation models:

- **Vanilla:** The simplest model, which utilizes bi-directional GRU as the object encoder and LSTM as the question decoder. The Guesser architecture, a MLP module, is trained with the LSTM dialogue history encoder. However, it is trained separately from the object encoder, the same as the baseline model.
- **Not Unified MLP Guesser:** The model that substitutes the object encoder and the question decoder in the Vanilla model with a standard transformer. Note that the object encoder in this model does not include the Guesser architecture; as an alternative, the Guesser is implemented with a multi-layer perceptron.
- **Not Unified:** The model that substitutes the Guesser module with the transformer. This model is the disassembled version of UniQer, whose QGen and Guesser modules are built on a single transformer encoder-decoder architecture.

Additionally, we conducted an extensive ablation to gain an understanding of the OTM. In the ablation, we substituted the OTM with a random action model, which chooses an action \( A_t \) randomly on every step. Besides, we tested this random model with force-stop condition, where the model automatically submits the answer at the end of a dialogue, which means the submission action is not required. We also investigated the hyper-parameter settings for top-k.

### Results.** The results on our full model are presented in Tab. 2. In the table, the average and the standard deviation

| Model                  | F1 score ± | Perfect Addr | Correct Addr ± |
|------------------------|------------|-------------|-----------------|
| UniQer (Ask3)          | 0.994      | 57.67       | 86.91           |
| UniQer (Ask4)          | 0.994      | 43.20       | 69.79           |

Table 1. The results for supervised training for both Ask3 and Ask4 datasets. F1 score measures the OET’s ability to find out the object candidates given a dialogue. Perfect Addr and Correct Addr stand for “perfect address ratio” and “correct address ratio”, respectively, which measures the QDT’s ability to generate a question that correctly addresses the target objects instructed by a group vector \( g \).

| Model                  | New Img ± | New Obj ± | New Img ± | New Obj ± |
|------------------------|-----------|-----------|-----------|-----------|
| Baseline               | 60.00 ±6.35 | 59.60 ±6.87 | 64.75 ±0.82 | 64.21 ±0.34 |
| Ours (v)               | 72.99 ±3.13 | 72.88 ±3.47 | 67.38 ±4.18 | 67.01 ±4.34 |
| Ours (num)             | 69.43 ±2.75 | 69.50 ±2.99 | 72.89 ±3.95 | 72.35 ±5.94 |
| Ours (full)            | 70.51 ±6.05 | 50.37 ±6.02 | 65.15 ±4.33 | 64.25 ±3.01 |

Table 2. Quantitative results on comparison and ablation study. The average and standard deviation of five runs for the task success ratio are shown. The bold numbers represent the best performance. The model “Ours (full)” represents our proposed UniQer and the other “Ours” models are ablated UniQer models; “Ours (v)” is the Vanilla model, “Ours (num)” is the Not Unified MLP Guesser model, and “Ours (nu)” is the Not Unified model.
of task success ratio is shown. The results demonstrate that UniQer outperformed the baseline with a large magnitude in both datasets and conditions, showing UniQer’s ability to discover a goal object in the task which requires descriptive question generation. In the new image setting, the task success rate of the baseline model was 60.00% and 64.75% for Ask3 and Ask4 datasets, respectively, while UniQer achieved 84.10% and 81.20%. Surprisingly, the results with the new object setting was on par with that of the new image setting, which is likely due to the fact that their objects share the same attributes.

The ablated results are also in Tab. 2. As shown in the table, all of the ablated conditions drop performances compared with UniQer, showing the advantage of our architectural design. Notably, the Not Unified model significantly drops the performance among the others in both datasets. This indicates the effectiveness of unifying the Guesser and the QGen.

The ablated results on the OTM module are shown in Tab. 3. The random condition scored the lowest as we expected, while the force-stop condition performs much better than it. This is because in the random condition, a chance of choosing a submission action is quite low. The results indicate that learning when to submit the answer is vital function in the OTM. We also found that, in our conditions, increasing $k$ does not always improve the results.

### Qualitative Results
We also inspected some of the dialogue samples and found that UniQer was actually capable of effectively generating descriptive questions to find out a goal object. Fig. 3 shows the representative dialogue examples for the test set images. In the upper example, the target object was the red metallic sphere. The baseline generated questions regarding “a cube”, however none of the referring expressions were used for narrowing down a referenced object among the cubes. Because there are multiple cubes in the image, this question is considered to be a non-informative question. On the other hand, our method generated expressions such as “a metal blue cube” and “a red metal sphere”. These questions are appropriate to distinguish the goal object among others, and considered to be informative.

In the lower example, the goal object was a small blue sphere which is located in a group of similar objects. The baseline generated referring expressions such as “in front of a sphere” and “behind a sphere”. This is because all of the objects in the image were spheres and this is insufficient to disambiguate the goal object. On the other hand, our method generated referring expressions such as “right of a blue sphere” and “in front of a blue sphere.” Although these expressions are not very human-friendly, they are sufficient and short enough to specify the relative relationships among the blue spheres.

### 7. Conclusion
In this research, we presented UniQer, a novel Questioner architecture for descriptive question generation with referring expressions in goal-oriented visual dialogue. Experimental results demonstrated that our model surpasses the baseline on the novel CLEVR Ask datasets, which require descriptive question generation. We also validated the components of our model with ablation studies, showing the structural advantages of our model. Finally, we investigated the generated samples qualitatively and found that our model successfully generated descriptive questions and discovered the goal objects.
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