Spot the Difference: A Cooperative Object-Referring Game in Non-Perfectly Co-Observable Scene

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Abstract

Visual dialog has witnessed great progress after introducing various vision-oriented goals into the conversation, especially such as GuessWhich and GuessWhat, where the only image is visible by either and both of the questioner and the answerer, respectively. Researchers explore more on visual dialog tasks in such kind of single- or perfectly co-observable visual scene, while somewhat neglect the exploration on tasks of non-perfectly co-observable visual scene, where the images accessed by two agents may not be exactly the same, often occurred in practice. Although building common ground in non-perfectly co-observable visual scene through conversation is significant for advanced dialog agents, the lack of such dialog task and corresponding large-scale dataset makes it impossible to carry out in-depth research. To break this limitation, we propose an object-referring game in non-perfectly co-observable visual scene, where the goal is to spot the difference between the similar visual scenes through conversing in natural language. The task addresses challenges of the dialog strategy in non-perfectly co-observable visual scene and the ability of categorizing objects. Correspondingly, we construct a large-scale multimodal dataset, named SpotDiff, which contains 87k Virtual Reality images and 97k dialogs generated by self-play. Finally, we give benchmark models for this task, and conduct extensive experiments to evaluate its performance as well as analyze its main challenges.

1 Introduction

Building a dialog agent that can intelligently communicate with people through comprehending and reasoning in vision and natural language is a challenging task in AI research (Strub et al., 2017a; Niu et al., 2019). Such visual dialog agents have broad prospects in social services and commercial applications, e.g., assisting the visually impaired people to understand the surroundings (Bigham et al., 2010), recommending products by dialog-based image retrieval (Guo et al., 2018), so that related researches (Das et al., 2017a; de Vries et al., 2017; Gan et al., 2019; Haber et al., 2019; Ilinykh et al., 2019; Chen et al., 2020; Wang et al., 2020; Cogswell et al., 2020; Takmaz et al., 2020; Le et al., 2021; Liang et al., 2021; Kottur et al., 2021; Chen et al., 2021; Xu et al., 2021) have attracted increasing attention.

In recent years, researchers have proposed many visual dialog tasks for different scene settings, including single-observable scene and perfectly co-observable scene. In single-observable scene, the scene is only visible to one interlocutor. For example, Das et al. (2017a) propose the task of Visual dialog, which requires the dialog agent to answer questions given an image and dialog history while the questioner cannot see the image. On the basis of the above task, GuessWhich (Das et al., 2017b; Murahari et al., 2019; Zhou et al., 2019; Lee et al., 2019; Zheng et al., 2021) introduces an image-guessing game. This task aims at enabling the questioner imagine the invisible target image and finally guess it, through conversing with the answerer who could access the target image. In co-observable scene, the scene is fully observed by all interlocutors. For example, GuessWhat?! (Zhang et al., 2017; Zhao and Tresp, 2018; Strub et al., 2017b; Shekhar et al., 2019; Shukla et al., 2019; Xu et al., 2020) focuses on locating the target object in an image, which is visible by both the questioner and the answerer, through dialog between them. Moon et al. (2020a) introduce the task of SIMCC, which addresses the task-oriented dialog scenario on shopping domain where a system dialog agent and a user share the co-observable scene.

However, in actual applications, there are many
situations where the visual scenes accessed by two people are similar but not be exactly the same. Take the remote abnormal troubleshooting as an example, the user can access the problem machine, while the quality inspector can access intact machine. They determine the fault location through conversation online or by telephone. At this time, it is more important to help each other to understand the partner’s scene and clarify the differences, through dialog interaction. Therefore, some researchers turn to investigate the visual dialog in such non-perfectly co-observable scene with the provision of a small-scale dataset. Lopes et al. (2018) study the dialog phenomenon under the setting of making two interlocutors to find differences between two similar scenes. They collect a dataset, which only contains 54 dialogs in 8 different cartoon scenes. More than that, lacking deeply analyzed challenges and corresponding solutions also makes its contribution to research community limited.

Two key challenges of the visual dialog in non-perfectly co-observable scene are not covered by the above tasks: 1) Difference-oriented dialog strategy. The two interlocutors participating in the dialog can only access their own part of the visual scenes, so they can only clarify the difference through the dialog. Therefore, to complete the goal of the dialog, the dialog interaction needs to constantly overcome the difficulty brought by differentiated visual information. 2) Categorization-oriented question strategy. Human understands the world usually through categorization, which requires subjective generalization and classification of objects (Rosch and Lloyd, 1978). Such ability can be necessary for advanced agents. Therefore, finding a question strategy that can efficiently categorize the objects in the scene may be a critical path to quickly locating the difference. Although categorization has been mentioned in GuessWhat?! all the questions in it are Yes/No questions, such as ‘is it a decoration?’. It ignores that an important purpose of categorization is induction, which often requires the abilities of accurate counting and clearly pointing out these objects, such as ‘I have three decorations, and you?’, ‘what are they?’.

Obviously, the ability to deal with these challenges is significant for advanced dialog agents. To develop these capabilities of machines, in this paper, we propose an object-referring game – Spot the Difference. As shown in Figure 1, the goal of Spot the Difference is to spot the different object between two similar images via conversing in natural language between a questioner and an answerer in a non-perfectly co-observable visual scene. To this end, we construct a large-scale multimodal dataset, named SpotDiff, which contains 87k images and 78k dialogs. First, we generate the images of SpotDiff with an elaborately designed scene simulator, taking into account the coherence of the real world. Then, based on the generated images, we generate the dialogs of SpotDiff through a well-designed two-stage dialog generation algorithm. Finally, we propose benchmark models for Spot the Difference, which are based on the multimodal pre-trained model LXMERT (Tan and Bansal, 2019). We evaluate the performance of the dialog system and the answerer agent, and analyze the model’s ability in dialog strategy and categorization.

Our main contributions are concluded as follows:

- We propose a new visual dialog task – Spot the Difference, which mainly addresses challenges of the dialog strategy in non-perfectly co-observable visual scene and the ability of categorizing objects.
- We construct the SpotDiff dataset, which consists of 87k Virtual Reality images and 95k programmatically simulated dialogs.
- We provide strong benchmark models for Spot the Difference. Experimental results show that the task performance can be improved by designing difference-oriented dialog strategy and categorization-oriented question strategy, both of which are the challenges that the task of non-perfectly co-observable scene hope to address. These provide insights for developing more intelligent visual dialog agents.

2 Spot the Difference Game

As illustrated in Figure 1, Spot the Difference is an object-referring game conducted by a questioner and an answerer. The questioner and answerer can see images $I^Q$ and $I^A$, respectively.

The goal of questioner is to spot the difference from $I^Q$ to $I^A$, i.e., the object in $I^Q$ that is not in $I^A$ (marked with a green box in Figure 1). The questioner constantly asks questions based on the image $I^Q$, such as asking the number of objects with specific conditions, the referential content of

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1The code and data are publicly available at: https://github.com/zd11024/Spot_Difference
Figure 1: An example of Spot the Difference. The green box indicates the different object from I^Q to I^A.

Figure 2: The generation process of SpotDiff images. (a)–(c) show the object-by-object generation process of scene. (c) and (d) are a pair of similar images. The green box in (c) represents the different object from (c) to (d).

the previous round, and the object at a specific location, e.g., q_1 = ‘There are four white objects?’, q_3 = ‘What are they?’, q_4 = ‘What is the leftmost thing on the tea table?’. After the questioner has located the different object, it terminates the conversation and makes a guess on the correct object list of I^Q.

Based on the image I^A and the question, the answerer gives the answer, which may be a number, a description of one or multiple objects, e.g., a_1 = ‘Four’, a_3 = ‘Two decorative plates and a vase’.

3 SpotDiff Dataset

In this section, we first describe how images and dialogs of the SpotDiff are generated in Section 3.1 and Section 3.2, respectively. Then we present the dataset analysis in Section 3.3.

3.1 Image Generation

First, we develop a scene simulator to generate SpotDiff images in Virtual Reality (VR) environment. Then for each image, we construct its scene graph, serving as the input to dialog generation.

3.1.1 Scene Simulator

The scene simulator generates similar image pairs with only one object different and the generation process of SpotDiff images is illustrated in Figure 2. First, the scene simulator generates a random scene by placing objects item by item. Then, it randomly selects one object from all the objects that can be replaced in the scene, and replace it with a random object of a different category, or that of the same category with different attributes. Finally, the scene simulator renders the scene in Unity3D (Unity Technologies, 2019) and takes screenshots with Unity Perception^2 (Unity Technologies, 2020).

Real world scenes appear as a composite of coherent objects (Galleguillos et al., 2008). To make VR scenes more reality, the scene simulator adopts an elaborately designed search algorithm, mainly considering the following aspects:

Richness of Objects. To generate richer scenes, more diverse objects are needed. We use 251 digital assets^3 which belong to 86 different categories.

Placement Relationship. A directed graph (please refer to Appendix A.2 for details) is defined to describe the placement relationship between categories. For example, bread can be placed on a plate, but not directly on the floor.

Spatial Arrangement^4. The scene should neither be too evacuated nor too compact. The former may cause the pixels of objects in the image to be too small, and the latter may cause mutual occlusion between objects.

Object Co-Occurrence^4. Related objects co-occur with high probability. For example, computers, mice and keyboards often appear together because they are all office supplies.

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^2A toolkit provided by Unity Corporation for generating large-scale computer vision datasets.
^3We obtain them from https://assetstore.unity.com/ and https://www.turbosquid.com/
^4We present the implementation details of spatial arrangement and object co-occurrence in Appendix A.3 and A.4, respectively.
3.1.2 Image Scene Graph

The scene graph\(^5\) contains the information of all objects in an image, including:
1) Attribute: Each Object is annotated with color and material.
2) Taxonomy: Taxonomy information is depicted by a predefined hierarchical tree of categories, which is in Appendix A.1. For example, pizza belongs to \{pizza, baked food, food\}.
3) Position: Position information is described by 2D bounding box and 3D bounding box, which are annotated when generating images with Unity Perception (Unity Technologies, 2020).

Color, material and categories are regarded as atomic properties of an object.

3.2 dialog Generation

With the image scene graph as input, we design a two-stage dialog generation approach as shown in Figure 3. In the first stage, a questioner simulator and an answerer simulator are used to generate a dialog action sequence through self-play (Section 3.2.1). In the second stage, the dialog action sequence is mapped to natural language through manually defined templates (Section 3.2.2).

3.2.1 Dialog Action Generation

Inspired by previous works (Moon et al., 2020b; Kottur et al., 2021), the dialog action sequence consists of question actions and answer actions, both of which are composed of a series of slot-value pairs.

The dialog action sequence is interactively generated by the questioner simulator and answerer simulator. In concrete, at each round, the questioner simulator produces a question action and the answerer simulator gives the corresponding answer action. The interaction is repeated until the questioner simulator could locate the target object.

Question actions are divided into nine subtypes, which belong to four types: 1) Count type (count-nohint and -hint) asks the number of objects with specific properties. Comparing with count-nohint type (e.g., 'how many white objects can you see?'), count-hint type adds a hint for counting, e.g., 'I have four white objects, how about you?'. 2) Extreme type (extreme-pic, -obj and -obj2) asks for a specific description of the object at a positional extreme among conditioned objects. For extreme-pic type, the conditioned objects are all objects in the picture, e.g., 'what is the rightmost thing?'. For extreme-2 and -3 types, the conditioned objects are objects placed on a given object, e.g., 'what is the rightmost thing on the tea table?'. 3) Query type (query-color and -material) asks for the color or attribute of the referent, which may not exist or cannot be uniquely determined. 4) Refer type (ref-it and -them) follows the count type, and requires the answerer to give a specific description of the objects referred to in the previous round. Ref-it type asks one object while ref-them asks multiple, e.g., 'what is it?' and 'what are they?'

At each round, the questioner simulator tracks visual state according to dialog history, then selects an appropriate question action based on the

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\(^5\)We show an example of scene graph in Appendix D.1.
tracked visual state and question strategy. A good questioner simulator can achieve the above goal by answering the following questions. Q1: How to accurately track the state of each object in an image, taking into account entailment relationships between properties of the object. For example, one won’t ask ‘is there any fruit?’ after knowing there is an apple; Q2: How to efficiently guide the conversation to avoid object-by-object mechanical enumeration.

Q1: Visual State Tracking. To maintain the state of the image as the dialog proceeds, the questioner simulator constructs an object state graph for each object. We define a property set as a combination of properties or an identifier for the object itself. As shown in Figure 4, the nightstand in red contain many property set, e.g, {white, nightstand} or {nightstand1}. Obviously, there are entailment relationships between property sets, inspiring us to describe the state of an object with a directed graph in the process of dialog.

To this end, we construct the object state graph for each object, where nodes represent property sets and edges represent entailment relationships between them. To clarify which property sets of an object are known or not, each node maintains a boolean value initialized to False, which we name as confirmation status. When a node is confirmed (its confirmation status is True), all reachable nodes from it are also confirmed. Conversely, for two confirmed nodes, whose property sets are denoted as $A$ and $B$ respectively, the node corresponding to the property set $|A \cup B|$ is also confirmed. In addition, each node corresponds to a description template set, which is used to map the property set to a phrase in the natural language generation stage, such as \{wooden,furniture\} $\rightarrow$ pieces of wooden furniture.

In addition, the questioner simulator also track a candidate object set $S_{cand}$, which includes objects whose existence has not been confirmed. In the beginning, $S_{cand}$ includes all objects in the image. As the dialog proceeds, an object will be removed from $S_{cand}$ after all nodes in its corresponding object state graph have been confirmed.

Q2: Categorization-Based Question Strategy. For efficient questioning, we propose a categorization-based question strategy whose main idea is to gather more information by generalizing half of the remaining objects as much as possible. As illustrated in Figure 3, $q_2$ – ‘How many decorations can you see’ generalizes the decorations in the image to confirm whether a decoration has been replaced. Therefore, we design an approach to simulate such a strategy. In concrete, the questioner simulator maintains a list of question types that could be performed. The count type is always in the list. When the size of the candidate object set $S_{cand}$ is less than $n$, the extreme and refer type is added to the list$^6$. When the question type of the previous round is count and the corresponding answer is less than $m$, the refer type is added to the list$^6$. The final question type is sampled from the list. After the question type is determined, the slot-value pairs are heuristically obtained as follows:

- Count type: First, the questioner simulator counts frequencies of all property sets, which are defined as the number of unconfirmed nodes correspond-

6$^6n$ and $m$ are hyper-parameters, which are empirically set to 5 and 4, respectively.
At this stage, each action is mapped to a natural language phrase in total. We refer readers to Appendix B.2 for details.

3.2.2 Natural Language Generation

At this stage, each action is mapped to a natural language sentence. Taking question action as an example (see Figure 5), we randomly select a question template according to the question subtype and fill the slot values into the question template to produce a question. Notably, the property sets are mapped to natural language phrases with description template sets. In addition, to make dialogs more fluid, we design transition sentences to concatenate adjacent rounds of dialog. There are 43 templates and 1659 human-annotated natural language phrases in total. We refer readers to Appendix B.2 for the details of templates.

3.3 Dataset Analysis

For each SpotDiff image pair, we generate 2 dialogs by changing the order between images, and the dialogs that fail to complete the task within 10 rounds are discarded. The SpotDiff dataset contains 78k dialogs and 87k SpotDiff images, and is split by randomly assigning 80%, 10% and 10% of image pairs and its corresponding dialogs to train, valid and test set. Table 2 shows the comparison results of SpotDiff with SIMCC 2.0 (Kottur et al., 2021) and CLEVR dialog (Kottur et al., 2019). The SpotDiff dataset has much more unique answers than CLEVR Dialog (4.0k vs 29), indicating the answerer in our task has a higher degree of freedom.

Figure 6 (a) shows the distribution on question subtypes. More than 70% of the questions in the SpotDiff dataset need to count objects with specific properties. Figure 6 (b) presents the distribution of answers. There are a total of 4.0k unique answers, of which the 6 most frequent unique answer account for 69% of the total answers, while remaining unique answers account for 30%, making the distribution a long-tailed distribution.

4 Task Formulation

Following previous work (de Vries et al., 2017), the Questioner Bot (Q-Bot) consists of Question Generator (QGen) and Guesser, which are responsible for asking questions and guessing the target object, respectively. The Answerer Bot (A-Bot) is a Visual Question Answering (VQA) model.

**QGen.** At round $t$, QGen asks a question $q_t$ given the dialog history $H_{t-1} = \{(q_1, a_1), \cdots, (q_{t-1}, a_{t-1})\}$ and the image $I^Q$, which could be formulated as:

$$q_t \sim P(q | H_{t-1}, I^Q).$$  \hspace{1cm} (1)

**A-Bot.** A-Bot predicts the answer $a_t$ from the candidate answer set, based on the question $q_t$, dialog history $H_{t-1}$, and the image $I^A$, which could be denoted as:

$$a_t \sim P(a | q_t, H_{t-1}, I^A).$$  \hspace{1cm} (2)

**Guesser.** After $T$ rounds of dialog, Guesser makes a guess on the correct object list $O_{\text{correct}}$ of $I^Q$ given the full dialog history $H_T$ as follow:

$$o^* \sim P(o | H_T, O_{\text{correct}}),$$  \hspace{1cm} (3)

where $T$ is the maximum number of dialog rounds, $O_{\text{correct}} = \{(c_1, p_1), \cdots, (c_M, p_M)\}$, $c_i$ and $p_i$ are the correct category and relative bounding box of the $i$-th object, respectively.
Table 2: The performance of the dialog system. GT-Q: ground truth question, GT-A: ground truth answer, GT-V: visual features extracted by ground truth box, SUCC: task success rate (%). ↑: higher is better.

| # | GT-Q | GT-A | GT-V | SUCC ↑ |
|---|------|------|------|--------|
| 1 | -    | -    | -    | 33.70  |
| 2 | -    | -    | √    | 42.01  |
| 3 | √    | -    | -    | 63.16  |
| 4 | -    | √    | -    | 32.67  |
| 5 | √    | √    | -    | 71.26  |

Figure 7: (a)/(b) shows the relationship between the task success rate and the accuracy/recall of Cate-Q.

5 Experiments

To explore the challenges arising from the task, we first train benchmark models and evaluate their performance on SpotDiff dataset. Then we conduct extensive experiments to analyze two main challenges: categorization and dialog strategy.

5.1 Benchmark Models

We train benchmark models on SpotDiff dataset:

1) **QGen**: A LXMERT (Tan and Bansal, 2019)-initialized encoder paired with a randomly initialized decoder. We also try initializing the decoder with pre-trained models, such as BERT (Devlin et al., 2019) and GPT-2 (Radford et al., 2019), but no gain is observed.

2) **A-Bot**: A VQA model with the multimodal pre-trained model LXMERT as encoder and an MLP head to predict the answer.

3) **Guesser**: A BERT (Devlin et al., 2019) encoder with a classification head to predict the target object. The three components are trained separately, please refer C.1 to for implementation details.

5.2 Dialog System Performance.

We investigate the performance of the dialog system under the setting of Spot the Difference. Specifically, QGen and A-Bot first interactively generate a 5-round Q-Bot-A-Bot dialog, and then Guesser makes a guess on the correct object list given the generated dialog. Table 2 shows the task success rate under different settings. GT-Q and GT-A indicate whether the ground truth question and ground truth answer are used, respectively. GT-V indicates whether the visual features are extracted by the ground truth bounding box. Comparing row 1 and row 2, it can be seen that correct object detection could improve task success rate. Comparing row 1/4 and row 3, it shows that the questioner model greatly limits the task success rate and the main challenge of the task lies in the modeling of QGen. Comparing row 1 and 5, there is still a large gap between the Q-Bot-A-Bot dialog and the ground truth data.

Counterintuitively, the GT-A variant underperforms the baseline, which may be caused by the inconsistency between the wrong question and the correct answer. For example, for a Q-Bot-generated question-‘I have three decorations, and you?’, the A-Bot would select answer from {two, three, four}, but the actual answer could be {zero, one}.

5.3 A-Bot Performance.

Although the challenges of our task lie in the modeling of the questioner, we verify A-Bot performance in term of accuracy on various question subtypes under classification setting. We observe that: 1) Count-hint (87.59%) surpasses count-nohint (83.23%) due to the hints about counting in count-nohint questions. 2) Extreme-pic (82.92%) outperforms extreme-obj (81.54%) and extreme-obj2 (76.75%) because the model’s spatial reasoning ability is more urgently required for extreme-obj and -obj2. 3) Query-color and -material achieve the accuracy of 91.02% and 88.54%, respectively. 4) Refer-it (89.78%) is better than refer-them (85.63%), considering that refer-them questions ask multiple objects while refer-it questions ask one.

5.4 Effect of Categorization

We name the count question that could generalize at least two different kinds of objects on an image as a Cate-Q. To investigate the effect of categorization ability on task success rate, we first obtain Q-Bot-A-Bot dialogs on the test set, and then group these dialogs in different ways, i.e., the accuracy rate and recall rate of Cate-Q in the dialog.

**Accuracy Rate of Cate-Q.** For each Q-Bot-A-Bot dialog, we first extract quantifiers and property sets

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1We also adopts GPT-2 (Radford et al., 2019) and UpDn (Anderson et al., 2018) as QGen and A-Bot, respectively. Please refer to Appendix C.3 and C.2 for details.

9The generated answers are corrected by the answerer simulator.
in all Cate-Q, and calculate the accuracy over Cate-Q in a dialog by matching with objects on the scene graph. Then we divide the Q-Bot-A-Bot dialogs according to the counting accuracy of Cate-Q, and examine the task success rate of each group. As shown in Figure 7 (a), as the accuracy of Cate-Q increases, the task success rate shows an increasing trend, demonstrating that accurate counting for Cate-Q could help to complete the task.

Recall Rate of Cate-Q. We extract the property sets of the Cate-Q for each Q-Bot-A-Bot dialog and corresponding ground truth dialog, which are denoted as $A$ and $B$, respectively. We define the recall rate of Cate-Q as $\frac{|A \cap B|}{|B|}$. The Figure 7 (b) shows the task success rate increases as the recall rate increases, indicating the importance of selecting appropriate property sets to raise Cate-Q for successfully completing the task.

5.5 Effect of Dialog Strategy

Action Transition. To investigate the relationship between action transition and task success rate, we group Q-Bot-A-Bot dialogs according to adjacent question action transitions. Question action transitions could be divided into deepening action transitions and converting action transitions according to whether the latter question deepens the previous one. Table 3 shows that dialogs with deepening action transitions achieve higher task success rate (35.85% vs 32.72%) because the deepening action transitions could help Q-Bot to narrow the scope of the target object.

Case Study. We conduct case studies to investigate the effect of dialog strategies in Figure 8. In the first Q-Bot-A-Bot dialog, the questioner successfully complete the task by gradually narrowing down the candidates. In the second Q-Bot-A-Bot dialog, $q_5$ asks about the green book instead of the black mouse after finding the difference in black objects.

6 Related Work

VQA and Captioning. Many work have been introduced for studying vision-and-language understanding, including VQA (Goyal et al., 2017; Anderson et al., 2018; Hudson and Manning, 2019) and image captioning (Vinyals et al., 2015; Tan et al., 2019; Li et al., 2020). Jhamtani and Berg-Kirkpatrick (2018) propose the task to describe the difference between two similar images and collect the spotting-the-difference dataset. In contrast, under our setting, the questioner could only access one image and understand the content of another image through dialog interaction.

Collaborative Dialog in Visual Scene. Numerical work (de Vries et al., 2017; Das et al., 2017a) pay attention on dialog in single or partially co-observable visual scene. Recently, some researchers focus on dialog in non-perfectly co-observable scene. Haber et al. (2019) introduce the PhotoBook dataset, whose goal is to determine the shared images through conversation between two interlocutors. Ilinykh et al. (2019) propose a two-player coordination game, named MeetUp!, and collect a multimodal corpus that contains 430 dialogs. The player can switch the unshared scene

| Action Transition | SUCC (%) |
|-------------------|----------|
| furniture → black → brown wooden furniture | 40.75 |
| furniture → black decoration | 39.70 |
| deepening action transition | 35.82 |
| white → furniture | 32.43 |
| white → toy | 29.38 |
| converting action transition | 32.72 |

Table 3: The relationship between action transition and task success rate. SUCC: task success rate (%).
by moving in a virtual environment, and meet with each other in a specific location during interaction. **Collaborative Dialog in Abstract Context.** Our work is also related to partially-observable collaborative game in abstract context (He et al., 2017; Udagawa and Aizawa, 2019, 2020; Fried et al., 2021). Udagawa and Aizawa (2019) introduce ONECOMMON, which addresses the challenges of dialog technology in continuous and partially-observable context. In this task, two players have different views of a game board, which consists of multiple dots described in continuous value.

7 Conclusion

In this paper, we propose a cooperative object-referring game – **Spot the Difference**, where the goal is to locate the different object between two similar images via conversing between questioner and answerer. The task addresses two challenges at visual dialog in non-perfectly co-observable scene, including the difference-oriented dialog strategy and the ability of categorization. We construct a large-scale dialog dataset **SpotDiff**, which contains 87k images and 78k dialogs. Additionally, we provide strong benchmark models and conduct extensive experiments to analyze the two key challenges.

References

Peter Anderson, Xiaodong He, Chris Buehler, Damien Teney, Mark Johnson, Stephen Gould, and Lei Zhang. 2018. Bottom-up and top-down attention for image captioning and visual question answering. In 2018 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2018, Salt Lake City, UT, USA, June 18-22, 2018, pages 6077–6086. IEEE Computer Society.

Jeffrey P. Bigham, Chandrika Jayant, Hanjie Ji, Greg Little, Andrew Miller, Rob Miller, Rob Miller, Aubrey Tatarowicz, Brandyn Allen White, Samuel White, and Tom Yeh. 2010. Vizwiz: nearly real-time answers to visual questions. Proceedings of the 23nd annual ACM symposium on User interface software and technology.

Feilong Chen, Xiuyi Chen, Fandong Meng, Peng Li, and Jie Zhou. 2021. GoG: Relation-aware graph-over-graph network for visual dialog. In Findings of the Association for Computational Linguistics: ACL-IJCNLP 2021, pages 230–243. Online: Association for Computational Linguistics.

Feilong Chen, Fandong Meng, Jiaming Xu, Peng Li, Bo Xu, and Jie Zhou. 2020. DMRM: A dual-channel multi-hop reasoning model for visual dialog. In The Thirty-Fourth AAAI Conference on Artificial Intelligence, AAAI 2020, The Thirty-Second Innovative Applications of Artificial Intelligence Conference, IAAI 2020, The Tenth AAAI Symposium on Educational Advances in Artificial Intelligence, AAAI 2020, New York, NY, USA, February 7-12, 2020, pages 7504–7511. AAAI Press.

Michael Cogswell, Jiasen Lu, Rishabh Jain, Stefan Lee, Devi Parikh, and Dhruv Batra. 2020. Dialog without dialog data: Learning visual dialog agents from VQA data. In Advances in Neural Information Processing Systems 33: Annual Conference on Neural Information Processing Systems 2020, NeurIPS 2020, December 6-12, 2020, virtual.

Abhishek Das, Satwik Kottur, Khushi Gupta, Avi Singh, Deshraj Yadav, José M. F. Moura, Devi Parikh, and Dhruv Batra. 2017a. Visual dialog. In 2017 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2017, Honolulu, HI, USA, July 21-26, 2017, pages 1080–1089. IEEE Computer Society.

Abhishek Das, Satwik Kottur, José M. F. Moura, Stefan Lee, and Dhruv Batra. 2017b. Learning cooperative visual dialog agents with deep reinforcement learning. In IEEE International Conference on Computer Vision, ICCV 2017, Venice, Italy, October 22-29, 2017, pages 2970–2979. IEEE Computer Society.

Harm de Vries, Florian Strub, Sarath Chandar, Olivier Pietquin, Hugo Larochelle, and Aaron C. Courville. 2017. Guesswhat?! visual object discovery through multi-modal dialogue. In 2017 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2017, Honolulu, HI, USA, July 21-26, 2017, pages 4466–4475. IEEE Computer Society.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 4171–4186, Minneapolis, Minnesota. Association for Computational Linguistics.

Daniel Fried, Justin T. Chiu, and Dan Klein. 2021. Reference-centric models for grounded collaborative dialogue.

Carolina Galleguillos, Andrew Rabinovich, and Serge J. Belongie. 2008. Object categorization using co-occurrence, location and appearance. In 2008 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR 2008), 24-26 June 2008, Anchorage, Alaska, USA. IEEE Computer Society.

Zhe Gan, Yu Cheng, Ahmed Kholy, Linjie Li, Jingjing Liu, and Jianfeng Gao. 2019. Multi-step reasoning via recurrent dual attention for visual dialog. In Proceedings of the 57th Annual Meeting of the
Association for Computational Linguistics, pages 6463–6474, Florence, Italy. Association for Computational Linguistics.

Yash Goyal, Tejas Khot, Douglas Summers-Stay, Dhruv Batra, and Devi Parikh. 2017. Making the V in VQA matter: Elevating the role of image understanding in visual question answering. In 2017 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2017, Honolulu, HI, USA, July 21-26, 2017, pages 6325–6334. IEEE Computer Society.

Xiaoxiao Guo, Hui Wu, Yu Cheng, Steven Rennie, Gerald Tesauro, and Rogério Schmidt Feris. 2018. Dialog-based interactive image retrieval. In Advances in Neural Information Processing Systems 31: Annual Conference on Neural Information Processing Systems 2018, NeurIPS 2018, December 3-8, 2018, Montréal, Canada, pages 676–686.

Janosch Haber, Tim Baumgärtner, Ece Takmaz, Lieke Gelderloos, Elia Bruni, and Raquel Fernández. 2019. The PhotoBook dataset: Building common ground through visually-grounded dialogue. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 1895–1910, Florence, Italy. Association for Computational Linguistics.

He He, Anusha Balakrishnan, Mihail Eric, and Percy Liang. 2017. Learning symmetric collaborative dialogue agents with dynamic knowledge graph embeddings. In Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 1766–1776, Vancouver, Canada. Association for Computational Linguistics.

Drew A. Hudson and Christopher D. Manning. 2019. GQA: A new dataset for real-world visual reasoning and compositional question answering. In IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2019, Long Beach, CA, USA, June 16-20, 2019, pages 6700–6709. Computer Vision Foundation / IEEE.

Nikolai Ilinykh, Sina Zarrieß, and David Schlangen. 2019. Meetup! a corpus of joint activity dialogues in a visual environment.

Harsh Jhamtani and Taylor Berg-Kirkpatrick. 2018. Learning to describe differences between pairs of similar images. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 4024–4034, Brussels, Belgium. Association for Computational Linguistics.

Satwik Kottur, Seungwhan Moon, Alborz Geramifard, and Babak Damavandi. 2021. Simmc 2.0: A task-oriented dialog dataset for immersive multimodal conversations.

Satwik Kottur, José M. F. Moura, Devi Parikh, Dhruv Batra, and Marcus Rohrbach. 2019. CLEVR-dialog: A diagnostic dataset for multi-round reasoning in visual dialog. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 582–595, Minneapolis, Minnesota. Association for Computational Linguistics.

Ranjay Krishna, Yuke Zhu, Oliver Groth, Justin Johnson, Kenji Hata, Joshua Kravitz, Stephanie Chen, Yannis Kalantidis, Li-Jia Li, David A. Shamma, Michael S. Bernstein, and Fei-Fei Li. 2016. Visual genome: Connecting language and vision using crowdsourced dense image annotations.

Hung Le, Chinnadhurai Sankar, Seungwhan Moon, Ahmad Beirami, Alborz Geramifard, and Satwik Kottur. 2021. DVD: A diagnostic dataset for multi-step reasoning in video grounded dialogue. In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers), pages 5651–5665, Online. Association for Computational Linguistics.

Sang-Woo Lee, Tong Gao, Sohee Yang, Jaejun Yoo, and Jung-Woo Ha. 2019. Large-scale answerer in questioner’s mind for visual dialog question generation. In 7th International Conference on Learning Representations, ICLR 2019, New Orleans, LA, USA, May 6-9, 2019. OpenReview.net.

Zhuowan Li, Quan Tran, Long Mai, Zhe Lin, and Alan L. Yuille. 2020. Context-aware group captioning via self-attention and contrastive features. In 2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition, CVPR 2020, Seattle, WA, USA, June 13-19, 2020, pages 3437–3447. IEEE.

Zujie Liang, Huang Hu, Can Xu, Chongyang Tao, Xibuo Geng, Yining Chen, Fan Liang, and Daxin Jiang. 2021. Maria: A visual experience powered conversational agent. In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers), pages 5596–5611, Online. Association for Computational Linguistics.

José Lopes, Nils Hemmingson, and Oliver Åstrand. 2018. The spot the difference corpus: a multi-modal corpus of spontaneous task oriented spoken interactions. In Proceedings of the Eleventh International Conference on Language Resources and Evaluation (LREC 2018), Miyazaki, Japan. European Language Resources Association (ELRA).

Seungwhan Moon, Satwik Kottur, Paul Crook, Ankita De, Shivani Poddar, Theodore Levin, David Whitney, Daniel Difranco, Ahmad Beirami, Eunjoon Cho, Rajen Subba, and Alborz Geramifard. 2020a. Situated and interactive multimodal conversations. In Proceedings of the 28th International Conference on Computational Linguistics, pages 1103–1121, Barcelona, Spain (Online). International Committee on Computational Linguistics.
Seungwhan Moon, Satwik Kottur, Paul Crook, Ankita De, Shivani Poddar, Theodore Levin, David Whitney, Daniel Diffnaco, Ahmad Beirami, Eunjoon Cho, Rajen Subba, and Albort Geramifard. 2020b. Situated and interactive multimodal conversations. In Proceedings of the 28th International Conference on Computational Linguistics, pages 1103–1121, Barcelona, Spain (Online). International Committee on Computational Linguistics.

Vishvak Murahari, Prithvijit Chattopadhyay, Dhruv Bartra, Devi Parikh, and Abhishek Das. 2019. Improving generative visual dialog by answering diverse questions. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 1449–1454, Hong Kong, China. Association for Computational Linguistics.

Yulei Niu, Hanwang Zhang, Manli Zhang, Jianhong Zhang, Zhiwu Lu, and Ji-Rong Wen. 2019. Recursive visual attention in visual dialog. In IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2019, Long Beach, CA, USA, June 16-20, 2019, pages 6679–6688. Computer Vision Foundation / IEEE.

Alec Radford, Jeff Wu, Rewon Child, David Luan, Dario Amodei, and Ilya Sutskever. 2019. Language models are unsupervised multitask learners.

Shaoqing Ren, Kaiming He, Ross B. Girshick, and Jian Sun. 2015. Faster R-CNN: towards real-time object detection with region proposal networks. In Advances in Neural Information Processing Systems 28: Annual Conference on Neural Information Processing Systems 2015, December 7-12, 2015, Montreal, Quebec, Canada, pages 91–99.

Eleanor Rosch and Barbara Bloom Lloyd. 1978. Cognition and categorization.

Ravi Shekhar, Aashish Venkatesh, Tim Baumgärtner, Elia Bruni, Barbara Plank, Raffaella Bernardi, and Raquel Fernández. 2019. Beyond task success: A closer look at jointly learning to see, ask, and Guess-What. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 2578–2587, Minneapolis, Minnesota. Association for Computational Linguistics.

Pushkar Shukla, Carlos Elmadjian, Richika Sharan, Vivek Kulkarni, Matthew Turk, and William Yang. 2019. What should I ask? using conversationally informative rewards for goal-oriented visual dialog. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 6442–6451, Florence, Italy. Association for Computational Linguistics.

Florian Strub, Harm de Vries, Jérémie Mary, Bilal Piot, Aaron C. Courville, and Olivier Pietquin. 2017a. End-to-end optimization of goal-driven and visually grounded dialogue systems. In Proceedings of the Twenty-Sixth International Joint Conference on Artificial Intelligence, IJCAI 2017, Melbourne, Australia, August 19-25, 2017, pages 2765–2771. ijcai.org.

Florian Strub, Harm de Vries, Jérémie Mary, Bilal Piot, Aaron C. Courville, and Olivier Pietquin. 2017b. End-to-end optimization of goal-driven and visually grounded dialogue systems. In Proceedings of the Twenty-Sixth International Joint Conference on Artificial Intelligence, IJCAI 2017, Melbourne, Australia, August 19-25, 2017, pages 2765–2771. ijcai.org.

Ece Takmaz, Mario Giulianelli, Sandro Pezzelle, Arabella Sinclair, and Raquel Fernández. 2020. Refer, Reuse, Reduce: Generating Subsequent References in Visual and Conversational Contexts. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 4350–4368, Online. Association for Computational Linguistics.

Hao Tan and Mohit Bansal. 2019. LXMERT: Learning cross-modality encoder representations from transformers. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 5100–5111, Hong Kong, China. Association for Computational Linguistics.

Hao Tan, Franck Demontcourt, Zhe Lin, Trung Bui, and Mohit Bansal. 2019. Expressing visual relationships via language. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 1873–1883, Florence, Italy. Association for Computational Linguistics.

Takuma Udagawa and Akiko Aizawa. 2019. A natural language corpus of common grounding under continuous and partially-observable context. In The Thirty-Third AAAI Conference on Artificial Intelligence, AAAI 2019, The Thirty-First Innovative Applications of Artificial Intelligence Conference, IAAI 2019, The Ninth AAAI Symposium on Educational Advances in Artificial Intelligence, EAAI 2019, Honolulu, Hawaii, USA, January 27 - February 1, 2019, pages 7120–7127. AAAI Press.

Takuma Udagawa and Akiko Aizawa. 2020. An annotated corpus of reference resolution for interpreting common grounding. In The Thirty-Fourth AAAI Conference on Artificial Intelligence, AAAI 2020, The Thirty-Second Innovative Applications of Artificial Intelligence Conference, IAAI 2020, The Tenth AAAI Symposium on Educational Advances in Artificial Intelligence, EAAI 2020, New York, NY, USA, February 7-12, 2020, pages 9081–9089. AAAI Press.

Unity Technologies. 2019. Unity. https://unity.com/.
Unity Technologies. 2020. Unity Perception package. https://github.com/Unity-Technologies/com.unity.perception.

Oriol Vinyals, Alexander Toshev, Samy Bengio, and Dumitru Erhan. 2015. Show and tell: A neural image caption generator. In IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2015, Boston, MA, USA, June 7-12, 2015, pages 3156–3164. IEEE Computer Society.

Yue Wang, Shafiq Joty, Michael Lyu, Irwin King, Caiming Xiong, and Steven C.H. Hoi. 2020. VD-BERT: A Unified Vision and Dialog Transformer with BERT. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 3325–3338, Online. Association for Computational Linguistics.

Yonghui Wu, Mike Schuster, Zhifeng Chen, Quoc V. Le, Mohammad Norouzi, Wolfgang Macherey, Maxim Krikun, Yuan Cao, Qin Gao, Klaus Macherey, Jeff Klingner, Apurva Shah, Melvin Johnson, Xiaobing Liu, Łukasz Kaiser, Stephan Gouws, Yoshikiyo Kato, Taku Kudo, Hideto Kazawa, Keith Stevens, George Kurian, Nishant Patil, Wei Wang, Cliff Young, Jason Smith, Jason Riesa, Alex Rudnick, Oriol Vinyals, Greg Corrado, Macduff Hughes, and Jeffrey Dean. 2016. Google’s neural machine translation system: Bridging the gap between human and machine translation.

Zipeng Xu, Fangxiang Feng, Xiaojie Wang, Yushu Yang, Huixing Jiang, and Zhongyuan Wang. 2020. Answer-Driven Visual State Estimator for Goal-Oriented Visual Dialogue, page 4271–4279. Association for Computing Machinery, New York, NY, USA.

Zipeng Xu, Fandong Meng, Xiaojie Wang, Duo Zheng, Chenxu Lv, and Jie Zhou. 2021. Modeling explicit concerning states for reinforcement learning in visual dialogue. In BMVC.

Zhou Yu, Jing Li, Tongan Luo, and Jun Yu. 2020. A pytorch implementation of bottom-up-attention. https://github.com/MILVLG/bottom-up-attention.pytorch.

Junjie Zhang, Qi Wu, Chunhua Shen, Jian Zhang, Jianfeng Lu, and Anton van den Hengel. 2017. Asking the difficult questions: Goal-oriented visual question generation via intermediate rewards. ArXiv preprint, abs/1711.07614.

Rui Zhao and Volker Tresp. 2018. Learning goal-oriented visual dialog via tempered policy gradient. In 2018 IEEE Spoken Language Technology Workshop (SLT), pages 868–875.

Duo Zheng, Zipeng Xu, Fandong Meng, Xiaojie Wang, Jiaan Wang, and Jie Zhou. 2021. Enhancing visual dialog questioner with entity-based strategy learning and augmented guesser. In Findings of the Association for Computational Linguistics: EMNLP 2021, pages 1839–1851, Punta Cana, Dominican Republic. Association for Computational Linguistics.

Mingyang Zhou, Josh Arnold, and Zhou Yu. 2019. Building task-oriented visual dialog systems through alternative optimization between dialog policy and language generation. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 143–153, Hong Kong, China. Association for Computational Linguistics.
A Image Generation

A.1 Taxonomy Information
We present the taxonomy information with a predefined hierarchical tree structure, which is illustrated in Table 6.

A.2 Placement Relationship
We empirically construct a directed graph of object placement relationship. As shown in Table 7, it describes which category of objects could be placed on a object of specific category.

A.3 Spatial Arrangement
Given an object \( o \) (the object to be placed), a rectangular area and existing objects, we put the unplaced object on the area as follows:

1) Randomly sample \( T \) points on the area.
2) Filter out the points whose distance from any existing object is less than \( X \) or that cross the boundary.
3) Select the point with the minimum L1 distance to its closet existing object, and place the object \( o \) at the point.

After taking screenshots, we retain the image where the pixels of objects in the image are all larger than \( Y \), to avoid the serious mutual occlusion between objects in the image.

A.4 Object Co-Occurrence
Considering the hierarchical tree structure of categories, we define the degree of divergence \( d_u \) for category \( u \) as:

\[
d_u = \sum_{v \in \text{child}(u)} [\exists o \in O \land v \in f(o)],
\]

where \( \text{child}(u) \) means the child categories of the category \( u \) (e.g., \( \text{child}(\text{fruit}) = \{\text{apple}, \text{banana}\} \)), \( O \) is the object list of the image, \( f(o) \) is the category set corresponding the object \( o \) (e.g., for an apple, its category set is \( \{\text{apple}, \text{fruit}, \text{food}\} \)), \([\] \) is 1 if and only the expression in the bracket is True.

To make the related objects co-occur with high probability, for each category \( u \), we limit \( d_u \) not to exceed \( K=3 \).

B Dialog Generation

B.1 Answer Action
The answer is divided into two types: 1) Count answer, which corresponds to the count question, gives the number of objects with specific conditions in the image. 2) Description answer responds to the extreme and refer questions, and describes one or multiple objects in natural language, e.g., ‘Black frame’, ‘A decorative plate, a nightstand and a plant’. 3) Attribute answer gives the specific attribute.

B.2 Templates
We present all templates used for dialogue generation in Table 8.

C Experiments

C.1 Implementation Details
We implement our method with Pytorch and conduct all experiments on four NVIDIA Tesla V100 GPU. For all models, we use Adam optimizer with a learning rate of \( 5e-5 \) and a mini-batch size of 32. We train QGen, A-Bot, Guesser for 10, 8, 30 epochs. For A-Bot and Guesser, we select the models with best accuracy on the val set. For QGen, we select the best performed model on the val set, under the game setting.

Formally, input sentences are tokenized by WordPiece (Wu et al., 2016) from BERT (Devlin et al., 2019). We follow Tan and Bansal (2019) to represent the visual features as a series of object representations, where objects are detected by the Faster-RCNN (Ren et al., 2015) pre-trained on Visual Genome (Krishna et al., 2016). For each object, its representation is a concatenation of pooling features provided by (Anderson et al., 2018; Yu et al., 2020) and 4-dim vector of relative bounding box.

C.2 Dialog System Performance Comparison
We implement different models for this task.

QGen. 1) GPT-2 (Radford et al., 2019): A decoder-only model with the pretrained language model GPT-2 as the backbone; 2) LXMERT (Tan and Bansal, 2019): Our benchmark QGen.
Figure 9: An Example of image scene graph. (a) gives a *SpotDiff* image and (b) displays its corresponding scene graph, where blue lines indicate placement relationships between objects.

![Image Scene Graph](image)

| QTYPE            | count-nohint | count-hint | extreme-pic | extreme-obj | extreme-obj2 | query-color | query-material | ref-it | ref-them | all  |
|------------------|--------------|------------|-------------|-------------|--------------|-------------|----------------|--------|----------|------|
| UpDn             | 68.89        | 75.86      | 74.12       | 66.57       | 64.47        | 84.51       | 79.00          | 86.27  | 71.77    | 73.49|
| LXMERT           | 83.23        | 87.59      | 82.92       | 81.54       | 76.75        | 91.02       | 88.54          | 88.78  | 85.63    | 85.89|

Table 5: A-Bot performance on various question subtypes. QTYPE means the question subtype.

**A-Bot.**
1) UpDn (Anderson et al., 2018): A representative VQA model with attention mechanism;
2) LXMERT: Our benchmark A-Bot.

As shown in Figure 4, row 4 (QGen: LXMERT, A-Bot: LXMERT) achieves the best performance among all comparing methods, demonstrating the superiority of multimodal pretrained model.

**C.3 A-Bot Performance Comparison**

We compare UpDn (Anderson et al., 2018) to LXMERT (Tan and Bansal, 2019) under VQA setting. As shown in Table C.3, LXMERT outperforms UpDn on all question subtypes, demonstrating the superiority of multimodal pretrained model.

**D Examples**

**D.1 Image Scene Graph**

We present an example of image scene graph in Figure 3.1.2.
| category                        | subcategories                                              |
|--------------------------------|------------------------------------------------------------|
| home appliance                 | large household appliance, small household appliance        |
| large household appliance      | fridge, television, floor lamp, washing machine            |
| small household appliance      | coffee machine, desk lamp                                  |
| furniture                      | table, chair, bench, sofa, nightstand, baby bed, cabinet, carpet, cloth tree, bed |
| table                          | dining table, tea table, study table                        |
| toy                            | animal toy, toy model                                      |
| animal toy                     | teddy bear, elephant toy, bunny toy, giraffe toy            |
| toy model                      | car model, airplane model, bike model, bus model           |
| food                           | fruit, drink, meat product, baked food                     |
| fruit                          | apple, banana, watermelon                                  |
| drink                          | cola, milk, tea, beer                                      |
| baked food                     | bread, pizza                                              |
| meta product                   | chicken leg, chicken nugget                                |
| sporting goods                 | ball, sports equipment                                    |
| ball                           | soccer, basketball, tennis, bowling pin                    |
| sports equipment               | bow, dumbbell, baseball bat, archery target, skateboard    |
| kitchenware                    | tableware, kettle                                         |
| tableware                      | plate, cup, fork, spoon                                    |
| office supply                  | stationery, office equipment, paper product                |
| stationery                     | pencil, palette                                           |
| paper product                  | paperbox, notebook                                        |
| office equipment               | computer, mouse, keyboard, headphone, plug plate, phone    |
| computer                       | laptop, desktop                                           |
| decoration                     | vase, decorative plate, frame                              |
| fashion item                   | fashion accessory, shoes, backpack                         |
| fashion accessory              | glasses, hat                                              |
| shoes                          | boots, sandals, canvas shoes                               |
| hat                            | cotton cap, top hat, baseball cap                          |

Table 6: The taxonomy information. The first column gives the category while the second column gives its corresponding subcategories.

| floor                          | furniture, shoes, fridge, floor lamp, trash can, plant, table |
|--------------------------------|---------------------------------------------------------------|
| dining table                   | kitchenware, drink, pizza, small household appliance, plate   |
| tea table                      | decoration, book, television, cup                             |
| study table                    | book, office supply, toy, sporting goods                      |
| carpet                         | tea table, toy, sporting goods, backpack                      |
| plate                          | fruit, bread, meat product                                   |
| nightstand                     | decoration, cup, glasses, hat                                 |
| cabinet                        | decoration                                                    |

Table 7: The placement relationship. The first column represents the category of objects, and the second column represents the categories that could be placed on objects of the category (in the first column).
Table 8: Templates used for dialog generation.