Ask No More: Deciding when to guess in referential visual dialogue

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Abstract

Our goal is to explore how the abilities brought in by a dialogue manager can be included in end-to-end visually grounded conversational agents. We make initial steps towards this general goal by augmenting a task-oriented visual dialogue model with a decision-making component that decides whether to ask a follow-up question to identify a target referent in an image, or to stop the conversation to make a guess. Our analyses show that adding a decision making component produces dialogues that are less repetitive and that include fewer unnecessary questions, thus potentially leading to more efficient and less unnatural interactions.

1 Introduction

The field of interactive conversational agents, also called dialogue systems, is receiving renewed attention not only within Computational Linguistics (CL) and Natural Language Processing (NLP) – its original and probably most natural locus – but also within the Machine Learning (ML) and the Computer Vision (CV) communities. The overarching challenge, in line with the long-term aims of Artificial Intelligence, is to develop data-driven agents that are capable of perceiving (and possibly acting upon) the external world and that we can collaborate with through natural language dialogue to achieve common goals.

Within the ML and CV communities, recent research on conversational agents combined with Deep Learning techniques has yielded interesting results on visually grounded tasks (Das et al., 2017a; de Vries et al., 2017; Mostafazadeh et al., 2017). In this line of research, the focus is mostly on improving model performance by investigating new machine learning paradigms (like reinforcement learning or adversarial learning) in end-to-end settings, where the model learns directly from raw data without symbolic annotations (Strub et al., 2017; Lu et al., 2017; Wu et al., 2017). Task accuracy, however, is not the only criterion by which a conversational agent should be judged. Crucially, the dialogue should be coherent, with no unnatural repetitions nor unnecessary questions — unlike the 5-turn dialogue shown in Figure 1. To achieve this, a conversational agent needs to learn a strategy to decide how to respond given the current context and the task at hand. These abilities are typically considered part of *dialogue management* and have been the focus of attention in dialogue systems research within the CL/NLP community (Larsson and Traum, 2000; Williams et al., 2008; Bohus and Rudnicky, 2009; Young et al., 2013).

Questioner	**Answerer**
1. Is it a person?	No
2. Is it the dog?	Yes
⇝ *success by our model*	
3. The dog?	Yes
4. Is it in the foreground?	No
5. Is it the whole dog?	Yes
⇝ *success by baseline model*	

Figure 1: Dialogue that leads to task success in the *GuessWhat?!* game by our model, which decides when to stop asking questions, and by the baseline model in de Vries et al. (2017), which does not.

In this paper, we thus take a step back: instead of focusing on learning paradigms, we focus on the system architecture. We argue that the time is ripe for exploring how the abilities brought in by a dia-

Data and code are available at https://vista-unitn-uva.github.io

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logue manager can be included in end-to-end conversational agents within the Deep Learning paradigm mostly put forward by the ML and CV communities. We make initial steps towards this general goal by augmenting the task-oriented visual dialogue model proposed by de Vries et al. (2017), not yet with a full-fledged dialogue manager, but with a decision-making component that decides whether to ask a follow-up question to identify a target referent in an image, or to stop the conversation to make a guess (see Figure 1). Our focus is on providing a thorough analysis of the resulting dialogues. Our results show that the presence of a decision making component leads to dialogues that are less repetitive and that include fewer unnecessary questions.

2 Related Work

Our system operates on both linguistic and visual information. Visually-grounded dialogue has experienced a boost in recent years, in part thanks to the construction of large visual human-human dialogue datasets built by the Computer Vision community (Mostafazadeh et al., 2017; Das et al., 2017a; de Vries et al., 2017). These datasets include two participants, a Questioner and an Answerer, who ask and answer questions about an image. For example, in the *GuessWhat?!* dataset developed by de Vries et al. (2017), which we exploit in the present work, a Questioner agent needs to guess a target object in a visual scene by asking yes-no questions (more details are provided in the next section).

Research on visually-grounded dialogue within the Computer Vision community exploits encoder-decoder architectures (Sutskever et al., 2014) — which have shown some promise for modelling chatbot-style dialogue (Vinyals and Le, 2015; Sordoni et al., 2015; Serban et al., 2016; Li et al., 2016a; Li et al., 2016b) — augmented with visual features. This community has mostly focused on model learning paradigms. Initial models, proposed by de Vries et al. (2017) and Das et al. (2017a), use supervised learning (SL): the Questioner and the Answerer are trained to generate utterances (by word sampling) that are similar to the human gold standard. To account for the intuition that dialogues require some form of planning, subsequent work by Das et al. (2017b) and Strub et al. (2017) makes use of reinforcement learning (RL). In all these approaches but Strub et al. (2017), however, the Questioner performs a non-linguistic action (i.e., selects an image or object within an image) after a fixed number of question-answer rounds. Thus, there is no decision making on whether further questions are or are not needed to identify a visual target. To address this limitation, Strub et al. (2017) put forward a more flexible approach: They let the Questioner ask at most 8 questions, but introduce an extra token (`stop`) within the vocabulary, which the question generation model has to learn. This strategy, however, is suboptimal: The question generator needs to generate probabilities for items that do not lie on the same distribution (the distribution of natural language words vs. the distribution of binary decisions *ask*/*guess*).[1] Our work addresses this limitation in a more principled way, by including a new decision-making module within the encoder-decoder architecture and analysing its impact on the resulting dialogues.

We build on work by the dialogue systems community. In traditional dialogue systems, the basic system architecture includes several components – mainly, a language interpreter, a dialogue manager, and a response generator – as discrete modules that operate in a pipeline (Jurafsky and Martin, 2009; Jokinen and McTear, 2009) or in a cascading incremental manner (Schlangen and Skantze, 2009; Dethlefs et al., 2012). The *dialogue manager* is the core component of a dialogue agent: it integrates the semantic content produced by the interpretation module into the agent's representation of the context (the *dialogue state*) and determines the next action to be performed by the agent, which is transformed into linguistic output by the generation module. Conceptually, a dialogue manager thus includes both (i) a *dialogue state tracker*, which acts as a context model that ideally keeps track of aspects such as current goals, commitments made in the dialogue, entities mentioned, and the level of shared understanding among the participants (Clark, 1996); and (ii) an *action selection policy*, which makes decisions on how to act next, given the current dialogue state. In the present work, we focus on incorporating a *decision-making module* akin to an action selection policy into a visually-grounded encoder-decoder architecture and leave

[1] We also note that on the *GuessWhat?!* GitHub page at `https://github.com/GuessWhatGame/guesswhat` it is mentioned that in the updated version of the system by Strub et al. (2017) "qgen [the question generator] stop learning to stop" (GitHub accessed on 16/03/2018).

the integration of other more advanced dialogue management aspects for future work.

In particular, work on incremental dialogue processing, where a system needs to decide not only *what* to respond but also *when* to act (Rieser and Schlangen, 2011), has some similarities with the problem we address in the present paper, namely, when to stop asking questions to guess a target.[2] Researchers within the dialogue systems community have applied different approaches to design incremental dialogue policies for how and when to act. Two common approaches are the use of rules parametrised by thresholds that are optimised with human-human data (Buß et al., 2010; Ghigi et al., 2014; Paetzel et al., 2015; Kennington and Schlangen, 2016) and the use of reinforcement learning (Kim et al., 2014; Khouzaimi et al., 2015; Manuvinakurike et al., 2017). For example, Paetzel et al. (2015) implement an agent that aims to identify a target image out of a set of images given descriptive content by its dialogue partner. Decision making is handled by means of a parametrised rule-based policy: the agent keeps waiting for additional descriptive input until either her confidence on a possible referent exceeds a given threshold or a maximum-time threshold is reached (in which case the agent gives up). The thresholds are set up by optimising points per second on a corpus of human-human dialogues (pairs of participants score a point for each correct guess). In a follow-up paper by Manuvinakurike et al. (2017), the agent's policy is learned with reinforcement learning, achieving higher performance.

We develop a decision-making module that determines, after each question-answer pair in the visually grounded dialogue, whether to ask a further question or to pick a referent in a visual scene. We are interested in investigating the impact of such a module in an architecture that can be trained end-to-end directly from raw data, without specific annotations commonly used in dialogue systems, such as dialogue acts (Paetzel et al., 2015; Manuvinakurike et al., 2017; Kennington and Schlangen, 2016), segment labels (Manuvinakurike et al., 2016), dialogue state features (Williams et al., 2013; Young et al., 2013; Kim et al., 2014), or logical formulas (Yu et al., 2016).

3 Dataset

To develop our model and perform our analyses, we use the *GuessWhat?!* dataset,[3] a dataset of approximately 155k human-human dialogues created via Amazon Mechanical Turk (de Vries et al., 2017). *GuessWhat?!* is a cooperative two-player game: both players see an image with several objects; one player (the Oracle) is assigned a target object in the image and the other player (the Questioner) has to guess it. To do so, the Questioner has to ask Yes/No questions to the Oracle. When the Questioner thinks he/she can guess the object, the list of objects is provided and if the Questioner picks the right one the game is considered successful. No time limit is given, but the Questioner can leave the game incomplete (viz. not try to guess). The set of images and target objects has been built from the training and validation sections of the MS-COCO dataset (Lin et al., 2014) by only keeping images that contain at least three and at most twenty objects and by only considering target objects whose area is big enough to be located well by humans ($area > 500px^2$). Further details are provided in Appendix A.

4 Models

de Vries et al. (2017) develop models of the Questioner and Oracle roles in *GuessWhat?!*. We first describe their models, which we consider as our baseline, and then describe our modified Questioner model. As explained below, de Vries et al. (2017) model the Questioner role by means of two disconnected modules: a Question Generator (QGen) and a Guesser, that are trained independently. After a fixed number of questions by QGen, the Guesser selects a candidate object. We propose and evaluate a model of the Questioner role that incorporates a decision-making component that connects the tasks of asking and guessing (which we take to be part of the planning capabilities of a single agent) and offers more flexibility regarding the number of questions asked to solve the game.

[2] Our system is not word-by-word incremental at this point, but given the incremental nature of encoder-decoder architectures, an extension in this direction should be possible. We leave this for future work.

[3] Available at: `https://guesswhat.ai/`

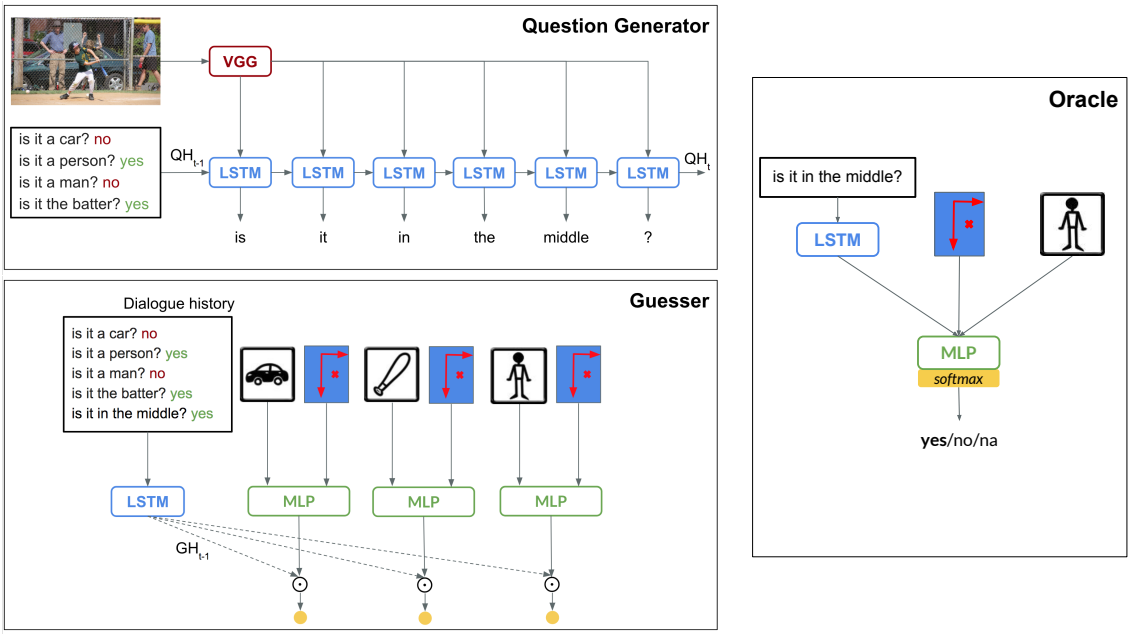

Figure 2: Baseline models. Lefthand side: Independent modules for the Questioner model: Question Generator (top) and Guesser (bottom). Righthand side: Oracle model.

4.1 Baseline Models

We provide a brief description of the models by de Vries et al. (2017), which we re-implement for our study. Further details on the implementation of each module are available in Appendix A.

Question Generator (QGen) This module is implemented as a Recurrent Neural Network (RNN) with a transition function handled with Long-Short-Term Memory (LSTM), on which a probabilistic sequence model is built with a Softmax classifier. Given the overall image (encoded by extracting its VGG features) and the current dialogue history (i.e. the previous sequence of questions and answers), QGen produces a representation of the visually grounded dialogue (the RNN's hidden state QH_{t-1} at time $t-1$ in the dialogue) that encodes information useful to generate the next question q_t. See the sketch on the top-right part of Figure 2.

Guesser The best performing model of the Guesser module by de Vries et al. (2017) represents candidate objects by their object category and spatial coordinates. These features are passed through a Multi-Layer Perceptron (MLP) to get an embedding for each object. The Guesser also takes as input the dialogue history processed by an LSTM, whose hidden state GH_{t-1} is of the same size as the MLP output. A dot product between both returns a score for each candidate object in the image. A diagram of the architecture is given on the bottom-right section of Figure 2.

Oracle The Oracle is aware of the target object and answers each question by QGen with Yes, No, or Not Applicable. The best performing model of the Oracle module by de Vries et al. (2017) takes as input embeddings of the target object category, its spatial coordinates, and the current question. These embeddings are concatenated into a single vector and fed to an MLP that outputs the answer, as illustrated in Figure 2, righthand side.

4.2 Our Questioner Model

We extend the Questioner model of de Vries et al. (2017) with a third module, a decision making component (DM) that determines, after each question/answer pair, whether QGen should *ask* another question or whether the Guesser should *guess* the target object. We treat this decision problem as a binary classification task, for which we use an MLP followed by a Softmax function that outputs probabilities for the two classes of interest: *ask* and *guess*. The Argmax function then determines the class of the next action.

With this approach, we bypass the need to specify any decision thresholds and instead let the model learn whether enough evidence has been accumulated during the dialogue so far to let the Guesser pick up a referent.[4]

We experimented with two versions of the DM component, DM1 and DM2, which differ with respect to the encoding of the linguistic input they have access to. Both decision makers have access to the image and implicitly to the linguistic dialogue history: DM1 exploits the dialogue encoding learned by QGen's LSTM, which is trained to record information relevant for generating a follow-up question. In contrast, DM2 leverages the dialogue encoding learned by the Guesser's LSTM, which is trained to capture the properties of the linguistic input that are relevant to make a guess. The two versions are illustrated in Figure 3. The DM takes as input the concatenation (s_t) of the visual features and of the dialogue history representation it gets either via QGen's hidden state QH_{t-1} (DM1) or the Guesser's hidden state GH_{t-1} (DM2). The resulting vector is passed through a MLP. The output is then scaled between 0 and 1 by the Softmax function and treated as a probability distribution.

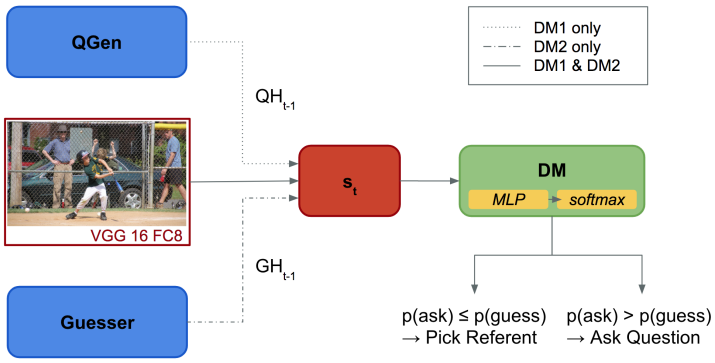

Figure 3: Our Questioner Model with two versions of the Decision Making module, DM1 and DM2.

We also implemented a hybrid DM module that receives as input both QH_{t-1} and GH_{t-1}, but we obtained worse performance. Instead of insisting on the hybrid architecture (left for future work), we maintain the two versions, DM1 and DM2, separated here so that we can focus on investigating their differences and their complementary contributions.[5]

5 Experiments and Results

Next, we present our experimental setup and accuracy results. In Section 6 we then provide an in-depth analysis of the games and dialogues.

5.1 Experimental setup

The modules in the system by de Vries et al. (2017) (QGen, Guesser, and Oracle) are trained independently with supervised learning. To allow for direct comparison with their model, we follow the same setup for training the three original modules and also our new decision making module. Details on hyperparameter settings are provided in Appendix A. We use the same train, validation, and test sets as de Vries et al. (2017).

Both DM1 and DM2 are trained with Cross Entropy loss in a supervised manner, which requires decision labels for the dialogue state after each question/answer pair. We use two different approaches to obtain decision labels from the *GuessWhat?!* ground truth dialogues. In the first approach, the question/answer pairs are labelled based on the human decision to *ask* or *guess*, obtained by checking whether there is a follow-up question in the human-human dialogues. We refer to this paradigm as *gt-label* (*gt* for *ground truth*). In the second approach, we label the question/answer pairs based on whether the Guesser module is able to correctly predict the target object given the current dialogue fragment. If the Guesser

[4]Note also that, since we have separate states for *ask* and *guess* decisions, we could potentially extend the approach to decide among multiple action types beyond the binary case.

[5]In principle, a decision-making module could also leverage the entropy of the scores for each candidate object produced by the Guesser. However, given the setup of the baseline Guesser (which we keep untouched for comparability), this would lead to implicitly using the symbolic object categories and spatial coordinates of each candidate object. This information, however, is not available to the humans at the time of deciding whether to guess or to continue asking: the list of candidate targets only becomes available once a participant decides to guess. Our DM modules only use the raw visual features, and thus are in a similar position to humans performing the task.

MaxQ	5	8	10	12	20	25	30
Baseline	41.18	40.7	39.8	38.96	36.02	35.918	35.88
DM1	40.45 (4.62)	40.12 (6.17)	40.02 (6.70)	40.00 (6.97)	39.87 (7.14)	39.68 (7.14)	39.68 (7.14)
DM2	42.19 (4.53)	41.30 (7.22)	41.12 (8.71)	39.73 (10.72)	37.75 (13.39)	36.86 (13.47)	36.83(13.51)

Table 1: Accuracy on the entire test set (all games, viz. including successful, unsuccessful, decided and undecided ones) for task success by varying the maximum number of questions allowed (MaxQ). Within brackets, the average number of questions asked for each setting. The baseline model always asks the maximum number of questions allowed.

module is able to make a correct prediction after a given question/answer pair, we label that dialogue state with *guess* and otherwise with *ask*. This is referred to as *guess-label*. DM1 can only be trained with *gt-label* (since it does not have access to information coming from the Guesser). For DM2, we treat the choice between these two labelling approaches as a hyperparameter to be tuned on the validation set. DM2 achieves better results when trained with *guess-label*. Experiments on the test set are then conducted with the optimal settings.

5.2 Accuracy Results

We first report results on task accuracy, i.e., the percentage of games where the task is successfully accomplished. Human accuracy is 90.8%. Humans can ask as many questions as they like and, on average, they guess after having asked 5.12 questions. Table 1 gives an overview of the accuracy results obtained by the baseline model, which always asks a fixed number of questions, and by our extended model with the two different versions of the DM, which decides when to ask or guess. We report the accuracy of our re-implementation of the baseline system, which is slightly better than the one reported by de Vries et al. (2017) for 5 questions.[6] To highlight the impact of including a DM module, we report the accuracies the models achieve when changing the maximum number of questions allowed (MaxQ). When MaxQ = 5, the accuracies of the model enriched with a DM module are very similar to the baseline model (slightly lower for DM1: 40.45%, and slightly higher for DM2: 42.19%), and the average number of questions asked by the DM models is also comparable to the 5 questions asked by the baseline, namely 4.62 (DM1) and 4.53 (DM2). However, if we observe how the model accuracy varies when increasing MaxQ, we see that the models equipped with a DM module tend to perform better than the baseline model and that they do so by asking fewer questions than the baseline on average. Furthermore, of the two models enriched with a decision maker, DM1 is more stable across the various settings both in terms of accuracy and of number of questions asked.

In the following analysis, unless indicated otherwise, we consider the baseline model with 5 questions, because it yields the highest baseline accuracy, and the DM models with MaxQ = 10, because more than 90% of the games solved by humans contain up to 10 questions.

6 Analysis

To better understand the results reported above and to gain insight on how the inclusion of a decision making component affects the resulting dialogues, we carry out an analysis of the behaviour of our models. We first examine how the complexity of the game (as determined by visual properties of the image) affects performance, and then analyse the quality of the linguistic interaction from the perspective of the Questioner role.

6.1 Complexity of the Game

Intuitively, the more complex the image involved in a round of the game, the harder it is to guess the target object. As a proxy for image complexity, we consider the following measures: (i) the number of objects in the image, (ii) the number of objects with the same category as the target object, and (iii) the

[6] de Vries et al. (2017) report an accuracy of 34% with a fixed number of 5 questions, while 40.8% is reported on the first author's GitHub page. Our re-implementation of the Oracle and Guesser obtain an accuracy of 78.47% (78.5) and 61.26% (61.3), respectively (in brackets, the original accuracies reported by de Vries et al. (2017)).

	successful vs. *unsuccessful*					*decided* vs. *undecided*	
	all games			decided games		all games	
	Baseline	DM1	DM2	DM1	DM2	DM1	DM2
# objects	-0.213094	-0.212920	-0.217468	-0.220929	-0.23967	-0.05292	0.144233
# objects same cat. as target	-0.150294	-0.144740	-0.150090	-0.148251	-0.165415	-0.058392	0.087068
% target object's area	4.88720	4.254	3.82114	4.15606	7.0496	1.59634	-2.38053

Table 2: Estimated regression coefficients for the logistic regression models distinguishing between *successful* vs. *unsuccessful* and *decided* vs. *undecided* games. A positive/negative coefficient indicates a positive/negative correlation between a predictor and the probability of the *successful* or *decided* class. The contribution of all predictors is statistically significant in all models ($p < 0.0001$).

size of the target object, which we compute in terms of the proportion of the cropped target object area with respect to the whole image. The distribution of games in the whole dataset is fairly balanced across these factors. See Appendix B for full details.

We fit a linear logistic regression model for the task of predicting whether a game will be successful or unsuccessful (i.e., whether the right target object will be selected), using the three measures above as independent predictor variables. It should be noted that in some cases our Questioner model may reach the maximum number of 10 questions without ever taking the action to guess. We refer to these games as *undecided*, whereas we call *decided* games those games where the DM lets the Guesser pick a referent within the maximum number of questions allowed. Out of the whole test set, the amount of decided games is 77.67% and 15.58% for DM1 and DM2, respectively.[7] It is critical to take this into account, since cases where the model is simply forced to make a guess are less informative about the performance of the DM module. Therefore, we fit two additional logistic regression models using the same three predictors: one where we consider only decided games and predict whether they are *successful* or *unsuccessful*, and one where the dependent variable to be predicted are the *decided* vs. *undecided* status of a game.

In Table 2, we report the regression coefficients for the different logistic regression models, estimated with iteratively reweighted least squares.[8] Plots of the predictor variables are available in Appendix B. Regarding the distinction between successful and unsuccessful games, we observe that the three image complexity measures we consider play a significant role. The three models (baseline, DM1, and DM2) are more likely to succeed in games that are intuitively easier — i.e., when the image contains fewer objects overall and fewer objects of the same category as the target (negative coefficients), and when the relative size of the target object is larger (positive coefficients). Interestingly, when we look into the distinction between decided and undecided games, we observe different behaviour for the two versions of the DM module. While DM1 tends to make a decision to stop asking questions and guess in easier games, surprisingly DM2 is more likely to make a guessing decision when the image complexity is higher (note the contrasting tendency of the coefficients in the last column of Table 2 for DM2). However, similarly to DM1, once DM2 decides to guess (decided games in Table 2), the simpler the image the more likely the model is to succeed in picking up the right target object.

6.2 Quality of the Dialogues

As stated in the introduction, we believe that a good visual dialogue model should not only be measured in terms of its task success but also with respect to the quality of its dialogues. In particular unnatural repetitions and unnecessary questions should be avoided. Hence, here we look into the dialogues produced by the different Questioner models comparing them with respect to these two criteria.

[7] To understand the rather big difference between the number of decided games in DM1 and DM2, we also evaluated the models using ground truth data for the QGen and Oracle modules. When human-human dialogues are used as input, the percentage of decided games is high and virtually identical for the two versions of the DM module (81.31% for DM1 and 81.30 for DM2.) This shows that DM2 is affected much more than DM1 by the errors produced by other modules. We leave an analysis of this aspect to future work. Throughout the present paper, all results and analyses reported are not based on ground truth data, but on the representations automatically generated by other modules.

[8] We use the R implementation of the logistic regression algorithm.

	All games						Decided games			
	Overall			Objects			Overall		Objects	
	Baseline	DM1	DM2	Baseline	DM1	DM2	DM1	DM2	DM1	DM2
across-games	98.07%	74.66%	84.05%	44.88%	32.94%	40.10%	69.18%	7.90%	67.05%	7.79%
within-game	45.74%	23.34%	39.27%	18.38%	11.61%	16.42%	31.28%	12.52%	30.06%	12.36%

Table 3: Percentages of repeated questions in all games and in decided games. Overall: all types of questions; Objects: only questions mentioning a candidate target object. All differences between the baseline and our models are statistically significant (Welch t-test with $p < 0.0001$).

Repeated questions Qualitative examination of the dialogues shows that the Questioner models often ask the same question over and over again. This results in unnatural linguistic interactions that come across as incoherent — see, for example, the dialogue in Figure 4 (bottom part). We analyse the dialogues produced by the models in terms of the amount of repetitions they contain. For the sake of simplicity, we only consider repeated questions that are exact string matchings (i.e., verbatim repetitions of entire questions). In this case, we consider the baseline model that asks 10 questions, as this makes for a fairer comparison with our models, where MaxQ = 10 (see end of Section 5).

Table 3 reports the percentage of dialogues that contain at least one repeated question (across-games) and the percentage of repeated questions within a dialogue averaged across games (within-game). We check the percentages with respect to both all the games and only decided games. When considering all games, we find that the baseline model produces many more dialogues with repeated questions (98.07% vs. 74.66% for DM1 and 84.05% for DM2) and many more repeated questions per dialogue (45.74% vs. 23.34% for DM1 and 39.27% for DM2) than our DM models. Among our models, the dialogues by DM1 are less repetitive than those by DM2. However, the difference between the two DM models is reversed when zooming into the decided games.

Our method for quantifying repeated questions is clearly simplistic: questions that have an identical surface form may not count as mere repetitions if they contain pronouns that have different antecedents. For example, a question such as "Is it the one on the left?" could be asked twice within the same dialogue with different antecedents for the anaphoric phrase "the one". In contrast, several instances of a question that includes a noun referring to a candidate object (such as "Is it a dog?") most probably are true repetitions that should be avoided. Therefore, as a sanity check, we perform our analysis taking into account only questions that mention a candidate object.[9] As shown in Table 3, this yields the same patterns observed when considering all types of questions.

Unnecessary questions Another feature of the dialogues revealed by qualitative examination is the presence of questions that are not repetitions of earlier questions but that, in principle, are not needed to successfully solve the game given the information gathered so far. For example, the last three questions in the dialogue in Figure 1 in the Introduction are not necessary to solve the game, given the evidence provided by the first two questions. By including a decision making component, our models may be able to alleviate this problem. In this analysis, we compare the baseline system that asks 5 questions to our models with MaxQ = 10 and look into cases where our models ask either fewer or more questions than the baseline.

Table 4 provides an overview of the results. When considering all the games, we see that the DM models ask many more questions (64.43% DM1 and 85.14% DM2) than the baseline. This is not surprising, since many games are undecided (see Section 6.1) and hence contain more questions than the baseline (10 vs. 5). Zooming into decided games thus allows for a more appropriate comparison. Table 4 also includes information on whether asking fewer or more questions helps (+ Change), hurts (– Change) or does not have an impact on task success (No Change) with respect to the baseline results. We observe that DM2 dramatically decreases the number of questions: in 95.17% of decided games, it asks fewer questions than the baseline; interestingly, in only 13.98% of cases where it asks fewer questions its performance is worse than the baseline — in all the other cases, either it achieves the same success

[9] A list of objects is provided in Appendix C.

	Decided games								All games	
DM	+ Change		– Change		No Change		Total		Total	
	Fewer	More	Fewer	More	Fewer	More	Fewer	More	Fewer	More
DM1	1.77	3.46	2.64	3.79	22.58	50.35	26.99	57.6	22.63	64.43
DM2	25.01	0.16	13.98	0.81	56.18	3.67	95.17	4.64	14.83	85.14

Table 4: Games played by DM with MaxQ=10, and the baseline with 5 fixed questions. Percentages of games (among all games and only decided games) where the DM models ask either fewer or more questions than the baseline. For the decided games, percentages of games where asking fewer/more questions helps (+ Change), hurts (– Change) or does not have an impact on task success w.r.t. the baseline result (No Change).

is it a person?	No		
is it an elephant?	Yes		
is it in the middle?	Yes	(DM2)	(status: success)
is it the one on the left?	Yes	(DM1)	(status: failure)
is it the one on the right?	Yes	(baseline)	(status: failure)

is it a person?	No		
is it on the table?	Yes		
is it in the front?	Yes		
is it in the front?	Yes		
is it in the left?	Yes	(baseline)	(status: failure)
is it in the 1st one?	Yes		
is it in the 1st one?	Yes	(DM1)	(status: success)

Figure 4: Examples where our model achieves task success by asking fewer or more questions than the baseline. Answers in red highlight Oracle errors. QGen often produces repeated or incoherent questions.

(56.18%) or even improves on the baseline results (25.01%). The latter shows that DM2 is able to reduce the number of unnecessary questions, as illustrated in Figure 1. On the other hand, DM1 does not seem to reduce the number of unnecessary questions in a significant way.

6.3 Discussion

Our analyses show that using a decision making component produces dialogues with fewer repeated questions and can reduce the number of unnecessary questions, thus potentially leading to more efficient and less unnatural interactions. Indeed, for some games not correctly resolved by the baseline system, our model is able to guess the right target object by asking fewer questions. DM2 is substantially better at this than DM1 (25.01% vs. 1.77% of decided games; see Table 4). By being restricted to a fixed number of questions, the baseline system often introduces noise or apparently forgets about important information that was obtained with the initial questions. Thanks to the DM component, our model can decide to stop the dialogue once there is enough information and make a guess at an earlier time, thus avoiding possible noise introduced by Oracle errors, as illustrated in Figure 4 (left). Qualitative error analysis, however, also shows cases where the DM makes a premature decision to stop asking questions before obtaining enough information. Yet in other occasions, the DM seems to have made a sensible decision, but the inaccuracy of the Oracle or the Guesser components lead to task failure. Further examples are available in Appendix D.

In some games with complex images, the information obtained with 5 questions (as asked by the baseline) is not enough to resolve the target. The flexibility introduced by the DM allows our model to reach task success by asking additional questions. Figure 4 (right) gives an example. Furthermore, if noise has been introduced at earlier stages of the dialogue, asking further questions can increase the chance to recover relevant information. However, we also observe that in some games correctly guessed

by the baseline system, asking more questions leads to failure since it opens the door to getting wrong information from the Oracle.

In the current analyses, we have not studied the behaviour of our DM models when using ground truth data instead of the noisy automatic output produced by the other modules. In part, this is motivated by our long-term goal of developing fully data-driven multimodal conversational agents that can be trained end-to-end. We leave for future work carrying out a proper ablation study that analyses the impact of using ground truth vs. automatic data on the DM component.

7 Conclusion

Research on dialogue systems within the Computational Linguistics community has shown the importance of equipping such systems with dialogue management capabilities. Computer Vision researchers have launched the intriguing Visual Dialogue challenge mostly focusing on comparing strong machine learning paradigms on task accuracy, and largely ignoring the aforementioned line of research on dialogue systems. Our goal is to explore how data-driven conversational agents, modelled by neural networks without additional annotations usually exploited by traditional dialogue systems, can profit from a dialogue management module. The present work is a first step towards this long-standing goal. We have taken the *GuessWhat?!* task as our testbed, since it provides a simple setting with elementary question-answer sequences and is task-oriented, which opens the door to using an unsupervised approach in the future. We have focused on augmenting the Questioner agent of the *GuessWhat?!* baseline, which consists of a Question Generator and a Guesser module, with a decision making component (DM) that determines after each question-answer pair whether the Question Generator should ask another question or whether the Guesser should guess the target object. The solution we propose is technically simple, and we believe promising and more cognitive principled than, for example, including a `stop` token as Strub et al. (2017). We show that incorporating a decision making component does lead to less unnatural dialogues. It remains to be seen whether a hybrid DM module that exploits the dialogue encodings of both the Question Generator and the Guesser modules could bring further qualitative and quantitative improvements.

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Appendix A: Details of *GuessWhat?!* Dataset and Experimental Setup

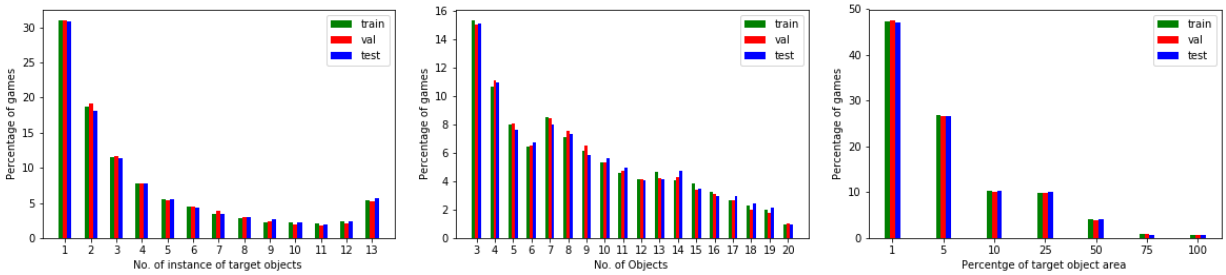
Dataset. The GuessWhat?! dataset contains 77,973 images with 609,543 objects and around 155K human-human dialogues. The dialogues contain around 821K question/answer pairs composed out of 4900 words (counting only words that occur at least 3) on 66,537 unique images and 134,073 target objects. Answers are Yes (52.2%), No (45.6%) and NA (not applicable, 2.2%); dialogues contain on average 5.2 questions and there are on average 2.3 dialogues per image. There are successful (84.6%), unsuccessful (8.4%) and not completed (7.0%) dialogues.

Games and Experimental Setting. In the baseline model, games consist of 5 turns each consisting of question/answer pairs asked by QGen and answered by the Oracle. The QGen module stops asking questions after having received the answer to the 5th question. It is then the turn of the Guesser.

All the modules are trained independently using Ground Truth data. For the visual features, 'fc8' of the VGG-16 network is used. Before visual feature calculation, all images are resized to 224X224. For each object, the module receives the representation of the object category, viz., a dense category embedding obtained from its one-hot class vector using a learned look-up table, and its spatial representation, viz., an 8-dimensional vector. The dialogue is encoded using variable length LSTM with 512 hidden size for Guesser and Oracle and 1024 hidden size for QGen. The LSTM, object category/word look-up tables and MLP parameters are optimized while training by minimizing the negative log-likelihood of the correct answer using ADAM optimizer with learning rate 0.001 for Guesser and Oracle. For QGen, the conditional log-likelihood is maximized based on the next question given the image and dialogue history. All the parameters are tuned on the validation set, training is stopped when there is no improvement in the validation loss for 5 consecutive epochs and best epoch is taken.

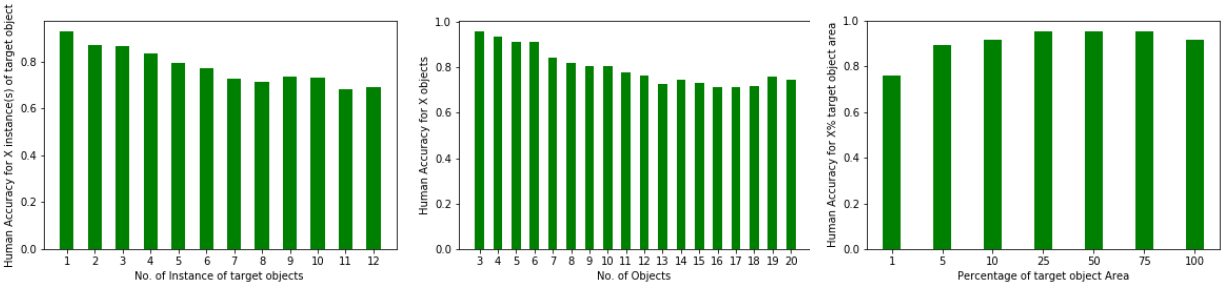
Appendix B: Analysis Regarding Image Complexity

Distribution of image complexity measures. Figure 5 shows the image distribution across the train, validation and test sets with respect to the image complexity measures, namely (a) the number of instances of the target object, (b) the number of objects, and (c) the percentage of target object area with respect to the overall image. We can see that the distribution with respect to these measures is very similar in the three sets. Figure 6 provides human performance based on the different image complexity measures. Human performance is similar to the model performance. While human accuracy is comparatively high, it also decreases when the image complexity increases.



(a) # instances of target object. (b) # of objects. (c) % area covered by target object.

Figure 5: Image distribution with respect to the image complexity measures in the different dataset splits.

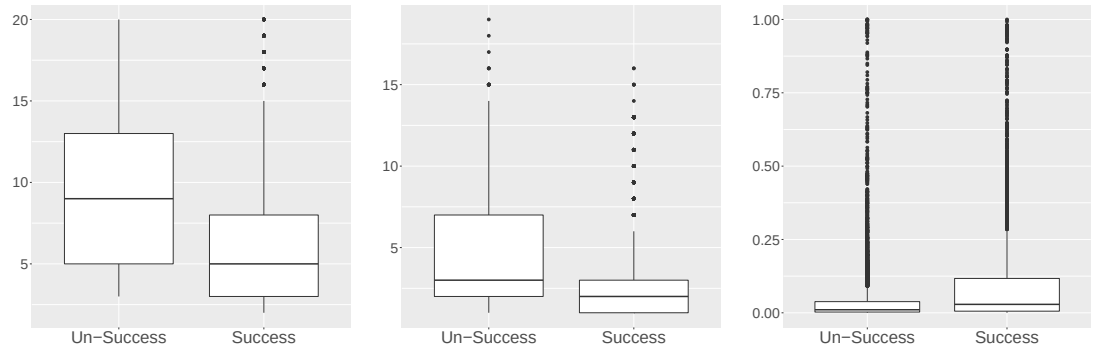


(a) no. of instances of target object. (b) no. of objects. (c) % area covered by target object.

Figure 6: Human accuracy distribution with respect to the image complexity features.

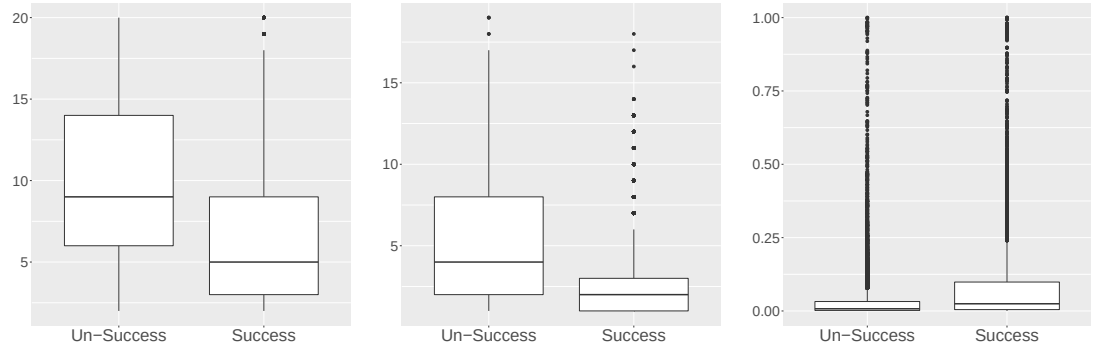
Image complexity measures as predictors in the logistic regression models. Figures 7 and 8 show plots of the image complexity measures in successful vs. unsuccessful games, for all games played by DM1 and DM2. As already noted in Section 6.1, fewer instances of the target object, fewer objects, and larger area of the target object correspond to higher chance of the game being successful, similarly to what we had noticed for humans. We observe the same trend when we restrict the analysis to decided games only, as shown in Figures 9 and 10 for DM1 and DM2, respectively

Figures 11 and 12 compare decided vs. undecided games played by the two DMs. In this case, we observe a difference: DM1 seems to exploit the image complexity measures in a way similar to humans, as noted earlier. DM2, however, decides more often when there are more instances of the target object and when the number of objects in the image is higher. Why this is the case remains unclear.



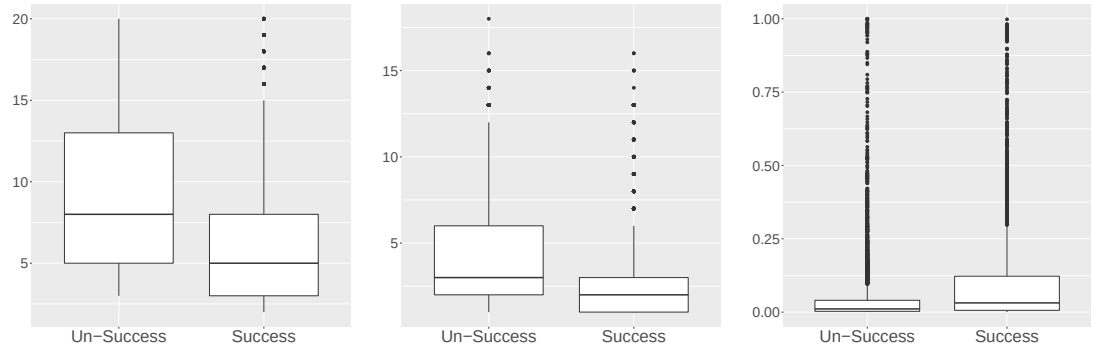
(a) no. of instances of target object. (b) no. of objects. (c) % area covered by target object.

Figure 7: Effect of image complexity measures on successful vs. unsuccessful games played by DM1.



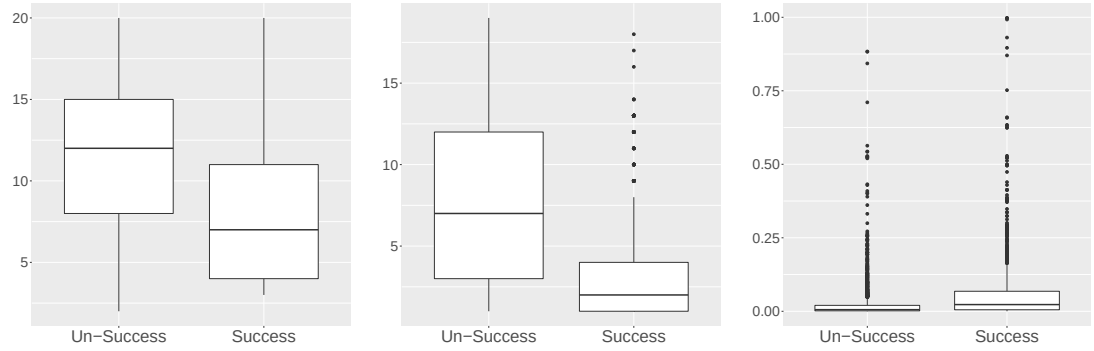
(a) # of instances of target object. (b) # of objects. (c) % area covered by target object.

Figure 8: Effect of image complexity measures on successful vs. unsuccessful games played by DM2.



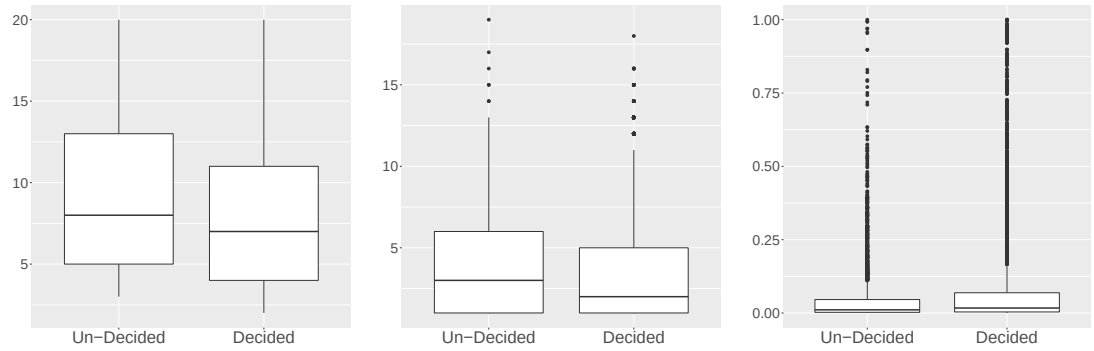
(a) # of instances of target object. (b) # of objects. (c) % area covered by target object.

Figure 9: Effect of image complexity measures on successful vs. unsuccessful *decided games* by DM1.



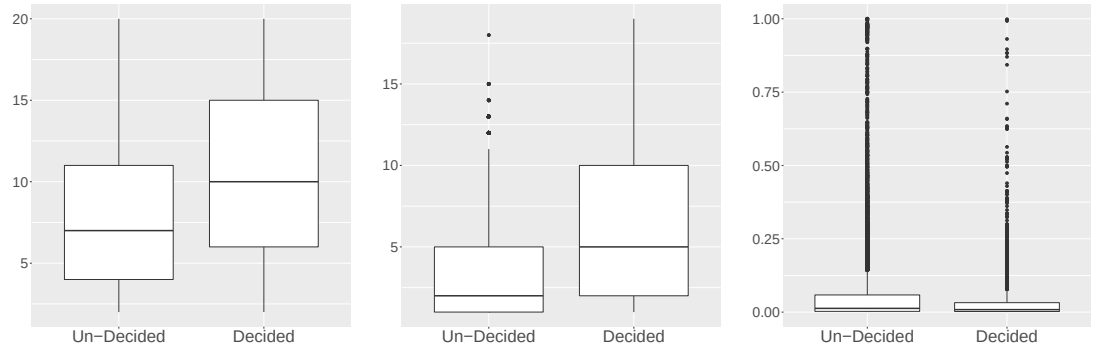
(a) # of instances of target object. (b) # of objects. (c) % area covered by target object.

Figure 10: Effect of image complexity measures on successful vs. unsuccessful *decided games* by DM2.



(a) no. of instances of target object. (b) no. of objects. (c) % area covered by target object.

Figure 11: Effect of image complexity measures on decided vs. undecided games played by DM1.



(a) no. of instances of target object. (b) no. of objects. (c) % area covered by target object.

Figure 12: Effect of image complexity measures on decided vs. undecided games played by DM2.

Appendix C: Repeated Questions

To automatically find the repeated questions in a generated game (see Section 6.2), we have used full string matching, i.e., a question is considered a repetition only when there is another question in the same game having exactly the same words. We have considered repetitions for three types of questions, namely, questions about Object type, Attributes, and Spatial location. Keyword matching is used to decide the type of question that is repetition. For instance, a repeated question is of Object type if it contains keywords such as 'dog', 'cat', etc. These keywords are created using MS-COCO object categories and super-categories, plus the following manually curated list: [man, woman, girl, boy, table, meter, bear, cell, phone, wine, glass, racket, baseball, glove, hydrant, drier, kite].

Appendix D: Example Dialogues

We provide some more examples of successful and unsuccessful games.

(1.) Is it a person? Yes
(2.) Is it the girl? Yes (DM2) (Success)
(3.) Is she in the background? No
(4.) Is she in the background? No
(5.) Is she wearing a white shirt? No (Baseline)(Fail)

(1.) Is it a bike? No
(2.) Is it a car? No
(3.) Is it a bike? No
(4.) Is it a person? Yes
(5.) Is it in the background? Yes (Baseline) (Fail)
(6.) Is it in the left side? Yes (DM1) (Success)

(1.) Is it a person? Yes
(2.) Is it in the foreground? No
(3.) the road? No
(4.) Is it in the foreground? No
(5.) Is it in the background? Yes (Baseline) (Fail)
(6.) the left side? Yes (DM2) (Success)

Figure 13: Successful games where the DM decides to ask more/fewer questions compared to the Baseline. Some of the target objects are very small and by allowing to agent to ask extra questions about the spatial location, the Guesser manages to correctly guess the target object.

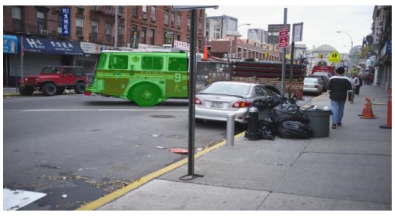
(1.) is it a person? Yes
(2.) in the foreground ? Yes (Oracle Error)
(3.) is it the person in the foreground? No (DM1) (Fail)
(4.) is it the person in the foreground? No
(Repetitive Question)
(5.) is it the person in the background? Yes (Success)

(1.) is it a person? Yes
(2.) is it a male? Yes
(3.) is he wearing a blue shirt? Yes (Oracle Error)
(4.) is he wearing a blue shirt? Yes DM1 (Fail)
(Oracle Error)(Repetitive Question)
(5.) is he wearing a black shirt? Yes (Baseline)
(Success)

(1.) is it a person? No
(2.) is it on the table? Yes
(3.) is it on the table? Yes (DM1) (Fail)
(Repetitive Question)
(4.) Is it the cake? Yes
(5.) Is it the cake? No (Baseline) (Success)
(Repetitive Question)

Figure 14: Unsuccessful games played by DM1, where the system decides to stop asking earlier than the baseline. These failures seem to occur due to the problems by QGen (which generates repeated questions) or the Oracle (which provides a wrong answer).

(1.) is it a person? Yes
(2.) in the foreground? Yes
(3.) the picture? Yes (DM2) (Fail)
(Oracle Error)
(4.) is it the left? No
(5.) Is it the right? Yes (Baseline) (Success)



(1.) is it a person? No
(2.) is it a vehicle? Yes
(3.) on the right? Yes (DM2) (Fail)
(Oracle Error)
(4.) is it the bus? Yes
(5.) is it the fire truck? No (Baseline) (Success)

Figure 15: Unsuccessful games played by DM2, where the system decides to stop asking earlier than the baseline. DM2 seems to be overconfident. Again, failures are often affected by Oracle errors.