VD-BERT: A Unified Vision and Dialog Transformer with BERT

Yue Wang^{1*}, Shafiq Joty², Michael R. Lyu¹, Irwin King¹, Caiming Xiong², and Steven C.H. Hoi²

¹ Department of Computer Science and Engineering

The Chinese University of Hong Kong, HKSAR, China

²Salesforce Research

¹{yuewang,lyu,king}@cse.cuhk.edu.hk ²{sjoty,cxiong,shoi}@salesforce.com

Abstract

Visual dialog is a challenging vision-language task, where a dialog agent needs to answer a series of questions through reasoning on the image content and dialog history. Prior work has mostly focused on various attention mechanisms to model such intricate interactions. By contrast, in this work, we propose VD-BERT, a simple yet effective framework of unified vision-dialog Transformer that leverages the pretrained BERT language models for Visual Dialog tasks. The model is unified in that (1) it captures all the interactions between the image and the multi-turn dialog using a single-stream Transformer encoder, and (2) it supports both answer ranking and answer generation seamlessly through the same architecture. More crucially, we adapt BERT for the effective fusion of vision and dialog contents via visually grounded training. Without the need of pretraining on external vision-language data, our model yields new state of the art, achieving the top position in both single-model and ensemble settings (74.54 and 75.35 NDCG scores) on the visual dialog leaderboard. Our code and pretrained models are released at https: //github.com/salesforce/VD-BERT.

1 Introduction

Visual Dialog (or VisDial) aims to build an AI agent that can answer a human's questions about visual content in a natural conversational setting (Das et al., 2017). Unlike the traditional single-turn Visual Question Answering (VQA) (Antol et al., 2015), the agent in VisDial requires to answer questions through multiple rounds of interactions together with visual content understanding.

The primary research direction in VisDial has been mostly focusing on developing various attention mechanisms (Bahdanau et al., 2015) for a bet-



Figure 1: Attention flow direction illustration. V: vision, H: dialog history, Q: question, A: answer. The arrow denotes the attention flow direction and the dashed line represents an optional connection.

ter fusion of vision and dialog contents. Compared to VQA that predicts an answer based only on the question about the image (Figure 1(a)), VisDial needs to additionally consider the dialog history. Typically, most of previous work (Niu et al., 2019; Gan et al., 2019; Kang et al., 2019) uses the question as a query to attend to relevant image regions and dialog history, where their interactions are usually exploited to obtain better visual-historical cues for predicting the answer. In other words, the attention flow in these methods is *unidirectional* – from question to the other components (Figure 1(b)).

By contrast, in this work, we allow for *bidirectional* attention flow between all the entities using a unified Transformer (Vaswani et al., 2017) encoder, as shown in Figure 1(c). In this way, all the entities simultaneously play the role of an "information seeker" (query) and an "information provider" (key-value), thereby fully unleashing the potential of attention similar to Schwartz et al. (2019). We employ the Transformer as the encoding backbone due to its powerful representation learning capability exhibited in pretrained language models like BERT (Devlin et al., 2019). Inspired by its recent success in vision-language pretraining, we further extend BERT to achieve simple yet effective fusion of vision and dialog contents in VisDial tasks.

Recently several emerging works have attempted to adapt BERT for multimodal tasks (Sun et al.,

^{*}This work was mainly done when Yue Wang was an intern at Salesforce Research Asia, Singapore.

2019; Lu et al., 2019; Tan and Bansal, 2019; Zhou et al., 2020). They often use self-supervised objectives to pretrain BERT-like models on large-scale external vision-language data and then fine-tune on downstream tasks. This has led to compelling results in tasks such as VQA, image captioning, image retrieval (Young et al., 2014), and visual reasoning (Suhr et al., 2019). However, it is still unclear how visual dialog may benefit from such vision-language pretraining due to its unique multi-turn conversational structure. Specifically, each image in the VisDial dataset is associated with up to 10 dialog turns, which contain much longer contexts than either VQA or image captioning.

In this paper, we present VD-BERT, a novel unified vision-dialog Transformer framework for Vis-Dial tasks. Specifically, we first encode the image into a series of detected objects and feed them into a Transformer encoder together with the image caption and multi-turn dialog. We initialize the encoder with BERT for better leveraging the pretrained language representations. To effectively fuse features from the two modalities, we make use of two *visually grounded* training objectives – Masked Language Modeling (MLM) and Next Sentence Prediction (NSP). Different from the original MLM and NSP in BERT, we additionally take the visual information into account when predicting the masked tokens or the next answer.

VisDial models have been trained in one of two settings: discriminative or generative. In the discriminative setting, the model ranks a pool of answer candidates, whereas the generative setting additionally allows the model to generate the answers. Instead of employing two types of decoders like prior work, we rely on a unified Transformer architecture with two different self-attention masks (Dong et al., 2019) to seamlessly support both settings. During inference, our VD-BERT either ranks the answer candidates according to their NSP scores or generates the answer sequence by recursively applying the MLM operations. We further fine-tune our model on dense annotations that specify the relevance score for each answer candidate with a ranking optimization module.

In summary, we make the following contributions:

• To the best of our knowledge, our work serves as one of the first attempts to explore pretrained language models for visual dialog. We showcase that BERT can be effectively adapted to this task with simple visually grounded training for capturing the intricate vision-dialog interactions. Besides, our VD-BERT is the first unified model that supports both discriminative and generative training settings without explicit decoders.

- We conduct extensive experiments not only to analyze how our model performs with various training aspects (§5.2) and fine-tuning on dense annotations (§5.3), but also to interpret it via attention visualization (§5.4), shedding light on future transfer learning research for VisDial tasks.
- Without the need to pretrain on external visionlanguage data, our model yields new state-of-theart results in discriminative setting and promising results in generative setting on the visual dialog benchmarks (§5.1).

2 Related Work

Visual Dialog. The Visual Dialog task has been recently proposed by Das et al. (2017), where a dialog agent needs to answer a series of questions grounded by an image. It is one of the most challenging vision-language tasks that require not only to understand the image content according to texts, but also to reason through the dialog history. Previous work (Lu et al., 2017; Seo et al., 2017; Wu et al., 2018; Kottur et al., 2018; Jiang et al., 2020; Yang et al., 2019; Guo et al., 2019a; Niu et al., 2019) focuses on developing a variety of attention mechanisms to model the interactions among entities including image, question, and dialog history. For example, Kang et al. (2019) proposed DAN, a dual attention module to first refer to relevant contexts in the dialog history, and then find indicative image regions. ReDAN, proposed by Gan et al. (2019), further explores the interactions between image and dialog history via multi-step reasoning.

Different from them, we rely on the selfattention mechanism within a single-stream Transformer encoder to capture such interactions in a unified manner and derive a "holistic" contextualized representation for all the entities. Similar to this, Schwartz et al. (2019) proposed FGA, a general factor graph attention that can model interactions between any two entities but in a pairwise manner. There are recent works (Nguyen et al., 2019; Agarwal et al., 2020) also applying the Transformer to model the interactions among many entities. However, their models neglect the important early interaction of the answer entity and cannot naturally leverage the pretrained language representations from BERT like ours.



Figure 2: The model architecture of our unified VD-BERT for both discriminative and generative settings.

Regarding the architecture, our model mainly differs from previous work in two facets: first, unlike most prior work that considers answer candidates only at the final similarity computation layer, our VD-BERT integrates each answer candidate at the input layer to enable its early and deep fusion with other entities, similar to Schwartz et al. (2019); second, existing models adopt an encoderdecoder framework (Sutskever et al., 2014) with two types of decoder for the discriminative and generative settings separately, while we instead adopt a unified Transformer encoder with two different self-attention masks (Dong et al., 2019) to seamlessly support both settings without extra decoders.

Pretraining in Vision and Language. Pretrained language models like BERT (Devlin et al., 2019) have boosted performance greatly in a broad set of NLP tasks. In order to benefit from the pretraining, there are many recent works on extending BERT for vision and language pretraining. They typically employ the Transformer encoder as the backbone with either a two-stream architecture to encode text and image independently such as ViLBERT (Lu et al., 2019) and LXMERT (Tan and Bansal, 2019), or a single-stream architecture to encode both text and image together, such as B2T2 (Alberti et al., 2019), Unicoder-VL (Li et al., 2020), VisualBERT (Li et al., 2019), VL-BERT (Su et al., 2020), and UNITER (Chen et al., 2019). Our VD-BERT belongs to the second group. These models yield prominent improvements mainly on vision-language understanding tasks like VQA, image retrieval (Young et al., 2014), and visual reasoning (Suhr et al., 2019; Zellers et al., 2019).

More recently, Zhou et al. (2020) proposed VLP which also allows generation using a unified Transformer with various self-attention masks (Dong et al., 2019). Their model was proposed for VQA and image captioning. Our model is inspired by

VLP and specifically tailored for the visual dialog task. Most closely related to this paper is the concurrent work VisDial-BERT by Murahari et al. (2019), who also employ pretrained models (i.e., ViLBERT) for visual dialog. Our work has two major advantages over VisDial-BERT: first, VD-BERT supports both discriminative and generative settings while theirs is restricted to only the discriminative setting; second, we do not require to pretrain on large-scale external vision-language datasets like theirs and still yield better performance (§5.1).

3 The VD-BERT Model

We first formally describe the visual dialog task. Given a question Q_t grounded on an image I at t-th turn, as well as its dialog history formulated as $H_t = \{C, (Q_1, A_1), ..., (Q_{t-1}, A_{t-1})\}$ (where C denotes the image caption), the agent is asked to predict its answer A_t by ranking a list of 100 answer candidates $\{\hat{A}_t^1, \hat{A}_t^2, ..., \hat{A}_t^{100}\}$. In general, there are two types of decoder to predict the answer: a *discriminative* decoder that *ranks* the answer candidates and is trained with a cross entropy loss, or a *generative* decoder that *synthesizes* an answer and is trained with a maximum log-likelihood loss.

Figure 2 shows the overview of our approach. First, we employ a unified vision-dialog Transformer to encode both the image and dialog history, where we append an answer candidate \hat{A}_t in the input to model their interactions in an early fusion manner (§3.1). Next, we adopt visually grounded MLM and NSP objectives to train the model for effective vision and dialog fusion using two types of self-attention masks – bidirectional and seq2seq. This allows our unified model to work in both discriminative and generative settings (§3.2). Lastly, we devise a ranking optimization module to further fine-tune on the dense annotations (§3.3).

3.1 Vision-Dialog Transformer Encoder

Vision Features. Following previous work, we employ Faster R-CNN (Ren et al., 2015) pretrained on Visual Genome (Krishna et al., 2017) to extract the object-level vision features. Let $O_I = \{o_1, ..., o_k\}$ denote the vision features for an image I, where each object feature o_i is a 2048-d Region-of-Interest (RoI) feature and k is the number of the detected objects (fixed to 36 in our setting). As there is no natural orders among these objects, we adopt normalized bounding box coordinates as the spatial location. Specifically, let (x_1, y_1) and (x_2, y_2) be the coordinates of the bottom-left and top-right corner of the *i*-th object, its location information is encoded into a 5-d vector: $p_i = (\frac{x_1}{W}, \frac{y_1}{H}, \frac{x_2}{W}, \frac{y_2}{H}, \frac{(x_2 - x_1)(y_2 - y_1)}{WH})$, where W and H respectively denote the width and height of the input image, and the last element is the relative area of the object. We extend p_i with its class id and confidence score for a richer representation.

Language Features. We pack all the textual elements (caption and multi-turn dialog) into a long sequence. We employ WordPiece tokenizer (Wu et al., 2016) to split it into a word sequence w, where each word is embedded with an absolute positional code following Devlin et al. (2019).

Cross-Modality Encoding. To feed both image and text into the Transformer encoder, we integrate the image objects with language elements into a whole input sequence. Similar to BERT, we use special tokens like [CLS] to denote the beginning of the sequence, and [SEP] to separate the two modalities. Moreover, to inject the multi-turn dialog structure into the model, we utilize a special token [EOT] to denote end of turn (Whang et al., 2019), which informs the model when the dialog turn ends. As such, we prepare the input sequence into the format as $\mathbf{x} = ([CLS], o_1, ..., o_k, [SEP],$ C, [EOT], Q_1A_1 , [EOT], ..., Q_tA_t , [SEP]). To notify the model for the answer prediction, we further insert a [PRED] token between the $Q_t A_t$ pair. Finally, each input token embedding is combined with its position embedding and segment embedding (0 or 1, indicating whether it is image or text) with layer normalization (Ba et al., 2016).

Transformer Backbone. We denote the embedded vision-language inputs as $\mathbf{H}^0 = [\mathbf{e}_1, ..., \mathbf{e}_{|\mathbf{x}|}]$ and then encode them into multiple levels of contextual representations $\mathbf{H}^l = [\mathbf{h}_1^l, ..., \mathbf{h}_{|\mathbf{x}|}^l]$ using *L*-stacked Transformer blocks, where the *l*-th Transformer block is denoted as $\mathbf{H}^{l} =$ Transformer $(\mathbf{H}^{l-1}), l \in [1, L]$. Inside each Transformer block, the previous layer's output $\mathbf{H}^{l-1} \in \mathbb{R}^{|\mathbf{x}| \times d_{h}}$ is aggregated using the multi-head self-attention (Vaswani et al., 2017):

$$\mathbf{Q} = \mathbf{H}^{l-1} \mathbf{W}_{l}^{Q}, \mathbf{K} = \mathbf{H}^{l-1} \mathbf{W}_{l}^{K}, \mathbf{V} = \mathbf{H}^{l-1} \mathbf{W}_{l}^{V},$$
(1)
$$\mathbf{M}_{ij} = \begin{cases} 0, & \text{allow to attend,} \\ -\infty, & \text{prevent from attending,} \end{cases}$$
(2)
$$\mathbf{A}_{l} = \text{softmax}(\frac{\mathbf{Q}\mathbf{K}^{T}}{\sqrt{d_{k}}} + \mathbf{M})\mathbf{V},$$
(3)

where $\mathbf{W}_{l}^{Q}, \mathbf{W}_{l}^{K}, \mathbf{W}_{l}^{V} \in \mathbb{R}^{d_{h} \times d_{k}}$ are learnable weights for computing the queries, keys, and values respectively, and $\mathbf{M} \in \mathbb{R}^{|\mathbf{x}| \times |\mathbf{x}|}$ is the self-attention mask that determines whether tokens from two layers can attend each other. Then \mathbf{A}_{l} is passed into a feedforward layer to compute \mathbf{H}^{l} for the next layer.

3.2 Visually Grounded Training Objectives

We use two *visually grounded* training objectives masked language modeling (MLM) and next sentence prediction (NSP) to train our VD-BERT. Particularly, we aim to capture dense interactions among both inter-modality (i.e., image-dialog) and intra-modality (i.e., image-image, dialog-dialog).

Similar to MLM in BERT, 15% tokens in the text segment (including special tokens like [EOT] and [SEP]) are randomly masked out and replaced with a special token [MASK]. The model is then required to recover them based not only on the surrounding tokens $\mathbf{w}_{\setminus m}$ but also on the image I:

$$\mathcal{L}_{MLM} = -E_{(I,\mathbf{w})\sim D}\log P(w_m | \mathbf{w}_{\backslash m}, I), \quad (4)$$

where w_m refers to the masked token and D denotes the training set. Following Zhou et al. (2020), we do not conduct similar masked object/region modeling in the image segment.

As for NSP, instead of modeling the relationship between two sentences (as in BERT) or the matching of an image-text pair (as in other visionlanguage pretraining models like ViLBERT), VD-BERT aims to predict whether the appended answer candidate \hat{A}_t is correct or not based on the joint understanding of the image and dialog history:

$$\mathcal{L}_{NSP} = -E_{(I,\mathbf{w})\sim D} \log P(y|S(I,\mathbf{w})), \quad (5)$$

where $y \in \{0,1\}$ indicates whether \hat{A}_t is correct, and $S(\cdot)$ is a binary classifier to predict the probability based on the [CLS] representation $T_{[CLS]}$ at the final layer. Below we introduce the discriminative and generative settings of VD-BERT. Discriminative Setting. For training in the discriminative setting, we transform the task of selecting an answer into a point-wise binary classification problem. Specifically, we sample an answer A_t from the candidate pool and append it to the input sequence, and ask the NSP head to distinguish whether the sampled answer is correct or not. We employ the *bidirectional* self-attention mask to allow all the tokens to attend to each other by setting the mask matrix M in Eq. (2) to all 0s. To avoid imbalanced class distribution, we keep the ratio of positive and negative instances to 1:1 in each epoch. To encourage the model to penalize more on negative instances, we randomly resample a negative example from the pool of 99 negatives w.r.t. every positive one at different epochs. During inference, we rank the answer candidates according to the positive class score of their NSP heads.

Generative Setting. In order to autoregressively generate an answer, we also train VD-BERT with the *sequence-to-sequence* (seq2seq) self-attention mask (Dong et al., 2019). For this, we divide the input sequence to each Transformer block into two subsequences, *context* and *answer*:

$$\mathbf{x} \triangleq (I, \mathbf{w}) = (\underbrace{I, H_t, Q_t}_{\text{context}}, \hat{A}_t).$$
(6)

We allow tokens in the context to be fully visible for attending by setting the left part of M to all 0s. For the answer sequence, we mask out (by setting $-\infty$ in M) the "future" tokens to get autoregressive attentions (see the red dots in Figure 2).

During inference, we rely on the same unified Transformer encoder with sequential MLM operations without an explicit decoder. Specifically, we recursively append a [MASK] token to the end of the sequence to trigger a one-step prediction and then replace it with the predicted token for the next token prediction. The decoding process is based on greedy sampling and terminated when a [SEP] is emitted, and the resulting log-likelihood scores will be used for ranking the answer candidates.

3.3 Fine-tuning with Rank Optimization

As some answer candidates may be semantically similar (e.g., "brown and tan" vs "brown" in Figure 2), VisDial v1.0 additionally provides dense annotations that specify real-valued relevance scores for the 100 answer candidates, $[s_1, ..., s_{100}]$ with $s_i \in [0, 1]$. To fine-tune on this, we combine the NSP scores from the model for all answer candidates together into a vector $[p_1, ..., p_{100}]$.

As dense annotation fine-tuning is typically a Learning to Rank (LTR) problem, we can make use of some ranking optimization methods (see the Appendix B.1 for more details). We adopt List-Net (Cao et al., 2007) with the top-1 approximation as the ranking module for VD-BERT:

$$\mathcal{L}_{ListNet} = -\sum_{i=1}^{N} f(s_i) \log(f(p_i)), \quad (7)$$

$$f(x_i) = \frac{\exp(x_i)}{\sum_{j=1}^{N} \exp(x_j)}, \ i = 1, ..., N.$$
 (8)

Here N is the number of answer candidates. For training efficiency, we sub-sample the candidate list and use only N = 30 answers (out of 100) for each instance. To better leverage the contrastive signals from the dense annotations, the sub-sampling method first picks randomly the candidates with non-zero relevance scores, and then it picks the ones from zero scores (about 12% of candidates are non-zero on average).

4 Experimental Setup

Datasets. We evaluate our model on the VisDial v0.9 and v1.0 datasets (Das et al., 2017). Specifically, v0.9 contains a training set of 82,783 images and a validation set of 40,504 images. The v1.0 dataset combines the training and validation sets of v0.9 into one training set and adds another 2,064 images for validation and 8,000 images for testing (hosted blindly in the task organizers' server). Each image is associated with one caption and 10 question-answer pairs. For each question, it is paired with a list of 100 answer candidates, one of which is regarded as the correct answer.

For the v1.0 validation split and a part of v1.0 train split (2,000 images), extra dense annotations for the answer candidates are provided to make the evaluation more reasonable. The dense annotation specifies a relevance score for each answer candidate based on the fact that some candidates with similar semantics to the ground truth answer can also be considered as correct or partially correct, e.g., "brown and tan" and "brown" in Figure 2.

Evaluation Metric. Following Das et al. (2017), we evaluate our model using the ranking metrics like Recall@K ($K \in \{1, 5, 10\}$), Mean Reciprocal Rank (MRR), and Mean Rank, where only one

answer is considered as correct. Since the 2018 VisDial challenge (after the acquisition of dense annotations), NDCG metric that considers the relevance degree of each answer candidate, has been adopted as the main metric to determine the winner.

Configurations. We use BERT_{BASE} as the backbone, which consists of 12 Transformer blocks, each with 12 attention heads and a hidden state dimensions of 768. We keep the max input sequence length (including 36 visual objects) to 250. We use Adam (Kingma and Ba, 2015) with an initial learning rate of 3e - 5 and a batch size of 32 to train our model. A linear learning rate decay schedule with a warmup of 0.1 is employed. We first train VD-BERT for 30 epochs on a cluster of 4 V100 GPUs with 16G memory using MLM and NSP losses (with equal coefficients). Here we only utilize one previous dialog turn for training efficiency. For instances where the appended answer candidate is incorrect, we do not conduct MLM on the answer sequence to reduce the noise introduced by the negative samples. After that, we train for another 10 epochs with full dialog history using either NSP in the discriminative setting or MLM on the answer sequence in the generative setting. For dense annotation fine-tuning in the discriminative setting, we train with the ListNet loss for 5 epochs.

5 Results and Analysis

We first compare VD-BERT with state-of-the-art models on VisDial datasets ($\S5.1$). Then we conduct ablation studies to examine various aspects of our model ($\S5.2$), followed by an in-depth analysis of fine-tuning on dense annotations ($\S5.3$). Lastly, we interpret how it attains the effective fusion of vision and dialog via attention visualization ($\S5.4$).

5.1 Main Results

Comparison. We consider state-of-the-art published baselines, including NMN (Hu et al., 2017), CorefNMN (Kottur et al., 2018), GNN (Zheng et al., 2019), FGA (Schwartz et al., 2019), DVAN (Guo et al., 2019b), RvA (Niu et al., 2019), DualVD (Jiang et al., 2020), HACAN (Yang et al., 2019), Synergistic (Guo et al., 2019a), DAN (Kang et al., 2019), ReDAN (Gan et al., 2019), CAG (Guo et al., 2020), Square (Kim et al., 2020), MCA (Agarwal et al., 2020), MReal-BDAI and P1_P2 (Qi et al., 2020). We further report re-

	Model	NDCG↑	MRR↑	R@1↑	R@5↑	R@10↑	$Mean \downarrow$
	' NMN	58.10	58.80	44.15	76.88	86.88	4.81
	CorefNMN	54.70	61.50	47.55	78.10	88.80	4.40
	GNN	52.82	61.37	47.33	77.98	87.83	4.57
	FGA	52.10	63.70	49.58	80.97	88.55	4.51
	DVAN	54.70	62.58	48.90	79.35	89.03	4.36
	RvA	55.59	63.03	49.03	80.40	89.83	4.18
lts	DualVD	56.32	63.23	49.25	80.23	89.70	4.11
Published Results	HACAN	57.17	64.22	50.88	80.63	89.45	4.20
۳	Synergistic	57.32	62.20	47.90	80.43	89.95	4.17
٩	Synergistic [†]	57.88	63.42	49.30	80.77	<u>90.68</u>	3.97
blis	DAN	57.59	63.20	49.63	79.75	89.35	4.30
Pu	DAN^{\dagger}	59.36	<u>64.92</u>	51.28	<u>81.60</u>	90.88	<u>3.92</u>
	$ReDAN^{\dagger}$	64.47	53.73	42.45	64.68	75.68	6.64
	CAG	56.64	63.49	49.85	80.63	90.15	4.11
	Square [†]	60.16	61.26	47.15	78.73	88.48	4.46
	MCA*	72.47	37.68	20.67	56.67	72.12	8.89
	MReal-BDAI ^{†*}	74.02	52.62	40.03	68.85	79.15	6.76
	P1_P2 ^{†*}	<u>74.91</u>	49.13	36.68	62.98	78.55	7.03
(ĹF	45.31	55.42	40.95	72.45	82.83	5.95
	HRE	45.46	54.16	39.93	70.45	81.50	6.41
Its	MN	47.50	55.49	40.98	72.30	83.30	5.92
esu	MN-Att	49.58	56.90	42.42	74.00	84.35	5.59
Leaderboard Results	LF-Att	49.76	57.07	42.08	74.82	85.05	5.41
- Ĕ{	MS ConvAI	55.35	63.27	49.53	80.40	89.60	4.15
Ť	UET-VNU [†]	57.40	59.50	45.50	76.33	85.82	5.34
ade	MVAN	59.37	64.84	<u>51.45</u>	81.12	90.65	3.97
۲_	SGLNs [†]	61.27	59.97	45.68	77.12	87.10	4.85
	VisDial-BERT*	74.47	50.74	37.95	64.13	80.00	6.28
l	Tohoku-CV ^{†*}	74.88	52.14	38.93	66.60	80.65	6.53
~ (VD-BERT	59.96	65.44	51.63	82.23	<u>90.68</u>	3.90
Ours	VD-BERT*	74.54	46.72	33.15	61.58	77.15	7.18
9	VD-BERT ^{†*}	75.35	51.17	38.90	62.82	77.98	6.69

Table 1: Summary of results on the test-std split of VisDial v1.0 dataset. The results are reported by the test server. " \dagger " denotes ensemble model and "*" indicates fine-tuning on dense annotations. The " \uparrow " denotes higher value for better performance and " \downarrow " is the opposite. The best and second-best results in each column are in bold and underlined respectively.

sults from the leaderboard¹ for a more up-to-date comparison, where some can be found in the arXiv, such as MVAN (Park et al., 2020), SGLNs (Kang et al., 2020), VisDial-BERT (Murahari et al., 2019), and Tohoku-CV (Nguyen et al., 2019).

Results on VisDial v1.0 test-std. We report the comparison results on VisDial v1.0 test-std split in Table 1 and make the following observations.

• New state of the art for both single-model and ensemble settings. Our single-model VD-BERT significantly outperforms all of its single-model counterparts across various metrics, even including some ensemble variants such as Synergistic, DAN (except R@10), and ReDAN (except NDCG). With further fine-tuning on dense annotations, the NDCG score increases quite sharply, from 59.96 to 74.54 with nearly 15% absolute improvement, setting a new state of the art in the single-model setting. This indicates that dense annotation finetuning plays a crucial role in boosting the NDCG

¹https://evalai.cloudcv.org/web/ challenges/challenge-page/161/

leaderboard/483#leaderboardrank-1

Model	MRR↑	R@1↑	R@5↑	R@10↑	$Mean\downarrow$					
inouci	Discriminative/Generative									
LF	58.07/51.99	43.82/41.83	74.68/61.78	84.07/67.59	5.78/17.07					
HRE	58.46/52.37	44.67/42.29	74.50/62.18	84.22/67.92	5.72/17.07					
HREA	58.68/52.42	44.82/42.28	74.81/62.33	84.36/68.17	5.66/16.79					
MN	59.65/52.59	45.55/42.29	76.22/62.85	85.37/68.88	5.46/17.06					
HCIAE	62.22/54.67	48.48/44.35	78.75/65.28	87.59/71.55	4.81/14.23					
CoAtt	63.98/55.78	50.29/46.10	80.71/ 65.69	88.81/71.74	4.47/14.43					
RvA	66.34/55.43	52.71/45.37	<u>82.97</u> /65.27	<u>90.73</u> / 72.97	3.93/10.71					
DVAN	<u>66.67/55.94</u>	<u>53.62/46.58</u>	82.85/ <u>65.50</u>	90.72/71.25	3.93 /14.79					
VD-BERT	70.04/55.95	57.79/46.83	85.34 /65.43	92.68 / <u>72.05</u>	4.04/13.18					

Table 2: Discriminative and generative results of various models on the val split of VisDial v0.9 dataset.

scores. Moreover, our designed ensemble version yields new state of the art (**75.35** NDCG), outperforming the 2019 VisDial challenge winner MReal-BDAI (74.02 NDCG) by over 1.3 absolute points.

• Inconsistency between NDCG and other metrics. While dense annotation fine-tuning yields huge improvements on NDCG, we also notice that it has a severe countereffect on other metrics, e.g., reducing the MRR score from 65.44 to 46.72 for VD-BERT. Such a phenomenon has also been observed in other recent models, such as MReal-BDAI, VisDial-BERT, Tohoku-CV Lab, and P1_P2, whose NDCG scores surpass others without dense annotation finetuning by at least around 10% absolute points while other metrics drop dramatically. We provide a detailed analysis of this phenomenon in §5.3.

• Our VD-BERT is simpler and more effective than VisDial-BERT. VisDial-BERT is a concurrent work to ours that also exploits vision-language pretrained models for visual dialog. It only reports the single-model performance of 74.47 NDCG. Compare to that, our VD-BERT achieves slightly better results (74.54 NDCG), however, note that we did not pretrain on large-scale external vision-language datasets like Conceptual Captions (Sharma et al., 2018) and VQA (Antol et al., 2015) as VisDial-BERT does. Besides, while VisDial-BERT does not observe improvements by ensembling, we endeavor to design an effective ensemble strategy to increase the NDCG score to 75.35 for VD-BERT.

Results on VisDial v0.9 val. We further show both discriminative and generative results on v0.9 val split in Table 2. For comparison, we choose LF, HRE, HREA, MN (Das et al., 2017), HCIAE (Lu et al., 2017), CoAtt (Wu et al., 2018), RvA, and DVAN as they contain results in both settings on the v0.9 val split. These models employ dual decoders for each setting separately. Our model continues to yield much better results in the discriminative setting (e.g., 70.04 MRR compared to DVAN's 66.67)

	Model	NDCG↑	MRR↑	$R@1\uparrow$	R@5↑	R@10↑	$Mean\downarrow$
	From scratch	56.20	62.25	48.16	79.57	89.01	4.31
(-)	Init from VLP	61.79	66.67	53.23	83.60	91.97	3.66
(a)	Init from BERT	63.22	67.44	54.02	83.96	92.33	3.53
	$\hookrightarrow only \ NSP$	55.89	63.15	48.98	80.45	89.72	4.15
	No history	64.70	62.93	48.70	80.42	89.73	4.30
(b)	One previous turn	63.47	65.30	51.66	82.30	90.97	3.86
(0)	Full history	63.22	67.44	54.02	83.96	92.33	3.53
	\hookrightarrow only text	54.32	62.79	48.48	80.12	89.33	4.27
	CE	74.47	44.94	32.23	60.10	76.70	7.57
(a)	ListNet	74.54	46.72	33.15	61.58	77.15	7.18
(c)	ListMLE	72.96	36.81	20.70	54.60	73.28	8.90
	ApproxNDCG	72.45	49.88	37.88	62.90	77.40	7.26
	Еросн	74.84	47.40	34.30	61.58	77.78	7.12
(1)	Length	75.07	47.33	33.88	62.20	78.50	7.01
(d)	RANK	75.13	50.00	38.28	60.93	77.28	6.90
	DIVERSE	75.35	51.17	38.90	62.82	77.98	6.69

Table 3: Extensive ablation studies: training with (a) various settings and (b) contexts on v1.0 val; dense annotation fine-tuning with (c) varying ranking methods and (d) various ensemble strategies on v1.0 test-std.

and comparable results with the state of the art in the generative setting (e.g., 55.95 MRR score vs. DVAN's 55.94). This validates the effectiveness of our VD-BERT in both settings using a unified Transformer encoder. By contrast, VisDial-BERT can only support the discriminative setting.

5.2 Ablation Study

We first study how different training settings influence the results in Table 3(a). We observe that initializing the model with weights from BERT indeed benefits the visual dialog task a lot, increasing the NDCG score by about 7% absolute over the model trained from scratch. Surprisingly, the model initialized with the weights from VLP that was pretrained on Conceptual Captions (Sharma et al., 2018), does not work better than the one initialized from BERT. It might be due to the domain discrepancy between image captions and multi-turn dialogs, as well as the slightly different experiment settings (e.g., we extract 36 objects from image compared to their 100 objects). Another possible reason might be that the VisDial data with more than one million image-dialog turn pairs can provide adequate contexts to adapt BERT for effective vision and dialog fusion. We also find that the visually grounded MLM is crucial for transferring BERT into the multimodal setting, indicated by a large performance drop when using only NSP.

We then examine the impact of varying the dialog context used for training in Table 3(b). With longer dialog history ("Full history"), our model indeed yields better results in most of the ranking metrics, while the one without using any dialog history obtains the highest NDCG score. This in-



Figure 3: The effects of dense annotation fine-tuning in our VD-BERT for two examples. GT: ground truth.

dicates that dense relevance scores might be annotated with less consideration of dialog history. If we remove the visual cues from the "Full history" model, we see a drop in all metrics, especially, on NDCG. However, this version still obtains comparable results to the "No history" variant, revealing that textual information dominates the VisDial task.

In Table 3(c), we compare Cross Entropy (CE) training with a bunch of other listwise ranking optimization methods: ListNet (Cao et al., 2007), ListMLE (Xia et al., 2008), and approxNDCG (Qin et al., 2010). Among these methods, ListNet yields the best NDCG and Mean Rank, while the approx-NDCG achieves the best MRR and Recall on Vis-Dial v1.0 test-std. Therefore, we employ the List-Net as our ranking module.

We also explore ways to achieve the best ensemble performance with various model selection criteria in Table 3(d). We consider three criteria, EPOCH, LENGTH, and RANK that respectively refer to predictions from different epochs of a single model, from different models trained with varying context lengths and with different ranking methods in Table 3(b)-(c). We use four predictions from each criterion and combine their diverse predictions (DIVERSE) by summing up their normalized ranking scores. We observe that EPOCH contributes the least to the ensemble performance while RANK models are more helpful than LENGTH models. The diverse set of them leads to the best performance.

5.3 Fine-tuning on Dense Annotations

In this section, we focus on the effect of dense annotation fine-tuning and try to analyze the reason of the inconsistency issue between NDCG and other ranking metrics (see Table 1) in the following.

Case Study. We provide two examples to qualitatively demonstrate how dense annotation finetuning results in better NDCG scores in Figure 3. For the example at the top, fine-tuning helps our model to assign higher ranks to the answers that share similar semantics with the ground truth answer and should also be regarded as correct ("yes, it is" and "yep" vs. "yes"). In the example at the bottom, we spot a mismatch between the sparse and dense annotations: the ground truth answer "no, it's empty" is only given a 0.4 relevance score, while uncertain answers like "i don't know" are considered to be more relevant. In this case, fine-tuning instead makes our model fail to predict the correct answer despite the increase of NDCG score.

Relevance Score and Question Type Analysis. We first show how various metrics change for finetuning in Figure 4. For this experiment, we randomly sample 200 instances from VisDial v1.0 val as the test data and use the rest for fine-tuning with the ListNet ranking method. We observe that NDCG keeps increasing with more epochs of fine-tuning, while other metrics such as Recall@K and MRR) drop. For further analysis, we classify the 2,064 instances in VisDial v1.0 val set based on the ground-truth's relevance score and question type (Table 4). We consider four bins $\{0.0, 0.2 \sim 0.4, 0.6 \sim 0.8, 1.0\}$ for the relevance score and four question types: Yes/no, Number, Color, and Others. We then analyze the NDCG scores assigned by DAN (Kang et al., 2019) and our VD-BERT with and without dense annotation fine-tuning. We choose DAN as it achieves good NDCG scores (Table 1) and provides the source code to reproduce their predictions.

By examining the distribution of the relevance scores, we find that only 31% of them are aligned well with the sparse annotations and 9% are totally misaligned. As the degree of such mismatch increases (relevance score changes $1.0 \rightarrow 0.0$), both DAN and our model witness a plunge in NDCG ($63.29 \rightarrow 43.86$ and $70.25 \rightarrow 48.07$), while dense annotation fine-tuning significantly boosts NDCG scores for all groups, especially for the most misaligned one ($48.07 \rightarrow 82.84$ for our model). These results validate that the misalignment of the sparse and dense annotations is the key reason for the inconsistency between NDCG and other metrics.

For question types, we observe that *Yes/no* is the major type (76%) and also the easiest one, while *Number* is the most challenging and least frequent one (3%). Our model outperforms DAN by over 10% in most of the question types except *Color*. Fine-tuning on dense annotations gives our model huge improvements across all the question types, especially for *Others* with over 30% absolute gain.



	All	Relevance Score				Question Type			
Models		1.0 (31%)	0.6~0.8 (35%)	0.2~0.4 (25%)	0.0 (9%)	Yes/no (76%)	Number (3%)	Color (11%)	Others (10%)
DAN	58.28	63.29	61.02	53.29	43.86	59.86	41.03	57.55	51.89
Ours	63.55	70.25	65.18	58.40	48.07	65.45	48.98	58.51	58.75
Ours (w/ ft)	89.62	95.38	89.76	84.63	82.84	91.05	74.41	84.00	89.12

Figure 4: Dense annotation fine-tuning on various metrics with the ListNet method.

Table 4: NDCG scores in VisDial v1.0 val split broken down into 4 groups based on relevance score and the question type. The % value in the parentheses denotes the corresponding data proportion.



Figure 5: Attention weight visualization in our VD-BERT for a sampled image-dialog example.

5.4 Attention Visualization

To interpret our VD-BERT, we visualize the attention weights on the top 10 detected objects from its caption in Figure 5(a). We observe that many heads at different layers can correctly ground some entities like person and motorcycle in the image, and even reveal some high-level semantic correlations such as person↔motorcycle (at L8H2) and motorcycle↔street (at L1H11). Besides, heads at higher layers tend to have a sharper focus on specific objects like the man and the motorcycles in the image.

Next, we examine how our VD-BERT captures the interactions between image and multi-turn dialog. In contrast to other vision-language tasks, visual dialog has a more complex multi-turn structure, thereby posing a hurdle for effective fusion. As shown in Figure 5(b), VD-BERT can ground entities and discover some object relations, e.g., helmet is precisely related to the man and the motorcycle in the image (see the rightmost red box). More interestingly, it can even resolve visual pronoun coreference of he in the question to the man in the image (see the middle red box). We provide more qualitative examples in Figure 6 and 7.

6 Conclusion

We have presented VD-BERT, a unified visiondialog Transformer model that exploits the pretrained BERT language models for visual dialog. VD-BERT is capable of modeling all the interactions between an image and a multi-turn dialog within a single-stream Transformer encoder and enables the effective fusion of features from both modalities via simple visually grounded training. Besides, it can either rank or generate answers seamlessly. Without pretraining on external visionlanguage datasets, our model establishes new stateof-the-art performance in the discriminative setting and shows promising results in the generative setting on the visual dialog benchmarks.

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Figure 6: More attention visualization examples showing that VD-BERT achieves the effective fusion of vision and dialog contents. LxHy: Layer x Head y ($1 \le x, y \le 12$). (a) It learns three apparent attention patterns for the example in Figure 5: attentions that a token puts to its previous token, to itself, and to the next token. Besides, some of its attention heads can precisely ground some entities between image and caption/multi-turn dialog: (b) pizza, beer, and table; (c) horse, wild, and giraffe; (d) teenage girl, hair, and phone.

Image + Caption	GT Dialog	DAN	VD-BERT	VD-BERT (w/ft)
a brown building stands at the corner of a street on a sunny day	11: is there any people in the photo? A1: yes far away A2: yes far away A2: yes A3: yes A3: yes A3: no A4: what kind of buildings appear in the photo? A4: older architectural building like all brary A5: is there any signs visible in the photo? A5: share is an entry sign C4: what kind of buildings? A6: no C7: can you see the sidewalk? A6: no C7: can you see the sidewalk? A9: no C9: are there any trees planted near the building? A9: there is a tree next to the building A10: tall	11: Is there any people in the photo? A1: yes 12: are there any street visible in the photo? A2: no on the street 13: are there cars parked along the streets? A3: no C4: what kind of buildings appear in the photo? A4: yes shogs C5: Is there any signs visible in the photo? A5: yes C6: are there traffic lights visible? A6: 1 light pool C7: cm you see the sidewalk? A7: yes C8: yes wery clean C9: are there any trees planted near the building? A9: yes C10: at he tree short or tall? A10: tall	Q1: Is there any people in the photo? A1: yes Q2: are there any streets visible in the photo? A2: yes Q3: are there cars parked along the streets? Q3: are there cars parked along the streets? A3: no Q4: what kind of buildings appear in the photo? A5: oter arkitetural building like all birary Q5: is there any signs visible in the photo? A5: yes Q6: are there traffic lights visible? A6: no Q7: yes the sidewalk? Q7: yes the sidewalks clean? Q6: are there any trees planet near the building? Q7: here is a tree next to the building? Q6: here there short or tall? A1: tall	11: Is there any people in the photo? A1: yes Q2: are there any streets visible in the photo? A2: yes Q3: are there cars parked along the streets? A3: no Q4: what kind of buildings appear in the photo? A4: not sure Q5: Is there any signs visible in the photo? A5: yes Q6: are there traffic lights visible? A6: no Q7: can you see the sidewalk? A5: yes the videwalks.clean? A6: yes the videwalks.clean? A7: yes th
man pointing at tv display in a store	Q1: is the picture in color? A1: yes Q2: how many people are in the picture? A2: is see 2 people A2: is see 2 people A2: is see 2 people A3: is see 2 people A4: yes A4: yes A4: yes A4: yes A5: yes	11: is the picture in color? A1: yes 02: how many people are in the picture? A2: 2 03: how many to's are in the picture? A2: 2 04: is 1 of the people a worker in the store? A4: yes, but they are taking a break 05: is there an image on the tv that he is pointing at? A5: yes it is an cantoon 06: is the man standing or sitting? A6: standing 07: what is the man of tv? A6: standing 07: what is the size of the tis? A6: any only they they the tis? A8: yes it is a list of rules A9: are there any other products in view? A9: there is papers all over the desk so i would say yes 10: what color is the floor? A10: blue	Q1: is the picture in color? A1: yes Q2: how many people are in the picture? A2: 2 A2: 3 A2: 4 A2	11: is the picture in color? A1: yes it is A1: yes it is A2: pow many people are in the picture? A3: pow many people are in the picture? A3: pow people are in the picture? A3: pow people are in the picture? A4: pow people are on the display but there are some in boxes as well A4: brear are no vollable worksrs A5: stere an image on the tv that he is pointing at? A5: yes A6: is there an inage on the tv that he is pointing? A6: standing A7: loan trul A6: any out fell what store it is? A8: no C9: are there any other products in view? A9: yes C10: what color is the floor? A10: but
a woman is smiling next to a decorated microwave	Q1: is there anyone in the room with the woman? A1: no Q2: is she young? A2: no Q3: what color is her hair? A2: blog microwave? A4: yes A4: yes A4: yes A5: no Q3: what is the woman wearing? A7: a shirt Q8: is her hair long? A8: no Q9: what color is the microwave? A9: white Q10: is the wearing glasses? A10: no	Q1: is there anyone in the room with the woman? A1: no, the is alone Q2: is she young? A2: no about 18 B3: what color is the rhair? A3: brown Macroscolin start start A4: normal size A5: normal size A6: normal size A6: normal size A7: normal size A6: normal size A7: normal size A7: normal size A6: normal size A7: horwan jacket A7: brown jacket A7: brown jacket A7: size A7: size A6: normal size A7: brown jacket A7: size A8: yes C3: size wasing gasses? A10: no	Q1: is there anyone in the room with the woman? A1: no Q2: is she young? A2: yes Q3: what color is her hair? A3: brown A4: yes A4: yes A5: bit bern any other appliances in the room? A6: no A7: black jeans and a shirt A8: her hair long? A7: black jeans and a shirt A8: her hair long? A9: what color is the microwave? A9: what color is the microwave? A9: white Q10: is he waring glasses? A10: no	Q1: is there anyone in the room with the woman? A1: no Q2: is she young? A2: yets Q3: what color is her hair? A3: brown A3: brown A4: yets Q5: is its uamy? A4: yets A5: can't tell A6: not that (can see A7: a black lock A8: not A9: white tom is the microwave? A8: not A9: white Q10: is her waring glasses? A10: not
an elephant sprays the person on its back	11: is the elephant large? A1: yes, bit doesn' look full grown 12: how many people are on the elephant? A2: ican only yes 1 C3: are there more elephants in the picture? A3: no C4: what is the peron wearing? A1: thin it's beron, hard to tell with the spray A1: thin it's beron, hard to tell with the spray A1: thin it's upper on wearing? A5: where is them C5: where is them C5: where is the appendic or maybe a river bank, not sure C6: is the water clean or dirty? A6: it looks pretty muddy, so I would say dirty C7: sinter grass anywhere near the water or mainly mud? A2: mainly mud? A2: mainly mud? A2: mainly mud? A2: mainly mud? A2: mainly mud? A2: mainly mud? A3: mainly mud? A3: mainly mud? A3: mainly mud? A3: mainly mud? A3: mainly mud? A3: mainly mud? A4: mainly mud? A5: mainly mud? A5: mainly mud? A6: tho upper the ploto? A9: yes A10: no you water water the ploto? A10: no	11: is the elephant large? A1: yes 12: how many people are on the elephant? 22: foru: 1 in each photo C3: are there more elephants in the picture? A3: no, just the 2 birds C4: what is the person warning? A4: a green button up C4: where is the elephant getting the water from? C4: where is the elephant getting the water from? C4: the water clean or dirty? C5: is the water clean or dirty? C6: is the vater clean or dirty? C6: is the regrass anywhere near the water or mainly mud? C6: are the start of grass, and a green reflection on the water C6: are the start of grass, and a green reflection on the water C6: are the start y C6: are write any trees in the photo? C9: are there any trees in the photo? C9: are there are and green C10: can you tell what type of trees? A10: I would think late spring or summer cause all the trees are ince and green	OL: Is the elephant large? A1; yes A2; yes A3; yes A3; yes A4; yes A3; yes A4; ye	11: is the elephant large? A1: yes 12: how many people are on the elephant? A2: 1 C3: are there more elephants in the picture? A3: no C4: what is the person wearing? A4: he is wearing? A4: he is wearing a picture C5: sithe water clean or dirty? A6: itobac pretty muddy, sol would say dirty C7: is there grass anywhere near the water or mainly mud? A7: no, there is 0 C9: are yet and yet any C9: A A8: no C9: are in the pictor. C9: A1: A1: A1: A1: A1: A1: A1: A1: A1: A1
a man wearing a hat holds a small white dog	Q1: age of man? A1: maybe 205 Q2: type of dog? A1: a while fully dog A1: a while fully dog A2: type Q4: can you see the head? A4: can see the dogs head and the man's head Q5: is the mouth open on the dog? A5: no A6: oregisses Q7: what color he dogs head and the man's head A6: eveglasses Q7: what color he his shirt? A2: tan hat CB: has has in his shirt? A9: hay are not shown A9: how are not shown Q10: is the man outside? A10: no, he is inside	Q1: age of man? A1: 40s Q2: type of odry dog? A2: a white Mil? A3: a wrape size A5: a wrape size A6: a jacket and a hat Q7: what color hat is k7 A7: brown G8: what color is his shirt? G9: what color his his parts? A9: black Q10: is the man outside? A10: no, he is inside	Q1: age of man? A1: 40s Q2: type of dog? A2: a white fluff v0 A2: a white fluff v1 A2: a white fluff v1 A4: ps A2: a white fluff v1 A4: ps A4: ps A5: a ps A6: a ps A7: can set the dogs head and the man's head A5: a packet and nat Q7: what color hat is k1? Q8: what color is his shirt? Q8: what color is his shirt? Q9: what color his his parts? A7: then hat Q1: when and outs ducts? A9: they are not shown Q10: is the man outside? A1: no, he is inside	Q1: age of man? A1: 405 Q2: type of dog? A2: ican'tell G2: type of dog? A2: ican'tell G4: anyou see the head? A4: yes Q4: anyou see the head? A4: yes C4: is the mouth open on the dog? A5: nope Q5: is the mouth open on the dog? A5: nope Q5: what color head? A6: evegisses Q7: what color head shi? A6: evegisses Q7: what color head shi? A7: it's brown Q8: what color head shi? A2: it's brown Q8: what color head shi? A2: it's brown Q8: what color head shi? A2: it's color head shi? A2: it's color head shi? A2: it's color head shi? A2: it's color head shi? A1: it's color h
a small bedroom with a hall with laundry in the background	11. do you see any people? 11. no 12. is there a bed in the bedroom? 12. yes 13. is the alge of laundry? 14. no 14. no 15. is the bedroem? 14. white and light gray 15. is the bedroem? 16. is the bedroem? 17. is the laundry hanging or piled or folded? 17. is the laundry hanging or piled or folded? 18. is the alight or dark wood floor? 18. is the bedroom a child's room, guest room, or day is the bedroom? 102. is three any other furniture in the bedroom? 102. is three any other furniture in the bedroom?	D1: do you see any people? A1: no Q2: to there a bed in the bedroom? Q2: no Q3: is it a big pile of is undry? A3: yes Q4: what color is the bedspread? A4: white and on blankets Q5: is the tilty transfer of the bedspread? A6: white and careted or hard floor? A6: is the hall careted or hard floor? A7: hanging Q8: is the light or dark wood floor? A8: just Q4: sith to do say Q6: is the hall show to make the ord floor? A8: ight dark wood floor? A9: is the droom a child's room, guest room, or days troom, or darked to say Q4: big there any other furniture in the bedroom? A10: a table and another bed	Office opuses any people? Alt no 22: Is there a bed in the bedroom? Alt no 22: Is a big pile of laundry? As no Q4: what color is the bedgmead? A4: what G1: Is the full carpeted or heard G2: Is the full carpeted or heard floor? A6: hand floor Z7: Is the laundry hanging or piled or folded? A7: hanging G8: Is that light or draft wood floor? A8: light G1: Is the hall carpeted or heard floor? A8: light G1: Is the hall carpeted or heard floor? A8: light G1: Is the hall carpeted or heard floor? A8: light G1: Is the hall carpeted or heard floor? A8: light G1: Is the reary other furniture in the bedroom? A10: a table and another bed	11. do you see any people? Air on 22. is there a bed in the bedroom? 42. yes 42. yes 43. is a big pile of laundry? 43. yes 44. white and light gray 45. is the bedspread? 44. white and light gray 45. is the dispread? 46. is the hall argented or hard floor? 46. is hard floor 27. is the laundry hanging or piled or folded? 47. hanging 48. is it a light to drark wood floor? 48. light 40. is the deform? 40. is the deform? 40. is the hall bedroom? 40. is the hall bedroom? 40. is the hall bedroom? 40. Dives

Figure 7: More qualitative examples in VisDial v1.0 val split for three model variants: DAN (Kang et al., 2019), VD-BERT, and VD-BERT with dense annotation fine-tuning. The second column is for ground truth (GT) dialog.