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

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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-

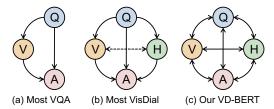


Figure 1: Attention flow direction illustration. V: vision, H: dialog history, Q: question, A: answer. The arrow denotes the attention flow direction and the dashed line represents an optional connection.

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 pre-trained 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 self-attention 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.

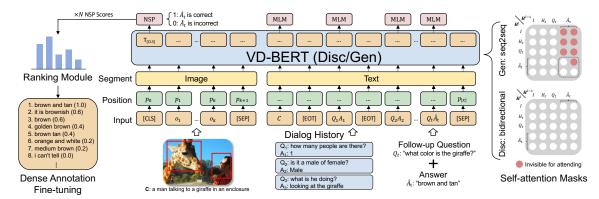


Figure 2: The model architecture of our unified VD-BERT for both discriminative and generative settings.

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. trained 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).

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 selfattention (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)
$$\mathbf{A}_{l} = \operatorname{softmax}(\frac{\mathbf{Q}\mathbf{K}^{T}}{\sqrt{d_{k}}} + \mathbf{M})\mathbf{V},$$
(3)

$$\mathbf{A}_{l} = \operatorname{softmax}(\frac{\mathbf{Q}\mathbf{K}^{T}}{\sqrt{d_{k}}} + \mathbf{M})\mathbf{V}, \tag{3}$$

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 A_l is passed into a feedforward layer to compute \mathbf{H}^l for the next layer.

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 $\mathbf{w}_{\backslash m}$ 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*:

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

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:

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

$$f(x_i) = \frac{\exp(x_i)}{\sum_{j=1}^{N} \exp(x_j)}, \quad i = 1, ..., N.$$
 (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 (§5.1). Then we conduct ablation studies to examine various aspects of our model (§5.2), followed by an in-depth analysis of fine-tuning on dense annotations (§5.3). Lastly, we interpret how it attains the effective fusion of vision and dialog via attention visualization (§5.4).

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 ↓
	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
i	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
£1	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
씸	Synergistic	57.32	62.20	47.90	80.43	89.95	4.17
<u>ر</u> ق	Synergistic [†]	57.88	63.42	49.30	80.77	90.68	3.97
Sig	DAN	57.59	63.20	49.63	79.75	89.35	4.30
P.	DAN^{\dagger}	59.36	64.92	51.28	81.60	90.88	3.92
i	$ReDAN^{\dagger}$	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 ^{†*}	74.91	49.13	36.68	62.98	78.55	7.03
(LF	45.31	55.42	40.95	72.45	82.83	5.95
i	HRE	45.46	54.16	39.93	70.45	81.50	6.41
lts.	MN	47.50	55.49	40.98	72.30	83.30	5.92
Leaderboard Results	MN-Att	49.58	56.90	42.42	74.00	84.35	5.59
꿈	LF-Att	49.76	57.07	42.08	74.82	85.05	5.41
\ ar }	MS ConvAI	55.35	63.27	49.53	80.40	89.60	4.15
Ğ.	UET-VNU [†]	57.40	59.50	45.50	76.33	85.82	5.34
ade	MVAN	59.37	64.84	51.45	81.12	90.65	3.97
್ಷ	$SGLNs^{\dagger}$	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
	Tohoku-CV ^{†*}	74.88	52.14	38.93	66.60	80.65	6.53
ا م	VD-BERT	59.96	65.44	51.63	82.23	90.68	3.90
Ours	VD-BERT*	74.54	46.72	33.15	61.58	77.15	7.18
) ~	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. "†" denotes ensemble model and "*" indicates fine-tuning on dense annotations. The "†" denotes higher value for better performance and "‡" 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 fine-tuning plays a crucial role in boosting the NDCG

Inttps://evalai.cloudcv.org/web/
challenges/challenge-page/161/
leaderboard/483#leaderboardrank-1

Model	MRR↑	R@1↑	R@5↑	R@10↑	Mean ↓				
1,10401	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	82.97/65.27	90.73/72.97	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 fine-tuning 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↑	R@5↑	R@10↑	Mean ↓
	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
(-)	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
(4)	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 approxNDCG achieves the best MRR and Recall on VisDial v1.0 test-std. Therefore, we employ the ListNet 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 fine-tuning 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.

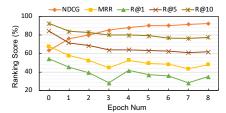


Figure 4: Dense annotation fine-tuning on various metrics with the ListNet method.

		Relevance Score			Question Type				
Models	All	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

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.

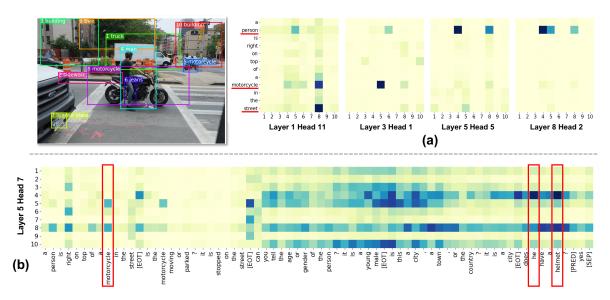


Figure 5: Attention weight visualization in our VD-BERT for a sampled image-dialog example.

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 the motorcycle (at L8H2) and motorcycle tat 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 vision-dialog 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 vision-language datasets, our model establishes new state-of-the-art performance in the discriminative setting and shows promising results in the generative setting on the visual dialog benchmarks.

Acknowledgements

We thank Chien-Sheng Wu, Jiashi Feng, Jiaxin Qi, and our anonymous reviewers for their insightful feedback on our paper. This work was partially supported by the Research Grants Council of the Hong Kong Special Administrative Region, China (No. CUHK 14210717, General Research Fund; No. CUHK 2300174, Collaborative Research Fund).

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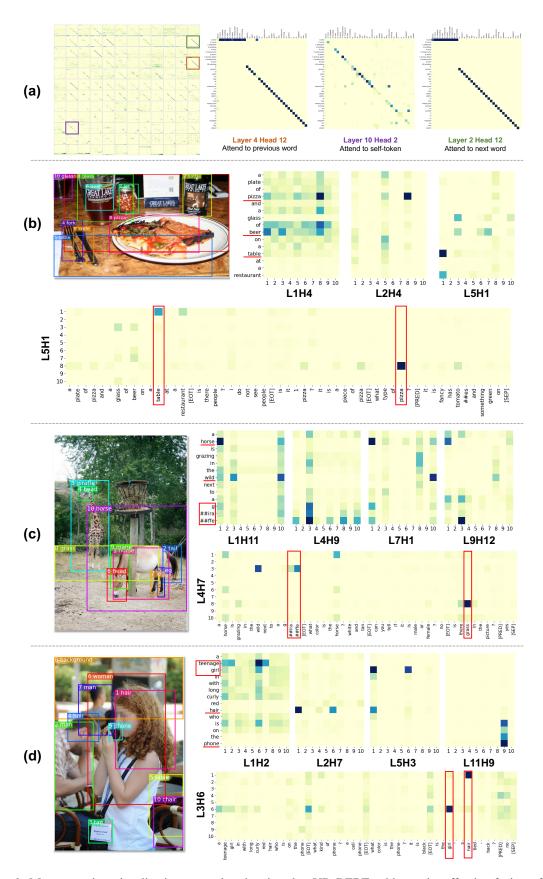


Figure 6: More attention visualization examples showing that VD-BERT achieves the effective fusion of vision and dialog contents. LxHy: Layer x Head y ($1 \le x, y \le 12$). (a) It learns three apparent attention patterns for the example in Figure 5: attentions that a token puts to its previous token, 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)
	Q1: is there any people in the photo? A1: yes far away	Q1: is there any people in the photo? A1: yes	Q1: is there any people in the photo? A1: yes	Q1: is there any people in the photo? A1: yes
Alle-	Q2: are there any streets visible in the photo? A2: yes	Q2: are there any streets visible in the photo? A2: no on the street	Q2: are there any streets visible in the photo? A2: yes	Q2: are there any streets visible in the photo? A2: yes
TANK T	Q3: are there cars parked along the streets? A3: no	Q3: are there cars parked along the streets? A3: no	Q3: are there cars parked along the streets? A3: no	Q3: are there cars parked along the streets? A3: no
To Telegraph and	A3: no Q4: what kind of buildings appear in the photo? A4: older architectural building like a library	Q4: what kind of buildings appear in the photo? A4: yes shops	A3: no Q4: what kind of buildings appear in the photo? A4: older architectural building like a library	Q4: what kind of buildings appear in the photo? A4: not sure
	Q5: is there any signs visible in the photo? A5: there is a no entry sign	Q5: is there any signs visible in the photo? A5: yes	Q5: is there any signs visible in the photo? A5: yes	Q5: is there any signs visible in the photo? A5: yes
北京 地方工具	Q6: are there traffic lights visible?			
	A6: no Q7: can you see the sidewalk?	A6: 1 light pole Q7: can you see the sidewalk?	A6: no Q7: can you see the sidewalk?	A6: no Q7: can you see the sidewalk?
a brown building stands at the	A7: yes Q8: are the sidewalks clean?			
corner of a street on a sunny day	A8: immaculate Q9: are there any trees planted near the building?	A8: yes very clean Q9: are there any trees planted near the building?	A8: yes Q9: are there any trees planted near the building?	A8: yes, they are clean Q9: are there any trees planted near the building?
	A9: there is a tree next to the building Q10: is the tree short or tall? A10: tall	A9: yes Q10: is the tree short or tall? A10: tall	A9: there is a tree next to the building Q10: is the tree short or tall? A10: tall	A9: no there isn't Q10: is the tree short or tall? A10: tall
	Q1: is the picture in color? A1: yes	Q1: is the picture in color? A1: yes	Q1: is the picture in color? A1: yes	Q1: is the picture in color? A1: yes it is
	Q2: how many people are in the picture? A2: i see 2 people	Q2: how many people are in the picture? A2: 2	Q2: how many people are in the picture? A2: 2	Q2: how many people are in the picture? A2: 1
	Q3: how many tv's are in the picture?	Q3: how many tv's are in the picture? A3: 2	Q3: how many tv's are in the picture?	Q3: how many tv's are in the picture?
	A3: 18 screens on the display but there are some in boxes as well Q4: is 1 of the people a worker in the store?	Q4: is 1 of the people a worker in the store? A4: yes, but they are taking a break	A3: 18 screens on the display but there are some in boxes as well Q4: is 1 of the people a worker in the store?	A3: 18 screens on the display but there are some in boxes as well Q4: is 1 of the people a worker in the store?
	A4: no it doesn't look like it Q5: is there an image on the tv that he is pointing	Q5: is there an image on the tv that he is pointing at?	A4: there are no visible workers Q5: is there an image on the tv that he is pointing	A4: there are no visible workers Q5: is there an image on the tv that he is pointing
	at? A5: yes it is an cartoon	A5: yes it is an cartoon Q6: is the man standing or sitting?	at? A5: yes it is an cartoon	at? A5: yes
	Q6: is the man standing or sitting? A6: standing	A6: standing Q7: what is the brand of tv?	Q6: is the man standing or sitting? A6: standing	Q6: is the man standing or sitting? A6: standing
0	Q7: what is the brand of tv? A7: i am unable to tell	A7: it's in japanese Q8: can you tell what store it is?	Q7: what is the brand of tv? A7: it's in lapanese	Q7: what is the brand of tv? A7: i can't tell
man pointing at tv display in a store	Q8: can you tell what store it is? A8: no	A8: yes it is a list of rules Q9: are there any other products in view?	Q8: can you tell what store it is? A8: no	Q8: can you tell what store it is? A8: no
	Q9: are there any other products in view? A9: i just see tv's and boxes	A9: there is papers all over the desk so i would say yes	Q9: are there any other products in view? A9: i just see tv's and boxes	Q9: are there any other products in view? A9: yes
	Q10: what color is the floor? A10: blue			
	Q1: is there anyone in the room with the woman?	Q1: is there anyone in the room with the woman?	Q1: is there anyone in the room with the woman?	Q1: is there anyone in the room with the woman?
	A1: no Q2: is she young?	A1: no, she is alone Q2: is she young?	A1: no Q2: is she young?	A1: no Q2: is she young?
	A2: no Q3: what color is her hair?	A2: no about 18 Q3: what color is her hair?	A2: yes Q3: what color is her hair?	A2: yes Q3: what color is her hair?
	A3: black Q4: is it a big microwave?	A3: brown Q4: is it a big microwave?	A3: brown Q4: is it a big microwave?	A3: brown Q4: is it a big microwave?
	A4: yes Q5: is it sunny?	A4: normal size Q5: is it sunny?	A4: yes Q5: is it sunny?	A4: yes Q5: is it sunny?
Clo .	A5: no Q6: is there any other appliances in the room?	A5: no Q6: is there any other appliances in the room?	A5: no Q6: is there any other appliances in the room?	A5: i can't tell Q6: is there any other appliances in the room?
	A6: no Q7: what is the woman wearing?	A6: no Q7: what is the woman wearing?	A6: no Q7: what is the woman wearing?	A6: not that i can see Q7: what is the woman wearing?
	A7: a shirt Q8: is her hair long?	A7: brown jacket Q8: is her hair long?	A7: black jeans and a t shirt Q8: is her hair long?	A7: a black jacket Q8: is her hair long?
a woman is smiling next to a decorated microwave	A8: no Q9: what color is the microwave? A9: white	A8: yes Q9: what color is the microwave? A9: silver	A8: no Q9: what color is the microwave? A9: white	A8: no Q9: what color is the microwave? A9: white
accordica interovare	Q10: is she wearing glasses? A10: no			
	Q1: is the elephant large? A1: yes, but doesn't look full grown	Q1: is the elephant large? A1: yes	Q1: is the elephant large? A1: yes	Q1: is the elephant large? A1: yes
	Q2: how many people are on the elephant? A2: i can only see 1	Q2: how many people are on the elephant? A2: four, 1 in each photo	Q2: how many people are on the elephant? A2: 2	Q2: how many people are on the elephant? A2: 1
	Q3: are there more elephants in the picture? A3: no	Q3: are there more elephants in the picture? A3: no. just the 2 birds	Q3: are there more elephants in the picture? A3: no	Q3: are there more elephants in the picture? A3: no
	Q4: what is the person wearing? A4: i think it's shorts, hard to tell with the spray	Q4: what is the person wearing? A4: a green button up	Q4: what is the person wearing? A4: a waterproof swimsuit thing	Q4: what is the person wearing?
	A4: i think it's shorts, hard to tell with the spray from the elephant	A4: a green button up Q5: where is the elephant getting the water from?	A4: a waterproof swimsuit thing Q5: where is the elephant getting the water from?	Q4: what is the person wearing? A4: he is wearing a jacket
	A4: i think it's shorts, hard to tell with the spray	A4: a green button up Q5: where is the elephant getting the water from? A5: it's either a large puddle or maybe a river bank, not sure	A4: a waterproof swimsuit thing	Q4: what is the person wearing? A4: he is wearing a jacket Q5: where is the elephant getting the water from? A5: cannot tell from the picture Q6: is the water clean or dirty?
	A4: I think it's shorts, hard to tell with the spray from the elephant OS: where is the elephant getting the water from? A5: it's either a large puddle or maybe a river bank, not sure OS: is the water clean or dirty?	A4: a green button up Q5: where is the elephant getting the water from? A5: it's either a large puddle or maybe a river bank, not sure Q6: is the water clean or dirty? A6: it looks pretty muddy, so i would say dirty	A4: a waterproof swimsuit thing Q5: where is the elephant getting the water from? A5: it's either a large puddle or maybe a river bank, not sure Q6: it looks pretty muddy, so i would say dirty A6: it looks pretty muddy, so i would say dirty	Q4: what is the person wearing? A4: he is wearing a jacket Q5: where is the elephant getting the water from? A5: cannot tell from the picture
To the	A4: I think it's shorts, hard to tell with the spray from the elephant 0.5: where is the elephant getting the water from? A5: it's either a large puddle or maybe a river bank, not sure 0.6: is the water clean or dirty? A6: it looks pretty muddy, so i would say dirty 0.7: is there grass anywhere near the water or	A4: a green button up 65: where is the elephant getting the water from? A5: it's either a large puddle or maybe a river bank, not sure (86: is the water clean or dirty? A6: it looks pretty muddy, so i would say dirty (27: is there grass anywhere near the water or mainly mud?	A4: a waterproof swimsuit thing Q5: where is the elephant getting the water from? A5: it's either a large puddle or maybe a river bank, not sure Q6: is the water clean or dirty?	Od: what is the person wearing? Ad: he is wearing a jacket OS: where is the elephant getting the water from? AS: cannot tell from the picture GS: is the water clean or dirty? AG: it looks pretty muddy, so I would say dirty OZ: is there grass anywhere near the water or
	A4: I think it's shorts, hard to tell with the spray from the elephant Q5: where is the elephant getting the water from? A5: It's either a large puddle or maybe a river bank, not sure Q6: is the water clean or dirty? A6: It looks pretty muddy, so i would say dirty	A4: a green button up OS: where is the elephant getting the water from? A5: it's either a large puddle or maybe a river bank, not sure G6: is the water clean or dirty? A6: it looks pretly muddy, so it would say dirty Q7: is there grass anywhere near the water or anywhere. Both of grass, and a green reflection on the water OS: can you see the sky?	Ad: a waterproof swimsuit thing OS: where is the elephant getting the water from? AS: it's either a large puddle or maybe a river bank, not sure OS: is the water clean or dirty? AS: it looks pretty muddy, so I would say dirty Q?: is there grass anywhere near the water or mainly mud?	Q4: what is the person wearing? A4: he is wearing a jacket Q5: where is the elephant getting the water from? A5: cannot tell from the picture Q6: is the water (celan or dirty? A6: it looks pretty muddy, so i would say dirty Q7: is there gras anywhere near the water or mainly mud? A7: no, there is 0
an elephant sprays the person on its	A4: I think it's shorts, hard to tell with the spray from the elephant getting the water from? A5: it's either a large puddle or maybe a river bank, not sure Q6: is the water clean or dirty? A6: it looks pretty muddy, so! would say dirty Q7: is there gras mywhere near the water or mainly mud? A7: mainly mud	A4: a green button up OS: where is the elephant getting the water from? A5: it's either a large puddle or maybe a river bank, not sure Q6: is the water clean or dirty? A6: it looks pretly muddy, so it would say dirty Q7: is there grass anywhere near the water or mainly mud? A6: the control of grass, and a green reflection on the three's a bit of grass, and a green reflection on C8: can you see the sky? A8: a very little part of if through the trees Q9: are there any trees in the photo?	A4: a waterproof swimsuit thing 05: where is the elephant getting the water from? A5: it's either a large puddle or maybe a river bank, not sure 06: is the water clean or dirty? A6: it boks prety muddy, soi would say dirty 07: is there grass anywhere near the water or mainly mud A7: mainly mud 08: can you see the sky?	Od: what is the person wearing? Ad: he is wearing a jucket Od: where is the elephant getting the water from? Ads: cannot tell from the picture Od: is the water clean or dirty? Ads: it books prety muddy, so it would say dirty Od: is there grass anywhere near the water or many of the control
an elephant sprays the person on its back	A4: I think it's shorts, hard to tell with the spray from the elephant getting the water from? A5: where is the elephant getting the water from? A5: it's either a large puddle or maybe a river bank, not sure (A6: it to book pretty muddy, so i would say dirty Q7: is there grass anywhere rear the water or mainly mud A7: mainly mud A8: an you see the sky? A8: no Q9: are there any trees in the photo? A9: yes Q10: can you tell what type of trees?	A4: a green button up OS: where is the elephant getting the water from? A5: it's either a large puddle or maybe a river bank, not sure Q6: is the water clean or dirty? A6: it looks previ muddy, so i would say dirty Q7: is there grass anywhere near the water or mainty mud? A7: there's a bit of grass, and a green reflection on the water water water water water water water water or water	A4: a waterproof swimsuit thing OS: where is the elephant getting the water from? A5: it's either a large puddle or maybe a river bank, not sure OS: is the water clean or dirty? A6: it looks pretty muddy, so il would say dirty Q7: is there grass anywhere near the water or mainly mud A7: mainly mud OS: can you see the sky? A8: no O9: are there any trees in the photo?	Od: what is the person wearing? Ad: he is wearing a jacket Ods: where is the elephant getting the water from? As: cannot tell from the picture Ods: is the water clean or dirty? As: it looks pretry muddy, so it would say dirty Q?: is there grass anywhere near the water or mainly mud? A?: no, there is O Oc. can you see the sky? Ods: an you see the sky? Ods: on you see the sky?
	A4: I think it's shorts, hard to tell with the spray from the elephant getting the water from? A5: rits either a large puddle or maybe a river bank, not sure A6: it books pretty muddy, so i would say dirty Q7: is there grass anywhere near the water or mainly mud? A7: mainly mud Q8: can you see the sky? A8: no Q9: are there any trees in the photo? A9: yes	A4: a green button up OS: where is the eliphant getting the water from? A5: it's either a large puddle or maybe a river bank, not sure O8: is the water clean or dirty? A6: it looks prethy muddy, so il would say dirty O7: is there grass anywhere near the water or mainly mud? A7: there's a bit of grass, and a green reflection on the water O8: can you see the sky? A8: a very little part of if through the trees O9: are there any trees in the photo? A9: yes, but there's hardy any leaves	A4: a waterproof swimsuit thing OS: where is the elephant getting the water from? A5: it's either a large puddle or maybe a river bank, not sure OS: is the water clean or dirty? A6: it looks pretty muddy, so il would say dirty Q7: is there grass anywhere near the water or mainly mud A7: mainly mud OS: can you see the sky? A8: no O9: are there any trees in the photo? A9: yes J00: can you tell what type of trees?	0.4: what is the person wearing? At: he is wearing a jacket 0.5: where is the elephant getting the water from? As: cannot tell from the picture 0.6: is the water clean or dirty? As: it looks pretry muddy, so it would say dirty 0.7: is there grass anywhere near the water or mainly mud? A?: no, there is 0 0.8: can you see the sky? A&: no 0.9: are there any trees in the photo? A.9: yes 0.10: can you tell what type of trees?
	A4: I think it's shorts, hard to tell with the spray from the elephant getting the water from? OS: where is the elephant getting the water from? SS: lit's either a large puddle or maybe a river bank, oct sure CS: it's the water clean or ditry? AS: it's the spray mody, so it would say dirty AC? is there grass anywhere near the water or manily mud? AS: mainly mud QS: can you see the sky? AS: no QS: are there any trees in the photo? AS: yes CS: are there any trees in the photo? AS: yes QS: are there any trees in the photo? AS: yes QS: are there any trees in the photo? AS: yes QS: are there any trees in the photo? AS: yes QS: are there any trees in the photo? AS: yes QS: are there any trees in the photo? AS: yes QS: are there any trees in the photo? AS: yes QS: are there any trees in the photo? AS: yes QS: are there any trees in the photo? AS: yes QS: Ye	A4: a green button up OS: where is the elephant getting the water from? A5: it's either a large puddle or maybe a river bank, not sure Q6: is the water clean or dirty? A6: it looks pretly muddy, so it would say dirty Q7: is there grass anywhere near the water or mashly mud? A6: it looks pretly muddy, so it would say dirty A7: is there grass anywhere near the water or mashly mud? A8: an eyu bit of grass, and a green reflection on the water. A8: a very little part of if through the trees Q6: can you see the sky? A8: a very little part of if through the trees Q7: are there any trees in the photo? A9: yes, but there's hardly any leaves? A10: it would think late spring or summer cause all the trees are ind green Q1: age of man? A1: 48:	A&: a waterproof swimsuit thing OS: where is the elephant getting the water from? AS: it's either a large puodle or maybe a river bank, not sure QB: is the water clean or dirty? AB: it looks pretty muddy, so it would say dirty OT: is there gasts anywhere near the water or AP: mainly mud AB: can you see the sky? AB: no OB: are there any trees in the photo? AB: pcs QD: can you tell what type of trees? A1D: no OI: age of man? A1: dgs	0.4: what is the person wearing? At: he is wearing a jacket O.5: where is the elephant getting the water from? A5: cannot tell from the picture O.6: is the water clean or dirty? A6: it looks pretry muddy, so! would say dirty O.7: is there grass anywhere near the water or mainly mud? A7: no, there is O O.8: can you see the sky? A8: no O.9: are there any trees in the photo? A9: you you see the sky? A0: no! Can't on you tell what type of trees? A10: no! can't O1: age of man? A1: 40s
	A4: I think it's shorts, hard to tell with the spray from the elephant getting the water from? A5: where is the elephant getting the water from? A5: it's either a large puddle or maybe a river bank, not sure G6: is the water clean or ditry? A6: it looks pretty muddy, so i would say dirty a6: it looks pretty muddy, so i would say dirty analym mud A7: mainly mud G8: can you see the sky? A8: no G9: are there any trees in the photo? A9: yes Q10: can you tell what type of trees? A10: no C11: age of man? A1: maybe 20: Q2: type of dog?	A4: a green button up OS: where is the elephant getting the water from? A5: it's either a large puddle or maybe a river bank, not sure G6: is the water clean or dirty? A6: it looks pretly muddy, so it would say dirty Q7: is there grass anywhere near the water or Q7: is there grass anywhere near the water or A7: there's a bit of grass, and a green reflection on the water G8: can you see the sky? A8: a very little part of if through the trees G9: are there any trees in the photo? A9: yes, but there's hardly any leaves Q10: can you tell what type of trees? A10: would think late spring or summer cause all the trees are and green U1: age of man? A1: 40s Q2: type of dog? A2: a white fluffy dog	A&: a waterproof swimsult thing 0.5: where is the elephant getting the water from? A&5 it's either a large puddle or maybe a river bank, not sure 0.6: is the water clean or dirty? A&1 it looks pretty muddy, so I would say dirty Only muddy A&2 many muddy A&3 many muddy A&4 many muddy A&5 many water best proposed to the say of the	0.4: what is the person wearing? At: he is wearing a jacket 0.5: where is the elephant getting the water from? AS: cannot tell from the picture 0.6: is the water clean or dirty? AS: it looks pretry muddy, so! would say dirty 0.7: is there grass anywhere near the water or mainly mud? A7: no, there is 0 08: can you see the sky? A8: no 09: are there any trees in the photo? A9: yes 010: can you tell what type of trees? A10: no! can't 01: age of man? A1: 405 02: type of dog? A2: can't tell
	A4: I think it's shorts, hard to tell with the spray from the elephant getting the water from? A5: where is the elephant getting the water from? A5: it's either a large puddle or maybe a river bank, not sure (A5: it's either a large puddle or maybe a river bank, not sure (A5: it's either a large puddle or maybe a river bank, not sure (A5: it's either a large water) and a large district (A5: it's either any bank) and water or A7: mainly mud (A7: mainly mud (A	A4: a green button up OS: where is the elephant getting the water from? A5: it's either a large puddle or maybe a river bank, not sure Q6: is the water clean or dirty? A6: it looks pretly muddy, so it would say dirty Q7: is there grass anywhere near the water or manihy mud? A6: it looks pretly muddy, so it would say dirty A7: is there grass anywhere near the water or manihy mud? A8: any up use the sky? A8: a very little part of if through the trees Q9: are there any trees in the photo? A9: yes, but there's hardly any leaves Q10: can you tell what type of trees? A10: it would think late spring or summer cause all the trees are indeed and green Q1: age of man? A1: 40s Q2: type of dog? A2: a white fuffy dog Q3: is its small? A3: average size	A&: a waterproof swimsuit thing OS: where is the elephant getting the water from? AS: it's either a large puddle or maybe a river bank, not sure QB: is the water clean or dirty? AB: it looks pretly muddy, so it would say dirty QT: is there gass anywhere near the water or AB: no look any ou see the sky? AB: no QB: are there any trees in the photo? AB: no QB: are there any trees in the photo? AB: no QB: are there any trees in the photo? AB: no QB: are there any trees in the photo? AB: no QB: are there any trees in the photo? AB: no QB: are there any trees in the photo? AB: no QB: are there any trees in the photo? AB: no QB: as the find find find find find find find find	Od: what is the person wearing? Ad: he is wearing a jucket Ods: where is the elephant getting the water from? AS: cannot tell from the picture Ods: is the water clean or dirty? AS: thools perfor muddy, so the would say dirty mainly mud? AS: no compare the water or mainly mud? AS: no Ods: are there any trees in the photo? AS: no Ods: are there any trees in the photo? AS: yes Ods: any ou sell what type of trees? ALO: no I can't Od: age of man? AL: 40s Ods: age of man.
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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.