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

Yue Wang[1*], **Shafiq Joty**[2], **Michael R. Lyu**[1], **Irwin King**[1], **Caiming Xiong**[2], and **Steven C.H. Hoi**[2]

[1] Department of Computer Science and Engineering
The Chinese University of Hong Kong, HKSAR, China
[2]Salesforce 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-
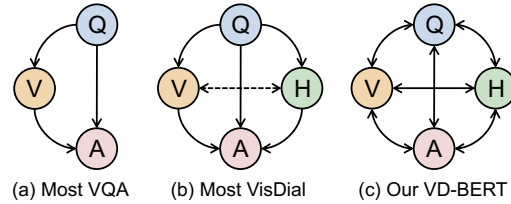

Figure 1: Attention flow direction illustration. V: vision, H: dialog history, Q: question, A: answer. The arrow denotes the attention flow direction and the dashed line represents an optional connection.

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 entities (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 some emerging work has attempted to adapt BERT for multimodal tasks (Sun et al., 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 VisDial 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.

- Without pretraining on external vision-language data, our model yields new state-of-the-art results in discriminative setting and promising results in generative setting on VisDial benchmarks (§5.1).

- 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.

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 complex 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 is recent work (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.
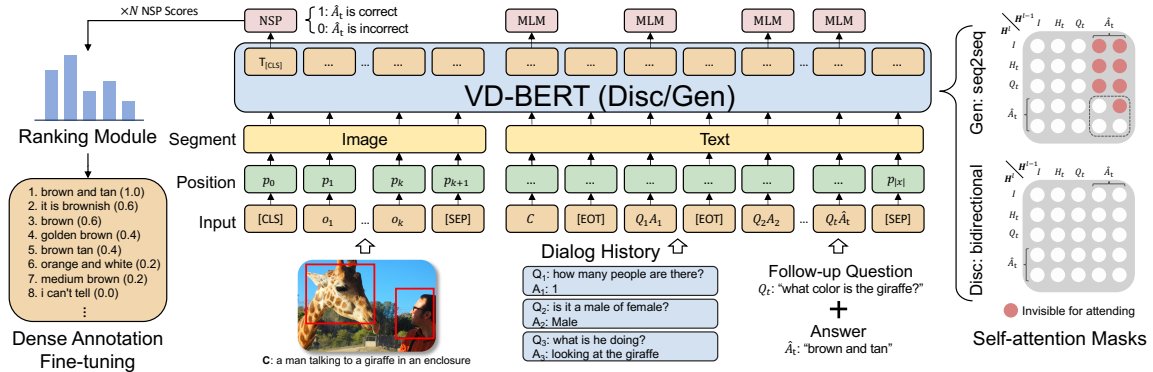
Figure 2: The model architecture of our unified VD-BERT for both discriminative and generative settings.

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 encoder-decoder 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 attempts to extend 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 $\mathbf{w}$, 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_1 A_1, $ [EOT]$, ..., Q_t \hat{A}_t, $ [SEP]$)$. To notify the model for the answer prediction, we further insert a [PRED] token between the $Q_t \hat{A}_t$ 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 $\mathbf{H}^l = \text{Transformer}(\mathbf{H}^{l-1}), l \in [1, L]$. 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):

$$\mathbf{Q} = \mathbf{H}^{l-1}\mathbf{W}_l^Q, \mathbf{K} = \mathbf{H}^{l-1}\mathbf{W}_l^K, \mathbf{V} = \mathbf{H}^{l-1}\mathbf{W}_l^V, \quad (1)$$

$$\mathbf{M}_{ij} = \begin{cases} 0, & \text{allow to attend,} \\ -\infty, & \text{prevent from attending,} \end{cases} \quad (2)$$

$$\mathbf{A}_l = \text{softmax}(\frac{\mathbf{Q}\mathbf{K}^T}{\sqrt{d_k}} + \mathbf{M})\mathbf{V}, \quad (3)$$

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 $\mathbf{w}_{\backslash m}$ 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 vision-language 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 $\mathbf{T}_{[CLS]}$ 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 pointwise binary classification problem. Specifically, we sample an answer $\hat{A}_t$ 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 $\mathbf{M}$ 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*:

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

We allow tokens in the context to be fully visible for attending by setting the left part of $\mathbf{M}$ to all 0s. For the answer sequence, we mask out (by setting $-\infty$ in $\mathbf{M}$) 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. After comparing various methods in Table 3(c), we adopt ListNet (Cao et al., 2007) with the top-1 approximation as the ranking module for VD-BERT:

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

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

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

We report main quantitative comparison results on both VisDial v1.0 and v0.9 datasets below.

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↓
Published Results	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
	DualVD	56.32	63.23	49.25	80.23	89.70	4.11
	HACAN	57.17	64.22	50.88	80.63	89.45	4.20
	Synergistic	57.32	62.20	47.90	80.43	89.95	4.17
	Synergistic†	57.88	63.42	49.30	80.77	<u>90.68</u>	3.97
	DAN	57.59	63.20	49.63	79.75	89.35	4.30
	DAN†	59.36	<u>64.92</u>	51.28	<u>81.60</u>	90.88	<u>3.92</u>
	ReDAN†	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
Leaderboard Results	LF	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
	MN	47.50	55.49	40.98	72.30	83.30	5.92
	MN-Att	49.58	56.90	42.42	74.00	84.35	5.59
	LF-Att	49.76	57.07	42.08	74.82	85.05	5.41
	MS ConvAI	55.35	63.27	49.53	80.40	89.60	4.15
	UET-VNU†	57.40	59.50	45.50	76.33	85.82	5.34
	MVAN	59.37	64.84	<u>51.45</u>	81.12	90.65	3.97
	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
	Tohoku-CV†*	74.88	52.14	38.93	66.60	80.65	6.53
Ours	VD-BERT	59.96	**65.44**	**51.63**	**82.23**	<u>90.68</u>	**3.90**
	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 leaderboard[1] 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

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

Model	MRR↑	R@1↑	R@5↑	R@10↑	Mean↓
	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	66.67/55.94	53.62/46.58	82.85/65.50	90.72/71.25	3.93/14.79
VD-BERT	**70.04**/55.95	**57.79**/46.83	**85.34**/65.43	**92.68**/72.05	4.04/13.18

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

	Model	NDCG↑	MRR↑	R@1↑	R@5↑	R@10↑	Mean↓
(a)	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
	Init from BERT	**63.22**	**67.44**	**54.02**	**83.96**	**92.33**	**3.53**
	↪ only NSP	55.89	63.15	48.98	80.45	89.72	4.15
(b)	No history	**64.70**	62.93	48.70	80.42	89.73	4.30
	One previous turn	63.47	65.30	51.66	82.30	90.97	3.86
	Full history	63.22	**67.44**	**54.02**	**83.96**	**92.33**	**3.53**
	↪ only text	54.32	62.79	48.48	80.12	89.33	4.27
(c)	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**
	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
(d)	Epoch	74.84	47.40	34.30	61.58	77.78	7.12
	Length	75.07	47.33	33.88	62.20	**78.50**	7.01
	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.

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 as VisDial-BERT does. Besides, while VisDial-BERT does not observe improvements by ensembling, we endeavor to design an effective ensemble strategy (see Table 3(d)) 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. 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)

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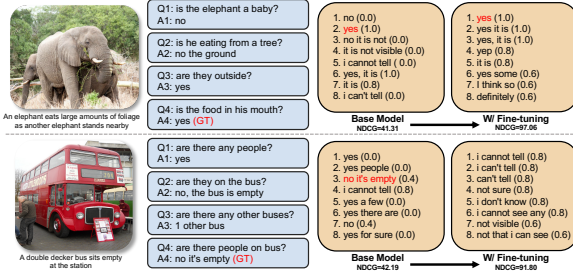
Figure 3: The effects of dense annotation fine-tuning in our VD-BERT for two examples. GT: ground truth.

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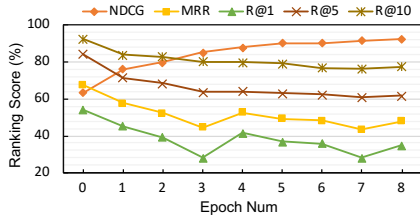
Figure 4: Dense annotation fine-tuning on various metrics with the ListNet method.

Models	All	Relevance Score				Question Type			
		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 either the relevance score or the question type. The % value in the parentheses denotes the corresponding data proportion.
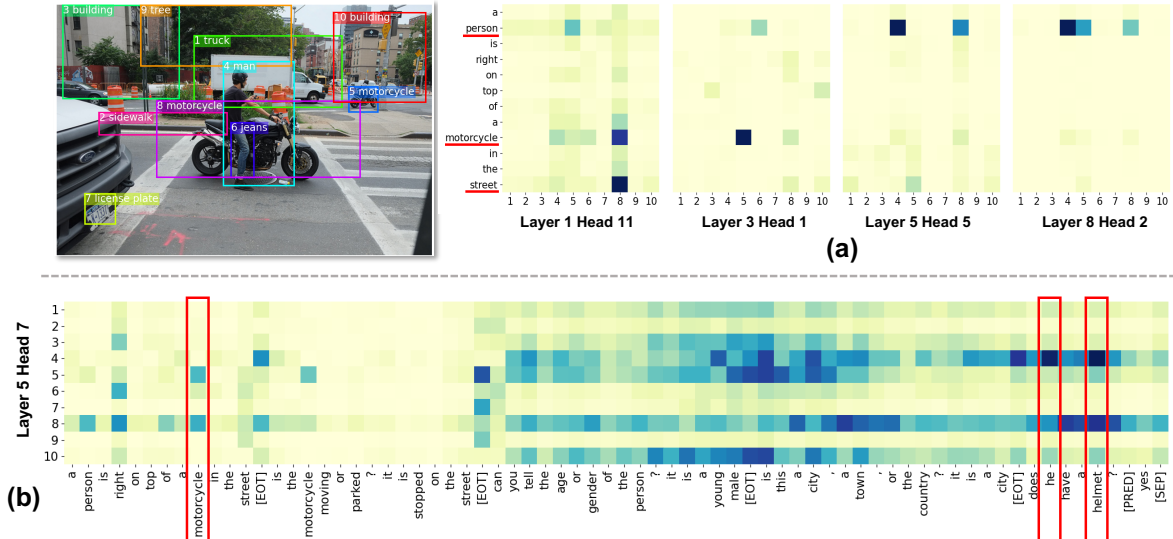

Figure 5: Attention weight visualization in our VD-BERT for a sampled image-dialog example.

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 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

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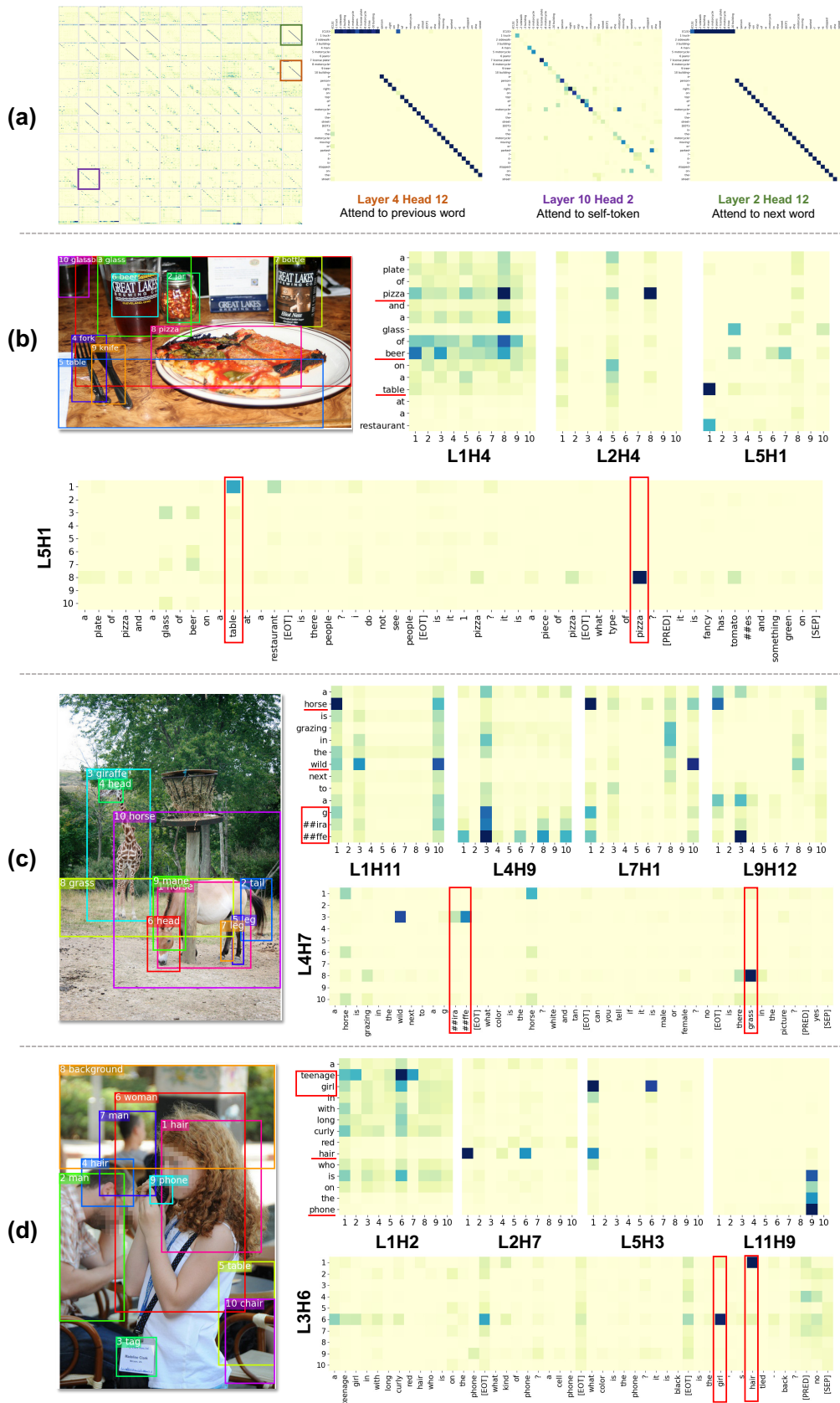
Figure 6: More attention visualization examples showing that VD-BERT achieves the effective fusion of vision and dialog contents. LxHy: Layer x Head y ($1 \leq x, y \leq 12$). (a) It learns three apparent attention patterns for the example in Figure 5: attentions that a token puts to its previous token, 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

GT Dialog:
Q1: is there any people in the photo?
A1: yes far away
Q2: are there any streets visible in the photo?
A2: yes
Q3: are cars parked along the streets?
A3: no
Q4: what kind of buildings appear in the photo?
A4: older architectural building like a library
Q5: is there any signs visible in the photo?
A5: there is a no entry sign
Q6: are there traffic lights visible?
A6: no
Q7: can you see the sidewalk?
A7: yes
Q8: are the sidewalks clean?
A8: immaculate
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

DAN:
Q1: is there any people in the photo?
A1: yes
Q2: are there any streets visible in the photo?
A2: no on the street
Q3: are cars parked along the streets?
A3: no
Q4: what kind of buildings appear in the photo?
A4: yes shops
Q5: is there any signs visible in the photo?
A5: yes
Q6: are there traffic lights visible?
A6: 1 light pole
Q7: can you see the sidewalk?
A7: yes
Q8: are the sidewalks clean?
A8: yes very clean
Q9: are there any trees planted near the building?
A9: no
Q10: is the tree short or tall?
A10: tall

VD-BERT:
Q1: is there any people in the photo?
A1: yes
Q2: are there any streets visible in the photo?
A2: yes
Q3: are cars parked along the streets?
A3: no
Q4: what kind of buildings appear in the photo?
A4: older architectural building like a library
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?
A7: yes
Q8: are the sidewalks clean?
A8: yes
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

VD-BERT (w/ft):
Q1: is there any people in the photo?
A1: yes
Q2: are there any streets visible in the photo?
A2: yes
Q3: are 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?
A7: yes
Q8: are the sidewalks clean?
A8: yes, they are clean
Q9: are there any trees planted near the building?
A9: no there isn't
Q10: is the tree short or tall?
A10: tall

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man pointing at tv display in a store

GT Dialog:
Q1: is the picture in color?
A1: yes
Q2: how many people are in the picture?
A2: i see 2 people
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?
A4: no it doesn't look like it
Q5: is there an image on the tv that he is pointing at?
A5: yes it is an cartoon
Q6: is the man standing or sitting?
A6: standing
Q7: what is the brand of tv?
A7: i am unable to tell
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
Q10: what color is the floor?
A10: blue

DAN:
Q1: is the picture in color?
A1: yes
Q2: how many people are in the picture?
A2: 2
Q3: how many tv's are in the picture?
A3: 2
Q4: is 1 of the people a worker in the store?
A4: yes, but they are taking a break
Q5: is there an image on the tv that he is pointing at?
A5: yes it is an cartoon
Q6: is the man standing or sitting?
A6: standing
Q7: what is the brand of tv?
A7: it's in japanese
Q8: can you tell what store it is?
A8: yes it is a list of rules
Q9: are there any other products in view?
A9: there is papers all over the desk so i would say yes
Q10: what color is the floor?
A10: blue

VD-BERT:
Q1: is the picture in color?
A1: yes
Q2: how many people are in the picture?
A2: 2
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?
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
Q6: is the man standing or sitting?
A6: standing
Q7: what is the brand of tv?
A7: it's in japanese
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
Q10: what color is the floor?
A10: blue

VD-BERT (w/ft):
Q1: is the picture in color?
A1: yes it is
Q2: how many people are in the picture?
A2: 1
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?
A4: there are no visible workers
Q5: is there an image on the tv that he is pointing at?
A5: yes
Q6: is the man standing or sitting?
A6: standing
Q7: what is the brand of tv?
A7: i can't tell
Q8: can you tell what store it is?
A8: no
Q9: are there any other products in view?
A9: yes
Q10: what color is the floor?
A10: blue

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a woman is smiling next to a decorated microwave

GT Dialog:
Q1: is there anyone in the room with the woman?
A1: no
Q2: is she young?
A2: no
Q3: what color is her hair?
A3: black
Q4: is it a big microwave?
A4: yes
Q5: is it sunny?
A5: no
Q6: is there any other appliances in the room?
A6: no
Q7: 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 she wearing glasses?
A10: no

DAN:
Q1: is there anyone in the room with the woman?
A1: no, she is alone
Q2: is she young?
A2: no about 18
Q3: what color is her hair?
A3: brown
Q4: is it a big microwave?
A4: normal size
Q5: is it sunny?
A5: no
Q6: is there any other appliances in the room?
A6: no
Q7: what is the woman wearing?
A7: brown jacket
Q8: is her hair long?
A8: yes
Q9: what color is the microwave?
A9: silver
Q10: is she wearing glasses?
A10: no

VD-BERT:
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
Q4: is it a big microwave?
A4: yes
Q5: is it sunny?
A5: no
Q6: is there any other appliances in the room?
A6: no
Q7: what is the woman wearing?
A7: black jeans and a t shirt
Q8: is her hair long?
A8: no
Q9: what color is the microwave?
A9: white
Q10: is she wearing glasses?
A10: no

VD-BERT (w/ft):
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
Q4: is it a big microwave?
A4: yes
Q5: is it sunny?
A5: i can't tell
Q6: is there any other appliances in the room?
A6: not that i can see
Q7: what is the woman wearing?
A7: a black jacket
Q8: is her hair long?
A8: no
Q9: what color is the microwave?
A9: white
Q10: is she wearing glasses?
A10: no

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an elephant sprays the person on its back

GT Dialog:
Q1: is the elephant large?
A1: yes, but doesn't look full grown
Q2: how many people are on the elephant?
A2: i can only see 1
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 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 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
Q10: can you tell what type of trees?
A10: no

DAN:
Q1: is the elephant large?
A1: yes
Q2: how many people are on the elephant?
A2: four, 1 in each photo
Q3: are there more elephants in the picture?
A3: no, just the 2 birds
Q4: what is the person wearing?
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 muddy, so i would say dirty
Q7: is there grass anywhere near the water or mainly mud?
A7: there's a bit of grass, and a green reflection on the water
Q8: can you see 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: i would think late spring or summer cause all the trees are nice and green

VD-BERT:
Q1: is the elephant large?
A1: yes
Q2: how many people are on the elephant?
A2: 2
Q3: are there more elephants in the picture?
A3: no
Q4: what is the person wearing?
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?
A6: it looks 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
Q10: can you tell what type of trees?
A10: no

VD-BERT (w/ft):
Q1: is the elephant large?
A1: yes
Q2: how many people are on the elephant?
A2: 1
Q3: are there more elephants in the picture?
A3: no
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?
A6: it looks pretty muddy, so i would say dirty
Q7: is there grass anywhere near the water or mainly mud?
A7: no, there is 0
Q8: can you see the sky?
A8: no
Q9: are there any trees in the photo?
A9: yes
Q10: can you tell what type of trees?
A10: no i can't

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a man wearing a hat holds a small white dog

GT Dialog:
Q1: age of man?
A1: maybe 20s
Q2: type of dog?
A2: a white fluffy dog
Q3: is it small?
A3: yes
Q4: can you see the head?
A4: i can see the dogs head and the man's head
Q5: is the mouth open on the dog?
A5: no
Q6: what else is the man wearing?
A6: eyeglasses
Q7: what color hat is it?
A7: tan hat
Q8: what color is his shirt?
A8: hard to tell, possibly a grey vest
Q9: what color is his pants?
A9: they are not shown
Q10: is the man outside?
A10: no, he is inside

DAN:
Q1: age of man?
A1: 40s
Q2: type of dog?
A2: a white fluffy dog
Q3: is it small?
A3: average size
Q4: can you see the head?
A4: yes
Q5: is the mouth open on the dog?
A5: yes
Q6: what else is the man wearing?
A6: a jacket and a hat
Q7: what color hat is it?
A7: brown
Q8: what color is his shirt?
A8: black
Q9: what color is his pants?
A9: black
Q10: is the man outside?
A10: no, he is inside

VD-BERT:
Q1: age of man?
A1: 40s
Q2: type of dog?
A2: a white fluffy dog
Q3: is it small?
A3: yes
Q4: can you see the head?
A4: i can see the dogs head and the man's head
Q5: is the mouth open on the dog?
A5: no
Q6: what else is the man wearing?
A6: a jacket and a hat
Q7: what color hat is it?
A7: tan hat
Q8: what color is his shirt?
A8: white
Q9: what color is his pants?
A9: they are not shown
Q10: is the man outside?
A10: no, he is inside

VD-BERT (w/ft):
Q1: age of man?
A1: 40s
Q2: type of dog?
A2: i can't tell
Q3: is it small?
A3: yes
Q4: can you see the head?
A4: yes
Q5: is the mouth open on the dog?
A5: nope
Q6: what else is the man wearing?
A6: eyeglasses
Q7: what color hat is it?
A7: it's brown
Q8: what color is his shirt?
A8: his shirt is white
Q9: what color is his pants?
A9: i can't see it
Q10: is the man outside?
A10: no

---

a small bedroom with a hall with laundry in the background

GT Dialog:
Q1: do you see any people?
A1: no
Q2: is there a bed in the bedroom?
A2: yes
Q3: is it a big pile of laundry?
A3: no
Q4: what color is the bedspread?
A4: white and light gray
Q5: is it dirty laundry or clean?
A5: clean
Q6: is the hall carpeted or hard floor?
A6: hard floor
Q7: is the laundry hanging or piled or folded?
A7: hanging
Q8: is it a light or dark wood floor?
A8: dark
Q9: is the bedroom a child's room, guest room, or adult bedroom?
A9: adult
Q10: is there any other furniture in the bedroom?
A10: yes

DAN:
Q1: do you see any people?
A1: no
Q2: is there a bed in the bedroom?
A2: no
Q3: is it a big pile of laundry?
A3: yes
Q4: what color is the bedspread?
A4: white and tan blankets
Q5: is it dirty laundry or clean?
A5: it's clean
Q6: is the hall carpeted or hard floor?
A6: wood
Q7: is the laundry hanging or piled or folded?
A7: hanging
Q8: is it a light or dark wood floor?
A8: light
Q9: is the bedroom a child's room, guest room, or adult bedroom?
A9: hard to say
Q10: is there any other furniture in the bedroom?
A10: a table and another bed

VD-BERT:
Q1: do you see any people?
A1: no
Q2: is there a bed in the bedroom?
A2: yes
Q3: is it a big pile of laundry?
A3: no
Q4: what color is the bedspread?
A4: white
Q5: is it dirty laundry or clean?
A5: clean
Q6: is the hall carpeted or hard floor?
A6: hard floor
Q7: is the laundry hanging or piled or folded?
A7: hanging
Q8: is it a light or dark wood floor?
A8: light
Q9: is the bedroom a child's room, guest room, or adult bedroom?
A9: adult
Q10: is there any other furniture in the bedroom?
A10: a table and another bed

VD-BERT (w/ft):
Q1: do you see any people?
A1: no
Q2: is there a bed in the bedroom?
A2: yes
Q3: is it a big pile of laundry?
A3: no
Q4: what color is the bedspread?
A4: white and light gray
Q5: is it dirty laundry or clean?
A5: clean
Q6: is the hall carpeted or hard floor?
A6: hard floor
Q7: is the laundry hanging or piled or folded?
A7: hanging
Q8: is it a light or dark wood floor?
A8: light
Q9: is the bedroom a child's room, guest room, or adult bedroom?
A9: adult
Q10: is there any other furniture in the bedroom?
A10: yes

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.