Modeling Text-visual Mutual Dependency for Multi-modal dialog Generation

Shuhe Wang♠, Yuxian Meng♣, Xiaofei Sun♠, Fei Wu♠, Rongbin Ouyang♣, Rui Yan※, Tianwei Zhang♣, Jiwei Li♣♣

♠ Shannon.AI, ♠ Peking University
♣ Zhejiang University, ※ Renmin University of China, ♣ Nanyang Technological University

{yuxian_meng, xiaofei_sun, jiwei_li}@shannonai.com
wangshuhe@stu.pku.edu.cn, ouyang@pku.edu.cn
wufei@zju.edu.cn, ruiyan@ruc.edu.cn, tianwei.zhang@ntu.edu.sg

Abstract

Multi-modal dialog modeling is of growing interest. In this work, we propose frameworks to resolve a specific case of multi-modal dialog generation that better mimics multi-modal dialog generation in the real world, where each dialog turn is associated with the visual context in which it takes place. Specifically, we propose to model the mutual dependency between text-visual features, where the model not only needs to learn the probability of generating the next dialog utterance given preceding dialog utterances and visual contexts, but also the probability of predicting the visual features in which a dialog utterance takes place, leading the generated dialog utterance specific to the visual context. We observe significant performance boosts over vanilla models when the mutual dependency between text and visual features is modeled.

1 Introduction

Multi-modal learning is of growing interest in recent years [12, 20, 30, 59], and jointly modeling multiple modalities has shown notable effectiveness in improving models’ ability to understand visual and textual semantics, such as image captioning [9, 76], visual question answering [8, 20, 46] and text-to-image generation [59, 60]. As an important subfield of multi-modal learning, multi-modal dialog generation, targets generating coherent and informative dialog utterances specific to the visual contexts. Although a few existing works have proposed to employ state-of-the-art multi-modal models for multi-modal dialog generation [11] [68] [69], they mainly focus on question-answering style dialog generation grounded in a single image, rather than each image per dialog turn. This learning paradigm limits the application scope of multi-modal dialog generation models on real-world scenarios where dialog takes place in visual contexts that change over time.

In this work, we propose frameworks to resolve a specific case of multi-modal dialog generation that better mimics multi-modal dialog generation in the real world, where each dialog turn is associated with the visual context in which it takes place. Specifically, we first propose vanilla visual models to extract and incorporate the visual features into sequence-to-sequence dialog generation, where each model extracts visual features at a different level: from using only textual features to using coarse-grained image-level features, and to the fine-grained object-level features. Further, we propose to model the mutual dependency between textual and visual features, where the dialog model not only needs to learn the probability of generating the next utterance given preceding dialog utterances and visual contexts, but also to model the backward probability of predicting visual features given the dialog utterance, leading the generated dialog utterance specific to the visual context.

1 Code is available at https://github.com/ShannonAI/OpenViDial
We conduct extensive experiments on the OpenViDial dataset [54], and experimental results show that incorporating visual features at a fine-grained granularity outperforms models that do not use visual features or only use coarse-grained visual features. Further, we observe significant performance boosts over vanilla visual models when the mutual visual-text dependencies are modeled, exhibiting its necessity when time-varying visual contexts needed to be considered. The proposed models can act as strong baselines for future related works.

2 Related Work

2.1 Textual Dialog Generation

Existing works on building reliable dialog systems are generally divided into two categories: chit-chat open-domain dialog generation [38, 72, 73] and task-oriented dialog generation [79]. Attempts to open-domain dialog generation include generating more coherent [1, 41, 42], diverse [5, 77], personalized [40, 55] utterances. With the emergence of task-oriented datasets [7, 17, 66, 74], more practice has been devoted to task-oriented dialog generation, which usually involves a pipeline of intent classification [67], dialog state tracking [25–27], dialog policy making [10, 45] and dialog generation [15]. Dialog state tracking, due to its importance in bridging the user’s intent and certain dialog states, has gained numerous attention over recent years [4, 16, 21, 28, 36, 44, 57, 75]. The prevalence of pretraining on large-scale unlabeled corpora also spurs a wealth of dialog generation systems under both the open-domain and task-oriented settings [22, 29, 49, 53, 62, 80], leading to new SOTA results on dialog benchmarks.

2.2 Jointly Modeling Visual and Textual Information

Multimodal models have proven their ability of modeling interactions between different modalities and better understanding the semantics behind textual utterances [13, 19, 32, 51, 56, 64, 65, 78], and pretraining on additional data gives further performance boosts for a variety of established vision-and-language tasks, such as visual question answering [3, 46, 52], visual commonsense reasoning [37, 43] and text-to-image generation [49, 59, 60]. However, these works focus on the QA style visual dialog, rather than the conversation style with which we are more concerned. Another strand of works address multi-turn dialog generation grounded with vision [2, 11, 18, 47, 63]. [56] studied the task of image-grounded conversations where utterances are generated about a shared image. [68] constructed Image-Chat, a collection of consecutive turns by two interlocutors about an image along with their style traits. They used residual networks [24] to encode images and Transformers to encode texts, and observed performance enhancement when incorporating visual information. [69] investigated combining different state-of-the-art dialog agents and vision models for multimodal dialog generation. By carefully selecting components and training strategies, the best model surpasses existing multimodal systems regarding both automated and engagingness metrics. Different from aforementioned works, we base this work on the intuition that the underlying semantics behind an image and a piece of text referring to the same event should be highly correlated, and we are motivated to study the effectiveness of mutual information between vision and text features in multi-modal dialog generation.

3 The OpenViDial Dataset and Task Statement

Different from previous datasets that focus on limited-domain multi-modal conversations such as E-commerce [18, 63] or communications grounded in a single image [68], the recently released large open-domain multi-modal dataset OpenViDial [54] contains millions of dialog turns, with each dialog turn associated with its specific visual context (image), in which the dialog utterance takes place, rather than a single image for the whole episode. This better mimics multi-modal dialog generation in the real world. Regarding the dialog episode, the average number of turns for each episode in OpenViDial is 14, which is the largest among existing open-domain multi-modal dialog datasets. Therefore, in this work, we use the OpenViDial dataset as the benchmark for designing and testing different multi-modal dialog generation models.

To be more detailed, OpenViDial consists of a set of dialog episodes \((X, Z) \in D\), where \(X = \{x_1, \cdots, x_n\}\) is a sequence of dialog turns in texts and \(Z = \{z_1, \cdots, z_n\}\) is a sequence of images.
We introduce three families of models to tackle this problem.

4 Vanilla Visual Dialog Models

In this section, we introduce three visual dialog models, as shown in Figure 1. These models use both textual and visual contexts and employ the self-attention mechanism [71] to model their interplay. The granularity of the visual features ranges from coarse-grained image features extracted from CNNs [23] to fine-grained object features extracted from Faster R-CNNs [61], each of which represents visual information at different levels.

4.1 The NoVisual (NV) Model

We first introduce a model that uses only dialog texts without visual information, where the model degenerates to a uni-modal dialog generation model. The model is optimized to minimize the
We find that sometimes, the CV and FV models still suffer from generating text utterances that are not very related or even unrelated to the visual contexts. This is due to the nature of objective of generative modeling, i.e., \( p(x_{j+1}|x_{\leq j}, f_{\leq j+1}) \): though the generation \( p(x_{j+1}) \) is conditioned on

\[
L_{NoVisual} = - \sum_{(X,Z) \in \mathcal{D}} \sum_{j=0}^{n-1} p(x_{j+1}|x_{\leq j})
\]

We use a standard Transformer architecture [71] as the model backbone. The numbers of encoder layer and decoder layer are both 3, with 8 heads in each layer and input dimension of 512. We pack the all preceding dialog histories \( x_{\leq j} \) into a long sequence with a special \([\text{SEP}]\) token as the delimiter between two consecutive dialog turns. Sentence-positional and token-positional positional embeddings are added to word representations, which are fed to the transformer as inputs.

### 4.2 The CoarseVisual (CV) Model

Our second model employs a naive approach to inject visual information into dialog generation, which we refer to as CoarseVisual (CV). More concretely, we first use a ResNet-50 model [23] pre-trained on ImageNet [14] to extract a high-dimensional feature \( f_j \) for image \( z_j \). Then, for all tokens \( w_{j,k} \) in the \( j \)-th dialog utterance, we add the image feature \( f_j \) to its word representation \( h_{j,k} \), forming the input layer representation \( h_{j,k}^0 \) as the input to the dialog model:

\[
h_{j,k}^0 = h_{j,k} + f_j
\]

The concatenation of all input token representations for the \( j \)-th dialog utterance is denoted by:

\[
h_j^0 = [h_{j,1}^0, \ldots, h_{j,n_j}^0]
\]

Hence, the input to the encoder is given by \{ \([\text{CLS}]\), \( h_j^0 \), \([\text{SEP}]\), \( h_j^0 \), \([\text{SEP}]\), \ldots, \( h_j^0 \), \([\text{SEP}]\), \( f_{j+1} \), \([\text{SEP}]\) \}. \( f_{j+1} \) represents the encoded feature of image \( z_{j+1} \). The CoarseVisual model is then trained to predict the forthcoming dialog utterance \( x_{j+1} \) by minimizing the NLL loss:

\[
L_{CoarseVisual} = - \sum_{(X,Z) \in \mathcal{D}} \sum_{j=0}^{n-1} p(x_{j+1}|x_{\leq j}, f_{\leq j+1})
\]

### 4.3 The FineVisual (FV) Model

While the CoarseVisual model is able to combine the vision and text modalities, it performs at a coarse level for extracting global image features. This might be insufficient to model fine-grained visual elements in images such as facial expressions, body gestures as well as physical motions. Hence, we use Faster R-CNN [61] pretrained on Visual Genome [35] to extract fine-grained visual semantic objects. For an input image \( z_j \), Faster R-CNN returns a set of detected objects in the image, each of which is captured by a dense feature representation. Let \( O_j = \{o_{j,1}, \ldots, o_{j,q}, \ldots, o_{j, m_j}\} \) denote the set of object features for image \( z_j \), where \( m_j \) is the number of extracted objects. Each extracted feature can be mapped back to a bounding box / region (i.e., Region-of-Interest (RoI)) in the original image. For each dialog turn \( x_{j+1} \) to generate, the input to the model is \{ \([\text{CLS}]\), \( O_1, \ldots, O_{j+1}, [\text{EOI}]\), \( x_{j+1} \), \([\text{SEP}]\), \ldots, \( x_{j} \), \([\text{SEP}]\) \}. \([\text{EOI}]\) is a special end-of-image token denoting the end of the sequence of object features. Similar to the CoarseVisual model, the FineVisual model is optimized to minimize the following NLL loss:

\[
L_{FineVisual} = - \sum_{(X,Z) \in \mathcal{D}} \sum_{j=0}^{n-1} p(x_{j+1}|x_{\leq j}, O_{\leq j+1})
\]

For visual features \{ \( O_1, \ldots, O_{j+1}, [\text{EOI}]\) \}, an image-specific positional feature highlighting objects across different images is added to object representations.

### 5 Modeling Visual-Text Mutual Dependency

We find that sometimes, the CV and FV models still suffering from generating text utterances that are not very related or even unrelated to the visual contexts. This is due to the nature of objective of generative modeling, i.e., \( p(x_{j+1}|x_{\leq j}, f_{\leq j+1}) \): though the generation \( p(x_{j+1}) \) is conditioned on
the preceding visual features \( f_{\leq j+1} \), there is no guarantee on whether or how much the evidence in \( f_{\leq j+1} \) is used. To strengthen the connection between visual features and text features, and enforce the model to generate utterances that are very specific to its visual contexts, we propose to incorporate the backward probability of generating features of visual contexts given text utterances. The model is trained to learn the mutual information (MI) between visual contexts and text features, as will be described below.

5.1 MI-CV

For the CV model, the text utterance to generate has the largest combination of the forward probability, i.e., generating the current text utterance given preceding dialog utterances and visual contexts \( p(x_{j+1}|x_{\leq j}, f_{\leq j+1}) \), and the backward probability, i.e., predicting the visual features in which a dialog utterance takes place \( p(f_{j+1}|x_{j+1}) \):

\[
\hat{x}_{j+1} = \arg \max_{x_{j+1}} \{ (1 - \lambda) \log p(x_{j+1}|x_{\leq j}, f_{\leq j+1}) + \lambda \log p(f_{j+1}|x_{j+1}) \}
\]

(7)

where \( \lambda \in (0, 1) \) is a hyperparameter that controls the trade-off between the forward and the backward probabilities. We use negative sampling to empirically compute \( \log p(f_{j+1}|x_{j+1}) \). Specifically, we use a light discriminative network to approximate this probability. We first concatenate the high dimensional visual feature \( f_{j+1} \) to the textual feature \( t_{j+1,k} \) of each token in \( x_{j+1} \). The textual feature \( t_{j+1,k} \) is produced by the model encoder. Then we feed the resulting sequence of high dimensional features into a single-layer feed forward network (FFN) of dimensionality of 512 followed by the sigmoid function to output the likelihood \( q(f_{j+1}, t_{j+1,k}) \) for each token. Last, we obtain \( \log q(f_{j+1}, x_{j+1}) \) by averaging all these token-level log-likelihoods:

\[
\log q(f_{j+1}, x_{j+1}) = \frac{1}{n_{j+1}} \sum_{k=1}^{n_{j+1}} \log q(f_{j+1}, t_{j+1,k})
\]

(8)

We treat \( \log q(f_{j+1}, x_{j+1}) \) as an approximate of \( \log p(f_{j+1}|x_{j+1}) \). To train the FNN, we randomly draw an image feature \( f_{i} \) (\( i \neq j+1 \)) to form negative examples for each positive \( (x_{j+1}, f_{j+1}) \) example and minimize the following loss:

\[
\mathcal{L} = - \sum_{(X,Z) \in \mathcal{D}} \sum_{j=0}^{n-1} \{ \log q(f_{j+1}, x_{j+1}) - \sum_{l} \log q(f_{l,l \neq j+1}, x_{j+1}) \}
\]

(9)

Another issue with Eq.(7) is that it is infeasible to iterative over all possible \( x_{j+1} \) to search for the optimal one as the search space grows exponentially large with respect to the length of the utterance \( x_{j+1} \). To reduce the search space, we build an N-best list \( \mathcal{N} \) which consists of the \( N \) dialog utterances with the highest probabilities decoded using the forward probability \( \log p(x_{j+1}|x_{\leq j}, f_{\leq j+1}) \), and then rerank the N-best list with the highest MI-interpolated probability in Eq.(7). As it is a common practice to model the mutual dependency between the dialog utterance \( x_{j+1} \) and the prior dialog utterance \( x_j \), we also incorporate the probability of generating \( x_j \) given \( x_{j+1} \), i.e., \( p(x_j|x_{j+1}) \) into Eq.(7) to build semantic connections between consecutive dialogs. Combining all, we can rewrite Eq.(7) by the following equation:

\[
\hat{x}_{j+1} = \arg \max_{x_{j+1} \in \mathcal{N}} \{ \lambda_1 \log p(x_{j+1}|x_{\leq j}, f_{\leq j+1}) + \lambda_2 \log p(x_j|x_{j+1}) + \lambda_3 \log q(f_{j+1}, x_{j+1}) \}
\]

(10)

where \( \lambda_{1,2,3} \) are three hyperparameters satisfying \( \sum_{i=1}^{3} \lambda_i = 1 \). We use two Transformer models respectively for \( p(x_{j+1}|x_{\leq j}, f_{\leq j+1}) \) and \( p(x_j|x_{j+1}) \). Both models have 3 encoder layers and 3 decode layers, with 8 heads in each layer and an input dimensionality of 512.

5.2 MI-FV

Different from the CV model, the FineVisual model is learning to generate the forthcoming dialog utterance \( x_{j+1} \) based on fine-grained object features. To adjust the MI structure to the FV model, we propose to predict the fine-grained object features given the forthcoming dialog utterance:

\[
\hat{x}_{j+1} = \arg \max_{x_{j+1} \in \mathcal{N}} \{ \lambda_1 \log p(x_{j+1}|x_{\leq j}, O_{\leq j+1}) + \lambda_2 \log p(x_j|x_{j+1}) + \lambda_3 \log q_2(O_{j+1}, x_{j+1}) \}
\]

(11)
We use the following metrics for automatic evaluation:

\[ \lambda_i = 1, 2, 3 \] are hyperparameters satisfying \( \sum_{i=1}^{3} \lambda_i = 1 \). For the term \( \log q_2(O_{j+1}, x_{j+1}) \), we first use dimension-wise mean pooling to compress the set of extracted features \( O_{j+1} \) into one high dimensional feature \( o_{j+1} \). Then we concatenate it to every high dimensional representation \( t_{j+1, k} \) produced by the encoder, forming a sequence of features as input to an FFN of dimensionality 512. Similar to what we do in MI-CV, we can get \( \log q_2(o_{j+1}, t_{j+1, k}) \) produced by the FFN model with the sigmoid function:

\[
\log q_2(O_{j+1}, x_{j+1}) = \frac{1}{n_{j+1}} \sum_{k=1}^{n_{j+1}} \log q_2(o_{j+1}, t_{j+1, k})
\]  

Again, we train the model by randomly sampling negative examples and minimizing the loss:

\[
\mathcal{L} = - \sum_{(X, \hat{X}) \in D} \sum_{j=0}^{n-1} \left\{ \log q_2(O_{j+1}, x_{j+1}) - \sum_{l} \log q_2(O_{l, l \neq j+1}, x_{j+1}) \right\}
\]  

### 6 Experiments

We train all models using the Adam [34] optimizer and decay the learning rate (LR) based on the inverse square root of the update number after the step of Warmup, which we set to 6000. For MI, the size of the N-best list \( N \) is set to 5. We also apply MI to the NV model as a baseline. The model is denoted by MI+NV.

#### 6.1 Automatic Evaluation

We use the following metrics for automatic evaluation:

- **BLEU**: Following [79, 70], we report BLEU scores for evaluation. BLEU scores measure the \( n \)-gram \( (n = 1, 2, 4) \) overlaps between the generated sequences and gold target sequences.
- **Diversity**: Following [39], we report the degree of diversity by calculating the number of distinct \( n \)-grams (Dis-\( n \), \( n = 1, 2, 3, 4 \)) in generated responses. The value is scaled by the total number of generated tokens to avoid favoring long sentences.
- **ROUGE-N**: To observe how much information contained in the reference is captured by our model, we report ROUGE-N [45]. ROUGE-N is a recall-related measure counting the number of overlapping units based on \( n \)-grams \( (n = 1, 2, 4) \) between the generated responses and the reference responses. For this evaluation, we only report F-score.

Results are shown in Table 1 and Table 2. For vanilla visual dialog models, we observe progressive performance boosts from NoVisual to FineVisual along with the increase of fine-grained visual features, indicating that integrating more fine-grained visual features leads to better multi-modal

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**Table 1**: Automatic evaluation results for vanilla models on the OpenViDial dataset.

| System | Model | BLEU-1 | BLEU-2 | BLEU-4 | Dis-1 | Dis-2 | Dis-3 | Dis-4 | ROUGE-1 | ROUGE-2 | ROUGE-4 |
|--------|-------|--------|--------|--------|-------|-------|-------|-------|---------|---------|---------|
| NV     | w/o MI| 14.06  | 3.80   | 0.95   | 0.0006 | 0.0019 | 0.0031 | 0.0043 | 0.06787 | 0.01464 | 0.00224 |
| CV     | w/o MI| 14.70  | 4.38   | 1.14   | 0.0023 | 0.0090 | 0.0178 | 0.0272 | 0.08773 | 0.02077 | 0.00238 |
| FV     | w/o MI| 14.85  | 4.61   | 1.19   | 0.0026 | 0.0112 | 0.0246 | 0.0406 | 0.09083 | 0.02085 | 0.00329 |

**Table 2**: Automatic evaluation results for vanilla and MI models on the OpenViDial dataset.

| System | Model | BLEU-1 | BLEU-2 | BLEU-4 | Dis-1 | Dis-2 | Dis-3 | Dis-4 | ROUGE-1 | ROUGE-2 | ROUGE-4 |
|--------|-------|--------|--------|--------|-------|-------|-------|-------|---------|---------|---------|
| NV     | w/ MI | 14.85  | 4.61   | 1.19   | 0.0026 | 0.0112 | 0.0246 | 0.0406 | 0.09083 | 0.02085 | 0.00329 |
| CV     | w/ MI | 14.85  | 4.61   | 1.19   | 0.0026 | 0.0112 | 0.0246 | 0.0406 | 0.09083 | 0.02085 | 0.00329 |
| FV     | w/ MI | 14.85  | 4.61   | 1.19   | 0.0026 | 0.0112 | 0.0246 | 0.0406 | 0.09083 | 0.02085 | 0.00329 |
| Model | No % | Unsure % | Yes % | No % | Unsure % | Yes % |
|-------|------|---------|-------|------|---------|-------|
|       | Without MI | With MI   |       |     |         |      |
| NV    | 34.6 | 28.6    | 37.8  | 32.0| 27.4    | 40.6  |
| CV    | 25.7 | 25.9    | 48.4  | 24.8| 25.3    | 49.9  |
| FV    | 24.6 | 25.1    | 50.3  | 23.3| 25.6    | 51.1  |

Table 3: Human evaluation results.

| Time Step $t - 2$ | Time Step $t - 1$ | Prediction (Time Step $t$) |
|-------------------|-------------------|----------------------------|
| ![Image](image1)  | ![Image](image2)  | ![Image](image3)            |
| **Context**: No.  | **Context**: The Land of OZ is already falling into ruin because of you. | **NV**: I’m sorry. I’m sorry. |
|                   |                   | **CV**: I’m not. I’m not.   |
|                   |                   | **FV**: But I’m not a princess. |
|                   |                   | **FV+MI**: I’m not a princess. I can’t do it. |
|                   |                   | **Truth**: No good can come from the reign of a fool. |

| ![Image](image4)  | ![Image](image5)  | ![Image](image6)            |
|-------------------|-------------------|----------------------------|
| **Context**: Happy birthday, honey. | **Context**: Bears love bunnies. | **NV**: No, no, no, no, no, no. |
|                   |                   | **CV**: Oh, my God.         |
|                   |                   | **FV**: I’m gonna take care of it. |
|                   |                   | **FV+MI**: I’m gonna go get some coffee. |
|                   |                   | **Truth**: We need to hurry up. |

| ![Image](image7)  | ![Image](image8)  | ![Image](image9)            |
|-------------------|-------------------|----------------------------|
| **Context**: Go! Lock! | **Context**: Officer down. Officer down. | **NV**: No, no, no, no. |
|                   |                   | **CV**: Get out of the way! |
|                   |                   | **FV**: Hey, hey, hey!     |
|                   |                   | **FV+MI**: I’m on the phone! |
|                   |                   | **Truth**: I need an ambulance at the Girard Street subway. |

Table 4: Examples from the test set generated by vanilla and MI models.

Dialog learning abilities. We observe further improvements on those evaluations (i.e., BLEU, diversity, ROUGE) for all three models, i.e., NV, CV, FV, when building mutual dependencies between visual contexts and text utterances. For example, the BLEU-4 score increases from 1.19 to 1.22 for the FV model when adding the MI component, and the Dis-4 score increases from 0.0406 to 0.0433, with an increment of 6.65%, the ROUGE-4 also increases from 0.00329 to 0.00338 getting an increment of 2.74%. These observations illustrate the effectiveness of modeling fine-grained visual features and visual-text mutual dependency in multi-modal dialog generation.
6.2 Adversarial Evaluation

The adversarial evaluation strategy is proposed by Kannan and Vinyals [33], Li et al. [42] to train a discriminator function to label dialogs as machine-generated (negative) or human-generated (positive). Positive examples are taken from training dialogs, while negative examples are decoded from a model. The input to the discriminator is the concatenation of features for constituent dialog turns, including the preceding features and the generated text. For each dialog turn, the feature includes both visual features extracted from the image using CNNs, and text features using word embeddings. A multi-layer transformer is built on top of the image, with the [CLS] feature fed to the sigmoid function, the output of which denotes the probability of whether the generated text is machine-generated or human-generated. We used examples from the dev set to train the discriminator, in which we treat half of the examples with original responses in the dataset as human-generated, and the other half with model generated responses as machine-generated. We test the trained model on the test set generated in the same way. We report adversarial success, which is the percentage of the generated responses that can fool the evaluator to believe that it is human-generated. Higher values of adversarial success indicate better dialog generation models. The vanilla NV, CV and FV models respectively obtain adversarial success values of 0.942, 0.917 and 0.890, demonstrating that integrating visual contexts facilitate generating responses more mimicking human conversations. Further, when combining with MI, MI+NV, MI+CV and MI+FV respectively obtain adversarial success values of 0.915, 0.904, 0.877, showing the advantages of the MI strategy over its vanilla correspondence.

6.3 Human Evaluation

Both automatic evaluations and adversarial evaluation suffer from disadvantages. For the former, there have been debates on their validity for dialog generation [50]; for the latter, it requires training another model (i.e., the discriminator) for evaluation. We thus conduct human evaluation for further validations. We employ crowdsourced judges to provide evaluations for a random sample of 1000 episodes from the test set. For each input context, we present annotators with both preceding text contexts, preceding visual contexts, and the current visual context, along with outputs from the three models, i.e., NV, CV and FV. Annotators were asked to score every model response on a 5-point scale (Strongly Agree, Agree, Unsure, Disagree, Strongly Disagree) based on three aspects: Relevance (whether the generated response is relevant to the contexts, both visual and textual), Diversity (whether the generated response has diverse words) and Readability (whether the generated response is grammatical). Ratings were later collapsed to 3 categories (Agree, Unsure, Disagree). Results are shown in Table 3. To verify the statistical significance of the reported results, we perform a pairwise bootstrap test [6,31] to compare the difference between the percentage of responses that are labeled as “yes”. We find that FV is significantly better than CV, which is significantly better than NV, with \( p \)-value < 0.01. This validates the importance of harnessing visual contexts for dialog generation. The MI strategy outperforms its vanilla counterpart also with \( p \)-value < 0.01, illustrating the effectiveness of modeling visual-text correspondence in dialog generation.

6.4 Examples

We randomly choose three examples from the test set and compare the responses generated by vanilla models and the FV+MI model. Results are shown in Table 4. These examples show that the NoVisual (NV) model and the CoarseVisual (CV) model tend to generate dull and meaningless responses because they discard some salient visual information needed to produce meaningful and context-related sentences. On the contrary, the other two models – FineVisual (FV) and FV+MI – can generate informative responses specific to the visual contexts.

7 Conclusion

In this paper, we propose frameworks to resolve the task of multi-modal dialog generation based on the newly released OpenViDial dataset. Specifically, we propose to model the mutual dependency between text-visual features, leading to the generation of dialog utterances specific to the visual contexts. We show that incorporating more fine-grained visual features and integrating MI into multi-modal dialog generation models bring performance improvements regarding both automatic evaluation, adversarial evaluation and human evaluation.
References

[1] Daniel Adiwardana, Minh-Thang Luong, David R So, Jamie Hall, Noah Fiedel, Romal Thoppi-lan, Zi Yang, Apoorv Kulshreshtha, Gaurav Nemade, Yifeng Lu, et al. Towards a human-like open-domain chatbot. arXiv preprint arXiv:2001.09977, 2020.

[2] Huda Alamri, Chiori Hori, Tim K Marks, Dhruv Batra, and Devi Parikh. Audio visual scene-aware dialog (avsd) track for natural language generation in dstc7. In DSTC7 at AAAI2019 Workshop, volume 2, 2018.

[3] Chris Alberti, Jeffrey Ling, Michael Collins, and David Reitter. Fusion of detected objects in text for visual question answering. arXiv preprint arXiv:1908.05054, 2019.

[4] Jacob Andreas, John Bufe, David Burkett, Charles Chen, Josh Clausman, Jean Crawford, Kate Crim, Jordan DeLoach, Leah Dorner, Jason Eisner, et al. Task-oriented dialogue as dataflow synthesis. Transactions of the Association for Computational Linguistics, 8:556–571, 2020.

[5] Ashutosh Baheti, Alan Ritter, Jiwei Li, and Bill Dolan. Generating more interesting responses in neural conversation models with distributional constraints. arXiv preprint arXiv:1809.01215, 2018.

[6] Taylor Berg-Kirkpatrick, David Burkett, and Dan Klein. An empirical investigation of statistical significance in NLP. In Proceedings of the 2012 Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning, pages 995–1005, Jeju Island, Korea, July 2012.

[7] Paweł Budzianowski, Tsung-Hsien Wen, Bo-Hsiang Tseng, Inigo Casanueva, Stefan Ultes, Osman Ramadan, and Milica Gašić. Multiwoz—a large-scale multi-domain wizard-of-oz dataset for task-oriented dialogue modelling. arXiv preprint arXiv:1810.00278, 2018.

[8] Yen-Chun Chen, Linjie Li, Licheng Yu, Ahmed El Kholy, Faisal Ahmed, Zhe Gan, Yu Cheng, and Jingjing Liu. Uniter: Learning universal image-text representations. arXiv preprint arXiv:1909.11740, 2019.

[9] Jaemin Cho, Jie Lei, Hao Tan, and Mohit Bansal. Unifying vision-and-language tasks via text generation. arXiv preprint arXiv:2102.02779, 2021.

[10] Heriberto Cuayáhuitl, Simon Keizer, and Oliver Lemon. Strategic dialogue management via deep reinforcement learning. arXiv preprint arXiv:1511.08099, 2015.

[11] Chen Cui, Wenjie Wang, Xuemeng Song, Minlie Huang, Xin-Shun Xu, and Liqiang Nie. User attention-guided multimodal dialog systems. In Proceedings of the 42nd International ACM SIGIR Conference on Research and Development in Information Retrieval, pages 445–454, 2019.

[12] Abhishek Das, Satwik Kottur, Khushi Gupta, Avi Singh, Deshraj Yadav, José M. F. Moura, Devi Parikh, and Dhruv Batra. Visual dialog, 2017.

[13] Abhishek Das, Satwik Kottur, José MF Moura, Stefan Lee, and Dhruv Batra. Learning cooperative visual dialog agents with deep reinforcement learning. In Proceedings of the IEEE international conference on computer vision, pages 2951–2960, 2017.

[14] Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li, and Li Fei-Fei. Imagenet: A large-scale hierarchical image database. In 2009 IEEE Conference on Computer Vision and Pattern Recognition, pages 248–255, 2009.

[15] Bhuwan Dhingra, Lihong Li, Xiujun Li, Jianfeng Gao, Yun-Nung Chen, Faisal Ahmed, and Li Deng. Towards end-to-end reinforcement learning of dialogue agents for information access. arXiv preprint arXiv:1609.00777, 2016.

[16] Mihail Eric and Christopher D Manning. A copy-augmented sequence-to-sequence architecture gives good performance on task-oriented dialogue. arXiv preprint arXiv:1701.04024, 2017.
[17] Mihail Eric, Rahul Goel, Shachi Paul, Abhishek Sethi, Sanchit Agarwal, Shuyang Gao, and Dilek Hakkani-Tür. Multiwoz 2.1: Multi-domain dialogue state corrections and state tracking baselines. 2019.

[18] Mauajama Firdaus, Nidhi Thakur, and Asif Ekbal. Multidm-gcn: Aspect-guided response generation in multi-domain multi-modal dialogue system using graph convolution network. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: Findings, pages 2318–2328, 2020.

[19] Zhe Gan, Yu Cheng, Ahmed El Kholy, Linjie Li, Jingjing Liu, and Jianfeng Gao. Multi-step reasoning via recurrent dual attention for visual dialog. arXiv preprint arXiv:1902.00579, 2019.

[20] Zhe Gan, Yen-Chun Chen, Linjie Li, Chen Zhu, Yu Cheng, and Jingjing Liu. Large-scale adversarial training for vision-and-language representation learning. arXiv preprint arXiv:2006.06195, 2020.

[21] Shuyang Gao, Abhishek Sethi, Sanchit Agarwal, Tagyoung Chung, and Dilek Hakkani-Tur. Dialog state tracking: A neural reading comprehension approach. In Proceedings of the 20th Annual SIGdial Meeting on Discourse and Dialogue, pages 264–273, Stockholm, Sweden, September 2019. Association for Computational Linguistics.

[22] Jing Gu, Qingyang Wu, Chongruo Wu, Weiyan Shi, and Zhou Yu. A tailored pre-training model for task-oriented dialog generation. arXiv preprint arXiv:2004.13835, 2020.

[23] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 770–778, 2016.

[24] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 770–778, 2016.

[25] Matthew Henderson, Blaise Thomson, and Steve Young. Deep neural network approach for the dialog state tracking challenge. In Proceedings of the SIGDIAL 2013 Conference, pages 467–471, 2013.

[26] Matthew Henderson, Blaise Thomson, and Jason D Williams. The second dialog state tracking challenge. In Proceedings of the 15th annual meeting of the special interest group on discourse and dialogue (SIGDIAL), pages 263–272, 2014.

[27] Matthew Henderson, Blaise Thomson, and Steve Young. Word-based dialog state tracking with recurrent neural networks. In Proceedings of the 15th Annual Meeting of the Special Interest Group on Discourse and Dialogue (SIGDIAL), pages 292–299, 2014.

[28] Ehsan Hosseini-Asl, Bryan McCann, Chien-Sheng Wu, Semih Yavuz, and Richard Socher. A simple language model for task-oriented dialogue. arXiv preprint arXiv:2005.00796, 2020.

[29] Minlie Huang, Xiaoyan Zhu, and Jianfeng Gao. Challenges in building intelligent open-domain dialog systems. ACM Transactions on Information Systems (TOIS), 38(3):1–32, 2020.

[30] Chao Jia, Yinfei Yang, Ye Xia, Yi-Ting Chen, Zarana Parekh, Hieu Pham, Quoc V Le, Yunhsuan Sung, Zhen Li, and Tom Duerig. Scaling up visual and vision-language representation learning with noisy text supervision. arXiv preprint arXiv:2102.05918, 2021.

[31] Roger W. Johnson. An introduction to the bootstrap. Teaching Statistics, 23(2):49–54, 2001.

[32] Gi-Cheon Kang, Jaeseo Lim, and Byoung-Tak Zhang. Dual attention networks for visual reference resolution in visual dialog. arXiv preprint arXiv:1902.09368, 2019.

[33] Anjuli Kannan and Oriol Vinyals. Adversarial evaluation of dialogue models. arXiv preprint arXiv:1701.08198, 2017.

[34] Diederik P Kingma and Jimmy Ba. Adam: A method for stochastic optimization. arXiv preprint arXiv:1412.6980, 2014.
[35] Ranjay Krishna, Yuke Zhu, Oliver Groth, Justin Johnson, Kenji Hata, Joshua Kravitz, Stephanie Chen, Yannis Kalantidis, Li-Jia Li, David A Shamma, et al. Visual genome: Connecting language and vision using crowdsourced dense image annotations. *International journal of computer vision*, 123(1):32–73, 2017.

[36] Wenqiang Lei, Xisen Jin, Min-Yen Kan, Zhaochun Ren, Xiangnan He, and Dawei Yin. Sequicity: Simplifying task-oriented dialogue systems with single sequence-to-sequence architectures. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1437–1447, 2018.

[37] Gen Li, Nan Duan, Yuejian Fang, Ming Gong, Daxin Jiang, and Ming Zhou. Unicoder-vl: A universal encoder for vision and language by cross-modal pre-training, 2019.

[38] Jiwei Li. *Teaching Machines to Converse*. PhD thesis, Stanford University, 2017.

[39] Jiwei Li, Michel Galley, Chris Brockett, Jianfeng Gao, and Bill Dolan. A diversity-promoting objective function for neural conversation models. *arXiv preprint arXiv:1510.03055*, 2015.

[40] Jiwei Li, Michel Galley, Chris Brockett, Georgios P Spithourakis, Jianfeng Gao, and Bill Dolan. A persona-based neural conversation model. *arXiv preprint arXiv:1603.06155*, 2016.

[41] Jiwei Li, Will Monroe, Alan Ritter, Michel Galley, Jianfeng Gao, and Dan Jurafsky. Deep reinforcement learning for dialogue generation. *arXiv preprint arXiv:1606.01541*, 2016.

[42] Jiwei Li, Will Monroe, Tianlin Shi, Sébastien Jean, Alan Ritter, and Dan Jurafsky. Adversarial learning for neural dialogue generation. *arXiv preprint arXiv:1701.06547*, 2017.

[43] Liunian Harold Li, Mark Yatskar, Da Yin, Cho-Jui Hsieh, and Kai-Wei Chang. Visualbert: A simple and performant baseline for vision and language. *arXiv preprint arXiv:1908.03557*, 2019.

[44] Shuyang Li, Jin Cao, Mukund Sridhar, Henghui Zhu, Shang-Wen Li, Wael Hamza, and Julian McAuley. Zero-shot generalization in dialog state tracking through generative question answering. *arXiv preprint arXiv:2101.08333*, 2021.

[45] Xiuju Li, Yun-Nung Chen, Lihong Li, Jianfeng Gao, and Asli Celikyilmaz. End-to-end task-completion neural dialogue systems. *arXiv preprint arXiv:1703.01008*, 2017.

[46] Xiuju Li, Xi Yin, Chunyuan Li, Pengchuan Zhang, Xiaowei Hu, Lei Zhang, Lijuan Wang, Houdong Hu, Li Dong, Furu Wei, et al. Oscar: Object-semantics aligned pre-training for vision-language tasks. In *European Conference on Computer Vision*, pages 121–137. Springer, 2020.

[47] Lizi Liao, Yunshan Ma, Xiangnan He, Richang Hong, and Tat-seng Chua. Knowledge-aware multimodal dialogue systems. In *Proceedings of the 26th ACM international conference on Multimedia*, pages 801–809, 2018.

[48] Chin-Yew Lin. ROUGE: A package for automatic evaluation of summaries. In *Text Summarization Branches Out*, pages 74–81, Barcelona, Spain, July 2004. Association for Computational Linguistics. URL https://www.aclweb.org/anthology/W04-1013.

[49] Junyang Lin, Rui Men, An Yang, Chang Zhou, Ming Ding, Yichang Zhang, Peng Wang, Ang Wang, Le Jiang, Xianyan Jia, et al. M6: A chinese multimodal pretrainer. *arXiv preprint arXiv:2103.00823*, 2021.

[50] Ryan Lowe, Michael Noseworthy, Iulian V Serban, Nicolas Angelard-Gontier, Yoshua Bengio, and Joelle Pineau. Towards an automatic turing test: Learning to evaluate dialogue responses, 2018.

[51] Jiasen Lu, Anitha Kannan, Jianwei Yang, Devi Parikh, and Dhruv Batra. Best of both worlds: Transferring knowledge from discriminative learning to a generative visual dialog model, 2017.

[52] Jiasen Lu, Dhruv Batra, Devi Parikh, and Stefan Lee. Vilbert: Pretraining task-agnostic visiolinguistic representations for vision-and-language tasks. In *Advances in Neural Information Processing Systems*, pages 13–23, 2019.
[53] Shikib Mehri, Evgeniia Razumovskaia, Tiancheng Zhao, and Maxine Eskenazi. Pretraining methods for dialog context representation learning. arXiv preprint arXiv:1906.00414, 2019.

[54] Yuxian Meng, Shuhe Wang, Qinghong Han, XiaoFei Sun, Fei Wu, Rui Yan, and Jiwei Li. Openvidial: A large-scale, open-domain dialogue dataset with visual contexts, 2020.

[55] Mohsen Mesgar, Edwin Simpson, and Iryna Gurevych. Improving factual consistency between a response and persona facts. In Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume, pages 549–562, Online, April 2021. Association for Computational Linguistics.

[56] Nasrin Mostafazadeh, Chris Brockett, Bill Dolan, Michel Galley, Jianfeng Gao, Georgios P Spithourakis, and Lucy Vanderwende. Image-grounded conversations: Multimodal context for natural question and response generation. arXiv preprint arXiv:1701.08251, 2017.

[57] Nikola Mrkšić, Diarmuid O Séaghdha, Tsung-Hsien Wen, Blaise Thomson, and Steve Young. Neural belief tracker: Data-driven dialogue state tracking. arXiv preprint arXiv:1606.03777, 2016.

[58] Yulei Niu, Hanwang Zhang, Manli Zhang, Jianhong Zhang, Zhiwu Lu, and Ji-Rong Wen. Recursive visual attention in visual dialog. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 6679–6688, 2019.

[59] Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, et al. Learning transferable visual models from natural language supervision. arXiv preprint arXiv:2103.00020, 2021.

[60] Aditya Ramesh, Mikhail Pavlov, Gabriel Goh, Scott Gray, Chelsea Voss, Alec Radford, Mark Chen, and Ilya Sutskever. Zero-shot text-to-image generation. arXiv preprint arXiv:2102.12092, 2021.

[61] Shaoqing Ren, Kaiming He, Ross Girshick, and Jian Sun. Faster r-cnn: Towards real-time object detection with region proposal networks. In Advances in neural information processing systems, pages 91–99, 2015.

[62] Stephen Roller, Emily Dinan, Naman Goyal, Da Ju, Mary Williamson, Yinhan Liu, Jing Xu, Myle Ott, Kurt Shuster, Eric M Smith, et al. Recipes for building an open-domain chatbot. arXiv preprint arXiv:2004.13637, 2020.

[63] Amrita Saha, Mitesh Khapra, and Karthik Sankaranarayanan. Towards building large scale multimodal domain-aware conversation systems. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 32, 2018.

[64] Idan Schwartz, Seunghak Yu, Tamir Hazan, and Alexander G Schwing. Factor graph attention. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 2039–2048, 2019.

[65] Paul Hongsuck Seo, Andreas Lehrmann, Bohyung Han, and Leonid Sigal. Visual reference resolution using attention memory for visual dialog. In Advances in neural information processing systems, pages 3719–3729, 2017.

[66] Pararth Shah, Dilek Hakkani-Tür, Gokhan Tür, Abhinav Rastogi, Ankur Bapna, Neha Nayak, and Larry Heck. Building a conversational agent overnight with dialogue self-play. arXiv preprint arXiv:1801.04871, 2018.

[67] Yangyang Shi, Kaisheng Yao, Le Tian, and Daxin Jiang. Deep lstm based feature mapping for query classification. In Proceedings of the 2016 conference of the North American chapter of the association for computational linguistics: Human language technologies, pages 1501–1511, 2016.

[68] Kurt Shuster, Samuel Humeau, Antoine Bordes, and Jason Weston. Image chat: Engaging grounded conversations. arXiv preprint arXiv:1811.00945, 2018.
[69] Kurt Shuster, Eric Michael Smith, Da Ju, and Jason Weston. Multi-modal open-domain dialogue. *arXiv preprint arXiv:2010.01082*, 2020.

[70] Alessandro Sordoni, Michel Galley, Michael Auli, Chris Brockett, Yangfeng Ji, Margaret Mitchell, Jian-Yun Nie, Jianfeng Gao, and Bill Dolan. A neural network approach to context-sensitive generation of conversational responses. *arXiv preprint arXiv:1506.06714*, 2015.

[71] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is all you need. In I. Guyon, U. V. Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, and R. Garnett, editors, *Advances in Neural Information Processing Systems 30*, pages 5998–6008. Curran Associates, Inc., 2017.

[72] Richard S. Wallace. *The Anatomy of A.L.I.C.E.*, pages 181–210. Springer Netherlands, Dordrecht, 2009. ISBN 978-1-4020-6710-5.

[73] Joseph Weizenbaum. Eliza—a computer program for the study of natural language communication between man and machine. *Communications of the ACM*, 9(1):36–45, 1966.

[74] Tsung-Hsien Wen, David Vandyke, Nikola Mrksic, Milica Gasic, Lina M Rojas-Barahona, Pei-Hao Su, Stefan Ultes, and Steve Young. A network-based end-to-end trainable task-oriented dialogue system. *arXiv preprint arXiv:1604.04562*, 2016.

[75] Qingyang Wu, Yichi Zhang, Yu Li, and Zhou Yu. Alternating recurrent dialog model with large-scale pre-trained language models. 2019.

[76] Qiaolin Xia, Haoyang Huang, Nan Duan, Dongdong Zhang, Lei Ji, Zhifang Sui, Edward Cui, Taroon Bharti, Xin Liu, and Ming Zhou. Xgpt: Cross-modal generative pre-training for image captioning. *arXiv preprint arXiv:2003.01473*, 2020.

[77] Jingjing Xu, Xuancheng Ren, Junyang Lin, and Xu Sun. Dp-gan: diversity-promoting generative adversarial network for generating informative and diversified text. *arXiv preprint arXiv:1802.01345*, 2018.

[78] Tianhao Yang, Zheng-Jun Zha, and Hanwang Zhang. Making history matter: History-advantage sequence training for visual dialog. 2019.

[79] Steve Young, Milica Gašić, Blaise Thomson, and Jason D Williams. Pomdp-based statistical spoken dialog systems: A review. *Proceedings of the IEEE*, 101(5):1160–1179, 2013.

[80] Yizhe Zhang, Siqi Sun, Michel Galley, Yen-Chun Chen, Chris Brockett, Xiang Gao, Jianfeng Gao, Jingjing Liu, and Bill Dolan. Dialogpt: Large-scale generative pre-training for conversational response generation. *arXiv preprint arXiv:1911.00536*, 2019.