Dial2Desc: End-to-end Dialogue Description Generation

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Abstract
We first propose a new task named Dialogue Description (Dial2Desc). Unlike other existing dialogue summarization tasks such as meeting summarization, we do not maintain the natural flow of a conversation but describe an object or an action of what people are talking about. The Dial2Desc system takes a dialogue text as input, then outputs a concise description of the object or the action involved in this conversation. After reading this short description, one can quickly extract the main topic of a conversation and build a clear picture in his mind, without reading or listening to the whole conversation. Based on the existing dialogue dataset, we build a new dataset, which has more than one hundred thousand dialogue-description pairs. As a step forward, we demonstrate that one can get more accurate and descriptive results using a new neural attentive model that exploits the interaction between utterances from different speakers, compared with other baselines.

introduction
Recently, a lot of novel techniques have been proposed to help people consume a large amount of text/audio data from the Internet or Daily life. Researchers and companies have successfully applied opinion mining or summarization into product reviews, news articles, scientific articles, etc. However, very little attention has been given so far to help people consume dialogue records which are generated every day. It is clear that automatic summarization of dialogues can be of benefit in dealing with this overwhelming amount of interactional information (Murray and Carenini 2008). Previous conversation summarization works including using extractive approaches (Xie, Liu, and Lin 2008; Riedhammer, Favre, and Hakkani-Tür 2010) or abstractive approaches (Oya et al. 2014; Banerjee, Mitra, and Sugiyama 2015; Shang et al. 2018) on meeting summarization, which generates summaries that allow people to prepare for an upcoming meeting or review the decisions of a previous group. There is also an increasing research interest in other conversation summarization, such as conversational telephone speech, broadcast news, lectures, and e-mails. Those tasks are mostly focusing on stating the events in a natural flow of raw conversations and can hardly string events together to form the thematic abstracts of the whole transcripts. However, most of the human conversations are involving some specific objects or actions, and speakers may have a clear picture of what they are talking about, which can not be described without stringing speakers’ statements together.

In this work, we proposed a novel task named Dial2Desc, which is a variant of conversation summarization. Unlike the previous works mentioned above, we pay more attention to a higher-abstractive-level of the dialogues, instead of maintaining the natural flow of the given conversations. The target of our task is to describe an object or an action of what speakers are talking about in a dialogue transcript.

In the last several years, we can see deep learning has boosted the development of summarization in written text, such as news articles. Researchers apply modern neural networks with attention mechanism on abstrac-
tive summarization (Rush, Chopra, and Weston 2015; Chopra, Auli, and Rush 2016; Nallapati et al. 2016; See, Liu, and Manning 2017; Paulus, Xiong, and Socher 2018) and reach the state-of-the-art results on several datasets. The availability of large-scale parallel summarization dataset and powerfulness on the representation of deep learning push this task into a new stage, where one can achieve good results without doing any complex preprocessing procedures. However, in conversation summarization, researchers tend to build unsupervised models and involve manual rules because of the lack of such high-quality datasets.

Inspired by current Image2Text works in computer vision, we find there are high-valued image-text-mixed datasets in Image Caption tasks, which is to use salient visual information into descriptive languages (Xu et al.), and VisualDialog, which requires an AI agent to hold a meaningful dialog with humans in natural, conversational language about visual content (Das et al. 2017). We now can use an image as a bridge to align the connected dialogue and description (that is where the name Dial2Desc comes from). One can intuitively find that this image is exactly what speakers are talking about or a picture in mind during the conversation, and the captions are the higher-abstractive-level way to describe the dialogues.

We collect 122,621 dialogues from VisualDialog Dataset (Das et al. 2017) and corresponding captions from the COCO dataset (Lin et al. 2014) to build our final dataset, which enables us to develop more advanced neural models for this task. One of the examples is shown in Table 1.

Directly applying neural models proposed for written text summarization is not a good idea, since spoken conversation languages have some additional issues, e.g., maintaining cross-speaker coherence (Zechnier 2001). Most of the neural abstractive summarization models are based on sequence-to-sequence framework (Sutskever, Vinyals, and Le 2014), which consider the whole input article as a source sequence and use recurrent ways or hierarchical ways to encode it. However, the interactions between speakers and the flows of dialogue play a more important role in dialogue modeling, which is overlooked.

To address this problem, we propose a novel neural encoder, which use co-attention mechanism and dense connection to enable interactions between speakers and use the transformer framework to maintain the message passing during dialogue turns. And we also apply the transformer as our decoder. The experiment results show that our encoder plus transformer decoder can achieve the highest performance over other summarization baselines.

In summary, we make the following contributions:

1. A novel task named Dial2Desc, which address the generation of higher-abstractive-level description over the objects or the actions that people are talking about.
2. A large-scale dataset built from existing public dialogue datasets for our task.
3. A novel neural attentive model that exploits the interaction between utterances from different speakers.

### Related Work

#### Image caption and visual Dialogue

Image caption has been widely studied (Vinyals et al. 2015; You et al.; Anderson et al. 2017). In general, researchers use Convolutional Neural Network to encode a given picture and then use Recurrent Neural Network, especially its variant Long-Short Term Memory (Hochreiter and Schmidhuber 1997) to decode this semantic representation. Visual Dialog (Das et al. 2017), is a task that when given an image, a dialog history, and a question about the image, the agent has to ground the question in the image, infer context from history, and answer the question accurately (Das et al. 2017). In this work, we build a bridge between this two tasks to build our dataset, since one of image caption datasets and the VisualDialog dataset are both evolved from MSCOCO dataset.

#### Conversation summarization

Recently, there is an increasing research interest in speech summarization. (Zechnier 2001) explored aspects of speech transcripts, e.g. disfluencies, to generate summaries for conversational telephone speech. (Maskey and Hirschberg 2005) explored supervised and unsupervised approaches with different kinds of features on broadcast news. (Zhang, Chan, and Fung 2007) used extractive methods on lecture speech transcripts. On mail thread summarization, (Nenkova and Bagga 2003) proposed a method to generate a summary for the first two levels of the thread discussion. (Rambow et al. 2004) used a machine learning technique and included features related to the thread as well as features of the email structure such as the position of the sentence in the thread, number of recipients, etc. And on meeting summarization, (Xie, Liu, and Lin 2008) treated this task as a binary classification problem. (Riedhammer, Favre, and Hakkani-Tür 2010) analyzed and compared two different methods for unsupervised extractive meeting summarization. Oya (Oya et al. 2014) leveraged the relationship between human-authored summaries and their source meeting transcriptions to select the templates for generating abstractive summaries for meetings. Banerjee (Banerjee, Mitra, and Sugiyama 2015) generated abstractive summaries by fusing important content from several utterances with the dependency graph. (Shang et al. 2018) combined the strengths of multiple recent approaches introduce a novel graph-based framework for unsupervised abstractive meeting summarization. Our task, different from these tasks, address higher-abstractive-level of dialogues, which targets on describing what people are talking about instead of stating events of conversations.

#### Neural attentive models and summarization

Neural attentive models play important roles in many tasks, such as machine translation (Sutskever, Vinyals, and Le 2014), text match-

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1. https://visualdialog.org
2. http://cocodataset.org/#home
ing (Chen et al. 2017), and question answering (Hermann et al. 2015). Attention mechanisms (Bahdanau, Cho, and Bengio 2014) make these models more performant and scalable, allowing them to look back at parts of the encoded input sequence while the output is generated.

Researchers introduce those models into text summarization (Rush, Chopra, and Weston 2015; Chopra, Auli, and Rush 2016; Nallapati et al. 2016). Nallapati et al. 2016 used different attention and pointer functions on the CNN and Daily Mail datasets combined. See, Liu, and Manning 2017 developed an abstractive summarization model on this dataset with an extra loss function. And (Paulus, Xiong, and Socher 2018) used intra-temporal to increase temporal coverage of the encoder attention.

To introduce Multi-head attention, we start from the scaled dot-product attention. Given a query \( q_i \in \mathbb{R}^d \) from all \( T \) queries, a set of keys \( k_t \in \mathbb{R}^d \) and values \( v_t \in \mathbb{R}^d \) where \( t = 1, 2, ..., T \), the scaled dot-product attention outputs a weighted sum of values \( v_t \), where the weights are determined by the dot-products of query \( q \) and keys \( k_t \). In practice, we pack \( k_t \) and \( v_t \) into matrices \( K = \{k_1, k_2, ..., k_T\} \) and \( V = \{v_1, v_2, ..., v_T\} \), respectively. The attention output on query \( q \) is:

\[
A(q, K, V) = V \frac{K^T q_i / \sqrt{d}}{\sum_{i=1}^{T} \exp(k_i^T q_i / \sqrt{d})}
\]

The multi-head attention consists of \( H \) paralleled scaled dot-product attention layers called "head", where each "head" is an independent dot-product attention. The attention output from multi-head attention is as below:

\[
MA(q_i, K, V) = [head_1, head_2, ..., head_H]W^O
\]

\[
head_j = A(W_j^Q q_i, W_j^K K, W_j^V V)
\]
where the projections are parameter matrices \( W^Q \in \mathbb{R}^{d_{model} \times d}, W^K \in \mathbb{R}^{d_{model} \times d}, W^V \in \mathbb{R}^{d_{model} \times d} \) and \( W^O \in \mathbb{R}^{Nd \times d_{model}} \). Both formulations of \( A \) and \( MA \) is quite general, and it represents the common cross-module attention. If queries, keys, and values are all the same, it is called Self-attention (Vaswani et al. 2017).

Enhanced Interaction Dialogue Encoder

In this section, we describe our encoder which is composed of the following four components: (1) utterance encoding layer, (2) utterance interaction layer, (3) densely connected recurrent layer, (4) memory output layer, to encode the dialogue into a memory. We denote Dialogues as \( A/B \) connected recurrent layer, (4) memory output layer, to encode the dialogue into a memory. We denote Dialogues as \( A/B \)

\[ v_A = \{v_{a_1}, v_{a_2}, ..., v_{a_{\ell_A}}\}; v_B = \{v_{b_1}, v_{b_2}, ..., v_{b_{\ell_B}}\} \] (6)

and we then employ bidirectional LSTM (Graves, Fernández, and Schmidhuber 2005) for preserving sequential information of \( A \) and \( B \) (we skip the description of the basic chain LSTM due to the space limit):

\[ h_{a_i} = biLSTM(v_{a_i}, h_{a_{i-1}}) \] (7)
\[ h_{b_i} = biLSTM(v_{b_i}, h_{b_{i-1}}) \] (8)

and obtain utterance representations:

\[ h_a = \{h_{a_1}, h_{a_2}, ..., h_{a_{\ell_A}}\}; h_b = \{h_{b_1}, h_{b_2}, ..., h_{b_{\ell_B}}\} \] (9)

**utterance interaction layer** uses attention mechanism in Equation (3) to re-encode the contexts from interaction perspective. The local interaction information \( s_{a_i} \) of the \( i^{th} \) word \( a_i \in A \), and \( s_{b_i} \) of the \( i^{th} \) word \( b_i \in B \) is computed by using scaled dot-product attention as follows:

\[ s_{a_i} = A(h_{a_i}, h_{b_i}, h_{b_i}); s_{b_i} = A(h_{b_i}, h_{a_i}, h_{a_i}) \] (10)

And we further enhance the local interaction information by computing the difference and the element-wise product for the tuple \( < h_{a_i}, s_{a_i} > \) as well as for \( < h_{b_i}, s_{b_i} > \) (Chen et al. 2017). The difference and element-wise product are then concatenated with the original vectors, \( h_{a_i} \) and \( s_{a_i} \), or \( h_{b_i} \) and \( s_{b_i} \), respectively, then we get:

\[ \tilde{s}_{a_i} = [h_{a_i}; s_{a_i}; h_{a_i} - s_{a_i}; h_{a_i} \odot s_{a_i}] \] (11)
\[ \tilde{s}_{b_i} = [h_{b_i}; s_{b_i}; h_{b_i} - s_{b_i}; h_{b_i} \odot s_{b_i}] \] (12)

densely connected recurrent layer uses another biLSTM to enable us to build up higher-level representation. Instead of directly inputting the encoded hidden features from the last layer, we concatenate them with the word embeddings, to preserve the encoded hidden features until they reach to the uppermost layer and all the previous features work for prediction as collective knowledge (Huang et al. 2017):

\[ h'_{a_i} = biLSTM(x_{a_i}, h'_{a_{i-1}}), x_{a_i} = [\tilde{s}_{a_i}; v_{a_i}] \] (13)
\[ h'_{b_i} = biLSTM(x_{b_i}, h'_{b_{i-1}}), x_{b_i} = [\tilde{s}_{b_i}; v_{b_i}] \] (14)

**memory output layer** We concatenate all the \( h'_{a_i} \) and \( h'_{b_i} \) in each turn \( k \) into a sequence of hidden memories \( M' \). Then we follow the work (Vaswani et al. 2017) to apply position encoding into \( M' \) and apply one transformer layer to output a turns-aware encoder memory bank \( M' \). The transformer layer contains two sublayers: (1) a self-attention layer, where we take the output of the previous layer as queries, keys, and values and employ multi-head attention mechanism. (2) a simple, position-wise fully connected feed-forward network which is applied to each position separately and identically:

\[ FFN(x) = \max(0, xW_1 + b_1)W_2 + b_2 \] (15)

In addition, we employ a residual connection (He et al. 2016) around each of the two sub-layers, followed by layer normalization (Ba, Kiros, and Hinton 2016). That is, the output of each sub-layer is \( \text{LayerNorm}(x + \text{Sublayer}(x)) \), where \( \text{Sublayer}(x) \) is the function implemented by the sub-layer itself. The overall encoder is shown in Figure 1.
Transformer-pointer Generator

We also use the transformer as the basic block of our description decoder, as shown in Figure 2. Then we use pointer network [Vinyals, Fortunato, and Jaitly 2015] to generate final outputs, as it allows both copying words via pointing and generating words from a fixed vocabulary.

We first put decoder inputs into an embedding layer, which is similar to encoder embedding layer. And we use position encoding in Equation (1) and (2) to make use of sequential information. For one decoder-transformer layer, there is an extra layer compared with encoder transformer layer: a context multi-head attention layer where the queries come from the previous decoder layer, and the memory keys and values come from the output of the encoder, \( M' \). After multiple transformer layers, we get decoder state \( s_t \) for each decoder timestep \( t \). Then we put \( s_t \) into one linear layer to produce the vocabulary distribution \( P_v \)

\[
P_v = \text{softmax}(V^T s_t + b)
\]  

where \( V \) and \( b \) are learnable parameters.

For each decode step \( t \), we take the attention weights of the second sub-layer of the last transformer layer as the encoder memory attention distribution \( a^t \). The generation probability \( p_{gen} \in [0, 1] \) for timestep \( t \) is calculated from the decoder state \( s_t \):

\[
p_{gen} = \sigma(w_{ptr}^T s_t + b_{ptr})
\]

where vectors \( w_{ptr} \) and scalar \( b_{ptr} \) are learnable parameters and \( \sigma \) is the sigmoid function. Then we use \( p_{gen} \) to choose between generating a word from the vocabulary by sampling from \( P_v \), or copying a word from the input sequence by sampling from the attention distribution \( a^t \). For each dialogue, we get an extended vocabulary from the union of the vocabulary and all words appearing in the source dialogue. We obtain the following probability distribution over the extended vocabulary:

\[
P(w) = p_{gen} P_v(w) + (1 - p_{gen}) \sum_{i:w_i=w} a^t_i
\]

This pointer generator models have advantages of producing OOV words compared to other seq2seq models which are restricted to their pre-set vocabulary.

During training, the loss for timestep \( t \) is the negative log likelihood of the target words \( w_t \) for that timestep:

\[
\text{loss}_t = -\log(w_t^{\ast})
\]

and the overall sequence loss is:

\[
\text{loss} = \frac{1}{T} \sum_{t=1}^{T} \text{loss}_t
\]

**Experiments**

In this section, we describe the dataset, experimental setup, evaluation metrics and the results of our experiments.

### Dataset

**Dial2Desc** dataset is based on two public data resources:

- **VisDial** (Das et al. 2017): Visual Dialog is a task that requires an AI agent to hold a meaningful dialog with humans in natural, conversational language about visual content. Using images from MSCOCO dataset (Lin et al. 2014). They paired 2 workers on AMT to chat with each other in real-time to build dialogues that have (1) temporal continuity, (2) grounding in the image, and (3) mimic natural conversational exchanges. VisDial v0.9 has been released and contains 1 dialog with 10 question-answer pairs on 120k images from COCO, with a total of 1.2M dialog-question answer pairs. And every dialogue in VisDial has 10 turns.

- **MSCOCO** (Lin et al. 2014): This dataset contains human annotated captions of over 120k images. Each image contains five captions from five different annotators. This dataset is a standard benchmark dataset for image caption generation task. In a majority of the cases, annotators describe the most prominent object/action in an image, which makes this dataset suitable for our setting.

We can find the dialogues from VisDial and captions from MSCOCO are from the same image set. The intuition is that when two speakers are talking about one object or scene, they may have a clear picture in their mind, which can be described using higher-level-abstractive captions.

To build our Dial2Desc dataset, we collected all the dialogues from VisDial, and find attached image captions from MSCOCO dataset. Then we selected distinct captions with their attached dialogues to create dialogue-to-description pairs. Finally, we got 122,621 training pairs. And we split them into train/dev/test set. Some statistics are shown in Table 2.

Furthermore, for test data, we collected 5 descriptions in total for each dialogue, to ensure the stability of evaluation.

### Baselines

We empirically find that some unsupervised summarization methods such as Maximal Marginal Relevance (MMR) cannot reach good results because our ground truth descriptions are so abstractive. So we compare our methods with several neural generative approaches as follows:

- **Attn-Seq2seq** is a base model described in [See, Liu, and Manning 2017], where the encoder is a single-layer bidirectional LSTM producing a sequence of encoder hidden states and the decoder is a single-layer unidirectional LSTM which exploit the information from the encoder hidden states via attention mechanism.

- **PGN** is a hybrid pointer-generator network that can copy words from the source text via pointing

### Table 2: An overview of Dial2Desc dataset

|         | #samples | mean #dialog tokens | mean #desc tokens |
|---------|----------|---------------------|-------------------|
| train   | 98,256   | 122.8               | 10.59             |
| dev     | 12,282   | 122.7               | 10.6              |
| test    | 12,083   | 122.6               | 10.6              |
Experimental setup

We use a vocabulary of 20k words, shared by both source (dialogues) and target (descriptions) for all of the models, to make use of copy-mechanism. For Attn-Seq2seq, we also try a larger vocabulary size of 28k (almost the same as the vocabulary of training data). And for all RNN-based models, 256-dimensional RNN hidden states and 128-dimensional word embeddings are applied. And we use Adagrad (Duchi, Hazan, and Singer 2011) with learning rate 0.15 and an initial accumulator value of 0.1 to train these models. For Onmt-transformer and our model, both the dimension of RNN hidden states and word embeddings are set to 256. Following the work (Vaswani et al. 2017), we use the Adam optimizer (Kingma and Ba 2014) with $\beta_1 = 0.9$, $\beta_2 = 0.98$ and $\epsilon = 10^{-9}$, and the warmup steps is set to 8000. Word embeddings are learned from scratch during training instead of using any pre-trained ones.

During training and at test time we truncate the utterance of each turn to 20 tokens and limit the length of the summary to 5–15 tokens for both training and at test time. We use PyTorch to conduct all the experiments, and all the models are trained in GTX 1080Ti GPU with a batch size of 16 for RNN-based models and a batch size of 4096 for transformer-based models.

Evaluation Metrics

Same as image caption task, we use several unsupervised automated metrics for NLG (Natural Language Generation) to evaluate baselines and our model. Those metrics include BLEU (Papineni et al. 2002), ROUGE-L (Lin 2004), METEOR (Lavie and Agarwal 2007), CIDEr (Vedantam, Zitnick, and Parikh 2015). When computing CIDEr, we compute IDF values using the reference sentences provided to adapt our setting, which is different with image caption task. We use nlg-eval to conduct evaluation.

Results

We perform experiments on Dial2Desc dataset, and report both qualitative and quantitative results of our approach.

Quantitative Results

The results of mentioned baselines and our model are listed in Table 3. As we can see, we have a significant improvement w.r.t. the baselines. We can find vocabularies is very important to those neural generative models. Attn-Seq2seq, which has no other way to generate OOV words, performs worst. And in fact, the larger vocabulary size does not seem to help. However, when copy mechanism is applied, models such as PGN, Onmt-brnn gain a very big improvement, compared with Attn-Seq2seq. Onmt-transformer with copy generator has also as good performance as RNN-based approaches. It reaches better scores on some metrics such as ROUGE-L, but has lower scores on other metrics than PGN and Onmt-brnn. Our model, however, takes advantage of interaction information from utterances and perform the best on all the metrics (it achieves very big improvement, compared with Attn-Seq2seq. Onmt-transformer with copy generator has also as good performance as RNN-based approaches. It reaches better scores on some metrics such as ROUGE-L, but has lower scores on other metrics than PGN and Onmt-brnn. Our model, however, takes advantage of interaction information from utterances and perform the best on all the metrics (it achieves

| Method                     | BLEU-1 | BLEU-2 | BLEU-3 | BLEU-4 | ROUGE-L | METEOR | CIDEr |
|----------------------------|--------|--------|--------|--------|---------|--------|-------|
| Attn-Seq2seq (20k vocab)   | 66.2   | 48.4   | 34.4   | 24.4   | 47.8    | 22.6   | 82.2  |
| Attn-Seq2seq (28k vocab)   | 65.0   | 47.7   | 33.8   | 23.9   | 46.7    | 22.3   | 80.5  |
| PGN                        | 67.5   | 49.9   | 35.4   | 25.1   | 48.4    | 22.9   | 85.6  |
| Onmt-brnn                  | 68.0   | 50.6   | 36.4   | 26.0   | 49.0    | 23.2   | 86.5  |
| Onmt-transformer           | 67.2   | 50.2   | 35.9   | 25.5   | 49.2    | 22.9   | 84.9  |
| Our model                  | 69.6   | 53.1   | 39.0   | 28.4   | 50.6    | 24.2   | 94.0  |

Table 3: Performance comparison of the proposed method with other methods on Dial2Desc dataset
Given two utterances from different two speakers:

Utterance A: how many are there

Utterance B: several, it is in a parking garage at least 10

Figure 4 visualize the attached co-attention in the utterance interaction layer, consisting of two parts: (1) words of utterance A attends to utterance B; (2) words of utterance B attends to utterance A. We can find in the left part, several, at, least, and 10 are paid more attention when many is the query. It is reasonable because those number-relevant words are exactly the answers of how many. On the other hand, when several or other words are treated as queries, many is paid more attention because many is the most informative word in utterance A.

Here we also provide one quality example of our experiments shown in Figure 5. The dialogue consists of 10 turns and most of them are question-answer pairs. Next to the dialogue is the attached image from MSCOCO dataset(notice the image is placed here just for better understanding the case, we do not involve any image in our setting). Several descriptions, including ground-truth and some system outputs, are placed below. The speakers are talking about a man sitting behind a table, where a group of different wines and a plate of grapes are placed. Speaker A keeps asking the details of the given picture while speaker B keeps answering those questions. However, different from question answering, the questions are popping up sequentially and each question may contain some word like they(Turn 2, A) to connect previous questions. From the results, we can find all the neural generative models perform well and generate a decent description of the dialogue. As we can summarize, the dialogue contains some key information: a man, a table, wine glasses with different wine, a plate of grapes. All of the generated descriptions are missing grapes information. Attn-Seq2seq and PGN generate some redundant or wrong pieces of information such as woman. Onmt-brnn does not mention wine glasses but misuses the word plate. Attn-Seq2seq, PGN, and Onmt-transformer miss the information of wines in wine glasses. The description generated by our model, however, is more accurate and comprehensive.

**Conclusion**

In this work, we propose a new task named Dial2Desc, which encode the input dialogue and decode a high-abstractive-level description. Unlike the previous conversa-
tion summarization tasks, we focus more on the object or the action which the speakers are talking about, instead of maintaining the natural flow of the given conversations. We link two open source dataset to create a well-aligned dialogue-
to-description dataset Dial2Desc. Furthermore, we propose a novel neural attentive model, including an enhanced inter-

| Ground | a man sitting behind a group of different wines ready to taste them. |
|---------|------------------------------------------------------------------|
| Attn-Seq2seq | a man and a woman sitting at a table with some wine glasses. |
| PGN | a man and a man sitting at a table with wine glasses. |
| Onmt-brnn | a man sitting at a table with a plate of wine. |
| Onmt-transformer | a man sitting at a table with wine glasses. |
| Our model | a man sitting at a table with wines in wine glasses. |

Figure 5: A case study
action dialogue encoder and transformer-pointer generator. Results on our Dial2Desc dataset demonstrated the effectiveness of our proposed method.

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