Generalized Conditioned Dialogue Generation Based on Pre-trained Language Model

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Abstract

We investigate the general problem of conditioned dialogue, in which a condition label is used as input to designate the type of the target response such as a persona. A major challenge for conditioned dialogue generation is the lack of substantial dialogue data labeled with con-Thus, we propose to complement the labeled dialogue data with labeled nondialogue text data, and fine-tune BERT based on them. Our fine-tuning approach utilizes BERT for both encoder and decoder via different input representations and self-attention masks in order to distinguish the source and target side. On the target (generation) side, we use a new attention routing mechanism to choose between generating a generic word or condition-related word at each position. Our model is instantiated to persona- and topicrelated dialogue. Experimental results in both cases show that our approach can produce significantly better responses than the state-ofthe-art baselines.

1 Introduction

In open-domain dialogue, many factors, in addition to the dialogue history, influence the next response (Zhao et al., 2017; Chen et al., 2019). For example, the persona of the speaker can influence the way that a response is formulated (Li et al., 2016b). When a conversation is made in a topic domain, responses may be more topic-related (Xing et al., 2017). Only exploiting the dialogue history often leads to general responses, or bland responses (Zhao et al., 2017) such as "I don't know what you mean".

In order to generate more appropriate responses, we investigate the general problem of *conditioned dialogue*, where a condition corresponds to the type of response we want to generate. In addition to the dialogue history, we also specify a condition label as input. A condition label designates the

type of the target response, which could be a label of persona (Li et al., 2016b), topic (Xing et al., 2017), dialogue act (Zhao et al., 2017), emotion (Zhou et al., 2018), situations (Sato et al., 2017), and so on. For example, when conditioning the generation on a persona, we expect the generated responses contain some personal language characteristics. When conditioning on a topic, we expect the responses use more domain-specific vocabulary. In spite of many different labels or features, a condition essentially specifies some preferences on words, phrases, and sentence structures in the generated responses. Thus, we consider the general conditioned conversational model, which can be instantiated to a specific case as long as the corresponding labeled dialogue data is available for training. Our study will show that this generalized approach to conditioned dialogue is possible. This is different from the previous studies (e.g. Luan et al. (2017)) which target a single condition.

The availability of labeled dialogue data has been a key issue in conditioned dialogue (Zhou and Wang, 2018). The approaches used in response style transfer (Luan et al., 2017; Niu and Bansal, 2018) usually learn a type of style from a text corpus and transfer the style characteristics to dialogue. Inspired by them, we leverage extra conditioned texts to alleviate the data scarcity problem. The texts can be, for example, those written by the same person (for persona-related dialogue), within the same topic domain (for topic-related dialogue), etc. The extra conditioned texts are much easier to collect than dialogue data. Nevertheless, the amount of dialogue and extra text data can still be limited. A general pre-trained language model trained on abundant raw texts in general domains can be leveraged. This latter incorporates rich general linguistic features, which is also crucial in dialogue (Wolf et al., 2019; Zheng et al., 2019).

In this study, to alleviate data scarcity problem,

we fully utilize data specific to a dialogue condition (i.e. labeled dialogue data and extra labeled text data) on top of a pre-trained language model. Inspired by the unified pre-trained language model (Dong et al., 2019), our fine-tuning approach uses BERT for both encoder and decoder by utilizing different input representations and self-attention masks to distinguish the source and target sides of dialogue. By viewing labeled texts as a type of dialogue that only has the target side, we can mix up two types of data in one training batch. The training objective that predicts the masked tokens on the target side is thus compatible with the two types of data. As a result, our method does not introduce extra model components which are usually needed in some response style transfer approaches in order to leverage extra texts. Furthermore, the fine-tuning process that use both text and dialogue data simultaneously prevents us from having the catastrophic forgetting problem (Phang et al., 2018), which is due to the sequential fine-tuning process: by first fine-tuning on labeled texts and then on conditioned dialogue data, the effect of the previous steps of training can be erased.

When text and dialogue data are used in finetuning, it is critical to use the data efficiently because the fine-tuning data, no matter how large it is, is much smaller than the pre-training data. To increase the fine-tuning efficiency, we first propose TF-IDF based masking which selects more condition-related tokens to mask, so that the finetuning process can focus on condition-related expressions rather than the general language features already captured by the pre-trained model. Second, for conditioned dialogue generation, we propose a non-parametric gating mechanism named attention routing, which chooses between generating a general word (necessary for general function words) or a condition-related word at each position. We experimentally show that both approaches can bring some improvements.

The contributions in this work are as follows 1 :

We propose a generalized approach for conditioned dialogue, and leverage extra labeled texts in fine-tuning a pre-trained BERT to overcome data scarcity problem. The extra text data is used together with dialogue data in fine-tuning, thus avoid the catastrophic forgetting problem and does not require an extra model.

- We design efficient methods to exploit limited fine-tuning data: TF-IDF based masking and an efficient non-parametric attention routing mechanism.
- The proposed model is general and can be instantiated to different conditions. Our experiments under two different conditions – persona- and topic-based dialogue, show that our approach outperforms other state-of-theart baselines.

2 Related Works

2.1 Conditioned Dialogue Generation

Many existing studies could be viewed as special cases of conditioned dialogue generation if their models are conditioned on something else than dialogue history. We categorize the related existing works into 3 categories. (1) A label designates a special type of response such as persona (Li et al., 2016b), topic (Xing et al., 2017; Dziri et al., 2019), dialogue act (Zhao et al., 2017; He et al., 2018), situations (Sato et al., 2017), or emotion (Li et al., 2017; Zhou et al., 2018; Zhou and Wang, 2018; Rashkin et al., 2019). It is assumed that a set of labeled dialogue data is available for model training. These studies usually utilize a trainable embedding vector to represent a label, which is then used in an RNN-based decoder. (2) The second category utilizes extra text data, such as persona descriptions (Zhang et al., 2018) or external knowledge (Galley et al., 2019). The extra text data have been concatenated with dialogue history. (3) The third category of work does not use manually labeled dialogue data. Instead, it creates latent variables and use them as conditions (Serban et al., 2017; Shen et al., 2018; Gu et al., 2018; Chen et al., 2019; Gao et al., 2019a,b). Our work is related to all the three categories of work in that (1) we also assume a set of labeled dialogue data, (2) we use a set of extra texts corresponding to the conditions, and (3) our approach can work with any type of label, including those created automatically. In this sense, our model is general and can be applied to different types of condition labels (as will be shown in our experiments).

Our approach bears several important differences from the previous work on conditioned dialogue. First, our model can work with any type of condition, while the previous methods are designed for one specific type of conditions (persona,

¹We will release our codes later.

emotion, etc.); Second, extra text data is used with dialogue data in a specifically designed fine-tuning process, while it was simply concatenated in the previous studies. In addition, compared to the previous extra text data, which is a description or knowledge about the persona, we only require the texts to be loosely related to the condition: texts written by the same person, or in the same topic area, which are much easier to collect than the text data used in previous studies.

2.2 Pre-training Based Transformer

Recently, pre-trained language model (Peters et al., 2018; Sun et al., 2019; Zhang et al., 2019; Dong et al., 2019) are widely applied to various NLP tasks including dialogue generation. Some approaches (Wolf et al., 2019; Lin et al., 2019) utilize a decoder-only transformer initialized with GPT (Generative Pre-Training) parameters (Radford et al., 2018). This decoder-only architecture encodes dialogue history using only left-to-right attention (i.e. attention is allowed only to previous positions), which does not allow exploit the full context in a sentence. Using bi-directional attention could enable the encoder to leverage richer context information in dialogue history. Zheng et al. (2019) utilizes an encoder-decoder transformer architecture (Vaswani et al., 2017) with a clear separation between encoder and decoder. This makes it more difficult for the fine-tuning process to update the encoder's parameters, as has been shown in some previous work on abstractive summarization (Liu et al., 2018). In contrast, we use BERT (Devlin et al., 2018) for both encoder and decoder. Similar approaches have been used in non-conditioned dialogue (e.g. Bao et al. (2020)). To cope with the difference between encoder and decoder, we use different input representations and self-attention masks, which will be described in detail.

2.3 Response Style Transfer

Style transfer in dialogue aims to learn a style from a text corpus and then incorporate it in a general sequence-to-sequence (seq2seq) generation model. Luan et al. (2017) utilizes a multi-task learning strategy, which iteratively trains a seq2seq response generator and an auto-encoder from texts to capture style features. By sharing the RNN decoder of these two models, it leverages the style of the texts in response generation to some extent. Niu and Bansal (2018) implements style transfer in two steps: training a style classifier on the text data

labeled with two styles and then using the classifier to guide the generative model to generate more specific responses, e.g. by reinforcement learning. These studies focus on transfer between two styles.

Our approach is inspired by style transfer based on extra texts. In style transfer, the approaches are designed to transfer between two specific styles. Therefore, texts corresponding to a style can be carefully selected. In contrast, conditioned dialogue works with hundreds of condition labels simultaneously. In our work, there is only a loose relationship between the collected extra text data and the conditions, which require us to design a general and robust model to handle multiple conditions. In addition, we also exploit a small set of dialogue data corresponding to the condition, which is not used in style transfer.

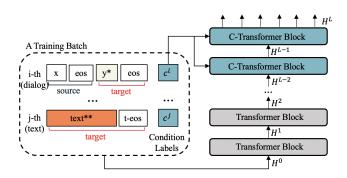
Although approaches to style transfer could be adapted to conditioned dialogue generation by considering dialogue under one condition as a distinct style transfer, we notice that the style transfer approaches capture style features from the extra texts by an additional model e.g. auto-encoder and style classifier. Thus, style can only be indirectly leveraged in dialogue generation. In contrast, our approach makes a tighter integration of labeled text data with dialogue data so as to directly impact the dialogue generation. We will see in our experiments that our approach can more efficiently leverage extra text data than the approaches to style transfer.

3 Method

We assume that we have two types of training data: a dialogue corpus labeled with conditions containing (dialogue history, condition, target response) samples, and a text corpus also labeled with conditions consisting of (condition, text) samples. Notice that the "condition" is any categorical label that indicates a type of target responses or texts. Our goal is to generate a response y that exhibits the desired characteristics of the type of responses given a dialogue history x and a condition c:

$$y = \operatorname*{arg\,max}_{y} P(y|x,c) \tag{1}$$

We construct our model based on pre-trained BERT. The following sections explain how labeled dialogue data and text data are used in fine-tuning BERT for our purpose.



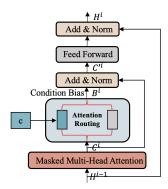


Figure 1: (Left) Overview of our fine-tuning model. * and ** denote that some tokens have been masked randomly or by TF-IDF based masking, and the corresponding outputs, e.g. \mathbf{h}_k^L , are required to predict the original tokens. Condition labels affect the last layers of transformer blocks. (Right) Detailed structures of a condition-aware transformer block with attention routing.

3.1 Masked Multi-Head Attention

The input representation $\mathbf{H}^0 \in \mathbb{R}^{n \times d_h}$, where n is the input length and $d_h = 768$ is the hidden dimension, is the sum of token embedding, position embedding, and type embedding at each position. Our fine-tuning model do not apply segment embeddings in BERT neither the loss to predict whether two segments are consecutive. We apply type embeddings to introduce a separation between encoder/source side and decoder/target side as shown in Figure 1 (Left) in order to warrant different treatments in the model. Then, \mathbf{H}^0 is encoded into hidden representations of i-th layer $\mathbf{H}^i = [\mathbf{h}^i_1, ..., \mathbf{h}^i_n]$ using multi-layer transformer blocks:

$$\mathbf{H}^i = \operatorname{Trans}^i(\mathbf{H}^{i-1}) \qquad i \in [1, L]$$
 (2)

The core component of a transformer block is the masked multi-head attention, whose outputs, i.e. contextualized representations, $\mathbf{C}^i = [\mathbf{c}^i_1, ..., \mathbf{c}^i_n]$, are computed via:

$$\mathbf{head}_{j} = \operatorname{softmax}(\frac{\mathbf{Q}_{j}\mathbf{K}_{j}^{T}}{\sqrt{d_{k}}} + \mathbf{M})\mathbf{V}_{j} \quad (3)$$

$$\mathbf{C}^i = \operatorname{Concat}(\mathbf{head}_1, ..., \mathbf{head}_h)$$
 (4)

where $\mathbf{Q}_j, \mathbf{K}_j, \mathbf{V}_j \in \mathbb{R}^{n \times d_k}$ are obtained by transforming $\mathbf{H}^{i-1} \in \mathbb{R}^{n \times d_h}$ using $\mathbf{W}_j^{iQ}, \mathbf{W}_j^{iK}, \mathbf{W}_j^{iV} \in \mathbb{R}^{d_h \times d_k}$ respectively. The self-attention mask matrix $\mathbf{M} \in \mathbb{R}^{n \times n}$ (with $\mathbf{M}_{ij} \in \{0, -\infty\}$) determines whether a position can attend to other positions. Namely, $\mathbf{M}_{ij} = 0$ allows the i-th position to attend j-th position and $\mathbf{M}_{ij} = -\infty$ prevents from it.

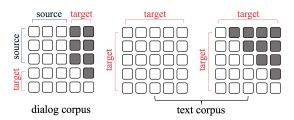


Figure 2: Self-attention masks M, for the dialogue corpus and the text corpus respectively. Shaded areas are blocked.

When leveraging two types of data for conditioned dialogue generation, we use different self-attention masks to account for the difference between them as illustrated in Figure 2. Specifically, for the dialogue data, the self-attention mask allows bi-directional attention on the source side to fully encode dialogue history and left-to-right attention on the target side to generate responses. For the extra text data, we randomly choose between the two types of attention. During training, labeled dialogue and text data are used together in a batch. In our experiment, we randomly mix up 3/4 dialogue and 1/4 text data in each training batch.

3.2 Position-wise Condition Bias

Position-wise condition bias aims to determine how much condition information should be utilized to bias word generation probability at a position. The core component to calculate the bias is the **Attention Routing** Mechanism. It is essentially a non-parametric gating method, which is based on attention to weigh the inputs. In contrast, other gate mechanisms usually employ parametric linear layers to calculate weights. We expect the attention routing is more training-efficient, which is particu-

larly important when data is insufficient. We will confirm its effectiveness compared to other gating methods.

Specifically, given a training sample (x, c, y), the condition label c is encoded using two sets of parameters: one parametric vector works as the key $\mathbf{k}^c \in \mathbb{R}^{d_h}$ and another one works as the value $\mathbf{v}^c \in \mathbb{R}^{d_h}$. Additionally, there is a special condition label g with a parametric vector \mathbf{k}^g as its key and a zero vector \mathbf{v}^g as its value. The former corresponds to the route of conditioned generation, while the latter to the general dialogue route that generates words only based on dialogue history. At each position, the model determines an attention weight to each route. More attention to the c route means that the position is more tuned to the condition.

More specifically, for each condition-aware transformer block as shown in Figure 1(Right), given $\mathbf{C}^i = [\mathbf{c}_1^i, ..., \mathbf{c}_n^i]$ as queries, the condition biases $\mathbf{B}^i = [\mathbf{b}_1^i, ..., \mathbf{b}_n^i]$ are calculated by:

$$\mathbf{B}^{i} = \operatorname{softmax}(\frac{\mathbf{C}^{i} \mathbf{K}_{b}^{T}}{\sqrt{d_{k}}} + \mathbf{M}_{b}) \mathbf{V}_{b}$$
 (5)

where $\mathbf{K}_b = [\mathbf{k}^c, \mathbf{k}^g]$ and $\mathbf{V}_b = [\mathbf{v}^c, \mathbf{v}^g]$. In this equation, we use the matrix $\mathbf{M}_b \in \mathbb{R}^{n \times 2}$ to prevent adding condition bias to positions on the source side because the condition only influences response generation on the target side.

3.3 Objectives

Following BERT, the fine-tuning model uses masked language model (LM), i.e. Cloze task, as training objective. In all our experiments, 25% tokens of the "target" side are randomly masked. The final hidden vectors H^L corresponding to the masked tokens are fed into an output softmax over the vocabulary, as in a standard LM. Recall that two types of data are mixed up in a training batch—3/4 labeled dialogue data and 1/4 conditioned text data in our experiments. The loss on both data is averaged in a batch. We fine-tune all the parameters end-to-end. Note that the fine-tuning model only has $(2C+1)\times d_h$ additional parameters on top of BERT, where C is the number of different condition labels.

As aforementioned, conditioned dialogue generation usually faces the problem of data scarcity. In our approach, we alleviate the problem by labeled text data that are much easier to collect. However, when random masking is applied, general tokens in the language could be masked. We believe that

these tokens are well covered by the pre-trained LM. The fine-tuning process should instead focus on tokens more specific to the condition. Therefore, we introduce **TF-IDF Based Masking** for the Cloze tasks – we sample tokens according to their TF-IDF values counted on the entire corpus. The TF-IDF masking is not applied to the dialogue data because we want to capture the dialogue style from that data for all tokens.

4 Experiments

Our model can work with any condition labels. To test its effectiveness and generalizability, we choose two tasks – dialogue with persona and topic conditions.

4.1 Datasets

We use public datasets, which are summarized in Table 1.

Persona Reddit We filtered the Reddit data from 2015 to 2019 that is provided by a third party ². Reddit data is a natural source of dialogue with multiple users – a post may have multiple comments by different users. We consider each user as a distinct persona. We extract (post, user, comment) tuples, where "user" is the label of the user who makes the "comment". We further filtered the data based on sentence length and users: sentences with more than 30 words or less than 4 words are removed, and we only keep comments from the 2000 most active users so that we can collect enough data for each user. As a result, the average length of dialogue history and target response are 14 and 11 words respectively and each user has 1291 samples (comments) on average. We build a labeled text corpus by collecting user's extra posts or comments on Reddit, that have been excluded from the dialogue data.

To evaluate the impact of the size of training data, we created a smaller training data (500K conditioned text and 250K dialogue samples) from Persona Reddit.

Topic-related Dialog Dziri et al. (2019) provides a high-quality 3-turns conversational dataset for topic aware response generation ³. Along with each (history, target) pair, there is a topic label and dozens of topic words that are predicted by an LDA model. We choose this dataset to show

²https://files.pushshift.io/reddit/

³https://github.com/nouhadziri/THRED

that our model can work with automatically generated (topic) condition labels. The dataset contains 9.2M samples, from which we sample 3M (history, topic, target) tuples as the labeled dialogue corpus and other 3M tuples as the labeled text corpus by keeping only their (topic, target) parts.

Dataset	Persona Reddit		Topic dialogue
dialogue Turns	2		3
Source of Labels	Personal ID		LDA
Number of Labels	2000		190
Labeled Texts	3M	500K	3M
dialogue Train	3M	250K	3M
dialogue Valid	80K	80K	80K
dialogue Test	10K	10K	10K

Table 1: Key characteristics of the two datasets.

4.2 Baselines

We choose two strong baselines specifically designed for personalized response generation and two others for topic-aware generation. Additionally, we choose some state-of-the-art transformer variants utilizing pre-training results.

Speaker Model (Li et al., 2016b): a seq2seq model for persona dialogue using four LSTM layers. Given a user label, the decoder transforms it into a user embedding and use it to generate a personalized response.

MT-Speaker: adapted from the style transfer approach using multi-task learning (Luan et al., 2017). It jointly trains a Speaker Model and a conditioned auto-encoder with shared decoder parameters.

TA-Seq2Seq (Xing et al., 2017) and **THRED** (Dziri et al., 2019): these models utilize topic words instead of topic labels predicted by the LDA model. TA-Seq2Seq leverages the topic information by a joint attention mechanism and a biased generation probability. THRED is built based on HRED and incorporates topic words via a hierarchical joint attention mechanism. These models have achieved strong performance on the second dataset.

C-GPT (Zheng et al., 2019): an encoder-decoder transformer initialized with GPT parameters. The decoder dynamically merges features from the dialogue history and the condition. In their paper, multiple fine-grained condition labels are extracted based on complex rules. In our experiments, we only provide general condition labels to the model. C-TTransfo (Wolf et al., 2019): a decoder-only transformer initialized with GPT parameters. The original model is not for conditioned dialogue gen-

eration. We extend its input representations by adding an extra parametric condition embedding to enable it to generate conditioned responses.

4.3 Implementation Details

We implement the speaker model and MT-Speaker model based on OpenNMT ⁴. Other models are directly taken from the available open-source code. Hyper-parameters are set following the original papers. Our model is implemented based on the open-source code of UniLM ⁵, which incorporates a pre-trained BERT. The last two layers are set to condition-aware transformer blocks. The warm-up proportion is 0.1. During decoding the beam size is 10, and we prevent duplicated bigrams. We fine-tune BERT (base, uncased) for four epochs on two P100 GPUs. With in total 6M training samples, each epoch takes twelve hours. The number of parameters and the average runtime of each tested approach are given in Appendix A.

4.4 Evaluation

Metrics We use the common metrics in the literature to measure the effectiveness ⁶: BLEU (Papineni et al., 2002) with n=1,2,3; ROUGE-L – longest common subsequence based statistics; and CIDEr (Vedantam et al., 2015) utilizing TF-IDF weighting for each n-gram. Besides, we evaluate response diversity using Distinct (Li et al., 2016a) indicating the proportion of unique n-grams (n=1,2) in the entire set of generated responses. We also report average length of the generated responses (avgLen). Two-sided t-test is used for statistical significance test.

Dialogue with Persona Table 2 gives automatic evaluation results on the large-scale and small-scale Persona Reddit dataset, and Table 9 (Appendix B) shows some generated responses. In general, our approach significantly outperforms the baselines on all the measures, either with large scale or small scale data. This strong result clearly demonstrates the effectiveness of our approach.

Sp-Model and MT-Speaker perform clearly worse than other models because they do not use pre-trained models. Our model and C-TTransfo outperform C-GPT because they do not separate encoder and decoder while C-GPT does. This result confirms the advantage of not separating en-

⁴http://opennmt.net/

⁵https://github.com/microsoft/unilm/

⁶We use an open-source evaluation tool: https://github.com/Maluuba/nlg-eval

Model	BLEU-1	BLEU-2	BLEU-3	ROUGE-L	CIDEr	Dist-1	Dist-2	avgLen
Sp-Model	10.539(**)	3.152(**)	1.396(**)	0.116(**)	0.056(**)	0.012(**)	0.044(**)	12.6
MT-Speaker	10.970(**)	3.488(**)	1.540(**)	0.118(**)	0.059(**)	0.009(**)	0.034(**)	12.7
C-GPT	13.548(*)	3.881(**)	1.529(**)	0.113(**)	0.045(**)	0.005(**)	0.025(**)	18.7
C-TTransfo	12.964(**)	4.182(**)	1.781(**)	0.117(**)	0.060(**)	0.023(**)	0.097(**)	16.7
Ours	14.052	4.891	2.149	0.122	0.070	0.024	0.098	23.3
-w/o condition	12.928(*)	4.405(/)	1.764(**)	0.119(**)	0.062(**)	0.014(**)	0.052(**)	26.1
-w/o ctext	13.015(*)	4.563(/)	1.956(/)	0.113(**)	0.061(**)	0.023(/)	0.106 (*)	25.7
-w/o tfidf	13.581(*)	4.705(/)	2.000(/)	0.118(**)	0.070(/)	0.023(/)	0.095(*)	24.0
Sp-Model	10.467(**)	3.039(**)	1.239(**)	0.116(**)	0.049(**)	0.007(**)	0.027(**)	12.3
MT-Speaker	10.286(**)	2.932(**)	1.174(**)	0.114(**)	0.047(**)	0.007(**)	0.030(**)	12.3
C-GPT	10.968(**)	3.247(**)	1.295(**)	0.106(**)	0.040(**)	0.001(**)	0.006(**)	14.7
C-TTransfo	11.263(**)	3.390(**)	1.274(**)	0.106(**)	0.043(**)	0.020(**)	0.075(**)	16.2
Two-Step FT*	9.585 (**)	3.064 (**)	1.300 (**)	0.110 (**)	0.048 (**)	0.015 (**)	0.042 (**)	12.1
Ours	13.517	4.517	1.988	0.119	0.068	0.021	0.066	16.4
-w/o condition	12.766(*)	4.195(*)	1.805(/)	0.118(/)	0.063(*)	0.022(/)	0.071(**)	15.3
-w/o ctext	11.776(**)	3.821(**)	1.631(**)	0.115(**)	0.059(**)	0.020(*)	0.062(**)	14.4
-w/o tfidf	13.475(/)	4.409(/)	1.853(/)	0.118(/)	0.064(*)	0.023(/)	0.078 (*)	16.7

Table 2: Evaluation results on large-scale (upper half) and small-scale (lower half) Persona Reddit. w/o condition means fine-tuning BERT on the dialogue dataset without condition labels (extra texts, TF-IDF masking). * (p < 0.05) or ** (p < 0.01) show statistically significant differences with our model by two-sided t-test.

Model	Score	Pair-wise
Sp-Model	0.59 (**)	(14.5, 48.0)
C-TTransfo	0.96 (/)	(28.0, 39.0)
w/o condition	0.77 (**)	(11.5, 40.0)
Ours	1.15	-

Table 3: Human evaluation of appropriateness for generated response on Persona Reddit. Pair-wise comparisons give the wining rates (%) of (baseline and ours).

coder and decoder, already shown in (Liu et al., 2018). Compared to C-TTransfo, our model uses bi-directional attention whenever possible, thus can leverage richer contextual information. In addition, C-TTransfo is adapted to take into account conditions in our experiments, but no extra text data is used. Compared with it, the superior performance of our model can be explained by the use of extra text data that helps the model to better learn the persona-related features.

Our model is shown to be effective with both large- and small-scale data. This indicates that even with limited labeled data, our model can efficiently capture useful features for persona-related dialogue.

Looking at Distinct measures (which only make sense when BLEU, ROUGE and CIDEr measures are comparable), we can see that our model generally performs better.

Some examples of generated responses are shown in Table 9 (Appendix B). We can see that MT-Speaker, C-TTransfo and our model all generate coherent responses, while the responses by our model are more similar to ground-truth responses.

We also performed manual evaluations on the appropriateness of the generated responses. We ask human evaluators to rate a response in $\{0, 1, 2\}$. A score of 0 means an unacceptable response, which might have flaw in fluency and logic or be incoherent. Special cases are for example completely coping from the dialogue history as the output, and a bland response such as "I don't know what you mean". A score of 1 represents an acceptable response that might be too generic. 2 represents a coherent and informative response. We also do a pair-wise evaluation to compare two models and indicate which one is better. The evaluation is based on 200 random samples. We only evaluate the best models according to the automatic metrics. Each generated response is rated by three annotators. Annotators are unaware of which model generates a response. The inter-rater annotation agreement in Cohen's kappa (Cohen, 1960) is 0.441 on average, which indicates moderate agreement. The human evaluation results are given in Table 3, which shows that our approach generally performs the best. When comparing our model against another, the annotators prefer more often the responses generated by our model.

In summary, the experimental results on Persona Reddit confirm that our model can work with a large number of personas (conditions) and conditioned dialogue can be helped by some extra text data corresponding to the conditions.

Topic-aware Dialogue The evaluation results on the Topic Dialogue dataset are shown in Table 4. Some examples of generated responses by differ-

Model	BLEU-1	BLEU-2	BLEU-3	ROUGE-L	CIDEr	Dist-1	Dist-2	avgLen
TA-Seq2Seq	10.197(**)	3.307(**)	1.602(**)	0.121(**)	0.098(**)	0.016(**)	0.051(**)	9.7
THRED	9.061(**)	3.035(**)	1.468(**)	0.118(**)	0.098(**)	0.015(**)	0.048(**)	8.8
C-GPT	13.990(**)	5.359(**)	2.689(**)	0.131(**)	0.147(**)	0.055(**)	0.222(**)	12.5
C-TTransfo	14.544(**)	5.475(**)	2.669(**)	0.136(**)	0.154(**)	0.046(**)	0.177(**)	13.2
Ours	15.639	6.484	3.455	0.140	0.185	0.060	0.243	13.0
-w/o condition	15.287(/)	6.243(/)	3.283(/)	0.141(/)	0.168(**)	0.057(**)	0.227(**)	12.5
-w/o ctext	15.491(*)	6.397(/)	3.399(/)	0.142(/)	0.190(*)	0.063(*)	0.262(**)	12.8
-w/o tfidf	15.393(/)	6.302(/)	3.351(/)	0.139(/)	0.185(/)	0.059(**)	0.230(**)	13.1

Table 4: Evaluation results on Topic Dialog. Models are compared with our approach, and scores are denoted with (p < 0.05) or ** (p < 0.01) for statistically significant differences, which are given by two-sided t-tests.

Model	Approp	riateness	Topic Consistency		
Model	Score	Pair-wise	Score	Pair-wise	
C-TTransfo	0.77 (/)	(26, 34)	0.71 (/)	(21, 31)	
w/o C-	0.55 (**)	(17, 40)	0.46 (**)	(16, 40)	
w/o tf-idf	0.69 (/)	(13, 26)	0.62 (*)	(11, 27)	
Ours	0.83	-	0.80	-	

Table 5: Human evaluation of generated responses for Topic-aware Dialogue. Pair-wise comparisons show the wining percentages of (baseline and ours).

ent models are provided in Table 10 (Appendix B). We can observe from Table 4 that our model outperforms all the baselines on all measures, and the differences are statistically significant. This is consistent with the observation on Persona Reddit data

In our manual evaluation, in addition to appropriateness, we also consider topic consistency with dialogue history. A generated response is rated in $\{0,1,2\}$ on topic consistency. the scores 0, 1 and 2 mean respectively that the response is off topic, somehow related and on topic. Cohen's κ is 0.412, indicating moderate agreement. The human evaluation results are given in Table 3. w/o condition means a vanilla fine-tuned BERT without condition labels. We can see that our approach generally performs the best, on both appropriateness and topic consistency.

It is worth noting that the conditions in this dataset are automatically generated by LDA, which roughly reflect the topics of the dialogue. Even with such noisy labels, our model can still leverage the labels and the extra texts. This second experiment confirms the robustness of our model to work with different types of label.

4.5 Analysis

Our model incorporated several ideas. We examine the impact of each of them in this section by ablation analysis. In Tables 2 and 4, we included the cases of our model without extra texts (w/o ctext) and without TF-IDF masking (w/o tfidf), as well as a vanila BERT fine-tuning method without taking into account the condition (w/o condition).

Impact of Conditioned Texts We can see from the tables that the extra conditioned texts improved the model performance on all the datasets. The impact is more obvious on Persona Reddit, where a large drop is observed in w/o ctext.

When only small-scale dialogue data is available (Persona Reddit), our approach without leveraging extra texts (and C-TTransfo which also does not use extra texts) becomes even worse than the vanilla BERT fine-tuning method (w/o condition). This indicates that the model cannot learn the condition-related features well from the limited labeled dialogue data. In this case, it is better not to ask the model to generate conditioned dialogue but to use a generic dialogue.

In contrast, the baseline model MT-Speaker also incorporated extra text data. However, this model does not improve much over another baseline model that does not use extra texts - Sp-Model. When data is small, it even performs worse than Sp-Model. This result, in contrast with our model, shows that our model can more efficiently leverage the extra texts for conditioned dialogue.

For Topic Dialogue, recall that the condition labels are generated automatically, so they are very noisy. As a result, the impact of extra texts is smaller than for Persona Reddit as shown in Table 4. Our explanation is that the extra texts do not truly correspond to a well defined topic, thus using them as if they reflect the topic is risky. The slight improvement brought by such extra data reflects the fact. Nevertheless, the noisy topic label can still generate some gain.

Impact of TF-IDF masking Using TF-IDF based masking, we enhanced the utilization of the labeled text data by masking more condition-related words. Table 2 shows that this brought some improvements in performance, which are however not always sta-

Model	BLEU-1	BLEU-2	Dist-2
Single Gate	13.880 (*)	4.853 (/)	0.090 (**)
Double Gates	13.988 (*)	4.889 (/)	0.094 (*)
Attn. Routing	14.052	4.891	0.098
Single Gate	11.703 (**)	3.891 (**)	0.090 (**)
Double Gates	11.336 (**)	3.698 (**)	0.091 (**)
Attn. Routing	13.517	4.517	0.066
Single Gate	15.926 (/)	6.527 (/)	0.230 (**)
Double Gates	15.990 (/)	6.472 (/)	0.208 (**)
Attn. Routing	15.639	6.484	0.243

Table 6: Comparison of gating mechanisms on largescale and small-scale Persona Reddit and Topic Dialogue.

tistically significant.

For Topic Dialogue dataset (Table 4), TF-IDF based masking does not improve much the similarity measures, but significantly improves the diversity of the generated responses. Moreover, in our manual evaluation (Table 5), we found that TF-IDF masking can generate more appropriate and significantly more topic-consistent responses.

Attention Routing vs. Parametric Gates As mentioned in section 3.2, the proposed attention routing mechanism is essentially a non-parametric gating mechanism. We expect it to be more efficient, meaning the model is able to choose the appropriate routes. This is particularly important when data is limited. Thus, we compare it with two common parametric gating mechanisms: 1) setting a single gate on C^i to get a weight; 2) setting gates on both C^i and v^c to get two weights. Then, we combine the weighted C^i and v^c to get C'^i as in attention routing. Experimental results on the three datasets are listed in Table 6. The results confirm that our attention routing is more efficient. Specifically, when data is small, the model with attention routing generates responses that are significantly more similar to the ground-truth. When data is large, the three gate mechanisms obtain similar BLEU scores, but our approach generates significantly more diverse responses.

The above observations suggest that the attention routing mechanism is potentially more efficient, especially for learning with small data.

Conclusion

In this paper, we investigated the general problem of conditioned dialogue generation. We assume that conditioned dialogue for any condition can be done in a similar way by providing a set of dialogue data and a set of extra texts corresponding to the condition. Our proposed approach takes advantage of pre-trained BERT, which is fine-tuned with both labeled dialogue and text data. Specific mechanims - attention routing and TF-IDF masking - are proposed to more efficiently leverage the limited training data. Our experiments on persona- and topic-related dialogue showed that our approach can be easily used for different conditions, and it outperforms the state-of-the-art baselines.

Although this study showed that it is possible to design a general conditioned dialogue model for any type of condition, in practice, different conditions may have specific characteristics that our general model cannot capture. So, it would be interesting to investigate how our general model can be further enhanced by condition-specific modules.

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A More Implementation Details

For large-scale datasets, performances of models usually stop to increase or start to decrease after the 4-th epoch. For the small-scale dataset, it usually is after the 6-th epoch. In Table 7, the average runtime is tested using a 1080Ti GPU device, and the batch size is set to take all of the GPU memories. TA-Seq2Seq and THRED are implemented in Tensor-Flow ⁷. Other models are implemented in PyTorch. Notice that the runtime will be influenced by code implementation in additional to model structure. When experimenting with the small-scale Persona Reddit dataset, we decrease the number of parameters of Sp-Model and MT-Speaker models to 48M and 52M respectively in order to avoid over-fitting. C-GPT loads the pre-training results of GPT. In the original paper, they pre-trained by themselves using a Chinese corpus, which cannot be used in our experiments. C-TTransfo utilizes the pre-training results of GPT-2.

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Model	Parameters	Runtime(min/M)
Sp-Model	80M	25
MT-Speaker	90M	40
TA-Seq2Seq	155M	150
THRED	174M	135
C-GPT	120M	180
C-TTransfo	126M	290
BERT	110M	140
Ours	113M	145

Table 7: The number of parameters of each tested approach and the average runtime (minutes) for every million training samples.

Hyper-parameters	Value
C-Tranformer layers	2
mask probability	0.25
max length	80
batch size	160
learning rate	3e-5
warmup proportion	0.1
label smoothing	0
weight decay	0.01
dropout probability	0.1

Table 8: Hyper-parameters for our fine-tuning approach.

B Generation Results

dialogue His.	ca n't wait to see the team at full strength
	when watt and clowney are back.
Gold Resp.	i 've been waiting a long time to see watt
-	and clowney healthy together
Sp-Model	i do n't think you know what the word means (0)
MT-Speaker	i do n't think the texans will be able to handle
•	the ball in the first half of the season (2)
C-GPT	i do n't know why you 're getting downvoted,
	i 'm just saying that you 're wrong . (0)
C-TTransfo	i 'm not sure if i 'd be surprised if they both
	get hurt . (2)
w/o condition	i ca n't wait to see watt and clowney at full
	strength when watt is back. (0)
Ours	i do n't think it 's going to happen, but i 'd
	love to see watt and clowney back . (2)
Sp-Model	i do n't think he is going to be a good qb. (0)
MT-Speaker	i 'm not sure if this is a good thing . (1)
C-GPT	i 'm not sure what you 're talking about . i
	do n't know what to say . (0)
C-TTransfo	i 'm not sure i 'd be surprised if they 're
	both back (2)
Two-Step FT*	i don't think that's what i'm talking (0)
w/o condition	i do n't think they 'll be able to do that . (2)
Ours	i 'd be so happy to see watt and clowney
	back . (2)

Table 9: Responses generated by baselines and our mode trained on the large-scale and small-scale Persona Reddit.

dialogue His.	what is your favorite food ? [SEP]
	ice cream .
Gold Resp.	what flavor ?
TA-Seq2Seq	what kind of ice cream ? (2;1)
THRED	what kind of ice cream ? (2;1)
C-GPT	ice cream is the best food i have ever eaten (2;1)
C-TTransfo	i 'm not sure if you 're joking but i 'm not sure
	if you 're serious . (0;0)
w/o condition	i do n't like ice cream . (2;1)
w/o tfidf	what kind of ice cream do you like ? (2;1)
Ours	i do n't like ice cream . it 's coarse
	and irritating and it gets everywhere . (2;2)

Table 10: Responses generated by baselines and our model trained on the large-scale Topic Dialog.

⁷https://github.com/nouhadziri/THRED