Abstract

Retrieval-based chatbot selects the appropriate response from candidates according to the context, which heavily depends on a response selection module. A response selection module is generally a scoring model to evaluate candidates and is usually trained on the annotated positive response and sampled negative responses. Sampling negative responses lead to two risks: a). The sampled negative instances, especially that from random sampling methods, are mostly irrelevant to the dialogue context and too easy to be fitted at the training stage while causing a weak model in the real scenario. b). The so-called negative instances may be positive, which is known as the fake negative problem. To address the above issue, we employ pre-trained language models, such as the DialoGPT to construct more challenging negative instances to enhance the model robustness. Specifically, we provide garbled context to the pre-trained model to generate responses and filter the fake negative ones. In this way, our negative instances are fluent, context-related, and more challenging for the model to learn, while can not be positive. Extensive experiments show that our method brings significant and stable improvements on the dialogue response selection capability.

1 Introduction

In recent years, building intelligent conversational agents (Shum et al., 2018; Kollar et al., 2018; Kim et al., 2020) is gaining more and more attention in the field of natural language processing. In various types of dialogue systems, retrieval-based dialog systems (Lowe et al., 2015; Wu et al., 2017; Zhang et al., 2018) are widely used in the industry because their responses are controllable, accurate, informative, and promising. In this work, we focus on multi-turn response selection task in retrieval-based dialog systems. This task aims to identify the best response from a set of candidate responses given a dialogue context, i.e., the conversation history.

For the response selection problem, most of the current practice (Wu et al., 2017; Zhou et al., 2018; Tao et al., 2019; Yuan et al., 2019) are to build utterance-response matching models based on attention mechanisms (Vaswani et al., 2017). These models output a score indicating the adequacy of individual response candidates in the dialogue context. Early works on this topic focus on fine-grained text encoding and better interactions between response candidates and conversation history, by specially designed matching networks (Wu et al., 2017; Zhou et al., 2016; Lu et al., 2019). Recently, pre-trained language models, e.g., BERT (Devlin et al., 2019), RoBERTa (Liu et al., 2019) and ELECTRA (Clark et al., 2020) have achieved significant performance improvements in the multi-turn response selection (Whang et al., 2020; Lu et al., 2021).
et al., 2020; Gu et al., 2020; Humeau et al., 2020).

Previous works usually construct the negative responses by the random sampling, which has explicit limitations. On the one hand, random sampled negative responses are usually easy to be distinguished, since they are usually irrelevant to the conversation history in terms of topic, and they can’t form coherence with the dialogue context. On the other hand, the model trained on such naive negative responses performs poorly on challenging negative responses (Lin et al., 2020), which are similar to the conversation history. An example is given in Figure 1, the random sampled negative response is too easy for the model because they show little relevance to the conversation history. While the challenging negative responses are more confusing to the model, they mentioned some identical keywords or phrases in the dialogue context, while they have no coherence with the history. Such challenging negative responses rarely appear in the training set, but they are common in real-world scenarios.

We aim to improve the model’s robustness by using challenging instances to train the model. The challenging instances are negative responses which are more confusing than the randomly sampled negative responses. These challenging responses should be more related to the conversation history, e.g., they may have some overlap words with history, but they are not proper to be a natural response to the history. Pre-trained language models such as DialoGPT (Zhang et al., 2020) can be used to generate responses according to the conversation history, though these responses are quite relevant to the history, most of which cannot be treated to be negative, since DialoGPT is pre-trained on large scale dialogue data, it is strong enough to generate relatively natural responses. To solve this problem, we design a set of conversation history garbling strategies, e.g., randomly exchange the positions of two turns of dialogue and replace some turns with random sampled utterances. The intuition behind this is that responses generated from garbled conversation history are more likely to be negative. Besides, to make generated responses more confusing to the model, we insert keywords that have been mentioned in the dialogue history to the generated responses. To address the fake negative issue, we calculate the perplexity of the response given the original conversation history as the metric to select the response which is most like negative.

The proposed negative response generation method is a simple and effective data augmentation approach and it can be applied to any response selection model without any changes to the model architecture or training objective function. Experiment results on four matching models and two benchmark datasets demonstrate that negative responses generated by our method leads to remarkable performance improvement consistently.

2 Related Work

Dialogue Responses Selection. In recent years, developing response selection model on multi-turn conversation has gained considerable attention (Lowe et al., 2015; Wu et al., 2017; Zhang et al., 2018). The formulation of the response selection task is defined as follows. Given a conversation history \( C \) and several candidate responses \( R_i \), the goal of the matching model \( M \) is to predict a score \( S = M(C, R_i) \) measuring the adequacy of the candidate \( R_i \) for the context \( C \), then choose the candidate with the highest score as the proper response.

Model Architecture. Early works mostly focus on design various neural architectures for fine-grained context encoding and matching between conversation history and candidate response. Lowe et al. (2015) designed a dual encoder network to better model the interaction between context and response. Wu et al. (2017) leveraged several matching matrices to match context and candidate responses and proposed a model named the sequential matching network. After the effectiveness of pre-trained language models, e.g., BERT (Devlin et al., 2019) and RoBERTa (Liu et al., 2019) based on self-attention mechanism (Vaswani et al., 2017) had been proved, subsequent works have applied it to the response selection task. Whang et al. (2020) first applied BERT on this task and obtained state-of-the-art performance by finetuning BERT on response selection datasets. Lu et al. (2020); Gu et al. (2020) proposed to model speaker information and showed its effectiveness.

Data Construction and Augmentation. In addition to the progress in the model architecture, Lin et al. (2020) argue that the binary classification training objective is less effective since the quality of candidate responses can be quite diverse. To address this issue, they use retrieval method and generation model to automatically construct greyscale
data and apply ranking objective to let the model learn this progressive relationship (ground truth response > greyscale response > random sampled response). However, their method is based on a strong hypothesis which is not necessarily reasonable. Different from their work, we suppose correct is correct, wrong is wrong, no matter how relevant response is to the conversation history, as long as it fails to form a coherent dialogue, it should be negative. So we still use binary classification as the training objective. Instead, we focus to construct more challenging negative responses for that the randomly sampled responses are too easy to be distinguished by the model.

3 Approach

3.1 Overview

The pipeline of our method mainly consists of three steps: 1) Fine-tuning DialoGPT on domain-specific datasets, 2) generating challenging negative responses using DialoGPT according to the garbled conversation history, 3) employing these generated negative instances together with an original dataset to train the response selection model.

Step 1 and step 3 use off-the-shelf methods, so we will mainly introduce step 2. Figure 1 depicts an overview of the negative response generation process named GGS, it is composed of Garbled Conversation Construction, Response Generation and Response Selection. We will describe each part in detail.

3.2 Challenging Negative Responses Definition

We aim to generate negative responses that are more challenging than random sampled negative responses. These negative responses have one or two of the following characteristics: a) They must be negative, that is, they are not proper to be the response of the given conversation history according to human language habits. b) They should be more or less similar to the conversation history, e.g., they contain some keywords or phrases which are also mentioned in the dialogue context. Such overlap in the content may confuse the model to make incorrect predictions. We design the negative sample generation approach according to these
characteristics.

3.3 Garbled Conversation Construction

State-of-the-art pre-trained language models, such as GPT2 (Radford et al., 2019), DialoGPT (Zhang et al., 2020) and T5(Raffel et al., 2020), have been proved to be effective to generate grammatically correct and coherent response given the correct conversation history. Most of these generated responses are not proper to be treated as negative responses. To address this issue, we propose two conversation history garbling strategies with the intuition that a response generated from a garbled conversation history is more likely to be negative to the original history, while at the same time, it maintains the relevance with the original history.

The first strategy is called flow distortion. Suppose the turn number of the conversation history is $N$, we randomly select an index $i \in [1, N - 1]$, and exchange the position of the utterance $u_i$ and $u_N$, as shown in Figure 1. By doing this, we expect the response generated by DialoGPT from this garbled history is relevant to the original conversation history in content, especially similar to the content of $\text{turn}_{i+1}$. Because these responses are not coherent with the latest utterance, so they can be treated as negative responses.

Another strategy is context destruction. In this strategy, we replace two or three latest conversation turns by randomly selected utterances in other dialogue, as shown in Figure 1. By doing this, the main information of the original conversation still exists, but the topic of the conversation has suddenly changed because of the random replacing. When using DialoGPT to generate a response based on this garbled history, we expect that despite the response is about another topic, it still contains the original context’s key information. Take the dialogue in Figure 1 as an example, though $R_3$ talks about the discount, but it still mentions pure cotton which is one of the keywords in the original conversation history. To ensure the key information of the original conversation history will be mentioned in the generated response, we leverage a keyword extraction algorithm to extract keywords and insert them into the generation process, we will introduce it in detail in the next section.

3.4 Response Generation

Different from Lin et al. (2020) training a response generation model from scratch, we load pre-trained language model Cdial-GPT (Wang et al., 2020) and fine-tune it on task-specific datasets. We then use the fine-tuned model as our response generation model considering the responses they generate are grammatically correct and often coherent with the given conversation history. We apply two types of generation approaches.

The first generation approach is the traditional decoding method used in Cdial-GPT. This approach takes the garbled conversations constructed by flow distortion strategy as input, we first concatenate all dialogue turns into a long text $C = [x_1, x_2, \ldots, x_N]$, where $N$ is the sequence length. The response generation model decodes the response word by word using top-p sampling conditioned on $C$. Responses generated using this method are likely to be similar to one of the utterances in the original conversation history.

To make the generated responses more confusing, we propose the second generation approach which takes garbled conversation constructed by context destruction strategy as the input, we first use the traditional decoding method to generate a response $R_0 = [r_1, r_2, \ldots, r_K]$, at the same time, we keep a matrix $P \in [K, V]$, where $K$ is the length of generated response, and $V$ is vocabulary size, saving the probability distribution over the whole vocabulary on every decoding time step. Then we extract keyword or key phrase $w_{\text{key}}$ in the original conversation history, the extraction algorithm we use is CKPE $^1$. Combining $w_{\text{key}}$ and probability matrix $P$ we can find the step $i$ with the highest $w_{\text{key}}$’s probability, it is the most likely position where we can insert $w_{\text{key}}$. We replace $r_i$ with $w_{\text{key}}$ and throw $r_{i+1}, r_{i+2}, \ldots, r_K$ away. So far, we get an incomplete response $R_1 = [r_1, r_2, \ldots, w_{\text{key}}]$, we use Cdial-GPT to generate the rest of the response based on $R_1$ and conversation history $C$, the R2 in Figure 1 is an example. In addition to insertion, we can also simply force the response to start with $w_{\text{key}}$, the R3 in Figure 1 is an example.

3.5 Response Selection

Though we use Cdial-GPT to generate responses based on garbled conversation history, the generated responses could still be positive which is known as the fake negative problem, for the reason that responses in the open-domain dialogue are quite diverse, and the content of the conversation is more extensive compared to task-oriented dialogue. To address this issue, we propose a response

$^1$github.com/dongrixinyu/chinese_keyphrase_extractor
Table 2: Statistics of the two multi-turn response selection datasets.

|          | Douban                      | E-Commerce                  |
|----------|-----------------------------|-----------------------------|
|          | Train | Val | Test | Train | Val | Test |
| Pos:Neg  |       |     |      |       |     |      |
| 1:1      | 1:1   |     | 1:9  | 1:1   |     | 1:9  |
| # Dialogues | 50K  | 25K | 1K   | 50K   | 5K  | 1K   |
| # Avg turns | 8.694 | 8.751 | 8.475 | 7.509 | 7.482 | 7.640 |

selection mechanism to select the response which is more negative.

To achieve this, we directly use Cdial-GPT to calculate the perplexity of generated responses based on the original conversation history. Because Cdial-GPT is pre-trained on a large-scale dialogue dataset and fine-tuned on a task-specific dataset, it has the capacity to distinguish whether a conversation is a natural human conversation. Reflecting on the perplexity metric, the lower the value, the more likely response is a natural response. We denote the original conversation history as $C = x_1, x_2, ..., x_N$, denote the generated response as $R_g = r_1, r_2, ..., r_K$, the conditional probability of $P(R_g|C)$ can be written as the product of a series of conditional probabilities:

$$P(R_g|C) = \prod_{i=1}^{K} p(r_i|x_1, x_2, ..., x_N, r_1, ..., r_{i-1})$$  \hspace{1cm} (1)

The perplexity score can be calculated as:

$$PPL(R_g) = P(R_g|C)^{-\frac{1}{n}}$$  \hspace{1cm} (2)

In the response generation process, we use top-p sampling and different decoding methods to generate multiple responses $R_{g1}, R_{g2}, ..., R_{gL}$, we calculate their perplexity scores using equation 2, and select the response with the highest perplexity score as the challenging negative response for this conversation history. In practice, if all the scores are too small, we randomly sample an utterance as the negative response.

Through the whole generation process, we can generate one challenging negative response for each conversation history, we add these negative responses into the original training dataset, getting a new training set 1.5x larger than the original one (positive: negative = 1: 2). At last, we train the response selection model with a binary classification objective on the new training set.

4 Experimental Setup

4.1 Datasets

We evaluate our model on two widely used datasets: **Douban Corpus** (Wu et al., 2017), and **E-Commerce Corpus** (Zhang et al., 2018). All datasets consists of multi-turn conversations, and their statistics are summarized in Table 2.

**Douban Corpus** consists of Chinese multi-turn daily conversations crawled from Douban website which is a popular social networking service.

**E-Commerce Corpus** is another Chinese multi-turn conversation corpus, it consists of conversations between customers and customer service staff from Taobao. The conversation talks about several types of topics, such as commodity recommendation, consultation, and negotiation.

4.2 Evaluation Metrics

Following prior works (Lowe et al., 2015; Wu et al., 2017; Zhou et al., 2018; Whang et al., 2021), we utilize several retrieval metrics to evaluate our negative response generation approach. For all the two datasets, we utilize $R_{n@k}(k = 1, 2, 5)$, that is 1 in recall at $k$, it gets 1 if a golden response is positioned in the $k$ selected responses and 0 otherwise, for these two datasets, $n$ is equal to 10. Besides, for the Douban dataset, we also employ the other three metrics MAP(mean average), MRR(mean reciprocal rank), and P@1(precision at one) to evaluate the model’s performance, since there may be more than one positive response among the candidates.

4.3 Baselines

**BERT-based Models.** Pre-trained language models, such as BERT (Devlin et al., 2019), ELECTRA (Clark et al., 2020) and their variants like SA-BERT (Gu et al., 2020) have been applied to the response selection task. In these models, conversation history and each candidate response are concatenated to a long sequence, and [CLS] token’s hidden state on the last layer is used as the sequence representation, which is then passed into a binary classifier to predict whether the candidate response is correct. Following Whang et al. (2021)

2https://www.douban.com
3https://www.taobao.com
Table 3: Evaluation results on Douban and E-Commerce datasets. Models named GGS-XXX are trained with challenging negative instances which leading to remarkable performance improvement consistently.

| Model               | MAP  | MRR  | P1   | R1   | R2   | R5   | Douban | Ecommerce |
|---------------------|------|------|------|------|------|------|--------|-----------|
| ELECTRA             | 0.602| 0.642| 0.465| 0.287| 0.483| 0.839| 0.609  | 0.804     |
| ELECTRA+            | 0.612| 0.655| 0.480| 0.301| 0.499| 0.836| 0.673  | 0.835     |
| BERT                | 0.591| 0.633| 0.454| 0.280| 0.470| 0.828| 0.610  | 0.814     |
| BERT+               | 0.609| 0.645| 0.463| 0.290| 0.505| 0.838| 0.725  | 0.890     |
| SA-BERT             | 0.619| 0.659| 0.496| 0.313| 0.481| 0.847| 0.704  | 0.879     |
| BIN-BERT-gen        | 0.565| 0.607| 0.424| 0.264| 0.431| 0.807| -      | -         |
| BIN-BERT-ret        | 0.592| 0.632| 0.441| 0.273| 0.480| 0.833| -      | -         |
| GGS-ELECTRA         | 0.611| 0.651| 0.483| 0.305| 0.484| 0.836| 0.651  | 0.829     |
| GGS-ELECTRA+        | 0.617| 0.658| 0.490| 0.308| 0.490| 0.848| 0.705  | 0.860     |
| GGS-BERT            | 0.596| 0.637| 0.459| 0.282| 0.475| 0.833| 0.661  | 0.847     |
| GGS-BERT+           | 0.631| 0.669| 0.504| 0.321| 0.519| 0.834| 0.754  | 0.900     |

5 Results and Analysis

5.1 Experiment Results

For negative response generation, we first fine-tune the pre-trained Cdial-GPT on two datasets individually with the learning rate equal to 5e-5, then we utilize the top-p sampling decoding method to generate responses according to garbled conversation history. For the response selection model, we use BERT and ELECTRA implemented from huggingface Transformers based on PyTorch framework (Paszke et al., 2019). We initialize model parameters from checkpoints bert-base-chinese-wwm(the whole-word masking strategy) and electra-base-chinese. We also utilize the checkpoints released by Whang et al. (2021), which is post trained on these two datasets separately by masked language model objective. For fine-tuning stage, we train the models with a batch size of 32, a learning rate of 3e-5 using the Adam optimizer with linear learning rate decay, the max sequence length is 512. We run all the experiments on four Tesla V100 GPUs.
5.2 Ablation Study

We conduct ablation studies for investigating the effect of different modules. We choose BERT and BERT+ as the base models and train them on E-Commerce dataset with five additional settings.

**Effect of Garbled History.** In this setting, we feed the original conversation history instead of the garbled history to Cdial-GPT to generate responses and use them as negative training instances. The experiment results listed in Table 4 shows that removing the history garbling mechanism makes the models’ performance drop significantly, even much worse than baseline. This indicates that the garbled history construction module makes an irreplaceable contribution to the generation of challenging negative instances. It is because Cdial-GPT is pre-trained on large-scale open-domain dialogue corpus, it is likely to generate a coherent and natural response, most of which could be fake negative.

**Effect of Response Selection.** Although the garbled conversation history can prevent Cdial-GPT to generate coherent and natural responses to a large extent, considering the diversity characteristic of the open-domain dialogue data, we still propose a selector to select responses that are more likely to be negative by ranking their perplexity score based on the original conversation history. We study the effect of the selector by replacing it with a random response selector.

Experiment results are listed in Table 5. Removing the response selection mechanism brings some performance drop, indicating the effectiveness of the proposed selector. Meanwhile, the extent of the performance drop is not as significant as removing garbled history, indicating garbled history is more important to avoid fake negative responses.

**Effect of Different Generation Methods.** As shown in Figure 1, there are two negative response generation methods. 1) Garble conversation history using flow distortion strategy first and then utilize Cdial-GPT directly generate the response based on the garbled history, denoted as gen1. 2) Use context destruction strategy to garble the conversation history, and generate responses that must contain the keyword of the original conversation history, denoted as gen2.

We study each method’s effect. Experiment results are listed in Table 6, removing any of these two methods causes the model’s performance to drop, indicating the effectiveness of them. Besides, removing gen2 leads to more performance drops indicating that gen2 contributes more than gen1. It is because responses generated by gen2 must contain a keyword which is also mentioned in the original conversation history, making the responses more confusing to the model.

**Effect of Challenging Instances.** We replace all challenging responses with random sampled negative responses, the experiment is denoted as ran-
The randomly sampled response is totally irrelevant to the conversation history, so it is easy to be distinguished by the model. Though the challenging responses generated by our method are not the proper responses because they have little coherence with the dialogue context. But they are quite confusing and challenging because they have some overlapped words or phrases with the conversation history, such as shipping address and taste. The model trained on the original training dataset tends to incorrectly classify the challenging instances to be positive. In contrast, after learning from the challenging instances, models can identify the improper pattern in the challenging negative responses.

| Conversation history | Responses |
|----------------------|-----------|
| X: 你们应该质量上也是这样吧?  | Golden:  | X: Should the quality be ok? |
| Y: 不用担心质量方面。小店有保证的。 | Random:  | Y: Don’t worry about the quality, it is guaranteed by our store. |
| X: 好甜吗？  | Challenging 1: | X: Is it sweet? |
| Y: 口感是偏甜的，湿度适中，可以当零食吃的。 | Golden:  | Y: It tastes sweet, has moderate moisture content, and can be eaten as snacks. |
| X: 我去拍。  | Challenging 2: | X: I’m going to place an order. |
| Y: 请核对一下收货地址哦。 | Random:  | Y: Please check the shipping address. |
| X: 对。谢谢。 | Challenging 3: | X: It’s correct, thanks. |

Table 7: A case from E-Commerce corpus. The original dialogue is in Chinese (the left), we also provide their English version (the right). Golden and random responses are directly copied from the original dataset. The three challenging responses are generated by our proposed method.

**5.3 Case Study**

Table 7 shows a case from the E-Commerce corpus. The randomly sampled response is totally irrelevant to the conversation history, so it is easy to be distinguished by the model. Though the challenging responses generated by our method are not the proper responses because they have little coherence with the dialogue context. But they are quite confusing and challenging because they have some overlapped words or phrases with the conversation history, such as shipping address and taste. The model trained on the original training dataset tends to incorrectly classify the challenging instances to be positive. In contrast, after learning from the challenging instances, models can identify the improper pattern in the challenging negative responses.

|          | Recall@1 | Recall@2 | Recall@5 |
|----------|----------|----------|----------|
| GGS-BERT | 0.661    | 0.847    | 0.977    |
| GGS-BERT+ | 0.754    | 0.900    | 0.989    |
| BERT     | 0.614↓   | 0.819↓   | 0.972↓   |
| random DA | 0.689↓   | 0.881↓   | 0.982↓   |

Table 8: Ablation experiment investigating the effect of challenging instances. Replacing challenging instances with random instances leads to a performance drop.

**6 Conclusion**

We propose a challenging instances generation method leveraging the large scale pre-trained language models for enhancing dialogue response selection models. Firstly, we garble the conversation history with two strategies to address the fake negative issue, then a fine-tuned DialoGPT is leveraged to generate response according to the garbled history using two decoding methods, at last, we utilize a response selector to choose the most negative responses. Compared to randomly sampled negatives, the challenging negative instances are more confusing and difficult to be distinguished which can help the model to learn more general and robust patterns about the natural dialogue response. Experiment results on two benchmark datasets and four models demonstrate that the challenging instances are valuable for training response selection models. Since our method is independent of model structure, we will apply it to more competitive response selection models in future work.
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