Abstract

As an essential component of dialogue systems, response selection aims to pick out the optimal response among candidates to continue the dialogue. In existing studies, this task is usually regarded as a binary classification problem, where every candidate is ranked respectively for appropriateness. To improve its performance, we reformulate this task as a multiple-choice problem that allows the best selection to be made in one-shot inference. This new view inspires us to propose an architecture called Panoramic-encoder with a novel Candidates Attention Mechanism (CAM), which allows context-wise attention between responses and leads to fine-grained comparisons. Furthermore, we investigate and incorporate several techniques that have been proven effective for improving response selection. Experiments on three benchmarks show that our method pushes the state-of-the-art while achieving approximately 3X faster inference speed.

1 Introduction

Nowadays, dialogue systems have gained increasing attention in the natural language processing community. Depending on the implementation, they can be categorized as retrieval-based (Lowe et al., 2015; Tao et al., 2019; Yuan et al., 2019) or generation-based (Vinyals and Le, 2015; Serban et al., 2016). The former converses with people by selecting the optimal response from a candidate pool, while the latter generates proper responses autoregressively via a sequence-to-sequence model. Response selection plays a vital role in both methods, with the rise of an approach called “sample-and-rank” (Adiwardana et al., 2020) in advanced generation-based chatbots (Zhang et al., 2019; Roller et al., 2020; Bao et al., 2021). This approach produces more coherent responses in the following way: (i) Generating and decoding multiple candidates from a generator. (ii) Passing them to a selector and finding the best one. (iii) Returning the best response to the user. In this paper, we pay more attention to the usage of response selection in generation-based chatbots.

After the advent of transformers (Vaswani et al., 2017) and pre-trained models (Devlin et al., 2018; Liu et al., 2019; Lan et al., 2019), various works have been proposed to progress the response selection task. Humeau et al. (2019) conducts comparisons between two commonly used architectures Cross-encoder and Bi-encoder. It proves that the former performs better than the latter in terms of effectiveness. Lu et al. (2020) and Gu et al. (2020) reveal the importance of speaker change information by incorporating speaker segmentation or speaker embeddings. Li et al. (2021) leverage contrastive learning and in-batch negative training to construct better matching representations. Whang et al. (2020) and Han et al. (2021) explore...
Despite a wide range of studies in this field, response selection has always been viewed as a binary classification problem. We pair a given context with every candidate response, then respectively classify the match as True if appropriate, otherwise False. To improve its effectiveness and efficiency, the proposing Panoramic-encoder reformulates this task as a multiple-choice problem, where all candidates can be assessed simultaneously, as shown in Figure 1. It exploits the Candidates Attention Mechanism (CAM) to conduct fine-grained comparisons between responses and yield the global optimal choice in one-shot inference. We conduct experiments on three benchmark datasets: PersonaChat (Zhang et al., 2018), Ubuntu Dialogue Corpus V1 (Lowe et al., 2015), and Ubuntu Dialogue Corpus V2 (Lowe et al., 2017). Results show our work achieves new state-of-the-art with significant speed-up at inference time.

2 Motivation

The multi-turn response selection task has long been regarded as: Given a dialogue context \( c = \{u_1, u_2, ..., u_N\} \) where each \( u_k \) represents a single utterance from either speaker, \( p = \{r_1, r_2, ..., r_M\} \) is a candidate pool that contains \( M \) individual responses. We pair every candidate \( r_i \) respectively with \( c \) and optimize \( m(c, r_i) \) to \( 1 \) if it is a proper match, otherwise \( 0 \). Since the fundamental goal of this task is to find out the best response to continue the conversation, there are two obvious drawbacks in the existing approach:

(i) Processing every candidate respectively slows down the training and inference speed by a large margin. (ii) It only regards the relatedness between the context and individual responses without directly comparing candidates. Thus, it is hard to distinguish the ground truth from some strong distractors, as illustrated in Figure 3.

To address the aforementioned issues, we propose a new formulation of the response selection task: Given a dialogue context \( c = \{u_1, u_2, ..., u_N\} \) where each \( u_k \) represents a single utterance from either speaker. A candidate pool \( p = \{r_1, r_2, ..., r_M\} \) contains \( M \) individual responses where \( r^*_i \) is the optimal choice for context \( c \). A selector model is trained to identify the gold label by fitting \( s(c, p) = i \). One explicit benefit of this approach is that it only requires one-shot predictions to select the global optimal response, increasing training and inference efficiencies. It can also improve accuracy by employing the attention mechanism between candidates to distinguish
In addition, we revisit some recent advances (Gu et al., 2020; Li et al., 2021; Xu et al., 2020) in this field and discover that numerous studies have been proven helpful in boosting the performance of response selection. Unfortunately, however, different designs may be incompatible with each other (Humeau et al., 2019). It motivates the development of our new framework that incorporates various techniques in this paper.

3 Methods

In this section, we first discuss several useful techniques in implementing a good response selector. Then we explain the proposing Panoramic-encoder with Candidates Attention Mechanism in detail and present how to combine these various techniques with necessary modifications.

3.1 Architecture

To the best of our knowledge, a model architecture called Cross-encoder is widely used as a response selector in many advanced chatbots (Bao et al., 2019). Like the typical BERT design (Devlin et al., 2018), such an architecture jointly encodes the concatenated context and response to make a prediction. Another popular Bi-encoder architecture (Reimers and Gurevych, 2019) encodes the context and the candidate separately, then scores the relatedness between their representations. Lowe et al. (2015), Yoshino et al. (2019), and Dinan et al. (2020) conduct corresponding experiments on the response selection task. Please refer to Figure 2 for a better understanding.
3.2 Speaker Change Information

Being aware of the speaker change information is essential to train a good model on dialogue data. There are two commonly used strategies to achieve this: adding speaker-aware embedding to the token representation and adding special tokens to segment utterances from different speakers. Wolf et al. (2019) and Wang et al. (2020) equip dialogue generation with these approaches while Lu et al. (2020) and Gu et al. (2020) verify their necessities for the response selection task. We can integrate this technique directly into Panoramic-encoder.

3.3 In-batch Negative Training

In studies related to contrastive learning, in-batch negative training is able to generate representations with better uniformity and alignment (Wang and Isola, 2020; Gao et al., 2021; Fang et al., 2020). Humeau et al. (2019) and Li et al. (2021) adapt this technique to the response selection task, but as described in Humeau et al. (2019), it is problematic to recycle the in-batch negative labels in the Cross-encoder architecture because the context and the response are jointly processed. However, since we concatenate candidates in Panoramic-encoder, it is natural to use the other labels in the same batch as negatives. Our ablation study in section 4.4 demonstrates this is an effective technique for enhancing performance.

3.4 Auxiliary Training Tasks

Models pre-trained on a large corpus have general abilities to understand the text. To fetch more in-domain knowledge, Xu et al. (2020) and Whang et al. (2021) investigate some self-supervised learning objectives that are multi-task trained with response selection. To keep the simplicity of our work, we do not explore various auxiliary tasks. We find that adding a single masked language model (MLM) loss to our model is straightforward and empirically powerful.

3.5 Domain Post-training

Similar to training with auxiliary tasks, post-training targets on further improving the domain adaption of pre-trained models in a self-supervised manner. It proceeds in the middle of pre-training and fine-tuning with the help of additional domain-specific data. Since it is an independent stage, it is compatible with all other methods. Whang et al. (2020) and Han et al. (2021) validate the usefulness of post-training on response selection, but we will not delve into this method in this paper.

3.6 Panoramic-encoder

As depicted in Figure 4, our Panoramic-encoder exploits a pre-trained transformer encoder (Vaswani et al., 2017) as the basis. It resembles the Cross-encoder (Humeau et al., 2019) but has several crucial distinctions: (i) The most apparent is all the candidates are concatenated and jointly encoded with the input context. (ii) We reuse the positional embeddings for different candidates to comply with the length limit. (iii) Each candidate is surrounded by $[\text{CLS}]$ and $[\text{SEP}]$ tokens, and two special $[\text{SPK}]$ tokens are used to segment the sentences from alternating speakers. (iv) We explore and utilize the Candidates Attention Mechanism (CAM) instead of the default self-attention.

We analyze three different types of CAM, as exhibited in Figure 5. Type (a) is identical to the all-to-all attention in Transformers. However, it has a position confusion problem in the current design. For illustration, the first token in candidate $i$ cannot distinguish its own second token from the other candidates’ because they share the same positional embeddings. To address this problem, we forbid explicit attention between candidates in type (b) CAM, but they can still exchange information indirectly through common connections with the context. In type (c) CAM, we try to further prohibit the attention from context to candidates, but the opposite direction is still allowed. We study the effects of three CAM versions on PersonaChat and put the results in Table 1. In the subsequent experiments, type (b) is decided as the default setting because of its superior and stable performance.

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In Panoramic-encoder, as mentioned in section 2, instead of assessing each response respectively, it compares all candidates simultaneously to find the global optimum in one shot.
logue context \( c = \{u_1, u_2, ..., u_N\} \) and the candidate pool \( p = \{r_1, r_2, ..., r_M\} \) are jointly encoded to yield output representations \( H \). As discussed earlier, the candidate pool in our implementation consists of the gold response and the other in-batch negative samples.

\[
H = \text{encode}(c, p)
\]

We then obtain an aggregated embedding \( E_i \) for each candidate by averaging all token representations belonging to it in \( H \). After aggregation, every \( E_i \) is reduced to a single logit, which is later merged and fed into a softmax operation.

\[
Y_{pred} = \text{softmax}(\{w(E_1), \ldots, w(E_m)\})
\]

A ground truth label is one-hot at the index of the only positive candidate. Then the model is optimized by minimizing the cross-entropy loss between the prediction and ground truth. We also plus an auxiliary MLM loss to the original training objectives.

\[
\ell^{ce} = \text{cross entropy}(Y_{pred}, Y_{label})
\]

\[
\ell = \ell^{ce} + \ell^{mlm}
\]

4 Experiments

4.1 Dataset

- PersonaChat (Zhang et al., 2018) is a crowdsourced dataset with two-speaker talks conditioned on their given persona, containing short descriptions of characters they will imitate in the dialogue.

- Ubuntu Dialogue Corpus V1 (Lowe et al., 2015) contains 1 million conversations about technical support for the Ubuntu system. We use the clean version proposed by (), which has numbers, URLs, and system paths replaced by special placeholders.

- Ubuntu Dialogue Corpus V2 (Lowe et al., 2017) has several updates and bug fixes compared to V1. The major one is that the training, validation, and test sets are split into different time periods.

4.2 Results

We initialize our implementation with the checkpoint provided by Huggingface\(^2\). All the reported results are fine-tuned on the BERT-base model (Devlin et al., 2018) without any post-training. We measure Re@k and mean reciprocal rank (MRR) on three benchmark datasets. Table 2 demonstrates the superiority of the Panoramic-encoder against the other state-of-the-art methods.

4.3 Inference Speed

The Panoramic-encoder has a significant advantage over the baseline in terms of efficiency. It is evidently because the Panoramic-encoder can find the optimal response among candidates in one shot rather than rank each candidate in turn. This feature remarkably reduces the number of inferences the Panoramic-encoder requires during evaluation. Therefore, for the sake of fair comparison, we control the peak GPU memory usages of all models to the same value by assigning them different batch sizes. Results in Table ?? verify that our model achieves approximately 3X speed up at inference time.

\(^2\)https://huggingface.co/models
Table 2: Evaluation on three benchmark datasets. All results reported in the table are fine-tuned on the naive Bert-base (Devlin et al., 2018) model without any post-training. Average and standard deviation are calculated on three runs with different seeds.

| Models                          | Persona-Chat | Ubuntu Dialogue Corpus V1 | Ubuntu Dialogue Corpus V2 |
|---------------------------------|--------------|----------------------------|---------------------------|
|                                 | R20@1 | MRR  | R10@1 | R10@2 | R10@5 | R10@1 | R10@2 | R10@5 |
| BERT(Devlin et al., 2018)       | 0.707  | 0.808 | 0.808  | 0.897  | 0.975  | 0.781  | 0.890  | 0.980  |
| BERT-CRA(Gu et al., 2021)       | 0.843  | 0.903 | N/A    | N/A    | N/A    | N/A    | N/A    | N/A    |
| SA-BERT(Gu et al., 2020)        | N/A    | N/A   | 0.855  | 0.928  | 0.983  | 0.830  | 0.919  | 0.985  |
| BERT-SL(Xu et al., 2020)        | N/A    | N/A   | 0.884  | 0.946  | 0.990  | N/A    | N/A    | N/A    |
| UMS-BERT(Whang et al., 2021)    | N/A    | N/A   | 0.843  | 0.920  | 0.982  | N/A    | N/A    | N/A    |
| BERT+FGC(Li et al., 2021)       | N/A    | N/A   | 0.829  | 0.910  | 0.980  | N/A    | N/A    | N/A    |
| Panoramic-encoder(Ours)         | 0.869  | 0.922 | 0.886  | 0.946  | 0.989  | 0.859  | 0.938  | 0.990  |
|                                 | ±0.001 | ±0.000| ±0.001 | ±0.001 | ±0.000 | ±0.001 | ±0.001 | ±0.000 |

Table 3: Comparisons of the efficiency between Panoramic-encoder and baseline method on Ubuntu V2.

| Model                          | Peak GPU Memory Allocated | Candidates | Inference Time |
|--------------------------------|---------------------------|------------|----------------|
| Bert Baseline                  | 1.017 GB                   | 189200     | 213.27s        |
| Panoramic-encoder              |                           |            | 74.62s         |

Table 4: Ablation studies on Ubuntu Dialogue Corpus V2.

4.4 Ablation Studies

Besides the novel architecture change for candidates concatenation, the Panoramic-encoder also benefits from other proposed techniques. In this part, we closely analyze their effects on model performance. Table 4 contains ablation studies conducted on the Ubuntu Dialogue Corpus V2.

5 Conclusion

We propose a new problem formulation for the dialogue response selection task. Based on this, we present the Panoramic-encoder architecture with the Candidates Attention Mechanism, which allows interactions between all candidates and selects the global optimal response in single inference. We investigate some proposed techniques and effectively unify them to push the state-of-the-art and achieve faster inference speed. Experiments on three benchmarks demonstrate the superiority of our work against other advanced studies.

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