Panoramic-Encoder: A Fast and Accurate Response Selection Paradigm for Generation-Based Dialogue Systems

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Abstract
Response selector is an essential component of generation-based dialogue systems and it aims to pick out an optimal response in a candidate pool to continue the dialogue. The current state-of-the-art methods are mainly based on the encoding paradigm called Cross-Encoder (Urbanek et al., 2019), which separately encodes each context-response pair and ranks the responses according to their fitness scores. However, Cross-Encoder repeatedly encodes the same lengthy context for each response, resulting in high computational costs. Moreover, without considering the relationship among the candidates, it is difficult to figure out which candidate is the best response purely based on the fitness score per candidate. We aim to address these problems through a new paradigm called Panoramic-Encoder. The proposed method encodes all candidates and the context at once and realizes the mutual interaction using a tailored candidate attention mechanism (CAM). It also enables the integration of some effective training techniques, such as the in-batch negative training, which cannot be used in Cross-Encoders. Extensive experiments across four benchmark datasets show that our new method significantly outperforms the current state-of-the-art with lower computational complexity.

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 one proceeds the conversation by selecting an optimal response from a candidate pool, while the latter continues the conversation using a proper response generated by a sequence-to-sequence model. Recent studies have shown that the generated-based solution can be a preferable choice in a dialogue system due to its intriguing property to generate more diverse and coherent responses (Roller et al., 2021). With the rise of the so-called "sample-and-rank" approach (Adiwardana et al., 2020), the conversation quality in such advanced generation-based chatbots (Zhang et al., 2020; Roller et al., 2021; Bao et al., 2021) heavily relies on identifying an optimal response in the candidate pool. The pipeline of this approach consists of first generating multiple response candidates from the generator and then selecting the best candidate as the response to the user by a selector.

Figure 1: In the training phase, existing methods treat the response selection task as a set of binary classification problems while the Panoramic-Encoder regards it as a multiple-choice selection problem.

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In this paper, we are particularly interested in improving the response selection performance in generation-based dialogue systems.

Increasing research efforts show that the advent of Transformer (Vaswani et al., 2017) and pre-trained models (Devlin et al., 2019; Liu et al., 2019; Lan et al., 2020) has led to remarkable progress in various natural language understanding tasks, including the dialogue response selection in our interest. Built on top of BERT (Devlin et al., 2019) or other pre-trained models, Cross-Encoder (Urbanek et al., 2019) has become the workhorse in response selection task for its superior performance compared to other methods, e.g., Bi-Encoder. It jointly encodes the historical context with every single candidate response, and gives a matching score per candidate. Despite its great performance, it still remains an open problem with its obvious defects, which will be explained in the following. Having such issues in mind, we propose a new paradigm, called Panoramic-Encoder, integrated with a novel Candidates Attention Mechanism (CAM), for the response selection task. The defects and our solutions can be summarized as follows:

1. The prevalent paradigm of the response selection task is modeled as a set of binary classification problems. That is, a network produces a matching score for each dialogue pair, concatenation of a given context and a response. Accordingly, selecting a response from a pool with such processing causes frequent recomputation of the lengthy context, which significantly increases the computational cost. In this paper, the proposed Panoramic-Encoder re-formulates the process as a "multiple-choice" problem, where all candidates can be assessed simultaneously. This new paradigm can select an optimal response with a one-shot prediction, as shown in Figure 1, and theoretically reduce the computational complexity.

2. The existing methods only consider the relatedness between the historical context and per every response, without interacting with different candidates. Thus, it cannot separate the ground truth from some hard distractors, as suggested in Figure 2. Our Panoramic-Encoder can mitigate this issue in a subtle way. Since a generation-based dialogue system has a dynamic but tiny candidate pool, we concatenate the context and all candidates to feed them jointly to the encoder in our design. With our newly proposed attention mechanism, relationships among all candidates can be perceived, and the optimal response can be highlighted.

3. Several practical techniques have been discovered to train a powerful response selector in recent studies (Gu et al., 2020; Li et al., 2021; Xu et al., 2020). However, some useful tricks, e.g., in-batch negative training, cannot be naturally integrated into the Cross-Encoders (Humeau et al., 2019). Our Panoramic-Encoder does the rescue of the compatibility issue with its novel architecture.

We conduct thorough experiments on four benchmark datasets: PersonaChat (Zhang et al., 2018), Ubuntu Dialogue Corpus V1 (Lowe et al., 2015), Ubuntu Dialogue Corpus V2 (Lowe et al., 2017), and Douban Conversation Corpus (Wu et al., 2017). Results show that our work is not only computationally more efficient but also able to push the state-of-the-art. For instance, our model achieves absolute improvements in $R@1$ by 2.9% and 2.6% on the Ubuntu Dialogue Corpus V2 and PersonaChat dataset, respectively.

![Figure 1: Example of how the Panoramic-Encoder distinguishes strong distractors. The bold value represents a correction in prediction confidence.](image-url)
2 Background and Related Work

In this section, we discuss various works that have been proposed to progress the dialogue response selection task. Besides explorations on model architectures, researchers also proposed some important training techniques such as in-batch negative training, domain post-training, etc. We will also introduce some of these important techniques in this section and briefly describe how our new method seamlessly integrates them into the new paradigm.

2.1 Model Architecture

*Cross-Encoder* (Urbanek et al., 2019) is the current state-of-the-art response selection method and widely used in many advanced chatbots (Bao et al., 2020). Like the typical BERT design (Devlin et al., 2019), such an architecture jointly encodes the concatenated context and response to make a prediction. Another popular architecture called *Bi-Encoder* (Reimers and Gurevych, 2019) encodes the context and the candidate separately, then scores the relatedness between their representations. Due to its simplicity and efficiency, *Bi-Encoder* often serves as a baseline method when a new dataset is introduced (Lowe et al., 2015; Dinan et al., 2018). Nevertheless, *Cross-Encoder* is preferable to generation-based dialogues systems in practice due to its high effectiveness (Urbanek et al., 2019; Humeau et al., 2019).

2.2 In-batch Negative Training

In contrastive learning, in-batch negative training is a standard recipe to generate representations with better uniformity and alignment (Fang et al., 2020; Gao et al., 2021). However, as stated in Humeau et al. (2019), despite the effectiveness of in-batch negative training for response selection, the *Cross-Encoder* architecture is problematic to recycle the in-batch negative representations because the context and the response are jointly processed. Li et al. (2021) attempt to adapt contrastive learning to this task with a specially designed strategy and obtain a significant performance gain. Our work differs from previous works in that it provides a seamless usage of in-batch negative training. Since the candidates are concatenated in the Panoramic-Encoder, it is natural to use the other labels in the same batch as the negatives. Our study demonstrates that in-batch negative training is an essential technique for response selection.

2.3 Adding Speaker Change Information

Being aware of the speaker change information proves to be important for training 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 adopt the special tokens strategy for its simplicity.

2.4 Domain Post-training

Post-training targets on improving the domain adaptation of pre-trained models in a self-supervised manner. It leverages additional domain-specific data through a second stage of pre-training. This method is compatible with all architectures since it is in an independent step. Whang et al. (2020) and Han et al. (2021) validate the usefulness of post-training on response selection. We also demonstrate that combining this method further improves the effectiveness of the *Panoramic-Encoder*.

2.5 Auxiliary Training Tasks

To further utilize target data, Xu et al. (2020) and Whang et al. (2021) investigate some self-supervised learning objectives such as next session prediction, utterance restoration, incoherence detection, masked language modeling, etc., as auxiliary tasks that are jointly trained with the response selection task. To keep the simplicity of our work, we only take the masked language model (MLM) as our auxiliary task.

3 Method

This section first proposes a new paradigm for the dialogue response selection task. This fresh view inspires us to develop a *Panoramic-Encoder* architecture with a novel candidate attention mechanism. We also integrate some existing effective techniques, e.g., in-batch negative training, into our *Panoramic-Encoder* seamlessly.

3.1 Motivation

Regardless of the underlying model architecture, the multi-turn response selection has long been modeled as a set of binary classification tasks. That is, given a dialogue context $c = \{u_1, u_2, \ldots, u_N\}$, where $u_k, k = 1, \ldots, N$ denotes a single utterance
from either speaker, the response selection task is required to choose an optimal response from a candidate pool, denoted by \( p = \{ r_1, r_2, ..., r_M \} \). Every candidate \( r_i \) is respectively paired with the context \( c \), e.g., \( m(c, r_i) \). The non-linear function \( m \) is optimized to predict the value of 1 for a proper match and 0 otherwise.

In such a paradigm, Cross-Encoder is more preferably employed by generation-based dialogue systems than the other typical architecture Bi-Encoder, as the former can yield better results (see Section 2.1). It is because the Cross-Encoder allows context and response to interact in the feature space, that is to say, all response representations are context-aware. However, this context-aware characteristic does not come for free; it requires the Cross-Encoder to encode the same lengthy context repeatedly for each candidate response, resulting in a much less efficient computation than Bi-Encoder.

To improve both the effectiveness and efficiency, we propose a new paradigm that kills two birds with one stone: With the dialogue context \( c = \{ u_1, u_2, ..., u_N \} \) and a candidate pool \( p = \{ r_1, r_2, ..., r_M \} \), the selector model is trained to identify the optimal choice \( r_i \) via fitting the objective function \( s(c, p) = i \). By encoding all the response candidates together with the context through a specifically designed attention method, our paradigm does not only take the context-aware concept in Cross-Encoder a step forward to become context-other-responses-aware, but also removes the necessity of computing context representation multiple times to achieve the same low computational complexity as Bi-Encoder (see Section 4.4).

### 3.2 Panoramic-Encoder

The innovation of paradigm inspires this design of the Panoramic-Encoder. It exploits a pre-trained transformer encoder (Vaswani et al., 2017) as a basis. As depicted in Figure 3(b) and Figure 4, it resembles the Cross-Encoder architecture (Figure 3(a)) but has several crucial distinctions:

1. It follows the new paradigm where candidate responses are concatenated and jointly encoded with the input context.
2. We reuse the positional embeddings for different candidates because they are all potential continuations of the context. It also helps to encode the same context length as Cross-Encoder does while complying with the length limit after response concatenation.
3. We develop and compare several Candidate Attention Mechanisms that allow candidate
responses to interact at different levels of granularity. It also ensures that the reusing of positional embeddings does not confuse the model’s understanding.

4. Multiple practical training techniques can be naturally incorporated and are analyzed in Section 4.2.

3.2.1 Candidate Attention Mechanism

We analyze three different types of candidate attention mechanisms, as exhibited in Figure 5. Type (a) is identical to the all-to-all attention in Transformers. However, it has two problems. First, it has a position confusion problem. 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. Second, attention has an averaging effect, hence too much interaction makes different candidates difficult to distinguish from each other. To address this problem, we forbid explicit attention between candidates and only allow context response attention(type (b)), but they can still exchange information indirectly through common connections with the context. In the third type, we further enhance the interaction on the basis of context-to-response attention by allowing the attention between $[	ext{CLS}]$ heads in responses.

We study the effects of these three attention mechanisms on Ubuntu Corpus V2 and list the results in Table 1. As can be seen, the ALL-to-ALL attention gets significantly worse results than the other two. But both Context-to-Response and CLS-to-CLS attention get similar results, which indicate that a small amount of interactions among candidates should be enough to get good performance. In the subsequent experiments, we will use context-to-response (type (b)) attention as our default setting because of its effectiveness and simplicity.

3.2.2 Implementation

In Panoramic-Encoder, as mentioned in section 3.1, instead of assessing each response respectively, it compares all candidates simultaneously to find the optimum in one shot. The given dialogue 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 $H$. To incorporate the speaker change information, each candidate is surrounded by $[\text{CLS}]$ and $[\text{SEP}]$ tokens, and two special $[\text{SPK}]$ tokens are used to segment the utterances from alternating speakers. In our implementation, a candidate pool consists of the gold response and other recycled negative samples from the same batch.

$$H = \text{encode}(c, p).$$

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.

$$Y_{\text{pred}} = \text{softmax}\{w(E_1), ..., w(E_m)\}.$$
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 classification objective as

\[ \ell = \ell_{ce} + \ell_{mlm}, \]

where \( \ell_{ce} \) is defined as:

\[ \ell_{ce} = \text{cross}_\text{entropy}(Y_{\text{pred}}, Y_{\text{label}}). \]

### 4 Experiments

#### 4.1 Dataset and Evaluation Metrics

In this section, we evaluate the proposed Panoramic Encoder across four standard datasets, i.e., PersonaChat (Zhang et al., 2018), Ubuntu Dialogue Corpus V1 (Lowe et al., 2015), Ubuntu Dialogue Corpus V2 (Lowe et al., 2017) and Douban Conversation Corpus (Wu et al., 2017).

- **PersonaChat** is a crowd-sourced 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** contains 1 million conversations about technical support for the Ubuntu system. We use the clean version proposed by Xu et al. (2017), which has numbers, URLs, and system paths replaced by special placeholders.

- **Ubuntu Dialogue Corpus V2** 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.

- **Douban Conversation Corpus** consists of web-crawled dialogs from a Chinese social networking website called Douban. Topics in this dataset are open-domain.

The statistics of four benchmark datasets are shown in Table 2. They vary greatly in volume, language, and topic. Several metrics are used to evaluate our model following previous works.

| Dataset          | Train | Valid | Test  |
|------------------|-------|-------|-------|
| PersonaChat      |       |       |       |
| Turn             | 65719 | 7801  | 7512  |
| Positive:Negative| 1:19  | 1:19  | 1:19  |
| Ubuntu V1        |       |       |       |
| Pairs            | 1M    | 0.5M  | 0.5M  |
| Positive:Negative| 1:1   | 1:9   | 1:9   |
| Ubuntu V2        |       |       |       |
| Pairs            | 1M    | 195.6k| 189.2k|
| Positive:Negative| 1:1   | 1:9   | 1:9   |
| Douban           |       |       |       |
| Pairs            | 1M    | 50k   | 6670  |
| Positive:Negative| 1:1   | 1:1   | 1.2:8.8|

#### Table 2: Statistics of four benchmark datasets.

| Models                        | Ubuntu Corpus V2 |
|-------------------------------|------------------|
|                               | R_{10}@1         | MRR              |
| Panoramic-Encoder             | 85.92*           | 91.51*           |
| (i) w/o. auxiliary MLM Loss   | 82.00 (-3.92)    | 88.89 (-2.62)    |
| (ii) w/o. Speaker Segmentation| 84.45 (-1.47)    | 90.40 (-1.11)    |
| (iii) w/o. Concatenation & In-batch | 79.92 (-6.00) | 88.10 (-3.41) |

#### Table 3: Ablation studies on Ubuntu Corpus V2 with different techniques. * represents the full effect of a Panoramic-Encoder model. Bold values are the most significant drops in performance. The component (iii) is innovative in our work, where the response concatenation allows the application of in-batch negative training.

The proposals use P@1 and mean average precision (MAP) values because it contains multiple positive candidates for a given context. It’s also noted that the proportion of the positive and negative samples of the validation set is significantly different from that of the test set in the Douban Conversation Corpus. To alleviate this discrepancy, we utilize the in-batch negative labels in the validation stage to determine an appropriate checkpoint for inference.

#### 4.2 Ablation Study

The proposed Panoramic-Encoder addresses the compatibility issue of using in-batch negative training techniques. It can also seamlessly incorporate some other effective techniques as described in the previous section, e.g., using auxiliary MLM loss and speaker segmentation. In this section, we conduct ablation studies to evaluate the effectiveness of each component for the proposed Panoramic-Encoder.

Table 3 reports the results on the Ubuntu Dialogue Corpus V2 dataset. We can find that each of the training techniques is an essential integration of the Panoramic-Encoder. Specifically, we can find that the auxiliary MLM loss is a powerful technique and improves the R_{10}@1 and MRR values by 3.92% and 2.62% respectively. Adding
Table 4: Evaluations on four benchmark datasets. All results reported in the table are fine-tuned based on the naive BERT-base (Devlin et al., 2019) model without any post-training. Average and standard deviation are calculated on three runs with different seeds. Computational complexities of different architectures are calculated in Section 4.4.

| Models                             | Ubuntu Corpus V1 | Models                             | Ubuntu Dialogue Corpus V1 |
|------------------------------------|------------------|------------------------------------|---------------------------|
|                                    | $R_{\text{top1}}$ | $R_{\text{top2}}$ | $R_{\text{top5}}$ |                                    | $R_{\text{top1}}$ | $R_{\text{top2}}$ | $R_{\text{top5}}$ |
| BERT (Devlin et al., 2019)         | 0.808            | 0.897                             | 0.975                   | BERT (Devlin et al., 2019)         | 0.808            | 0.897                             | 0.975                   |
| Panoramic-Encoder (Ours)           | 0.886            | 0.946                             | 0.989                   | Panoramic-Encoder (Ours)           | 0.886            | 0.946                             | 0.989                   |
| SA-BERT (Gu et al., 2020)          | 0.855            | 0.928                             | 0.983                   | UMS$_{BERT}$                       | 0.875            | 0.942                             | 0.988                   |
| BERT-CRA (Gu et al., 2021)         | 0.829            | 0.910                             | 0.980                   | UMS$_{BERT}$                       | 0.829            | 0.910                             | 0.980                   |
| Panoramic-Encoder (Ours)           | 0.886            | 0.946                             | 0.989                   | BERT+FGC (Li et al., 2021)         | 0.911            | 0.962                             | 0.994                   |
|                                    | ±0.000           | ±0.001                            | ±0.000                  | BERT+FGC (Li et al., 2021)         | 0.911            | 0.962                             | 0.994                   |
| BERT (Devlin et al., 2019)         | 0.781            | 0.890                             | 0.980                   | BERT (Devlin et al., 2019)         | 0.808            | 0.897                             | 0.975                   |
| Poly-Encoder360 (Humeau et al., 2019) | 0.809            | 0.911                             | 0.985                   | BERT+FGC (Li et al., 2021)         | 0.911            | 0.962                             | 0.994                   |
|                                    | ±0.000           | ±0.001                            | ±0.000                  |                                 |                  |                                  |                         |
| SABERT (Gu et al., 2020)           | 0.830            | 0.919                             | 0.985                   |                                 |                  |                                  |                         |
| BERT-CRA (Gu et al., 2021)         | 0.830            | 0.919                             | 0.985                   |                                 |                  |                                  |                         |
|                                    | ±0.000           | ±0.001                            | ±0.000                  |                                 |                  |                                  |                         |
| BERT+FGC (Li et al., 2021)         | ±0.000           | ±0.001                            | ±0.000                  |                                 |                  |                                  |                         |
|                                    | ±0.000           | ±0.001                            | ±0.000                  |                                 |                  |                                  |                         |

Table 5: Panoramic-Encoder further boosts the performance of the state-of-the-art post-trained models on Ubuntu Dialogue Corpus V1.

the speaker segmentation technique also brings performance gains in both metrics, reading as 1.47% and 1.11%. As explained in Section 2.2, in-batch negative training can only be applied with the response concatenation in Panoramic-Encoder. As shown in Table 3, it achieves the most significant improvement over the $R_{\text{top1}}$ and MRR metrics by 6.00% and 3.41% respectively. This positive observation indicates our design is reasonable, and we will also verify its superiority compared to the state-of-the-art methods.

4.3 Comparison to State-of-the-art

To fully demonstrate the superiority of the Panoramic-Encoder against the other state-of-the-art methods. We first initialize our implementation with the naive BERT checkpoint provided by Huggingface\(^1\). All the reported results in Table 4 are fine-tuned on the BERT-base model (Devlin et al., 2019) without any post-training.

As we can see, the Panoramic-Encoder achieves better overall performances with relatively small standard deviations PersonaChat, Ubuntu V1, and Ubuntu V2 datasets. Our models also outperform previous works in four of the six metrics on the Douban Corpus, demonstrating its overall superiority. However, on this dataset, they possess larger variances during evaluation and have weaknesses in $P_{\text{top1}}$ and $R_{\text{top1}}$. Some explanations come to mind: First, the discrepancy between the validation set and test set in Douban Conversation Corpus (discussed in Section 4.1) makes this dataset more challenging. Second, the training pipeline of Panoramic-Encoder, which leverages response concatenation and in-batch negative training, can help to separate the positive sample away from the negative samples in the semantic space. However, the presence of multiple positive candidates at inference time (but not in training) may confuse the network about ranking the top responses.

Next, recalling the introduction from Section 2.4, post-training is a common approach to shift the general pre-trained knowledge to a target domain. It continues the models’ training on domain-specific texts before fine-tuning them on downstream tasks in order to obtain better performances. To explore the upper bound of our method’s capability, we attempt to build the Panoramic-Encoder upon the two most advanced post-trained models UMS$_{BERT}$ (Whang et al., 2021) and BERT-FP (Han et al., 2021). Table 5 indicates the Panoramic-Encoder can further boost their results. Our best model achieves 0.916 in $R_{\text{top1}}$ on the Ubuntu Dialogue Corpus V1, which is the universal highest result as far as we know. Our source code and model

\(^1\)https://huggingface.co/models
# Examples

1. A: so now i’m going to try it with the snapshot version of the PPA instead and see if it crashes again.  
   B: Are you looking at your computer’s CPU temperature?  
   A: no but i havent ever had any trouble with temp before ... where do i go to see its temp typervenche ?  
   Cross: do i not know. Panoramic: That depends on your hardware and kernel. The Ubuntu guys can help you with that.

2. A: I’m trying to backup a computer using grsync.  
   A: There is one file in a directory I’ve excluded, that I like to backup.  
   A: I listed that file and it’s path in the include file, but it doesn’t over ride the exclude file, is it possibly to do this?  
   B: dont exclude it..?  
   Cross: cheers Panoramic: example?

3. A: nobody know Jin.. :(  
   B: i guess not. try contacting the programs developers. you can find their contact info in the software centre  
   Cross: Thanks Panoramic: thx unfortunately the program isn’t installed from the repositories

4. A: Any vim experts around?  
   B: you may want a vim chatroom  
   A: yes, trying my luck in #vim as well  
   Cross: cheers. Panoramic: also google is your friend :P

5. A: i am stuck on the loading screen for xubuntu, is there a hotkey to leave it to see what it does in text?  
   B: ctrl+f1  
   Cross: ok Panoramic: doesn’t work :\  
   A: Any way to disable that?  
   B: Open it up and clean out the heatsink and fan!  
   Cross: thanks Panoramic: Sometimes it just heats up, it's not consistent but it suggests a fan/controllr type issue

Table 6: Examples from the Ubuntu Corpus V2 for comparing Cross- and Panoramic- Encoder

Checkpoints will be released for reproducibility and future research\(^2\).

## 4.4 Lower Computational Cost

In addition to the accuracy improvement, Panoramic-Encoder possesses a lower computational complexity than Cross-Encoder. Before showing the theoretical proof, we need to clarify some features of the generation-based dialogue system: (i) Since language decoding is expensive, its candidate pool usually consists of only a few generated responses. Even if responses are concatenated in our paradigm, their total length is typically no longer or at least comparable to the given context. (ii) The candidate pool is not only small but also dynamic because all the responses are newly generated in each turn. As a side effect, Bi-Encoder cannot pre-compute and reuse cached candidate representations to accelerate its process as does in retrieval-based systems.

With these points in mind, the computational complexity of Bi-, Cross-, and Panoramic-Encoder can be formulated as follows: Let \(c\) and \(r\) respectively denote the average sequence length of context and every response; Given a candidate pool consists of \(p\) responses; It also straightforward to deduce that \(pr \leq c\) due to the feature (i); The self-attention mechanism has a quadratic complexity to the input length (Vaswani et al., 2017) and we omit the dimensionality of representations for simplicity in following calculations:

- **Bi-Encoder** encodes the context and the candidate separately. The number of operations is \(c^2 + p * r^2 = O(c^2)\).

- **Cross-Encoder** repeatedly encodes the lengthy context with each response. Therefore, we have \((c + r)^2 * p = O(pce^2)\).

- In **Panoramic-Encoder**, candidates are concatenated and jointly encoded with the context. The computational complexity equals \((c + pr)^2 = O(c^2)\).

It is now evident to say, Panoramic-Encoder theoretically outperforms Cross-Encoder in terms of efficiency as well. Even though Bi-Encoder has the same complexity level as ours, the drop in accuracy makes it infeasible in practice. As can be seen in Table 4, Poly-Encoder (Humeau et al., 2019) (a variant of Bi-Encoder that is dedicated to high effectiveness) is inferior to all other Cross-Encoders, except for the BERT baseline, by a large margin.

## 4.5 Qualitative Analysis

To verify the advantages of the proposed Panoramic-Encoder as compared to the Cross-Encoder, we provide the qualitative analysis of the Ubuntu Corpus V2 dataset. We select some
reader-friendly cases from the test set. The best Cross-Encoder implementation, i.e., the method without concatenation and in-batch negative training ((iii) in Table 3), is employed as our competitor. Results in Table 6 suggest that Panoramic-Encoder can select very diverse and coherent responses. In contrast, even though some results of the Cross-Encoder are not logically problematic, those responses are very generic, which indicates that the quality of the responses is far inferior to ours.

5 Conclusion

In this paper, we propose a new paradigm for the dialogue response selection task. To this end, we present the Panoramic-Encoder architecture that integrates with a novel candidate attention mechanism. The proposed method simultaneously processes all candidate responses to select the optimum in one-shot prediction. Also, the parallel computation fashion in our paradigm allows using the in-batch negative training seamlessly, which again boosts its performance. By incorporating other common practices in training, our method pushes state-of-the-art results across four benchmarks, with significantly lower computational costs. Thorough empirical results also show the superiority of our proposal.

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