Building an Efficient and Effective Retrieval-based Dialogue System via Mutual Learning

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Abstract
Establishing retrieval-based dialogue systems that can select appropriate responses from the pre-built index has gained increasing attention from researchers. For this task, the adoption of pre-trained language models (such as BERT) has led to remarkable progress in a number of benchmarks. There exist two common approaches, including cross-encoders which perform full attention over the inputs, and bi-encoders that encode the context and response separately. The former gives considerable improvements in accuracy but is often inapplicable in practice for large-scale retrieval given the cost of the full attention required for each sample at test time. The latter is efficient for billions of indexes but suffers from sub-optimal performance. To further improve the effectiveness of our framework, we train the pre-retrieval model and the re-ranking model as a more complicated architecture (such as cross-encoder). To improve the effectiveness of our framework, we train the pre-retrieval model and the re-ranking model at the same time via mutual learning, which enables two models to learn from each other throughout the training process. We conduct experiments on two benchmarks and evaluation results demonstrate the efficiency and effectiveness of our proposed framework.

Introduction
Building a smart human-computer conversation system has been a long-standing goal in the area of artificial intelligence. Recent years have witnessed increasing interest in building an open-domain dialogue system through data-driven approaches with advances in deep learning techniques (Sutskever, Vinyals, and Le 2014; Vaswani et al. 2017; Devlin et al. 2019) and the availability of a huge amount of human conversations on social media. By selecting a proper response from the pre-built index with information retrieval techniques (Lowe et al. 2015; Whang et al. 2020) or synthesizing a response with text generation techniques (Vinyals and Le 2015; Zhang et al. 2019), existing neural models are now naturally able to reply to user prompts. In this paper, we focus on retrieval-based dialogue systems as they can return fluent and informative responses (Tao et al. 2019) and have powered industrial applications such as the social chatbot Microsoft Xiaoice (Shum, He, and Li 2018) and the virtual assistant Amazon Alexa (Ram et al. 2018).

Existing retrieval-based dialogue systems usually follow the two-stage retrieval and ranking paradigm (Wang et al. 2013; Li et al. 2017) where the model first retrieves a bundle of response candidates from a pre-built index through a fast retrieval model and then selects an appropriate one as the output response with a more sophisticated response selection model. While index building and pre-retrieval methods have been well studied in the information retrieval area, they are less studied in the area of dialogue systems. Until recently, most of retrieval-based dialogue systems (Li et al. 2017; Shum, He, and Li 2018) depend on traditional term-based information retrieval (IR) methods (such as BM25 (Robertson, Zaragoza, and Taylor 2004; Qiu et al. 2017) or TF-IDF (Ji, Lu, and Li 2014)) to perform the fast pre-retrieval. While these hand-crafted features are efficient, they fail to capture the semantics of the context and response candidates beyond lexical matching and remain a major performance bottleneck for the task.

Recently, the use of pre-trained language models (such as BERT (Devlin et al. 2019) for information retrieval has led to remarkable progress in several tasks. Several studies on dense retrieval methods begin to use pre-trained bi-encoder to cast the input query and index entries into dense representations in a vector space and rely on fast maximum inner-product search (MIPS) (Shrivastava and Li 2014) to complete the retrieval. These approaches have demonstrated significant retrieval improvements over traditional IR baselines on open-domain question answering (Karpukhin et al. 2020). On the other hand, in the response re-ranking stage, two approaches are common: bi-encoders (Lowe et al. 2015; Henderson et al. 2019) or poly-encoder (Humeau et al. 2020) encoding the context and response separately and cross-encoders (Whang et al. 2020) performing full attention over the inputs. The former is efficient for billions of indexes but suffers from sub-optimal performance. The latter gives considerable improvements in accuracy but is often inapplicable in practice for large-scale retrieval given the cost of the full attention required for each sample at test time. Hence, the challenge we consider is the following: How to benefit from accurate cross-attention mechanisms while preserving the fast and scalable response matching?
In this work, instead of configuring new architectures for response re-ranking, we investigate how to build an efficient and effective retrieval-based dialogue system by combining the best of both worlds. Specifically, we train a fast bi-encoder architecture to replace the traditional feature-based pre-retrieval model (such as BM25) and perform the response pre-retrieval with the help of MIPS. In the response re-ranking stage, we employ a more complicated and powerful architecture (e.g., cross-encoder) (named response selector) to re-rank a small number of most promising candidates provided by the fast pre-retrieval model. To further improve the effectiveness of our overall systems, we also introduce to train the pre-retriever and the response selector at the same time via mutual learning, which enables two models to learn from each other throughout the training process. By combining the fast pre-retriever and smart response selector, our framework can achieve impressive performance while demonstrating acceptable efficiency over the state-of-the-art cross-encoders.

We conduct experiments with two benchmarks, including Ubuntu Dialogue Corpus (Lowe et al. 2015) and the response selection track of Dialog System Technology Challenge 7 (Gunasekara et al. 2019). On both benchmarks, the model is required to select the most appropriate response from a bundle of candidates or the large index. Evaluation results indicate that: 1) we bring consistent improvements over both the fast bi-encoder and smart cross-encoder with the mutual learning method that transfers knowledge from each other during training. 2) our combined two-stage model is significantly better than the existing models, while also performing at a faster and acceptable test speed.

Our contributions in the paper are four-fold:

- First exploration of using the dense pre-retrieval method in retrieval-based dialogue systems;
- Proposal of combining the efficient pre-retriever and effective response selector for response retrieval;
- Proposal of jointly learning the pre-retriever and the response selector with a mutual learning framework;
- Empirical verification of the effectiveness and efficiency of the proposed framework and learning approach on two public data sets.

Related Works

**Retrieval-based Dialogues** Early work for retrieval-based chatbots studies single-turn response selection where the input of a matching model is a message-response pair (Wang et al. 2013; Hi, Lu, and Li 2014; Wang et al. 2015). Recently, more attention is drawn to context-response matching for multi-turn response selection. Representative methods include the dual LSTM model (Lowe et al. 2015), the multi-view matching model (Zhou et al. 2016), the sequential matching network (SMN) (Wu et al. 2017), the deep attention matching network (DAM) (Zhou et al. 2018), and the multi-hop selector network (MSN) (Yuan et al. 2019).

Recently, pre-trained language models (Devlin et al. 2019; Liu et al. 2020) on large corpus have shown significant benefits for various downstream NLP tasks, and some researchers have tried to apply them on response selection: to exploit BERT to represent each utterance-response pair and fuse these representations to calculate the matching score (Vig and Ramea 2019); to treat the context as a long sequence and conduct context-response matching with BERT (Wang et al. 2020). During the post-training on dialogue corpus, this model also introduces the next utterance prediction and masked language model tasks borrowed from BERT to incorporate in-domain knowledge for the matching model; to heuristically incorporate speaker-aware embeddings into BERT to promote the capability of context understanding in multi-turn dialogues (Gu et al. 2020).

**Efficient Information Retrieval** Existing information retrieval models (Wang et al. 2013; Qu et al. 2017; Nogueira and Cho 2019; Nogueira et al. 2019) usually adopt a pipeline where an efficient first-stage retriever retrieves a small set of candidates from the entire corpus, and then a powerful but slow second-stage ranker reranks them. However, most of the models rely on traditional lexical-based methods (such as BM25) to perform the first stage of retrieval and the ranking models of different stages are learned separately. Recently, as a promising approach, Dense Retrieval (DR) has been widely used for Ad-hoc retrieval (Zhan et al. 2020; Chang et al. 2020; Luan et al. 2021) and open-domain question answering (Lee, Chang, and Toutanova 2019; Karpukhin et al. 2020; Xiong et al. 2020) because it is as fast as traditional methods and can achieve impressive performance. In retrieval-based dialogue, Humeau et al. (2020) present the Poly-encoder, an architecture with an additional learnt attention mechanism that represents more global features from which to perform self-attention, resulting in performance gains over Bi-encoders and large speed gains over PLM-based models. Besides, Henderson et al. (2020) introduce ConveRT which is a compact dual-encoder pretraining architecture for neural response selection. Tahami et al. (2020) utilize knowledge distillation to compress the cross-encoder network as a teacher model into the student bi-encoder model.

To the best of our knowledge, this paper makes the first attempt to use the dense pre-retrieval method in retrieval-based dialogues and combines the efficient pre-retriever and effective response selector for building an effective and efficient response retrieval system. Besides, different from previous single-directional distillation (Tahami et al. 2020), we jointly train the pre-retriever and the response selector with a mutual learning framework (Zhang et al. 2018), which is similar to mutual distillation and enables the knowledge transfer from each other.

**Problem Formalization**

Given a data set $D = \{(y, c, r)\}_{i=1}^{N}$ where $c = \{u_1, ..., u_n\}$ represents a $n_c$ turns of conversation context with $u_i$ the $i$-th turn, $r$ is a response candidate, and $y \in \{0, 1\}$ denotes a label with $y = 1$ indicating $r$ a proper response for $c$ and otherwise $r = 0$. The goal of the task of response selection is to build a matching model $\phi(\cdot, \cdot)$ from $D$. For any input context $c$ and a candidate response $r$, $\phi(c, r)$ gives a score that reflects the matching degree between $c$ and $r$. According to $\phi(c, r)$, one can rank a set of response candidates for response selection. In particular, the definition of $\phi(\cdot, \cdot)$ can be a single-stage model or a two-stage model.
Overall Framework

Retrieval models re-use existing human conversations and select a proper response from a group of candidates for a new user input. Our method is designed within the framework of search engines. Given a message or a conversation context (i.e., a message with several previous turns as conversation history), the pre-retriever searches response candidates from an index of existing conversations, and then the response selector re-ranks the candidates based on the matching degree between the input and the candidates. Specifically, we use a dense retrieval method based on a fast pre-trained bi-encoder architecture as the pre-retrieval model. In the response re-ranking stage, we employ a more complicated and powerful architecture (such as cross-encoder) to re-rank a small number of most promising candidates provided by the fast pre-retrieval model. To further improve the effectiveness of the overall system, we also propose to train the pre-retrieval model and the re-rank model at the same time via mutual learning, which enables two models to learn from each other throughout the training process.

Pre-Retriever

Inspired by the recent dense retrieval [Lee, Chang, and Toutanova 2019; Zhan et al. 2020; Karpukhin et al. 2020], we use a bi-encoder architecture to construct a learnable retriever. The architecture utilizes a separate pre-trained encoder to cast the input context message and index entries into dense representations in a vector space and relies on fast maximum inner-product search (MIPS) to complete the retrieval. Without loss of generality, we use two BERT [Devlin et al. 2019] models for both encoders, as it is trained on large amounts of unlabelled data and provides strong “universal representations” that can be finetuned on task-specific training data to achieve good performance on downstream tasks.

Specifically, given a context $c = \{u_1, u_2, \ldots, u_n\}$, where the $t$-th utterance $u_t = \{w_{t,1}, \ldots, w_{t,l_t}\}$ is a sequence with $l_t$ words, a response candidate $r = \{r_1, r_2, \ldots, r_{l_r}\}$ consisting of $l_r$ words and a label $y \in \{0, 1\}$, we first concatenate all utterances in the context as a consecutive token sequence with special tokens separating them, which can be formulated as $x = \{[CLS], u_1, [EOT], u_2, [EOT], \ldots, [EOT], u_n, [EOT], [SEP]\}$. Here [CLS] and [SEP] are the classification symbol and the segment separation symbol of BERT, [EOT] is the “End Of Turn” tag designed for multi-turn context. For each word of $x$, token, position and segment embeddings of $x$ are summed and fed into pre-trained transformer layer (a.k.a. BERT), giving us the contextualized embedding sequence. We then project the [CLS] representation to a vector as the context representation following [Lee, Chang, and Toutanova 2019]. Formally,

$$v_c = W_c \text{BERT}_c [CLS]$$

where BERT$_c$ is the context encoder, $W_c$ is the projection matrix for the context [CLS] representation, and $v_c$ is the final context representation containing dialogue history information. We then follow the same scheme to obtain the response representation for a response candidate $r_j$:

$$v_r = W_r \text{BERT}_r [CLS]$$

where BERT$_r$ is the response encoder, $W_r$ is the projection matrix for the response [CLS] representation, and $v_r$ is the final response representation. Finally, the retrieval score is computed as

$$g(c_i, r_j) = v_c^T v_r$$

For each training sample, the loss function of the response retriever is defined by

$$L_{\Theta_2}(c_i, r_i^+, r_{i,1}^-; \ldots, r_{i,j}^-) = - \log \left( \frac{e^{g(c_i, r_i^+)} + \sum_{j=1}^{|\delta_r|} e^{g(c_i, r_{i,j}^-)}}{e^{g(c_i, r_i^+)} + \sum_{j=1}^{|\delta_r|} e^{g(c_i, r_{i,j}^-)}} \right)$$

where $r_i^+$ is the true response for a given $c_i$, $r_{i,j}^-$ is the $j$-th negative response candidate randomly sampled from the training set, $\delta_r$ denotes the number of negative response candidate, $\Theta_2$ represents the parameters of the pre-retriever.

Response Selector

To further re-rank a small number of promising candidates provided by the fast pre-retrieval model, we consider a powerful pre-trained cross-encoder architecture [Devlin et al. 2019] to build the response selector, as it has demonstrated impressive results on various response selection task [Whang et al. 2020; Gu et al. 2020]. Consistent with previous studies [Gu...
Specifically, we first concatenate all utterances in the context as well as the response candidate as a single consecutive token sequence with special tokens separating them formulated as $x = \{[CLS], u_1, [EOT], u_2, [EOT], \ldots, [EOT], u_m, [EOT], [SEP], r, [SEP]\}$. Similarly, token, position and segment embeddings are also used. After being processed by BERT, the input sequence is transformed into a contextualized embedding sequence. BERT$_r$[CLS] is an aggregated representation vector that contains the semantic interaction information for the context-response pair. We then fed BERT$_c$[CLS] into a multi-layer perception to obtain the final matching score for the context-response pair:

$$s(c, r) = \sigma(W_2 \cdot f(W_1 BERT_c [CLS] + b_1) + b_2)$$

where $W_{[1,2]}$ and $b_{[1,2]}$ are trainable parameters, $f(\cdot)$ is a tanh activation function, $\sigma(\cdot)$ stands for a sigmoid function.

Finally, the training objective of the response selector $L_{\theta_r}(\cdot)$ can also be defined as the negative log-likelihood loss similar to Equation (4).

### Mutual Learning

Traditional supervised method individually trains two models to predict the correct labels for the training samples. To improve the effectiveness of our overall systems, we train the pre-retriever and the response selector at the same time via mutual learning (Zhang et al. 2018), which enables two models to learn or transfer knowledge from each other throughout the training process. Formally, for a batch of training examples $\{c_i, r_{i,j}\}_{i=1, j=1}^{N, j=K, +1}$, the probability that $(c_i, r_{i,j})$ is a true context-response pair given by the pre-retriever $\Theta_g$ is computed as

$$p_{m} = \frac{\exp(g(c_i, r_{i,m})/\tau)}{\sum_{j=1}^{K+1} \exp(g(c_i, r_{i,j})/\tau)}$$

where $g(c_i, r_{i,j})$ is the output logit of response pre-retriever, $\tau$ is the temperature to soften $g(c_i, r_{i,j})$. The output probability of response selector can be computed by the similar way and is denoted as $q = \{q_1, \ldots, q_{K+1}\}$.

To improve the generalization performance of response pre-retriever $\Theta_g$, we utilize response selector $\Theta_s$ to provide training experience in the form of its posterior probability $q$. We adopt the Kullback Leibler (KL) Divergence (Kullback 1997) to measure the distance of the two network’s predictions $p$ and $q$, which are predicted by $\Theta_g$ and $\Theta_s$ separately. Formally, the KL distance from $p$ to $q$ is computed as

$$D_{KL}(q \parallel p) = \sum_{i=1}^{N} \sum_{m=1}^{M} q_{i,m} \log \frac{p_{i,m}}{q_{i,m}}$$

The overall loss function $L_{\theta_g}$ for response pre-retriever ($\Theta_g$) can be re-defined as

$$L_{\theta_g} = L_{\theta_g} + \alpha \cdot D_{KL}(q \parallel p)$$

where $\alpha$ is the weight for the trade-off two losses. Similarly, we can also use the posterior probability of the response pre-retriever $\Theta_g$ to provide training experience for the response selector. The objective loss function $L_{\theta_s}$ for response selector can be re-defined as

$$L_{\theta_s} = L_{\theta_s} + \alpha \cdot D_{KL}(p \parallel q)$$

In this way, the pre-retriever and response selector both learn to correctly predict the true label of training instances (supervised loss $L_{\theta_{(g,s)}}$) as well as to match the probability estimate of its counterpart (KL mimicry loss). The mutual learning method can also be regarded as a mutual distillation process that transfers knowledge estimating the relative quality of the response candidates by each other. Algorithm 1 describes the pseudo-code of our mutual learning method.

### Inference

After learning models from D, we first rank the response index according to $g(c, r)$ and then select top $n_r$ response candidates $\{r_1, \ldots, r_{n_r}\}$ for the subsequent response re-ranking process. Here we consider two strategies to predict the final response. In the first strategy, we directly use the matching score of the response selector to obtain the final matching score and output the response with the highest score.

In the second strategy, the final matching score is defined as an integration of the score computed by the pre-retriever and response selector,

$$\hat{s}(c, r) = g(c, r) + s(c, r)$$

The intuition of the above operation is that the pre-retriever focuses on coarse-grained semantic matching based on discourse-level representation, while the response selector focuses on fine-grained word-by-word interaction. We hope to make more accurate predictions with the help of both parties. We compare the two strategies through empirical studies, as will be reported in the next section.
Experiments
We evaluate the proposed method on two benchmark datasets for both single-stage and two-stage multi-turn response selection tasks.

Datasets and Evaluation Metrics
The first dataset is the track 2 of Dialog System Technology Challenge 7 (DSTC7) [Gunasekara et al. 2019]. The dataset is constructed by applying a new disentanglement method [Kummerfeld et al. 2018] to extract conversations from an IRC channel of technical help for the Ubuntu system. We use the copy shared by [Humeau et al. 2020] where contains about 2 million context-response pairs for training. At test time, the systems were provided with conversation histories, each paired with a set of response candidates that could be the next utterance in the conversation. Systems needed to rank these options. We test our model on two sub-tasks. For each dialog context in sub-task 1, a candidate pool of 100 is given and the contestants are expected to select the best next utterance from the given pool. In sub-task 2, one large candidate pool of 120,000 utterances is shared by validation and testing datasets. The next best utterance should be selected from this large pool of candidate utterances. In both sub-tasks, there are 5,000 and 1,000 dialogues for validation and test respectively.

The second dataset is the Ubuntu Dialogue Corpus (v2.0) [Lowe et al. 2015], which consists of multi-turn English dialogues about technical support and is collected from chat logs of the Ubuntu forum. We use the copy shared of [Hua et al. 2020], which has 1.6 million context-response pairs for training, 19,560 pairs for validation, and 18,920 pairs for test. The ratio of positive candidates and negative candidates is 1 : 9 in training, validation set, and test set.

Following [Humeau et al. 2020], we employ hits@k and Mean Reciprocal Rank (MRR) as evaluation metrics, where hits@k measures the probability of the positive response being ranked in top k positions among candidates.

Baselines
We compare our method on both the traditional multi-turn response selection scenario as well as the two-stage retrieval scenario. In particular, the following state-of-the-art multi-turn response selection models are selected to compare with our results.

- **DAM** [Zhou et al. 2018]: the model follows the representation-matching-aggregation paradigm and the representation is obtained with self and cross attention.
- **ESIM** [Chen and Wang 2019]: the model is the modifications and extensions of the original ESIM [Chen et al. 2017] developed for natural language inference.
- **IMN** [Gu, Ling, and Liu 2019]: the model is a hybrid model with sequential characteristics at the matching layer and hierarchical characteristics at the aggregation layer.
- **Bi-Encoder** [Humeau et al. 2020]: the model is the same as our pre-retriever.
- **Poly-Encoder** [Humeau et al. 2020]: the model represents the context and response candidates separately and lets the response interact with the context through an improved attention mechanism.
- **Cross-Encoder** [Humeau et al. 2020]: the model is the state-of-the-art models based on pre-trained model.

Implementation Details
Following [Humeau et al. 2020], we select English uncased BERTbase (110M) pre-trained on reddit corpus [https://github.com/huggingface/transformers] as the context-response matching model and implement our model with transformers library provided by huggingface [https://github.com/huggingface/transformers]. The maximum lengths of the context and response are set to 300 and 72. Intuitively, the last tokens in the context and the previous tokens in the response candidate are more important, so we cut off the previous tokens for the context but do the cut-off in the reverse direction for the response candidate if the sequences are longer than the maximum length. We choose 8 as the size of mini-batches for training. We implement the MIPS with Facebook AI Similarity Search library [https://github.com/facebookresearch/faiss]. During training, we vary $\alpha$ (Equation [5]) in $\{0.5, 1, 2, 3, 4, 5\}$, and find that $\alpha = 1.0$ is the best choice on both data sets. We set the number of negative response candidates $\delta_r = 32$ during the training. In two-stage retrieval scenario, we test $n_r$ in $\{10, 50, 100, 200, 500, 800\}$ and set $n_r = 100$ for the trade off the efficiency and effectiveness. The model is optimized using Adam optimizer with a learning rate set as $3e^{-5}$. The learning rate is scheduled by warm-up and linear decay. $\tau$ is set as 3. A dropout rate of 0.1 is applied for all linear transformation layers. The gradient clipping threshold is set as 10.0. Early stopping on the corresponding validation data is adopted as a regularization strategy.

Evaluation Results

**Results of traditional response selection.** We first validated the effectiveness of our framework on traditional response selection scenario. Table 1 report the evaluation results on sub-task 1 of DSTC7 and UbuntuV2 where 10 and 100 response candidates are provided for each input context. We can observe that the performance of pre-retriever (e.g., Bi-Enc) and response selector (e.g., Cross-Enc) improve on almost all metrics after they are jointly trained with mutual learning, indicating that the effectiveness of mutual learning on the multi-turn response selection task. Notably, mutual-learning brings more significant improvement to the bi-encoder than cross-encoder on both datasets. The results may stem from the fact that cross-encoder (a stronger model) can provide bi-encoder (a weaker model) with more useful knowledge during the mutual learning phase, but less on the contrary. With mutual learning, a simple bi-encoder even performs better than the original cross-encoder and poly-encoder on both datasets, although the cross-encoder involves more
We use the Bi-Enc (ML) as the pre-retriever, and Cross-Enc (ML) or the ensemble method (as formulated in Eq. (10)) as Enc (ML) respectively. We can find that Table 3: Evaluation results on task2 of DSTC7 dataset. We set Table 2: Comparison of single-stage models and two-stage models on the sub-task1 of DSTC7 dataset. We set Table 1: Results on UbuntuV2 and sub-task1 of DSTC7. Numbers marked with * mean that improvement to the state-of-the-art is statistically significant (t-test, p < 0.05). Numbers marked with ◦ mean that improvement to the original models mean that improvement to the state-of-the-art is statistically significant (t-test, p < 0.05). Numbers marked with * mean that improvement to the state-of-the-art is statistically significant (t-test, p < 0.05).

| Model              | Sub-task1 of DSTC7 | UbuntuV2 |
|--------------------|--------------------|----------|
|                   | hits@1  | hits@10 | hits@50 | MRR | hits@1  | hits@2  | hits@5  |
| DAM (Zhou et al. 2018) | 34.7    | 66.3    | -       | 35.6 | -       | -       | -       |
| ESIM (Chen and Wang 2019) | 64.5    | 90.2    | 99.4    | 73.5 | 73.4    | 86.6    | 97.4    | 83.5 |
| IMN (Gu, Ling, and Liu 2019) | -       | -       | -       | -   | -       | 77.1    | 88.6    | 97.9 |
| Bi-Enc (Humeau et al. 2020) | 70.9    | 90.6    | -       | 78.1 | 83.6    | -       | 98.8    | 90.1 |
| Poly-Enc (Humeau et al. 2020) | 71.2    | 91.5    | -       | 78.2 | 83.9    | -       | 98.8    | 90.3 |
| Cross-Enc (Humeau et al. 2020) | 71.7    | 92.4    | -       | 79.0 | 86.5    | -       | 99.1    | 91.9 |
| Bi-Enc (Our implementation) | 67.5    | 91.6    | 98.9    | 76.1 | 83.1    | 92.7    | 98.8    | 89.9 |
| Cross-Enc (Our implementation) | 71.2    | 93.2    | 99.2    | 78.8 | 86.6    | 94.3    | 99.3    | 92.0 |
| Bi-Enc (ML)       | 72.4◦  | 93.7◦  | 99.2◦  | 80.1◦ | 85.7◦  | 93.8◦  | 99.0◦  | 91.5◦ |
| Cross-Enc (ML)   | 73.9◦  | 93.9◦  | 99.4◦  | 81.3◦ | 87.4◦  | 94.7◦  | 99.2◦  | 92.6◦ |
| Ensemble (ML)    | 75.3*  | 94.5*  | 99.4*  | 82.3* | 87.6*  | 94.8*  | 99.2*  | 92.6* |

Table 1: Results on UbuntuV2 and sub-task1 of DSTC7. Numbers marked with * mean that improvement to the original models is statistically significant (t-test, p < 0.05). Numbers marked with ◦ mean that improvement to the state-of-the-art is significant.

| Model              | hits@1  | hits@2  | hits@5  | MRR | Test (ms/case) |
|--------------------|---------|---------|---------|-----|----------------|
| Poly-Enc           | 70.9    | 81.1    | 87.0    | 79.2 | 46             |
| Bi-Enc (ML)        | 72.4    | 81.5    | 88.7    | 80.1 | 45             |
| Cross-Enc (ML)     | 73.9    | 83.0    | 90.4    | 81.3 | 188            |
| Bi-Enc (ML) → Cross-Enc (ML) | 73.9    | 82.8    | 90.1    | 80.9 | 64             |
| Bi-Enc (ML) → Ensemble-Enc (ML) | 75.2*  | 83.7*   | 90.9*   | 81.8* | 64             |

Table 2: Comparison of single-stage models and two-stage models on the sub-task1 of DSTC7 dataset. We set n_r = 10 in the two-stage models and report the score of hits@k (k = 1, 2, 5) since only 100 response candidates are given for each dialog context. Numbers marked with * mean that improvement to the state-of-the-art is statistically significant (t-test, p < 0.05).

| Model              | hits@1  | hits@2  | hits@5  | MRR | Test (ms/case) |
|--------------------|---------|---------|---------|-----|----------------|
| BM25               | 1.4     | 2.0     | 4.2     | 6.0  | 11.9           | 10.0 | -             |
| Bi-Enc             | 8.6     | 12.2    | 18.7    | 23.2 | 38.1           | 13.6 | -             |
| Bi-Enc (ML)        | 10.8    | 16.4    | 23.8    | 30.0 | 46.2           | 17.3 | -             |
| BM25 → Bi-Enc      | 6.9     | 9.6     | 12.4    | 13.6 | 15.8           | 9.3  | 45            |
| BM25 → Poly-Enc    | 7.2     | 9.7     | 12.6    | 13.9 | 15.8           | 9.4  | 46            |
| BM25 → Cross-Enc   | 8.0     | 10.4    | 13.5    | 14.6 | 15.8           | 10.3 | 188           |
| BM25 → Bi-Enc (ML) | 8.1     | 10.1    | 12.7    | 13.8 | 15.6           | 10.0 | 45            |
| BM25 → Cross-Enc (ML) | 8.8    | 11.8    | 13.9    | 15.0 | 15.7           | 11.0 | 188           |
| Bi-Enc → Cross-Enc | 10.9    | 16.1    | 23.8    | 30.9 | 44.6           | 17.3 | 188           |
| Bi-Enc (ML) → Cross-Enc (ML) | 12.6*  | 17.4*   | 25.2*   | 30.8 | 48.3*          | 18.8* | 188          |
| Bi-Enc (ML) → Ensemble-Enc (ML) | 12.9*  | 18.6*   | 25.6*   | 32.9* | 49.2*          | 19.3* | 188          |

Table 3: Evaluation results on task2 of DSTC7 dataset. We set n_r = 100 in all two-stage models. It is worth noting that the pre-retrieval with faiss library is very fast and we do not report this part of the time. Numbers marked with * mean that improvement to the state-of-the-art is statistically significant (t-test, p < 0.05).

Heavy interaction. Besides, compared with single-stage models, the ensemble of the pre-retriever and response selector achieves consistently better performance over all metrics on two data sets, demonstrating the advantages of combining matching features of different aspects.

**Results of two-stage response retrieval.** We further conduct experiments on two-stage response retrieval scenario. Table 2 gives the evaluation results of the sub-task1 of DSTC7. We use the Bi-Enc (ML) as the pre-retriever, and Cross-Enc (ML) or the ensemble method (as formulated in Eq. 10) as the response selector, and denote the two models as Bi-Enc (ML) → Cross-Enc (ML) and Bi-Enc (ML) → Ensemble-Enc (ML) respectively. We can find that Bi-Enc (ML) → Cross-Enc (ML) achieves slightly worse performance than the cross-encoder. The results are rational since not all the correct response is in the top 10 candidates obtained by Bi-Enc (ML). However, the two-stage models are about three times faster than Cross-Enc (ML) in inference. In addition, our two-stage model with the ensemble selector is significantly better than the baseline method while also performing at an acceptable test speed.

Table 3 contains the evaluation results of the sub-task2 of DSTC7. In this task, the model is expected to select the best response from a shared candidate pool of 120,000 responses, which is more challenging. Due to the huge number of indices, we make use of the MIPS to perform the pre-retrieval,
and the time spent in this stage is negligible compared with
the response selecting stage. According to the results, we can
observe that: 1) Compared with using BM25 as pre-retriever,
Bi-encoder can bring consistent and significant improvement
to the overall retrieval system on both datasets, indicating
the effectiveness of dense retrieval on the response selection
task; 2) Mutual learning can improve the performance of
both single-stage models (e.g., Bi-Enc vs Bi-Enc (ML)) and
two-stage models (e.g., the models in last two rows); 3) By
combining the bi-encoder model and smart cross-encoder
model, our two-stage retrieval framework can achieve im-
pressive performance while showing reasonable efficiency
constraints compared with other baseline methods, and there-
fore has good practicality.

Discussions

The impact of $n_r$ We first check the effectiveness and ef-
ciency of re-ranking performance with respect to the number
of top $n_r$ candidates returned from the pre-retriever. Figure 2
illustrates how the hit@1 score of the two-stage model varies
under different $n_r$ on sub-task2 of DSTC7 (shown as red
lines) and average test speed under different $n_r$ when using
the Cross-Enc or Bi-Enc as the selector. We can observe
that the retrieval performance increase monotonically as $n_r$
keeps increasing and the improvement becomes smaller when
context length reaches 500. Besides, it can be found that re-
ranking as few as 10 or 50 candidates out of 120 thousand
from the pre-retriever is enough to obtain good performance
under reasonable efficiency constraints.

Training curve of pre-retriever and response selector
We are curious if the response pre-retriever and response
selector can co-improve when they are jointly trained with
mutual learning. Figure 3 shows how the hits@1 score of
Bi-Encoder, Cross-Encoder, Bi-Encoder and Cross-Encoder
with mutual learning changes with the number of epochs on
the validation set of sub-task1 of DSTC7. The number of
testing samples in the three bins is 339, 356, 305 respectively.

The impact of context length We further conduct a study
to investigate how the length of context influences the perfor-
mance of these models. Figure 4 shows how the performance
of the models changes with respect to different lengths of
contexts on sub-task1 of DSTC7. We observe a similar trend
for all models: they increase monotonically when context
length keeps increasing. The phenomenon may come from the
fact that the longer context can provide more useful in-
formation for response matching. Besides, we can find that
mutual learning can bring performance improvements for
both the bi-encoder and cross-encoder across all different
context lengths, but the improvement is more obvious in the
long context (e.g., (100,360]) for cross-encoder and more
obvious in the short context (e.g., (0, 50]) for bi-encoder.

Conclusion

In this paper, to build an efficient and effective retrieval-based
dialogue system, we propose to combine the fast pre-retriever
and the smart response selector. Specifically, we employ a
fast bi-encoder to replace the traditional feature-based pre-
retrieval model and set the response re-ranking model as a
more complicated architecture. To further improve the effec-
tiveness of our framework, we train the pre-retrieval model and the re-ranking model at the same time via mutual learning, which enables two models to learn from each other throughout the training process. Experimental results on two public benchmarks demonstrate the efficiency and effectiveness of our proposed framework.

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