On Task-Adaptive Pretraining for Dialogue Response Selection

Tzu-Hsiang Lin¹, Ta-Chung Chi¹, and Anna Rumshisky²

¹Language Technologies Institute, Carnegie Mellon University
²Department of Computer Science, University of Massachusetts Lowell
tzuhsial@alumni.cmu.edu, tachungc@cmu.edu, arum@cs.uml.edu

Abstract

Recent advancements in dialogue response selection (DRS) are based on the task-adaptive pre-training (TAP) approach, by first initializing their model with BERT (Devlin et al., 2019), and adapt to dialogue data with dialogue-specific or fine-grained pre-training tasks. However, it is uncertain whether BERT is the best initialization choice, or whether the proposed dialogue-specific fine-grained learning tasks are actually better than MLM+NSP. This paper aims to verify assumptions made in previous works and understand the source of improvements for DRS. We show that initializing with RoBERTa achieve similar performance as BERT, and MLM+NSP can outperform all previously proposed TAP tasks, during which we also contribute a new state-of-the-art on the Ubuntu corpus. Additional analyses shows that the main source of improvements comes from the TAP step, and that the NSP task is crucial to DRS, different from common NLU tasks.

1 Introduction

Recent advances in dialogue response selection (DRS) (Wang et al., 2013; Al-Rfou et al., 2016) have mostly adopted the Task-adaptive Pre-training (TAP) approach (Gururangan et al., 2020) and can be divided into three steps. Step one: initialize the model using a pre-trained language model checkpoint. Step two: perform TAP on the DRS training data with data augmentation. Step three: fine-tune the TAP on the DRS dataset.

For step one, surprisingly, all previous works have exclusively chosen the original BERT (Devlin et al., 2019). We hypothesize this is due to the Next Sentence Prediction (NSP) task in BERT having the same formulation as DRS, and previous works have thus assumed BERT contains more knowledge related to DRS. Nonetheless, it is well-known in NLP literature that BERT is under-trained and that removing the NSP task during pre-training improves downstream task performance (Liu et al., 2019). For step two, while earlier work uses MLM+NSP for TAP (Whang et al., 2020; Gu et al., 2020), more recent works have assumed that MLM+NSP is too simple or does not directly model dialogue patterns, and thus proposed various dialogue-specific learning tasks (Whang et al., 2021; Xu et al., 2021) or fine-grained pre-training objectives to help the DRS models better learn dialogue patterns and granular representations (Su et al., 2021). However, Han et al. (2021a) recently uses MLM with a simple variant of NSP for TAP and outperforms almost all of them, raising questions on whether these dialogue-specific fine-grained learning tasks are actually better.

This paper aims to verify the assumptions made in previous works and understand the source of improvements from the TAP approach. First, we include RoBERTa (Liu et al., 2019) as an additional initialization checkpoint to BERT and use MLM+NSP for TAP. Experiments on Ubuntu, Douban and E-commerce benchmarks show that (1) BERT and RoBERTa performs similarly, and (2) MLM+NSP can outperform all previously proposed dialogue specific and fine-grained pre-training tasks. Then, we conduct analyses and show that (3) the main source of improvements of DRS come from the training time of TAP in step two, which can even mitigate lack of a good initialization checkpoint, (4) NSP task is crucial to DRS, as opposed to common NLU tasks that can work with only MLM, (5) and the low N-gram train/test overlap % and low number of distinct N-grams explains why TAP does not improve Douban, and why overfitting occurs for E-commerce.

In short, we make the following contributions: (1) Contrary to previous beliefs, we show that BERT may not be the best initialization checkpoint, and MLM+NSP can outperform all previously proposed dialogue-specific fine-grained learning TAP tasks. (2) We present a set of analyses that iden-
The source of improvements for TAP, and DRS benchmark characteristics, and (3) contribute a new state-of-the-art on the Ubuntu corpus.

2 Task-adaptive Pre-training with BERT

2.1 Task Formulation

Given a multi-turn dialogue \( c = \{u_1, u_2, \ldots, u_T\} \) where \( u_t \) stands for the \( t^{th} \) turn utterance, let \( r_i \) denote a response candidate, and \( y_i \in \{0, 1\} \) denotes a label with \( y_i = 1 \) indicating that \( r_i \) is a proper response for \( c_i \). (otherwise, \( y_i = 0 \)). Dialogue Response Selection (DRS) aims to learn a model \( f(c, r_i) \) to predict \( y_i \). With the cross-encoder binary classification formulation, DRS shares the exact form as the Next Sentence Prediction (NSP) task used in BERT (Devlin et al., 2019).

2.2 Step 1: Initialize from Checkpoint

All previous works have exclusively used BERT (Devlin et al., 2019) as their initialization checkpoint and does not consider other open-source pre-trained language models. We hypothesize this is due to BERT’s NSP task and DRS sharing the same task formulation and thus may learn representations that are more helpful to DRS. However, RoBERTa (Liu et al., 2019) has shown that BERT is undertrained and removing the NSP task improves downstream task performance, raising questions on whether BERT is the best choice for DRS.

To verify this assumption, we use both BERT and RoBERTa in our experiments. To the best of our knowledge, we are the first to include RoBERTa for DRS, and that show both achieves similar performance.

2.3 Step 2: Task-adaptive Pre-training

2.3.1 Data Augmentation

All previous works have performed data augmentation to generate more data for Task-adaptive Pre-training. While several works have devised fine-grained data augmentation methods such as utterance insertion/deletion (Whang et al., 2021), or next session prediction (Xu et al., 2021), we use a standard data augmentation methodology that is commonly used in dialogue literature (Mehri et al., 2019; Gunasekara et al., 2019).

Given a context-response pair instance \( (c = \{u_1, \ldots, u_T\}, r) \) in the original training set, we generate additional \( T - 1 \) context response pairs \( \{(c_1, r_1), \ldots, (c_T, r_T)\} \), where \( c_t = \{u_1, \ldots, u_t\}, r_t = u_{t+1}, t \in \{1, \ldots, T - 1\} \) with a total of \( T \) pre-training instances.

Table 1: Dataset statistics. Pre-train set is generated from train set using the method in Section 2.3.1.

2.3.2 Pre-training Task

While BERT’s MLM+NSP objective naturally works as a default TAP choice (Whang et al., 2020), most recent works have hypothesized that MLM+NSP is not capable of modeling dialogue patterns, and designed dialogue-specific tasks such as incoherence detection (Xu et al., 2021), order shuffling (Whang et al., 2021), fine-grained matching (Li et al., 2021), etc. However, Han et al. (2021a) achieved a new cross-encoder state-of-the-art with a simple variant of MLM+NSP, raising questions on whether these dialogue-specific fine-grained tasks actually learn better.

In our experiments, we follow the input representation of (Whang et al., 2020) and use MLM+NSP for TAP and achieve a new state-of-the-art results on Ubuntu.

2.4 Step 3: Finetuning

Last, TAP models are fine-tuned on the original datasets on the DRS/NSP task to ensure a fair comparison. Considering the same task formulation, our MLM+NSP in step 2 can be viewed as multi-task learning with MLM as an auxiliary task and NSP as the primary task (Ruder, 2017).

3 Experimental Setup

3.1 Implementation Details

We used the open-source PyTorch-Lightning framework (Falcon et al., 2019; Paszke et al., 2019; Wolf et al., 2020) to implement our models. We use the BERTBase model architecture with the Adam (Kingma and Ba, 2015) optimizer, and performed grid search over learning rates of \( \{1e - 5, 5e - 5, 1e - 4\} \) for both TAP and fine-tuning. For TAP, we trained for 50 epochs and
Table 2: Results on response selection benchmarks. We bold-faced best results and underline second-best results.

### 3.2 Evaluation

We follow previous works’ protocol and evaluate on three standard response selection benchmarks: (1) Ubuntu corpus (Lowe et al., 2015), (2) Douban corpus (Wu et al., 2017), and (3) E-commerce corpus (Zhang et al., 2018). We report recall at 1, 2, and 5 for all 3 sets, and include precision at 1, mean average precision (MAP) and mean reciprocal rank (MRR) for Douban.

### 3.3 Baselines

**Cross-encoders** Cross-encoders performs self-attention over the context, response pairs. BERT-VFT (Whang et al., 2020) uses MLM+NSP for TAP; SA-BERT (Gu et al., 2020) includes speaker embeddings in the input representation; SA-BERT+HCL (Su et al., 2021) adopts curriculum learning on top of SA-BERT; UMS$_{B}}^R_{ERT}$ (Whang et al., 2021) and BERT-SL (Xu et al., 2021) develop dialogue-specific learning tasks, while UMS$_{B}}^R_{ERT}$+FGC (Li et al., 2021) and BERT-FP (Han et al., 2021a) uses more fine-grained objectives. Our model also fall under this category.

**Bi-encoders** Bi-encoders encode context and response separately, resulting in faster inference and allows large number of negative samples per positive instance. We report DR-BERT and DR-BERT w/o CL from Lan et al. (2021) that uses MLM for TAP and focuses on step 3. As DR-BERT uses a pos:neg ratio of 1:63, we include the latter that uses a pos:neg ratio of 1:1 for a fair comparison with our model.

### 4 Results and Discussion

#### 4.1 Main Results

We report our TAP and fine-tuning results in Table 2. With MLM+NSP, we achieve a new state-of-the-art (SOTA) result on the Ubuntu corpus, and second-best results on Douban and E-commerce, only falling behind DR-BERT. This suggests that previously proposed dialogue-specific or fine-grained learning tasks are not necessarily required for these standard DRS benchmarks. And to properly evaluate whether these learning tasks capture more fine-grained linguistic patterns, one potential method is to construct adversarial test sets that contain these patterns (Han et al., 2021b).

We observe that BERT and RoBERTa resulted in similar performance, with the former outperforming the latter on Ubuntu and E-commerce, while underperforming on Douban. This shows that despite DRS/NSP share the same task formulation, BERT does not always contain more knowledge than RoBERTa for DRS, and other pre-trained models can be explored in the future.

We also notice that fine-tuning achieves better performance for Ubuntu but not for Douban and E-commerce. We further discuss this in Section 4.5.

Though DR-BERT achieves SOTA on Douban and E-commerce, our model still outperforms DR-BERT w/o CL on the latter two, suggesting that the larger negative sampling ratio (NSR) is the key to DR-BERT’s superior performance. Considering that the cross-encoder architecture has to inference...
Figure 1: Test $R_{10}^{@1}$ of (a) Ubuntu, (b) Douban, and (c) E-commerce at 5, 10, 25, and 50 pre-training epochs.

Figure 2: Ubuntu TAP with different initialization.

each and every context response pair, thus cannot scale NSR efficiently, we leave exploring this hyper-parameter with bi-encoder architectures in future work.

4.2 Effects of Initialization

We analyze the effects of different initialization checkpoint by plotting the Ubuntu validation $R_{10}^{@1}$ for (1) BERT, (2) RoBERTa and (3) initialization from scratch in Figure 2. (1) and (2) perform similarly across training time with the monotonically increasing performance. While (3) has a large gap with (1) and (2) at the beginning, the gap gradually closes with more training time, indicating that the main source of improvements come from TAP and can mitigate the lack of a pre-trained checkpoint.

4.3 Effect of TAP Epochs

We plot both TAP and fine-tuning $R_{10}^{@1}$ for epochs at 5, 10, 25, and 50 in Figure 1. We can see that all 3 datasets exhibit different characteristics. On the Ubuntu and E-commerce corpus, both TAP and finetuning performance monotonically increases with more epochs. On the Douban corpus, the performance saturates around 25 epochs for both BERT and RoBERTa, and further training reduces performance. This suggests that TAP for longer can improve Ubuntu and E-commerce, but not so for Douban. We further discuss this in section 4.5.

4.4 Effect of TAP Tasks

We perform TAP with different pre-training tasks and report fine-tuning results on Ubuntu with BERT in Table 3. We observe that MLM underperforms NSP by a large margin (0.842 vs. 0.905) and multi-tasking MLM+NSP achieves the best results. This shows that NSP is important for DRS, which is different from common NLU tasks (Wang et al., 2018) where NSP is not helpful (Liu et al., 2019).

4.5 Ngram Analysis

We compute overlapping N-grams and discovered that Ubuntu, Douban, and E-commerce’s test set had 80.98%, 9.44%, and 99.66% of their 5-grams appearing in their training set, respectively. Douban’s low n-gram % explains why more TAP does not improve on Douban, and a further inspection shows that Douban’s test sets are constructed using corpus from a different domain (Wu et al., 2017). Next, we discovered that despite all having 1 million training instances, Ubuntu, Douban and E-commerce’s training set has 25m, 44m, and 900k different 5-grams, respectively. The lower variation of N-gram in E-commerce is a potential reason why fine-tuning resulted in overfitting.

5 Conclusion

We have verified assumptions regarding initialization and pre-training task choices in previous works and achieved a new SOTA on Ubuntu and strong results on Douban and E-commerce. Our analyses reveal that the main source of TAP-based DRS comes from more training time, NSP task is crucial for DRS, and that TAP improvements can be estimated by their N-gram overlaps and variations.
6 Limitations

From Section 4.3, we discover that our main source of improvements comes more TAP epochs. While training for longer monotonically improves performance for Ubuntu and E-commerce, the marginal gains decrease over time, which can be time-consuming and costly. Another limitation is the cross-encoder formulation that jointly encodes the context-response pairs. This prevents our model to effectively increase the negative sampling ratio to compare with the bi-encoder architectures such as DR-BERT that has shown superior performance on Douban and E-commerce.

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A Hyperparameter Details

We use the PyTorch-Lightning framework (Paszke et al., 2019; Falcon et al., 2019) to implement our models.

We use pre-trained weights and tokenizers from HuggingFace for initialization checkpoints. For BERT initialization, we use BERT-BASE-UNCASED for Ubuntu corpus, and BERT-BASE-CHINESE for Douban and E-commerce. For RoBERTa initialization, we use ROBERTA-BASE for Ubuntu, and CHINESE-ROBERTA-WWM-EXT for Douban and E-commerce.

We trained one run for each TAP model, and use the BERTBase model architecture with 12 layers, 12 attention heads, with 768 as hidden size.

We set batch size to 256 (except for RoBERTa on Ubuntu that uses 192), and use the Adam optimizer with learning rate $1e^{-5}$, $\beta_1 = 0.9$ and $\beta_2 = 0.99$. We set gradient normalization to 1.0 and used 500 warm up steps with linear schedule.

We set maximum length $L$ of the context response pair with special tokens to 256. If the length exceeds $L$, we truncate the input by maintaining a 3:1 ratio between context and response as in Han et al. (2021a). These configurations to both task-adaptive pre-training and fine-tuning to avoid discrepancy between them.

For TAP, we first perform grid search over learning rates of $\{1e^{-5}, 5e^{-5}, 1e^{-4}, 5e^{-4}\}$ and picked the best model based on validation recall and further train it until 50 epochs. We train only 1 run and use random seed of 1234.

For fine-tuning, we first perform grid search over the same set of learning rates on BERT/RoBERTa models without TAP, and choose the best learning rate based on recall on the validation set for the TAP models with the same initialization and datasets. The fine-tuning model keeps all model weights when possible, which includes the NSP head. We fine-tune for 1 epoch on the original training set and average results over 3 random seeds 1234, 5678, and 10111213.

We used an AWS p3.16x instance and employed mixed-precision (Micikevicius et al., 2018) to speed up training. Pre-training one epoch on Ubuntu, Douban, and E-commerce corpus took around 1.5 hour, 1 hour, and 1 hour, respectively.