Grayscale Data Construction and Multi-Level Ranking Objective for Dialogue Response Selection

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Abstract

Response selection plays a vital role in building retrieval-based conversation systems. Recent works on enhancing response selection mainly focus on inventing new neural architectures for better modeling the relation between dialogue context and response candidates. In almost all these previous works, binary-labeled training data are assumed: Every response candidate is either positive (relevant) or negative (irrelevant). We propose to automatically build training data with grayscale labels. To make full use of the grayscale training data, we propose a multi-level ranking strategy. Experimental results on two benchmark datasets show that our new training strategy significantly improves performance over existing state-of-the-art matching models in terms of various evaluation metrics.

1 Introduction

Building human-like conversation systems (Kollar et al., 2018) is gaining more and more attention in recent years. A core module in such kind of conversation systems is response selection (Ritter et al., 2011; Hu et al., 2014; Wu et al., 2017; Tao et al., 2019): Identifying the best response from a set of possible candidates given a dialogue context, i.e., conversation history.

For the response selection problem, it is a common practice to build neural matching models (Ji et al., 2014; Wang et al., 2015; Xu et al., 2016; Wu et al., 2017; Zhou et al., 2018; Lu et al., 2019) for measuring the matching scores between the dialogue context and individual response candidates. Most recent works (Wu et al., 2017; Zhou et al., 2018; Lu et al., 2019; Gu et al., 2019) on this topic focus on designing more and more powerful and sophisticated neural networks.

In almost all these previous works, binary-labeled training data are assumed. Each response in the training data is either labeled positive (i.e., a good response to the dialogue context) or negative (i.e., a bad response). In the case that only positive responses are available (as ground truth), negative responses are automatically constructed by random sampling from all responses in the training data. Based on such kind of training data, a binary classifier is often built.

One limitation of this training strategy is that in real-world scenarios the matching models are often confronted with more difficult tasks: to select the best response from other strong response candidates. An example is given in Table 1. During training, the matching models are trained to distinguish the ground truth G and the randomly sampled response R1, where R1 shows little relevance to the dialogue context. Matching models trained on such training data have little experience to identify the ground truth response G from a set of strong distractor responses such as R2 and R3.

To address this problem, we propose a grayscale-data-enhanced, multi-level ranking strategy for
training matching models. Intuitively, a good matching model should be able to not only distinguish good responses from random ones (usually totally irrelevant) as conveyed by the binary classification objective in previous works, but also capture the fine-grained differences in matching degrees among competitive candidates. To this end, we propose to automatically construct multi-level grayscale labeled responses from binary-labeled training data. In a binary-labeled training data, assuming that positive responses have score 1 and negative ones have score 0, our goal is to automatically obtain a list of responses having scores in (0, 1). We rely on the results of retrieval algorithms and generation models to achieve this goal. Intuitively, in most cases, the responses from retrieval systems (or generation models) are better than randomly sampled ones, but worse than the ground truth response. Therefore we form a progressive relationship: ground truth > retrieval > random. To make full use of such relationships, we propose a multi-level ranking objective that combines multiple binary contrastive estimations in a joint manner. The proposed training approach partly simulates the real-world scenarios thus reduces the gap between training and testing, leading to a better distinguishing ability for strong response distractors.

Our contributions are three-folds: (1) We propose to automatically construct grayscale labeled training data and introduce a multi-level ranking objective to train a better model for response selection. (2) Experimental results show that our new training strategy leads to significant performance improvement compared to state-of-the-art approaches. (3) Our approach is orthogonal to some techniques like co-teaching and therefore has the potential to combine with these techniques to further improve performance.

2 Background

The task of response selection can be formulated as follows: Given a dialogue dataset $D = \{(c_i, r_i)\}$, where $c_i$ represents a dialogue context and $r_i$ is the human-written ground truth response. The goal is to learn a matching model $s(\cdot, \cdot)$ from $D$ so that $s(c, r)$ measures the matching degree between a dialogue context $c$ and a response candidate $r$.

For most previous work (Wu et al., 2017; Zhou et al., 2018; Lu et al., 2019), to train such matching models, a binary-labeled training set is constructed as follows: The human-written ground truth response is designated as positive instances (labeled as 1), and a set of randomly sampled responses $N_i$ are treated as negative ones (labeled as 0). The learning objective of $s(\cdot, \cdot)$ is then to maximize the following binary classification loss:

$$\log s(c, r) + \mathbb{E}_{r^- \in N_i} \log (1 - s(c, r^-)).$$  \hspace{1cm} (1)

The problem with the above learning paradigm is that most of the randomly sampled negative responses are distant from the corresponding positive responses in terms of matching degree, which could lead to serious drawbacks when some strong distractors are presented during testing (Zhou et al., 2018; Zhang et al., 2018). Our work starts with enriching the range of the negative response set $N_i$ in terms of response quality and leads to a multi-level ranking strategy for learning to capture the fine-grained differences in matching degrees.

3 Proposed Approach

We first present our methods for automatically constructing grayscale data in §3.1. Then our multi-level ranking objective for leveraging the grayscale data is introduced in §3.2. Figure 1 depicts an overview of our training strategy. First, different tiers of responses are acquired from various sources: the ground truth, retrieval systems, generation models, and random sampling. Then, the labeled responses are sorted by estimated quality to form progressive relationships. Lastly, a multi-level ranking objective is designed to learn such relationships.

3.1 Grayscale Data Construction

To construct training data that better simulates the testing, we sample three types of grayscale responses for each dialogue besides the human response that treated as the ground truth. Those four
types of responses from different sources can be categorized into three tiers according to their relevance to the dialogue: ground truth samples are ranked tier-1, responses from retrieval systems and generation models are ranked tier-2, and the random samples are ranked tier-3.

**Ground Truth Samples** The last utterances of dialogues are our ground truth responses. Obviously, these human-written responses are much better than any type of grayscale data. As a result, the ground truth samples are ranked as tier-1.

**Retrieval Samples** Retrieval results are obtained by feeding the dialogue context to an information retrieval system. Retrieval results are typically better than random samples, because they are more or less relevant to the dialogue context. On the other hand, retrieval results are on average worse than the ground truth, because their quality and relevant cannot be guaranteed. Therefore retrieval results are ranked tier-2.

To gain retrieval samples for each dialogue, we split the multi-turn dialogue into a series of single-turn input-response pairs. Then we index the input-response corpus and retrieve response candidates using the last utterance of dialogue by an inline retrieval algorithm.

As the retrieval system can potentially return a large set of results, we choose part of them through three heuristic rules: in $n$ retrieval results, candidates correspond to the top-$k$ matching score at the current step are picked as “strong retrieval samples”, candidates correspond to the $k$ lowest scores are picked as “weak retrieval samples”, and the arbitrary $k$ results are denoted as “average retrieval samples”. In practice, we set $n = 100$ and $k = 5$.

**Generated Samples** Generated samples, that are also ranked tier-2, are obtained by feeding the dialogue context to a single-turn Seq2seq model. It is treated as the supplement to the retrieval samples. Comparing with retrieval samples that rely on keyword matching, generated samples can show more semantic relationships with the dialogue instead of tracking the overlap of words or phrases. As shown in previous works (Xing et al., 2018; Xu et al., 2019), well-designed generation models can generate confident responses while elementary models tend to generate specious responses that may have grammar errors or be meaningless like “safe response”. Thus, similar to the retrieval samples, the generated samples should be better than the randomly selected samples but worse than the ground truth samples.

To meet our needs for an elementary generator, we choose Seq2Seq with the attention mechanism (Bahdanau et al., 2015) as our generation model. The Seq2Seq is not a powerful generator but can
also generate reasonable responses. We adopt the same corpus used in the retrieval system to train the generation model. Then, we use this model to generate samples for each dialogue. Moreover, we make use of the beam search to generate multiple responses by setting different beam width.

**Random Samples** Random samples are ranked tier-3, because they are less relevant to the dialogue context. Similar to Wu et al. (2017), we randomly select the responses of other dialogues.

Each of the above four types of samples might be useful in training. Learning a matching model only from (tier-1, tier-2) pairs may be too aggressive at the warm-up phase because both of them are hard to distinguish from the ground truth. Contrariwise, as introduced in §2, only learning from (tier-1, tier-3) pairs may suffer from a great gap between training and testing. Therefore, it’s essential to take all three types of grayscale data together to balance the learning problem.

### 3.2 Multi-Level Ranking Objective

The goal of our training approach is to make use of the fine-grained differences existing in different responses during training. However, previous works (Wu et al., 2017; Zhou et al., 2018) formulate the training of a matching model as the binary classification learning, which is insufficient to simultaneously learn the progressive relationship between the diverse response candidates. Instead, we propose a multi-level ranking objective that captures the multi-level difference between the human response and grayscale responses.

After adopting the grayscale-data-enhanced strategy, the training set can be re-organized as $D = \{(c_i, R_i)\}_{i=1}^N$, where $R_i = \{r_i, e_i, g_i, \tilde{r}_i\}$ is the response set enhanced by grayscale data. In details, $r_i$ denotes the ground truth responses, while $e_i$, $g_i$, and $\tilde{r}_i$ refer to retrieval responses, generated responses, and random responses, respectively. To effectively utilize these samples, we introduce three training paths:

- **Random path** is a basic one that models the relationship between ground truth samples $r_i$ and random samples $\tilde{r}_i$: $r_i$ are better than $\tilde{r}_i$.

- **Retrieval path** is a more fine-grained path that models the relationship among ground truth samples $r_i$, retrieval samples $e_i$, and random samples $\tilde{r}_i$: $e_i$ are better than $\tilde{r}_i$, but worse than $r_i$.

- **Generation path** is similar to the retrieval path but utilizes the generated samples $g_i$ instead of the retrieval samples $e_i$: $g_i$ are better than $\tilde{r}_i$, but worse than $r_i$.

Specifically, the objective of random path is given by:

$$L_1 = \max\{0, \mu - s(c, r_i) + s(c, \tilde{r}_i)\},$$

where $\mu$ is a hype-parameter and represent the minimum acceptable score margin between two tiers. Besides, $s(\cdot, \cdot)$ is the matching score given by a matching model.

The retrieval path teaches matching models to leverage the fine-grained relationships between grayscale responses. Concretely, the matching scores of retrieval responses are restricted to be lower than the ground truth but higher than random responses, which can be formulated as:

$$L_2 = \max\{0, \mu - s(c, r_i) + s(c, e_i)\} + \max\{0, \mu - s(c, e_i) + s(c, \tilde{r}_i)\},$$

where $e_i$ denotes the retrieval responses. Through the objective, matching models are constrained to enlarge the matching scores between strong response distractors, which thus meets the requirement in real-world testing scenarios.

Then, the generation path plays a similar role to the retrieval path but supplements the capability that considers more on the overlapping word. It’s objective is defined as:

$$L_3 = \max\{0, \mu - s(c, r_i) + s(c, g_i)\} + \max\{0, \mu - s(c, g_i) + s(c, \tilde{r}_i)\},$$

where $g_i$ stands for the generated responses.

Finally, we combine three paths and formulate the multi-level ranking objective as:

$$L = L_1 + L_2 + L_3.$$
4 Related Work

Existing works for developing open-domain conversa-
tion systems can be categorized into generation-
based methods (Shang et al., 2015; Mou et al.,
2016; Xing et al., 2017; Liu et al., 2018; Qiu et al.,
2019; Chan et al., 2019) and retrieval-based meth-
ods (Ji et al., 2014; Wang et al., 2015; Yan et al.,
2016; Zhou et al., 2018; Tao et al., 2019; Gu et al.,
2019). Our work studies the problem of response
selection, the key task for building a retrieval-based
conversation system.

In recent years, various neural architectures have
been proposed for building a context-response
matching model for response selection (Hu et al.,
2014; Wang et al., 2015; Lowe et al., 2015; Zhou
et al., 2016). Among them, Wu et al. (2017) pro-
posed the sequential matching network (SMN) that
models the utterances in multi-turn dialogue con-
text and aggregates the distance between context
and response based on a convolutional neural net-
work. Zhou et al. (2018) proposed the deep atten-
tion matching network (DAM) that models the dia-
logue context at different levels of representations
with stacked self-attention and across-attention.

More recent works (Gu et al., 2019; Tao et al., 2019;
Yuan et al., 2019) further extended the matching
and attention architectures of SMN and DAM, and
designed more sophisticated models.

From another perspective, some researchers also
studied how to improve the performance of exist-
ing matching models with a better learning method.
Wu et al. (2018) proposed to leverage a Seq2Seq
model as a weak annotator to assign a score for
each response candidate of the dialogue and learn
matching models through the scores. Feng et al.
(2019) introduced the co-teaching framework (Han
et al., 2018) for eliminating the effect of training
noises. The learning approach maintains two match-
ing models and makes them teach each other. Dif-
ferent from previous works, our method makes use
of grayscale data from heterogeneous sources and
learns progressive quality relationships.

5 Experiment

5.1 Experimental Setup

We test our training approach on two public multi-
turn response selection datasets:

Ubuntu Dialogue Corpus It consists of English
multi-turn dialogues about technical support col-
clected from the Ubuntu Forum (Lowe et al., 2015).
The dataset contains 500 thousand dialogue con-
texts for training, 50 thousand for validation and
test. Each dialogue has different numbers of re-
sponses. The ratio between positive and negative
responses is 1:1 in the training set, and 1:9 in both
development and test sets. We use the same evalua-
tion metrics as in previous works (Wu et al., 2017).
Concretely, we calculate the recall of the true pos-
tive responses among the $k$ selected ones as the
mean evaluation metric, denoted as $R_n@k$.

Douban Conversation Corpus It is a multi-turn
Chinese dialogue dataset crawled from Douban

5.2 Base Models

We select the following two matching models as
our base models.

SMN (Wu et al., 2017) uses CNN and attention
mechanisms to match a response with each utter-
ance and then maps interaction matrices into matching
vectors with an RNN.

DAM (Zhou et al., 2018) applies stacked self-
attention and cross-attention to perform matching
manner. The DAM obtains matching vectors of text
segments at different granularities with the stacked
self-attention. The matching vectors are finally
mapped into a matching score with an RNN.

5.3 Model Variants

We train the SMN and DAM with different objec-
tives, as listed below.

- $L_1$ denotes the model trained by the random
  path in Eq. 2 only.
- $L_{all}$ is the same as above but equally takes all
  grayscale responses as negatives.

We release the retrieval samples and generation samples used
for training at https://ai.tencent.com/ailab/nlp/dialogue/datasets/grayscale_data_release.zip
| Model          | Douban       | Ubuntu       |
|----------------|--------------|--------------|
|                | MAP  | MRR  | P@1 | R@10@1 | R@10@2 | R@10@5 | R@2@1 | R@10@1 | R@10@2 | R@10@5 |
| SMN            | 0.529 | 0.569 | 0.397 | 0.233  | 0.396  | 0.724  | 0.926 | 0.726  | 0.847  | 0.961  |
| $+L_1$         | 0.541 | 0.590 | 0.403 | 0.240  | 0.418  | 0.768  | 0.932 | 0.745  | 0.862  | 0.965  |
| $+L_1^{ML}$    | 0.552 | 0.592 | 0.410 | 0.244  | 0.416  | 0.766  | 0.931 | 0.747  | 0.863  | 0.964  |
| $+L_1 + L_3$   | 0.551 | 0.597 | 0.421 | 0.256  | 0.410  | 0.772  | 0.930 | 0.756  | 0.857  | 0.962  |
| $+L_1 + L_3^A$ | 0.554 | 0.597 | 0.421 | 0.253  | 0.415  | 0.773  | 0.932 | 0.750  | 0.862  | 0.963  |
| $+L_1 + L_3^W$ | 0.559 | 0.608 | 0.436 | 0.268  | 0.424  | 0.767  | 0.938 | 0.764  | 0.868  | 0.968  |
| $+L_1 + L_3^S$ | 0.562 | 0.608 | 0.439 | 0.267  | 0.431  | 0.768  | 0.934 | 0.755  | 0.867  | 0.966  |
| $+L_1^A$       | 0.560 | 0.602 | 0.434 | 0.266  | 0.429  | 0.722  | 0.935 | 0.759  | 0.864  | 0.963  |
| $+L_1^W$       | 0.561 | 0.611 | 0.439 | 0.270  | 0.430  | 0.774  | 0.941 | 0.771  | 0.870  | 0.974  |
| $+L_1^S$       | 0.564 | 0.615 | 0.443 | 0.271  | 0.439  | 0.781  | 0.938 | 0.765  | 0.873  | 0.969  |
| DAM            | 0.550 | 0.601 | 0.427 | 0.254  | 0.410  | 0.757  | 0.938 | 0.767  | 0.874  | 0.969  |
| $+L_1$         | 0.559 | 0.604 | 0.423 | 0.253  | 0.435  | 0.784  | 0.940 | 0.773  | 0.881  | 0.966  |
| $+L_1^{ML}$    | 0.558 | 0.605 | 0.427 | 0.252  | 0.422  | 0.782  | 0.941 | 0.772  | 0.884  | 0.970  |
| $+L_1 + L_3$   | 0.563 | 0.619 | 0.439 | 0.266  | 0.449  | 0.788  | 0.942 | 0.777  | 0.886  | 0.977  |
| $+L_1 + L_3^A$ | 0.574 | 0.621 | 0.443 | 0.262  | 0.440  | 0.789  | 0.941 | 0.774  | 0.881  | 0.968  |
| $+L_1 + L_3^W$ | 0.584 | 0.630 | 0.456 | 0.281  | 0.460  | 0.819  | 0.945 | 0.788  | 0.891  | 0.982  |
| $+L_1 + L_3^S$ | 0.577 | 0.624 | 0.449 | 0.270  | 0.447  | 0.801  | 0.942 | 0.780  | 0.884  | 0.971  |
| $+L_1^A$       | 0.579 | 0.622 | 0.440 | 0.264  | 0.443  | 0.788  | 0.946 | 0.784  | 0.892  | 0.982  |
| $+L_1^W$       | 0.586 | 0.633 | 0.460 | 0.284  | 0.463  | 0.821  | 0.948 | 0.791  | 0.896  | 0.989  |
| $+L_1^S$       | 0.588 | 0.637 | 0.464 | 0.284  | 0.466  | 0.822  | 0.946 | 0.789  | 0.891  | 0.986  |

Table 2: Result of the SMN and DAM trained by different objectives on Douban and Ubuntu datasets. Results of SMN are directly cited from Wu et al. (2017), and DAM from Zhou et al. (2018).

- $L_1 + L_3^A$ denotes the model trained by retrieval path in Eq. 3. Moreover, the average retrieval samples are selected in training.
- $L_1 + L_2^W$ is the same as above but takes weak retrieval samples instead of the average retrieval samples in training.
- $L_1 + L_3^S$ is the same as above but takes strong retrieval responses instead of the weak retrieval samples in training.
- $L_1 + L_3$ denotes the model trained by generation path in Eq. 4.
- $L^X$ (also marked $L_1 + L_3^X + L_3$) denotes the model trained by the multi-level objective in Eq. 5, and X may be A, W, or S that represent different types of retrieval samples (average, weak, strong).

5.4 Implementation Details

We implement our purposed training approach based on source codes that are released by Wu et al. (2017) and Zhou et al. (2018). The word embedding is pre-trained with the Word2Vec on the training set. The utterance length is limited to 50 and the maximum context length is 10, for which truncation or padding is applied when necessary. Adam algorithm is chosen to update the weights of matching models. The learning rate is initialized as 1e-3 and gradually decreased during training.

We first pre-train the model with objective $L_1$ and then use the weights to initialize other models trained under different objectives. We find that such a process makes the training process stabilize. For the grayscale-data-enhanced strategy, each dialogue is given three types of responses. To ensure a fair comparison, the number of various grayscale responses for each dialogue is fixed at 5. The size of mini-batches for the SMN is 200, and 50 for the DAM. We tune the margin $\mu$ in $\{0.01, 0.02, 0.03, 0.05, 0.07, 0.1, 0.3, 0.5\}$, and choose 0.02 for SMN on Douban, 0.05 for DAM on Douban, 0.1 for SMN on Ubuntu, and 0.3 for DAM on Ubuntu, respectively. For different training paths, we use the same $\mu$. All models are fine-tuned with the same validation sets and results are reported on the same test sets.

5.5 Evaluation Results

Experimental results on all datasets are listed in Table 2, from which we can observe that:

1) Both SMN and DAM consistently get sig-
Table 3: Experimental results of matching models trained with the combination strategy of our approach and the co-teaching framework. We report the results of SMN+CoT and DAM+CoT from Feng et al. (2019) on Douban and we supplement the results of two models trained with the co-teaching framework on Ubuntu. We initialize the weights of the SMN/DAM+LX objectives from the models trained with LX objectives.

| Model          | Douban | Ubuntu |          |          |          |          |          |          |          |          |
|----------------|--------|--------|----------|----------|----------|----------|----------|----------|----------|----------|
|                | MAP    | MRR    | P@1      | R10@1    | R10@2    | R10@5    | R2@1     | R10@1    | R10@2    | R10@5    |
| SMN            | 0.529  | 0.569  | 0.397    | 0.233    | 0.396    | 0.724    | 0.926    | 0.726    | 0.847    | 0.961    |
| +CoT           | 0.559  | 0.601  | 0.424    | 0.260    | 0.426    | 0.764    | 0.933    | 0.759    | 0.862    | 0.961    |
| +LW            | 0.561  | 0.611  | 0.439    | 0.270    | 0.430    | 0.774    | 0.941    | 0.771    | 0.870    | **0.974** |
| +LS            | 0.564  | 0.615  | 0.443    | 0.271    | 0.439    | 0.781    | 0.938    | 0.765    | 0.873    | 0.969    |
| +LW+CoT        | 0.568  | 0.620  | 0.457    | 0.273    | 0.433    | 0.785    | **0.944** | **0.776** | **0.881** | 0.971    |
| +LS+CoT        | **0.569** | **0.622** | **0.458** | **0.278** | **0.442** | **0.793** | 0.942    | 0.771    | 0.875    | 0.970    |
|                |        |        |          |          |          |          |          |          |          |          |
| DAM            | 0.550  | 0.601  | 0.427    | 0.254    | 0.410    | 0.757    | 0.938    | 0.767    | 0.874    | 0.969    |
| +CoT           | 0.583  | 0.628  | 0.451    | 0.276    | 0.454    | 0.806    | 0.944    | 0.782    | 0.884    | 0.967    |
| +LW            | 0.586  | 0.633  | 0.460    | 0.284    | 0.463    | 0.821    | 0.948    | 0.791    | **0.896** | **0.989** |
| +LS            | 0.588  | **0.637** | **0.464** | 0.284    | 0.466    | 0.822    | 0.946    | 0.789    | 0.891    | 0.986    |
| +LW+CoT        | **0.591** | 0.636  | **0.464** | 0.285    | **0.469** | **0.827** | 0.949    | 0.794    | 0.893    | 0.985    |
| +LS+CoT        | 0.589  | 0.636  | **0.464** | **0.286** | 0.464    | 0.821    | **0.951** | **0.796** | 0.892    | 0.981    |

2) It’s noticed that the grayscale data potentially augments the training data, which is known to probably improve the performance of neural networks. Indeed, models trained by $L^q_{1u}$ that directly takes all grayscale data as negative samples outperform the basic SMN and DAM, but still fall behind those models trained by multi-level ranking objective. This result indicates that the improvements are not only come from the data augment but also owed to our training approach.

3) Retrieval path with strong retrieval responses achieves the best performance on Douban while weak retrieval responses work on Ubuntu. This difference may come from the nature of the datasets. The candidates in the test set of Douban are come from a retrieval system and labeled by human annotators, making it harder to distinguish. Hence, models learned from the strong retrieval responses can better capture the fine-grained differences among the highly correlated candidates and thus beat other strategies. On the contrary, candidates in the test set of the Ubuntu data are constructed by random sampling and show relatively weak relevance to the dialogue. So the weak retrieval responses simulating such a weak relationship can help the matching models learn better.

5.6 Compatibility with Co-teaching

We have noticed that Feng et al. (2019) adopts the co-teaching framework to train a matching model and aims to learn a robust matching model from noisy training data. From their experiment, the co-teaching framework with dynamic margins is proven to effectively eliminate the effect from noise responses (Some sampled responses may also be proper candidates for a given dialogue context). We believe that our approach and co-teaching framework can benefit each other. Therefore, we combine
Table 4: Two cases from the test set of Douban are listed and both of them have Response 1 as a ground truth response. Though each dialogue has ten candidates, we show only two of them due to space limitations. The dialogues are in Chinese (the left) and we also provide their translated version in English (the right).

| Case 1 given by DAM | A: 处女天蝎有艳遇的么？ | A: Is there any long-distance relationship between Scorpio and Virgo people? |
|---------------------|------------------------|--------------------------------------------------------------------------------|
| B: 我认为你心不在焉，快5个月了也不知道能不能继续走下去，哎，没准你们说还是加油吧，没事也是油嘴吧 | B: In the same country but different cities, torturing me everyday. It's been almost five months and I don't know if we can keep going. Anyway, I will try my best until he dump me. |
| A: 要不都加油 | A: Similar to what happens to me. Let's cheer up! |
| B: 其实已经分开了，说你们好运，加油 | B: We have already broken up. Good luck guys! Cheer up! |
| A: 呃，其实说实话挺残酷的，希望我和他能坚持吧 | A: Actually, the reality is cruel. Hope we can hold on. |
| Response 1 (Ground Truth): 呃，现代确实残酷！ | Response 1 (Ground Truth): Hoho, the reality is grim, indeed! |
| Response 2 (Distractor): 其实海选已经是最残酷的一个选拔了，坚持就是胜利。这样的事其实在现实里吧多少是惨了点的 | Response 2 (Distractor): Actually, One Piece is an escapism. Persistence makes dreams come true. However, it does not always happen in the real-world. |

| Case 2 given by SMN | A: 亚洲特价票在哪里改名 | A: How can I change the passenger name of the discount ticket of AirAsia Airline? |
|---------------------|------------------------|--------------------------------------------------------------------------------|
| B: 我象不想换啦，我也是这特价票,然后换名,你可以去问 | B: It seems to be free. I have once bought a discount ticket and then changed the passenger name. You can ask them first. |
| A: 我想8月份买的 | A: I bought the ticket in this August. |
| B: 具体的我也不太清楚了,但是改名应该是可以的吧,只要提供有效的身份证明 | B: I am not sure about the details. But changing passenger name ought to be allowed as long as you provide valid identification. |
| Response 1 (Ground Truth): 这样子的啊,好的,谢谢楼主 | Response 1 (Ground Truth): Ok, I see. Thank you! |
| Response 2 (Distractor): 我是说具体位置 | Response 2 (Distractor): I mean the details of location. |

Table 4: Two cases from the test set of Douban are listed and both of them have Response 1 as a ground truth response. Though each dialogue has ten candidates, we show only two of them due to space limitations. The dialogues are in Chinese (the left) and we also provide their translated version in English (the right).

5.7 Effect of Margin Size

The hyper-parameter $\mu$ denotes the minimum distance between two tiers in matching scores, which may affect the performance of matching model. We conduct a series of sensitivity analysis experiments to study how the $\mu$ affects the performance of our training. We choose the objective $L^S$ to train matching models for the Douban dataset, and the $L^W$ for the Ubuntu. All models are evaluated in terms of $R_{10}@1$.

Referring to Figure 2, we can see that both SMN and DAM have a similar trend on Douban: the curves first increase and then drop as the $\mu$ increases. This is mainly because response candidates on Douban are of high relevance. When the $\mu$ is too large, matching models have no idea to handle strongly relevant distractors. However, when the $\mu$ is too small, matching models will become too sensitive and mistake to give high scores for responses with less relevance to dialogue context.

Results on Ubuntu show a completely different behavior: the performances grow in step with the $\mu$. The reason may be that the response distractors of Ubuntu have relatively large margins in semantic and matching models need to make strong discrimination between the ground truth and other grayscale responses. As a result, models learned with the large $\mu$ can fit such data distribution.

5.8 Case Study

As shown in case 1 of Table 4, response 2 contains some irrelevant content about the comic “One Piece”, but it is still selected by DAM as the best response. In case 2, SMN selects the totally irrelevant response 2 as the best response, which may because this response has some overlapped words with the dialogue. These are consistent with the problem introduced in §2 that these models may mistake the fuzzy-candidate with few improper details for the best response due to the gap between training and testing. In contrast, the grayscale-data-enhanced SMN and DAM correctly identify the improper content in the negative responses and successfully select response 1 as the best response.

6 Conclusions

We presented a novel training strategy for response selection models. It leverages different types of grayscale responses and simulates the real-world scenarios of the retrieval-based conversation systems. A multi-level ranking objective was introduced to learn the progressive relationships in
grayscale data. Experimental results on two benchmark datasets demonstrate the effectiveness of the proposed training strategy and prove it is orthogonal to other techniques like co-teaching.

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