



Small Changes Make Big Differences: Improving Multi-turn Response Selection in Dialogue Systems via Fine-Grained Contrastive Learning

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Abstract

Retrieve-based dialogue response selection aims to find a proper response from a candidate set given a multi-turn context. The sequence representations generated by pre-trained language models (PLMs) play key roles in the learning of matching degree between the dialogue contexts and the responses. However, context-response pairs sharing the same context but different responses tend to have a greater similarity in the sequence representations calculated by PLMs, which makes it hard to distinguish positive responses from negative ones. Motivated by this, we propose a novel Fine-Grained Contrastive (FGC) learning method for the response selection task based on PLMs. This FGC learning strategy helps PLMs to generate more distinguishable pair representations of each dialogue at fine grains, and further make better predictions on choosing positive responses. Empirical studies on two benchmark datasets demonstrate that the proposed FGC learning method can generally and significantly improve the model performance of existing PLM-based matching models.

Index Terms: dialogue system, human-computer interaction, computational paralinguistics

1. Introduction

Multi-turn response selection is the task of predicting the most appropriate response using a retrieval model by measuring the matching degree between a multi-turn dialogue context and a set of response candidates. Most recently, pre-trained language models (PLMs) have achieved substantial performance improvements in multi-turn response selection [1, 2, 3]. PLM-based models take the concatenation of dialogue context and response as the input, and utilize the $[CLS]$ representation to predict a score indicating the matching degree. By further post-training PLMs with in-domain data and auxiliary self-supervised tasks [4, 5, 6], PLMs achieve state-of-the-art results on benchmarks.

Despite the success of PLM-based models on multi-turn response selection, prior studies point out that the $[CLS]$ representations are still narrowed in a small space, providing insufficient discrimination between positive dialogues and negative ones [7, 8]. A more distinguishable representation could provide a wider margin and more fault-tolerance for classifier on making prediction. Contrastive learning (CL) could be a possible solution on enlarging the margin between representations, which use contrastive loss to punish meaning representations with short distance between every example pairs [9]. However, the standard CL is not suitable for the multi-turn response selection task, since $[CLS]$ representations of similar dialogues are still not separable, especially dialogues with the same context but different responses. Standard CL pays too much attention on the representations of semantic of dialogues, instead of pair representations indicating the relationships between con-

texts and responses. A good pair representation for the response selection task should satisfy two properties that (1) expressing consistent signals indicating for all positive dialogues or all negative ones, and (2) providing sufficient gap for classifier given two dialogues with the same context but different responses.

To address the aforementioned issues, we propose a Fine-Grained Contrastive learning (FGC) approach to fine-tune pair representations for the response selection task. FGC introduces contrastive learning on each example with the same context but different responses. In contrast to the off-the-shelf contrastive learning method, which takes every other context-response pair as negative examples, FGC takes context and response as separate parts and focuses on distinguishing between positive and negative examples with the same context. Each context-response pair is augmented into a new pair with the same context and a response with the same semantic meaning but different expressions. The pair representation of a dialogue is asked to be close to its augmentation, while the one with a positive response should be far away from the one with a negative response. FGC works totally in a self-supervised way that no additional supervision is required besides the classification label used for response selection training.

We conduct experiments on two response selection benchmarks: the Ubuntu Dialogue Corpus [10] and the Douban Corpus [11]. Our empirical results demonstrate that FGC is able to consistently improve PLMs by up to 3.2% absolute improvement with an average of 1.7% absolute improvement in terms of $R_{10}@1$. Besides, We also compare our method with standard-contrastive-learning-enhanced PLMs, which demonstrates the effectiveness of our proposed fine-grained contrastive objective.

In summary, our contributions in the paper are three-fold:

- We propose FGC, a novel fine-grained contrastive learning method, which helps generate better representations of dialogues and improves the response selection task.
- FGC shows good generality of effectiveness with various pre-trained language models for enhancing performance.
- Experimental results on two benchmark datasets demonstrate that FGC can significantly improve the performance of various strong PLM-based matching models.

2. Related Work

Our work focuses on multi-turn response selection task. RNN-based dialogue modeling strategies has been discussed for a long period [11, 12, 13, 14]. Most recently, pre-trained language models (e.g., BERT [15]) have shown an impressive performance in the response selection. The post-training method, which helps transfer the representations of BERT from the general domain to the dialogue domain, was proposed by Whang et al. and obtained state-of-the-art results [4]. Subsequent researches [2, 1] focused on incorporating speaker information into BERT and showed its effectiveness in multi-turn response

selection. Further, Whhang et al. and Xu et al. indicated that incorporating well-designed self-supervised tasks according to the characteristics of the dialogue data into BERT fine-tuning can help with the multi-turn response selection [5, 6]. Han et al. proposed a fine-grained post-training method for enhancing the pre-trained language model, while the post-training process is computationally expensive than fine-tuning a classification model [16]. Su et al. proposed a hierarchical curriculum learning framework for improving response selection with PLMs [17].

Our method also relates to contrastive learning. There have been several investigations for contrastive learning for neural models. Oord et al. proposed a framework for contrastive learning to learn visual representations based on contrastive predictive coding, which predicts the features in latent space by using powerful autoregressive models [18]. Knosla et al. investigated supervised contrastive learning, allowing to leverage label information effectively [19]. Following this trend, some researchers verified the effectiveness of constructive learning in specific NLP tasks. For example, Fang et al. proposed pre-training language representation models with a contrastive self-supervised learning objective at the sentence level, outperforming previous methods on a subset of GLUE tasks [20]. Gunel et al. combined the cross-entropy with a supervised contrastive learning objective, showing improvements over fine-tuning RoBERTa-Large on multiple datasets of the GLUE benchmark [21]. Our work differs from previous works in that we do not directly make contrast on one example with all the other examples. The granularity of negative samples using by these approaches is too coarse to provide sufficient discrimination with the positive ones.

3. Methodology

The response selection task is to select the best candidate to respond a given multi-turn dialogue context from a pool of candidate responses. In this paper, we propose a **Fine-Grained Contrastive Learning method (FGC)** based on PLM models, which consists of two complementary contrastive objectives: (1) an instance-view contrastive objective (IVC); and (2) a category-view contrastive objective (CVC). We will introduce each part of our model in the following sections.

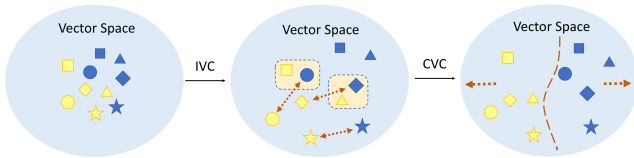


Figure 1: FGC contains two objectives. IVC pushes away examples with the same context but different responses (icons in the same shape), while examples that belong to different categories may still be similar (as shown in orange boxes). CVC further solves this problem by pulling all examples into two distinguishable clusters.

3.1. Response Selection with Pre-trained Language Model

We take a pre-trained language model (PLM), e.g., BERT, as a basis for response selection. Applying a PLM for response selection usually involves two steps. The first step is domain-adaptive post-training, which continues to train a standard PLM with a domain-specific corpus. This step helps to transfer the

original PLM into the target domain. The second step is to fine-tune the PLM with the response selection task. Given a context $c = \{u_1, \dots, u_m\}$ where u_t is the t -th turn of the dialog context, and a response r , the model is asked to predict a score \hat{y} to represent the matching degree between c and r . To achieve this, the special token $[CLS]$, context c and response r are concatenated and passed into PLM model. The PLM model returns a sequence of vectors with the same length as the concatenated input. The vector $s_{[CLS]}$ from the $[CLS]$ position is used to compute a relevance score between c and r , as well as a binary classification loss.

$$\hat{y} = \sigma(\mathbf{W}_{sel} s_{[CLS]} + b)$$

$$\mathcal{L}_{sel} = -(y \log \hat{y} + (1 - y) \log(1 - \hat{y})), \quad (1)$$

where \mathbf{W}_{sel} and b are parameters and \hat{y} denotes for the ground truth binary label.

3.2. Dialogue Data Augmentation

Data augmentation takes an important role in contrastive learning [22, 23]. Similar to standard contrastive learning (e.g., CERT), the first step of FGC is to create augmentations for every context-response pair. Given a context-response pair, we make an augmentation on the response to generate an augmented response. The context and augmented response pair form the augmentation of the original context-response pair. Inspired by [24], we adopt three types of rule-based augmentation operations:

- **Random deletion:** Each token in the utterance is randomly and independently deleted with a probability p_{del} .
- **Random swapping:** Each token in the utterance is randomly swapped with another token in the utterance with a probability p_{swap} .
- **Synonym replacing:** Randomly replace a non-stop-word token to one of its synonyms with a probability p_{syn} .

Given a response utterance r and an augmentation strength $p \in [0, 1]$, we randomly pick out one of these three augmentation methods to apply with the probability being p . After augmentation, the response r is converted into another augmented response \bar{r} . The augmentation strength p is a hyper-parameter that controls how much difference is there between r and \bar{r} .

3.3. Instance-View Contrastive Objective

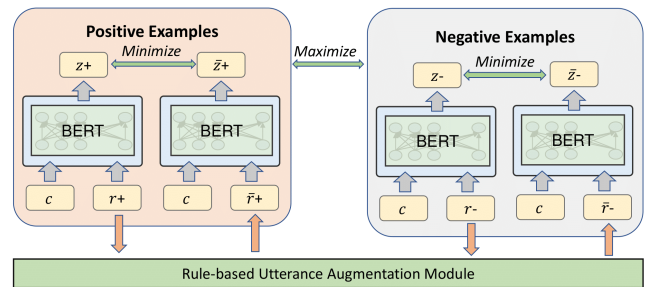


Figure 2: An overview of IVC. The input is a dialogue context c and a pair of positive and negative responses ($r+$, $r-$). Both responses are augmented to form a new pair ($\bar{r}+$, $\bar{r}-$). BERT takes four examples as input and outputs a projection vector \mathbf{z} for each of them. IVC aims to maximize the dissimilarity of \mathbf{z} between positive examples and negative examples, as well as maintains high cohesion within positive and negative cases.

The instance-view contrastive (IVC) objective aims at introducing more discrepancy between a pair of examples with the same context but positive/negative responses, as shown in Figure 1. Feeding a context-response pair into BERT, BERT helps to make internal interactions by attention mechanism and generate latent vectors representing the pair. The output vector of the $[CLS]$ position $\mathbf{s}_{[CLS]}$ stands for an aggregated pair representation of both context and response. Moreover, we apply another projection layer to convert $\mathbf{s}_{[CLS]}$ into a smaller vector \mathbf{z} . This projection is made through an MLP with one hidden layer. Through this projection, each coherent pair with positive responses (c_i, r_i+) is transformed into a projection vector \mathbf{z}_i+ , and each incoherent pair (c_i, r_i-) is transformed into \mathbf{z}_i- . The augmentations of the positive and negative pairs are also converted into two vectors, i.e., $\bar{\mathbf{z}}_i+$ and $\bar{\mathbf{z}}_i-$. Here $+$ and $-$ indicates the item belongs to the positive or the negative class, and the bar indicates this item comes from an augmented example.

As analysed by recent studies [25, 26], the embedding vectors of different utterances are distributed in a narrow cone of the vector space, showing less distinguishability. This phenomenon is even worse when two utterances are semantically similar, e.g., two examples sharing the same context. Thus, we leverage the IVC objective on these projection vectors \mathbf{z} to distinguish between positive and negative responses given the same context. IVC objective regards the projection vector \mathbf{z} as a representation of response r given context c . This loss is applied on the projection vector \mathbf{z} , which helps to maximize the similarity between a response with its augmentation given the same context, as well as minimize the similarity between each positive response and negative response pair. The maximum and minimum are achieved as a set of pair-wise comparisons:

$$\begin{aligned} \forall i \quad \text{sim}(\mathbf{z}_i+, \bar{\mathbf{z}}_i+) &> \text{sim}(\mathbf{z}_i+, \mathbf{z}_i-), \text{sim}(\mathbf{z}_i+, \bar{\mathbf{z}}_i-) \\ &\quad \text{sim}(\bar{\mathbf{z}}_i+, \mathbf{z}_i-), \text{sim}(\bar{\mathbf{z}}_i+, \bar{\mathbf{z}}_i-) \\ \forall i \quad \text{sim}(\mathbf{z}_i-, \bar{\mathbf{z}}_i-) &> \text{sim}(\mathbf{z}_i-, \mathbf{z}_i+), \text{sim}(\mathbf{z}_i-, \bar{\mathbf{z}}_i+) \\ &\quad \text{sim}(\bar{\mathbf{z}}_i-, \mathbf{z}_i+), \text{sim}(\bar{\mathbf{z}}_i-, \bar{\mathbf{z}}_i+). \end{aligned} \quad (2)$$

Here we adopt the NT-Xent Loss [27] to model the similarities of projection vectors. By writing this pair-wise comparison into a loss function, the IVC loss is formulated as

$$\begin{aligned} l(\mathbf{z}, \bar{\mathbf{z}}) &= -\log \frac{\exp(\text{sim}(\mathbf{z}, \bar{\mathbf{z}})/\tau)}{\sum_{\mathbf{z}_k \neq \mathbf{z}} \exp(\text{sim}(\mathbf{z}, \mathbf{z}_k)/\tau)} \\ \mathcal{L}_{ivc} &= \sum_{i=1}^N (l(\mathbf{z}_i+, \bar{\mathbf{z}}_i+) + l(\mathbf{z}_i-, \bar{\mathbf{z}}_i-)), \end{aligned} \quad (3)$$

where $\tau > 0$ is a scalar temperature parameter that controls the separation of positive and negative classes; \mathbf{z}_k ranges from $\{\mathbf{z}+, \bar{\mathbf{z}}+, \mathbf{z}-, \bar{\mathbf{z}}-\}$; and N is the total number of examples.

Notice that the IVC objective aims to separate the representation of positive and negative responses given the same context, so that we do not take all the other in-batch examples as negative examples in the same way as in standard contrastive learning.

3.4. Category-View Contrastive Objective

The IVC objective ensures a high difference between examples with the same context, while it cannot guarantee that the learned representations are suitable for classification. The representations of a positive example may be close to the representation of another negative example with a different context, as is shown in Figure 1. Thus, we introduce another category-view contrastive (CVC) objective into model training, which aims

at bunching examples that belong to the same category (positive/negative) into a cluster and separate these two clusters.

There are two categories for the response selection task, i.e., the positive category that indicates the response is a proper response for the given context, and the negative category in vice versa. The CVC objective is applied between examples from the two classes. It captures the similarity of projection vectors of the same class and contrasts them with projection vectors from the other class, i.e.,

$$\begin{aligned} \forall i, j, k, l \quad \text{sim}(\mathbf{z}_i+, \mathbf{z}_j+) &> \text{sim}(\mathbf{z}_k+, \mathbf{z}_l-) \\ \forall i, j, k, l \quad \text{sim}(\mathbf{z}_i-, \mathbf{z}_j-) &> \text{sim}(\mathbf{z}_k+, \mathbf{z}_l-). \end{aligned} \quad (4)$$

This category-view contrastive loss works with a batch of representation vectors of size $2N$, where the number of both positive examples and negative examples is N . Denote $\{\mathbf{z}_1, \mathbf{z}_2, \dots, \mathbf{z}_{2N-1}, \mathbf{z}_{2N}\}$ to be all representation vectors in a batch, where $\{\mathbf{z}_1, \mathbf{z}_2, \dots, \mathbf{z}_N\}$ are representation vectors for positive examples and their augmentations, and $\{\mathbf{z}_{N+1}, \mathbf{z}_{N+2}, \dots, \mathbf{z}_{2N}\}$ are representation vectors for negative examples and their augmentations. The CVC objective works as an additional restriction to punish the high similarity between positive-negative pairs and low similarity within all positive and negative examples.

$$\begin{aligned} l(\mathbf{z}_i, \mathbf{z}_j) &= \log \frac{\exp(\mathbf{z}_i \cdot \mathbf{z}_j / \tau)}{\sum_{i \neq r} \exp(\mathbf{z}_i \cdot \mathbf{z}_r / \tau)} \\ \mathcal{L}_{cvc} &= -\frac{1}{N-1} \sum_{i=1}^{2N} \sum_{i \neq j} \mathbf{1}_{\bar{y}_i = \bar{y}_j} l(\mathbf{z}_i, \mathbf{z}_j) \end{aligned} \quad (5)$$

Finally, the PLM model is fine-tuned with the standard response selection loss \mathcal{L}_{se1} and both IVC and CVC loss. A weighted summation is computed as

$$\mathcal{L} = \mathcal{L}_{se1} + \lambda(\mathcal{L}_{ivc} + \mathcal{L}_{cvc}), \quad (6)$$

where λ is a hyper-parameter that controls the balance between response selection loss and FGC loss.

4. Experiments

4.1. Dataset

Dataset	Ubuntu			Douban		
	Train	Val	Test	Train	Val	Test
# dialogues	1M	500K	500K	1M	50K	6670
#pos:#neg	1:1	1:9	1:9	1:1	1:1	1.2:8.8
# avg turns	10.13	10.11	10.11	6.69	6.75	6.45

Table 1: Statistics of two datasets.

- **Ubuntu Dialogue Corpus V1**

The Ubuntu Dialogue Corpus V1 [10] is a domain-specific multi-turn conversation dataset. Conversations in this dataset are dumped from the multi-party chat room whose topic is the Ubuntu operating system.

- **Douban Corpus**

The Douban Corpus[11] is a Chinese dataset collected from an online social network website named Douban. Douban Corpus is an open-domain conversation corpus, whose topic is much wider than that of Ubuntu Corpus.

The statistics of these two datasets are shown in Table 1. These two datasets vary greatly in both language and topic. Following previous works, we take $R_{10}@k$ as evaluation metric, which measures the probability of having the positive response in the top k ranked responses.

Models	Ubuntu			Douban					
	R ₁₀ @1	R ₁₀ @2	R ₁₀ @5	MAP	MRR	P@1	R ₁₀ @1	R ₁₀ @2	R ₁₀ @5
non-PLM-based methods									
Multi-View [28]	0.662	0.801	0.951	0.505	0.543	0.342	0.292	0.350	0.729
SMN [11]	0.726	0.847	0.961	0.529	0.569	0.397	0.233	0.396	0.724
DUA [29]	0.752	0.868	0.961	0.551	0.599	0.421	0.243	0.421	0.780
DAM [12]	0.767	0.874	0.961	0.550	0.601	0.427	0.254	0.410	0.757
MRFN [13]	0.786	0.886	0.976	0.571	0.617	0.448	0.276	0.435	0.783
IoI [30]	0.796	0.894	0.974	0.573	0.621	0.444	0.269	0.451	0.786
IMN [31]	0.794	0.889	0.974	0.576	0.618	0.441	0.268	0.458	0.796
MSN [14]	0.800	0.899	0.978	0.587	0.632	0.470	0.295	0.452	0.788
PLM-based Methods									
BERT	0.820	0.906	0.978	0.597	0.634	0.448	0.279	0.489	0.823
BERT+FGC	0.829	0.910	0.980	0.614	0.653	0.495	0.312	0.495	0.850
BERT-DPT [4]	0.862	0.935	0.987	0.609	0.645	0.463	0.290	0.505	0.838
BERT-DPT+FGC	0.881	0.945	0.990	0.620	0.660	0.495	0.322	0.495	0.850
BERT-UMS [32]	0.875	0.942	0.988	0.625	0.664	0.499	0.318	0.482	0.858
BERT-UMS+FGC	0.886	0.948	0.990	0.627	0.670	0.500	0.326	0.512	0.869
ELECTRA	0.826	0.908	0.978	0.602	0.642	0.465	0.287	0.483	0.839
ELECTRA+FGC	0.832	0.912	0.980	0.625	0.668	0.499	0.313	0.502	0.850
BERT-Small	0.792	0.888	0.972	N/A	N/A	N/A	N/A	N/A	N/A
BERT-Small+FGC	0.800	0.890	0.974	N/A	N/A	N/A	N/A	N/A	N/A

Table 2: Evaluation results on the two data sets. Numbers in bold indicate that the PLM-based models using FGC outperforms the original models with a significance level p -value < 0.05 .

4.2. Experimental Results

The comparison results between PLMs and FGC-enhanced PLMs is shown in Table 2. All PLM-based methods outperform non-PLM-based methods. By applying our proposed FGC on PLM-based models, the performance of all models is significantly improved. The maximum improvements of a standard-sized BERT for the two datasets are 1.9% and 3.2% respectively in terms of R₁₀@1. The average performance improvements also achieve 1.1% and 2.2%. Besides, our proposed method can also enhance the current state-of-the-art method BERT-UMS by 1.1% and 0.8% on two datasets in terms of R₁₀@1. In addition to a standard-sized BERT model, we also find an absolute gain of 0.9% by adding FGC on the BERT-Small model, which is about 10× smaller than a standard one. The success of these two datasets demonstrates the effectiveness of our proposed FGC across different models, languages, and dialogue topics on multi-turn response selection.

FGC separates representation vectors of examples into different latent spaces according to their types of relevance between contexts and responses. On the one hand, IVC helps distinguish between positive and negative responses given the same context. On the other hand, CVC separates representations of examples from two categories so that these representations can have better distinguishability. As a result, the representation of context-response pairs for positive and negative responses are forced to stay away from each other. These better representations ensures higher accuracy in selecting the positive response given a set of candidate responses.

4.3. Discussion

Effect of Data Augmentation Alone. Data augmentation, working as a kind of data noise, shows positive effect on training models with robustness in natural language processing. One may concern that can data augmentation alone help with the response selection task. We conducted experiments with data augmentation alone, i.e., no contrastive learning strategy is included. The results are shown in Table 3. It can be observed from the table that data augmentation alone cannot enhance the model or even harm the accuracy significantly. Only by combining data augmentation methods with fine-grained contrastive

learning that can bring positive effects for the multi-turn response selection task.

	Ubuntu	Douban
BERT-DPT	0.862	0.290
+Aug	0.837 (-2.5%)	0.278 (-1.2%)
BERT-UMS	0.875	0.318
+Aug	0.851 (-2.4%)	0.292 (-2.6%)

Table 3: Performance with data augmentation alone.

Compare with Standard Contrastive Learning. The main difference between our proposed FGC and standard contrastive learning (e.g., CERT [20] and SimCSE [33]) is that we only take examples with the same context but different responses as negative examples, instead of using all in-batch examples as negative ones. We compare FGC with those methods, whose results are shown in Table 4. Standard contrastive learning can bring less gain (or even harm) on the response selection task, while contrastive learning with fine-grained negative examples leads to a significant gain on this task.

Contrastive Method	R ₁₀ @1	R ₁₀ @2	R ₁₀ @5
BERT-DPT	0.862	0.935	0.987
BERT-DPT + CERT	0.855	0.931	0.985
BERT-DPT + SimCSE	0.864	0.936	0.987
BERT-DPT + FGC	0.881	0.944	0.990

Table 4: Result on comparing with standard CL methods.

5. Conclusion

In this paper, we propose FGC, a fine-grained contrastive learning method, which helps to improve the multi-turn response selection task with PLM-based models. FGC consists of an instance-view contrastive (IVC) objective that helps to differentiate positive response and negative response with the same context, and a category-view contrastive (CVC) objective that separate positive examples and negative examples into two distinguishable clusters. Experiments and analysis on two benchmark datasets and five PLM-based models demonstrates the effectiveness of FGC to significantly improve the performance of multi-turn dialogue response selection.

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