Interactive Matching Network for Multi-Turn Response Selection in Retrieval-Based Chatbots

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Abstract

In this paper, we propose an interactive matching network (IMN) to enhance the representations of contexts and responses at both the word level and sentence level for the multi-turn response selection task. First, IMN constructs word representations from three aspects to address the challenge of out-of-vocabulary (OOV) words. Second, an attentive hierarchical recurrent encoder (AHRE), which is capable of encoding sentences hierarchically and generating more descriptive representations by aggregating with an attention mechanism, is designed. Finally, the bidirectional interactions between whole multi-turn contexts and response candidates are calculated to derive the matching information between Experiments on four public datasets show that IMN significantly outperforms the baseline models by large margins on all metrics, achieving new state-of-the-art performance and demonstrating compatibility across domains for multi-turn response selection.

Introduction

Building a chatbot that can converse naturally with humans on open domain topics is a challenging yet intriguing problem in artificial intelligence. Recently, human-computer conversation has attracted increasing attention due to its promising potential and commercial value (Chen et al., 2017a; Young et al., 2017; Gu et al., 2018). Existing work on building chatbots includes generationbased methods (Shang et al., 2015; Serban et al., 2016) and retrieval-based methods (Lowe et al., 2015; Wu et al., 2017; Zhou et al., 2018; Zhang et al., 2018). Response selection, which aims to select the best-matched response from a set of candidates given the context of a conversation, is an important retrieval-based task for chatbots.

Many previous studies focus on single-turn dialogue, which takes the context of only the last utterance into consideration (Wang et al., 2013; Ji et al., 2014). However, extended multi-turn dialogue, which contains more information, is more practical and has attracted more attention. The existing work on multi-turn response selection can be categorized into two main architectures: concatenating all utterances in a conversation (Lowe et al., 2015; Kadlec et al., 2015; Lowe et al., 2017) and separating utterances followed by aggregation (Wu et al., 2017; Zhou et al., 2018; Zhang et al.,

The techniques of word embeddings and sentence embeddings are important to response selection as well as many other natural language processing (NLP) tasks. The context and the response must be projected to a vector space appropriately to capture their relationships, which are essential for the subsequent procedures. Recently, there has been growing interest in models for the word-level (Mikolov et al., 2013; Pennington et al., 2014; Dong and Huang, 2018) and sentence-level (Wang et al., 2017; Chen et al., 2017b) representations using neural networks, which have helped classification or inference algorithms to achieve better performance on many NLP tasks.

Another key technique to the response selection task lies in context-to-response matching. Modelling the semantic matching degree between two sentences is challenging. Chen et al. (2017b) showed that interactions between pairs of sentences can provide useful information to help matching. This type of matching method relies on only alignment and is fully computationally decomposable with respect to a pair of sentences.

In this paper, we propose a novel neural network architecture, called the interactive matching network (IMN), for multi-turn response selection in retrieval-based chatbots. To alleviate the issue of a large number of out-of-vocabulary (OOV) words, IMN constructs word representations with a combination of general pretrained word embedding vectors, those estimated on the task-specific training set and character-level embeddings vec-Then, an attentive hierarchical recurrent encoder (AHRE) that is capable of encoding sentences hierarchically and generating more descriptive representations by aggregating with an attention mechanism is designed. Finally, IMN accounts for interactions between the context and the response by considering each whole multi-turn context as a single sequence. The context collects matching information from the response to enrich its representations, and the response does the same from the context. This global and bidirectional context-response interaction helps the context and response to capture information from each other to enhance the matching information.

We test our model on two English datasets, Ubuntu Dialogue Corpus V1 (Lowe et al., 2015) and Ubuntu Dialogue Corpus V2 (Lowe et al., 2017), and two Chinese datasets, Douban Conversation Corpus (Wu et al., 2017) and E-commerce Dialogue Corpus (Zhang et al., 2018), which are large-scale datasets that are publicly available for research on multi-turn conversation. The results show that our model can significantly outperform the baseline models by large margins on all metrics, achieving a new state-of-the-art performance and showing compatibility across domains for multi-turn response selection.

In summary, our contributions in this paper are twofold. (1) This paper proposes a new model, named IMN, for multi-turn response selection in retrieval-based chatbots. (2) The empirical results show that our proposed model outperforms the baseline models by large margins in terms of all metrics on four datasets, achieving new state-of-the-art performance for multi-turn response selection.

2 Related Work

Chatbots aim to engage users in human-computer conversations in the open domain and are currently receiving increasing attention because they can target unstructured dialogue without a priori logical representation of the information exchanged during the conversation. Existing work on building chatbots includes generation-based methods (Shang et al., 2015; Serban et al., 2016)

and retrieval-based methods (Lowe et al., 2015; Kadlec et al., 2015; Lowe et al., 2017; Wu et al., 2017; Zhou et al., 2018; Zhang et al., 2018). Generation-based models maximize the probability of generating a response given the previous dialogue. This approach enables the incorporation of rich context when mapping between consecutive dialogue turns. Retrieval-based chatbots have the advantage of informative and fluent responses because they select a proper response for the current conversation from a repository by means of response selection algorithms.

Previous work on retrieval-based chatbots focuses on response selection for single-turn conversation (Wang et al., 2013; Ji et al., 2014). Recently, researchers have extended the focus to multi-turn conversation, which is more practical for real applications. For example, Lowe et al. (2015), Kadlec et al. (2015) and Lowe et al. (2017) matched a response with the literal concatenation of context utterances. Zhou et al. (2016) improved multi-turn response selection with a multi-view model, including an utterance view and a word view. Wu et al. (2017) proposed the sequential matching network (SMN) to first match the response with each utterance and then to accumulate matching information by recurrent neural network (RNN). Zhang et al. (2018) refined utterance and employed self-matching attention to route the vital information in each utterance based on the SMN. Zhou et al. (2018) constructed representations at different granularities with stacked self-attention. Our proposed IMN model is based on the SMN (Wu et al., 2017) and improves it by (1) constructing word representations from three aspects, (2) enhancing sentence representations through AHRE and (3) capturing bidirectional interactions between contexts and responses.

3 Interactive Matching Network

3.1 Problem Formalization

Given a dialogue dataset \mathcal{D} , an example of the dataset can be represented as (c,r,y). Specifically, $c=\{u_1,u_2,...,u_n\}$ represents a conversation context with $\{u_k\}_{k=1}^n$ as the utterances. r is a response candidate, and $y\in\{0,1\}$ denotes a label. y=1 indicates that r is a proper response for c; otherwise, y=0. Our goal is to learn a matching model g(c,r) from \mathcal{D} . For any context-response pair (c,r), g(c,r) measures the matching degree between c and r.

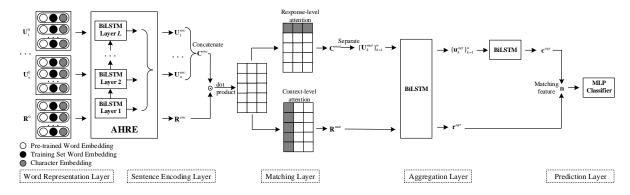


Figure 1: An overview of our proposed IMN model.

3.2 Model Overview

We present here our proposed IMN model, which is composed of five components: word representation layer, sentence encoding layer, matching layer, aggregation layer and prediction layer. Figure 1 shows an overview of the architecture.

IMN first constructs word representations with a combination of general pretrained word embeddings, those estimated on the task-specific training set and character-level embeddings. Then, utterances and a response are encoded with an attentive hierarchical recurrent encoder. Furthermore, IMN uses mutual context-level and response-level attention to collect matching information between context and response. Moreover, these highorder representations are fed into an RNN to obtain a set of utterance embeddings or response embeddings. The set of utterance embeddings are sent to another RNN following the chronological order of the utterances in the context to obtain the context embeddings. Finally, the context embeddings and the response embeddings are used to form the matching feature vectors, which are processed by a multi-layer perceptron to compute the matching score between the context utterances and the response.

IMN has the following characteristics for multiturn response selection. First, IMN can significantly alleviate the issue of a large number of OOV words. Second, AHRE is designed to encode the sentence hierarchically and aggregate with an attention mechanism to generate more descriptive representations. Third, collecting matching information bidirectionally can help to enrich the representations of the context and the response. In summary, the characteristics benefit the final feature vectors for response selection.

For the matching part of a model, in con-

trast to the ESIM model (Chen et al., 2017b), which matches a sentence with a sentence, IMN performs matching between a sentence (i.e., response) and a sequence of sentences (i.e., multiturn contexts). Moreover, in contrast to the SMN model (Wu et al., 2017), which computes wordlevel and sentence-level similarities directly to distill a matching vector, IMN calculates bidirectional interactions between responses and whole contexts to collect matching information. IMN also improves the word representation and sentence encoding components, while both ESIM and SMN are constructed with only pretrained word embeddings and a single-layer RNN encoder.

Details about each layer are provided in the following sections.

3.3 Word Representation Layer

One challenge of large dialogue corpora is the large number of OOV words. To address this issue, Dong and Huang (2018) proposed an algorithm that combines the general pretrained word embeddings with those estimated on a task-specific training set. To further enhance the word embeddings, a convolutional neural network (CNN) was employed to model the morphology information at the character-level (Lee et al., 2017) and has shown its effectiveness at addressing OOV words.

Formally, the embeddings of the k-th utterance in a conversation and a response candidate at this layer are denoted as $\mathbf{U}_k^0 = \{\mathbf{u}_{k,i}^0\}_{i=1}^{l_{u_k}}$ and $\mathbf{R}^0 = \{\mathbf{r}_j^0\}_{j=1}^{l_r}$, respectively. $\mathbf{u}_{k,i}^0$ and $\mathbf{r}_j^0 \in \mathbb{R}^d$ are embeddings of a d-dimensional vector.

3.4 Sentence Encoding Layer

The recurrent neural network (RNN) (Mikolov et al., 2010) has been proven to be good at

modelling chronological relationships in language sequences, and multi-layer RNNs have achieved good performance in many NLP tasks, such as neural machine translation (NMT) (Bahdanau et al., 2014). Encoding sequences with deep neural networks can help to capture deeper and more useful information. Typically, the outputs of the top RNN layer are regarded as the final sentence representations, and the other layers are neglected. However, the lower layers can also provide useful sentence descriptions, such as part-of-speech tagging and syntax-related information (Hashimoto et al., 2017).

To make full use of the representations at all hidden layers, we propose a new sentence encoder, called the attentive hierarchical recurrent encoder (AHRE). This encoder is motivated by the method of embeddings from language models (ELMo) (Peters et al., 2018), which combines the internal states of multi-layer RNNs. Specifically, an AHRE learns a linear combination of the vectors stacked above each input word, which improves the performance compared to using only the top RNN layer.

Furthermore, bidirectional LSTMs (BiLSTMs) (Hochreiter and Schmidhuber, 1997) are employed as our basic building blocks. In an L-layer RNN, each l^{th} layer takes the output of the $l-1^{th}$ layer as its input. We denote the calculations as the follows,

$$\mathbf{u}_{k,i}^{l} = \mathbf{BiLSTM}(\mathbf{U}_{k}^{l-1}, i), i \in \{1, ..., l_{u_k}\}, \quad (1)$$

$$\mathbf{r}_{j}^{l} = \mathbf{BiLSTM}(\mathbf{R}^{l-1}, j), j \in \{1, ..., l_r\}.$$
 (2)

where $\mathbf{U}_k^l = \{\mathbf{u}_{k,i}^l\}_{i=1}^{l_{u_k}}$ and $\mathbf{R}^l = \{\mathbf{r}_j^l\}_{j=1}^{l_r}, l \in \{1,...,L\}$. The weights for these two BiLSTMs are shared in our implementation. Due to space limitations, we omit the description of basic chain LSTMs; the reader can refer to Hochreiter and Schmidhuber (1997) for details.

Finally, we obtain a set of L representations $\{\mathbf{U}_k^1,...,\mathbf{U}_k^L\}$ and $\{\mathbf{R}^1,...,\mathbf{R}^L\}$ for the k-th utterance in a conversation and a response candidate through the L-layer RNNs. Typically, \mathbf{U}_k^L or \mathbf{R}^L , i.e., the outputs of the top layer, are used as the final encoded vectors. Here, we propose to combine the set of representations to obtain enhanced representations $\mathbf{u}_{k,i}^{enc}$ and \mathbf{r}_{j}^{enc} by learning the attention weights of all the layers.

Mathematically, we have

$$\mathbf{u}_{k,i}^{enc} = \sum_{l=1}^{L} w_l \mathbf{u}_{k,i}^l, i \in \{1, ..., l_{u_k}\},$$
 (3)

$$\mathbf{r}_{j}^{enc} = \sum_{l=1}^{L} w_{l} \mathbf{r}_{j}^{l}, j \in \{1, ..., l_{r}\}.$$
 (4)

where $\mathbf{U}_k^{enc} = \{\mathbf{u}_{k,i}^{enc}\}_{i=1}^{l_{u_k}}, \mathbf{R}^{enc} = \{\mathbf{r}_j^{enc}\}_{j=1}^{l_r}$ and w_l are the softmax-normalized weights shared between utterances and responses, which need to be estimated during the training process. As a result, representations given by our encoder are expected to capture and fuse multi-level characteristics of sentences.

3.5 Matching Layer

Interactions between the context and the response provide important information for deciding the matching degree between them. Unlike previous work, which matches the response with each utterance in the context separately in an utteranceto-response manner (Wu et al., 2017; Zhou et al., 2018; Zhang et al., 2018), IMN matches the response with the whole context in a global contextto-response way, i.e., considering the whole context as a single sequence. The goal of utterance-toresponse matching is to collect the relevant parts in each utterance while neglecting the possible premise that the whole utterance is irrelevant to the response. Collecting any part of an irrelevant utterance introduces noise for the matching process. Instead, global context-to-response matching can help to select the most relevant parts of the whole context and neglect the irrelevant parts.

First, the context representation $\mathbf{C}^{enc} = \{\mathbf{c}_i^{enc}\}_{i=1}^{l_c}, l_c = \sum_{k=1}^n l_{u_k}$ is formed by concatenating the set of utterance representations $\{\mathbf{U}_k^{enc}\}_{k=1}^n$.

$$\mathbf{C}^{enc} = Concatenate(\{\mathbf{U}_k^{enc}\}_{k=1}^n) \qquad (5)$$

Then, an attention-based alignment is employed to collect information between two sequences by computing the attention weight between each representation tuple $\{\mathbf{c}_i^{enc}, \mathbf{r}_i^{enc}\}$ as

$$e_{ij} = (\mathbf{c}_i^{enc})^T \cdot \mathbf{r}_j^{enc} \tag{6}$$

Furthermore, local inference is determined by the attention weights e_{ij} computed above to obtain the local relevance between a context and a

response bidirectionally. For a word in the context, its response-level relevant representation carried by the response is identified and composed using e_{ij} as

$$\bar{\mathbf{c}}_{i}^{enc} = \sum_{j=1}^{l_r} \frac{exp(e_{ij})}{\sum_{k=1}^{l_r} exp(e_{ik})} \mathbf{r}_{j}^{enc}, i \in \{1, ..., l_c\},$$

where $\bar{\mathbf{C}}^{enc} = \{\bar{\mathbf{c}}_i^{enc}\}_{i=1}^{l_c}$ and $\bar{\mathbf{c}}_i^{enc}$ is a weighted summation of $\{\mathbf{r}_j^{enc}\}_{j=1}^{l_r}$. Intuitively, the contents in $\{\mathbf{r}_j^{enc}\}_{j=1}^{l_r}$ that are relevant to \mathbf{c}_i^{enc} are selected to form $\bar{\mathbf{c}}_i^{enc}$. The same calculation is performed for each word in the response to form the context-level representations as

$$\bar{\mathbf{r}}_{j}^{enc} = \sum_{i=1}^{l_{c}} \frac{exp(e_{ij})}{\sum_{k=1}^{l_{c}} exp(e_{kj})} \mathbf{c}_{i}^{enc}, j \in \{1, ..., l_{r}\}.$$
(8)

where $\bar{\mathbf{R}}^{enc} = \{\bar{\mathbf{r}}_j^{enc}\}_{j=1}^{l_r}$. To further enhance the collected information, we compute the differences and the element-wise products between $\{\mathbf{C}^{enc}, \bar{\mathbf{C}}^{enc}\}$ and between $\{\mathbf{R}^{enc}, \bar{\mathbf{R}}^{enc}\}$. The differences and element-wise products are then concatenated with the original vectors to obtain the enhanced representations, as follows,

$$\mathbf{C}^{mat} = [\mathbf{C}^{enc}; \bar{\mathbf{C}}^{enc}; \mathbf{C}^{enc} - \bar{\mathbf{C}}^{enc}; \mathbf{C}^{enc} \odot \bar{\mathbf{C}}^{enc}]$$
(9)

$$\mathbf{R}^{mat} = [\mathbf{R}^{enc}; \bar{\mathbf{R}}^{enc}; \mathbf{R}^{enc} - \bar{\mathbf{R}}^{enc}; \mathbf{R}^{enc} \odot \bar{\mathbf{R}}^{enc}]$$
(10)

Thus far, we have collected the relevant information between the context and the response; now, we have to convert the concatenated context back to separate utterances.

$$\{\mathbf{U}_{k}^{mat}\}_{k=1}^{n} = Separate(\mathbf{C}^{mat}) \qquad (11)$$

3.6 Aggregation Layer

An RNN followed by a pooling operation is typically employed as the aggregation method to compose and obtain the sentence embeddings. Here, BiLSTM and a combination of max pooling and last hidden state pooling are employed to obtain the utterance and response embeddings.

First, the utterance and response embeddings are composed by the enhanced local matching information \mathbf{U}_k^{mat} and \mathbf{R}^{mat} as

$$\mathbf{u}_{k,i} = \mathbf{BiLSTM}(\mathbf{U}_k^{mat}, i), i \in \{1, ..., l_{u_k}\}, (12)$$

$$\mathbf{r}_{i} = \mathbf{BiLSTM}(\mathbf{R}^{mat}, j), j \in \{1, ..., l_{r}\}.$$
 (13)

The weights for these two BiLSTMs are shared in our implementation. Then, the aggregated embeddings are calculated by pooling operations as

$$\mathbf{u}_{k}^{agr} = [\mathbf{u}_{k,max}; \mathbf{u}_{k,lu_{k}}], k \in \{1, ..., n\}, \quad (14)$$

$$\mathbf{r}^{agr} = [\mathbf{r}_{max}; \mathbf{r}_{l_r}]. \tag{15}$$

Furthermore, the set of utterance inference vectors $\{\mathbf{u}_k^{agr}\}_{k=1}^n$ is fed into another BiLSTM in chronological order of the utterances in the context as

$$\mathbf{c}_k = \mathbf{BiLSTM}(\mathbf{U}^{agr}, k), k \in \{1, ..., n\}.$$
 (16)

Another pooling operation is performed to obtain the aggregated context embeddings as

$$\mathbf{c}^{agr} = [\mathbf{c}_{max}; \mathbf{c}_n]. \tag{17}$$

The final matching feature vector is the concatenation of the context embeddings and the response embeddings as

$$\mathbf{m} = [\mathbf{c}^{agr}; \mathbf{r}^{agr}]. \tag{18}$$

3.7 Prediction Layer

We then input the matching feature vector **m** into a multi-layer perceptron (MLP) classifier. An MLP is a feedforward neural network that is estimated in a supervised manner using examples of features together with known labels. Here, the MLP is designed to predict whether a context and response pair match appropriately according to the matching feature **m**. Finally, the MLP returns a score to denote the degree of matching.

3.8 Training Criteria

We learn g(c,r), which provides the probability that r is a proper candidate to c by minimizing the sigmoid cross entropy from \mathcal{D} . Let Θ denote the parameters of IMN; then, the objective function $\mathcal{L}(\mathcal{D},\Theta)$ of learning can be formulated as

$$\mathcal{L}(\mathcal{D}, \Theta) = -\sum_{(c,r,y)\in\mathcal{D}} [ylog(g(c,r)) + (1-y)log(1-g(c,r))]$$
(19)

Dataset	Ubuntu V1		Ubuntu V2			Douban			E-commerce			
Dataset	Train	Valid	Test	Train	Valid	Test	Train	Valid	Test	Train	Valid	Test
pairs	1M	356k	355k	1M	195k	189k	1M	50k	10k	1M	10k	10k
positive:negative	1: 1	1: 9	1: 9	1: 1	1: 9	1: 9	1: 1	1: 1	1: 9	1: 1	1: 1	1: 9
positive/context	1	1	1	1	1	1	1	1	1.18	1	1	1
turns/context	8.44	2.66	2.65	6.29	5.86	6.03	6.69	6.75	5.95	5.51	5.48	5.64
words/utterance	20.38	21.16	21.17	14.06	15.28	15.28	18.56	18.50	20.74	7.02	6.99	7.11

Table 1: Statistics of the datasets that our model is tested on.

4 Experiments

4.1 Datasets

We tested IMN on two English public multi-turn response selection datasets, Ubuntu Dialogue Corpus V1 (Lowe et al., 2015) and Ubuntu Dialogue Corpus V2 (Lowe et al., 2017), and two Chinese datasets, Douban Conversation Corpus (Wu et al., 2017) and E-commerce Dialogue Corpus (Zhang et al., 2018). Ubuntu Dialogue Corpus V1 and V2 contain multi-turn dialogues about Ubuntu system troubleshooting in English. V2 is an updated version of V1, in that V2 separates the training/validation/testing sets by time, which more closely mimics the real-life implementation of training a model on past data to predict future data. In both of the Ubuntu corpora, the positive responses are true responses from humans, and the negative responses are randomly sampled. The Douban Conversation Corpus was crawled from a Chinese social network on open-domain topics. It was constructed in a similar way to the Ubuntu corpus. The Douban Conversation Corpus collected responses via a small inverted-index system, and labels were manually annotated. The Ecommerce Dialogue Corpus collected real-world conversations between customers and customer service staff from the largest e-commerce platform in China. Some statistics of these datasets are provided in Table 1.

4.2 Evaluation Metrics

We used the same evaluation metrics as those used in previous work (Wu et al., 2017). Each model was tasked with selecting the k best-matched responses from n available candidates for the given conversation context c, and we calculated the recall of the true positive replies among the k selected responses, denoted as $\mathbf{R}_n@k$, as the main evaluation metric. In addition to $\mathbf{R}_n@k$, we considered the mean average precision (MAP) (Baeza-Yates et al., 1999), mean reciprocal rank (MRR) (Voorhees et al., 1999) and precision-

at-one ($\mathbf{P}@1$), especially for the Douban corpus, following the settings of previous work.

4.3 Training Details

The Adam method (Kingma and Ba, 2014) was employed for optimization, with a batch size of 96 for the two English datasets and 128 for the two Chinese datasets. The initial learning rate was 0.001 and was exponentially decayed by 0.96 every 5000 steps. Dropout (Srivastava et al., 2014) with a rate of 0.2 was applied to the word embeddings and all hidden layers. embeddings for the English datasets were concatenations of the 300-dimensional GloVe embeddings (Pennington et al., 2014), 100-dimensional embeddings estimated on the training set using the Word2Vec algorithm (Mikolov et al., 2013) and 150-dimensional character-level embeddings with window sizes of {3, 4, and 5}, each consisting of 50 filters. The word embeddings for the Chinese datasets were concatenations of the 200dimensional embeddings from Song et al. (2018) and the 200-dimensional embeddings estimated on the training set using the Word2Vec algorithm. Character-level embeddings were not employed for the two Chinese datasets due to the large number of Chinese characters. The word embeddings were not updated during training. All hidden states of the LSTM had 200 dimensions. The number of BiLSTM layers in the AHRE was 3. The MLP at the prediction layer had a hidden unit size of 256 with ReLU (Nair and Hinton, 2010) activation. The maximum word length was set to 18, the maximum utterance length was set to 50, and the maximum context length was set to 10. We padded with zeros if the number of utterances in a context was less than 10; otherwise, we kept the last 10 utterances. We used the development dataset to set the stop condition to select the best model for testing.

All codes were implemented in the TensorFlow framework (Abadi et al., 2016) and will be published to help replicate our results after paper

	Ubuntu Corpus V1				Ubuntu Corpus V2			
	$R_2@1$	R ₁₀ @1	$\mathbf{R}_{10}@2$	$\mathbf{R}_{10}@5$	$R_2@1$	$\mathbf{R}_{10}@1$	$\mathbf{R}_{10}@2$	$R_{10}@5$
TF-IDF (Lowe et al., 2015, 2017)	0.659	0.410	0.545	0.708	0.749	0.488	0.587	0.763
RNN (Lowe et al., 2015, 2017)	0.768	0.403	0.547	0.819	0.777	0.379	0.561	0.836
LSTM (Lowe et al., 2015, 2017)	0.878	0.604	0.745	0.926	0.869	0.552	0.721	0.924
Multi-View (Zhou et al., 2016)	0.908	0.662	0.801	0.951	-	-	-	-
DL2R (Yan et al., 2016)	0.899	0.626	0.783	0.944	-	-	-	-
MV-LSTM (Wan et al., 2016)	0.906	0.653	0.804	0.946	-	-	-	-
Match-LSTM (Wang and Jiang, 2016b)	0.904	0.653	0.799	0.944	-	-	-	-
RNN-CNN (Baudiš et al., 2016)	-	-	-	-	0.911	0.672	0.809	0.956
CompAgg (Wang and Jiang, 2016a)	0.884	0.631	0.753	0.927	0.895	0.641	0.776	0.937
BiMPM (Wang et al., 2017)	0.897	0.665	0.786	0.938	0.877	0.611	0.747	0.921
HRDE-LTC (Yoon et al., 2018)	0.916	0.684	0.822	0.960	0.915	0.652	0.815	0.966
SMN (Wu et al., 2017)	0.926	0.726	0.847	0.961	-	-	-	-
DUA (Zhang et al., 2018)	-	0.752	0.868	0.962	-	-	-	-
DAM (Zhou et al., 2018)	0.938	0.767	0.874	0.969	-	-	-	_
IMN	0.945	0.777	0.880	0.974	0.945	0.771	0.886	0.979
IMN(Ensemble)	0.950	0.794	0.893	0.978	0.950	0.791	0.899	0.982

Table 2: Evaluation results of IMN and previous methods on Ubuntu Dialogue Corpus V1 and Ubuntu Dialogue Corpus V2.

	Douban Conversation Corpus							E-commerce Corpus		
	MAP	MRR	P@1	$\mathbf{R}_{10}@1$	$R_{10}@2$	$R_{10}@5$	$\mathbf{R}_{10}@1$	$R_{10}@2$	$R_{10}@5$	
TF-IDF	0.331	0.359	0.180	0.096	0.172	0.405	0.159	0.256	0.477	
RNN	0.390	0.422	0.208	0.118	0.223	0.589	0.325	0.463	0.775	
LSTM	0.485	0.527	0.320	0.187	0.343	0.720	0.365	0.536	0.828	
Multi-View	0.505	0.543	0.342	0.202	0.350	0.729	0.421	0.601	0.861	
DL2R	0.488	0.527	0.330	0.193	0.342	0.705	0.399	0.571	0.842	
MV-LST	0.498	0.538	0.348	0.202	0.351	0.710	0.412	0.591	0.857	
Match-LSTM	0.500	0.537	0.345	0.202	0.348	0.720	0.410	0.590	0.858	
SMN	0.529	0.569	0.397	0.233	0.396	0.724	0.453	0.654	0.886	
DUA	0.551	0.599	0.421	0.243	0.421	0.780	0.501	0.700	0.921	
DAM	0.550	0.601	0.427	0.254	0.410	0.757	-	-	-	
IMN	0.570	0.615	0.433	0.262	0.452	0.789	0.621	0.797	0.964	
IMN(Ensemble)	0.576	0.618	0.441	0.268	0.458	0.796	0.672	0.845	0.970	

Table 3: Evaluation results of IMN and previous methods on the Douban Conversation Corpus and E-commerce Corpus. All the results except ours are copied from Wu et al. (2017); Zhang et al. (2018); Zhou et al. (2018).

acceptance¹.

4.4 Experimental Results

Table 2 and Table 3 present the evaluation results of IMN and previous methods. All the results except ours are from the existing literature. IMN significantly outperforms the other models on all metrics and datasets, which demonstrates its ability to select the best-matched response and its compatibility across domains (system troubleshooting, social network and e-commerce). The Douban Conversation Corpus is different from the other three datasets in that it includes multiple correct candidates for a context in the test set, which leads to low $\mathbf{R}_n@ks$, e.g., if there are 3 correct responses, the maximum $\mathbf{R}_{10}@1$ is 0.33. Hence, \mathbf{MAP} and \mathbf{MRR} are recommended for reference. Our proposed model outperforms the baseline model

SMN by a large margin of 5.1% in terms of **R**₁₀@1 on Ubuntu Dialogue Corpus V1; 4.1% in terms of MAP and 4.6% in terms of MRR on the Douban Conversation Corpus; and 16.8% in terms of \mathbf{R}_{10} @1 on the E-commerce Dialogue Corpus. Moreover, our proposed model outperforms the present state-of-the-art methods on the respective datasets by a margin of 1.0% in terms of \mathbf{R}_{10} @1 on Ubuntu Dialogue Corpus V1; 11.9% in terms of \mathbf{R}_{10} @1 on Ubuntu Dialogue Corpus V2; 2.0% in terms of MAP and 1.4% in terms of MRR on the Douban Conversation Corpus; and 12.0% in terms of \mathbf{R}_{10} @1 on the E-commerce Dialogue Corpus, achieving new state-of-the-art performance on all datasets. Furthermore, we provide ensemble models built by averaging the outputs of four single models with identical architectures and different random initializations. The ensemble models further improves the response selection performance.

¹https://github.com/JasonForJoy/IMN

	Ubuntu Corpus V1					
	${\bf R}_{2}@1$	$\mathbf{R}_{10}@1$	\mathbf{R}_{10} @2	$\mathbf{R}_{10}@5$		
IMN	0.945	0.777	0.880	0.974		
- AHRE	0.941	0.767	0.874	0.972		
- Char emb	0.934	0.749	0.863	0.969		
- Match	0.938	0.763	0.868	0.970		

Table 4: Ablation tests of a single model on the Ubuntu Dialogue Corpus V1 test set.

5 Ablations and Analysis

To demonstrate the importance of each component in our proposed model, various parts of the architecture were ablated, and the results were reported for the test set of Ubuntu Dialogue Corpus V1, as shown in Table 4.

AHRE The number of layers in the AHRE was tuned on the validation set, as shown in Fig 2, and was set to 3. The AHRE proposed in this paper can be considered to be a generalized recurrent encoder that degenerates into a single-layer RNN when the number of layers in the AHRE is set to 1. We found that IMNp with a single-layer RNN encoder outperformed SMN by a large margin of 4.1% in terms of \mathbf{R}_{10} @1 and achieved slightly better performance than DAM, while DAM requires a multi-layer self-attention encoder. The softmaxnormalized weights of every layer in the AHRE are listed in Table 5, which indicates that each layer of the multi-layer RNNs contributes to the sentence embeddings.

Char emb The character embeddings in the word representation layer were ablated, which resulted in a performance decrease. Additionally, we found that the lower layers of the RNN in the AHRE constitute the most weight, as shown in Table 5. These two results lead to the conclusion that morphology information is very important to the response selection task, possibly because morphology information can help to match similar words literally. A response with more literally similar words may be more appropriate.

Match The matching layer in IMN was replaced with the method used in the SMN, that is, computing word-level and sequence-level similarities, followed by distilling information through an alternation of convolution and pooling operations to form a matching vector. The decreased performance indicates that bidirectional interactions between the context and the response are beneficial

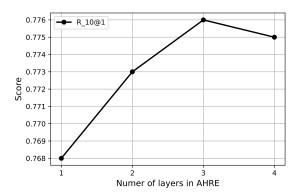


Figure 2: Performance of IMN for different numbers of layers in the AHRE.

	Layer 1	Layer 2	Layer 3
Weights	0.4912	0.2234	0.2854

Table 5: Layer-wise weights of the three-layer AHRE used in our experiments.

for collecting matching information and making decisions on whether the context and response match.

6 Conclusion

In this paper, we propose an interactive matching network for the multi-turn response selection task. This model enhances the representations of the context and the response at both the word level and sentence level. It also establishes bidirectional and global context-to-response interactions to help capture matching information. An empirical study on four public datasets shows that our proposed model significantly outperforms the baseline models by a large margin on all metrics, achieving new state-of-the-art performance and showing compatibility across domains for multi-turn response selection. However, given a long response composed of multiple utterances, we have neglected the relationships between utterances. Modelling a response consisting of multiple utterances and establishing relationships between them will be the focus of our future work.

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