Abstract

We consider matching with pre-trained contextualized word vectors for multi-turn response selection in retrieval-based chatbots. When directly applied to the task, state-of-the-art models, such as CoVe and ELMo, do not work as well as they do on other tasks, due to the hierarchical nature, casual language, and domain-specific word use of conversations. To tackle the challenges, we propose pre-training a sentence-level and a session-level contextualized word vectors by learning a dialogue generation model from large-scale human-human conversations with a hierarchical encoder-decoder architecture. The two levels of vectors are then integrated into the input layer and the output layer of a matching model respectively. Experimental results on two benchmark datasets indicate that the proposed contextualized word vectors can significantly and consistently improve the performance of existing matching models for response selection.

1 Introduction

Human-machine conversation is one of the fundamental problems of natural language processing (NLP). While previous research focuses on building task-oriented dialog systems (Young et al., 2010) that can fulfill specific tasks in vertical domains for people via conversations; more recent attention is drawn to developing non-task oriented chatbots which can naturally and meaningfully converse with humans on open domain topics (Vinyals and Le, 2015). Existing approaches to building a chatbot include generation-based methods (Shang et al., 2015; Serban et al., 2016) which synthesize a response with natural language generation technologies, and retrieval-based methods (Lowe et al., 2015; Wu et al., 2017a) which select a response from a pool of candidates. In this work, we study multi-turn response selection for retrieval-based chatbots, because retrieval-based methods can return fluent and informative responses, and are the core of many real products such as the social-bot Xiaoice from Microsoft (Shum et al., 2018) and the E-commerce assistant AliMe Assist from Alibaba Group (Li et al., 2017a).

A key step to multi-turn response selection is measuring the matching degree between a conversational context consisting of a sequence of utterances and a response candidate with a matching model. Existing models, such as dual LSTM (Lowe et al., 2015) and sequential matching network (SMN) (Wu et al., 2017a), are defined in neural architectures. Although these models vary in structures, they are commonly built upon word embeddings which are pre-trained on large-scale unlabeled text with algorithms such as Word2Vec (Mikolov et al., 2013) and GloVe (Pennington et al., 2014). Indeed, the pre-trained word embeddings are crucial to a matching model, as they carry useful syntactic and semantic information learned from the unlabeled text to the matching task. On the other hand, words appear in specific contexts (e.g., sentences), and the same word could have different meanings in different contexts. The widely used embeddings, however, represent words in a context-independent way. As a result, contextual information of words in the unlabeled text is lost in the matching task.

In this work, we study how to leverage pre-trained contextualized word representations to improve matching models for multi-turn response selection in retrieval-based chatbots. A baseline method is integrating the state-of-the-art contextualized word vectors such as CoVe (McCann et al., 2017) and ELMo (Peters et al., 2018) into matching models. Although both CoVe and ELMo have proven effective on various NLP tasks, they are
never applied to conversation tasks. Therefore, it is not clear if CoVe and ELMo are as effective on the task of response selection as they are on other tasks such as question answering (Rajpurkar et al., 2016), textual entailment (Bowman et al., 2015), and sentiment analysis (Socher et al., 2013), etc. On the other hand, we argue that directly applying CoVe or ELMo to conversation modeling might be problematic, as there is a discrepancy between conversation data and the data used to train the two models. First, conversation data is often in a hierarchical structure, and thus there are both sentence-level contexts and session-level contexts for a word. A sentence-level context refers to an utterance that contains the word, and represents a kind of local context, and a session-level context means the entire conversation session (i.e., all utterances of the conversation history in question) that contains the word, and provides a global context for the word. CoVe and ELMo, however, only encode local contextual information of words when applied to a conversation task. Second, word use in conversation data is different from that in the WMT data which are used to train CoVe and ELMo. Words in conversations could be informal (e.g., “srry”, which means “sorry” and is among the top 10% high-frequency words in Ubuntu dialogues) or domain-specific (e.g., “fstab”, which means a system configuration file on Unix and Unix-like computer systems, and is among the top 1% high-frequency words in Ubuntu dialogues), and thus rarely appear in the WMT data. As a result, these words cannot be accurately represented by the two models. The discrepancy on data raises new challenges to leveraging contextualized word vectors in matching for response selection.

To address the challenges, we propose pre-training contextualized word representations with large-scale human-human conversations. Specifically, we employ a hierarchical encoder-decoder architecture, and learn a dialogue generation model with the conversations. Local contextual information and global contextual information for a word are naturally encoded by the utterance-level recurrent neural network (RNN) and the context-level RNN of the encoder of the generation model respectively. Thus, we take the hidden states of the utterance-level RNN and the context-level RNN as sentence-level and session-level contextualized word representations respectively, and name them ECMo (embeddings from a conversation model) representations. In matching, we integrate the sentence-level representation into the input layer of a matching model where words are initialized, and exploit the session-level representation in the output layer of the matching model where a matching score is calculated. By this means, we transfer the knowledge in large-scale unlabeled human-human conversations to the learning of the matching model.

We conduct experiments on two benchmark datasets: the Ubuntu Dialogue Corpus (Lowe et al., 2015) and the Douban Conversation Corpus (Wu et al., 2017a). Experimental results indicate that the performance of matching models slightly drops when they are combined with ELMo, and slightly improves when CoVe is integrated. On the other hand, we observe significant improvement when matching models are equipped with ECMo. On Ubuntu data, the improvements to SMN and dual LSTM on R10@1 are 3.2% and 2.2% respectively; and on Douban data, the improvements to SMN and dual LSTM on MAP are 2.3% and 1.6% respectively.

Our contributions are three-fold: (1) we test CoVe and ELMo on benchmark datasets of response selection; (2) we propose a new approach to pre-training contextualized word representations that can well adapt to the task of response selection; (3) we verify the effectiveness of the proposed model on the benchmark datasets of response selection.

2 Related Work

Existing methods on building a chatbot are either generation-based or retrieval-based. Regarding to the former, on top of the basic sequence-to-sequence with attention architecture (Vinyals and Le, 2015; Shang et al., 2015), various extensions have been made to address the “safe response” problem (Li et al., 2015); to leverage extra knowledge (Mou et al., 2016; Xing et al., 2017a; Serban et al., 2017a); to model the hierarchical structure of conversational contexts (Serban et al., 2016; Sordoni et al., 2015; Xing et al., 2017b); to generate responses with some specific persona or emotions (Li et al., 2016a; Zhou et al., 2017); to speed up response decoding (Wu et al., 2017b); and to pursue better optimization strategies (Li et al., 2017b, 2016b). Different from generation-based methods, retrieval-based methods focus on designing a matching model of a human input
and a response candidate for response selection. Early work along this line studies single-turn response selection where the human input is set as a single message (Lu and Li, 2013; Wang et al., 2013; Ji et al., 2014; Hu et al., 2014; Wang et al., 2015). Recently more attention is paid to context-response matching for multi-turn response selection. Representative methods include the dual LSTM model (Lowe et al., 2015), the deep learning to respond architecture (Yan et al., 2016), the multi-view matching model (Zhou et al., 2016), and the sequential matching network (Wu et al., 2017a). In this work, we study the problem of multi-turn response selection for retrieval-based chatbots. Rather than designing a matching model in a sophisticated structure, we are interested in how to leverage pre-trained contextualized word embeddings to generally improve the performance of the existing matching models. The contextualized embeddings are obtained from a dialogue generation model learned with large-scale human-human conversations apart from the training data of the matching models.

Pre-trained word vectors have become a standard component of most state-of-the-art models in NLP tasks. A common practice is to learn a single context-independent word representation from large-scale unlabeled data (Mikolov et al., 2013; Pennington et al., 2014; Bojanowski et al., 2017), and initialize the task-specific models with the representation. Recently, researchers begin to study pre-training context-dependent word representations for downstream tasks (Melamud et al., 2016; Peters et al., 2017; Dai and Le, 2015; Ramachandran et al., 2017). For example, McCann et al. (2017) train an encoder-decoder model on large-scale machine translation datasets, and treat the hidden states of the encoder as contextualized representations of words. Peters et al. (2018) learn a multi-layer LSTM based language model on large-scale monolingual data, and use hidden states of different layers of the LSTM as contextualized word vectors. In this work, we study how to pre-train contextualized word representations for the task of response selection which is never explored before. In addition to the application of CoVe and ELMo, we propose pre-training contextualized word representations by learning a dialogue generation model from large-scale conversations with a hierarchical encoder-decoder. Different from the existing models, the dialogue generation model allows us to form two levels of contextualized word representations that encode both local and global contextual information for a word in conversations.

3 Background: Learning a Matching Model for Response Selection

Given a dataset \( \mathcal{D} = \{(y_i, s_i, r_i)\}_{i=1}^N \) where \( s_i = \{u_{i,1}, \ldots, u_{i,n_i}\} \) represents a conversational context with \( \{u_{i,k}\}_{k=1}^{n_i} \) as utterances; \( r_i \) is a response candidate; and \( y_i \in \{0, 1\} \) denotes a label with \( y_i = 1 \) indicating \( r_i \) a proper response for \( s_i \); and otherwise \( y_i = 0 \), the goal of the task of response selection is to learn a matching model \( g(\cdot, \cdot) \) from \( \mathcal{D} \). For any context-response pair \((s, r)\), \( g(s, r) \) gives a score that reflects the matching degree between \( s \) and \( r \), and thus allows one to rank a set of response candidates according to the scores for response selection.

For any \( u_{i,k} \) in \( s_i \) and \( r_i \) in \( \mathcal{D} \), suppose that \( u_{i,k} = (w_{i,k,1}, \ldots, w_{i,k,n_i}) \) and \( r_i = (v_{i,1}, \ldots, v_{i,n_i}) \), where \( w_{i,k,j} \) and \( v_{i,j} \) denote the \( j \)-th words of \( u_{i,k} \) and \( r_i \) respectively, a common practice of learning of \( g(\cdot, \cdot) \) is that \( w_{i,k,j} \) and \( v_{i,j} \) are first initialized with some pre-trained word vectors and then fed to an neural architecture. With the word vectors either fixed or optimized together with other parameters of the neural architecture, \( g(\cdot, \cdot) \) is learnt by maximizing the following objective:

\[
\sum_{i=1}^N \left[ y_i \log(g(c_i, r_i)) + (1 - y_i) \log(1 - g(c_i, r_i)) \right]. \tag{1}
\]

Existing work pre-trains word vectors with either Word2Vec (e.g., SMN (Wu et al., 2017a)) or GloVe (e.g., dual LSTM (Lowe et al., 2015)) which loses contextual information in the representations of words. Therefore, inspired by the recent success of CoVe (McCann et al., 2017) and ELMo (Peters et al., 2018) on downstream NLP tasks, we consider incorporating contextualized word representations into the learning of \( g(\cdot, \cdot) \). On the other hand, contexts of a word in conversations are usually in casual language, and sometimes with domain-specific knowledge (e.g., the Ubuntu Dialogue Corpus (Lowe et al., 2015)). The contexts are naturally in a hierarchical structure where utterances and conversation sessions (i.e., sequences of utterances) that contain the word provide contextual information from a local and a global perspective respectively. The characteristics of conversation data motivate us to learn new
contextualized representations of words that can well adapt to the task of response selection.

4 ECMo: Embedding from a Conversation Model

Heading for contextualized word representations that can well capture semantics and syntax of conversations, we propose learning a dialogue generation model from large-scale human-human conversations. We first present the architecture of the generation model, and then elaborate how to extract two levels of contextualized representations from the model and exploit them in matching.

4.1 Hierarchical Encoder-Decoder Model

In order to represent contextual information in both utterances and the entire session of a conversation, we learn a hierarchical encoder-decoder (HED) model for multi-turn dialogue generation. Figure 1 gives the architecture of HED. HED consists of a two-level encoder and a decoder. The first layer of the encoder is an utterance-level encoder where HED reads utterances in conversation history one by one, and represents the word sequence of each utterance as a sequence of hidden vectors by a bidirectional RNN with Gated Recurrent Units (biGRUs) (Bahdanau et al., 2014). The hidden vectors of each utterance are then processed by a max pooling operation and transformed to an utterance vector. The second layer of the encoder is a context-level encoder which embeds another GRU to transform the sequence of each utterance as a sequence of hidden vectors $W_s$, $W_r$, $W_z$, $V_z$, $V_r$, $V_z$ are parameters. The backward GRU reads $u_i$ in its reverse order (i.e., from $u_{i1}$ to $u_{iT_i}$) and generates $\{\tilde{h}_{i,k}\}_{k=1}^{T_i}$ with a parameterization similar to the forward GRU.

The output of the utterance-level encoder is a sequence of utterance vectors $\{v_1^u, \ldots, v_{u_i}^u, \ldots, v_n^u\}$ where $v_i^u$ is the representation of $u_i$ with the $j$-th element as

$$v_i^u(j) = \max(h_{i1}(j), \ldots, h_{iT_i}(j)), \quad (4)$$

where $h_{i1}(j)$ and $h_{iT_i}(j)$ are the $j$-th elements of $h_{i1}$ and $h_{iT_i}$ respectively.

Context-Level encoder: the context-level encoder takes the output of the utterance-level encoder as input, and represents the entire conversation session $s$ as a sequence of hidden vectors.
(h₁, ..., hₙ). ∀i ∈ {1, ..., n}, hᵢ is calculated by
\[
h_i = \text{GRU}_s(h_{i-1}^s, v_i^s),
\]
where \(\text{GRU}_s(\cdot, \cdot)\) is parameterized in the same way as Equation (3).

**Decoder:** the decoder of HED is an RNN language model (Mikolov et al., 2010) which predicts the next utterance \(u_{n+1}\) word by word conditioned on \(h_n^s\). Suppose that \(u_{n+1} = (w_{n+1,1}, ..., w_{n+1,T_{n+1}})\), then the generation probability of \(u_{n+1} = (w_{n+1,1}, ..., w_{n+1,T_{n+1}})\) is defined as
\[
p(u_{n+1} | u_1, ..., u_n) = \prod_{t=2}^{T_{n+1}} p(w_{n+1,t} | h_n^s, w_{n+1,1}, ..., w_{n+1,t-1}),
\]
where
\[
p(w_{n+1,t} | h_n^s, w_{n+1,1}, ..., w_{n+1,t-1}) = \text{softmax}(h_t^d \cdot e_{n+1,t-1}).
\]
(6)

\(h_t^d\) is the hidden state of the decoder at step \(t\) which is defined as
\[
h_t^d = \text{GRU}_d(h_{t-1}^d, v_{n+1,t-1}),
\]
where \(e_{n+1,t-1}\) is the embedding of \(w_{n+1,t-1}\).

**Learning objective:** we estimate the parameters of HED by maximizing the likelihood of a dataset \(D' = \{s_j\}_{j=1}^{N'}\) where \(s_j\) is a conversation session. The source of \(D'\) could be different from that of \(D\) and \(N'\) could be much larger than \(N\), as will be seen in our experiments later. Thus, we can transfer the knowledge in large scale unlabeled conversations to the learning of a matching model. Suppose that \(s_j = (u_{j,1}, ..., u_{j,n_j})\), then the learning of HED can be formulated as maximizing the following objective:
\[
\sum_{j=1}^{N'} \sum_{i=1}^{n_j} \log [p(u_{i,j} | u_{i,1}, ..., u_{i,j-1})].
\]

\(4.2 \text{ ECMo}\)

ECMo are representations defined by the hidden states of the two-level encoder of HED. Given a word \(w_{i,k}\) in an utterance \(u_i\) in a conversation session \(s\), the sentence-level contextualized representation of \(w_{i,k}\) is defined by
\[
\text{ECMo}_{\text{local}}(w_{i,k}) = h_{i,k}
\]
where \(h_{i,k}\) is given by Equation (2). The session-level contextualized representation of \(w_{i,k}\) is defined by
\[
\text{ECMo}_{\text{global}}(w_{i,k}) = h_i^s,
\]
where \(h_i^s\) is given by Equation (5).

**4.3 Using ECMo for Matching Models**

Given a pre-trained HED and a matching model, we incorporate ECMo representations into both the input layer and the output layer of the matching model by running the encoder of the HED on a conversational context (i.e., a conversation session) and a response candidate (treated as a special conversation session with only one utterance) simultaneously. Existing matching models share a common architecture at the input layers where words are initialized with pre-trained vectors, and act in a common manner at the output layers where a context-response pair is transformed to a score, which allows us to add ECMo in a unified way.

Formally, suppose that the input of a matching model \(g(\cdot, \cdot)\) is a conversational context \(s = (u_1, ..., u_i, ..., u_n)\) with \(u_i\) the \(i\)-th utterance and a response candidate \(r\), let \(u_i = (w_{i,1}, ..., w_{i,k}, ..., w_{i,n_i})\) and \(r = (v_1, ..., v_k, ..., v_n)\), where word \(w_{i,k}\) and word \(v_k\) are initialized by pre-trained context-independent representations \(e_{i,k}^u\) and \(e_k^r\) respectively, we then form a new representation for \(w_{i,k}\) as
\[
\tilde{e}_{i,k}^u = [e_{i,k}^u; \text{ECMo}_{\text{local}}(w_{i,k})].
\]

Similarly, we form a new representation for \(v_k\) as
\[
\tilde{e}_k^r = [e_k^r; \text{ECMo}_{\text{local}}(v_k)].
\]

We then initialize the embedding of \(w_{i,k}\) and \(v_k\) at the input layer of \(g(\cdot, \cdot)\) with \(\tilde{e}_{i,k}^u\) and \(\tilde{e}_k^r\) respectively. At the output layer of \(g(\cdot, \cdot)\), in addition to \(g(s, r)\), we define a new matching score by
\[
g'(s, r) = \sigma(\tilde{e}^s \cdot W \cdot \tilde{e}^r + b),
\]
where \(\tilde{e}^s = \frac{1}{n} \sum_{i=1}^{n} \frac{1}{n_i} \sum_{k=1}^{n_i} \text{ECMo}_{\text{global}}(w_{i,k})\), \(\tilde{e}^r = \frac{1}{n_r} \sum_{v=1}^{n_r} \text{ECMo}_{\text{global}}(v_v)\), and \(W\) and \(b\) are parameters. We then re-define the matching model \(g(s, r)\) as
\[
g(s, r) = g(s, r) + g'(s, r),
\]
In learning of the matching model, one can either freeze the parameters of the pre-trained HED or continue to optimize those parameters with the cross entropy loss given by Equation (1). We empirically compare the two strategies in our experiments.

5 Experiments

We test CoVe, ELMo, and ECMo on two benchmark datasets for multi-turn response selection.

5.1 Experiment Setup

Ubuntu Dialogue Corpus: the Ubuntu Dialogue Corpus (Lowe et al., 2015) is an English dataset collected from chat logs of the Ubuntu Forum. We use the version provided by Xu et al. (2016) (i.e., Ubuntu Dialogue Corpus v1). There are 1 million context-response pairs for training, 0.5 million pairs for validation, and 0.5 million pairs for the test. In the data, responses from humans are treated as positive responses, and negative responses are randomly sampled. In the training set, the ratio of positive responses and negative responses is 1:1. In the validation set and the test set, the ratios are 1:9. Following (Lowe et al., 2015), we employ $R@k$ as evaluation metrics.

Douban Conversation Corpus: the Douban Conversation Corpus (Wu et al., 2017a) is a multi-turn Chinese conversation dataset crawled from Douban group\footnote{\url{https://www.douban.com/group}}. The dataset consists of 1 million context-response pairs for training, 50 thousand pairs for validation, and 6,670 pairs for the test. In the training set and the validation set, the last turn of each conversation is regarded as a positive response and the negative responses are randomly sampled. The ratio of positive responses and negative responses is 1:1 in training and validation. In the test set, each context has 10 response candidates retrieved from an index whose appropriateness regarding to the context is judged by human labelers. Following (Wu et al., 2017a), we employ mean average precision (MAP), mean reciprocal rank (MRR) and precision at position 1 (P@1) as evaluation metrics.

5.2 HED Pre-training

The HED models for both datasets are trained using Adam (Kingma and Ba, 2015) with a mini-batch 40. The learning rate is set as $1 \times 10^{-3}$. The size of the hidden vectors of the utterance-level RNN, the context-level RNN, and the decoder RNN are 300. Since the utterance-level RNN is bidirectional, the dimension of ECMo$_{local}$ vectors is 600, which is the same as CoVe. We set the maximum length of a session as 10 and the maximum length of an utterance as 50.

For the Ubuntu data, we crawl 10 million multi-turn conversations from Twitter, covering 2-month period from June 2016 to July 2016. As pre-processing, we remove URLs, emotions, and usernames, and transform each word to lower case. On average, each conversation has 9.2 turns. The HED model is first trained on the Twitter data, and then is fine-tuned on the training set of the Ubuntu data. By this means, we encode both the semantics in the casual conversations of Twitter and the domain knowledge in the Ubuntu dialogues. In training, we initialize word embeddings with 300-dimensional GloVe vectors (Pennington et al., 2014). The vocabulary is constructed by merging the vocabulary of the Ubuntu data (the size is 60k) and the vocabulary of the Twitter data (the size is 60k). The size of the final vocabulary is 99,394. Words that are out of the vocabulary are randomly initialized according to a zero-mean normal distribution. After the first stage of training, the HED model achieves a perplexity of 70.3 on a small validation set of the Twitter data (20k). The perplexity of the final HED model on the validation set of the Ubuntu data is 59.4.

For the Douban data, we train the HED model on a dataset published at 
\url{http://tcci.ccf.org.cn/conference/2018/dldoc/trainingdata05.zip}. The data set contains 5 million conversations crawled from Sina Weibo\footnote{www.weibo.com}. On average, each conversation has 4.1 turns. Since conversations from Weibo cover a wide range of topics which are similar to those in the Douban Conversation Corpus, we only train the HED model on the Weibo data. Word embeddings are initialized by running Word2Vec (Mikolov et al., 2013) on the Weibo data. The final model achieves a perplexity of 123.7 on the validation set of the Douban data.

5.3 Baselines

We consider the following baselines:

- **Basic models**: models including TF-IDF, RNN, CNN, dual LSTM (a.k.a., LSTM) and BiLSTM in
Table 1: Evaluation results on the two datasets. Numbers in bold mean that improvement to the original models brought by ECMo is statistically significant (t-test, p-value < 0.01). Numbers marked with ∗ mean that improvement to ELMo (fine-tune) is statistically significant. We do not include the results of CoVe and ELMo enhanced models on the Douban data because the two models are not available for Chinese data.

|                      | Ubuntu Corpus | Douban Corpus |
|----------------------|---------------|---------------|
|                      | $R_2@1$       | $R_{10}@1$    | $R_{10}@2$ | $R_{10}@5$ | MAP | MRR | P@1 |
| TF-IDF               | 0.659 | 0.410 | 0.545 | 0.708 | 0.331 | 0.359 | 0.180 |
| RNN                  | 0.768 | 0.403 | 0.547 | 0.819 | 0.370 | 0.422 | 0.208 |
| CNN                  | 0.848 | 0.549 | 0.684 | 0.896 | 0.417 | 0.440 | 0.226 |
| Multi-View           | 0.908 | 0.662 | 0.801 | 0.951 | 0.505 | 0.543 | 0.342 |
| DL2R                 | 0.899 | 0.626 | 0.783 | 0.944 | 0.488 | 0.527 | 0.330 |
| Dual LSTM            | 0.901 | 0.638 | 0.784 | 0.949 | 0.485 | 0.527 | 0.320 |
| Dual LSTM + Cove     | 0.897 | 0.639 | 0.792 | 0.943 | -     | -     | -     |
| Dual LSTM + ELMo     | 0.895 | 0.627 | 0.779 | 0.942 | -     | -     | -     |
| Dual LSTM + ELMo (fine-tune) | 0.899 | 0.643 | 0.796 | 0.945 | -     | -     | -     |
| Dual LSTM + ECMo     | 0.904 | **0.660** | **0.806** | 0.946 | **0.501** | **0.537** | **0.334** |
| SMN                  | 0.923 | 0.723 | 0.842 | 0.956 | 0.526 | 0.571 | 0.393 |
| SMN + Cove           | 0.930 | 0.738 | 0.856 | 0.963 | -     | -     | -     |
| SMN + ELMo           | 0.917 | 0.720 | 0.835 | 0.953 | -     | -     | -     |
| SMN + ELMo (fine-tune) | 0.922 | 0.724 | 0.847 | 0.957 | -     | -     | -     |
| SMN + ECMo           | 0.933 | **0.755** | **0.866** | **0.975** | **0.549** | **0.593** | **0.409** |

5.4 Evaluation Results

Table 1 reports the evaluation results on the two datasets. We can see that the performance of dual LSTM and SMN improves on most metrics after they are combined with CoVe or ECMo, indicating that contextualized vectors are useful to the multi-turn response selection task. One can expect similar improvement on other models, such as Multi-View and DL2R. ECMo brings more significant and more consistent improvement to matching models, which verifies the effectiveness of the proposed method. With ECMo, a simple dual LSTM even performs better than DL2R on both datasets and is comparable with Multi-View on the Ubuntu data, although both DL2R and Multi-View are in more complicated structures, and thus are capable of capturing more semantic information in conversational contexts.

The performance of dual LSTM and SMN consistently slightly drops with ELMo. The reason might be that the language model in ELMo is more sensitive than the sequence-to-sequence model in CoVe to the discrepancy between data. Fine-tuning the parameters of ELMo model on the Ubuntu corpus can improve the performance of dual LSTM and SMN on the task of response selection. However, its performance is still worse than the model combined with ECMo regardless whether a fine-tuned biLM is used.

5.5 Analysis

Model ablation: we investigate how different configurations of ECMo affect the performance...
Table 2: Evaluation results of model ablation.

|                | Ubuntu Corpus |                          | Douban Corpus |
|----------------|---------------|--------------------------|---------------|
|                | R@1 | R@10 @1 | R@10 @2 | R@10 @5 | MAP | MRR | P@1 |
| Dual LSTM + ECMoL | 0.899 | 0.648 | 0.796 | 0.946 | 0.491 | 0.533 | 0.322 |
| Dual LSTM + ECMoG | 0.902 | 0.658 | 0.805 | 0.945 | 0.498 | 0.540 | 0.342 |
| Dual LSTM + ECMoL (twitter) | 0.893 | 0.637 | 0.788 | 0.940 | -    | -    | -    |
| Dual LSTM + ECMoG (twitter) | 0.890 | 0.618 | 0.781 | 0.939 | -    | -    | -    |
| Dual LSTM + ECMo (twitter) | 0.889 | 0.617 | 0.778 | 0.937 | -    | -    | -    |
| SMN + ECMoL    | 0.904 | 0.660 | 0.806 | 0.946 | 0.501 | 0.537 | 0.334 |
| SMN + ECMoG    | 0.932 | 0.747 | 0.862 | 0.966 | 0.540 | 0.584 | 0.399 |
| SMN + ECMoL (twitter) | 0.929 | 0.743 | 0.859 | 0.962 | -    | -    | -    |
| SMN + ECMoG (twitter) | 0.917 | 0.718 | 0.841 | 0.951 | -    | -    | -    |
| SMN + ECMo (twitter) | 0.918 | 0.716 | 0.844 | 0.953 | -    | -    | -    |
| SMN + ECMo     | 0.933 | 0.755 | 0.866 | 0.975 | 0.549 | 0.593 | 0.409 |

Table 3: The results of the models with fixed or continue-trained ECMo representations.

|                | Ubuntu Corpus |                          | Douban Corpus |
|----------------|---------------|--------------------------|---------------|
|                | R@1 | R@10 @1 | R@10 @2 | R@10 @5 | MAP | MRR | P@1 |
| Dual LSTM + ECMo | 0.904 | 0.660 | 0.806 | 0.946 | 0.501 | 0.537 | 0.334 |
| Dual LSTM + ECMo (continue-train) | 0.906 | 0.662 | 0.808 | 0.948 | 0.515 | 0.557 | 0.357 |
| SMN + ECMo | 0.933 | 0.755 | 0.866 | 0.975 | 0.549 | 0.593 | 0.409 |
| SMN + ECMo (continue-train) | 0.935 | 0.749 | 0.866 | 0.968 | 0.544 | 0.587 | 0.406 |

Does further optimization under the matching loss help? So far, we fix the pre-trained ECMo representations in matching. Then it is interesting to know if we can obtain more improvement when we continue to train the parameters of HED under the cross entropy objective (i.e., Objective (1)) of matching. Table 3 compares the two settings where models whose ECMo is optimized under the matching objective are denoted as model+ECMo (continue-train). We find that “continue-train” can further improve the performance of dual LSTM but makes the performance of SMN drop on both datasets. This phenomenon is mainly due to the different complexity of the two models. Since SMN is far more complicated and contains more parameters than dual LSTM, it is more prone to over-fitting with the additional parameters coming from HED. On the other hand, for dual LSTM, the generalization ability of the model is limited by its structure, and thus the additional parameters may bring some benefits.

6 Conclusion

We propose pre-training a dialogue generation model from large-scale conversations with a hierarchical encoder-decoder architecture, and extracting both local and global contextualized word representations from the model to enhance matching models for multi-turn response selection. Experimental results on two benchmark datasets indicate that the proposed method can bring significant and consistent improvement to the performance of the existing matching models.
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