Sequence to Backward and Forward Sequences: A Content-Introducing Approach to Generative Short-Text Conversation

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Abstract

Using neural networks to generate replies in human-computer dialogue systems is attracting increasing attention over the past few years. However, the performance is not satisfactory: the neural network tends to generate short, safe universal replies which carry little meaning. In this paper, we propose a content-introducing approach to neural network-based generative dialogue systems. We first use pointwise mutual information (PMI) to predict a noun as a keyword, reflecting the main topic of the reply. We then propose seq2BF, a “sequence to backward and forward sequences” model, which generates a reply containing the given keyword. Experimental results show that our approach significantly outperforms traditional sequence-to-sequence models in terms of human evaluation and the entropy measure.

1 Introduction

Automatic human-computer conversation is a hot research topic in natural language processing (NLP). In past decades, researchers have developed various rule- or template-based systems, which are typically in vertical domains, e.g., transportation [Ferguson et al. 1996] and education [Graesser et al. 2005]. In the open domain, data-driven approaches play an important role, because the diversity and uncertainty make it virtually impossible to design rules for open dialogues. [Isbell et al. 2000] and Wang et al. 2013 use information retrieval methods to search for a reply from a pre-constructed databases; Ritter et al. 2011 formalize conversation as a statistical machine translation task.

Recently, the renewed prosperity of neural networks brings new opportunities to open-domain conversation [Vinyals and Le 2015; Shang et al. 2015; Serban et al. 2016a; Li et al. 2016a]. In these studies, researchers leverage sequence-to-sequence (seq2seq) models to encode a query (user-issued utterance) as vectors and to decode the vector into a reply. In both encoders and decoders, an RNN keeps one or a few hidden layers; at each time step, it reads a word and changes its state accordingly. RNNs are believed to be well capable of modeling word sequences, benefiting machine translation [Sutskever et al. 2014], abstraction summarization [Rush et al. 2015] and other tasks of natural language generation. Contrary to retrieval methods, neural network-based dialogue systems are generative in that it can synthesize new utterances: results in the literature also show the superiority of seq2seq to phrase-based machine translation for dialogue systems [Shang et al. 2015]. In our study, we focus on neural network-based generative short-text conversation, by which we mean we do not consider context information as in Wang et al. [2013] and Shang et al. [2015].

Despite these, neural networks’ performance is far from satisfactory in human-computer conversation. A notorious problem is the universal reply, that is, the RNN refers to generate short, safe sentences with little meaning, e.g., “something” [Serban et al. 2016a] and “I don’t know” [Li et al. 2016a]. One problem may lie in the objective of decoding. If we choose a reply with the maximal estimated probability (either greedily or with beam search), it is probable to obtain such universal replies, because they do appear frequently in the training set. Another potential problem is that, the query may not convey sufficient information for the reply, and thus the encoder in seq2seq is less likely to obtain an informative enough vector for decoding.

In this paper, we propose a content-introducing approach to generative short-text conversation systems, where a reply is generated in a two-step fashion: (1) First, we predict a keyword, that is, a noun reflecting the main topic of the reply. This step does not capture complicated semantic and syntactic aspects of natural language, but estimates a keyword with the highest mutual information against query words. The keyword candidates are further restricted to nouns, which are not as probable as universal words (e.g., “I” and “you”), but can introduce substantial content to reply generation. (2) We then use a modified encoder-decoder model to synthesize a sentence containing the keyword. In traditional seq2seq, the decoder predicts the reply from the first word to the last in sequence, which prevents introducing certain content (i.e., a given word) to the reply. To tackle this problem, we propose seq2BF, a novel “sequence to backward and forward sequences” model, which decodes the reply starting from a keyword and generates the remaining previous and future words subsequently. In this way, the predicted keyword can appear at an arbitrary position in the generated reply.

2 Our Approach

In this section, we present our content-introducing generative dialogue system in detail. Subsection 2.1 provides an overview. Subsection 2.2 introduces the keyword predictor, and Subsection 2.3 elaborates the proposed seq2BF model. We describe training methods in Subsection 2.4.

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2.1 Overview

Figure 1 depicts the overall architecture of our approach, which comprises two main steps:

**Step I:** We first use PMI to predict a keyword for the reply, as shown in Figure 1a.

**Step II:** After keyword prediction, we generate a reply conditioned on the keyword as well as the query. More specifically, reply generation is based on the proposed seq2BF model, which generates the backward half of the sequence (Figure 1b) and then the forward half (Figure 1c).

Notice that, the above RNNs do not share parameters (indicated by different colors) because they differ significantly from each other. Moreover, the encoder and decoder do not share parameters either, which is standard in seq2seq. For clarity, we do not assign different colors for encoders and decoders in the figure, but separate them with a long arrow in Figures 1b and 1c.

2.2 Keyword Prediction

In this step, we use pointwise mutual information (PMI) to predict a keyword for the reply. We leverage such surface statistics because this step outputs a single keyword, which does not capture complicated syntactic and semantic aspects of queries and replies. Our goal of content introducing is to suggest a word that is especially suited to the query, instead of predicting a most likely (common) word. Hence, the pointwise mutual information is an appropriate statistic for keyword prediction.

Formally, we compute PMI of a query word \( w_q \) and a reply word \( w_r \) using a large training corpus by

\[
\text{PMI}(w_q, w_r) = \log \frac{p(w_q, w_r)}{p(w_q)p(w_r)}
\]  

When predicting, we choose the keyword \( w^*_r \) with the highest PMI score against query words \( w_{q1}, \ldots, w_{qn} \), i.e., \( w^*_r = \arg\max_{w_r} \text{PMI}(w_{q1}, \ldots, w_{qn}, w_r) \), where

\[
\text{PMI}(w_{q1}, \ldots, w_{qn}, w_r) = \log \frac{p(w_{q1}, \ldots, w_{qn}, w_r)}{p(w_{q1}, \ldots, w_{qn})} = \sum_i \text{PMI}(w_{qi}, w_r)
\]  

The approximation is due to the independency assumptions of both the prior distribution \( p(w_{qi}) \) and posterior \( p(w_{qi} | w_r) \) distributions. While the two assumptions may not be true, we use them in a pragmatic way so that the word-level PMI is additive for an utterance. Experiments show that this treatment generally works well.

Compared with max a posteriori inference, PMI penalizes a common word by dividing its prior probability; hence, PMI prefers a word that is most “mutually informative” with the query. Moreover, we manually restrict classification candidates to nouns, so that we can introduce substantial content to reply generation, as will be discussed in the next part.

2.3 The seq2BF Model

To plug the predicted keyword into sequence generation, we cannot use the traditional seq2seq model. In existing approaches, when modeling the output sequence \( y = y_1y_2\cdots y_m \) given an input sequence \( x = x_1x_2\cdots x_n \), we usually decompose the probability as

\[
p(y_1, \ldots, y_m | x) = p(y_1 | x)p(y_2 | y_1, x)\cdots p(y_m | y_1 \cdots y_{m-1}, x)
\]  

\[
= \prod_{i=1}^n p(y_i | y_1 \cdots y_{i-1}, x)
\]  

and predict the output sentence in sequence from \( y_1 \) up to \( y_m \) either greedily or with beam search. I personally believe such decomposition is mainly inspired by the observation that humans always say a sentence from the beginning to the end.

However, in the content-introducing approach to generative dialogue systems, the predicted keyword could appear at the
beginning \((y_1)\), the middle \((y_2 \text{ to } y_{n-1})\), or the end \((y_n)\) of the reply. It is then natural to decompose the probability starting from the given word. In particular, the predicted keyword \(k\) splits a reply into two (sub-)sequences.

Backward sequence: \(y_{k-1}, \ldots, y_1\)
Forward sequence: \(y_{k+1}, \ldots, y_m\)

and the joint probability is

\[
p(y_{k-1}, \ldots, y_1, y_{k+1}, \ldots, y_m | y_k, x) = \prod_{i=1}^{k} p_b(y_i | y_{i-1}, y_1, x) \prod_{i=k+1}^{m} p_f(y_i | y_{i-k}, x, \cdot) \tag{6}
\]

where \(p(\cdot \mid \cdot | y_k, x)\) refers to the probability of the backward and forward subsequences given the split word \(y_k\) and its encoded query \(x\).

Notice that both the backward sequence and forward sequence generators include a wildcard allowing rich inner-sentence and/or inter-sentence dependencies. In our previous study of backward-and-forward (B/F) language modeling [Mou et al. 2015], we propose three variants: (1) \texttt{sep-B/F}: The backward and forward sequences are generated separately. (2) \texttt{syn-B/F}: The backward and forward sequences are generated synchronously using a single RNN, two output layers at each time step for both sequences. (3) \texttt{asyn-B/F}: The two sequences are generated asynchronously, that is, we first generate the backward “half” sequence, conditioned on which we then generate the forward “half.” Our previous experiments show that the asyn-B/F is the most natural way of modeling backward and forward sequences, and thus we adopt it in this model.

Specifically, our \texttt{seq2BF} model works as follows. A \texttt{seq2seq} model encodes a query and decodes a “half” reply, where words are in the reversed order (Figure 1p). Another \texttt{seq2seq} model encodes the query again, but decodes the entire reply, provided that the first half of the reply is given (Figure 1q). In both backward and forward \texttt{seq2seq} models, we use gated recurrent units (GRUs) for information processing [Cho et al. 2014], given by

\[
\begin{align*}
    r_i &= \sigma(W_r x_i + U_r h_{t-1} + b_r) \\
    z_i &= \sigma(W_z x_i + U_z h_{t-1} + b_z) \\
    \tilde{h}_i &= \tanh(W_h x_i + U_h (r \circ h_{t-1}) + b_h) \\
    h_i &= (1 - z_i) \circ h_{t-1} + z_i \circ \tilde{h}_i
\end{align*}
\]

where \(W\)’s and \(U\)’s are weights and \(b\)’s are bias terms. \(x_i\) is the word embedding; \(h_t\) is the hidden state at the time step \(t\).

### 2.4 Model Training

Training (i.e., estimating parameters) is always a most important thing in the neural network regime, and oftentimes, problems arise when we prepare the dataset.

Fortunately, the \texttt{seq2BF} can be trained without additional labels. We randomly sample a word in the reply as the split word, take the first half, and reverse its word order; in this way, we obtain the training data for the backward sequence generator. The forward sequence generator is essentially a \texttt{seq2seq} encoder and decoder from queries to replies. The difference between pure \texttt{seq2seq} and our \texttt{seq2BF} lies in the inference stage: in our approach, we ignore the query-reply \texttt{seq2seq} generator’s output at the beginning steps, but feed it with the “half” reply obtained by our backward sequence generator; then we let the \texttt{seq2seq} model generate subsequent words.

It should be emphasized that, the backward sequence generator requires “half” replies, starting from the split word, as training data, and that we cannot train the model with a full reversed sentence. Otherwise, the backward part will undesirably generate an entire reversed reply, and the forward part cannot add much to it.

### 3 Experiments

#### 3.1 Dataset

We evaluated our approach on a massive Chinese dataset of conversation data crawled from the Baidu Tiebaootnote{http://tieba.baidu.com}. We used 500,000 query-reply pairs to train the \texttt{seq2BF} model. We had another unseen 2000 and 27,871 samples for validation and testing, respectively. To obtain PMI statistics in the first step (Figure 1J) of our method, we use a much larger dataset containing 100M query-reply pairs.

Chinese is different from Latin languages in that a Chinese character carries more semantics than a Latin alphabets. For example, the characters 黑 and 板 mean “black” and “board” in English, respectively; the term 黑板 means “blackboard.” Because we have far more Chinese terms than English words, our \texttt{seq2BF} is trained in character level out of efficiency concerns. But we train the keyword predictor with noun terms, by noticing that blackboard is different from board, despite some subtle relations. Fortunately, the two granularities can be integrated together straightforwardly: during backward sequence generation, we only need to condition the model on the sequence of characters in the key term instead of a single keyword. In our study, we kept 2.5k noun terms as candidate keywords and 4k characters for \texttt{seq2BF} generation.

#### 3.2 Hyperparameters

In our study, word embeddings and recurrent layers were 500d. We used rmsprop to optimize all parameters except embeddings, with initial weight uniformly sampled from \([-0.08, 0.08]\), initial learning rate 0.002, moving average decay 0.99, and a damping term \(\epsilon = 10^{-8}\). Because word embeddings are sparse in use [Peng et al. 2015], we optimized embeddings asynchronously by stochastic gradient descent with learning rate divided by \(\sqrt{t}\). We set the batch size to 50. These values were mostly chosen by following [Karpathy et al. 2015], also used in our previous study of backward and forward language modeling [Mou et al. 2015]; they generally work well in our scenarios. We did not tune the hyperparameters in this paper, but are willing to explore their role in dialogue generation as future work.

The validation set (containing 2k query-reply samples) was used for early stop only. We chose the parameters yielding the highest character-level BLEU-2 score on our validation set.

#### 3.3 Performance

We evaluated our results in terms of the following metrics:

- **Human Evaluation**. We had three volunteers\footnote{3All volunteers are well-educated native speakers of Chinese and have received a Bachelor’s degree or above.} to annotate the results of our content-introducing \texttt{seq2BF} model and
Table 1: The performance of our content-introducing seq2BF (denoted as seq2BF+) dialogue system in comparison with pure seq2seq and seq2BF without predicted keywords (seq2BF−).

| Method    | Human | Length | Entropy |
|-----------|-------|--------|---------|
| seq2seq   | 0.58  | 5.61   | 6.96   |
| seq2BF−   | 0.46  | 5.60   | 6.97   |
| seq2BF+   | 0.67  | 5.31   | 9.13   |
| Groundtruth | –     | 9.19   | 8.83   |

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| seq2BF+   | 0.67  | 5.31   | 9.13   |
| Groundtruth | –     | 9.19   | 8.83   |

The volunteers were asked to annotate a score indicating the appropriateness of a reply to a given query: 0 = bad reply, 2 = good reply, and 1 = borderline. We did not define what is a "good" or "bad" reply. While different annotators may have different criteria of "goodness," the ranking of average scores reflects the comparison of different dialog systems. (In our study, the ranking is consistent among all three annotators.)

- **Length.** The length of an utterance is an objective, surface metric that reflects the substance of a generated reply.

- **Entropy.** Entropy is another objective metric, which shows the serendipity of a reply by measuring the amount of information contained in the utterance. We compute the averaged character-level entropy, given by

\[
\frac{1}{|R|} \sum_{w \in R} \log p(w) \tag{11}
\]

where \( R \) refers to all replies, and \( p(\cdot) \) is the unigram probability of a character in the training set.

The latter two metrics are "intrinsic," by which we mean no reference (groundtruth reply) is needed to compute the metric. They are used in Serban et al. [2016b] to ensure the quality of evaluation, we randomly sampled 100 replies in the test test for human annotation, but objective metrics were computed with all test samples.

Notice that we do not include BLEU scores as our evaluation criteria, which are used in Li et al. [2016a]. In our study, two volunteers wrote their own replies to 50+ queries. One obtained 1.69% BLEU-4 score. (The result is lower than 1.74% obtained by the other volunteer.) We do not define what is a "good" or "bad" reply. While different annotators may have different criteria of "goodness," the ranking of average scores reflects the comparison of different dialog systems. (In our study, the ranking is consistent among all three annotators.)

4 Related Work

4.1 Dialogue Systems

Automatic human-computer conversation has long attracted the attention of researchers. In early decades, people design rule- or template-based systems, but they are mainly in vertical domains (Ferguson et al., 1996; Misu and Kawahara, 2007). Although such approaches can also be extended to the open domain (Han et al., 2015), their generated sentences are subject to predefined forms and thus are highly restricted. For open dialogues, researchers have applied retrieval methods (Isbell et al., 2000; Wang et al., 2013), phrase-based machine translation (Ritter et al., 2011), and recurrent neural networks (Sordoni et al., 2015; Shang et al., 2015).

A hot research topic in human-computer conversation is mixed-initiative systems, for example, the TRAINS-95 system for route planning (Ferguson et al., 1996) and AutoTutor for learner advising (Graesser et al., 2005). In our previous work, we propose a retrieval-based proactive dialogue system that can introduce new topics when a stalemate occurs (Li et al., 2016b). The system is chatbot-like and in the open domain; an external knowledge base is used for content introducing.

5 Due to Chinese-English translation, some characteristics cannot be fully presented in the English text, e.g., the position of the given word and the length of the reply. Nevertheless, we present the predicted keyword in bold and thus the aforementioned characteristics can be visually demonstrated to some extent.
### Table 2: Examples of generated replies. Predicted keywords are in bold.

| Query | Chinese | English (translated) |
|-------|---------|---------------------|
| seq2seq | 李有男友公开过了 | It’s known that Li* has a boyfriend.* |
| seq2BF- | 我是男的 | I am a male |
| seq2BF+ | 我是你的头像 | My boyfriend |
|  | 有绯闻男友 | Has a rumored boyfriend |
| seq2seq | 人天回复飘过 | Passed second-round exam of Renming Univ. |
| seq2BF- | 这么牛，什么专业 | Cool, what’s your major |
| seq2BF+ | 分数是什么 | What is your score |
| seq2seq | 是的，谢谢 | Thank you |
| seq2BF- | 是的，谢谢 | Yes, thank you |
| seq2BF+ | 谢谢夸奖 | Thank you for praising |
| seq2seq | 我要换头像了！ | Want to change a photo |
| seq2BF- | 我要换头像了！ | What do you like... |
| seq2BF+ | 打算换成什么啊～ | I’m in your photo |
| seq2BF- | 打算换成什么啊～ | I’m in your photo |
| seq2BF+ | 第一张图像是谁 | Who is in your first photo |

5 Conclusion and Future Work

In this paper, we proposed a content-introducing approach to generative short-text conversation systems. Instead of generating a reply sequentially from the beginning word to the end as in existing approaches, we used pointwise mutual information to predict a keyword, i.e., a noun term, for the reply. Then we proposed a “sequence to backward and forward sequences” (seq2BF) model to generate a reply containing the predicted keyword. The seq2BF mechanism ensures the keyword can appear at an arbitrary position in the reply, but the generated utterance is still fluent. Experimental results show that our approach significantly outperforms the pure seq2seq model in dialogue systems in terms of human evaluation and the entropy measure.

In future work, we would like to apply different keyword prediction techniques (e.g., neural sentence models); the proposed seq2BF model can also be extended to other applications like generative question-answering.

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