Neural Contextual Conversation Learning with Labeled Question-Answering Pairs

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Abstract
Neural conversational models tend to produce generic or safe responses in different contexts, e.g., reply “Of course” to narrative statements or “I don’t know” to questions. In this paper, we propose an end-to-end approach to avoid such problem in neural generative models. Additional memory mechanisms have been introduced to standard sequence-to-sequence (seq2seq) models, so that context can be considered while generating sentences. Three seq2seq models, which memorize a fix-sized contextual vector from hidden input, hidden input/output and a gated contextual attention structure respectively, have been trained and tested on a dataset of labeled question-answering pairs in Chinese. The model with contextual attention outperforms others including the state-of-the-art seq2seq models on perplexity test. The novel contextual model generates diverse and robust responses, and is able to carry out conversations on a wide range of topics appropriately.

1 Introduction
A conversational dialogue model generates an appropriate response based on contextual information (e.g., circumstance, location, time, chatting history) and a conversational stimulus (i.e. utterance here). Many studies have attempted to create dialogue models by learning from large datasets, e.g., Twitter or movie subtitles. Data-driven approaches of statistical machine translation (Ritter et al., 2011) and neural sequence-to-sequence (seq2seq) generation (Vinyals and Le, 2015) have been adapted to generate conversational responses. Their major challenges are context-sensitivity, scalability and robustness.

The great successes of recent neural language models (Bengio et al., 2006; Schwenk, 2007; Mnih and Hinton, 2007; Le et al., 2011) inspired the studies of neural seq2seq learning. A significant work by Sutskever et al. (2014) suggests using two recurrent neural networks (RNNs) to map sequences with different lengths (Figure 1). It builds an end-to-end machine translation model from English to French without any sophisticated feature engineering, in which a model is used to encode source sentences into fixed-length vectors, and another to generate target sentences according to the vectors. Bahdanau et al. (2014) introduced an attention mechanism on a bidirectional RNN-encoder and produced the state-of-the-art machine translation results. These works provide a clear guideline for the subsequent seq2seq studies. Vinyals and Le (2015) trains an end-to-end conversational system using the same vanilla seq2seq model. It generates related responses, but they tend to be generic, e.g., “Of course” or “I don’t know”.

Recent works introduce various approaches (Serban et al., 2016; Sordoni et al., 2015; Li et al., 2015; Yao et al., 2015) to avoid such problems, and gain remarkable improvements by either encoding previous...
utterance as additional inputs or optimizing on a mutual-information function instead of cross-entropy. However, they do not specify particular memory mechanism to memorize context and do not come to any conclusion about computing efficiency of contextual information. Human conversation is smooth, because we are able to identify latent topics of chatting in different environments and thus provide adaptive responses. To simulate that, we design a conversational process that identifies the change of latent topics. We find that such additional contextual information is helpful for seq2seq model to generate domain-adaptive responses and is effective on learning long-span dependencies.

In this paper, our neural network is first trained on a community question-answering (cQA) dataset, and then is trained continuously on another conversation dataset. A convolutional neural network (CNN) has been used to extract text features and to infer latent topics of utterance. A standard long short-term memory (LSTM) architecture is applied to process the source sentence, and another contextual LSTM is used to compute the target sentence. The CNN-encoder and the RNN-encoder are both connected to the RNN-decoder. They together estimate a conditional probability distribution of output sentences, given input sentences and contextual labels. Our main contributions are: (1) We improve the conversational response generation by inventing the contextual training; (2) Our conversation learning is an end-to-end approach without feature engineering nor external knowledge; (3) We create three different mechanisms that memorizes contextual information and evaluate them.

2 Related Work

Natural language conversation has been a popular topic in the field of natural language processing. In different practical scenarios, conversations are reduced to some traditional NLP tasks, e.g., question-answering, information retrieval and dialogue management. Recently, neural network-based generative models have been applied to generate responses conversationally, since these models capture deeper semantic and contextual relevancy. With the help of user-generated contents such as Twitter and cQA websites, these conversational corpora has become good resources as large-scaled training data (Sordoni et al., 2015; Serban et al., 2016). Following this strategy, researchers have started to solve more challenging tasks, such as dynamic contexts (Sordoni et al., 2015), discourse structures with attention and intention (Yao et al., 2015), and response diversity by maximizing mutual information (Li et al., 2015).

The evaluation of conversations, i.e., to judge if a conversation is “good”, still lacks of good measurement metrics. Ideally, a good conversation should be not only coherent, but also informative. Shang et al. (2016) has proposed four criteria to judge the appropriateness of responses: Coherent, topically relevant, context-independent and non-repetitive. However, this task focuses on single-round responses; it does not consider the contexts thus is different from our goal. Moreover, it is difficult to quantify these criteria automatically with computational algorithms.

In the field of machine translation, the bilingual evaluation understudy (BLEU) algorithm has been traditionally used to evaluate the quality of translated texts. This measurement captures the language model from the word level, and achieves a high correlation with human judgments. However, in recent years, the perplexity measurement shows a better performance on judging languages in open domains (Luong et al., 2014). It is widely used to evaluate neural network-based language learning tasks. Note that the scale of perplexity scores of tasks in different languages differ greatly. For example, an RNN encoder-decoder model for English-to-French translation has a perplexity score of 45.8 (Cho et al., 2014), while an attention-free German to English translation model has a score of 12.5, and 8.3 in reverse (Luong et al., 2015). Moreover, for English to French it could be even lower at 5.8 (Sutskever et al., 2014). This is natural since the complexity of languages differ from each other. Nevertheless, the relative differences of models on the same task could still reflect the improvement. For example, Vinyals and Le (2015) has proved the effectiveness of an seq2seq recurrent model over the traditional n-gram based methods: It shows the perplexity scores of 8 and 17 for the seq2seq model, compared with 18 and 28 for the n-gram model, on a close-domain of IT helpdesk troubleshooting and an open domain of movie conversations, respectively. In our experiments (in Chinese), the absolute perplexity scores tend to be higher; but similarly, the comparison could demonstrate the effectiveness of our model with relatively lower scores.
3 Contextual Models

Our contextual seq2seq model follows the architecture of Figure 2. It takes advantage of an additional CNN-encoder that memorizes useful information from the context, thus it achieves better performance of sentence generation.

![Figure 2: The Context-LSTM models architecture.](image)

3.1 CNN Contextual Encoder

Instead of depending on external topic models (Mikolov and Zweig, 2012; Ghosh et al., 2016), we have a CNN topic inferencer to learn topic distribution from questions and their labels. We build the CNN based on a simple but effective sentence classifier by Kim (2014), and add a dynamic k-max pooling layer and choose different hyperparameters to better fit the Chinese character-level learning (Figure 3). The widths of first-layer filters are fixed to the embedding size as suggested by Kim (2014). Meanwhile, their heights are set from 1 to 4, as over 99% of the Chinese words consist of no more than four characters in the cQA dataset. The CNN firstly extracts basic word features, then computes syntactic features and infers semantic representation at the succeeding layers.

![Figure 3: Structure of the CNN contextual encoder.](image)

Instead of producing classification results, the CNN model generates a fix-sized vector representing a probability distribution in the topic space. We infer the topic vector from a concatenated utterance of historical conversation in the following equation:

\[ c_\tau = g(X_\tau \cap X_{\tau-1} \cap \ldots) \]

where \( c_\tau \) and \( X_\tau \) indicates topic representation and character sequence of utterance at round \( \tau \). In this setting, it is flexible to compute various length of context but does not increase gradient computation, in comparison to an RNN contextual encoder.

3.2 RNN Contextual Decoder

A basic RNN computes output \( y_t \) from an input \( x_t \) in sequence \( x_1, x_2, \ldots, x_T \) at time \( t \) as following:

\[ h_t = f(W_{hx}x_t + W_{hh}h_{t-1}) \]
\[ y_t = W_{yh}h_t \]

Please refer to Section 4.1 for the explanation of the labels.
We apply the encoder-decoder seq2seq approach (Sutskever et al., 2014) on conversation learning. The model estimates the conditional probability $p(y_1, \ldots, y_{T'} \mid x_1, \ldots, x_T)$ of the source sequence $(x_1, \ldots, x_T)$ and the target sequence $(y_1, \ldots, y_{T'})$. To compute this probability, the LSTM-encoder computes the fix-sized representation $v$ from the source, and then the decoder computes the target sequence by:

$$p(y_1, \ldots, y_{T'} \mid x_1, \ldots, x_T) = \prod_{t=1}^{T'} p(y_t \mid v, y_1, \ldots, y_{t-1})$$

In this paper, we add another CNN-encoder to the seq2seq architecture. The RNN decoder depends not only on an RNN-encoder but also on this CNN-encoder. As mentioned previously, the CNN produces a contextual vector $c$ from the question. Our contextual seq2seq model estimates a slightly different conditional probability:

$$p(y_1, \ldots, y_{T'} \mid x_1, \ldots, x_T) = \prod_{t=1}^{T'} p(y_t \mid v, c, y_1, \ldots, y_{t-1})$$

We build three types of contextual encoder-decoder models with different structures to memorize the contextual information. The models share a same structured CNN-encoder and RNN-encoder, but have different contextual RNN decoders.

### 3.3 Context-In Model

The idea of the first model is to let the LSTM memorize the context with language together. The LSTM uses a forget gate $f_t$ and an input gate $i_t$ to update its memory. With the contextual vectors, a contextual-LSTM (CLSTM) (Ghosh et al., 2016) is able to compute the gates with contexts, by:

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f + W_{cx}c)$$

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i + W_{cx}c)$$

$$C_t = f_t * C_{t-1} + i_t * \tanh(W_C[h_{t-1}, x_t] + b_C + W_{cx}c)$$

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o + W_{cx}c)$$

$$h_t = o_t * \tanh(C_t)$$

where $c$ is the contextual vector and $W_{cx}$ is the weight of the vector.

Hence the Context-In model is built as shown in Figure 4(a).

### 3.4 Context-IO model

Inspired by Mikolov and Zweig (2012), the decoder network observes context both at the hidden input layer and the output layer. Instead of improving a basic RNN language model (in the original paper), we apply such settings in the LSTM decoder of a standard seq2seq model to build the Context-IO model (shown in Figure 4(b)):

$$s(t) = \text{LSTM}(W_s x_{t-1} + W_{cx}c \cdot C_{t-1})$$

$$y(t) = \text{softmax}(W_s y_{t-1} + W'_{cx}c)$$
3.5 Context-Attention model

The previous models apply the context computation intuitively. An advanced strategy is to involve contextual vectors in the attention computation. The Context-Attention (Context-Attn) model applies a novel contextual attention structure shown in Figure 4c. It uses gates to update the attention inputs. Each gate is computed by the source output $h_t$ and the contextual vector $c$ by:

$$g_t = \sigma(W^c_t \cdot c + W^h_t \cdot h_t + b_c)$$

The updated source outputs are sent to a one-layer CNN to compute the attention vector. The attention vector is computed at each target input of its RNN-decoder.

4 Experiments

4.1 The Topic-Aware Dataset

In cQA websites, users post questions under specific categories. After a question is posted, other users will then answer it, just as providing appropriate responses. Considering the question category as the context, these question-answer (QA) pairs can be used as good sources of topic-aware sentences and responses. We list a few examples in Table 1.

Table 1: Examples of the cQA data.

| Category | Question-Answer Pair |
|----------|----------------------|
| Movie    | Q: 2015年有成龙的电影嘛 Are there any movies by Jackie Chan in 2015? A: 有两部,《天将雄师》,另外一部是好莱坞电影《跨境追捕》 There are two of them: Dragon Blade and the other one Skiptrace from Hollywood. |
| Sports   | Q: 麦布朗詹姆斯明年还能进决赛吗 Will LeBron James be in the NBA final next year? A: 不好说，得看乐福和欧文能否康复 It depends on the recovery of Love and Kyrie Irving. |
| Science  | Q: 天空为什么是蓝色的 Why is the sky blue? A: 阳光被空气分子散射了，蓝色的光波长较短，更容易被散射，而红色的光波长较长，不太容易被散射。 A clear cloudless sky appears to be blue, because the air molecules scatter blue light from the sun more than red light. |

We have collected over 200 million QA pairs from two biggest commercial cQA websites in China: Baidu Zhidao and Sogou Wenwen\(^2\). In these websites, the categories are organized in a hierarchical structure; users may choose a category in any level. To reduce the errors introduced by users, we manually select 40 categories according to three aspects: popularity, overlapping with other categories, and ambiguity of the category definition. For example, the categories literature, music, movie, and medical are selected, but the categories entertainment, dating, and neurology are not selected. We have also merged the category trees from different websites before the selection.

Some of the questions do not have good answers for whatever reasons. Otherwise, at least one of the answers is marked as the best answer by human. This mark is a good indicator of the quality of questions and answers. Therefore, we select QA pairs that have at least one best answer within the 40 categories, resulting in ten million in total.

4.2 Conversational Dataset

The conversation dataset is acquired from two popular forum websites: Baidu Tieba and Douban\(^3\). We have collected approx. 100 million open-domain posts with comments. The data is then cleaned and organized to sets of independent dialogues, in which each dialogue contains multiple turns of chats between two people alternately (Table 2). For training, each adjacent chat – a pair of sentences – is treated as the source and target utterance, while the sentences before them are used to infer contextual topics.

\(^2\)Baidu Zhidao: http://zhidao.baidu.com/, Sogou Wenwen: http://wenwen.sogou.com/

\(^3\)Baidu Tieba: https://tieba.baidu.com/, Douban: https://www.douban.com/
Table 2: Examples of the conversation data.

| Role | Utterance |
|------|-----------|
| Alice | 我真的很想要一个数学大师带领我前进。 |
| Bob   | 他们可能正在遭受各种考试的折磨... |
| Alice | 不一定哦 // 也许人家是天才 |
| Bob   | 为了理想的职业只能奋斗啊... But they have to work hard for their dreams too. |

4.3 Experiment Settings and Results

Our proposed contextual models rely on a CNN-encoder, pre-trained on questions and their category labels. Given an utterance as the input, the CNN-encoder turns it into a topic vector of size 40. To prove its efficiency, cross validations of label classification is conducted on the Chinese dataset. The model of Kim (2014) produces an accuracy of 75.8% trained on the same dataset, by contrast, 77.2% is reported by our CNN model. In our experiments, the topic vectors with a fixed size are computed on the previous utterance and the current utterance. It is used as the contextual information in the succeeding experiments.

We evaluate two types of the encoder-decoder networks, two baseline models, and three contextual models. The baseline models include Sutskever et al. (2014) and Bahdanau et al. (2014), using the same settings in the original papers. They all have the same RNN-encoder, implemented with a 3-layer LSTM, sized 1,000. The dropout technique is applied in each LSTM cell and output layers. All these models are trained on the cQA dataset and then on the conversation dataset. For the contextual models, contextual vectors are computed by current questions when training on the cQA dataset and computed by concatenated utterances of previous and current chats while training on the conversation dataset. We apply the Adam optimizer (Kingma and Ba, 2014) on training with GPU accelerators. For testing, we randomly select 2,000 pairs of utterances from both datasets, exclusively from the training set.

Table 3: Perplexities of models on sentences of different lengths.

| Models                  | Short Sentences (length < 20) | Long Sentences (length > 30) |
|-------------------------|-------------------------------|------------------------------|
| Sutskever et al. (2014) | 15.50                         | 33.46                        |
| Bahdanau et al. (2014)  | 14.10                         | 28.12                        |
| Context-In              | 14.20                         | 30.50                        |
| Context-IO              | 14.10                         | 29.50                        |
| Context-Attn            | 13.75                         | 27.00                        |

In these experiments, we learn conversation on the character level too. The performances are evaluated by perplexity. However, the perplexity differ greatly between short sentences and long sentences, hence we divide them into two groups for a clearer comparison. Generally, shorter sentences generated by the models are better – with smaller perplexity – than longer sentences. It is most likely that the gradients are vanishing in long recursions, though LSTM is already applied.

From Table 3 we see that the Context-Attn model achieves overall the best perplexity. It works surprisingly well for the conversation learning task, since the additional memory structure creates local connections from each source LSTM to each target LSTM. The attention mechanism is an independent process from RNN, thus it reduce the long-span learning problem by establishing direct dependencies. Models with context settings achieve smaller perplexity scores than the vanilla LSTM model (Sutskever et al., 2014), since the additional memory of context is static. While decoding target sequences, it helps to further avoid the gradient vanishing problem by feeding the additional information to decoder RNN at each time. It explains why combining attention and context in Context-Attn gains better performance.

However, perplexity only indicates how well a model predicts a target sequence. Low perplexity does not imply good quality of generating conversation or answering questions. Therefore, we apply beam search to sample the most likely sequences on the RNN-decoder. Based on human evaluations, we find that the
Context-Attn model performs slightly better than others and it is able to overcome the generic-generating problem. The following examples demonstrate the conversation quality of Context-Attn:

**Chatting (Sports)**

| Human | Machine | Context-Attn |
|-------|---------|--------------|
| 我喜欢体育运动吗 | Do you like sports? | Yes, I like fitness. |
| 平常都去哪家健身房 | Where do you workout usually? | I'd like to go to Haosha Fitness. |
| 我不太喜欢健身，太累了。你喜欢篮球吗 | I don’t really like workout, it’s too heavy. Do you like basketball? | I like basketball. |
| 你觉得库里和詹姆斯谁能夺得总冠军 | Who do you think will win the final champion, Curry or James? | I believe James will win. |

**Chatting (Movie)**

| Human | Machine | Context-Attn |
|-------|---------|--------------|
| 最近上映了好多电影 | Many movies are released recently. | |
| 什么电影 | What movies? | |
| 儿童片空间蛮不错的 | Inception is pretty impressive. | |
| 当然好看了 | Of course, it is good. | |
| 你最喜欢哪部电影 | Which movie do you like best? | |
| 我最喜欢白蛇传 | I love Legend of the White Snake. | |
| 白蛇传是谁演的 | Who was in the movie? | |
| 霍建华演的* | Wallace Huo played. | |
| 为什么许仙不能和白素贞在一起 | Why couldn’t Xu Xian and Bai Suzhen be together? | |
| 因为许仙也是女人* | Because Xu Xian was a woman too. | |
| 好吧，你赢了 | OK, you win. | |
| 哈哈 | Haha! | |

**Question Answering**

| Human | Machine | Context-Attn |
|-------|---------|--------------|
| 美国总统是谁 | Who is the president of the United States? | |
| 奥巴马 | Obama. | |
| 中国有多少人口 | How many people live in China? | |
| 14亿多 | About 1.4 billion. | |
| 世界最高峰在哪里 | Where is the highest mountain in the world? | |
| 珠穆朗玛峰 | The peak of Mount Everest. | |
| 谁发明了电灯 | Who invented the light bulb? | |
| 爱迪生发明了电灯 | Edison invented the light bulb. | |
| 法国工业革命什么时候 | When did the industrial revolution take place in France? | |
| 文艺复兴时期* | It was during the Renaissance period. | |
| 中国的国歌是什么 | What is the Chinese national anthem? | |
| 国歌是义勇军进行曲 | The national anthem is March of the Volunteers. | |

These examples illustrate that our proposed model generates reasonable responses with domain-specific vocabulary, while avoid safe but general answers to some extent. Even for the task of question answering, it shows the capability of providing (mostly) correct answers. The reason is that the contextual attention structure memorizes important (or frequent) information, which is usually the answer to the question. In some cases (marked with * in the examples), the answers are incorrect. For example, Wallace Huo has played in neither movies nor TV series on the Legend of the White Snake; Xu Xian was actually a man (although in a TV show he was played by an actress); and the industrial revolution in France took place more than 300 years after the Renaissance. It indicates the memory itself works differently from a real question-answering mechanism.

To further demonstrate the efficiency of our contextual settings, we visualize the weights in original soft attention and our contextual gated attention in Table 4. For the background of the sentence, darker color represents larger value of weights. Sentences are translated to English literally to show the correspondence of words. The Context-Attn model estimates a conditional probability distribution of responses given source sentences and context vectors. The additional gates in the contextual attention automatically determine which to augment and which to eliminate by computing contextual information. Therefore, context is able to manipulate the generation process of the characters in the LSTM model. That explains why Titanic and James have higher weights. The contextual attention helps generate domain-adaptive sentences. It is also considered to be flexible and efficient, since such a gated attention works similarly to a standard soft attention and is able to simulate a hard attention in extreme case at the same time.
Table 4: Visualization of weights in the soft attention and contextual attention.

| Context | Question | Answer |
|---------|----------|--------|
| Movie   | Titanic is by whom performed | 有很很多(There are many many actors.) |
|         | 铁达尼号是由谁主演的 | 萊昂納多．迪卡普里奧(Léonard DiCaprio.) |
| Sports  | Curry and James, who is the MVP | 那要看情况(It depends.) |
|         | 库里和詹姆斯谁是MVP | 答案是詹姆斯(The answer is James.) |

4.4 Robust Chatting

While we were talking about the four criteria of Shang et al. (2016) of coherency, relevancy, context-independence and non-repetitiveness for judging a good conversation, at the end of this article, we wish to mention another important dimension of conversation: robustness. No matter how well we can chat, if the chatting works only along a very narrow pathway, and the chatbot does not tolerate any variations, the user experience would be very bad. This problem has been troubling template-based chatting systems for being too restrictive, and keyword-based systems for having too many false positives.

Our Context-Attn model solves this problem as a side product wonderfully, as the following off-hand random experiment reveals. Italic words denote some noises in the sentences.

| Human | 我渴了怎么办 | I am thirsty, what do I do? |
|-------|-------------|--------------------------|
| Machine | 喝水 | Drink water. |
|       | (1) 我有点渴了怎么办 | I am a bit thirsty, what do I do? |
|       | (2) 我x有点渴了怎么办 | I x a bit thirsty, what do I do? |
| Human | 我中国有点渴了怎么办 | I China a bit thirsty, what do I do? |
|       | (4) 我来中国有点渴了怎么办 | I come a bit thirsty, what do I do? |
| Machine | 多喝水 | Drink more water. |
| Human | 我北京有点渴了怎么办中国 | I Beijing a bit thirsty, what do I do China? |
| Machine | 喝王老吉 | Drink Wong Lo Kat (a popular Chinese herbal tea drink). |
| Human | 蝴蝶我北京有点渴了怎么办中国 | butterfly I Beijing a bit thirsty, what do I do China? |
| Machine | 喝点水 | Drink a bit water. |
| Human | 蝴蝶我北京有点渴了怎么办中国 | butterfly I Beijing a bit thirsty, what do I do China? |
| Machine | 吃东西 | Eat something. |
| Human | 蝴蝶在北京有没有怎么办国 | butterfly in Beijing are there any what do I do China? |
| Machine | 有啊，在北京 | Yes there are (butterflies), in Beijing. |

5 Conclusion

In this paper, we target on domain-adaptive and robust conversation generation by end-to-end learning without any feature-engineering. We have introduced a CNN-encoder to infer latent topics of source sentences to seq2seq models and created various external memory structure for considering contexts; the gated attention mechanism is the most efficient mechanism to capture the contextual information, reflected in the generated responses. The Context-Attn model also outperforms traditional seq2seq models on perplexity tests. The experiments reveal that training on the QA dataset helps conversation generation from two aspects: 1) Gain context-awareness from the question-label learning; 2) Gain additional robustness from the question-answer learning. Our proposed model is demonstrated to generate interesting and context-sensitive responses from variations of source sentences. Our future works will be further improving the robustness and consistency.

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