THINK: A Novel Conversation Model for Generating Grammatically Correct and Coherent Responses

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Abstract

Many existing conversation models that are based on the encoder-decoder framework have focused on ways to make the encoder more complicated to enrich the context vectors so as to increase the diversity and informativeness of generated responses. However, these approaches face two problems. First, the decoder is too simple to effectively utilize the previously generated information and tends to generate duplicated and self-contradicting responses. Second, the complex encoder tends to generate diverse but incoherent responses because the complex context vectors may deviate from the original semantics of context. In this work, we proposed a conversation model named “THINK” (Teamwork generation Hover around Impressive Noticeable Keywords) to make the decoder more complicated and avoid generating duplicated and self-contradicting responses. The model simplifies the context vectors and increases the coherence of generated responses in a reasonable way. For this model, we propose Teamwork generation framework and Semantics Extractor. Compared with other baselines, both automatic and human evaluation showed the advantages of our model.

1 Introduction

Open-domain dialogue generation is a challenging task of natural language processing (NLP). Early chatbots tend to generate generic and dull responses. During the past few years, many neural conversation models have been proposed that leverage the power of the encoder-decoder architecture (Shang et al., 2015; Sordoni et al., 2015). These models generate diverse responses with reduced blandness and dullness through more complex context vectors (Bahdanau et al., 2015; Luong et al., 2015; Vaswani et al., 2017; Tao et al., 2018; Li et al., 2016b; Ghazvininejad et al., 2018; Huber et al., 2018; Bowman et al., 2016; Zhao et al., 2017). However, these work still face problems.

First, despite the added complexity to the context vectors, existing encoder-decoder approaches still employ relatively simpler decoders, e.g., long-short term memory (LSTM) (Hochreiter and Schmidhuber, 1997), gated recurrent unit (GRU) (Cho et al., 2014), and transformer decoder. Many studies and empirical evidences (Bahdanau et al., 2015; Vaswani et al., 2017; Tao et al., 2018; Zhao et al., 2017) have shown that these decoders tend to generate duplicated and self-contradicting responses (see Table 1). As shown in Figure 1, in the decoding process of the encoder-decoder framework, the previously generated tokens \(y_1, y_2, \ldots, y_{i-2}\)
are indirectly used to generate $y_i$. For LSTM or GRU decoder, the indirect input information has to pass through the “gate”, which makes it easy to be changed or be forgot. For the transformer decoder, the indirect input information will be reconstructed through the self-attention mechanism (Vaswani et al., 2017). Since the attention mechanism selects information generally through the inner product, some important information will be ignored during the computation.

Second, high complexity of the context vectors often negatively impact the coherence of the generated responses. Past encoder-decoder approaches often focus on making the context vectors more complicated with external messages (Li et al., 2016b; Huber et al., 2018; Ghazvininejad et al., 2018) or latent variables (Bowman et al., 2016; Zhao et al., 2017; Gao et al., 2019). However, the single-turn dialogue datasets hardly contain an external message, resulting in the latent variables easily producing incoherent responses. For instance, when given the post Everything about this movie is awesome! as context, the CVAE model generated Caves would never say yes, but I’d love to know. (Gao et al., 2019).

Thus, the simplicity of the decoder coupled with the high complexity of the context vectors often lead to grammatically-incorrect and incoherent generate responses. To address this problem, we propose Teamwork Generation framework (TG), and Semantics Extractor (SE). TG makes the decoding process more complex by directly and explicitly utilizing the previous generated tokens during the generating process. This would effectively mitigate the problem of the generated responses being duplicated and self-contradicting. Inspired by the divide-and-conquer strategy and Map-Reduce framework, TG divides the task of generating one response into the task of generating $N$ tokens (see Section 2.2 for details).

SE is used to simplify the context vectors. Examining the phenomena as shown in Figure 2 and sentence classification task (Kim, 2014; Kalchbrenner et al., 2014; Yu and Koltun, 2016), we find that keywords are more important than other word for understanding sentence semantics. Therefore, we propose SE to extract the possible keyword-combinations that are semantically-linked with possible responses (see Section 2.4 for details), which could effectively increase the coherence between responses and contexts.

In this work, we focus on the single-turn dialogue generation task, i.e., giving a post (context) and generating a response, and proposed a novel conversation model based on the proposed Teamwork generation framework and Semantics Extractor. We named it Teamwork generation Hover around Impressive Noticeable Keywords (THINK). The model is significantly different from existing conversation models. Our contributions are summarized as follows: (1) We propose a new End-to-End framework (named Teamwork generation) to ensure that all previous generated tokens can be directly utilized during generating process, which can effectively address the duplicate and self-contradicting responses. (2) We propose a Semantics Extractor that is based on the deformable convolution idea to extract semantic features, which is helpful to generate coherent responses. This is the first study to our knowledge of the utilization of deformable convolution idea in dialog generation task. (3) We perform detailed experiments to verify the ability of THINK on generating grammatically-correct and coherent responses.

## 2 Model

### 2.1 Overview

Figure 3 illustrates the framework of the THINK model. TG works by saving all previous generated tokens and directly utilizing them, which could effectively address the problem with responses being duplicated and self-contradicting. SE extracts impressive and noticeable keywords instead of complex context vectors, which is helpful to increase coherence of the generated responses.

### 2.2 Teamwork generation framework

A dialogue generation model using the encoder-decoder framework generates duplicated and self-contradicting responses as the decoder forgets the previously generated tokens. Therefore, to mitigate this problem, we proposed the TG framework.

![Figure 2: Conversation samples that various responses consider different keyword-combination](image)
The TG framework consists of two components: a Generator pool and a Control center, which are shown in Figure 3(a). The Generator pool contains $N$ generators and force each generator to only generate one token. The Control center is responsible for managing the inputs and outputs of all generators. First, the Control center gives each generator a sequence number and requires the $i$th generator to generate the $i$th token of a response. In addition, the Control center also saves all generated tokens, and put the 1st, 2nd, \ldots, $(i-1)$th generated tokens as input of the $i$th generator. The steps of TG is shown in (1).

\begin{align}
\text{response} &= \text{Concatenate}(t_1, t_2, \ldots, t_N) \quad (1) \\
t_i &= \text{idx2word}(\arg \max (\text{generator}_i(\text{X}_i))) \\
\text{X}_i &= \text{Embed}(\text{Concatenate}(C, t_1, t_2, \ldots, t_{i-1})),
\end{align}

where response is the generated response of the original context $C$, $t_i$ denotes the $i$th token of the response, generator$_i$ denotes the $i$th generator that is responsible for generating $t_i$. The function idx2word is used to convert the probability into token, and $\text{X}_i$ represents the embedding result of the $i$th context. When $C$ is input, the generator$_1$ will generate $t_1$. Control center then combines $t_1$ with $C$ as the 2nd context and inputs it to generator$_2$ to obtain $t_2$. This is repeated until the last generator produces $t_N$ after which the controller concatenates all tokens as a response.

**2.3 Generator**

We employ $SE$ and a Multilayer Perceptron (MLP) as the generator, which is shown in Figure 3(b). $SE$ first extracts the semantics features $f_{\text{se}}$ from the input sentence embedding $X$, and then the MLP utilizes $f_{\text{se}}$ to compute the probability of output tokens $p_t$, which is shown in (2).

\[ p_t = \text{MLP}(f_{\text{se}}), \text{where } f_{\text{se}} = SE(X) \quad (2) \]

**2.4 Semantics extractor**

Convolutional neural network (CNN) is popular for extracting the semantic features in sentence classification tasks (Kim, 2014; Kalchbrenner et al., 2014; Yu and Koltun, 2016; Kaiser et al., 2018). Therefore, we propose Semantics Extractor ($SE$) which extracts relevant semantic information from context sentence using CNN. Due to inability to capture long-distance dependent features, the standard CNN will cause certain problems when it is directly applied to NLP tasks. Existing methods mainly apply two strategies to mitigate this problem with CNN: the first is to increase the depth of the CNN model, and the other is to change the convolution kernel (e.g., Dilated Convolution).

To extract long-distance dependent features, we propose multi-head discretely-deformable convolution as $SE$, which is inspired from the deformable convolution (Dai et al., 2017), gumbel softmax (Jang et al., 2017) and multi-head strategy (Tao...
The workflow is shown as (3).
\[
f_{\text{f}} = \text{Concatenate}(f_{f_1}^{\text{final}}, f_{f_2}^{\text{final}}, \ldots, f_{f^{\text{head}}})
\]
\[
f_{f_1}^{\text{final}} = \text{Flatten}(\text{DiscretelyDC}_i(X_i, K_{f_1}^{\text{final}}))
\]
and \(K_{f_1}^{\text{final}} = (k, m, 1, p)\).

where \(\text{DiscretelyDC}\) denotes the proposed \textit{discretely-deformable convolution} and \(K_{f_1}^{\text{final}}\) denotes its parameters. Two hyper-parameters \textit{head} and \(p\) for adjusting the effect of the results: \textit{head} is the number of \(\text{DiscretelyDC}\), and \(p\) is the channel of the final convolution operation.

### 2.4.1 Discretely-deformable convolution

The original deformable convolution trains an offset to make the convolution kernel shift to the middle position of the sentence embedding matrix, and it introduces too much unreasonable features and semantic errors for dialogue generation task. Therefore we modify the original definition and propose \textit{discretely-deformable convolution} (\textit{DiscretelyDC}) which is more suitable for handling sentences. \textit{DiscretelyDC} trains a translation matrix, which makes sure that the deformable process only focuses on the relationship between words rather than the dimensions of the vector, to replace the offsets and linear interpolation. Figure 3(c) shows the implementation of \textit{DiscretelyDC}.

For a given sentence embedding matrix \(X_{n \times m}\) (where \(n\) represents the actual number of tokens and \(m\) represents the dimension of word embedding), we first perform a convolution operation with \(K (k, m, 1, n)\), where \(k\) is an adjustable parameter indicating the receptive field size. The \textit{stride} size of convolution is set as 1.

\[
f = \text{Conv}(X, K, \text{stride})
\]

We then transpose \(f\) to form a matrix \(M_f^T\), and construct a trainable variable \(W\).

\[
P_{n \times n} = \text{SoftMax}(M_f^T \ast W)
\]

A probability matrix \(P_{n \times n}\) is obtained and \(p_{ij} \in P_{n \times n}\) denotes the probability that the token at position \(j\) will shift to position \(i\). Then, we use \textit{gumbel softmax} to implement the discretization process.

\[
P_{n \times n}^h = \text{discrete_process}(P_{n \times n})
\]

Since we focus on the extreme situations, it can be simple as \(P_{n \times n}^h = \text{stop_graidnet}(P_{n \times n}^{\arg \max} - P_{n \times n}) + P_{n \times n}\), where \(P_{n \times n}^{\arg \max}\) is the results after argmax process. The elements of \(P_{n \times n}^h\) are 0 or 1. Then, we get the new \(X_{\text{deform}}\):

\[
X_{\text{deform}} = P_{n \times n}^h \ast X
\]

Finally, after the last convolution operation with \(K_{f_1}^{\text{final}} = (k, m, 1, p)\), we get the final feature:

\[
f_{f_1}^{\text{final}} = \text{Conv}(X_{\text{deform}}, K_{f_1}^{\text{final}}, \text{stride})
\]

### 2.5 Training step

During training, we use the TeacherForcing (Williams and Zipser, 1989) method with the loss function shown in (9):

\[
\text{loss} = \text{CrossEntropy}(\text{logits}, R)
\]

\[
\text{logits} = \text{Concatenate}(\text{logit}_1, \text{logit}_2, \ldots, \text{logit}_{r \cdot \text{len}})
\]

\[
\text{logit}_i = p_{i}^{q_i} = \text{generator}_i(X_i)
\]

\[
X_i = \text{Slice}(X_{UE}, i + c_{\text{len}} - 1)
\]

\[
X_{UE} = \text{Embed}(\text{Concatenate}(C, R))
\]

where \(R\) is true response, \(C\) is the context sentence, \(c_{\text{len}}\) and \(r_{\text{len}}\) means the length of \(C\) and \(R\) respectively. For improving the training speed and preventing overfitting, we employ L2 regularization and label smoothing (Szegedy et al., 2016).

### 3 Experiments

#### 3.1 Dataset

We use two public dialogue datasets in our experiments and modify them as single-turn dialog data. The first dataset, named DailyDialog (Li et al., 2017b), consists of dialogues that reflect human daily communication patterns and cover various topics about our daily life. After processing, the training, validation and testing sets contain 76,052, 7,069 and 6,740 pairs, respectively. For improving the training speed and preventing overfitting, we employ L2 regularization and label smoothing (Szegedy et al., 2016).

#### 3.2 Evaluation metrics

For auto-evaluation metrics, we choose the \textit{distinct-\textit{n}} (Li et al., 2016a) and \textit{coherence} (Xu et al., 2018). However, these metrics are not perfect. Since \textit{distinct-\textit{n}} only focuses on the quantity of distinct \(n\)-grams and overlooks the quality of \(n\)-grams, even the random generated response gets a high \textit{distinct-\textit{n}} value (Gao et al., 2019), which couldn’t evaluate the duplicate and self-contradict
responses. Meanwhile, the coherence only focus on the sentence embedding level, which is not comprehensive enough. Therefore, based on these metrics, we propose two better metrics: the q_phrase-n to evaluate the quality of responses on phrases level, and the mix_coh to evaluate the coherence of responses. (see follow subsections for details)

For human evaluation, 200 randomly sampled contexts and their generated responses are given to three crowd workers, who are required to give the comparison results (e.g. win, loss or tie) between our model and baselines based on quality. The quality means that the response is syntactically correct and has a good correlation to its context.

3.2.1 q_phrase
Different from distinct, we propose the q_phrase-n which is calculated through (10).

\[ q_{\text{phrase}}(n) = \frac{\text{effective}(ngrams)}{\text{total\_occur}(ngrams)} \]  

(10)

The effective(ngrams) is an intersection of unique(ngrams) and vocab(ngrams), where unique(ngrams) is a set of unique n-grams and vocab(ngrams) is a set that represents the n-grams vocabulary extracted from the real data. We suppose that vocab(ngrams) hardly includes duplicate and self-contradict n-grams, so the effective(ngrams) only contains n-grams without grammatical errors. For example, the distinct-3 of (“I am fine”, “I are you”, “are are”) is 1, while q_phrase-3 is 0.2. Since only “I am fine” is a grammatically correct phrase, the q_phrase-3 is more reasonable.

3.2.2 mix_coh
The mix_coh consists of three levels: word level, word embedding level, and sentence embedding level. For word level, we choose BLEU and take the average value of BLEU-{1,2,3} as the avg(B). Besides, we employ the embedding-based metrics to reflect the correlation of word embedding level. Using the average value of embedding-{greedy, average, extrema} as the avg(E). As for sentence embedding level, we adopt the coherence.

\[ \text{mix}_i \text{coh} = B \text{score}_i + E \text{score}_i + C \text{score}_i \]

\[ B \text{score}_i = \frac{\text{avg}(B_i)}{\sum_{i \in M} \text{avg}(B_i)} \]

\[ E \text{score}_i = \frac{\text{avg}(E_i)}{\sum_{i \in M} \text{avg}(E_i)} \]

\[ C \text{score}_i = \frac{\text{Coherence}_i}{\sum_{i \in M} \text{Coherence}_i} \]

(11)

In (11), \( M \) is a set of models in this paper. \( mix_{coh} \) represents the \( mix_{coh} \) of model_i.

3.3 Training details
We set the vocabulary size to 23,000 and 32,000 for DailyDialog and CornellMovie, respectively. For a fair comparison among all models, we employ 256-dimensional word embeddings. The numbers of hidden nodes are all set as 256, and batch sizes are set as 64. The c_len and the r_len are all set as 25. The head is set as 6 and p is set as 8. Adam is utilized for optimization. The init_lr is set to be 0.001, and \( w \text{\_step} \) is set as 4000. We run all models on a Titan RTX GPU card with Tensorflow. We train all models in 100 epochs. And we use greedy search to generate responses for evaluating.

3.4 Baseline models
We compare the proposed model with the following baseline models: Seq2Seq with attention (Babdanau et al., 2015), CVAE (Zhao et al., 2017), Transformer (TransFM) (Vaswani et al., 2017) and CMHAM (Tao et al., 2018).

4 Results and Analysis
4.1 Results of conversation models
4.1.1 Auto-evaluation metrics
Table 2 shows the results of auto-evaluating metrics. We can see that on the q_phrase-3,5 metric, our THINK almost achieved the best results on both two datasets. This result demonstrates that our THINK generates the most diverse and meaningful 3,4,5-grams (phrases).

Meanwhile, the THINK has the best performance on both mix_coh and coherence metrics for two datasets, which means THINK tends to better understand the context and generate the coherent response. For the details of avg(B) (word level), avg(E) (word embedding level) and coherence (sentence embedding level), the THINK also get a good performance in virtually all cases.

We also tested the impact of head and p on distinct-n, and found that head increases the number of keywords that the model pays attention to and p appear to improve the ability of understanding the keywords.

4.1.2 Human evaluation analysis
We use human evaluation to further evaluate our model and baseline models. The results of human evaluation are shown in Table 3. In this table, the
| Model   | q_phrase-3 | q_phrase-4 | q_phrase-5 | avg(B) | avg(E) | coherence | mix_coh |
|---------|------------|------------|------------|--------|--------|-----------|---------|
| Seq2Seq | 0.1554     | 0.1538     | 0.1170     | 0.2267 | 0.4744 | 0.4885    | 0.5781  |
| CVAE    | 0.2453     | 0.1513     | 0.0985     | 0.2536 | 0.4734 | 0.5116    | 0.6082  |
| TransFM | 0.2946     | 0.2349     | 0.1542     | 0.2532 | 0.4533 | 0.4855    | 0.5888  |
| CMHAM   | 0.3053     | 0.2739     | 0.1996     | 0.2684 | 0.4560 | 0.4917    | 0.6044  |
| THINK   | 0.3620     | 0.3326     | 0.2662     | 0.2680 | 0.4757 | 0.5117    | 0.6205  |
| Seq2Seq | 0.1083     | 0.1055     | 0.0770     | 0.2405 | 0.4599 | 0.4891    | 0.5854  |
| CVAE    | 0.1766     | 0.0744     | 0.0234     | 0.2530 | 0.4503 | 0.4903    | 0.5913  |
| TransFM | 0.2533     | 0.1953     | 0.1043     | 0.2624 | 0.4494 | 0.4961    | 0.6006  |
| CMHAM   | 0.2245     | 0.1946     | 0.1293     | 0.2657 | 0.4540 | 0.4966    | 0.6053  |
| THINK   | 0.2731     | 0.2140     | 0.1112     | 0.2668 | 0.4652 | 0.5126    | 0.6175  |

Table 2: Results of automatic evaluation metrics on DailyDialog dataset and CornellMovie dataset.

| Model   | our model vs(%) | kappa |
|---------|------------------|-------|
|         | win              | loss  | tie   |
| Seq2Seq | 24.00            | 10.50 | 65.50 | 0.427 |
| CVAE    | 28.67            | 2.33  | 69.00 | 0.436 |
| TransFM | 26.83            | 4.34  | 68.83 | 0.476 |
| CMHAM   | 26.17            | 5.83  | 68.00 | 0.455 |
| Seq2Seq | 26.83            | 8.17  | 65.00 | 0.475 |
| CVAE    | 27.17            | 4.00  | 68.83 | 0.485 |
| TransFM | 25.33            | 5.17  | 69.50 | 0.483 |
| CMHAM   | 23.83            | 7.33  | 68.83 | 0.491 |

Table 3: The human evaluation results on DailyDialog dataset (up) and CornellMovie dataset (down).

The number under label **win** means that the percentage of sample responses generated by our model is better than that of the baseline model. From Table 3, we can see that the percentage of the **win** is always larger than that of the **loss**, which demonstrates that our **THINK** significantly outperforms baselines. The **kappa** denotes the Kappa coefficient (Fleiss, 1971), used for consistency check of different annotators. The possible results of **kappa** are between -1 and 1, which demonstrates that the consistency degree is moderate.

### 4.1.3 Dialog sample analysis

Table 4 shows several examples of conversations, which illustrates that the response generated by our model has a higher quality. The first example demonstrates the ability of semantics-understanding of **THINK**. Observing the responses of each model, only “sorry” generated by Seq2Seq can have a relationship with context, but the generated text is extremely poor. Our proposed **THINK** can better understand the semantics of context through keywords and gives a more relevant and better response. The second example shows the advantages of **THINK** over other models. We can see that the **THINK** model can extract core semantic features from context sentence. Meanwhile, the **TG** framework makes sure that the generated response will be non-repeated and consistent through the constrict of previous generated information.

| Context:  | there are cockroaches in my room . |
|-----------|-----------------------------------|
| Seq2Seq:  | sorry, sir, sir, sir, sir, sir, sir, sir, sir, sir, sir, sir, sir, sir, sir |
|          | CVAE: you sure, sir, but, ’m n’t your but you have |
| TransFM:  | there are many cities. |
| CMHAM:    | why are you going to tell her that he is too late. |

**THINK:** what’s the big deal ?

| Context:  | are you a goal-oriented person ? |
|-----------|---------------------------------|
| Seq2Seq:  | no, i don’t. i don’t know what i do. |
|          | CVAE: , i am. that’ve make an collect. no ... |
| TransFM:  | yes, i do. i was thinking of the whole day, yes. |
| CMHAM:    | yes, it’s all. |

**THINK:** yes, i am. that’s why i make plans before i do anything.

Table 4: The responses produced by the proposed models and comparison models.
Table 5: Results of q_phrase-n on DailyDialog dataset (left) and CornellMovie dataset (right).

| Model     | q_phrase-3 | q_phrase-4 | q_phrase-5 | q_phrase-3 | q_phrase-4 | q_phrase-5 |
|-----------|------------|------------|------------|------------|------------|------------|
| Seq2Seq   | 0.1554     | 0.1538     | 0.1170     | 0.1083     | 0.1055     | 0.0770     |
| -w. TG    | 0.4069     | 0.4082     | 0.3543     | 0.2730     | 0.2477     | 0.1623     |
| CVAE      | 0.2453     | 0.1513     | 0.0985     | 0.1766     | 0.0744     | 0.0234     |
| -w. TG    | 0.2629     | 0.1979     | 0.1191     | 0.1857     | 0.1474     | 0.0753     |
| TransFM   | 0.2946     | 0.2349     | 0.1542     | 0.2533     | 0.1953     | 0.1043     |
| -w. TG    | 0.3709     | 0.3615     | 0.3084     | 0.3179     | 0.2882     | 0.2192     |
| CMHAM     | 0.3053     | 0.2739     | 0.1996     | 0.2245     | 0.1946     | 0.1293     |
| -w. TG    | 0.4066     | 0.4678     | 0.4734     | 0.3711     | 0.3893     | 0.3633     |

Table 6: The responses produced by the baseline models without TG framework and with TG framework.

| Model     | generated response                      |
|-----------|----------------------------------------|
| Seq2Seq   | oh, i’m sorry. i’m sorry. i’m sorry.   |
| -w. TG    | i am sorry, there is no window seat.   |
| TransFM   | well, now we don’t what can we do?     |
| -w. TG    | well, now we’re stuck. what can we do? |

4.2 Ablation study

4.2.1 Teamwork generation framework

We employ each baseline model as a generator in TG framework to build a comparison. The results of q_phrase-n are shown in Table 5, and the better results are marked through bold font. For instance, the first line in Table 5 reports the q_phrase-{3,4,5} of “Seq2Seq”, and the second line shows the results of “Seq2Seq” with the TG framework. From the data in the Table 5, we found that the baseline models get better performance on q_phrase-n while they equipping the TG framework. These results demonstrate the effectiveness of the TG framework in improving the q_phrase-n metric of generated responses.

Then, we extract some dialogue cases based on the q_phrase-4 and distinct-4 from baseline models and baseline models with TG framework, which shown in Table 6. The generated responses we extracted are almost with high distinct-4 but low q_phrase-4, which could explicitly show the strength of our TG framework and prove the effectiveness of our proposed q_phrase-n metric in evaluating the grammatical quality.

4.2.2 Semantics Extractor

We adopt a topic classification task to illustrate that DiscretelyDC is powerful in extracting semantic keywords, and evaluate the effectiveness of results based on precision, recall, F1-measure(F1) and accuracy.

Figure 4: Results of topic classification task

To verify the advantages of DiscretelyDC, we use the results of DiscretelyDC as the benchmark, and then calculate the percentage of results of other models to the benchmark. As shown in Figure 4, all models have a small gap on accuracy, and the self-attention (Transformer) and DiscretelyDC results are similar, which is only a little better than the ordinary convolution (Conv) and Gate Recurrent Unit (Rnn). However, considering the precision, recall, and f-values (F1) for each category, the result of DiscretelyDC is the best.

In order to observe the DiscretelyDC in detail, we extract the middle process results of it. Then we extract a few clear samples and draw them as the following Figure 5 after statistical process. Since the actual coordinate values are all integers, it is difficult to watch the concern degree of tokens. Therefore, we increase the abscissa of each point by random numbers within range -0.25-0.25, while the ordinate adds a random number between -0.125 and 0.125 to make the difference clearer. In Figure 5, ‘Health’, ‘Politics’, ‘Finance’, ‘School Life’ represents the topic of sentences. We selected two sentences for each topic, and marked the keywords
Health
- I don’t know, doctor. I’m ill...
- Oh, I have a horrible toothache.

Politics
- You turned 18 in an election year. Will you be voting?

Finance
- Impf bank, Li Lan speaking, how may I help you?
- If you..., you could have your loan by the end of the week.

School Life
- What kind of scholarship is it?
- What did you major in?

Figure 5: Visualization of middle processing in DiscretelyDC

that the DiscretelyDC focuses on. For example, we extracted two samples (“what did you major in?” and “what kind of scholarship is it?”) for the ‘School Life’ topic. Figure 5 shows that the DiscretelyDC can focus on some keywords of related topics. For instance, the DiscretelyDC finds ‘major’ and ‘scholarship’ for ‘School Life’ topic. Therefore, the SE is able to directly extract semantic keywords-combination, which can replace the complex context vectors for providing semantic information in dialogue generation task.

5 Related work

5.1 Dialogue generation methods

Since the early dialogue models often generate general and dull responses, many works enrich the context vector with external information to address this problem in recent years. Taking a panoramic view of these works, there are three main directions for generating diverse responses: 1) using attention mechanism (Bahdanau et al., 2015; Luong et al., 2015; Xu et al., 2015; Vaswani et al., 2017; Tao et al., 2018), 2) using variational auto-encoder (VAE) structure (Bowman et al., 2016; Zhao et al., 2017; Fu et al., 2019; Gu et al., 2019a) and 3) using external information (Li et al., 2016b; Ghazvininejad et al., 2018; Huber et al., 2018). However, these methods complicate the context vector, which makes the semantics of context get deviation from original semantics of contexts, which leads to generate diverse but incoherent responses.

Therefore, two kinds of methods were proposed recently to address the diverse but incoherent responses problem. One introduced the reinforcement learning (Li et al., 2016c; Zhang et al., 2018; Liu et al., 2020), the other utilized the generative adversarial network (Li et al., 2017a; Gu et al., 2019b; Feng et al., 2020). However, no matter how complex these approaches are, it always employs a simple decoder, which could not effectively utilize the previous generated information, and then often tends to generate the duplicate and self-contradict responses. Different from the existing dialogue models, we proposed TG framework to utilize the previous generated information directly and explicitly during generating process.

5.2 Convolution used in NLP

Convolution neural network (CNN) was first introduced in sentence classification task (Kim, 2014; Kalchbrenner et al., 2014; Yih et al., 2014; Shen et al., 2014). However, the main problem that uses the CNN in NLP task lies in CNN’s inability to capture long-distance dependent features. Nowadays this problem can be easily addressed by two groundbreaking methods: using hierarchical model structure (Hu et al., 2014; Meng et al., 2015; Zhang et al., 2017) and using novel convolution kernel (e.g. Dilated Convolution (Yu and Koltun, 2016), Depthwise Separable Convolutions (Kaiser et al., 2018)). In addition, CNN could provide global information of the sentence, and allows parallelization on each element in the sentence, which is helpful for some NLP tasks (Kalchbrenner et al., 2016; Gehring et al., 2017). These works enrich the theoretic foundation of CNN models and indicate that CNN models are applicable for many NLP tasks.

6 Conclusion

In this paper, we propose a dialogue model named THINK (Teamwork generation Hover Impressiveness Noticeable Keywords) to generate grammatically correct and coherent responses. The THINK is based on the proposed Teamwork generation framework and Semantics Extractor. The TG framework is proposed for addressing duplicate and self-contradict responses caused by simple decoder. The SE is presented to overcome the incoherent responses caused by the complex context vectors. In conversation experiments, both automatic evaluation results and results of human evaluation are given to show the advantages of our THINK. We did ablation study to illustrate that TG framework effectively boosts the quality of responses and SE makes it easy to understand semantics.
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