Abstract

Knowledge-driven dialogue generation has recently made remarkable breakthroughs. Compared with general dialogue systems, superior knowledge-driven dialogue systems can generate more informative and knowledgeable responses with pre-provided knowledge. However, in practical applications, the dialogue system cannot be provided with corresponding knowledge in advance. In order to solve the problem, we design a knowledge-driven dialogue system named DRKQG (Dynamically Retrieving Knowledge via Query Generation for informative dialogue response). Specifically, the system can be divided into two modules: query generation module and dialogue generation module. First, a time-aware mechanism is utilized to capture context information and a query can be generated for retrieving knowledge. Then, we integrate copy Mechanism and Transformers, which allows the response generation module produces responses derived from the context and retrieved knowledge. Experimental results at LIC2022, Language and Intelligence Technology Competition, show that our module outperforms the baseline model by a large margin on automatic evaluation metrics, while human evaluation by Baidu Linguistics team shows that our system achieves impressive results in Factually Correct and Knowledgeable.

Keywords:

1. Introduction

Response generation has always been a significant challenge in dialogue systems, and related research has rapidly evolved from seq2seq model [1] to the pre-trained language models(PrLMs). Various approaches have been proposed [2, 3], which are able to generate fluent responses. However, these approaches only utilize utterances from the dialogue history and tend to generate uninformative and dull responses such as “I am fine”, “You are right”, that spoil the user experience severely. Thus, knowledge-based dialogue systems [4–6] have recently received extensive attention because these dialogue systems can utilize the provided structured or unstructured knowledge to produce more knowledgeable response.

Most of the research on knowledge dialogue systems has focused on knowledge injection tasks. For example, some works use a complex attention mechanism to fuse knowledge and context [7], and several works add an additional knowledge selection task before generation [8, 9] so that the model can combine the most context-relevant knowledge to generate responses. The purpose of these works is to enhance the decoder's understanding of relevant knowledge. However, a basic and critical issue is that knowledge is not provided in advance in reality. In other words, the above methods require pre-identified knowledge, but it is not feasible for a practical dialogue system to acquire the knowledge needed to generate responses from the beginning. Hence, retrieval of knowledge is a necessary step in practical applications. Although information retrieval has been proven effective in many fields, especially open-domain question answering(QA) [10, 11], the response generation task is not similar to the QA task in which the question can be used as a natural query [12]. Therefore, naturally, we hope there is a method that can spawn a query and utilizes search engines to retrieve relevant knowledge.

On the other hand, numerous studies have achieved the generation of meaningful responses using the provided knowledge and showed satisfactory performance. But most of them have not demonstrated their effectiveness under real retrieval conditions.

In order to alleviate the above problems, make the knowledge dialogue system more suitable for practical application scenarios, in this paper we propose a novel knowledge-driven dialogue system named DRKQG. Specifically, as illustrated in Figure ??, the system can be divided into two simple but effective modules: a query generation module which produces responses derived from the context and retrieved knowledge. Experimental results at LIC2022, Language and Intelligence Technology Competition, show that our module outperforms the baseline model by a large margin on automatic evaluation metrics, while human evaluation by Baidu Linguistics team shows that our system achieves impressive results in Factually Correct and Knowledgeable.
from context and knowledge.

In summary, our main contributions are as follows:

- We propose the DRKQG model, which integrates query generation and response generation, enabling the dialogue system to use search engine knowledge for open-domain dialogue interaction, and further improving the practicality of knowledge-driven dialogue systems.
- We employs some simple but effective methods to make our modules accomplish their respective tasks. For the query generation module, we develop a time-aware mechanism that can more reasonably assign attention weights to utterances. For the response generation module, we utilize an knowledge headed attention to obtain representations of knowledge and we copy tokens from context and knowledge to improve the informative of generated response further.
- Our experimental results in the LIC2022 demonstrate that our model outperforms several baseline models. Moreover, human evaluation by Baidu’s professional linguistics team shows that our model performs well in real-world environments.

2. Related Work

Benefiting from the development of deep learning technology, especially the prosperity of pre-trained language models in recent years such as Bert [15] and Bart [16], remarkable achievements have been made in response generation task [17, 18]. In general, the task can be regarded as a natural language generation (NLG) task that produce satisfactory responses by given the dialogue history. However, these dialogue systems can always generate dull and meaningless responses due to the inherent flaws of NLG tasks [19].

In order to tackle the above problems, dialogue systems with knowledge injection like [20, 21] have received widespread attention recently, and their experiments proved that the knowledge information can enhance the performance of response generation. Several works focus on fusing knowledge information with dialogue context. For example, Prabhumoye et al.[14] uses an additional multi-head attention to obtain the representation of knowledge information, and Cao et al.[22] propose a attention fusion mechanism to fuse document information and context information. Some other works intergrate knowledge selection with response generation [8, 9, 23]. Specifically, these methods first filter knowledge irrelevant to the context, and then they generates responses based on the selected knowledge. Moreover, Wu et al.[24], Liu et al.[25] and Bai et al.[26] believe that the goal of dialogue session can provide implicit guidance for knowledge-driven dialogue system. The above works all assume that knowledge will be provided in advance, however, this assumption is not valid for a real dialogue system. Therefore, the focus of our work is to allow the dialogue system to automatically acquire relevant knowledge through some methods, such as retrieval through search engines.

3. Model Description

3.1. Task Formalization

Suppose we have a dataset $D = \{(U_i, Y_i, Q_i, K_i)\}_{i=1}^N$ where $U_i = (u_{i1}, u_{i2}, ..., u_{il})$ represents the dialogue history, $Q_i = (q_{i1}, q_{i2}, ..., q_{il})$ is the query produced by dialogue history $U_i$, and $K_i = (k_{i1}, k_{i2}, ..., k_{il})$ is the knowledge relevant to the context, which is provided by the dataset during training but retrieved by Q in reality. The response $Y_i = (y_{i1}, y_{i2}, ..., y_{il})$ should be generated by the context $U_i$ and the relative knowledge $K_i$. Here, $N$ represents the size of the dataset, and $I_o, I_q, I_k$ and $I_l$ denote the numbers or tokens in the dialogue history, query, knowledge and response, respectively. The final goal of our model is generating a response on the ground of the context and knowledge. In the training stage, the knowledge is provided by the dataset, however, the knowledge should be retrieved by the produced query in the inference stage.

3.2. Model Overview

Our system consists of two modules, a query generation module and a response generation module, as illustrated in Figure 1. The query generation module can generate a suitable query, and then a search engine API can be called to retrieve relevant knowledge. Subsequently, the response generation module can generate an informative response based on the context and the retrieved knowledge. The main framework of each module is a transformer-based [28] encoder-decoder (CPT [29]), and each module has its own additional mechanisms to make them better adapted to their respective tasks. Below, we first introduce the query generation module we proposed (Section 3.3), especially the time-aware mechanism applied to it. Then, we introduce the response generation module (Section 3.4) which utilizes an additional knowledge headed attention and copy mechanism to produce a response. Finally, we detail the training strategy (Section 3.5).

Some other methods also guides our work. For example, we use a pointer network [27] to copy tokens from context and knowledge to further improve the knowledgeable of generated response. What is more, inspired by Malhotra et al.[13], we propose a time-aware mechanism to capture context information so that the more recent utterances can get more attention.
3.3. Query Generation Module

In this section, we will introduce our proposed query generation model, which combines a special time-aware mechanism so that the later utterances in the dialogue history are assigned greater attention weights, as shown in Figure 2.

**Context Representation** We concatenate the utterances in dialogue history and their corresponding generated queries, denoted as \( X = (\text{utterance}^1; \text{query}^1; ...; \text{utterance}^n) \) and we believe that for the same dialogue session, the query that has been generated should have a certain prompting effect on the query to be generated. Then, we take \( X \) as the input of encoder and obtain the representation \( H_x \) of the context via CPT Encoder:

\[
H_x = \text{CPT}_\text{Encoder}(X); H_x \in \mathbb{R}^{l \times d}
\]  

where \( l \) is the length of encoder input. Likewise, we obtain the representation \( H_y \) of the response \( Y \) by:

\[
H_y = \text{CPT}_\text{Encoder}(Y); H_y \in \mathbb{R}^{l_y \times d}
\]

where \( l_y \) is the length of decoder input.

**Time-aware Attention** Intuitively, the topic of the conversation will change as the conversation progresses, and we humans generally only focus on the topic just discussed. Therefore, usually, the purpose of generating a query is to retrieve knowledge and use it to reply to what the user has just said. Inspired by Malhotra et al. [13], we apply a time-aware attention mechanism which can learn the importance of utterances according to the order in which they appear in the dialogue history:

\[
\text{Attention}_T = \text{Softmax}(\frac{QK^{\text{Trans}}}{\sqrt{d}})V; T \in \mathbb{R}^l, T' = N_d(i) \]

Here, the \( Q, K, \) and \( V \) represent the Query, key and value in a Attention function respectively, and the \( T \) will keep increasing with the number of dialogue turns. In this way, the weight of the dot product of query and key increases with time, and we can get the time-aware representations of the context.

The original time aware mechanism in [13] uses the memory network to store the encoder hidden state for each utterance, and then exploits the nearby hidden states maintained in a memory to obtain the representation at every point in the dialogue. However, our time-aware mechanism does not obtain the representation on the encoder side for each utterance based on their nearby context, but enables the decoder to more reasonably allocate attention to the dialogue history.

**Decoder** Now, each decoder layer consists of the following functions:

\[
H = \text{LayerNorm} (\text{SelfAttention}(H_x, H_y, H_y))
\]

\[
H = \text{LayerNorm} (\text{Attention}_T (H, H_x, H_y))
\]

\[
H = \text{LayerNorm} (\text{FFN}(H))
\]

We replace CrossAttention in the Transformer Decoder-block with our proposed time-aware attention mechanism. Compared with general CrossAttention, this mechanism of making the decoder pay more attention to the more recent conversations allows the model to generate a more reasonable query.

3.4. Response Generation Module

Once the query is generated, we can obtain knowledge through the search engine API. Next, we introduce our response generation module in this section, which can use the retrieved knowledge and context to generate an knowledgeable response, as shown in Figure 3.
**Context Representation** Following the work of Prabhuyam et al. [14], we concatenate the retrieved knowledge and the context so that we can get our knowledge-context representation $h_{kc}$ by:

$$H_{kc} = CPT\_Encoder([K; X]); H_{kc} \in \mathbb{R}^{(l+k)xd}$$

(5)

and we then utilize the same CPT encoder to obtain the representation of the knowledge alone:

$$H_k = CPT\_Encoder(K); H_k \in \mathbb{R}^{ld}$$

(6)

**Knowledge Headed Attention** Usually, a transformer decoder block contains a SelfAttention layer and a CrossAttention layer. The SelfAttention layer allows each position in the decoder to assign attention to its own position and the position before itself, while the CrossAttention layer enables the source sequence aware of the encoder output, allowing their representations to be fused. However, in this module, we have two encoder outputs, representing knowledge-context information and context information respectively. Therefore, we add an additional CrossAttention layer (called as CrossAttention$_{kc}$), which attends over the knowledge and context. At the same time, the original CrossAttention layer (called as CrossAttention$_{k}$) can focus only on knowledge information:

$$CrossAttention_{kc} = Attention(H, H_{kc}, H_{kc})$$

(7)

$$CrossAttention_{k} = Attention(H, H_{k}, H_{k})$$

(8)

**Decoder** Now, each decoder layer in this module consists of the following functions:

$$H = LayerNorm(SelfAttention(H_{s}, H_{s}, H_{s}))$$

$$H = LayerNorm(CrossAttention_{kc}(H, H_{kc}, H_{kc}))$$

$$H = LayerNorm(CrossAttention_{k}(H, H_{k}, H_{k}))$$

(9)

In this way, the module can fully extract knowledge and contextual features, and the probability distributions of token generation $P_v$ can be obtained by:

$$P_v = \text{Softmax}(W^{Trans}_{head} H + b)$$

(10)

where $W_{head}$ and $b$ are learnable parameters.

**Pointer Network** To further improve the consistency and accuracy of knowledge in the generated responses, we also incorporate a pointer network into this module. Unlike the ordinary pointer network, we did not consider the oov problem, and we used a simple way to combine the copy mechanism with the language model. Specifically, the decoder contains $N$ decoding layers, and we take the mean of the attention distributions of these decoding layers over the knowledge-context representation as our pointer. Thus, each token generation can be determined with a soft gate that can control the probability of generation or copy:

$$gen = \sigma(W^{Trans}_{head} H)$$

(11)

where $W^{Trans}_{head}$ is a learnable parameters. Finally, the probability of the vocabulary can be defined as:

$$P = gen \times P_v + ((1 - gen) \times P_{copy})$$

(12)
where $P_{copy}$ is the mean of the attention distributions of all decoding layers over the knowledge-context representation.

### 3.5. Training

We use two loss functions, because we train the two modules separately. The query generation module uses the dialogue history and previously used queries to generate an appropriate new query, while the response generation module generates responses based on the currently retrieved knowledge and context. Dialogue history, previously used queries, and knowledge are provided by the dataset during the training phase:

$$L_{query}(\theta_1) = -\frac{1}{|Q|} \sum_{r=1}^{|Q|} \log(P(q^t|q^{1:t-1}, U, Q_{past}))$$

$$L_{res}(\theta_2) = -\frac{1}{|Y|} \sum_{r=1}^{|Y|} \log(P(y^t|y^{1:t-1}, U, K))$$  \hspace{1cm} (13)

where $Q_{past}$ represents the queries that have been produced in the same dialogue session.

### 4. Experiments

#### 4.1. Dataset

We only used the Dusinc [30] dataset provided in LIC2022\(^1\), because as far as we know, there is no other dataset that is suitable for both query generation and response generation tasks in knowledge-driven dialogue systems.

**Dusinc** The DuSinc dataset is an open-domain Chinese dialogue dataset that contains a wide range of dialogue topics from real human conversations. During the data collection process, the dialogue participants are required to play the roles of the USER and the BOT respectively. The BOT can query the search engine in real time during the chat and conduct in-depth dialogue and interaction with the USER. The dataset consists of 2200 dialogues session with 11466 turns, 10413/1053 used for train/valid, and each turn of BOT includes whether a search engine is used, as well as the query and the knowledge. Therefore, we can train our modules separately. What is more, there are another 350/750 samples for testing query/response generation.

In the dusinc dataset, sometimes for a certain round of dialogue, the query and knowledge provided are empty, which means that the BOT does not use extra knowledge to generate the response, such as "OK, I got it". For the case where the provided knowledge is empty, we do not do any other processing and directly send it to the model for training like other samples. For the case where the query is empty, we discuss it in Appendix a.

#### 4.2. Comparison Models

We implement our model on dataset Dusinc. However, most of existing models cannot handle both the query generation task and the response generation task, and they did not perform any experiments on Dusinc. Consequently, for automatic evaluation metrics, we implement these comparison models, and compare each module of our system separately with the corresponding models.

**Query Generation** Few studies focus on query generation in knowledge-driven dialogues. Thus, we compare our query generation module with: **Transformer Encoder**: This model is a baseline model provided by LIC2022, which consists of 12-layer transformers and is pre-trained on a large Chinese dialogue dataset. **CPT-large**: CPT is a pretrained language model that we used in our module, and it has achieved outstanding results on several Chinese datasets.

**Response Generation** We compare our Response generation module with: **Transformer Encoder**: This model is a baseline model provided by LIC2022. **CPT-large**: CPT is a pretrained language model that we used in our module. **CPT-KIC**: KIC model is proposed by [7], and it has achieved impressive results on several knowledge-based dialogue datasets. We implement the recurrent knowledge interaction and knowledge copy method in KIC model with CPT. **CPT-sw**: The original model GPT2-sw is proposed by Cao et al.[22], which can generate response with multiple input sources. Here, we make some minor changes to the method of multiple input source information fusion, thus the method can be applied in a Encoder-Decoder model. **DoHA**: a model which can building knowledge-context representation and enabling specific attention to the knowledge-context [14], and we used it as backbone of our response generation module.

#### 4.3. Metrics

For performance evaluation, we utilize automatic evaluation and human evaluation.

**Automatic Evaluation** Following the setting of LIC2022, we use F1, BLEU1/2, DISTINCT1/2 to evaluate our query generation module and response generation module. Specifically, Q_F1 indicates the word granularity matching score between the predicted query and the golden query is matched; Q_BLEU represents the BLEU1/2 value of the word granularity between the predicted query and the golden query, estimating the fluency of generated query; D_F1 can measure the word granularity matching score between the predicted response and the golden response; D_BLEU represents the word-granularity BLEU1/2 value; D_DISTINCT1/2 is an automatic evaluation metric of the diversity of response content.

**Human Evaluation** Human evaluations are provided by Baidu’s professional linguistics team, which tests our system.

\(^1\)https://aistudio.baidu.com/aistudio/competition/detail/158/0/introduction
Table 1: The experimental results for query generation task. Here, * means the comparison model is implemented by ourself.

| Model                  | Q_F1   | Q_BLEU-1 | Q_BLEU-2 | Parameters |
|------------------------|--------|----------|----------|------------|
| Ours(CPT+Time aware)   | 0.471  | 0.416    | 0.370    | 407M       |
| Transformer Encoder    | 0.163  | 0.108    | 0.106    |            |
| CPT-Large*             | 0.424  | 0.351    | 0.317    |            |

| Model                  | D_F1   | D_BLEU-1/2 | D_DISTINCT-1/2 |
|------------------------|--------|-------------|-----------------|
| Ours(CPT-DoHA+copy)    | 0.333  | 0.308/0.216 | 0.117/0.588     |
| Transformer Encoder    | 0.2    | 0.137/0.088 | 0.148/0.535     |
| CPT-Large*             | 0.295  | 0.246/0.171 | 0.173/0.660     |
| CPT-KIC*               | 0.283  | 0.223/0.143 | 0.075/0.392     |
| CPT-sw*                | 0.303  | 0.237/0.163 | 0.164/0.641     |
| CPT-DoHA*              | 0.314  | 0.255/0.184 | 0.168/0.671     |

Table 2: The experimental results for response generation task. Here, * means the comparison model is implemented by ourself.

4.4. Implementation

We implement our model by the Pytorch. CPT-large is used as the backbone of our model, which consists of 20-layer Transformer encoder and 4-layer Transformer decoder. The hidden size is 1024 and the vocabulary size is 21128. We use Adam optimizer and train each module on two GPUs (RTX TITAN), the batch size is 12 and the learning rate is $4e^{-5}$. What is more, we apply a scheduler which warmup the training with 200 steps. All the above settings are the same for both modules.

In particular, the knowledge and the dialogue are encoded by a shared CPT-Encoder in the response generation module, and we implement the pointer network inspired by Vinyals et al.[27]. The sequence length for knowledge and context are both 128, the maximum sequence length of output is 128 and we use 2 epochs to train the response generation module. However, for query generation module, the maximum sequence length of output is 16 and we train it with 3 epochs.

4.5. Result and analysis

4.5.1. Automatic Evaluation

Query Generation  The automatic evaluation results of the query generation module on dataset Dusinc are shown in Table 1. Our query generation module outperforms the baseline model by a large margin over all evaluation metrics, and it also achieves significant improvement compared with CPT-Large, which strongly demonstrates the effectiveness of the time-aware mechanism we proposed. Specifically, our query generation module has 11.1%, 18.5% and 16.7% improvement over CPT-Large on F1, BLEU-1, and BLEU-2, which indicates that our time aware mechanism can effectively capture clues from more recent conversations and generate more accurate and fluent queries than general attention mechanisms that automatically assign weights to the entire dialogue history.

Response Generation  The automatic evaluation results of the query generation module on dataset Dusinc are shown in Table 2. Our response generation module still outperforms other comparison models over most of the automatic metrics. Specifically, our response generation module has 6.0%, 20.7% and 17.0% improvement over CPT-DoHA on F1, BLEU-1, and BLEU-2, but drops by 30.3% and 12.3% on DISTINCT-1 and DISTINCT-2. The above results show that combining the pointer network with the pre-trained language model can indeed make the knowledge-driven dialogue system generate more knowledge-coherent responses, because the pointer network will directly copy words from the knowledge to the output. However, the copy mechanism also inevitably limits the diversity of responses generated. What surprises us in this result is that the metrics of CPT-KIC have decreased compared
Dialogue session
A: Have you watched Zhu Yilong's latest movie?
B: Of course, his new film "Lighting Up The Stars" has been finalized, as well as "Infinite Depth", "Cloudy Mountain", etc.
A: Really? What kind of story does "Lighting Up The Stars" tell?
B: Telling the story of Wu Sanmei, a mortician who was released after serving his sentence, met the orphan Wu Xiaowen during a funeral, and unexpectedly changed Wu Sanmei's attitude towards career and life.
A: Zhu Yilong in the film played the role of Lian Chengbi, the young master of Wugou Villa in "Xin Xiao Eleven Lang".
B: Haha, so Zhu Yilong is really a master in playing the elegant, civil, and military young master in "Xin Xiao Shi Yi Lang".

Table 3: The result of human evaluation. Compared with other top contestants, our final generated responses are outstanding in terms of Knowledgeable and Factually Correct.

| Team  | Knowledgeable | Factually correct | Consistent | Engaging |
|-------|---------------|-------------------|------------|----------|
| Team-A| 0.526         | 0.481             | 0.855      | 0.869    |
| Team-B| 0.712         | 0.674             | 0.786      | 0.81     |
| Team-C| 0.568         | 0.526             | 0.755      | 0.804    |
| Team-D| 0.486         | 0.423             | 0.84       | 0.854    |
| Ours  | 0.627         | 0.607             | 0.639      | 0.641    |
| Team-E| 0.568         | 0.518             | 0.7        | 0.668    |
| Team-F| 0.621         | 0.531             | 0.649      | 0.673    |
| Team-G| 0.514         | 0.454             | 0.645      | 0.671    |
| Team-H| 0.495         | 0.435             | 0.617      | 0.581    |
| Team-I| 0.284         | 0.235             | 0.564      | 0.543    |

Figure 4: An example of multi-turn communication between our dialogue system and a tester. There are a total of 6 turns of dialogue in this session. After user A enters a sentence, a query will be generated based on the context and used to retrieve relevant knowledge, and then a response will be produced derived from the retrieved knowledge and context.

4.5.2. Human Evaluation

In human evaluation, our system needs to strictly perform the steps of query generation, knowledge retrieval, and response generation. The evaluator will evaluate the quality of the final generated response in the field of: Knowledgeable, Factually Correct, Consistent, Engaging. We compare our results with those of the other top ten contestants in LIC2022, as shown in Table 3. The response generated by our system has achieved outstanding results in the term of Knowledgeable and Factually correct, indicating that our query generation module can generate appropriate queries to retrieve context-relevant knowledge, and our response generation module can effectively utilize the retrieved knowledge to generate informative responses. However, our generated responses are less consistent and engaging compared to some contestants, which may affect its performance in terms of Knowledgeable and Factually Correct to some extent. Results on Consistent and Engaging are not surprising to us, as our main work is to make knowledge-driven dialogue systems leverage relevant knowledge in real-world settings. In the following subsection, we will further illustrate the strengths and weaknesses of our model with a case.

4.5.3. Case Study

We present an example of multi-turn communication between our dialogue system and a tester, as illustrate in Figure 4. Here, speaker A represents our tester, and speaker B is our dialogue system. Tester A first confirms a dialogue topic and continuously constructs new inputsguide the conversation. The dialogue system dynamically produces queries, and generates responses derived from the retrieved knowledge and the context. In this example, the tester and our dialogue system had a discussion about an actor and the movie he was in. In the previous four turns of dialogue, our model generated accurate queries and fluent and informative responses, demonstrating that both modules we proposed can perform their respective tasks well. However, our query generation module performed poorly when generating the query for the 5th turn of dialogue. It generated only the actor’s name but not the title of the corresponding movie, which resulted in the retrieval of unmatched knowledge, and the final response was inconsistent with the context.

The possible reason for the above is that our time-aware mechanism assign too little attention weight to the 3rd trun of dialogue when generating the query for the 5th turn, as Our time-aware mechanism learns the importance of utterances according to the order in which they appear in the dialogue his-
tory. Therefore, the query generation module did not understand "the film" in the 5th turn of dialogue, referring to the "Lighting Up The Stars"

5. Conclusion

This paper proposes a knowledge-driven dialogue system which can dynamically retrieve knowledge via query generation as the conversation progresses and generate knowledgeable responses. We propose a simple time-aware mechanism which performs well in our query generation module, and we demonstrate the effectiveness of our system in a real application environment. Both our proposed query generation module and response generation module outperform their respective comparison models, and the results of human evaluation also present that our dialogue system can generate informative responses. Our work can inspire future researchers to think about "where does knowledge come from" and make future dialogue systems more relevant to our lives. For future work, we think it is meaningful to reduce the difference between the query generation module and the response generation module, or use the same module to generate query and response, because it can greatly reduce the amount of parameters of the whole system, which is more suitable for industrialization.

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