Proactive Knowledge-Goals Dialogue System Based on Pointer Network

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Abstract. Human-machine dialogue is the hot spot of current research. In this paper, we proposed an end-to-end dialogue system based on external knowledge, which realized active guidance and topic transfer in multiple rounds of dialogue. Our system is built on the pointer generator model so that the output token in the response can be generated or copied from the conversation history or background knowledge according to a trainable action probability distribution. At the same time, with the data processing and optimization of the model structure, the designed system is capable of generating high quality responses. In the 2019 NLP Language and Intelligence Challenge, our proposed dialogue system ranked third in the automatic evaluation, and ranked fifth in the manual evaluation.

Keywords: pointer network, attention mechanism, background knowledge, proactive dialogue

1 Introduction

Human-machine dialogue is a basic challenge to artificial intelligence. It involves key technologies such as language understanding, dialogue management and language generation, and has received extensive attention on academia and industry. The current human-machine dialogue technology is still in its infancy, and most of the machines are in the form of passive dialogue, that is, the machine's reply is only used to respond to the user's input, and it is impossible to conduct multiple rounds of dialogue interaction like a human. Many scholars hope to introduce knowledge graph information into human-machine dialogue, so that machines can obtain more valuable reply information, or further use background knowledge information to actively guide users to communicate. Recently, the 2019 Language and Intelligent Technology Challenge (LIC2019) which was jointly organized by the China Computer Federation (CCF), the Chinese Information Processing Society of China (CIPSC) and Baidu Inc. have released a large-scale, high-quality proactive conversation dataset DuConv

This work was supported by the Science Foundation of China University of Petroleum-Beijing under grant No. 2462018YJRC007

based on knowledge graph [1]. This will greatly promote the development of Chinese human-machine dialogue.

Recently, neural networks of dialogue generation have attracted attention, and a lot of works have focused on how to use context to generate fluent, consistent responses [2,3,4,5]. There are also works to introduce large-scale knowledge graph as background information on the dialogue process, giving the dialogue system the ability to expand thinking. The corresponding evaluation dataset includes the bAbI dialogue and Stanford multi-domain dialogue (SMD), etc[6,7]. In practical applications, a simple reply-type dialogue system cannot capture the interests in communicators. Giving the dialogue system the ability of actively chat can make it smarter.

In this evaluation task, the DuConv provided by the organizer has a total of 30,000 sessions, about 120,000 rounds of dialogue, including 100,000 training sets, 10,000 development sets, and 10,000 test sets. Each of these dialogues includes knowledge background information, context history, and dialogue goals. The data comes from the knowledge of chat value in the field of movies and entertainment characters, such as box office, director, evaluation, etc., organized in the form of triad *SPO*. The topic in the dialogue target is movie or entertainment character entity. The task of the evaluation is to give the dialogue targets *G* and related knowledge information $K=f_1, f_2, \ldots, f_n$, and ask the dialog system to output the machine response u_t applicable to the current conversation sequence $H=u_1, u_2, \ldots, u_{t-1}$, makes the conversation natural, informative and consistent with the goals of the dialogue. During the conversation, the machine is active, guiding users to talk from one topic to another. This task is extremely challenging We design the overall dialogue system through data preprocessing, model construction, model precision tuning and optimization, and data post-processing. Experiments show that the model we designed can effectively complete the evaluation task. In the 2019 Language and Intelligent Technology Competition evaluation, our system obtained 0.464, 0.422 and 0.289 in the machine evaluation, F1, BLEU1 and BLEU2 respectively. At the same time, in the manual evaluation, the task completion score of 1.79 and the consistency score of 2.3 were obtained.

In this paper, we present an end-to-end deep learning model to solve this problem. We introduce our work from the aspects of data preprocessing, model structure, model implementation details, experimental results, etc., and summarize the article in the last part.

2 Related works

2.1 Dialogue systems

Machine learning based dialogue systems are mainly explored by following two different approaches: modularized and end-to-end. For the modularized systems [8], a set of modules for natural language understanding [9,10], dialogue state tracking [11], dialogue management, and natural language generation are used. These approaches achieve good stability via combining domain-specific knowledge and slot-filling techniques, but additional human labels are needed. On the other hand, end-to-end approaches have shown promising results recently. Some works view the task as a next utterance retrieval problem. Sequence-to-sequence model [12] has been a popular approach to many domains including neural response generation, to name just a few. Attention mechanism has been crucial in a lot of NLP tasks such as machine translation[13], machine reading comprehension [14] and natural language inference [15].

2.2 Pointer network

Vinyals et al. uses attention as a pointer to select a member of the input source as the output [16]. Such copy mechanisms have also been used in other natural language processing tasks, such as question answering, neural machine translation, language modeling, and text summarization[17]. In task-oriented dialogue tasks, Eric & Manning first demonstrated the potential for the copy augmented Seq2Seq model, which shows that generation based methods with simple copy strategy can surpass retrieval-based ones. Later, Eric et al. augmented the vocabulary distribution by concatenating KB attention, which at the same time increases the output dimension [7]. To integrate external knowledge [18], employed memory network for encoding facts with great progress. Madotto et al. applied memory network to store dialog history and structured knowledge base and used pointer generator to copy token from dialog history or knowledge base token for task-oriented dialog systems [19].

2.3 Baselines

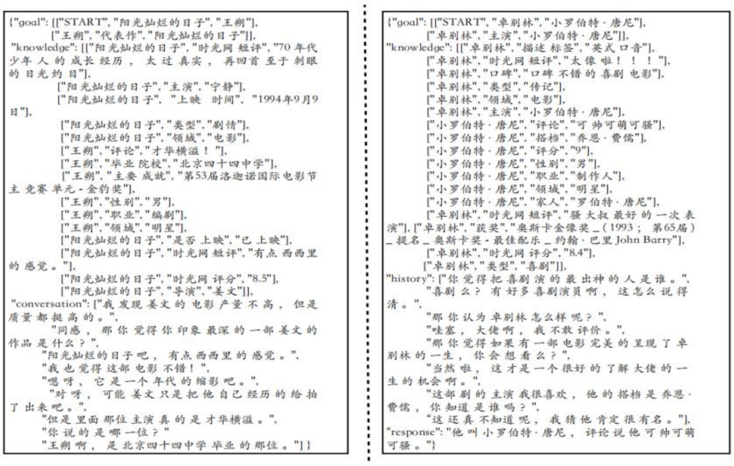
The evaluation task provides two baseline systems [1]. For the search and generation formulas, the search method needs to construct candidate sets, and then use the transformer model to rank the sentence. The generative model is a reference to the work from Rongzhong Lian et al. [20], and the posterior knowledge distribution is used to guide knowledge selection.

3 Data processing

3.1 Dataset

In this paper, except for the official dataset, we only use the pre-trained Chinese word vector, and no other external data was used. Official dataset is divided into training set, validation set, and test set. The training set and the validation set are organized in the form of session. Each session includes Dialogue Goal, Background Knowledge and Conversation. In the test set, Each sample includes Dialogue Goal, Background Knowledge and History, the participating model is required to lead the conversation according to the current dialogue history, that is, it only needs to simulate the actions of the agent. The various parts of the data are described below. And Figure 1 presents an example from training/test sets respectively.

- Dialogue Goal (goal): It contains two lines: the first contains the given dialogue path i.e.,["Start", TOPIC_A, TOPIC_B]. The second line contains the relationship of TOPIC_A and TOPIC_B.
- Knowledge: Background knowledge related to TOPIC_A and TOPIC_B.
- Conversation: 4 to 8 turns of conversation.
- Dialogue History: Conversation sequences before the current utterance, empty if the current utterance is in the start of the conversion.



{"goal": [["START", "阳光灿烂的日子", "王朔"],
["王朔", "代表作", "阳光灿烂的日子"]],
"knowledge": [["阳光灿烂的日子", "时光网 短评", "70 年代少年人的成长经历，太过真实，再回首至于刺眼的日光灼目"],
["阳光灿烂的日子", "主演", "宁静"],
["阳光灿烂的日子", "上映 时间", "1994年9月9日"],
["阳光灿烂的日子", "类型", "剧情"],
["阳光灿烂的日子", "领域", "电影"],
["王朔", "评论", "才华横溢！"],
["王朔", "毕业 院校", "北京四十四中学"],
["王朔", "主要 成就", "第53届洛迦诺国际电影节主竞赛单元 - 金豹奖"],
["王朔", "性别", "男"],
["王朔", "职业", "编剧"],
["王朔", "领域", "明星"],
["阳光灿烂的日子", "是否 上映", "已 上映"],
["阳光灿烂的日子", "时光网 短评", "有点西西里的感觉。"],
["阳光灿烂的日子", "时光网 评分", "8.5"],
["阳光灿烂的日子", "导演", "姜文"]],
"conversation": ["我发现姜文的电影产量不高，但是质量都挺高的。",
"同感，那你觉得你印象最深的一部姜文的作品是什么？",
"阳光灿烂的日子吧，有点西西里的感觉。",
"我也觉得这部电影不错！",
"嗯呀，它是一个年代的缩影吧。",
"对呀，可能姜文只是把他自己经历的给拍了出来吧。",
"但是里面那位主演真的是才华横溢。",
"你说的是哪一位？"
"王朔啊，是北京四十四中学毕业的那位。"]}

{"goal": [["START", "卓别林", "小罗伯特 · 唐尼"],
["卓别林", "主演", "小罗伯特 · 唐尼"]],
"knowledge": [["卓别林", "描述 标签", "英式口音"],
["卓别林", "时光网 短评", "太像啦！！！"],
["卓别林", "口碑", "口碑不错的喜剧 电影"],
["卓别林", "类型", "传记"],
["卓别林", "领域", "电影"],
["卓别林", "主演", "小罗伯特 · 唐尼"],
["小罗伯特 · 唐尼", "评论", "可帅可萌可骚"],
["小罗伯特 · 唐尼", "搭档", "乔恩 · 费儒"],
["小罗伯特 · 唐尼", "评分", "9"],
["小罗伯特 · 唐尼", "性别", "男"],
["小罗伯特 · 唐尼", "职业", "制作人"],
["小罗伯特 · 唐尼", "领域", "明星"],
["小罗伯特 · 唐尼", "家人", "罗伯特 · 唐尼"],
["卓别林", "时光网 短评", "骚大叔最好的一次表演"], ["卓别林", "获奖", "奥斯卡金像奖 _（1993； 第65届）_ 提名 _ 奥斯卡奖 - 最佳配乐 _ 约翰 · 巴里 John Barry"],
["卓别林", "时光网 评分", "8.4"],
["卓别林", "类型", "喜剧"]],
"history": ["你觉得把喜剧演的最出神的人是谁。",
"喜剧么？有好多喜剧演员啊，这怎么说得清。",
"那你认为卓别林怎么样呢？",
"哇塞，大佬啊，我不敢评价。",
"那你觉得如果有一部电影完美的呈现了卓别林的一生，你会想看么？",
"当然啦，这才是一个很好的了解大佬的一生的机会啊。",
"这部剧的主演我很喜欢，他的搭档是乔恩 · 费儒，你知道是谁吗？",
“这还真不知道呢，我猜他肯定很有名。"],
“response": "他叫小罗伯特 · 唐尼，评论说他可帅可萌可骚。"}

Fig. 1. Examples in the dataset

3.2 Data preprocessing

For each session in the dataset, we split it into multiple sets of conversations as training data. Each group of conversations includes GOAL, KNOWLEDGE, HISTORY, and RESPONSE. Among them, HISTORY and RESPONSE are from the data set CONVERSATION, in which the machine's reply is RESPONSE, and the previous conversation history information is HISTORY. We analyzed all the samples in training set. We learned that the background information contains a total of 44 types of relationships, such as domain, type, time network short comment, career, starring and so on. Since the dataset contains a large number of English translation nouns and some proper nouns, they are broken up after the word segmentation, and cannot be used as a complete word to table lookup and other operations, which affects the system accuracy. At the same time, the dataset contains a large number of names of people and movies, resulting in a too large vocabulary or some words out of vocabulary problems. Therefore, we processed the data as follows. And in Figure 2, the processed data sample is shown:

- For the two topic words in GOAL, we use "video_topic_a" or "person_topic_a" and "video_topic_b" or "person_topic_b" instead.

- For the background information in KNOWLEDGE, we have selected eight types of relationships, including ['Representatives', 'Stars', 'Friends', 'Directors', 'Partners', 'Husband', 'Wife', 'Family'], the substitution of entity words for these types of triples, using specific characters instead of corresponding entity words.
- The words that are substituted in each set of dialog data are stored in a dictionary, and the final generated result is inversely replaced. For the HISTORY and RESPONSE sections, we use the alternative word dictionary for replacement.
- Context-sensitive entity tag. If the entity word in the background knowledge appears in the last round of conversation in HISTORY, it is marked as 'A', and if not, marked as 'O'.

Raw session	{"**goal**": [["START", "儿童 法案", "理查德 • 艾尔"], ["儿童 法案", "导演", "理查德 • 艾尔"]], "**knowledge**": [["儿童 法案", "类型", "剧情"], ["儿童 法案", "口碑", "口碑 很 差"], ["儿童 法案", "上映 时间", "2018 年 8 月 24 日"], ["儿童 法案", "领域", "电影"], ["儿童 法案", "导演", "理查德 • 艾尔"], ["理查德 • 艾尔", "评论", "电影 的 诗歌"], ["理查德 • 艾尔", "星座", "白羊座"], ["理查德 • 艾尔", "出生 日期", "1943 - 3 - 28"], ["理查德 • 艾尔", "性别", "男"], ["理查德 •艾尔", "职业", "导演"], ["理查德 • 艾尔", "领域", "明星"]], "**conversation**": ["我们 老师 让 我们 看 了 一部 电影 ， 是 今年 8 月 上映 的 。", "那 算是 蛮 新 的 了 ， 是 哪 部 ？", "叫做 儿童 法案 。", "我 好像 了解 过 。 口碑 很 差 诶 。", "嗯 ， 也 不太 好看 。", "就是 啊 ， 好看 也 不会 口碑 差 吧 。", "不会 ， 导演 可是 白羊座 的 。", "导演 是 谁 啊 ？", "1943 年 3 月 28 日 出生 的 理查德 • 艾尔 。", "你 一说 我 想起来 了 。"]}
One processed data	**Input information:** GOAL [0] video_topic_a [0] 导演 [0] person_topic_b [0] video_topic_a [0] 类型 [0]剧情 [0] 口碑[0] 口碑 [0] 很 [0] 差 [0] 上映 时间 [A] 2018 年 8 月 24 日 [A] 领域 [0] 电影 [A] person_topic_b [0] 评论 [0] 电影 [A] 的 [0] 诗歌 [0] 星座 [0] 白羊座 [0] 出生 日期 [0] $出生日期 longB$ [0] 性别 [0] 男 [0] 职业 [0] 导演 [0] 领域 [0] 明星 [0] HISTORY [0] 我们 [0] 老师 [0] 让 [0] 我们 [0] 看 [0] 了 [0] 一部 [0] 电影 [0] ， [0] 是 [0] 今年 [0] 8 月 [0] 上映 [0] 的 [0] 。 [0] 那 [0] 算是 [0] 蛮 [0] 新 [0] 的 [0] 了 [0] ， [0] 是 [0] 哪 [0] 部 [0] ？ [0] **Response:** 叫做 video_topic_a 。
Topic list	{"video_topic_a": "儿童 法案", "person_topic_b": "理查德 • 艾尔", "$出生日期 longB$": "1943 年 3 月 28 日"

Fig. 2. Sample data preprocessing

3.3 Answer processing

This process is used to correct the answers which are directly generated by the model to make it closer to the real response. It mainly includes the following two procedures:

- Replace the replacement words contained in the answer according to the entity vocabulary.
- The statistical machine recovery length average is 12.37, 70% of the sentence length is concentrated between 8 and 16, so we set the minimum length of the sentence in the decoding process to 8, to ensure that the response contains enough information.

4 Model structure

We use G, K and H to represent Goal, Background knowledge and Dialogue History respectively, and R to represent the response. The task is to find $\overline{R}$ that:

$$\overline{R} = \arg\max_{R} \Pr ob(R \mid G, K, H) \tag{1}$$

Words generated in $\overline{R}$ are either from *G*, *K H* or from a vocabulary *V*. Figure 2 shows the basic structure of the model we designed.

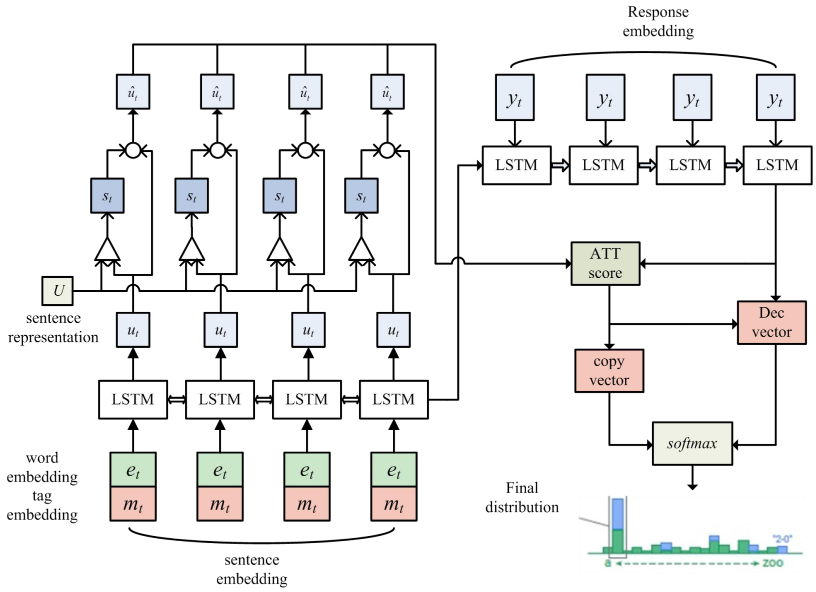


Fig. 3. End-to-end dialog system for the model with context choosing, gated self-attention and pointer network

4.1 Goal, Knowledge and History Encoding

Context choosing. We used bi-directional LSTM to present the encoding process. In Eq. 2, u_t represents the LSTM hidden state at time step *t*, *U* is the concatenated representation of the forward and backward passes.

$$U = \{[\vec{u}_t, \overleftarrow{u}_t]\}_{t=1}^{M} \tag{2}$$

$$u_t = LSTM^E(u_{t-1}, [e_t, m_t]) \tag{3}$$

In Eq. 3, e_t is the word embedding representation of word x_t concatenated by *G*, *K* and *H*. m_t is the meta-word representation of whether word x_t is in or outside the last sentence of *H*. [*a*,*b*] represents the concatenation of vector *a* and *b*. We call this approach context choosing which is similar to the techniques in Yao Zhao's work [21]. For applications, it is essential to be able to generate response that is coherent to a context.

Gated Self-attention. Our gated self-attention mechanism is designed to aggregate information from the whole background knowledge and embed vector, to refine the encoded knowledge-context representation at every time step. The first step is taking encoded U as input and conducting matching against itself to compute self matching representation. The specific calculation method is embodied in Eq.4 and Eq.5. W_s is a trainable weight matrix, a_t is the weighted sum of all words' encoded representation in passage based on their corresponding matching strength to current word. s_t is the final self matching representation. Secondly, combining the input with self matching representation using a feature fusion gate. The self matching representation s_t is combined with original knowledge-context representation u_t as the new self matching enhanced representation f_t, Eq. 6. A learnable gate vector g_t, Eq. 7, chooses the information between the original representation and the new self matching enhanced representation to form the final encoded knowledge-context representation $\hat{u}_t$.

$$a_t = soft\max(U^T W u_t) \tag{4}$$

$$s_t = U * a_t \tag{5}$$

$$f_t = \tanh(W_f [u_t, s_t]) \tag{6}$$

$$g_t = sigmoid(W_g [u_t, s_t]) \tag{7}$$

$$\hat{u}_t = g_t \cdot f_t + (1 - g_t) \cdot u_t \tag{8}$$

Through the context keyword choosing mechanism and the gated self-attention mechanism, we obtain a more effective background knowledge-context encoding vector.

4.2 Decoding with attention mechanism and pointer network

In the decoding process, we also use LSTM neural network as a decoder. It generates each word in order, with the result of each generation depending on the output of the encoder and the state of the decoder at the previous moment.

$$d_t = LSTM^D(d_{t-1}, e_{t-1}) \tag{9}$$

$$p(y_t \mid \{y_{<t}\}) = soft\max(W \cdot d_t) \tag{10}$$

In Eq. 9, d_t represents the hidden state of the LSTM at time t, where d_0 is passed from the final hidden state of the encoder. y_t stands for the word generated at time t,and e_t is used to represent the word embedding of y_t. In Eq. 10, projects d_t to a space with vocabulary-size dimensions, then a softmax layer computes a probability distribution over all words in a vocabulary V.

Attention Mechanism. At each time step t, the decoder focuses on different parts of encoder inputs via the attention mechanism. We use Luong attention mechanism to compute raw attention scores at shown in Eq. 11. An attention layer, Eq. 13 is applied above the concatenation of decoder state d_t and the attention context vector c_t, its output is used as the new decoder state. W_a and W_b is a trainable weight matrix.

$$a_t = soft\max(U^T W_a d_t) \quad (11)$$

$$c_t = U \cdot a_t \quad (12)$$

$$\hat{d}_t = \tanh(W_b[d_t, c_t]) \quad (13)$$

Pointer Network. Pointer network was introduced to allow both copying words from input via pointing, and generating words from a predefined vocabulary during decoding. Our pointer mechanism leverages raw attention scores, over the input sequence which has a vocabulary of *X*. In the vocabulary *V*, the score of the irrelevant word is set to negative infinity, which will be masked by the downstream *softmax* function. The final score on one word is calculated as the sum of all scores (*V* and *X*) pointing to the same word.

No_repeated Beam Search. Since we use the attention mechanism in the decoder, the model may focus more on background knowledge or words that have been previously generated in the context of the conversation. To improve fluency, hypotheses with repeated bi-grams are removed from further consideration during beam search. To improve fluency, hypotheses with repeated bi-grams are removed from further consideration during beam search [22].

5 Experiments

The experiment environment was as follows: Ubuntu 18.04 64-bit operating system, Intel(R) Xeon(R) Silver 4110 processor, 2.10 GHz frequency, 32 GB memory, Nvidia-RTX2080ti.

5.1 Model parameter

During training, we set the minimum count of 8 to select the top 15000 words as vocabulary for generation. We used the pretrained 300-dimension Chinese word2vec embedding to initialize word embedding and kept fixed [23]. Embeddings for OOV tokens, if found in word2vec, were used. Otherwise, their embeddings were randomly initialized. For optimization, we used SGD with momentum. Learning rate was initially set to 0.3 and halved since epoch 8 at every 2 epochs afterwards. Models were totally trained with 20 epochs. Other hyper-parameters are shown in Table 1.

Table 1. Hyper-parameter settings

Name	Value
Vocabulary size	15000
Word embedding size	300
LSTM layers size	2
LSTM hidden size	256
Batch size	64
Beam size	6
N-gram repeat	2
Learning rate for SGD	0.3
Maximum gradient norm	5.0
dropout	0.3
Min decode step	8
Max decode step	35

5.2 Evaluation results and discussion

We began to optimize the model from the baseline system. In Table 2, we show the improvement of the effect of each part of the optimization. The result is the performance of the online test set automatic evaluation, which is evaluated by three indicators: F1, BLEU1 and BLEU2.

Table 2. The impact of various parts of the model on the system

Model	total	Δ	F1	BLEU1	BLEU2
Baseline_retrieval	0.764	/	31.72	0.291	0.156
Baseline_generation	0.795	/	32.65	0.300	0.168
Pointer network base	0.933	+0.138	38.27	0.345	0.205
+raw dataset processing	0.962	+0.031	39.16	0.351	0.219
+result processing	1.052	+0.090	41.90	0.386	0.247
+Gated Self-attention	1.065	+0.013	42.64	0.386	0.253
+Context choosing	1.086	+0.021	43.78	0.392	0.256
+topical words replacement	1.108	+0.022	44.29	0.412	0.254
+Partial knowledge replacement	1.138	+0.024	45.07	0.418	0.270
+No_repeat beam search	1.175	+0.037	46.40	0.422	0.289

As indicated from the above experimental results, our data processing methods and model structure improvements have positive effects on the online evaluation results. Among them, at the very beginning, we used the pointer network innovatively to generate external knowledge-driven dialogue, which has achieved great improvement compared with the baseline method. From the perspective of model structure, improvements such as gated self-attention mechanism, context keyword tagging, and de-duplication of beam search decoding are effective for this task. In terms of data processing, the substitution of subject words and knowledge background entity words, and the length control of generated sentences have greatly improved the results. Our final result on leaderboard is from the single model introduced above. After the game, we have model ensemble, and the overall result of the offline valid dataset evaluation can be improved by about 0.02 compared with the single model.

Manual evaluation mainly evaluates the system from two aspects: target completion and dialogue consistency. The submitted model ranked fifth in the manual evaluation stage, and the results are shown in the table 3.

Table 3. Manual evaluation of the system

Model	score	goal completion (0,1,2)	Coherence (0,1,2,3)
Single model	1.662	1.79	2.30

5.3 Sample analysis

In Figure 3, we selected a piece of data from the test set for analysis. Through the multiple rounds of dialogue with the dialogue system, it can be seen that the designed model can achieve the transfer of the dialogue goal, while having a certain context coherence. However, it can be found that the dialogue process is very different from the process set in the original sample, but both modes of dialogue can complete the set tasks, and the model has good generalization performance.

```
Goal and Knowledge
{"goal":
    [["START", "星球大战前传二：克隆人的进攻", "阿凡达"],
    ["星球大战前传二：克隆人的进攻", "国家", "美国"],
    ["阿凡达", "国家", "美国"]]
"knowledge":
    [["星球大战前传二：克隆人的进攻","幕后 花絮", "• 本 片 片 长 142 分钟 ， 是
最  长 的 星战 电影 。"],
    ["星球大战前传二：克隆人的进攻", "获奖", "青少年选择奖 _ (2002 ； 第 4 届 ) _
获  奖 _ 青少年选择奖 - 最佳 剧情 / 动作 冒险 电影 女演员 _娜塔莉 • 波特曼
    Natalie Portman"],
    ["星球大战前传二：克隆人的进攻", "上映 时间", "2002 年 7 月 12 日"],
    ["星球大战前传  二：克隆人的进攻", "类型", "奇幻"],
    ["星球大战前传二：克隆人的进攻", "领域", "电影"],
    ["星球大战前传二：克隆人的进攻", "国家", "美国"],
    ["阿凡达", "类型", "奇幻"],
    ["阿凡达", "时光网 短评", "电影 就是 机械 造 的 梦"],
    ["阿凡达", "发布 日期 信息", "5 年前 上映"],
    ["阿凡达", "领域", "电影"],
    ["阿凡达", "国家", "美国"],
    ["星球大战前传二：克隆人的进攻", "票房", "4500.0 万"],
    ["星球大战前传二：克隆人的进攻", "口碑", "口碑 一般"],
    ["星球大战前传二：克隆人的进攻", "类型", "动作"]]}
```

```
our model conversation:
    Chatbot: 你 喜欢 看 什么 类型 的 电影 ?
    Person: 我 喜欢 看 美国 电影 。
    Chatbot: 给 你 推荐 一部 美国 的 动作 电影 《 星球大战前传二：克隆人的进
攻 》 。
    Person: "这 部 电影 怎么样 。"
    Chatbot: "本 片 片 长 142 分钟 ， 是 最长 的 星战 电影 。"
    Person: "那 确实 挺长 的 。"
    Chatbot: "再 给 你 推荐部 美国 电影 吧 。"
    Person: "好的 ， 什么 电影。"
    Chatbot: "阿凡达 ， 是 一部 奇幻 类型 的 电影 。"
    Person: "好 啊 ， 有 时间 我 一定 去 看看 。"
    Chatbot: " 我 觉得 你 会 喜欢 的 。"
raw conversation:
    Person1: "这个 美国 电影 真 的 很一般 。"
    Person2: "美国 电影 一般 是 大 制作 啊 。"
    Person1: "真是 不 怎么 好 ,《 星球大战前传二：克隆人的进攻 》 票房 也不 高 "
    Person2: "有 原因 的 吧 。",
    Person1: "口碑 不好 ， 看 的 人 少 吧 。"
    Person2:  "口碑 对 一部 电影 来说 很重要 了 。"
    Person1: "还有 一部 美国 电影 叫 阿凡达 ， 很好看 的 哦 ！"
    Person2: "我 还 没看过 这个 电影 呢 。"
    Person1: "这 是 一部 奇幻 类型 的 电影 ， 相信 你 会 喜欢 呢 ！"
    Person2: "好 啊 ， 有 时间 我 一定 去 看看 。"]}
```

Fig. 4. Sample model generation result

6 Conclusion

The LIC2019's knowledge-driven dialogue challenge provides high-quality multiple rounds conversation dataset based on background information. We improved the pointer generator model by adding a gated self-attention mechanism and a context choosing method that replicates OOV words in session context and background knowledge, and produces diverse and coherent responses through optimized decoding strategies. After the data processing, precision tuning and other optimization methods, we achieved 0.464/0.422/0.289 in the automatic evaluation index F1/BLEU1/BLEU2, and also achieved the task completion score of 1.79 and the consistency score of 2.3 in the manual evaluation.

References

1. Wenquan Wu, Zhen Guo, Xiangyang Zhou. 2019 Proactive Human-Machine Conversation with Explicit Conversation Goals. In ACL.
2. Vinyals, O., and Le, Q. V. 2015. A neural conversational model. In ICML.
3. Shang, L.; Lu, Z.; and Li, H. 2015. Neural responding machine for short-text conversation. In Proceedings of ACL.
4. Sordoni, A.; Galley, M.; Auli, M.; Brockett, C.; Ji, Y.; Mitchell, M.; Nie, J.-Y.; Gao, J.; and Dolan, B. 2015. A neural network approach to context-sensitive generation of conversational responses. In Proceedings of NAACL-HLT.
5. Wen, T.-H.; Gasic, M.; Mrksic, N.; Rojas-Barahona, L. M.; Su, P.-H.; Ultes, S.; Vandyke, D.; and Young, S. 2016. Conditional generation and snapshot learning in neural dialogue systems. In Proceedings of the conference on empirical methods in natural language processing (EMNLP).
6. Antoine Bordes and Jason Weston. Learning end-to-end goal-oriented dialog. International Conference on Learning Representations, abs/1605.07683, 2017.
7. Mihail Eric and Christopher Manning. A copy-augmented sequence-to-sequence architecture gives good performance on task-oriented dialogue. In Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics: Volume 2, Short Papers, pp. 468–473, Valencia, Spain, April 2017. Association for Computational Linguistics. URL http://www.aclweb.org/anthology/E17-2075.
8. Jason D Williams and Steve Young. Partially observable markov decision processes for spoken dialog systems. Computer Speech & Language, 21(2):393–422, 2007
9. Steve Young, Milica Gasi c, Blaise Thomson, and Jason D Williams. Pomdp-based statistical spoken dialog systems: A review. Proceedings of the IEEE, 101(5):1160–1179, 2013.
10. Yun-Nung Chen, Dilek Hakkani-Tur, Jianfeng Gao, and Li Deng. End-to-end memory networks with knowledge carryover for multi-turn spoken language understanding. 2016
11. Chien-Sheng Wu, Andrea Madotto, Genta Winata, and Pascale Fung. End-to-end dynamic query memory network for entity-value independent task-oriented dialog. In 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pp. 6154–6158, April 2018.
12. Sutskever, I.; Vinyals, O.; and Le, Q. V. 2014. Sequence to sequence learning with neural networks. In Advances in Neural Information Processing Systems.

13. Bahdanau, D.; Cho, K.; and Bengio, Y. 2015. Neural machine translation by jointly learning to align and translate. In Proceedings of the International Conference on Learning Representations.
14. Seo, M.; Kembhavi, A.; Farhadi, A.; and Hajishirzi, H. 2017. Bidirectional attention flow for machine comprehension. In Proceedings of ICLR.
15. Wang, S., and Jiang, J. 2017. Machine comprehension using match-lstm and answer pointer. In Proceedings of ICLR.
16. Oriol Vinyals, Meire Fortunato, and Navdeep Jaitly. 2015. Pointer networks. In Neural Information Processing Systems
17. Abigail See, Peter J Liu, and Christopher D Manning. 2017. Get to the point: Summarization with pointer-generator networks. arXiv preprint arXiv:1704.04368.
18. Ghazvininejad, M.; Brockett, C.; Chang, M.-W.; Dolan, B.; Gao, J.; Yih, W.-t.; and Galley, M. 2018. A knowledgegrounded neural conversation model. In AAAI.
19. Madotto, A.; Wu, C.-S.; and Fung, P. 2018. Mem2Seq: Effectively incorporating knowledge bases into end-to-end task-oriented dialog systems. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics, 1468–1478. Association for Computational Linguistics.
20. Fan Wang Jinhua Peng Hua Wu Rongzhong Lian, Min Xie. Learning to select knowledge for response generation in dialog systems. arXiv preprint arXiv:1902.04911, 2019.
21. Yao Zhao; Xiao-chuan Ni. 2018. Paragraph-level Neural Question Generation with Maxout Pointer and Gated Self-attention Networks. In EMNLP
22. Yik-Cheung Tam; Jiachen Ding. 2019. Cluster-based Beam Search for Pointer-Generator Chatbot Grounded by Knowledge. In AAAI
23. Shen Li; Zhe Zhao; Renfen Hu; Wensi Li; Tao Liu; Xiaoyong Du. 2018 Analogical Reasoning on Chinese Morphological and Semantic Relations. In ACL.