Prediction, Selection, and Generation: 
Exploration of Knowledge-Driven Conversation System 

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Abstract 
In open-domain conversational systems, it is important but challenging to leverage background knowledge. We can use the incorporation of knowledge to make the generation of dialogue controllable, and can generate more diverse sentences that contain real knowledge. In this paper, we combine the knowledge bases and pre-training model to propose a knowledge-driven conversation system. The system includes modules such as dialogue topic prediction, knowledge matching and dialogue generation. Based on this system, we study the performance factors that maybe affect the generation of knowledge-driven dialogue: topic coarse recall algorithm, number of knowledge choices, generation model choices, etc., and finally made the system reach state-of-the-art. These experimental results will provide some guiding significance for the future research of this task. As far as we know, this is the first work to study and analyze the effects of the related factors.

1 Introduction 
It has been a long-term goal of artificial intelligence to deliver human-like conversations, where background knowledge plays a crucial role in the success of conversational systems\(^{[10,18]}\). The arrival of the pre-training model era has also greatly promoted the generation of dialogue in the open-domain. For example, CDial-GPT2\(^{[21]}\) and OpenAI GPT-2 have demonstrated that transformer models trained on a large-scale dataset can capture long-term dependencies in textual data and generate fluent diverse text. Such models have the capacity to capture textual data with fine granularity and produce output with a high-resolution that closely emulates real-world text written by humans. If we want these models to generate texts that contain correct realistic knowledge or
Generating dialogue responses without using knowledge

| User: 你好，你知道周杰伦吗？（Hello, do you know Jay Chou?） |
| Bot: 当然知道了，他可是我的偶像呢。（Of course I know, he is my idol） |
| User: 那你听过他的《以父之名》这首歌吗？（And have you heard his song "In the Name of the Father"?） |
| Bot: 听过啊，很好听的一首歌。（I've heard it, it's a great song.） |
| User: 你知道这首歌是什么时间发行的吗？（Do you know when this song was released?） |
| Bot: 这个我还真不知道。（This I really do not know.） |

Generating dialogue responses with using knowledge

| User: 你好，你知到周杰伦吗？ |
| Bot: 当然啦，他的成績有《Fast Company》全球百大創意人物，获得十五座金曲奖。 (knowledge: [周杰伦主要成就获得十五座金曲奖, 周杰伦主要成就《Fast Company》全球百大創意人物]) |
| Of course, his achievements include "fast company" top 100 creative people in the world, won 15 Golden Melody Awards. (knowledge: [Jay Chou's major achievements won fifteen Golden Melody Awards, Jay Chou’s major achievements Fast Company’s Top 100 Creative People in the World]) |
| User: 那你听过他的《以父之名》这首歌吗？ |
| Bot: 听过，这首歌是洪敬尧编曲的一首歌。（knowledge: [以父之名编曲洪敬尧, 以父之名填词黃俊郎]) |
| I've heard of it. It's a song arranged by Hong Jing Yao. (knowledge: ["In the Name of the Father" is arranged by Hong Jing Yao, "In the Name of the Father" with lyrics by Huang Junliang]) |
| User: 你知道这首歌是什么时间发行的吗？ |
| Bot: 它是2003年07月16日发行的。知道它是哪家唱片公司发行的吗？(knowledge: [以父之名发行时间2003年07月16日]) |
| It was released on July 16, 2003. Do you know which record label it was released by? (knowledge: ["In the Name of the Father” release date July 16, 2003]) |

Figure 1: Two examples of using knowledge-driven or not. Both examples use the same model that is trained in our experiments, the first example is generated without adding external knowledge and the second example is generated with adding external knowledge. Sentences marked in red indicate the result of knowledge-driven generation.

controllable content, we can incorporate additional knowledge information to generate.

Integrating knowledge into dialogue generation can make the generated results more diverse and controllable [9]. For example, incorporating laughter knowledge into a Generative Model can generate humorous dialogue [22]. In an open-domain conversation system, it is very important but challenging to use background knowledge for effective interaction. Background knowledge can be expressed as a knowledge graph, unstructured text [6] or a descriptive corpus.

In order to explore the factors that affect the generation effect of the knowledge-driven dialogue system, in this paper, we propose a knowledge-driven conversation generation system, and use different models to conduct experiments on the dataset KdConv [26] under this system, and finally find the main factors affecting the generation effect, and make the system has reached state-of-the-art
results.
Our contributions are threefold: (1) We propose a general knowledge-driven dialogue generation system which covers the entire process from topic prediction, knowledge selection and dialogue generation. (2) We study the relevant factors affecting the correct knowledge selection rate and find that the highest accuracy is achieved by using the LAC algorithm for rough recall and Sentence-Bert [17] is better than Pairwise Model for sorting for fine recall. (3) We investigate the factors affecting the generation effect, such as generation model selection, multi-task, and knowledge number selection, and find that using the Bert2Transformer framework model works better than CDial-GPT2, and in this case selecting 3 pieces of knowledge generates better results than selecting 1 piece of knowledge.

2 Related Works

Open-domain Conversations Generation. In traditional open-domain conversations, the model predicts the next sentence given the previous sentence or sentences in the conversation [20]. The responses generated by such systems tend to be safe response [7] and do not contain knowledge that does not appear in the context. In order to generate multiple diverse responses, many approaches resort to enhanced beam search [7,8]. Additional studies allow the model to generate a diversity of responses rather than in the post-processing stage. For example, some researchers augment the Seq2Seq model with a multi-mapping mechanism to learn the one-to-many relationship for multiple diverse response generation [2,16]. However these efforts do not allow the model to generate responses that contain knowledge that is not in the context. Application of Knowledge. Knowledge is now used in a variety of tasks. Some researchers use knowledge to pre-train a model (ERNIE) so that it can use the knowledge information for downstream tasks [24]. And some researchers enrich the state-of-the-art neural natural language inference models with external knowledge [3]. Other researchers introduce a neural reading comprehension model that integrates external knowledge, encoded as a key value memory [13]. Incorporating external knowledge can give more information to the model, which is believed to be the trend. Knowledge-driven Conversation. On dialogue tasks, there are also a number of studies that focus on making models to incorporate knowledge to produce more diverse and knowledge-inclusive responses. Some of them focus on the choice of knowledge. For examples, DiffKS [25] proposed a difference-aware knowledge selection method to facilitate the selection of more appropriate knowledge. And some studies focus on conversation generation. MGCC [11] is an architecture of multi-goal driven conversation generation framework that requires the input of goals, knowledge, and other information to generate conversation responses. The premise of this system is that it knows the knowledge it needs to use to generate responses before it starts the conversation, unlike open-domain conversations where the system does not know what it needs to talk about before it starts. In actual dialogue, however, we need a model or system to select appropriate knowledge based on background
and history to generate dialogue by itself. Some works focus on this issue such as [6], in which knowledge selection is considered and the model performs simple knowledge selection before generation, but the selection method is very crude and each generation selects a large number of different types of knowledge for generating a response, thus introducing a large amount of noise and reducing the generation quality.

In this paper, we propose a system framework that covers accurate knowledge selection and response generation for knowledge-driven conversation generation and explore the key factors affecting its performance.

3 Methodology

In this section, we will introduce our experimental models and methods. We experiment with multiple elements, which intuitively work for dialogue generation, to explore how each element is critical to the task.

3.1 Task Formulation

In the case of our task, there are differences between the training and inference phases. In the training phase, we have three models to train: a topic prediction model, a knowledge matching model, and a conversation generation model. We process the data into the standard training data needed for each model, so there is no connection between these models. But the inference phase is more like our conversations in reality, where we only have the historical conversational corpus, which requires the individual models to work together to generate responses with real knowledge. So it is different from traditional multi-turn dialogue, knowledge-driven multi-turn dialogue should include knowledge selection work in addition to dialogue generation.

We suppose that we have datasets \( D_{kc} = \{(s_i)\}_{i=1}^{N} \) and \( K_{kc} = \{k_j\} \) from dataset KdConv, where \( s_i = \{u_{i,1},...,u_{i,n}\} \) represents a dialogue scene with \( n \) rounds utterances, \( k_j \) stands for relevant knowledge base or knowledge graph. Our goals are to use these data to train the system to generate reasonable responses and explore the factors that affect its performance.

3.1.1 Training Phase

In the training phase, we reconstruct the datasets \( D_{kc} \) and \( K_{kc} \) as different training datasets \( D_{topic}, D_{kg}, D_{cg} \) for different models. **Topic Prediction Model.** \( D_{topic} = \{(h_i,m_i)\}_{i=1}^{n} \), where \( n \) means there are \( n \) pieces of training data, \( h_i = \{u_{i,1},...,u_{i,n}\} \) represents a conversation context with \( u_{i,n} \) as a utterance, and \( m_i \) is the label of the topic from the dataset \( K_{kc} \). **Knowledge Matching Model.** \( D_{kg} = \{(h_i,k_i,l_i)\}_{i=1}^{n} \), where \( n \) means there are \( n \) pieces of training data, \( h_i = \{u_{i,1},...,u_{i,n}\} \) represents a conversation context with \( u_{i,n} \) as a utterance, \( k_i \) is the knowledge sampled in the ratio of positive and negative samples 1:4. And \( l_i \) indicates the corresponding label, if \( k_i \) is the relevant
knowledge to be replied then it is 1, otherwise, it is 0. **Conversation Generation Model.** $D_{cg} = \{(h_i, k_i, r_i, p_i)\}_{i=1}^{n}$, where $n$ means there are $n$ pieces of training data, $h_i = \{u_{i,1}, ..., u_{i,n}\}$ represents a conversation context with $u_{i,n}$ as a utterance, $k_i$ is the knowledge. And $r_i$ indicates the corresponding reply sampled in the ratio of positive and negative samples 1:1. $p_i$ indicates the label of whether the $r_i$ is the positive sample, if $p_i$ is the correct reply then it is 1, otherwise, it is 0. The positive and negative sample responses $r_i$ and $p_i$ are constructed for multi-task training, see section 3.6 for details.

### 3.1.2 Inference Phase

At this phase, we have only dialogue history and knowledge, just as we talk in reality. Different models are required to work together to generate the corresponding response $r_i$ using datasets $D_{ip}$ and $K_{kc}$, where $D_{ip} = \{u_1, ..., u_n\}$ represents a conversation context with $u_n$ as a utterance. And response $r_i$ is then incorporated into dataset $D_{ip}$ for subsequent generation.

### 3.2 System Architecture

The architecture of our system is shown in Figure 2. The training and inference processes are different: For training, we only need to use the sampled reconstructed data from KdConv for model training. Inference, on the other hand, requires multiple models to work together.

In the inference phase, when the user says a sentence, the system first concatenates it behind the historical utterances. And the system conducts a rough recall of the topics based on the historical utterances, then use these topics and memory unit to roughly recall the corresponding knowledge in the knowledge base. The Topic Prediction Model sorts topics based on the historical utterances, and compare the results with the topics of the rough recall in the previous step, and select the most suitable topic. Next, it input the knowledge consistent with the best topic in rough recall and the historical utterances into the Knowledge Matching Model, and rank the knowledge to get the best knowledge. Finally, the best knowledge and historical utterances are sent to the Generative Model to generate a reply, which will be added to the end of the historical utterances.

### 3.3 Rough Recall

The conversation system needs to generate replies quickly. In the pre-training era, if every piece of knowledge were sent to the deep learning model for processing, the response speed can not meet the conversation requirement. So we propose to use mature and fast algorithms to roughly recall topics and knowledge. We will compare the three algorithms of Tfidf, Ner, and Aho-Corasick.

**Tfidf.** Tfidf is a text keyword extraction algorithm. Here we use the Tfidf tool provided by jieba.

![https://github.com/fxsjy/jieba](https://github.com/fxsjy/jieba)
Figure 2: System Architecture. In the training phase, we sample the data from KdConv and reconstruct the samples needed for training, as shown in Section 3.1.1. The reconstructed data is then used to train the modules separately. In the inference phase, the utterance of user and model response are packaged into a historical corpus, which is processed collaboratively by Topic and Knowledge Rough Recall algorithm, Topic Prediction Model, and Knowledge Matching Model to find the best knowledge before being sent to the Dialogue Generative Model for sentence response generation.

LAC[^2]. The full name of LAC is Lexical Analysis of Chinese, which is a joint lexical analysis tool developed by Baidu’s Natural Language Processing Department to realize Chinese word segmentation, part-of-speech tagging, proper name recognition and other functions. In this project, we use LAC tools for part-of-speech tagging and entity recognition. LAC tool supports importing self-built dictionary for searching.

Aho-Corasick. The Aho-Corasick algorithm is a classic algorithm in multi-pattern matching and is currently used in many practical applications. Here we use the ahocorasick[^3] tool to perform the Aho-Corasick algorithm.

[^2]: https://github.com/baidu/lac
[^3]: https://github.com/WojciechMula/pyahocorasick
We assume that $T_0$ is the result set of the topics and $K_0$ is the related knowledge set of $T_0$. One of the topics as the root node will be related to multiple pieces of knowledge. As the root node, *In the Name of the Father* is connected to a lot of knowledge, as shown in Figure 7. So in the next steps, we also need to recall the related topics and knowledge.

### 3.4 Topic Prediction

The Topic Prediction Model needs to output the probability value of each topic in the knowledge base based on historical dialogue, as shown in Figure 3. Here we use the pre-trained model RoBERTa-wwm-ext [4] for fine-tuning. We put the [CLS] hidden state vector into a linear layer which outputs the final classification results $o_e$ whose dimensions are the sum of the number of topics:

$$O_e = \text{softmax} \left( \text{linear} \left( O_{\text{bert}} \right) \right)$$

where $O_{\text{bert}}$ are the outputs of the RoBERTa-wwm-ext. In order to calculate faster, we can also directly use the outputs of the linear layer as the results $O_e$ without using the softmax function.

Since $O_e$ is the probability value of all topics, we only need to find the topic with the largest probability value at the same time it is also in $T_0$, which is the best topic. When we select the best topic, we need to filter out the knowledge that is not related to it in $K_0$, and the remaining knowledge related to the best topic is the set $K_1$.

![Figure 3: Topic Prediction. The Topic Prediction Model is a multi-classification model that can output all topic scores $O_e$. We sort the topics according to the value of the score and then choose the topic with the highest score in $T_0$ as the best knowledge.](https://example.com/fig3.png)

### 3.5 Knowledge Matching

**Sentence-Bert** [17]. We use Sentence-Bert as the knowledge Matching Model and use pre-trained RoBERTa-wwm-ext to initialize the Bert [5] module inside the model. Because some historical data or knowledge is too long to too much data will be truncated and the calculation time will be too much when they are sent to RoBERTa-wwm-ext after splicing. Sentence-Bert can greatly alleviate...
this situation. The twin BERT of the Sentence-Bert is used to process history
and knowledge separately, it can accommodate longer data and reduce calcula-
tion time. As shown in Figure 4, the knowledge Matching Model is a two-class

![Figure 4: Sentence-Bert. Knowledge Matching Model is a two-classification model that can output a knowledge score \( s_j \). This score measures how well the knowledge \( k_j \) matches the histories \( h_1, \ldots, h_n \) of the conversation.]

model. We respectively encode the historical utterances and knowledge by the
BERT and use the \([CLS]\) hidden states vector as vector \( a \) and vector \( b \) respectively. Then perform the corresponding splicing calculation operation on vector \( a \) and vector \( b \) and put the result vector to a linear layer which outputs the final classification results \( S_j \). We train the model for ranking knowledge using cross-entropy loss:

\[
L_{bert} = - \sum_{j \in J_{pos}} \log (s_j) - \sum_{j \in J_{neg}} \log (1 - s_j)
\]

where \( s_j \) is a score for each candidate knowledge in \( K_1 \) independently. \( J_{pos} \) is the set of indexes of the appropriate candidate knowledge and \( J_{neg} \) is the set of indexes of the non-appropriate candidates’ knowledge in \( K_1 \). We sort all the candidate knowledge in set \( K_1 \) according to the scores \( s \) and then select the first \( n \) pieces of knowledge in the ranking result for dialogue generation.

**Pairwise Model.** We also try the pairwise ranking strategy \([14]\) to expect a better result. The Pairwise Model model is the same with Topic Prediction
Model, but the difference was the input data: We input up to three historical utterances together with one positive and one negative knowledge samples into the model. We trained the model with the following loss:

\[ L_{\text{ranking}} = - \sum_{i \in J_{\text{pos}}, j \in J_{\text{neg}}} \log (s_{i,j}) - \sum_{i \in J_{\text{neg}}, j \in J_{\text{pos}}} \log (1 - s_{i,j}) \]

where \( s_{i,j} \) is a score for each pair candidate’s knowledge in \( K_1 \). \( J_{\text{pos}} \) is the set of indexes of the relevant candidates’ knowledge and \( J_{\text{neg}} \) is the set of indexes of the non-relevant candidates’ knowledge in \( K_1 \).

3.6 Conversation Generation

At the core of our approach is language modeling [1]. We first concatenate the utterances in a multi-turn dialogue session into \( N - 1 \) samples (\( N \) is the number of utterances). Each sample is concatenated into a long text \( S = k_n, s_1, ..., s_{n-1} \) (\( s_i \) is the historical utterances of the current reply where \( i \in [1, n - 1] \). \( k_n \) is the response-related knowledge.) by the dialog history and response-related knowledge, ending with an end-of-text marker. And we denote the target sentence (ground truth response) as \( s_n \), the conditional probability of \( P(s_n | S) \) can be written as the product of a series of conditional probabilities:

\[ p(s_n | S) = p(s_n | k_n, s_1, ..., s_{n-1}) \]

where, \( n \in [2, N] \). The generation condition probability of each token in \( s_n \) is \( P(w_i | S, w_1, ..., w_{i-1}) \), and the generation condition probability of \( P(s_n) \) is as follows :

\[ p(s_n) = \prod_{i=1}^{m} p(w_i | S, w_1, ..., w_{i-1}) \]

where, \( m \) is the number of tokens in \( s_n \).

In order to explore the effect of different models using knowledge generation, we use Bert2Transformer and CDial-GPT [23] as the generation models. At the same time, in the training phase, we designed a multi-task what is similar to the NSP in Bert [5], hoping to allow the generation model to learn to distinguish sentences that are close in literal distance but farther away in the semantic distance. eg: Suppose our context is talking about dogs, the model may generate one of the following two sentences: ["Hello, my dog is cute", "Hello, my cat is cute"]. For the model, the generation probabilities of these two sentences are too close and maybe generated incorrectly. So we construct a multi-task: a two-classification task, let the model judge whether the current reply is a suitable reply. As shown in Figure 5 and Figure 6, because the last token of the generation task has global information, we take the hidden states vector of the last token from the reply into the linear layer and activation function and then output the logits as the binary-classification result.
The $\mathcal{L}_{total}$ is calculated as follows:

$$
\mathcal{L}_{total} = \alpha \mathcal{L}_{LM} + (1 - \alpha) \mathcal{L}_{NSP}
$$

where $\mathcal{L}_{total}$ is the total loss of training, $\mathcal{L}_{LM}$ is the language model’s loss and the $\mathcal{L}_{NSP}$ is the MultitaskNSP’s loss. In this experiment, if the reply in the current training sample is suitable, $\alpha$ is taken as 0.5. Otherwise, $\alpha$ is taken as 0.

**Bert2Transformer.** As shown in Figure 5, the Bert2Transformer model is based on the Transformer [19] framework, but the encoder is Bert base and the decoder is a 12-layers Transformer’s decoder. In order for the decoder to obtain some prior information, we use Bert’s embedding to initialize both the embedding and output layer of the decoder. At the same time, we compare whether the embedding of the encoder and the decoder share parameters so as to affect the generation effect. At the same time, compare the different performance of whether the encoder embedding layer and the decode embedding layer share parameters.

**CDial-GPT2.** As shown in Figure 6, CDialGPT2 is a 12-layer GPT2 which is pre-trained for 70 epochs on the Chinese novel dataset [21] and post-trained for 30 epochs on LCCC-base [21].

### 4 Experiments

All models are based on the transformers[5] framework and use pre-trained models RoBERTa-wwm-ext, RoBERTa-wwm-ext-large[6] and CDial-GPT2_LCCC-base[7] to fine-tuning respectively. And using CrossEntropyLoss as an optimizer for training. At the same time, all deep learning models were optimized by the AdamW [12] optimizer and the learning rate decay method. We created a schedule with a learning rate that decreases linearly from the initial learning rate set in the optimizer to 0.

### 4.1 Data Process

We used the KdConv[8] for experiments. KdConv is a Chinese multi-domain knowledge-driven conversation dataset, which grounds the topics in multi-turn conversations to knowledge graphs. The corpus contains 4.5K conversations from three domains (film, music, and travel), and 86K utterances with an average turn number of 19.0.

In order to explore the factors that may affect the generation of the reply, we need to process and structure the dataset into the format required by chapter 3.1. As for the knowledge graph, we just need to read in all of it and search when needed, as shown in Figure 7.

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[5] https://github.com/huggingface/transformers
[6] https://github.com/ymcui/Chinese-BERT-wwm
[7] https://github.com/thu-coai/CDial-GPT
[8] https://github.com/thu-coai/KdConv
Figure 5: Bert2Transformer. The encoder is Bert base and the decoder is 12-layers Transformer's decoder. And using Bert’s embedding to initialize the embedding and output layer of the decoder. Training this model through multi_task: LM task and take the last token as a binary classification task (NSP task).

For all training models, the input data starts with [CLS] token and ends with [SEP] token.

4.2 Evaluation Metrics

On all the dataset we use average BLEU [15] score for 1, 2, 3, 4-gram and Distinct-2 [7] to measure the final generation quality. We use BLEU to measure the similarity between the generated sentences and labels. Distinct measures the degree of diversity by calculating the number of distinct unigrams and bigrams in generated responses.

4.3 Rough Recall Implementation Details and Results

In the Rough Recall stage, we compared Tfidf, LAC and Aho-Corasick algorithms respectively. Because they are all ready-made tools, we directly use all the training data as the test samples for testing. For each sample, we can take up to the last 10 sentences of dialogue history as the historical utterances.

Tfidf. We took all the knowledge root nodes in the knowledge graph as topics and added them to the Tfidf dictionary so that the jieba tool can correctly cut
Figure 6: CDialGPT2. CDialGPT2 is a 12-layer GPT2, we fine-tuning this model by multi_task: LM task and take the last token as a binary classification task (NSP task).

Figure 7: Training Corpus. In each training sample, history_utt is the context history; response is the corresponding response and knowledge is the selected knowledge; label is the label of knowledge, if knowledge is suitable then label is 1, otherwise 0; mention is the topic prediction label, if the value is −100, the Topic Prediction Model does not need to train this sample.

the knowledge nodes during word segmentation. After cutting the historical dialogue utterances with jieba and removing the stop words, they were sent to the Tfidf algorithm, and the first $n$ results of the outputs were taken as the result set.

LAC. We took all the knowledge root nodes in the knowledge graph as topics and added them to the LAC dictionary so that the LAC algorithm could accurately identify the topics. Because the results of the LAC algorithm were generated in the order of the input utterances, we took the last $n$ results generated from LAC as the result set.

Aho-Corasick. We used the ahocorasick algorithm’s Automaton class as a trie and added the knowledge root nodes regarded as the topics and their associated
value to this trie. In the test, we inputted the historical utterances, took all the output results, and sorted the results according to the string length from large to small, and took the first n results as the result set.

We used accuracy as a measure and compared the accuracy of the correct topics in the first n ∈ [1, 50] outputs of the three of them, which means that we test the accuracy of 50 different values. Assuming there are T evaluation samples, in this experiment T = 62938, the specific formula is as follows:

\[
y_{it} = \begin{cases} 
1, & \text{if } k_t \in O_{it} \\
0, & \text{if } k_t \notin O_{it}
\end{cases}
\]

\[
acc_i = \frac{\sum_{t=1}^{T} y_{it}}{T} \times 100\%
\]

where \( i \in (0, 1, 2) \) respectively indicates which algorithms of Tfidf, Ner and Aho-Corasick is used, \( k_t \) represents the true topic of the \( t \)-th sample, \( O_{it} \) represents the result set predicted by the \( i \)-th algorithm for the \( t \)-th sample, correspondingly, \( y_{it} \) is the score calculated on the \( t \)-th sample using the \( i \)-th algorithm and \( acc_i \) is the final accuracy rate of the \( i \)-th algorithm.

The results of different coarse recall algorithms are as follows Figure 8. In the case of selecting different numbers of topics, different algorithms perform differently. The LAC algorithm performs best when the number of recalled topics is larger. In the process of matching the topics of coarse recall with the results predicted by the Topic Prediction Model, we hope that the accuracy the higher, the better. So in the next experimental process, we chosen LAC as our coarse recall algorithm. The accuracy rate of LAC can reach 94% when selecting the first 50 topics.

4.4 Topic Prediction Model Training Details and Results

Because there are a total of 12149 topics, the Topic Prediction Model is a 12149 classification model. We used historical utterances as input data and the node element of the triad in the knowledge graph is the classification label, as shown in Figure 7. Among them, the longest input data length was truncated to 400,
Figure 9: Rough Recall Results. The abscissa represents the number of topics that are roughly recalled by different algorithms, and the ordinate represents the accuracy of different algorithms under the number of recalled topics. When selecting the first 50 topics, the accuracy rate of LAC can reach 94% and the last 10 sentences of the historical corpus were used at most. At the same time, using [SEP] token to separate different dialogue utterances.

**Base.** Fine-tuning through RoBERTa-wwm-ext. The learning rate was initialized to 2e-5. The batch size was set to 14.

**Large.** Fine-tuning through RoBERTa-wwm-ext-large. The learning rate is initialized to 1e-5. The batch size was set to 2.

The results are shown in Table 1. We compared the accuracy of the base model and the large model on the validation set and test set respectively. It can be seen that the large model is slightly better than the base model in performance.

Table 1: Topic Prediction Model evaluation. The accuracy here refers to the accuracy when the model is correctly multi-classified, and it measures the model’s performance in recall historical dialogue topics.

| Model                | Valid Accuracy | Test Accuracy |
|----------------------|----------------|---------------|
| RoBERTa-wwm-ext      | 90.38%         | 85.23%        |
| RoBERTa-wwm-ext-large| 91.19%         | 86.06%        |
4.5 Knowledge Matching Model Training Details and Results

The knowledge Matching Model is a two-classification model, which inputs knowledge and dialogue historical utterances, and outputs a logits value or probability value. The longest historical utterances data length and knowledge length were respectively controlled within 400, and at most the last 10 sentences of the historical corpus were used as historical utterances data. Using [SEP] token to separate different dialogue utterances. Since Sentence-Bert was used as the knowledge Matching Model, we tested the results of using the same Bert to encode historical utterances and knowledge data separately and two different Bert to encode historical utterances and knowledge data separately.

**Base.** Fine-tuning through RoBERTa-wwm-ext. The learning rate was initialized to 3e-5. The batch size was set to 14.

**Large.** Fine-tuning through RoBERTa-wwm-ext-large. The learning rate is initialized to 1e-5. The batch size was set to 2.

**Pairwise Model.** We fine-tuning this model through RoBERTa-wwm-ext. The maximum input data length is controlled within 500. And the learning rate is initialized to 2e-5. The batch size was set to 14.

The results are shown in Table 2. We compared the accuracy of different models on the validation set and test set. The accuracy here is only the accuracy of the model's binary classification of data, which is different from the accuracy of the final knowledge selection.

From the results, the performance of using twin Bert is much better than using two different Bert. This is maybe because two Berts are used to separately encode the knowledge and historical utterances, so they only learn part of the data, but not the other side's data, and the data lacks sufficient interaction.

Table 2: knowledge Matching Model evaluation. The accuracy is only the accuracy of the model to correctly classify the data, not the knowledge selection accuracy."-diff" means using two different Bert to encoding knowledge and historical utterances.

| Model                  | Valid Accuracy | Test Accuracy |
|------------------------|----------------|---------------|
| Sentence-Bert-base     | 96.09%         | 95.54%        |
| Sentence-Bert-base-diff| 94.75%         | 73.49%        |
| Sentence-Bert-large    | 96.14%         | 95.38%        |
| Pairwise Model         | 90.12%         | 89.64%        |

The accuracy of the final knowledge selection is shown in Table 3. This shows the accuracy from rough recall to final knowledge selection. The rough recall stage we use the LAC algorithm, input up to the last 10 historical utterances, and output 50 topics for subsequent model processing. We respectively compared the accuracy of the correct knowledge in the knowledge with the highest one probability, the top three probability and the top five probability after sorting.

From the results, the Pairwise Model is not suitable for knowledge matching.
Our intention is to allow the model to pay more attention to the interaction between positive sample knowledge and negative sample knowledge, so as to determine more appropriate knowledge. But judging from the results, the added knowledge seems to become noise, which interfered with model judgment. For Sentence-bert, the model was more concerned with an alignment between knowledge and dialogue history. The better the aligned knowledge, the more appropriate the model thought it was.

Table 3: Knowledge Selection Accuracy. This shows the accuracy from rough recall to final knowledge selection. And we respectively show the accuracy of correct knowledge contained in the first 1, 3, and 5 pieces of knowledge after sorting. ‘✓’ indicates the fine-tuned pre-training model used in the current experiment. ‘∅’ means not used or not tested.

| Topic Prediction Model | Sentence-Bert | Pairwise Model | The number of selected knowledge |
|------------------------|---------------|----------------|---------------------------------|
|                        | base | large | base | large | Model | 1       | 1-3     | 1-5     |
| ✓                      | ∅    | ✓     | ∅    | ✓     | ∅     | 28.66%  | 49.12%  | 60.25%  |
| ✓                      | ∅    | ∅     | ✓    | ✓     | ∅     | 21.86%  | 47.03%  | 59.23%  |
| ∅                      | ✓    | ✓     | ∅    | ✓     | ∅     | 28.94%  | 49.80%  | 61.05%  |
| ∅                      | ✓    | ∅     | ✓    | ✓     | ∅     | 22.10%  | 47.59%  | 59.83%  |
| ✓                      | ∅    | ∅     | ∅    | ✓     | ✓     | 9.92%   | ∅       | ∅       |
| ∅                      | ✓    | ∅     | ∅    | ∅     | ✓     | 10.06%  | ∅       | ∅       |

4.6 Conversation Generation Model Training Details and Results

We used CDial-GPT2 and Bert2transformers as generation models for experiments. Using the last 10 historical utterances and $m$ pieces of knowledge as input to generate a reply where $m = 1, 3$, to explore the influence of different knowledge numbers on generation. The longest data length of the sum of historical utterances data length and knowledge length was controlled within 400. Using [speaker1] [speaker2] tokens to separate different historical utterances and [SEP] token to separate different knowledge.

**CDial-GPT2.** Fine-tuning through CDial-GPT2_LCCC-base. The learning rate was initialized to 3e-5. The batch size was set to 6.

**Bert2transformers.** Fine-tuning through RoBERTa-wwm-ext-base. We used the Seq2Seq architecture, where RoBERTa-wwm-ext-base was used as the encoder to encode the input data, and the transformer as the decoder to generate the response. The learning rate is initialized to 1e-5. The batch size was set to 2.

**MultitaskNSP.** If CDial-GPT2 or Bert2transformers add MultitaskNSP task, set the batch size to 2 respectively, and other parameters are the same as the above settings.
Table 4: Generation Results. "Seq2Seq" and "HRED" come from the baseline of the corresponding Generative Model in the dataset KdConv. " + NSP" means the model trained by multitasking, refer to Chapter 4.6 "MultitaskNSP". " + 1kb" means the model contains one of knowledge per training sample during training; " + 3kb" means the model contains three of knowledge per training sample during training; " + share" means encoder share embedding with decoder; "AVG.B" means average BLEU score for 1, 2, 3, 4-gram.

| Model                        | Valid | Test  |        |        |
|------------------------------|-------|-------|--------|--------|
|                              | AVG.B | Dis-2 | AVG.B  | Dis-2  |
| Use true knowledge to generate |       |       |        |        |
| Seq2Seq + know                |    18.95  | 11.32 |        |        |
| HRED + know                   | 18.87  | 11.03 |        |        |
| CDial-GPT2 + 1kb              | 28.55  | 13.22 | 27.51  | 12.22  |
| CDial-GPT2 + 3kb              | 29.79  | 14.07 | 28.94  | 12.83  |
| CDial-GPT2 + 1kb + NSP        | 26.76  | 12.35 | 25.35  | 11.26  |
| CDial-GPT2 + 3kb + NSP        | 24.61  | 13.97 | 23.35  | 13.23  |
| Bert2Transformer + 1kb        | 35.07  | 18.21 | 35.16  | 16.40  |
| Bert2Transformer + 3kb        | 35.74  | 18.10 | 35.92  | 16.32  |
| Bert2Transformer + share + 1kb| 35.36  | 18.56 | 35.10  | 16.61  |
| Bert2Transformer + share + 3kb| 34.92  | 17.74 | 35.10  | 16.61  |
| Use one piece of knowledge to generate |       |       |        |        |
| CDial-GPT2 + 1kb              | 15.86  | 12.10 | 15.34  | 11.17  |
| CDial-GPT2 + 3kb              | 15.52  | 12.29 | 15.09  | 11.49  |
| CDial-GPT2 + 1kb + NSP        | 14.72  | 10.83 | 13.93  | 10.43  |
| CDial-GPT2 + 3kb + NSP        | 14.94  | 12.67 | 14.00  | 12.19  |
| Bert2Transformer + 1kb        | 20.00  | 16.52 | 19.59  | 15.52  |
| Bert2Transformer + 3kb        | 19.57  | 16.96 | 18.88  | 15.82  |
| Bert2Transformer + share + 1kb| 20.06  | 16.56 | 19.65  | 15.75  |
| Bert2Transformer + share + 3kb| 19.88  | 16.53 | 19.22  | 15.21  |
| Use three pieces of knowledge to generate |       |       |        |        |
| CDial-GPT2 + 3kb              | 14.79  | 13.67 | 13.87  | 13.03  |
| CDial-GPT2 + 3kb + NSP        | 14.81  | 13.78 | 13.28  | 13.40  |
| Bert2Transformer + 3kb        | 23.71  | 17.17 | 23.24  | 15.93  |
| Bert2Transformer + share + 3kb| 23.52  | 16.74 | 22.75  | 15.74  |
In the response generation stage, the Topic Prediction Model and knowledge Matching Model use large and base respectively. We experiment with two types of models based on CDial-GPT2 and Bert2transformer, and the results are shown in the following Table 4. Here we show the generation results with real knowledge, one recall knowledge, and three recall knowledge. Where for the knowledge recall stage we use the method with the best results in Table 3.

From the results, the model that selects three pieces of knowledge for training has greater potential than the model that selects one piece of knowledge for training. It can be seen that choosing the right knowledge is very helpful to improve the generation effect. And multi-task training does not improve model performance but decrease. Bert2Transformer using three pieces of knowledge has the best performance, reaching SOTA. It should be because the choice of three pieces of knowledge increases the probability of including correct knowledge. But for GPT2, using three pieces of knowledge to generate, the overall effect is lower than using only one piece of knowledge. Extra knowledge turn into noise, which affect the generation effect of GPT2. It can be seen that GPT2 is not as good as the transformer architecture model for extracting key information.

5 Conclusion

Knowledge-driven Conversation is very important because it makes the generated text more like humans. In this paper, we proposed a knowledge-driven conversation system, which includes three modules such as topic prediction, knowledge matching and dialogue generation. Based on this system and the KdConv dataset, we explore the key factors that influence the task of generating knowledge-driven conversation: For coarse recall, using the LAC algorithm to recall more topics can improve the accuracy of the system’s topic prediction, in this paper we reach 94It is better to use RoBERTa-wwm-ext-large for the Topic Prediction Model and Sentence-Bert-base for the knowledge Matching Model. For the Generative Model, choose the Bert2Transformer model and use more knowledge to generate text, the effect is better.

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