SINC: Service Information Augmented Open-Domain Conversation

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Abstract

Generative open-domain dialogue systems can benefit from external knowledge, but the lack of external knowledge resources and the difficulty in finding relevant knowledge limit the development of this technology. To this end, we propose a knowledge-driven dialogue task using dynamic service information. Specifically, we use a large number of service APIs that can provide high coverage and spatiotemporal sensitivity as external knowledge sources. The dialogue system generates queries to request external services along with user information, get the relevant knowledge, and generate responses based on this knowledge. To implement this method, we collect and release the first open domain Chinese service knowledge dialogue dataset DuSinc. At the same time, we construct a baseline model PLATO-SINC, which realizes the automatic utilization of service information for dialogue. Both automatic evaluation and human evaluation show that our proposed new method can significantly improve the effect of open-domain conversation, and the session-level overall score in human evaluation is improved by 59.29% compared with the dialogue pre-training model PLATO-2. The dataset and benchmark model will be open sourced.

1 Introduction

The progress in open-domain dialogue is exciting, benefiting from studies on large-scale language models. These Transformer-based models are trained on large self-supervised dialog datasets. And the knowledge and logic of dialog are stored in the model’s weights. During inference, they receive dialog context as input and autoregressively generate responses (Adiwardana et al., 2020; Roller et al., 2020; Bao et al., 2021; Thoppilan et al., 2022). But unfortunately, both training data and model weights are frozen at a certain point in time and difficult to update in real-time, which leads to inaccessibility of more valuable information beyond the model in the dialogue system.

Some previous works tried to introduce external knowledge sources, such as text, QA, or knowledge graphs, into open-domain dialogs to improve the effect of dialog generation (Dinan et al., 2018; Wu et al., 2019; Zhou et al., 2020). However, this static external knowledge is difficult to update in time and can not meet the requirements of open-domain dialog in terms of coverage, timeliness, and personalization. Recently, some works try to use the web page text information of search engines as external knowledge for generation (Komeili et al., 2021; Nakano et al., 2021). This information has high coverage and timeliness, but they are challenging to support the everyday needs for personalization, skills, and other knowledge in dialog, such as “What delicious restaurant is there near me?”, “Help me calculate 6754 divided by 37!”. At the same time, the web text is more complex, and the knowledge that can be used for dialogue generation is not easy to be selected (Shuster et al., 2022).

To this end, we propose to use service informa-
tion in knowledge-driven open-domain conversation. Service information refers to all kinds of information queried through the API interface. They receive a query and return related information resources. With the rapid development of information technology, many API services cover all kinds of knowledge and skills required in daily life. For example, search engines, question-answering systems, weather queries, information about nearby restaurants, numerical calculation, text translation, etc. Service information is dynamic and has more comprehensive coverage than static knowledge sources and web information. They are spatiotemporally sensitive and can return time-sensitive, personalized information based on the user’s geographic location and time. Meanwhile, service information is usually in the form of simple text after in-depth processing, which is easier to use by the dialogue system directly. We aggregate multiple industrial-grade APIs as external service information sources. Our system requests these services in dialog, gets the required service knowledge according to the current dialog state and generates appropriate responses using the context and knowledge.

To train and evaluate the model’s ability to use service information, we collect a Chinese open-domain multi-turn dialogue dataset DuSinc. Two annotators play the role of USER and BOT, respectively; USER has personalized interests and locations and chats around this information. The BOT must determine whether external input is required according to the current dialogue context. If necessary, it will write a query, get the service knowledge through the APIs, and write a reply concerning the knowledge; otherwise, it will reply directly.

Further, based on the dialogue pre-training model PLATO-2 (Bao et al., 2020), we built a model PLATO-SINC that uses external service information. The model simulates the BOT behavior recorded in the DuSinc dataset, generates queries, requests service information, and generates responses. We detail the role of service knowledge on dialogue effects and the influence of different pre-trained model sizes on the ability to use service knowledge. We conducted a comprehensive manual analysis of PLATO-SINC’s multi-turn dialog ability under normal, deep, and special topics. Both automatic and human evaluations show that our proposed model significantly improves the performance of all aspects of dialog compared to the original pretrained model.

In summary, this paper makes the following contributions:

- We innovatively propose a knowledge-driven dialogue generation task augmented by service information, which requests services in real-time to get relevant knowledge in dialog, and generates responses based on context and knowledge.
- We collect DuSinc, an open-domain Chinese human-human conversation dataset, for dialogue generation research with service information augmentation. It contains over 1,700 topics, 6,000 conversations, and 30,000 service requests.
- We provide benchmark models on this dataset and conduct extensive experiments. The results show that introducing service information can significantly improve the effect of open domain dialogue, and there is still much room for further research.

2 Related Work

State-of-the-art open-domain dialogue systems are usually implemented by training end-to-end generative models on large amounts of dialogue data. In the process, they generate responses using knowledge learned from static training data, frozen in model parameters (Adiwardana et al., 2020; Roller et al., 2020; Bao et al., 2021; Gu et al., 2022). Many studies in recent years have found that access to external knowledge can improve the knowledgable of dialogue content and reduce the rate at which models hallucinate in generated responses (Zhou et al., 2021; Meng et al., 2020; Kim et al., 2020). Some datasets like TopicalChat, DuConv, KdConv, etc., given a standard knowledge (graph or document) and analyze whether the model can use them in the dialogue (Gopalakrishnan et al., 2019; Wu et al., 2019; Zhou et al., 2020). But they did not focus on the knowledge retrieval process, which is difficult and important for open-domain conversations.

Some works attempt to introduce knowledge retrieval processes in open domain dialogues and use richer external knowledge sources. More representative is the Wikipedia of Wizard (WoW), which retrieves knowledge documents from Wikipedia and obtains relevant knowledge required for dialogue (Dinan et al., 2018). LaMDA improves the grounding in generating responses by collecting a
dataset of conversations using a retrieval system (Thoppilan et al., 2022). The work that is closer to ours is Wizard of Internet (WizInt), which expands the scope of the knowledge source, uses a search engine with solid timeliness and high coverage to retrieve web text, and verifies that this method can improve the informativeness and factual accuracy of dialogue (Komeili et al., 2021). On this basis, (Shuster et al., 2022) added a process of further summarizing the retrieved knowledge to reduce the interference of the noise in the web page text knowledge on the dialogue generation. Unlike these studies, we use service information as an external knowledge source for dialogue, covering a broader range of knowledge sources, including knowledge bases, search engines, and personalized recommendations. Meanwhile, it is the processed short text, not the original web page.

There are few human-labeled knowledge-grounded dialog datasets in Chinese, as shown in Table 1. DuConv is a human-annotated dataset of knowledge dialogues in the movie domain, using triple text as an external knowledge source (Wu et al., 2019). KdConv expands the domain of knowledge dialogue to three: film, music, and travel (Zhou et al., 2020). DuRecdial includes conversations in 7 domains and integrates different capabilities such as knowledge dialogue and dialogue recommendation at the same time (Liu et al., 2020). Our dataset is the first open-domain Chinese knowledge dialogue dataset. Our knowledge source is service information that can be dynamically requested in real-time rather than static triple text.

| Dataset       | Know. Type | Dynamic Know. | Personalized Know. | Domain            | Language | Avg. # chars per uttr | # uttrs |
|---------------|------------|---------------|--------------------|-------------------|----------|----------------------|--------|
| CMU DoG       | Text ×     | ×             | Film               | English           | 11.8     | 130K                 |
| OpenDialKG    | Graph ×    | ×             | Film, Book, Sport, Music | English           | -        | 91K                  |
| Topcial Chat  | Text ×     | ×             | Open Domain        | English           | 19.6     | 235K                 |
| WoW           | Text ×     | ×             | Open Domain        | English           | -        | 202K                 |
| WizInt        | Web Text ✓ | ✓             | Open Domain        | English           | 19.1     | 94K                  |
| DuConv        | Text & Graph × | × | Film               | Chinese           | 10.6     | 270K                 |
| KdConv        | Text & Graph × | × | Film, Music, Travel | Chinese           | 20.8     | 86K                  |
| DuSinc (ours) | Service Text ✓ ✓ | Open Domain | Chinese           | 22.1     | 63K                  |

Table 1: Comparison between our DuSinc and other human-labeled knowledge-grounded dialogue datasets.

3 Data Collection

In DuSinc’s data collection, we consider the following setup: two participants engage in a chat around a topic and allow the topic to change naturally during the conversation. There is information asymmetry between the two participants. One of them plays the role of the USER, who is set in a specific geographic location and has a topic of interest; the other participant plays the role of the BOT, who can access external service information in the conversation. We hope the dialogue system needs to simulate the BOT’s behavior and can use the service information to complete the dialogue like a human, including generating queries, requesting services, and generating responses.

3.1 USER Settings

A participant playing USER should follow: "I’m a person in a specific location, and I want to chat with each other around a topic that interests me." Before starting the conversation, USER will be randomly assigned a geographic location with latitude and longitude (a city from China), and they are allowed to have a conversation based on their geographic location information, such as "What’s the weather like today?", "What’s the food nearby?" We follow WizInt’s setting on topic selection (Komeili et al., 2021), and provide multiple candidate topics. Participants need to choose the one they are interested in to have more in-depth conversations around this topic. The difference is that we have designed a three-level topic system. The first-level categories are preset and unmodifiable, including life, entertainment, sports, technology, etc. The second-level categories are preset but can be modified or supplemented, such as life-fishing,
Table 2: Statistics of DuSinc.

| DuSinc Statistics | Train | Valid | Test | Total |
|-------------------|-------|-------|------|-------|
| # dialogs         | 5,093 | 500   | 500  | 6,093 |
| # utterances      | 52,644| 5,142 | 5,132| 62,918|
| Avg. # chars per USER uttr | 17.18 | 16.49 | 16.55 | 17.07 |
| Avg. # chars per BOT uttr | 27.18 | 25.99 | 26.11 | 26.99 |
| Avg. # chars per query | 6.45  | 6.42  | 6.28  | 6.43  |
| Avg. # chars per service text | 307.00 | 288.38 | 300.07 | 304.90 |
| Avg. # service turn percent | 52.58% | 52.14% | 50.90% | 52.41% |
| Avg. # other service | 0.27  | 0.28  | 0.24  | 0.27  |
| # topics level 1/2/3 | 12/207/1,523 | 12/83/284 | 12/77/233 | 12/231/1,743 |
| # locations       | 416   | 294   | 292  | 416   |

sports-badminton, etc. The third-level category, which needs to be supplemented by participants, is a further refinement of the topic, which determines that our dialogue domain is open, such as sports-badminton-Lin Dan.

3.2 BOT Settings

A participant playing BOT should follow “I need to have a coherent dialogue with the USER and judge whether replying to the current context requires external knowledge, if necessary, query the service, and compose a response based on the service information if no direct reply is required”. The topic and location of USER’s interests are visible to the BOT player. At the same time, we require that when BOT uses external services, the queries written by BOT should be specific short sentences, rather than simply copying the keywords or entities mentioned in the context, which will make the queried knowledge more detailed and suitable for the current context. In addition, we believe that the actual dialogue scene does not need to use external knowledge all the time, so in the dialogue collection, we access the state-of-the-art dialogue model PLATO-XL auxiliary annotation. BOT can see the responses generated by the current turns of PLATO-XL (Bao et al., 2021). If the generated responses already meet the requirements, they can make adjustments on this basis without using external services.

3.3 Service Information

In this task, service information retrieval can be regarded as a black box system, which receives the search query and the latitude and longitude information of the USER’s geographic location and returns a relevant knowledge paragraph. In terms of the specific implementation, we have developed a dynamically updated, real-time accessible system that aggregates industrial-grade end-to-end DeepQA services, location-based recommendation services, skill-based services (such as calculators, perpetual calendars, and translations), and many more. The system is used for both data collection and model system deployment.

3.4 Quality Control

To ensure the quality of the collected data, we have carefully optimized the annotators, tools, specifications, and processes.

- The annotators are volunteers recruited from Chinese universities rather than the staff of the crowdsourcing platform, which greatly contributes to the topical diversity and overall quality of the conversation.
- We have developed a customized annotation tool, which supports online dialogue, role assignment, user information setting, service system, etc., improving annotation efficiency and specification. More details are shown in the appendix A.
- Responses written by participants should be colloquial rather than directly replicating knowledge, which is especially important for dialogue coherence.
- Each group of conversations has at least five turns and requires at least two turns of in-depth chat using the service system. Nonsense turns such as hello, goodbye, etc., are prohibited, which do not help our task.
- BOT can query external services multiple times if unsatisfied with the found results. All queries and knowledge are logged, even if not used in response writing.
• After the conversation is over, the USER will rate the overall dialog quality of the BOT.

More quality control methods are in Appendix A.

3.5 Overall Dataset

As shown in Table 1, DuSinc is the first open-domain Chinese knowledge-grounded dialogue dataset containing 1743 topics. More information on topic distribution is in Appendix A. Meanwhile, DuSinc is the first dataset to use service information as external knowledge in conversation. And the average number of characters per utterance reaches 22.1, which means the conversation is informative. We calculate Distinct-2, the diversity metric for users and bots, respectively. The value of DuSinc is 0.37/0.45, which is only 0.13/0.22 in DuConv and 0.24/0.23 in KdConv. As can be seen, the dialogue in DuSinc is more diverse.

In total, more than 200 volunteers participated in data collection. As shown in Table 2, the overall collected data includes 6,093 sets of dialogs with 62,918 utterances, which divided into 52,655 utterances for training, 5,142 utterances for validation, and 5,132 utterances for testing. 52.4% of BOT turns used external knowledge, indicating that it integrates chitchat and knowledge-grounded conversations, which we believe is consistent with the knowledge distribution in real conversations. The average character in the query is 6.4, which indicates that in most cases, the query is a specific short utterance, not just a keyword, which is the key to querying accurate service information. The service text is a paragraph with an average length of 304.9 characters, which is different from a long-form webpage or a graph triple with less information. In knowledge-used turns, there were an average of 0.41 requests for services, but no use, and these behaviors may also be worth investigating.

4 Method

We build a model PLATO-SINC that can use knowledge from external services. The system generates a response \( R = b_t \) given the USER information \( M \) and multi-turns of context \( C = \{u_1, b_1, \ldots, u_{t-1}, b_{t-1}, u_t\} \). Specifically, as shown in Figure 2, the model first generates a query \( Q = q_t \) to request the service system, gets relevant knowledge \( K = k_t \), and further adds the \( K \) to generate a response. Among them, \( u_t \) represents the utterance of the USER turn \( t \), \( b_t \) represents the utterance of the BOT turn \( t \). The system is used to simulate the actions of the BOT.

We divide the system into two stages: query generation and response generation. We will introduce the details of these two modules in the following subsections.

4.1 Query Generation

The functions of the Query generation module include 1) judging whether to use external knowledge and 2) generating query text to request the service system. We are fine-tuning the PLATO-2 model to generate a query and a particular piece of text "no query" when no external knowledge is required (Bao et al., 2020). The input to the model is the sum of the corresponding token, type, and position embeddings of \( M \) and \( C \). During training, we minimize the following negative log-likelihood (NLL)
Table 3: Automatic evaluation results of different models on the DuSinc test set, the best scores are shown in bold.

| Model           | Parameters | Share Weights | ACC  | F1   | PPL ↓ | F1   | KF1  | PPL ↓ | DIS-2 |
|-----------------|------------|---------------|------|------|-------|------|------|-------|-------|
| PLATO-Query     | 1.6B       | ×             | 0.563| 0.450| 2.786 | /    | /    | /     | /     |
| PLATO-Response  | 1.6B       | ×             | /    | /    | /     | 0.271| 0.087| 12.561| 0.496 |
| PLATO-SINC      | 108M       | ✓             | 0.563| 0.455| 2.918 | 0.258| 0.084| 16.869| 0.480 |
| PLATO-SINC      | 0.6B       | ✓             | 0.602| 0.486| 2.712 | 0.270| 0.082| 14.491| 0.506 |
| PLATO-SINC      | 1.6B       | ✓             | 0.618| 0.488| 2.671 | 0.278| 0.095| 13.432| 0.536 |
| PLATO-SINC      | 11B        | ✓             | 0.603| 0.476| 2.551 | 0.288| 0.095| 13.432| 0.536 |

Table 4: Automatic evaluation of the model on the DuSinc test set when using different types of knowledge.

| Model           | Knowledge                                      | F1   | KF1  | PPL ↓ | DIS-2 |
|-----------------|-----------------------------------------------|------|------|-------|-------|
| PLATO-2         | no knowledge                                  | 0.170| 0.035| 432.745| 0.428 |
| PLATO-FT        | no knowledge                                  | 0.219| 0.041| 17.399| 0.436 |
| PLATO-SINC      | golden knowledge                              | 0.278| 0.095| 13.432| 0.536 |
| PLATO-SINC      | golden query service knowledge                | 0.261| 0.080| /     | 0.534 |
| PLATO-SINC      | predict query service knowledge               | 0.233| 0.058| /     | 0.523 |

4.2 Dialog Generation

Similarly, we fine-tune the PLATO-2 model to generate $R$, given $M$, $C$, and $K$ (if any). Different input parts are distinguished using typed embeddings. We minimize the following NLL loss:

$$\mathcal{L}_{NLL,Q} = -\mathbb{E} \log p(Q|M, C)$$

$$= -\mathbb{E} \sum_{j=1}^{[Q]} \log p(q_j|M, C, Q_{<j})$$

(1)

Where $q_{<j}$ denotes previously generated tokens in query $Q$. Then we use the generated query and user information to request the service system to get the relevant service knowledge $K$.

5 Experiments

5.1 Experiment and Evaluation Settings

We carry out service information augmented conversation task experiments on the DuSinc dataset. We finetune the most advanced Chinese dialogue pre-training model - the PLATO family (Bao et al., 2019; Bao et al., 2020; Bao et al., 2021), including 128M, 0.6B, 1.6B, 11B different parameter models. For all the models, when generating query, we set the decoding strategy to topk-Sampling, where the value of the topk is 5, and the sampling number is 10; when generating response, we use the same decoding strategy and set the topk value to 10. Appendix B provides all model training details.

The proposed model has been evaluated under two settings: 1) automatic evaluation and 2) human evaluation. For automatic evaluation, we consider two tasks: query generation and response generation. In Query generation, we leverage several standard metrics: Accuracy, which measures the accuracy of whether external knowledge needs to be retrieved. The F1 value is used to evaluate the consistency between the predicted and golden queries when the golden query exists. PPL can determine the coherence of the predicted query to a certain extent. In response generation, we used four metrics of F1, KF1, PPL, and DISTINCT1/2 (Li et al., 2016) to evaluate the predicted response’s fluency, relevance, and diversity.

We use the end-to-end dynamic evaluation
Method for human evaluation to compare the performance of the 1.6B parameters PLATO-2 and PLATO-SINC. We selected 60 topics as the initial utterances of conversation, including normal, deep, and special topics (topics related to timeliness, personalization, skills, etc.). First, the annotator chats with the system to be evaluated to collect multi-turn conversations. The annotator initiates the conversations according to a given topic, and each conversation lasts at least five turns. The collected conversations are scored at turn-level and session-level by additional annotators. Among them, at the turn level, we mainly focus on the four metrics of consistency, knowledgeability, factual correctness, and engagingness, with a score of 0 or 1. The session level is an overall metric with a score of 0-5. More specific meanings of metrics are provided in Appendix C.

5.2 Automatic Evaluation Results

Share weights. We verify whether the shared weights between query and response generation tasks are effective. We use the same pre-trained model to fine-tune these two tasks separately, and the resulting models are denoted as PLATO-Query and PLATO-Response. The experimental results are shown in Table 3. In the query generation, the shared weight training model is better than the single training model in all automatic metrics. In the response generation, in addition to the PPL, the model sharing weights also take advantage. This shows that the learning of these two tasks can promote each other.

Parameter scale. By fine-tuning the PLATO model with different parameters, we explore the relationship between the parameters of the dialog generation model and the ability to use external service information. We uniformly use the method of sharing weights between two tasks for model training and automatically evaluate the two tasks separately. The experimental results are shown in Table 3. In the query generation task, the PPL metric positively correlates with the parameter size. Regarding accuracy and F1 value, the model with 1.6 billion parameters achieved the best results; However, the 11 billion parameter model parameters are nearly seven times that of it, so there is no additional benefit in the task. We believe that this is related to the complexity of the task. In response generation, all automatic metrics positively correlate with the parameter size. We can see that improving the model’s parameters can effectively enhance the ability to generate dialog responses using external service information.

Use knowledge. In the response generation task, we evaluate the impact of whether to use knowledge. We compare the original pre-trained model PLATO-2, the fine-tuned model PLATO-FT using only the context and the reply in DuSinc, and the proposed PLATO-SINC. As shown in Table 4, the PPL value of PLATO-2 on the DuSinc test set exceeds 432, which reveals that the original pre-trained model is challenging to fit human-labeled high-quality dialogues. Fine-tuning with DuSinc training data can improve dialogue even without knowledge. All automatic metrics show that the introduction of external knowledge by PLATO-SINC can improve the consistency, coherence, and diversity of the generated responses.

Human-labeled golden knowledge is not available in practice; we further evaluate the effect of dynamic serving knowledge. First, we use the golden query to request the service source. The knowledge requested using the golden query is also different from golden knowledge because the service source changes dynamically. As seen in Table 4, the use of dynamic knowledge is lossless in terms of dialogue diversity. The values of F1 and KF1 are calculated separately from the golden reply and golden knowledge, and it is reasonable to have a decrease compared to using golden knowledge. Further, we first predict the query and use the predicted query to request service knowledge for response generation, which is an end-to-end evaluation close to reality. It can be seen that using knowledge of external services has advantages over methods that do not use knowledge.

5.3 Human Evaluation Results

As shown in Table 5, under all dialog topics, the PLATO-SINC model using external service information improves significantly compared to the original dialogue pre-training model PLATO-2. Specifically, on the turn level, the dialogue consistently increases by 11.20%, the knowledgeable increases by 8.68% to 95.15%, and the ratio of factually incorrect decreases by 5.45%. It is worth mentioning that the engagement significantly improved by 31.31%. On the session level, the overall score of PLATO-SINC reached 4.03, compared with PLATO-2’s only 2.53, a relative improvement of 59.29%. In the actual dialog, the replies of PLATO-
SINC are more informative. The average length of responses of PLATO-SINC is 19.92 characters, while that of PLATO-2 is only 11.44.

We further analyzed the performance of PLATO-SINC on different types of dialog topics, as seen in table 5. On normal topics, PLATO-SINC has significantly improved the effect. In particular, 92.69% of the responses are considered engaging, and the overall score has also increased by 41.00%. There is a slight loss in the accuracy of factual accuracy; we consider that the reply of PLATO-SINC tends to use knowledge more, and PLATO-2 is always avoiding it. On the deep topic, the advantages of PLATO-SINC are more significant. The overall score has increased by 58.14%, and the proportion of factual incorrect has also decreased by 6.07%. On special topics such as timeliness, personalization, and skills, PLATO-2 performs poorly because this knowledge is difficult to learn in pre-training. However, the overall score of PLATO-SINC has been improved by 88.00%, and the improvement of turn level metrics is also amazing. Some real dialogue cases, shown in Appendix D.

6 Conclusion

We propose a knowledge-driven dialogue task using dynamic service information and collect a high-quality Chinese service knowledge dialogue dataset DuSinc. We build a benchmark model, PLATO-SINC, and evaluate the model’s ability to use service knowledge on this dataset. The evaluation results show that service information can significantly improve the effect of open domain dialogue.

In future work, we consider continuously expanding the number of conversations in DuSinc and the types of service information. At the same time, we hope to explore the introduction of Task-oriented dialog capabilities and multi-modal resources into open-domain dialogue generation by accessing external service information.

7 Limitations

The PLATO-SINC model also faces the same problem as the current language model. The dialogue responses generated by the model can follow the knowledge provided by the service to a certain extent, but the hallucination problem cannot be avoided. At the same time, it is also challenging for the model to find whether the queried knowledge is irrelevant to the dialogue. Using irrelevant knowledge may lead to the loss of dialogue consistency. To ensure the generality of the system, all the services we aggregated receive natural language queries, which may make it difficult for some specific forms of query services to access the system directly.

8 Ethical Considerations

This section explores various policies and tactics for ensuring correct and ethical usage of our work by schools, research laboratories, commercial corporations, and so on.

Firstly, due to potential concerns and illegal usage, we would release the DuSinc dataset and the
PLATO-SINC model to the public under the CC-BY-SA license. Second, the failure of chatbots to discern incorrect language is a possible ethical concern with DuSinc and PLATO-SINC. To address this problem, we have invited professional collectors, and in the collection stage of the DuSinc dataset, anti-social words such as offensive types will be eliminated. We will utilize existing resources, such as profanity dictionaries, and develop computational algorithms to recognize problematic statements in real-time. We will replace them with more appropriate terms to minimize any possible negative impacts on users, particularly children, and teenagers.

Finally, we will devise several safeguards and techniques to ensure that PLATO-SINC is safe and ethically sound when used as an instructional program. With this in mind, we’ll develop automated tools to monitor the interactions between PLATO-SINC and its users and identify possible grooming activities. Using and storing session data will also be done by norms and standards established by the legal system.

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### A Data Collection Details

We developed a data collection tool, which is different on the USER side and the BOT side, Figures 3 and 4 are their corresponding screenshots. The USER will enter the matching state after completing the topic selection, and the BOT can directly enter the matching state. Two different roles that are in the matching state will be matched together. At this time, the topic and location information of the USER will be synchronized to the BOT. The BOT side requires the annotator to choose whether to use the knowledge when submitting the reply, and the system will judge whether the conversation reply highly duplicates the knowledge.

Figure 5 shows the distribution of first-level topics for the DuSinc data we collected. The first-level topics are randomly provided to the USER for selection. From the collected data, it can be seen that the topics that users are most interested in focus on entertainment, life and shopping.

![Figure 3: Screenshot of the USER side of the annotation tool.](image)

![Figure 4: Screenshot of the BOT side of the annotation tool.](image)

![Figure 5: First-level topic distribution in DuSinc dataset.](image)

### B Model Hyper-parameters

we use 8 Nvidia Tesla A100 40G GPU cards for fine-tuning training of the PLATO model. Among them, for the models of 128M, 0.6B, and 1.6B scale, we set the learning rate to 1e-5, batch_size to 65536 tokens, the warm-up strategy is used and warm-up steps is 100. The learning rate of 11B model is 5e-6, the warm-up steps is 200 steps, and the batch_size is 32768 tokens.

### C Human Evaluation

In human evaluation, evaluators have multi-turn of conversations with different systems on the same topic. The collected dialogue is scored by two annotators, and the final result is the average score of the two. Among them, Consistent means whether the reply is coherent with the text of the conversation and the reply itself. Knowledgeable means whether the reply contains knowledge or common sense information. Factual Accuracy means whether the knowledge in the reply is wrong or con-
trary to common sense. **Engaging** means whether the reply is attractive and whether it is willing to continue the dialogue with the BOT. **Overall Score** means the comprehensive score of the session on each topic, 0 means bad, 5 means perfect.

### D Case Study

Figures 6 and 7 are dialog examples for service information enhancement.
用户位置：北京市海淀区

用户：现在几点了，是不是该吃饭了？

用户：现在几点了，是不是该吃饭了？

知识：现在是晚上6点36分，今天辛苦了。

知识：附近有个老乡鸡风味炸鸡餐厅，距离您129米。

用户：没呢，有什么好吃的推荐吗？

用户：没呢，有什么好吃的推荐吗？

知识：附近有个老乡鸡风味炸鸡餐厅，距离您129米。

知识：附近有个老乡鸡风味炸鸡餐厅，距离您129米。

用户：嗯，好，我去简单吃点吧。

用户：嗯，好，我去简单吃点吧。

知识：附近有个老乡鸡风味炸鸡餐厅，距离您129米。

知识：附近有个老乡鸡风味炸鸡餐厅，距离您129米。

用户：吃完可以溜溜弯。对身体好。

用户：吃完可以溜溜弯。对身体好。

知识：附近有个老乡鸡风味炸鸡餐厅，距离您129米。

知识：附近有个老乡鸡风味炸鸡餐厅，距离您129米。

用户：我超级喜欢刘亦菲，她很少演电视剧吧。

用户：我超级喜欢刘亦菲，她很少演电视剧吧。

知识：刘亦菲主演的电视剧有《仙剑奇侠传》……

知识：刘亦菲主演的电视剧有《仙剑奇侠传》……

用户：那我来考考你，27加89等于多少？

用户：那我来考考你，27加89等于多少？

知识：27加89等于116。

知识：27加89等于116。

用户：你还挺诚实，你这么聪明，还会什么呀。

用户：你还挺诚实，你这么聪明，还会什么呀。

知识：27加89等于116。

知识：27加89等于116。

用户：明天天津天气怎么样？

用户：明天天津天气怎么样？

知识：天津明天天气怎么样。

知识：天津明天天气怎么样。