1 Introduction

Benefiting from the recent progress in the large-scale language model, the level of multi-turn dialog system is approaching the human (Roller et al., 2021a). It is well known that standard large language models can fluently generate responses but cannot update knowledge in time, and it is not easy to perceive the spatiotemporal state of the world (Shuster et al., 2021). It can only use the knowledge frozen in the model weights and cannot pay attention to the external world in a dialog like human beings (Lazaridou et al., 2021). In other words, humans not only rely on their own knowledge (similar to the model weights), but also on the world in which interlocutors are located. Therefore, linking the world is the key to making dialog systems like a human or even beyond a human.

The external world that the dialogue system pays attention to contains dynamic knowledge and spatiotemporal state (Hagoort et al., 2004; Hoffart et al., 2011; Venhuizen et al., 2019). Several recent advances only focused on how to construct world knowledge. They attempt to introduce external information sources into the dialogue system to supplement the inside, such as text (Dinan et al., 2019a), QA (Lee et al., 2019), and graphs (Adolphs et al., 2021). However, these static knowledge bases are difficult to update promptly and cannot cover extensive topics. Wizard of Internet (Komeili et al., 2022a) tries to utilize search engines as dynamic knowledge sources, improving timeliness and knowledge. Still, complex web pages seem challenging to be loaded directly by language mod-
els (Shuster et al., 2022). Meanwhile, world knowl-
edge should also include common skills. LAMDA
is an initial attempt to introduce calculator and
translation skills into the dialogs (Thoppilan et al.,
2022). Above all, none of those methods can incor-
porate a spatiotemporal state, which is significant
for building more human-like dialog systems.

Based on these considerations, we use the service
information to obtain external information
required by the dialogue system, similar to how
humans link world knowledge through various ser-
vice APIs. Service Information has the following
characteristics: 1) Dynamic and spatiotemporal-
aware, the resources linked by service APIs are
dynamically changing, including highly timely in-
formation and location-based services; 2) Vari-
ous resources, service information not only in-
cludes search engines, personalized recommenda-
tions, question answering system, and also supports
skills such as calculator, joke telling, stock query,
and even multi-modal resources; 3) Concise, differ-
ent from the web page, the information returned is
often condensed paragraphs, which will be more
helpful for language model understanding. In this
paper, we aggregate multiple industrial-grade ser-
vice APIs into an information source to which the
dialog system can link.

In order to make language models use ser-
vice information, we collect DuSinc, a Service-
information augmented open-domain conversa-
tion dataset in Chinese. The two annotators play the
roles of USER and BOT, respectively; USER starts
discussions based on their specific interests and
whereabouts. Based on the current dialog context
and the spatiotemporal state of the user, the BOT
must determine whether more world information is
needed. If needed, it constructs a request to get the
service information and then provides a response
based on that information; otherwise, it responds
directly.

Furthermore, we develop a benchmark that con-
sists of two tasks query generation and response
generation based on service information. We dem-
strate that using dynamic spatiotemporal awareness information can improve the dialogue
ability of different pre-trained models. Our method
is general and performs well even on unseen top-
ics, and it shows greater advantages over dialogue
systems that use web page knowledge. We also an-
alyze the model parameter scale and the impact of
different training methods. Both automatic metrics
and human evaluations show that our method has
significant consistency, informativeness, factuality,
and engagingness. Compared with the methods
without linking the world, the overall session-level indicators are improved by 60.87%.

In summary, this paper makes the following con-
tributions:

1. We propose a method to link the world
through service information so that the dia-
log system can utilize dynamic knowledge
and spatiotemporal state awareness.
2. We collect DuSinc, the first open-domain Chi-
nese service information augmented human-
human dialogue dataset. It contains more than
2,500 topics, close to 10,000 conversations,
and 50,000 service requests. This dataset will
be open-sourced soon;
3. We build strong benchmarks on the DuSinc
dataset using state-of-the-art large-scale pre-
trained models for both query generation and
response generation. Extensive experiments
demonstrate that linking the world through
service information can significantly improve
conversational performance.

2 DuSinc Collection

This section mainly introduces the collection of the
DuSinc dataset and the service information. We
considered the following setting for data collection:
two participants chat around a topic, which can
change naturally during the conversation. There
is an information asymmetry between the two par-
ticipants. One of them plays the role of USER,
who is set in a specific geographic location and has
a topic of interest; the other participant plays the
role of BOT and can use service information in the
conversation. The conversation is initiated by the
USER, and both sides speak alternately.

2.1 Service Information

The service API is a real-time updated source of in-
formation for chatbots to link the world. It accepts
a request that consists of a query and an spatiotem-
poral state, and then delivers accurate relevant in-
formation. Specifically, we have developed a dynami-
cally updated, real-time accessible system, which
is an aggregation of many industrial-grade informa-
tion sources. These include industrial-grade end-to-
end deep Q&A services, location-based personal-
ized recommendation services (such as weather of
today, nearby western restaurants suitable for eating with children, driving routes to Beijing Railway Station, etc.), skill-based services (such as calculators, perpetual calendar, translation, stock price inquiry, etc.). The returned information is sensitive to spatiotemporal circumstances and could satisfy the external knowledge needs of open domain chat in a comprehensive manner. The system serves both data collection and model deployment inference.

2.2 USER Settings

A participant playing USER should comply with: I am 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?. To engage in more in-depth discussions on this topic, participants must pick the subtopic that most interests them. We have created a three-tiered topic system. The first-level categories are fixed and cannot be altered; they include 12 sorts such as life, sports, technology, etc. Figure 2 shows the distribution of first-level topics, where users are most interested in entertainment, life, and local services. The second-level categories are preset but can be modified or supplemented, such as life-fishing, 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.

2.3 BOT Settings

A participant playing BOT should comply with: I need to have a coherent dialogue with the USER and judge whether replying to the current context requires external knowledge, if necessary, access to the service system, and compose a response based on the service information. The topic and location of interest to the USER are visible to the BOT player. When BOT uses the service system, the query in request written by BOT should be specific short sentences, rather than simply copying the keywords or entities mentioned in the context. This 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 dataset 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., 2021a). If the generated responses already meet the requirements, they can make adjustments on this basis without using external services.

Figure 2: First-level topic distribution in DuSinc dataset.
### 2.4 Quality Control

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

- The annotators are volunteers recruited from Chinese universities, which increases the variety and quality of the conversation.
- We build a customized annotation tool to improve annotation efficiency and specification. It supports online chat, role assignment, user information configuration, and the service system.
- For dialog coherence, responses participants should be colloquial rather than copying information.
- Each discussion group has five turns and at least two in-depth turns utilizing the service system. Hello, farewell, etc., are banned since they hinder our work.
- BOT may repeatedly ask for external services if dissatisfied. Even if not utilized, requests and knowledge are recorded.
- The USER rates the dialog quality of BOT after the interaction.

More quality control strategies are discussed in Appendix A.

### 2.5 Dataset Statistics

As demonstrated in Table 1, DuSinc is the first open-domain Chinese knowledge-grounded dialogue dataset containing 2,361 topics. More information on topic distribution is in Appendix A. Meanwhile, DuSinc is the first dialog dataset to use the dynamic service information and is spatiotemporal aware, while it contains more skill knowledge. And the average number of characters per utterance reaches 21.7, which means the conversation is informative. We calculate Distinct-2 (Li et al., 2016a), the diversity metric for users and bots, respectively. The value of DuSinc is 0.32/0.39, which is only 0.13/0.22 in DuConv (Wu et al., 2019) and 0.24/0.23 in KdConv (Zhou et al., 2020). As can be seen, the dialogue in DuSinc is more diverse.

In total, more than 300 volunteers participated in data collection. As shown in Table 2, the overall collected data includes 9,949 sets of dialogs with 102,147 utterances, which are divided into 86,765 utterances for training, 5,117 utterances for validation, and 5,159 utterances for seen testing, and 5,106 utterances for unseen testing. The second-level topics in the test set have never appeared in the training set. 52.30% 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 6.35, 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 317.78 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 0.24 requests for services but no use. These behaviors may help to build more appropriate requests.

### Table 2: Statistics of DuSinc.

| DuSinc Statistics | Train | Valid | Seen Test | Unseen Test | Total |
|-------------------|-------|-------|-----------|-------------|-------|
| # dialogs         | 8,449 | 500   | 500       | 500         | 9,949 |
| # utterances      | 86,765| 5,117 | 5,159     | 5,106       | 102,147|
| Avg. # chars per USER uttr | 15.44 | 15.26 | 15.19     | 15.93       | 15.44 |
| Avg. # chars per BOT uttr  | 24.67 | 24.47 | 25.01     | 25.55       | 24.72 |
| Avg. # chars per query   | 6.33  | 6.31  | 6.19      | 6.96        | 6.35  |
| Avg. # chars per service text | 317.19| 338.59| 323.69    | 300.80      | 317.78|
| Avg. # service turn percent | 52.39%| 51.81%| 52.63%    | 50.98%      | 52.30%|
| # topics level 1/2/3   | 12/339/2,055 | 12/77/219 | 12/76/216 | 10/12/127 | 12/378/2,361 |
| # locations          | 416   | 297   | 297       | 298         | 416   |

Table: Statistics of DuSinc.

3 Method

We develop a model that is capable of incorporating information 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 3, the model first generates the query $Q = q_t$ according to $C$ and the spatiotemporal state $S$, and uses the request composed of $S$ and
to access the service system, gets relevant knowledge \( K = k_t \), and further adds the \( K \) to generate a response. Among them, \( u_t \) denotes the utterance of the USER turn \( t \), \( b_t \) denotes 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: request construction and response generation. We will introduce the details of these two modules in the following subsections.

### 3.1 Request Construction

The request contains spatiotemporal state and query. The state can be obtained automatically, so the functions of this module include judging whether to use external knowledge and generating a query. We fine-tune the pre-trained model to generate \( Q \) and a particular piece of text "no request" when no external knowledge is required. The input to the model is the sum of the corresponding token, type, and position embeddings of \( S \) and \( C \). During training, we minimize the following negative log-likelihood (NLL) loss:

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

(1)

Where \( q_{<j} \) denotes previously generated tokens in query \( Q \). Then, we use the request to access the service system and get the relevant service knowledge \( K \).

### 3.2 Response Generation

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

\[
L_{\text{NLL},R} = -\mathbb{E} \log p(R|S, C, K)
= -\mathbb{E} \sum_{j=1}^{|R|} \log p(r_j|S, C, K, R_{<j})
\]

(2)

\( r_{<j} \) denotes previously generated tokens in response \( R \). The model weights model in the query and response generation tasks are shared during model training. We append additional task labels "Query" or "Response" to the input text to distinguish different tasks. Therefore, the loss function for system optimization is:

\[
L_{\text{NLL}} = L_{\text{NLL},Q} + L_{\text{NLL},R}
\]

(3)

### 4 Experiments

#### 4.1 Evaluation Settings

We carry out service information augmented conversation task experiments on the DuSinc dataset. These methods perform both automatic and human evaluations.

**Automatic evaluation settings.** 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 (Dinan et al., 2019b) value is used to evaluate the consistency between the predicted and golden queries when the golden query exists. PPL (Meister and Cotterell, 2021) can determine the coherence of the predicted query to a certain extent. In response generation, we additionally used BLEU-1 (Chen and Cherry, 2014) to evaluate the consistency of predicted responses with standard responses, KF1 (Dinan et al., 2019b) to evaluate the relevance of responses to knowledge, and Distinct-2 (Li et al., 2016a) to evaluate the diversity of responses in the test set (Li et al.,
### Table 3: Automatic evaluation results of different models on the DuSinc test set, the best scores are shown in bold.

| Model                 | Parameters | Query Generation | Response Generation |
|-----------------------|------------|------------------|---------------------|
|                       |            | ACC              | F1                  | F1   | KF1 | BLEU | DIS   |
|                       |            | UnSeen Test      | Seen Test           |
| **T5 (golden kg)**    | 620M       | 67.2/65.9        | 49.7/48.7           | 24.2/23.3 | 12.6/13.1 | 47.6/50.9 | 45.1/46.2 |
| **T5 (no kg)**        |            | 62.0/59.3        | 43.5/43.4           | 15.4/15.5 | 7.0/7.0  | 35.2/47.7 | 26.9/25.6 |
| **BART (golden kg)**  | 580M       | 69.5/70.2        | 52.8/54.8           | 29.2/29.2 | 17.3/19.7 | 49.8/48.9 | 54.0/49.3 |
| **BART (no kg)**      |            | 68.2/68.5        | 49.0/44.2           | 19.0/19.3 | 12.6/9.3 | 47.6/41.0 | 45.1/43.0 |
| **EVA2.0 (golden kg)**| 970M       | 59.0/57.1        | 39.6/38.0           | 19.7/18.5 | 4.5/4.6  | 29.6/29.4 | 33.1/28.1 |
| **EVA2.0 (no kg)**    |            | 58.6/57.4        | 33.4/32.3           | 11.0/10.6 | 2.7/2.9  | 20.5/19.1 | 65.9/65.1 |
| **PLATO (golden kg)** | 68.5/69.1  | 54.5/55.4        | 29.8/30.1           | 12.9/16.2 | 52.9/51.3 | 55.7/50.6 |
| **PLATO (no kg)**     | 65.9/66.9  | 53.6/54.1        | 24.9/25.0           | 6.2/6.2  | 40.1/39.7 | 43.1/38.6 |

### Table 4: PLATO’s automated evaluation results using different types of external knowledge, the best scores are shown in bold.

| Model                     | Knowledge Access | Seen | Unseen |
|---------------------------|------------------|------|--------|
|                           | ACC              | F1   | KF1    | BLEU  | DIS   | F1   | KF1  | BLEU  | DIS   |
| **PLATO**                 | no knowledge     | 19.9 | 4.0   | 31.1  | 41.3  | 19.7 | 4.4  | 31.3  | 36.7  |
| **PLATO-FT**              | no knowledge     | 24.9 | 5.8   | 40.1  | 43.1  | 25.0 | 6.5  | 39.7  | 38.6  |
| **PLATO-FID**             | Web Top 16       | 24.8 | 8.2   | 41.6  | 51.0  | 25.1 | 8.1  | 40.2  | 45.8  |
| **PLATO-SINC**            | Web Top 1        | 25.8 | 11.1  | 42.7  | 51.9  | 25.7 | 12.4 | 40.2  | 47.3  |
| **PLATO-SINC**            | Service          | 28.1 | 8.4   | 45.0  | 54.3  | 28.3 | 10.3 | 46.8  | 49.2  |

### Table 5: The impact of query generation and response generation shared parameter training.

| Model                  | Query Generation | Response Generation |
|------------------------|------------------|---------------------|
|                        | ACC              | F1                 | PPL \* | F1   | KF1 | BLEU | DIS | PPL | \* |
| **PLATO-Query**        | 67.8/69.8        | 53.5/55.7          | 2.69/3.0 | /   | / | /   | /   | /   | /   |
| **PLATO-Response**     | /                | /                  | /      | 30.6/31.2 | 15.6/18.8 | 51.8/53.6 | 56.5/51.0 | 11.75/12.7 | /   |
| **PLATO-SINC**         | 67.2/68.3        | 54.2/56.6          | 2.53/2.79 | 30.2/30.6 | 16.2/19.1 | 52.9/53.0 | 58.1/51.6 | 11.84/12.88 | /   |

We experiment on multiple Chinese pre-trained language models, including T5 (Xue et al., 2021), BART (Liu et al., 2020), EVA2.0 (Gu et al., 2022), and PLATO (Bao et al., 2021b). In addition, we investigate the performance of the model at various parameter scales and the differentiation between various categories of knowledge as world information.

**Human evaluation settings.** We collect multi-turn human-machine dialogue for human evaluations on competitive methods in automatic evaluation. To comprehensively evaluate the ability of the methods to utilize the world information, we selected 60 topics as the initial sentences of the conversations, which can be divided into chitchat topics, in-depth topics, and spatiotemporal & skill topics. The annotator initiates the conversations according to a given topic, and each conversation lasts at least five turns. Additional annotators score the collected dialogues at turn level and session level. Among them, at the turn level, we mainly focus on the four metrics which score is 0 or 1. 1) Consistency, whether the reply is coherent with the context and the reply itself. 2) Knowledgeable, whether the reply contains knowledge or common sense information. 3) Factual Accuracy, whether the knowledge in the reply is wrong or contrary to common sense. 4) Engaging, whether the reply...
Figure 4: The influence of pre-trained PLATO models with different parameter scales on the service information augmented conversation task.

is attractive and whether it is willing to continue the dialogue with the bot. The session level overall score is a comprehensive metric with a score of 0-5, where 0 means bad and 5 means perfect.

4.2 Automatic Evaluation Results

Pre-training models. As shown in Table 3, golden kg means using the DuSinc dataset to train service information augmented models and using golden knowledge for inference. No kg means using only the dialogue context when training and inference. Adding service information can significantly improve the effect of query and response generation in the four pre-training models. At the same time, we can also see that in the seen and unseen test sets, the model with service information has little difference in automatic metrics, which shows that the method is generalized and can transfer domains and topics. Experiments were conducted using a pre-training model with comparable parameters. In comparison, PLATO and BART have better performance. PLATO has more advantages in F1, BLEU, and Distinct, while BART is reflected in KF1. We believe that pre-training corpus of BART contains a lot of knowledge text, which may be closer to service knowledge so that it is more inclined to use knowledge. PLATO seems to have a more robust dialogue generation ability. EVA2.0 performs the worst among them, which we attribute to the pre-training conversation average duration data being shorter.

Knowledge access methods. We compare the effects of generating responses given different external information, experimenting on PLATO with 1.6 billion parameters. We investigated the following settings: PLATO is an untuned pre-trained model, PLATO-FT is a model fine-tuned using only conversation context, PLATO-FID (Izacard and Grave, 2021) is a model capable of fusing several bits of knowledge during decoding, and PLATO-SINC is our suggested model for service information augmentation. For knowledge access, no knowledge means not using external information. The web is the text from web pages. We get the relevant web pages through the Chinese search engine, and select the topk paragraphs in them through the DPR (Karpukhin et al., 2020) method. Service is the service information we propose. For Web and Service, we use the same query predicted by the model.

As demonstrated in Table 4, incorporating external information may enhance the capabilities of various conversation system components. Service information is more favorable than web pages based on most automated criteria, particularly the consistency and diversity metrics F1 and DIS. The KF1 metric among them is pretty low. We consider it since the length of the online text is often more significant than that of the service information, which is typically shorter.

Share weights. We verify that the shared weights between query and response generation tasks are effective on the PLATO model. 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 both tasks, the shared-weight training model can approach or exceed the single training model on automatic metrics, with equal performance on the seen and unseen test sets. This shows that the learning of these two tasks can promote each other.

Parameter scale. By fine-tuning the PLATO model with 128M, 0.6B, 1.6B, and 11B parameters, we explore the relationship between the parameters of the dialogue generation model and the ability to use information from external services. We uniformly use the method of sharing weights between the two tasks of query generation and response generation for model training and automatically evaluate the two tasks separately. The experimental results are shown in Figure 4. The PPL metric
was positively correlated with the parameter scale in both tasks. However, on the F1 metric, the query generation of the model with 11 billion parameters is lower than that of the model with 1.6 billion parameters. Therefore, increasing the model size can improve the ability of the dialogue system to use world information, but for query generation tasks, fewer parameters can already have a good effect.

4.3 Human Evaluation Results

As demonstrated in Table 6, the model PLATO-SINC, which uses service information, is significantly improved compared to the methods that do not link the world through web information. Specifically, compared to PLATO, the dialogue consistency increases by 11.91%, the knowledgeable increases by 11.83% to 98.30%, and the ratio of factually incorrect decreases by 7.43%. It is worth mentioning that the engaging significantly improved by 27.42%, the session-level overall score from 2.53 to 4.07, a relative improvement of 60.87%. In our opinion, it makes responses more interesting by adding dynamic spatiotemporal information. Compared with the method of using web knowledge, our method is also more advantageous in various dimensions, which benefits from the service information providing broader and more accurate knowledge.

We further analyze the performance of each method under different types of dialogue topics. On the topic of chitchat, PLATO-SINC showed a slight improvement in consistency and factual accuracy. We consider that the completion of such topics require little external information. The increase in knowledge leads to a decrease in factual accuracy, but still a significant increase in engaging and overall score. A certain amount of external information is required on in-depth topics to complete the conversation. The impact of the PLATO-SINC approach employing service information has significantly improved, mainly based on 98.13% knowledgeable, where the factual error is only 7.01%. On the topic of spatiotemporal sensitivity and skills, service information shows its powerful capabilities. The factually incorrect of our method is only 7.77%, when the other methods are at least 22.41%. Sensing time and location and possessing comprehensive abilities effectively is beneficial for enhancing conversational engaging. The overall score improved to 4.16, which is unprecedented. A dialog case on information seeking and response generation is in Appendix B, and we will add more cases later.

5 Related Work

State-of-the-art open-domain dialogue systems are usually implemented by training end-to-end generative models on large amounts of dialog corpus. They generate responses using knowledge learned from static training data, frozen in model weights (Adiwardana et al., 2020; Roller et al., 2021b; Bao et al., 2021a; Gu et al., 2022). Many studies in recent years have found that external information can improve the knowledgability of dialogue responses and reduce the rate of hallucinations (Zhou et al., 2021; Meng et al., 2020; Kim et al., 2019; Zhou et al., 2018). TopicalChat (Gopalakrishnan et al., 2019), DuConv (Wu et al., 2019), KdConv (Zhou et al., 2020), PersonaChat, etc., provide conversation-related information such as textual knowledge or user portraits, and analyze whether chatbots can use them in conversations. However, these static sources of information are difficult to cover the world knowledge in the open field. And they do not focus on how to retrieve this information, which is important for open-domain dialogue.

Some work attempts to get chatbots to retrieve external information in conversations. A representative example is Wikipedia of Wizard, which uses conversational context to match relevant knowledge documents from Wikipedia (Dinan et al., 2019a). LaMDA can generate queries to access a question-and-answer database as well as calculator and translation skills to generate responses (Thoppilan et al., 2022). The work that is closer to us is Wikipedia of Internet, which obtains relevant web page texts by accessing search engines, expands the scope of information sources, improves the timeliness and coverage of information, and verifies that this method can improve dialog informativeness and factual accuracy (Komeili et al., 2022b). On this basis, Shuster et al. (2022) further proposes to condense the retrieved web pages into concise text knowledge to reduce the interference of the noise in the web page text knowledge to the system. Different from these studies, our goal is to build a chatbot that can link to the real world, acquires world knowledge and state in service information, and has the ability to perceive the spatiotemporal scene like a human.

As shown in Table 1, human-labeled open-domain dialogue datasets based on external infor-
Table 6: Human evaluation results for different types of topics.

| Model             | Knowledge Access | Consistent | Knowledgeable | Factually Incorrect ↓ | Engaging | Overall Score |
|-------------------|------------------|------------|---------------|-----------------------|----------|---------------|
| **All Topics**    |                  |            |               |                       |          |               |
| PLATO no knowledge|                  | 75.44%     | 86.47%        | 14.99%                | 58.82%   | 2.53          |
| PLATO-SINC web top 1 |                  | 83.48%     | 97.48%        | 13.33%                | 78.33%   | 3.52          |
| PLATO-SINC service |                  | 87.35%     | 98.30%        | 7.56%                 | 86.27%   | 4.07          |
| **Chitchat Topics** |                  |            |               |                       |          |               |
| PLATO no knowledge |                  | 81.25%     | 89.29%        | 5.36%                 | 66.07%   | 3.00          |
| PLATO-SINC web top 1 |                  | 81.48%     | 97.22%        | 8.17%                 | 83.80%   | 3.92          |
| PLATO-SINC service |                  | 83.64%     | 98.60%        | 7.94%                 | 84.58%   | 3.93          |
| **In-depth Topics** |                  |            |               |                       |          |               |
| PLATO no knowledge |                  | 75.64%     | 90.60%        | 16.24%                | 61.54%   | 2.58          |
| PLATO-SINC web top 1 |                  | 86.32%     | 97.58%        | 12.74%                | 81.13%   | 3.65          |
| PLATO-SINC service |                  | 87.38%     | 98.13%        | 7.01%                 | 86.45%   | 4.13          |
| **Spatiotemporal & Skill Topics** |                  |            |               |                       |          |               |
| PLATO no knowledge |                  | 69.34%     | 78.77%        | 24.06%                | 49.06%   | 2.00          |
| PLATO-SINC web top 1 |                  | 82.76%     | 97.57%        | 22.41%                | 70.69%   | 2.98          |
| PLATO-SINC service |                  | 91.26%     | 98.54%        | 7.77%                 | 87.86%   | 4.16          |

In future work, we consider expanding the kinds of service information in DuSinc. Exploring the introduction of cross-genre, cross-modal information into open-domain conversations through linking the world.

7 Ethical Considerations

This section addresses strategies and techniques for schools, laboratories, corporations, etc., to utilize our work ethically. First and foremost, we will only collect the spatiotemporal data of user with their permission. We would release the DuSinc dataset and PLATO-SINC model under CC-BY-SA to prevent illegal usage. Second, DuSinc and PLATO-SINC should identify incorrect wording. Professional collectors will delete abusive remarks from DuSinc. We will use profanity dictionaries and algorithmic approaches to detect problematic utterances. Children and teenagers will benefit from more appropriate language. We will design safeguards and tactics to make PLATO-SINC safe and ethical. Automated systems will groom PLATO-SINC and its users. Using and maintaining session data is regulated by law.
References

Daniel Adiwardana, Minh-Thang Luong, David So, Jamie Hall, Noah Fiedel, Romal Thoppi-lan, Zi Yang, Apoorv Kulshreshtha, Gaurav Nemade, Yifeng Lu, et al. 2020. Towards a human-like open-domain chatbot. arXiv preprint arXiv:2001.09977.

Leonard Adolphs, Kurt Shuster, Jack Urbanek, Arthur Szlam, and Jason Weston. 2021. Rea-son first, then respond: Modular generation for knowledge-infused dialogue. arXiv preprint arXiv:2111.05204.

Siqi Bao, Huang He, Fan Wang, Hua Wu, Haifeng Wang, Wenquan Wu, Zhen Guo, Zhibin Liu, and Xinchoa Xu. 2021a. Plato-2: Towards building an open-domain chatbot via curriculum learning. In Findings of the Association for Computational Linguistics: ACL-IJCNLP 2021, pages 2513–2525.

Siqi Bao, Huang He, Fan Wang, Hua Wu, Haifeng Wang, Wenquan Wu, Zhibin Wu, Zhen Guo, Hua Lu, Xinxian Huang, et al. 2021b. Plato-xl: Exploring the large-scale pre-training of dialogue generation. arXiv preprint arXiv:2109.09519.

Boxing Chen and Colin Cherry. 2014. A systematic comparison of smoothing techniques for sentence-level bleu. In Proceedings of the 9th Workshop on Statistical Machine Translation, pages 362–367.

Emily Dinan, Stephen Roller, Kurt Shuster, Angela Fan, Michael Auli, and Jason Weston. 2019a. Wizard of wikipedia: Knowledge-powered conversational agents. In International Conference on Learning Representations.

Emily Dinan, Stephen Roller, Kurt Shuster, Angela Fan, Michael Auli, and Jason Weston. 2019b. Wizard of wikipedia: Knowledge-powered conversational agents. International Conference on Learning Representations.

Karthik Gopalakrishnan, Behnam Hedayatnia, Qinglang Chen, Anna Gottardi, Sanjeev Kwatra, Anu Venkatesh, Rafeer Gabriel, Dilek Hakkani-Tür, and Amazon Alexa AI. 2019. Topical-chat: Towards knowledge-grounded open-domain conversations. In INTERSPEECH, pages 1891–1895.

Peter Hagoort, Lea Hald, Marcel Bastiaansen, and Karl Magnus Petersson. 2004. Integration of word meaning and world knowledge in language comprehension. science, 304(5669):438–441.

Gautier Izacard and Édouard Grave. 2021. Leveraging passage retrieval with generative models for open domain question answering. In Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume, pages 874–880.

Vladimir Karpukhin, Barlas Oguz, Sewon Min, Patrick Lewis, Ledell Wu, Sergey Edunov, Danqi Chen, and Wen-tau Yih. 2020. Dense passage retrieval for open-domain question answering. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 6769–6781.

Byeongchang Kim, Jaewoo Ahn, and Gunhee Kim. 2019. Sequential latent knowledge selection for knowledge-grounded dialogue. In International Conference on Learning Representations.

Mojtaba Komeili, Kurt Shuster, and Jason Weston. 2022a. Internet-augmented dialogue generation. In Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 8460–8478.

Mojtaba Komeili, Kurt Shuster, and Jason Weston. 2022b. Internet-augmented dialogue generation. In Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 8460–8478.

Angeliki Lazaridou, Adhi Kuncoro, Elena Gri-bovskaya, Devang Agrawal, Adam Liska, Tay-
fun Terzi, Mai Gimenez, Cyprien de Masson d’Autume, Tomas Kocisky, Sebastian Ruder, et al. 2021. Mind the gap: Assessing temporal generalization in neural language models. *Advances in Neural Information Processing Systems*, 34:29348–29363.

Kenton Lee, Ming-Wei Chang, and Kristina Toutanova. 2019. Latent retrieval for weakly supervised open domain question answering. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 6086–6096, Florence, Italy. Association for Computational Linguistics.

Jiwei Li, Michel Galley, Chris Brockett, Jianfeng Gao, and Bill Dolan. 2016a. A diversity-promoting objective function for neural conversation models. In *Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 110–119.

Jiwei Li, Michel Galley, Chris Brockett, Jianfeng Gao, and Bill Dolan. 2016b. A diversity-promoting objective function for neural conversation models. In *Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 110–119, San Diego, California. Association for Computational Linguistics.

Yinhan Liu, Jiatao Gu, Naman Goyal, Xian Li, Sergey Edunov, Marjan Ghazvininejad, Mike Lewis, and Luke Zettlemoyer. 2020. Multilingual denoising pre-training for neural machine translation. *Transactions of the Association for Computational Linguistics*, 8:726–742.

Clara Isabel Meister and Ryan Cotterell. 2021. Language model evaluation beyond perplexity. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing*, volume 1, pages 5328–5339. Association for Computational Linguistics.

Chuan Meng, Pengjie Ren, Zhumin Chen, Weiwei Sun, Zhaochun Ren, Zhaopeng Tu, and Maarten de Rijke. 2020. Dukenet: A dual knowledge interaction network for knowledge-grounded conversation. In *Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval*, pages 1151–1160.

Stephen Roller, Emily Dinan, Naman Goyal, Da Ju, Mary Williamson, Yinhan Liu, Jing Xu, Myle Ott, Eric Michael Smith, Y-Lan Boureau, et al. 2021a. Recipes for building an open-domain chatbot. In *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume*, pages 300–325.

Stephen Roller, Emily Dinan, Naman Goyal, Da Ju, Mary Williamson, Yinhan Liu, Jing Xu, Myle Ott, Eric Michael Smith, Y-Lan Boureau, et al. 2021b. Recipes for building an open-domain chatbot. In *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume*, pages 300–325.

Kurt Shuster, Mojtaba Komeili, Leonard Adolphs, Stephen Roller, Arthur Szlam, and Jason Weston. 2022. Language models that seek for knowledge: Modular search & generation for dialogue and prompt completion. *arXiv preprint arXiv:2203.13224*.

Kurt Shuster, Spencer Poff, Moya Chen, Douwe Kiela, and Jason Weston. 2021. Retrieval augmentation reduces hallucination in conversation. *Findings of the Association for Computational Linguistics: EMNLP 2021*.

Romal Thoppilan, Daniel De Freitas, Jamie Hall, Noam Shazeer, Apoorv Kulshreshtha, Heng-Tze Cheng, Alicia Jin, Taylor Bos, Leslie Baker, Yu Du, et al. 2022. LAMDA: Language models for dialog applications. *arXiv preprint arXiv:2201.08239*.

Noortje J Venhuizen, Matthew W Crocker, and Harm Brouwer. 2019. Expectation-based comprehension: Modeling the interaction of world knowledge and linguistic experience. *Discourse Processes*, 56(3):229–255.

Wenquan Wu, Zhen Guo, Xiangyang Zhou, Hua Wu, Xiyuan Zhang, Rongzhong Lian, and Haifeng Wang. 2019. Proactive human-machine conversation with explicit conversation goal. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 3794–3804.
Linting Xue, Noah Constant, Adam Roberts, Mihir Kale, Rami Al-Rfou, Aditya Siddhant, Aditya Barua, and Colin Raffel. 2021. mt5: A massively multilingual pre-trained text-to-text transformer. In NAACL-HLT.

Hao Zhou, Minlie Huang, Yong Liu, Wei Chen, and Xiaoyan Zhu. 2021. Earl: Informative knowledge-grounded conversation generation with entity-agnostic representation learning. In Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing, pages 2383–2395.

Hao Zhou, Chujie Zheng, Kaili Huang, Minlie Huang, and Xiaoyan Zhu. 2020. Kdconv: A chinese multi-domain dialogue dataset towards multi-turn knowledge-driven conversation. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 7098–7108.

Kangyan Zhou, Shrimai Prabhumoye, and Alan W Black. 2018. A dataset for document grounded conversations. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 708–713.
A Data Collection Details

We developed a data collection tool, which is different on the USER side and the BOT side, Figures 5 is the corresponding screenshot. 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 replies highly duplicates the knowledge.

Figure 5: Screenshots of DuSinc data collection tool.

B Case Study

Spatiotemporal state (Time: 2022.08.12 15:00; Location: Haidian district, Beijing, China)

| Context | Request | Knowledge Seeking | Response Generation |
|---------|---------|-------------------|---------------------|
| user: It's the weekend soon, I'm going to go on an outing with my friends. 马上到周末了，我打算和朋友去郊游 | query generation: weekend weather; Latitude: ***; Longitude: *** | In the next 2 days in Beijing, the weather will be mainly cloudy, tomorrow will be 18 degrees to 26 degrees, cloudy; the day after tomorrow, 16 degrees to 21 degrees, with light rain. | The weather in Beijing will be cloudy tomorrow, suitable for going out to play, there will be light rain the day after tomorrow. |
| bot: That's great, enjoy your vacation. 那很棒呀，好好享受假期时光。 | | 北京未来2天内，天气以多云为主，明天18度～26度，多云，后天16度～21度，小雨。 | 北京明天天气多云，适合出去玩，后天有小雨。 |
| user: Hope for good weather. 希望能有个好天气。 | no_passages_used | Good weather. good mood. | |

| Knowledge Seeking | Response Generation |
|-------------------|---------------------|
| service knowledge | The weather in Beijing will be cloudy tomorrow, suitable for going out to play, there will be light rain the day after tomorrow. |
| no knowledge | Good weather. good mood. |
| web knowledge | There will be showers during the day on Saturday, please pay attention to traffic safety. |
| | (Facts are not accurate) |

| Knowledge Seeking | Response Generation |
|-------------------|---------------------|
| web knowledge | There will be showers during the day on Saturday, please pay attention to traffic safety. |
| | (Facts are not accurate) |

Table 7: Cases of seek knowledge and generate responses by our model and baselines.