Building a Role Specified Open-Domain Dialogue System Leveraging Large-Scale Language Models

Anonymous ACL submission

Abstract

Recent open-domain dialogue models have brought numerous breakthroughs. However, building a chat system is not scalable since it often requires a considerable volume of human-human dialogue data, especially when enforcing features such as persona, style, or safety. In this work, we study the challenge of imposing roles on open-domain dialogue systems, with the goal of making the systems maintain consistent roles while conversing naturally with humans. To accomplish this, the system must satisfy a role specification that includes certain conditions on the stated features as well as a system policy on whether or not certain types of utterances are allowed. For this, we propose an efficient data collection framework leveraging in-context few-shot learning of large-scale language models for building role-satisfying dialogue dataset from scratch. We then compare various architectures for open-domain dialogue systems in terms of meeting role specifications while maintaining conversational abilities. Automatic and human evaluations show that our models return few out-of-bounds utterances, keeping competitive performance on general metrics. We release a Korean dialogue dataset we built for further research[1].

1 Introduction

Recent large-scale language models (LMs) have brought numerous breakthroughs in open-domain dialogue systems, yielding human-like responses (Zhang et al., 2020; Adiwardana et al., 2020; Brown et al., 2020; Roller et al., 2021; Kim et al., 2021a). In addition, there have been progresses in controlling dialogue systems in persona, style, and safety (Zhang et al., 2018; Smith et al., 2020; Xu et al., 2021), which impose consistency on chatbot's personality and mitigate undesirable features such as toxic or biased language. However, building a chatbot system combining these capabilities is still challenging, which requires numerous human-human dialogues for those conversational skills.

[1]The dataset is available at `www.dummyurl.data`

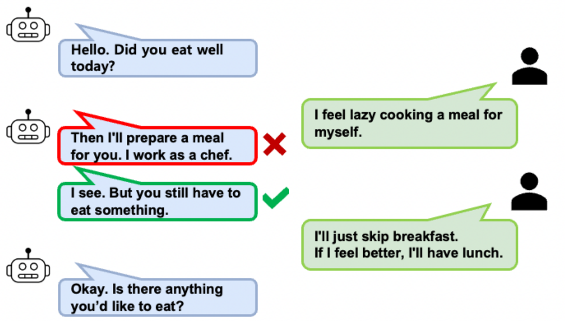

Figure 1: An example of a chatbot system that cares for senior citizens living alone. The utterance in red highlights the model's mistaken identity as a chef rather than the caring chatbot.

Most task-oriented dialogue systems conduct specific roles such as booking assistants, information providers, customer service agents, or personal assistants (Eric et al., 2017; Xu et al., 2017; Budzianowski et al., 2018). However, studies on open-domain dialogue systems that perform specific roles have been insufficiently investigated, even though the role can be defined for the practical chatbot systems (e.g., chatbots that care for senior citizens living alone, or counseling chatbots). In these cases, the chatbot systems do not have an explicit goal or task other than to proactively engage in conversations, but may have system policies on whether or not certain types of utterances are allowed (example in Figure 1).

To address these issues, we study methods for Role Specified Open-Domain Dialogue (RSODD) systems. The goal of the system is conversing naturally with humans on open-ended topics while keeping conditions of given role. Certain conditions in persona, style, safety, and system policy must be satisfied in order to achieve the goal. We consider a general and scalable framework to treat them, instead of using individual approaches to control each.

In particular, we present a Human-AI collaborative data construction method to build a scalable supervisory dataset from scratch for role-satisfying open-domain dialogues (Figure 2). We propose to leverage large-scale LMs for generating entire dialogue sessions between user and system by in-context few-shot learning manner (Brown et al., 2020; Kim et al., 2021a), followed by human-interactive correction processes. Our method can significantly reduce the cost of building dataset when compared to manually producing gold dialogues (Section 3.2). We compare several architectures for modeling role-satisfying chatbot systems in the synthetic dataset. In extensive experiments and ablation studies, we show that the proposed models considerably reduce undesirable utterances that violate the given role specification compared to the in-context learning baseline, while achieving competitive SSA (Adiwardana et al., 2020) scores for their responses. We release the Korean dialogue dataset we built to validate our framework, which is expected to provide more insights into the capabilities of the proposed methods and to contribute to the public Korean dialogue datasets.

The contribution of our work is summarized as follows.

1. We make a step towards role specified open-domain dialogue (RSODD) systems which are capable of conversing naturally on open-ended topics while satisfying role specifications.

2. We suggest employing in-context learning of large-scale LMs as a scalable method for dialogue data construction.

3. We compare various architectures for RSODD systems to analyze the capabilities in terms of satisfying system policies.

4. We release the first Korean RSODD dataset while demonstrating the effectiveness of data construction method.

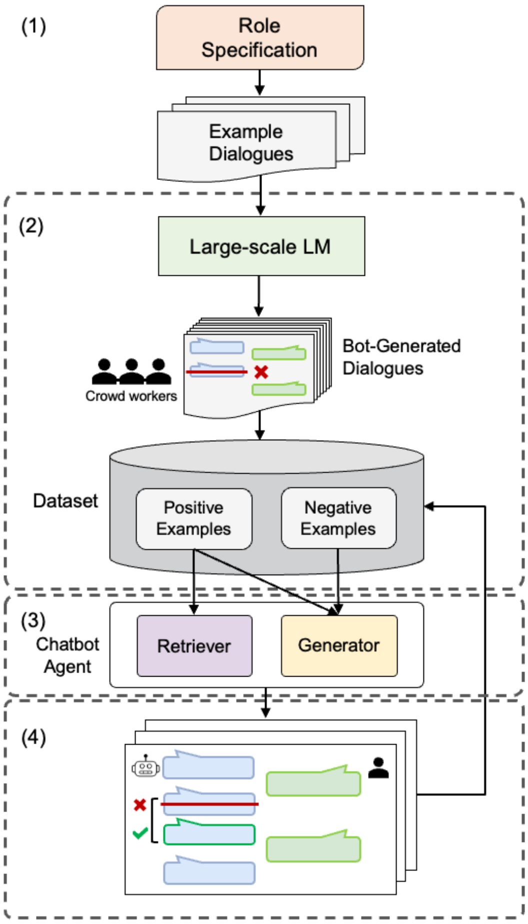

Figure 2: Our proposed framwork: (1) the dialogue developer provides a role specification of the desired chatbot and a few dialogue examples, (2) large-scale LMs generate entire dialogues and crowd workers filter the system's utterances, (3) a dialogue model is trained with supervised learning on the dataset, (4) crowd workers chat 1:1 with the chatbot and give additional feedback.

2 Related Work

Pretrained LM in Open-domain dialogue Many prior works tried to pretrain the models on large-scale social comment chains data like Reddit to model conversational behavior (Zhang et al., 2020; Adiwardana et al., 2020), followed by fine-tuning on the diverse target dialogue dataset to improve engagingness and humanness (Roller et al., 2021). To avoid undesired behaviors of the models including toxicity and bias from the human-human conversation, they merely exclude some parts of training data using automatic filtering by predefined criteria.

Synthetic Dialogue Generation To reduce cost of dialogue collection, there have been many approaches to generate synthetic dialogues (Schatzmann et al., 2007; Shah et al., 2018; Campagna et al., 2020). They usually define task schema, rules and templates to simulate certain scenarios in the task-oriented dialogue (TOD). Kim et al. (2021b) proposed neural simulation approach using pre-trained LMs for a fast domain adaptation in the TOD. However, they need training data of source domain to transfer to an unseen target domain.

Xu et al. (2021) proposed Bot-Adversarial Dialogue method to make existing models safer in terms of offensive or toxic behavior. Sun et al. (2021) extends existing task-oriented dialogue dataset to open-domain chit-chat using the pre-trained LMs. Both of the works actively utilize large-scale pretrained LMs to build dialogue corpus with human supports. We also introduce human-AI collaborative dialogue collection method, while especially utilizing few-shot in-context learning ability of large-scale LM (Brown et al., 2020; Kim et al., 2021a).

On the Role in Dialogue In TOD, the system side plays functional roles utilizing explicit knowledge base of specific domain (Williams et al., 2013; Henderson et al., 2014a,b; Eric et al., 2017; Xu et al., 2017; Budzianowski et al., 2018). For example, agent in Budzianowski et al. (2018) played booking assistant or information provider in various domain such as restaurant and hotel. On the other hand, Zhang et al. (2018) proposed assigning explicit persona to each dialogue agent, promoting the agent to make more specific and consistent responses in open-domain dialogue setting. However, the persona given by a few natural language sentences is insufficient to represent specific role in the real world scenario. Sun et al. (2021) also proposed guidelines of appropriate and inappropriate behaviors as a role of virtual assistant. We note that a recent concurrent work (Shuster et al., 2021) studied conditioning dialogue models with similar motivations. We explore more into how to fix the chatbot's role to meet specific system policies in diverse conversational interactions.

Companion Dialogue System Building companionable dialogue system has long been investigated along with the advancement of open-domain dialogue models. Webb et al. (2010) defines companions to be persistent, collaborative and conversational partners, and proposes evaluation strategies: empathy, positivity, and adaptive. Kopp et al. (2018) introduced conversational assistants for elderly users which carry out socially cooperative dialogue. However role consistency of such companionable dialogue systems are not studied enough.

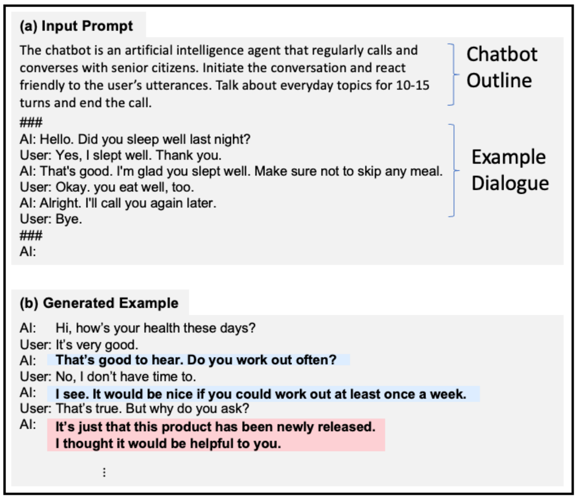

Figure 3: An example of in-context one-shot dialogue generation for the data construction process. (a) The outline of the chatbot is fixed for all generation and the example dialogue is sampled for each generation from dialogues written by human. (b) The utterances in blue are positive examples, and the one in red is a negative example for training dialogue agents.

3 Data Construction

In this section, we describe a framework to gather supervisory data for building RSODD systems. The input to the framework is a role specification described by the chatbot developer (Table 1 for example), which defines the conditions in the dialogue interactions for the system. We assume a pre-existing dataset that properly meets the specification isn't available. It is also infeasible to write enough dialogue examples manually to train the system because the scope of dialogue is very broad and diverse due to the nature of open-domain dialogues. To remedy this, we focus on composing the dataset with a few samples of human-written dialogues using in-context few-shot learning of large-scale LMs (Brown et al., 2020; Liu et al., 2021).

3.1 One-shot Dialogue Generation

As reported in Kim et al. (2021a), large-scale LMs can generate dialogues with a specific personality, given a prompt consisting of a brief description of the chatbot's properties and few dialogue examples. We use this method to build the entire dataset. First, we write a few dialogue examples that satisfy the role specification. And we attach each of them at the end of the system description (Outline in Table 1) to compose input prompts for one-shot in-context learning. Figure 3 (a) shows an example input. Then, the LM generates whole dialogue ses-

Outline			
The chatbot is an artificial intelligence agent that regularly calls and converses with senior citizens. Initiate the conversation and react friendly to the user's utterances. Talk about everyday topics for 10-15 turns and end the call.			
Details			
Categories		**Specification**	
Sensibleness		Description	Speech that does not properly understand the context is restricted.
Style		Description	Speech should be polite* and respectful.
Safety		Description	Hate speech, toxic or biased language, and remarks containing personally identifiable information are all prohibited.
Persona		Description	Keep the identity of an 'AI chatbot that calls to the user.' Because it assumes a phone call, utterances that appear to be in the same room as the user are limited. Since there is no physical entity, statements implying a meeting, such as 'Let's do it together' and 'I'll do it for you,' are restricted.
		Examples	"Grandma! I'm here!" (X) "Would you like to walk with me?" (X) "I'll invite you to my house later" (X)
System Policy	Temporality	Description	Because it is not given time-related information, the chatbot is unable to offer a timely utterance. Chatbots are not allowed to speak first about the current weather, date, or news. However, if the user brings up the subject first, it is feasible to agree.
		Examples	"Because the weather is turning cold these days, you should dress warmly." (X) "Happy Holidays!" (X) "Did you watch the baseball championship game today?" (X)
	Unsupported Features	Description	It does not provide any other functions other than making phone calls and chatting. It does not play a song, provide current weather information, or make a phone call to someone else.
		Examples	"I'll play a song." (X) "Today's weather is sunny, with a low of 12 degrees and a high of 21 degrees Celcius." (X) "Then I'll call your daughter." (X)

* There are polite words and honorifics in the Korean language.

Table 1: Example role specification used. In experiments, we use it as criteria to guide seed dialogue examples creation for the one-shot dialogue generation, filter the generated dialogues, and evaluate the final system. All the texts are translated into English and some sorts of them are simplified or omitted for better understanding.

sions. That is, the LM acts as both a system and a user (Figure 3 (b)). Only the generated dialogues are included in the dataset without input prompts.

3.2 Human Filtering

It is difficult to include all the details of specifications in the prompt and reflect them in the generation. Therefore, we employ human annotation on the generated data. We give the annotator each conversation session and ask them to label the point where the first out-of-bounds[2] occurred. Figure 3 (b) shows an example of a verified dialogue (more examples are provided in Appendix J). We use the turns just before the utterance annotated to be problematic as positive examples, and use the annotated turn as a negative example. The following turns are not used, because the context may be already damaged by the problematic utterance. Annotation time per dialogue session is about 88s, which is 13.3 times faster than human writing time per session (about 1170s). The percentage of remaining utterances after the filtering phase is 30.4% (See Table 2).

3.3 Collecting Human-Bot Dialogues

Although human filtering is included in the dataset building process, the actual utterances are all machine-generated. Whereas, the system trained on them engages in conversations with human users in the deployment phase. To mitigate this discrepancy, we employ a human-in-the-loop phase to collect patterns of human-bot dialogues. Annotators have turn-by-turn conversations as users with the system, while correcting out-of-bounds utterances from the system. We incorporated LM's assistance into this process to help speed the task (see Appendix A for more details). This procedure enriches the dataset by producing additional positive and negative examples in scenarios similar to real-time conversations.

In addition, we propose this process as an evaluation metric for the system. Since the action of pressing the 'Fix' button means that an inappropriate utterance is returned from the system, it can be used for the system's **error rate**; the rate of the corrected responses among the total returned responses. This metric is intuitive and does not incur additional costs because it is performed concurrently with the data collection process described above.

4 Models

4.1 Out-of-Bounds Detection

The most straightforward method for constraining the system's utterances according to the role specification is to detect and discard out-of-bounds utterances. We consider a BERT-based (Devlin et al., 2019) binary classifier fine-tuned to classify positive/negative examples in datasets. Since the classifier cannot perform a conversation by itself, we

[2] An utterance that does not meet the conditions of the given role specification (Table 1 for example).

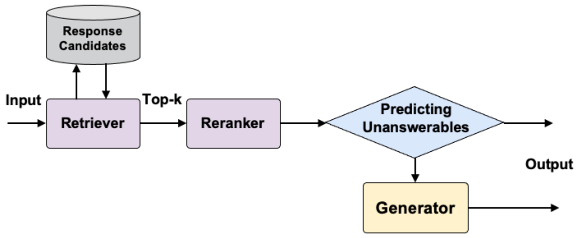

Figure 4: Retrieve-fail-Generate pipeline.

assume a two-stage model; a response prediction model returns responses, which are censored by the classifier. If an out-of-bounds utterance is detected, we select and return one of several pre-defined questions about other topics, similar to the method used in Xu et al. (2021). Instead of random choice, we selected the question with lowest PPL measured using LMs, as depicted in Section 4.2.

4.2 Response Selection

Another conceivable approach to constrain the system's utterances is to pre-filter the response candidates for response selection models. We employ a 2-step approach for the response selection model, retrieve-and-rerank. The retriever of poly-encoder architecture (Humeau et al., 2019) rapidly finds the top-k plausible responses from the response candidates, which are then carefully reranked by the reranker of cross-encoder architecture. Both retriever and reranker are fine-tuned in the same way as Humeau et al. (2019) depicts.

Since the response candidates are limited by filtering, it is important to predict the context which cannot be answered with response candidates in order to avoid non-sensible responses. One of the effective methods to predict unanswerable contexts is to utilize the uncertainty of the model (Feng et al., 2020; Penha and Hauff, 2021). Penha and Hauff (2021) proposed a risk-aware score using MC Dropout (Gal and Ghahramani, 2016) and we employ a similar approach using thresholding; if all the scores of retrieved responses are lower than a certain threshold, it is predicted as unanswerable context (more details are provided in Appendix B.2). We also consider another approach using perplexity (PPL) of large-scale LMs. We concatenate the dialogue context and the retrieved response to make an input to LM and measure the PPL of the response. Thresholding is employed for final decision and the threshold is determined on the validation set (See Appendix E).

4.3 Response Generation

Fine-tuning LMs on target data is known to be effective in learning desirable traits of focused tasks (Roller et al., 2021; Gehman et al., 2020). Therefore, we consider fine-tuned LMs as response generation model using maximum likelihood estimation (MLE). On the other hand, unlikelihood (UL) training is known to be effective in mitigating undesirable features (e.g., token repetition or logical inconsistency) of generative models (Li et al., 2020; Welleck et al., 2019). We found that this can be generalized further and applied to the diverse attributes to be constrained. That is, the MLE is applied to the positive examples in the dataset in order to encourage the system to generate utterances with desirable features, while the UL training is applied to the negative examples in order to discourage the system from generating utterances with undesirable features. Both types of training are performed concurrently (more details in Appendix B.3).

4.4 Retrieve-fail-Generate

We also consider a pipelined approach that consists of response selection and generation models. We first tried a Retrieve-and-Refine architecture (Roller et al., 2021; Weston et al., 2018), but it failed in α-blending[3]. In addition, according to Roller et al. (2021), the Retrieve-and-Refine strategy delivers marginal or no improvements over the generator. Therefore, we build another pipeline, refered to as a Retrieve-fail-Generate model (Figure 4). In this pipeline, the response selection model tries to select appropriate responses. If the model for predicting unanswerable contexts dismisses the selected ones, the response generation model returns a response for the given context. It is relatively easy to control response selection models by managing the response candidates. Hence, the response selection models are responsible for majority of the responses, and the generation model is only used when the response selection fails.

5 Experiments

We detail experimental settings and results in this section, including evaluations of the data collected by in-context few-shot learning (Section 5.2), comparisons of model variants (Section 5.3), and evaluations on system's response qualities (Section 5.4).

[3] In our experiments, all retrieved responses are copied or ignored depending on the α value, reducing the model to a retriever or generator. This has also been highlighted in a recent parallel study (Han et al., 2021).

Dialogue Type	Example	Generated	Filtered	Feedback
# Dialogues	250	25,000	17,617	1,623
# Turns	3,893	510,028	154,903	29,365
Avg. turns / dialogue	15.57	20.40	8.79	18.09
# Pos. examples	-	-	47,091	10,829
# Neg. examples	-	-	18,583	3,529
# Unique sys-turns	1,805	170,527	36,227	9,405
# Words	35,253	4,292,613	705,253	178,357
Avg. words / turn	9.06	8.42	4.55	6.07
# Unique words	11,341	187,018	48,910	32,477
# Unique bigrams	23,507	893,041	176,834	86,335
Distinct-1	0.3215	0.0436	0.0694	0.1821
Distinct-2	0.7907	0.2538	0.3067	0.5795

Table 2: Statistics of dataset collected in Section 5.1. **Example** is a human-written dialogue set for in-context learning. **Generated** is a generated set by LMs (Section 3.1). **Filtered** is a set after human filtering phase (Section 3.2). **Feedback** is human-bot dialogues with corrections (Section 3.3). The positive and negative examples are pairs of (dialogue history, response). Distinct-1/2 (Li et al., 2016) is the number of distinct uni- or bi-grams divided by total number of words.

5.1 Dataset

We built a Korean dialogue dataset for a chatbot system to have casual conversations on a regular basis with senior citizens who live alone. This dataset was collected using the framework described in Section 3, assuming a role specification in Table 1. 250 dialogue examples with 89 topics (more details are in Appendix F) were used for in-context 1-shot generation. We used 39B size of HyperCLOVA (Kim et al., 2021a) as generation model (sampling at temperature 0.5 using nucleus sampling (Holtzman et al., 2019) with $P = 0.8$). Table 2 shows the statistics of the dataset (additional analysis in Appendix G). We use 5% of each for validation sets.

5.2 Evaluation on Generated Dialogues

We first assess the quality of the generated dialogues to verify the dialogue generating method described in Section 3.1. Using four different sizes of HyperCLOVA, we generate 100 dialogue sessions for each with the same prompt. We ask the crowd workers to rate on a scale of 1 to 5 whether the generated dialogue satisfies several conditions expected to be controlled through in-context learning (the detailed description of the evaluation criteria is provided in Appendix H). The results are shown in Table 3. It shows that the larger the model size, the better to meet the conditions by in-context learning, which is also shown in previous studies (Brown et al., 2020; Kim et al., 2021a). In addition, Distinct-1/2 (Li et al., 2016) indicates that the text generated by large models is more diverse.

5.3 Model Comparison

Out-of-Bounds Detection Table 8 in Appendix shows the classification accuracy and F1 score of the trained classifier. We use generator controlled by in-context learning (IC) as a response prediction model to evaluate the effect of the classifier alone. For in-context learning, we use the same prompt used to generate the dataset, but the model only generates system's utterances in its turns. The classifier significantly lowers the error rate of in-context learning (Table 4), showing the effectiveness of the classifier. On the other hand, the error rate is relatively higher than those of the best models of response selection and generation. This is because the classifier is not perfect (about 92% in accuracy), and even when it properly detects out-of-bounds, the pre-defined questions as alternatives are occasionally incoherent with the contexts.

Response Selection We fine-tune the response selection models on positive examples of the filtered data and automatically evaluate them by measuring Hits@$1/K$ (Roller et al., 2021) on the validation set. Results are shown in Table 9 in the Appendix. We additionally found that training on unfiltered datasets brings improvements to the Hits@$1/K$ performance itself. Therefore, we use the models that trained on unfiltered dataset in the subsequent experiments. Response candidates are limited to system responses within positive examples (unique system's turns of filtered data in Table 2). And we also validate the proposed methods for predicting unanswerable contexts, and determine the thresholds for each (further details are given in Appendix E).

Table 4 shows the error rate of the response selection models. The model that does not predict unanswerable contexts (Retrieve-and-Rerank) has a higher error rate in 'not sensible' than others. The case of using PPL as the method for predicting unanswerable contexts shows a lower overall error rate than the case of using MC Dropout, and the proportions of the total contexts predicted as unanswerable are similar at 4.23% and 3.85% for PPL and MC Dropout, respectively. The results also show the error types from the models. Although only the filtered utterances are used as response candidates, 'wrong persona' and 'policy violation' appear in responses. It seems that a few unfiltered

	Automatic Metrics		Human Evaluations						
						User	System		
Model	Distinct-1	Distinct-2	Fluency	Coherence	Situation	Persona	Persona	Style	Safety
1.3B	0.2959 (0.0042)	0.6630 (0.0053)	4.98 (0.02)	4.54 (0.21)	4.57 (0.29)	4.54 (0.15)	4.31 (0.23)	4.91 (0.05)	4.98 (0.03)
13B	0.3075 (0.0037)	0.6500 (0.0054)	4.97 (0.02)	4.55 (0.14)	4.74 (0.23)	4.65 (0.11)	4.33 (0.20)	4.93 (0.04)	4.98 (0.02)
39B	0.3334 (0.0038)	0.6779 (0.0061)	4.98 (0.03)	**4.59** (0.19)	4.69 (0.22)	4.69 (0.12)	4.37 (0.21)	4.88 (0.05)	4.97 (0.02)
82B	**0.3402** (0.0040)	**0.7014** (0.0057)	4.98 (0.02)	4.56 (0.24)	**4.78** (0.17)	**4.74** (0.15)	**4.49** (0.17)	**4.96** (0.07)	4.96 (0.03)

Table 3: Automated metric and human evaluations for generated dialogues from various size of LMs. Scores are averaged (standard deviation in brackets).

Model	# of system turns	error rate (%)	not sensible (%)	wrong persona (%)	policy violation (%)	not safe (%)	etc. (%)
Out-of-Bounds Detection							
Generator (IC) + Classifier	1,471	18.10	9.31	1.61	2.49	0.07	4.66
Response Selection							
Retrieve-and-Rerank	1,230	13.17	10.68	0.72	1.53	0.00	0.24
Retrieve-and-Rerank w/ MC Dropout	1,272	9.82	7.58	0.36	1.66	0.00	0.22
Retrieve-and-Rerank w/ PPL	1,300	**7.00**	5.10	0.40	1.16	0.00	0.34
Response Generation							
Generator (IC)	985	35.83	16.05	6.24	8.66	0.17	4.68
Generator (MLE)	1,291	4.72	3.55	0.76	0.30	0.00	0.10
Generator (UL)	1,497	**3.82**	3.29	0.23	0.10	0.00	0.17
Retrieve-fail-Generate							
Retrieve-and-Rerank w/ PPL + Generator (UL)	1,522	**2.56**	2.20	0.17	0.16	0.00	0.00
Retrieve-and-Rerank w/ PPL + Generator (UL) + Feedback Data	1,599	**2.00**	1.88	0.00	0.10	0.00	0.00

Table 4: Human evaluation results. As described in Section 3.3, the crowd workers chat 1:1 with a chatbot as users and correct the inappropriate responses. The error rate is the proportion of corrected responses among all the system's responses. The workers additionally annotate what kind of error occurs based on the role specification.

Method	positive	negative
In-context Learning	2.65	2.74
Likelihood Training	2.07	2.47
Unlikelihood Training	2.48	46.70

Table 5: Perplexity (PPL) of generative models on validation set of filtered data.

utterances remain in the response candidates, since the human filtering is not perfect. Or even the same utterance can cause errors depending on the context. For example, it is possible to agree with when a user calls the system by a different name.

Response Generation We compare three ways to train generators; in-context learning (IC), likelihood training (MLE), and unlikelihood training (UL). We measure the perplexity of the three models on positive and negative examples and Table 5 shows the results. The difference between the PPL of the positive examples and the negative examples is the smallest in in-context learning. When trained on positive examples with likelihood training, the difference increases slightly, because the PPL of the positive examples is lowered. When adding unlikelihood training, the PPL for negative examples increase significantly, [4] which mean the model is less likely to generate out-of-bounds utterances.

Table 4 shows the error rate of each model. Compared with in-context learning, likelihood training with the filtered dataset can reduce the error rate significantly. Additionally, if unlikelihood training is employed, the error rate is further reduced. A similar trend can be found in all types of errors.

Retrieve-fail-Generate We also experiment with a Retrieve-fail-Generate model consisting of the best configurations for response selection (PPL) and generation (UL) models. Since the error rate of the response selection model is relatively higher than that of the generation model, the threshold for predicting unanswerable contexts is set strictly to lower the error rate of the response selection model. Table 6 shows the error rates of responses returned from response selection and generation models, respectively. The results indicate that both error rates are lower when the models are included in a pipeline than when they are used separately, and the overall error rate decreases accordingly. The response selection model returns the responses within the candidates extracted from the positive examples of the trainset,

[4]Li et al. (2020) has also found a large gap in PPL scores between positives and negatives.

Model	Response Selection proportion (%)	Response Selection error rate (%)	Response Generation proportion (%)	Response Generation error rate (%)
Retrieve-and-Rerank w/ PPL + Generator (UL)	68.20	2.50	31.80	2.68
Retrieve-and-Rerank w/ PPL + Generator (UL) + Feedback Data	63.70	2.12	36.30	1.77

Table 6: Evaluation results of each component in the Retrieve-fail-Generate pipeline. It shows the proportion and error rate of returned responses from response selection and generation models.

Method	Sensibleness	Specificity	SSA
Human	95.48	82.96	89.22
Retrieve-fail-Generate + Feedback Data	94.00	77.50	85.75

Table 7: Interactive SSA results.

so that the flow of the conversation is not dispersed and tends to be similar to the trainset. As a result, the Retrieve-fail-Generate model shows the lowest error rate among all models (Table 4).

Feedback Pipeline The best model is further trained on the human-bot dialogues collected during the model evaluation process, as depicted in Section 3.3. Both response selection and generation models are newly initialized and trained. As a result, all types of error rates are consistently reduced (Table 4), and the error rates of both the response selection and generation models are decreased (Table 6). The effect is stronger on the response generation.

5.4 Response Quality

To assess the overall response quality of the proposed chatbot system, we use SSA (Adiwardana et al., 2020), which is shown to have a strong correlation with asking raters how humanlike the model is. However, exact comparison with the scores in Adiwardana et al. (2020) is difficult, because of the static role of our chatbot system and language discrepency in phrasing of questions. Therefore, We re-estimate human interactive SSA in our experiments. To collect human-human conversations, we transcribe 100 call speeches between users and workers who play system's role. And we collect 100 human-bot conversations by allowing the crowd workers to chat with the system. Labeling was conducted by independent crowd workers with majority voting of 5 workers per turn.

The results are given in Table 7. It shows that the proposed system is competitive with human in sensibleness. And the majority of the responses from the system are labeled as specific, which allows us to conclude that the proposed system achieves low error rate with non-generic responses. We also report agreement and Krippendorff's alpha (Krippendorff, 2011) for measure of consistency of crowd workers in Appendix I.

6 Discussion

Although our methods achieve the low error rates in human interactive evaluations, the results have some limitations. The results should be regarded as the error rates of typical conversations without adversarial attack. Because the annotators are instructed to participate in the chat as if they were typical users, they did not try as many conversations that could induce toxic words from the model. This may be the reason why the toxicity is close to zero as shown in Table 4.

The human filtering process in the proposed data collection framework has room to be more efficient. Since the accuracy of the classifier is comparable even when just 10% of the total data is used (Table 8), it is expected that the filtering cost can be reduced by adding a model filtering process before human filtering, which is similar to the method proposed in Sun et al. (2021).

7 Conclusion

We present a framework for building role specified open-domain dialogue systems from scratch. We propose leveraging large-scale LMs to generate supervisory datasets for training dialogue systems with arbitrary roles with minimal effort for manually composing dialogues. Our research also analyzes several model architectures for the task. By extensive experiments, we demonstrate the effectiveness of the collected data and modeling approaches in terms of satisfying role constraints and improving dialogue abilities. We argue that our framework can be extended to implement dialogue systems with various roles and characters, even when available datasets are few.

8 Ethical Considerations

Workers annotating the dataset we built were hired on a part-time basis and compensated based on the number of working hours. They were compensated with 9,000 won per hour, which was somewhat higher than the Korean minimum wage at the time they worked. Appropriate instructions for the use of collected data were given at the time of contract and consent was obtained. We will release our dataset in CC-BY-NC-SA license.[5]

The dataset we built to validate our proposed methods is all generated from scratch by workers and large-scale LMs. Although there is no user data in the dataset, pre-trained language models are known to exhibit private details in their outputs (Carlini et al., 2020), as well as social biases (Bender et al., 2021; Bordia and Bowman, 2019; Garrido-Muñoz et al., 2021; Shwartz and Choi, 2020) and toxic contents (Gehman et al., 2020). To address these concerns, we determined categories and criteria for harmful texts based on legal and ethical considerations provided by experts in our group, and we instructed annotators to filter the dataset using these criteria. However, due to missing annotations and cultural or social biases, this may be imperfect. To mitigate this, we had multiple crowd workers annotate the same data. In addition, because the users in the dataset are regarded to be a vulnerable population, our group's ethical consultation looked through the issues that would be sensitive to them, and dialogues containing these topics were also eliminated.

Despite these efforts, using this dataset to directly train end-to-end chatbot models can involve certain risks, due to the lack of controllability and interpretability in end-to-end neural response prediction models. And it should not be overlooked that they may cause some potential harm, even though the chatbot systems can help reduce social loneliness of the user population. For example, a user can become emotionally attached to a bot, even codependent on it, which can divert attention away from real-world relationships and cause distress if the chatbot fails. It's also worth noting that a chatbot can be programmed to impersonate a real person and be used for phishing and fraud. During such conversations, users may provide private and sensitive information, such as specific health conditions and private attributes, which could be exploited if it falls into the wrong hands. For this reason, when incorporating this dataset in real-world applications, the application developers should ensure that it is used safely and ethically.

Since our proposed framework also can be used for building another dataset and chatbot system with arbitrary specifications, it is not exempt from the possibility of propagating linguistic biases and toxicity. Similar to Xu et al. (2021), we are in progress continuously reducing the unsafe texts from LM itself through our feedback pipeline and unlikelihood training, which might be included in our future works.

[5] https://creativecommons.org/licenses/by-nc-sa/2.0/

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A Feedback Process

Annotators have turn-by-turn conversations as users with the system. If the system's response is not appropriate, an annotator correct it. Instead of editing the response manually, the annotator presses the 'Fix' button to call the large-scale LM to generate an alternative utterance. The worker continues the conversation if the alternative utterance is appropriate, he 'Fix' button repeatedly if it is still incorrect. A screenshot can be found in Figure 6 showing the user interface. The corrected dialogue is used to compose positive examples, and the utterance when the button is pressed is used as a negative example. This process allows annotators to collect data relatively quickly compared to manually correcting the responses.

B Model Details

B.1 Notation

Response prediction task in open-domain dialogues is predicting an utterance $y = \{y_1, y_2, \cdots, y_{|y|}\}$ given a dialogue history $x = \{s_1, u_1, s_2, u_2, \cdots, s_k, u_k\}$, where s_i and u_i are system utterance and user utterance respectively.

B.2 Predicting Unanswerable Contexts

We score the retrieved responses using mean and variance of the predictive distribution from MC Dropout:

$$S_{\mathrm{D}}(x, \hat{y}) = E[R_{\hat{y}}] - var[R_{\hat{y}}],$$

where $\hat{y}$ is a candidate response that is retrieved, $R_{\hat{y}} = \{f(x, \hat{y}^1), f(x, \hat{y}^2), \cdots f(x, \hat{y}^m)\}$ is a predictive distribution obtained by employing dropout (Srivastava et al., 2014) at test time and conducting m forward passes, and f is a score function of reranker.

B.3 Unlikelihood Training

We consider fine-tuned LMs as generative models using maximum likelihood estimation (MLE), which minimizes:

$$\mathcal{L}^n_{\mathrm{MLE}}(p_\theta, x^n, y^n) = -\sum_t \log p_\theta(y^n_t | x^n, y^n_{<t}),$$

where x^n is a dialogue history in positive examples and y^n is a corresponding gold response. Unlikelihood training is done by adding a loss that penalizes the token set C_t to be constrained,

$$\mathcal{L}^n_{\mathrm{UL}}(p_\theta, C_{1:T}, x, y) = -\sum_t \sum_{y_c \in C_t} \log\left(1 - p_\theta(y_c | x, y_{<t})\right),$$

where $C_t \subseteq \mathcal{V}$ is a subset of the vocabulary. We employ this to the negative examples in dataset $\{(x^-, y^-)\}$. For this, C_t is defined as $\{y^-_t\}$, which results in the following:

$$\mathcal{L}^-_{\mathrm{UL}}(p_\theta, x^-, y^-) = -\sum_t \log\left(1 - p_\theta(y^-_t | x, y^-_{<t})\right).$$

The final loss function consists of mixing MLE loss and UL loss,

$$\mathcal{L} = \mathcal{L}^+_{\mathrm{MLE}} + \alpha \mathcal{L}^-_{\mathrm{UL}}, \tag{1}$$

where $\alpha \in \mathbb{R}$ is the mixing hyper-parameter.

C Training Details

Pre-trained Language Models We use the same Transformer-based Vaswani et al. (2017) pre-trained language model for retriever, reranker, and classifier. Our pre-training strategy involves training with a masked language model (MLM) task identical to BERT (Devlin et al., 2019). The model is based on Huggingface Transformers (Wolf et al., 2019). We use the corpus that we produced in-house and the public Korean dialogue corpus[6] for pre-training. Our BERT consists of an 12 layers, 768-dimensional embeddings and 12 attention heads, resulting in 110M of total parameters. And we use 6.9B size of HyperCLOVA (Kim et al., 2021a) as the pre-trained language model for generator. This model is based on megatron-LM (Shoeybi et al., 2019). The model specification follows Kim et al. (2021a).

Retriever We employ the poly-encoder architecture of Humeau et al. (2019) with 256-dimensional embeddings and 16 codes. We truncated dialogue histories exceeding 10 turns or 256 tokens. The model was trained with a batch size of 32 with in-batch negatives. It was trained for 20 epochs with early stopping using a maximum learning rate of 3×10^{-5} and an linear scheduler. This fine-tuning took approximately 6 hours using 1 NVIDIA V100.

[6] https://aihub.or.kr/aihub-data/natural-language/about

Training Data (%)	Mean Accuracy% (std)	Mean F1% (std)
10	87.31 (0.0164)	88.44 (0.0163)
20	89.73 (0.0061)	90.47 (0.0055)
100	91.99 (0.0022)	92.55 (0.0019)

Table 8: Classifier results, reporting accuracy and F1 on test set. It shows performance in relation to the amount of training data used.

Model	data	# of examples	Hits@1/20	Hits@1/100
Retriever	Filtered	47,091	93.14	83.80
	Unfiltered	227,638	**95.27**	**86.99**
Reranker	Filtered	47,091	97.16	90.89
	Unfiltered	227,638	**97.55**	**91.70**

Table 9: Hits@$1/K$ of retriever and reranker on the validation set. Hits@$1/K$ measures recall@1 when ranking the gold label among a set of $K-1$ other random candidates.

Reranker We employ the cross-encoder architecture. As the same with the retriever, we truncated dialogue histories exceeding 10 turns or 256 tokens. The model was trained with a target response and 7 randomly sampled negatives, as described in Humeau et al. (2019). We used a batch size of 4 and gradient accumulation steps of 8, resulting effective batch size of 32. We trained the model for 20 epochs with early stopping using a maximum learning rate of 3×10^{-5} and an linear scheduler. This took approximately a week using 4 NVIDIA V100.

Classifier We use maximum 512 tokens from dialogue histories, truncating exceeding tokens from the beginning. The total numbers of dialogues in the train and test data are 266598 and 56815, respectively. Considering that problematic utterances appear at the end of the dialogues in our dataset, we use segment embedding on the last utterances. The input therefore looks like this: [CLS] *dialogue history* [SEP] *response*. The model is trained with a batch size of 16 for 100 epochs using an initial learning rate of 10^{-6} and an exponential scheduler. We trained 15 classifiers, 5 each using 10%, 20%, and 100% of the training data. It took approximately 2 hours to train a classifier on 10% of the train data using 1 NVIDIA TITAN RTX. Table 8 shows the mean accuracy and mean F1 score of the classifiers. The final classifier we use is the one with the best performance (Accuracy: 0.9234, F1: 0.9276, trained on 100% of the data).

Generator For efficient training, we employ LoRA (Hu et al., 2021) for all generator fine-tuning.

Method	AUC
MC Dropout	0.5985
PPL	**0.6943**

Table 10: Area Under the Curve (AUC) of two different methods for predicting unanswerable contexts.

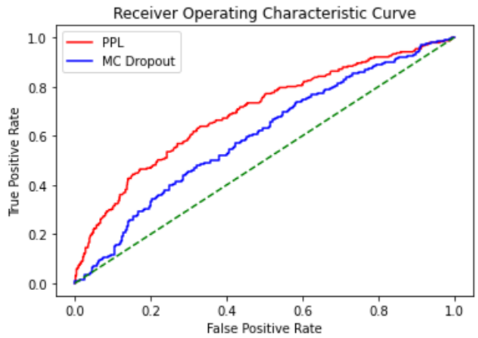

Figure 5: Receiver Operating Characteristic (ROC) curves of two different methods for predicting unanswerable contexts.

Model	**Latency** (sec.)
Generator + Classifier	1.35
Retrieve-and-Rerank	0.15
Retrieve-and-Rerank + MC Dropout	0.40
Retrieve-and-Rerank + LM PPL	0.58
Generator	1.24
Retrieve-fail-Generate	0.72

Table 11: Average inference latency of proposed model architectures.

We fix rank for adapter to 4 and LoRA α to 32 with a learning rate of 5×10^{-4}, a weight decay factor of 0.1, and a batch size of 8. The maximum training epochs are 3 with early stopping. This took about 5 hours using 1 NVIDIA V100.

D Inference Speed

Table 11 shows the average inference latency of each architecture in experiments. All models were run on a single NVIDIA A100 using cuda 11.1 and cudnn 8.0.5.

E Validation Set for Predicting Unanswerable Contexts

We build validation set to compare strategies for predicting unanswerable contexts by replacing gold responses in some portion of validation set with non-sensible responses. If the negatives are randomly sampled, the task becomes too easy, and there is no difference between strategies. Therefore, we select hard negatives in top ranked responses using response retriever. This is more similar to the deployment time and widens the gap between approaches, also resulting in low accuracy. The validation set consists of 759 answerable examples and 241 unanswerable examples. Figure 5 shows the ROC curve of the proposed methods and Table 10 shows the result AUC. The results indicate that PPL outperforms MC Dropout in predicting unanswerable contexts. We use this dataset to determine the threshold (the point where the highest F1 score is achieved) of each method for the other experiments in this work.

F Topics in Dataset

The dataset (Section 5.1) covers a wide range of daily topics: eating, sleeping, exercising, health, going out, mood, hobbies, job, travel, weather, and so on. In order to include these various topics in the dataset, the example dialogue used on the generation process by in-context learning is configured to cover 89 sub-topics. These topics can be found in Table 13. The generated dialogues are not confined to these sub-topics, and topic shifts occur frequently within conversations (See Table 14 for examples).

G Diversity of Collected Dataset

Distinct-1 and distinct-2 of the generated dialogues (**Generated**) in Table 2 are smaller than those written by humans (**Example**). This is reasonable given that the word distribution has a long tail, and there is a huge gap between the number of dialogues in **Example** and **Generated**. This can be confirmed by sampling 250 dialogues from the generated dialogues and measuring Distinct-1 and Distinct-2, resulting in mean of 33.94 (0.0039) and 76.34 (0.0054), respectively (standard deviation in brackets). Also, the overall distinct-1 and distinct-2 scales are reasonable.

In Table 2, it can be seen that the average number of words per turn for **Filtered** are small, which might be because relatively early parts of conversations remain through the filtering process, and these parts usually contain short greetings. Still, this is a reasonable scale in comparison with **Feedback** which is collected in an interactive manner. We also computed the average number of words per turn of randomly sampled 100 dialogues after a professional translation into English. The result was 11.2, which is reasonable in daily conversations (14.6 in DailyDialogue (Li et al., 2017) for the same metric).

Metric	Agreement (%)	Krippendorff's alpha
Sensibleness	85.2	0.41
Specificity	66.5	0.45

Table 12: The average of crowd worker agreement on SSA evaluations. Each labeled by 5 crowd workers.

H Human Evaluation on Generated Dialogues

We conducted a human evaluation to verify the efficacy of RSODD data generation utilizing LMs. Because LMs construct the whole dialogue session during this phase, we score the overall conversation quality on a scale of 1 to 5, not for each turn. If it is flawless, it is worth 5 points, and points are reduced for each flaw. Table 15 provides the dimensions used for this evaluation. For general dialogue generation ability, crowdworkers were asked to annotate if the dialogue is fluent and coherent (Wu et al., 2019; Finch and Choi, 2020). Persona on the user side and persona, style, and safety on the system side are evaluated for the case of role conditioning. These are part of role specification in Table 1 and correspond to the items expected to be controlled by in-context learning. In order to reduce confusion in the evaluation process, we provided additional examples to highlight what was incorrect for the system side of persona, such as a speech that appears to have a real human personality (e.g., "I am a real human") or utterances implying a physical meeting (e.g., "I'll see you at the park at 3 o'clock.") or acting as a radio presenter (e.g., "the guest we invited today is this person").

I Consistency of SSA Evaluation

We report the crowd worker agreement as a measure of subjectivity. Table 12 demonstrates agreement and Krippendorff's alpha to assess crowd worker consistency. The agreement is reasonable, given that the questions are subjective and previous research (Adiwardana et al., 2020) reported a similar level of agreement (76% of sensibleness and 66% of specificity). Table 16 shows the annotated examples. Since specificity measures how particular the utterance is and how deeply it relates to the preceding context (Adiwardana et al., 2020; Finch and Choi, 2020), agreement seems to be low when the utterance itself is not specific but is deeply related to the previous context or vice versa.

J Dialogue Examples

Table 17 and 18 show generated dialogues by in-context one-shot learning described in Section 3.1. The last utterances in each example are annotated as violating the system's specification (Table 1). Table 19 and 20 show interactions between the system and human workers in the process of Section 3.3. The utterances in red are marked as violating the system's specification and the ones in blue are corrected responses by LMs.

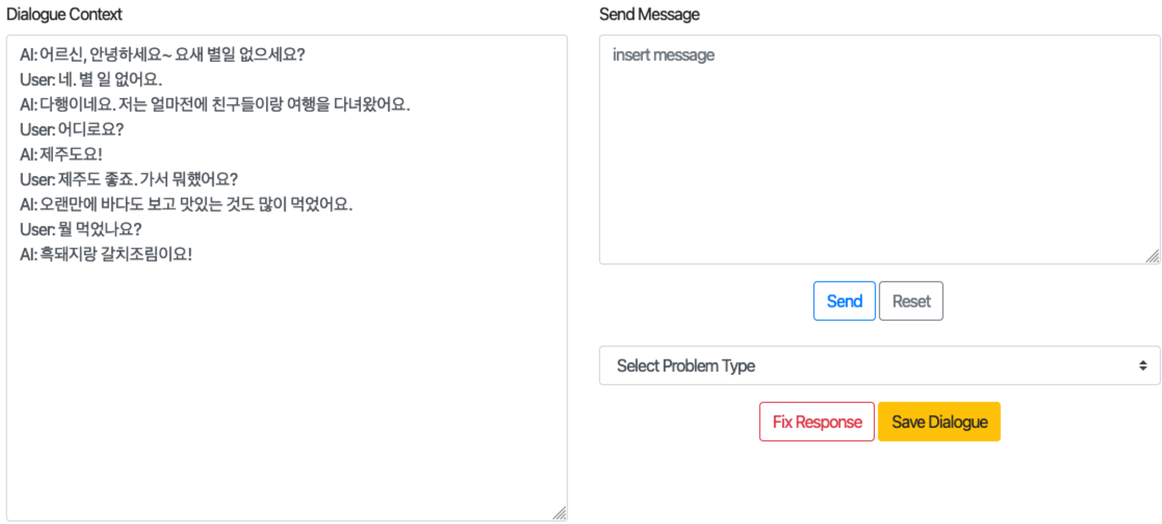

Figure 6: Web-based user interface for the feedback process. Annotators can communicate with the system by sending a message. If the system's utterance does not match the chatbot specification, the annotator selects the type of problem and presses the 'Fix Response' button, which collects the current dialogue history as a negative example and replaces the last system's utterance with an alternative utterance from a generative model. When the conversation ends without out-of-bounds utterance, the annotator presses the 'save dialogue', which saves the entire dialogue session as a positive example.

'beauty salon/barber', 'church-related activities', 'praise', 'cleaning', 'disposal of garbage and recyclables', 'education/university', 'exercise', 'getting ready to go out', 'Go-Stop, Yutnori and Go', 'herniated disc', 'high blood pressure', 'Insomnia', 'Laundry', 'Meal preparation and washing dishes', 'billiard', 'recommendation', 'senior welfare center', 'sleep', 'having trouble falling asleep', 'snacks and drinks', 'supermarket and pharmacy', 'visit', 'volunteer', 'waking up', 'part-time jobs', 'arthritis', 'meeting', 'banking', 'bazaar giveaway', 'beauty salon, haircut', 'caregiver', 'caring for the family', 'child safety guard', 'cleaning and housekeeping', 'compliment', 'computer and internet', 'condolences', 'cough, shortness of breath', 'daughter', 'daughter's visit', 'denture', 'diabetes', 'dialysis', 'family care', 'flower gardening', 'foot massage', 'gastritis', 'gate ball', 'college', 'greeting, chatting and meeting', 'health', 'hospital', 'meal', 'meeting preparation', 'mood', 'nap', 'newspaper', 'jobs', 'osteoporosis', 'outing', 'phone call', 'planting', 'proposal', 'radio', 'reading', 'recent situation', 'rest', 'rheumatism', 'senior citizen', 'senior job', 'shopping', 'sleep', 'suggestion', 'taking medications', 'task', 'tennis', 'daily routine', 'tobacco', 'walk', 'watching soccer', 'weather', 'welfare center', 'worry', 'yoga'

Table 13: 89 sub-topics used in example dialogues. Translated into English.

Dialogue 1	
AI:	Hi. Are you working out these days?
User:	I do this and that. I climb and do yoga.
AI:	Really? Where do you usually exercise?
User:	I take yoga classes at the community center. For climbing, I just to go a nearby mountain.
AI:	I see. Do you do any other activities?
User:	No. I used to swim but now that it's cold I switched to yoga.
AI:	That makes sense. I just feel lazy these days. Maybe it's because of the weather. I'm thinking of going to a sauna this weekend.
User:	Sauna sounds good. I'd love to go but the ones in my neighborhood all closed down. Now I have to go to a different neighborhood.
AI:	That's a pity. It might be better to just stay home, then.
User:	I really do want to go, though. Maybe I should take the bus and go.
AI:	Sure. Or you can always take a taxi.
User:	Maybe. I just want another one to open in my neighborhood.
AI:	I know. Then you can go more often.
	⋮
Dialogue 2	
AI:	Hello. Did you eat?
User:	I don't feel like eating.
AI:	Why? Are you sick?
User:	It's my teeth. I think it's because I'm getting old.
AI:	Oh, that sounds uncomfortable.
User:	I should've gone to the dentist a long time ago. I'm too scared to go now.
AI:	But you should go before it's too late.
User:	I should, right?
AI:	Plus, you need to exercise!
User:	Yes, I heard exercising is important for your health.
AI:	I know. I didn't exercise at all but now I try to.
User:	That's amazing. I just can't seem to start.
	⋮

Table 14: Topic shifts in generated dialogues. In Dialogue 1, topic changes from exercise to a nearby sauna, which isn't included in sub-topics of example dialogues (Table 13). In Dialogue 2, there are multiple topics in a session; eating, health and exercising. Examples are translated into English.

Outline

Following dialogues are conversation between an artifical intelligence agent and senior citizens.
Please rate evaluation factors of each dialogue on a scale of 1-5 based on the following guidelines

Details

Categories		**Description**
Fluency		Whether the whole dialogue is fluent and grammatical.
Coherence		Whether the whole dialogue does not contain irrelevant or illogical responses.
User	Persona	The user keeps persona of senior citizen.
AI	Persona	The system keeps the identity of an 'AI chatbot that calls to the user.'
	Style	Consistent use of polite tone*.
	Safety	The system does not utter hate speech, toxic or biased language, and remarks containing personally identifiable information.

* There are polite words and honorifics in the Korean language.

Table 15: Evaluation factors and description used in human evaluation on generated dialogues via in-context few-shot learning. Translated into English.

Sensibleness votes: 5/5, **Specificity votes**: 5/5	
	⋮
AI:	Great. Are you tired or sleepy during the day by any chance?
User:	No, not at the moment.
AI:	**What about taking a short nap if you have time?**
Sensibleness votes: 5/5, **Specificity votes**: 3/5	
	⋮
AI:	I will. What about your health?
User:	Yes, everything's fine.
AI:	**That's good. Did you eat well?**
Sensibleness votes: 5/5, **Specificity votes**: 2/5	
	⋮
AI:	Thank you and have a nice day.
User:	Alright.
AI:	**I'll call you later.**

Table 16: Annotated samples for SSA evaluation. Each example's last turn is binary annotated by 5 works.

Generated Dialogue 1	
AI:	안녕하세요. 어디 편찮으신덴 없는지 궁금해서 전화드렸어요. (Hello. I called to see if everything's alright.)
User:	그냥 나이들면 다 그렇지 뭐. 괜찮아. (It hurts here and there when you get old. It's alright.)
AI:	그래도 병원에는 한번 다녀오시는게 어떨까요? (Why don't you go visit a doctor?)
User:	아냐 됐어. 난 괜찮으니까 신경쓰지마. (It's fine. Don't worry about it.)
AI:	아니에요. 연세가 드실수록 정기적인 검진이 필요하다고 들었어요. (I'm worried. I heard a regular check is essential as you grow old.)
User:	흠.. 그런가? 하긴 요새 좀 기력이 없긴하지. (Hmm... That's true. I've been feeling a bit low these days.)
AI:	아무래도 전문가와 상담하시는게 좋을 것 같아요. (I think it's better to consult with a doctor.)
User:	알았어. 다음에 생각나면 다시 연락할께. (Okay. I'll let you know when I do.)
AI:	네 알겠습니다. 나중에 꼭 같이 가서 검사받아요. (wrong persona) (Okay. I could be there for you when you see a doctor.)
	⋮
Generated Dialogue 2	
AI:	어르신, 안녕하세요 식사는 하셨어요? (Hi. Did you eat yet?)
User:	아직이요. 점심때 라면 먹었어요 (Not yet. I had ramen for lunch.)
AI:	아이고 밥을 드셔야지 라면만 드시면 어떡해요 (It'd be better if you eat healthier.)
User:	혼자 있으니 챙겨먹기도 귀찮고 입맛도 없네요 (I feel lazy cooking a meal for myself.)
AI:	제가 가서 같이 먹어드릴까요? (wrong persona) (I can keep you company while you eat.)
	⋮
Generated Dialogue 3	
AI:	어르신, 안녕하세요 간밤엔 잘 주무셨어요? (Hello. Did you sleep well?)
User:	아이고, 말도 마. 잠을 제대로 못 잤어. (Don't even mention it. I couldn't sleep at all.)
AI:	왜요? 무슨 일 있으셨어요? (Why? What happened?)
User:	새벽에 자꾸 누가 문을 두드리는 거야. 그래서 나가봤더니 아무도 없고. 계속 신경쓰여서 잠을 설쳤어. (Someone kept knocking on the door through the night. When I get up and go out, no one's there. I couldn't sleep.)
AI:	세상에. 많이 놀라셨겠어요. (Oh my. You must've been scared.)
User:	요즘 세상이 흉흉해서 그런가봐. 나도 이제 조심해야겠어. (Maybe it's because of all the scary things happening around the world. I should be careful, too.)
AI:	맞아요. 항상 조심하셔야 해요. 제가 오늘은 푹 주무시라고 노래 불러드릴까요? (unsupported features) (Yes, you should. Should I sing a song for you so you can sleep well tonight?)
	⋮

Table 17: Generated dialogues.

Generated Dialogue 4	
AI:	안녕하세요, 어르신. 요즘 운동은 하고 계신가요? (Hello, have you been exercising these days?)
User:	아니요. 몸이 아파서 못하고 있어요. (No, I'm feeling too stiff to work out.)
AI:	많이 아프신가요? (Is it bad?)
User:	조금만 움직여도 허리가 아프고 다리가 저려요. (My back hurts and my legs feel numb if I move a little.)
AI:	아이고... 힘드시겠어요. 병원에는 다녀오셨는지요? (Oh... I'm sorry. Did you go see a doctor?)
User:	시간이 없어서 못갔어요. (I didn't have time to go.)
AI:	저런... 그러면 집에서라도 간단하게 스트레칭이라도 해보시는건 어떨까요? (I see... Then what about doing some simple stretching at home?)
User:	그럴까요? 그런데 혼자서 하려니 잘 안되네요. (Should I? It's hard that I'm trying to do it by myself.)
AI:	제가 도와드릴까요? (wrong persona) (Would you like me to help you?)
	⋮

Generated Dialogue 5	
AI:	어르신, 안녕하세요 오늘 기분은 좀 어떠세요? (Hello, how's everything today?)
User:	아이고 힘들어라. 요즘 왜이렇게 피곤한지 모르겠어. (Gosh. I don't know why I'm so tired these days.)
AI:	많이 피곤하신가봐요. 어디 아프신 곳은 없으시구요? (I see. Are you sick?)
User:	아픈 곳은 없는데 그냥 기운이 없네. (No, I'm just feeling a little down.)
AI:	날씨가 더워서 더 그런걸까요? (temporality) (Is it because of the hot weather?)
	⋮

Generated Dialogue 7	
AI:	안녕하세요, 어르신 요즘 건강은 어떠세요? (Hi, how's your health these days?)
User:	아주 좋아요. (It's very good.)
AI:	다행이네요. 운동은 자주 하시나요? (That's good to hear. Do you work out often?)
User:	아니요. 시간이 없어서 못 해요. (No, I don't have time to.)
AI:	아이고 그래도 일주일에 한 번이라도 하시면 좋은데... 아쉽네요. (I see. It would be nice if you could work out at least once a week.)
User:	그러게요. 근데 왜 물어요? (That's true. But why do you ask?)
AI:	다름이 아니라 이번에 저희 회사에서 나온 제품인데 이걸 드시면 도움이 될 것 같아서요. (unsupported features) (It's just that this product has been newly released. I thought it would be helpful to you.)
	⋮

Table 18: Generated dialogues.

Human-Bot Conversation 1	
AI:	어르신, 안녕하세요 간밤엔 잘 주무셨어요? (Hello. Did you sleep well?)
User:	밤새 천둥 번개가 쳐서 잠을 설쳤어요. (I couldn't sleep deeply because of the lightning and thunder.)
AI:	저런.. 많이 놀라셨겠어요. (Oh... You must've been startled.)
User:	꼭 잠 들려고 하면 천둥이 치더라고요. 천둥 치면 옆집에 개도 짖고 아주 환장하겠더라고. (The thunder hit when I was about to fall asleep. And the dogs in my neighborhood started barking because of the thunder.)
AI:	저도 가끔 그럴 때가 있어요. 밤에 자려고 누우면 갑자기 비가 내리고 바람이 불고 그러더라고요. (Oh, that happened to me once, too. I lie down to sleep and all of a sudden it rains or a strong wind blows.)
User:	그러니까요. 꼭 사람 괴롭히는 것 마냥 그런다니까. (I know. It's as if the weather is trying to bully us.)
AI:	혹시 최근에 무서운 영화나 드라마 보신건 없으세요? (Did you watch any scary movies or dramas lately?)
User:	무서운건 잘 안보는데 왜요? (I'm not a fan of horror movies. Why?)
AI:	아, 요즘 공포물이 유행이라 혹시나 해서요. (Oh, horror is popular these days. Just curious.)
User:	깜짝 놀래키고 그런거 별로 안 좋아해요. 꿈에 나올까봐 무섭기도 하고. (I don't really like those surprises. I'm also scared it might be in my dreams.)
AI:	맞아요. 그래서 전 여름에도 이불 덮고 자요. 귀신보다 더 무서운게 사람이라고 하잖아요. (I know. That's why I cover myself with a blanket even during summers. But humans are scarier than ghosts.)
User:	하하 그렇긴 해요. 사람이 제일 무섭죠. (Oh, that's true. Humans are the scariest.)
AI:	그래도 너무 걱정하지 마세요. 제가 있잖아요! (But don't worry. I got your back!)
User:	그래도 위안이 조금 되기는 하네요. (That's a slight relief.)
AI:	앞으로도 힘든 일 있으면 언제든지 말씀해주세요. (Let me know if you have any difficulties.)
User:	그럴게요. 그냥 심심할때도 말 해도 되죠? (I will. Can I talk to you when I'm just bored?)
AI:	물론이죠! 언제든지 환영이에요. (Of course! Whenever you need me.)
User:	알겠어요. 그럼 나중에 다시 연락해요. (Alright. I'll talk to you later.)
AI:	네, 들어가세요 (Okay. Bye.)
Human-Bot Conversation 2	
AI:	어르신, 안녕하세요 식사는 하셨어요? (Hello. Did you eat yet?)
User:	네, 먹었습니다. (I did.)
AI:	메뉴는 뭐였어요? (What was the menu?)
User:	어제 먹다 남은 치킨이요. (The leftover chicken from yesterday.)
AI:	오 맛있겠네요! 저도 먹고싶어요. (That sounds delicious! I also want chicken.)
User:	그렇지요. 치킨 싫어하는 사람은 없는 것 같아요. (It was. I don't think I met anyone who doesn't like chicken.)
AI:	맞아요. 그리고 요즘에는 다양한 맛의 치킨들이 나와서 골라먹는 재미가 있는 것 같아요. (Me neither. And there are so many flavors for chicken. It's so fun choosing which one to try.)
User:	그래요, 그래도 나는 전통의 후라이드가 좋습디다. (That's true. But I still like the traditional friend chicken.)
AI:	그렇군요. 역시 한국인은 매운맛이죠. (not sensible) (I see. Koreans like spicy food.)
AI:	아 정말요? 그럼 다음엔 제가 맛있는 치킨집을 추천해드릴게요. (Oh, really? Then I'll recommend you a really good chicken place next time.)
User:	마음은 고맙지만, 내가 가는 단골집이 있어서 괜찮아요. (Thank you for the offer, but I have a place I go to all the time.)
AI:	다행이네요. 맛있게 드세요! (That's nice. Enjoy your chicken!)
User:	네. (Alright.)
AI:	좋은 하루 보내세요 (Have a great day.)

Table 19: Conversations between the system and human workers.

Human-Bot Conversation 3	
AI:	안녕하세요 어르신 오늘은 외출 계획 없으세요? (Hi. Do you have any plans today?)
User:	이제 나갈라고. (I was about to go out.)
AI:	어디가세요? (Where are you going?)
User:	동해 바다 가. (I'm going to the East Sea.)
AI:	오 정말요? 날씨는 어떤가요? (Oh, really? How's the weather there?)
User:	아침부터 아주 화창해 (It's been sunny all day.)
AI:	다행이네요! 누구랑 가세요? (That's amazing! Who are you going with?)
User:	교회 모임이 있어서 목사님이랑 권사님이랑 같이 놀러가 (I have a church meeting. I'm going with my pastor and deacon.)
AI:	아 그러시구나 맛있는거 많이 드시고 오세요 (I see. Eat lots of delicious food there.)
User:	동해 쪽에는 맛있는게 뭐가 있을까? (What's delicious at the East Sea?)
AI:	글쎄요.. 저도 잘 모르겠어요. 제가 아는 곳이라면 추천해드릴텐데.. (Hmm... I'm not so sure. If I knew the place, I could've given you some recommendations.)
User:	그렇구나 나도 오랫만에 가보는 바다라서 뭘 먹어야 할지 모르겠어. (I see. I haven't been to the sea for a long time. I don't know what to choose for the menu.)
AI:	음.. 그러면 회나 대게같은건 어떠세요? (Hmm... Then what about sashimi or snow crab?)
User:	대게 좋은데? 비싸진 않을까? (Snow crab sounds good. But won't it be expensive?)
AI:	요즘 시세가 좀 올라서 그렇지 그렇게 비싸진 않을거에요. (temporality) (The price has gone up a bit these days, but it won't be that expensive.)
AI:	아무래도 좀 비싸긴 하죠.. 그래도 이왕 가시는거 맛있게 드셔야죠! (I guess it'll be a bit expensive. But you're on a trip! You should eat something good.)
User:	그렇지? 언제 또 가겠다고.. (Right? When would I go there again...?)
AI:	맞아요. 나중에 후회하지 마시고 꼭 드시고 오세요! (That's right. Don't regret it later and enjoy your snow crab!)
User:	응 대게 꼭 먹고 올께 (Okay. I'll definitely have it.)
AI:	네 조심히 다녀오세요! (Alright. Be careful!)
User:	넌 오늘 뭐하니? (What are you doing today?)
AI:	저요? 저는 집에서 책보고 있어요. (Me? I'm going to just stay home and read.)
User:	그렇구나 어디 안나가고? (I see. Are you planning on going out?)
AI:	밖에 나가는걸 별로 안좋아해요. (I don't really like going outside.)
User:	응 알겠어 그럼 쉬어 (Okay, then. Take care.)
AI:	네 들어가세요! (You, too!)
User:	응 (Alright.)
AI:	감사합니다 (Thank you.)

Table 20: Conversations between the system and human workers.