Textual Dataset for Situated Proactive Response Selection

Anonymous ACL submission

Abstract

Recent data-driven conversational models are able to return fluent, consistent, and informative responses to many kinds of requests and utterances in task-oriented situations. However, these responses are typically limited to just the immediate local topic instead of being wider-ranging and proactively taking the conversation further, for example making suggestions proactively to help customers achieve their goals. This inadequacy reflects a lack of understanding of the interlocutor's situation and implicit goal. To address the problem, we introduce a task of proactive response selection based on situational information. We present a manually-curated dataset of 1.7k English conversation examples that include situational background information plus for each conversation a set of responses, only some of which are acceptable in the situation. A responsive and informed conversation system should select the appropriate responses and avoid inappropriate ones; doing so demonstrates the ability to adequately understand the initiating request and situation. Our benchmark experiments show that this is not an easy task even for strong neural models, offering opportunities for future research. The dataset can be used to develop conversationally informed and proactive dialogue engines. We will release the dataset upon acceptance.

1 Introduction

Conversational assistant systems have recently shown significant improvements for understanding users' inquiries along with background knowledge, conducting requested operations, and returning natural language responses. Yet, typical systems are likely to be *passive* and only process user-initiated requests or merely ask values for domain-specific slots (Williams et al., 2013; Ammari et al., 2019). In contrast, human assistants like hotel concierges are more *proactive*, acting to address unmentioned needs and expected future events (Cho et al., 1996; Bellini and Convert, 2016). They do not only make

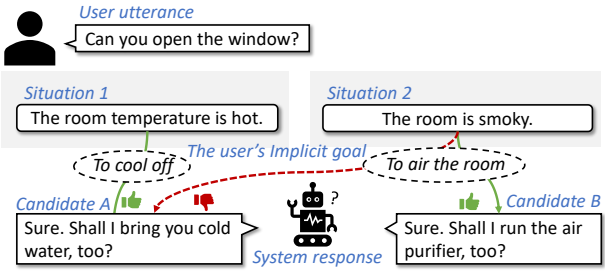

Figure 1: An example of situated goal-aware proactive response selection. The response candidate A is appropriate in Situation 1 but not in Situation 2.

a direct response or a clarification question to their interlocutors but also provide personalized information/assistance based on context and knowledge.

To push the frontier of task-oriented conversation technologies, we propose a task of *proactive* response selection for single-turn help-seeking conversations in English. We mean by proactive that a system engages in an interaction in a cooperative manner (Grice, 1975) and suggests something helpful to a user. The proposed task touches upon two crucial aspects of help-seeking conversations: situation-awareness and goal-awareness.

Situation: Situational information plays an important role in conversations as we illustrate in Figure 1. The example shows a user utterance "Can you open the window?" (top) and two response candidates (bottom). Although both candidates here sound helpful, their appropriateness varies depending on context: When the room is hot, suggesting a cold drink is appropriate assistance (left), but on the other hand, if the room is smoky, then running an air purifier is more helpful (right). Likewise, different situations make different responses more appropriate. A fair amount of situational information can be perceived as visual image, sound, and other kinds of sensory signals, and some of those are effectively incorporated into multi-modal conversational systems (Crook et al., 2019; Kottur et al., 2019). Yet, there are many other types of

information that modern conversation assistance systems have access to, for example, via external APIs such as calendars and maps. In this study, we represent situation statements of six semantic categories (location, possession, etc.) in free English texts, which are more explicit as a semantic representation than just maintaining conversation histories (Lowe et al., 2015; Li et al., 2017; Henderson et al., 2019) and more flexible than structured representations of limited vocabulary (Williams et al., 2013; Budzianowski et al., 2018).

Goal: In the aforementioned example, the two actions address two different goals associated with opening a window, namely, *to cool off* and *to air the room*. While often being unspoken, underlying goals provide important semantic connections among context and utterances on many occasions (Allen and Perrault, 1980) particularly when language is indirect (Perrault, 1980; Walker et al., 2011; Stevens et al., 2015). We use goal information as a stimulus for soliciting naturalistic and proactive responses from human annotators in data collection.

We introduce a dataset of **S**it**U**atated, **G**oal-**A**ware, and proactive **R**esponses (SUGAR; §3). SUGAR contains 1,761 single-turn English conversation examples, each of which has a user request anchored by an implicit goal, three response candidates with three-point appropriateness ratings, and 12 sentences of situational information. We harvested user utterances and goals from commonsense knowledge bases, ATOMIC (Sap et al., 2019) and ConceptNet (Speer et al., 2017), and collected proactive responses and supporting situational information by crowdsourcing. We then used a language generation model, COMET (Bosselut et al., 2019; Hwang et al., 2021) to generate additional situation statements. Finally, we selected inappropriate (negative) responses for each reference response by an adversarial method to form examples of three-choice response selection. To ensure the data quality, we performed multiple manual validation steps in data collection. Our experiments on SUGAR show that Transformer-based rankers merely achieve Precision@1 of 60-70%, indicating the difficulty of situated reasoning for response selection.

Contributions: (1) We introduce a task of situated proactive response selection and present a high-quality dataset of 1,761 examples by a carefully designed data collection pipeline. (2) We perform experiments on our dataset and show that Transformer-based response rankers are not sensitive enough to situational information, which offers opportunities for future research.

2 Related Work

2.1 Conversational Dataset

Acquisition and annotation of real(istic) conversational data has been an essential step for developing conversation engines that imitate human communication (Serban et al., 2018). Various datasets have been constructed with a focus on different aspects of communication.

With regard to target communicative aspects, the most relevant to our work is SIMMC (Moon et al., 2020). SIMMC encompasses surrounding situational information that gives a basis for verbal interactions in task-oriented scenarios in the shopping domain. Moon et al. collected visually-grounded conversation examples from pairs of human annotators interacting with each other in a virtual environment (Crook et al., 2019), where one annotator seeks help for shopping, and the other provides assistance. SUGAR is also concerned with how human interlocutors perform situated conversations in a help-seeking setting. Our work extends this direction to scenarios other than shopping and includes more diverse types of information that modern conversational assistants could access via sensors or external APIs (e.g., temperature and schedule) by representing situational information in a textual form as opposed to visual images.

The choice of modality is motivated by existing conversational datasets that express various kinds of background information in plain text: the persona of an interlocutor (Zhang et al., 2018; Dinan et al., 2020), emotional states (Rashkin et al., 2019), and related documents (Dinan et al., 2019). These examples demonstrate the utility of textual forms for representing both explicit and implicit information of various kinds.

Some existing datasets are concerned with information-seeking conversations like restaurant recommendation where suggestions by assistants naturally occur (e.g., "If you like French cuisine, how about RestaurantX?", "I can find transportation for you."). However, it is not trivial to solicit such naturalistic proactive utterances in more diverse help-seeking scenarios. In many cases, the minimum objective of a conversation can be

achieved by responding to user-initiated inquiries, and such kinds of responses are relatively easy to collect from non-expert annotators (Budzianowski et al., 2018; Byrne et al., 2019; Eric et al., 2020).

We address this problem by leveraging implicit goals behind user requests. The comprehension of goals in conversations has been recognized to be important not only in task-oriented dialog research but also in a broad range of research areas such as linguistics, psychology, and artificial intelligence. (Schank and Abelson, 1977; Clark and Schaefer, 1989; Gordon and Hobbs, 2004; Rahimtoroghi et al., 2017). Human interactions often involve indirect speech acts (Perrault, 1980; Gibbs and Bryant, 2008) and indirect responses like non-yes/no answers to polar questions (Hockey et al., 1997; de Marneffe et al., 2009; Stevens et al., 2015; Louis et al., 2020). These studies motivate our strategy for soliciting natural-sounding proactive responses from crowd workers.

In contrast to most datasets we introduced here, SUGAR only contains single-turn conversation examples due to the ease of data collection and quality control. Yet, our primary focus is on conversational assistance, which is likely to be completed within a few turns (Völkel et al., 2021). Thus, we believe that single-turn examples are still useful for system development. It is possible to extend our problem setting and data collection approach to a multi-tern setting, which we leave as future work.

2.2 Response Selection

Automatic response models can be divided into two approaches: response generation and response selection. Response generation directly generates natural language response text from scratch, and response selection selects a response from a candidate pool built by humans, templates, or language generation systems. The latter approach is widely used in many real-world applications cases because of the controllability of responses and the easiness of evaluation (Deriu et al., 2020). In this study, we study the task of response selection. We assume that an external response generation system generates candidates based on the system's functionality and focus on picking the appropriate ones.[1]

To train and evaluate a response selection system, each example must have distractors (negative responses), but typically, conversational datasets only contain ground truth responses. Thus, it has been commonly practiced to pick negative responses by random sampling (Lowe et al., 2015; Henderson et al., 2019). This approach is practically advantageous but may introduce negative responses that are clearly off-topic or false negatives (Akama et al., 2020; Hedayatnia et al., 2022). To alleviate this problem, we use an adversarial filtering algorithm (Zellers et al., 2018; Sakaguchi et al., 2019; Bhagavatula et al., 2020) to select competitive distractors and recruit crowd workers to rate candidates, allowing each example to have multiple acceptable responses.

3 Task and Data

The goal of this study is to provide a resource for developing a system that can observe situational information and return a proactive response to a user. We consider six categories of observable *situational information*[2]: location (where the user is), possession (what the user has), time, date, behavior (what the user is/was doing), and environment (temperature, etc.) We define a *proactive* response to be a response that provides *suggestions* to help users achieve their goals.

3.1 Problem Formulation

Our task has five components: (1) a user utterance u, (2) situation statements $S = \{s_i\}_{i=1,\cdots,l}$, where l is the number of statements, (3) responses $R = \{r_i\}_{i=1,\cdots,m}$, where m is the number of response candidates[3], (4) their appropriateness ratings $Y = \{y_i\}_{i=1,\cdots,m}$, where y_i is a three-point Likert scale, and (5) an implicit goal g. S can include distractors that are not directly relevant to the conversation. u, S, and R are given as input, and the task is to rerank R. Response selection systems are trained and evaluated by Y.

3.2 Data

SUGAR contains 1,761 high-quality examples, each of which has three response candidates and 12 sentences of situational information. Table 1 shows the dataset statistics. We constructed the dataset with the eight steps shown in Figure 2. We describe them below.[4]

[1] Training and evaluating generation systems on SUGAR is also possible and is an interesting direction for future research.

[2] See Appendix D for more details.

[3] We pick $m - 1$ responses automatically such that they are less appropriate than the reference response in a given context (See Step 7). Nevertheless, there usually exist one or more acceptable responses to a given user utterance. We thus annotate all acceptable responses manually (Step 8).

[4] See also Appendix B for more details.

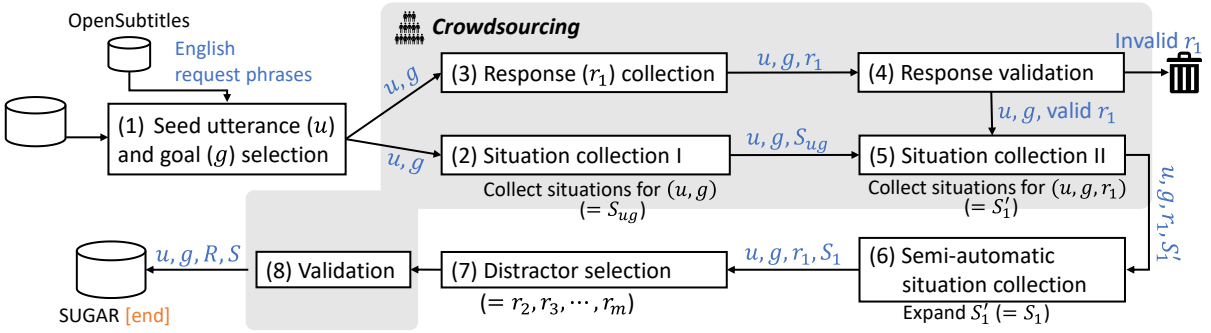

Figure 2: Pipeline for data collection. We start with existing common-sense knowledge bases (ATOMIC and ConceptNet) and extract utterance and goal events as a seed (1). We collect responses and situation statements for each seed by crowdsourcing (2-5), acquire more situation statements semi-automatically (6), and select distractor responses and situations to form response selection examples (7). We finally validate the examples manually (8). Steps (2) and (3-4) are executed in parallel.

	u	r	g	s
Sent types.	370	1,754	431	4,363
Tokens	12,172	29,389	7,501	146,526
Avg. tokens per ex.	6.9	16.7	4.3	83.2

Table 1: Dataset statistics. The total number of examples is 1,761 (34,590 sentences).

(1) Seed Utterance & Goal Selection: We harvested action and goal events from two common-sense knowledge bases, ATOMIC (Sap et al., 2019) and ConceptNet (Speer et al., 2017), where knowledge is represented as nodes representing events or concepts and edges connecting them with semantic relations. The collected action-goal node pairs served as the seed utterance-goal for soliciting responses and situational statements in the following data collection steps. First, we extracted nodes consisting of verb phrases (VPs) that appear at least five times within English request phrases (e.g., Please `VP`, Could you `VP`?, etc.) in the OpenSubtitles corpus (Henderson et al., 2019). These request expressions were also used as the surface form of u. Two of the authors then selected 563 events that can be achieved within a reasonable time span, can be assisted by someone else, and can be triggered by a goal. We retrieved their implicit goals g by goal-related edges in ATOMIC and ConceptNet. Specifically, we used `xNeed` in the reverse direction and `xIntent` in ATOMIC and `HasPrerequisite` in the reverse direction and `MotivatedByGoal` in ConceptNet. Finally, two of the authors evaluated the node pairs and picked 501 (u, g) pairs for which we can naturally say "I do u to achieve g." We also merged synonymous expressions (e.g., *go to a market* and *go to a supermarket*) into a single entry and corrected grammatical errors and unnatural phrases.

(2) Situation Collection I: We collected situation statements in two phases to simplify annotation work. The first phase focuses on u and g, and the second phase considers r in addition to u and g. In this step, we presented a pair of u and g texts to crowd workers and instructed them to specify situational information that is required to guess the goal based on the utterance. For example, an implicit goal "to cool off" can be naturally inferred by situations like "The user is home. The room temperature is hot." We asked workers to write *observable* facts in the six semantic categories (§3). For example, "The room temperature is hot." is valid, but "The user feels hot." is invalid as assistance systems cannot *observe* the user's feeling. We recruited one worker for each (u, g) pair and paid \$0.12 per HIT[5] (one (u, g) pair/HIT).

(3) Response Collection: In parallel to Step (2), we recruited two crowd workers for each (u, g) pair to collect responses. The workers created at least two responses: one of the responses accepts and the other rejects the request. We asked the workers to write a *proactive* response, a response providing suggestions for goal fulfilment.[6] To solicit responses closely connected to implicit goals rather than to domain knowledge, we instructed the workers to avoid posing a clarification question like "Sure, I'll turn on the air conditioner for you.

[5]Human Intelligence Task, a unit of task in MTurk.

[6]For a response that rejects a user's request, we instructed the workers to provide a reason for rejection (*e.g.,* we cannot brew coffee *because we are out of coffee filters*) in addition to a suggestion.

Loc.	Poss.	Time	Date	Behav.	Env.
1,991	3,567	1,084	149	1,688	2,794

Table 2: Number of situation statements ($\in S_1$).

Would you like it on a high or low setting? (= clarification)" The workers were presented one u-g pair in each HIT and were paid $0.30/HIT.

(4) Response Validation: We present the utterances, goals, and collected responses to crowd workers and evaluated the helpfulness of the response. A response is considered to be valid if it satisfies the following criteria: (1) the response suggests or requests something new, and (2) the suggestion or request is helpful for achieving the goal. Each response was evaluated by three workers. We then picked the responses that were approved by two or three workers. We call a verified response *a reference response* r_1 hereafter. Each HIT contains up to seven responses, and one of them is a dummy question for evaluating crowd workers. For quality control, we filtered out crowd workers who participated in the task twice or more and did not reach 0.75% accuracy for the dummy questions. The workers were paid $0.18 for this task.

(5) Situation Collection II: We collected situation statements from crowd workers with the following two goals: (1) to collect situation statements that cover the reference response r_1 and (2) to verify the situation statements collected in Step (2). We presented (u, g, r_1) with the statements obtained in Step (2) and again instructed crowd workers to write observable facts. The results of Step (2) were provided as editable initial values, and we encouraged workers to update the texts when it is necessary. We recruited one crowd worker for each (u, g, r_1) with the reward of $0.42/HIT.

(6) Semi-automatic Situation Collection: We found that the collected situations were often under- or over-specified. We addressed this by automatic situation generation and manual verification.

One of the authors examined all the situation statements, discarded/modified inappropriate situations, and categorized them into six categories. We then used the cleaned and labeled texts to fine-tune a neural sequence-to-sequence to generate more situations. Specifically, we fine-tuned BART (Lewis et al., 2020) trained on ATOMIC$^{20}_{20}$ (Hwang et al., 2021)[7] to take a concatenation of u, g, and r_1 as input and generate a text for a given situation category as illustrated in Figure 3. We performed a beam search of width 3 and took top-3 generation results for each input and relation. Finally, we manually verified the generated situations, resulting in 4,375 unique situations (6.4 ± 1.3 statements per example). We denote the situation statements attached to (u, g, r_1) by S_1. Table 2 shows the distribution of situation categories in SUGAR. Statements about possession and environment appear most frequently, which is reasonable because such situational information often decides actions that can be carried out (e.g., to drink coffee, coffee must be available). The other categories are less frequent, but 64% of examples have at least one time or date information, and 69% have a statement about behavior.

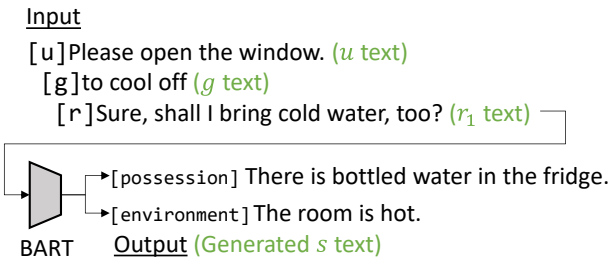

Figure 3: Example of automatic situation generation by BART (Step 6). [*] is a special symbol to denote the type of the following text. The first token of output is given as a prompt to control the semantic category of output.

(7) Distractor Selection: The examples collected in the previous steps only contain reference responses r_1 and supporting situation statements S_1. We added $m - 1$ response candidates along with their relevant situational information as distractors so that all examples have m response candidates and l situation statements. We set $m = 3$ and $l = 12$. In this section, we describe the high-level idea of our algorithm. Appendix C presents technical details.

Distractors can be obtained by random sampling as practiced in many studies (Henderson et al., 2019) or by advanced methods such as adversarial filtering (Li et al., 2019; Gupta et al., 2021). However, such approaches may introduce off-topic responses that are easy to rule out and false nega-

[7] Note that the framework of pre-training Transformer models on common-sense knowledge bases was originally proposed by Bosselut et al. (2019).

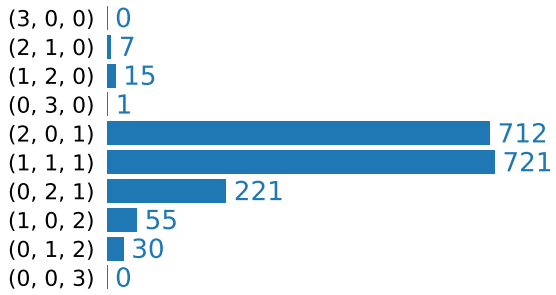

Figure 4: Result of rating annotations (Step 8). The labels denote (the number of *Bad* options, the number of *Acceptable* options, number of *Best* options). We removed one example with three *Acceptable* responses (0, 3, 0) from the dataset.

tives — acceptable responses treated as negative examples, degrading system performance as well as reliability of evaluation (Akama et al., 2020; Hedayatnia et al., 2022).

To alleviate this problem, we combine lexical matching and adversarial filtering (Zellers et al., 2018; Sakaguchi et al., 2019; Bhagavatula et al., 2020) to construct distractors and validate them manually (see Step 8). We first created an initial dataset by a lightweight method based on sentence embeddings and lexical matching. We then performed $J = 3$ rounds of adversarial filtering. In each round, we split the dataset into $K = 10$ folds, and for each split, we trained a binary logistic regression classifier that takes sentence embeddings of u, S_1, and a response candidate. We computed sentence embeddings by SentenceTransformers (Reimers and Gurevych, 2019) with MPNet (Song et al., 2020). We used the trained classifier to identify easy distractors and replace them with more confusing ones with respect to the score function. We sampled $m - 1 = 2$ responses for each example. All response candidates in the same example have the same polarity. Finally, we expanded S_1, which only contains relevant information to u and r_1, to obtain a set of $l = 12$ situations S such that some of them are related to distractors but do not disqualify r_1, and statements do not contradict with each other. We again used sentence embeddings to find topically related situational information and avoid contradiction with keyword-based heuristics.

(8) Validation: There are usually multiple appropriate responses in one conversational context, and therefore, some of the challenging "distractors" picked in the previous step can be acceptable or even more appropriate than the reference r_1. To avoid introducing false negatives, we rated all response candidates on a three-point Likert scale (*Bad, Acceptable,* or *Best*) by crowdsourcing. We recruited three crowd workers per example with the reward of $0.25/each and asked them to pick an appropriate response candidate (Krippendorff's α (Krippendorff, 2004) of 0.484). We then aggregated ratings by the statistical model proposed by Zhou et al. (2014) to obtain the final rating Y.[8] We discarded one example in this validation step and obtained 1861 examples with all responses rated. Figure 4 shows the annotation result. As we expected, a fair number of examples (56%) have more than one *Best* or *Acceptable* responses.

4 Experiments

We evaluate several baseline models on SUGAR to explore two questions concerned with the nature of the proposed task and dataset: (1) Is understanding of situational information required to identify proactive responses in SUGAR? (2) Can standard matching-based systems capture relevant situational information and solve the task?

4.1 Baselines

We evaluate a lexical-matching approach and several Transformer-based response selection systems. A variety of neural networks have been proposed for the task of response selection Tao et al. (2021), but we opted to focus on the direct application of pre-trained Transformers rather than equipping them with extra modules/resources as Transformers have proven effective in conversation tasks with minimal adaptation (Budzianowski and Vulić, 2019; Han et al., 2021) and are also used as a basis of many recent complex approaches.

TF-IDF ranker: As the simplest approach in our evaluation, we used a lexical-matching baseline system that ranks response candidates by cosine similarity of TF-IDF vectors of context and a response candidate (Lowe et al., 2015). We calculated TF-IDF weights on a training split with `scikit-learn` library.

Transformer ranker: We fine-tuned and evaluated three variants of Transformer-based rankers:

[8] In the first run, all candidates were rated as equally good or bad in 18 examples. We updated and re-annotated 17 examples.

1. **BERT-FP:** We fine-tuned the BERT-FP model (Han et al., 2021) trained on Ubuntu Dialogue Corpus (Lowe et al., 2015) on SUGAR. BERT-FP is a response selection model based on uncased $\text{BERT}_{\text{base}}$ (Devlin et al., 2019), a 12-layer Transformer model ($\approx$ 110M parameters) pre-trained on BookCorpus and English Wikipedia. Han et al. fine-tuned the model on Ubuntu Dialogue Corpus (Lowe et al., 2015) by fine-grained post-training and supervised learning and reported high performance on the Ubuntu dataset.
2. **BERT:** We also fine-tuned $\text{BERT}_{\text{base}}$without the additional training mentioned above in order to analyze the benefit of the additional training on conversational texts in a different domain. We used a cased model following BERT-FP. In the experiments of Hedayatnia et al. (2022), the BERT ranker performed on par with BERT-FP.
3. **RoBERTa:** To analyze the effect of an underlying Transformer model, we evaluated cased $\text{RoBERTa}_{\text{base}}$ (Liu et al., 2019) to rank response candidates in the same way we did with BERT. $\text{RoBERTa}_{\text{base}}$is a 12-layer Transformer model($\approx$ 125M parameters) trained with an improved training configuration, and Liu et al. report that RoBERTa outperforms BERT in multiple tasks and datasets.

We optimize model parameters with Adam (Kingma and Ba, 2015) to minimize max-margin loss.

4.2 Experimental Setup

Input format: We concatenated context and a response candidate for the Transformer rankers. To address our questions, we experimented with three variants of context:

1. u: Utterance (u)-only
2. $u + S_1$: Utterance (u) plus relevant situation (S_1)
3. $u + S$: Utterance (u) plus relevant and irrelevant situation (S)

Training and Test: We performed five-fold cross-validation (training:validation:test=6:2:2).[9] For each round, we trained a Transformer ranker for 10 epochs with a batch size of 32 and evaluated the model by nDCG@3 on the validation split every epoch. We then selected the best checkpoint for evaluation. To stabilize training, we applied weight decay of 0.05, set the maximum gradient norm to 5.0, and used a linear learning rate scheduler with 5% ($\approx$ 20) warm-up steps. We further performed light-weight grid-search for hyperparameter tuning based on an average nDCG@3 score on validation splits, with learning rate $\in \{5e-5, 1e-5\}$, and margin for the max-margin loss $\in \{1.0, 0.5, 0.1\}$. One epoch of training took 1-2m on GeForce GTX TITAN X. We report the average Precision@1 and nDCG@3 on the test splits.

[9]We removed examples without *Bad* response options from the validation and test splits

System	Context	Prec.@1	nDCG@3
TF-IDF	u	$.6044_{\pm.0390}$	$.8329_{\pm.0136}$
	$u + S_1$	$.7541_{\pm.0106}$	$.9130_{\pm.0037}$
	$u + S$	$.5350_{\pm.0372}$	$.8408_{\pm.0124}$
BERT-FP	u	$.6269_{\pm.0184}$	$.8732_{\pm.0078}$
	$u + S_1$	$.7728_{\pm.0137}$	$.9262_{\pm.0027}$
	$u + S$	$.6371_{\pm.0219}$	$.8764_{\pm.0070}$
BERT	u	$.7053_{\pm.0099}$	$.9007_{\pm.0054}$
	$u + S_1$	$.8128_{\pm.0135}$	$.9408_{\pm.0056}$
	$u + S$	$.7081_{\pm.0232}$	$.9044_{\pm.0081}$
RoBERTa	u	$.7155_{\pm.0113}$	$.9059_{\pm.0040}$
	$u + S_1$	$.8140_{\pm.0096}$	$.9432_{\pm.0026}$
	$u + S$	$.7047_{\pm.0152}$	$.9065_{\pm.0056}$

Table 3: Average test scores over five-fold cross-validation. Prec.@1 stands for Top-1 precision.

4.3 Results

Table 3 shows the average test scores over five-fold cross-validation. We can see two general patterns: (1) The transformer-based models except for BERT-FP outperformed the TF-IDF baseline, and (2) the systems that are only given relevant statements S_1 along with u outperformed their counterparts with different context settings. With regard to the key questions, the result provides several interesting findings:

1. Comparing two context settings u and $u + S_1$, we can see that relevant situational information brings in a clear performance boost as we expected (e.g., +0.11 in Precision@1 and +0.04 in nDCG@3 with BERT).
2. The performance gain from S_1 can be attributed to increased word overlaps between context and the right responses as the result

of TF-IDF indicates. However, with a few distractor statements added in the $u + S$ setting, the performance of the TF-IDF baseline dropped substantially (-0.22 in Precision@1 and -0.07 in nDCG@3). This means that our dataset successfully avoids superficial clues, calling for a higher-level understanding of situational information.

3. Interestingly, the performance of Transformer rankers also decreased drastically, to the same level as their corresponding systems without situational statements in input.
4. The additional pre-training of BERT-FP was not beneficial to our task, which is consistent with the observation of Hedayatnia et al. (2022). We speculate that this is due to the domain mismatch of training corpora. BERT-FP is pre-trained on technical topics related to Ubuntu, but SUGAR is concerned with a wider range of topics in daily life.

These observations provide insights into our questions. First, the understanding of situational information is necessary for accurately selecting proactive responses, indicating that SUGAR is an effective resource to develop and evaluate situated conversation systems. Second, it is not trivial for Transformer rankers to pick up useful clues out of a mixture of relevant and irrelevant situation statements.

5 Limitations

Data size: SUGAR is relatively small compared to recently published datasets. This is due to the complexity of our problem setting and annotation pipeline. We prioritized quality over quantity and performed multiple steps of manual intervention to reduce errors, false negatives, and annotation artifacts. These problems have been reported in various NLP tasks not limited to conversational tasks (Gururangan et al., 2018; Akama et al., 2020; Elazar et al., 2020). Nonetheless, our experiment has shown that pre-trained Transformer models can be trained to outperform a TF-IDF ranker by a clear margin, which is encouraging. In addition, we could automatically induce noisy but large-scale training instances from existing resources, for example, by harvesting event pairs that can be used as u and r from event knowledge bases such as ATOMIC$^{20}_{20}$and generating situation statements using our generator (§3).

Representation of situation information: In SUGAR, situation information is represented in textual expressions. In real-world applications, such information could be collected via external APIs (e.g., calendar and map) and sensors (e.g., camera) and stored in non-textual forms. Our study is a proof-of-concept that shows the understanding of situational information is very important for response selection. Future research should explore ways to process situation information that is expressed in other forms of data (e.g., structured texts, numbers, images). Even if the value is structured or images, we could transform them into textual forms as done in data-to-text research (Shen et al., 2020; Miura et al., 2021). Besides, we acknowledge that situational information is often under-specified in SUGAR because some information is considered to be common-sense (e.g., a room has a door) or presupposed (e.g., "Please open the door" presupposes that the door is closed.), and such information was not explicitly stated by human annotators during data collection. Therefore, response selection systems should be equipped with a mechanism to handle implicit knowledge to solve the task.

6 Conclusion and Future Work

We proposed a task of situated proactive response selection for developing and evaluating conversational assistants that can help users proactively in various help-seeking scenarios. We constructed a dataset of 1.7k examples by crowdsourcing and semi-automatic generation.

There are several interesting directions for future research. First, as shown in our experiments, it is challenging to pick up relevant situational information and use it to reason about user requests and potential assistance. To achieve this, conversational systems will need to be equipped with world knowledge to effectively align situation information with an interaction. One promising approach is knowledge-based response models such as graph neural networks, which recently has shown to be effective in various NLP tasks (Zhang et al., 2020; Zhou et al., 2022; *inter alia*). Second, although we leveraged implicit goals only for soliciting proactive responses in data collection in this study, understanding of goals should be necessary for building better conversation engines as claimed in early studies (Allen and Perrault, 1980; *inter alia*). We believe SUGAR can facilitate future research in this direction.

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A Ethical Considerations

Undesired bias and abusive content: A multitude of sources have reported that data-driven conversational systems can (re)produce undesired bias or abusive language existing in language resources used for development. To minimize such a risk, we carefully curated conversation examples in SUGAR. Our target task is response selection, where systems only produce language in a pre-compiled response list, and therefore, it is not likely that resulting systems yield harmful content. However, users of SUGAR should be cautious when it is used for developing generation systems in future work.

Human subjects: Crowd workers in Amazon Mechanical Turk (MTurk) participated in our data collection pipeline. Our annotation tasks were reviewed by the institutional review process before being published in MTurk to avoid ethical issues. We did not collect any personally identifiable information of workers other than (anonymized) Turker IDs. Task rewards were decided by several rounds of trials so that workers can receive at least $6.50 hourly.

Use of external data and tools: We used external datasets such as ATOMIC$^{20}_{20}$and ConceptNet and tools such as spaCy and Transformers library. We have confirmed that the use of these resources for our research does not violate usage restrictions.

B Manual Annotation

We recruited non-expert crowd workers in Mturk in annotation steps (2-5). In all steps, crowd workers were required to meet the following qualification requirements: (i) Their number of tasks approved $\geq$ 5k, (ii) the task approval rate $\geq$ 99%, (iii) their location is the US, and (iv) they answer an exercise question correctly. Figure 5 shows our annotation interfaces for crowdsourcing.

Two of the authors were involved in the annotation steps (1), (4), (5), and (8). They are ESL with a degree in computer science from a school in the US (one holds a master's degree, and the other holds a Ph.D.). They all have backgrounds in NLP/CL research.

C Distractor Selection

This section presents the technical details of the distractor selection method (Step 7). Below, tunable parameters like thresholds on scores and the number of iterations were empirically selected based on several pilot runs.

C.1 Response Selection

Our method selects distractor responses from all the responses in the dataset in two steps: We first create an initial dataset by a light-weight method (Algorithm 1) and then perform adversarial filtering (Algorithm 2).

First Step (Algorithm 1)

The objective of the first step is to avoid including false-negative responses (Lines 3-6). We discard responses that are too similar to r_1 in terms of the overlap coefficient of content words (noun, verb, adjective, and adverb).

$$\text{Overlap}(x, y) = \frac{|\text{CW}(x) \cap \text{CW}(y)|}{\min\left(|\text{CW}(x)|, |\text{CW}(y)|\right)}, \quad (1)$$

where $\text{CW}(x)$ is a set of content words in x. We set the threshold of overlap coefficient to 0.75. We use the same constraint on their goal texts. We also measure their closeness by the cosine similarity of their sentence embeddings (denoted as EmbSim) and discard candidates whose similarity is 0.5 or higher. We then sample $m-1$ responses from this filtered response pool one by one (Lines 11-15). To diversify response options, we remove similar responses to the picked one from the pool based on overlap coefficient (Line 16-19).

Second Step (Algorithm 2)

We then perform $J = 3$ rounds of adversarial filtering. Our method is a slightly modified version of the algorithm used by Bhagavatula et al. (2020). In each round, we split the dataset into $K = 10$ folds (Line 6), and for each split, we train a binary logistic regression classifier that takes sentence embeddings of u, S_1, and a response candidate $r \in R$ (Line 8). We pre-compute their sentence embeddings with the pre-trained Sentence-Transformers (Reimers and Gurevych, 2019) with MPNet (Song et al., 2020). Once the classifier is trained, we score response candidates in each example and identify distractors whose scores are lower than that of the reference response r_1 plus a margin $= 0.05$. We replace these *easy* distractors with more confusing ones (Line 14-16). In this way, we repeatedly update the dataset (Line 17) and output the final result (Line 18).

Algorithm 1 Create an initial dataset by light-weight filtering

Input: m, Dataset $\mathcal{D} = \{(u^{(i)}, g^{(i)}, r_1^{(i)}, S_1^{(i)})\}_{i=1,\cdots,N}$, ▷ $N :=$ number of examples in the dataset.
Output: $\mathcal{D}' = \{(u^{(i)}, g^{(i)}, R^{(i)}, S_1^{(i)})\}_{i=1,\cdots,N}$ ▷ $R^{(i)} := \{r_1^{(i)}, \cdots, r_m^{(i)}\}$ ▷ Initial dataset

function INITDATASET($m, \mathcal{D}$)
  $\mathcal{D}' \leftarrow \varnothing$
  for $i : 1..N$ **do**
    $\mathcal{P} \leftarrow \{r_1^{(j)}\}_{j=i,\cdots,i-1,i+1,\cdots,N}$ ▷ All the responses in $\mathcal{D}$ but $r_1^{(i)}$
    `# (1) Remove too similar responses`
    for $j : 1..N$ **do**
      if i=j **then**
        continue
      if Overlap$(u^{(i)}, u^{(j)}) \geq 0.75$ **or** Overlap$(g^{(i)}, g^{(j)}) \geq 0.75$ **or** EmbSim$(u_1^{(i)}, r_1^{(j)}) \geq 0.5$) **then**
        Remove $r_1^{(j)}$ from $\mathcal{P}$
    `# (2) Pick` $m-1$ `similar responses`
    $R^{(i)} \leftarrow \{r_1^{(i)}\}$
    for $j : 1..m-1$ **do**
      Sample $r \in \mathcal{P}$
      Add r to $R^{(i)}$
      `# (3) Remove similar responses from the pool`
      for all $r' \in \mathcal{P}$ **do**
        if Overlap$(r, r') \geq 0.75$ **then**
          Remove r' from $\mathcal{P}$
    Add $(u^{(i)}, g^{(i)}, R^{(i)}, S_1^{(i)})$ to $\mathcal{D}'$
  return $\mathcal{D}'$

C.2 Situation Selection

Next, we update S_1, which only contains relevant information to u and r_1, to include l statements in total such that some of them are associated with distractors or not directly related to the conversation. Otherwise, reference responses can be easily identified by superficial clues. Having irrelevant situation statements is also for simulating real use cases, where a conversational system has access to a wide range of sensory information or external APIs, but most of them are unimportant for addressing a user's request.

It is required that (a) additional situation statements do not disqualify the reference response, and (b) they do not contradict others. To this end, we again use sentence embeddings with keyword-based heuristics. We first combine the statements associated with distractor responses and create a pool of candidates. Here, we drop statements that are similar to the response candidates in terms of the overlap coefficient of content words with a threshold of 0.75. We also used manually defined keywords to discard situation statements that tend to contradict others (e.g., the time is midnight, the user is injured, etc.). We then iterate over six categories and pick situation statements from the pool one by one. We score statement s of category c using the function below:

$$f(s; R, S') = \max_{r \in R} \text{EmbSim}(s, r) \quad (2)$$
$$- \max_{s' \in S'_c} \text{EmbSim}(s, s') \quad (3)$$
$$- \frac{1}{2} \max_{s' \in S'_{\mathcal{C} \setminus \{c\}}} \text{EmbSim}(s, s'), \quad (4)$$

where S' is the current situation statements, $S'_c \subset S'$ represents the statements in S of category c, and $\mathcal{C}$ denotes a set of situation categories. We pick distractor statements until we exhaust all the candidates in the pool or the maximum score does not reach 0. We then draw statements from the entire dataset in the same way until $|S|$ reaches $l = 12$. For time, date, behavior, and location categories, we pick zero or one statement as those categories are not likely to have more than one value.

Algorithm 2 Adversarial filtering (AF) for R

Input: m, Dataset $\mathcal{D} = \{(u^{(i)}, g^{(i)}, r_1^{(i)}, S_1^{(i)})\}_{i=1,\cdots,N}$, ▷ $N :=$ number of examples in the dataset.
Output: $\mathcal{D}' = \{(u^{(i)}, g^{(i)}, R^{(i)}, S_1^{(i)})\}_{i=1,\cdots,N}$ ▷ $R^{(i)} := \{r_1^{(i)}, \cdots, r_m^{(i)}\}$

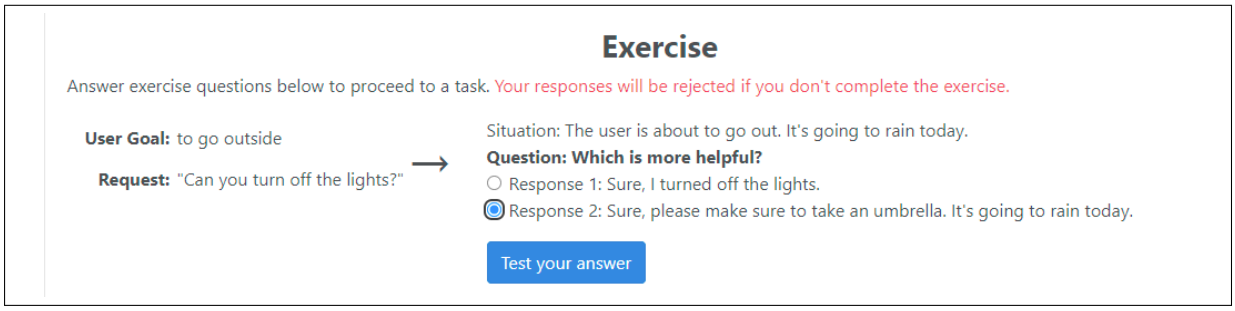
$\mathcal{P} \leftarrow \{(r_0)_i\}$ ▷ All responses in $\mathcal{D}$
`(1) Create an initial dataset` D_0
$\mathcal{D}_0 \leftarrow$ INITDATASET$(m, \mathcal{D})$ ▷ See Algorithm 1
`(2) Run AF for` J `rounds`
for $j : 1..J$ **do** ▷ We set $J = 3$
  Split $\mathcal{D}_{j-1}$ into K-folds $\{(\mathcal{T}^k, \mathcal{V}^k)\}_{k=1,\cdots,K}$ ▷ We set $K = 10$
  for $k : 1..K$ **do**
    Train a binary logistic regression classifier $\mathcal{M}$ on $\mathcal{T}^k$
    for all $(u, g, R, S_1) \in \mathcal{V}^k$ **do**
      for all $r \in R \setminus \{r_1\}$ **do**
        (f: $\mathcal{M}$'s score function)
        if $f(r) + \gamma \leq f(r_1)$ **then** ▷ γ is a margin, which we set to 0.05.
          Remove r from R
          Pick r' s.t. $f(r') - \gamma > f(r_1)$
          Add r' to R
          Update $\mathcal{V}^k$ with the new R
  $\mathcal{D}_j \leftarrow \bigcup_{k=1}^{K} \mathcal{V}_k$
$\mathcal{D}' \leftarrow \mathcal{D}_K$ ▷ End

D Situations

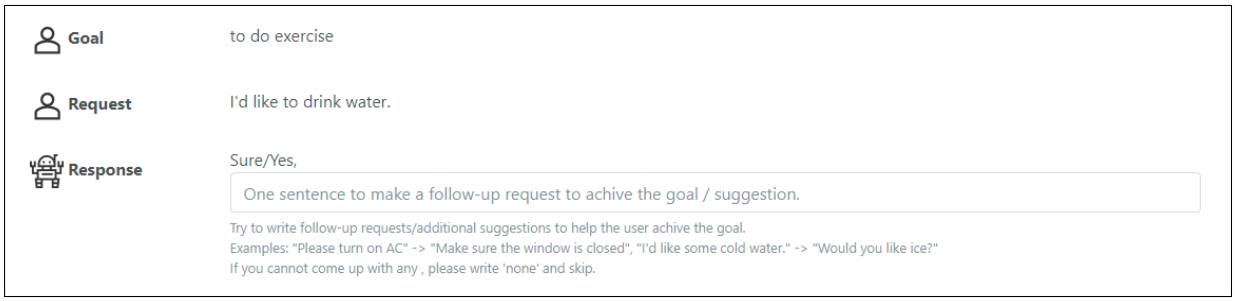
We provide the definitions and examples of situation categories in Table 4.

E Examples in SUGAR

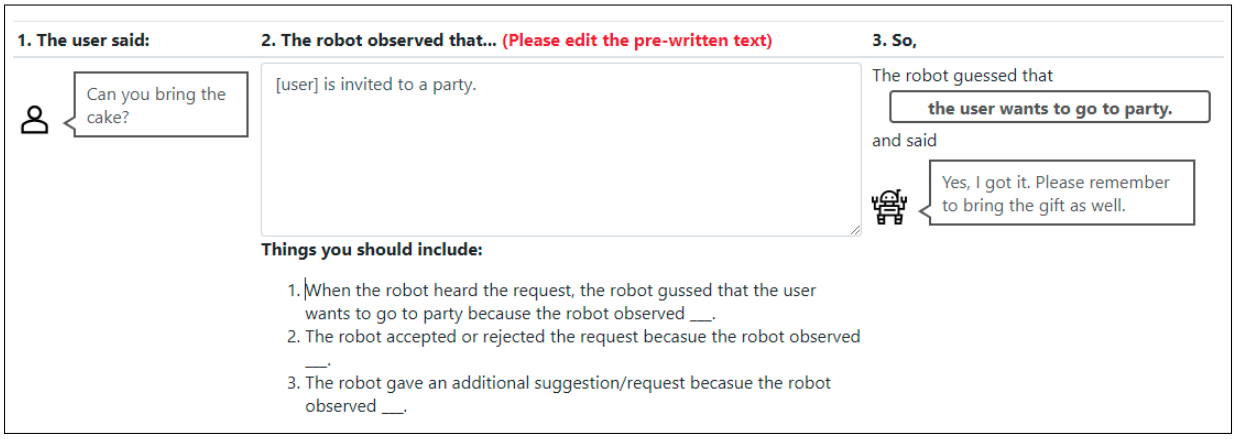
Table 5 shows one example in SUGAR.



(a) In addition to annotation guidelines, we provide one exercise question per task to train crowd workers. We used exercise questions in all the crowdsourced annotation tasks in our pipeline.



(b) In Step 2 (response collection), we instructed workers to write suggestions to achieve the given user goal.



(c) In Step 3 (situation collection), we guided workers to write observable facts for filling the gap among the provided user utterance, goal, and response.

Figure 5: Annotation interfaces for Step 2 (response collection) and Step 3 (situation collection)

Category	Definition	Example
Location	Information about the user's current location.	The user is home. / The user is at the entrance of a house.
Possession	Information about what the user possesses.	The user owns a car. / There are apples in the kitchen.
Time	Information about time.	It's midnight. / It's morning.
Date	Information about date and season.	It's the user's birthday. / It's summer.
Behavior	Information about the user's behavior.	The user has just woken up. / The user came back from jogging.
Environment	Information about non-user entities (person, objects, etc.).	The room temperature is hot. / The user's car has a flat tire.

Table 4: Definitions of the situation categories.

Utterance	Please turn on the TV.
Situations	It is evening now. [user] is home. [user] is in the living room. [user] is sitting on the couch. [user] has a TV in the house. [user] has an outfit on the bed. [user] has drinks and snacks in the kitchen. [user] has game cards on the shelf. The TV is off. [someone]'s birthday is today. There are several sports games available to watch. There is a basketball game scheduled.
Responses	Sure. Would you like me to check today's sports listings? *(Best)* Sure. Shall I pour a drink and bring some snacks for the game? *(Acceptable)* Sure, shall I select an outfit for you? *(Bad)*

Table 5: Response selection example in SUGAR